On the volatilities of tourism stocks and oil

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Abstract

We examine the impact of oil volatility on the volatility of tourism related firms' stocks in the United States (U.S). In doing so, a novel fixed effect panel heterogeneous autoregressive (HAR) model with its extensions (by decomposing good and bad volatilities as well as signed jump variations) is estimated using 5-min interval data of 105 listed firms. Oil volatility, with a short-run positive impact, improves both in-sample and out-of-sample volatility forecast of tourism related firms.

1. Introduction

According to Becken (2001), tourism is an oil intensive sector. The dependence of tourism on oil is largely due to its inherent transport component. Tourists move between origins and destinations with services that are frequently provided by tourism-related companies, and even the decisions about buying a tourism service might be, in part, driven by oil fluctuations, with longer movements becoming less attractive in periods of large oil price fluctuations. Consequently, we might state the tourism and related supporting industries heavily rely on car and air transport, where oil is used as a fuel, or directly have oil expenses included among the costs, like for the cruise segment. Furthermore, other tourism activities such as scenic flights, jet boating, and boat cruises (Becken and Simmons, 2002) are particularly vulnerable due to their substantial dependence on fossil fuels (Becken and Lennox, 2012).

Despite the importance of oil, the models forecasting tourism revenues or tourism-related stock performances rarely consider the impact due to variations in oil prices.[1] However, the impact of oil in the tourism sector is becoming of topical interest due to the energy-intense nature of this industry (Becken, 2008; Gössling et al., 2005). Changes in oil price can harm economic and tourism activities due to effects of oil prices on disposable income, production costs, transportation and economic uncertainty (Becken, 2008; Balli et al., 2018). Therefore, regardless of the possibility to shift away from oil-based transport, higher oil prices will still make tourism trips more expensive and will negatively affect the global tourism demand (Yeoman et al., 2007). Additionally, rise in airfares would cause tourists to shift from distant to closer destinations (Gillen, 2004). Overall, several authors suggest that higher oil prices negatively impact on the tourism sector; see Becken, (2011), Becken and Lennox (2012), and Yeoman et al. (2007),

[1] The study of Draper et al., (2009) is an exception.

among others. Moreover, oil price movements are expected to have an immediate and negative impact on tourism, mainly because tourism is regarded as a luxury good (Dritsakis, 2004; Lim et al., 2008; Nicolau, 2008).

Although, the nexus between oil price movements and the performances of the tourism sector has been addressed by the literature, the relation within the risk dimension has not received much attention. Notably, the financial market participants are concerned and exposed to the volatility of their investments. Consequently, the volatility has an important role in portfolio formulation, risk management and hedging decision, and particularly in derivative and option pricing. The tourism industry portfolio is not an exception, and investments in tourism companies must be analyzed not just in the return dimension but also in the risk dimension. By switching the point of view, a possible question emerges, as it might become of interest to analyze the link between the risk associated with oil prices and the risk of tourism-related investments. When focusing on the crude oil market, we observe that the worldwide volatility is increasing, and knowing if it impacts on the future volatility of tourism stocks might be of a prominent relevance for investors, in particular if oil volatility could help in predicting tourism stocks volatility. Notably, when focusing on the oil market risk, among the various possible measures of risk, we chose to focus on the implied oil volatility index (OVX), a variable that has become one of the most followed indicators in the energy markets. Our choice builds on the fact that this indicator is a forward-looking measure thus it contains the information on the expectation of future market changes by the investors, a relevant aspect when pointing at a predictive analysis. On the tourism stocks side, we decided to build risk measures starting from high frequency data for the US market. This approach allows us to estimate the volatility on a daily basis accounting for the occurrence of unexpected price movements, price jumps, unrelated to the oil price dynamic. With our dataset,

we evaluate the relation between the tourism volatility and the implied volatility of oil. Our results will help in understanding how the expectations about risk are transferred from one market to another.

Our contribution, to our best knowledge, is the first examining the ability of oil market's volatility in predicting the future volatility of tourism stock from both an in- and out-of-sample perspective. Our empirical evidences show that crude oil volatility predicts the volatility of tourism firms mainly in the short-run. This predictability can be attributed to the information transmissions from the oil market to the stock market. Our results can help in understanding the economic sources of changes in tourism stock volatility and thus assist tourism organizations, policy makers and investors in periods of higher uncertainty.

The paper proceeds as follows. Section 2 outlines the panel HAR model we use for forecasting tourism volatility with the impact of OVX. Section 3 describes data, different volatility measures used in this study and reports the findings. Section 4 concludes the paper.

2. Methodology

In analyzing the role of tourism stocks' volatility dependence on oil volatility (OVX), we use the heterogeneous autoregression (HAR) model (Corsi, 2009, and Müller et al., 1997) within a panel setting as in Patton and Sheppard (2015). The standard HAR equals

$$\bar{y}_{h,t+h} = \mu + \phi_d y_t + \phi_w \left(\frac{1}{4} \sum_{i=1}^{4} y_{t-i} \right) + \phi_m \left(\frac{1}{17} \sum_{i=5}^{21} y_{t-i} \right) + \epsilon_{t+h} \qquad (1)$$

where y_t is a daily volatility measure for day t, and $\bar{y}_{h,t+h} = \frac{1}{h}\sum_i^h y_{t+i}$ is the h-day average volatility. Moreover, we use $\bar{y}_{w,t}$ to denote the average value over lags 2 to 5 ($\frac{1}{4}\sum_{i=1}^{4} y_{t-i}$) and $\bar{y}_{m,t}$ indicates the mean value between 6-22 days lag ($\frac{1}{17}\sum_{i=5}^{21} y_{t-i}$). These two quantities proxy for the weekly and monthly volatility, thus tracking different investment horizon making the model coherent with the presence in the market of heterogeneous agents. The above model has an inherent predictive nature, related to the parameter h, the forecast horizon. In our analyses, we estimate the model for values of the forecast horizons ranging from h=1 to 22 days thus up to, roughly, one month.

Following Patton and Sheppard (2015), the panel HAR, in its simplest specification, is given as follows

$$\bar{y}_{h,i,t+h} = \mu_i + \phi_d y_{i,t} + \phi_w \bar{y}_{w,i,t} + \phi_m \bar{y}_{m,i,t} + \epsilon_{i,t+h} \qquad (2)$$
$$i = 1,\ldots,n_t, \quad t = 1,\ldots,T,$$

where μ_i is the firms' fixed effect and n_t is the number of companies active at time t.. Let $Y_{i,t} = [y_{i,t}, \bar{y}_{w,i,t}, \bar{y}_{m,i,t}]'$; then the model for the realized variance can be compactly expressed as:

$$\bar{y}_{h,i,t+h} = \mu_i + \boldsymbol{\phi}' Y_{i,t} + \epsilon_{i,t+h} \quad i = 1,\ldots,n_t, \quad t = 1,\ldots,T. \qquad (3)$$

Following Patton and Sheppard (2015), define $\tilde{y}_{h,i,t+h} = \bar{y}_{h,i,t+h} - \hat{\upsilon}_{h,i}$ and $\tilde{Y}_{i,t} = Y_{i,t} - \hat{Y}_i$, where $\hat{\upsilon}_{h,i}$ and $\hat{Y}$ are the weighted least squares estimates of the mean of $\bar{y}_{h,i}$ and Y_i, respectively. Then, we might estimate the model parameters by a pooling estimator equal to

$$\widehat{\boldsymbol{\Phi}} = \left(T^{-1} \sum_{t=1}^{T} \left(n_t^{-1} \sum_{i=1}^{n_t} w_{i,t} \tilde{Y}_{i,t} \tilde{Y}_{i,t}' \right) \right)^{-1} \times \left(T^{-1} \sum_{t=1}^{T} \left(n_t^{-1} \sum_{i=1}^{n_t} w_{i,t} \tilde{Y}_{i,t} \tilde{y}_{h,i,t+h} \right) \right), \tag{4}$$

where $w_{i,t}$ are the weights; see Patton and Sheppard (2015) for details on the weight estimation as well as for the asymptotic distribution of the estimator that allows performing inference on the estimated parameters.

3. Data and findings

To recover a proxy of tourism-related stocks, we use high-frequency 5-min interval transaction prices[2] of tourism related stocks that were part of Russel 3000 index between October 5, 2007, and June 29, 2018. The start date is dictated by the availability of oil volatility index (OVX) data. We select 105 tourism stocks[3] that are continuously available during the sample period. The stock prices data comes from Kibot.com[4] and are filtered to include only those occurring during the regular market trading session, i.e. between 9:30:00 and 16:00:00 (inclusive). The OVX is published by the Chicago Board of Trade (CBOE) from the middle of 2007 and measures the market's expectation of 30-day volatility of crude oil prices.

[2] Liu et al. (2015) have compared between more than 400 volatility estimators in terms of accuracy and show that alternate volatility estimators are unable to significantly beat 5-min realized volatility.
[3] The firms which belong to "Travel & Leisure" sector as classified by the Industry Classification Benchmark (ICB) developed by Dow Jones and FTSE and is the most widely used global standard for company classification.
[4] This data provider is less know compared to competitors, but its data quality is comparable to that of New York Stock Exchange's TAQ database. A comparison of the two databases is available upon request.

Using the 5-minutes data we calculate the realized variance ($RV = \sum_{i=1}^{n} r_i^2$ where $r_i = p_i - p_{i-1}$), and the bi-power variation (BV), proposed by Barndorff-Nielsen and Shephard (2006), that equals $BV = \mu_1^{-2} \sum_{t=2}^{n} |r_i||r_{i-1}|$ where $\mu_1 = \sqrt{2/\pi}$. The two quantities differ as in the BV case the estimator adopted takes into account the existence of price jumps, removing their impact on the evaluation of the volatility. Consequently, BV estimates only the continuous component of volatility while RV accounts also for the discontinuous component. Further, we compute the realized semi-variance estimators, following Barndorff et al., (2010), as: $RS^+ = \sum_{i=1}^{n} r_i^2 I_{[r_i>0]}$, and $RS^- = \sum_{i=1}^{n} r_i^2 I_{[r_i<0]}$. These two quantities allow us to disentangle the role of good volatility (associated with positive returns) from that of bad volatility (coming from negative returns). Finally, we compute the jump variation, i.e. the contribution of price jumps, to the total risk that characterize the daily returns, defined as:

$$\Delta J^2 \equiv RS^+ - RS^- \tag{5}$$

To examine the asymmetry between positive and negative jump variation (whether the impact of positive jump variations is higher than negative jump variation or vice versa), we use a simple specification through an indicator function, mimicking Patton and Sheppard (2015) $\Delta J_t^{2+} = (RS_t^+ - RS_t^-) I\{(RS_t^+ - RS_t^-) > 0\}$ and $\Delta J_t^{2-} = (RS_t^+ - RS_t^-) I\{(RS_t^+ - RS_t^-) < 0\}$.

The collection of quantities we take into account allow us to evaluate the role of the various component of the daily volatility, namely the continuous and discontinuous component, as well as to evaluate the possible differences associated to good or bad volatility.

Table 1 reports the summary statistics of the various quantities we compute. The average values and selected quantiles are in the upper panel. The average daily RV for the sampled tourism firms was 10.7%. The ratios of averages of BV and RV reveal that variation due to jumps represents around 5% of total quadratic variation. The lower panel shows the first-order autocorrelation of the volatility series which ranges from 0.54 to 0.70 for RV, BV, RS^+, and RS^- and for the signed jump variation from 0.13 to 0.22.

Table 1. Summary statistics of the tourism stocks' data

	Mean	$\boldsymbol{Q_{.05}}$	**Median**	$\boldsymbol{Q_{.95}}$
a). Averages				
RV	10.676	2.144	5.463	28.925
BV	10.134	1.744	5.338	27.580
RS^+	5.353	1.075	2.785	14.779
RS^-	5.323	1.053	2.780	14.013
ΔJ^2	0.030	-0.336	0.075	0.646
ΔJ^{2+}	1.221	0.243	0.635	3.458
ΔJ^{2-}	-1.191	-2.901	-0.586	-0.223
b). Autocorrelations				
RV	0.562	0.206	0.578	0.855
BV	0.706	0.408	0.703	0.983
RS^+	0.487	0.190	0.475	0.839
RS^-	0.542	0.223	0.563	0.827
ΔJ^2	0.137	-0.088	0.063	0.682
ΔJ^{2+}	0.225	0.026	0.189	0.724
ΔJ^{2-}	0.210	0.028	0.165	0.788

Notes: The first part (a) of this table shows the averages of RV = realized variance, BV = bipower variation, RS^+ and RS− = positive and negative semivariance, ΔJ^2 = jump variation, and ΔJ^{2+} and ΔJ^{2-} = signed jump variation (all scaled by 100). We report average, median, and 5% and 95% quantiles values of the panel of 105 stocks. Panel (b) contains the first autocorrelation for the same series.

The descriptive analyses seem to suggest the good and bad volatility are almost equivalent, thus indicating an equal contribution coming from returns of positive and negative sign. Signed jumps are also closer, taking into account that they have, by construction, different signs. All quantities also show expected findings in terms of serial correlation: weak serial dependence for jumps and much stronger evidences for volatility estimators

Tables 2 contains the estimated parameters and respective t-statistics for the basic HAR model that adopts the realized volatility as proxy for the tourism stock risk, and for the HAR model where RV is decomposed into RS^{+} and RS^{-}. In both specifications we also evaluate the effects of the introduction of the OVX. Finally, we consider three different horizons, of 1, 5 and 22. Days. In line with general findings of the volatility literature, the results of HAR estimations show high persistence, as ϕ_d+ϕ_w+ ϕ_m is close to 1. Further, the role of recent information, as captured by ϕ_d decreases with the increase in the horizon. The basic HAR estimations with OVX as additional information source show that oil volatility has a positive impact on 1 and 5 day ahead cumulative volatility of tourism stocks. This impact is not significant for 22 days ahead forecast. The last row of each column shows the R^2 values computed using the WLS estimates. The explanatory power of the models increases with the increase in the forecast horizon h and when OVX is added to any specification.

In Figure 1a, we plot the parameter estimates of OVX across all horizons from 1 to 22 days with the respective pointwise confidence intervals. The impact of OVX on future volatility of tourism stocks is positive and significant. However, this impact decreases with the increase of horizon. We also fit this specification to the individual firm series, and show the median and percentiles (10th and 90th percentiles) of OVX coefficients for 105 firms in Figure 1b. The OVX estimates are all positive and indicate a strong directional effect from OVX on future volatility of tourism related stocks.

Panel (b) of Table 2 reports the results of HAR where RV is decomposed into positive and negative semivariance (the good and bad volatility respectively). Note that one expects $\phi_d^{+} = \phi_d^{-} = \phi_d$ if no information is added by decomposing RV into RS^{+} and RS^{-}. We note that for all horizons, the negative semivariance has larger impacts than the positive semivariance. In

addition, to account for classic leverage effect, we use a lagged squared returns interacted with an indicator for negative returns (Glosten et al., 1993). The coefficient of this interaction term for the RV is significant but small, and for OVX, the parameter estimates of asymmetries are insignificant. Again, the OVX has a positive and significant effect on the future cumulative volatility of tourism stocks at 1 and 5 days horizons.

So far, we examine the role of OVX and also decomposing realized variances into positive and negative realized semivariance in explaining the future volatility of tourism stock. Next, we use a simply approach to isolate the information from signed jump variation, $\Delta J_t^2 \equiv RS_t^+ - RS_t^-$. This difference will be positive (negative) if a day is dominated by an upward (downward) jump and if no jumps occurs then is a mean 0 noise. In examining the role of signed jumps in explaining the future variance, our specification includes signed jump variation and the variation arising due to the continuous part (bipower variation). Results of signed jumps model with and without OVX are reported in Table 3a. The effect of signed jump variation, ΔJ_t^2, is uniformly positive and significant for 1 and 5 days horizons showing that days dominated by positive (negative) jumps lead to higher (lower) future volatility. Further, to see as if the positive and negative jump variations have similar effect, one would expect to find $\varphi^{J+} = \varphi^{J-} = \varphi^{J}$. The results of extended specification of signed jumps are reported in the last six columns of Table 3b. We note that the effect of both signed jump components is opposite, and for *h*=22 (the longest horizons), both coefficients are equal in magnitude but opposite in sign. For the shorter horizons (*h*=1 and *h*=5), the negative (positive) jump component has a negative (positive) effect, implying that the future volatility increases more following a positive jump compared to decrease following a

negative jump.[5] This finding is interesting and is possibly due to very cyclical nature of the tourism sector and seasonal factors. Tourism sector might draw huge profits during economic booms but at the same time, the uncertainty about future performance may rise too.

[5] To establish a statistically significant difference among the effect of signed jump components, we also test the null $H_0: \varphi^{J+} = \varphi^{J-}$ and reject for 1 days horizon.

Table 2. HAR estimation results - estimation results for the panel of 105 tourism stocks, cumulative volatility

$$\overline{RV}_{h,t+h} = \mu + \phi_d RV_t + \phi_d^+ RS_t^+ + \phi_d^- RS_t^- + \gamma RV_t I_{[r_t<0]} + \phi_{OVX} OVX_t + \gamma_{OVX} OVX_t I_{[r_t<0]} + \phi_w \overline{RV}_{w,t} + \phi_m \overline{RV}_{m,t} + \epsilon_{t+h}$$

	a). Basic HAR						**b)**. HAR with decomposed RV					
	HAR-RV			HAR-RV-OVX			HAR-S-RV			HAR-S-RV-OVX		
	h=1	*h*=5	*h*=22	*h*=1	*h*=5	*h*=22	*h*=1	*h*=5	*h*=22	*h*=1	*h*=5	*h*=22
ϕ_d	0.546	0.362	0.234	0.545	0.360	0.233						
	(44.5)	(32.2)	(17.6)	(44.7)	(32.3)	(17.7)						
ϕ_d^+							0.477	0.277	0.155	0.472	0.274	0.152
							(27.0)	(30.0)	(13.1)	(26.5)	(28.6)	(13.1)
ϕ_d^-							0.565	0.404	0.280	0.561	0.401	0.278
							(37.0)	(21.1)	(13.4)	(37.4)	(21.2)	(13.6)
γ							0.049	0.043	0.035	0.056	0.045	0.037
							(4.9)	(5.6)	(4.6)	(4.9)	(5.1)	(3.7)
ϕ_{OVX}				0.035	0.050	0.052				0.037	0.050	0.052
				(4.2)	(2.8)	(1.5)				(4.3)	(2.9)	(1.5)
γ_{OVX}										-0.006	-0.002	-0.003
										(-1.4)	(-0.5)	(-0.6)
ϕ_w	0.269	0.331	0.284	0.267	0.328	0.281	0.270	0.333	0.285	0.269	0.330	0.283
	(30.6)	(27.7)	(13.7)	(30.2)	(27.3)	(13.6)	(31.3)	(27.9)	(13.7)	(30.9)	(27.5)	(13.6)
ϕ_m	0.123	0.187	0.293	0.120	0.182	0.287	0.124	0.187	0.293	0.120	0.182	0.288
	(16.7)	(13.7)	(13.3)	(15.9)	(13.3)	(13.5)	(16.9)	(13.7)	(13.3)	(16.0)	(13.4)	(13.5)
R^2	0.268	0.464	0.407	0.284	0.491	0.443	0.270	0.475	0.478	0.299	0.498	0.480

Notes: The *h* stands for the forecast horizon. The first model (HAR-RV) is the reference model which uses only realized variance. The second model (HAR-S-RV) is the extended version of basic HAR model where realized variance is decomposed into its negative and positive realized semivariances, and this specification also includes an asymmetric term. In all cases, the last row reports the average value of R^2s for 105 individual firms. The t-statistics (robust) are in parentheses.

Table 3. Extended HAR estimation results - Impact of signed jump variations future volatility for the panel of 105 tourism stocks, cumulative volatility

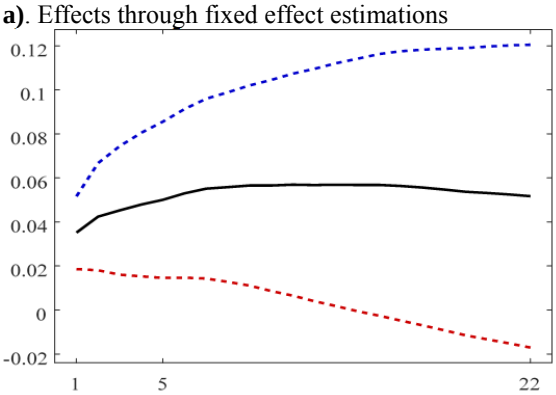
$$\overline{RM}_{h,t+h} = \mu + \phi_J J_t^2 + \phi_{J^+} J_t^{2+} + \phi_{J^-} J_t^{2-} + \phi_C BV_t + \gamma RV_t I_{[r_t<0]} + \phi_{OVX} OVX_t + \gamma_{OVX} OVX_t I_{[r_t<0]} + \phi_w \overline{RV}_{w,t} + \phi_m \overline{RV}_{m,t} + \epsilon_{t+h}$$

	a). HAR with jump variations						**b)**. HAR with signed jump variations					
	HAR-CJ			HAR-CJ-OVX			HAR-S-CJ			HAR-S-CJ-OVX		
	h=1	*h*=5	*h*=22	*h*=1	*h*=5	*h*=22	*h*=1	*h*=5	*h*=22	*h*=1	*h*=5	*h*=22
ϕ_J	0.164	0.076	0.028	0.144	0.063	0.019						
	(11.0)	(7.7)	(2.6)	(9.7)	(6.2)	(1.7)						
ϕ_{J^+}							0.635	0.353	0.213	0.586	0.321	0.192
							(31.5)	(25.6)	(10.3)	(29.0)	(24.4)	(9.9)
ϕ_{J^-}							-0.475	-0.310	-0.233	-0.444	-0.289	-0.220
							(-21.2)	(-13.7)	(-7.7)	(-19.8)	(-13.2)	(-7.4)
ϕ_C	0.034	0.035	0.029	0.032	0.033	0.027	0.029	0.031	0.025	0.028	0.030	0.024
	(10.4)	(5.9)	(4.8)	(9.8)	(5.7)	(4.6)	(9.1)	(5.4)	(4.4)	(8.8)	(5.3)	(4.3)
γ	0.276	0.194	0.133	0.358	0.245	0.166	0.209	0.151	0.103	0.276	0.193	0.129
	(22.2)	(18.1)	(11.6)	(25.7)	(20.4)	(11.8)	(16.3)	(15.4)	(10.9)	(18.9)	(17.6)	(11.3)
ϕ_{OVX}				0.084	0.083	0.076				0.073	0.076	0.070
				(8.8)	(4.4)	(2.1)				(7.8)	(4.0)	(2.0)
γ_{OVX}				-0.092	-0.063	-0.046				-0.070	-0.048	
				(-19.7)	(-11.7)	(-7.7)				(-14.9)	(-9.5)	
ϕ_w	0.483	0.477	0.370	0.461	0.461	0.359	0.437	0.448	0.352	0.423	0.437	0.344
	(57.6)	(32.2)	(15.3)	(55.6)	(32.4)	(15.3)	(53.5)	(32.3)	(15.6)	(52.1)	(32.4)	(15.7)
ϕ_m	0.186	0.225	0.322	0.176	0.216	0.313	0.174	0.219	0.317	0.166	0.210	0.309
	(24.5)	(15.9)	(14.2)	(22.6)	(15.3)	(14.4)	(23.4)	(15.6)	(14.2)	(21.7)	(15.1)	(14.4)
R^2	0.260	0.410	0.473	0.285	0.422	0.479	0.265	0.414	0.475	0.269	0.416	0.476

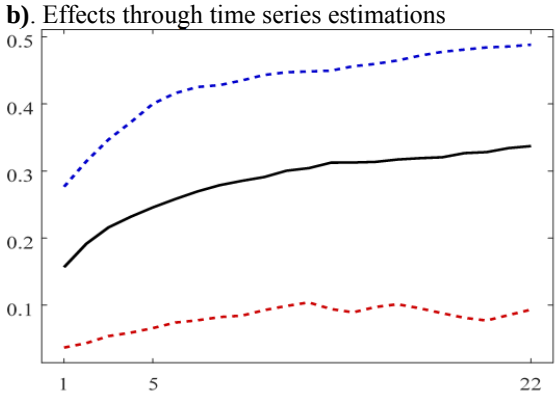
Notes: The *h* stands for the forecast horizon. HAR-CJ model includes signed jump information where quadratic variation has been decomposed into signed jump variation, ΔJ^2, and its continuous component using bipower variation, BV. HAR-S-CJ mode includes ΔJ_t^{2+} and ΔJ_t^{2-} obtained by decomposing ΔJ^2 using an indicator variable for the sign of the difference where $\Delta J_t^{2+} = \Delta J^2 I_{[RS_t^+ - RS_t^- > 0]}$. In all cases, the last row reports the average value of R^2s for 105 individual firms. The t-statistics (robust) are in parentheses.

Figure 1. Estimated coefficients for OVX

a). Effects through fixed effect estimations



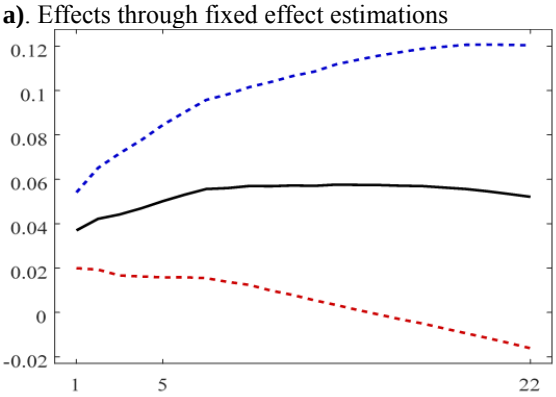
b). Effects through time series estimations



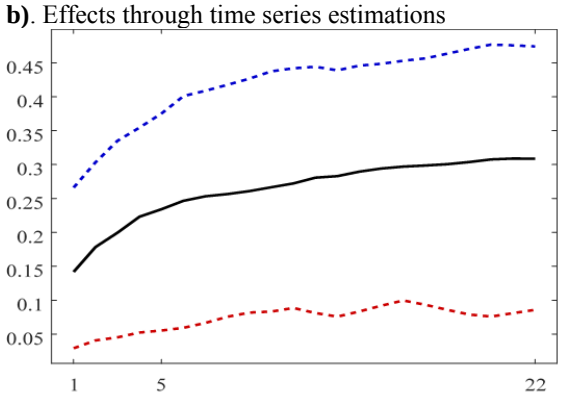
Notes: In Fig. a). the dashed lines indicate 95% confidence intervals. In Fig. b). the black line show median value of OVX coefficients for 105 firms, blue and red dashed lines are 10 and 90 percentiles respectively. X-axis shows forecast horizons.

Figure 2. Estimated coefficients for OVX

a). Effects through fixed effect estimations



b). Effects through time series estimations



Notes: In Fig. a). the dashed lines indicate 95% confidence intervals. In Fig. b). the black line show median value of OVX coefficients for 105 firms, blue and red dashed lines are 10 and 90 percentiles respectively. X-axis shows forecast horizons.

Next, we use a pseudo out-of-sample (OOS) forecasting exercise to re-inforce that the in-sample gains lead to better OOS forecasts. In doing so, we again consider all four classifications with and without inclusion of OVX, each with two variations. These forecasts are obtained through a rolling WLS regressions with a fixed estimation window of 1,004 observations (4 years), and then updating it daily.[6]

[6] The time series containing at least 500 OOS data points are retained which reduces the sample from 105 to 95 individual firms. Since, forecasts can be occasionally negative (approximately .004%), following Patton and

The forecast performance is assessed through unconditional Diebold and Mariano (1995) and Giacomini and White (2006) tests, by using the negative of the gaussian quasilikelihood as the loss function; $L\left(\widehat{RV}_{h,t+h|t}, \overline{RV}_{h,t+h}\right) = ln\left(\widehat{RV}_{h,t+h|t}\right) + \frac{\overline{RV}_{h,t+h}}{\overline{RV}_{h,t+h}}$. The results of forecast analysis are reported in Table 4a where each pair compares two variations (with and without OVX) of a speicifc forecasting models. Two related columns show the percentage (out of the 95 individual firms) that favors a competing model using a two-sided 5% test. The DM test statistic rejects the null of equal performance when using semivarinace based HAR with OVX in 35% to 45% of individual firms. Furthermore, the OVX variable appears to help more in explaining the tourism stocks' volatility at short horizons. Table 4b also shows the R^2 values for the eight different specifications. Again, the semivariance based alternative to a baseline HAR specification with OVX generates gains in out-of-sample R^2 of 57.1% (*h*=1) and 72.0% (*h*=5).

Table 4. Out-of-sample forecast comparison for the alternative models used in the forecast evaluation

	$\widehat{RV}^{HAR}$	$\widehat{RV}^{HAR-OVX}$	$\widehat{RV}^{RS-GJR}$	$\widehat{RV}^{RS-GJR-OVX}$	$\widehat{RV}^{\Delta J^2}$	$\widehat{RV}^{\Delta J^2-OVX}$	$\widehat{RV}^{\Delta J^{2\pm}}$	$\widehat{RV}^{\Delta J^{2\pm}-OVX}$
a). Out-of-sample forecast comparison								
h=1	1.3	**3.9**	0.0	**44.7**	2.6	**28.9**	3.9	**5.3**
h=5	1.3	**2.6**	6.6	**35.5**	3.9	**15.8**	0.0	**3.9**
h=22	2.6	2.6	13.2	13.2	1.3	**5.3**	5.3	5.3
b). Out-of-sample R^2								
h=1	48.6	51.2	55.3	**57.1**	50.2	51.7	48.8	51.0
h=5	59.3	62.9	70.6	**72.0**	69.6	70.0	64.3	65.8
h=22	60.9	60.6	**62.1**	61.3	60.0	59.3	60.2	59.2

Note: The results of tests for equal predictive accuracy are reported in each column of (a). Each of the two consecutive columns show the percentage (out of 95 individual firms) of loss differentials rejecting the null of equal performance, using a 5% two-sided test. The out-of-sample R^2 values are computed as one minus the ratio of model-based MSE to the MSE from a forecast that includes only a constant.

4. Conclusion

Sheppard (2015) an "insanity filter" is applied to ensure that forecasts are not smaller than the smallest realization noted in estimation window.

Oil volatility, with a short-run positive impact, improves both in-sample and out-of-sample volatility forecast of tourism related firms. Tourist firm managers and investors cam hedge their exposure to oil risk by taking long position in oil volatility futures. However, this risk hedging strategy would depend on the cost involved in maintaining a dynamic hedge position and thus requires attention. We leave this question for future research.

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