Economics Bulletin

Volume 43, Issue 2

Twitter sentiment and stock return volatility of US travel and leisure firms

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Abstract

This paper examines the impact of firm-specific sentiment extracted from Twitter messages on the stock return volatility of US Travel & Leisure stocks. To this end, linear and nonlinear impulse response functions are estimated based on local projection techniques. We find that the return volatility of US Travel & Leisure firms increases in response to twitter messages in the short-term, particularly during periods of high uncertainty. Positive tweets have a stronger effect on stock return volatility than negative tweets, reflecting that positive Twitter sentiment has a clear incentive effect on retail investors in the US Travel & Leisure industry.

Citation: Syed jawad hussain Shahzad and Elie Bouri and Román Ferrer, (2023) "Twitter sentiment and stock return volatility of US travel and leisure firms", *Economics Bulletin*, Volume 43, Issue 2, pages 1133-1142
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Submitted: May 23, 2022. **Published:** June 30, 2023.

1. Introduction

Social media platforms like Twitter offer valuable insights into current social trends and opinions about multiple aspects, including investment and finance. For example, the stock rally of the American video game retailer GameStop in January 2021 illustrates the power of small investors communicating on social media to drastically alter the price and volatility dynamics of shares.[1] On a related front, travellers tend to rely on Twitter to get feedback from other tourists and to expand their knowledge on trendy destinations (Mehraliyev et al., 2022). Furthermore, in an analysis of the impact of Twitter sentiment on cruise tourism and its determinants during the COVID-19 pandemic, Lu and Zheng (2022) highlight the value of sentiment analysis as a crucial tool in tourism research. Therefore, it is commonly accepted that personal opinions and comments of tourists expressed via social media affect the reputation and image of tourist destinations and businesses and, hence, have a noticeable impact on tourism activity (Sigala, 2020). In this context, the key research question in this paper is whether the well-known influence of user-generated content on online social networks such as Twitter on tourist decision-making also translates, through its impact on corporate reputation (Dijkmans et al., 2015), in a significant impact on the volatility of tourism stock returns. Given the critical importance of the tourism industry (10.4% of global GDP in 2019), its extreme vulnerability to exogenous shocks, such as natural disasters, health crises, etc. (Jalkh et al., 2021; Shahzad et al., 2022)[2], and the increasing role of social media, it seems natural to think that the massive flow of information shared in Twitter can have a substantial effect on the stock market performance of tourism firms, mainly during turbulent times. Importantly, a good forecasting accuracy for stock volatility is essential to investors in order to make optimal investment and hedging decisions. Excessive volatility, price bubbles and other market inefficiencies fuelled by viral content on social media are also an area of concern for policy makers. However, the existing literature has not addressed so far the effect of social networks on the volatility of tourism stocks.

In this paper, we extend the behavioural finance literature by investigating the impact of Twitter activity related to US Travel & Leisure firms on the return volatility of stocks of these firms under different regimes of uncertainty. Using linear and nonlinear impulse response functions based on local projection methods, the empirical results show a significant positive impact of the volume of tweets on volatility of Travel & Leisure stocks in the short-term. Furthermore, the increase in Travel & Leisure stocks' volatility in response to Twitter messages is higher during the high uncertainty regime, suggesting that retail investors pay more attention to Twitter in times of heightened uncertainty and risk aversion. In addition, a novel analysis of asymmetry finds that positive tweets have a stronger impact on tourism stock volatility than negative tweets. This asymmetric pattern supports the view that positive information on Twitter about tourism firms has a clear incentive effect on retail investors, encouraging them to invest in tourism firms and, hence, generating increased stock volatility.

[1] GameStop stock prices surged by more than 700% in one week in January 2021 because of the coordinated action of thousands of retail investors from the Reddit WallStreetBets community.

[2] There is a rapidly increasing academic literature highlighting the adverse impact of the COVID-19 pandemic on most financial markets. For example, Mishra et al. (2020) document strong negative returns in several Indian financial markets during the COVID-19 outbreak. In turn, Sahoo and Rath (2022) find a significant causal effect of the COVID-19 crisis on Bitcoin returns in the time-frequency space.

This paper is closely related to a growing literature on the role of Twitter as a source of valuable information to financial markets (Zhang et al., 2016; You et al., 2017; Bouri et al., 2022) and tourism firms (Philander and Zhong, 2016). For instance, Philander and Zhong (2016) highlight the usefulness of Twitter sentiment analysis to identify trends and make timely actions in the hotel industry. However, our research differs from previous work in three main ways. First, we focus on stock return volatility, an aspect that has been ignored so far in the literature on the Travel & Leisure industry. Second, linear and non-linear models are used to capture possible different responses of US Travel & Leisure stock volatility to Twitter sentiment depending on the scenario of market uncertainty.[3] Third, special attention is paid to the asymmetric effect of positive and negative tweets on return volatility of tourism stocks.

2. Methodology

Range-based estimators of volatility are used in this study because they are much more efficient than the traditional estimators based on daily closing prices. The principal advantage of range-based measures of volatility over the classic standard deviation is that they take into consideration some type of intraday information and, therefore, can detect intraday volatility even if two consecutive closing prices are the same (Díaz-Mendoza and Pardo, 2020). Specifically, three range-based volatility estimators are considered in this research.

First, the range-based volatility measure of Parkinson (1989) is given by:

$$PK_t = \frac{(h_t - l_t)^2}{4ln2} \qquad (1)$$

where PK_t is the range-based volatility estimator of Parkinson (1980) and $h_t = H_t - O_t$ and $l_t = L_t - O_t$, being O_t, H_t and L_t the log of the daily opening, highest and lowest prices at day *t*, respectively.

The volatility estimator of Garman and Klass (1980) is an extension of the measure proposed by Parkinson and includes the highest, lowest, opening and closing prices of the traded session. The Garman-Klass measure can be calculated as follows:

$$GK_t = 0.511(h_t - l_t)^2 - 0.019(c_t(h_t + l_t) - 2h_t l_t) - 0.383c_t^2 \qquad (2)$$

where GK_t denotes the volatility estimator of Garman and Klass (1980) and $c_t = C_t - O_t$, being c_t the log of the opening price at day *t*.

Unlike the two previous estimators, the volatility measure of Rogers and Satchell (1991) allows for an arbitrary drift, which improves its efficiency. An interesting property of this estimator is that it remains unbiased for any value of the drift. The Rogers-Satchell estimator takes the following form:

$$RS_t = h_t(h_t - c_t) + l_t(l_t - c_t) \qquad (3)$$

where RS_t is the volatility estimator of Rogers and Satchell (1991) at day *t*.

[3] There is a growing body of literature seeking to identify nonlinear dynamics in many financial markets. For example, Sahoo et al. (2019) employ linear and non-linear Granger causality tests to examine the price-volume relationship in the Bitcoin market.

Following Patton and Sheppard (2009), the range-based volatility estimator employed in our empirical analysis is the simple average of the above three estimators, adjusted for the overnight price variation, as follows:

$$V_t = J_t + 3^{-1}(PK_t + GK_t + RS_t) \tag{4}$$

where V_t denotes the volatility of the price of a given stock at day t and the overnight price variation J_t is calculated as $J_t = [O_t - C_{t-1}]^2$.

The motivation behind using a naïve (equally weighted) average of range-based estimators of volatility is based on the assumption that there is no previous information about which estimator might be more accurate. Thus, taking an average of the volatility estimators makes it possible to mitigating to some extent the uncertainty around the choice of the best estimator.

To examine the impact of information flow on Twitter on the volatility of US Travel & Leisure stock returns, we use the local projection method of Jordà (2005) and its threshold extension proposed by Ahmed and Cassou (2016), both of which are applied to panel data. The model of Jordà (2005) used to quantify linear impulse response functions (IRFs) is as follows:

$$V_{i,t+s} = \alpha_{i,s} + TWS_{i,t}\beta_s + \epsilon_{i,t+s}, \text{ for } s = 0,1,2, \dots h, \tag{5}$$

where $V_{i,t}$ denotes the volatility of the return of stock i in day t calculated in Eq. (1), s is the length of the forecast horizons, with h being its maximum value, $TWS_{i,t}$ represents the number of tweets related to company i posted in day t, $\alpha_{i,s}$ reflects the firm fixed effect, β_s measures the response of stock return volatility at time $t + s$ to a TWS shock at time t and $\epsilon_{i,t+s}$ is a residual term. The linear IRFs are built as a sequence of β_s estimated separately for each horizon s using simple linear squares.

The nonlinear extension of Ahmed and Cassou (2016) captures the nonlinearity in the link between Twitter sentiment and volatility of US Travel & Leisure stocks by examining the impact of Twitter activity on stock return volatility under high and low uncertainty regimes separately. In other words, this framework allows testing whether the impact of Twitter posts is contingent upon the degree of uncertainty in the stock market. Formally, this approach is a threshold model based on a smooth transition function, $F(z_t)$, wherein the IRFs can differ across scenarios of uncertainty:

$$Y_{i,t+s} = \left(1 - F(z_{t-1})\right)\left[\alpha_{i,s}^{R_H} + TWS_t\beta_s^{R_H}\right] + F(z_{t-1})\left[\alpha_{i,s}^{R_L} + TWS_t\beta_s^{R_L}\right] + \epsilon_{i,t+s}, \text{ for } s = 0,1,2, \dots h \tag{6}$$

$$F(z_t) = exp(-\gamma z\_t\ )/1 + exp(-\gamma z_t), \gamma > 0, \tag{7}$$

where $F(z_{t-1})$ is the logistic function that indicates the uncertainty regime and z_t is a switching variable that serves to distinguish between a high uncertainty regime and a low uncertainty regime. This variable is normalized to have unit variance and zero mean. The smooth transition function $F(z_t)$ varies between 0 and 1 and reflects the probability of being in a specific uncertainty regime depending on z_t. Values of $F(z_t) \approx 0$ correspond to a high uncertainty regime (R_H), whereas values close to 1 imply a low uncertainty regime (R_L).

There are several well-known econometric techniques, such as Vector Autoregression (VAR) estimation, that can alternatively be utilized to compute IRFs over different forecast horizons. However, as highlighted by Jordà (2005), the local projection method has numerous advantages: (1) it can be estimated using solely simple linear regressions that are available in standard regression packages; (2) it is more robust to misspecification than VAR models; (3) joint or point-wise analytic inference is simply conducted; and (4) it can be easily adapted to nonlinear frameworks (i.e., different regimes).

3. Data and empirical findings

Our sample consists of the 22 US Travel & Leisure (T&L) companies listed on the S&P 500 index in 2019 (additional details in Table 1). [4] For each company, two types of data are considered: (1) daily opening, high, low and closing stock prices, which are used to compute volatility estimators; and (2) daily Twitter posts related to the firm collected from Bloomberg. [5] The sample period runs from January 2019 to February 2021, totalling 12,386 firm-day observations. Furthermore, the CBOE Volatility index (VIX), which captures the level of uncertainty in the US economy and is commonly seen as a measure of risk aversion in the stock market, is used as a regime variable. [6]

Fig. 1 shows the IRF of US T&L stock volatility to one standard deviation shock in Twitter posts for a horizon of 24 days under the linear model in Eq. (5). A TWS shock leads to an immediate significant positive effect on the volatility of tourism stocks, although the impact deteriorates substantially after the first two days. This indicates that increased investors' attention on Twitter raises the future volatility of T&L stocks in the very short-term.

The volume of messages on social media platforms such as Twitter is often interpreted as a measure of retail investors' attention and retail investors are generally considered to be uninformed noise traders who exacerbate stock market volatility, which leads to a positive link between postings on Twitter and stock volatility. It is also in agreement with Gu and Kurov (2020), who document that firm-specific information from Twitter helps predict future US stock returns.

Fig. 2 gives estimates of the state-contingent IRFs of T&L stock volatility to one standard deviation Twitter shock for a horizon of 24 days calculated using the nonlinear model in Eq. (6) for the high uncertainty (left panel) and low uncertainty (right panel) regimes. Clearly, the impact of TWS shocks on the volatility of tourism stocks depends upon the level of risk aversion measured by the VIX. Stock volatility reacts positively to TWS shocks over the full horizon during the regime of high uncertainty, even though the effect is particularly pronounced during the first two days. In fact, the estimated IRFs under this regime are very similar to the linear IRFs. In contrast, the impact of TWS shocks during the low uncertainty regime is markedly different in terms of persistence of the response from that observed during the high uncertainty regime. Thus, after a vigorous immediate positive effect, the response sharply decays until it takes negative values after four days and fluctuates in a narrow range of small values over the remaining time horizon. These findings are in the spirit of Andrei and Hasler (2015), who state that investors pay greater attention to the market during "panic states" where volatility is high. Conversely, when the level of uncertainty and risk aversion in the stock market are low, investors are less anxious and give less importance

[4] The Travel & Leisure industry includes airlines, gambling, hotels, recreational services, travel and restaurant and bars.

[5] Bloomberg uses machine learning algorithms to identify firm-specific tweets and classify them into positive, negative or neutral tweets. A firm's daily Twitter count is derived from the messages posted in Twitter over the last 24 hours.

[6] To check the robustness of the empirical results, the US Economic Policy Uncertainty (EPU) index has been used as an alternative regime variable to the VIX index. The results associated with the EPU are very similar to those obtained with the VIX. They are available from the authors upon request.

to information contained in tweets, so that an increase in T&L stock volatility is less likely to occur.

For a more in-depth understanding of the nexus between Twitter information flows and T&L stock volatility, next we examine the impact of positive and negative tweets on stock volatility separately. Figs. 3 and 4 give the estimated IRFs of T&L stock volatility to positive and negative TWS shocks, respectively, for the two uncertainty scenarios. Interestingly, Fig. 3 shows that the response of T&L stock volatility to a positive shock exhibits a very similar pattern to that of aggregate shocks (Fig. 2) for both uncertainty regimes. In the high uncertainty state, a positive TWS shock has a positive effect over the entire horizon, although it declines strongly after two days. Positive shocks have, however, a much less persistent positive effect on T&L stock volatility in the low uncertainty state, with responses close to zero after four days. The impact of negative TWS shocks on T&L stock volatility is weaker (see Fig. 4) than that of positive shocks for the two uncertainty scenarios and also smaller than that of aggregate shocks. Similar to the previous cases, a different pattern of response to negative shocks is identified for the high and low uncertainty conditions. These findings reveal an asymmetric effect of positive and negative Twitter comments on volatility of tourism stocks, whereby positive tweets exert a greater influence on tourism stock volatility than negative tweets. A possible explanation is that positive information on Twitter about a company encourages retail investors, who are the main Twitter users, to invest in stocks of that company, thus increasing stock volatility. More precisely, since retail investors can buy any stock but rarely recur to short selling, news that captures their attention leads, on average, to retail purchases and positive price pressure. The stronger reaction to optimistic tweets is also supported by Barber and Odean (2008). Moreover, the recent GameStop stock phenomenon has clearly demonstrated the huge potential of positive news about a company on social media to drive stratospheric increases in the stock prices and volatility of that company.

4. Conclusion

This paper analyses the effect of Twitter sentiment on the return volatility of US T&L stocks contingent upon the degree of uncertainty in the US stock market and the nature of tweets. The empirical findings confirm the increasingly important role of social media in stock exchange trading, showing that Twitter activity has a significant positive impact on volatility of US T&L stocks in the very short-term. This influence is more pronounced during periods of heightened uncertainty, consistent with the view that retail investors are particularly concerned about firm-specific news on Twitter in a context of rising uncertainty to avoid potential large losses. A novel analysis of asymmetry finds that positive tweets have a stronger impact on T&L stock volatility than negative tweets, revealing the clear incentive effect on retail investors of positive Twitter sentiment. Accordingly, investors should consider the significant influence of Twitter on T&L stock volatility in the short-term when designing their investment and hedging strategies. Policy makers and firm managers in the T&L industry should be also aware that firm-specific Twitter posts can be an important source of volatility for T&L stocks. Since this paper focuses exclusively on US T&L firms, future studies could overcome this limitation examining the impact of Twitter activity on the volatility of T&L stocks in European or BRIC countries that also have a powerful tourism industry. Another potential avenue of future research could be to broaden the scope of the analysis by considering other industries in order to determine whether their stock market behaviour is also influenced by Twitter activity.

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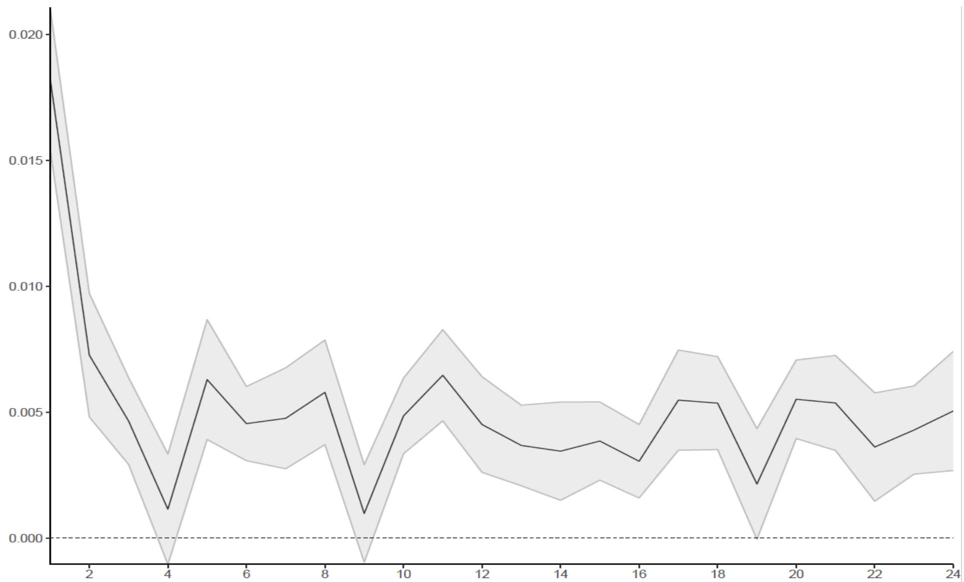
Figures and Tables

Figure 1. Linear IRF to Twitter shocks



Note: The figure shows linear IRF estimates to one standard deviation shock in Twitter posts for a horizon of 24 days. The shaded area represents the 95% confidence interval calculated based on panel corrected standard errors.

Figure 2. Regime-dependent IRFs to Twitter shocks

High uncertainty

Low uncertainty

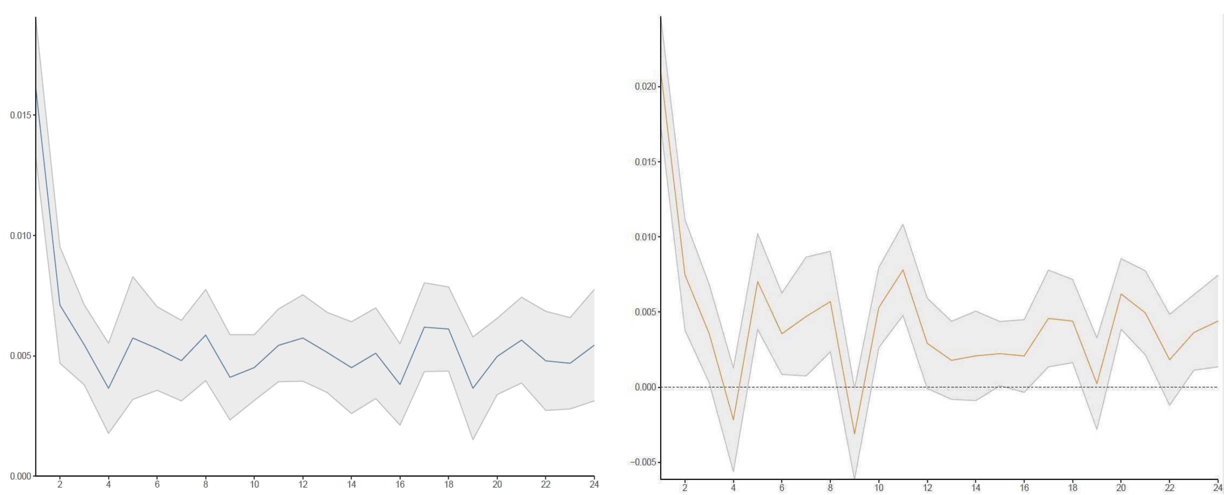


Figure 3. IRFs to positive Twitter shocks

High uncertainty | Low uncertainty

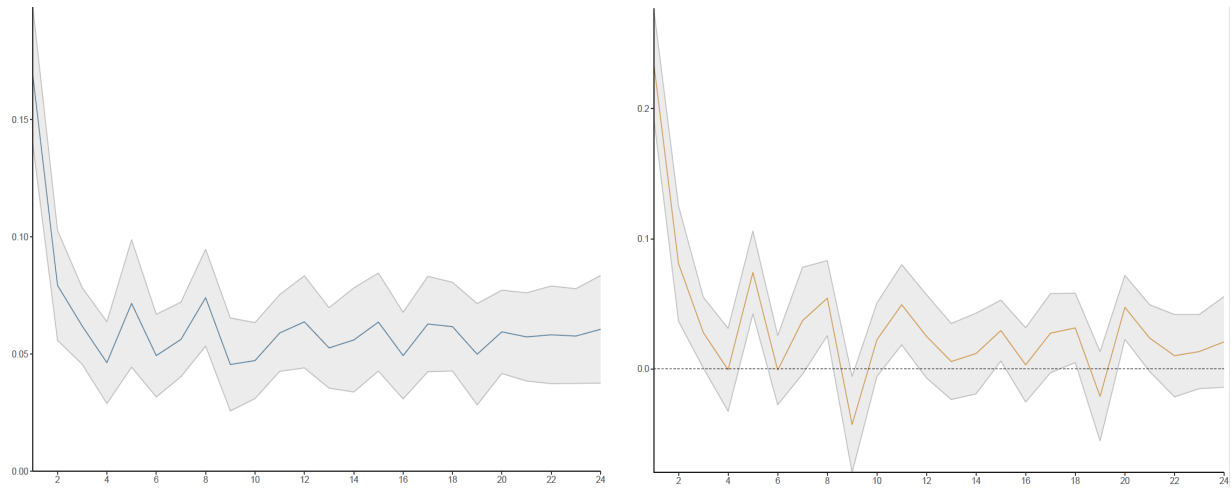


Figure 4. IRFs to negative Twitter shocks

High uncertainty | Low uncertainty

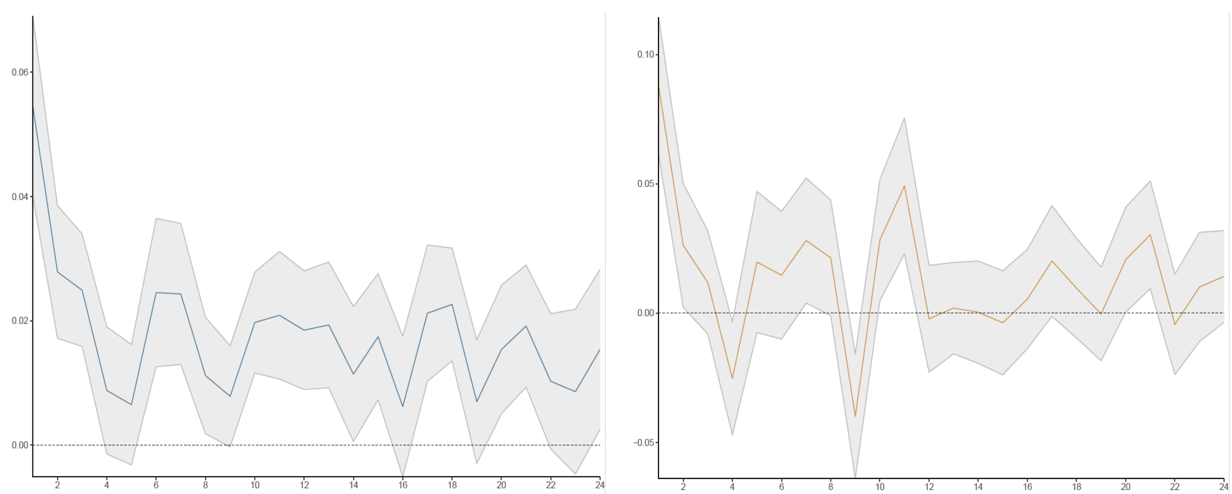


Table 1. T&L firms included in the S&P 500 index

Ticker	Name
MCD	MCDONALDS CORP
SBUX	STARBUCKS CORP
BKNG	BOOKING HOLDINGS
MAR	MARRIOTT INTL-A
LVS	LAS VEGAS SANDS
CMG	CHIPOTLE MEXICAN
LUV	SOUTHWEST AIR
HLT	HILTON WORLDWIDE
YUM	YUM! BRANDS INC
DAL	DELTA AIR LI
CCL	CARNIVAL CORP
EXPE	EXPEDIA GROUP IN
RCL	ROYAL CARIBBEAN
LYV	LIVE NATION ENTE
MGM	MGM RESORTS INTE
DRI	DARDEN RESTAURAN
UAL	UNITED AIRLINES
WYNN	WYNN RESORTS LTD
DPZ	DOMINO'S PIZZA
AAL	AMERICAN AIRLINE
NCLH	NORWEGIAN CRUISE
ALK	ALASKA AIR GROUP