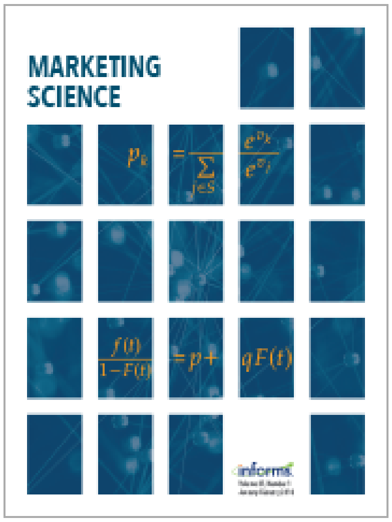

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Profiting from the Decoy Effect: A Case Study of an Online Diamond Retailer

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Abstract. The decoy effect (DE) has been robustly documented across dozens of product categories and choice settings using laboratory experiments. However, it has never been verified in a real product market in the literature. In this paper, we empirically test and quantify the DE in the diamond sales of a leading online jewelry retailer. We develop a diamond-level proportional hazard framework by jointly modeling market-level decoy–dominant detection probabilities and the boost in sales upon detection of dominants. Results suggest that decoy–dominant detection probabilities are low (11%–25%) in the diamond market; however, upon detection, the DE increases dominant diamonds' sale hazards significantly (1.8–3.2 times). In terms of the managerial significance, we find that the DE substantially increases the diamond retailer's gross profit by 14.3%. We further conduct simulation studies to understand the DE's profit impact under various dominance scenarios.

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1. Introduction

The decoy effect (DE; Huber et al. 1982), also called the attraction or asymmetric dominance effect, refers to the phenomenon of consumers having different preferences for existing choice alternatives with and without dominated (i.e., decoy) options in their choice sets. By design, these decoys are inferior to some, but not to all, existing choice options. When such decoys exist, all else equal, dominant options' choice likelihoods get larger compared with cases when the decoys are not present. Since its introduction, the decoy effect has become one of the most popular and frequently cited context effects in the consumer behavior literature, and it has been thoroughly examined across dozens of product categories and choice domains using laboratory experiments (see, e.g., Huber et al. 1982, Huber and Puto 1983, Wedell 1991, Lehmann and Pan 1994, Royle et al. 1999).

Despite its popularity, the DE's practical validity has been severely challenged recently by a series of unsuccessful replication attempts that shed light on the limits and boundaries of the effect. Frederick et al. (2014) showed that the DE can be observed only in very stylized settings, such as the presentation of two products with two numerically depicted attributes. Yang and Lynn (2014) provided additional support to these findings and questioned whether the DE has any practical significance or is just an experimental artifact. The lack of documentation on the practice of the DE in product markets was noted by Huber et al. (2014), and this has further put the practical validity and significance of the DE into question. In this paper, in response to these recent studies, we provide strong empirical evidence that not only validates the DE in a real product market but also illustrates its managerial significance through quantifying the substantial profit impact.

Even though it has been almost four decades since the DE was introduced, to the best of our knowledge, there has been no empirical study that tests and quantifies the DE with field data. To achieve this, one must consider and resolve a few key challenges. First, a researcher needs to *calibrate* decoy–dominant relationships among product alternatives. Because products typically have horizontal attributes—such as brand, taste, size, and packaging—and consumers have heterogeneous preferences for them, decoys to some consumers may not be decoys to others. Therefore, in most product markets, strict decoy–dominant relationships may not exist, let alone permit calibration. Second, consumers should be able to *detect* the decoy–dominant relationships. Unlike in laboratory experiments where alternatives with only two or three attributes are presented, choice scenarios in real life are far more complex: in a typical consumer product category, alternatives have a much larger number of attributes, for example, brand, size, design, color, weight, packaging, taste, and price, to name a few. Thus, it is much harder for consumers to fully evaluate the trade-offs and detect existing decoy–dominant relationships, so that, as noted in Huber et al. (1982, p. 95), "the effect may be lessened," and the lack of detection becomes one important mitigating factor of the DE (Huber et al. 2014). For consumers to detect decoy–dominant relationships, the choice decision must be salient and require enough cognitive processing that consumers' preferences can be constructed rather than already revealed (Huber et al. 2014). For example, for trivial decisions, consumers may just make their choices without paying much attention to the alternatives; consequently, they may not be able to detect existing decoys/dominants. Similarly, for repeat-purchase products, added decoys may not impact the choices of consumers who have already developed clear preferences for existing alternatives. From a technical perspective, Simonson (2014) further called for a systematic study separating decoy–dominant detection from the DE (i.e., sales boost in dominants upon detection). Last, it is quite possible that decoy pricing strategies, that is, introducing decoy–dominant relationships by charging higher prices for the same or inferior quality products, may not generate positive profit impacts for firms, which limits the existence of the *decoy pricing practice* in the real world.

Because of the abovementioned challenges, to empirically test and quantify the DE, we need data from a product category (1) with a reasonably small number of vertical product attributes, (2) that is important to consumers but not repeatedly purchased, and (3) that has the decoy pricing practice. The online diamond market is a highly appropriate case for this purpose: diamonds are commodity-type products with quality clearly defined on a few vertical attributes such as carat, color, cut, and clarity (the four Cs (4Cs)); diamond purchases are important but not repeated lifetime decisions; and, finally, we frequently observe decoy pricing patterns in the online diamond market.

We use diamond pricing and sales data from a major U.S. online jewelry retailer to empirically test the DE's existence, quantify its magnitude, and show its significance for firm profitability. We validate that a diamond's value is predominantly determined by its most important vertical attributes, that is, the 4Cs. Yet, we also observe significant price variation in the market for diamonds with the same characteristics, and we construct dyadic decoy–dominant relationships among diamond pairs based on their 4Cs and prices for our analysis. Data patterns show that dominants have significantly larger sale probabilities than diamonds that are neither decoys nor dominants, whereas the opposite is true for decoys. The effect for dominants, interestingly, is double that for decoys (29% versus 14%). Sales share regressions reveal that increasing the proportion of dominants in the market would extract a disproportionally larger sales share from other diamonds. These data patterns are consistent with the predictions of the DE but could also be explained *qualitatively* by alternative mechanisms such as the reference price effect (RPE) and consumer search. We develop formal statistical tests to show that, *quantitatively*, there are strong statistical supports favoring the DE over the reference price explanation and that the observed price variation are consistent with the DE coexisting with consumer search but cannot be explained solely by consumer search.

Given the data providing evidence of the DE, we formally develop a proportional hazard framework in our empirical analysis. Modeling the impact of decoy diamonds on sales of their dominants requires us to separate the market-level decoy–dominant detection from the sales boost once diamonds are detected as dominants. To achieve that, we incorporate two critical components into our proposed hazard framework: *market-level decoy–dominant detection probability* and *dominant boost hazard* upon dominant detection. Thus, in our setting, upon the dominant detection, the dominant boost hazard component is used to test the existence and measure the magnitude of the DE.

In the estimation, we use a diamond's characteristics, daily demand factors, competition from other similar diamonds, and the observed decoy–dominant structure to control for the differences in the sale hazards of diamonds. To capture potential consumer heterogeneity in response to decoy pricing, we divide the diamonds into three price segments (low, \$2K–\$5K; medium, \$5K–\$10K; and high, \$10K–\$20K) and estimate segment-specific detection probabilities and sale boosts upon dominant detection. Furthermore, to capture the unobserved heterogeneity and correlations in diamond sales, we use a diamond-level random effect specification. Results suggest that the market-level detection probability for a decoy (or dominant) diamond is quite low, ranging from 11% in the high-price segment to 25% in the low-price segment. The low decoy–dominant detection probabilities confirm that modeling the detection probabilities explicitly is required to quantify the DE accurately. As opposed to low detection probabilities, upon detection, we find that a dominant diamond's sale hazard gets 2.7, 1.8, and 3.2 times larger in the low-, medium-, and high-price segments, respectively. This finding validates the DE in the field in response to recent studies questioning this aspect, including Frederick et al. (2014) and Yang and Lynn (2014).

Next, we quantify the profit impact of the DE and find that the DE improves the retailer's gross profit by 14.3%. This finding shows that the DE is not only real but also highly substantive managerially. Finally, through additional simulation studies, we show that the profit impact of the DE gets larger as the number of decoys increases, as the price variation increases, and as the market-level detection probability remains similar, decreases, and increases in the low-, medium-, and high-price segments, respectively.

To reiterate our contribution, we advance the literature on the DE by empirically separating the market-level decoy–dominant detection from the DE boost of decoys on dominants. More importantly, for the first time in the literature, we (1) validate the existence of the DE in a real market, (2) quantify its magnitude across different segments, and (3) show its substantive profit impact. This paper thus attenuates the recent concerns (Frederick et al. 2014, Yang and Lynn 2014) about the practical validity of this classical context effect beyond traditional laboratory settings.

2. Literature Review

This paper contributes to two streams of literature: the general consumer behavior literature on context-dependent choices (in particular, the DE) and the empirical consumer choice–modeling literature in marketing and economics.

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 (IIA; Luce 1959). In contrast, consumer behavior researchers adopted the notion of constructed preference (Bettman et al. 1998), and they extensively documented context effects in consumer choices (Tversky 1972, Simonson 1989). The DE (Huber et al. 1982), which is a classic example of such context effects, violates both regularity and IIA principles. The DE has been examined across dozens of product categories and choice domains (see, e.g., Huber et al. 1982, Huber and Puto 1983, Wedell 1991, Lehmann and Pan 1994, Royle et al. 1999). Furthermore, the literature features investigations of cognitive processes and mechanisms moderating the DE and related context effects (see, e.g., Ratneshwar et al. 1987, Heath et al. 1995, Khan et al. 2011, Müller et al. 2014, Guo and Wang 2016, Morewedge et al. 2019). In this domain, Khan et al. (2011) studied the influence of choice construal on context effects and found that high construal as opposed to low increases the size of the DE. Morewedge et al. (2019) demonstrated that when comparisons of alternatives for choice makers require social comparisons, the context effects get stronger. Guo and Wang (2016) studied underlying causes of context effects and found that the response time can mediate the compromise effect, but the context information cannot. Despite an ample amount of research devoted to the DE, empirical testing and quantification of the effect in a real product market have not yet been achieved. Our paper fills this important gap by validating the DE in the field.

Despite its wide acceptance, the limits and boundaries of the DE have been debated by multiple studies recently. Frederick et al. (2014) stated that the DE could only be observed in very stylized laboratory settings with 2×2 numerical depictions of the products (two products with two attributes, with a decoy to one product added to the choice set later). Through 38 replication attempts, their study showed that when the product attributes are depicted with perceptual representations and verbal descriptions (rather than numerical), the DE weakens, dies, or gives way to the repulsion effect. Through 91 replication attempts, Yang and Lynn (2014) also showed that replicating the DE is very difficult with verbal and pictorial depictions of product attributes. With the current research, we respond to concerns of Frederick et al. (2014) and Yang and Lynn (2014) by providing strong empirical evidence of the existence of the DE in a real product market.

In response to Frederick et al. (2014) and Yang and Lynn (2014), Simonson (2014) underlined the importance of recognizing the set formation, that is, subjects being aware of decoy–dominant relationships, in being able to replicate the DE. He argued that consumers' choices require them to make multiple trade-off contrasts simultaneously. As a result, they may not be able to make their decisions based on existing decoy–dominant configurations, especially if such configurations are difficult to detect. He thus called for a systematic study on the drivers of decoy–dominant detection. In addition, Huber et al. (2014) recognized the lack of practice of the DE in today's product markets, noting that it is difficult to observe the DE in a real product market because the detection of decoys is typically very hard for consumers because of numerous alternatives with many attributes. With this research, we respond to the call of Simonson (2014) by explicitly modeling decoy–dominant detection in the studied online diamond market to empirically quantify the DE.

Our study is also closely related to consumer choice models in economics and marketing literature. Classic multinomial logit and probit models are built upon the revealed preference assumption; thus, they cannot directly account for context effects. A few empirical and analytical methods have been developed to incorporate the context effects into the choice models. Tversky (1972) formulated his well-recognized elimination-by-aspects model to account for the similarity effect. Kamakura and Srivastava (1984) modified the standard multinomial probit model 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) developed an analytical choice model to study the decoy and compromise effects under the loss-aversion assumption. Rooderkerk et al. (2011) proposed an empirical choice model that can incorporate decoy, compromise, and similarity effects all together. They used choice-based conjoint data to estimate their proposed model and showed that ignoring context effects significantly biases the choice model's predictions. Our paper adopts a different approach by developing a proportional hazard model that explicitly accounts for the DE using pricing and sales data.

Because the studied online diamond retailer offers a large number of diamonds daily, as discussed earlier, we separate the detection of decoys/dominants and the boost in sales upon dominant detection. Accordingly, our decoy/dominant detection component serves the role of a market-level consideration model. Because of that, our research is also related to the empirical literature that separately considers consumers' consideration sets and choices. Existing studies in that domain use consumer-level data to model consumers' consideration and choice decisions together. Some studies use purchase data only (see, e.g., Siddarth et al. 1995, Chiang et al. 1998, Van Nierop et al. 2010), whereas others use purchase along with search-related data (see, e.g., De los Santos et al. 2012, Honka 2014). Unlike those studies, we do not observe either purchase or search behaviors at the individual level. Hence, we derive a diamond-level hazard model from individual primitives, including consideration sets and choice. Consequently, our hazard specification provides a framework to separately estimate the market-level decoy/dominant detection from the DE by solely utilizing the aggregate product pricing and sales data.

In the following sections, we first describe the online diamond market, our data set, and how we calibrate the decoy–dominant relationships, then we provide data evidence on the existence of the DE in this market. We develop our model framework in Section 5, and we present the estimation results and illustrate the DE's managerial implications in the subsequent two sections. Finally, we conclude with a discussion of the current study's limitations and offer directions for future research.

3. Data

3.1. Online Diamond Market

Several U.S. retailers emerged in the online market for diamonds and jewelry products in the past two decades. We use panel data from a major retailer in this market. In fiscal year 2015, the retailer reported net sales of $480 million. According to industry reports, it has around 50% market share of the U.S. online diamond market, with sales approximately three times greater than those of its closest competitor. These figures clearly indicate that the retailer is the leading player in the market.

The retailer sells a variety of jewelry products to end consumers, such as unbranded loose diamonds, gemstones, engagement and wedding rings,[1] bracelets, necklaces, and earrings. Loose diamonds account for the core part of the retailer's business in terms of revenue contribution. According to its annual report, the retailer works with dozens of diamond suppliers worldwide under an exclusivity agreement, which requires suppliers to sell their diamonds only through the retailer's online channel, and not through their own or other competing online and offline channels. For listed diamonds, the identities of the suppliers are not revealed on the retailer's website so that consumers cannot differentiate diamonds based on the suppliers. Instead, consumers recognize only the retailer name as the diamond brand. To operate in a cost-efficient manner, the retailer uses a drop-shipping business model, that is, the retailer, in most cases, does not physically carry inventories of loose diamonds listed on its website. Instead, it purchases diamonds from corresponding suppliers when consumers place their orders with the retailer. Unlike traditional brick-and-mortar stores, where only a limited number of diamonds are available, this drop-shipping model allows the retailer to list more than a hundred thousand diamonds every day.

In this setting, suppliers list their diamonds on the retailer's website and establish wholesale prices. The retailer then adds a fixed percentage markup to the wholesale prices. Per the retailer's annual report, the markup is fixed at around 18%–20% for all diamonds. Because the retailer chooses a fixed margin over wholesale prices, the decoy pricing structure ultimately comes from the suppliers.[2] Nevertheless, consumers are expected to respond to the decoy–dominant structure regardless of whether the retailer or the suppliers create it. That being the case, as we demonstrate later, the dominance structure still affects the retailer's sales and ultimately its profitability to a large extent.

Because more than a hundred thousand diamonds are listed each day, the retailer provides filtering and sorting tools that help consumers to search for diamonds. On the website, a consumer can filter diamonds based on a desired range of diamond characteristics (such as price, carat, clarity, etc.). The website then returns a list of all the diamonds that fall into the filtering criteria on a single page in the default ascending price order. This one-page structure requires the consumer to scroll down to check all diamonds filtered. The web page displays each diamond in a row with its carat, cut, color, and clarity (the 4Cs) and price information. The consumer needs to further click into a diamond's details page to check other less significant characteristics such as symmetry and polish. The website also allows the consumer to sort the diamonds based on any one of the 4Cs or price. Given abundant diamonds from the retailer, the consumer would still face a long list of diamonds (hundreds to thousands) even after a few rounds of filtering and sorting. The list typically includes many decoys and dominants that are not easy to detect without laborious investigation. In addition, because consumers are presented with a list of diamonds according to their set criteria, this search process resembles the nonsequential search that is consistent with our derivation of the diamond-level hazard model from individual primitives (see Web Appendix B for the details).

3.2. Data Description

We construct a panel data set of diamond prices and sales from this online retailer. We collect our daily data from the retailer's website through a web crawler for the period from February 2011 to September 2011. For each diamond listed during our sample period, we observe the diamond's inherent physical characteristics and daily prices until the diamond is sold. In the data, diamond prices typically change over time: on average, each diamond's price changes once every 21 days, conditional upon it being unsold. Figure 1 provides an example of price dynamics among three 1.0-carat diamonds from the day of introduction in the market till the end of the observation period.

As seen in Figure 1, the diamond prices can go up and down, and each diamond may have a unique price pattern over time. We infer that a diamond is sold through the retailer's website on the last day it is listed as available, based on its unique stock-keeping unit (SKU)number.[3] On average, it takes about 50 days to sell a diamond.

In our analysis, we focus specifically on round-shaped diamonds with prices ranging between \$2K and \$20K. Round-shaped diamonds are the most popular ones among those listed (74%) and sold (78%).[4] Diamonds in different price ranges might be more attractive to different segments of buyers with various budget levels. To account for the potential heterogeneity in the DE across consumer segments, we further divide the diamonds into low-price (\$2K–\$5K), medium-price (\$5K–\$10K), and high-price (\$10K–\$20K) segments based on their first-day market prices.

Before calibrating the decoy–dominant structure, we first examine what determines diamond prices. We run a linear regression with (log of) daily diamond prices as our dependent variable and the diamonds' physical characteristics as independent variables to uncover the secret diamond-pricing formula. To control for potential demand variation across periods, we also add day fixed effects to the regression. We report the regression results in Table 1. The adjusted R^2 measure for the model with 4Cs, along with day fixed effects, is as high as 96.67%. Individual regressions for each day yield adjusted R^2 measures ranging between 94.92% and 96.57%. The results provide evidence that the 4Cs are the predominant attributes in determining diamond prices.

To further check the robustness, we ran several regressions by incorporating other diamond attributes, such as symmetry and polish, into our regression model. Overall, the R^2 measure does not improve. Moreover, these additional variables have mostly insignificant estimates that are notably smaller in magnitude compared with the 4C estimates. For example, the implied price difference contributed by symmetry and polish turns out to be less than 0.5%. Thus, we have strong statistical evidence to conclude

Figure 1. (Color online) Diamond Price Patterns over Time

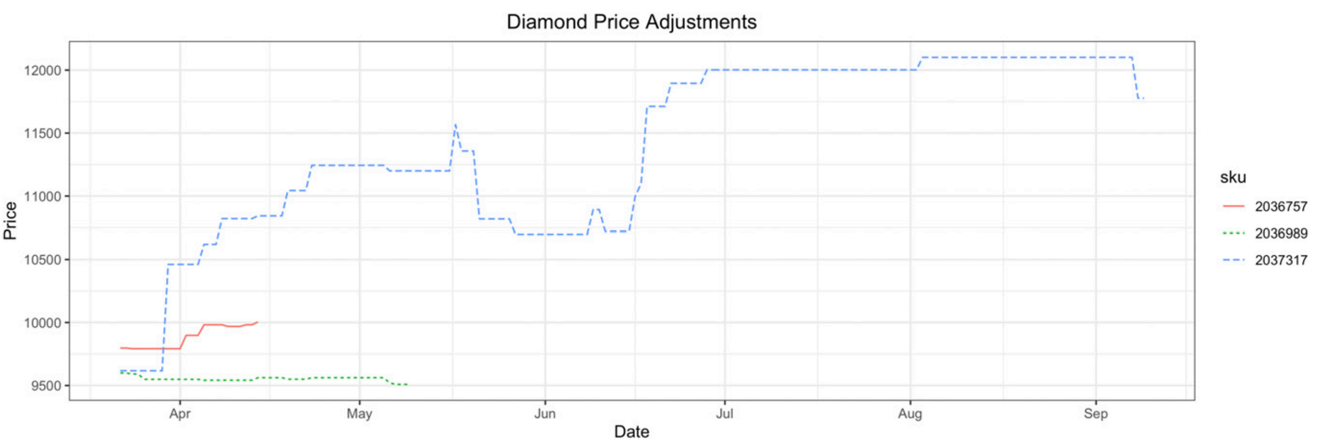

Table 1. Diamond Price Regression Model: ln(*Price*) on 4Cs and Day Fixed Effects

Variable	Estimate	S.E.
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 (low to high)		
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
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	
Adjusted R^2	96.67%	
Adjusted R^2 without daily dummies	95.27%	
Adjusted R^2 with daily separate regressions	94.92%–96.57%	

Note. S.E., Standard error.
**Significant at the 0.05 level.

that 4Cs of a diamond can represent its quality very precisely. Accordingly, in our analysis, we label each unique 4C combination as a *grade*.

Characterizing a diamond as a combination of its 4Cs and price is, indeed, quite consistent with industry reports on diamond valuations and with articles educating consumers on purchasing diamonds. Even though the variation in diamonds' physical attributes explains a large portion of the price variation, we still observe significant within-grade and within-day price variation. Specifically, in the data, the average of the ratios of price standard deviation to the mean price at each day–grade combination is 0.1, indicating a sufficiently large within-grade and within-day price variation. This variation is essential to characterizing the dyadic decoy–dominant relationship among every diamond pair, as discussed next.

3.3. Dominance Construction

By definition, a diamond B is a decoy to another diamond A when B is inferior to A in at least one attribute but has no superior attribute. In our specific setting, we define a diamond as a decoy under two conditions: (1) in terms of 4Cs, B is inferior in at least one attribute to A and has no attribute superior to A but has the same or a higher price than A, and (2) B has the same 4Cs as A but is priced at least 5% higher.[5] Under the two decoy definitions, for any two diamonds on a particular day, we define the relationship between them as follows: A dominates B ($A \succ B$), B dominates A ($B \succ A$), and no dominance ($A \sim B$).

In our data sample, every pairwise decoy–dominant relationship between all listed diamonds is constructed for each day.[6] For a particular diamond j, for each day t, we create two measures: number of diamonds that are decoys (N_{jt}^{Decoy}) and dominants ($N_{jt}^{Dominant}$) to that diamond. The median number of decoys and dominants that a diamond has is seven in the data, and the distribution is right skewed. Because the number of diamonds varies across different grades significantly, there exist large variation in the number of decoys/dominants across grades. Hence, we normalize the two measures by dividing them by the number of diamonds in the grade on the same day and label the grade-level percentage measures of decoys and dominants as R_{jt}^{Decoy} and $R_{jt}^{Dominant}$, respectively.

4. Data Evidence of the DE

In this section, we discuss some data patterns and reduced-form analyses that are suggestive of the DE. We show that important data patterns cannot be

Table 2. Summary Statistics Across Diamond Types

Diamond type	Diamond-day observations	Daily percentage sales (%)
Neither decoy nor dominant	27,077	1.96
Decoy only	404,283	1.68
Dominant only	340,456	2.53
Both decoy and dominant	1,945,009	2.08
Total	2,716,825	2.07

solely explained by alternative mechanisms such as the reference price effect or consumer search without considering the DE.

4.1. Dominance Types and Diamond Sales

Based on the dominance construction, on day t, diamond j can belong to one of the four mutually exclusive groups: (1) neither decoy nor dominant, $R_{jt}^{Decoy} = 0$ and $R_{jt}^{Dominant} = 0$; (2) decoy only, $R_{jt}^{Decoy} = 0$ and $R_{jt}^{Dominant} > 0$; (3) dominant only, $R_{jt}^{Decoy} > 0$ and $R_{jt}^{Dominant} = 0$; and (4) both decoy and dominant, $R_{jt}^{Decoy} > 0$ and $R_{jt}^{Dominant} > 0$. The middle column of Table 2 shows the count of diamond-day observations for each diamond type. Because of the significant within-grade price variation, we observe that a majority of the diamonds fall into the *both decoy and dominant* type. However, even in the smallest group, that is, *neither decoy nor dominant*, we have a sufficient number of observations (27,077) to allow the identification of our model, as we discuss later.

We summarize the percentage of diamonds sold in the total diamond-day observations across different diamond types in the last column of Table 2. Each cell is calculated by dividing the number of diamonds sold in each diamond type by that type's total diamond-day observations. For example, there are 404,283 *decoy only* diamond-day observations, out of which 6,792 were sold, yielding the average sale probability of 1.68%. Table 2 shows that *decoy only* diamonds have the lowest average sale probability (1.68%), whereas the opposite is true for *dominant only* diamonds (2.53%). The *both* type diamonds have a slightly higher average sale probability than the *neither* type.

In addition, we explore how the overall dominance structure impacts the sales shares of different diamond types using two linear regressions. We use the daily sales share of decoys (in percentage) and the sales share of dominants as the dependent variables and include price-segment dummies and percentage of *decoy only* and percentage of *dominant only* diamonds in each segment as independent variables. Results reported in Table 3 show that the percentage of *decoy only* diamonds significantly increases the decoys' sales share, whereas the percentage of *dominant only* diamonds significantly increases the sales share of dominants but reduces that of decoys.

Qualitatively, the patterns presented in Tables 2 and 3 could be explained by reference price effect or consumer search. Dominants are in general more preferred by consumers because their prices are relatively lower than comparable diamonds, whereas the opposite is the case for decoys (reference price effect). Beyond the relative price disadvantage, a *decoy only* diamond may also be detected as a decoy by a segment of consumers who search extensively, and it would never be purchased upon detection, leading to a further reduction in the sale probability (consumer search). Notably, the average sale probability of a decoy is still much larger than zero; thus, it is critical to control for decoy detection in our analysis. The sales share regression results in Table 3 are also directionally consistent with consumer search, because having relatively more *decoy only* diamonds in the market would reduce the chances of consumers discovering these decoys along with their dominants. In other words, as there is a larger share of *decoy only* diamonds, the size of the market segment detecting them as decoys is expected to decrease, leading the sales share of decoys to increase. Similarly, as the percentage of *dominant only* diamonds increases, consumers are more likely to include them in their search process, leading to an increase in the sales share of dominants.

Quantitatively, however, the magnitude of differences in the average sale probabilities across the diamond types and the magnitude of the regression estimates could be suggestive of additional effects beyond reference price and consumer search. The average sale probability difference between a *dominant only* and a *neither* type diamond (0.57%) is twice

Table 3. Diamond Sales Share Regression

	Decoy sales share		Dominant sales share	
Variable	Estimate	S.E.	Estimate	S.E.
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
Adjusted R^2	0.118		0.117	

Notes. The average values of *% decoys* and *% dominants* are 0.14 and 0.13, respectively. S.E., Standard error.
**Significant at the 0.05 level.

the difference between a *neither* type and a *decoy only* diamond (0.28%). Because buying decoys and dominants can be seen (by consumers) as monetary losses and gains, respectively, based on the prospect theory (Tversky 1972), reference price effect would predict the exact *opposite* pattern, that is, the former probability difference is expected to be smaller than the latter. Consumer search, on the other hand, could explain the significant reduction in the average sale probability for decoys (due to the segment detecting them never purchasing them), but it could hardly explain the significant boost in the sales of dominants, especially when the effect is twice that of decoys. In addition, we would expect the sales share of dominants to increase proportionally with the increase in the percentage of dominants based on random consumer search, yet the estimated elasticity is as high as 1.97, significantly larger than 1.0, suggesting that including additional *dominant only* diamonds would extract a disproportionally larger sales share from other diamonds. All this evidence suggests that there is a significant boost effect in the sale probabilities for dominants, which is not completely explained by reference price effect or consumer search, yet is very consistent with the predictions from the DE.

We further develop formal statistical tests to show evidence consistent with the DE instead of reference price effect and beyond consumer search explanations in the following subsections.

4.2. Decoy Effect vs. Reference Price Effect

The marketing literature has extensively examined the importance of relative price comparisons in consumers' purchase decisions (Monroe 1973). The reference prices could be formed based on contextual factors such as the distribution of market prices (Biswas and Blair 1991, Rajendran and Tellis 1994), or temporal anchoring stimuli such as a product's past prices (Lynch et al. 1991, Rajendran and Tellis 1994). In our particular context, given that diamonds are not repeat-purchase products and there are thousands of diamonds available each day, it is more likely that consumers form reference prices based on contextual factors rather than temporal anchors (Kalyanaram and Winer 1995). When consumers use the average grade-level price as the reference, the prospect theory (Kahneman and Tversky 1979) predicts that (1) consumers will respond positively to dominants (in the monetary gain domain) and negatively to decoys (in the loss domain), and (2) the response to decoys will be stronger than that to dominants (of the same size) because of loss aversion.

Even though the reference price effect and decoy effect may look similar at first glance, we would like to emphasize a few notable differences that we illustrate in Figure 2. First, the RPE gradually vanishes as the monetary gains or losses approach zero. In other words, the RPE predicts the sale probability function to be continuous as the price of a diamond moves from the gain to the loss domain (i.e., around the reference price point). To the contrary, under the decoy effect, we expect a discrete jump in the sale probability function around the reference point—because, as a nondecoy diamond turns into a decoy one, a market segment emerges with zero probability of purchasing it upon detection, resulting in a downward jump in the sale probability function around the decoy threshold price. The opposite becomes the case as a nondominant

Figure 2. (Color online) Sale Probability Function According to Different Theories

diamond turns into a dominant one: a market segment with significantly large purchase probability emerges, and this segment induces the sale probability to jump upward around the dominant threshold price. Thus, the sale probability function is expected to be discontinuous around the reference price point with the decoy effect. Furthermore, the magnitude of the discrete jump (around the reference price) depends on the market-level detection probabilities for decoys, and on both the market-level detection probabilities and the strength of the DE (i.e., sales boost) for dominants.

Second, the predicted relative effects across the domains (loss to gain/decoy to dominant) are different under the RPE and the DE. The RPE predicts the slope of the sale probability function to be steeper for decoys than for dominants. We would argue the opposite is more likely to be the case under the DE explanation, because further reducing the prices of dominants would not only increase the size of the consumer segment who detects them as dominants but also elevate the attractiveness of these dominants (i.e., the sales boost level) upon detection. However, as prices of decoys increase, it gets easier for consumers to detect them, that is, the size of the market segment that fails to detect them decreases. Note that only this shrinking segment would respond to the increasing prices (or monetary losses) of decoys because the other segment would eliminate them upon detection irrespective of the loss amount's size. Therefore, with the DE, the sale probability function is expected to have a steeper slope in the gain domain and a flatter slope in the loss domain.

We estimate three diamond-level logistic sales regressions to test whether our data support the DE theory rather than the RPE. The results of these three specifications are reported in Table 4. In the regressions, we control for the following variables: a diamond's 4Cs, daily demand effects such as weekday and holiday dummies, the Google search indexes for diamond-related keywords, and the number of diamonds in the same grade. We define the reference price as the average price of diamonds belonging to the same grade. Central to our test, we include separate intercepts and separate price slopes (*PGain* and *PLoss* as percentage differences relative to the reference price) for diamonds in the *Gain* and *Loss* domains in the first regression. We replace the definitions of *Gain* and *Loss* with *Dominant* and *Decoy*, respectively, and the relative prices with interactions with the *Dominant* and *Decoy* dummies in the second and third regressions. The difference between the last two specifications is that the definitions of *Dominant* and *Decoy* are based on whether a diamond has any decoys or dominants in specification (I), whereas in specification (II) we use a stricter definition of whether a diamond is a *decoy only* or *dominant only* type. The regression specifications follow the tradition in empirical tests of the RPE (Hardie et al. 1993, Bell and Lattin 2000).

The results show a very consistent pattern, with the price coefficient more negative in the gain/dominant domain than in the loss/decoy domain across the three regressions. The differences between the slopes (loss minus gain) are all significantly positive at the 0.05 level, as shown in the table. In addition, intercepts for dominants are significantly positive, whereas those for decoys are significantly negative, in the last two regressions, indicating the existence of a discrete jump around the reference price point. This is consistent with our earlier discussion about the role of the DE. Last, the models with the DE outperform the RPE-only model based on the Akaike information criterion (AIC). These results are all robust to alternative model specifications, such as separating the effects across the three price

Table 4. Diamond Sales Response Function with Logistic Regressions

	Gain/loss		Decoy/ dominant (I)		Decoy/ dominant (II)	
Variable	Estimate	S.E.	Estimate	S.E.	Estimate	S.E.
Controls	Included		Included		Included	
Intercept—*Gain*	−0.028	0.019				
Intercept—*Loss*	−0.006	0.019				
Intercept—*Dominant*			0.152**	0.014	0.140**	0.018
Intercept—*Decoy*			−0.186**	0.014	−0.205**	0.019
Slope—*PGain*	−2.444**	0.145				
Slope—*PLoss*	−1.733**	0.156				
Slope—*PGain* × *Dominant*			−1.491**	0.131	−1.831**	0.192
Slope—*PLoss* × *Decoy*			−1.059**	0.137	−0.567**	0.211
Slope difference (*Loss* − *Gain*)	0.686**	0.215	0.432**	0.218	1.264**	0.292
AIC	525,333		525,016		525,191	

Note. S.E., Standard error.
**Significant at the 0.05 level.

segments and including quadratic terms for relative prices. Overall, our test results show strong statistical support favoring the DE over the RPE, as illustrated in Figure 2.

4.3. Decoy Effect vs. Consumer Search

As Simonson (2014) emphasized, consumers' detection of decoy–dominant relationships is a precondition for the DE. Given the extremely large number of alternatives in the online diamond market, consumers rely on search to finalize their consideration sets. Thus, consumer search is an inherent component in our test for the DE (see Section 5). In this subsection, we develop a formal statistical test to check whether the data patterns can be solely explained by consumer search, or if there is evidence of the DE in addition to consumer search. Our test relies on the observed market price dispersion and sales information. We provide the details of this test in Web Appendix A. The intuition behind the test is that under pure consumer search without the DE, a supplier sets prices to maximize the expected profit of each individual diamond, and thus identical diamonds with different prices are expected to generate the same level of profit for the supplier in equilibrium (Burdett and Judd 1983). However, if there is DE along with consumer search, a supplier needs to consider the price optimization beyond each individual diamond because decoys would serve as "loss leaders" helping the supplier get higher expected profits from the dominants. Consequently, one would expect the profit contribution of dominants to be higher than that of decoys.

Under the hypothesis of no DE (i.e., there is only search effect), we can utilize the observed prices and sales information to recover the cost of each diamond j on day t (c_{jt}) from the corresponding supply-side pricing optimality conditions. Recovered costs should be approximately the same for diamonds with identical 4Cs, and exactly the same for the same diamond over time. However, if there exists DE along with consumer search, because of the positive profit externality from decoys to dominants, the recovered costs from the optimality conditions will be higher for decoys and lower for dominants, compared with their true costs. This essentially leads to a positive correlation between the diamonds' recovered costs and their relative price levels. The test of the pure search effect versus the search effect along with the DE thus becomes the same as testing whether recovered costs are increasing with relative prices. Accordingly, we conduct two statistical tests: (1) using cross-diamond price variation (labeled as Test I) and (2) using within-diamond price variation over time (labeled as Test II). Results (see Table A1 in Web Appendix A) consistently reject the null hypothesis of a pure consumer search explanation across all three diamond price segments. All the estimated coefficients of relative price levels (rp_{jt}) are positive and significant, and thus are directionally consistent with the hypothesis supporting the existence of the DE together with consumer search in our data.

To sum up, our data analyses yield the following results: (1) A diamond's sale probability largely depends on whether it is a decoy and/or a dominant. (2) It is critical to account for decoy–dominant detection in validating the DE. (3) There is suggestive evidence of the DE beyond alternative mechanisms of the RPE and consumer search. Hence, empirical investigation of the decoy phenomenon requires a deliberately developed model, which we introduce in the next section.

5. Model

We develop a diamond-level proportional hazard model to study daily diamond sales. We control for the effect of diamond characteristics and market demand and supply factors in a baseline *daily diamond sale hazard* component. We further capture the role of the DE on diamond sales with our *dominance hazard* component. Separating the DE from other factors that affect diamond sales is a challenging task because consumer-level search and purchase behaviors are unobserved in our setting. To achieve the objective, we derive our diamond-level proportional hazard from underlying consumer primitives including *consumer arrival process*, *search*, *consideration set formation*, and *conditional choice probabilities with the embedded DE*. Please see Web Appendix B for the details of our derivation including how the DE is embedded into consumers' conditional choice probabilities and how the proposed hazard specification is used to quantify the DE at the market level. Following this derivation, we use the following to denote the hazard that diamond j will be sold on day t:

$$h_j(t) = \psi_j\left(X_{jt};\beta\right) \cdot \phi_j\left(D_{jt};\gamma\right), \tag{1}$$

where $\psi_j(\cdot)$ and $\phi_j(\cdot)$ are the daily diamond sale hazard and the dominance hazard components, respectively. We next discuss each component with the choice and rationale of the corresponding variables. We present an overview of the variables in Table 5.

5.1. Daily Diamond Sale Hazard

The daily diamond sale hazard component ($\psi_j(\cdot)$) captures the baseline daily diamond sale likelihoods without the DE consideration. In general, a diamond's daily sale likelihood depends on a few essential factors. First, because diamond buyers with various budgetary constraints have different preferences for the 4Cs, diamonds at different price levels and grades are likely to have different sale likelihoods. Second, the sale likelihood of a diamond is

Table 5. List of Variables Used in Model Estimation

	Variable name	Description
Daily diamond sale hazard (X_{jt})		
K_j	Diamond segment	Segment dummies, low (\$2K–\$5K), medium (\$5K–\$10K), and high (\$10K–\$20K)
Z_t	Google search indexes	Daily Google search trends index of diamond-related keywords
	Weekday dummies	Dummy variables of weekdays
	Holiday dummies	Dummy variables for Valentine's Day and federal holidays
H_j	Diamond characteristics	Dummy coded cut, color, and clarity of diamond *j*; log of carat of diamond *j*; indicator of carat 1.0 for diamond *j*
p_{jt}	Diamond price	Daily price of diamond *j* (in \$1,000)
W_{jt}	Daily competitiveness	Log of number of diamonds of the same grade
Dominance hazard (D_{jt})		
rp_{jt}	Relative price index	% price difference between diamond *j* and its grade-level average
R_{jt}	Percentage decoys	Number of diamond *j*'s decoys/number of diamonds in *j*'s grade
	Percentage dominants	Number of diamond *j*'s dominants/number of diamonds in *j*'s grade
sp_{jt}	Price standard deviation	Standard deviation of prices in diamond *j*'s grade on day *t*

expected to decrease as the number of similar diamonds listed increases. Third, because consumers may have different purchase intentions on different days, the sale likelihoods of diamonds may also change over time. For example, consumers may have different purchase likelihoods on different days of a week, or special occasions and holidays. Accordingly, we model the daily diamond sale hazard $\psi_j(\cdot)$ as an exponential function of (1) diamond *j*'s price segment (dummy-coded low, medium, or high price, labeled as K_j); (2) dummy-coded cut, color, and clarity, log of carat[7] (labeled as H_j); (3) its price (labeled as p_{jt}); (4) log of the number of diamonds with the same 4Cs (labeled as W_{jt}); and (5) Google search trends to capture consumer interest and weekday and holiday dummies (labeled as Z_t).

With $X_{jt} = \{K_j, H_j, p_{jt}, W_{jt}, Z_t\}$ and $\beta = \{\beta_K, \beta_H, \beta_p, \beta_W, \beta_Z\}$, we define the daily diamond sale hazard as

$$\psi_j(X_{jt};\beta) = \exp\left(b_j + K_j\beta_K + H_j\beta_H + p_{jt}\beta_p + W_{jt}\beta_W + Z_t\beta_Z\right). \quad (2)$$

We use a random effect specification, that is, $\exp(b_j) \sim \Gamma(1, \sigma^2)$, to allow the intercept term to be diamond specific.[8] The random coefficient specification helps in capturing unobserved correlations in sale likelihoods among diamonds. This is important in our setting because if there exist demand shocks affecting two diamonds at the same time, without such specification, the effect of one diamond on the other one's demand would likely be inferred with biases. We adopt the Gamma distribution assumption following Lancaster (1979), where the random effect can be analytically integrated out.

5.2. Dominance Hazard

We capture the DE by our dominance hazard component $\phi_j(\cdot)$. Per our derivation in Web Appendix B, a diamond's sale likelihood further depends on (1) the size of the market segment detecting it to be a decoy/dominant and (2) the sale boost upon it being detected as a dominant. We separate these two parts as the market-level decoy–dominant detection and the dominant boost hazard.

5.2.1. Market-Level Decoy–Dominant Detection. The likelihood of detecting decoys and dominants in the diamond market may depend on various context-related factors. First of all, it should naturally depend on the decoy–dominant structure in the market. As consumers typically sample diamonds based on their desired grades using the filtering and sorting tools, a diamond with a larger percentage of decoys/dominants in its grade would have a higher chance of being included together with its decoys/dominants in the consideration sets. Second, the relative price of a diamond in its grade matters because a diamond is more likely to stand out either on the top or the bottom of the returned lists under the default price-sorting design when its absolute relative price differences get larger. Third, diamond purchases are unique, first-time experiences for most consumers who have limited knowledge regarding diamond pricing. Thus, learning about the prices becomes an inherent part of their decision process. A greater variation in the prices of comparable diamonds indicates more opportunities to save, which will likely motivate consumers to spend more time on the retailer's site searching and comparing alternatives. Consequently, they will be more likely to detect existing decoy–dominant relations. As such, we expect the grade-level price dispersion to be another moderator of dominance detection. Based on the above rationales, we model the market-level decoy–dominant detection part of our dominance hazard as a function of the following variables: (1) percentages of decoys and dominants that diamond *j* has (R_{jt}^{Decoy} and $R_{jt}^{Dominant}$), (2) the relative price measurement (rp_{jt}), and (3) the price standard deviation in diamond j's grade (sp_{jt}).

We denote the *market-level decoy and dominant detection probabilities* as $\Pr_{jt}^{Decoy}(\cdot)$ and $\Pr_{jt}^{Dominant}(\cdot)$, respectively. Given $D_{jt} = \{K_j, R_{jt}^{Decoy}, R_{jt}^{Dominant}, rp_{jt}, sp_{jt}\}$, we model these two terms as follows:

$$\begin{aligned}\Pr_{jt}^{Dominant}(D_{jt};\gamma) &= I\left(N_{jt}^{Decoy} > 0\right)\\ &\quad\times \frac{\exp\left(V_{jt}^{Dominant}\right)}{1+\exp\left(V_{jt}^{Dominant}\right)},\\ \Pr_{jt}^{Decoy}(D_{jt};\gamma) &= I\left(N_{jt}^{Dominant} > 0\right)\\ &\quad\times \frac{\exp\left(V_{jt}^{Decoy}\right)}{1+\exp\left(V_{jt}^{Decoy}\right)},\end{aligned} \tag{3}$$

where $I(\cdot)$ is the indicator function, and $V_{jt}^{Dominant}$ and V_{jt}^{Decoy} are specified as

$$\begin{aligned}V_{jt}^{Dominant} &= K_j\gamma_0^{Dominant} + \gamma_1^{Dominant}\ln\left(R_{jt}^{Decoy}\right)\\ &\quad+ \gamma_2^{Dominant} I(rp_{jt} < 0)(-rp_{jt}) + \gamma_3^{Dominant}\\ &\quad\times sp_{jt},\\ V_{jt}^{Decoy} &= K_j\gamma_0^{Decoy} + \gamma_1^{Decoy}\ln\left(R_{jt}^{Dominant}\right)\\ &\quad+ \gamma_2^{Decoy} I(rp_{jt} > 0)(rp_{jt}) + \gamma_3^{Decoy} sp_{jt}.\end{aligned} \tag{4}$$

The intercept terms ($\gamma_0^{Dominant}$ and γ_0^{Decoy}) are modeled at each of the diamond price segments because decoy–dominant detection probabilities defined in Equation (3) might differ across various market segments with different consumer budgetary levels. The other γ's capture how the percentage measures of decoys/dominants, the relative price, and standard deviation of the grade-level prices would impact the decoy–dominant detection probabilities.

5.2.2. Dominant Boost Hazard. Upon a diamond being detected as a dominant, the size of the boost in its sale likelihood, that is, the DE, may also depend on a few important context-related factors. First, all else equal, dominants with more decoys are likely to become more *attractive* (the DE is also called the attraction effect) compared with diamonds with fewer decoys, especially when consumers engage in multiple comparisons. Second, based on the prospect theory (Kahneman and Tversky 1979), a consumer's purchase decision depends on whether the price paid is perceived as fair with respect to her reference price point. Because diamonds are not repeat-purchase products, a consumer is expected to form her reference price based on the prices of available diamonds rather than the past price histories (Mazumdar et al. 2005). Thus, upon detection of a dominant, we expect its sale likelihood to increase as the size of the price gain relative to comparable diamonds increases. Last, following our discussion on consumer learning in dominance detection, we expect consumers to spend less time as the variation of the grade-level prices decreases. Accordingly, we expect that with a smaller price dispersion, consumers become more likely to settle down with their detected dominants rather than continuing the search for other diamonds. As such, we expect the sale boost of a detected dominant to be more substantial as the within-grade price variation decreases. Given these rationales, we include the same set of variables as in the dominance detection component. We label $D_{jt} = \{K_j, R_{jt}^{Decoy}, R_{jt}^{Dominant}, rp_{jt}, sp_{jt}\}$ and define the dominant boost hazard Q_{jt} as follows:

$$\begin{aligned}Q_{jt}(D_{jt};\gamma) = \exp\Big[&K_j\gamma_0^{Boost} + \gamma_1^{Boost}\ln\left(R_{jt}^{Decoy}\right) + \gamma_2^{Boost}\\ &\times I(rp_{jt} < 0)(-rp_{jt}) + \gamma_3^{Boost} sp_{jt}\Big].\end{aligned} \tag{5}$$

Similar to the intercept term of the market-level decoy–dominant detection probabilities, we model the intercept term (γ_0^{Boost}) at each of the diamond price segments because the dominant boost sizes might differ across market segments. The other γ's capture how the percentage measures of decoys/dominants, the relative price, and standard deviation of the grade-level prices would impact the sales boost upon dominant detection.

Given market-level detection probabilities and dominant boost hazard specifications, we operationalize the dominance hazard as follows:

$$\phi_j(t|\cdot) = \begin{cases} 1 & \text{if } j \text{ is } \textit{Neither},\\ \left(1-\Pr_{jt}^{Decoy}\right) & \text{if } j \text{ is } \textit{Decoy Only},\\ \left(1-\Pr_{jt}^{Dominant}\right) + \Pr_{jt}^{Dominant} Q_{jt} & \text{if } j \text{ is } \textit{Dominant Only},\\ \left(1-\Pr_{jt}^{Decoy}\right)\left[\left(1-\Pr_{jt}^{Dominant}\right) + \Pr_{jt}^{Dominant} Q_{jt}\right] & \text{if } j \text{ is } \textit{Both}.\end{cases} \tag{6}$$

We would like to note that we make an implicit assumption in the derivation of the dominance hazard in Equation (6). We assume that once a consumer detects a specific diamond to be a decoy, she would never purchase it, as she can always choose the dominant one. This assumption is consistent with the existing literature. For example, Huber et al. (1982, p. 95) verified that fully informed subjects would seldom choose decoys in laboratory experiments. We argue that it is highly unlikely for a consumer to buy a detected decoy diamond given that diamonds are high-ticket products and the monetary cost of doing so is significant.

Equation (6) shows how the dominance hazard depends on a diamond's type: if it is *neither decoy nor dominant*, the DE has no impact on the sale hazard of the diamond, that is, the dominance hazard is normalized to one. If the diamond is of the *decoy only* type, it is considered only by the consumer segment that fails to detect it as a decoy under our assumption. Furthermore, the DE does not play a role in the sale hazard of the diamond given no detection, resulting in the overall dominance hazard being the size of this segment, that is, $\phi_j(\cdot) = 1 - \Pr_{jt}^{Decoy}(\cdot)$. For a *dominant only* type diamond, there exist two market segments: the segment that fails to detect the diamond as a dominant and the segment that is able to. The DE does not have any impact on the former segment (i.e., $Q_{jt}(\cdot) = 1$), whereas we expect a boost in sale hazard (i.e., $Q_{jt}(\cdot) > 1$) for the latter. The overall sale hazard thus becomes the expression in the third line of Equation (6). Finally, if the diamond is of the *both decoy and dominant* type, it is considered for purchase only by the consumer segment that fails to detect it as a decoy, with the size of the segment being $1 - \Pr_{jt}^{Decoy}(\cdot)$. Similar to the *decoy only* case, the remaining consumer segment never purchases it, that is, $Q_{jt}(\cdot) = 0$. The segment that fails to detect the diamond as a decoy can be divided into two subsegments: the subsegment that fails to detect the diamond as a dominant and the one that is able to do so. Similar to the *dominant only* case, the former subsegment with size $1 - \Pr_{jt}^{Dominant}(\cdot)$ will not be impacted by the DE, that is, $Q_{jt}(\cdot) = 1$, whereas the sale hazard from the other subsegment will be boosted by $Q_{jt}(\cdot) > 1$. Combining all the scenarios, for the dominance hazard, we have the expression in the last line of Equation (6).

5.3. Model Estimation

Based on the model components outlined above, we can further arrange the terms and derive the following log-hazard representation (see Web Appendix C for details):

$$\ln h_j(t) = \underbrace{b_j + X_{jt}\beta}_{\text{daily diamond sale hazard}} \underbrace{-I(Decoy)\ln\left(1+e^{D_{jt}^{Decoy}\gamma^{Decoy}}\right)}_{\text{dominance hazard of a decoy}} \underbrace{+I(Dominant)\left[\begin{array}{l}\ln\left(1+e^{D_{jt}^{Dominant}\left(\gamma^{Dominant}+\gamma^{Boost}\right)}\right)\\ -\ln\left(1+e^{D_{jt}^{Dominant}\gamma^{Dominant}}\right)\end{array}\right]}_{\text{dominance hazard of a dominant}}, \tag{7}$$

where $D_{jt}^{Decoy} = \{K_j, \ln R_{jt}^{Dominant}, I(rp_{jt} > 0)rp_{jt}, sp_{jt}\}$ and $D_{jt}^{Dominant} = \{K_j, \ln R_{jt}^{Decoys}, I(rp_{jt} < 0)(-rp_{jt}), sp_{jt}\}$. The effects of being a decoy and being a dominant on the sale hazards are clearly outlined in the last two terms of this representation.

Denote the total number of days from diamond j (in total, J diamonds) entering the 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. Following the derivation in Lancaster (1979) for the random effect hazard model, the total likelihood we use for estimation becomes the following:

$$L = \prod_{j=1}^{J}\left\{\left[I\left(T_j^s \le T_j\right)\left(S_j\left(T_j^s - 1\right) - S_j\left(T_j^s\right)\right)\right] \times \left[I\left(T_j^s > T_j\right)S_j\left(T_j^s\right)\right]\right\}, \tag{8}$$

where $S_j(t) = [1 + \sigma^2 \sum_{\tau=1}^{t} \bar{h}_j(\tau)]^{-\sigma^{-2}}$ is the survivor function and $\bar{h}_j(\tau)$ is the mean value of the hazard $h_j(\tau)$, where $b_j = 0$. Notice that $\lim_{\sigma^2 \to 0} S_j(t) = \prod_{\tau=1}^{t} e^{-\bar{h}_j(\tau)}$, that is, it reduces to the case without random effects. We estimate the model by using the maximum likelihood approach.

We now discuss a few properties of our model. First, the unit of our analysis is each diamond, which is different from classic choice models. Second, in terms of how to model the DE conditional on dominant detection, we choose to use a scalar function $Q_{jt}(\cdot)$. When $Q_{jt}(\cdot) > 1$, our specification becomes consistent with the DE theory, that is, upon detection, there is a boost in sales for dominant diamonds. In other words, under our framework, testing the existence of the DE becomes the same as testing whether $Q_{jt}(\cdot) > 1$. Details of this test are provided in Web Appendix B. Third, it is quite possible that consumers are heterogeneous, so we allow our daily diamond sale hazard $\psi_j(\cdot)$ and the dominance hazard $\phi_j(\cdot)$ to differ across different diamond price segments.

5.4. Model Identification

Our identification strategy relies on the fact that it takes different numbers of days to sell different types of diamonds (*neither decoy nor dominant*, *decoy only*, *dominant only*, or *both decoy and dominant*), or, equivalently, the sale hazards vary across different diamond types. Accordingly, we use different parts of the data to identify different components of our specification. First, based on the normalization in the first line of Equation (6), the sale hazard for the *neither* type equals the daily diamond sale hazard. Thus, we use the portion of the data regarding the sales of *neither* type diamonds with different K_j, H_j, W_{jt}, and Z_t in X_{jt} to identify the parameters β in the daily diamond sale hazard component. Second, conditional on the identification of β, we identify the parameters related to the detection probabilities and dominant boost hazard. Because decoy diamonds could be purchased only by the market segment that fails to detect them as decoys (see the second line of Equation (6)), we use the portion of the data regarding the sales of *decoy only* diamonds with different $R_{jt}^{Dominant}$, rp_{jt}, and sp_{jt} in D_{jt} to identify the parameters of the market-level decoy detection probabilities, that is, γ^{Decoy} (also see the second component of Equation (7)). Third, as seen in the third and fourth lines of Equation (6), it is not possible to separately identify the parameters of the market-level dominant detection probabilities ($\gamma^{Dominant}$) and of the dominant boost hazard (γ^{Boost}) because $\Pr_{jt}^{Dominant}$ and Q_{jt} are always bundled together in the form of $(1 - \Pr_{jt}^{Dominant}) + \Pr_{jt}^{Dominant} Q_{jt}$. To separately identify $\gamma^{Dominant}$ from γ^{Boost}, we make the following assumption: $\gamma^{Decoy} = \gamma^{Dominant}$; that is, all else equal, the market-level probability of detecting a diamond with n decoys as a dominant is identical to the probability of detecting a diamond in the same grade with n dominants as a decoy. Because the decoy–dominant relationships are calibrated at the diamond-pair level, the probability of discovering one diamond dominating another is the flip side of discovering that one is dominated by the other. Thus, it is reasonable to assume parameters quantifying the decoy and dominant detection probabilities in the diamond market to be the same.[9]

Based on this symmetric market-level detection assumption, and conditional on the dominant detection parameters ($\gamma^{Dominant}$) being identified, we use portion of the data regarding the sales of *dominant only* and *both decoy and dominant* type diamonds with different D_{jt} to identify the parameters of the dominant boost hazard, γ^{Boost}. In our empirical setting, the diamond prices change over days and subsequently the decoy–dominant structure also changes daily. This data variation empowers the identification of our model parameters (β, γ^{Decoy}, and γ^{Boost}). Finally, variation in the time it takes to sell diamonds with similar X_{jt} and D_{jt} enables identification of the unobserved heterogeneity parameter (i.e., σ^2).

In addition, the identification of the parameters relies on our exclusion restrictions. Specifically, we observe two types of variables in the data—the ones that are directly observable by consumers (such as diamond physical attributes and daily demand factors, that is, X_{jt}) and the ones that require extensive consumer search and comparisons (i.e., the context-related variables, D_{jt}). The daily diamond sale hazard component captures the baseline sale hazard of a diamond that does not depend on deliberate diamond comparisons. Hence, we exclude context-related variables (D_{jt}) in the modeling of this component. In contrast, the dominance hazard component captures the critical impact of potential context effect under study. Accordingly, we exclude the variables that are directly observable to consumers without extensive search (X_{jt}).[10]

Finally, given that the derived log-hazard specification is highly nonlinear, a valid concern is whether various components in the function can be identified accurately. We confirm that our statistical test of dominance is valid through Monte Carlo simulations (see details in Web Appendix D). We simulate diamond sales by using the proposed model specification under various detection and dominant boost levels. Estimation with these simulated datasets yields that we can correctly recover the assumed parameters with high precision. Furthermore, we show that the dominance hazard component is not identifiable without the existence of the dominance effect in the simulated data, assuring that the quantified DE is not an artifact of the specific nonlinear functional form.

6. Results

6.1. Main Estimation Results

We report our estimation results in Table 6. Results suggest that the daily diamond sale hazard increases with the diamond's carat size. In addition, 1.0-carat diamonds are significantly easier to sell. As expected, as a diamond's price increases, its sale hazard decreases. Regarding the cut, color, and clarity attributes, we observe an inverse-U-shaped relationship; that is, the daily diamond sale hazard is the largest for diamonds with moderate cut, color, and clarity levels.[11] Estimates of daily demand proxies suggest that Google search indexes for diamond-related keywords are significant proxies for the sales. The daily diamond sale hazard increases significantly when the search indexes on the keywords of "engagement ring" and the studied retailer's name are high, whereas it decreases when the search intensity is high on the keywords of "diamond," "diamond ring," and the competitor's name. The daily diamond sale hazard also differs significantly across weekdays, with Thursday being the best day for diamond sales and Saturday and Sunday being the worst days. The results also suggest that diamonds are easier to sell during holidays. Regarding the competition from other diamonds, we find that, intuitively, as the number of same-grade diamonds increases, the daily sale hazard decreases. Last, the estimated variance of the random effect is reasonably large, that is, the standard deviation is around 27% of the intercepts, highlighting the importance of controlling for unobserved correlations in the sale likelihoods among diamonds.

We now discuss the estimation results regarding the market-level decoy–dominant detection probabilities and the dominant boost hazard, which are the most critical components of our model for addressing this paper's central research questions. First, our

Table 6. Model Estimates

Variable	Estimate	S.E.
Daily diamond sale hazard		
Low-price segment (\$2K–\$5K)	−3.349**	0.114
Medium-price segment (\$5K–\$10K)	−3.169**	0.121
High-price segment (\$10K–\$20K)	−3.312**	0.131
ln(*Carat*)	0.462**	0.079
Is 1.0 carat	0.542**	0.018
Price (in \$1000)	−0.057**	0.006
Cut: Poor	0.000	
Cut: Good	0.325**	0.096
Cut: Very Good	0.835**	0.095
Cut: Ideal	1.227**	0.094
Cut: Signature Ideal	0.431**	0.127
Color: J	0.000	
Color: I	0.075**	0.029
Color: H	0.228**	0.030
Color: G	0.248**	0.031
Color: F	0.299**	0.032
Color: E	0.065*	0.035
Color: D	0.046	0.039
Clarity: SI2	0.000	
Clarity: SI1	0.166**	0.023
Clarity: VS2	0.310**	0.025
Clarity: VS1	0.248**	0.027
Clarity: VVS2	0.078**	0.031
Clarity: VVS1	−0.112**	0.036
Clarity: IF	−0.564**	0.044
Clarity: FL	−0.300	0.415
Google search: "diamond"	−0.205*	0.110
Google search: "diamond ring"	−0.527**	0.065
Google search: "wedding ring"	−0.003	0.057
Google search: "engagement ring"	0.079**	0.031
Google search: retailer's name	0.183**	0.020
Google search: competitor's name	−0.446**	0.064
Weekday: Monday	0.000	
Weekday: Tuesday	−0.026*	0.014
Weekday: Wednesday	−0.053**	0.014
Weekday: Thursday	0.052**	0.014
Weekday: Friday	−0.186**	0.015
Weekday: Saturday	−1.737**	0.026
Weekday: Sunday	−1.158**	0.021
Is Holiday	0.033**	0.013
ln(# *diamonds of the same grade*)	−0.026**	0.011
σ^2 (variance of the random effect)	0.787**	0.012
Dominance hazard—Market-level detection probability		
Low-price segment (\$2K–\$5K)	−1.341**	0.114
Medium-price segment (\$5K–\$10K)	−1.850**	0.190
High-price segment (\$10K–\$20K)	−2.430**	0.388
$\ln(R_{jt}^{Dominant})$	0.241**	0.041
$I(rp_{jt} > 0)(rp_{jt})$	1.816**	0.734
sp_{jt}	0.265*	0.151
Dominance hazard—Dominant boost hazard		
Low-price segment (\$2K–\$5K)	0.965**	0.090
Medium-price segment (\$5K–\$10K)	0.552**	0.155
High-price segment (\$10K–\$20K)	1.072**	0.305
$\ln(R_{jt}^{Decoy})$	0.072**	0.027
$I(rp_{jt} < 0)(-rp_{jt})$	1.227**	0.496
sp_{jt}	0.087	0.082
Log-likelihood	−257,666	
AIC	515,432	

Note. S.E., Standard error.
* and ** indicate significance at the 0.10 and 0.05 levels, respectively.

results suggest that the base market-level detection probability of a decoy (or dominant) diamond is the highest for diamonds in the low-price segment and the lowest in the high-price segment. One potential explanation is that consumers of the low-price ($2K–$5K) segment are usually on tight budgets and are more motivated to spend extra time searching for better prices, leading to larger consideration sets. As a result, they are more likely to detect existing decoy–dominant relationships. The positive significant estimate of the (log of) grade-level percentage of decoys/dominants (0.241) shows that when a larger percentage of diamonds are decoys in a diamond's grade, it gets relatively easier for the market to detect that diamond as a dominant. The positive significant estimate of the relative price index (1.816) shows that the further a decoy/dominant diamond is priced from the average grade-level price, the higher is the probability of decoy/dominant detection in the diamond market. In addition, results suggest that as the price variation increases in a grade, the market-level detection probabilities of decoys/dominants marginally increase. This finding suggests that as the within-grade price variation gets larger, consumers search more to identify decoys (and dominants). By using our model estimates, we next calculate the market-level decoy–dominant detection probabilities. Interestingly, we find that these probabilities are quite low: 0.25 for the low-price segment, 0.17 for the medium-price segment, and 0.11 for the high-price segment. These findings show that our real-life scenario with a large number of diamonds defined on 4Cs and price with many decoys and dominants greatly contrasts with usual laboratory settings, in which participants are almost always aware of the decoy–dominant relationships.

Second, the intercept estimates of our dominant boost hazard component are all positive, confirming that, upon dominant detection, the sale hazard would be significantly boosted. This provides direct and conclusive evidence of the existence of the DE in a real product market. The demand boost effect is lower for the medium-price segment (0.552) compared with the low- (0.965) and high-price (1.072) segments. The parameter estimate for the (log of) percentage of decoys is positive and significant (0.072), indicating that having more decoys would increase the dominant diamonds' sale hazards. The relative price measure is also positive and significant (1.227), suggesting that as a dominant is discounted further away from the grade-level average price, its sale likelihood is boosted more. The estimate of the grade-level price dispersion turns out to be insignificant. We next calculate the average dominant boost effect in proportional terms using the estimates. We find that, conditional on a diamond being detected as a dominant, its sale hazard increases by 2.7 times for the low-price segment, 1.8 times for the medium-price segment, and 3.2 times for the high-price segment, suggesting that—because of the DE—there is a substantial boost in the sale hazards of dominant diamonds.

In summary, our estimation results show that, in general, consumers have a low chance of detecting the decoy–dominant relationships in the online diamond market, especially among diamonds in the high-price segment. Thus, it is critical to model the decoy–dominant detection process in real product markets in order to correctly quantify the sales impacts of decoys on dominants. On the other hand, even though the market-level decoy–dominant detection probabilities are low, once an alternative is detected as a dominant, its sale hazard increases quite significantly, especially in the low- and high-price segments. With this finding, we not only provide strong field evidence about the existence of the DE, but also respond to Frederick et al. (2014) and Yang and Lynn (2014), who questioned the practical validity and usefulness of the DE.

6.2. Model Comparison and Robustness

In addition to our main model estimation, we conduct comparisons with two simpler modeling approaches and check the robustness of the results with three alternative specifications. We show that one would obtain worse data fits and biased inferences of the DE under these alternative approaches. We also confirm that the estimates are very robust under alternative specifications with other ways of heterogeneity control and different specifications of the reference price.

One important modeling contribution of this paper is the separation of the DE from decoy–dominant detection. To test the importance of this separation, in our first model comparison, we estimate a benchmark proportional hazard model by including the same set of controls directly in the baseline hazard. Specifically, the log-hazard specification in Equation (7) becomes the following:

$$\ln\big(h_j(t)\big) = b_j + X_{jt}\beta + D_{jt}^{Decoy}\gamma^{Decoy} + D_{jt}^{Dominant}\gamma^{Dominant}. \quad (9)$$

The second column of Table 7 (column "No detection") reports the estimates of the dominance variables for decoys (decoy shrinkage hazard) and dominants (dominant boost hazard). This simple modeling approach is outperformed by our proposed model based on the AIC, suggesting that explicitly separating the market-level decoy–dominant detection from the dominant boost hazard better explains data variation. More importantly, the alternative model's estimates have a compound effect of detection and boost on diamonds'

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Table 7. Model Comparisons and Robustness Checks

Variable	No detection	Homogeneous	Reference price	Fixed effect
Diamond random effects	Included		Included	Included
Day fixed effects				Included
$PGain: I(rp_{jt} < 0)rp_{jt}$			–1.251** (0.209)	
$PLoss: I(rp_{jt} > 0)rp_{jt}$			–0.599** (0.222)	
Market-level detection probability/decoy shrinkage hazard				
Low-price segment	–0.245** (0.025)	–1.548** (0.110)	–1.376** (0.120)	–1.578** (0.145)
Medium-price segment	–0.090** (0.029)	–2.048** (0.208)	–1.993** (0.217)	–1.742** (0.156)
High-price segment	–0.095** (0.037)	–3.205** (0.413)	–2.388** (0.433)	–2.176** (0.265)
$\ln(R_{jt}^{Dominant})$	–0.044** (0.008)	0.205** (0.047)	0.243** (0.041)	0.293** (0.045)
$I(rp_{jt} > 0)(rp_{jt})$	–0.621** (0.198)	1.164(0.836)		0.752(0.829)
sp_{jt}	–0.046 (0.029)	0.587** (0.141)	0.261(0.167)	0.304** (0.140)
Dominant boost hazard				
Low-price segment	0.314** (0.027)	0.720** (0.089)	0.989** (0.092)	1.118** (0.114)
Medium-price segment	0.050* (0.029)	0.415** (0.168)	0.493** (0.173)	0.416** (0.130)
High-price segment	0.064* (0.033)	1.446** (0.334)	0.941** (0.321)	0.722** (0.202)
$\ln(R_{jt}^{Decoy})$	0.076** (0.007)	–0.040* (0.027)	0.078** (0.027)	0.027* (0.030)
$I(rp_{jt} < 0)(-rp_{jt})$	1.237** (0.220)	0.910* (0.508)		1.768** (0.560)
sp_{jt}	0.088** (0.028)	–0.010 (0.085)	0.095(0.089)	0.107** (0.007)
Number of parameters	50	49	50	247
Log-likelihood	–257,679	–262,156	–257,669	–254,071
AIC	515,458	524,410	515,438	508,636

Notes. Numbers reported are mean estimates and standard errors. Other controls (diamond 4Cs, competition, etc.) are included in the models but not reported here to save space.
* and ** indicate significance at the 0.10 and 0.05 levels, respectively.

sale hazards, causing inaccurate inferences in understanding the magnitude of the DE if one directly uses these estimates. Results suggest that dominant boost hazards from this benchmark model are much smaller (ranging from 1.1 to 1.4 times) compared with ones from the proposed model (1.8 to 3.2 times). Thus, not explicitly controlling for the market-level detection causes a significant underestimation of the DE's magnitude.

One potential explanation for the observed sales patterns is heterogeneous competitive effects. For example, there could exist two diamond segments with different competition intensities, where diamonds in the first segment are minimally affected by competition, whereas those in the second are highly affected. Furthermore, the likelihood of being in the second segment depends on a diamond's relative price in the grade. Accordingly, if a dominant diamond is priced significantly lower than other similar diamonds, the competitive effect plays a role, implying a boost in the diamond's sale likelihood and vice versa.[12] To test this alternative explanation, we use a simple two-segment latent-class model with diamond price segment dummies and absolute relative price differences determining the competitive segment membership, and a competition hazard (conditional on being in the competitive segment) that is modeled by the (log of) number of competing diamonds in the same grade. This specification yields a much higher AIC compared with our proposed specification (516,718 versus 515,432), strongly supporting the DE over the heterogeneous competitive effects explanation.

We also conduct a series of robustness checks with alternative model specifications and report the results in Table 7. The first specification omits the random effect in the hazard specification (column "Homogeneous"), the second adopts a RPE specification with the relative price variables entering into the daily diamond sale hazard component instead of our dominance hazard specification (column "Reference price"), and the last specification includes day fixed effects instead of Google search indexes and weekday dummies as the control for demand effects across days (column "Fixed effect"). Across these three specifications, we find consistent and robust results: most of the estimates have the same direction and similar magnitude as in our main model. One notable difference is that the relative magnitude of the DE is reversed for the low- and high-price segments under the homogeneous model. We believe our random effect specification captures more unobserved heterogeneity across diamonds and thus should be more accurate, with the log-likelihood also much improved. The change in moving the relative price variables into the diamond daily hazard component seems to make little impact on the model estimates. In addition, the estimates again show that the sales function is more responsive in the gain domain than in the loss domain, consistent with the findings in our data pattern explorations. Finally, including day fixed effects could improve the model fit, but it comes at the cost of almost 200 additional parameters. Importantly, the coefficient estimates for the dominance hazard component remain almost the same. Thus, we prefer our main model specification for being parsimonious.

7. Managerial Significance

We now explore the managerial implications of our study. We first quantify the DE's overall profit impact to the retailer using model estimates. We also explore through simulation studies how sensitive the DE's profit impact is with respect to changes in different aspects of dominance structure. These exercises shed new light on the DE's practical significance, showing that it is not simply an experimental artifact.

To quantify the DE's profit impact, we start with the retailer's profit for a given diamond j at time t that can be calculated as

$$\pi_{jt} = \Pr_j(t|\cdot) \times (p_{jt} - w_{jt}), \tag{10}$$

where p_{jt} is the price, and w_{jt} is the wholesale price, which can be easily calculated by subtracting out the retailer's markup of 18% (provided in retailer's annual report) from the observed daily retail prices. The discrete-time hazard, or the probability that diamond j would be sold on day t, conditional on not being sold until that day, is $\Pr_j(t|\cdot) = 1 - \exp(-h_j(t|\cdot))$. The DE's impact on profit can be quantified by calculating the differences in the sale probability $\Pr_j(t|\cdot)$ with and without setting the dominant boost hazard component $Q_{jt}(\cdot)$ to 1.

We present the results in Table 8. Without the DE, on average, each diamond contributes \$22.89 in gross profit each day, whereas with the DE, the contribution becomes \$26.16. The DE increases the retailer's overall gross profit by 14.3%, or, equivalently, the DE contributes a 12.5% share of the retailer's gross profit. The profit increase due to the DE is the largest in the low-price segment (25.4%), whereas the opposite is the case in the medium-price segment (8.6%). Based on the financial information of the retailer, this percentage increase would translate into an annual profit increase of \$9 million. This result shows that even though decoy–dominant detection probabilities are low in the online diamond market, the DE still has a substantial profit impact due to the significant boost in sale likelihoods upon dominance detection. Indeed, this profit impact is what matters the most from the substantive point of view.

Table 8. The Impact of the DE on Retailer's Gross Profit

Effect	\$2K–\$5K	\$5K–\$10K	\$10K–\$20K	Overall
Average daily profit per diamond without the DE	8.71	30.17	43.67	22.89
Average daily profit per diamond with the DE	10.92	32.76	49.72	26.16
Percentage profit increase due to the DE (%)	25.37	8.58	13.85	14.29

We next investigate the sensitivity of the DE's profit impact to different dominance configurations in the diamond market. In the simulation studies, we implement changes in the dominance structure within the range of observed data. In the first simulation study, we check how the DE's profit impact changes when each existing decoy/dominant diamond has one more decoy and/or dominant in the market. Results are presented in the top portion of Table 9. We find that, intuitively, having one more decoy increases the DE's profit impact by 0.37% because of the effect of decoys in boosting the sales of dominants, whereas when one more dominant is added, the DE's profit impact decreases by 0.24% because the decoy detection probability increases, leading to a decrease of sales from the decoys. The DE's profit impact slightly increases (0.14%) if each decoy/dominant diamond has one more decoy and one more dominant.

We examine the effect of price dispersion on the DE's profit impact in the second simulation study. Specifically, we enlarge or shrink the relative price of 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. By preserving the mean price level, we change the price of this diamond to \$10,500 (dispersion factor of 0.5), \$10,800 (dispersion factor of 0.8), \$11,200 (dispersion factor of 1.2), and \$11,500 (dispersion factor of 1.5) in our simulation study. The middle portion of Table 9 reports the results of this simulation study. Results suggest that the DE's profit impact increases with the increase in price dispersion (between the dispersion factors of 0.5 and 1.5). Based on our model estimates, an expanded price dispersion would increase both the detection probabilities of decoys/dominants and the effect of demand boost on dominants. The profit gains from dominants (due to higher detection and sales boost) outperform the losses from decoy sales (due to higher detection), leading to an increase in the retailer's profit in the studied dispersion range.[13]

Given that dominance detection is a critical precondition for the DE, we evaluate the profit impact of the DE under different dominance detection levels in our last simulation study. By changing the intercepts in the detection equation, we set the market-level detection probabilities at 5%, 10%, 20%, 30%, and 40%. The detection probabilities are between 25% for the low-price segment and 11% for the high-price segment in the data. Results reported in the bottom portion of Table 9 suggest that the DE's profit impact gets larger when the detection probability is lower in the medium-price segment and higher in the high-price segment, as compared with the current levels. On the other hand, the DE's profit impact is highest around the current detection level in the

Table 9. Percentage Changes in the DE's Profit Impact as the Dominance Structure Changes

	\$2K–\$5K	\$5K–\$10K	\$10K–\$20K	Overall
Changing the number of decoys/dominants				
Each diamond has 1 more decoy (%)	0.43	0.25	0.39	0.37
Each diamond has 1 more dominant (%)	−0.26	−0.25	−0.17	−0.24
Each diamond has 1 more decoy and dominant (%)	0.16	0.01	0.22	0.14
Changing the price variation				
Multiplying the dispersion by 0.5 (%)	−0.52	−0.28	−1.08	−0.60
Multiplying the dispersion by 0.8 (%)	−0.19	−0.10	−0.44	−0.23
Multiplying the dispersion by 1.2 (%)	0.17	0.10	0.46	0.22
Multiplying the dispersion by 1.5 (%)	0.37	0.22	1.17	0.53
Changing the market-level detection probabilities				
Market-level detection probability in the data	0.25	0.17	0.11	0.19
Market-level detection probability of 0.05 (%)	−3.36	1.49	−2.51	−1.41
Market-level detection probability of 0.10 (%)	−1.71	0.99	−0.25	0.01
Market-level detection probability of 0.20 (%)	−0.13	−0.78	2.45	1.00
Market-level detection probability of 0.30 (%)	−0.45	−4.03	2.98	−0.04
Market-level detection probability of 0.40 (%)	−2.28	−7.65	1.66	−2.40

low-price segment. These patterns are driven by the fact that dominance detection has an opposite impact on the profits from decoys versus those from dominants. Thus, the DE's profit impact varies based on the detection levels and the magnitude of the DE across the diamond price segments.

In summary, our study offers a framework to guide marketing researchers about how to quantify decoy–dominant detection probabilities in real product markets with pricing and sales information. We show that the DE has a substantial impact on the studied retailer's profitability. Furthermore, we find that the retailer could potentially gain additional profits from the DE when (1) there are more decoys in the market, (2) within-grade price variation increases, and (3) dominance detection probabilities stay similar, decrease, and increase in the low-, medium-, and high-price diamond segments, respectively. Having a better understanding of the profit impact could enable the retailer to more effectively utilize the DE in its marketing and operations activities. One interesting observation is that the retailer recently included a new section of comparable alternatives on the details pages of a selected list of diamonds, in which their decoys/dominants are displayed for some of the diamonds. This practice could likely change the chances of consumers detecting decoys and dominants.

8. Conclusions

In this research, we empirically validate the DE by using unique panel data from a leading online jewelry retailer. We estimate a proportional hazard model (derived from consumer primitives) with embedded market-level decoy–dominant detection probabilities and the sales boost upon dominant detection (i.e., the DE). We find that the market-level probability of detecting decoys or dominants is quite low (11%–25%). However, when a dominant is detected, its sale hazard increases by 1.8 to 3.2 times. Thus, we empirically validate the existence of the DE in a real product market. Our model comparisons reveal that not controlling for decoy–dominant detection yields biased inferences regarding the DE's magnitude. We show that our estimates are robust under various alternative specifications. In addition to validating the DE in the field, we contribute to the substantive issue of measuring the DE's profit impact, that is, the DE's managerial significance. We quantify the profit impact of the DE using model estimates and find that it improves the retailer's gross profit by 14.3%. We explore how sensitive this profit impact is with respect to changes in the dominance structure and find that the profit impact could potentially increase with more decoys, a larger price variation, and changes in the market-level decoy–dominant detection probabilities.

Our study is the first empirical attempt to quantify the widely documented DE in the consumer behavior literature. It is exciting to apply the well-developed context-dependent choice theory to real-life data and empirically quantify the managerial implications. Accordingly, we would like to note that the studied online diamond market is a unique setting to test the DE because diamonds have vertical attributes, and decoys and dominants are widely observed. That being said, we believe it is possible to find other market settings that also allow the DE to be tested. For example, it is common that multiple sellers carry different price stickers when selling identical products with the same shipping/return policies and warranties in e-commerce platforms such as Amazon, where the more expensive alternatives serve the role of decoys. Similarly, in used-goods platforms such as eBay, it is often possible to observe products in inferior condition from low-rating sellers to be more expensive than some of those in better condition from top sellers. These decoy alternatives may boost the sale likelihood of less expensive and/or better-condition dominants. Furthermore, to substantiate the effect of such decoys on their dominants, these retail platforms can make decoy–dominant detection easier or more difficult by either changing the order of the product listings or recommending the products of particular sellers. However, such operations may have practical limitations for platform designers due to creating equality concerns and discouraging the participation of smaller sellers. In addition to within-product price variation on retail platforms, some producers price their product bundles the same as their main product to make the bundle more attractive. For example, Dyson offers the V11 Torque Drive cordless vacuum with extra extension hose at the same price as the vacuum itself. Last, as opposed to these strict decoy examples, retailers may position some products as near decoys. For example, the price difference between the iPhone X with 512 GB and that with 256 GB is the same as the difference between those with 256 GB and 64 GB, making upgrading to 512 GB more attractive to some consumers. In the future, quantifying the DE across various product categories might help researchers to better understand the DE's limits and boundaries.

We believe there are multiple dimensions that can be pursued to extend understanding of the DE in future research. One direction is to investigate how consumers learn and respond to decoy–dominant relationships in their search process. We face significant modeling challenges in the current context given the aggregate nature of our data. Future research could potentially address such issues when consumer-level search data are available. Another 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 because our focus is the DE on the demand side. Modeling the suppliers' pricing decisions under the DE might be an avenue for future study if such supplier-level information is observed. A third direction is to consider the DE across multiple retailers because consumers might search products from different retailers. In our setting, because the retailer captures about 50% of the market share in the United States, this issue was not a major concern. It might be worth pursuing in a different product market when data of multiple retail outlets are available. Finally, as Bell and Lattin (2000) studied the impact of price response heterogeneity in quantifying loss aversion, it is worthwhile to investigate the same factor for the DE. We partially achieve this by allowing the DE to differ across diamond price segments. When consumer-level panel data are available, the heterogeneity in both price responses and the DE could be better formulated in the future.

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Endnotes

[1] Buying a diamond ring from the retailer requires a consumer to choose his or her loose diamond first and then a ring setting. Consumers pay the total price, and the diamond ring is then assembled by the retailer. Typically, the loose diamond accounts for more than 90% of the total price paid by the consumer.

[2] We note that the supplier price variation may exist for multiple reasons. First, because of consumer search costs, the observed prices can be the outcome of a mixed-strategy price equilibrium on the supplier side. Second, suppliers might have different costs, resulting in different pricing functions. Third, suppliers may change prices at different times. Understanding the source of the price variation is beyond the scope of the current study. Instead, we focus on quantifying the DE given the observed price variation in our data.

[3] We believe this is a reasonable approach because, as discussed earlier, the suppliers are under an exclusive channel agreement with the retailer so that the diamond sale would not have happened through other channels. Accordingly, until a diamond is sold, its supplier is expected to keep listing the diamond on the retailer's website. That said, we acknowledge the sale time of a diamond to be inferred based on its removal day as a limitation of the current research.

[4] Diamond shape can be considered a horizontal attribute. Thus, including only round-shaped diamonds would not affect our decoy–dominant constructions because no decoy–dominant relationships exist across diamond shapes. Furthermore, we believe most consumers commit to a particular shape before choosing among other attributes.

[5] Under the strict definition, two same-grade diamonds with different prices must have a dominance relationship. However, in real purchase situations, consumers may not care much about (or even notice) small price differences. Thus, we use a conservative approach, defining a dominance relationship only if the price difference between the two is larger than 5%. This 5% rule helps us avoid the potential problem of defining a false dominance relationship when the dominated diamond is, indeed, superior in other noncritical attributes such as symmetry and polish. Our regressions show that the price premium contributed by these noncritical attributes is less than 0.5%. As a robustness check, we replicate our analysis under the 1% and 10% rules and obtain similar results.

[6] We would like to acknowledge that omitting diamonds from competing retailers may create biases in the estimated size of the DE if the majority of consumers search and compare diamonds from multiple retailers. Given that the studied retailer is the dominant player in the market with about 50% market share, we expect such practices to be less common. Even if consumers search across competitors, it is laborious for them to compare diamonds from multiple retailers altogether because each retailer provides its search/filtering tools; that is, pooling diamonds from different retailers is not trivial. As discussed earlier, even with the focal retailer's filtering tools, the lists of diamonds consumers face tend to be very large. In other words, it is very difficult for consumers to detect the decoy–dominant relationships from a single retailer—a fact also confirmed by our estimated decoy–dominant detection probabilities—let alone comparing across sites. Finally, each retailer's brand may be perceived as a horizontal attribute, making decoy–dominant calibrations invalid across retailers. That being said, if consumer search data across multiple retailers become available, modeling the DE beyond a single retailer could be an interesting future research direction.

[7] Because 1.0-carat diamonds are more preferred in our data, in addition to controlling for carat as a continuous variable, we use an indicator variable that takes a value of 1 if diamond j's carat is equal to 1.0.

[8] We would like to note that modeling the unobserved heterogeneity beyond the intercept term is not possible in our setting because of a lack of consumer-level panel data. That being said, ignoring price response heterogeneity may cause overestimation of the DE's magnitude if there is selection in the market where more price-sensitive consumers enter into the market only when the market prices are low (for the overestimation of the magnitude of loss aversion in the absence of controlling price response heterogeneity, see Bell and Lattin 2000). This type of selection might be less an issue in our particular setting because a diamond is a one-time purchase product category in which consumers are less likely to have well-formed reference prices from past experiences. In addition, the average price within each grade stays almost constant week over week, making it less likely for the retailer to attract a substantially different consumer segment (i.e., more price-sensitive) on a weekly basis.

[9] 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. Because of the stringent data requirement, we leave this exercise for future research.

[10] It might be possible that some context-related variables such as the relative price and the price variation could directly affect choice instead of the DE as we operationalize. Similarly, it is possible that diamond physical attributes could also moderate the extent of the DE. We conduct robustness checks that (a) include relative price and price variation in the baseline component and (b) move diamond 4C attributes to the dominance hazard component. Our main model specification in the paper generally outperforms these alternative specifications based on the AIC. More importantly, the quantified detection probabilities and DE remain quantitatively similar compared with our main model specification. Details are available upon request.

[11] As mentioned previously, our unit of analysis is each individual diamond; thus, the basic sale hazard would be determined by both consumer demand for and the supply level of diamonds. Therefore, an inverse-U-shaped relationship does not imply that, given the same price, a consumer does not prefer diamonds with better physical attributes.

[12] We thank the associate editor for pointing this out. Because of the aggregate nature of our data, it is not possible to identify the segment-specific log hazards and the segment sizes simultaneously. Thus, for identification purposes, we normalize the hazard for diamonds in the first segment to one, which represents no competitive effect.

[13] Additional analyses reveal that as the dispersion levels further increase to a few times, the DE's profit impact levels off and the retailer's profit starts to decrease because of the DE.

References

Bell DR, Lattin JM (2000) Looking for loss aversion in scanner panel data: The confounding effect of price response heterogeneity. *Marketing Sci.* 19(2):185–200.

Bettman JR, Luce MF, Payne JW (1998) Constructive consumer choice processes. *J. Consumer Res.* 25(3):187–217.

Biswas A, Blair EA (1991) Contextual effects of reference prices in retail advertisements. *J. Marketing* 55(3):1–12.

Burdett K, Judd KL (1983) Equilibrium price dispersion. *Econometrica* 51(4):955–969.

Chiang J, Chib S, Narasimhan C (1998) Markov chain Monte Carlo and models of consideration set and parameter heterogeneity. *J. Econometrics* 89(1–2):223–248.

De los Santos B, Hortaçsu A, Wildenbeest MR (2012) Testing models of consumer search using data on web browsing and purchasing behavior. *Amer. Econom. Rev.* 102(6):2955–2980.

Frederick S, Lee L, Baskin E (2014) The limits of attraction. *J. Marketing Res.* 51(4):487–507.

Guo L, Wang W (2016) Compromise effects explained by contextual deliberation reveal the rationality in preference construction. Working paper, Chinese University of Hong Kong, Hong Kong.

Hardie BGS, Johnson EJ, Fader PS (1993) Modeling loss aversion and reference dependence effects on brand choice. *Marketing Sci.* 12(4):378–394.

Heath TB, Chatterjee S, France KR (1995) Mental accounting and changes in price: The frame dependence of reference dependence. *J. Consumer Res.* 22(1):90–97.

Honka E (2014) Quantifying search and switching costs in the us auto insurance industry. *RAND J. Econom.* 45(4):847–884.

Huber J, Puto C (1983) Market boundaries and product choice: Illustrating attraction and substitution effects. *J. Consumer Res.* 10(1):31–44.

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

Huber J, Payne JW, Puto CP (2014) Let's be honest about the attraction effect. *J. Marketing Res.* 51(4):520–525.

Kahneman D, Tversky A (1979) Prospect theory: An analysis of decisions under risk. *Econometrica* 47(2):263–292.

Kalyanaram G, Winer RS (1995) Empirical generalizations from reference price research. *Marketing Sci.* 14(3):G161–G169.

Kamakura WA, Srivastava RK (1984) Predicting choice shares under conditions of brand interdependence. *J. Marketing Res.* 21(4): 420–434.

Khan U, Zhu M, Kalra A (2011) When trade-offs matter: The effect of choice construal on context effects. *J. Marketing Res.* 48(1):62–71.

Kivetz R, Netzer O, Srinivasan V (2004) Alternative models for capturing the compromise effect. *J. Marketing Res.* 41(3):237–257.

Lancaster T (1979) Econometric methods for the duration of unemployment. *Econometrica* 47(4):939–956.

Lehmann DR, Pan Y (1994) Context effects, new brand entry, and consideration sets. *J. Marketing Res.* 31(3):364–374.

Luce RD (1959) *Individual Choice Behavior* (John Wiley & Sons, New York).

Luce RD (1977) The choice axiom after twenty years. *J. Math. Psych.* 15(3):215–233.

Lynch JG Jr, Chakravarti D, Mitra A (1991) Contrast effects in consumer judgments: Changes in mental representations or in the anchoring of rating scales? *J. Consumer Res.* 18(3):284–297.

Mazumdar T, Raj SP, Sinha I (2005) Reference price research: Review and propositions. *J. Marketing* 69(4):84–102.

Monroe KB (1973) Buyers' subjective perceptions of price. *J. Marketing Res.* 10(1):70–80.

Morewedge CK, Zhu M, Buechel EC, Morales AC (2019) Hedonic contrast effects are larger when comparisons are social. *J. Consumer Res.* 46(2):286–306.

Müller H, Schliwa V, Lehmann S (2014) Prize decoys at work—New experimental evidence for asymmetric dominance effects in choices on prizes in competitions. *Internat. J. Res. Marketing* 31(4):457–460.

Orhun AY (2009) Optimal product line design when consumers exhibit choice set-dependent preferences. *Marketing Sci.* 28(5): 868–886.

Rajendran KN, Tellis GJ (1994) Contextual and temporal components of reference price. *J. Marketing* 58(1):22–34.

Ratneshwar S, Shocker AD, Stewart DW (1987) Toward understanding the attraction effect: The implications of product stimulus meaningfulness and familiarity. *J. Consumer Res.* 13(4): 520–533.

Rooderkerk RP, Van Heerde HJ, Bijmolt THA (2011) Incorporating context effects into a choice model. *J. Marketing Res.* 48(4): 767–780.

Royle JR, O'Connor DJ, Reynolds GM, Bottomley PA (1999) The robustness of the asymmetrically dominated effect: Buying frames, phantom alternative, and instore purchases. *Psych. Marketing* 16(3):225–243.

Siddarth S, Bucklin RE, Morrison DG (1995) Making the cut: Modeling and analyzing choice set restriction in scanner panel data. *J. Marketing Res.* 32(3):255–266.

Simonson I (1989) Choice based on reasons: The case of attraction and compromise effects. *J. Consumer Res.* 16(2):158–174.

Simonson I (2014) Vices and virtues of misguided replications: The case of asymmetric dominance. *J. Marketing Res.* 51(4):514–519.

Tversky A (1972) Elimination by aspects: A theory of choice. *Psych. Rev.* 79(4):281–299.

Van Nierop E, Bronnenberg B, Paap R, Wedel M, Franses PH (2010) Retrieving unobserved consideration sets from household panel data. *J. Marketing Res.* 47(1):63–74.

Wedell DH (1991) Distinguishing among models of contextually induced preference reversals. *J. Experiment. Psych.: Learn., Memory, Cognition* 17(4):767–778.

Yang S, Lynn M (2014) More evidence challenging the robustness and usefulness of the attraction effect. *J. Marketing Res.* 51(4): 508–513.