Time-Varying Predictability of Oil Market Movements Over a Century of Data: The Role of US Financial Stress

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Abstract

In this paper we analyze whether a news-based measure of financial stress index (FSI) in the US can predict West Texas Intermediate oil returns and (realized) volatility over the monthly period of 1889:01 to 2016:12, using a dynamic conditional correlation multivariate generalized autoregressive conditional heteroscedasticity (DCC-MGARCH) model. Our results show that, standard linear Granger causality test fail to detect any evidence of predictability. However, the linear model is found to be misspecified due to structural breaks and nonlinearity, and hence, the result of no causality from FSI to oil returns and volatility cannot be considered reliable. When we use the DCC-MGARCH model, which is robust to such misspecifications, in 75 percent and 80 percent of the sample periods, FSI in fact do strongly predict the oilvreturns and volatility respectively. Overall, our results highlight that FSI is helpful in predicting oil returns and volatility, when one accounts for nonlinearity and regime changes through a robust time-varying model.

Keywords: US Financial Stress Index; DCC-MGARCH; WTI Oil Returns; Realized Volatility.

JEL Codes: C32, Q41.

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1 Introduction

Oil market movements (in both return and volatility) are known to predict recessions (Hamilton, 1983, 2008, 2009, 2013; Elder and Serletis, 2010; Plakandaras *et al.*, 2017), as well as inflation (Stock and Watson, 2003). Naturally, accurate prediction of oil market movements is of tremendous importance for the economy in general. Understandably, there exists a large literature (see Baumeister (2014), Lux *et al.*, (2016), Degiannakis and Filis (2017a, b), and Gupta and Wohar (2017) for detailed reviews) aiming to predict oil price movements using various types of econometric methodologies (univariate and multivariate; linear and nonlinear), and predictors (macroeconomic, financial, behavioural, institutional).

In this regard, recent studies have related oil returns and volatility to financial stress (see for example, Chan *et al.*, (2011), Morana (2013), Bagliano and Morana (2014), Chen *et al.* (2014), Nazlioglu *et al.*, (2015), Wan and Kao (2015), and Reboredo and Uddin (2016)), and have detected statistically significant relationship between these variables.[1] As pointed out by Nazlioglu *et al.*, (2015), the dynamic link between oil prices and financial stress exists through two primary channels: their impact on economic activity and on investor behavior. On one hand, a rise in oil prices depresses economic activity, which in turn, is likely to put pressure on credit markets, and negatively affect stock markets and the banking system. On the other hand, increased financial stress would cause economic activity to slow down and lead to low energy demand and declining oil prices. As far as the second channel is concerned, investors see oil markets as alternative investment options relative to financial markets. Naturally, when investors adjust their portfolios with respect to oil price movements, there will be repercussions felt on financial asset prices. At the same time, increased financial stress is likely to cause investors to change their portfolios and hence, have an impact on oil markets. In addition, financial stress also influences economic activity through the bank lending channel via decreasing the amount of available credits and through financial leverage via changes in creditworthiness of borrowing businesses. In sum, the causal effects between oil price movements and financial stress is bi-directional, with both variable acting as likely predictor of future paths of each other. From an econometric modelling perspective, this then implies that while trying to predict oil returns and volatility, we cannot treat financial stress as an exogenous variable in the model. Given this, the objective of this paper is to predict monthly West Texas Intermediate (WTI) oil returns and (realized) volatility (computed based on daily data) over the historical period of 1899:01 to 2016:12, based

[1] At this stage, it is important to point out that there is of course a huge literature analysing the relationship between individual asset (such as, equities, bonds, currencies) markets (and other commodity markets) with the oil market (see, Gupta and Yoon (2017) for a detailed review of this literature).

on a news-based index of historical financial stress in the US. For our modelling purpose, we use a dynamic conditional correlation multivariate generalized autoregressive conditional heteroscedasticity (DCC-MGARCH) model of predictability. The decision to use the DCC-MGARCH model is twofold: First, this approach being a time-varying method allows us to capture the possible nonlinearity and regime changes between oil return or volatility with financial stress, which in turn, is likely to exist in our long-span data set, and something that we show to hold in our case. Second, we prefer to use this causal model over a (time-varying) predictive regression, since this controls for the issue of endogeneity discussed above. To the best of our knowledge, this is the first attempt to predict oil market movements based on the information content of financial stress using a time-varying (DCC-MGARCH) model covering over a century of history involving the oil and financial markets of the US economy. Given that we use a time-varying approach and a long span of data set to analyze the relationship between oil price movements and financial stress, is what distinguishes our work from the existing literature on this topic, which in turn, uses constant parameter model, and at best only three decades of recent data. The use of historical data in a time-varying manner not only helps us track the longest evolution of oil and financial markets possible, but also avoids the sample-size selection bias. The remainder of the paper is organized as follows: Section 2 presents the econometric methodology, while Section 3 discusses the data and results, with Section 4 concluding the paper.

2 Methodology

We use the DCC-MGARCH Hong test (Lu *et al.*, 2014) to study time-varying Granger causality between the oil market dynamics and the financial stress. Consider two series of residuals from an ARMA-GARCH model denoted by X_t and Y_t, respectively. We estimate dynamic correlations in the process $Z_t(j) = (X_t, Y_t)'$ (where j represents the lag order) using the following DCC-MGARCH model:[2]

$$\begin{aligned} Z_t(j)|I_{t-1} &\sim N\left(0, D_{t,j}R_{t,j}D_{t,j}\right) \\ D^2_{t,j} &= \text{diag}\{\omega_{i,j}\} + \text{diag}\{\kappa_{i,j}\} \circ Z_t(j)Z^{'}_t(j) + \text{diag}\{\lambda_{i,j}\} \circ D^2_{t-1,j} \\ u_{t,j} &= D^{-1}_{t-1,j}Z_t(j) \\ Q_{t,j} &= S \circ \Big(\iota\iota^{'} - A - B\Big) + Au_{t-1,j}u^{'}_{t-1,j} + BQ_{t-1,j} \\ R_{t,j} &= \text{diag}\{Q_{t,j}\}^{-1}Q_{t,j}\text{diag}\{Q_{t,j}\}^{-1} \end{aligned} \tag{1}$$

[2]see Engle (2002) for details.

Consider the DCC-MGARCH(1,1) and its associated dynamic correlation estimator, $\rho_{pq,t}(j)$, which is defined as

$$\begin{aligned}\rho_{pq,t}(j) &= \overline{\rho_{pq}}(j) + \alpha_j\left(u_{p,t-1}u_{q,t-1-j} - \overline{\rho_{pq}}(j)\right) + \beta_j\left(\rho_{pq,t-1}(j) - \overline{\rho_{pq}}(j)\right) \\ & r_{pq}(j)\,\frac{\rho_{pq}(j)}{\sqrt{\rho_{11,t}\rho_{22,t}(j)}}\end{aligned} \tag{2}$$

where $p, q = 1, 2$.

The unidirectional time-varying test for Granger causality from Y_t to X_t is given by

$$H_{1,t}(k) = \frac{T\sum_{j=1}^{T-1} k^2\left(\frac{j}{M}\right) r_{12,t}^2(j) - C_{1T}(k)}{\sqrt{2D_{1T}(k)}} \tag{3}$$

where M denotes a positive integer and $k(\cdot)$ represents the Bartlett kernel function; $C_{1T}(k) = \sum_{j=1}^{T-1}\left(1-\frac{j}{T}\right)k^2\left(\frac{j}{M}\right)$; $D_{1T}(k) = \sum_{j=1}^{T-1}\left(1-\frac{j}{T}\right)\left(1-\frac{j+1}{T}\right)k^4\left(\frac{j}{M}\right)$.

The null hypothesis is that of mutually independent processes X_t and Y_t. According to Engle and Sheppard (2001), $\alpha_j \sim N\left(0, \frac{\sigma_{1,j}^2}{T}\right)$ and β_j represent nuisance parameters under the null. As such, we cannot identify the asymptotic distribution of dynamic correlations $r_{12,t}(j)$. Nonetheless, we have $\sqrt{T}r_{12,t}(j) = \mathcal{O}_p(1)$ under the null.

When $\overline{\rho_{pq}}(j) = \rho_{pq,0}(j) = \hat{\rho}_j = \frac{\sum_{t=j}^{T} X_t Y_{t-j}}{\sqrt{\sum_{t=1}^{T} X_t^2 \sum_{t=1}^{T} Y_t^2}}$, $\rho_{11,t12,t}(j) = \hat{\rho}_j + \hat{\alpha}_j \sum_{s=1}^{t} \hat{\beta}_j^{s-1}\xi_{t-s,j}$, where $\xi_{t,j} = u_{1,t}u_{2,t-j} - \hat{\rho}_j$, then $\rho_{11,t12,t}(j)$ is equal to $\hat{\rho}_j$, not taking into account the second term. Consequently, we have that $H_{1,t}(k) \overset{as.}{\sim} N(0,1)$, in other words, the unidirectional DCC-MGARCH Hong test is asymptotically normally distributed under the null hypothesis that X_t and Y_t are mutually exclusive.

3 Data

Our analyses is based on variables related to the oil market and a measure of financial stress, covering the monthly period of 1889:01 to 2016:12, with the start and end dates being purely driven by data availability of the financial stress metric. WTI oil price data is obtained from the Global Financial Database, and we compute monthly log-returns (RET, i.e., first-differences of the natural logarithm of nominal oil price), and monthly realized volatility (RV; i.e., sum of daily squared returns over a month (Andersen and Bollerslev, 1998)).[3] Noticing that RV has long-memory, we fit a Heterogeneous Autoregressive (HAR) model of the form: $RV_t = \alpha_0 + \alpha_1 RV_{t-1} + \alpha_2 RV_{t-1,\bar{\omega}_1} + \alpha_3 RV_{t-1,\bar{\omega}_2} + \varepsilon_t$, where $RV_{t-1,\bar{\omega}_i} = (RV_{t-1} ... + RV_{t-\bar{\omega}_i-1})/\bar{\omega}_i$, i=1, 2, with $\bar{\omega}_1$=3, and $\bar{\omega}_2$=12 corresponding

[3]Note that only monthly WTI oil price data is available for the period of 1919 to 1976. Hence, the RV over this period is computed as squared returns.

to a quarter and a year respectively. We then use the residuals from the model in the DCC-MGARCH as the persistence-adjusted measure of RV_{adj}.

The corresponding historical news-based financial stress data is derived from Püttmann (2018). The author constructs the Financial Stress Index (FSI) from the titles of articles published in five U.S. newspapers (the Boston Globe, Chicago Tribune, Los Angeles Times, Wall Street Journal and Washington Post), by following three steps: Püttmann (2018) defines eleven topics ("bonds," "business," "central banks," "economy," "general," "gold/silver," "inflation," "railroads," "stocks," "trade," and "trouble") comprised of 120 words. If a title contains one of these 120 words, he classifies the article as pertaining to financial markets. Püttmann (2018) then uses four sentiment dictionaries to measure the sentiment of each title flagged in the first step. For a given dictionary, the author treats a title as having a net negative connotation if it includes more negative than positive words. This approach yields a raw monthly FSI for each newspaper-dictionary combination,[4] and; Finally Püttmann (2018) standardizes the raw monthly FSI for each newspaper-dictionary combination to a mean of 100 and a unit standard deviation from 1889 to 2016. Averaging across all 20 such combinations by month yields the monthly FSI. We take the natural logarithm of the FSI.[5]

4 Results

We first present results from a linear Granger causality test using two VAR models with processes $(RET, FSI)'$ and $(RV_{adj}, FSI)'$, respectively and a lag order of 6 for both based on the Akaike Information Criterion (AIC).

Table 1: Linear Granger causality tests

	$\chi^2(6)$-stat	p-value
FSI does not GC RET	11.12	0.08
FSI does not GC RV_{adj}	3.52	0.74
RET does not GC FSI	9.68	0.14
RV_{adj} does not GC FSI	9.06	0.17

Notes: RET: returns of oil market; RV_{adj}: realized volatility of oil market; FSI: financial stress index; "GC": Granger-cause.

As shown in Table 1, we fail to reject the null hypothesis of no Granger causality at the 5

[4] Specifically, the raw indicator value for a given newspaper-dictionary-month is (the number of titles pertaining to financial markets) times (the share of such titles with a net negative connotation) divided by (the number of all titles).

[5] Further details and the data is available for download from: http://www.policyuncertainty.com/financial_stress.html.

percent level of significance in all cases. In other words, the linear Granger causality tests conclude financial stress cannot help predict the dynamics of key oil market variable, and *vice versa*.

As a next step in our analysis, we implement the Bai and Perron (2003) test for detecting structural breaks based on the RET and RV_{adj} equations of the corresponding VAR model. Table 2 show that we identify 5 structural breaks.

Table 2: Bai-Perron multiple breakpoint tests (1 to M globally determined breaks)

VAR Equation	Estimated breaks
RET	Mar. 1914, Jun. 1933, Jan. 1954, Feb. 1974, May 1996
RV_{adj}	Oct. 1909, Nov. 1928, Jan. 1948, Feb. 1972, Mar. 1991

Furthermore, we apply the Brock *et al.* (1996) test on the residuals of the RET and RV_{adj} equations of the VAR models to investigate the existence of latent nonlinearity. Results suggest that residuals are not independently and identically distributed, an indication of the presence of nonlinearity (see Table 3).

Table 3: BDS test

	RET equation		RV_{adj} equation	
m	z-stat	p-value	z-stat	p-value
2	12.21	0.00	12.97	0.00
3	14.81	0.00	13.82	0.00
4	17.26	0.00	15.23	0.00
5	19.84	0.00	16.22	0.00
6	22.89	0.00	17.11	0.00

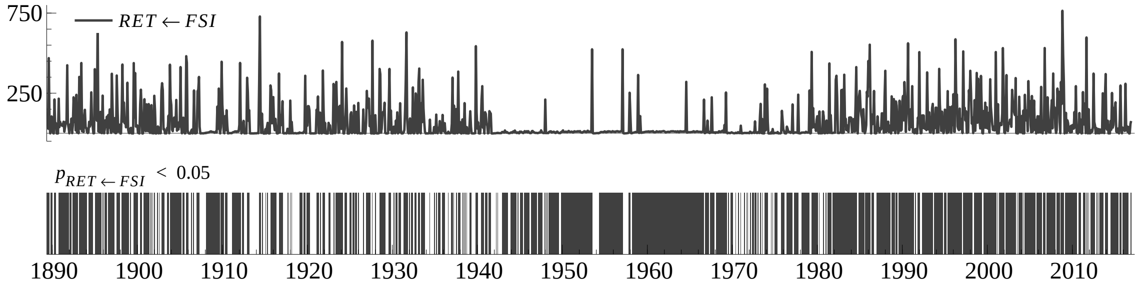
Notes: m denotes the embedded dimension; the z-statistic is based on the residuals of the RET or RV_{adj} equation in the VAR(6) model; the p-value corresponds to the test of i.i.d. residuals based on the BDS test's z-statistic.

DCC-MGARCH Time-varying causality test results

Given that we find evidence of structural breaks and latent nonlinearity in the systems, the constant parameter VAR models are misspecified. As such, we cannot rely on the these models to detect the existence or not of information spillovers between the variables under study. This then motivates implementing our analysis using the DCC-MGARCH

Hong test for time-varying Granger causality. This testing approach does not suffer from misspecifications characterizing the constant parameter VAR models as we point out above.[6]

Figure 1: Causality between returns of oil market & financial stress index



Notes: The Figure at the top plots the value of the test statistic; The shaded Figure at the bottom shows periods during which the test rejects the null hypothesis of no information spillover at the 5 percent level of significance.

Based on a period covering 1531 months, Figure 1 shows that financial stress dynamics have predictive power for oil market returns over most of the sample. Precisely, we find evidence of causality running from financial stress to oil market returns during 1150 months, that is 75 percent of the entire period (see Table 4).

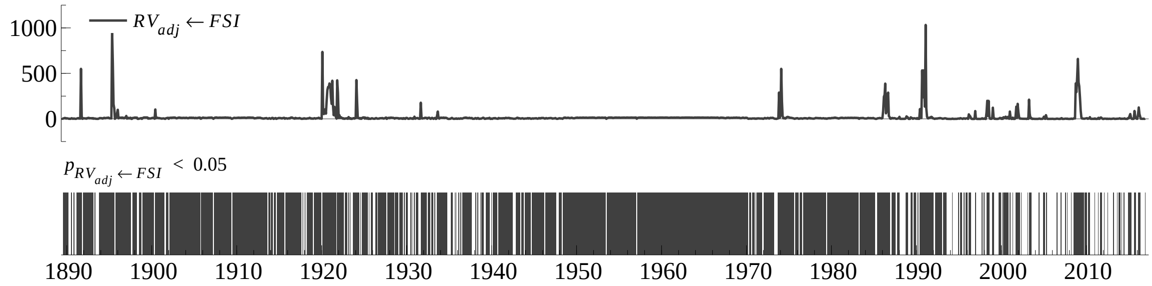
Furthermore, as shown in Figure 2, there is also evidence of time-varying information spillover from financial stress to realized oil market volatility, and this, in 80 percent (see Table 4). Therefore, in contrast with the linear Granger causality outcome, the DCC-MGARCH Time-varying causality test show that financial stress dynamics can help forecast key oil market variables, that is, returns as well as realized volatility.

On the other hand, according to Figure 3, we detect the presence of information spillover from oil market returns to financial stress over 89 percent (see Table 4) of the entire sample. In the same vein, Figure 4 shows that realized volatility does also contain predictive power for financial stress; this being the case in 96 percent of the total sample period (see Table 4).

In all, evidence of bidirectional time-varying causality between oil market returns and financial stress has emerged, in contrast with the linear Granger causality outcomes.

[6]To get a preliminary understanding of the sign of the time-varying relationship between WTI returns or volatility with the FSI, we estimated various DCC, Asymmetric DCC (ADCC), and Generalized Orthogonal (GO)-GARCH models as in Basher and Sadorsky (2016). In general over the sample period, we observed that the relationship between oil returns and the FSI is negative, while that of volatility with financial stress is positive. These results are in line with our intuition (discussed in the introduction) regarding how these variables should be related, and are also similar to those reported by Nazlioglu *et al.*, (2015) and Reboredo and Uddin (2016). Since the focus of this study is on predictability, these results have been suppressed from the paper to save space, but are available upon request from the authors.

Figure 2: Causality between realized volatility of oil market & financial stress index



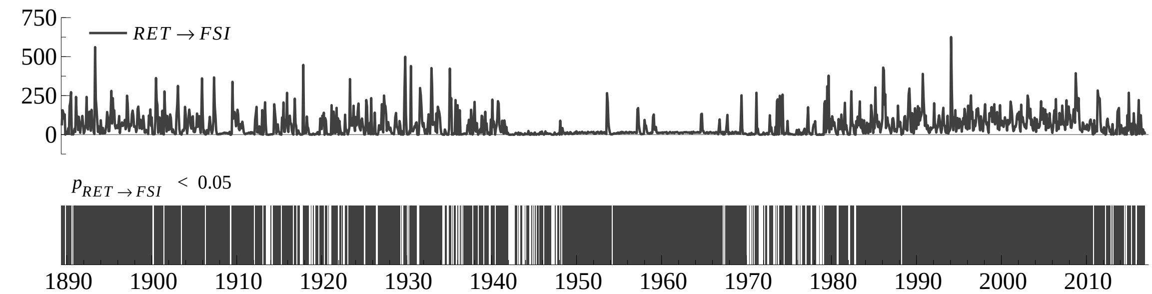
Notes: see Figure 1.

Table 4: Detected causality

Causality	Number of months	Share in total sample (%)
$RET \leftarrow FSI$	1150	75
$RV_{adj} \leftarrow FSI$	1223	80
$RET \rightarrow FSI$	1363	89
$RV_{adj} \rightarrow FSI$	1470	96

Notes: Total sample size: 1531

Figure 3: Causality between returns of oil market & financial stress index

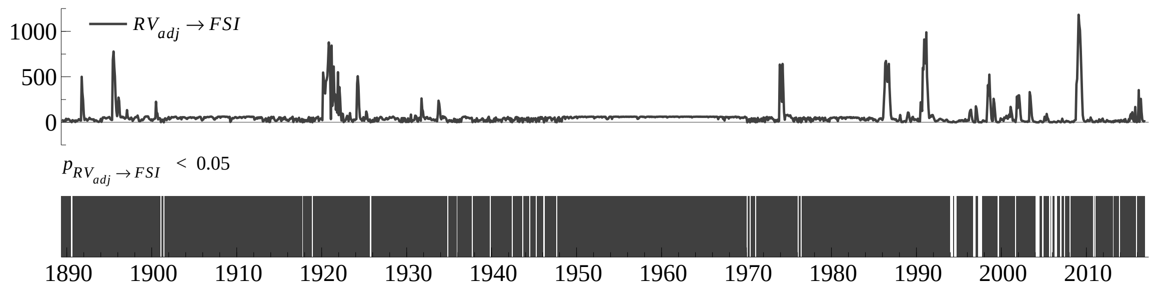


Notes: see Figure 1.

Based on the latter, we fail to detect any evidence of information spillover between oil market returns and financial stress.[7]

[7]As a robustness check, analyses based on quarterly (1889Q1-2016Q4) and daily (16/02/2000 - 26/05/2017) data are consistent with unidirectional information spillovers from oil market returns to financial stress in emerging economies (see Table A1 in the Appendix). Also note that, while the quarterly version of the FSI index is derived from Püttmann (2018), daily data on the same for the US, other advanced countries, emerging markets and global is derived from the Office of Financial research (OFR: `https://www.financialresearch.gov/financial-stress-index/)`. To compute RV at the daily frequency, we use five-minutes intraday data on WTI futures prices, sourced from `TickData.com`. Again, appropriate HAR models were used to filter out the long-memory in the RV estimate at the

Figure 4: Causality between realized volatility of oil market & financial stress index



Notes: see Figure 1.

5 Conclusion

In this paper, we test the hypothesis that a news-based measure of financial stress in the US can predict the WTI oil returns and volatility over the monthly period of 1889:01 to 2016:12, using a dynamic conditional correlation multivariate generalized autoregressive conditional heteroscedasticity (DCC-MGARCH) model. Our results show that, standard linear Granger causality tests fail to detect any predictability emanating from financial stress for oil returns and volatility. However, the linear framework is found to be misspecified due to structural breaks and nonlinearity, and hence, the result of no causality from financial stress to oil returns and volatility cannot be considered reliable. When we use the DCC-MGARCH model, which is robust to such misspecifications, we find that financial stress in fact does strongly predict the WTI returns and volatility in 75 percent and 80 percent of the sample periods respectively. In sum, our results highlight the importance of information contained in financial stress in predicting oil returns and volatility over a century of historical data, when one accounts for nonlinearity and regime changes through a robust time-varying model. Given this positive in-sample evidence of predictability, as part of future research, it would be interesting to see if our results hold over out-of-sample periods in a full-fledged forecasting exercise, since the former does not necessarily guarantee the latter (Rapach and Zhou, 2013).

quarterly and daily frequencies. On the other hand, robustness check exercises based on quarterly and daily data corroborate the finding of two-way information spillover between financial stress and realized volatility for advanced, emerging and US economies as well as globally (see Table A1 in the Appendix).

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6 Appendix

Table A1: Robustness

Causality	Number of periods	Share in total sample (%)
Quarterly (508 obs.)		
$RET \leftarrow FSI$	200	39
$RV_{adj} \leftarrow FSI$	27	5
$RET \rightarrow FSI$	396	78
$RV_{adj} \rightarrow FSI$	0	0
Daily (4334 obs.)		
$RET \leftarrow Ad.FSI$	0	0
$RV_{adj} \leftarrow Ad.FSI$	4318	100
$RET \rightarrow Ad.FSI$	1928	44
$RV_{adj} \rightarrow Ad.FSI$	4327	100
$RET \leftarrow Em.FSI$	0	0
$RV_{adj} \leftarrow Em.FSI$	4295	99
$RET \rightarrow Em.FSI$	4334	100
$RV_{adj} \rightarrow Em.FSI$	4319	100
$RET \leftarrow Ov.FSI$	0	0
$RV_{adj} \leftarrow Ov.FSI$	4330	100
$RET \rightarrow Ov.FSI$	841	19
$RV_{adj} \rightarrow Ov.FSI$	4334	100
$RET \leftarrow US.FSI$	6	0
$RV_{adj} \leftarrow US.FSI$	4334	100
$RET \rightarrow US.FSI$	0	0
$RV_{adj} \rightarrow US.FSI$	4334	100

Notes: Ad.: Advanced economies; Em.: Emerging economies; Ov.: overall; US.: United States.