Price Analysis of Luxury Watches: Trends and Determinants

Exploring Price Variations in Premium Watches

Abey Thomas s4059720,Ananya George Martin s4109526,Samuel John s4119690

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Introduction

Luxury timepieces are more than just instruments for keeping time; they embody craftsmanship, tradition, and status. This research seeks to dissect the myriad factors influencing the cost of luxury watches, focusing on materials, movement types, and additional features. The research utilizes statistical tools such as descriptive statistics, hypothesis testing, and correlation studies to provide a comprehensive understanding of these influences. The overarching objective is to aid retailers and consumers in making informed decisions in the luxury watch market by highlighting the significance of various features.

- **Categorical Variables**:Brand,Case Material,Movement Type,Dial Color
- **Numeric Variables** (scales):Case Diameter (mm),Case Thickness (mm),Band Width (mm),Price (USD)

Objective

The objective of this study is to provide valuable insights into the factors influencing the cost of luxury timepieces, with a focus on how materials, movement types, and features affect pricing. By employing a range of statistical techniques, the study aims to inform both retailers and consumers, aiding in making more educated and strategic decisions within the luxury watch market.

Problem Statement:

Luxury watches are renowned for their craftsmanship and status, yet the factors driving their prices remain complex and multifaceted. This study investigates the relationship between key variables—such as strap material, case dimensions, and movement type—and the cost of luxury watches. By analyzing descriptive statistics, conducting hypothesis testing, and exploring correlations, the research seeks to demystify the pricing mechanisms and provide actionable insights for stakeholders in the luxury watch industry.

- **Statistical Approach**:
  - ***Descriptive Statistics****: Analyze mean, median, and price range.*
  - ***Hypothesis Testing****:*
    - T-tests for price differences based on most common strap materials
    - Chi-square tests for categorical associations (movement type vs. strap material).
  - ***Correlation****: Study for Price and various features.*

Data

Data Description

- The *Luxury Watches Price Dataset* includes a variety of luxury watch listings, capturing attributes such as brand, model, price, materials, and features.

Data Collection Method

- The dataset was downloaded directly from Kaggle.
- **Source**: Rattanaporn K (n.d.) *Luxury Watches Price Dataset*, Kaggle website, accessed 19 October 2024. https://www.kaggle.com/datasets/rkiattisak/luxury-watches-price-dataset/data

Preprocessing Steps

- Converted categorical variables into factors (e.g., **Movement Type**)
- Cleaned and standardized missing data
- Adjusted numeric variables for scaling and normalization
- Ensured proper type conversions (e.g., **Price** to numeric)

Importing the Dataset

We used readr package to import the csv file.

```
#Reading the file using read_csv
watch <- read_csv("C:\\Users\\abeyt\\Downloads\\Luxury watch.csv")
```

Lets have a look on the variable names

```
#display the names of the variable
colnames(watch)
```

Lets check the number of unique values in each column

```
# Sample data frame
data <- watch

# Apply sapply to get the number of unique values for each column
num_unique_values <- sapply(data, function(x) length(unique(x)))
```

```
# Print the results
num_unique_values
```

Our analysis will primarily focus on the prices of watches, specifically examining the most common strap materials.

```
#Check for number of unique values of strap material
watch$`Strap Material` %>% table()
```

Most strap materials are Leather and Stainless Steel, so we will focus on these watches. We will remove columns like Complications and Power Reserve, assuming they are less important. Additionally, we'll convert Water Resistance from a character variable to ordered factors, along with some other character variables to factors. These are the preprocessing steps for our analysis.

```
# FIlter the data based on most common strap materials
watch2 <- watch %>% filter(`Strap Material` %in% c("Leather", "Stainless Steel"))
```

```
#We are ignoring 3 columns for easiness
watch2 <- watch2[, !names(watch2) %in% c("Complications", "Power Reserve")]
```

```
#Checking the unique values in `Water Resistance` and the possibility of conversion to ordered factor
watch2$`Water Resistance` %>% table()
```

```
# Convert Water Resistance to numeric
watch2$`Water Resistance` <- as.numeric(gsub("[^0-9]", "", watch2$`Water Resistance`))

# Define the categories based on the unique water resistance values
watch2 <- watch2 %>%mutate(`Water Resistance Category` = cut(`Water Resistance`,breaks =
c(-Inf, 60, 150, 300,Inf),labels = c("Low", "Medium", "High", "Very High"),right = TRUE))
```

```
# Convert to an ordered  factor
watch2$`Water Resistance Category` <- factor(watch2$`Water Resistance Category`, levels = c("Low", "Medium", "High", "Very High"),
         ordered = TRUE)
```

```
#Dropping the old variable
watch2 <- watch2[, !names(watch2) %in% "Water Resistance"]
```

```
#Other data type conversions
watch2$`Case Material` = as.factor(watch2$`Case Material`)
watch2$`Strap Material` = as.factor(watch2$`Strap Material`)
watch2$`Movement Type` = as.factor(watch2$`Movement Type`)
watch2$`Dial Color` = as.factor(watch2$`Dial Color`)
watch2$Brand = as.factor(watch2$Brand)
```

We verified all the type conversions that are required and now we have factors, numeric and characters(Brand and Model).

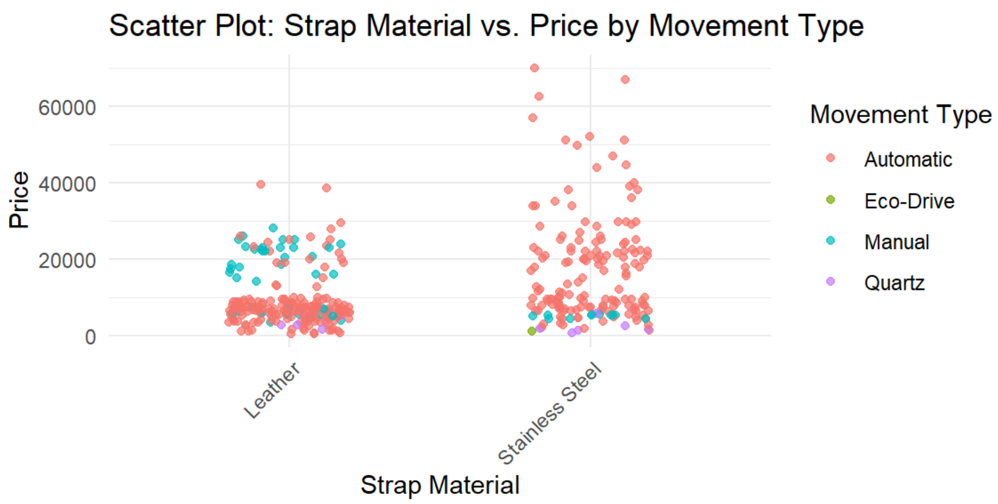
Descriptive Statistics and Visualisation

As Price is our key variable in our analysis, lets check the Price data

Strap Material	Min	Q1	Median	Q3	Max	Mean
<fct>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
Leather	495	5200	6900	9500	39500	9401.741
Stainless Steel	650	6500	10550	22000	70000	16595.181

2 rows

```r
#Scatter Plot: Strap Material vs. Price by Movement Type
ggplot(watch2, aes(x = `Strap Material`, y = `Price (USD)`, color = `Movement Type`)) +
  geom_jitter(width = 0.2, alpha = 0.7) +
  labs(title = "Scatter Plot: Strap Material vs. Price by Movement Type",
       x = "Strap Material",
       y = "Price") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
```



Our dataset encompasses over 35 distinct brands, providing a diverse range of luxury timepieces. Among the popular strap materials, leather and stainless steel stand out prominently. Water resistance in these watches varies significantly, ranging from 30 meters to a robust 300 meters. The dataset also features seven shades of black, illustrating the nuances in color offerings. Prices span from a modest $485 to an extravagant $70,000, showcasing the wide economic spectrum within the luxury watch market. Notably, automatic movement watches dominate the collection, and stainless steel straps are more prevalent compared to leather.

Outliers and Missing Value Treatment

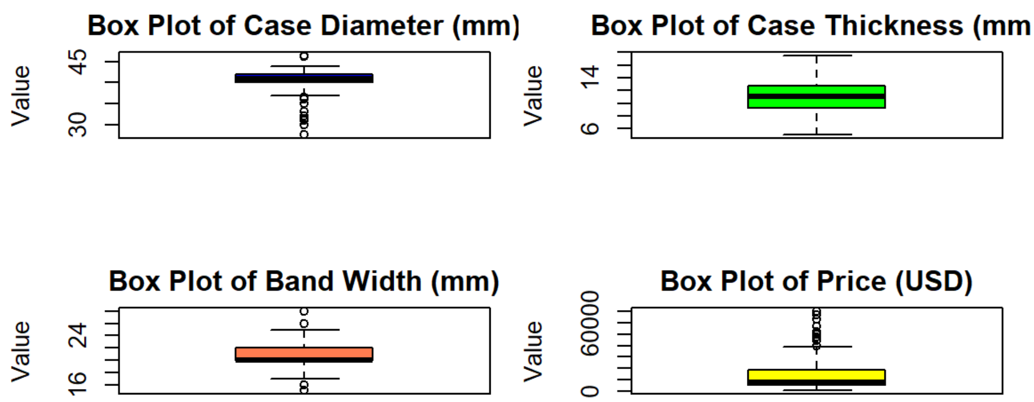
```
#Summary of all vaiables
summary(watch2)
```

We have four numerical columns: Case Diameter (mm), Case Thickness (mm), Band Width (mm), and Price (USD). We need to check for missing values and outliers before analysis.

```
#Verifying the missing values in individual column
colSums(is.na(watch2))
```

```
##                    Brand                    Model            Case Material
##                        0                        0                        0
##           Strap Material            Movement Type       Case Diameter (mm)
##                        0                        0                        0
##      Case Thickness (mm)          Band Width (mm)               Dial Color
##                        0                        0                        0
##        Crystal Material              Price (USD) Water Resistance Category
##                        0                        0                        0
```

```
# Set up the plotting area for 2x2 grid
par(mfrow = c(2, 2), mar = c(4, 4, 2, 1))

# Box plots and capturing outliers
Out1 <- boxplot(watch2$`Case Diameter (mm)`, main = "Box Plot of Case Diameter (mm)", ylab = "Value", col = "blue")$out
Out2 <- boxplot(watch2$`Case Thickness (mm)`, main = "Box Plot of Case Thickness (mm)", ylab = "Value", col = "green")$out
Out3 <- boxplot(watch2$`Band Width (mm)`, main = "Box Plot of Band Width (mm)", ylab = "Value", col = "coral")$out
Out4 <- boxplot(watch2$`Price (USD)`, main = "Box Plot of Price (USD)", ylab = "Value", col = "yellow")$out
```




```
#Check the number of outliers in each
length(Out1)
length(Out2)
length(Out3)
length(Out4)
```

We found outliers in Case Thickness, Case Diameter, Band Width, and Price (USD). These represent real luxury watch data, so we preserved the outliers in diameter and price. For Band Width, we used a capping method, assuming the variations are genuine. Aware that outliers can skew distributions, we applied transformations to normalize the data, ensuring we retain key information while improving analysis reliability.

```
# Set the percentile thresholds for capping
lower_bound <- 0.06  # 1st percentile
upper_bound <- 0.95  # 99th percentile
```

```
# Define a function to cap the outliers
cap_outliers <- function(x, lower_bound, upper_bound) {
  # Compute the percentile values
  lower_val <- quantile(x, probs = lower_bound, na.rm = TRUE)
  upper_val <- quantile(x, probs = upper_bound, na.rm = TRUE)

  # Cap the values below the lower bound and above the upper bound
  x[x < lower_val] <- lower_val
  x[x > upper_val] <- upper_val
  return(x)
}

# Apply the capping to 'Band Width (mm)'
watch2$`Band Width (mm)` <- cap_outliers(watch2$`Band Width (mm)`, lower_bound, upper_bound)
```

```
# Check the summary after capping
summary(watch2$`Band Width (mm)`)
```

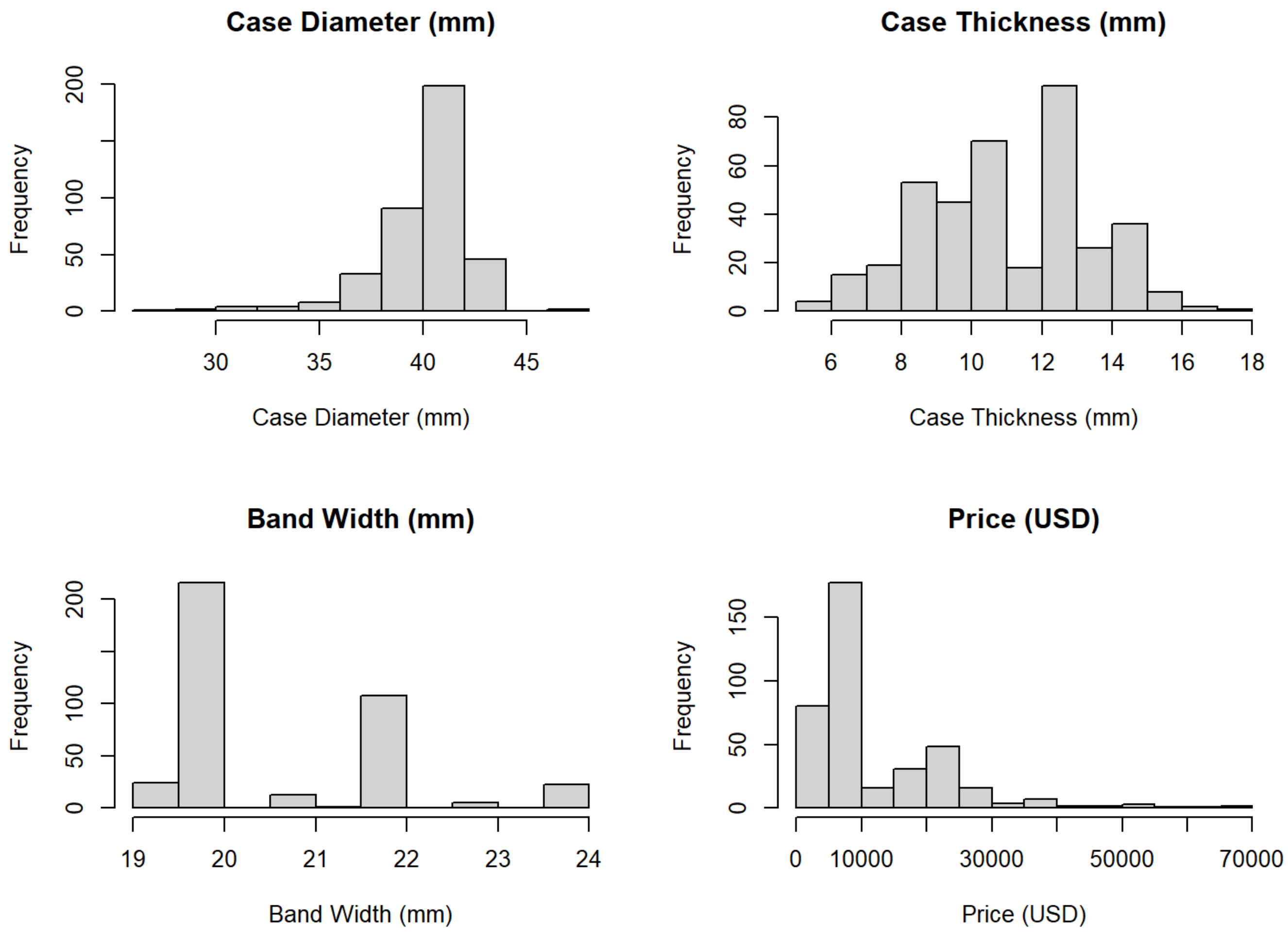
```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   19.34   20.00   20.00   20.82   22.00   24.00
```

```
# Create the boxplot for band width and save the outliers
out_ct2 <- boxplot.stats(watch2$`Band Width (mm)`)
outliers <- out_ct2$out

# Verify the outliers
outliers
```

```
## numeric(0)
```

Thus by capping we eliminated outliers in Band Width (mm).Now lets look for the distribution of our numeric variables.

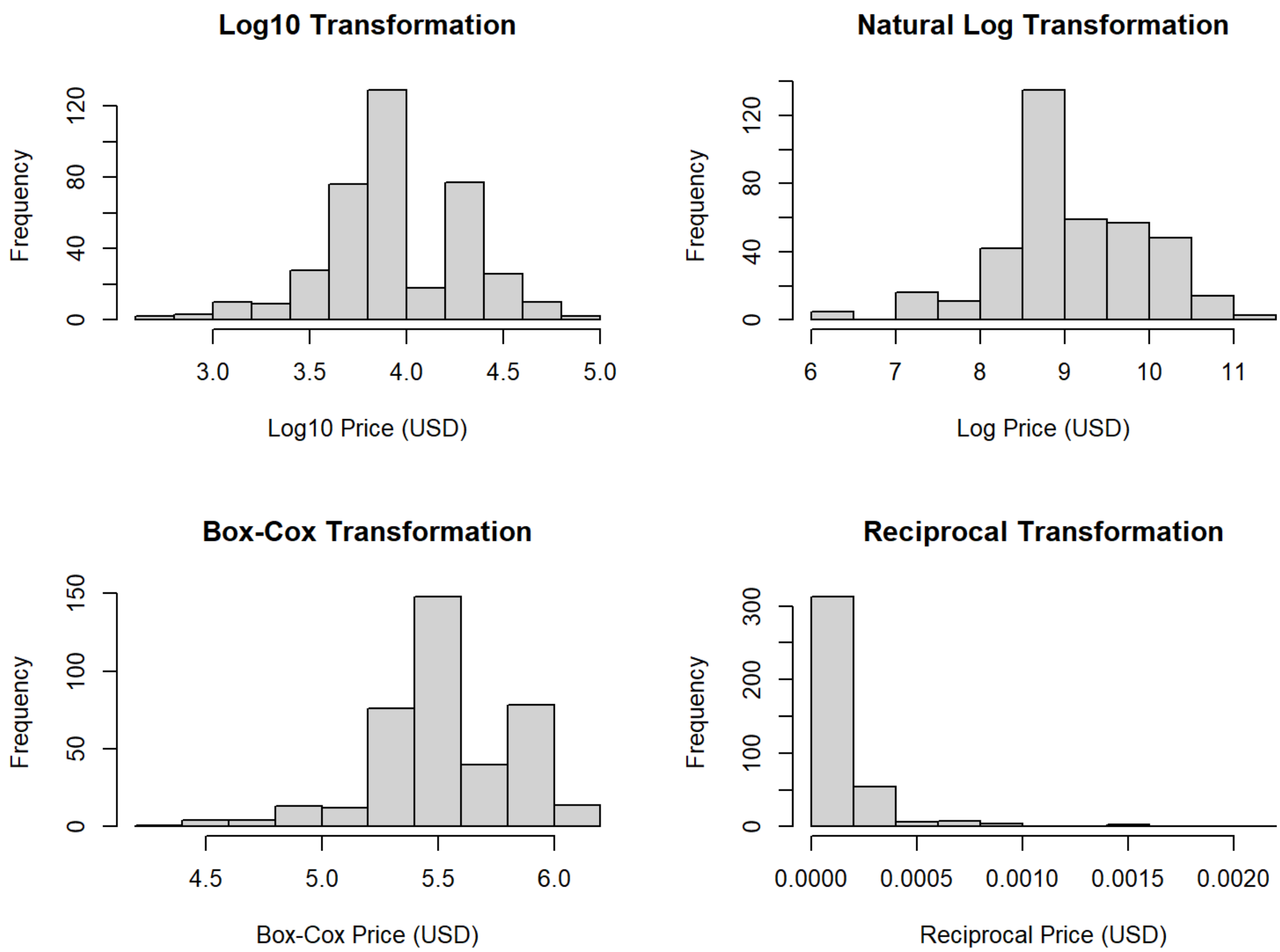
```
# Set up the plotting area to have 2 rows and 2 columns
par(mfrow = c(2, 2))

# Plot each histogram
hist(watch2$`Case Diameter (mm)`, main = "Case Diameter (mm)", xlab = "Case Diameter (mm)")
hist(watch2$`Case Thickness (mm)`, main = "Case Thickness (mm)", xlab = "Case Thickness (mm)")
hist(watch2$`Band Width (mm)`, main = "Band Width (mm)", xlab = "Band Width (mm)")
hist(watch2$`Price (USD)`, main = "Price (USD)", xlab = "Price (USD)")
```



As Price (USD) is our key variable and we could see skeweness in the data, we will transform this using log base 10, natural log, box cox, and reciprocal methods

```
# Set up the 2x2 plotting layout
par(mfrow = c(2, 2))

# Transformation using base 10 log
log_price <- log10(watch2$`Price (USD)`)
#Histogram of transformed data
hist(log_price,main = "Log10 Transformation", xlab = "Log10 Price (USD)")

# Transformation using base 10 log
log_price2 <- log(watch2$`Price (USD)`)
#Histogram of transformed data
hist(log_price2,main = "Natural Log Transformation", xlab = "Log Price (USD)")

# Transformation using Box Cox
BoxCox_price<- BoxCox(watch2$`Price (USD)`,lambda = "auto")
#Histogram of transformed data
hist(BoxCox_price,main = "Box-Cox Transformation", xlab = "Box-Cox Price (USD)")
```

```
# Transformation using Reciprocal
reci_price <- 1/(watch2$`Price (USD)`)
#Histogram of transformed data
hist(reci_price, main = "Reciprocal Transformation", xlab = "Reciprocal Price (USD)")
```



As we have log10 transformation gave the best distribution we will do our analysis based on this price.Now our data is set and will start our statistical analysis in the coming sections.

Hypothesis Testing and Confidence Interval

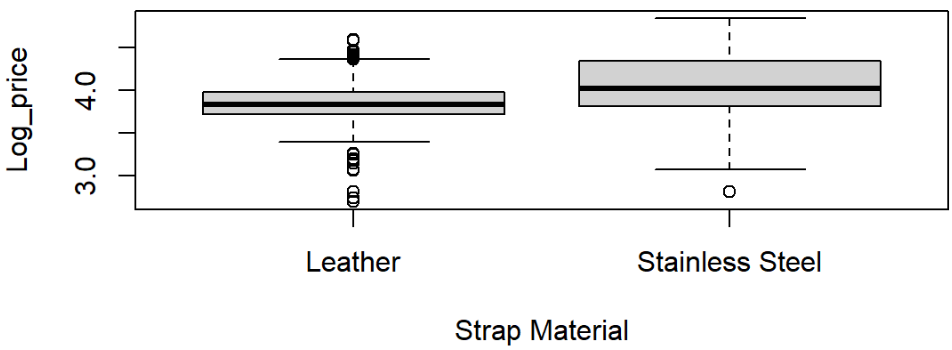
Understanding the factors influencing pricing among luxury watches is crucial, with strap material being a significant aspect. This analysis investigates whether there's a significant price difference between watches with Leather and Stainless Steel straps.

The two-sample t-test assumes the populations are independent, have equal variance, and, for small samples, are normally distributed. These assumptions must be checked before interpreting the results.

- **Null Hypothesis (H0)**: There is no significant difference in the mean price of watches with Leather and Stainless Steel straps.
- **Alternative Hypothesis (H1)**: There is a significant difference in the mean price of watches with Leather and Stainless Steel straps.

```
# Creating a new column as the log10 of Price (USD)
watch2$log_price <- log10(watch2$`Price (USD)`)
```

```
# Box plot for Log Price and Strap Material
watch2 %>% boxplot(`log_price` ~ `Strap Material`, data = ., ylab = "Log_price")
```



While it's close, Stainless Steel watches appear to have higher prices. The two-sample t-test will determine if this difference is statistically significant.

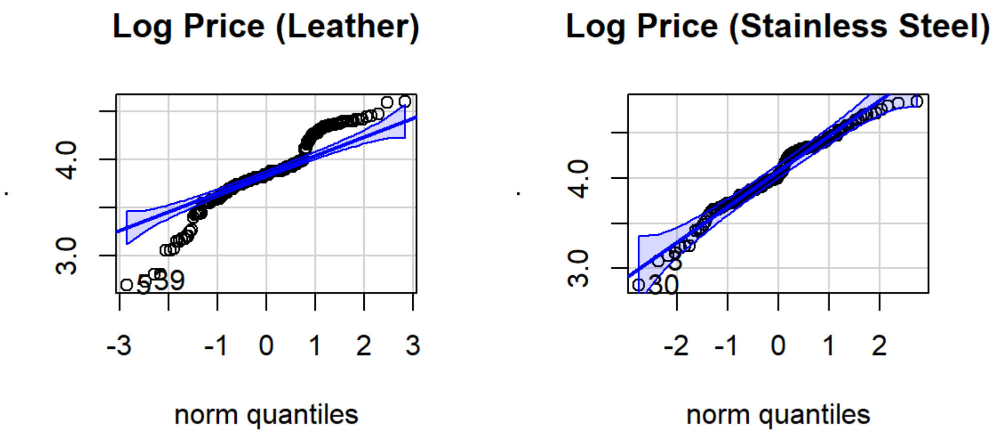
Testing the Assumption of Normality

We need to check each category of strap material, i.e, Leather and Stainless Steel follow normal distribution .

```
# Set up a 1x2 plotting layout to display both QQ plots side by side
par(mfrow = c(1, 2))

# Filtering the Leather data
log_price_leather <- watch2$log_price[watch2$`Strap Material` == "Leather"]

# Filtering the Stainless Steel data
log_price_steel <- watch2$log_price[watch2$`Strap Material` == "Stainless Steel"]

# Plot QQ Plot for Leather
log_price_leather %>% qqPlot(dist = "norm", main = "Log Price (Leather)")
```

```
## [1]  5 39
```

```
# Plot QQ Plot for Stainless Steel
log_price_steel %>% qqPlot(dist = "norm", main = "Log Price (Stainless Steel)")
```




```
## [1] 30  3
```

Points outside the distribution's tails suggest they are heavier than expected under a normal distribution, indicating it does not follow a normal distribution.

Despite the non-normal distributions, we can assume normality due to the large sample size (n > 30) and utilize the Central Limit Theorem. Let's proceed with the parametric test: the two-sample independent t-test.

Test- two sample independent t test

We have to verify for Homogeneity of Variance before proceeding. Homogeneity of variance, is tested using the Levene's test. The Levene's test has the following statistical hypotheses:

H0:σ21=σ22 HA:σ21≠σ22

```r
#Applying  Levene's test
leveneTest(log_price ~ `Strap Material`, data = watch2)
```

	Df	F value	Pr(>F)
	<int>	<dbl>	<dbl>
group	1	11.60658	0.0007259226
	388	NA	NA

2 rows

Based on the results of Levene's Test for Homogeneity of Variance, the null hypothesis of equal variances is rejected because the p-value (0.0007259) is less than the significance level (0.05). This suggests that the variances between the two groups are not equal.Since the variances are not equal, we should not use the standard independent two-sample t-test that assumes equal variances. Instead, we should use Welch's t-test, which adjusts for unequal variances between the two groups.

```r
#testing two independent samples using Welch's t-test with unequal variance and assume normality
t.test(
  log_price ~ `Strap Material`,
  data = watch2,
  var.equal = FALSE,
  alternative = "two.sided"
  )
```

```
##
##  Welch Two Sample t-test
##
## data:  log_price by Strap Material
## t = -5.716, df = 326.67, p-value = 2.459e-08
## alternative hypothesis: true difference in means between group Leather and group Stainless Steel
is not equal to 0
## 95 percent confidence interval:
##  -0.2882736 -0.1406527
## sample estimates:
##          mean in group Leather mean in group Stainless Steel
##                       3.853550                      4.068013
```

p-value indicates a very strong rejection of the null hypothesis.The results indicate that there is a statistically significant difference in the mean `log_price` between watches with Leather straps and those with Stainless Steel straps, as the p-value is extremely small (2.459e-08), which is much lower than the typical significance level of 0.05.We got t-value of -5.716, a negative t-value suggests that the mean of `log_price` for Leather straps is lower than for Stainless Steel. Similarly, 95% confidence interval [-0.288, -0.141].This range does not contain 0, reinforcing the conclusion that there is a significant difference between the groups. Mean estimates: - Leather strap group: 3.854 (log price). - Stainless Steel strap group: 4.068 (log price).The alternative hypothesis is supported, meaning there is a true difference in means between the two groups, with Leather straps having a lower mean `log_price` compared to Stainless Steel.

We need to back-transform the log_price values and interpret the results in terms of the original price, we can exponentiate the mean log_price values.

```
# Mean log prices from Welch's t-test
mean_log_leather <- 3.853550
mean_log_steel <- 4.068013

# Back-transform the log prices to the original price scale
mean_price_leather <- 10^mean_log_leather
mean_price_steel <- 10^mean_log_steel

# Display the back-transformed prices
mean_price_leather
```

```
## [1] 7137.564
```

```
mean_price_steel
```

```
## [1] 11695.34
```

The mean price of watches with Leather straps is approximately $7,142.06.The mean price of watches with Stainless Steel straps is approximately $11,623.28.The significant p-value from the Welch's t-test indicates that this difference in prices is statistically significant.In conclusion, watches with Stainless Steel straps have a significantly higher mean price compared to watches with Leather straps

Categorical association- Chi-Square Test

We have few assumptions for this test,Independence: Each observation should be independent of the others. Expected Frequencies: Generally, each cell in the contingency table should have an expected frequency of at least 5. If we have many cells with expected counts less than 5, the Chi-Square test might not be appropriate. Then Both variables should be categorical. Our hypothesis are;

Null Hypothesis (H0): No association between strap material and movement type. Alternative Hypothesis (H1): Significant association between strap material and movement type.

```
# Lets check if `Movement Type` is meeting the assumptions
watch2$`Movement Type` %>% table()
```

```
## .
## Automatic Eco-Drive    Manual    Quartz
##       327          1        50        12
```

We need to eliminate the Eco-Drive for meeting the assumptions of the test, hence we exclude that particular row.

```
# Remove rows where Movement Type is 'Eco-Drive'
watch3 <- watch2[watch2$`Movement Type` != "Eco-Drive", ]

# Drop unused factor levels
watch3$`Movement Type` <- droplevels(watch3$`Movement Type`)
```

We need to make a contingency table with our interest variables;

```
# creating contingency table of variables that we are interested
chi_table <- table(watch3$`Strap Material`,watch3$`Movement Type`)
```

Now our data is ready for chi square test

```
#applying the CHi.square test to the data
chi_square_result <- chisq.test(chi_table)

# Output the result
print(chi_square_result)
```

```
##
##  Pearson's Chi-squared test
##
## data:  chi_table
## X-squared = 9.8979, df = 2, p-value = 0.007091
```

p-value of 0.007 is astonishingly small, indicating that we can reject the null hypothesis. That means, there is a strong connection between the type of strap and the type of movement in luxury watches. In simple terms, the kind of strap a watch has (like Leather or Stainless Steel) is related to the kind of mechanism inside the watch (like Automatic or Quartz). This significant relationship means that the choice of strap is not random and is linked to the movement type in your dataset. Certain straps are more likely to be paired with specific movement types.

Correlation

We will explore the relationship between the log-transformed price of watches (log_price) and available other three numeric variables: Case Diameter (mm), Case Thickness (mm), and Band Width (mm). Understanding these relationships can provide insights into how different physical characteristics of watches might influence their price.

```
#Selecting numerical variables
watch_data <- watch2[, c("Case Diameter (mm)", "Case Thickness (mm)", "Band Width (mm)", "log_price")]

#Calculate the correlation matrix
corr_matrix <- cor(watch_data, use = "complete.obs")

# Print the correlation matrix
print(corr_matrix)
```

```
##                     Case Diameter (mm) Case Thickness (mm) Band Width (mm)
## Case Diameter (mm)           1.0000000           0.5056543      0.48516739
## Case Thickness (mm)          0.5056543           1.0000000      0.35006356
## Band Width (mm)              0.4851674           0.3500636      1.00000000
## log_price                   -0.0505082          -0.4113477     -0.07505524
##                       log_price
## Case Diameter (mm)  -0.05050820
## Case Thickness (mm) -0.41134770
## Band Width (mm)     -0.07505524
## log_price            1.00000000
```

```r
# Initialize a results list
ci_results <- list()

# Calculate correlations and CIs for log_price vs each variable
for (variable in c("Case Diameter (mm)", "Case Thickness (mm)", "Band Width (mm)")) {
  r <- cor(watch2$log_price, watch2[[variable]], use = "complete.obs")
  n <- nrow(watch2)
  ci <- CIr(r, n)
  ci_results[[paste("log_price vs", variable)]] <- ci
}
# Print the results
ci_results
```

```
## $`log_price vs Case Diameter (mm)`
## [1] -0.14906278  0.04903998
##
## $`log_price vs Case Thickness (mm)`
## [1] -0.4906096 -0.3253347
##
## $`log_price vs Band Width (mm)`
## [1] -0.17306756  0.02442905
```

Correlation analysis reveals varying relationships between the physical characteristics of watches and their log-transformed prices. Case thickness has a moderate negative impact on price, while case diameter and band width show minimal influence. These insights can help manufacturers and retailers in pricing and designing products. Notably, larger case diameters often coincide with thicker cases and wider bands, indicating a design trend. The weak to moderate negative correlation between price and other measurements suggests that larger watches do not necessarily cost more. Further analysis could explore additional variables.

Conclusion

Findings

This study identified key factors affecting the price of luxury timepieces. The correlation analysis revealed varied relationships between price and specific features. Hypothesis testing demonstrated significant price differences based on strap materials, while Chi-square tests illuminated associations between movement types and strap materials.

Strengths

The strength of this research lies in its comprehensive statistical approach, combining descriptive analysis, hypothesis testing, and correlation studies to deliver a multi-faceted understanding of the luxury watch market.

Limitations

A limitation of this study is the potential for sample bias, given that the data may not be fully representative of the entire luxury watch market. Additionally, the analysis focused on only a few parameters, which may limit the scope of our findings.

Future Directions

Future research could expand on these findings by incorporating a larger and more diverse sample, exploring non-linear relationships, and examining the impact of brand reputation and market trends on watch prices. This expanded scope could yield deeper insights and more robust conclusions.

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