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Comparative analysis and price modelling of natural and lab-grown diamonds

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Abstract: This work analyses a natural and lab-grown diamonds dataset collected from an online retailer. Exploratory analysis demonstrates that natural and lab-grown diamonds differ in all aspects of attributes. A price model integrates both types into the analytical framework. According to the model, carat weight has an enormous influence on the price of both types followed by colour and clarity. Hypothesis-driven comparison of these two diamond categories reveals distinct carat prices across carat subgroups. We organise the dataset into structured subgroups using pivot tables assembled by carat range, colour, and clarity. The resulting price-difference matrix is converted to heat maps for round and fancy-shaped diamonds. The findings confirm that natural diamonds consistently achieve higher per-carat values than lab-grown diamonds for these two shapes of diamonds. This analysis provides insights into the factors driving the pricing structures of both diamond types, contributing to an improved understanding of their respective market dynamics.

Keywords: carat price; big data; commodity; round shape; fancy shape.

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Biographical notes: Chong Huang is a faculty member at the Eberhardt School of Business with over 15 years of interdisciplinary experience spanning advanced manufacturing, engineering, and high-tech industries. He holds a PhD in Electrical Engineering from the University of Texas at Austin and completed the Wharton Program for Working Professionals at the University of Pennsylvania. His research integrates business analytics, commodity pricing, and sustainability. He has authored publications in journals such as *Journal of Applied Physics*, *Journal of Magnetism and Magnetic Materials*, and holds 20 patents.

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1 Introduction

During recent decades, the sales of lab-grown diamonds (LGDs) sales have continued to grow in both scale and quality within the jewellery industry. The rise of this new category is changing the global jewellery industry through reshaping consumer preferences, the supply chain and its sustainability narratives (Kelley, 2008; Chan et al., 2020). Nowadays, it is an important commodity in the jewellery market. LGD, also called synthetic diamond, possesses identical physical and chemical properties as natural or mined ones. They are both composed of pure carbon atoms and have the same cubic crystal lattice. The consumer market and the trade react differently to these two products mainly because they are formed in two distinct ways. The formation of natural diamonds (NDs) is a geological process that takes place over tens of millions of years under extreme heat and pressure in the deep mantle (Jablon and Navon, 2016). Lab-grown diamonds, on the other hand, are synthesised in a controlled environment within a short period of time in the laboratory. It avoids many human rights and ecological issues inherent to mined diamonds. As a result, their formation process, cost, and environmental impact are different. This difference leads to the challenge of long-held images about luxury, authenticity, and environmental impact of the diamond market. Two synthesis methods are used to grow jewellery quality single crystalline diamond: high pressure high temperature (HPHT) and microwave plasma-assisted chemical vapour deposition (MPCVD) (Arnault et al., 2022). Diamonds formed by both methods are considered lab-grown in trade and grading laboratories.

The argument that LGD should be treated as a separate segment from ND has been increasingly acknowledged ever since they were first introduced in grading laboratories. However, in grading laboratories, gemmologists occasionally find ND mixed with their lab-grown counterparts. Hence, the need for diamond verification instruments (DVI) continues to grow to identify and separate undisclosed LGDs from ND (Dupuy and Phillips, 2019). The development of identification techniques further supports the argument that natural and LGD can be marketed and traded with clear distinctions.

Previously, many studies have developed price models and hedonic analyses for ND using large dataset collected online (Scott and Yelowitz, 2010; Lee et al., 2014; Mamonov and Triantoro, 2018; Arcos-Vargas et al., 2019). Nevertheless, the comparative studies on lab-grown diamonds and their mined counterparts remain sparse, especially those involving direct comparisons using large-scale data. This study uses a data-driven framework to provide empirical insights into their differences. Further, it lays the groundwork for research in applied economics, asset diversification, and jewellery market analysis, which have thus far focused mainly on natural diamonds.

In contrast to ND, which has been widely recognised for centuries, LGD represents a competitive alternative in luxury markets. Although it is considered a different category, this commodity inherits the pricing method of its natural counterpart. Through analysing the distinct pricing structures of these two commodities, we provide a more nuanced understanding of the key determinants within each category. The discussion of Federal Trade Commission (FTC) labelling and consumer confusion between natural and lab-grown diamonds, as noted in Kelley's research (2008), also affirms the factors examined in this study.

This work, based on large datasets collected from the wholesale market, offers a consumer-oriented perspective on the pricing structures of both natural and lab-grown diamonds. We collected 183,538 datasets from an online retailer, <http://www.bluenile.com>, with 76% being natural and 24% being lab-grown in April 2025. After data preparation, we conduct a two-part comparative analysis. First, we analysed the distribution patterns and compared key grading characteristics influencing natural and LGD through comparative exploratory study. A general linear price model is then developed to describe both ND and their lab-grown counterparts. Through this model, we tested two hypotheses which examine different dimensions of the relationship between natural and LGD. These findings help in explaining the significant differences between these two categories and pave the way for future study in investment portfolio analysis, price modelling, and attribute-based evaluation.

The rest of this paper is structured as follows. Section 2 reviews natural diamond price modelling and market segmentation. Section 3 reports exploratory data analysis and illustrates the two different commodities. Section 4 investigates price models of natural and LGD. Section 5 discusses the results. Section 6 concludes.

2 Literature review

The pricing model of ND has been extensively studied previously, with a primary focus on its main characteristics including carat, cut, colour, and clarity (4Cs) as the dominant determinants of price, along with other contributing factors. Cardoso and Chambel (2005) studied the price model based on 4Cs and certification using data published online. The

research shows that diamonds with certificates from reputable laboratories are sold at a higher price. Scott and Yelowitz (2010) collected 136,420 datasets from Blue Nile, Union Diamond, and Amazon and illustrated how ND are priced. The nonlinear diamond price model emphasises how carat weight impacts price while controlling various attributes of diamonds, including colour, cut, and clarity. Their study indicates significant price jumps at specific ‘focal points’. The research only examines diamonds weighing between 0.4 and 2.5 carats and excludes other value-affecting attributes including symmetry and fluorescence. Additionally, using the total price instead of the price per carat in this research hinders normalised comparisons of different-sized diamonds and fails to show how the per-carat price changes with size. Larger diamonds often command a higher carat price due to their rarity and desirability. A comparative study on diamond prices evaluated by different gemmological grading laboratories suggests potential inconsistencies in grading practices across gemmological laboratories, which can impact consumers’ perceptions of diamond value (Lee *et al.*, 2014). Hence, the other consideration in this comparative study is that the diamonds’ grading certifications are restricted to those authenticated by the top two grading laboratories: Gemmological Institute of America (GIA) and International Gemmological Institute (IGI). Specifically, GIA is globally recognised authority in the diamond ‘4Cs’ (cut, clarity, colour, and carat weight) grading system and consistency and reliability in assessing diamond quality.

Natural diamond prices are primarily determined by key characteristics such as carat, colour, clarity and cut. Though symmetry, polish and fluorescence, while less influential, remain important in trade evaluations. Vaillant and Wolff (2013) used an unconditional quantile regression model to analyse how various natural diamond attributes influence pricing. The findings show that carat weight has a dominant impact, accounting for approximately 95% of price variation. Among these 3Cs, colour becomes more critical as the diamond size increases, particularly for higher-quality brilliant cuts. On the other hand, clarity has a substantial impact on the price of smaller, high-quality diamonds. The shape of the cut is especially significant for smaller diamonds (0.5 to 1 carat) across all cut styles. Wolff (2016) collected datasets of 112,155 round brilliant ND from info-diamond, the online diamond market. The pricing model confirms that carat weight impacts diamond prices significantly, followed by colour and clarity. Cut quality, polish, and symmetry were found to have almost no influence on the price.

Recent research (Kigo *et al.*, 2023) evaluates multiple machine learning models to predict natural diamond prices based on attributes including carat, cut, colour, clarity, table, and depth. The study uses datasets from Kaggle that contain around 53,000 ND sold by a US-based retailer from 2008 to 2018. Comparative results show that random forest (RF) is the best-performing natural diamond price model. Given that the data collected spans ten years, it introduces variability due to changes in market dynamics, inflation, and consumer demand, making the model predictions questionable. Besides, in diamond grading, the table and depth are key components of the cut factor, which significantly influences a diamond’s price. Including these variables separately in the model without examining correlation between table, depth and cut will lead to overrepresentation of the same attributors and making price model more complex than necessary.

In early times, both the industry and the academic community indicated that lab-grown diamonds pose a challenge to the luxury goods market and could potentially disrupt its pricing structure (Spar, 2006; McAdams and Reavis, 2008). A study shows that ethical consumers are increasingly considering LGD as a viable option which is more

affordable, sustainable, and ethical than their natural counterpart (Schulte et al., 2021; Keech et al., 2020). Although LGD is a significant sector of the jewellery market nowadays, there have been no comparative studies on natural and LGD from the perspectives of price modelling and market segmentation. Contrary to mined diamonds, the pricing model of synthetics is underdeveloped.

As consumer demand for sustainability and ethical sourcing is growing, it can drive the market towards higher acceptance of LGD. Dibb's (1998) research points out that a checklist of validated segment characteristics is the key to successful implementation of market segmentation. Kotler's (1988) study listed measurable, substantial, accessible, and actionable as four key segment assessment criteria. This framework has proved to be theoretically sound but also practically viable for market segmentation (Tkaczynski et al., 2018; Keech et al., 2020). Equity market investors have considered ND as a possible option for risk management. Previous research (Auer and Schuhmacher, 2013; Low et al., 2016) shows the potential of adding ND as an investment asset, particularly for the purpose of portfolio diversification (PD). Diversifying precious metals with ND offers downside diversification potential. LGD, on the other hand, has yet to be examined in existing literature as viable assets for portfolio diversification strategies.

According to Rosen (1974), products are conceptualised as packages of characteristics, and market prices reflect the implicit prices associated with each attribute. Within this framework, the market price of a product is modelled as a function of its measurable characteristics. The hedonic price function therefore describes how market prices vary with product attributes, providing a basis for understanding how individual characteristics contribute to observed prices. Subsequent research has applied hedonic price models to empirically examine how product attributes influence prices in differentiated markets (Roma and Dominici, 2016). Natural diamond is a typical example of such differentiated goods, where its value is determined by well-recognised attributes. The hedonic perspective therefore can provide a useful conceptual background for understanding price formation of natural diamonds. In contrast, the rapid growth of lab-grown diamonds introduces a new dimension of product differentiation, where two types of diamonds with similar observable characteristics may exhibit different pricing patterns. Understanding these differences is particularly relevant not only for market valuation but also for portfolio management considerations, as distinct pricing structures may imply different value dynamics, risk profiles, and investment strategies. In this context, a comparative analysis of price differences between natural and lab-grown diamonds provides an important foundation toward understanding how these two categories function within diamond markets. In summary, despite the rapid expansion of the lab-grown diamond market, prior research has primarily focused on natural diamond pricing. The structural differences and attribute-price relationships between ND and LGD remain insufficiently understood. To address the research gaps, this study develops a general pricing model for both natural and lab-grown diamonds using large dataset from the online diamond wholesaler. Through the hypothesis tests, this study compares the attributes that influence the carat price of each type. In this price model, we include minor factors including polish, symmetry and fluorescence, which contribute to the price of both types but were overlooked in previous studies. The diamond geometric dimensions that were used as independent variables in the previous price model were omitted, as these variables were included in the diamond cut grading. The matrices of price differences between ND and LGD for both round and fancy shapes

are organised and visualised as heat maps to analyse value patterns. The exploratory comparison across key attributes reveals structural disparities between ND and LGD and provides empirical insights that may inform research on ethical marketing strategies for specific consumer segments. These findings establish a foundation for further investigation of ND-LGD differences, refined pricing models, and diamond valuation studies. They may also contribute to market segmentation theory by highlighting LGD as a distinct market segment, inform hedonic pricing research on attribute-price relationships, and offer preliminary insights relevant to portfolio diversification.

3 Data and descriptive statistics

3.1 Data preparation

Nowadays, customers purchase diamonds, mounted or unmounted, mainly through local jewellery stores, trade shows, and online retailers. Although there are many well-known online diamond retailers, their supply channels follow a similar structure. To avoid maintaining a large inventory, they tend to rely on manufacturers' in-stock faceted diamonds. Sometimes, this information comes from the same vendors, predominantly those in India due to their low-cost labour, large-scale operations, and expertise in diamond cutting and polishing (Kumar et al., 2023). This means diamonds with the same 4Cs may be priced differently across online platforms due to variations in marketing and pricing strategies. Further, Wolff (2015) indicates a positive correlation between diamond quality and price dispersion. Excluding data from multiple wholesalers helps mitigate price dispersion across online platforms. To avoid the risk of duplicate entries, we restrict our dataset to information collected exclusively from one source. We select Blue Nile because it is considered as a trusted authority and maintains one of the largest inventories of unmounted diamonds (Thompson, 2008; Alstete and Meyer, 2011). We collected 139,653 natural and 43,885 lab-grown unmounted diamonds, both round brilliant cut and fancy cut, datasets from its website (<http://www.bluenile.com>) in this cross-sectional study in April 2025.

3.2 Independent variables

The pricing of diamonds has historically been evaluated based on specific attributes, most notably the 4Cs: carat, colour, clarity and cut (King et al., 2008; Moses et al., 2004; Cowing, 2014). These 4Cs framework was originally developed as part of the trade education through the Gemmological Institute of America (GIA). Later, it is adopted through education organisations, trade, and certification reports worldwide. With the development of optical measurement technologies, fluorescence, polish and symmetry were adopted in this grading variable systems and making is more rigorous. Nowadays, the world's most reputable diamond grading laboratories use these variables as grading standards in their certification reports.

Table 1 shows the seven variables used in this study. While variables like colour, cut, and symmetry are reported as simple categorical grades in diamond certification, their assessment is more nuanced. The grading laboratory analyses multiple continuous variables and synthesises them into a single classification. For example, diamond colour is measured through a colorimeter. The instrument illuminates a diamond with a

daylight-equivalent lamp and collects a diamond hue, tune, and saturation. The colour grade of a diamond is determined by these parameters after being compared with a virtual master set of diamonds. This virtual master set is based on a grading laboratory database, which comprises millions of colour records. Cut and symmetrical grades are derived from a set of parameters based on the optical measurements of a diamond geometry. Key continuous variables, such as crown angle, pavilion angle, girdle thickness, and facet lengths, are analysed to assess the overall performance of the light-diamond interaction (Moses et al., 2004). These measures are compared against visual models to assign an overall cut and symmetry grades.

Table 1 List of independent variables

<i>Variable</i>	<i>Description</i>
Carat	Measures the weight of a diamond in carat. A metric ‘carat’ is defined as 200 milligrams.
Colour	Measures the degree of colourlessness of a diamond. Ranges from D (colourless) to Z (light yellow)
Clarity	Describes the number, size, relief, nature, and position of internal and external characteristics, i.e., inclusions and blemishes in a diamond.
Cut	Measures how well a diamond’s facets interact with light, it reflects the quality of the diamond’s cut.
Fluorescence	Describes the light emission from a diamond when it is stimulated by a UV light source.
Polish	Describes the surface smoothness of a diamond.
Symmetry	Measures the precision and consistency of a diamond’s facet alignment.

Using only a small fraction of these parameters, such as the table, length, width, and depth, will introduce bias on cut grading. Therefore, in this study, we do not include the dimensions of the diamond, specifically the table, length, width, and depth as independent variables. Because the cut grade already encapsulates all these factors through a standardised measuring and evaluation process in grading laboratory, we use it as a reliable variable in this work.

Fluorescence is a key independent variable when comparing mined vs. lab-grown diamond. In grading laboratories, fluorescence mapping is commonly used to distinguish naturally fluorescent diamonds from HPHT treated or irradiated ones (Luo and Breeding, 2013). Fluorescence spectroscopy also serves as a fast tool to distinguish naturals from lab-grown diamonds.

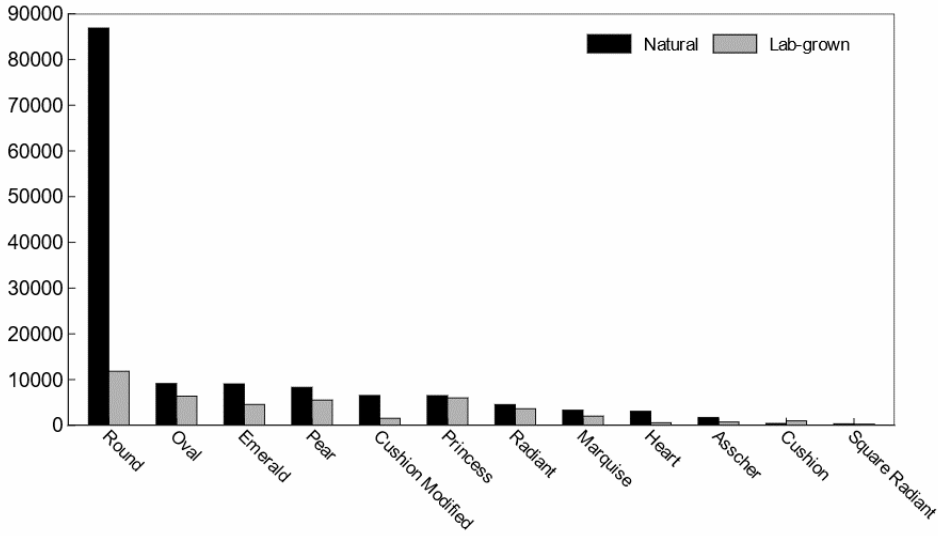
3.3 *Summary statistics and comparison*

The following section provides a detailed analysis of the natural and lab-grown diamond dataset, highlighting all attributes across the various categories.

The shape distribution between ND and LGD as shown in Figure 1 reveals distinct patterns in consumer preferences and market dynamics. Round shape is the most common in both categories, comprising 62.2% and 26.9% of the total count, respectively. This overwhelming preference for round diamonds in both categories reflects the market’s favour for the brilliant round cut. The lower percentage of round diamonds in LGD reflects different market demands, cutting constraints, and supply characteristics

between natural and LGD. In the jewellery and diamond industry, any non-round diamond is categorised as fancy-shaped diamonds. Among which oval, emerald, and pear shapes hold moderate shares. While other less common fancy shapes such as cushion, princess, radiant, marquise, heart and Asscher each represent a smaller portion of the market, ranging from 1% to 5%.

Figure 1 Shape distribution of natural and lab-grown diamonds



LGD, while still favouring round shapes, demonstrates a more balanced distribution across different shapes, with a notably higher preference for oval, princess, pear and emerald shapes. This is because in controlled growth processes, the lab-grown rough diamond crystal structural contains fewer defects compared to natural rough diamonds. Hence, it minimises damage risks during laser cutting and polishing. These high-quality lab-grown rough diamonds are suitable for non-round shapes, as they reduce material waste compared to round cutting. This distribution suggests that while LGD favours a broader variety of shapes, some shapes still maintain a modest presence, contrasting with the more concentrated round shape preferences observed in ND.

The colour distribution of ND shows a broader spread across the colour grades, reflecting the natural variability that occurs during their formation. The wider distribution suggests that ND exhibits more variation in colour and is potentially appeals to a wider market range. Additionally, ND has a considerable presence in lower colour grades for both round and fancy shapes. These lower colour grades, which show more yellowish colour, are less common in LGD, indicating that ND is more likely to display a range of colour intensities. LGD shows a much more concentrated distribution in the highest colour grades. Most LGD are found in the D, E, and F grades, which are considered colourless or near colourless in trade. These three grades account for 79.25% of the lab-grown diamond colour. The concentration in the higher colour grades indicates that lab-grown processes are optimised to produce diamonds with minimal yellowish colour. Different from ND, the lab-grown ones have much less representation in colour grades

lower than G. This lack of lower-grade colours suggest a deliberate focus in the LGD industry on producing diamonds that meet the highest standards of colour quality.

Figure 2 Colour distribution of (a) natural and (b) lab-grown diamonds

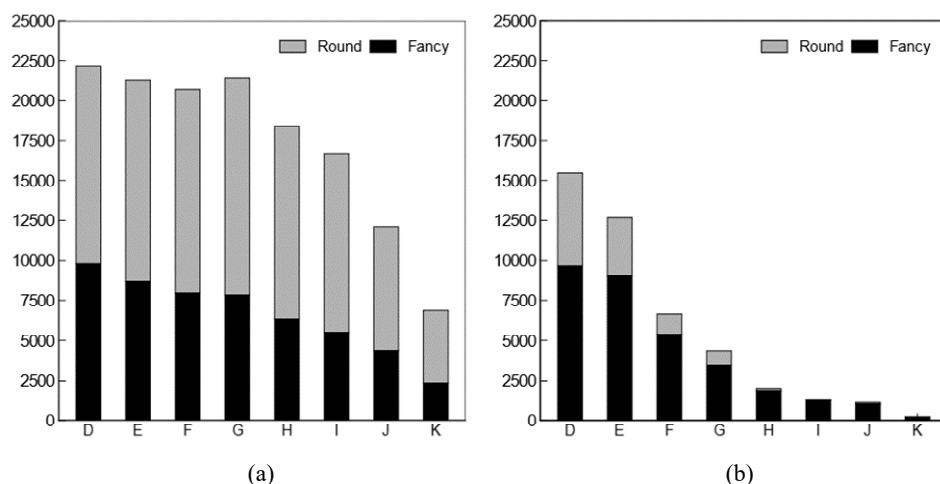
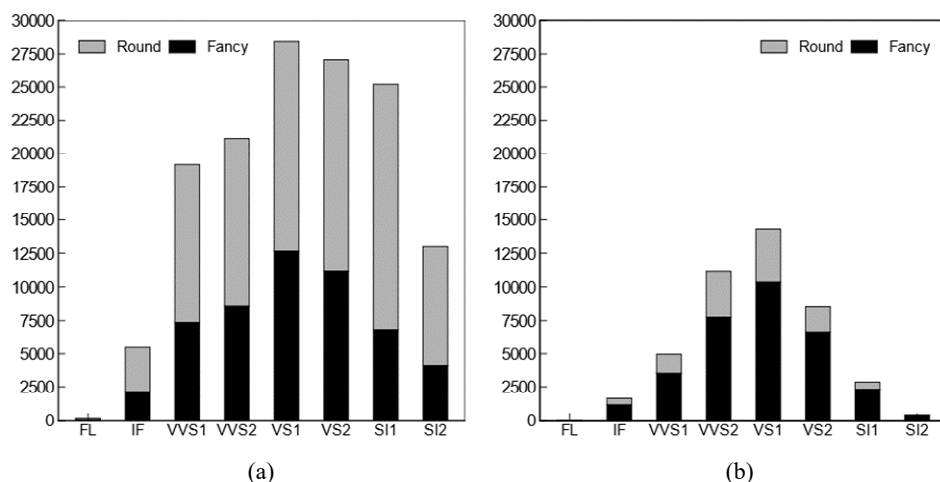


Figure 3 Clarity distribution of (a) natural and (b) lab-grown diamonds



According to Figure 3, ND shows a relatively even distribution across a range of clarity grades, with significant representation in VVS, VS and SI grades. There is also a noticeable presence in the IF (3.93%) and a very small fraction of FL (<0.1%) grades, which represent the highest clarity. Unlike the flat clarity grade distribution of mined diamonds, lab-grown diamonds show a clearer concentration in VVS and VS. This indicates that the majority (>90%) of LGD have very few or no visible inclusions. This is because the controlled synthesis conditions can minimise the presence of various defects to meet higher clarity standards.

Figure 4, 5 and 6 shows the distribution of cut, polish, and symmetry grades across natural and lab-grown, segmented by round brilliant and fancy-shaped cuts. ND are heavily skewed toward round excellent cuts, showing a clear preference for highest possible cut quality in that combination. Lab-grown diamond has a more even distribution across cut grades, with round shapes leading in excellent and fancy shapes showing up more in ideal. Across both types, the excellent polish overwhelmingly dominates, while very good and good are relatively rare. As for symmetry, we found similar trends that both natural and lab-grown lean heavily towards excellent and very good categories.

Figure 4 Cut distribution of (a) natural and (b) lab-grown diamonds

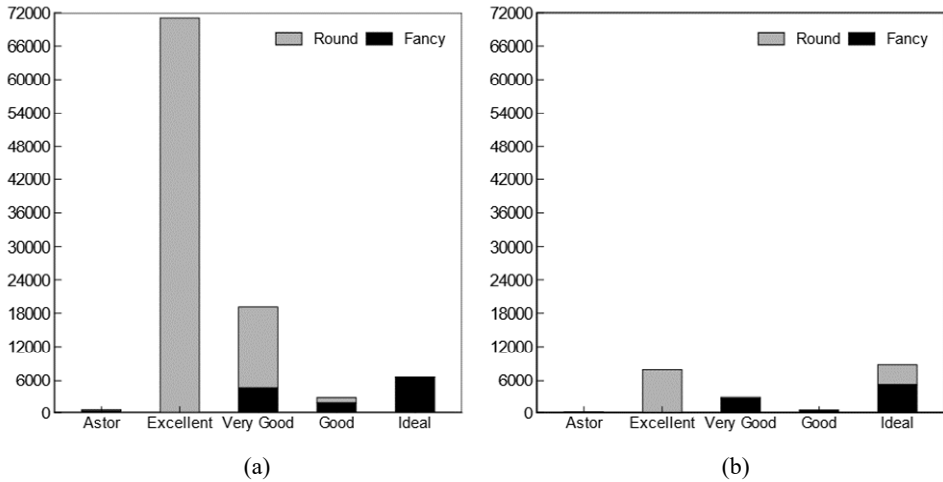


Figure 5 Polish distribution of (a) natural and (b) lab-grown diamonds

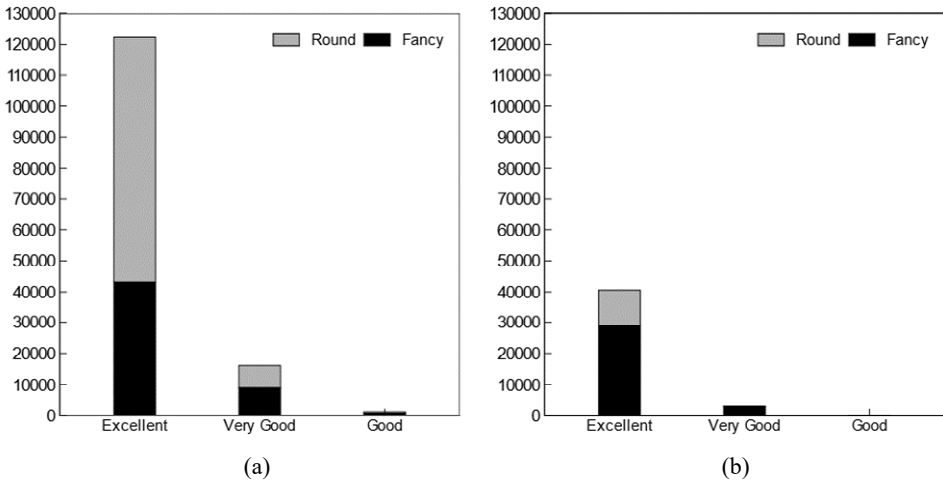
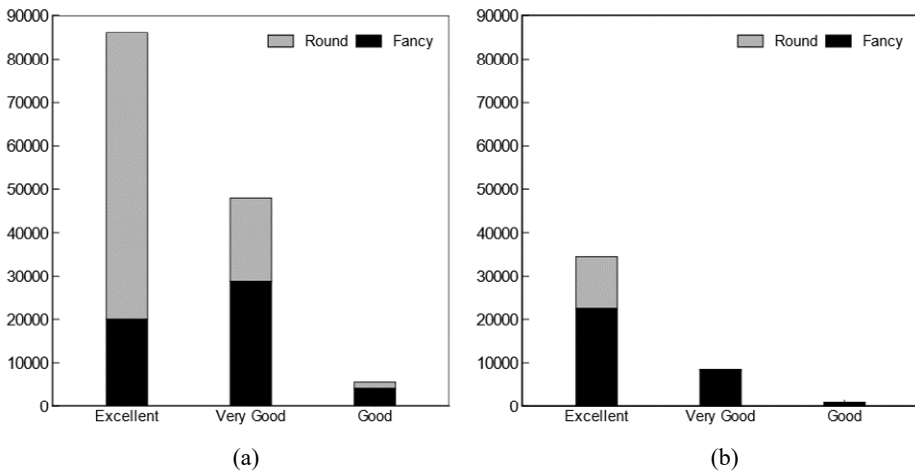
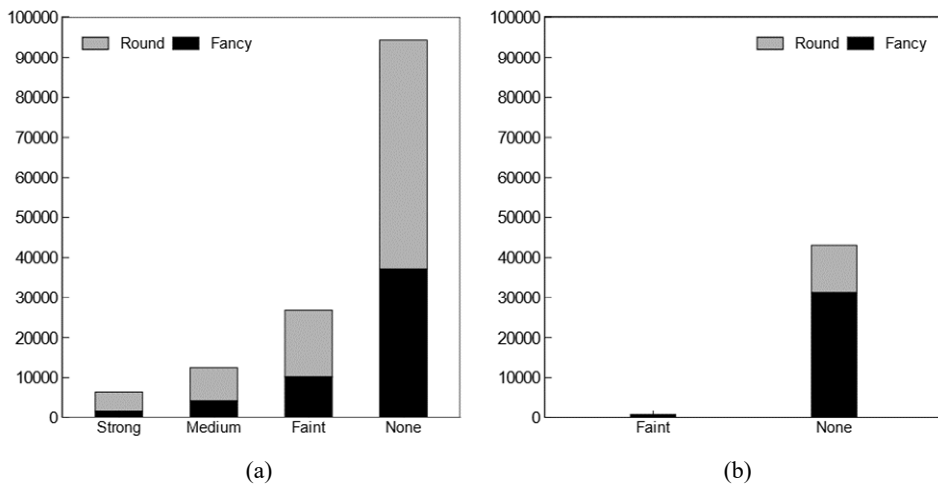


Figure 6 Symmetry distribution of (a) natural and (b) lab-grown diamonds**Figure 7** Fluorescence grade of (a) natural and (b) lab-grown diamonds

Both round and fancy shape ND, in Figure 7(a), demonstrate a broader distribution across fluorescence levels. It reflects the inherent diversity from natural growing conditions. A significant portion still has no fluorescence. On the other hand, only 1.8% of lab-grown show faint fluorescence. Given that fluorescence in diamonds lowers their carat price, manufacturers will continue to reduce defects, such as impurities and vacancies, to increase their value. Therefore, we predict that the proportion of fluorescent lab-grown diamonds will continue to decline in the future.

The data also confirms that GIA dominates the natural diamond certification market for its strong trust and credibility within the trade for grading natural stones. Due to its higher certification fees, GIA is losing market share to IGI whose low-priced grading services are better in line with the cost management strategy of lab-grown diamond manufacturers and retailers. Unlike most high-value natural diamonds that come with certification, jewellery traders only select some high-value laboratory-grown gemstones

for certification to reduce overall costs. Therefore, the dataset size for lab-grown are smaller than those for natural diamonds. In general, ND has more varied quality characteristics reflecting their mining conditions. LGD tend to have better cut, colour, clarity, symmetry, polish, and fluorescence quality compared to natural. LGDs also have larger carat sizes on average. These big data characteristics reflect manufacturers' systematic approaches to enhancing the value of lab-grown commodities.

4 Price modelling and hypothesis test

We developed a general linear model with 4Cs, polish, symmetry, and fluorescence for comparative study between these two categories. According to previous studies, polish, symmetry, and fluorescence have less impact but still play roles in fine-tuning the final price, especially for lower-sized diamonds or when distinguishing other similar diamonds (Vaillant and Wolff, 2013). Through hypothesis testing of this model, we aim to assess how each factor affects the diamond prices of these two types. Diagnostic tests reveal significant heteroskedasticity between ND and LGD, as evidenced by systematic differences in price volatility. To account for this variance structure, we implement a grouped heteroskedasticity setting in the error term, i.e., different residual variances are set according to diamond types. This approach enhances the robustness of parameter estimation and ensures valid statistical inference, particularly for likelihood ratio tests.

$$y = X\beta + \varepsilon, \quad \varepsilon \sim N(0, \Sigma)$$

where

- $y = (lp_1, \dots, lp_n)^T$ is the response vector, with each element $lp_i = \log(Price_i)$ denoting the logarithm of the diamond price
- $X = [1|Ic|Z^{(type)}|Z^{(Cut)}|Z^{(Clarity)}|Z^{(Symmetry)}|Z^{(Polish)}|Z^{(Fluorescence)}]$, with each block containing the dummy variables for the corresponding categorical factor (reference level omitted)
- $\beta^T = (\beta_0, \beta_1, \beta_2, \beta^{CutT}, \beta^T, \beta^{ClarityT}, \beta^{SymmetryT}, \beta^{PolishT}, \beta^{FluorescenceT})$
- $\Sigma = diag(\sigma_{type(1)}^2, \dots, \sigma_{type(n)}^2)$, allowing different variances for natural (σ_0^2) and lab-grown (σ_1^2) diamonds.

The analysis results show that the carat has the greatest impact on the price of natural and lab-grown diamonds followed by colour and clarity. Cut, symmetry, polish and fluorescence have a relatively small impact on the price. To examine the difference between these two commodities, we test the following two hypotheses based on the price model.

- H0_1 There is no significant difference in the overall average carat price between ND and LGD.
- H1_1 There is a significant difference in the overall average carat price between ND and LGD.

- H0_2 For each carat bin, controlling for the 4Cs (cut, colour, clarity and carat) and other quality attributes (polish, fluorescence and symmetry), the average per-carat price of natural diamonds is not higher than that of lab-grown diamonds, for both round and fancy-shaped stones.
- H1_2 For each carat bin, controlling for the 4Cs (cut, colour, clarity, and carat) and other quality attributes (polish, fluorescence, and symmetry), the average per-carat price of natural diamonds is higher than that of lab-grown diamonds, for both round and fancy-shaped stones.

The first hypothesis is a baseline comparison aiming to establish foundational carat price difference between the two categories. It is a fundamental test of whether these two types have different average prices overall before going into more nuanced questions across defined subgroups. If rejected, it suggests that on average, natural and lab-grown diamonds differ in price.

Table 2 Summary of model parameters

<i>Symbol</i>	<i>Interpretation</i>	<i>Reference level</i>	<i># Dummy columns</i>
β_0	Intercept: mean log-price at all reference levels	-	1
β_1	Slope for log (<i>Carat</i>)	-	1
β_2	Effect of LGD vs. ND	natural	1
β^{Cut}	Effect of <i>Cut</i> grades	Ideal	5 (Astor, excellent, very good, good, N/A)
β^{Colour}	Effect of <i>Colour</i> grades	E	7 (D, F, G, H, I, J, K)
$\beta^{Clarity}$	Effect of <i>Clarity</i> grades	VS1	7 (FL, IF, VVS1, VVS2, VS2, SI1, SI2)
$\beta^{Symmetry}$	Effect of <i>Symmetry</i> grades	Excellent	2 (very good, good)
β^{Polish}	Effect of <i>Polish</i> grades	Excellent	2 (very good, good)
$\beta^{Fluorescence}$	Effect of <i>Fluorescence</i> intensity	None	3 (faint, medium, strong)

Note: After grouping by carat weight, some carat ranges lack observations for certain levels of specific attributes (e.g., FL level in clarity). Therefore, when setting the reference levels, we selected those categories that appear most frequently across all subsamples (e.g., E level in colour).

The second hypothesis aims to determine whether the difference in average carat prices persists when major independent variable is controlled rather than an overall average. It refines the comparison by splitting the entire diamond carat price dataset into a series of bin (subgroups) using industry-standard classifications. We divide diamond data into subgroups based on the carat weight for a price comparison across categories. Specifically, the pricing data is used to form four tabular pricing reports classified as:

- 1 round natural
- 2 round lab-grown
- 3 fancy-shaped natural
- 4 fancy-shaped lab-grown.

Our price model shows that carat weight plays a vital role in deciding the diamond price. Therefore, we use weight in carat as a primary segmentation criterion, with diamonds grouped into a series of pivot-style pricing tables. The dataset was organised by key attributes including carat, colour, clarity, and shape (round and fancy) to facilitate comparison of pricing patterns. Each cell within the table displays the average per-carat price in hundreds of US dollars for diamonds that fall within the specified colour and clarity combination for a given carat weight range. Using major independent variables, these price matrix tables offer a structured pricing benchmark to supplement the second hypothesis test.

To test these two hypotheses, we build the following regression model, referred to as model A:

$$lp = \beta_0 + \beta_1 \cdot lc + \beta_2 \cdot Z_{type} + \varepsilon_i, \quad \varepsilon \sim \begin{cases} N(0, \sigma_0^2), & \text{natural} \\ N(0, \sigma_1^2), & \text{synthetic} \end{cases}$$

Then the null and alternative hypotheses for Hypothesis 1 can be stated as:

$$H_{0-1} : \beta_2 = 0 \quad H_{0-1} : \beta_2 \neq 0$$

To complete the testing process, we establish a regression model that does not include the *type* term, Z_{type} , named model B:

$$lp = \beta_0 + \beta_1 \cdot lc + \varepsilon_i, \quad \varepsilon_i \sim \begin{cases} N(0, \sigma_0^2), & \text{natural} \\ N(0, \sigma_1^2), & \text{synthetic} \end{cases}$$

Next, conduct a likelihood ratio test. Likelihood ratio statistic (LRS) is defined as:

$$\Lambda = -2(l_0 - l_1)$$

where

- l_0 is the log-likelihood of model B (excluding *type*)
- l_1 is the log-likelihood of model A (including *type*).

Under the large sample normality assumption, if H_{0-1} is true,

$$\Lambda \sim \chi_k^2$$

where k is the difference in degrees of freedom between the two models. At significance level α , the rejection rule is:

$$\text{Reject } H_{0-1} \Leftrightarrow -2(l_0 - l_1) > \chi_{1,1-\alpha}^2$$

Table 3 Model comparison results for round-shaped diamonds

<i>Model</i>	<i>df</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>Test</i>	<i>L.Ratio</i>	<i>p-value</i>
Model B	4	96,900.35	96,938.35	-48,446.18			
Model A	5	67,770.39	67,817.89	-33,880.20	B vs. A	29,131.96	<.0001

Table 4 Model comparison results for fancy-shaped diamonds

<i>Model</i>	<i>df</i>	<i>AIC</i>	<i>BIC</i>	<i>logLik</i>	<i>Test</i>	<i>L.Ratio</i>	<i>p-value</i>
Model B	4	137,684.4	137,721.8	-68,838.22			
Model A	5	106,043.0	106,089.7	-53,016.48	B vs. A	31,643.48	<.0001

For round-shaped diamonds, Table 3 shows that model A, which includes the variable Z_{type} , fit significantly better than model B, which does not include this variable. The likelihood ratio test statistic is $L.Ratio = 29,131.96$, with a p -value < 0.0001 , indicating a significant difference between the two models. Thus, the null hypothesis is rejected, suggesting that diamond type has a significant effect on the price (lp) of round-shaped diamonds.

For fancy-shaped diamonds, Table 4 shows that model A also fits significantly better than model B, with the likelihood ratio test statistic being $L.Ratio = 31,643.48$ and a p -value < 0.0001 . This again indicates a significant difference between the two models. The null hypothesis is therefore rejected, confirming that Z_{type} also has a significant effect on the price (lp) of fancy-shaped diamonds. In summary, the likelihood ratio test consistently shows significant differences between the two models. The null hypothesis is rejected in both cases, supporting the alternative hypothesis. This means Z_{type} serves as an important factor for diamond pricing and ND and LGD differ significantly in their average carat price.

Hypothesis 2

We divide the samples into the following 13 bins (subgroups) based on carat: 0.3–0.39, 0.4–0.49, 0.5–0.69, 0.7–0.89, 1.0–1.49, 1.5–1.99, 2.0–2.99, 3.0–3.99, 4.0–4.99, 5.0–5.99, 6.0–6.99, 7.0–7.99, 8.0–8.99, 9.0–9.99.

To account for multiple comparisons across the 17 carat subgroups, we applied a Bonferroni correction and set a significance threshold of $0.05/17$ (0.0029).

For each carat bin, using the full regression model introduced in IV, then the null and alternative hypotheses for Hypothesis 2 can be stated as:

$$H_{0-2} : \beta_2 \geq 0; \quad H_{1-2} : \beta_2 < 0$$

Next, as in Hypothesis 1, establish a regression model that does not include type and conduct a likelihood ratio test. The results show in Table 5.

For round-shaped diamonds (Table 5), almost all carat subgroup exhibited highly significant model differences. The $L.Ratio$ values ranges from 182.726 to 9,751.393, with all p -values < 0.0001 , indicating that the inclusion of Z_{type} substantially improves model fit across most weight ranges.

For fancy-shaped diamonds (Table 6), the results are largely consistent. Significant differences are observed across most carat groups, with the strongest effects found in the 1.0–1.49 and 1.5–2.99 carat range. Even in smaller groups (e.g., 0.3–0.39 carats) or larger groups (e.g., 8.0–8.99 carats), where test statistics are relatively smaller; the results remain statistically significant.

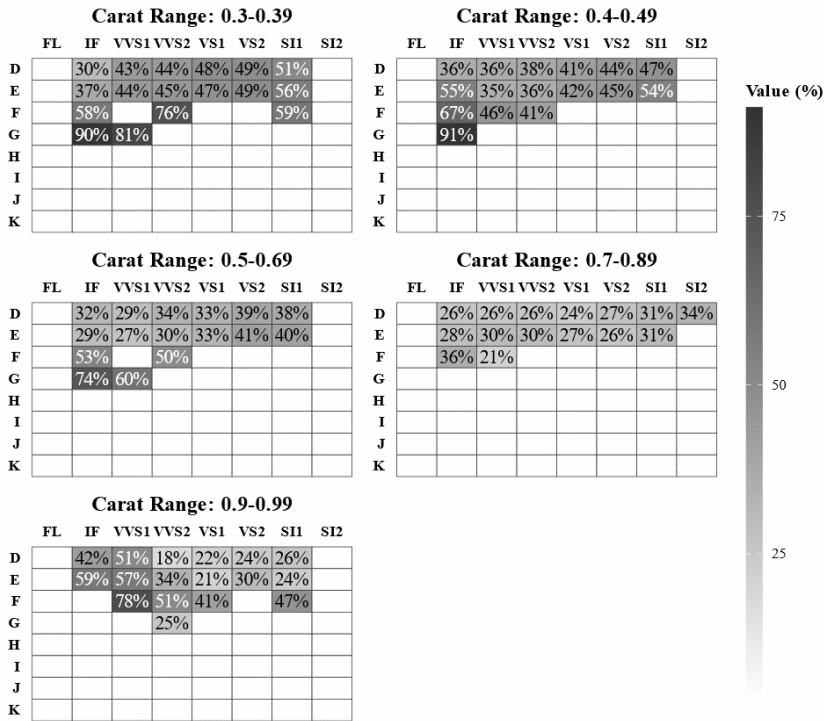
Table 5 Test statistics and P-values for different carat subgroups (round shape)

<i>Carat subgroup</i>	<i>L.Ratio</i>	<i>P-value</i>
0.3–0.39	1,311.952	2.86×10^{-287}
0.4–0.49	1,224.023	3.67×10^{-268}
0.5–0.69	863.728	7.54×10^{-190}
0.7–0.89	1,002.357	5.52×10^{-220}
0.9–0.99	182.726	1.23×10^{-41}
1.0–1.49	9,052.614	0
1.5–1.99	9,751.393	0
2.0–2.99	8,498.442	0
3.0–3.99	3,255.981	0
4.0–4.99	NA	NA
5.0–5.99	790.315	6.88×10^{-174}
6.0–6.99	NA	NA
7.0–7.99	NA	NA
8.0–8.99	NA	NA
9.0–9.99	NA	NA

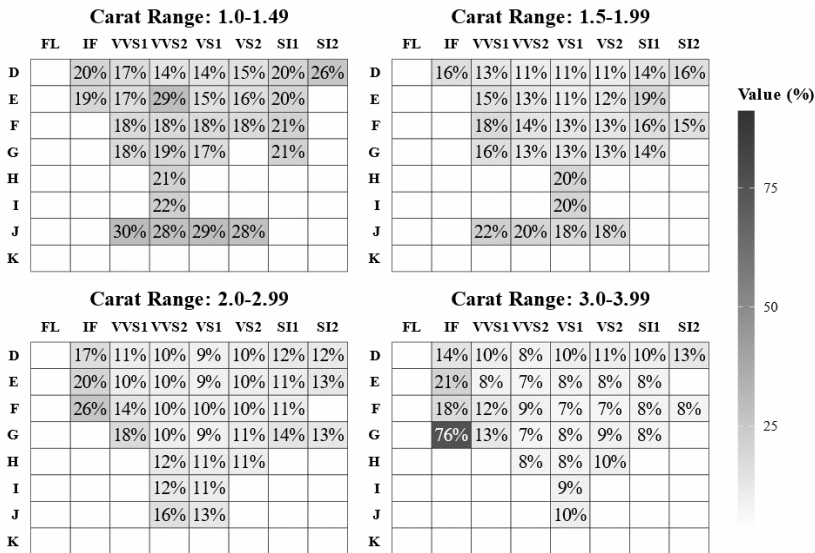
Table 6 Test statistics and P-values for different carat subgroups (fancy shape)

<i>Carat subgroup</i>	<i>L.Ratio</i>	<i>P-value</i>
0.3–0.39	169.044	1.20×10^{-38}
0.4–0.49	206.519	7.90×10^{-47}
0.5–0.69	632.825	1.21×10^{-139}
0.7–0.89	4,942.029	0
0.9–0.99	1,373.994	9.41×10^{-301}
1.0–1.49	15,070.646	0
1.5–1.99	4,072.284	0
2.0–2.99	7,494.291	0
3.0–3.99	3,143.027	0
4.0–4.99	412.593	9.99×10^{-92}
5.0–5.99	847.618	2.40×10^{-186}
6.0–6.99	132.285	1.30×10^{-30}
7.0–7.99	NA	NA
8.0–8.99	34.515	4.23×10^{-9}
9.0–9.99	NA	NA
10.0–10.99	NA	NA
11.0–11.99	NA	NA

Figure 8 (a) Comparative heat map of round-shaped LGD and ND across the small carat weight range (b) Comparative heat map of round-shaped LGD and ND across the medium carat weight range (c) comparative heat map of round-shaped LGD and ND across the large carat weight range

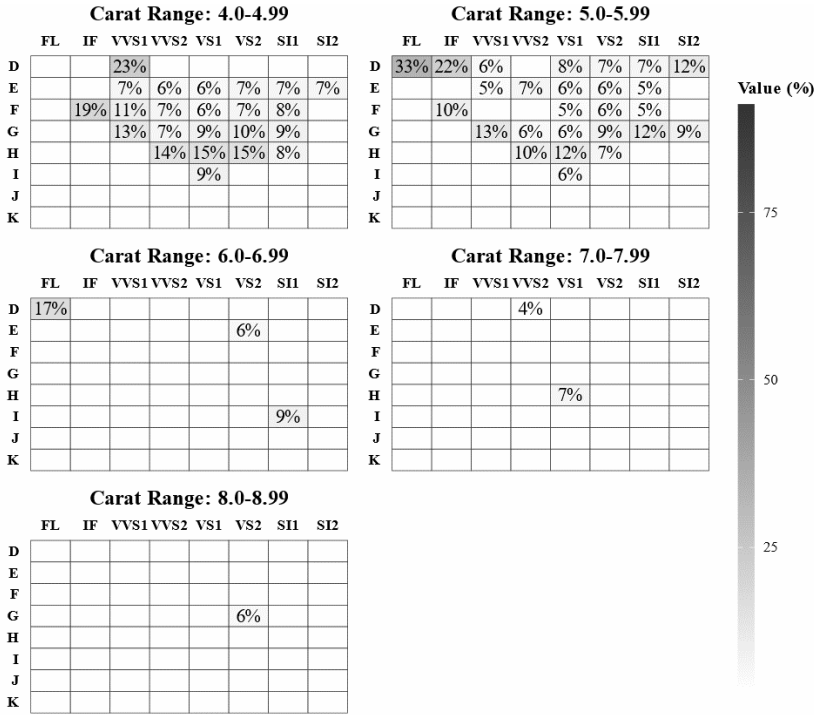


(a)



(b)

Figure 8 (a) Comparative heat map of round-shaped LGD and ND across the small carat weight range (b) Comparative heat map of round-shaped LGD and ND across the medium carat weight range (c) comparative heat map of round-shaped LGD and ND across the large carat weight range (continued)



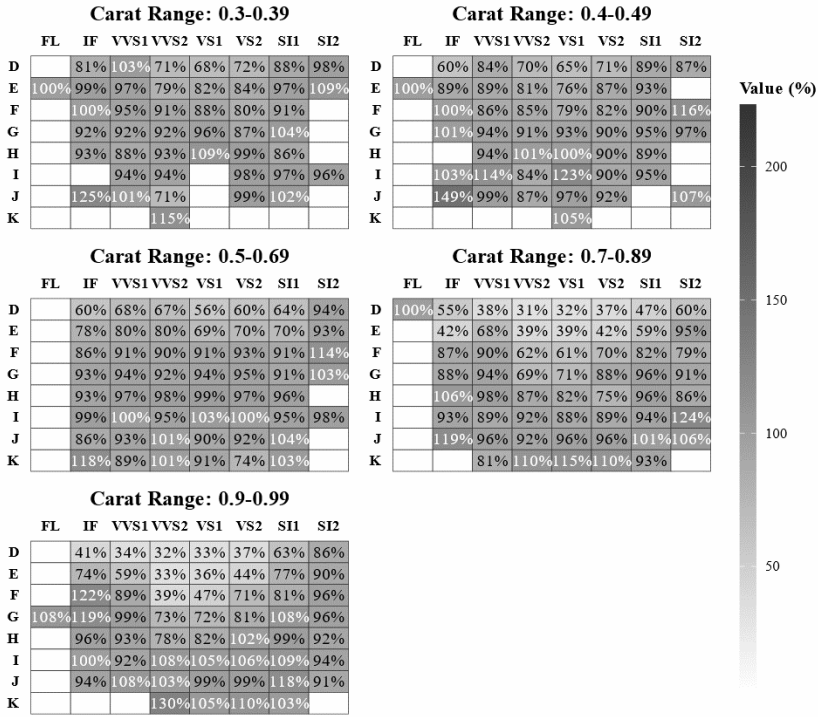
(c)

Overall, likelihood ratio tests consistently reject the null hypothesis across nearly all carat groups, thereby supporting the alternative hypothesis. This indicates that, after controlling for the 4Cs, polish, fluorescence, symmetry, and certification, ND systematically command higher per-carat prices than LGD.

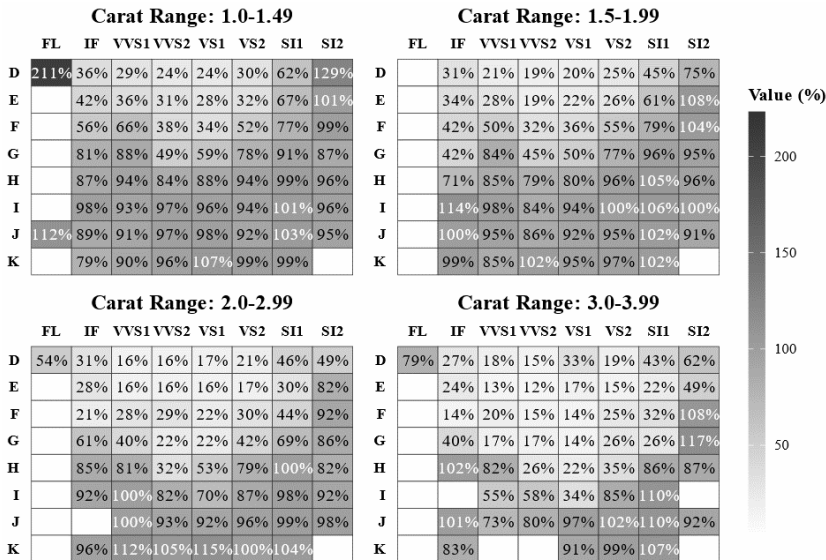
These findings provide strong evidence for hypothesis testing. The null hypothesis posits no systematic difference in per-carat prices between natural and LGD once gemmological characteristics are controlled. However, the results consistently reject this assumption across almost all carat groups, supporting the alternative hypothesis. Diamond type therefore remains a critical determinant of price.

From a market perspective, this result has clear implications. Even after adjusting for cut, colour, clarity, and other quality factors, ND maintains a significant price premium. This suggests that their scarcity, consumer perception, and brand value continue to drive higher valuations. The effect is most pronounced in the 1.0–3.0 carat range, which represents the core of consumer demand, highlighting stronger consumer preference and willingness to pay for ND in this segment. Although the effect sizes are relatively smaller in very small or very large carat groups, the differences remain statistically significant, reflecting the pervasive influence of diamond type.

Figure 9 (a) Comparative heat map of fancy-shaped LGD and ND across the small carat weight (b) Comparative heat map of fancy-shaped LGD and ND across the medium carat weight (c) Comparative heat map of fancy-shaped LGD and ND across the large carat weight

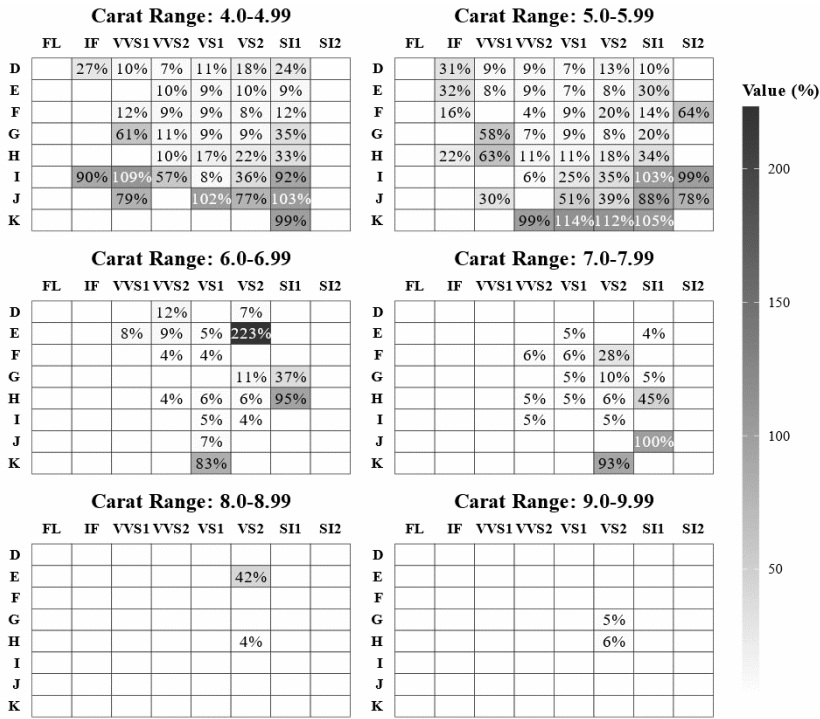


(a)



(b)

Figure 9 (a) Comparative heat map of fancy-shaped LGD and ND across the small carat weight (b) Comparative heat map of fancy-shaped LGD and ND across the medium carat weight (c) Comparative heat map of fancy-shaped LGD and ND across the large carat weight (continued)



(c)

In some carat groups, the ‘NA’ values in likelihood ratio test (LRT) are caused by insufficient data. When an interval contains observations from only one diamond type, either natural or lab-grown, the absence of the comparison group makes it impossible to estimate the type effect and compute the LRT statistic. Secondly, in groups with very small sample sizes, the distribution of control variables (e.g., colour, clarity or cut) is too sparse to support stable parameter estimation. Although the model may achieve numerical convergence, the limited data prevent reliable assessment of differences between nested models, and the LRT result is therefore reported as ‘NA’. In short, the ‘NA’ values reflect the constraints of limited sample size in certain groups, rather than computational error or methodological flaws.

Further, we developed two heat maps using the lab-grown to natural carat price ratio (LNR), calculated by dividing lab-grown prices by natural diamond carat prices for round shapes (Figure 8) and fancy shapes (Figure 9) respectively. According to Figure 8, lab-grown round-shaped diamonds consistently have a lower carat price than ND across all weight brackets. This supports the second hypothesis test. After accounting for the most important factors affecting diamond prices including weight range, colour, and clarity, ND exhibits higher carat prices across all subgroups. Noticeably, as weight, colour, and clarity vary within each grouping, the LNR varies.

For fancy shapes, the overall trend shows that ND being more expensive. Unlike round shape heat maps, 92 out of 587 subgroups show that lab-grown fancy shaped diamonds have a higher average carat price than their natural counterparts, as indicated in the heat map. The anomalies are due to the variation in carat price among different fancy shapes.

5 Analysis and discussion

The natural diamond supply chain starts with the extraction of rough diamonds from mining countries worldwide. The selected gem-level rough diamonds are then traded through related entities such as the central selling organisation (CSO). The rough diamonds are sent for cutting and polishing followed by certification by grading laboratories. After that, diamonds are distributed to retail markets around the world. For LGD, the process begins with the synthesis of single crystalline diamonds using HPHT or MPCVD methods, followed by the trading of pre-faceted crystals. Subsequently, manufacturers, mainly in India, will cut and submit them for certification. Certified diamonds are then distributed to wholesalers or retailers.

LGD has a significant impact on the natural diamond sector's notion of scarcity in the jewellery industry (Grynberg et al., 2014; Kretschmer, 2003). Even though they are identical materials with the same physical properties, there are significant differences in consumer perception because of distinct perceived value, ethical implications, and consumer preferences. According to Kotler's (1988) framework for evaluating market segment, two diamonds jewellery segments can be clearly quantified and distinguished by factors including price, carat, cut, colour, clarity, polish, symmetry and fluorescence of the diamond. Due to their rarity, ND command higher prices than that of lab-grown at all divisions. In contrast, LGD often demonstrate better colour, clarity, cut and symmetrical quality.

Secondly, our exploratory data analysis indicates that both types have substantial market demand, but they serve different customer bases in the jewellery market. ND appeals to value-seeking customers, and its demand is largely driven by wedding-related consumption, reinforced by marketing campaigns such as 'a diamond is forever' by De Beers (Francis-Tan and Mialon, 2015). LGD, which diverges into a more affordable category, attracts a growing segment of buyers who appreciate the ethical and sustainable aspects of lab-grown jewellery (McAdams and Reavis, 2008; Keech et al., 2020). Therefore, these two types are not interchangeable commodities. Instead, they serve distinct consumer segments with divergent values.

Accessibility plays a significant role in differentiating the two segments. ND derives their value due to scarcity, particularly when exhibiting unique inclusions or rare colours. It takes over millions of years to form gem quality diamonds naturally, which makes each ND unique. The mining process is also time-consuming, costly, and geographically constrained. LGDs are manufactured in controlled environments within days using HPHT or in weeks through MPCVD. Their supply is not constrained. Besides, as technology keeps advancing, synthetics can be made on a massive scale with reduced costs and higher quality. Finally, different marketing strategies or actions can be effectively tailored to each segment. ND is marketed with a focus on exclusivity, higher value, and appealing to wedding customers. Effective action for LGD is crucial as the jewellery

market is traditionally dominated by ND. Study shows that (Keech et al., 2020), marketers that promote LGD can position them by their ethical and sustainable attributes to attract low materialistic consumers.

Our findings suggest that the price patterns of natural and lab-grown diamonds may reflect different value dynamics. This may have implications for portfolio diversification, as investors could consider different asset allocation strategies for these two categories when incorporating diamonds into their portfolios. From the hedonic pricing perspective (Rosen, 1974), diamond prices reflect the combined valuation of measurable attributes discussed in this paper. The present study does not seek to estimate a hedonic price function. Rather, we focus on a comparative analysis of price patterns between natural and lab-grown diamonds with similar observable characteristics. A detailed hedonic analysis of attribute-specific implicit prices is beyond the scope of this paper and is left for future research.

The diamond industry typically recognises ten distinct shapes: round, princess, cushion, oval, emerald, pear, Asscher, heart, radiant and marquise. In this research, we create pivot tables for all fancy-cut diamonds by grouping them using the same rules applied to round diamonds. Given the low and uneven supply of certain fancy shapes, combining all fancy diamonds price into a single tabular pricing report provides a streamlined solution for comparative study. Different from the round shape, this much broader categorisation causes anomalies when comparing average carat price between lab-grown and natural fancy shapes diamonds.

Further, the higher average prices of lab-grown fancy shapes are not caused by being inherently more expensive. This anomaly is because of a disproportionately higher number of princess and radiant shapes in LGD, and their prices are comparable to natural diamond prices. Exploratory analysis of these 92 subgroups shows that natural fancy shapes like cushion, oval, pear, Asscher, heart and marquise are much more expensive than their lab-grown counterparts but unrepresented in LGD. Because princess and radiant diamonds are often considered premium fancy cuts, their higher carat price among lab-grown stones skew the average upward. Furthermore, compared to other fancy cuts which typically have 58 facets, the radiant shaped diamond has 70 facets, offering greater brilliance and complexity. Because diamonds are the hardest mineral gem, the cutting and polishing cost of radiant is higher than those of other fancy-cut counterparts. Therefore, what appears to be an anomaly where LGD shows higher per-carat pricing is, in fact, a structural outcome of shape composition imbalance. Despite these occasional anomalies, the overall trend remains stable. ND are generally more expensive than their lab-grown equivalents due to factors like rarity, mining origin, and long-term value perception.

In principle, the model could incorporate interaction terms between diamond type and other attributes to allow heterogeneous effects across market segments. However, such specifications were not supported by the available data, particularly in higher carat ranges where observations are sparse, resulting in unstable estimates and non-identifiable parameters (as reflected by the 'NA' entries in Tables 5 and 6). Accordingly, we adopt a more parsimonious specification that assumes homogeneous attribute effects across types, which should be interpreted as an approximation. This limitation also constrains the generalisability of our results for larger stones. In addition, fluorescence may not carry the same pricing relevance across natural and lab-grown diamonds and may further decline in importance for lab-grown stones as production technologies improve.

6 Conclusions

This study conducts a comparative analysis of natural and lab-grown diamonds through large scale dataset collected from a leading diamond online retailer. We developed a general linear diamond price model with seven attributes for both types. Unlike other diamond price models, this study focuses on real key attributes to ensure each independent variable remains non-overlapping in its influence. We exclude continuous variables that overlap with cut and symmetry. The model incorporates fluorescence as a new independent variable which is rarely observed in lab-grown diamonds. The general price model shows that these variables have similar impacts on both types. Among which, the weight affects the most on the price of both commodities. Colour and clarity play a secondary role in determining the prices of both types of diamonds.

The distributional differences and hypothesis tests indicate that LGD represents a distinct class from ND. Natural diamonds demonstrate significantly higher market price than that of lab-gowns. Organising the dataset by carat range, colour, and clarity for round and fancy diamonds allow clearer comparison of pricing patterns between natural and lab-grown stones and highlights differences relevant to market valuation. The results show that natural diamonds consistently exhibit higher per-carat values than lab-grown diamonds, and this pattern holds across all the subgroups in heat map of the round shape diamond. 16% of the subgroups in the fancy-shape heat map show high sampling variability due to sparse data in those subgroups. The heat map of round and fancy shape diamonds confirmed the hypothesis test. The results highlight statistically significant divergences across multiple dimensions, supporting the classification of LGD as a separate market and material segment. The comparative analysis of natural and lab-grown diamond prices in this study provides initial evidence that the two categories may exhibit different value dynamics. These results provide a foundation for future research applying hedonic frameworks and examining their implications for portfolio diversification.

Declarations

All authors declare that they have no conflicts of interest.

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