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Consumer attention and company performance: Evidence from luxury companies

Hamid Cheraghali [a], Hannah Høydal [b], Caroline Lysebo [b], Peter Molnár [a,b,c,d,*]

[a] University of Stavanger, Stavanger, Norway
[b] Norwegian University of Science and Technology, Trondheim, Norway
[c] Prague University of Economics and Business, Prague, Czech Republic
[d] Nicolaus Copernicus University, Torun, Poland

A R T I C L E I N F O

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A B S T R A C T

Previous research has shown that investor attention, measured by Google searches for company tickers, can predict companies' returns. However, for companies offering luxury goods in consumer-driven industries, consumer attention might be even more important. Therefore, for each company in the S&P Global Luxury Index we construct a measure of consumer attention based on Google searches for brands related to each company. Our findings suggest that consumer attention predicts the stock returns of these companies to a greater degree than investor attention. The economic significance of these findings is demonstrated by highly profitable trading strategies.

1. Introduction

Investors determine stock prices by using publicly available information. However, investors are not able to process all the available information perfectly due to their human nature, and therefore, it matters which information captures their attention. Several measures of investor attention have been proposed in the literature, such as news article count (Gidófalvi, 2004; Shynkevich et al., 2015), information extracted from Twitter (Gjerstad et al., 2021), the specialized investor social network StockTwits (Cookson and Niessner, 2020; Cookson et al., 2020, 2022), and other social media (Nikfarjam et al., 2010), or their combinations (Audrino et al., 2020).

Since Google made search data publicly available via Google Trends in 2006, Google searches have gradually become one of the most common ways to measure attention (Jun et al., 2018). Google Trends allows researchers to gain insight into the search volume time series for all words and phrases (keywords). The time series represents how search volumes fluctuate and can function as a proxy for attention (Da et al., 2011). Google search volume data, henceforth referred to as search volume index (SVI), has been utilized in various research fields. Two research fields that are particularly relevant for our research are (1) forecasting of stock returns with SVI for company names or tickers as a proxy for investor attention, and (2) forecasting of demand and sales with SVI for company products as a proxy for consumer attention. By combining these two fields, we examine whether consumer attention can predict stock returns.

There are two main economic mechanisms by which information extracted from Google Trends predicts stock returns: (1) attention-induced overpricing due to buying pressure of uninformed investors and (2) mispriced fundamentals. Much of the literature about investor attention is built on Miller (1977)'s mechanism regarding attention-induced overpricing and future low returns,

* Corresponding author at: University of Stavanger, Stavanger, Norway.
E-mail address: poto.molnar@gmail.com (P. Molnár).

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mainly due to uninformed investors. Barber and Odean (2008) show that individual investors are more likely to be net buyers of attention grabbing stocks than institutional investors. Da et al. (2011) find results in accordance with the attention-induced overpricing: uninformed retail investors continually buy stocks that have recently received increased attention; this pushes prices up, causing subsequent returns to be low. Investor attention has been commonly estimated from Google Trends by searches for company tickers or company names.

On the other hand, consumer attention possibly reflects information about future demand and sales of a company's products. Future prospects of a company are relevant, and thus this information should be reflected in the stock price. If the information about future demand and sales is not already incorporated in the stock price, then analyzing consumer attention could provide valuable information in forecasting returns.

By using Google searches as a proxy for consumer attention, researchers build on the observation that a high percentage of consumers use Google as a tool in relation to an event, such as buying a product or traveling to a new place. Research shows that a high share of consumers use the internet as an information source before buying (Ratchford et al., 2001). This share is especially high within the luxury goods segment, where 70% of purchases are estimated to be influenced by online interactions (von Helversen et al., 2018). Google might be the main source of this information, due to its market share of 92% worldwide (Statcounter, 2020).

Roy et al. (2015) state Google's usefulness in forecasting consumer behavior in the fashion industry, while Park (2017) uses SVIs to predict demands in tourism, Zhang (2017) presents its value in predicting consumer confidence, and Paturohman et al. (2018) find that Google Trends empowers the estimation of bank deposits. Other research states the value of using SVIs as a proxy for consumer attention to forecast sales of specific products. Significant results have been presented for the automobile industry (Wijnhoven and Plant, 2017), the food industry (Boone et al., 2017), and the housing market (Wu and Brynjolfsson, 2013).

The investor approach aims to utilize Google Trends in stock market predictions under the assumption that Google is used by investors before they trade a stock. As professional investors likely use paid data sources for information, Google Trends mainly measures attention from retail investors (Da et al., 2011). This limits the share of investors' attention that search volume data is set to measure. Nevertheless, Da et al. (2011) find that even if SVI presumably measures only the attention of retail investors, it still predicts stock prices. Joseph et al. (2011) find that Google searches for tickers of US companies predict abnormal stock returns and trading volumes, particularly for stocks that are harder to arbitrage. Similar results are found by Takeda and Wakao (2014) in the Japanese market, where they find a strong association between search intensity and trading volume and a weak association between search intensity and stock returns.

Kim et al. (2019) find that Google searches neither correlate nor predict future abnormal returns, while on the other hand, Swamy and Dharani (2019) find that SVI can predict stock price movements. Heyman et al. (2019) find that the best performing stocks are likely to revert after a surge in Google search volumes. Ding and Hou (2015) show how the attention of retail investors affects shareholder base and stock liquidity. Yoshinaga (2020) look at 57 large Brazilian companies and find that lagged Google search volume is followed by changes in abnormal returns. Nguyen et al. (2019) find that increased Google search volume has a negative impact on stock returns in the Philippines, Thailand, and Vietnam. Challet and Ayed (2013) observe that the choice of keywords is crucial, and when applied to suitable assets, it yields profitable strategies. Resom et al. (2018) develop a profitable Dow Jones Index trading strategy based on a SVI and hypothesize that similar methodologies are likely to be profitable to numerous other assets as well. Ekinci and Bulut (2021) find that Google searches are associated with positive returns but do not predict positive returns in the next period.

We compare the predictive power of consumer attention and investor attention on companies offering costly goods and services, as high-involvement purchases are usually connected with more research before action (Yang et al., 2015; Ratchford et al., 2001). This leads us to the S&P Global Luxury Index which consists of demand-driven luxury companies, offering expensive products to primarily private consumers. Because luxury companies have distinct brands, it is easier to measure consumer attention to these companies.

We find that our proposed measure of consumer attention (Google searches for a company's brands) predicts a company's performance (excess returns) significantly more strongly than investor attention (Google searches for a company's ticker). Our results are particularly interesting in relation to Madsen and Niessner (2019), Focke et al. (2020), who find that advertising has a significant impact on consumer attention but not on stock returns. This indicates that our measure of consumer attention captures attention beyond that which is a result of advertising.

The rest of the paper is organized as follows: Section 2 describes the data sources and collection methods we use. Section 3 presents the methodology. Section 4 describes the results and Section 5 concludes.

2. Data

We select the set of companies from the S&P Global Luxury Index. For a company to be included, it must have been a constituent of the index at least once within the sample period, and it must have trading data available for at least two months within the sample period. This leaves us with the 100 companies listed in Appendix. Our data consists of a weekly time series from the period beginning in January 2004 until the end of May 2022 (18.4 years).

We use six explanatory variables in our analyses; two variables measured by Google search volumes (one representing investor attention and another representing consumer attention) and four stock market data variables (volatility, return, bid–ask spread, and abnormal trading volume).

2.1. Google trends data

The two search volume indices (SVIs) created from Google Trends are:

1. **SVI^T (investor attention):** This SVI consists of searches for the company ticker, which is the keyword used to measure investor attention in previous research (e.g Da et al. (2011)). To exemplify, for the company *Porsche*, the SVI^T is created from the keyword *"PSHG"*.
2. **SVI^B (brand consumer attention):** This SVI is created from keywords that are mainly brand names. For example, for *Porsche*, the SVI^B variable is constructed from the keywords *"Porsche, Volkswagen, Audi, SEAT, SKODA, Bentley, Bugatti, … "*, which are all brands under the *Porsche* corporation.

2.1.1. Keyword selection

1. **SVI^T:** The company ticker is collected from Refinitiv's company data catalogue.[1] Some are adjusted by removing endings related to the country or stock exchange. This is done to make the tickers more "search friendly".
2. **SVI^B:** For the brand-specific keywords, we research each company manually and gather data regarding each company's portfolio of brands. For example, for *Prada* the firm specific keywords are *"Prada"*, *"Miu Miu"*, *"Coach"* etc.

An overview of all the tickers and brands is provided in Appendix.

2.1.2. Search volume index generation

The time series for each keyword, k, is accessed through an R Google Trends API (*gtrendsR*). We use global search volume data.

The SVI for investor attention (SVI^T) is created by extracting the search volume index time series (G_t) for a specified ticker. It is calculated as abnormal attention by subtracting the logarithm of the rolling 7-week G_t median preceding the week for G_t from each SVI_t.

$$SVI_t = \log(G_t) - \log[Med(G_{t-1}, \dots, G_{t-8})] \tag{1}$$

The SVI for consumer attention (SVI^B) is created by extracting the search volume time series (G_t^k) for each keyword k. The number of keywords is denoted by N. The SVI_t^B is calculated by the equation:

$$SVI_t^B = \frac{1}{N}\sum_{k=1}^{N}\left(G_t^k - [Mean(G_{t-1}^k, \dots, G_{t-8}^k)]\right) \tag{2}$$

In the end, for each company (stock), there is only one SVI^T, and one SVI^B. The construction of SVI^T follows Da et al. (2011), and it is therefore comparable with the existing literature. We design the construction of SVI^B. We use the average instead of the median and the ordinary difference instead of the log-difference because there are too many zeros for some brand searches.

2.2. Market data

For each company, we collect the daily closing, opening, bid, ask, high, and low prices, in addition to the daily trading volumes. This data is obtained from Refinitiv's company data catalogue (Anon, 2022).

2.2.1. Volatility

Volatility is included as a parameter in the model because of the positive relationship between volatility and future returns (Banerjee et al., 2007). We use the Garman and Klass (1980) volatility estimator, as recommended by Molnár (2010). We use the opening, closing, high, and low prices during a trading day to calculate the realized volatility for that day:

$$\sigma_d^2 = \frac{1}{2}(h_d - l_d)^2 - (2log(2) - 1)c_d^2 + j_d^2 \tag{3}$$

with:

$c_d = log(close_d) - log(open_d)$
$l_d = log(low_d) - log(open_d)$
$h_d = log(high_d) - log(open_d)$
$j_d = log(open_d) - log(close_{d-1})$

Weekly variance is calculated as:

$$\sigma_t^2 = \sum_{d\in t}\sigma_d^2 \tag{4}$$

And then weekly volatility is calculated as:

$$\sigma_t = \sqrt{\sigma_t^2} \tag{5}$$

where t is the week, d is the day, $high_d$, low_d, $open_d$ and $close_d$ are the highest, the lowest, opening, and closing prices on a given day.

[1] https://eikon.thomsonreuters.com

2.2.2. Return

We use the equation below to calculate weekly returns:

$$r_t = \frac{close_t - close_{t-1}}{close_{t-1}} \tag{6}$$

where $close_t$ is the closing stock price of Monday in week t. Monday's closing price is used due to the way in which Google Trends provides weekly data. A week is defined as the query average from Monday to Sunday. We therefore apply the closing price of the upcoming trading day; Monday.

Stock returns of individual companies are partly driven by overall market movements. We are interested in the impact of consumer attention on the performance of companies. Therefore the excess return eR_i, the return minus risk-free rate, is used as the dependent variable. The weekly risk-free rates are obtained from Kenneth R. French's data library. Moreover, the S&P Global Luxury Index excess return (L) is also used.

2.2.3. Abnormal trading volume

Weekly abnormal trading volume is included as a variable in the model. We calculate the abnormal trading volume as:

$$V_t = \frac{v_t - \frac{1}{52}\sum_{i=0}^{52} v_{t-i}}{SD_{v,t}} \tag{7}$$

where V_t is the abnormal trading volume, v_t is the raw trading volume, and $SD_{v,t}$ is the standard deviation of volume v for the year preceding week t.

2.2.4. Bid–ask spread

We use the equation below to calculate the daily bid–ask spread:

$$S_d = \frac{ask_d - bid_d}{\frac{1}{2}(ask_d + bid_d)} \times 100 \tag{8}$$

The weekly bid–ask spread S_t for the week t is calculated as an average of the daily bid–ask spread.

2.2.5. Standardization

To make the variables comparable in the panel data regressions, all time series are standardized by subtracting the sample mean and dividing by the sample standard deviation.

3. Methodology

In this section, the methodology is described. We use two approaches: panel data regression models and trading strategies based on rolling-window regressions, which are estimated for each stock separately.

3.1. Panel data regression models

To compare the predictive power of SVI^B and SVI^T, we conduct panel data regressions with month fixed-effects: one forecasting model (Eq. (9)) and one explanatory model (Eq. (10)). We also conduct regressions using only one SVI as a predictor in both cases. The regression equations are given by:

$$eR_{i,t} = \alpha + \beta_1 SVI^B_{i,t-1} + \beta_2 SVI^T_{i,t-1} + \mu_m + \nu_{i,t} \tag{9}$$

$$eR_{i,t} = \alpha + \beta_1 SVI^B_{i,t} + \beta_2 SVI^T_{i,t} + \mu_m + \nu_{i,t} \tag{10}$$

where i is the company, t is the week, m is the month, α, β_1 and β_2 are regression coefficients and μ_m are month fixed effects.

Next, panel data regressions are conducted to compare the predictive power of SVIs with that of other variables. In addition, a single explanatory variable regression is performed for each variable. The regression model takes the form:

$$eR_{i,t} = \alpha + \beta_1 L_{t-1} + \beta_2 SVI^B_{i,t-1} + \beta_3 SVI^T_{i,t-1} + \beta_4 eR_{i,t-1} + \beta_5 \sigma_{i,t-1} + \beta_6 V_{i,t-1} + \beta_7 S_{i,t-1} + \mu_m + \nu_{i,t} \tag{11}$$

where i is the company, t is the week, m is the month, α, $\beta_1, \dots \beta_7$ are regression coefficients and μ_m are month fixed effects. As all variables are standardized, all coefficients can be interpreted relative to each other.

3.2. Trading strategy

To evaluate the possibility of financial gains by using consumer attention (denoted as SVI^B) in forecasts, we create four simple trading strategies that differ only in the way we forecast returns. For each stock in the S&P Global Luxury Index, we forecast returns in four ways.

The first forecasting model is based on financial variables only and does not include any SVI. The financial variables that are included in this model (and also the remaining three models) are L, r, σ and V, and the regression model is given by:

$$eR_{i,t} = \alpha_i + \beta_{1,i} L_{t-1} + \beta_{2,i} eR_{i,t-1} + \beta_3 \sigma_{i,t-1} + \beta_4 V_{i,t-1} + \mu_i \tag{12}$$

where i is the company, t is the week, m is the month, α, β_1, $\dots \beta_7$ are regression coefficients and μ_m are month fixed effects.

The second forecasting model also includes consumer attention SVI^B:

$$eR_{i,t} = \alpha_i + \beta_{1,i} SVI^B_{i,t-1} + \beta_{2,i} L_{t-1} + \beta_3 \sigma_{i,t-1} + \beta_4 V_{i,t-1} + \mu_i \tag{13}$$

The third forecasting model includes investor attention SVI^T instead of consumer attention SVI^B:

$$eR_{i,t} = \alpha_i + \beta_{1,i} SVI^T_{i,t-1} + \beta_{2,i} L_{t-1} + \beta_3 \sigma_{i,t-1} + \beta_4 V_{i,t-1} + \mu_i \tag{14}$$

The fourth forecasting model includes both investor attention SVI^T and consumer attention SVI^B:

$$eR_{i,t} = \alpha_i + \beta_{1,i} SVI^B_{i,t-1} + \beta_{2,i} SVI^T_{i,t-1} + \beta_{3,i} L_{t-1} + \beta_4 \sigma_{i,t-1} + \beta_5 V_{i,t-1} + \mu_i \tag{15}$$

In this way, we can compare whether the basic model can be improved by including attention, and determine which type of attention (investor or consumer) matters more.

We train the forecasting models on a two-year rolling interval, meaning we use the data from week $t-104$ to week $t-1$ to estimate the regression parameters for predicting excess return in week t. The predictions are performed over the period from January 2010 until May 2022 (12 years and 5 months). Companies in which to invest are selected based on the predicted excess returns, and actual returns are used to calculate the portfolio's value.

We create a trading strategy for each model. These trading strategies always buy four stocks with the predicted highest returns and sell short four stocks with the predicted lowest returns. All stocks have equal weight. We do re-balancing each week based on the models' predictions for the upcoming week.

Transaction costs are set to be 10 basis points for each trade (0.1%). This is a conservative measure, estimated based on a 0.02% brokerage fee and half a bid/ask spread of 0.16% (average for the companies in the index). We disregard stock size and trading volume issues. Hence, we assume we will always have the option to buy the desired amount of any stock at the Monday closing prices and that the trades are not affecting the market.

3.3. Comparison of panel data models with trading strategy approach

With both approaches, the panel data regressions and the trading strategy, we seek to answer whether consumer attention can predict stock returns of luxury companies, and whether it works better than investor attention for this purpose.

It is important to note that the trading strategy approach is much more flexible than panel data models. In panel data models, we estimate a single set of coefficients for the whole data set. On the contrary, in our trading strategy a separate model is estimated for each stock, and coefficients are therefore allowed to differ across stocks. Moreover, since we also apply rolling-window regressions in the trading strategy, coefficients will vary across both time and stocks.

Since our panel data regressions might be too restrictive, the main focus should be on our trading strategy. Moreover, in the case of panel data for stock returns, various econometric issues such as cross-correlation need to be addressed, and therefore it is impossible to design a perfect panel data model for stock returns.

However, as a classic saying states: "All models are wrong, but some are useful", panel data models still serve our purpose. These models allow us to see the broad picture and easily summarize if the impact of a particular variable is positive or negative.

4. Results

In this section, we present and discuss the results. First, we compare the measure of consumer attention (SVI^B) with the measure of investor attention SVI^T. The models use excess return ($r_t - r_{ft}$) as the dependent variable. We then create a trading strategy to evaluate the benefits of including consumer attention in forecasting returns.

To see whether the proposed measure of consumer attention (SVI^B) has the potential to provide additional information to that which has already been provided by the other explanatory variables applied in earlier papers (σ, r, V, S and SVI^T), we first look at the correlation between the variables.

The correlation matrix reported in Table 1 reveals small degrees of correlation among the proposed measures and the other variables, as the correlation coefficients are all close to zero. This implicates that there is no clear relationship and that the measure of consumer attention can potentially provide additional information. The correlation matrix shows that we do not have highly correlated variables.

The low correlation of SVI^B with other variables, can demonstrate that the proposed measure of consumer attention exposes information reflecting trends, media pressure, sentiment, or other factors related to consumer attention, which have not been

Table 1
Correlation matrix of variables. This table shows average of correlations between variables grouped by stocks. In other words, we calculate such correlation matrix for each stock, and report an average of these correlations.

	σ	r	V	S	SVI^T
r	−0.108				
V	0.300	−0.041			
S	0.154	−0.027	0.012		
SVI^T	0.020	0.005	0.002	−0.011	
SVI^B	−0.033	0.028	−0.016	−0.003	0.032

Table 2
Explanatory model using weekly SVI^B and SVI^T from the same week as independent variables. Columns (1) and (2) present results using a single SVI to explain excess returns. Column (3) presents results from the regression, including both variables. All regressions include month fixed-effects. Standard errors are clustered at the time and stock levels and reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: eR_t		
	(1)	(2)	(3)
SVI_t^T	0.002		0.002
	(0.004)		(0.004)
SVI_t^B		0.003	0.003
		(0.004)	(0.004)
Observations	69,655	68,984	68,982
R^2	0.081	0.080	0.080

Table 3
Regression results on excess return using the lagged weekly SVI^B and SVI^T as independent variables. Columns (1) and (2) present results using a single SVI to explain excess returns. Column (3) presents results from the regression, including both variables. All regressions include month fixed-effects. Standard errors are clustered at the time and stock levels and reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: eR_t		
	(1)	(2)	(3)
SVI_{t-1}^T	−0.007**		−0.007*
	(0.004)		(0.004)
SVI_{t-1}^B		0.011***	0.011***
		(0.004)	(0.004)
Observations	69,653	68,982	68,980
R^2	0.081	0.080	0.081

incorporated within the other variables. Events causing changes in σ, r, V, and SVI^T could be such events as earnings releases, company and industry news, recommendations from analysts, central bank announcements, interest rate changes, or heard mentalities. The spikes in SVI^B might be caused by social media hype, campaigns, changes in advertising exposure, or other factors. Consequently, the measure of consumer attention could reflect indicators not captured by the other variables. The next step is to evaluate whether information incorporated in consumer attention is valuable to stock return forecasting.

4.1. Panel data models

We compare the predictive power of the suggested measure of consumer attention (SVI^B) to the common measure of investor attention (SVI^T). We estimate their predictive power by first conducting panel data regressions with only one independent variable and excess return as the dependent variable. This allows us to analyze the ability of each single variable to explain excess returns. We also perform the regression with both variables included. In addition, we conduct an explanatory model to evaluate whether the variables are able to explain the present.

Tables 2 and 3 present the results from the regressions. Table 2 reveals that neither investor attention nor consumer attention is correlated with stock returns. Next we look at a more interesting question: Can these attention measures predict stock returns? In Table 3 we observe that high investor attention predicts negative returns, while high consumer attention predicts positive returns. Luo and Zhang (2013) also find that consumer attention, measured by social media buzz and traffic directed at specific companies, drives stock returns in a positive direction. On the other hand, previous literature is inconclusive about the impact of investor attention on stock returns, for example Da et al. (2011) find a positive impact, while Bijl et al. (2016) find a negative impact.

Table 4
This table shows the results of regressing consumer attention (SVI^B) on investors' attention (SVI^T), and using the residual to predict excess return (eR). $Residual_t$ denotes the residual of regressing time$t$ SVIs, and $Residual_{t-1}$ represents the residual of regressing the first lag of SVIs. All regressions include month fixed-effects. Standard errors are clustered at the time and stock levels and reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: eR_t	
	(1)	(2)
$Residual_t$	0.015***	
	(0.004)	
$Residual_{t-1}$		0.011***
		(0.004)
Constant	−0.0001	0.00004
	(0.004)	(0.004)
Observations	68,980	68,980
R^2	0.0002	0.0001

The models indicate that stock returns for the selected companies can be better predicted by consumer attention than by investor attention. Model (3) in Table 3 reveals that investor attention is not significant at the 1% or 5% confidence level, while consumer attention is significant at the 1% significance level. A linear hypothesis test reveals that these coefficients are different at the 1% significance level ($p = 0.00093$). We therefore conclude that consumer attention predicts stock returns better than investor attention.

Lastly, as a robustness check, we regress consumer attention (SVI^B) on investor attention (SVI^T), and use the residual to predict excess returns. If the residual of the regression, which is part of SVI^B but orthogonal to SVI^T, has statistically significant power to predict excess returns, this suggests that SVI^B contains relevant information that is absent in SVI^T but is able to explain returns. Results reported in Table 4 show that these residuals are indeed significant in predicting returns, i.e. SVI^B contains information that is absent in SVI^T and is able to explain returns.

In total, consumer attention adds value to predicting excess returns. Whether this holds only for the companies in the S&P Global Luxury Index, or if it can be extended to other industries and companies is a question for further research. SVI^B outperforming SVI^T could be due to SVI^T only consisting of one keyword (company ticker), while SVI^B is constructed from several search terms (brands). A larger diversity of keywords could be capable of capturing attention or information to a greater extent.

To determine the value of using consumer attention (SVI^B) compared to volatility (σ), past excess return (eR), past return of the luxury index (L), bid–ask spread (S), or abnormal trading volume (V) as predictors of excess return, we perform panel data regression. By interpreting the coefficients and R^2-values, we estimate the additional effect of adding the variable to the model. We observe in Table 5 that all these variables, except bid–ask spread, can predict returns when included as the only explanatory variable in the panel data regression. However, when these variables are included in the regression together, some of them become insignificant, including our main variable of interest, consumer attention (SVI^B). The most significant variables are past returns, both past index returns and past company returns.

4.2. Trading strategy

Trading strategy starts in 2010, because two years of data were needed for the rolling regressions, and before 2008, data quality was too low for a trading strategy (too few stocks, Google searches etc.).

We need to consider the model's assumptions when it comes to whether the proposed strategy will yield a payoff in the real world. First, we assume transaction costs of 0.1%. This can be regarded as relatively conservative; therefore, we can expect the actual transaction costs to be lower and not negatively affect the return. The strategy also assumes buying arbitrary share sizes, without considering the stock size, in addition to always buying at the Monday closing price. These assumptions are unlikely feasible when applying the strategy in the real world, and they can have a slightly negative impact. However, this impact can be expected to be small and, therefore, not considered.

Fig. 1 shows the performance of the S&P Global luxury index and the performance of trading strategies, including transaction costs. Note that these strategies are long-short strategies where 4 stocks are bought and 4 stocks are sold with equal weights, dynamically. The actual performance of the S&P Global Luxury Index is included to put the portfolios' performance into perspective.

Table 6 presents the same results in a table format, showing returns for each year, as well as the annualized return over the whole period.

First of all, the findings show that all considered trading strategies outperform the S&P Global Luxury Index. Therefore, we can conclude that all the considered strategies are able to predict the strongly and poorly performing stocks.

Second, it seems that trading strategies are improved by including consumer attention (SVI^B) in the prediction model, while they are not improved by including investor attention (SVI^B). The strategy that includes only SVI^T performs worse than even a benchmark strategy that includes no SVI.

To statistically check the effect of including consumer attention (SVI^B) in the prediction model, we use both CAPM and the Fama–French 3-factor model to test if returns from our constructed portfolio can be explained with those models. Table 7 shows the

Table 5
Predictive regression results for weekly excess return (eR_t). Columns (1)-(7) present results using a single independent variable regression to explain excess returns. Column (8) presents results from the regression including all variables. All regressions include month fixed-effects. Standard errors are clustered at the time and stock levels and reported in parentheses. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable:							
	excess return (eR_t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
σ_{t-1}	0.044***							0.017
	(0.016)							(0.016)
L_{t-1}		0.499***						0.491***
		(0.007)						(0.006)
eR_{t-1}			−0.098***					−0.042***
			(0.008)					(0.008)
V_{t-1}				0.029***				0.012***
				(0.008)				(0.004)
S_{t-1}					−0.003			−0.002
					(0.004)			(0.004)
SVI^T_{t-1}						−0.007*		−0.005
						(0.004)		(0.003)
SVI^B_{t-1}							0.011***	0.003
							(0.004)	(0.004)
Observations	63,226	63,555	63,386	62,669	68,712	69,653	68,982	61,498
R^2	0.090	0.285	0.097	0.090	0.083	0.081	0.080	0.292

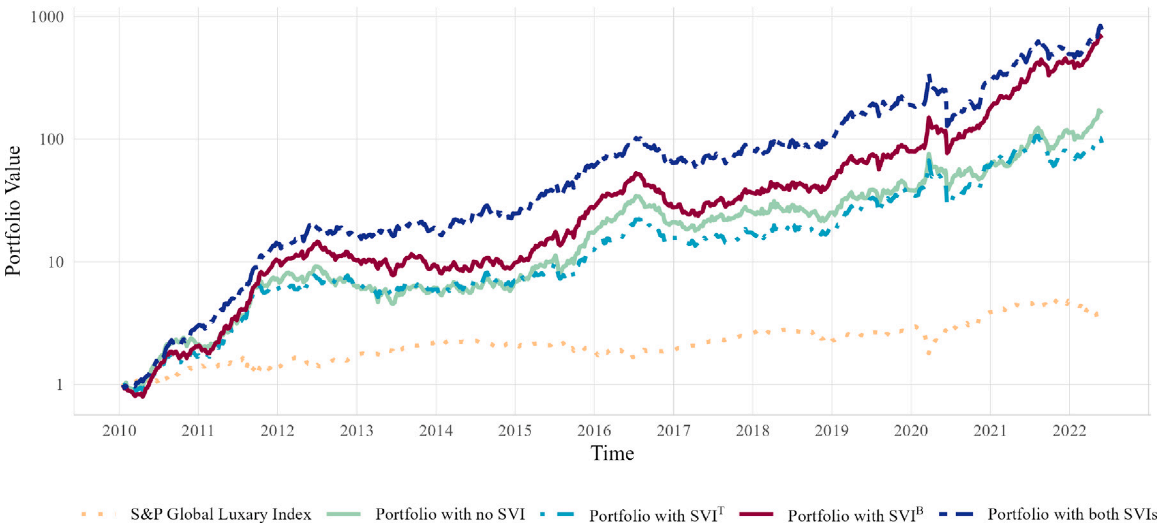

Fig. 1. Illustration of how the trading strategy plays out, with and without consumer attention, using actual data from the test period (January 2019 to May 2022). Transaction costs are included in the calculation of the cumulative returns from the constructed portfolios.

results of regressing the constructed portfolios' excess returns on the market excess returns. The alphas in the first four regressions are significant, which denotes that the market excess return does not explain the excess returns of the portfolios.

To check whether including consumer attention (SVI^B) and investor attention (SVI^T) can provide additional information to explain the portfolio returns, we regressed the difference in the returns of two strategies on the excess returns of the market. Regression (6) shows whether the inclusion of (SVI^B) improves the trading strategy. The alpha is significant at the $p < 0.1$ level, which shows that adding (SVI^B) has explanatory power. The same applies to the difference in returns of strategies based on SVI^B and SVI^T. Similar results are achieved, showing that the strategy that includes SVI^B performs significantly better than the comparable strategy that includes SVI^T instead. In regression (5), we observe an insignificant alpha where the difference between returns from strategies with the inclusion of SVI^T and the exclusion of SVI is regressed, and therefore, it seems that the SVI^T alone does not improve the model predictions. Table 8 shows a similar test using the three-factor model. The results confirm what we observe in the previous table. Thus, we can conclude that adding (SVI^B) significantly increases trading strategy performance.

5. Conclusion

Google search volumes for company tickers or company names have been used as a measure of investor attention and applied to financial forecasting. However, consumer attention could be an important indicator of the future prospects of a company, and

Table 6
Cumulative yearly returns of trading strategies and the Luxury index. The returns for 2022 include only 5 months of trading; the annualized returns correspond to 12 years and 5 months.

Year	Luxury index	No SVI	SVI^T	SVI^B	Both SVIs
2010	37%	107%	68%	103%	197%
2011	−3%	256%	283%	415%	382%
2012	23%	−16%	−2%	−2%	15%
2013	33%	−4%	−6%	−10%	13%
2014	−5%	14%	19%	6%	32%
2015	−5%	152%	76%	180%	140%
2016	6%	22%	26%	1%	8%
2017	35%	23%	11%	32%	26%
2018	−14%	−2%	7%	31%	25%
2019	26%	52%	91%	64%	87%
2020	39%	54%	69%	122%	51%
2021	21%	90%	24%	137%	71%
2022	−20%	44%	25%	59%	58%
Annualized	12%	51%	44%	69%	71%

Table 7
Portfolios excess returns regressed on market excess return - CAPM. All dependent variables are excess returns. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable:						
	No SVI (1)	SVI^T (2)	SVI^B (3)	Both SVIs (4)	SVI^T - No SVI (5)	SVI^B - No SVI (6)	SVI^B - SVI^T (7)
Mkt.RF	−0.213**	−0.176*	−0.171*	−0.083	0.038	0.042	0.005
	(0.098)	(0.095)	(0.096)	(0.098)	(0.049)	(0.046)	(0.056)
α	1.033***	0.936***	1.241***	1.261***	−0.107	0.198*	0.296**
	(0.229)	(0.223)	(0.224)	(0.229)	(0.115)	(0.108)	(0.131)
Observations	628	628	628	628	628	628	628
R^2	0.008	0.005	0.005	0.001	0.001	0.001	0.00001

Table 8
Portfolios excess returns on Fama–French three-factor model. All dependent variables are excess returns. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable:						
	No SVI (1)	SVI^T (2)	SVI^B (3)	Both SVIs (4)	SVI^T - No SVI (5)	SVI^B - No SVI (6)	SVI^B - SVI^T (7)
Mkt.RF	−0.222**	−0.172*	−0.183*	−0.097	0.050	0.039	−0.011
	(0.103)	(0.101)	(0.101)	(0.103)	(0.052)	(0.048)	(0.059)
SMB	0.183	0.041	0.151	0.082	−0.142	−0.032	0.111
	(0.188)	(0.184)	(0.184)	(0.188)	(0.095)	(0.089)	(0.108)
HML	−0.213	−0.112	−0.126	0.019	0.102	0.088	−0.013
	(0.139)	(0.136)	(0.136)	(0.139)	(0.070)	(0.065)	(0.079)
α	1.028***	0.931***	1.240***	1.266***	−0.107	0.202*	0.300**
	(0.229)	(0.224)	(0.224)	(0.229)	(0.115)	(0.108)	(0.131)
Observations	628	628	628	628	628	628	628
R^2	0.013	0.007	0.008	0.001	0.008	0.004	0.002

even has the potential to be more useful in forecasting performance. We therefore create a measure of consumer attention utilizing Google searches for carefully selected keywords (such as brand names) related to a particular company. Since demand for luxury goods is highly driven by consumer attention, and high-involvement purchases are usually connected with more research before action, we consider companies included in the S&P Global Luxury Index.

We find that consumer attention is weakly correlated with investor attention and financial variables, and thus captures other types of information. The results further reveal that consumer attention predicts stock returns significantly more strongly than investor attention.

To evaluate the practical implications of our findings, we construct a simple trading strategy that incorporates consumer attention as one of the prediction variables. The trading strategy yields an average return of 69% per year, compared to 51% when consumer attention is excluded. A model combining financial variables and consumer attention is able to provide solid predictions for both the best and worst performing companies. This illustrates the importance of including consumer attention when forecasting financial performance.

CRediT authorship contribution statement

Hamid Cheraghali: Data curation, Formal analysis, Writing – review & editing. **Hannah Høydal:** Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **Caroline Lysebo:** Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **Peter Molnár:** Supervision, Conceptualization, Methodology, Writing – review & editing.

Data availability

The authors do not have permission to share data.

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Appendix

See Table A.1 and Table A.2.

Table A.1
Companies included from the S&P global luxury index, their respective tickers and keywords used for SVI^T.

Company name	Ticker	Keyword	Company name	Ticker	Keyword
ABERCROMBIE & FITCH COMPANY	ANF	ANF	MILLENNIUM & COPTHORNE HOTELS	MCK.NZ	MCK
ACCORDIA GOLF CO LTD	2131.TˆC17	2131	MONCLER SPA	MONC.MI	MONC
AMOREPACIFIC CORP	090430.KS	090430	MOVADO GROUP INC	MOV	MOV
ASTON MARTIN LAGONDA GLOBAL	AML.L	AML	NIKE INC	NKE	NKE
BANG & OLUFSEN A/S	BO.CO	BO	NIKON CORP	7731.T	7731
BAYER MOTOREN WERKE AG	BMWG.DE	BMWG	NORDSTROM INC	JWN	JWN
BENETEAU SA	CHBE.PA	CHBE	NORWEGIAN CRUISE LINE HLDGS	NCLH.K	NCLH
BLUE NILE INC	NILE.OˆB17	NILE	OXFORD INDUSTRIES INC	OXM	OXM
BROWN FORMAN CORP	BFb	BFb	PARADISE CO LTD	034230.KQ	34230
BURBERRY GROUP PLC	BRBY.L	BRBY	PERNOD RICARD SA	PERP.PA	PERP
CALLAWAY GOLF CO	ELY	ELY	POLARIS INC	PII	PII
CANADA GOOSE HLDG	GOOS.TO	GOOS	PORSCHE AUTOMOBIL HOLDING SE	PSHG_p.DE	PSHG
CARNIVAL CORPORATION & PLC	CCL	CCL	PRADA SPA	1913.HK	1913
CHOW SANG SANG HOLDINGS INTERNATIONAL LTD.	0116.HK	0116	PVH CORP	PVH	PVH
CHOW TAI FOOK JEWELLERY	1929.HK	1929	RALPH LAUREN CORP	RL	RL
CHRISTIAN DIOR	DIOR.PA	DIOR	REALREAL INC (THE)	REAL.O	REAL
CIE FINANCIERE RICHEMONT AG	CFR.S	CFR	REMY COINTREAU	RCOP.PA	RCOP
CROWN RESORTS LTD	CWN.AX	CWN	RESORTTRUST INC	4681.T	4681
DAVIDE CAMPARI-MILANO N.V.	CPRI.MI	CPRI	REVOLVE GROUP LLC	RVLV.K	RVLV
DECKERS OUTDOOR CORP	DECK.K	DECK	RH	RH	RH
DIAGEO PLC	DGE.L	DGE	ROYAL CARIBBEAN CRUISES LTD	RCL	RCL
DUFRY AG	DUFN.S	DUFN	SALVATORE FERRAGAMO SPA	SFER.MI	SFER
EMPEROR WATCH & JEWELLERY LTD	0887.HK	0887	SANDS CHINA LTD	1928.HK	1928
ESTEE LAUDER COS. A	EL	EL	SECOO HOLDING LTD -ADS	SECO.O	SECO
ETHAN ALLEN INTERIORS INC	ETD	ETD	SHANGRI-LA ASIA LTD	0069.HK	0069
FARFETCH LTD	FTCH.K	FTCH	SHINSEGAE INTL CO LTD	004170.KS	004170
FERRARI NV	RACE.MI	RACE	SHISEIDO CO LTD	4911.T	4911
FOSSIL INC	FOSL.O	FOSL	SIGNET JEWELERS LTD	SIG	SIG
GALAXY ENTERTAINMENT GROUP	0027.HK	0027	SJM HOLDINGS LTD	0880.HK	0880
HARLEY-DAVIDSON INC	HOG	HOG	SLEEP NUMBER CORP	SNBR.O	SNBR
HARMAN INTL INDUSTRIES INC	HARˆC17	HAR	SOTHEBY'S	BIDˆJ19	BID
HENGDELI HOLDINGS LTD.	3389.HK	3389	SPARKLE ROLL GROUP LTD.	0970.HK	0970
HERMES INTL	HRMS.PA	HRMS	STARWOOD HOTEL & RESORT WORLD	HOTˆI16	HOT
HILTON WORLDWIDE HOLDINGS	HLT	HLT	SWATCH GROUP AG	UHR.S	UHR
HOTEL SHILLA LTD	008770.KS	008770	TAPESTRY INC	TPR	TPR
HUGO BOSS AG	BOSSn.DE	BOSSn	TEMPUR SEALY INTL INC	TPX	TPX
INTER PARFUMS INC	IPAR.PA	IPAR	TESLA INC	TSLA.O	TSLA
INTERCONTINENTAL HOTELS GRP	IHG.L	IHG	THE STAR ENTERTAINMENT GROUP	SGR.AX	SGR
KANGWON LAND INC	035250.KS	35250	TIFFANY & CO	TIFˆA21	TIF
KERING	PRTP.PA	PRTP	TOD'S GROUP SPA	TOD.MI	TOD
LAS VEGAS SANDS CORP	LVS	LVS	TOLL BROTHERS INC	TOL	TOL
LUK FOOK HLDGS	0590.HK	0590	TREASURY WINE ESTATES LTD	TWE.AX	TWE
LULULEMON ATHLETICA INC	LULU.O	LULU	TRINITY LTD.	0891.HK	0891
LUXOTTICA GROUP SPA	LUX.MIˆC19	LUX	UNDER ARMOUR INC A	UAA	UAA
LVMH MOET HENNESSY LOUIS V	LVMH.PA	LVMH	VAIL RESORTS INC	MTN	MTN

(continued on next page)

Table A.1 (*continued*).

Company name	Ticker	Keyword	Company name	Ticker	Keyword
MARRIOTT INTL INC	MAR.O	MAR	VF CORP	VFC	VFC
MELCO INTL DEVELOPMENT LTD	0200.HK	0200	WILLIAMS-SONOMA INC	WSM	WSM
MELCO RESORTS & ENTERTAINMENT	MLCO.O	MLCO	WOLVERINE WORLD WIDE INC	WWW	WWW
MERCEDES-BENZ GROUP AG	MBGn.DE	MBGn	WYNN MACAU LTD	1128.HK	1128
MGM CHINA HOLDINGS LTD	2282.HK	2282	WYNN RESORTS LTD	WYNN.O	WYNN

Table A.2
Brand-related Search Volume Index (SVI^B) keywords.

Company	Brands
ABERCROMBIE & FITCH COMPANY	Hollister, Abercrombie & Fitch, abercrombie kids, Moose, Seagull, Gilly Hicks, Social Tourist
ACCORDIA GOLF CO LTD	Accordia Golf Asset Godo Kaisha, Golf Pro Staff, Golf Alliance, Accordia Garden, Heartree, Accordia Garden Koshienhama, Narita Golf Club, TOKYO BAY GOLF, Grandvert Kyoto Golf Club, Next Golf Management Corporation, Accordia Asset Holding 01, Accordia Asset Holding 02, Accordia Golf
AMOREPACIFIC CORP	Amore Pacific, Sulwhasoo, Laneige, Mamonde, Innisfree, Etude
ASTON MARTIN LAGONDA GLOBAL	Aston Martin, Lagonda
BANG & OLUFSEN A/S	BANG & OLUFSEN, Beocord, Beomaster, Beogram, Beolab, Beovox, Beolit, Beosystem, Beocenter, Beomic, BeoCom & BeoTalk, Beovision, Beosound, Beotime, Beoplayer, Beoplay, Beosound Edge, Serene, Serenata, Beosound Shape, Beoplay H95
BAYER MOTOREN WERKE AG	BMW , MINI , Rolls Royce , BMW M
BENETEAU SA	BENETEAU SA, Figaro BENETEAU SA, Oceanis, Flyer, Barracuda, Antares, Gran turismo, Swift trawler, Grand trawler, BENETEAU SA, Figaro BENETEAU SA, Oceanis, Flyer, Barracuda, Antares, Gran turismo, Swift trawler, Grand trawler
BLUE NILE INC	Blue Nile
BROWN FORMAN CORP	Brown Forman, Jack daniels, woodford reserve, old forester, coopers craft, slane irish whiskey, the benriach, the glendronach, herradura, el jimador, pepe lopez, finlandia, chambord, korbel, fords gin
BURBERRY GROUP PLC	Burberry
CALLAWAY GOLF CO	Callaway, Ogio, TravisMathew, Jack Wolfskin, Big Bertha, Cuater, Odyssey, Top Flite, Strata
CANADA GOOSE HLDG	CANADA GOOSE HLDG
CARNIVAL CORPORATION & PLC	Carnival cruise , AIDA Cruises , Costa Cruises , Cunard , Holland America Line , P&O Cruises , Princess , Seabourn
CHOW SANG SANG H. I. LTD.	Chow Sang Sang Group, Chow Sang Sang
CHOW TAI FOOK JEWELLERY	Chow Tai Fook, Tudor, Rolex
CHRISTIAN DIOR	Christian Dior Couture, Christian Dior, Moet & Chandon, Veuve Clicquot, Hennessy, Dom Perignon, Louis Vuitton, Fendi, Marc Jacobs, Kenzo brands, Guerlain, Givenchy, Dior, TAG Heuer, Chaumet, Zenith brands, Sephora, DFS, Le Bon Marche
CIE FINANCIERE RICHEMONT AG	Buccelati, Cartier, Van Cleef & Arpels, A. Lange & Sohne, Baume & Mercier, IWC Schaffhausen, Jaeger-LeCoultre, Panerai, Piaget, Roger Dubuis, Vacheron Constantin, Watchfinder & Co., YOOX NET-A-PORTER, Alaia, Chloe, Dunhill, Montblanc, Peter Millar, Purdey, Serapian
CROWN RESORTS LTD	CROWN RESORTS LTD, Crown Melbourne, Crown Perth, Crown Aspinalls, Betfair Australasia, DGN Games, Chill Gaming, CROWN RESORTS LTD, Crown Melbourne, Crown Perth, Crown Aspinalls, Betfair Australasia, DGN Games, Chill Gaming
DAVIDE CAMPARI-MILANO N.V.	DAVIDE CAMPARI-MILANO N.V., aperol, campari, skyy vodka, wild turkey, wrey and nephew
DECKERS OUTDOOR CORP	Deckers , Ugg , Koolaburra , Hoka one one , Teva , Sanuk , Deckers , Ugg , Koolaburra , Hoka one one , Teva , Sanuk
DIAGEO PLC	DIAGEO PLC, black & white, buchanans, J&B, johnnie walker, grand old parr, lagavulin, the singleton, talisker, windsor, bulleit, crown royal, ciroc, ketel one, smirnoff, bundaberg, captain morgan, ron zacapa, baileys, casamigos, don julio, tanqueray, Mcdowells, Shui Jing Fang, Yeni raki, Ypioca, Guinness, DAVIDE CAMPARI-MILANO N.V.
DUFRY AG	Dufry, World Duty Free, Nuance, Hellenic Duty Free, Colombian Emeralds, Duty Free Uruguay, Hudson, Duty Free Shop Argentina, RegStaer
EMPEROR WATCH & JEWELLERY LTD	Audemars Piguet, Baume & Mercier, Cartier, Omega, Jaeger-LeCoultre, Montblanc, Tissot, Rolex, Emperor Watch & Jewellery
ESTEE LAUDER COS. A	AERIN Beauty, Bobbi Brown, Clinique, DECIEM by Brandon Truaxe, Dr. Jart+, Estee Lauder, GLAMGLOW, La Mer, Lab Series, MAC Cosmetics, Origins, Darphin Paris, Smashbox, Too Faced [29], Tom Ford Beauty, Aramis, Kilian Paris, Editions de Parfums Frederic Malle, Jo Malone London, Lauder (Fragrances), Le Labo, Aveda, Bumble and bumble
ETHAN ALLEN INTERIORS INC	Ethan Allen
FARFETCH LTD	Farfetch, Browns, Stadium Goods, New Guards Group, Violet Gray, Wannaby
FERRARI NV	FERRARI NV
FOSSIL INC	Fossil, Relic, Michele Watch , Skagen Denmark, Misfit, WSI, Zodiac Watches
GALAXY ENTERTAINMENT GROUP	Galaxy Entertainment Group, Starworld Hotel, Galaxy Macau, Broadway Macau
HARLEY-DAVIDSON INC	Harley-Davidson, Harley, Harley Davidson
HARMAN INTL INDUSTRIES INC	AKG Acoustics, Audio Access, Becker Autosound, BSS Audio, Crown International, dbx Professional Products, DigiTech, harman kardon, Infinity, JBL, Lexicon, Mark Levinson, QNX, Revel, Soundcraft, Studer

(*continued on next page*)

Table A.2 (*continued*).

Company	Brands
HENGDELI HOLDINGS LTD.	Hengdeli Holdings Limiteda, Hengdeli
HERMES INTL	Hermes Paris, Crystal Saint-Louis, John Lobb, Puiforcat, Metaphores, Bucol, Verel de Belval, Le Crin, J3L
HILTON WORLDWIDE HOLDINGS	Hilton , Waldorf Astoria , LXR , Conrad , Canopy , Signia , Curio , Doubletree , TAPESTRY INC , Embassy suites , Tempo , Motto , Hilton Garden Inn , Hampton , tru , Homewood Suites , Home2 , Hilton Grand Vacations
HOTEL SHILLA LTD	HOTEL SHILLA LTD, The Shilla Seoul, The Shilla Jeju, The Shilla, The Shilla Seoul, The Shilla Jeju
HUGO BOSS AG	HUGO BOSS AG, BOSS, HUGO
INTER PARFUMS INC	Abercrombie & Fitch, Karl Lagerfeld, Anna Sui, Kate Spade, Boucheron, Lanvin, Coach, MCM, Mont Blanc, Dunhill, Graff, Guess, Hollister, Jimmy Choo, Oscar de la renta, Paul Smith, Repetto, Rochas, s.t. dupont, van cleef & arpels
INTERCONTINENTAL HOTELS GRP	INTERCONTINENTAL HOTELS GRP, Kimpton, Regent, Hotel Indigo, Crowne Plaza, Hualuxe, Holiday Inn, Voco, Staybridge, Candlewood, Avid, Even Hotels
KANGWON LAND INC	Kangwonland
KERING	Kering, Bottega Venata, Alexander McQueen, Brioni, Gucci, Saint Laurent, Balenciaga, Pomellato, DoDo, ulysse nardin, girard perregaux, boucheron, boucheron, puma, cartier
LAS VEGAS SANDS CORP	Las Vegas Sands, Sands, The venetian las vegas, Sands Macau, The Venetian Macau, The palazzo Las Vegas, The Parisian Macau, Marina Bay Sands, Sands Cotai Central, Las Vegas Sands, Sands, The venetian las vegas, Sands Macau, The Venetian Macau, The palazzo Las Vegas, The Parisian Macau, Marina Bay Sands, Sands Cotai Central
LUK FOOK HLDGS	Lukfook jewellery, LUK FOOK HLDGS
LULULEMON ATHLETICA INC	Lululemon
LUXOTTICA GROUP SPA	Alain Mikli, Arnette eyewear, Costa Del Mar, Eye Safety Systems (ESS), Eye Safety Systems, ESS, Luxottica, Native Eyewear, Oakley, Oliver Peoples, Persol, Ray-Ban, Sferoflex, Vogue Eyewear, Luxottica
LVMH MOET HENNESSY LOUIS V	Christian Dior, Fendi, Givenchy, Marc Jacobs, Stella McCartney, Loewe, Loro Piana, Kenzo, Celine, Sephora, Princess Yachts, TAG Heuer, Bulgari, Tiffany & Co., LVMH
MARRIOTT INTL INC	Marriott Bonvoy , Edition , The Ritz-Carlton , The Luxury collection , Stregis , W hotels , JW Marriott , Marriott , Sheraton , Delta hotels , Westin , Le Meridien , Renaissance hotels , Autograph collection hotels , Tribute portfolio , Design hotels , Courtyard , Four points , Springhill suites , Fairfield , Protea hotels , aloft hotels , Moxy hotels , Homes & villas , Residence inn , Townplace suites , Marriott executive apartments , element
MELCO INTL DEVELOPMENT LTD	Melco , Entertainment gaming asia , Mocha Club, Nuwa, City of Dreams, The House of Dancing Water, Studio City, Altira Macau
MELCO RESORTS & ENTERTAINMENT	Altira, City of Dreams, Studio City, City of Dreams Manila, Cyprus Operations, Melco resorts and entertainment, Melco, City of dreams, Studio city, Altira Macau, City of dreams manila
MERCEDES-BENZ GROUP AG	Daimler, Mercedes-Benz, Smart, Freightliner, FUSO, Western Star, BharatBenz, Setra, Thomas Built
MGM CHINA HOLDINGS LTD	MGM, MGM Macau, MGM Cotai
MILLENNIUM & COPTHORNE HOTELS	Millennium Hotel, Millennium Hilton, Copthorne King's Hotel, Copthorne Hotel, Millennium, Grand Millennium, Millennium & Copthorne Hotels
MONCLER SPA	MONCLER SPA
MOVADO GROUP INC	Movado, Concord, Olivia Burton, Ebel, MVMT, Coach, FERRARI NV watch, HUGO BOSS AG watch, Lacoste watch, Tommy hilfiger watch, Movado, Concord, Olivia Burton, Ebel, MVMT, Coach, FERRARI NV watch, HUGO BOSS AG watch, Lacoste watch, Tommy hilfiger watch
NIKE INC	Nike, Jordan brands,, Cole Haan, Converse, Hurley, Nike Golf, Umbro
NIKON CORP	Nikon, Nikkor
NORDSTROM INC	NORDSTROM INC
NORWEGIAN CRUISE LINE HLDGS	NORWEGIAN CRUISE LINE HLDGSs
OXFORD INDUSTRIES INC	Tommy Bahama, Lilly Pulitzer, Southern Tide, Billy London, Oxford, Oxford America , Geoffrey Beene, Kenneth Cole, Reaction by Kenneth Cole, Dockers, Nick Graham, Andrew Fezza
PARADISE CO LTD	Paradise , Art paradiso , Paradise Hotel Busan , Paradise Casino , Paradise Spa Dogo , Paradise Tour , Vino Paradise , Paradise City , Paradise hotel & resort , Art Paradiso , Paradise hotel Busan , Paradise Casino
PERNOD RICARD SA	PERNOD RICARD SA, royal salute, mumm, martell, beefeater, chivas regal, absolut vodka, havana club, jameson, the glenlivet, perrier-jouet, malibu, ricard, ballantines, kenwood, campo viejo, brancott estate, jacobs creek, royal stag, imperial blue, 100 pipers, passport scotch, clan campbell, seagrams gin, ramazzotti, pastis 51, olmeca, ararat
POLARIS INC	POLARIS INC , RZR , POLARIS INC ranger , POLARIS INC sportsman , POLARIS INC general , ACE , Hammerhead off-road , Indian motorcycle , Slingshot , GEM , AIXAM , Goupil industrie , POLARIS INC timbersled , POLARIS INC pro XD , Taylor-Dunn , Bennington , Godfrey , Hurricane
PORSCHE AUTOMOBIL HOLDING SE	Porsche , Volkswagen , Audi , SEAT , SKODA , Bentley , Bugatti , Lamborghini , Ducati , Scania , MAN , SJM HOLDINGS LTD , SJM , Casino Grand Lisboa , Casino Taipa , Casino Casa Real , Casino Diamond , Casino Eastern , Casino Fortuna , Casino Golden Dragon , Casino Grandview , Casino Landmark , Casino Royal Dragon , Porsche , Volkswagen , Audi , SEAT , SKODA , Bentley , Bugatti , Lamborghini , Ducati , Scania , MAN
PRADA SPA	PRADA SPA , Miu miu , Coach , Marchesi

(*continued on next page*)

Table A.2 (*continued*).

Company	Brands
PVH CORP	PVH, Calvin Klein, Tommy hilfiger, Van Heusen, IZOD, Arrow, Warner's, Olga, True&Co, Geoffrey Beene, PVH, Calvin Klein, Tommy hilfiger, Van Heusen, IZOD, Arrow, Warner's, Olga, True&Co, Geoffrey Beene
RALPH LAUREN CORP	Ralph Lauren, Polo ralph lauren, lauren ralph lauren, chaps, club monaco, Ralph Lauren luxury
REALREAL INC (THE)	REALREAL
REMY COINTREAU	Remy Cointreau
RESORTTRUST INC	RESORTTRUST INC, Sun members, Hotel Trusty
REVOLVE GROUP LLC	Advance Holdings, Revolve Group, Revolve, FWRD
RH	RH, RH modern, RH ski house, RH beach house, RH interior design
ROYAL CARIBBEAN CRUISES LTD	Royal Caribbean International, Celebrity Cruises, Silversea Cruises, Pullmantur Cruises, TUI Cruises, Holistica, Island Cruises , CDF Croisieres de France, SkySea Cruise Lines, Azamara Cruises
SALVATORE FERRAGAMO SPA	SALVATORE FERRAGAMO SPA, Museo
SANDS CHINA LTD	SANDS CHINA LTD, The Venetian Macao, Sands Macao, The Plaza Macao, Sands Cotai Central, The Parisian Macao, The Venetian Resort-Hotel-Casino, Sands Expo and Convention Center, Marina Bay Sands, Sands Bethlehem, SANDS CHINA LTD, The Venetian Macau, Sands Cotai Central, The Parisian Macau
SECOO HOLDING LTD -ADS	Secoo Holding Limited, Secoo
SHANGRI-LA ASIA LTD	Shangri-La Hotels and Resorts , Kerry Hotels , JEN by Shangri-La , Traders , Shangri-La , Lobster Bar and Grill , Shang Palace , Shang Social , Restaurant Petrus , The Back Room
SHINSEGAE INTL CO LTD	VOV, G-Cut, Design United, J. Holic, Giorgio Armani, Dolce & Gabbana, DIESEL, MONCLER SPA, GAP, BANANA REPUBLIC, Shinsegae
SHISEIDO CO LTD	SHISEIDO CO LTD, cle de peau, NARS, bareMinerals, Anessa, Dolce & Gabbana, Drunk elephant, d program, Elixir, IPSA, Laura Mercier, Senka, Tory Burch
SIGNET JEWELERS LTD	SIGNET JEWELERS LTD, Signet, Kay jewelers, Zales, Jared, H. Samuel, Ernest Jones, Peoples, Pagoda, James Allen, SIGNET JEWELERS LTD, Signet, Kay jewelers, Zales, Jared, H. Samuel, Ernest Jones, Peoples, Pagoda, James Allen
SJM HOLDINGS LTD	SJM , Casino Grand Lisboa , Casino Taipa , Casino Casa Real , Casino Diamond , Casino Eastern , Casino Fortuna , Casino Golden Dragon , Casino Grandview , Casino Landmark , Casino Royal Dragon
SLEEP NUMBER CORP	Sleep number
SOTHEBY'S	Sotheby, Sotheby's
SPARKLE ROLL GROUP LTD.	Sparkle Roll, Jade Dynasty Group Ltd, New Sparkle Roll
STARWOOD HOTEL & RESORT WORLD	St. Regis, The Luxury Collection, W, Westin, Le Meridien, Sheraton, Four Points, Four Points by Sheraton, Aloft, Element
SWATCH GROUP AG	Brequet, Harry Winston, Blancpain, Glashutte, Jaquet droz, Leon Hatot, Omega, Longines, Rado, Union, Tissot, Balmain, Certina, Mido, Hamilton, Calvin Klein, Swatch, Flik flak
TAPESTRY INC	TAPESTRY INC , Coach , Kate Spade , Stuart Weitzman
TEMPUR SEALY INTL INC	TEMPUR SEALY INTL INC, Tempur pedic, Stearns & foster, Sealy, Tempur
TESLA INC	TESLA INC, Cybertruck, Roadster, Model S, Model 3, Model Y, TESLA INC Semi
THE STAR ENTERTAINMENT GROUP	Star entertainment, The Star Club, The Star Sydney, The Star Gold Coast, Treasury Brisbane, Gold Coast Convention and Exhibition Centre, The star entertainment group, The star club, The star Sydney, The star Gold Coast, Treasury Brisbane, Gold Coast Convention and Exhibition Centre
TIFFANY & CO	Tiffany, Tiffany&Co, Elsa Peretti, Jean Schlumberger, Paloma Picasso
TOD'S GROUP SPA	Tods, Roger Vivier, Hogan, Fay
TOLL BROTHERS INC	Metro Crossing, Porter Ranch, Rafferty, Regency at Folsom Ranch, Toll Brothers
TREASURY WINE ESTATES LTD	TREASURY WINE ESTATES LTD, 19 crimes, acacia vineyard, annies lane, beaulieu vineyard, belcreme de lys, beringer, blossom hill, coastal estates, coldstream hills, embrazen, etude, fifth leg, heemskerk, hewitt vineyard, ingoldby, jamieson's run, killawarra, leo buring, lindeman's, maison de grand esprit, meridian, metala, penfolds, pepperjack, provenance, rawson's retreat, rosemount estate
TRINITY LTD.	Kent Curwen, Gieves Hawke , Cerruti 1881, D'URBAN, Trinity
UNDER ARMOUR INC A	UNDER ARMOUR, UA, HEATGEAR, COLDGEAR, HOVR, PROTECT THIS HOUSE, I WILL, UA Logo, ARMOUR FLEECE, ARMOUR BRA
VAIL RESORTS INC	Vail, Beaver Creek, Breckenridge, Park City, Keystone, Crested Butte, Heavenly, Northstar, Kirkwood, Whistler Blackcomb, Perisher, Wilmot Mountain, Afton Alps, Mt. Brighton, Rock Resorts, Grand Teton
VF CORP	Dickies, Altra, Eastpak, Icebreaker, And1 Lab, JanSport, Kipling, The North Face, Napapijri, SmartWool, Supreme, Timberland, Vans, Vanity Fair lingerie, 7 for All Mankind, Splendid, Eagle Creek, Ella Moss, Majestic Athletic, Nautica, Bulwark Protective Apparel, Chef Designs, Kodiak, Liberty, Red Kap, Terra, VF Solutions, Walls, Work Authority, Workrite Fire Service, VF CORP
WILLIAMS-SONOMA INC	Williams Sonoma, Williams Sonoma Home, Pottery Barn, Pottery Barn Kids, PBteen, West Elm, Mark and Graham, Rejuvenation, Williams Sonoma
WOLVERINE WORLD WIDE INC	Merrell, Sperry, Hush Puppies, Saucony, Wolverine, Keds, Stride Rite, Sebago, Chaco, Bates, HYTEST, Soft Style, Wolverine
WYNN MACAU LTD	WYNN MACAU LTD
WYNN RESORTS LTD	WYNN RESORTS LTD, Wynn Palace Cotai, Encore Boston harbor, Wynn Las Vegas, WYNN MACAU LTD

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