Measuring the Impact of President Donald Trump's Tweets on the Mexican Peso/U.S. Dollar Exchange Rate

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1 Abstract

This study explores whether the comments made by the recently-elected American President Donald Trump on the social network Twitter have an impact on the daily Mexican peso/U.S. dollar currency exchange rate. We collect data from the social network Twitter and the Chicago Mercantile Exchange & Chicago Board of Trade. We study whether certain types of comments made by Donald Trump about Mexico and American foreign policy posted over the period starting in June 16, 2015, (when he announced his candidature in the 2016 Republican Party presidential primaries) until February 21, 2017 (a month after he was sworn in as president of the United States), affected the daily value of the Mexican peso in terms of U.S. dollars. We analyze 7429 tweets and rank 64 of them as "negative" based on the tone and content of the message delivered. The results of this paper suggest that the tweets classified as negative had an impact on the daily volatility of the Mexican peso/U.S. dollar exchange rate, possibly leading to market inefficiencies and arbitrage opportunities.

Keywords: Foreign exchange rates, Twitter, GARCH.

JEL Classifications: D72, F31, G02.

2 Introduction

"I believe it's really important to hear directly from our leadership (referring to Donald Trump)." "And I believe it's really important to have these conversations out in the open, rather than have them behind closed doors. So if we are all to suddenly take these platforms away, where does it go? What happens? It goes in the dark. And I just don't think that's good for anyone." "The complicated part, is just what does this mean to have a direct line to how he's thinking in real time and to see that. So we're definitely entering a new world where everything is on the surface and we can all see it in real time and we can all have conversations about it."

Jack Dorsey, Twitter CEO.

The issue of whether the release of certain information can create market uncertainties in currency and stock markets has been studied since Kahneman and Tversky (1979) who performed an experiment to analyze people's behavior given certain probabilities and payoffs. Other examples of studies that modeled market uncertainties and its impact on foreign currency exchange rates are: Frenkel (1981), Meese and Rogoff (1983), MacDonald and Taylor (1992), Engle and Ng (1993), Cheung and Chinn (2001), Papaioannnou et al.(2013). These papers examine how new information that is delivered through news, government policies, political speeches, or social network websites can be used to improve predictions on the future value of currency equities.

In this paper we examine whether certain comments posted on the social network Twitter between June 16, 2015 and February 21, 2017 by the recently-elected American president, Donald Trump, created market uncertainties that affected the Mexican peso/U.S. dollar exchange rate. We focus solely on tweets made by Donald Trump because of the controversial, protectionist, and nationalistic comments that he made about implementing immigration laws to eradicate illegal immigration, building a wall between the American and Mexican border, and imposing taxes on American companies that invest in Mexico. We also focus solely on his tweets because of his high influence given his professional background as a successful businessman, a television personality, and more recently, a leader of the largest economy in the world, the U.S.

During this period, Donald Trump participated and succeeded in two major American elections. First, he participated in the Republican Party presidential primaries between February 1, 2016 and June 7, 2016 where he defeated 16 opponents. Later, he participated in the U.S. presidential elections that took place on November 8, 2016 where he defeated the leader of the Democratic Party, Hillary Clinton. We believe that the end goal of his controversial comments on Twitter was not to weaken the value of the Mexican peso in terms of American dollars, but to get the American adult population to vote for him.

The social network Twitter was created in 2006 and is one of the most dynamic and popular methods of interaction among people because of their free access, easiness to use, and extensive scope. Just in 2016, Twitter had 313 million active users and approximately 1 billion visits per month.[1] Twitter is an instant communication microblog website where users can express their ideas in less than 140 characters called *"tweets"* which can also contain links to other websites, images, and/or videos. Tweets can be posted as private tweets, which can be read only by users that are within the original users social circle, and as public tweets, which can be read by anyone. Users can send tweets from a computer, a smart phone, or a tablet that is connected to the Internet and in some countries like the U.S. or Canada Twitter users can also send tweets via cell phone text messages.

Twitter is also one of the most visited websites worldwide. In fact, it has approximately 100 million daily users and an average traffic of 500 million tweets sent per day.[2] Due to its free access and high popularity, several groups of people have benefited from using Twitter. For instance, business owners use it to advertise promotions or new products. Artists use it to promote their new releases or presentations. Sport players

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[1]Refer to: https://dev.twitter.com/streaming/overview

[2]Refer to: https://blog.twitter.com/engineering/en_us/a/2013/new-tweets-per-second-record-and-how.html

use Twitter to share their accomplishments. Journalists use it to share real time news. Politicians use Twitter to express their ideas on matters of domestic and international policy, culture, and news, in order to reach a large amount of people and to increase their popularity among voters.

The analysis of Donald Trump comments on Twitter is important because his tweets have an influence on people's behavior whether positive or negative.[3] Moreover, Donald Trump is the first political leader who continuously uses Twitter to express his ideas on a wide variety of topics in a controversial manner. The main advantages of using Donald Trump's tweets as a possible influence on market uncertainty, rather than reports on his interjections made on radio, television, and/or newspapers, is that the message carried via tweets is delivered directly by him at a faster pace than through news. Moreover, his tweets allow Donald Trump to actively interact with people from the Twitter community.

In this study we evaluate Donald Trump's tweets as a possible contributor to the uncertainty on the exchange rate market. The type of content, time of delivery, and frequency of his daily tweets, are unpredictable and random, as it is difficult to determine what, when, and how many times Donald Trump is going to tweet. We are interested in exploring whether his comments create market uncertainties that affect the volatility of the Mexican peso/U.S dollar exchange rate. This volatility, in turn, can lead to market inefficiencies that cause arbitrage opportunities. We model these uncertainties using a time series Auto-Regressive Conditional (ARCH)/Generalized Auto-Regressive Conditional (GARCH) process.

The topic of foreign exchange rates has been widely studied as the value of a currency affects directly the price of exports and imports, foreign debts, reserves, inflation levels, and domestic wages. Messe and Rogoff (1983) concluded that fluctuations on the foreign exchange rates follow a random walk process. Cassel (1918) studied the purchasing power parity model that states that the currency exchange rate equilibrium between two countries is equal to the ratio of their relative price levels. Dornbusch (1976) introduced

[3] Refer to the variety of people's responses to Donald Trump comments on his official Twitter account: https://twitter.com/realDonaldTrump.

the monetary model with his sticky-price variant model which states that prices always adjust to changes in monetary policy. Engle (1982) presented that the time series of exchange rates are characterized by conditional heteroskedasticity and volatility clustering. Bollerslev (1986) proved that the estimation of exchange rate volatility was highly predictable, whereas currency price forecast was not.

Moreover, several studies have also argued that people's opinions have the potential to create market uncertainties that affects investors' strategies. Frenkel (1981) showed that unanticipated events such as news concerning inflationary expectations influenced currency exchange rates. Shiller (2003) argued that people's sentiments play an important role for taking decisions on a financial matter. Prast and de Vor (2005) showed that an important factor that affected variations between the Euro and U.S. dollar currency exchange rates was people's reactions to political and economic news. Similarly, Laakkonen and Lanne (2009) categorized and analyzed the impact of positive and negative news on the Euro and U.S dollar currency exchange rate. Clark and Tunaru (2005) defined "political risk" as political events that had an economic impact on a global scale or on an individual country.

More recently, Papaioannou et al. (2013) and Ozturk and Ciftci (2014) showed that information carried on comments posted in the social network Twitter by a large number of users could be used to forecast currency exchange rates in a high-frequency intra-daily trading scale. Similarly to these papers, our study uses Twitter to analyze fluctuations on the currency exchange rates. By contrast, our study focuses solely on the comments of one unique individual: Donald Trump, who was a former business man, T.V. host of the American reality show "The Apprentice",[4] Republican candidate, and current American President;.

To the best of our knowledge, our research is the first paper to assess whether the controversial tweets made by Donald Trump about Mexico create distortions on the daily Mexican peso/U.S. dollar currency exchange rate. We use the information conveyed in

[4] More details about the biography of Donald Trump can be found on: https://www.biography.com/people/donald-trump-9511238.

Donald Trump's tweets as new information that may influence expectations regarding the value of the Mexican Peso/U.S. dollar exchange rate. Our conjecture is based on the Saltelli et al. (2000) idea of "signal extraction problems" in which agents update their beliefs in order to compensate for the uncertainty caused by the release of certain new information.

A category of models that is well-suited to capture the role of such news in volatility is the GARCH class. We estimate such a process and find that the econometric model provides a good fit for our data. The results of this model show that the tweets made by Donald Trump that we classify as "negative" contain important information that affects the daily volatility of the Mexican peso/U.S. exchange rate.

Our results show that the negative tweets increase the variance of the daily value of the Mexican Peso in terms of 1 U.S. dollar by 0.0000171 at the 5% confidence level. This represents increases in average of the daily volatility by 21.6%, the maximum daily volatility by 1.21% and the minimum daily volatility by 96.61%. Consequently, an investment made in periods of low Mexican peso/U.S. dollar exchange rate volatility and after Donald Trump posted a negative tweet, could double their return by exploiting the differences in prices between the Mexican peso and U.S dollar.

The next sections of this paper are organized as follows. Section 3 introduces the literature review. Section 4 shows the description of the data that was obtained from Twitter and the Chicago Mercantile Exchange & Chicago Board of Trade. Section 5 presents the descriptive statistics. Section 6 describes the econometric model used to analyze the relationship between the negative tweets made by Donald Trump and the fluctuations on the daily Mexican peso/U.S. dollar currency exchange rates. Finally, Section 7 outlines the conclusion of our paper.

3 Literature Review

Several studies have been conducted on the topic of financial economics to explain fluctuations in the stock market and in currency exchange. These studies are largely based on two main approaches. The first approach is the “Random Walk Hypothesis” in which current stock prices are uncorrelated to past stock prices. In this approach, fluctuations in the stock market are completely random and do not depend on past events (Cootner, 1964). The second approach is the “Efficient Market Hypothesis (EMH) in which asset prices reflect all available information of a market. In this approach, investors are unable to purchase undervalued stocks or currencies as they are always traded at a fair value (Fama, 1965).

Messe and Rogoff (1983) stated that changes in the foreign exchange rates followed a random walk process. However, many researchers have challenged this idea by forecasting changes in currency exchange rates using the purchasing power parity (Rogoff, 1996), the covered interest rate parity (Frankel, 1979), and the uncovered interest rate parity condition (Chaboud and Wright, 2005). In addition, other researchers have used Markov switching models (Engel, 1994), support vector regression (Cao and Tay, 2003) and neural networks (Kimoto et al., 1990) to explain fluctuations of foreign exchange rates.

Fama (1965) argued that it was challenging to predict currency exchange rate fluctuations as several observed as well as unobserved variables affected foreign exchange markets. According to his EMH, fluctuations in market prices fully reflected all available information and were not affected by speculations. Consequently, currencies were always traded at fair prices and investors could not benefit of buying and selling undervalued currencies. In the EMH model, individuals behaved rationally and were risk adverse.

However, behavioral economics has challenged the EMH based on the assumption that people’s beliefs and emotions have an impact on investors’ financial decisions (Shleifer, 2000; Nofsinger, 2005; Shiller, 2003). Behavioral economics was pioneered by Kahneman and Tversky (1979) who presented the concept of “prospect theory” to analyze the link between risk, uncertainty, and decision making based on probabilities and monetary outcomes. As a result, several papers tried to model the impact of new information on investors' behavior which in turn can affect prices and create market inefficiencies (Hong et al., 2000; Barberis and Thaler, 2003).

In this literature review, we present evidence that the information carried in tweets has an impact on people and market behavior. This supports my research hypothesis that tweets can be used to model fluctuations of the currency exchange rate.

The clearest evidence that tweets have an impact on market behavior, is what occurred on April 23, 2013 at 1:07 p.m., a week after the terrorist attack against the Boston Marathon in the U.S. that killed 3 individuals and left more than 200 people wounded. The Associated Press, an American non-profit news agency, falsely reported on Twitter that the President of the United States at that time, Barack Obama, and other White House members were injured in two separate explosions at the White House. As a result of this false information, between 1:08 p.m. and 1:10 p.m., the Standard & Poors 500 Index fell about 1% decreasing approximately $136 billion U.S. dollars in value and the Dow Jones Industrial Average dropped 143.5 points. The yields on the 10-year U.S. Treasury notes benchmark dropped approximately 0.06% points and the U.S. dollar weakened to approximately 0.7% before recovering to its previous value, after the report was discredited.[5,6]

According to an article published by the Financial Times on February 9, 2017, Donald Trump tweets that contained positive or negative comments about American companies have an immediate effect on their stock prices that lasts approximately 1 hour after the tweet is posted.[7] Similarly, an article published by The Economist on February 14, 2017, showed that the impact of Donald Trump positive or negative tweets on companies' stock prices lasts approximately 100 minutes after the comment is posted.[8] Both articles

[5]Refer to: https://www.bloomberg.com/news/articles/2013-04-23/a-fake-ap-tweet-sinks-the-dow-for-an-instant

[6]Refer to: http://www.nj.com/business/index.ssf/2013/04/errant_tweet_about_explosions.html

[7]Refer to: https://www.ft.com/content/a962c1f8-ee44-11e6-930f-061b01e23655

[8]Refer to: http://www.economist.com/blogs/graphicdetail/2017/02/daily-chart-9

conclude that these variations are almost insignificant and meaningless as they happen several times within a day.

Bollen et al. (2011) categorized 9,853,498 tweets according to people's sentiments for 2.7 million Twitter users, between February 28, 2008 and December 19, 2008. They found that the predictions of the daily fluctuations in the closing values of the Dow Jones Industrial Average (DJIA) index are 87.6% accurate when they include certain metrics extracted from Twitter, such as people's level of happiness and level of calmness. Our research is similar to the study presented by Bollen et al., as we analyze tweets that contain negative comments that may impact the value of the Mexican peso. What distinguishes our research from this study, is that we focus solely on tweets made by one specific person: Donald Trump.

Tweets also have been used to study a wide range of other topics. For instance, Baylis (2015) categorized more than a billion tweets according to people's sentiments on days of extreme heat and extreme cold. This study concluded that extremely cold days did not have an impact on people's level of happiness. On the other hand, the study found that extremely hot days had a negative impact on people's level of happiness which was reflected on people's comments posted on Twitter. Twitter was also used in Halberstam et al. (2016) to study people's interactions and the diffusion of political information on social networks. This study presented new evidence on how asymmetric exposure to information on social networks could influence people's political emotions and preferences.

Nofer and Hinz (2014), used 100 million German tweets, posted between January, 2011 and November, 2013 to analyze whether mood contagion that was spread via the number of followers of a given user had an impact on the German stock market. They found that positive mood that is spread through tweets increased German trading volume up to 36% within a six-month period. Tetlock (2007) used financial content analysis posted in the "Abreast of the Market" column of the American newspaper "Wall Street Journal" to study the relationship between media and stock market fluctuations. He found that negative sentiment about the market had a negative impact on the daily market trading volume.

Papaioannou et al. (2013), collected 20,250 tweets to model and forecast fluctuations between the Euro and the U.S. dollar currency exchange rate in a high-frequency intradaily trading scale using Autoregressive (AR), Autoregressive with exogenous inputs (ARX), and Artificial Neural Networks (ANN) models. Similarly, Ozturk and Ciftci (2014) classified tweets as positive, negative, or neutral and used a logit regression model to study the relationship between the amount of tweets and the U.S. dollar/Turkish lira currency exchange rates fluctuations. This study showed that using data from Twitter it was possible to better predict variability in exchange rates.

These articles presented evidence that data from Twitter can be used to model the impact of people's beliefs on stock market and foreign exchange rate fluctuations. Similarly, our research presents an in-depth analysis of whether new information conveyed by Donald Trump's tweets has the potential to create market uncertainties that affect the Mexican peso/U.S dollar exchange rate. In particular, we examine whether Donald Trump's tweets can affect people's beliefs and lead to foreign exchange market inefficiencies.

4 Description of the data

Using the social network Twitter, we analyze 7429 tweets that were posted on Donald Trumps official Twitter account (@realDonaldTrump) from June 16, 2015 (the date that Donald Trump announced his candidacy for the Republican Party presidential primaries) until February 21, 2017 (one month after he was officially presented as the 45th President of the U.S.). In this study, we only consider tweets that the original author is Donald Trump, as the aim of this paper is to measure whether his tweets have any power to affect the value of the Mexican peso in comparison with the U.S. dollar. Consequently, we only take into consideration 4999 tweets posted by Donald Trump.

Out of these 4999 tweets, we rank 63 of them as negative because of the type of message and tone that Donald Trump used. We classify as negatives, tweets from the election days and tweets that contained some keywords like: Mexico, Mexican, illegals, wall, border, drugs, immigrants, crime, visa. For instance, we consider comments such as: "We must build a wall to secure our border. It will save lives and help Make America Great Again!" or "We will stop heroin and other drugs from coming into New Hampshire from our open southern border. We will build a WALL and have security"[9] as examples of negative tweets.

Our data also consists of daily closing spot and future prices of the Mexican peso in terms of 1 U.S. dollar, covering weekdays between June 16, 2015 and February 21, 2017. This sample represents a total of 441 observations and is obtained from the financial market company "Chicago Mercantile Exchange & Chicago Board of Trade" (CME Group) through the financial data terminal "FactSet".

In this research, we study whether Donald Trump's tweets posted between 4:00 p.m. Eastern Standard Time (EST) of the previous day and 4:00 p.m. EST of the current day affects the Mexican peso / U.S. dollar currency exchange rate of the current day. We use 4:00 p.m. EST as a reference because it is the closure time of the New York Stock Exchange (NYSE).

Our research thus includes data from Monday to Friday because the data for the spot and future exchange rates is not released over the weekends. However, to not lose any information from Donald Trump's tweets posted over the weekend, we add these tweets (made from Friday at 4:00 p.m. EST until Monday at 8:00 a.m.) to those made on the following Monday.

5 Descriptive Statistics

According to our analysis, between June 16, 2015 and February 21, 2017, Donald Trump posted 4999 tweets at an average rate of 8 tweets per day and he used the word "Mexico" 52 times. The highest quantity of tweets in a given day was on October 20, 2016 when

[9]Refer to Table 7 of the Annex to see the 63 tweets classified as negative.

he posted 64 tweets[10] (20 days before the U.S. presidential election) and there were only 8 days in which he didn't use Twitter. In order to study the impact of his tweets on the currency exchange rate between the Mexican Peso and the U.S. dollar, we classify 63 of his tweets as negative based on the type of comment used by Donald Trump.

Table 1: Descriptive statistics - Daily weekday figures between 06/16/2015 - 02/21/2017

Statistic	Spot exchange rate	Future exchange rate	Amount of tweets (including weekends)
Mean	18.178	18.258	8.102
Standard Error	0.073	0.074	0.236
Median	18.192	18.258	7
Mode	15.654	18.657	4
Standard Deviation	1.542	1.559	5.872
Minimum	15.246	15.370	0
Maximum	21.955	22.124	64
Quantity	N/A	N/A	4999
Count	441	441	617

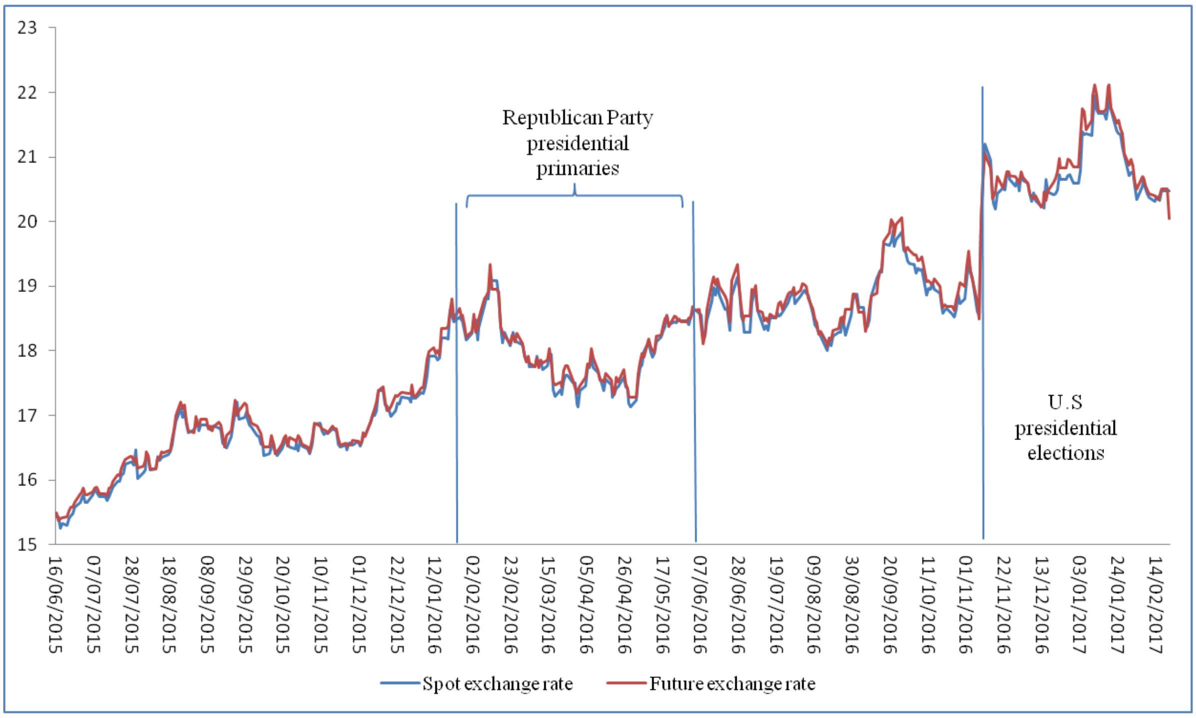
Note: The daily spot and future exchange rates are expressed as the amount of Mexican pesos that 1 U.S. dollar can buy. Data on spot and future exchange rates obtained from the CME Group using financial terminal FactSet. Data on tweets are obtained from the social network Twitter.

During the same period of time, according to Table 1 the average spot exchange rate was 18.178 MXN/USD (Mexican pesos that 1 U.S. dollar can buy), the maximum exchange rate in a day reached 21.955 MXN/USD and the minimum exchange rate in a day decreased to 15.246 MXN/USD. Meanwhile, the average future exchange rate was at 18.258 MXN/USD, the maximum future exchange rate in a day reached 22.124 MXN/USD and the minimum future exchange rate in a day decreased to 15.370 MXN/USD.

Figure 1 shows that the spot and future exchange rate between the Mexican peso and the U.S. dollar follow a very similar path which is consistent with financial theory. It also shows that during the period of the Republican Party presidential primaries the Mexican peso initially gained some value and then returned to its value before the elections. The

[10] Refer to Figure 3 in the Annex to see the daily amount of Donald Trump tweets.

Figure 1: Daily weekday spot and future exchange rates



Note: The daily spot and forward exchange rates are expressed as the amount of Mexican Pesos that 1 U.S. Dollar can buy.

biggest drop in the value of the Mexican Peso occurred between November 8, 2016, the date of the U.S. presidential election, and November 11, 2016, days after the election's results were official. The exchange rate jumped from 18.498 to 21.053 Mexican pesos per 1 U.S. dollar.

6 Econometric model

To model the daily variation of the exchange rate we start by using the model proposed by Fama (1984) called "forward price model" which uses spot and forward exchange rates. The spot exchange rate is the exchange rate seen at time t and we represent it using the notation s_t. On the other hand, the forward exchange rate is the value of the exchange rate seen at time $t+1$ that is observed at time t. We use the covered interest rate parity (CIP) which is a no-arbitrage condition that studies the relationship between interest rates and spot exchange rates between 2 countries to model the forward exchange rate which we define as f_t. Consequently, the forward exchange rate is modeled as:

$f_t = s_t \frac{1+i_f}{1+i_d}$

Here i_f is the interest rates observed at time t in the foreign currency and i_d is the foreign interest rate observed at time t in the domestic currency. The forward exchange rate also represents the certainty equivalent of the spot exchange rate. Fama models this certainty equivalent as follows:

$$F_t = E_t(S_{t+1}) + P_t \tag{1}$$

Where F_t is equivalent to the natural logarithm of the forward exchange rate: $ln(f_t)$, S_{t+1} is equivalent to the natural logarithm of the exchange rate at time $t+1$: $ln(s_{t+1})$, $E(S_{t+1})$ represents the expected spot rate at time $t+1$ conditional on all information available at time t, and P_t represents the risk premium at time t. As noted by Fama, the natural logarithm is used to make the analysis indifferent of whether exchange rates are expressed as the amount of Mexican pesos that one U.S. dollar can buy or the amount of U.S. dollars that one Mexican peso can buy.

Sosvilla-Rivero et al. (1992) further studied this relationship from a risk neutrality perspective in which they dropped the risk premium (P_t) condition to show that the forward exchange rate is an unbiased predictor of the future spot exchange rate. This relationship is known as the unbiasedness hypothesis or EMH:

$F_t = E_t(S_{t+1})$

Fama subtracts the spot exchange rate from both sides of equation (1) to obtain

$F_t - S_t = E_t(S_{t+1}) + P_t - S_t$

And as $E_t(S_t) = S_t$, then

$F_t - S_t = E_t(S_{t+1}) + P_t - E_t(S_t)$

$F_t - S_t = P_t + E_t(S_{t+1} - S_t)$

We use Fama's regression model, equation (2), to study if the current forward-spot differential $(F_t - S_t)$ has any influence to predict future daily change of the spot exchange rate $(S_{t+1} - S_t)$. The only difference in our model is that instead of using forward exchange rates, we use daily future exchange rates as forward and future exchange rates are both contracts between two parties to buy or sell a quantity of a foreign currency at given price in domestic currency on a specific future date. In fact, future exchange contracts are defined as forward exchange contracts that are traded on a public exchange market. The data on future exchange rate between the Mexican peso and the U.S. dollar is accessible from the CME Group through the financial terminal Factset. The use of future exchange rates instead of forward exchange rates does not have an impact on the results of this paper as the main objective of this research is to analyze whether Donald Trumps tweets have any power to create disruptions in the Mexican peso/U.S. dollar currency exchange rate.[11]

The econometric model is given by the following equation:

$$S_{t+1} - S_t = \mu_1 + \beta_1(F_t - S_t) + e_{1,t+1} \tag{2}$$

Here, $e_{1,t+1} \sim N(0, \sigma^2)$

This basic version is estimated by the ordinary least squares (OLS) model that assumes that the expected value of the squared error terms is the same at any given point in time.

[11] Cox et al. (1981) stated that forward and future prices follow similar paths, which supported Cornell and Reinganum (1985) finding that the mean differences between forward and future exchange rates are not economically and statistically significant.

This assumption is known as homoskedasticity and it is tested later in our research. We use this model because it presents an easy and straightforward way to study the relationship between the future-spot differential and the daily difference in the exchange rate.

The results are presented in Table 2. We expect to find that changes in the future-spot differential are equivalent to fluctuations in the daily change of the spot exchange rate. Our results show this feature, as the coefficient on the future-spot differential $\hat{\beta}_1$ is 0.687. The adjusted R-squared is 0.133 and the log-likelihood is 1464.442. The main contribution of this model is to show that the future exchange rate observed at time t has information on the spot exchange rate observed at time $t+1$. However, some of the potential issues of this model are given by the Jarque Bera (JB) test in which we reject the null hypothesis that the residuals follow a normal distribution. Also, by the Durbin-Watson test that is equal to 1.551, which shows the existence of 1st-order autocorrelation in the residuals.

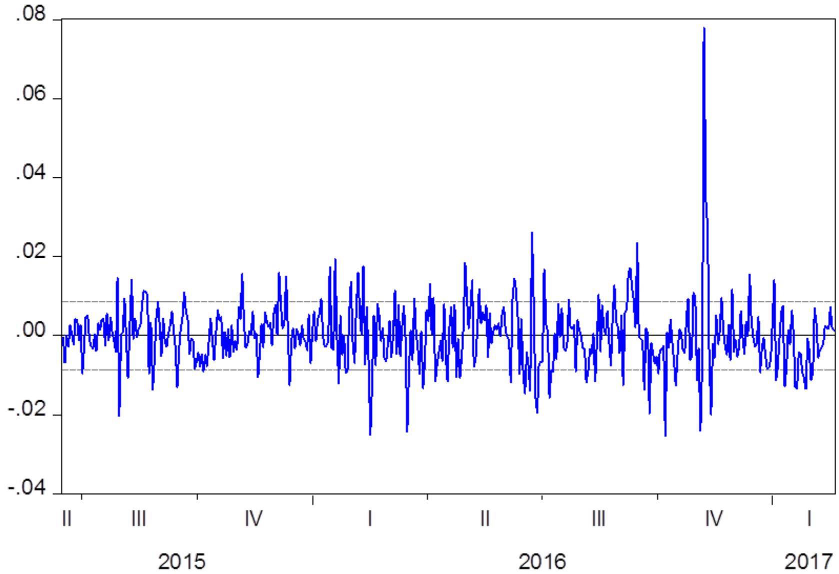
Table 2: Ordinary Least Squares - Equation (2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
μ_1	-0.002417	0.000555	-4.353311	0.0000
$F_t - S_t$	0.687123	0.082941	8.284534	0.0000
Adjusted R-squared	0.133496	Akaike info criterion		-6.647462
Log likelihood	1464.442	Schwarz criterion		-6.628886
F-statistic	68.63351	Durbin-Watson stat		1.551386
Prob(F-statistic)	0.000000	Jarque-Bera test		4308.870
Heteroskedasticity Test: ARCH - 4 lags				
F-statistic	6.598629	Prob.F(4,431)		0.0000

Note: Dependent Variable: $S_{t+1} - S_t$. Sample (adjusted): 16/06/2015-20/02/2017. Included observations: 440 after adjustments.

We also plot the residuals in Figure 2. The figure shows some "volatility clustering" which is the tendency of large (small) fluctuations in exchange rates to be followed by large (small) fluctuations in exchange rates (Mandelbrot, 1963). This feature that can be capture by ARCH/GARCH processes as this volatility is dependent on past realizations and past volatilities.

Figure 2: OLS residuals $(S_{t+1} - S_t)$



In Table 2, we show the results of a test for ARCH effects that includes 4 lags. Engle (1982) proposed this test to assess whether a series of residuals exhibit conditional heteroskedasticity in a time series data. The results of Table 2 indicate the presence of ARCH effects as we strongly reject the null hypothesis that no ARCH effects are present, therefore the results of the OLS model contain some bias. Baillie and Bollerslev (1989) showed that ARCH/GARCH effects are strongly statistically significant on daily exchange rate data. Therefore, we proceed to estimate first an ARCH process and then a GARCH process in order to improve the results of the OLS model.

The ARCH process allows the conditional variance of the error term to depend on the past values of the squared residuals, and its main role is to model volatility. Engle and Bollerslev (1986) showed that one of the main features of the foreign exchange market is its time-varying volatility. As a result, we estimate an ARCH(1) model which is given by the conditional mean equation, which describes how the daily change in the level of the exchange rate varies over time:

$$S_{t+1} - S_t = \mu + \beta_t(F_t - S_t) + \varepsilon_t \tag{3}$$

Here, $\varepsilon_t \sim N(0, \sigma^2{}_t)$

The conditional variance equation of the ARCH(1) is given by:

$$\hat{\sigma}^2{}_t = \alpha_0 + \alpha_1 \hat{\varepsilon}^2{}_{t-1} \tag{4}$$

Results are presented in Table 3. They show that the ARCH process is a better fit than the OLS model because of its higher log-likelihood value and because of its smaller Akaike and Schwarz criterion.[12] The results from the mean equation show that the estimated $\hat{\mu}$ is -0.0025 and that the coefficient of the future-spot differential $\hat{\beta}_t$ is 0.716. Both coefficients are statistically significant at the 1% confidence level. The results from the variance equation show that $\hat{\varepsilon}^2{}_{t-1}$ is 0.078, but is not statistically significant at the 10% confidence level.

The results of the Heteroskecasticity test using 4 lags show that we do not reject the hypothesis that there is no ARCH effects at the 10% confidence level. However, other model diagnostics show that this model is still not adequate on many levels. For instance, there is still evidence of 1st-order autocorrelation which is explained by the Durbin-Watson test, the adjusted R-squared is still small and the JB test rejects the assumption that the residuals follow a normal distribution.

[12] The Akaike information criterion (AIC) and Schwarz criterion, also known as Bayesian information criterion (BIC), provide means for selecting the best model relative to other models based on the likelihood function. The model with the lowest information criterion is the one that fits better the data (Brooks, 2014)

Table 3: ARCH process - Equations (3) and (4)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
μ	-0.002538	0.000543	-4.670023	0.0000
$F_t - S_t$	0.716185	0.078885	9.078805	0.0000
		Variance Equation		
α_0	$6.81E-05$	$2.64E-06$	25.80168	0.0000
${\varepsilon^2}_{t-1}$	0.078455	0.050627	1.549683	0.1212
Adjusted R-squared	0.133252	Akaike info criterion		-6.671581
Log likelihood	1471.748	Schwarz criterion		-6.634428
Durbin-Watson stat	1.544147	Jarque-Bera test		5241.790
Heteroskedasticity Test: ARCH - 4 lags				
F-statistic	2.046325	Prob.F(4,431)		0.0870

Note: Dependent Variable: $S_{t+1} - S_t$. Convergence achieved after 13 iterations. Coefficient covariance computed using outer product of gradients. Presample variance: backcast (parameter = 0.7). Sample (adjusted): 16/06/2015-20/02/2017. Included observations: 440 after adjustments

Given these issues and as changes in volatility do not necessarily happen at particular times, we estimate a GARCH(1,1) process studied by Bollerslev (1986) to model the stochastic daily exchange rate volatility between the Mexican peso and U.S. dollar. The GARCH(1,1) model is useful because of its simplicity and great explanatory predictive power compared to the ARCH process. According to Akgiray (1989), the GARCH process is superior for forecasting exchange rate volatility in high frequency data.

One main characteristic of the GARCH process is that allows the conditional variance of the error term to depend on the past values of the conditional variance and also on past values of the squared residuals. Similarly to the ARCH(1) model, the conditional mean equation which describes how the daily change in the level of the exchange rate varies over time is given by equation (3) where $\varepsilon_t \sim N(0, {\sigma^2}_t)$. Nevertheless, the conditional variance equation of the GARCH(1,1) is given by:

$$\hat{\sigma}^2{}_t = \alpha_0 + \alpha_1 \hat{\varepsilon}^2{}_{t-1} + \phi \hat{\sigma}^2{}_{t-1} \tag{5}$$

This conditional variance $\sigma^2{}_t$ varies over time. By contrast, the unconditional variance of ε_t is time invariant and as long as $\alpha_1 + \phi < 1$ the unconditional variance is given by:

$var(\varepsilon_t) = \frac{\alpha_0}{1-(\alpha_1+\phi)}$

If $\alpha_1 + \phi \geq 1$, then the unconditional variance of ε_t is not defined which is known as "non-stationary in variance".

If $\alpha_1 + \phi = 1$, then this is known as "unit root in variance" or "Integrated GARCH".

Given the normality assumption for the errors, the maximization of the log-likelihood function of the GARCH(1,1) is

$maxL(\mu, \beta_t, \sigma^2{}_t) = -\frac{T}{2} - \frac{1}{2}\sum_{t=1}^{T} log(\sigma^2{}_t) - \frac{1}{2}\sum_{t=1}^{T} \frac{(S_{t+1}-S_t-\mu-\beta_t(F_t-S_t))^2}{\sigma^2{}_t}$

This equation is used to estimate recursively the parameters of the GARCH(1,1) and to construct their standard errors.

The basic GARCH(1,1) results from Table 4 show that it takes 20 iterations to maximize the likelihood function. The mean equation shows that the intercept coefficient μ is -0.003 and the future-spot differential $F_t - S_t$ is 0.766. Both variables are statistically significant at 1%.This model also shows that the future exchange rate from time t has information about the spot exchange rate observed at time $t+1$. According to the EMH, all relevant information are instantaneously included in the foreign currency exchange market, consequently fluctuations in the exchange rate are not predictable. The best estimation of tomorrow's exchange rate is the exchange rate of the previous day.

The variance equation of Table 4 shows that the coefficients of the lagged residual squared and lagged variance are 0.234 and 0.684 respectively. Both coefficients are statistically significant at the 1%, confidence level. Also, we notice that these coefficients sump up to a number less than one which is required to have a mean reverting variance process.

The Heteroskedasticity test using 4 lags show that there are no ARCH effects left in our data. The Akaike and Schwarz information criterion are -6.798 and -6.751 which are smaller than the results from the ARCH model and the log-likelihood is 1500.50 which is higher than the log-likelihood from the ARCH model. This implies that the GARCH(1,1) is a better fit to model the Mexican peso/U.S. dollar exchange rate volatility. However, the results of the JB test reject normality of the residuals; consequently, the foreign exchange market is not efficient. Moreover, the Durbin-Watson test shows the presence of 1st-order autocorrelation in the residuals.

Table 4: GARCH process - Equations (3) and (5)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
μ	-0.002562	0.000401	-6.396112	0.0000
$F_t - S_t$	0.766256	0.065559	11.68812	0.0000
Variance Equation				
α_0	$8.04E-06$	$2.92E-06$	2.753648	0.0059
${\varepsilon^2}_{t-1}$	0.234009	0.037096	6.308220	0.0000
${\sigma^2}_{t-1}$	0.684534	0.064057	10.68639	0.0000
Adjusted R-squared	0.131200	Akaike info criterion		-6.797713
Log likelihood	1500.497	Schwarz criterion		-6.751273
Durbin-Watson stat	1.530741	Jarque-Bera test		342.0025
Heteroskedasticity Test: ARCH - 4 lags				
F-statistic	0.878659	Prob.F(4,431)		0.4766

Note: Dependent Variable: $S_{t+1} - S_t$. Convergence achieved after 20 iterations. Coefficient covariance computed using outer product of gradients. Presample variance: backcast (parameter = 0.7). Sample (adjusted): 16/06/2015-20/02/2017. Included observations: 440 after adjustments.

We can now study the impact of the daily Donald Trump's tweets on the Mexican peso/U.S. dollar exchange rate. We extend the GARCH(1,1) process by including an indicator variable called $Neg.tweet$ in the conditional variance equation:

$$\hat{\sigma}^2{}_t = \alpha_0 + \alpha_1 \hat{\varepsilon}^2{}_{t-1} + \phi \hat{\sigma}^2{}_{t-1} + \tau Neg.tweet_t + v_t \tag{6}$$

The $Neg.tweet$ variable takes the value of 1 every time that Donald Trump made a negative comment against Mexico and 0 otherwise. According to our tweets classification, we found that Donald Trump made at least one negative comment against Mexico on 63 days between June 16, 2015 until February 21, 2017.

The results from Table 5 show that it takes 31 iterations to maximize the likelihood function. Similarly to the basic GARCH(1,1), the results from the mean equation show that the intercept coefficient is -0.003 and that the future-spot differential is 0.761. Both variables are statistically significant at 1% which implies that the future exchange rate from time t has important information about the spot exchange rate observed at time t+1. From the variance equation the coefficients of the lagged residual squared and lagged variance are 0.218 and 0.668 respectively. Both coefficients are statistically significant at the 1% confidence level. Also notice that these coefficients sump up to a number less than one which is required to have a mean reverting variance process. The Heteroskedasticity test that includes 4 lags shows that there are no ARCH effects in the residuals.

More importantly, the coefficient of the variable $Neg.tweets_t$ is positive and statistically significant at 5% confidence level. This shows that the negative comments posted in Twitter by Donald Trump have increase the volatility of the Mexican peso/U.S. dollar exchange rate. For every negative comment in Twitter made by Donald Trump the daily volatility of the Mexican peso/U.S. dollar increases by 0.0000171. Consequently, extremely large investments can benefit from selling Mexican pesos that are bought right after Donald Trump posts a negative tweet.

Given our estimates, we construct the conditional daily volatility series and calculate its average, its minimum and its maximum. We then calculate the ratio of the estimate of the negative tweet dummy on these three measures which we express as percentages. We find that Donald Trump negative tweets represent an increase in the average of the daily volatility by 21.6%, the maximum daily volatility by 1.21% and the minimum daily volatility by 96.61%. Higher volatility means higher uncertainty and therefore a bigger risk of losing when making an investment requiring an exchange of currency from Mexican peso to U.S. dollar or the reverse, compared to the risk incurred during the absence of such tweets.

The Akaike and Schwarz information criterion of this model are -6.803 and -6.747 respectively. The Akaike information criterion of this model is smaller than the one from the basic GARCH(1,1) model that does not include the Donald Trump's negative tweets. Moreover, the log-likelihood of this model is 1502.725 which is greater than the basic GARCH(1,1).

Table 5: GARCH process adding negative tweets in the variance equation

Equations (3) and (6)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
μ	-0.002640	0.000436	-6.051556	0.0000
$F_t - S_t$	0.760502	0.069439	10.95214	0.0000
Variance Equation				
α_0	$7.39E-06$	$3.41E-06$	2.166121	0.0303
${\varepsilon^2}_{t-1}$	0.218153	0.040219	5.424197	0.0000
${\sigma^2}_{t-1}$	0.668547	0.071128	9.399189	0.0000
$Neg.tweet_t$	$1.71E-05$	$7.62E-06$	2.238444	0.0252
Adjusted R-squared	0.131822	Akaike info criterion		-6.803297
Log likelihood	1502.725	Schwarz criterion		-6.747568
Durbin-Watson stat	1.532835	Jarque-Bera test		329.7141
Heteroskedasticity Test: ARCH - 4 lags				
F-statistic	1.268948	Prob.F(4,431)		0.2814

Note: Dependent Variable: $S_{t+1} - S_t$. Convergence achieved after 31 iterations. Coefficient covariance computed using outer product of gradients. Presample variance: backcast (parameter = 0.7). Sample (adjusted): 16/06/2015-20/02/2017. Included observations: 440 after adjustments

These results show some evidence that the comments made by Donald Trump in Twitter that we classify as negative do have an impact on the volatility of the Mexican peso/U.S. dollar currency exchange rate. However, the results of the JB test reject normality of the residuals and the Durbin-Watson test shows the presence of 1st-order autocorrelation in the residuals. This could be due to outliers being present in the data. We examine this possibility next in the context of a robustness check.

It has been suggested by the Federal Reserve Bank of Saint Louis[13] that election surprises such as the results of the last U.S. presidential elections, have a large effect on exchange rates. As a result, we conduct a robustness exercise to verify if our results are driven by the American election results or if there is a more systematic effect from the tweets.

Table 6 explores whether the impact of the negative tweets was driven by the results of the American presidential elections as the largest drop in the Mexican value occurred between November 8, 2016 (date of the American presidential elections), and November 11, 2016 (three days after the election's results were official). Between this period, the Mexican peso/U.S. dollar exchange rate jumped from 18.498 to 21.053 Mexican pesos per 1 U.S. dollar. For this robustness check, we constrain our sample to the period before the elections which was between June 16, 2015 and November 7, 2016, to study if the negative tweets made by Donald Trump had an impact on the value of the Mexican peso in terms of American dollars.

The results of the mean equation from Table 6 show that the intercept coefficient is -0.003 and that the future-spot differential is 0.856 which is an improvement compared to the results from Table 5. Both variables are statistically significant at 1% which also implies that the future exchange rate from time t has important information about the spot exchange rate observed at time t+1. From the variance equation the coefficients of the lagged residual squared and lagged variance are -0.0162 (statistically significant at 10% level) and 1.026 (statistically significant at 1% level) respectively.

[13] Refer to: https://www.stlouisfed.org/on-the-economy/2017/march/election-surprises-affected-exchange-rates

More importantly, the coefficient of the variable $Neg.tweets_t$ increases the volatility of the Mexican peso/U.S. dollar exchange rate by 0.00000312 and it is statistically significant at 1% confidence level. We also find that Donald Trump negative tweets increases the average daily volatility by 5.23%, the maximum daily volatility by 32.67% and the minimum daily volatility by 3.3%.

Table 6: GARCH process adding negative tweets in the variance equation

Sample before the American elections results were released. Equations (3) and (6)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
μ	-0.002966	0.000543	-5.466275	0.0000
$F_t - S_t$	0.855662	0.092131	9.287424	0.0000
Variance Equation				
α_0	$6.17E-07$	$5.63E-07$	-1.096890	0.2727
${\varepsilon^2}_{t-1}$	-0.016183	0.008402	-1.926080	0.0541
${\sigma^2}_{t-1}$	1.026053	0.000124	8283.976	0.0000
$Neg.tweet_t$	$3.12E-06$	$1.20E-06$	2.607815	0.0091
Adjusted R-squared	0.193339	Akaike info criterion		-7.0422259
Log likelihood	991.9163	Schwarz criterion		-6.964371
Durbin-Watson stat	1.698633	Jarque-Bera test		2.481454
Heteroskedasticity Test: ARCH - 4 lags				
F-statistic	2.347746	Prob.F(4,356)		0.0541

Note: Dependent Variable: $S_{t+1} - S_t$. Convergence achieved after 80 iterations. Coefficient covariance computed using outer product of gradients. Presample variance: backcast (parameter = 0.7). Sample: 16/06/2015 to 07/11/2016.

The Akaike and Schwarz information criterion of our model are -7.042 and -6.964 respectively, which are smaller than the results from Table 5 that used the full sample. The main improvement is that the JB test shows that the residuals now follow a normal distribution. The Heteroskedasticity test using 4 lags show that we do not reject the hypothesis that there is no ARCH effects at the 10% confidence level. However, the

Durbin-Watson test still shows the presence of 1st-order autocorrelation in the model. This is likely to be a minor problem since all the other model diagnostics show that our proposed model is well-suited for capturing the uncertainty in exchange rate changes.

7 Conclusion

In this research, we explore whether certain tweets made by the 45th President of the United States of America, Donald Trump, that contained specific information about American foreign policy that targeted Mexico have an impact on the daily currency exchange rate between the Mexican peso and the U.S. dollar. Using a GARCH model including a dummy variable for negative tweets, we show that fluctuations between the Mexican peso/U.S. dollar exchange are not only influenced by past changes in the foreign exchange rate, but also by Donald Trump daily negative tweets.

Our research is just a brief introduction to the study of how the comments in social networks of certain political leaders such as Donald Trump have an impact on people's expectations that creates market uncertainties that can lead to arbitrage opportunities. As social networks keep rapidly increasing their popularity, it will be interesting to see how the diffusion of information through them impact people's and market's behavior.

8 Annex

Figure 3: Daily amount of Donald Trump tweets

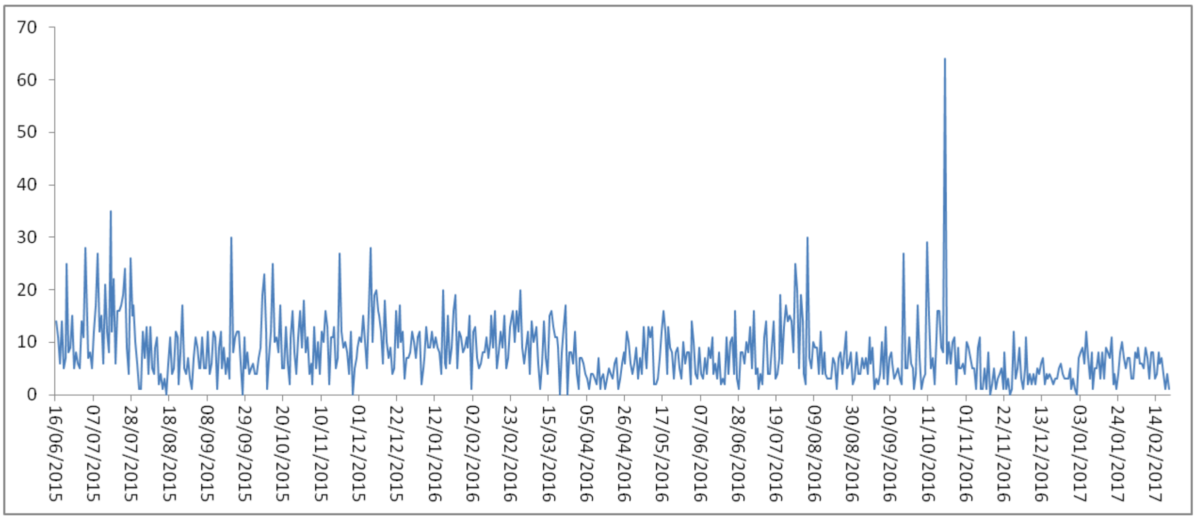


Table 7: Tweets classified as negative

Date	Tweet
22/06/2015	Mexico is killing the United States economically because their leaders and negotiators are FAR smarter than ours. But nobody beats Trump!
25/06/2015	I love Mexico but not the unfair trade deals that the US so stupidly makes with them. Really bad for US jobs, only good for Mexico.
26/06/2015	Anyone who wants strong borders and good trade deals for the US should boycott @Univision.
29/06/2015	Only very stupid people think that the United States is making good trade deals with Mexico.Mexico is killing us at the border and at trade!
30/06/2015	I love the Mexican people, but Mexico is not our friend. They're killing us at the border and they're killing us on jobs and trade. FIGHT!
03/07/2015	Mexican leaders and negotiators are much tougher and smarter than those of the U.S. Mexico is killing us on jobs and trade. WAKE UP!
06/07/2015	I said simply that the Mexican leaders and negotiators are smarter than ours and that the Mexican gov't is pushing their hard core to U.S.
13/07/2015	Mexico's biggest drug lord escapes from jail. Unbelievable corruption and USA is paying the price. I told you so!
14/07/2015	Mexicos totally corrupt govt looks horrible with El Chapos escapetotally corrupt. U.S. paid them $3 billion.
21/07/2015	This story is no longer about John McCain, its about our horribly treated vets. Illegals are treated better than our wonderful veterans.
22/07/2015	Rick Perry did an absolutely horrible job of securing the border. He should be ashamed of himself. Gov. Abbott has since been terrific.
27/07/2015	"@gpavlik7 1/2 of new California drivers licenses go to undocumented immigrants. Read the Sac' Bee, July 17th. Go get'em, Trump!"
28/07/2015	We must build a wall to secure our border. It will save lives and help Make America Great Again! https://t.co/u25yI5T7E8
29/07/2015	A nation WITHOUT BORDERS is not a nation at all. We must have a wall. The rule of law matters. Jeb just doesnt get it.
11/08/2015	Again, illegal immigrant is charged with the fatal bludgeoning of a wonderful and loved 64 year old woman. Get them out and build a WALL!
21/08/2015	We are going to make our country so strong again, so great again. No more ripping off the United States. We will MAKE AMERICA GREAT AGAIN!
25/08/2015	Jeb Bush just talked about my border proposal to build a "fence." It's not a fence, Jeb, it's a WALL, and there's a BIG difference!

Date	Tweet
31/08/2015	For those that dont think a wall (fence) works, why dont they suggest taking down the fence around the White House? Foolish people!
28/09/2015	Marco Rubio is a member of the Gang Of Eight or, very weak on stopping illegal immigration. Only changed when poll numbers crashed.
26/10/2015	Word is that Ford Motor, because of my constant badgering at packed events, is going to cancel their deal to go to Mexico and stay in U.S.
12/11/2015	We, as a country, either have borders or we don't. IF WE DON'T HAVE BORDERS, WE DON'T HAVE A COUNTRY!
01/12/2015	Jamiel Shaw was incredible on @foxandfriends this morning. His son, who was viciously killed by an illegal immigrant, is so proud of pop!
02/12/2015	Illegal immigrant children, non-Mexicans surge across border at record rate https://t.co/V6TP55dRAC
10/12/2015	Our VISA system is broken, like so much else in our country. We better get it fixed really fast. MAKE AMERICA GREAT AGAIN!
07/01/2016	Man shot inside Paris police station. Just announced that terror threat is at highest level. Germany is a total mess-big crime. GET SMART!
14/01/2016	United States looks more and more like a paper tiger. Won't be that way if I win!
26/01/2016	Obama's deal vs. Trump's deals- https://t.co/UpQ3LkUUpm
08/02/2016	The New Hampshire drug epidemic must stop. If elected POTUS-I will create borders & the drugs will stop pouring in. https://t.co/YdEnhqdTbS
10/02/2016	We will stop heroin and other drugs from coming into New Hampshire from our open southern border. We will build a WALL and have security.
15/02/2016	Now an additional 600-700 jobs in America (2,000) being eliminated for move to Mexico- via Hartford Courant. https://t.co/bOIYQLqGRG
15/03/2016	North Carolina lost 300,000 manufacturing jobs and Ohio lost 400,000 since 2000. Going to Mexico etc. NO MORE IF I WIN, WE WILL BRING BACK!
23/03/2016	Watch this clip from earlier this year. Time & time again I have been right about terrorism. Its time to get tough! https://t.co/8mnY3GFRzw
24/03/2016	It is amazing how often I am right, only to be criticized by the media. Illegal immigration, take the oil, build the wall, Muslims, NATO!
28/03/2016	Nobody will protect our Nation like Donald J. Trump. Our military will be greatly strengthened and our borders will be strong. Illegals out!

Date	Tweet
04/04/2016	We must build a great wall between Mexico and the United States! https://t.co/05SjuRJFbf
02/05/2016	Everybody is talking about the protesters burning the American flags and proudly waving Mexican flags. I want America First - so do voters!
25/05/2016	The protesters in New Mexico were thugs who were flying the Mexican flag. The rally inside was big and beautiful, but outside, criminals!
31/08/2016	Former President Vicente Fox, who is railing against my visit to Mexico today, also invited me when he apologized for using the ”f bomb.”
01/09/2016	Mexico will pay for the wall!
08/09/2016	Mexico has lost a brilliant finance minister and wonderful man who I know is highly respected by President Pea Nieto.
20/10/2016	Drugs are pouring into this country. If we have no border, we have no country. Thats why ICE endorsed me. #Debate #BigLeagueTruth
08/11/2016	TODAY WE MAKE AMERICA GREAT AGAIN!
09/11/2016	Watching the returns at 9:45pm.
10/11/2016	Such a beautiful and important evening! The forgotten man and woman will never be forgotten again. We will all come together as never before
18/11/2016	Just got a call from my friend Bill Ford, Chairman of Ford, who advised me that he will be keeping the Lincoln plant in Kentucky - no Mexico
03/01/2017	General Motors is sending Mexican made model of Chevy Cruze to U.S. car dealers-tax free across border. Make in U.S.A.or pay big border tax!
04/01/2017	Thank you to Ford for scrapping a new plant in Mexico and creating 700 new jobs in the U.S. This is just the beginning - much more to follow
09/01/2017	Dishonest media says Mexico won't be paying for the wall if they pay a little later so the wall can be built more quickly. Media is fake!
10/01/2017	Ford said last week that it will expand in Michigan and U.S. Instead of building a BILLION dollar plant in Mexico. Thank you Ford & Fiat C!
26/01/2017	The U.S. has a 60 billion dollar trade deficit with Mexico. It has been a one-sided deal from the beginning of NAFTA with massive numbers...
27/01/2017	Mexico has taken advantage of the U.S. for long enough. Massive trade deficits & little help on the very weak border must change, NOW!
30/01/2017	There is nothing nice about searching for terrorists before they can enter our country. This was a big part of my campaign. Study the world!
13/02/2017	The crackdown on illegal criminals is merely the keeping of my campaign promise. Gang members, drug dealers & others are being removed!

Source: Donald Trump official Twitter account (@RealDonaldTrump). Tweets are presented as they appear on Twitter. Capitalization is attributed to Donald Trump.

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