Domestic Accessories Market Trend and Future Insights

Sales and Seasonality in Focus

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Sales and Seasonality in Focus

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1. Market Trends Overview

In this section, we probe the overarching trends influencing the accessory market.

We evaluate annual sales patterns and key sales phases within the fashion and accessory sector.

Moreover, we gauge the magnitude of the online fashion market through transaction volumes,

and highlight the trends in online shopping usage rates segmented by age.

01
Yearly
Sales Trends

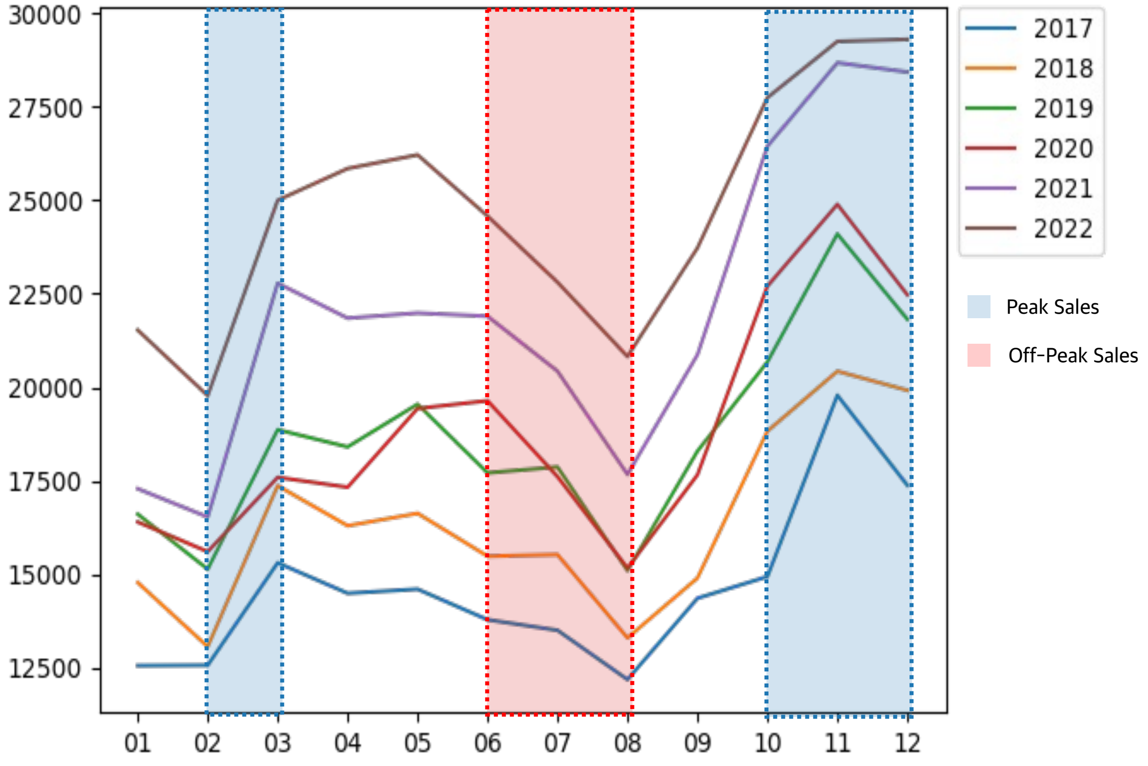
02
Online and Mobile
Sales Scale

03
Online Shopping
Engagement
by Age Group

1.1. Market Trends Overview: Annual Sales Patterns

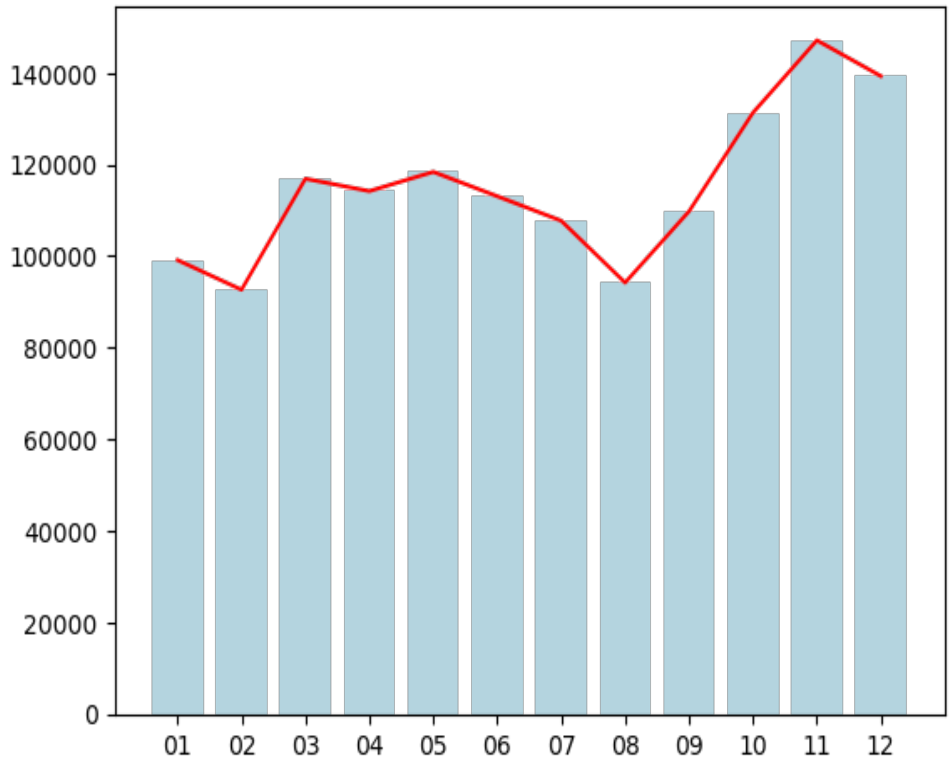
[2017-2022 Online Transactions in Fashion]

Source: KOSIS | Categories: Clothing, Shoes, Bags, Accessories | Units: 100 Million KRW



[2017-2022 Monthly Cumulative Transactions in Fashion]

Source: KOSIS | Categories: Clothing, Shoes, Bags, Accessories | Units: 100 Million KRW

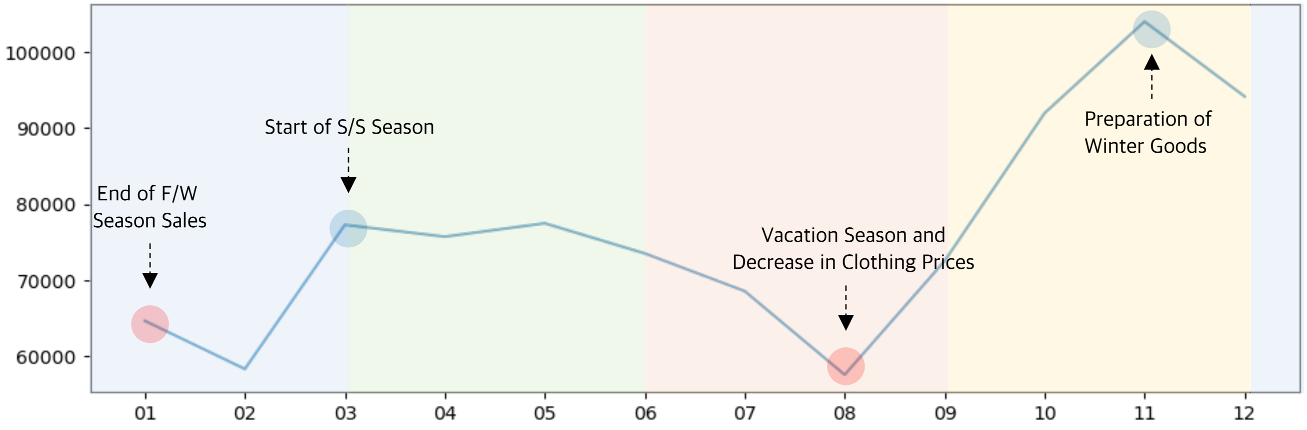


Fashion trends are seasonal, a feature even more pronounced in Korea's distinct seasons and trend-sensitive market.

1.1. Market Trends Overview: Annual Sales Patterns

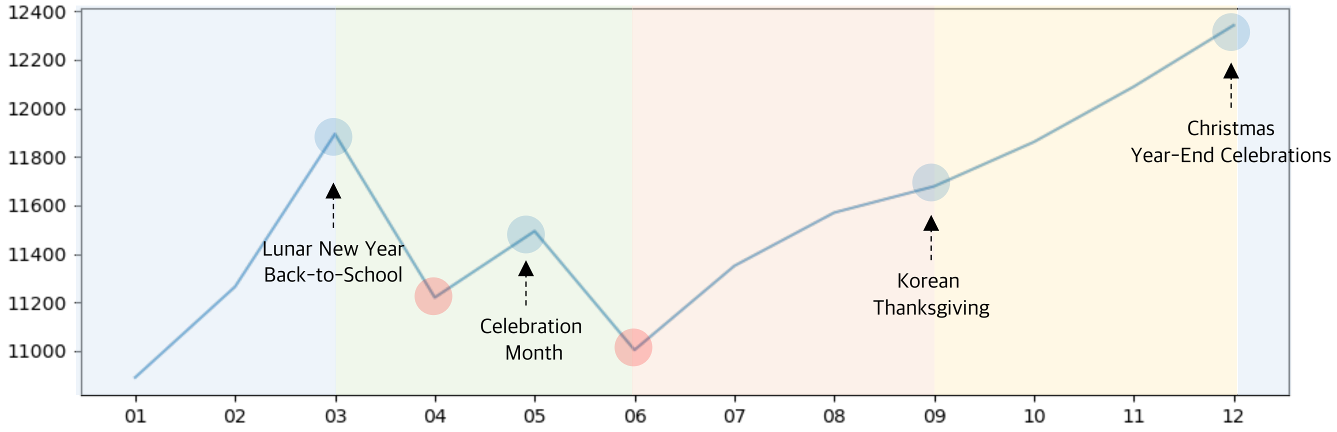
[2017-2022 Cumulative Monthly Online Transactions: Clothing]

Source: KOSIS | Categories: Clothing, Shoes, Bags, Other Accessories | Units: 100 Million KRW



[2017-2022 Cumulative Monthly Online Transactions: Bags]

Source: KOSIS | Categories: Clothing, Shoes, Bags, Other Accessories | Units: 100 Million KRW



The distinct seasonality of the accessory category becomes clearer when contrasted with clothing. While clothing follows the rise and fall of seasons, accessories' trends align with previously discussed four themes.

1. December-February: Clothing sees decreased transactions due to winter's end, while accessories rise, driven by Lunar New Year and Back-to-School events.

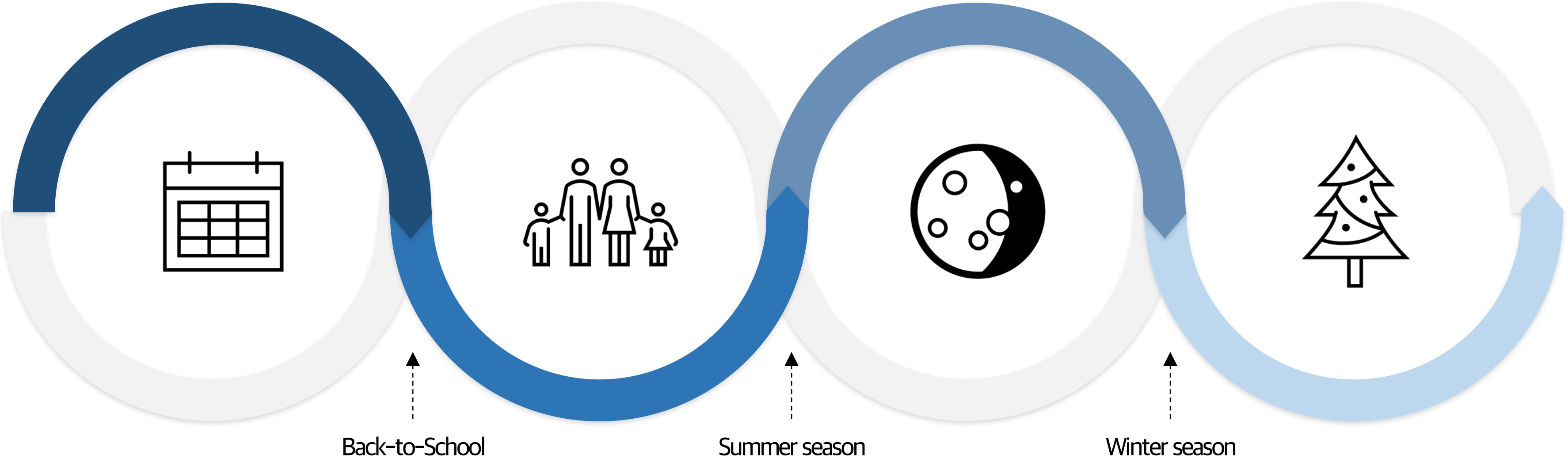
2. March-May: Clothing transactions remain steady, but accessories peak in May, coinciding with the Celebration Month.

3. June-August: Clothing transactions trend downwards, while accessories ascend in preparation for Chuseok.

4. September-November: Clothing experiences a transaction peak, whereas accessories maintain an upward trend.

1.1. Market Trends Overview: Annual Sales Patterns

[Annual Themes and Peak Sales Periods for the Accessory Market]



January-February
- Lunar New Year

May
- Celebration Month (Children's Day, Parents' Day, Teachers' Day, and Couple's Day

September-October
- Korean Thanksgiving

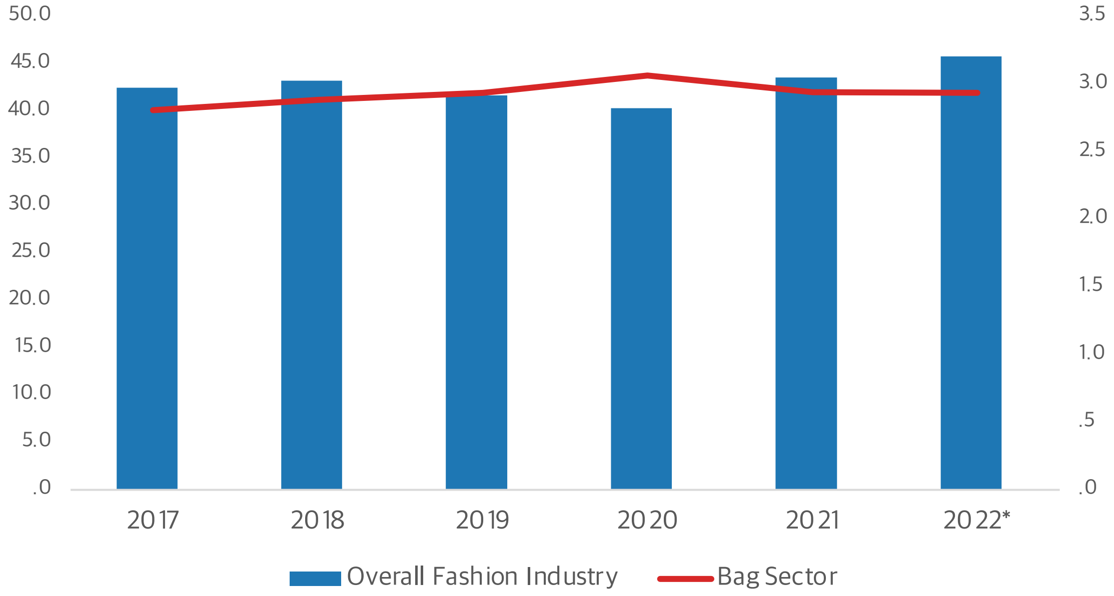
December
- Christmas
- Year-end celebrations

The annual sales in the accessory market hinge largely on four peak periods that occur roughly every three to four months.

1.2. Market Trends Overview: Sales Volume by Channel

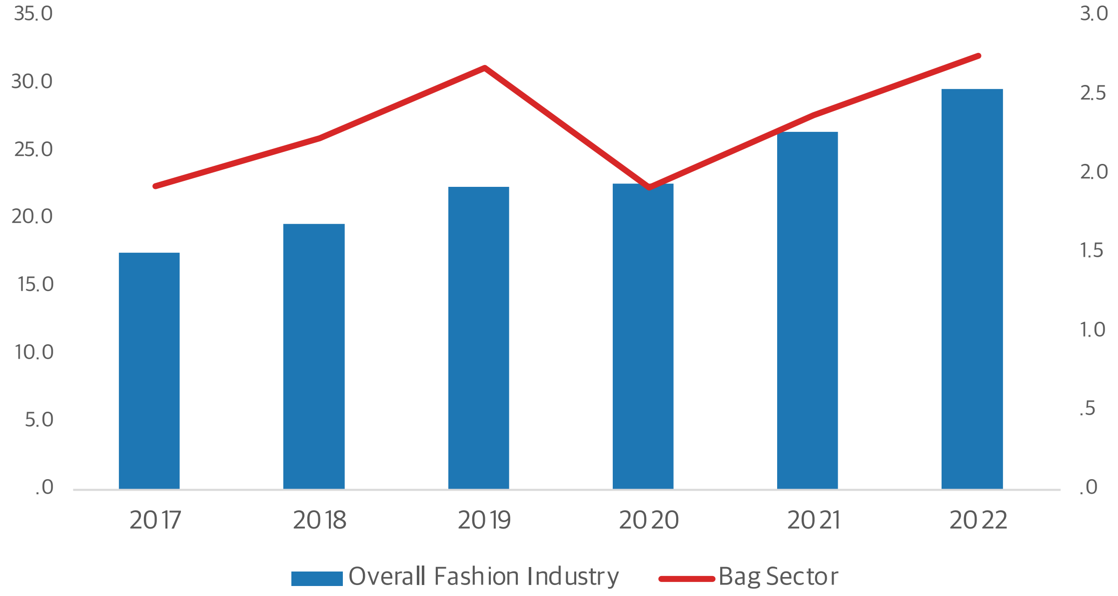
[2017-2022 Fashion Market Size]

Source: KOFOTI | Categories: Clothing, Shoes, Bags | Unit: Trillion KRW | *2022 figure is estimated



[2017-2022 Online Fashion Transaction Volume]

Source: KOSIS | Categories: Clothing, Shoes, Bags, Other Accessories | Unit: Trillion KRW



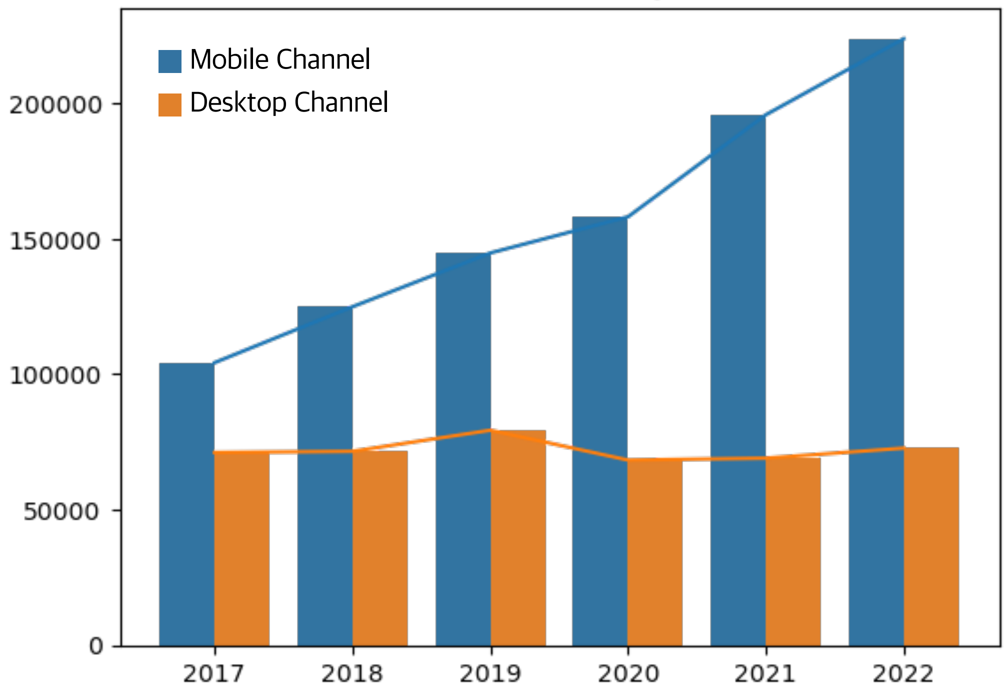
* A direct comparison between the two surveys is not feasible.

While the bag sector comprises approximately 6-8% of the total fashion market, its proportion elevates to 9-12% within online fashion sector.
Since 2017, the overall bag market has seen a 5% growth, whereas the online bag market has surged by an impressive 43%, marking a 16% rise from the previous year.

1.2. Market Trends Overview: Sales Volume by Channel

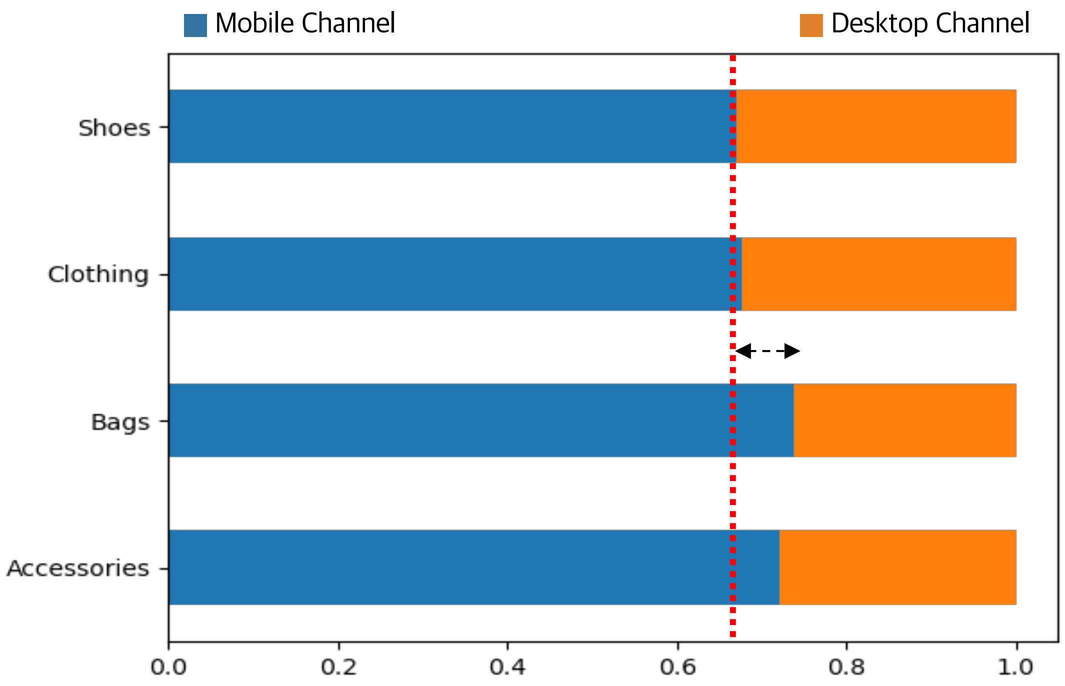
[2017-2022 Fashion Category Transaction Volume by Channel]

Source: KOSIS | Categories: Clothing, Shoes, Bags, Accessories | Unit: 100 million KRW



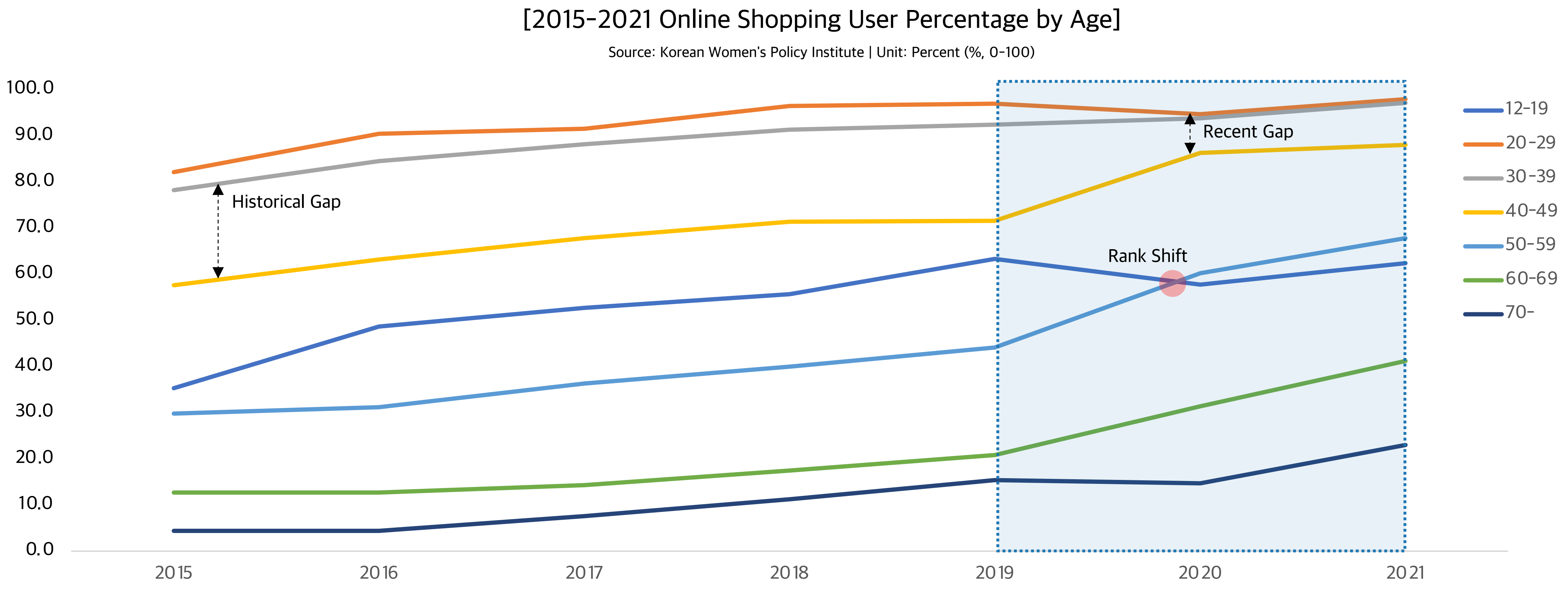
[2017-2022 Fashion Category Transaction Share by Channel]

Source: KOSIS | Categories: Clothing, Shoes, Bags, Accessories | Unit: Ratio (0-1)



Over the past five years, mobile channel transactions in the fashion category have surged by over 200%, representing a 14% year-on-year growth.
Bags command the largest share in mobile transactions, which is about 6 percentage points greater than the lowest - shoes.

1.3. Market Trends Overview: Online Shopping by Age Group

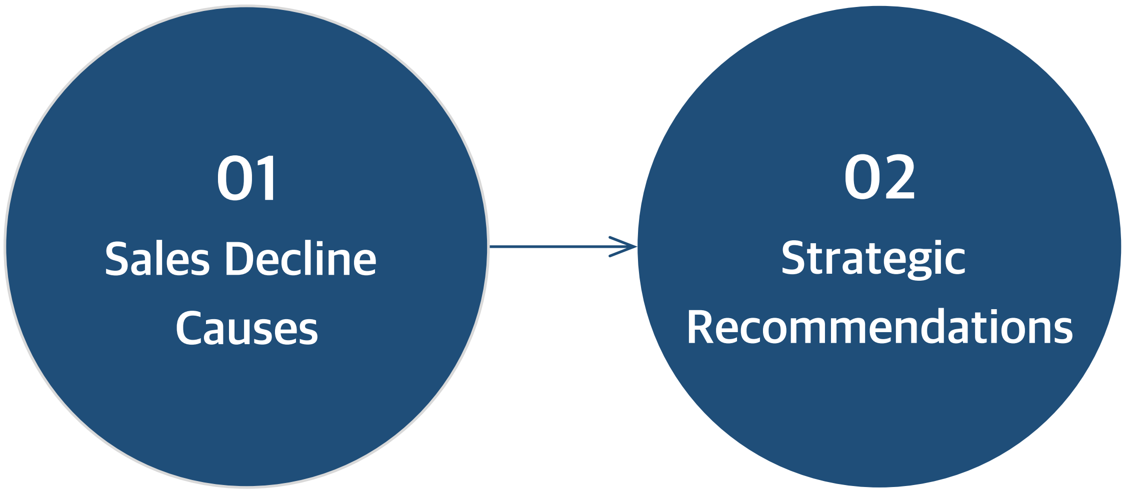


From 2019 onwards, the online shopping user percentage for the 40s and 50s age groups has substantially increased, narrowing the gap with the 20s and 30s age groups. Remarkably, users in their 50s now exceed users under 20.

2. Bag Category Dynamics

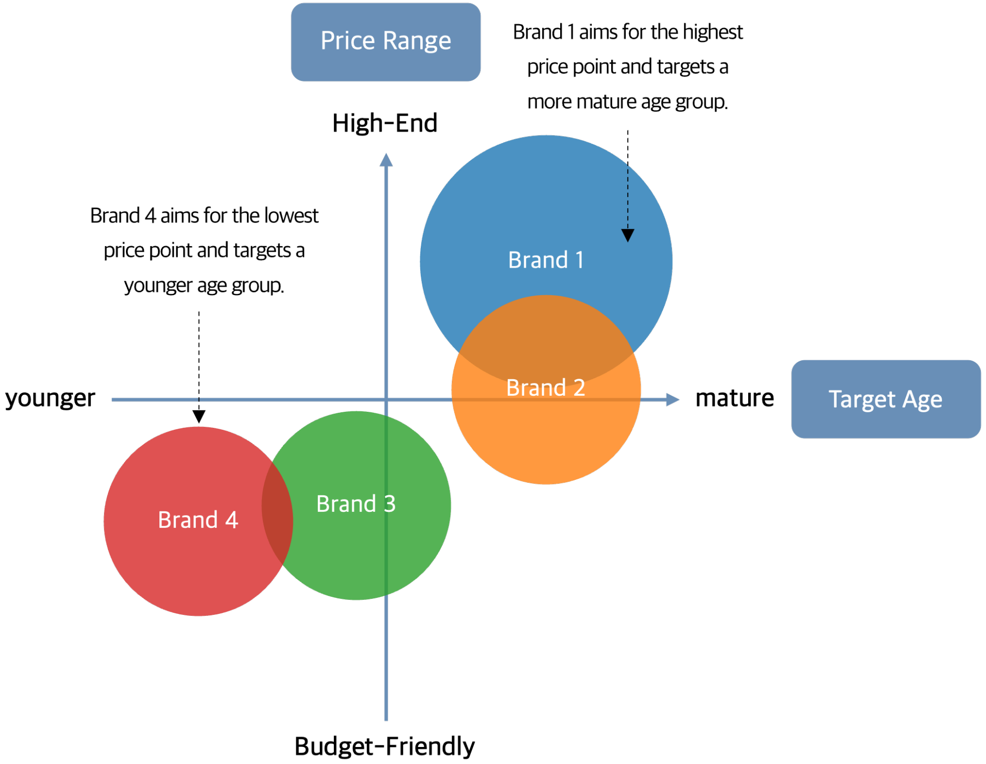
In this section, we delve deeply into the dynamics of the bag category.

Despite the accessory sector's historical strength, there has been a noticeable decline in sales in recent times. Through examining the broader market conditions and specific challenges facing the bag category, we aim to discern the underlying reasons for this downturn and pinpoint actionable solutions. Our primary objective is to diagnose prevailing challenges in the domestic bag market and suggest a viable path forward



2.1. Sales Decline Causes: (1) Market Erosion from Internal Competition

[Positioning of Brands within Company A's Accessories Category]



By examining brand positioning example within Company A, a leading South Korean fashion company,
we gain insight into the complexities of managing multiple brands while ensuring each retains its distinct exclusivity.

2.1. Sales Decline Causes: (1) Market Erosion from Internal Competition

[Comparative Product Analysis within Company A's Accessory Category]

Shopper Bags | Patterned Bags | Rattan / Raffia Bags | Silk Scarves | Checkered Handbags

Comparison Brand 1

Comparison Brand 2

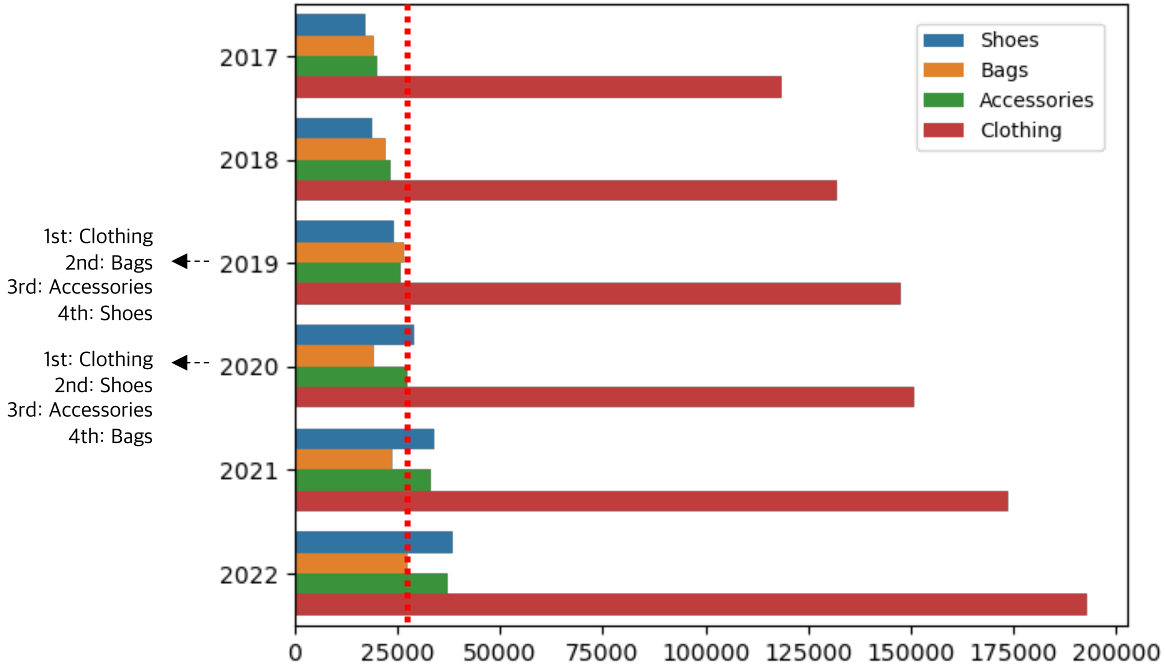
* Comparison Brands 1 and 2 are distinct brands within Company A's accessories portfolio.

Within Company A's accessories category, various brands target distinct customer segments and price points. However, their recurrent introduction of products with similar themes and designs may have inadvertently caused internal brand competition, eroded market differentiation, and potentially led to a decline in sales.

2.1. Sales Decline Causes: (2) Underperformance of Bag Category

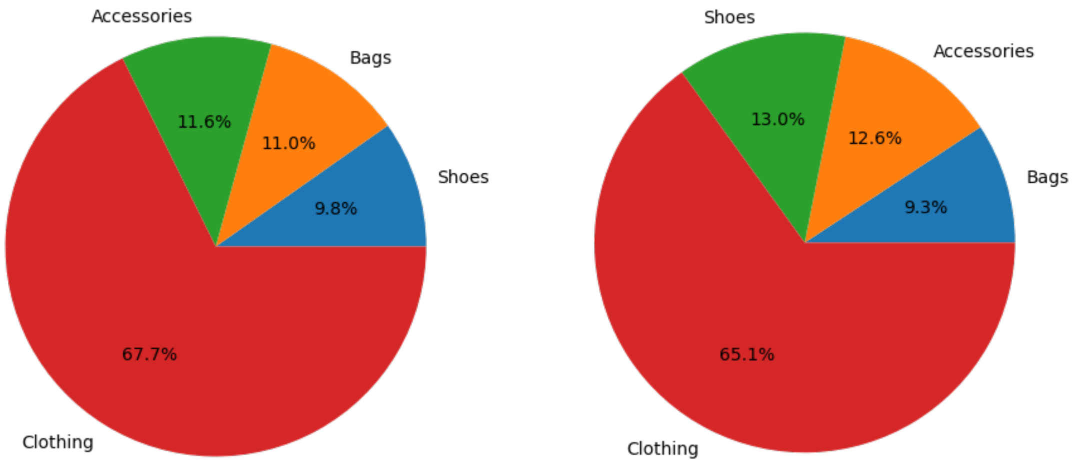
[2017-2022 Annual Transaction Amount by Fashion Category]

Source: KOSIS | Categories: Clothing, Shoes, Bags, Accessories | Unit: 100 Million KRW



[2017 vs. 2022 Annual Transaction Proportions by Fashion Category]

Source: KOSIS | Categories: Clothing, Shoes, Bags, Accessories | Unit: Percent (%, 0-100)



As of 2022, while the bag category has regained its transaction volume to pre-pandemic levels,
its share has diminished by 0.5 percentage points over the past five years. This contrasts with the sustained growth exhibited by other categories.

2.1. Sales Decline Causes: (3) Threats from External Factors

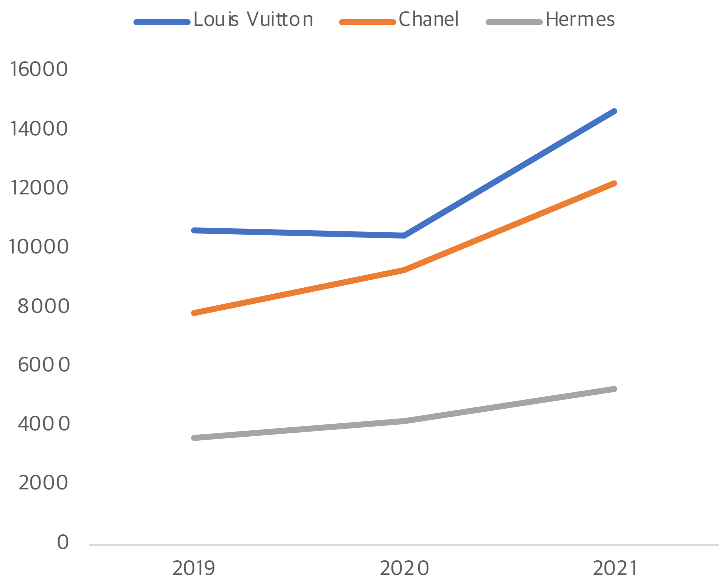
	Key Item 1: Handbags	Key Item 2: Wallets	Key Item 3: Belts
Past Trend	 **Heyday of 4 Domestic Handbag brands** DAKS, Louis Quatorze, MCM, Lovcat	 **Widespread Cash Use** Leather wallets for men and women	 **Mandatory Suit-Wearing in Offices** Leather automatic belts for men.
New Trend	 **Luxury/MZ Brands' Rapid Growth** The domestic handbag market is progressively contracting, facing reputation competition with high-end foreign luxury brands, and price competition with low-cost trendy items.	 **Mobile Payment Convenience** In 2022, the use of convenient payment services via mobile devices accounted for approximately 50%, constituting 22% of the total payment amount. Hence, the need for traditional wallets continuously decreases.	 **Homewear / Business Casual Trend** The demand for traditional design belts is decreasing due to changes in company dress codes. (effects of homewear introduction and business casual adoption due to remote working during the pandemic)

As a result of various external threats, it's becoming increasingly challenging to maintain stable sales for the key items in the accessories category.

2.1. Sales Decline Causes: (4) Expansion of Luxury Market

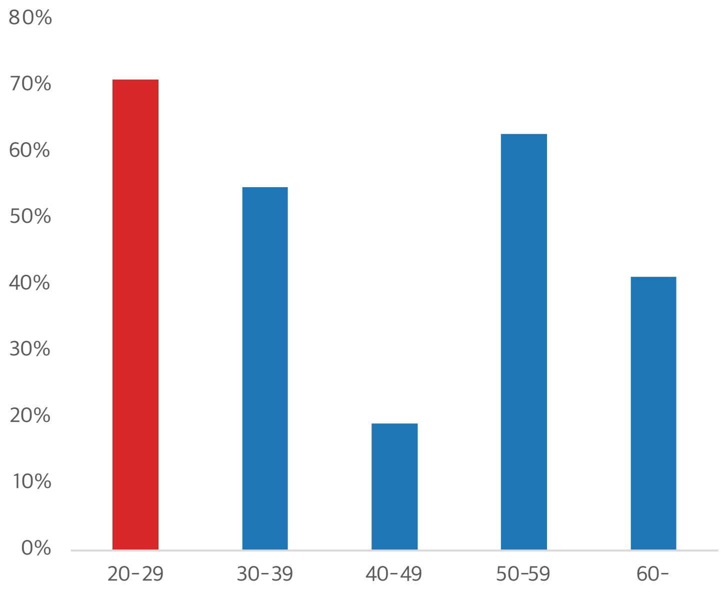
[Sales Trend of Top 3 Luxury Brands]

Source: Financial Supervisory Service | Unit: 100 Million KRW



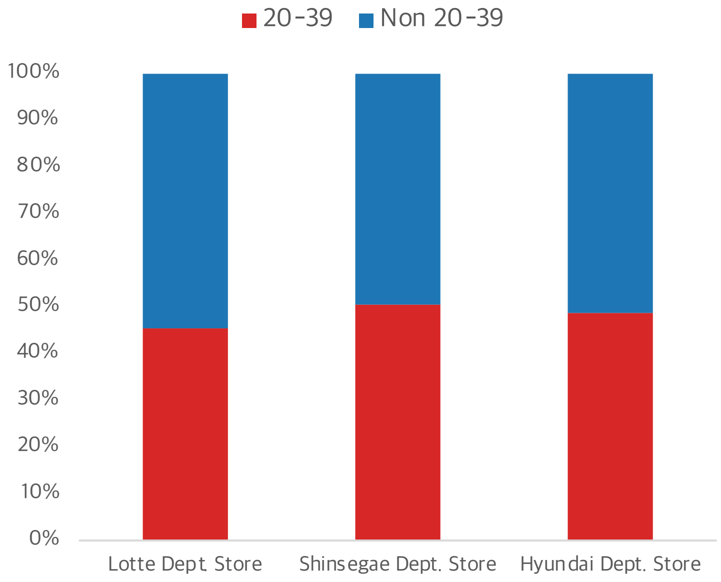
[2021 Luxury Purchases Growth by Age Group]

Source: Lotte | Unit: Percentage (%) | Compared to 2018



[2021 Luxury Purchases: Share by Ages 20-30]

Source: SJ KPMG Economic Research Inst. | Unit: Percentage (%)



*Customer Lifetime Value (CLV): A measure predicting the total net profit a company can make from any given customer.

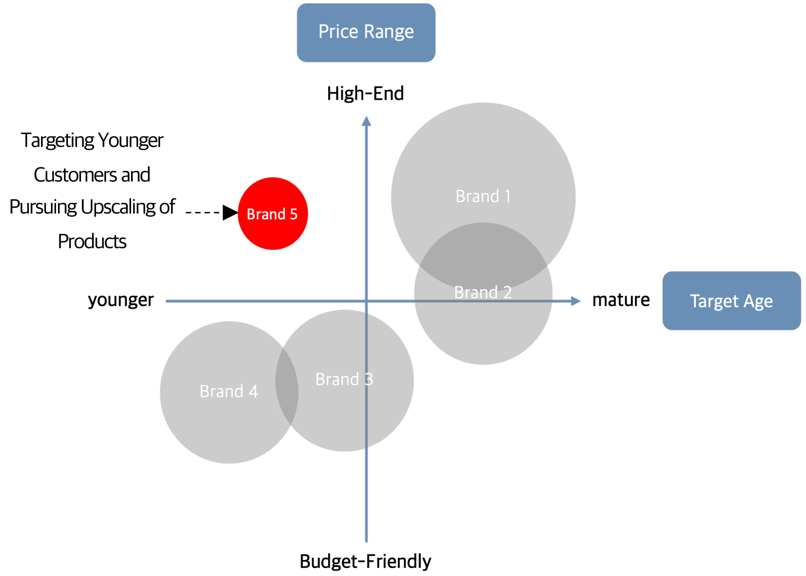
Foreign luxury brands are increasingly dominating the accessories category, outperforming domestic fashion company A, in terms of brand reputation. Additionally, the rise of the MZ generation in the luxury market is impacting A's customer lifetime value negatively.

2.2. Strategic Solutions

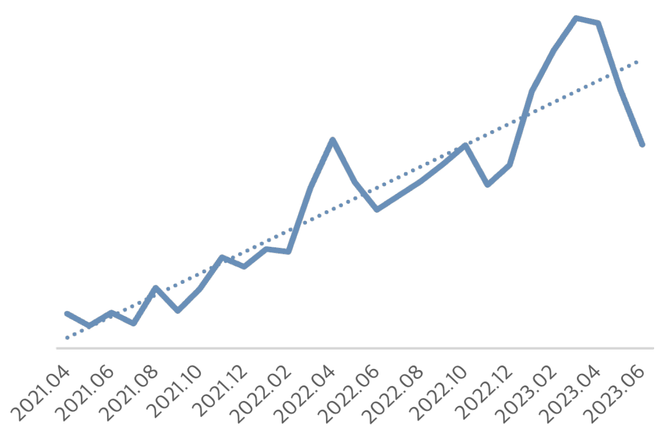
Issue Recognition	Strategic Solutions
Market Erosion from Internal Competition	Implement Distinctive Brand Positioning
Underperformance of Bag Category	Foster Data-Driven Operational Innovation
Threats from External Factors	Reframe and Scale the Accessories Division
Expansion of Luxury Market	Harness MZ Generation's Luxury Purchasing Insights

2.2. Strategic Solutions: (1) Market Erosion from Internal Competition

Distinct Brand Positioning + Product Diversification Reflecting Trends = Securing Market Stability



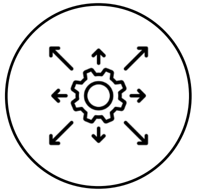
[Sales Trajectory of Company A's New Brand]



Company A's launch of Brand 5 effectively demonstrates the power of targeted brand positioning, identity creation, and product diversification. This approach provides insights for combating market share reduction due to internal competition.

2.2. Strategic Solutions: (2) Underperformance of Bag Category

Addressing the decline in the bag category requires **a holistic consideration** of internal and external factors, and calls for a fresh approach.



Redefine the Category

We need to look beyond our current focus on bags. It's time to diversify, segment our accessories category, and utilize these skills across various other categories. (Refer to pages 23 - 24)

Target the MZ Generation

Get inside the mindset of 20-39 and their attitudes towards luxury purchases. Let's reflect this understanding in our product strategy. If necessary, consider introducing a new, youthful brand to recapture the MZ generation. (Refer to pages 25 - 26)

Embrace Data-Driven Strategy

Leverage machine learning and AI for advanced product planning, sales, operation, and promotion. Use Self Business Intelligence for data-driven decision making and to streamline our business strategies.

2.2. Strategic Solutions: (2) Underperformance of Bag Category

[Generative AI: Unlocking the future of Fashion]

Source: McKinsey & Company (2023/03/28)

Product Planning

- Rely on generative AI for upcoming designs instead of just trend reports or market research.
- Allow real-time analysis of unstructured data, integrating insights from various data sources like videos and social media for thorough customer sentiment analysis.

Sales

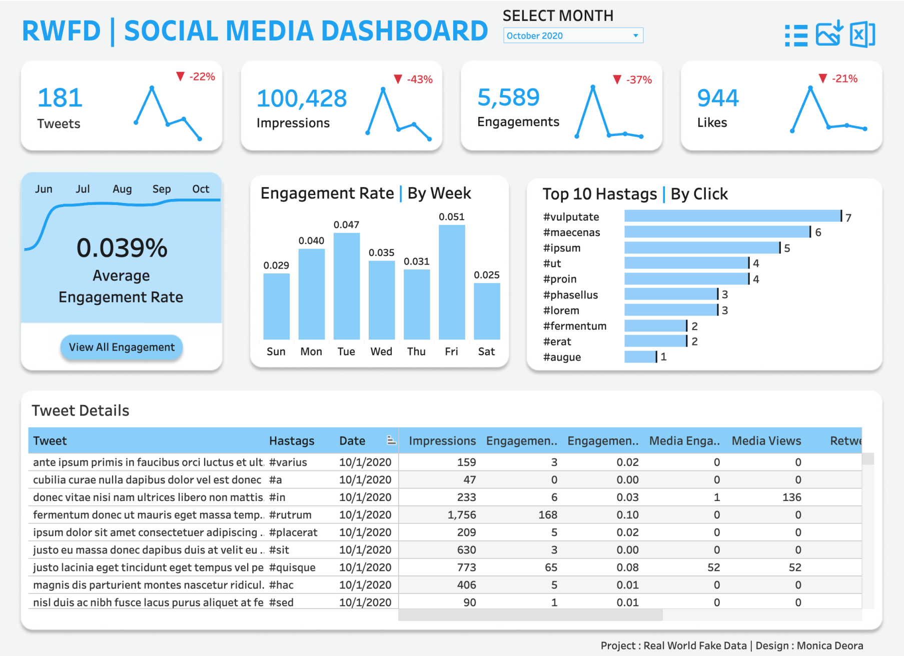
- Improve customer interactions using conversational chatbots and virtual assistants.
- Personalize communications such as style recommendations based on individual profiles, fostering real-time online engagements.

Marketing

- Employ generative AI to understand the dynamics of viral marketing, plan new content accordingly to boost success probability.
- Implement automated customer segmentation for streamlined marketing strategy application.

[Example of a Tableau Keyword Dashboard]

Original text: RWFD Social Media Dashboard | Source: Tableau Public



Reversing the declining sales trend in the bag category demands innovative decision-making.
Developments in data technology, such as unstructured data analysis and Self-BI tools, can offer valuable support for these strategic shifts.

2.2. Strategic Solutions: (3) Threats from External Factors

Existing Accessory Category

Non-Apparel Segment		
Bags	Accessory	Shoes
Leather Bags, Fabric Bags	Wallets, Belts	Dress Shoes, Sandals/Slippers, Boots, Rain Boots, Sneakers, Indoor Shoes···
Travel Bags, Sports Bags···	Card Wallets, Women's Belts, Hats, Umbrellas/Parasols, Scarves, Gloves, Phone Cases, Sunglasses...	

Items Likely Impacted by External Threats

Aligning with market trends

Expanding post-pandemic market

Avoiding conflicts with existing categories

Ideas for Broadening the Accessories Category

Gentle Monster Sunglasses

MLB Baseball Caps

Prada Bucket Hats

Casetify Phone Cases

Acne Scarves

Hunter Boots

Hermes Slippers

Loewe Rattan/Raffia Bags

Helen Kaminski Visor

Gucci Belt

Expanding our accessories assortment (adopting a more segmented category strategy, not solely focused on bags) can help build resilience against external variations and threats.

2.2. Strategic Solutions: (3) Threats from External Factors

Fashion Label 'Gentle Monster'

Cosmetics Line 'Tamburins' (Hand Cream)

'Tamburins' Product Range Expansion

The successful entry of fashion label 'Gentle Monster' into the cosmetics market with 'Tamburins' demonstrates the potential of a bi-directional (internal and external) expansion strategy within the accessories category to mitigate external threats.

2.2. Strategic Solutions: (4) Expansion of Luxury Market

Luxury Consumption in Middle-Aged Group	VS	Luxury Consumption in 20-39 Age Group
Displaying Social Status		Expressing Self and Individuality
Valuing Brand Recognition		Embracing Trends (Limited Editions, Collaborations)
Utilizing Traditional Distribution Channels		Engaging in Both Offline and Online Shopping
Trusting Recommendations from Friends, Family, Colleagues, and Brand Reputation		Trusting Influencers and Celebrities

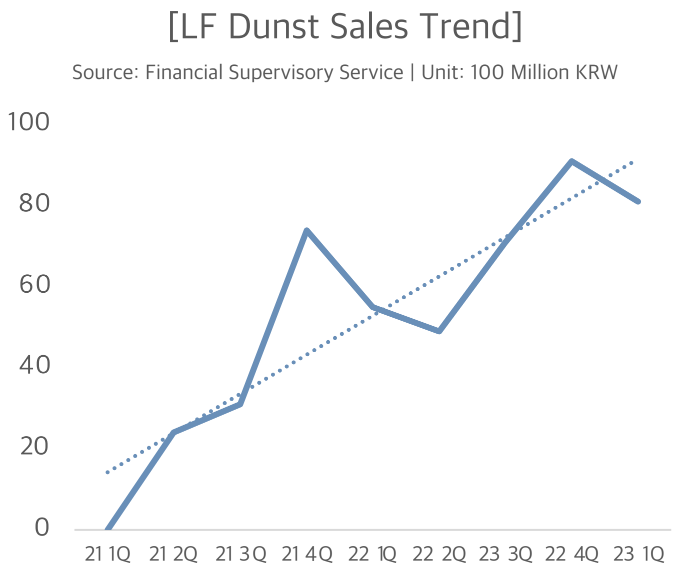
Harnessing the luxury purchasing insights of the MZ generation is crucial in driving post-pandemic growth in the luxury market. By precisely analyzing the core motivations behind their luxury purchases and devising targeted strategies, there is a promising opportunity to re-engage and attract the younger customer base.

2.2. Strategic Solutions: (4) Expansion of Luxury Market

Brand Spin-off into a Separate Entity → **Distinct MZ Generation Targeting** = **Securing a Solid Position in the Market**

LF — Spin-Off / New Identity → CR D&L

- Citidots' millennial casual brand 'Dunst' selects Blackpink's Jisoo as its official ambassador, expanding its influence to the global market...
- 29CM, 29 Gallery X Dunst year-end pop-up store event...
- LF street casual brand 'Dunst' enters Paris showroom...
- LF Dunst to host 'Kakao Shopping Live' on the 23rd at 7:30 p.m...



Dunst's success in independently targeting the MZ generation showcases a solution for differentiating the target customers within a mother company. Replicating this approach in the accessories market can effectively attract and engage young luxury consumers entering the market.

3. Appendix: Time Series Analysis

Using Historical Data to Predict the Future

Data analysis involves identifying patterns in past data to make predictions about the future.
These predictions are most accurate and reliable when certain assumptions are met, such as independence, consistent variability, and stationarity.
However, real-world data often deviates from these assumptions. Time series data, in particular, tends to violate these assumptions as it changes over time.

[Assumptions for Building an Accurate Prediction Model]

Independence
The relationship between data points does not influence each other.

+

Homoscedasticity
The variability of errors is constant across all levels of independent variables.

+

Stationarity
The statistical properties of data remain constant over time.

»

Linear Regression
Predicting the outcome variable accurately using independent variables.

Autocorrelation can reduce the accuracy of predictions.

Uneven distribution of prediction errors affects the consistency of the model.

Without stationarity, we cannot be confident in the validity of analysis results.

Linear regression has limitations when dealing with time series data due to autocorrelation, non-stationarity, seasonality, and trends.

3. Appendix: Time Series Analysis

[Time Series Factors Influencing Fashion Sales]

Seasonality

Fashion trends and demand vary with the seasons, showing distinct sales patterns related to spring, summer, fall, and winter collections.

Year-Round Events

Special days, holidays, and sales events like Black Friday and Boxing Day significantly impact fashion purchasing trends.

Trend Lifecycles

Fashion is highly sensitive to trends. As new trends emerge and old ones fade, buying patterns adapt accordingly.

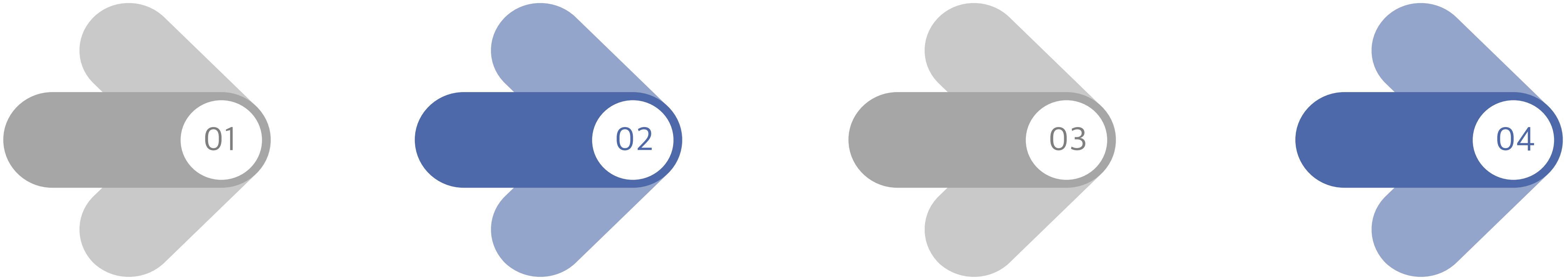
Economic Factors

Broader economic conditions, such as economic growth or downturns, can influence consumer spending on fashion items.

Analyzing fashion sales data requires employing time series analysis techniques to forecast future sales.

3. Appendix: Time Series Analysis

[Time Series Data Analysis Steps]



Prepare Time Series Data

- Gather time series data.
- Address missing values and identify anomalies.
- If necessary, normalize and scale the data.

Check Data Stationarity

- Visualize the data.
- Apply Box-Cox transformation, KPSS test, ADF test, and ACF plot to assess stationarity.
- If the data is non-stationary, perform differencing to remove trends or seasonality and reevaluate stationarity.

Model Design and Evaluation

- Select suitable time series models such as Seasonal Naïve, ETS, ARIMA, SARIMA, LSTM.
- Train the model using the training data and assess its accuracy using metrics like AICc.

Model Selection and Deployment

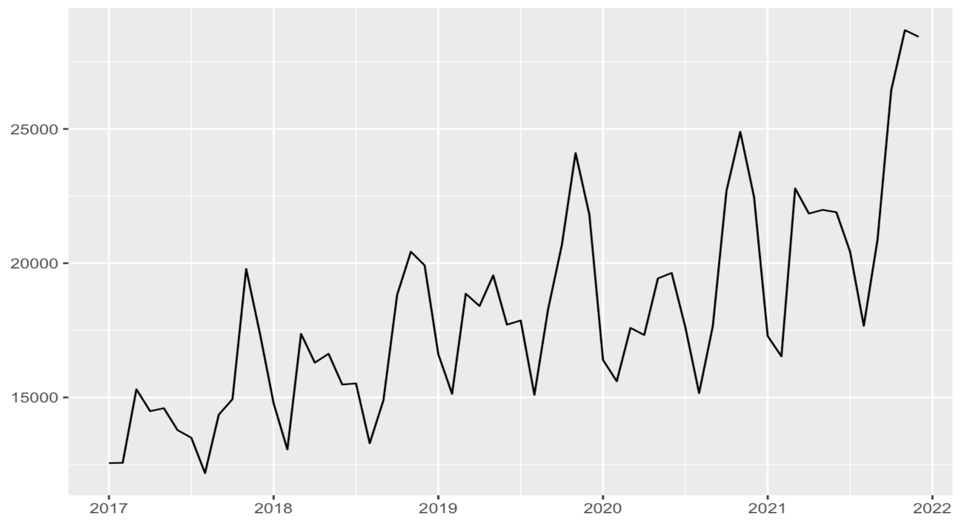
- Choose the model with the best predictive performance. (e.g., lowest RMSE on the test data)
- Apply the selected model for making actual predictions.

3. Appendix: Time Series Analysis

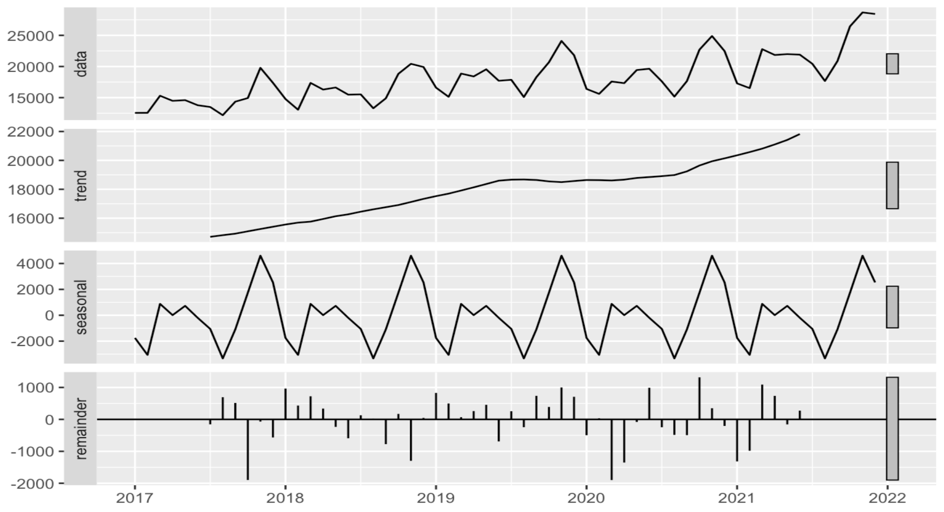
Data Name: Domestic Online Shopping Transaction by Channel and Product Category
Data Source: KOSIS
Survey Period: January 2017 - March 2022
Unit: 100 million KRW

Check Data Stationarity

[Original Data Graph]



[Decomposed Time Series Graph (Additive)]



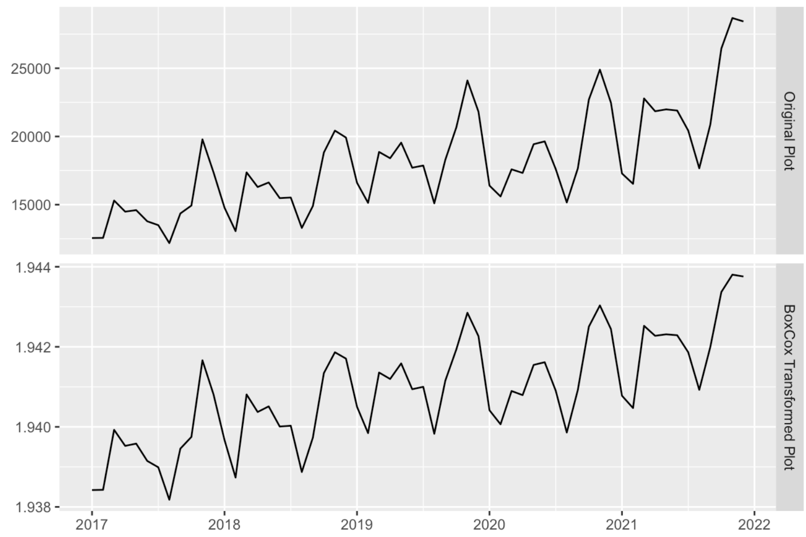
Decomposing time series data into trend, seasonal, and irregular components.

Through a relatively simple visual inspection, it is apparent that the given time series data does not meet the stationarity criteria.

3. Appendix: Time Series Analysis

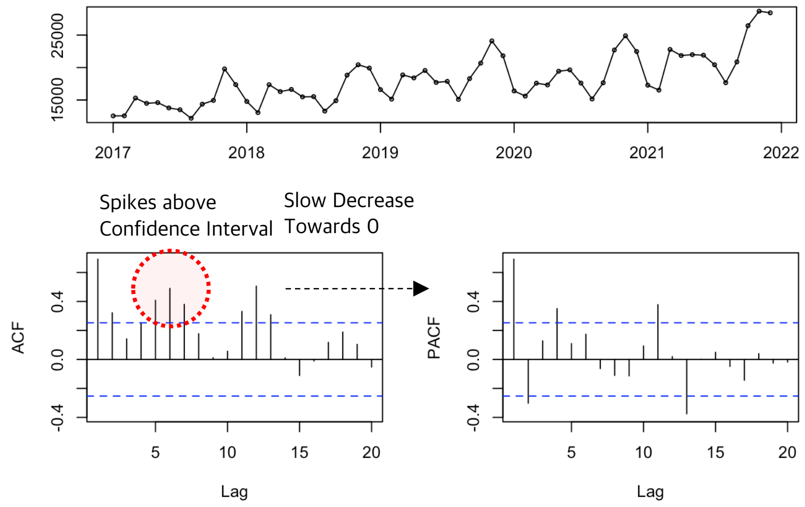
Check Data Stationarity

[BoxCox Transformation]



* BoxCox Lambda: -0.5117632

[ACF Plot]



*Strong autocorrelation within the data is observed through the ACF plot.

[KPSS and ADF Test]

KPSS Test for Level Stationarity
data: df_train
KPSS Level = 1.2782, Truncation lag parameter = 3, p-value = 0.01 (< 0.05, Accept Alternative Hypothesis: Non-stationary)

Augmented Dickey-Fuller Test
data: df_train
Dickey-Fuller = -3.6217, Lag order = 3, p-value = 0.03898 (< 0.05, Accept Alternative Hypothesis: Stationary)

*KPSS Test: Null Hypothesis (Stationary), Alternative Hypothesis (Non-stationary)

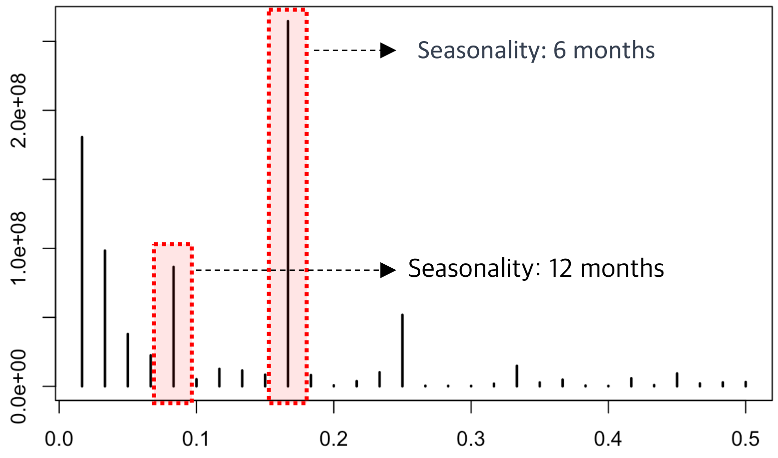
*ADF Test: Null Hypothesis (Non-stationary), Alternative Hypothesis (Stationary)

Through the ACF plot and KPSS test, it is reaffirmed that the given time series data does not meet the stationarity criteria.

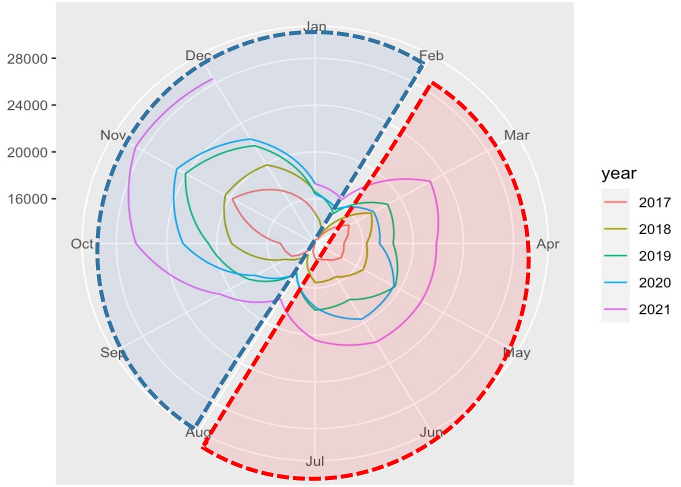
3. Appendix: Time Series Analysis

Check Data Stationarity

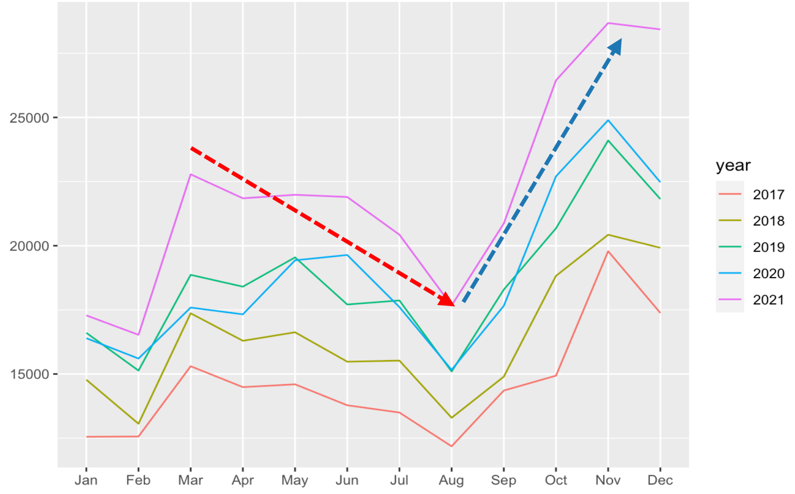
[Periodogram]



[Seasonal Plot (Polar = TRUE)]



[Seasonal Plot (Polar = FALSE)]



Upon analyzing the graph, it is evident that there's a consistent upward trend in the data. Furthermore, the periodogram and seasonality plot reveal periodic fluctuations occurring at six-month intervals. This discernable pattern is a strong indicator of non-stationarity within our time series data.

3. Appendix: Time Series Analysis

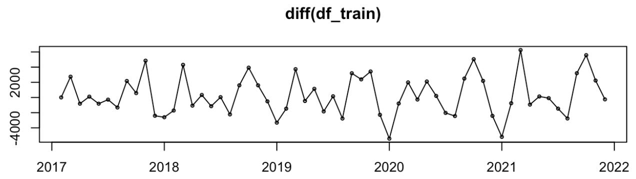
Check Data Stationarity

Differencing: Calculate the difference between each data point and the one before it to remove certain patterns or trends in the data.

First-order differencing: Subtract the previous point from each data point to remove overall trends in the data.

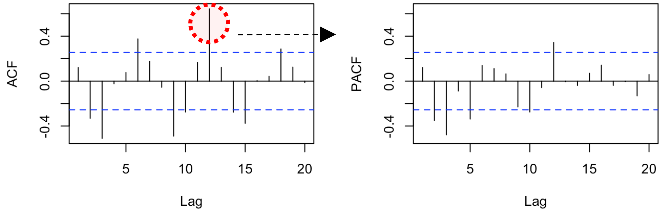
Seasonal differencing: Subtract the data point from an earlier season from each current data point to remove seasonal patterns. (e.g. Subtract data from 12 months ago to remove the yearly pattern)

[First order Differencing]

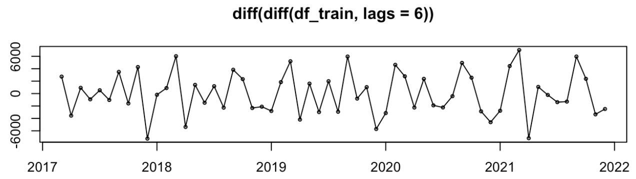


Spikes above Confidence Interval

Fast Decrease Towards 0

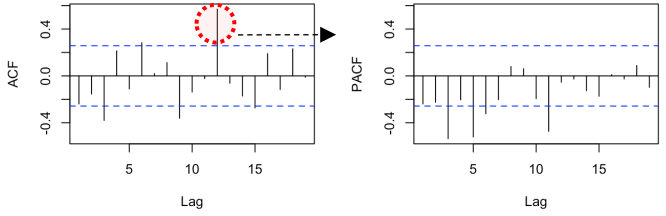


[Seasonal Differencing]

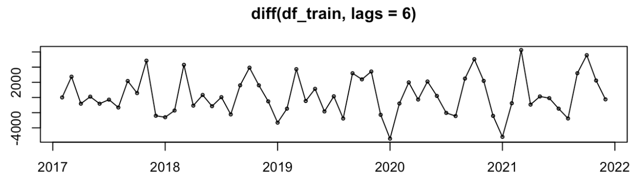


Spikes above Confidence Interval

Fast Decrease Towards 0

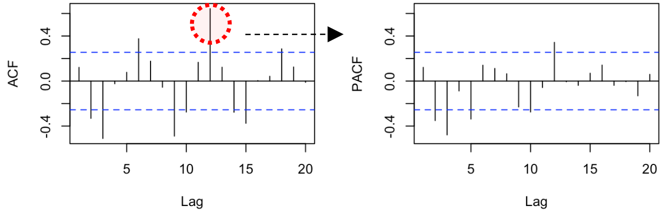


[1st Order + Seasonal Differencing]



Spikes above Confidence Interval

Fast Decrease Towards 0



First-order and seasonal differencing, individually or combined, can help remove trends and autocorrelation from data.
It's crucial to account for any trends or seasonal patterns when crafting models.

3. Appendix: Time Series Analysis

Model Design and Evaluation

Time Series Prediction Models

Seasonal Naïve

1. Type: Simple, quick baseline model*.
2. Assumption: Upcoming season mirrors the last.
3. Use Case: Works best with strong, stable seasonal patterns.
4. Simplicity: No need for parameter estimation, thus low computational cost.
5. Caveat: Struggles with data showing trends or non-seasonal elements.

*A baseline model is a simple reference model used to compare and validate more complex ones.

ETS

1. Type: An enhanced multiple linear regression model.
2. Assumption: Time series comprises Error, Trend, and Seasonality.
3. Use Case: Ideal for data with trends and seasonal patterns.
4. Complexity: Requires parameter estimation (additive, multiplicative).
5. Caveat: Limited in capturing non-linear patterns.

ARIMA / SARIMA

1. Type: Handles both linear and non-linear patterns.
2. Assumption: Presumes data stationarity (applies differencing for non-stationary data).
3. Use Case: Suitable for trends, seasonality, and assumes independent errors.
4. Complexity: Requires estimating several parameters; SARIMA also considers seasonal elements.
5. Caveat: Performance can vary greatly with different parameter settings.

TBATS

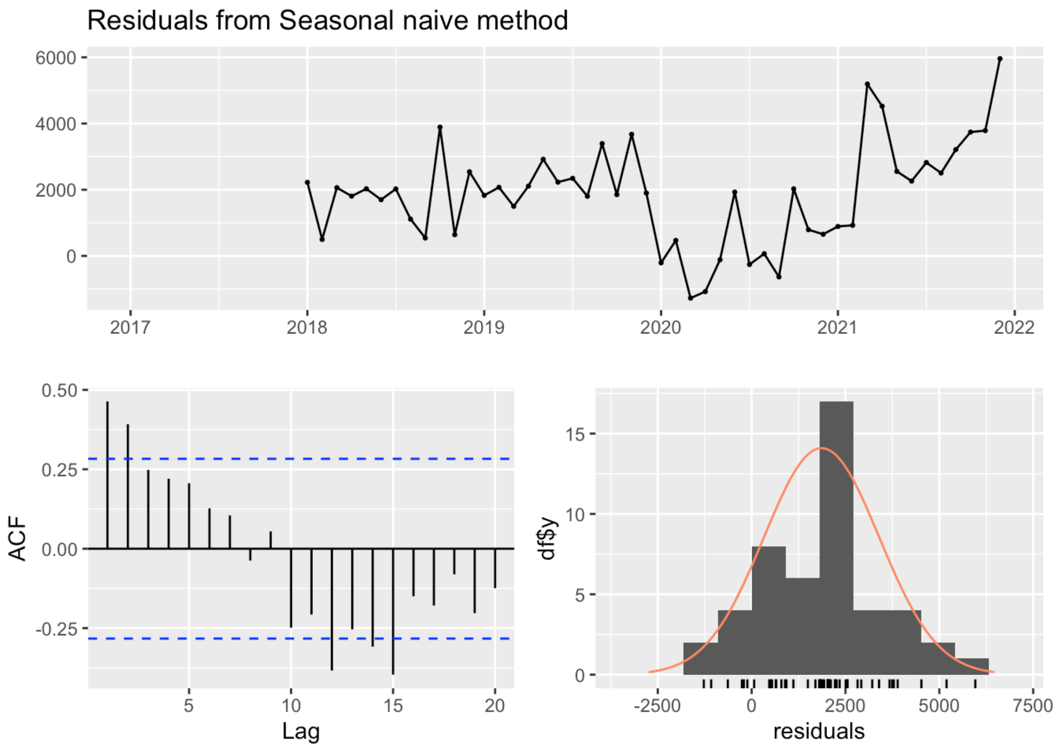
1. Type: Similar to ARIMA but manages multiple seasonalities.
2. Assumption: Potential for multiple seasonality patterns*.
3. Use Case: Ideal for time series data with more than one seasonal pattern.
4. Complexity: Estimates seasonal levels, periods, and trends simultaneously.
5. Caveat: Complexity may result in longer computation times.

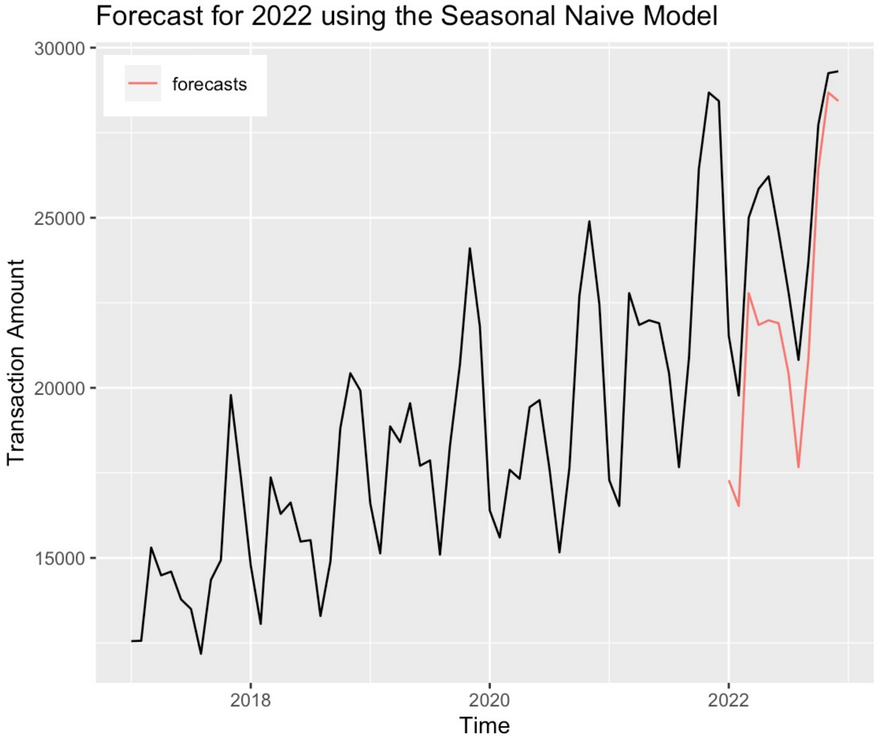
*Multiple seasonal patterns refers to situations where a time series exhibits more than one repeating pattern or cycle over different lengths of time.

3. Appendix: Time Series Analysis

Model 1. Seasonal Naïve

Training data: 01/2017 - 12/2021 | Test data: 01/2022 - 12/2022 | Ljung-Box test p-value: 8.129e-06 | RMSE (Training): 2404.290 (100M KRW) | RMSE (Test): 2902.843 (100M KRW)

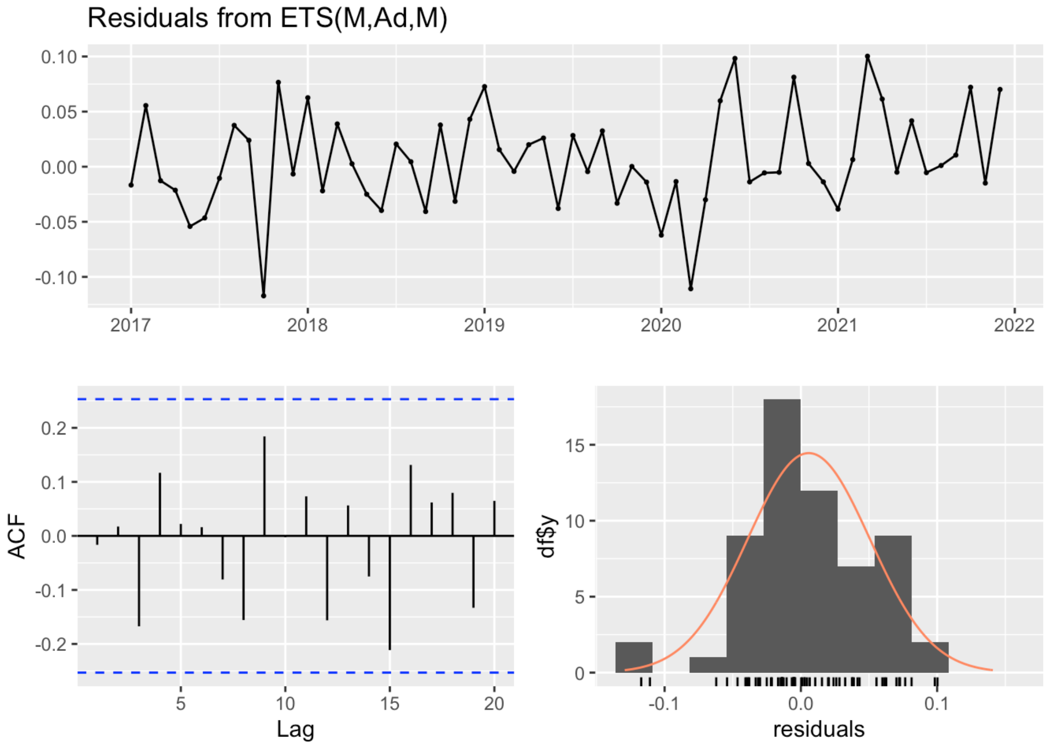


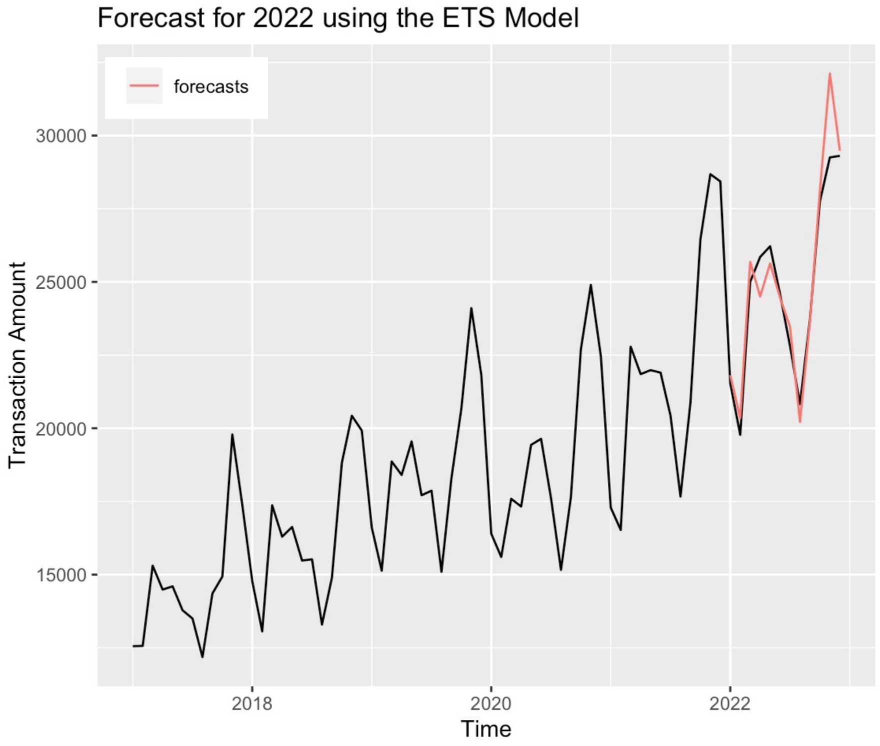


3. Appendix: Time Series Analysis

Model 2. ETS (Error, Trend, Seasonality)

Training data: 01/2017 - 12/2021 | Test data: 01/2022 - 12/2022 | Ljung-Box test p-value: 0.6349 | AICc: 1099.800 | RMSE (Training): 847.3451 (100M KRW) | RMSE (Test): 1010.9793 (100M KRW)

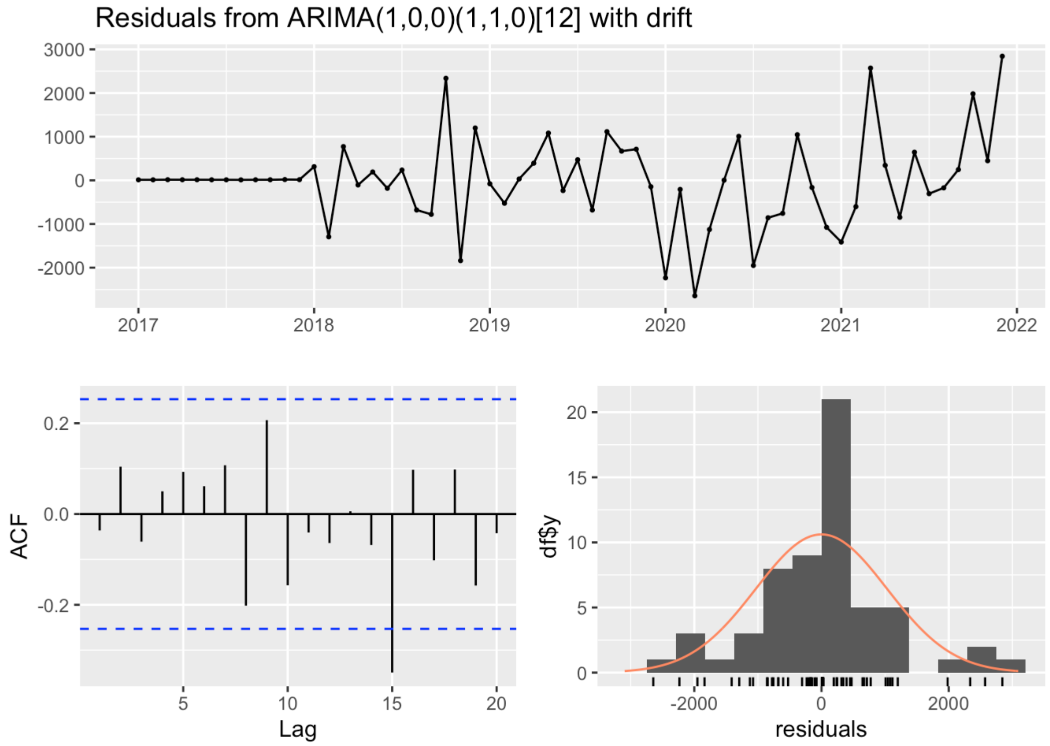


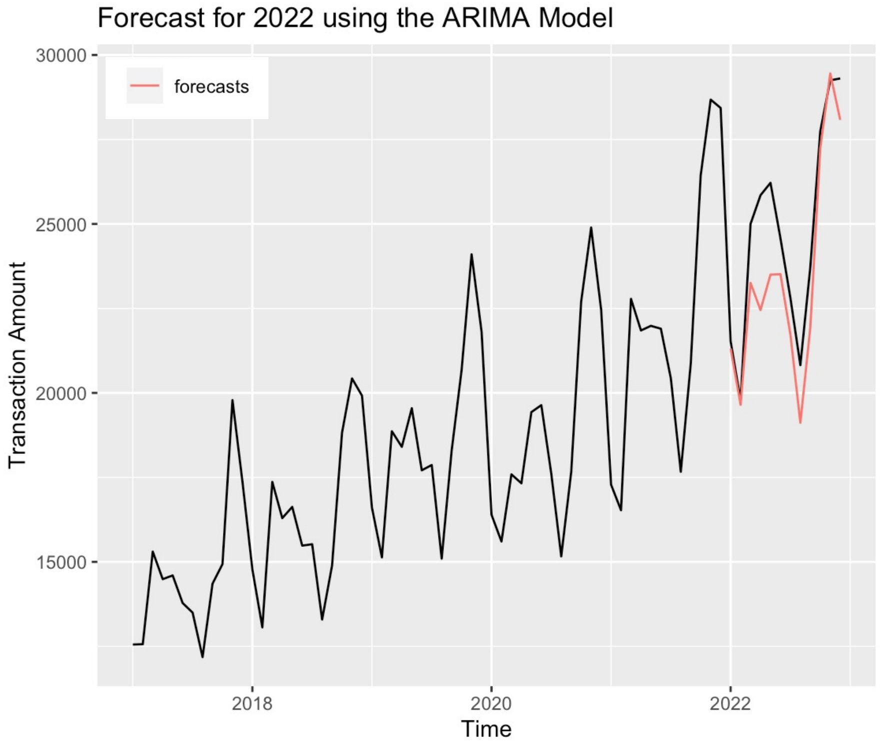


3. Appendix: Time Series Analysis

Model 3. ARIMA (Auto Regressive + Moving Average)

Training data: 01/2017 - 12/2021 | Test data: 01/2022 - 12/2022 | Ljung-Box test p-value: 0.345 | AICc: 825.18 | RMSE (Training): 1022.652 (100M KRW) | RMSE (Test): 1638.319 (100M KRW)

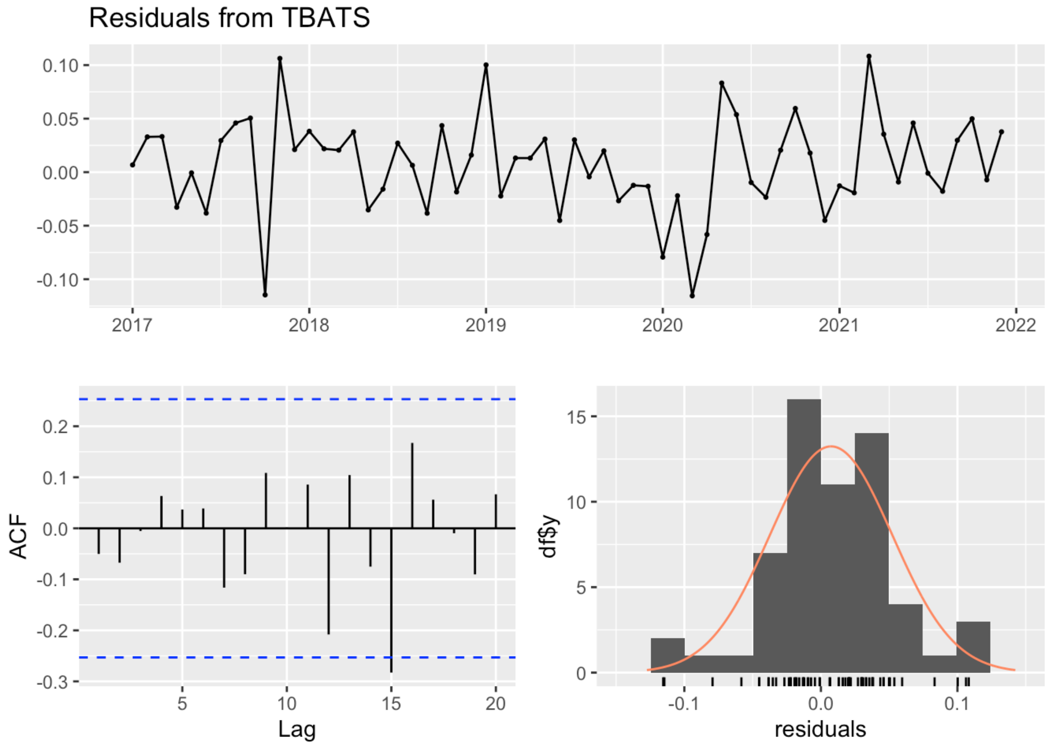


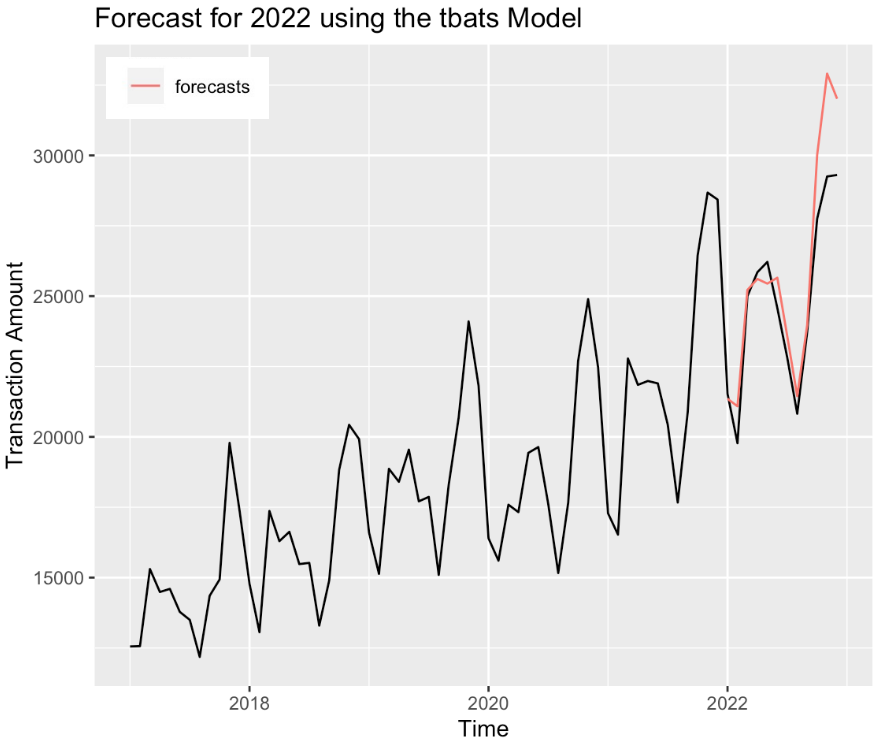


3. Appendix: Time Series Analysis

Model 4. TBATS

Training data: 01/2017 - 12/2021 | Test data: 01/2022 - 12/2022 | Ljung-Box test p-value: 0.843 | RMSE (Training): 832.3611 (100M KRW) | RMSE (Test): 1593.6982 (100M KRW)





3. Appendix: Time Series Analysis

Model Design and Evaluation

	Seasonal Naïve	ETS	ARIMA	TBATS
Training data	01/2017 - 12/2021 (60 data points)			
Test data	01/2022 - 12/2022 (12 data points)			
Ljung-Box test p-value	8.129e-06 (< 0.05)	0.6349	0.345	0.843
AICc		1099.800	825.18	
RMSE (Training)	2404.290 (100 million KRW)	847.3451 (100 million KRW)	1022.652 (100 million KRW)	832.3611 (100 million KRW)
RMSE (Test)	2902.843 (100 million KRW)	1010.9793 (100 million KRW)	1638.319 (100 million KRW)	1593.6982 (100 million KRW)
Final Model	X	O	X	X

- Ljung-Box Test: Checks residual independence. A p-value under 0.05 signals non-independent residuals, suggesting some time series information may have been overlooked during modeling.
- AICc: Measures model fit relative to complexity. A lower AICc indicates a better-fitting model, but doesn't assure test data performance.

Upon thorough consideration of performance evaluation factors for time series data, the ETS model was selected.

3. Appendix: Time Series Analysis

Model Selection and Deployment

[Choice of ETS(m,ad,m) Model]

- ETS(m,ad,m) Model
  - Multiplicative Errors: Variance in observations increases over time.
  - Additive Trend: Data exhibits a linear trend.
  - Multiplicative Seasonality: The strength of seasonal patterns escalates in relation to the time series level
- Trend and Seasonality
  - The given time series data displays an ascending trend and biannual seasonality.
  - The ETS model is proficient when clear trend and seasonality elements are evident in the data.
- Data Stability
  - The used time series data shows minimal shifts in statistical attributes like mean and variance over time (BoxCox Lambda: -0.512).

[Online Fashion Transaction Amount]

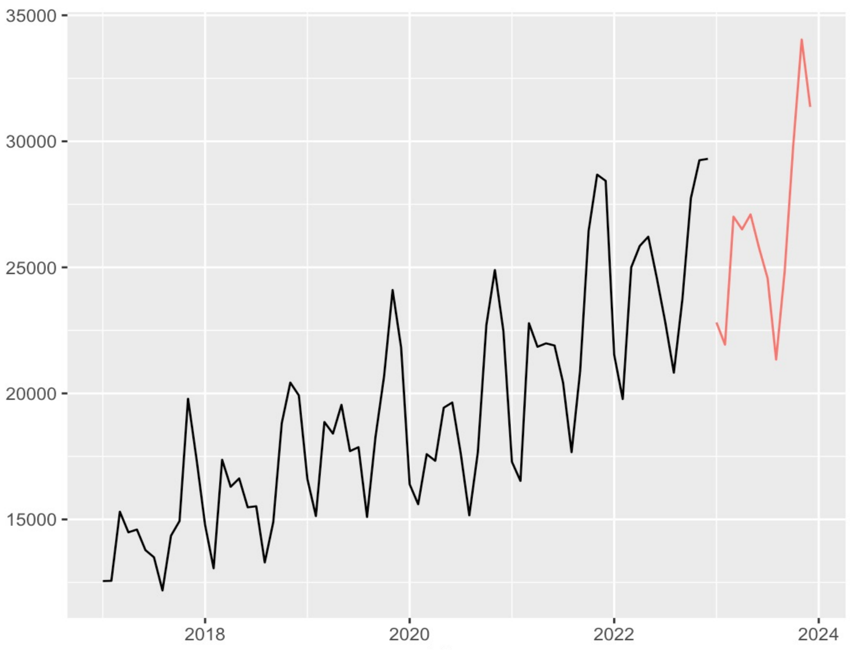
(p) denotes a prediction | Unit: 100 million KRW

Year	Transaction Amount	Growth Rate (%)
2017	1754,25	
2018	196,490	12%
2019	224,113	14%
2020	226,479	1%
2021	264,851	17%
2022	296,608	12%
*2023 p)	317,069	7%

*2023 1Q Predicted Transaction Amount: 71,760 (+8%)
*2023 1Q Actual Transaction Amount: 71,941 (+9%)

[2023 Prediction Online Fashion Transaction Amount]

Method: Time Series Analysis | Model: ETS(m,ad,m) | Unit: 100 Million KRW



The estimated transaction volume for online fashion in Korea in 2023, predicted through the ETS model, is approximately 31.7 quadrillion KRW.
This suggests a slowdown in growth compared to previous years.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