FAKE NEWS AND OPTIONS TRADING

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Abstract

Research suggests that AI-powered social bots manipulate social media sites, evidently during the 2016 US presidential election, where 25% of X posts have been identified to spread either fake or extremely biased news. I hypothesize that on top of financial news, fake news induces options trading activity and analyze if X-based measures of financial market uncertainty (XMU) affect expectations about equity volatility. I identify such expectations in financial market prices by studying volatility dependent claims, claims that provide insurance against future volatility. XMU is expected to be an incremental predictor of variance risk and, hence, an increase in XMU negatively predict the premium on short straddles, constructed from equity option prices. I find that a managed S&P500 short straddle portfolio that decreases the exposure to variance risk when XMU is high significantly outperforms an unmanaged portfolio by nearly 9% annually. In line with my fake news hypothesis, the effect is particularly strong during the 2016 US presidential election, is substantially stronger when reposts are incorporated and cannot be explained with available financial news.

Keywords: AI, X, Social Bots, Financial Market Uncertainty, Volatility dependent claims, Variance Risk, Short Straddles.
JEL-Classification: G11, G12, G14

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"The task of separating truth from falsehood has plagued policymaking for centuries. During the Roman civil war following the death of Julius Caesar, Octavian famously prevailed over Mark Antony by spreading "fake news" about his fitness for office. He did so via slogans forged on specially commissioned coins – an early version of a tweet. Today, this task of distilling the truth is more urgent than ever."

Christine Lagarde, ECB, November 29th 2019
Lectio Magistralis at the Accademia Nazionale dei Lincei

Motivation

Social bots — (AI-powered) automated message posting systems — can manipulate social media sites like X and spread misleading information (e.g. Allcott and Gentzkow (2017)). Since the 2016 US presidential election, the term "fake news" has made its way into the popular lexicon. Bovet and Makse (2019) analyze the dynamics and influence of fake news on X in the five months preceding the election day. They use a dataset of 171 million posts to identify 30 million posts, from 2.2 million users, which contain a link to news outlets. Based on a classification of news outlets, they find that 25% of these posts spread either fake or extremely biased news. In other cases, bad actors use AI to exploit the fragility of financial systems. False information is spread via X posts to manipulate entire markets. The Australian airline Qantas experienced a more than 10 percent drop in stock price in 2010 following the appearance of posts about false reports of a plane crash. Similarly, a fake post in 2013 that claimed President Obama had been hurt in a White House explosion caused the S&P 500 Index to drop by 0.9 percent, or $130 billion, in stock value. According to Bloomberg, on May 22nd 2023, it may have been the first time that an AI-generated image moved the entire stock market. For a few minutes, an ominous image of black smoke billowing from what appeared to be a government building near the Pentagon set off investor fears, sending stocks tumbling. It first appeared on Facebook and then quickly spread to X via accounts with large followings, including the financial news site ZeroHedge and the Kremlin-controlled RT. In other occasions, X's AI chatbot, Grok, is spreading fake news. It typically generates news headlines and content based on what's trending. But what happens if what's trending is a fake news story? For example, on April 4th 2024, verified users on X started sharing a Grok generated fake news story, claiming that Iran attacked Israel. Overall, according to the 29-country global survey of Ipsos, one of the largest market research companies, a majority think there is more lying and misuse of facts in politics and media than there was 30 years ago. There is a high level of awareness of the possibility of using AI to generate very realistic fake news and AI is going to make misinformation and disinformation worse.

The X database of posts has been used to quantify concepts related to financial market uncertainty in a daily X-based Market Uncertainty (XMU) indicator (the related X-based economic uncertainty indicator is discussed in Baker et al. (2021)). Four indices are constructed. The first consists of the total number of daily English-language posts containing both ‘Uncertainty’ terms as well as ‘Financial Market’ terms. Another index works to isolate the number of these posts that originates from users in the United States using a geo-tag-based classifier. US users make up about 50 percent of the English language X population in the sample. In my analysis, I mainly make use of a variant of this index that also incorporates reposts and weights each post by (1+log(1+# of reposts)). Finally, to control for changes in X usage intensity over time, another index scales the number of posts each day by X usage, e.g. the number of posts on that day that contain the word 'have'. While, overall, fake news is found to spread faster than true news on X, empirical evidence suggests that posts containing falsehoods are 70% more likely to be reposted (Vosoughi et al. (2018)) and only 0.1% of users were responsible for the sharing of 80% of fake news (Grinberg et al. (2019)). My results hold for various versions of the index, but, in line with other studies, my results are strongest for the reposts-weighted index.

I hypothesize that the X-based market uncertainty measure is related to financial market news but is contaminated by manipulated news. In order to isolate the effect of financial market news, I make use of a daily newspaper-based financial market uncertainty indicator, the equity market volatility (EMV) index derived in Baker et al. (2019) that tracks the aggregate volatility in the US stock market. I assume that journalists can distinguish fake news from true news and, hence, a newspaper-based financial market uncertainty indicator can be assumed not to be contaminated by manipulated news. Baker et al. (2019) construct their index of equity market uncertainty through an analysis of articles from US news outlets containing terms related to equity market uncertainty. For this exercise, they use newspapers in the US from Access World New's NewsBank service, which covers well over 1000 news outlets in recent years. The authors analyze the articles' content to evaluate the journalists' assessments of the news stories, events, worries, and expectations that might influence equities return volatility. These news outlets range from large national papers like USA Today to online newspapers and small local newspapers. The index is based on daily counts of articles containing the term 'uncertainty' or 'uncertain', the terms 'economic' or 'economy' and one or more of the following terms: 'equity market', 'equity price', 'stock market', or 'stock price'. Social media-based measures reflect the perceptions and expressed views of a broad cross-section of social media users, which can differ from those of journalists, experts, business leaders, and financial market participants. In particular, there are reasons why the views and perceptions of X users and journalists might contain different information on financial market uncertainty. The demographics of X users do not accurately reflect those of the US public; they skew younger and more towards Democrats. Hence, despite the enormous volume of available posts, one eventually only captures the beliefs and opinions of a specific cross-section of the US public. Posts are also shorter (a maximum of 280 characters) and more informal compared to newspaper articles, regulatory filings, Federal Reserve Beige Books, and earnings conference calls. However, it is unclear to what extend these differences would structurally affect the financial uncertainty measure.

More importantly, the XMU measure can be assumed to be affected by fake or biased news, too. My 'fake news hypothesis' suggests that X-based market uncertainty is related to financial market news, like it is the case for EMV, but additionally contaminated by manipulated news. Indeed, during the five months preceding the 2016 presidential election day analyzed in Bovet and Makse (2019), the X-based market uncertainty is on average more than 40% higher compared to all other days in my sample, which is significant at the 1% level. In contrast, in the same period, the EMV is on average not significantly different and the VIX is on average roughly 10% lower compared to all other days in the sample, which is also significant at the 1% level. Given the significantly lower VIX, one would expect the short straddle portfolio to perform particularly well in that period; surprisingly this is not the case[1].

[1] One major event that occurred in this period is the Brexit referendum in the UK. One can observe a spike in the time series on June 24th, 2016, where Prime Minister David Cameron made a statement in Downing Street on the outcome of the referendum on the UK's membership of the European Union. However, results are not driven by this single observation. Another spike occurred outside the five months window on November 8th,2016, the actual US presidential election day.

Apparently, one might conjecture that the X-based Market Uncertainty is unrelated to financial market stress. Hence, in addition to the news-based indicator (EMV), I further measure financial market stress using three different proxies: VIX, the VIX range and a flight-to-safety dummy. The VIX is typically considered by market participations as a kind of fear index, high levels can be associated with financial uncertainty. As an alternative measure of financial stress, I make use of the daily VIX range and characterizes the magnitude of intraday fluctuations of the VIX during a trading day relative to the closing level of the VIX. Lehnert (2024) shows that this simple measure is weakly correlated with the volatility of the VIX (VVIX) but embeds superior priced information and predicts the excess returns of S&P 500 straddles, synthetic S&P 500 variance swaps and VIX futures. Flight-to-safety (FTS) is a financial market phenomenon occurring when investors sell what they perceive to be higher-risk investments (equity) and purchase safer investments, such as bonds or gold. Using a model averaging approach for stock and bond returns, Baele et al. (2020) identify FTS days. They find that FTS days comprise less than 2% of their sample and are associated with a 2.7% average bond-equity return differential. Supporting my fake news hypothesis, I find that X-based market uncertainty is correlated with EMV (32%), but has a low correlation with the VIX (23%) and the VIX range (26%), and is unrelated to FTS episodes (XMU is on average 95.6 during FTS periods vis a vis 80.4 otherwise, which is insignificantly different). As a comparison, and to put this into context, during FTS episodes, e.g. EMV is substantially higher (on average 76.6 vs. 41.3) and the VIX is on average twice as high (roughly 30% vs. 15%) compared to non-FTS days, which is both significant at the 1% level.

In a related paper, Kogan et al. (2024) examine an undercover SEC investigation into the manipulation of financial news on social media. While fraudulent news had a direct positive impact on retail trading and prices, revelation of the fraud by the SEC announcement resulted in significantly lower retail trading volume on all news, including legitimate news, on these platforms. My reasoning is the following: While the newspaper-based measure EMV subsumes all relevant financial market news, XMU incorporates the same information to a certain extent, but is furthermore contaminated by fake news. I hypothesize that fake news further induces options trading activity and analyze if X-based measures of financial market uncertainty (XMU) affect expectations about equity volatility. I identify such expectations in financial market prices by studying volatility dependent claims, claims that provide insurance against future volatility. Hence, in contrast to EMV, XMU is expected to be an incremental predictor of variance risk and, hence, an increase in XMU negatively predicts the premium on short straddles, constructed from equity option prices. In the next section, I explain the computation of the variance sensitive asset used in my analysis.

Variance Sensitive Assets

Variance asset returns are constructed in the following way. In line with Johnson (2017), I use excess returns of a variance-sensitive asset with a 1-month maturity to proxy for the variance risk premium. This approach has the advantage to investigate the exposures of variance assets to variance risk factors while holding the forecast horizon and holding period fixed. I make use of a variance-sensitive asset[2] derived from option prices studied in Johnson (2017).

[2] The advantage of relying on this data set is the comparability with previous results. The original sample studied in Johnson (2017) contains 4445 observations from 1996 through 2013. The data is available from the author. I make use of an updated sample that contains 5912 observations from 1996 through 2019.

As in Coval and Shumway (2001), at-the-money S&P 500 straddle returns can be computed by using the most liquid at-the-money options with only a few positions and small transactions costs. The returns for a 1-month maturity S&P straddle strategy are:

$$r_{T,t+1}^{ST} = \frac{\frac{T-S_1}{S_2-S_1} Straddle_{t+1}(K; t+S_1) + \frac{S_2-T}{S_2-S_1} Straddle_{t+1}(K; t+S_2)}{\frac{T-S_1}{S_2-S_1} Straddle_{t}(K; t+S_1) + \frac{S_2-T}{S_2-S_1} Straddle_{t}(K; t+S_2)} - 1$$

where $Straddle_t(t+S)$ is the price of an at-the-money straddle with maturity $t+S$ at time t. Hence, the strategies use a mixture of the 2 maturity dates nearest to a target maturity date that is always T = 1 month from the current date.

Based on previous literature, I make use of known timely indicators for variance risk premia and assess their ability to incrementally predict future variance asset returns. In addition to the VIX as my explanatory variable, I define a measure that makes use of the daily VIX range and characterizes the magnitude of intraday fluctuations of the VIX during a trading day t relative to the closing level of the VIX:

$$VIX\ Range_t = \frac{(VIX_t^{High} - VIX_t^{Low})}{VIX_t^{Close}}$$

where VIX_t^{High} (VIX_t^{Low}) is the intraday high (low) level of the VIX and VIX_t^{Close} is the VIX closing level. Lehnert (2024) shows this simple measure that quantifies the intraday fluctuations of the VIX conveys information about the price of variance risk. Lehnert (2024) finds that the VIX range is weakly correlated with the VVIX but embeds superior priced information and predicts the excess returns of S&P 500 straddles. The VIX range is a significant, incrementally positive predictor of variance asset returns, which implies that when the VIX range is abnormally low, variance risk premia are higher and therefore variance assets have more negative abnormal returns.

Predicting and trading variance risk premia

My main research hypothesis suggests that the XMU is an incremental predictor of variance risk. In this section, I make use of a trading strategy based on short straddles to evaluate the economic value to investors. Due to the availability of the X-based measures and the short straddle returns, my sample period is June 1st 2011 until June 28th 2019, covering a total of 2033 days. In a strict out-of-sample exercise, I compare various trading strategies using short S&P 500 straddles. The first unconditionally sells S&P 500 straddles with a constant maturity of 1 month. When shorting straddles, Regulation T requires the proceeds, along with 20% of the index value, be posted as margin. Hence, short straddle returns can be computed as:

$$r_t^{Short\ Straddle} = \frac{Straddle_{t-1} - Straddle_t}{0.2 \times SP500_{t-1}}$$

The findings of Coval and Shumway (2001) suggest that assets whose value is increasing (decreasing) in market volatility earn negative (positive) risk premia, hence, short straddles are known to deliver on average positive excess returns. Based on my previous discussion, I hypothesize that on average the relationship between XMU and next-day short straddle returns is negative. XMU is contaminated by fake news and an increase in XMU has a positive impact on expected equity volatility. Hence, an increase in XMU has a positive impact on portfolios that buy volatility, e.g. long straddles. Therefore, the optimal strategy would be to reduce the exposure to portfolios that sell volatility, e.g. short straddles, once XMU increases. As a result, for the dynamic trading strategy, I use the XMU in period t-1 to scale the daily short straddle excess returns in period t in order to achieve a given target. The scaled portfolio weight in the original short straddle portfolio at time t is given by $w_t = \frac{XMU_{t-1}^{Target}}{XMU_{t-1}}$. The choice of the target is arbitrary, but I implement the trading strategy completely out-of-sample. Hence, in order to calculate the target in t-1, I always use the average of the daily XMU measures during the previous six months. Hence, my trading exercise starts on December 1st 2011. In order to show that the typical investor can benefit from the strategy even under a leverage constraint, I cap the weights to be smaller than 2 (a leverage of 100%). As alternative explanatory variables, I use the EMV, the VIX and the VIX range and implement dynamic trading strategies in the same way. Unlike other papers (e.g. Filipovic, Gourier, and Mancini (2016) or Aıt-Sahalia et al. (2020)), the goal of the exercise is not to compute an optimal portfolio strategy, but rather to document that the predictability of the XMU for variance risk is economically significant.

In the following, I report the results from a regression of the managed portfolios on the unmanaged benchmark, the short straddle portfolio. Overall, on a variance risk-adjusted basis, results suggest that the XMU-managed short straddle portfolio takes significantly less variance risk, a beta of less than 1, and outperforms the unmanaged portfolio by 3.45 basis points daily (8.7% annually), which is highly significant at the 1% level[3]. In contrast, the EMV-managed portfolio takes more risk, but does not significantly outperform the unmanaged portfolio. Apparently, XMU and EMV are correlated, but XMU embeds superior priced information. Therefore, I do not consider the EMV strategy further. Results also suggest that the VIX-managed (the VIX Range-managed) portfolio outperforms the unmanaged portfolio by 1.86 (1.90) basis points daily (4.7% (4.8%) annually), which is significant at the 1% (5%) level. At the same time, the XMU-managed portfolios significantly outperform the other managed portfolios.

[Figure 1]

In Figure 1, I compare the XMU-managed, the VIX-managed and the VIX range-managed short straddle portfolios with the original (unmanaged) portfolio. I also highlight the five months preceding the 2016 US presidential election day.

Short straddle returns are known to exhibit left skewness (e.g. -3.39 in my sample); hence the Sharpe ratio would not be appropriate to evaluate the trading strategies. I use the Sortino ratio, which adjusts the excess returns by the downside standard deviation. Results indicate that XMU-managing the portfolio improves the Sortino ratio to 2.23 for the reposts-weighted XMU (e.g. 2.06 for the scaled XMU) compared from 1.63 for the unmanaged portfolio and e.g. 1.79 for the EMV-managed portfolio. During the five months preceding the 2016 presidential

[3] My findings hold for various versions of the index, but, in line with other studies, my results are strongest for the reposts-weighted index.

election day, which evidently represents a period with excessive spreading of fake news (e.g. Bovet and Makse (2019)), the XMU-managed portfolio significantly outperforms the unmanaged portfolio by 8.7 basis points daily on a variance risk-adjusted basis, from on average 3.1 basis points during other days. In this period, the XMU-managed portfolio doubles the Sortino ratio from 1 to more than 2 compared to the unmanaged portfolio. Interestingly, the EMV-, VIX- or VIX Range-managed portfolios do not outperform (even underperform) the unmanaged portfolio during the same period. Hence, results imply that by reducing the exposure to variance risk, the XMU-based trading strategy is particularly attractive in the presence of fake news, suggesting that fake news positively affects expected equity volatility.

The relationship of my market stress indicator (FTS) with the (unmanaged) short straddle returns can be assumed to be negative. Given that market stress, e.g. flight to safety, is strongly related to increased market volatility, one can expect the short straddle portfolio to perform poorly during these periods. Indeed, while during normal times the average daily return is 7.7 basis points, during FTS episodes it decreases to -136 basis points. Similarly, when controlling for the EMV (VIX), the average return during normal times is 6.1 (10.6) basis points, while it decreases to -1.8 (-27.7) basis points during days when the EMV (VIX) is in the top decile. The correlation between XMU and FTS is low, but in order to better understand their joint impact on the predictability for variance asset returns, I differentiate between FTS days and run the following regression

$$r_t^{XMU} = \alpha_0 + \alpha_1 D_{FTS,t-1} + \beta_0 r_t^{Short\ Straddle} + \beta_1 D_{FTS,t-1} r_t^{Short\ Straddle} + \epsilon_t$$

which gives the relative beta of the managed portfolio (r_t^{XMU}) conditional on FTS days compared to the unconditional estimate, where $D_{FTS,t-1}$ is a dummy, controlling for FTS days at the same time when the XMU signal is observed. I find that β_1 is smaller than 0, which suggests that the dynamic strategy takes less variance risk during FTS episodes, but the effect is insignificant. However, on a variance risk-adjusted basis, the performance of the managed portfolio is not different during both periods, resulting in α_1 being very small and insignificant. Hence, periods of high levels of XMU are not necessarily controlling for episodes of market stress.

Another typical concern is that the observed relation between the XMU and returns of variance sensitive assets is driven by risk, and due to the weak, but positive correlation of XMU and e.g. EMV. Hence, I control for EMV being in the top 10% of days, e.g. days with substantial (negative) financial market news, and run the following regression

$$r_t^{XMU} = \alpha_0 + \alpha_1 D_{EMV\_High,t-1} + \beta_0 r_t^{Short\ Straddle} + \beta_1 D_{EMV\_High,t-1} r_t^{Short\ Straddle} + \epsilon_t$$

where $D_{EMV\_High,t-1}$ is a dummy that controls for the EMV being in the top 10% of days at the same time when the XMU signal is observed. I find that β_1 is substantially and significantly smaller than 0, which suggests that the dynamic strategy takes substantially less variance risk during the days when EMV is high. However, the managed portfolio still outperforms the unmanaged benchmark on a variance risk-adjusted basis on average by 2.6 basis points daily also during normal times, which is significant at the 5%. Hence, the XMU measure is only partly related to market stress, e.g. flight to safety days or high EMV periods.

My working hypothesis is that the XMU measure is contaminated by fake news, and, hence, I would like to understand the impact of extreme levels of XMU. I control for XMU being in the top 10% of days, and run the following regression

$$r_t^{XMU} = \alpha_0 + \alpha_1 D_{High,t-1} + \beta_0 r_t^{Short\ Straddle} + \beta_1 D_{High,t-1} r_t^{Short\ Straddle} + \epsilon_t$$

where $D_{High,t-1}$ is a dummy that controls for the XMU being in the top 10% of days at the same time when the XMU signal is observed. I find that β_1 is substantially and significantly smaller than 0, which suggests that the dynamic strategy takes substantially less variance risk during the days when the XMU is high and presumably contaminated by fake news. By taking less risk, the managed portfolio outperforms the unmanaged benchmark in these periods on a variance risk-adjusted basis by 2.2 basis points daily, which is significant at the 1% level. Interestingly, I do not observe the same effect for the EMV-, VIX- and VIX Range-managed portfolios during high XMU episodes.

Another typical concern is that the observed relation between the XMU and returns of variance sensitive assets is driven by extreme observations. I control for XMU being in the bottom 10% of days, and run the following regression

$$r_t^{XMU} = \alpha_0 + \alpha_1 D_{Low,t-1} + \beta_0 r_t^{Short\ Straddle} + \beta_1 D_{Low,t-1} r_t^{Short\ Straddle} + \epsilon_t$$

where $D_{Low,t-1}$ is a dummy that controls for the XMU being in the bottom 10% of days at the same time when the XMU signal is observed. I find that β_1 is substantially and significantly larger than 0, which suggests that the dynamic strategy takes substantially more variance risk during the days when the XMU is low. However, the managed portfolio still outperforms the unmanaged benchmark on a variance risk-adjusted basis by 3.8 basis points daily during normal times, which is significant at the 1%. Hence, the performance of the XMU-managed portfolio is not driven by increased risk-taking during low XMU episodes.

Conclusions

Research suggests that AI-powered social bots manipulate social media sites, evidently during the 2016 US presidential election, where 25% of X posts have been identified to spread either fake or extremely biased news. I hypothesize that on top of financial news, fake news induces options trading activity and analyze if X-based measures of financial market uncertainty (XMU) affect expectations about equity volatility. I identify such expectations in financial market prices by studying volatility dependent claims, claims that provide insurance against future volatility. XMU is expected to be an incremental predictor of variance risk and, hence, an increase in XMU negatively predict the premium on short straddles, constructed from equity option prices. I find that a managed S&P500 short straddle portfolio that decreases the exposure to variance risk when XMU is high significantly outperforms an unmanaged portfolio by nearly 9% annually. In line with my fake news hypothesis, the effect is particularly strong during the 2016 US presidential election, is substantially stronger when reposts are incorporated and cannot be explained with available financial news.

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Figure 1 – Performance of the dynamic trading strategy

The Figure presents the performances of the X market uncertainty (XMU)-managed short straddle portfolio vis à vis the unmanaged one and other dynamic trading strategies based on $100 invested on November 30th, 2011. I also highlight the five months preceding the 2016 US presidential election day.

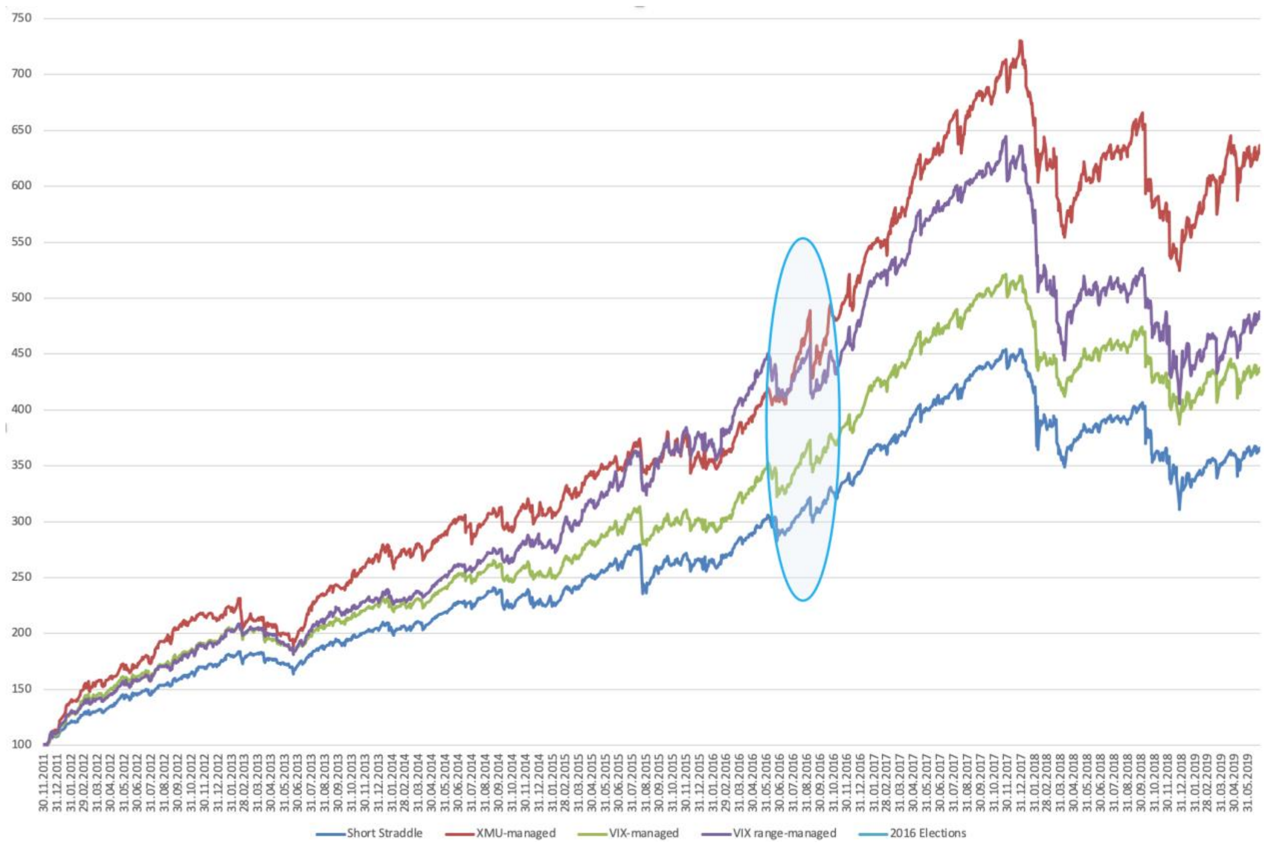

Table 1 – Summary Statistics

The table presents the summary statistics of the 1-month short straddle returns (in %), EMV, VIX (in %), VIX Range (in %) and the various X-based uncertainty measures used in the study. The full sample period ranges from June 1st 2011 to June 28th 2019, covering a total of 2033 days. XMU_ENG consists of the total number of daily English-language posts containing both 'Uncertainty' terms as well as 'Financial Market' terms. XMU_USA works to isolate the number of these posts that originates from users in the United States using a geo-tag-based classifier. XMU_WGT incorporates reposts and weights each post by (1+log(1+# of reposts)). In order to control for changes in X usage intensity over time, XMU_SCA scales the number of posts each day by X usage, e.g. the number of posts on that day that contain the word 'have'.

	Mean	Median	Std.	Min	Max
Short Straddle Returns	0.05	0.18	1.11	-13.56	5.76
EMV	41.95	21.62	63.82	4.80	897.41
VIX	16.22	14.72	5.51	9.14	48.00
VIX Range	10.76	9.45	6.14	2.77	108.49
XMU_ENG	85.37	74.37	67.44	7.28	1229.92
XMU_USA	83.24	66.90	79.90	2.52	1293.32
XMU_WGT	80.70	64.00	78.82	3.32	1297.20
XMU_SCA	109.90	82.40	109.91	3.86	1979.21