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Does the Fear Index Incessantly Affect Stock Performance in the Lodging Industry?

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ABSTRACT
This study investigates the impact of fear on stock returns of the lodging companies for two specific periods (January 1997–December 2007 and January 2008–June 2018). While the literature has adequately studied the relationship for general stock returns, it has underemphasized a sector-based approach, including the lodging industry, toward understanding the connection. The study contributes to the literature by focusing on the short-term dynamic connection for the lodging firms and by providing theoretical propositions that could advance the theory building process. The results show that the fear index has lost its forward-looking capacity on stock performance in the lodging industry after 2018.

Key words: investor sentiment, VIX, stock returns, S&P 500, lodging industry, instrumental variable regression

Introduction

Return and price swings in equities mostly co-vary with investors' sentiment (i.e., fear or greed) in broader indices (e.g., S&P 500) globally. Both individual and institutional investors become wiser in their investment practices and activities and rely heavily on analysts' recommendations and investors' fear or trust gauge in the markets to form efficient portfolios, and thus reap higher financial benefits. Hence, a more nuanced understanding of how the "heterogeneous crowd psychology" is calibrated and priced in markets, which eventually affects stock returns, is critical. The preceding discussion is even more critical for firms that have a unique history of volatile financial structure (i.e., high levels of capital expenditure, unstable earnings, free cash flow, low liquidity, and reduced possibilities for risk diversification) that adversely affects the risk premiums. Thus, these companies are mostly small- and mid-caps rather than established large-cap firms (Kizildag & Ozdemir, 2017; Kizildag, 2015; Ozdemir, Kizildag, & Upneja, 2013; Madanoglu, Kizildag, & Karadag, 2012; Madanoglu, Kizildag, & Ozdemir, 2018; Ozdemir & Kizildag, 2017). Also, in the lodging industry, companies are affected by the seasonal and cyclical effects that influence a variation of macroeconomic factors (Dogru, Sirakaya-Turk, & Crouch, 2017; Khalilzadeh, Kizildag, Ridderstaat, & Madanoglu, 2018; Kizildag, Barber, & Goh, 2010). Given these discussions, our interest has been aroused regarding the financial nature of the lodging firms. Thus, we believe that measuring the association between investors' sentiment and stock returns for those firms over time is worthwhile.

This study investigates the short-term influence of the fear index on the stock returns in the lodging industry for two explicit time frames. Specifically, the study considers how cycles of the VIX, Chicago Board Option Exchange's (CBOE) market volatility index, affect those of stock returns of a comparable set of hotels and lodging businesses for two periods (January 1997–December 2007 and January 2008–June 2018). Cycles are defined in this study as wavelike upward and downward data movements around the long-term trend (Keating & Wilson,

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2019). They are non-periodical in nature and arise from endogenous forces and/or exogenous shocks (Bails & Peppers, 1993).

The literature has adequately covered the connection between the VIX and stock returns (e.g., Antonakakis, Chatziantoniou, & Filis, 2013; Fleming, Ostdiek, & Whaley, 1995; Giot, 2005; Grechi, Ossola, & Tanda, 2017; Hibbert, Daigler, & Dupoyet, 2008; Obi, Sil, & Abuizam, 2015), finding a significant negative effect. However, a sector-based analysis of the connection has remained limited, in that, as far as the authors could have assessed, only one study has looked into this connection for the tourism industry (Obi et al., 2015). That study found no connection with the short-term phase of the data. The limited emphasis of the literature on the connection between the VIX and the lodging industry makes this topic an interesting area for further exploration.

This study contributes in several ways to the literature. First, the study expands and enriches the literature on the relationship between the VIX and stock returns by looking at the short-term connection between these variables, specifically for the lodging firms, using the cyclical (or short-term) element of the data, which was derived from a sophisticated method of data decomposition. Second, the study adds value to the literature by looking at the dynamic effects of the relationship between the VIX and the stock returns of the lodging firms using two specified periods. This provides a better understanding of the effects. Third, as a case study, the investigation contributes to the literature by providing building blocks for advancing the theory building process through theoretical propositions (Amaratunga & Baldry, 2001; Eisenhardt & Graebner, 2007; Smith, 2010; Veal, 2006; Yin, 2009). The ultimate goal of the study is not to seek results that may have general representation (Veal, 2006), but to articulate new ideas from the analysis (Smith, 2010; Madanoglu, Castrogiovanni, & Kizildag, 2018).

This paper is structured as follows: After the introductory section, the paper will analyze the relevant literature, which allows for a better understanding of the purpose of this study. The methodological procedures are presented subsequently, followed by the empirical results and a discussion of the findings. The conclusion section is presented last and contains, besides a summary of outcomes, the managerial implications, study limitations, and lines for future research.

Literature Review

The VIX as an Early Warning System

Since its initial introduction by Whaley (1993) as a forward-looking index to benchmark short-term (30-day) market volatility in the futures market, the CBOE's measure of market volatility, commonly known as VIX, has grown to be recognized as the forerunner metric in measuring market volatility (Chung, Tsai, Wang, & Weng, 2011; Poon & Granger, 2003; Smales, 2017). Unlike many popular metrics, i.e., the Dow Jones Industrial Average (DJIA), Standard and Poor's 500 (S&P 500), Nikkei Stock Average (Nikkei 225), and the Financial Times Stock Exchange 100 Index (FTSE 100), which are historical indices, the VIX currently utilizes both historical data from the S&P 500 along with a weighted average of monthly futures contracts to provide a forward-looking indicator (Smales, 2017; Whaley, 2008), based on the implied volatility of the market (Whaley, 1993; 2000; 2008). Its forecasting strength is in its ability to continuously adjust to new tick data and information. Considering these characteristics, researchers and practitioners have shown preference to the VIX above other implied volatility proxies because it reduces the probability of measurement errors, thus producing more accurate future realized volatility forecasts (Blair, Poon, & Taylor, 2010; Copeland & Copeland, 1999; Fleming et al., 1995; Koopman, Jungbacker, & Hol, 2005).

Initially, the VIX was calculated using the S&P 100 and eight different at-the-money put and call options. This occurred because when the index was created, S&P 100 options represented 75% of the total index options market, and the index requires a large number of options trades to accurately reflect investor sentiment. As the market and investing habits changed over the years, where the S&P 500 options became the most traded, the VIX calculation was altered accordingly in 2003 to remain current. Later in 2014, the limitation on the S&P 500 monthly options was relaxed to allow the use of the weekly options, which improved the accuracy of the index.

Relationship of the VIX with Stock Returns

For the most part, previous literature has found a significant negative relationship between implied volatility—measured by the VIX—and stock returns (Antonakakis et al., 2013; Fleming et al., 1995; Giot, 2005; Grechi et al., 2017; Hibbert et al., 2008; Obi et al., 2015). This relationship has been found to be asymmetric (Fleming et al., 1995; Giot, 2005; Hibbert et al., 2008); that is, negative returns translate into larger changes in VIX than positive ones. Fleming et al. (1995) found this negative relationship to be strong for current equity values, but the relationship turns to a positive moderate effect when lagged. Similarly, Giot (2005) found that this negative relationship is simultaneous and "is much sharper in low-volatility trading environment" (p. 3), but future positive returns are correlated to very high values of the VIX, regardless of the time horizon. Hibbert et al. (2008) also confirm this short-term relationship, finding a negative and asymmetric association of daily and intraday VIX values and stock returns. Another study supporting the non-contemporaneous relationship between implied volatility and stock returns is by Copeland and Copeland (1999), who found that changes in the VIX values will cause lagged changes (1–20 days) in returns of future contracts; however, higher VIX values will benefit large-cap portfolios, while lower VIX values will benefit small-cap portfolios. Finally, Banerjee, Doran, and Peterson (2007) found that the VIX strongly predicts the returns of most portfolios—but especially high beta ones—and leads to stronger predictions for 60-day, rather than 30-day, returns. Whaley (2008) examined the performance of the VIX as a predictor index by evaluating 274 months of historical data and found that the VIX was reasonably successful as a predictor of 30-day future S&P 500 rate of return. Investors across the market demanded higher returns during periods of higher volatility thus driving stock prices down. Conversely, in periods of market growth, investors are less demanding when considering dividend payouts, as they expect to be partially compensated for their risk via appreciation in stock value (Smales, 2017). This reality supports the asymmetric nature of the VIX, which reacts quickly to expectations of negative outcomes in the market, and more slowly when investors are expecting periods of growth (Bekiros, Jlassi, Naoui, & Uddin, 2017).

On the business level, Wang (2010) examined the concept of industry-specific volatility by studying the individual volatility found in each of 30 different industries over the period of July 1963 through June 2008 and found that different industries behave differently in times of greater uncertainty and unrest. However, these economic-segment type of studies are more the exception rather than the rule.

Synthesis

While the literature has adequately covered the connection of the VIX with stock returns, little is known about how the VIX impacts stock returns of a particular economic segment, such as the tourism industry. A study by Obi et al. (2015) found that the VIX had a negative effect on long-run stock returns but insignificant influence in the short-run. Particularly the latter result is interesting and shows that the VIX does not always function as an early warning indicator for stock returns. However, while that study applied the appropriate econometric tools, the data used does not seem to have been corrected for seasonal effects. The latter could possibly bias the findings of this study, even when first difference data were used. Working with deseasonalized data is a precondition for estimating the impact of the VIX on stock returns.

Several studies have emphasized both long- and short-term effects, implying static influences of the VIX in both time spans. Possible dynamics within the long- and short-term dimensions have, as far as the authors could have assessed, remained outside the scope of studies covering the VIX-stock return connections. The current study addresses both deficiencies by analyzing the short-term effect dynamics of the cyclical patterns of the VIX on the stock returns cycles of the lodging industry over two periods of data. The methodological foundations will be discussed next.

Methodological Procedures

Data, Sample, and Foundational Framework

Longitudinal equity and return data (monthly) for each comparable hotel and lodging firm along with market data were gathered and compiled from CRSP/COMPUSTAT merged files and Capital IQ

fillings between January 1997 and June 2018. We are aware of the fact that the most straightforward and efficient method involving any financial performance analysis is done against a broader market index that measures the value-weighted average price movements (Elton, Gruber, & Blake, 1996). Thus, we picked the S&P 500 Composite Index as a market benchmark in our estimations.

To capture true and unbiased equity return cycles driven by investors' sentiment, we employed the "market-generated" sentiment and fear with a smoothing of 30-day ex-post price volatility implied by S&P 500 index options (VIX) to form our econometric models for ex-ante return calibrations and estimations. Our chief intention was to draw equity return cycles with a market perceived volatility in either upward or downward direction signaling how optimistic or pessimistic investors feel about the capital markets and the overall state of the macro economy. Including the VIX in our analyses is critical because the VIX subsumes any information on how historical market reactions contributed to the equity return volatility and it mirrors and/or reflects any incremental information pertaining to a possible future return activity. We drove geometric average of VIX to match the equity return time frame so that we can produce economically significant outcomes.

We specifically considered the length of firm-year records. Firm equity observations must have had a record of at least two years to mitigate the backfilling and survivorship biases (Fama & French, 1993). Due to a lack of data and data gaps, we could not analyze some other sub-segments of the hospitality industry (i.e. gaming, cruise lines, etc.), and hence, our final sample has a minor selection bias that could be attributed to this selection factor. Further, we have kept the outliers, which do not lie only on one side of the distribution, so that our results can be free of estimation bias. Taken all together, we believe that we adequately captured a sufficient sample size for the hotel and lodging industry. When all eliminations and the screening process had been completed, 38 of 56 firms formed the final sample.

Additionally, our study considered two dummy variables to represent the influence of two key periods of financial crisis that have caused global economic distress along with leading indicators in Table 1. The first period has to do with the consequences of the terrorist attacks in New York and in Washington. Immediately before these events, the world economy was already showing signs of slowing down (International Monetary Fund, 2001), and the September 11, 2001, terrorist attacks only complicated the situation further. Besides the loss of lives, these attacks were responsible for both direct (estimated at about ¼ of the U.S. annual GDP) and indirect costs (undermining of consumer and investor confidence) (Johnston & Nedelescu, 2005). The second period is related to the global financial crisis of 2007–2009, which hit a wide variety of countries in the world, including the United States, causing, among other, reversed capital flows, depreciated currencies, and collapse in credit and in some balance sheet problems (Berkmen, Gelos, Rennhack, & Walsh, 2009).

Table 1. List of Applied Variables

Variable Name	Description
SD_LR_C	Cycle of return of hospitality corporations (standardized)
SD_VIX_C	Cycle of volatility index (implied) (standardized)
SD_SP500_C	Cycle of S&P 500 stock return hospitality industry (standardized)
D_SEP11	Dummy for the effects of the terrorist attacks on September 11, 2001
D_GLOBCRIS	Dummy for the global financial crisis (2007–2009)

The key foundation and the premise of this study are that stock returns of the lodging firms are predated by both investors' fear, enumerated by the VIX index (VIX), and the S&P 500 index (SP500). Specifically, the current research looks at how cycles of the VIX and S&P 500 affect the cyclical development in stock return of the lodging companies. Figure 1 provides a schematic overview of the relationship between the three constructs. Both the VIX and the S&P 500 are expected to be leading indicators for future cyclical developments in the return of the lodging companies. The analysis period is from January 1997 to June 2018 and covers two key periods, before and after 2008, in line with the paper written by Kizildag and Ozdemir (2017).

Estimation Procedures and Models

Before initiating the investigation, we subjected the data to several procedures to make them ready for analysis. The central idea was to use only the cycle component of the data. Generally, time series

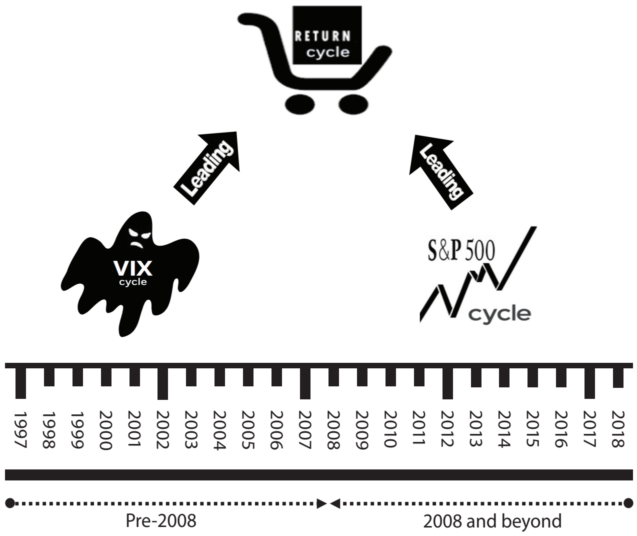

Figure 1. Study Framework.

data consist of four components (Bails & Peppers, 1993; Gaynor & Kirkpatrick, 1994; Keating & Wilson, 2019; Makridakis, Wheelwright, & Hyndman, 1998), namely a trend, cycle, seasonal, and irregular element. The trend component (T) denotes the long-term change (increase or decrease) of the data. The seasonal component (S) refers to an annually recurring pattern of change in the data (Gaynor & Kirkpatrick, 1994), in a somewhat similar fashion. The irregular factor (I) designates the erratic or irregular movements in the data, after correcting for the trend, seasonal and cyclical factors (Bails & Peppers, 1993). The cycle component (C) represents the non-periodical recurring variations around the trend, and originate from endogenous forces and/or exogenous shocks (Bails & Peppers, 1993).

The relationship between the four components can be either additive or multiplicative in nature (Gaynor & Kirkpatrick, 1994). The additive form considers the construct of the data as a summation of the different components (T + S + I + C). The multiplicative form views the relationship as a multiplication of the factors (T*S*I*C). The distinction between additive and multiplicative models is relevant for the applied decomposition technique, where the data is assumed to be additive in nature. For this reason, the authors transformed all applied variables into a logarithm. In the case of a multiplicative model, a logarithm transformation implies that the relationship between the components changes from multiplicative to additive (for example Log ab = Log a + Log b). When the data is already additive, a logarithm transformation will leave the additive structure unchanged.

To decompose the data, the authors applied the unobserved component model, which contemplates a series as a construct of several unobservable components (Enders, 2010). The model is used to split a time series into a trend, seasonal, cyclical, and irregular components (StataCorp, 2013). UCMs are also called structural models (SAS Institute, Inc., 2014), and can be formally presented as follows:

$$Y = T_t + S_t + C_t + \beta X_t + I_t \tag{1}$$

Where,

Y = Time series variable;
T = Trend;
S = Seasonal factor;
C = Cyclical factor;
β = Vector of coefficients;
X = Vector of exogenous variables in the structural models.

The cyclical output (C) of each variable from the UCM procedure will be further used in this investigation. Before doing that the data have to be made comparable through standardization, where the transformed variables have means that are equal to zero and standard deviations equivalent to 1 (Gujarati & Porter, 2009). With the standardized variables, the authors tested these for stationarity. In general, variables could be non-stationary, with periods of increases and decreases, a characteristic that may cause a biased standard error and untrustworthy relationships in regression analyses (Mahadeva & Robinson, 2004). For the testing procedure, the authors applied the Augmented Dickey-Fuller (ADF) (Dickey & Fuller, 1979) and the Phillips-Perron (PP) tests (Phillips & Perron, 1988), which are two regularly applied assessments. The result from the unit root testing will provide an indication of the form (level or first difference) of inclusion of the variables in the regression analysis.

Next, the authors tested whether there were long-term relationships (co-integration) between the three selected variables, using the Autoregressive Distributed Lags (ARDL) bound test method. This

method, suggested by Pesaran, Shin, & Smith (2001), tests a null hypothesis (H_0) as the absence of the co-integrating relations against the alternative (H_1) of co-integration. The test is run by comparing a joint F-statistic (Wald statistic) with either a lower or an upper bound critical value, the latter depending on the unit root tests outcomes. For variables integrated at the level form (I(0)), the lower bound critical value must be applied. For I(1) variables (variables that become stationary when in first difference form), the comparison must be made against the upper bound critical value. Five possibilities could result from the comparison procedure (Ridderstaat, Oduber, Croes, Nijkamp, & Martens, 2014):

1. All variables are I(0), and the calculated F-statistic is lower than the lower bound critical value → no co-integration (rejection of H_1).
2. All variables are I(0), and the calculated F-statistic is higher than the lower bound critical value → co-integration (rejection of H_0).
3. All variables are I(1), and the calculated F-statistic is lower than the upper bound critical value → no co-integration (rejection of H_1).
4. All variables are I(1), and the calculated F-statistic is larger than the upper bound critical value → co-integration (rejection of H_0).
5. Mixed outcome, where some variables are I(0) and others are I(1) → co-integration if the variable is I(0) (rejection of H_0) and no co-integration if the variable is I(1) (rejection of H_1).

Having done the aforementioned tests, the authors determined subsequently the effects of the cycles of the fear index and the S&P 500 index on those of the return of the lodging firms. The model includes no intercept, because this will always be zero when the variables are standardized (Gujarati & Porter, 2009). The model for this analysis is as follows:

$$SD\_LR\_C_t = \alpha_0 SD\_VIX\_C_{t-m} + \alpha_1 SD\_SP500\_C_{t-n} + \alpha_2 D\_SEP11_t + \alpha_3 D\_GLOBCRIS_t + \varepsilon_t \tag{2}$$

where,

t = Time;
m and n = Lags;
$\alpha_0, \alpha_1, \alpha_2, \alpha_3$ = Coefficients;
ε = Error term.

We considered the possibility that one or more of the endogenous variables may be correlated with the error term, and, in such cases, applying ordinary least squares will be biased (Kennedy, 2008). That is why the authors applied the instrumental variable approach (IV), specifically the Limited Information Maximum Likelihood (LIML) technique. This method has been suggested by Hayashi (2000), Poi (2006), and Stock, Wright, and Yogo (2002) where the sample size was small. According to Stock and Yogo (2005), tests based on the LIML were also more robust to weak instruments than those based on two-stage least squares. The IV approach requires the use of instrument variables, which are correlated with the presumable endogenous variable(s) in the model but are not correlated with the residual term (Gujarati, 2015). The followed procedures to select the instrument variables were: (1) the variables must be correlated either positively or negatively with the endogenous variable(s) in the model; (2) the instrument variable must not be correlated with the related endogenous variable for which it acts as an instrument; and (3) the instrument variables must not be part of the model.

Empirical Results and Discussion

Chart 1 presents a group of charts comparing the standardized cycles of returns of the lodging firms in respect to the fear index and the S&P 500 index, considering three periods. The first chart (Chart 1.1) presents a blurry picture of both cycles, which hinders a good visual interpretation. Looking at Chart 1.2, which covers the period from January 1997 to December 2007, it provides a more interpretable view of simultaneous increases in one cycle and decreases in the other. The actual relationship between both cycles is expected to be negative, i.e., an increase in fear will negatively affect return patterns in the lodging industry. Similarly, Chart 1.3 shows visually opposite movements between the

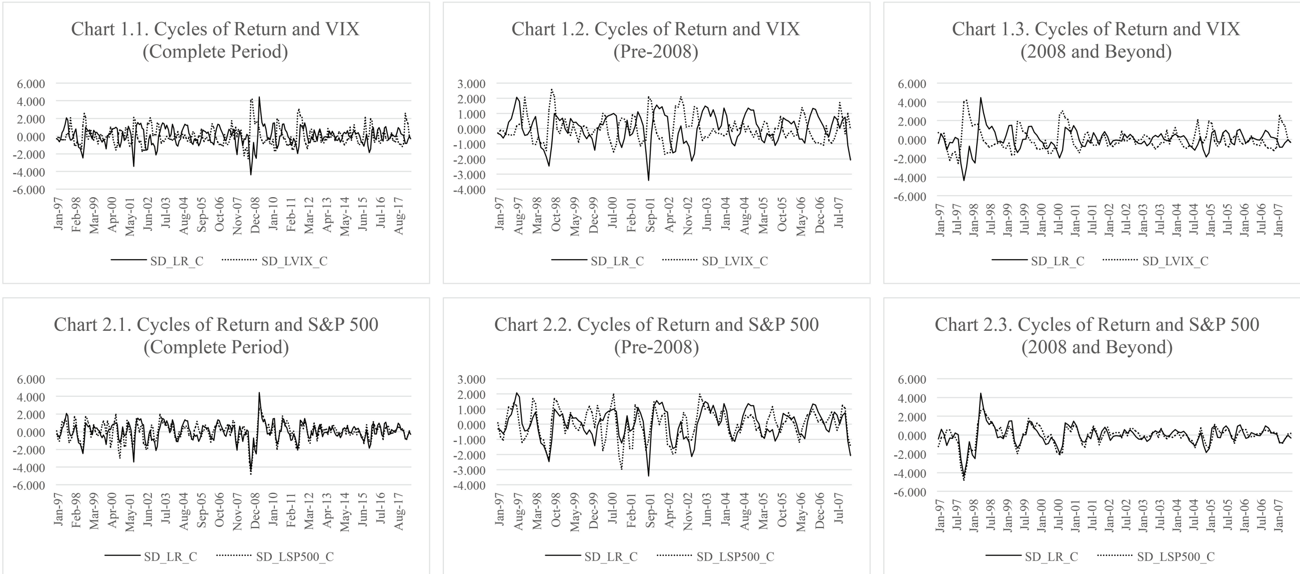

Chart 1. Comparison of Standardized Cycles of Stock Returns, VIX, and the Benchmark.

Table 2. Unit Root Test

Variable Name		ADF	PP	Conclusion
		Complete Period		
SD_LR_C	Level	−4.9722***	−6.3718***	I(0) or I(1)
	First difference	−8.9110***	−18.3771***	
SD_VIX_C	Level	−10.0537***	−6.4211***	I(0) or I(1)
	First difference	−10.0126***	−43.6612***	
SD_SP500_C	Level	−5.4479***	−5.9997***	I(0) or I(1)
	First difference	−7.6788***	−33.2918***	
		Pre-2008		
SD_LR_C	Level	−7.2146***	−3.4919***	I(0) or I(1)
	First difference	−6.5046***	−10.5448***	
SD_VIX_C	Level	−7.5900***	−5.0850***	I(0) or I(1)
	First difference	−8.8828***	−22.7355***	
SD_SP500_C	Level	−8.9738***	−4.7336***	I(0) or I(1)
	First difference	−3.8288***	−17.6086***	
		2008 and Beyond		
SD_LR_C	Level	−5.7510***	−6.0470***	I(0) or I(1)
	First difference	−13.6748***	−10.8705***	
SD_VIX_C	Level	−6.7934***	−4.5394***	I(0) or I(1)
	First difference	−10.0289***	−18.8307***	
SD_SP500_C	Level	−6.1813***	−4.8824***	I(0) or I(1)
	First difference	−7.0164***	−12.6514***	

Note: *** indicates significance at 1%.

return cycle and the cyclical movement of the fear index. When comparing the return cycle with that of the S&P 500 index, the results show a more comparable relationship of almost matching movements (Chart 1.4). The parallel movements are also being shown in Charts 1.5 (the period before 2008) and 1.6 (2008 and beyond). Visual inspection is the first step, but further analysis is needed to understand the relationship between the three variables.

Unit root test results are provided in Table 2, considering the complete period and the pre-2008 and 2008 and beyond ones. All variables appear to

Table 3. Bounds Test

F-statistic	Without a Trend	Critical Values					
		1%		5%		10%	
		Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Whole Data Set							
FSD_LR_C (SD_LR_C|SD_LVIX_C SD_LSP500_C)	23.6710***	3.880	5.300	2.720	3.830	2.170	3.190
Pre-2008							
FSD_LR_C (SD_LR_C|SD_LVIX_C SD_LSP500_C)	32.9604***	3.880	5.300	2.720	3.830	2.170	3.190
2008 and Beyond							
FSD_LR_C (SD_LR_C|SD_LVIX_C SD_LSP500_C)	7.5688***	3.880	5.300	2.720	3.830	2.170	3.190

Note: The symbols *, **, and *** indicate significance at, respectively, 1%, 5%, and 10%.

Table 4. Estimated Lags (Based on Adjusted R^2)

	Lag = 0	Lag = 1	Lag = 2	Lag = 3	Lag = 4
Whole Data Set					
SD_LR_C versus SD_LVIX_C	0.1174	0.0027	0.0638	0.0497	0.0530
SD_LR_C versus SD_LSP500_C	0.5790	0.3530	0.0515	0.0024	0.0007
Pre-2008					
SD_LR_C versus SD_LVIX_C	0.1195	0.0000	0.0716	0.0549	0.0123
SD_LR_C versus SD_LSP500_C	0.4119	0.3652	0.0479	–0.0005	0.0135
2008 and beyond					
SD_LR_C versus SD_LVIX_C	0.1180	0.0043	0.0592	0.0462	0.0462
SD_LR_C versus SD_LSP500_C	0.7537	0.3416	0.0534	0.0131	0.0024

Note: The symbols, *, **, and *** indicate significance at, respectively, 1%, 5%, and 10%.

be stationary at both the level and first difference forms, in all three periods of analysis. This means that shocks are only transitory and will not permanently affect the future developments of cycles, and there is a possibility of co-movements between the dependent variable and the independent ones (Croes, Ridderstaat, & Rivera, 2018).

The bounds test results are provided in Table 3 and show co-integrating (long-term) relationships between the three variables in all three-time frames, although the power of the F-statistic seems to become much smaller from 2008 onwards, which could signal a decreasing long-term relationship.

With these results, the authors proceeded in estimating the effect of, respectively, the fear and S&P 500 cycles on lodging firm return cycles. To conduct this test, the researchers established first whether there was a lag relationship between the dependent and the independent variables using the coefficient of determination (R^2) in simple ordinary least squares, following Ghatak and Zhang (2009) and Bhatta (2011). This statistic provides information about the proportion of the total variance in the dependent variable that is explained by that of the independent variable. Table 4 shows the results of this analysis, indicating a zero-lag relationship between the cycle of lodging firms' return and that of, respectively, the fear index and the S&P 500 index. This no-lag relationship was found in all three-time frames and indicates an almost immediate reaction of the lodging firms' return on impulses of fear and the S&P 500.

With the estimated lag relationships, the authors estimated the elasticity effects of the cycles of both the fear index and the S&P 500 index on that of lodging industry return, using the LIML instrumental variable approach discussed in the previous section. These results are presented in Table 5, and given the standardized nature of the data, we will indicate the coefficients in z-scores (or betas), which are defined as the ratio of the estimated coefficient of a specific variable (α) and its standard error (se) $\frac{\alpha}{se}$. Providing the coefficients in z-scores allows for comparison of the strength of each coefficient in determining the

Table 5. Elasticity Effect Estimation (The Fear Index and the S&P 500)

Dependent Variable	Z-score SD_LVIX_C	Z-score SD_LSP500_C	D_GLOBCRIS	D_SEP11	Kleibergen-Paap rk LM statistic (χ2)	P-value	Kleibergen-Paap rk Wald F statistic
Whole Period	−2.1300**	0.8197***	0.0578	0.1851	26.4990	0.0000	9.9020
Pre-2008	−2.0500**	4.7600***	−0.7700	0.5200	18.0450	0.0001	11.0810
2008 and Beyond	−0.9000	4.3100***	0.0600		14.6240	0.0007	7.7000

Dependent Variable	Stock-Yogo weak ID test critical values (maximal LIML size)				Hansen J statistic (Overidentification test of all instruments; H0: variables are exogenous)	P-value	Endogeneity test of endogenous regressors	P-value
	10%	15%	20%	25%				
Whole Period	4.72	3.39	2.99	2.79	1.160	0.5600	4.538	0.1034
Pre-2008	5.44	3.81	3.32	3.09	0.008	0.9306	1.830	0.4005
2008 and Beyond	5.44	3.81	3.32	3.09	2.482	0.1151	0.326	0.8495

Note: The symbols *, **, and *** indicate, respectively, the 1%, 5%, and 10% significance levels.

dependent variable. This is relevant when the independent variables have different scales. Interpreting a z-score is as follows: with a z-score of 0.25, this means that a 1 standard deviation increase in an independent variable will lead to a 0.25 standard deviation increase in the dependent variable, if all other variables in the model remain unchanged (the so-called ceterus paribus principle). Back to Table 5, the z-score in the first column represents the influence of the fear index, and indicate statistical significance in the full period (α_0 = −2.1300**) and the period before 2008 (α_0 = −2.0500**), but not for the period of 2008 onwards (α_0 = −0.9000). The sign of these results was anticipated, given that fear in the market is generally expected to have negative repercussions on stock return. The result for 2008 onwards was remarkable, given that it indicates that fear in the market has lost influence on the return over time, at least in the lodging industry. Regarding the S&P 500 index, the results show continued statistical significance over time, though the effect 2008 onwards has decreased somewhat compared to the period before 2008. The additional tests related to the applied model indicate that the equation was not under-identified. The Kleibergen-Paap rk LM statistic coefficient rejected the null hypothesis of model under-identification. In other words, the excluded instruments were not deemed relevant, or correlated with the endogenous variables. The Kleibergen-Paap Wald rk F statistics were larger than the critical values of Stock and Yogo (2005) at 10%, 15%, 20%, and 25%, indicating that the model had no weak instrument variables. Put differently, the excluded instruments were not found to be weakly correlated with the endogenous variables, which, otherwise, could have negatively affected the effectiveness of the instrumental variable approach. The Hansen J statistic was not significant in all cases, indicating that the model was not over-identified, and that the applied instruments were valid for the model, while the excluded instruments were correctly omitted from the estimated equation.

The preceding analysis has shown that the fear index indeed has a negative impact on stock returns of the lodging companies, similar to what the literature has found for other industries. However, this relationship does not hold for 2008 onwards, suggesting a nonlinear connection.

Conclusion, Implications, and Future Directions

This study investigated the influence of the VIX on stock returns of the lodging industry, for two specific periods (January 1997–December 2007 and January 2008–June 2018). The results show that the VIX had a negative impact when considering the overall of both periods and the period before 2008. However, as of 2008, the VIX has lost influence on the stock performance of this sector. The findings are important because they shed light on the chronological workings of the VIX as a determinant of short-term stock returns of the lodging industry. The literature barely considered this impact of VIX on the highly-levered and capital-intensive lodging industry. Our major contribution in this paper is that we tried to overcome this challenge and understand the reasons the VIX has a gradually reduced effect on stock returns in the lodging industry.

The theoretical contribution through the lenses of sentiment and information theories and propositions are stemming from our results, which are: (a)

Considering the short term, the VIX has a nonlinear impact on stock returns of the lodging industry, and (b) The short-term effect of the VIX is decreasing over time. Under the framework of these theories, the conceptualization of our results has valuable merits and critical relevancy for practice and policymakers. Lodging companies usually have volatile earnings, solvency, and liquidity conditions due to a speculative risk exposure through daily VIX outcomes. Also, these firms are usually more difficult to value in the markets and more subjective to speculative demand. The outcomes of VIX has generally larger negative impacts on lodging firm stocks. Taken together, it is our utmost suggestion that lodging companies should come up with key practices and strategies for a better asset allocation in their target portfolios and optimal diversification with lesser capital gains taxes to fund a reasonable number of future capital/asset investments with the lowest possible weighted average cost of capital.

There are some limitations and minor exclusions in our study. First, the study considered only a prespecified period (January 1997–December 2007 and January 2008–June 2018) and did not investigate other possible time spans, for example, the September 11, 2001, terrorist attacks and their aftermath and the financial crisis of 2007–2009, even though the study considered them as dummy variables. Second, the study only considered the data on a monthly basis. Higher frequency in the data could also affect the results.

The connection between the VIX and stock returns in the lodging industry and other sub-sectors of hospitality industry offers many possibilities of investigation to unravel the true nature of the relationship. Therefore, future studies should elaborate on the nonlinearity effect of the VIX by looking at different timeframes and time frequencies than the ones investigated in this research. This could assist in providing a better understanding of the conditions under which the effect of the VIX on stock returns of the lodging industry will vary. Upcoming studies should also analyze other industries individually and/or collectively to assess whether the effect of these indicators are also temporary in nature. Also, the analysis of both long- and short-term effects of the VIX is a possibility worthy of exploration. An additional avenue to explore is whether the relationship between the VIX and the stock returns in the lodging firms is bilateral of nature, implicating that both indicators can affect each other. Our results did not reflect or calculate the compensation for risks (i.e., systematic and/or idiosyncratic risk). Parallel to this, our work did not extend to risk-adjusted performance proxies (i.e., Upside Probability, Sharpe Ratio, Treynor Index, etc.) to quantify equity returns. Last, analyses concentrating on the likelihood of financial distress and bankruptcy/default-risk along with the lodging portfolio aggregate risk levels can also move the related research forward.

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