Does the @realDonaldTrump Really Matter to Financial Markets?[*]

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Abstract: Does the @realDonaldTrump really matter to financial markets? Research shows that new information about the likely future policy direction of government affects financial markets. In contrast, we argue that new information can also arise about the likely future government's resolve in following through with its policy goals, affecting financial markets as well. We test our argument using data on US president Donald J. Trump's Mexico-related policy tweets and the US dollar/Mexican peso exchange rate. We find that Trump's Mexico-related tweets raised Mexican peso volatility while his policy views were unknown as well as thereafter, as they signaled his resolve in carrying out his Mexico-related agenda. By helping politicians disseminate policy information to voters and voters hold governments accountable for their policy performance, social media allows investors to gather information about the likely policy direction and policy resolve of government, especially those of newcomers whose direction and resolve are unknown.

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Does the @realDonaldTrump really matter to financial markets? Anecdotal evidence suggests that economic policy statements made by US President Donald J. Trump via microblogging website Twitter have the power to rattle financial markets. As one market analyst notes, it is "important for market participants to be aware of the potential for increased volatilities facing individual equities related to a [Trump] Twitter release."[1] As another observes, "[w]ith Trump's approach to governance via Twitter, it's no wonder that [currency market] volatility has increased."[2] Yet, other analysts claim that Trump's economic policy tweets have no impact on financial markets, with asset price values and volatility reflecting information about economic fundamentals rather than Trump's Twitter feed. Some even note that firms targeted in his tweets often outperform their markets.[3]

While market analysts present two contrasting views about the impact of Trump's economic policy tweets on financial markets, the academic literature suggests that his tweets should not matter to investors. Financial economists argue that financial markets are efficient, with asset prices reflecting all publicly available information (Fama 1970, 1991). Political economists build on this to suggest that only new and unanticipated information about the future political and economic policy direction of government should affect investors' views about the future value of their assets (e.g., Garfinkel, Glazer and Lee 1999; Freeman, Hays and Stix 2000; Pantzalis, Stangeland and Turtle 2000; Bernhard and Leblang 2006; Leblang and Bernhard 2006; Fowler 2006; Mosley and Singer 2008; Bechtel 2009; Sattler 2013). By this logic, Trump's economic policy tweets should have only mattered to financial markets while his policy agenda was unknown; once the direction of his economic policy views were clear, his tweets would not have provided any new information to investors, leaving financial markets untouched.

Yet, research also clarifies the conditions under which news about the likely future political orientation of government affects financial markets, suggesting another way that Trump's economic policy tweets might matter. Distinguishing politicians' policy agenda

[1]https://www.fxcm.com/insights/president-trumps-twitter-impact-forex-markets-stocks/.
[2]https://www.bloomberg.com/news/articles/2017-04-28/fx-traders-finding-trump-s-first-100-days-are-good-for-business.
[3]http://www.wsj.com/graphics/trump-market-tweets/.

from policy capacity, scholars argue that news about the likely future policy direction of government triggers stronger financial market reactions when governments enjoy greater political institutional capacity to implement policy change (Bernhard and Leblang 2006; Fowler 2006; Bechtel 2009; Sattler 2013; Freeman, Hays and Stix 2000; Mosley and Singer 2008). In a distinct line of study, scholars argue that news about the likely future political orientation of government triggers stronger investor reactions when it concerns lesser-known non-incumbent candidates or political newcomers (Bernhard and Leblang 2006; Jensen and Schmith 2005; Fowler 2006). The policy pledges of newcomers are less credible than those of incumbent candidates and experienced politicians, who have previously revealed their policy preferences and willingness to follow through when in office (Jensen and Schmith 2005; Fowler 2006).

Yet, this last line of research treats politicians' expected policy direction and policy credibility as interchangeable, two things that we argue should be treated as distinct. It is possible for both newcomer and seasoned politicians to clarify their economic policy goals and shift in their resolve to follow them through. With this in mind, we introduce two theoretical innovations. First, we disentangle investors' concern with the likely economic policy direction of government from their concern with its likely economic policy resolve. Second, we allow both policy direction and policy resolve to vary with new information. We argue that, just as new and unanticipated information about the policy direction of government affects investors' views about the future value of their assets, so too does news about the resolve of government to carry out its stated economic policy goals. By our logic, Trump's economic policy tweets would have mattered to financial markets before his economic policy agenda was known—as investors adjusted their holdings to news about his policy views—as well as after his policy agenda was clear—as investors adjusted to news about his likely resolve in following through.

We test our argument by examining the impact of Trump's Mexico-related policy tweets on the US dollar–Mexican peso (USD/MXN) exchange rate. This data is ideal for three reasons. First, Trump was a newcomer to national US politics, raising the chances that his economic policy statements contained new information about his economic policy views and his economic policy resolve. Second, during the period under examination (January 2015 to February 2018), Trump restated what are clearly negative views about the effect of the cross-border movement of people and production between the US and Mexico on the US economy. Third, Trump frequently expressed his Mexico-related policy views via Twitter. Politicians use social media to disseminate policy news, establish issue positions, and engage in national policy debates (Gainous and Wagner 2013; Kreiss 2016; Stier et al. 2018), forcing traditional media outlets to respond to (rather drive reports of) politicians' policy views. It is the speed through which social media transmits information directly from politicians to voters (Gainous and Wagner 2013) that we argue raises its value to investors seeking timely, market-relevant news.

If investors only respond to news about the likely future economic policy direction of government, then Trump's Mexico-related policy tweets should have affected the USD/MXN exchange rate early in his campaign, before his Mexico-related agenda became clear. If, as we argue, investors respond to news about both the future economic policy direction and the future policy resolve of government, Trump's Mexico-related tweets would have affected the exchange rate both before and after his Mexico-related policy views were known. Analysis of daily USD/MXN exchange rates shows that Trump's Mexico-related policy tweets mattered to financial markets in both periods, in line with our argument. In making this argument, we contribute to research on politics and financial markets by revealing that two types of economic policy information matter to investors: information about likely government policy direction and information about likely government policy resolve. Although we focus on a political newcomer to make this point, incumbent candidates and experienced politicians can also surprise investors with shifts in policy preferences and in their resolve in following through. As such, we argue that investors will seek out news about all potential future and current governments' likely future policy direction and policy resolve, regardless of the level of experience of the politicians in them.

Two Arguments About Government Economic Policy Information and Financial Markets

Information about Economic Policy Direction

The (semi-strong form) Efficient Markets Hypothesis (EMH) states that asset prices reflect all publicly available information, including historic prices and any additional relevant publicly available information (Fama 1970, 1991; Bernhard and Leblang 2006). Scholars have interpreted this to mean that new and unanticipated information about the likely future political orientation—and thus economic policy direction—of government leads investors to adjust their expectations about the future value of their holdings. Known and anticipated information leaves financial markets untouched (Bernhard and Leblang 2006).

Empirical evidence—often based on highly disaggregated (daily, hourly) time series data—supports this view (Freeman, Hays and Stix 2000; Leblang and Mukherjee 2004, 2005; Bernhard and Leblang 2006; Leblang and Bernhard 2006; Goodell and Vähämaa 2013; Kelly, Pástor and Vernonesi 2016). Cross-national time-series analyses of highly aggregated data (monthly, quarterly) also indicate that government selection periods produce greater financial market volatility (Garfinkel, Glazer and Lee 1999; Pantzalis, Stangeland and Turtle 2000; Bernhard and Leblang 2006; Fowler 2006; Białkowski, Gottschalk and Wisniewski 2008; Bechtel 2009; Boutchkova et al. 2012; Frot and Santiso 2013; Waisman, Ye and Zhu 2015). It is during these periods that news tends to arrive about the likely future economic policy direction of government, raising the frequency and magnitude of investor adjustment.[4] By this logic, news about the likely future economic policy direction of government will affect investors' views about the value of their assets.

[4] News also arises during cabinet changes (Leblang and Bernhard 2006; Bernhard and Leblang 2008; Kelly, Pástor and Vernonesi 2016).

Information about Economic Policy Resolve

Yet, a related line of research shows that news about the future political orientation of government triggers stronger financial market reactions when governments enjoy greater political capacity to implement policy change. Fewer veto players—as a result of majority or unified government (Bernhard and Leblang 2006; Fowler 2006; Bechtel 2009; Sattler 2013)—and weaker regulatory frameworks—as a result of weak monetary policy commitment or shareholder protections (Freeman, Hays and Stix 2000; Mosley and Singer 2008)—produce greater volatility during and after government selection. For these scholars, the impact of news about the likely future economic policy direction of government on financial markets is distinct from news about their political capacity to follow through. In another, related line of work, scholars argue that news about the likely future political orientation of government triggers stronger investor reactions when it concerns lesser-known non-incumbent candidates or political newcomers (Bernhard and Leblang 2006; Jensen and Schmith 2005; Fowler 2006). For these scholars, the economic policy promises of newcomers are less credible, that is, less likely to be implemented—and their governments thus more uncertain and risky for investors—than those of experienced politicians who have already revealed their policy agenda and demonstrated their resolve in following through when in office (Jensen and Schmith 2005; Fowler 2006).

Interestingly, this last line of research treats the likely policy direction and likely policy credibility of government as interchangeable and constant through time. Yet, it is possible for politicians to clarify their policy positions and shift in the credibility of their intention in following through. We argue that a potential future or current government's likely future economic policy goals should be considered separately from its policy resolve. By "policy resolve," we refer to the level of certainty surrounding or strength in a government's intention of following through with its policy goals (Weeks 2008). When governments are resolute, they adhere to their policy goals with precision and implement them to the fullest extent. When they are not resolute, they may deviate in some way or fully renege. We choose the term "policy resolve" for two reasons. First, we seek to capture a politician's intention of following through with her stated policy goals in a way that is conceptually distinct from her stated policy positions, similar to Callander (2008). Second, we seek to distinguish policy resolve from policy salience—the importance a politician places on her policy goals—as well as policy capacity—the political (institutional) capacity of a politician to follow through.

With this in mind, we argue that news can arise both about a government's likely economic policy direction as well as about its likely economic policy resolve, with each affecting investors' views about their assets through distinct causal paths. Research shows that incumbent politicians establish the credibility of their policy agenda and intention of following through by building a reputation for faithfully implementing prior policy promises (Shepsle 1991; Aragonès, Postlewaite and Palfrey 2007). Lesser-known non-incumbents and political newcomers cannot leverage previous policy reputations, but they can signal the credibility of their policy agenda and resolve in following through with publicly-made statements (Aragonès, Postlewaite and Palfrey 2007; Callander 2008). By making clear, precise domestic policy promises, politicians raise the "reputational" costs of deviation by enabling voters to hold them accountable (Aragonès, Postlewaite and Palfrey 2007; Asako 2015). By making clear, progressively stronger foreign policy promises, incumbent governments raise the domestic "audience" costs of backing down (Fearon 1994; Tomz 2007; Weeks 2008).[5] Even if such domestic and foreign policy promises are not binding—as they do not disable future policy discretion (Shepsle 1991)—they create a benchmark against which politicians' future policy performance can be compared (Fearon 1994; Aragonès, Postlewaite and Palfrey 2007; Tomz 2007; Weeks 2008), and thereby act as a signal of their policy resolve in following through.

Building on this logic, we thus argue that, just as politicians' economic policy statements initially provide information to investors about the likely future economic policy direction of government, these same economic policy statements continue to provide in-

[5]Because voters pay attention to politicians' (domestic and foreign) policy promises and punish them for deviation, such reputational or audience costs should be of concern to politicians (Tomz 2007; Naurin, Soroka and Markwat 2019). Voters more harshly judge the deviation of politicians whose policy agenda (direction) is closest to their own (Naurin, Soroka and Markwat 2019) and whose escalation (resolve) seemed greatest (Tomz 2007).

vestors with incremental evidence of the sincerity of politicians' intentions of following through once their policy views are known. It is in solidifying this benchmark—against which their future policy implementation can be compared—that politicians signal their economic policy resolve to investors. In response, investors update their expectations about the future value of their assets to both types of economic policy news, affecting financial markets in turn. New and unanticipated statements revealing the potential economic policy orientation of government as well as new and unanticipated statements signaling the potential economic policy resolve of government (once its policy views are known) should therefore matter to investors. In making this argument, we extend traditional applications of the EMH in two ways. First, we extend it from news about economic policy direction to news about economic policy resolve. Second, we clarify the role of politicians' economic policy statements in providing information about policy direction as well as policy resolve.

Empirical Strategy: Trump's Mexico-Related Tweets and Mexican Peso Volatility

Why Examine Trump's Mexico-Related Tweets?

We evaluate support for our argument through an examination of Trump's Mexico-related policy tweets and US dollar/Mexican peso (USD/MXN) exchange rate volatility. We choose this focus for several reasons.

Trump was a newcomer to the US national political arena, raising the chances that his economic policy statements contained new information about his policy views and resolve in following through. Testing our argument would be difficult using data on seasoned politicians whose economic policy statements might be devoid of news about their policy agenda or resolve.

Trump's Mexico-related policy agenda was consistently negative for the Mexican economy. On immigration, Trump stated: "When Mexico sends its people, they're not sending their best...I will immediately terminate President Obama's illegal executive order on immigration..." On the border: "I will build a great, great wall on our southern border..." On jobs: "I'll bring back our jobs...from Mexico..."[6] On economic cooperation, "I intend to immediately renegotiate the terms of that (NAFTA) agreement to get a better deal...If they do not agree...America intends to withdraw from the deal."[7] Testing our argument would be difficult using data from politicians making only vague policy statements.

Trump's capacity to enact his Mexico-related policy agenda was unequivocal. A border wall needs congressional funding but increased patrols and deportations need only presidential orders to the Department of Homeland Security (Noland et al. 2016). Under NAFTA, the president need only proclaim the return of Mexico to "Most Favored Nation" status and can raise duties in consultation with Congress. The president also enjoys other executive tools to justify tariffs or quotas (Noland et al. 2016). Testing our argument would be difficult using data from political contexts preventing policy change.

Trump regularly stated his Mexico-related policy goals via Twitter, sending over 400 Mexico-related policy tweets from 1 January 2015 to 2 February 2018, the period we examine. Market analysts often noted that these tweets rattled the Mexican peso market. For example, a January 2017 border wall tweet ("Big day planned on NATIONAL SECURITY tomorrow...we will build a wall.")[8] and two August 2017 NAFTA tweets (NAFTA is the "worst trade deal ever made") were thought to have sent the peso tumbling.[9] Testing our argument would be difficult using economic policy statements disseminated via traditional media, since such reporting likely responds to Trump's Twitter feed.

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[6]http://time.com/3923128/donald-trump-announcement-speech/.

[7]https://assets.donaldjtrump.com/DJT_DeclaringAmericanEconomicIndependence.pdf.

[8]http://www.independent.co.uk/news/business/news/donald-trump-mexican-peso-value-weaken-mexico-border-wall-comment-us-president-currency-us-dollar-a7544951.html.

[9]https://www.cnbc.com/2017/08/28/reuters-america-emerging-markets-mexico-peso-tumbles-as-trump-renews-nafta-threats.html.

Why Examine Mexican Peso Volatility?

We examine the impact of Trump's Mexico-related tweets on USD/MXN exchange rate volatility, not value. Financial economists have difficulty forecasting exchange rate values due to investor heterogeneity (Lyons 2001; Dominguez and Panthaki 2006; Cheung et al. 2018). Currency investors often hold different expectations about the impact of the same political and economic news on their holdings (Lyons 2001). They also often differ in their trading strategies in response. Technicals-oriented traders—driven by short-term price history—buy (sell) while fundamentals-oriented investors (driven by long-term economic fundamentals) sell (buy) when asset prices rise (fall) (Lyons 2001). Currency investors also differ in their portfolio strategies (Glen and Jorion 1993); some hold currencies for speculative purposes, but others for managing currency exposure in other assets (Campbell, Medeiros and Viceira 2010). Whether news translates into currency price shifts often depends on the balance among heterogeneous investors at that point in time (Dominguez and Panthaki 2006; Cheung et al. 2018).

Investor heterogeneity is relevant for the Mexican peso. Even though many currency investors are guided by Mexico's macroeconomic fundamentals, others with heterogeneous trading and portfolio strategies confound the impact of news on peso value (Sidaoui, Ramos-Francia and Cuadra 2011; García-Verdú and Zerecero 2014). Further complicating forecasts, the Mexican peso is one of three emerging market currencies (with the South African Rand and the Turkish Lira) traded 24 hours a day, five days a week, and plays a crucial role in expressing concern about emerging markets. Instead of trading in or out of emerging market assets, many investors take long (optimistic) or short (pessimistic) positions on the Mexican peso to hedge local currency exposure.[10]

Even so, the arrival of political and economic news raises currency volatility, precisely because of investor heterogeneity. Currency volatility reflects the bounds around which some investors anticipate appreciation and others depreciation of a currency, with greater volatility capturing greater dispersion and greater market uncertainty. News that

[10]https://www.cnbc.com/2017/03/03/trumps-fallout-effect-on-the-mexican-peso.html.

simultaneously reinforces some investors' optimistic and other investors' pessimistic views about future currency prices leads them to reevaluate their reserve prices and to buy and sell currencies, respectively (Epps 1975; Tauchen and Pitts 1983), raising trading volume and price volatility (Dominguez and Panthaki 2006; Bauwens, Rime and Sucarrat 2008).[11] Traders' activities also provide currency dealers with private information about these views, triggering additional trading and volatility (Dominguez and Panthaki 2006; Bauwens, Rime and Sucarrat 2008). Investors' heterogeneous trading and portfolio strategies in response to news further raises trading volume and volatility. We thus expect news about Trump's economic policy direction and resolve to affect USD/MXN exchange rate volatility, even if we do not expect it to affect exchange rate value (although we allow for this possibility below).

Currency volatility is important for investors and governments. It harms companies when settling foreign transactions, hurting profits and valuations (Papaioannou 2006). It harms international trade and investment, given investors' aversion to currency risk (Guzman, Ocampo and Stiglitz 2018). Excess volatility can lead to speculative currency attacks and devaluations with macroeconomic and distributional effects (Leblang 2002). Firms can hedge currency exposure, but only larger ones enjoy this capacity (Papaioannou 2006). Portfolio investors can hedge as well, but this requires costly planning (Campbell, Medeiros and Viceira 2010). Governments mindful of the impact of currency volatility can intervene, but this depletes foreign reserves and has macroeconomic and distributional consequences (Frieden 2015). Mexican central bank officials complained that Trump's tweets forced them to undertake costly measures to defend the peso, with traders joking that it would be cheaper for them to buy Twitter and shut it down.[12]

[11]Currency volatility can also result from homogenous investors shifting their expectations together, although this is less likely in larger markets.

[12]http://www.reuters.com/article/us-mexico-peso-trump/mexican-central-banker-says-trumps-tweets-modified-peso-strategy-idUSKBN17803N.

How Trump's Tweets Signal Policy Direction

Most prior studies argue that news about the economic policy direction of government affects financial markets, with known and anticipated information having no effect. Accordingly, Trump's Mexico-related policy tweets should have affected the USD/MXN market until he launched his bid for the GOP nomination on 16 June 2015; during this period his views were first being considered.[13] Investors would have examined his tweets for news about his Mexico-related agenda and updated their holdings—however remote the possibility he would win—raising USD/MXN exchange rate volatility. The impact of Trump's Mexico-related policy tweets would have disappeared by the time he launched his GOP bid on 16 June 2015 in a policy speech (and again on 28 June 2015) where he outlined his Mexico-related goals. His Mexico-related tweets would have also provided no new information after his GOP bid launch, after his GOP nomination on 19 July 2016, his election win on 8 November 2016, and his 20 January 2017 inauguration.

We consider the impact of Trump's Mexico-related tweets across these periods because investors might have expected Trump to deploy different policy strategies during the presidential selection process. Models of electoral competition note that primary election voters tend to be staunch party supporters with more extreme policy views, so primary candidates tend to choose more extreme positions to maximize the chances of selection (Burden 2004). General election voters tend to be more moderate, so candidates tend to moderate positions during general elections to maximize their appeal (Burden 2004). Investors' interest in anticipating Trump's most likely economic policy orientation (should he win) would have raised their sensitivity to the fact that he might strategically shift policy positions at different points to maximize support.

However, even if investors anticipated Trump would adopt extreme policy stances during the primary period, the impact of his Mexico-related tweets on the Mexican peso would have remained the same. Because Trump's Mexico-related views remained unchanged, his

[13] It was suspected by early 2015 that Trump was considering a run for president. He had a political team in place in 2013 and chose not to renew his television contract for "The Apprentice" in February 2015. http://www.tvguide.com/news/donald-trump-presidential-campaign-timeline/.

tweets offered no new information during the primary campaign. Even if investors were surprised to find Trump's Mexico-related policy views unchanged after he won the GOP nomination, the impact of his Mexico-related tweets on the USD/MXN exchange rate during this period would have remained largely the same as well. The EMH predicts that investors immediately adjust their holdings to new information, something that would have left the lion's share of Trump's Mexico-related tweets during his four month-long general election campaign devoid of news about his views. Therefore, by the logic of the EMH for news about policy direction, Trump's Mexico-related tweets should have had no discernible impact on the USD/MXN exchange rate during any period after he announced his candidacy (e.g., the GOP primaries, general election period, post-election period, or after he took office). We thus expect (see Table 1):

H1: Donald Trump's Mexico-related policy tweets will raise USD/MXN exchange rate volatility before his 16 July 2015 bid for the GOP presidential nomination, but will have no effect on volatility thereafter.

[**Table 1 about here**]

How Trump's Tweets Signal Policy Resolve

Recent research suggests that information about government economic policy resolve might also matter to investors. We argue that Trump's Mexico-related policy tweets provided news not just about his likely policy direction but also about his likely policy resolve. Our argument is twofold. First, in line with the argument above, Trump's Mexico-related policy tweets would have affected the Mexican peso market in the run-up to his bid for the GOP nomination in June 2015, when his Mexico-related policy views were first becoming known. Second, in contrast to the argument above, we argue that Trump's Mexico-related policy tweets would have affected the USD/MXN exchange rate after his June 2015 campaign launch (i.e., during the GOP nomination, presidential election, and inauguration). After his views were known, Trump's Mexico-related tweets clarified the benchmark against which his future policy performance could be compared. By gradually raising the reputational costs of deviation, Trump's Mexico-related policy tweets progressively raised investors' expectations about his Mexico-related policy resolve, repeatedly raising USD/MXN exchange rate volatility in turn.

It is investors' concern not just with government policy direction but also with its policy resolve that raises their awareness of the potential for strategic policy shifts. If investors anticipated Trump would adopt an extreme policy stance during the primary process, they would not have considered his Mexico-related tweets for news about his policy resolve. Trump's tweets would thus have had no effect on the peso during this period. If investors were later surprised by the lack of moderation of Trump's Mexico-related policy stance after his GOP nomination, they would have immediately adjusted their views in response. Most of Trump's Mexico-related tweets during the sixteen-week general election campaign would have been devoid of any news about his policy position.

However, in contrast to the argument above, we argue that investors seeking information about Trump's Mexico-related policy resolve would have considered his post-GOP nomination tweets for evidence of it, triggering bouts of USD/MXN exchange rate volatility throughout the general election period. Moreover, even though Trump's Mexico-related policy views were well known after his November 2016 election and January 2017 inauguration, his Mexico-related policy tweets would have continued to provide incremental information about his policy resolve during these periods as well, leading to increased exchange rate volatility. Of course, some investors might have believed that Trump sent his Mexico-related policy tweets during these latter two periods to influence Congress (on the border wall or immigration), foreign direct investors (considering operations in Mexico), or the Mexican government (on NAFTA). But it is precisely in anticipation of these negotiations that he would have sought to strengthen the credibility of his policy resolve through repeated, consistent policy statements, leading to USD/MXN exchange rate volatility in the way we argue here. We thus expect (see Table 1):

H2: Donald Trump's Mexico-related policy tweets will raise USD/MXN exchange rate volatility before his 16 July 2015 bid for the GOP presidential nomination, and will raise USD/MXN exchange rate volatility after his 19 July 2016 GOP primary election victory.

Data

Our main dependent variable is the percentage change in the daily USD/MXN exchange rate from 1 January 2015 to 2 February 2018. We transformed the series into the daily percentage change in the USD/MXN exchange rate, such that rising (falling) values reflect the depreciation (appreciation) of the Mexican peso relative to the US dollar. Unit root tests in the Supplemental Information (SI, p. 1) indicate that the dependent variable is stationary. Exchange rate data is available for all days markets are open. All data sources are noted in the SI (p. 1).

Figure 1 plots the raw peso-dollar exchange rate and the transformed % Change Peso. The exchange rate faced periods of substantial volatility, with the most notable spike just after the 2016 US presidential election. We examine USD/MXN exchange rates in nominal rather than real (or other adjusted) rates since investors' short-term currency expectations are based on the former, and research shows that they do not consider purchasing power parity, interest and inflation rate differentials, or productivity when taking currency positions (Cheung and Chinn 2001; Chinn and Quayyum 2012). Mexico's foreign exchange commission (the secretary and two deputy secretaries of the finance ministry, the governor and two subgovernors of the central bank) also bases its interventions (implemented by the central bank) on short-term nominal exchange rates (García-Verdú and Zerecero 2014).

[**Figure 1 about here**]

Our main explanatory variable is the daily presence of a Mexico-related policy tweet. We use information from the Trump Twitter Archive, which archives all tweets sent by @realDonaldTrump on GitHub. Trump sent over 14,500 tweets between 1 January 2015 to 2 February 2018. We searched these tweets for topics related to Trump's Mexico-related policy agenda based on 17 relevant keywords—see Figure 2a—yielding 438 Mexico-related tweets sent on 239 days in our sample. Figure 2a shows the proportion of days when a Mexico-related term was mentioned for each of the 17 keywords. Figure 2b shows the monthly count of keywords. There is a large spike in mid-2015—after Trump announced his bid for the GOP nomination on 16 June 2015—but he regularly sent Mexico-related tweets before, during, and after the US presidential selection process.

[**Figure 2 about here**]

Modeling Strategy

We use generalized autoregressive conditional heteroskedasticity (GARCH) models for our analysis. These have been used to model a variety of political economy applications concerning unanticipated shocks to markets (e.g., Gronke and Brehm 2002; Leblang and Bernhard 2006; Hellwig 2007), although other approaches such as event study designs with synthetic controls are also possible (e.g., Bechtel and Schneider 2010). We rely on the GARCH approach because we are interested in understanding how tweets affect volatility in the USD/MXN exchange rate, while allowing for the possibility that they might affect its value. GARCH models allow us to model both the conditional mean and the conditional error variance as a function of lagged variance, lagged stochastic shocks, and exogenous covariates. Our model appears as:

$$\text{Pct. Peso}_t = \beta_0 + \phi \text{Pct. Peso}_{t-1} + \mathbf{x}\boldsymbol{\beta} + \varepsilon_t + \psi\sigma^2_{t-1} \tag{1}$$

where the dependent variable—the daily percentage change in the USD/MXN exchange rate—is modeled by a constant, its own lag, a vector of exogenous independent variables $\mathbf{x}$, a stochastic error term with mean zero and variance that may be conditional on t: $\varepsilon_t \sim N(0, \sigma^2_t)$, and the lagged error variance itself σ^2_{t-1}, since greater volatility in previous periods may affect current changes in the USD/MXN exchange rate.

We include the following explanatory variables:

- *Tweet Dummy* is a dummy variable equal to one if Trump sent any Mexico-related tweets on a particular day, zero otherwise.

- *Trump Pre-Primary Candidate* is a dummy variable equal to one from 1 January to 15 June 2015, zero otherwise, indicating the days until Trump launched his GOP nomination bid.

- *Trump Primary Candidate* is a dummy variable equal to one from 16 June 2015 to 18 July 2016, zero otherwise, indicating the days during Trump's GOP candidacy until his GOP nomination.

- *Trump GOP Nominee* is a dummy variable equal to one from 19 July 2016 to 8 November 2016, zero otherwise, indicating the days from Trump's GOP nomination through the 8 November presidential election, since the election was decided after the most active trading hours.

- *President-Elect* is a dummy variable equal to one from 9 November 2016 to 20 January 2017, zero otherwise, indicating the period after Trump won the US presidential election until his inauguration.

- *Trump Presidency* is a dummy variable equal to one starting the day after Trump took office on 20 January 2017, zero otherwise, indicating the period under his presidency.

Since the Mexican economy is vulnerable to US political events (Nippani and Arize 2005; Schaub 2017), we include:

- *US Presidential Election* is a dummy variable equal to one on 9 November 2016, the day after the 8 November 2016 US presidential election, zero otherwise. We also include its lag.

- *NAFTA* is a dummy variable equal to one during NAFTA-related events (US public hearings, announced NAFTA negotiations and negotiating objectives, four NAFTA rounds in 2017), zero otherwise.

Since the Mexican peso is susceptible to US and Mexican macroeconomic performance and policy shocks (Nippani and Arize 2005; Schaub 2017), we include:

- *S&P 500*$_{t-1}$ is the lagged percentage change in the US S&P 500 stock market index, capturing shifts in expectations about US economic performance which affect views about the Mexican economy and the USD/MXN exchange rate.[14]

- *Bond Spread*$_{t-1}$ is the lagged percentage change in the 10 year Mexico–US bond spread.

- *Banxico US \$ Sales* is a dummy variable equal to one if Mexico's central bank (at the behest of the foreign exchange commission) offered US dollar auctions or dollar futures contracts that day, zero otherwise.

- $\Delta\ln$(*Banxico US\$ Stock*$_t$) is the change in the log of the Mexican central bank's reported weekly US dollar reserves.

- Δ*Overnight Rate Difference*$_t$ is the difference between the Mexican central bank's overnight interest rate and the US federal funds rate.

GARCH models allow us to account for heteroskedasticity as a function of lagged values of the error and its variance. One of the most common models is a GARCH(1,1):

$$\sigma_t^2 = \omega\varepsilon_{t-1}^2 + \alpha\sigma_{t-1}^2 + exp(\mathbf{z}_t\boldsymbol{\gamma}) \tag{2}$$

where the variance at time t is a function of the previous residual squared ε_{t-1}^2 (the ARCH(1) term, since it shows how previous shocks—such as unanticipated news—affect the variance over time), the lagged variance σ_{t-1}^2 (the GARCH(1) term, since it allows volatility to be persistent across time), and a vector of variables $\mathbf{z}_t$ (including a constant) thought to influence the error variance. GARCH models allow us to examine whether tweets affect exchange rate volatility, while allowing them to affect exchange rate value.

[14]We use this rather than the Mexican stock market index since the two are highly correlated, and vector error-correction models in the SI (pp. 23-25) suggest that the S&P 500 drives the Mexican stock market, rather than the reverse.

Results

We begin the statistical analysis by examining the impact of Trump's Mexico-related tweets (*Tweet Dummy*) on the percent change in the USD/MXN exchange rate, in Table 2, Model 1. We first estimate a dynamic regression with no ARCH effects in Equation 1, where we assume $\varepsilon_t \sim N(0, \sigma_t^2 = \sigma^2)\ \forall\ t$. A Lagrange multiplier test for autoregressive conditional heteroskedasticity rejected the null hypothesis of no ARCH process for up to five lags in Model 1, suggesting that we should use the GARCH approach to relax the assumption that the error variance is constant over time.[15]

[Table 2 about here]

Given that there appear to be periods of low and high volatility in the USD/MXN exchange rate (Figure 1), we next examine the effect of Trump's tweets on the USD/MXN exchange rate using a GARCH(1,1) model that includes one ARCH term ε_{t-1}^2 and one GARCH term σ_{t-1}^2, shown in Table 2, Model 2. For this model (and all others), we ensure that the resulting scaled residuals are white noise using the approach suggested by Enders (2010, p. 150).[16] Recall that we suspect that Trump's tweets will have no impact on the percentage change in the USD/MXN exchange rate (the "mean equation" in Table 2). This is the case: *Tweet Dummy* does not achieve statistical significance in Table 2, Model 2, nor does its lag. The parameter on the lagged dependent variable in the mean equation in Model 2 is positive but not statistically significant, suggesting that there is no persistence in fluctuations in the USD/MXN exchange rate over time.

Importantly, both the ARCH and GARCH terms in Table 2, Model 2 are statistically significant, suggesting that the conditional variance is a function of lagged unanticipated shocks (the ARCH effect), as well as the previous value of the conditional variance (the GARCH effect). The GARCH parameter is closer to one than to zero, suggesting that

[15]The LM statistic was 2.68 (p-value: 0.10), 5.83 (0.054), 27.26 (0.00), 27.23 (0.00), and 27.99 (0.00), for the first five lags, respectively.

[16]This involved calculating the Ljung-Box Q statistic on the residuals—and residuals squared—scaled by the conditional standard deviation to check for remaining autocorrelation and ARCH effects, respectively. All GARCH models fail to reject the null hypothesis of white noise for both tests.

the conditional variance is highly persistent over time and days of high (low) volatility are followed by days of similarly high (low) volatility. The ARCH term also suggests that unanticipated information may affect volatility in the USD/MXN exchange rate. To ascertain whether Trump's Mexico-related tweets affect USD/MXN exchange rate volatility, we next examine their impact on both value and volatility in the USD/MXN exchange rate in Table 2, Model 3. We include dummy variables for the US election cycle periods, as well as two macroeconomic variables—the S&P 500 and 10-year bond spreads—since they might affect volatility as well. The results for the mean equation show that *Tweet Dummy* has no impact on the value of the USD/MXN exchange rate. The results for the variance equation show that *Tweet Dummy* also has no statistically significant effect on conditional variance during the day in which a Mexico-related tweet occurs, at least across the entire sample.

To test the competing hypotheses, however, we must examine the impact of Trump's tweets on the USD/MXN exchange rate by different periods during the government selection process, in order to distinguish periods when investors would have been searching Trump's Mexico-related tweets for information about his policy direction, policy resolve, or neither of the two. We thus add interactions between our dichotomous *Tweet Dummy* variable and each of the US presidential election period dummy variables to both the mean and the variance equations in Table 2, Model 4. In the mean equation, the interaction terms are not statistically significant, as expected, with the exception of the negative coefficient for term capturing the period after Trump became president, suggesting that post-inauguration tweets might have raised peso value.

However, in Table 2, Model 4's variance equation, we observe two time periods during which Trump's Mexico-related tweets drove substantial increases in USD/MXN exchange rate volatility: after Trump secured the GOP nomination and after he was elected US president but before he took office. These are periods during which Trump's policy views would have been widely known. Even so, the coefficients in the variance equation cannot be easily interpreted because they affect variance in multiplicative exponentiated form (see Equation 2). We thus developed a new technique to probe the impact of Trump's tweets on USD/MXN exchange rate volatility based on stochastic simulation methods and created plots of the expected conditional error variance over time. Stochastic simulation methods have been developed to assess statistical and substantive significance of time series models (e.g., Williams and Whitten 2011; Jordan and Philips 2018*a*,*b*) but we are the first to extend this approach to GARCH models. Full details of our innovation are available in the SI (p. 3).

Figure 3 shows the posterior densities of 6000 simulated predictions of the expected conditional error variance over time from Table 2, Model 4, setting all continuous variables to their means and assuming that a tweet occurs on the third day ($t = 3$) and on that day only. During the GOP nominee and president-elect periods—the two periods with positive and significant coefficients in the variance equation—Trump's tweets produced a statistically significant increase in USD/MXN exchange rate volatility, with this effect taking over a week to dissipate thanks to the large GARCH effect. Since variance is strictly positive, the confidence intervals exhibit upward-skew behavior, as can be seen on the fourth day ($t = 4$). Figure 3 thus shows that Trump's Mexico-related tweets raised USD/MXN volatility after he became the GOP nominee and that this volatility continued after he became president-elect, periods when Trump's Mexico-related policy views would have been known to investors.

[**Figure 3 about here**]

Because we argue that repeated, consistent policy promises raise the costs of policy deviation, thereby raising evidence of politicians' policy resolve, we must also show that greater tweet intensity—captured in terms of frequency and tone—leads to greater investor adjustments and greater peso volatility. We thus conduct three additional analyses. First, we create an ordinal tweet variable to capture whether there were none (0), one (1), or two or more (2) tweets in a day.[17] As above, we find no evidence in Table 3, Model 5 that tweets affect exchange rate value or exchange rate volatility across the entire sample. However, in Table 3, Model 6—depicted in Figure 4—we see that there is

[17]Models with additional orders would not converge.

a statistically significant increase in volatility when Trump posts Mexico-related tweets after he became the GOP nominee as well as after he became president-elect, with this effect greatest on days when there were two or more tweets. Figure 4's "Pre-candidate" plot also reveals a small increase in volatility associated with Mexico-related tweets in the pre-primary period, with this effect greatest where there were two or more Mexico-related tweets. Moreover, the increase in volatility takes over a week to dissipate due to the large GARCH term. Greater numbers of Mexico-related tweets thus led to greater USD/MXN exchange rate volatility during periods when Trump's policy views were unclear as well as when they were known.

[**Table 3 about here**]

[**Figure 4 about here**]

Second, we examine "retweets"—when a user reposts a tweet from another source to their followers—and "favorites"—when a user expresses agreement with a tweet from another source, two continuous measures. Retweets averaged 3,700 and favorites 9,860 across the sample (see the SI (pp. 3-4) for time series plots.) Retweets and favorites should matter to peso volatility, since such secondary sources would have provided additional information to investors. Retweets and favorites might also serve as a proxy for the extent to which investors act on Trump's policy tweets. Table 3, Models 7 and 8 show the impact of the log number of retweets of Trump's Mexico-related tweets (i.e., where the tweet variable equals the log of retweets, zero otherwise) on the USD/MXN exchange rate.[18] Table 3, Models 9 and 10 show the impact of favorites of Trump's Mexico-related tweets on the USD/MXN exchange rate.

Using our stochastic simulation technique, Figure 5 presents the expected value of volatility under two scenarios using our continuous retweet measure from Table 3, Model 8. A Mexico-related tweet with the average number of retweets produced substantial increases in volatility during the "GOP Nominee" and "President-Elect" periods. This

[18]If multiple Mexico-related tweets occurred on the same day, we took the average number of retweets.

effect is even stronger among tweets that had retweets in the 90th percentile (about 27,500). Figure 6 shows the results using the continuous favorites measure from Table 3, Model 10. Mexico-related tweets with the average and the 90th percentile (about 111,000) favorites also affected USD/MXN exchange rate volatility after Trump became the "GOP Nominee" and "President-Elect." Economic policy news thus appears to affect financial markets most when investors are paying greatest attention to it.

Figures 5 and 6 also reveal that USD/MXN exchange rate volatility rose in response to retweets and favorites during the "Pre-candidate" period, as found with ordinal tweet intensity. Investors thus updated their views about the possible future direction of Trump's Mexico-related policy in response to his tweets prior to the GOP primaries, although this effect was small because he was still an unlikely contender and unlikely presidential victor at this point. In sum, peso volatility rose in response to greater numbers of Mexico-related retweets and favorites, both before Trump's policy views were known (during the "Pre-Candidate" period)—as investors responded to news about his policy direction—and after (during the "GOP Nominee" and "President-Elect" periods)—as investors responded to news about his policy resolve—in line with our argument.

[**Figure 5 about here**]

[**Figure 6 about here**]

Third, we examine the tone of Trump's Mexico-related tweets. Investors might pay more attention to tweets that are particularly negative. We create a new "Tweet" variable equal to one if the net tone of a tweet is negative, zero otherwise, using the sentiment analysis package `syuzhet` (Jockers 2015).[19] The results in Table 4, Models 11 and 12 are similar to those above: particularly negative tweets raise volatility during the "GOP Nominee" and "President-Elect" periods. We also examine tweets coded as "positive." In contrast to "negative" tweets—which tended to be anti-Mexican—"positive" tweets tended to be pro-US. For example, the 24 February 2015 tweet "The Mexican legal system

[19]We use a dichotomous rather than continuous measure due to convergence issues, although continuous results are available in the SI (pp. 9-11).

is corrupt, as is much of Mexico. Pay me the money that is owed me now–and stop sending criminals over our border" is coded as negative, whereas the 6 June 2015 tweet "Just made the point at #NCGOPcon that we have to protect our border & I think everyone here knows, nobody can build a wall like Trump!" is coded as positive. Table 4, Models 13 and 14 show that tweets with a net positive sentiment affect volatility as above, with nearly the same magnitude. These results are robust to other sentiment codings in the SI (pp. 9-11). Peso volatility thus rose in response to Mexico-related tweets with stronger sentiment, after his policy views were known (during the "GOP Nominee" and "President-Elect" periods), in line with expectations.

[**Table 4 about here**]

Figures 4, 5, and 6 also suggest that, once Trump took office in January 2017, his Mexico-related tweets may have lowered USD/MXN exchange rate volatility, although this effect is not statistically significant. At first glance, this suggests that investors were no longer gathering information about his Mexico-related policy direction or resolve, with both having been established by this time. At second glance, the time period covered (21 January 2016 to 2 February 2018) may be too broad. The impact of Trump's Mexico-related tweets on peso volatility during his presidency may have had different effects, depending on progress in NAFTA rounds with Mexico or budgetary negotiations with Congress on border wall funding. The results also show that the *US Presidential Election* reduced the value of the Mexican peso across all models, although *NAFTA* negotiations had no effect. *Banxico US $ Sales* to defend the peso had no effect, although rising *Overnight Rate Difference* contributed to rising peso value. Neither the *S&P 500* nor the US–Mexico *Bond Spread* appears to have affected Mexican peso value, although they both affected peso volatility (negatively and positively, respectively). The ARCH-in-Mean term is negative and statistically significant across nearly all models, suggesting that increased volatility one day results in a stronger peso the next.

That our different tweet measures produced the same results—including those for the GOP primary interlude where we expected no effect—strengthens our conclusion that investors reacted to Trump's pre-primary tweets as a source of news about his likely policy direction and his post-GOP nominee and post-election tweets as a source of news about his likely policy resolve. Had the competing argument found support, we would have observed only pre-candidate period volatility.

Alternative Arguments and Robustness

The impact of Trump's Mexico-related policy tweets on USD/MXN exchange rate volatility after Trump's official GOP nomination might be due to their role in providing news about his Mexico-related policy goals instead of news about his resolve in seeing them implemented. Yet, Trump's Mexico-related tweets, retweets, and favorites raised USD/MXN exchange rate volatility after his 8 November 2016 election victory. Even if investors had only been informed about Trump's Mexico-related views via Twitter during the US presidential campaign, they would have been fully informed by his presidential victory. The impact of Trump's tweets on peso volatility after the presidential race could only be the result of their role in providing information about his policy resolve. It could also be that the impact of Trump's tweets was driven by irrational, uninformed "noise" traders (Black 1986) reacting to his tweets without consideration of their content. However, that Trump's tweets did not rattle the peso during the GOP primary shows that rational, informed investors dominated the peso market.

There could also be a mismatch between the time tweets are sent and when they are examined by investors. The Mexican peso is traded from Sunday 5:00PM Eastern Standard Time (EST) to Friday 5:00PM EST, but most trades occur during New York and London market hours. If Trump tweets after these markets close, they may impact USD/MXN volatility the next day. We deploy two additional tweet codings in Table 5. Models 15 and 16 examine 7:00-21:00 UTC (3:00AM - 5:00PM EST), when either the London or New York markets are open, with later tweets coded the following day. Models 17 and 18 examine 12:00-16:00 UTC (8:00AM - 12:00PM EST), when both markets are open, with later tweets coded the next day. The 7:00-21:00 UTC results are nearly identical to those above. The 12:00-16:00 UTC results are similar but not statistically significant, probably due to the brevity of the period.

[Table 5 about here]

We provide additional evidence of the robustness of our findings in the SI. Tweets disaggregated by trade and immigration produce similar results, with topics usually considered within the foreign policy realm (immigration) affecting financial markets (pp. 11-13). Prediction market data on the probability of Trump's presidential victory show that his tweets mattered more to USD/MXN exchange rate volatility when his chance of winning was less clear, mostly in the months leading up to the election (i.e., the "GOP nominee" period) (pp. 6-8). Various "placebo" tweet subjects—like China or Ted Cruz—do not affect the peso (pp. 15-17). Future research might examine whether Trump's Mexico-related tweets also affect NAFTA partner Canada or whether China-specific tweets matter to that nation's currency. We find that tweets affect Mexican-US bond spreads, but not the Mexican stock market (pp. 17-20). Future work might address this difference using a small-scale model (e.g., Sattler, Brandt and Freeman 2010), as well as incorporating GARCH terms in a vector autoregressive approach (Bollerslev, Engle and Wooldridge 1988). Alternative exchange rate measures—the percentage change daily high or daily low—produce similar results (pp. 13-14).

Conclusion

The original aim of this study was to contribute to research on politics and financial markets but it also contributes to research on politics and social media. Politicians use social media to disseminate campaign information, establish issue positions, competence, and reputations, and to engage in policy debates (Gainous and Wagner 2013; Parmelee 2014; Stier et al. 2018). This allows citizens to hold politicians accountable (Vanhommerig and Karré 2014; Kang et al. 2018), by establishing a benchmark against which performance can be compared. We argue that politicians' social media policy posts are similarly useful to investors. Not only do social media posts allow investors to determine the likely future policy direction of government, they allow investors to gather information on the benchmark against which politicians seek to be evaluated and thus on politicians' level of resolve to implement their policy goals.

We also contribute to research on social media and financial markets. Social media is unmediated (Gainous and Wagner 2013), enhancing its usefulness to investors seeking unfiltered, timely information. Financial economists have examined the impact of headline news from traditional media outlets on financial markets (e.g., Baker, Bloom and Davis 2016) but headline news is often driven by the social media posts of political players (Gainous and Wagner 2013; Parmelee 2014; Kreiss 2016). Traditional media headlines thus might not contain much political news. Although scholars have begun to examine how social media posts by important financial market players affect market dynamics (Piñeiro-Chousa, Vizcaíno-González and Pérez-Pico 2017; Li, van Dalen and van Rees 2018; Gholampour and van Wincoop 2017), they have not yet examined how posts by political players might also matter to investors.[20] Our research shows this is the case.

[20] An exception is Born, Myers and Clark (2017).

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Table 1: Competing Hypotheses About Trump's Mexico Tweets and the USD/MXN Exchange Rate

	Pre-Primary Candidate	Primary Candidate	GOP Nominee	President-Elect	POTUS
H1	Volatility	No Effect	No Effect	No Effect	No Effect
H2	Volatility	No Effect	Volatility	Volatility	Volatility

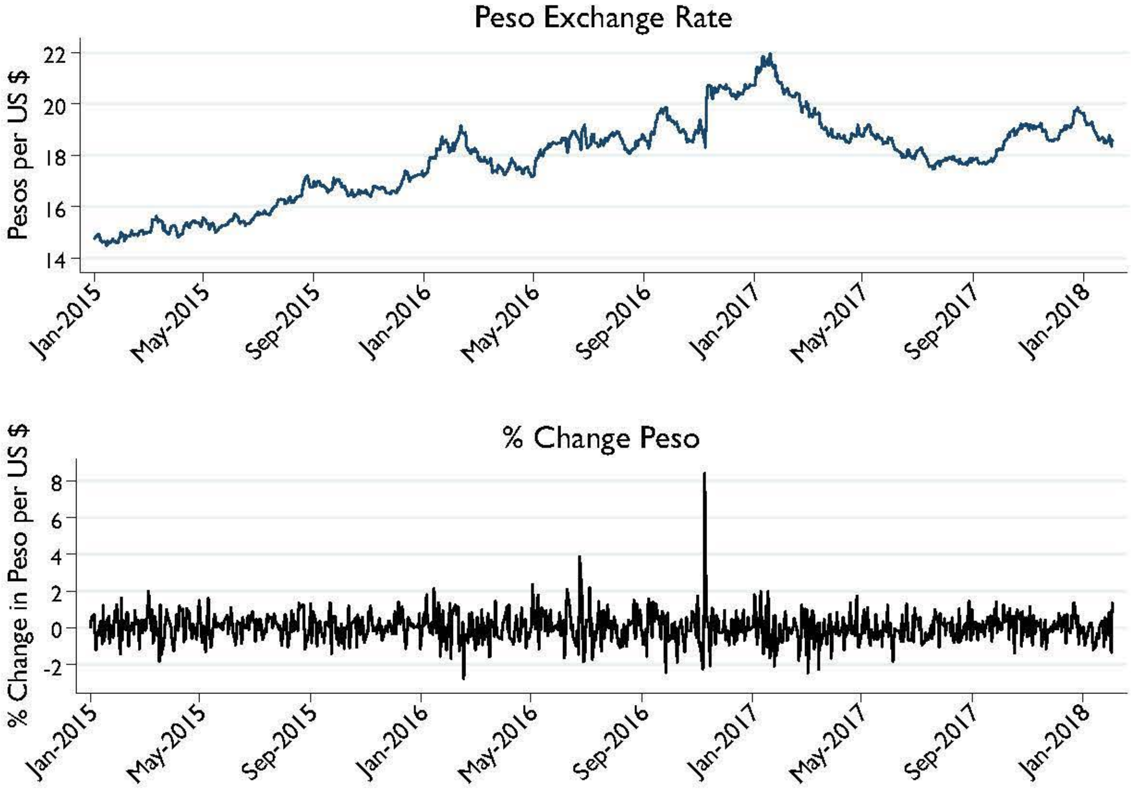
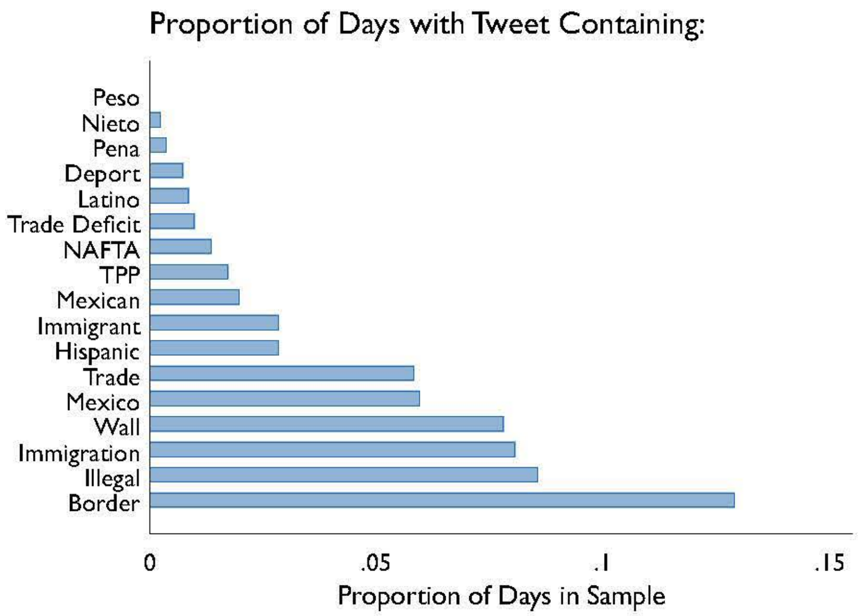
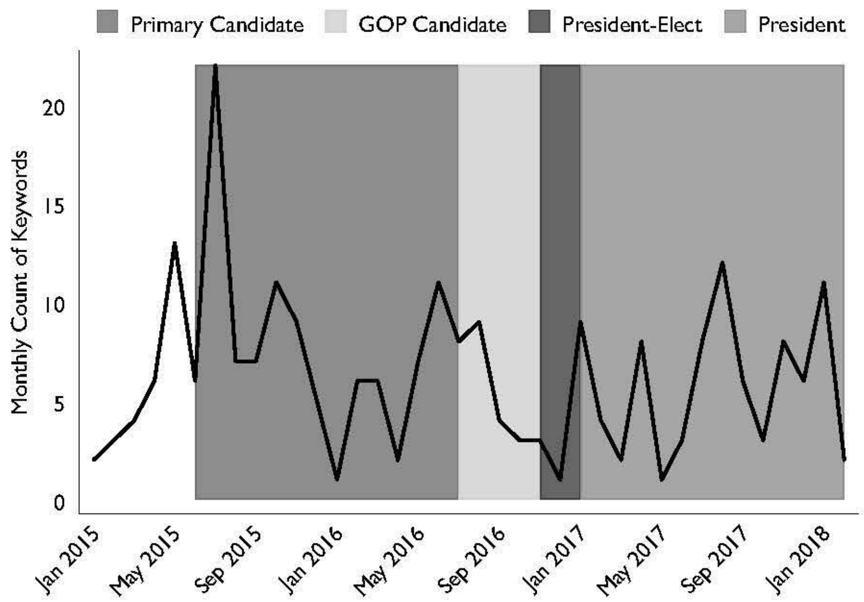


Figure 1: Peso-Dollar Exchange Rate



(a) Subject of Mexico-Related Tweets



(b) Mexico-Related Tweets are Consistent Over Time

Figure 2: Details on Tweets

Table 2: ARCH Effects and GARCH(1,1) Models Using *Tweet Dummy*

	(1)		(2)		(3)		(4)	
Mean Equation								
Pct. Peso_{t-1}	0.036	(0.039)	0.013	(0.043)	0.006	(0.040)	0.007	(0.039)
Tweet Dummy_t	0.012	(0.062)	-0.001	(0.059)	-0.023	(0.058)		
S&P 500_{t-1}	0.078*	(0.041)	0.060	(0.043)	0.064	(0.044)	0.065	(0.043)
Bond Spread_{t-1}	0.045*	(0.023)	0.034	(0.023)	0.030	(0.023)	0.028	(0.023)
Δ ln(Banxico US$ Stock_t)	17.948	(17.842)	11.572	(16.271)	12.695	(16.615)	11.320	(16.715)
Δ Overnight Rate Diff_t	-1.095*	(0.580)	-1.269**	(0.590)	-1.277**	(0.615)	-1.278**	(0.625)
Banxico US$ Sales_t	0.162**	(0.069)	0.106*	(0.064)	0.079	(0.065)	0.064	(0.066)
US Presidential Election_t	-1.558*	(0.797)	-1.548	(2.265)	-1.563	(1.072)	-1.518	(1.099)
US Presidential Election_{t-1}	8.398***	(0.798)	9.722***	(1.283)	8.389***	(1.169)	8.471***	(1.196)
Trump Primary Candidate_t	0.055	(0.088)	0.046	(0.080)	0.062	(0.089)	0.010	(0.107)
Trump GOP Nominee_t	0.089	(0.121)	0.033	(0.123)	0.102	(0.151)	0.096	(0.170)
President-Elect_t	0.203	(0.137)	0.187	(0.133)	0.266	(0.182)	0.197	(0.175)
Trump Presidency_t	-0.035	(0.092)	-0.067	(0.083)	-0.109	(0.089)	-0.085	(0.110)
NAFTA Rounds_t	0.169	(0.188)	0.168	(0.161)	0.202	(0.153)	0.223	(0.153)
Tweet $\text{Dummy}_t \times \text{Pre-Candidate}_t$							-0.061	(0.156)
Tweet $\text{Dummy}_t \times$Primary Candidate_t							0.072	(0.094)
Tweet $\text{Dummy}_t \times$GOP Nominee_t							0.144	(0.217)
Tweet $\text{Dummy}_t \times \text{President-Elect}_t$							0.401	(0.368)
Tweet $\text{Dummy}_t \times \text{Presidency}_t$							-0.156*	(0.091)
Constant	-0.064	(0.083)	0.137	(0.125)	0.256	(0.157)	0.294*	(0.176)
$\text{ARCH-in-Mean}_{t-1}$			-0.272	(0.196)	-0.441*	(0.255)	-0.482*	(0.268)
Variance Equation								
ARCH(1)			0.099***	(0.033)	0.055**	(0.026)	0.046*	(0.025)
GARCH(1)			0.754***	(0.071)	0.822***	(0.058)	0.840***	(0.051)
Tweet Dummy_t					-0.340	(0.512)		
Trump Primary Candidate_t					0.030	(0.228)		
Trump GOP Nominee_t					0.415	(0.281)		
President-Elect_t					0.119	(0.382)		
Trump Presidency_t					-0.085	(0.220)		
Tweet $\text{Dummy}_t \times \text{Pre-Candidate}_t$							-0.333	(0.969)
Tweet $\text{Dummy}_t \times$Primary Candidate_t							-0.436	(0.683)
Tweet $\text{Dummy}_t \times$GOP Nominee_t							0.972**	(0.431)
Tweet $\text{Dummy}_t \times \text{President-Elect}_t$							1.088*	(0.617)
Tweet $\text{Dummy}_t \times \text{Presidency}_t$							-0.594	(0.576)
S&P 500_{t-1}					-0.294	(0.234)	-0.422**	(0.166)
Bond Spread_{t-1}					0.332***	(0.088)	0.335***	(0.076)
Constant			0.091***	(0.032)	-2.706***	(0.430)	-2.848***	(0.410)
AIC	1910.45		1894.20		1891.23		1889.09	
Ljung Box-Q of $\frac{\varepsilon_t}{h_t}$	—		0.601		0.543		0.624	
Ljung Box-Q of $(\frac{\varepsilon_t}{h_t})^2$	—		0.060		0.225		0.744	

Note: Dependent variable is daily percentage change in USD/MXN exchange rate. $T = 804$. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

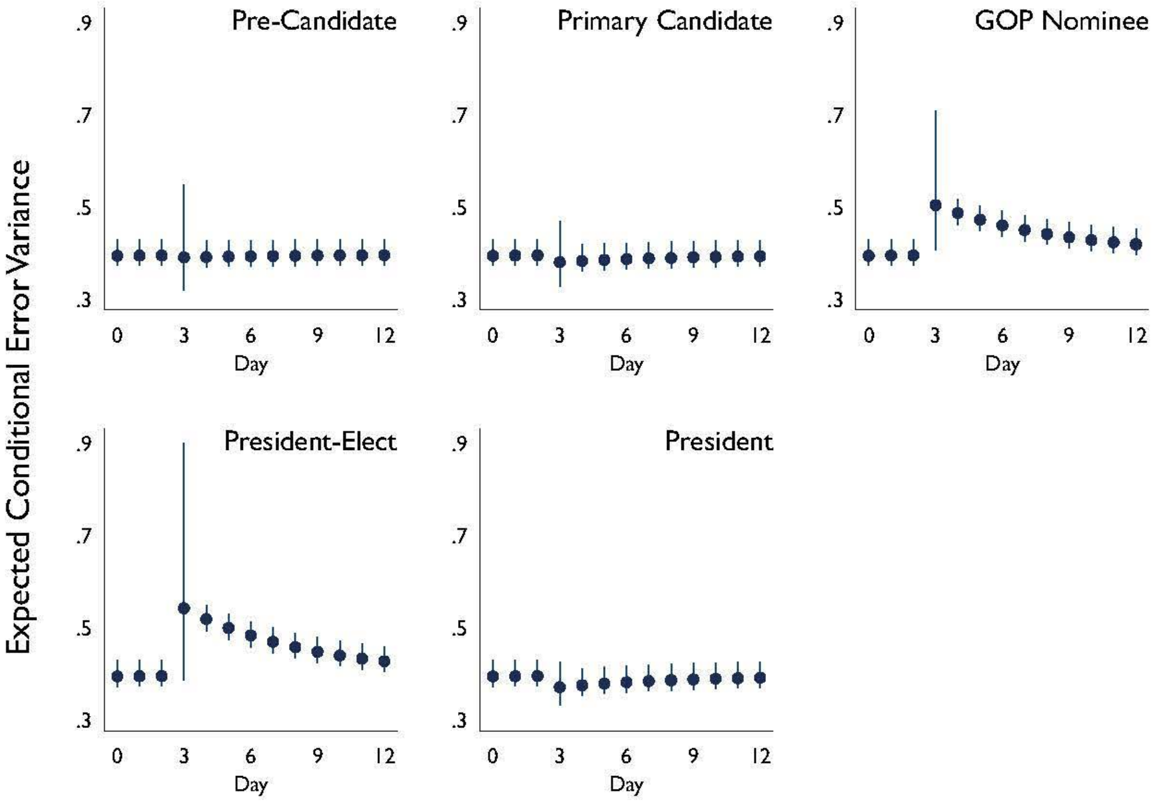


Figure 3: Predictions from Table 2, Model 4

Note: Expected means shown with 95 percent confidence intervals. Tweet occurs at $t = 3$.

Table 3: Intensity of Tweets, Weighting by Retweets and Favorites

	(5) 0, 1, 2+ Tweets		(6) 0, 1, 2+ Tweets		(7) Weight by ln(Retweet)		(8) Weight by ln(Retweet)		(9) Weight by ln(Favorite)		(10) Weight by ln(Favorite)	
Mean Equation												
Pct. Peso_{t-1}	0.007	(0.040)	0.010	(0.039)	0.007	(0.040)	0.007	(0.039)	0.007	(0.040)	0.007	(0.039)
Tweet_t	-0.014	(0.039)			-0.003	(0.007)			-0.003	(0.006)		
S&P 500_{t-1}	0.067	(0.043)	0.068	(0.043)	0.069	(0.043)	0.069	(0.043)	0.070	(0.043)	0.070	(0.043)
Bond Spread_{t-1}	0.030	(0.023)	0.030	(0.023)	0.030	(0.023)	0.028	(0.023)	0.030	(0.023)	0.028	(0.023)
Δ ln(Banxico US$ Stock_t)	12.809	(16.656)	11.535	(16.646)	12.495	(16.651)	10.832	(16.770)	12.519	(16.654)	10.764	(16.760)
Δ Overnight Rate Diff_t	-1.250**	(0.615)	-1.256**	(0.622)	-1.219**	(0.615)	-1.227**	(0.618)	-1.212**	(0.615)	-1.218**	(0.617)
Banxico US$ Sales_t	0.078	(0.066)	0.058	(0.067)	0.085	(0.065)	0.074	(0.066)	0.087	(0.065)	0.074	(0.066)
US Presidential Election_t	-1.562	(1.064)	-1.540	(1.101)	-1.565	(1.040)	-1.527	(1.065)	-1.566	(1.037)	-1.530	(1.061)
US Presidential Election_{t-1}	8.395***	(1.165)	8.497***	(1.214)	8.401***	(1.146)	8.483***	(1.163)	8.403***	(1.145)	8.477***	(1.160)
Trump Primary Candidate_t	0.062	(0.090)	0.002	(0.105)	0.068	(0.093)	0.040	(0.109)	0.069	(0.094)	0.039	(0.109)
Trump GOP Nominee_t	0.107	(0.153)	0.090	(0.165)	0.130	(0.155)	0.147	(0.172)	0.134	(0.155)	0.136	(0.171)
President-Elect_t	0.271	(0.187)	0.158	(0.170)	0.290	(0.195)	0.232	(0.177)	0.292	(0.196)	0.230	(0.176)
Trump Presidency_t	-0.115	(0.089)	-0.093	(0.106)	-0.115	(0.092)	-0.072	(0.107)	-0.115	(0.092)	-0.073	(0.108)
NAFTA Rounds_t	0.198	(0.153)	0.213	(0.151)	0.206	(0.154)	0.224	(0.152)	0.208	(0.154)	0.230	(0.152)
$\text{Tweet}_t \times$ Pre-Candidate_t			-0.037	(0.109)			-0.006	(0.033)			-0.007	(0.031)
$\text{Tweet}_t \times$ Primary Candidate_t			0.048	(0.057)			0.011	(0.012)			0.010	(0.011)
$\text{Tweet}_t \times$ GOP Nominee_t			0.074	(0.152)			0.013	(0.024)			0.014	(0.021)
$\text{Tweet}_t \times$ President-Elect_t			0.400	(0.282)			0.039	(0.037)			0.034	(0.032)
$\text{Tweet}_t \times$ Presidency_t			-0.129**	(0.062)			-0.016*	(0.009)			-0.015*	(0.008)
Constant	0.276*	(0.152)	0.305*	(0.161)	0.307**	(0.147)	0.311*	(0.161)	0.312**	(0.146)	0.314*	(0.163)
$\text{ARCH-in-Mean}_{t-1}$	-0.473*	(0.251)	-0.481*	(0.248)	-0.536**	(0.243)	-0.558**	(0.252)	-0.545**	(0.242)	-0.559**	(0.253)
Variance Equation												
ARCH(1)	0.053**	(0.025)	0.048*	(0.025)	0.050**	(0.024)	0.044*	(0.024)	0.050**	(0.024)	0.044*	(0.024)
GARCH(1)	0.831***	(0.055)	0.843***	(0.049)	0.833***	(0.055)	0.838***	(0.050)	0.835***	(0.055)	0.838***	(0.050)
Tweet_t	-0.184	(0.342)			-0.008	(0.047)			-0.003	(0.041)		
Trump Primary Candidate_t	0.020	(0.229)			0.001	(0.234)			-0.008	(0.233)		
Trump GOP Nominee_t	0.410	(0.283)			0.401	(0.289)			0.394	(0.288)		
President-Elect_t	0.114	(0.386)			0.140	(0.390)			0.134	(0.391)		
Trump Presidency_t	-0.091	(0.220)			-0.090	(0.231)			-0.099	(0.230)		
$\text{Tweet}_t \times$ Pre-Candidate_t			-0.084	(0.668)			-0.077	(0.207)			-0.059	(0.180)
$\text{Tweet}_t \times$ Primary Candidate_t			-0.263	(0.431)			-0.017	(0.074)			-0.012	(0.068)
$\text{Tweet}_t \times$ GOP Nominee_t			0.684**	(0.281)			0.111**	(0.043)			0.101**	(0.040)
$\text{Tweet}_t \times$ President-Elect_t			0.900*	(0.501)			0.107*	(0.059)			0.095*	(0.052)
$\text{Tweet}_t \times$ Presidency_t			-0.477	(0.480)			-0.053	(0.054)			-0.045	(0.049)
S&P 500_{t-1}	-0.320	(0.216)	-0.429**	(0.172)	-0.323	(0.204)	-0.387**	(0.164)	-0.327	(0.201)	-0.389**	(0.164)
Bond Spread_{t-1}	0.336***	(0.088)	0.332***	(0.079)	0.333***	(0.089)	0.334***	(0.073)	0.334***	(0.089)	0.337***	(0.073)
Constant	-2.789***	(0.410)	-2.904***	(0.391)	-2.835***	(0.418)	-2.842***	(0.381)	-2.850***	(0.418)	-2.861***	(0.389)
AIC	1891.44		1887.35		1891.66		1889.41		1891.58		1889.33	
Ljung Box-Q of $\frac{\varepsilon_t}{h_t}$	0.54		0.72		0.59		0.71		0.59		0.71	
Ljung Box-Q of $(\frac{\varepsilon_t}{h_t})^2$	0.29		0.88		0.28		0.72		0.28		0.67	

Note: Dependent variable is daily percentage change in USD/MXN exchange rate. $T = 804$. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

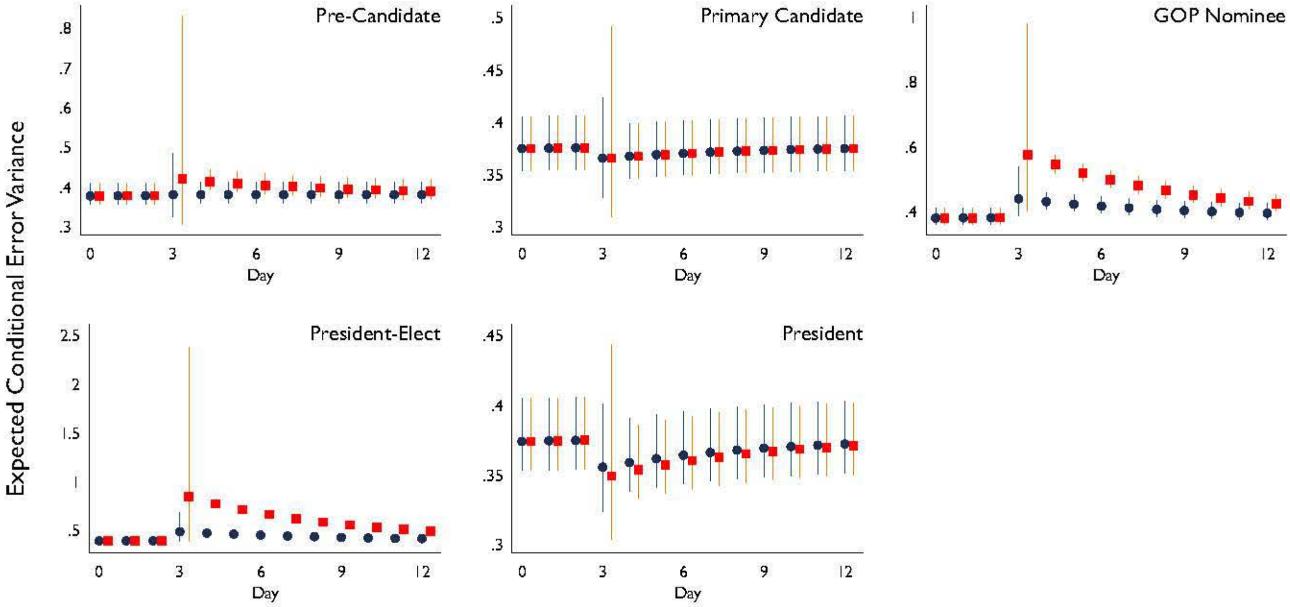


Figure 4: Coding the Intensity of Tweets (Model 6)

Note: Expected means shown with 95 percent confidence intervals. Blue circles indicate 1 tweet; Red squares indicate 2+ tweets. Tweet occurs at $t = 3$. Time slightly staggered for clarity.

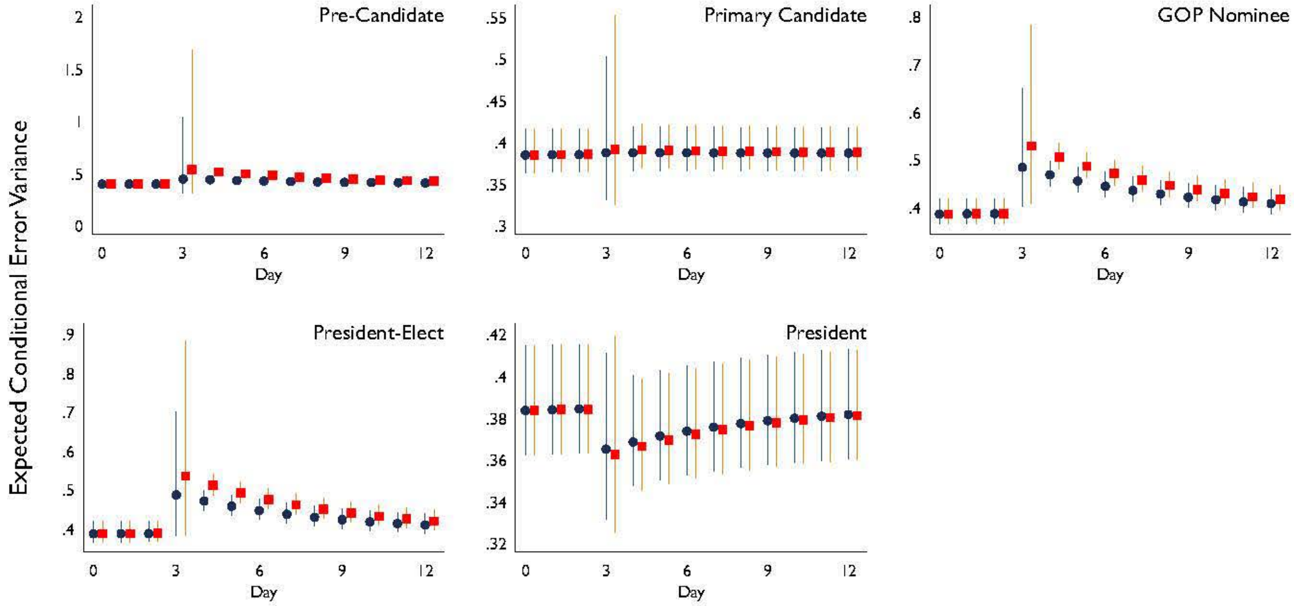


Figure 5: Weighting by ln(Retweet) (Model 8)

Note: Expected means shown with 95 percent confidence intervals. Blue circles depict a tweet with average number of retweets; Red squares depict 90th percentile of retweets. Time slightly staggered across two scenarios for clarity.

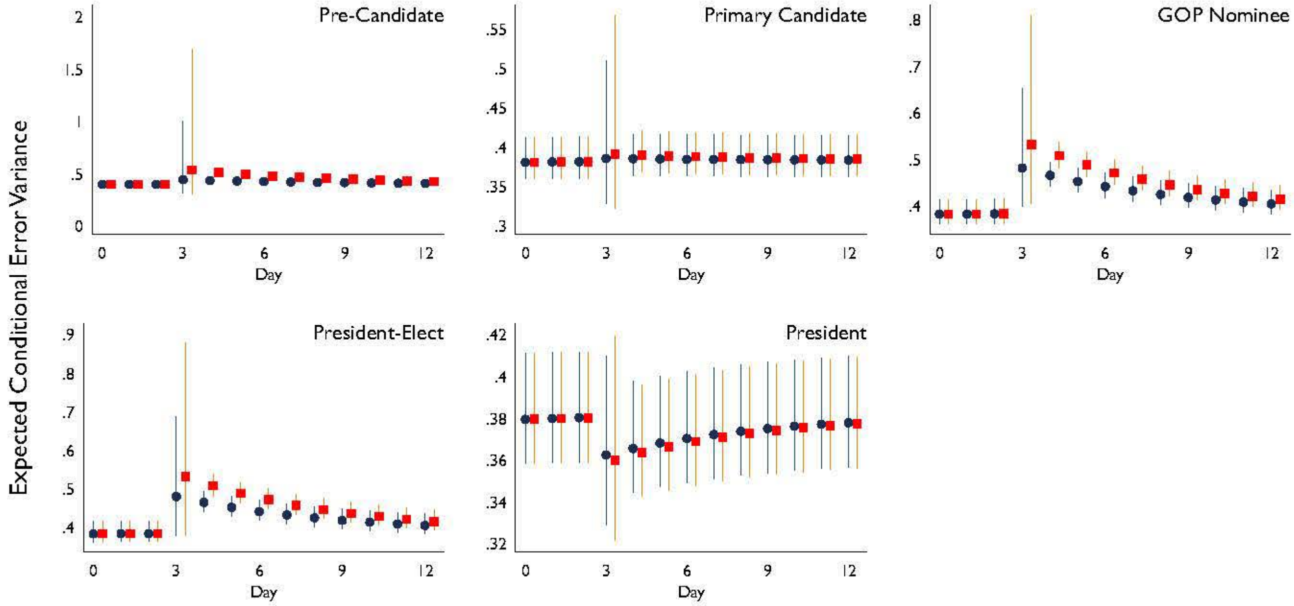


Figure 6: Weighting by ln(Favorites)

Note: Expected means shown with 95 percent confidence intervals. Blue circles depict a tweet with average number of favorites; Red squares depict 90th percentile of favorites. Time slightly staggered across two scenarios for clarity.

Table 4: Tone of Tweets

	(11) Negative Sentiment Tweets		(12) Negative Sentiment Tweets		(13) Positive Sentiment Tweets		(14) Positive Sentiment Tweets	
Mean Equation								
Pct. Peso_{t-1}	0.004	(0.040)	0.006	(0.039)	0.009	(0.039)	0.016	(0.039)
Tweet_t	0.028	(0.038)			-0.067*	(0.037)		
S&P 500_{t-1}	0.062	(0.043)	0.066	(0.043)	0.067	(0.042)	0.067	(0.042)
Bond Spread_{t-1}	0.032	(0.023)	0.028	(0.023)	0.031	(0.023)	0.033	(0.023)
Δ ln(Banxico US$ Stock_t)	11.772	(16.563)	11.643	(16.675)	17.115	(17.081)	12.989	(16.749)
Δ Overnight Rate Diff_t	-1.286**	(0.607)	-1.283**	(0.624)	-1.176*	(0.640)	-1.248**	(0.637)
Banxico US$ Sales_t	0.061	(0.064)	0.056	(0.066)	0.074	(0.065)	0.054	(0.065)
US Presidential Election_t	-1.552	(1.078)	-1.480	(1.127)	-1.544	(1.067)	-1.562	(1.046)
US Presidential Election_{t-1}	8.385***	(1.162)	8.515***	(1.217)	8.379***	(1.127)	8.392***	(1.103)
President-Elect_t	0.237	(0.174)	0.226	(0.171)	0.291	(0.194)	0.172	(0.175)
Trump Presidency_t	-0.124	(0.087)	-0.114	(0.088)	-0.120	(0.088)	-0.076	(0.093)
Trump Primary Candidate_t	0.032	(0.088)	0.025	(0.096)	0.062	(0.088)	0.016	(0.096)
Trump GOP Nominee_t	0.064	(0.145)	0.144	(0.164)	0.116	(0.144)	0.026	(0.141)
NAFTA Rounds_t	0.197	(0.154)	0.188	(0.154)	0.179	(0.149)	0.209	(0.153)
$\text{Tweet}_t \times \text{Pre-Candidate}_t$			-0.014	(0.232)			-0.063	(0.159)
$\text{Tweet}_t \times$Primary Candidate_t			0.099	(0.102)			0.043	(0.103)
$\text{Tweet}_t \times$GOP Nominee_t			0.133	(0.265)			0.220	(0.288)
$\text{Tweet}_t \times \text{President-Elect}_t$			0.808	(0.660)			0.486	(0.391)
$\text{Tweet}_t \times \text{Presidency}_t$			-0.025	(0.118)			-0.250**	(0.106)
Constant	0.245*	(0.135)	0.298**	(0.128)	0.284**	(0.139)	0.233*	(0.123)
$\text{ARCH-in-Mean}_{t-1}$	-0.400*	(0.211)	-0.505**	(0.231)	-0.460**	(0.217)	-0.359*	(0.189)
Variance Equation								
ARCH(1)	0.055**	(0.026)	0.043*	(0.023)	0.037*	(0.020)	0.042*	(0.022)
GARCH(1)	0.821***	(0.058)	0.853***	(0.042)	0.884***	(0.041)	0.868***	(0.044)
Tweet_t	-0.310	(0.281)			-1.429	(1.692)		
Trump Primary Candidate_t	0.074	(0.226)			-0.019	(0.226)		
Trump GOP Nominee_t	0.447	(0.284)			0.378	(0.287)		
President-Elect_t	0.134	(0.381)			0.104	(0.394)		
Trump Presidency_t	-0.069	(0.221)			-0.110	(0.228)		
$\text{Tweet}_t \times \text{Pre-Candidate}_t$			-1.325	(4.679)			-2.123	(5.503)
$\text{Tweet}_t \times$Primary Candidate_t			-0.476	(0.887)			-1.755	(1.652)
$\text{Tweet}_t \times$GOP Nominee_t			1.351***	(0.412)			1.156*	(0.614)
$\text{Tweet}_t \times \text{President-Elect}_t$			1.620**	(0.684)			1.545**	(0.778)
$\text{Tweet}_t \times \text{Presidency}_t$			-0.703	(1.121)			-1.508	(2.158)
S&P 500_{t-1}	-0.297	(0.234)	-0.436***	(0.162)	-0.474**	(0.200)	-0.500***	(0.166)
Bond Spread_{t-1}	0.346***	(0.088)	0.341***	(0.079)	0.330***	(0.089)	0.349***	(0.081)
Constant	-2.768***	(0.398)	-2.992***	(0.333)	-3.089***	(0.399)	-3.052***	(0.368)
AIC	1889.05		1890.49		1887.48		1886.10	
Ljung Box-Q of $\frac{\varepsilon_t}{h_t}$	0.55		0.64		0.63		1.08	
Ljung Box-Q of $(\frac{\varepsilon_t}{h_t})^2$	0.19		1.43		0.39		0.48	

Note: Dependent variable is daily percentage change in USD/MXN exchange rate. $T = 804$. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Active Trading Times

	(15) 7:00-21:00 UTC		(16) 7:00-21:00 UTC		(17) 12:00-16:00 UTC		(18) 12:00-16:00 UTC	
Mean Equation								
Pct. Peso_{t-1}	0.006	(0.040)	0.008	(0.039)	0.008	(0.040)	0.011	(0.039)
Tweet_t	-0.004	(0.058)			-0.016	(0.058)		
S&P 500_{t-1}	0.065	(0.044)	0.066	(0.043)	0.067	(0.043)	0.062	(0.042)
Bond Spread_{t-1}	0.030	(0.023)	0.029	(0.023)	0.030	(0.023)	0.031	(0.023)
Δ ln(Banxico US$ Stock_t)	12.439	(16.598)	13.549	(16.732)	12.986	(16.746)	14.400	(16.820)
Δ Overnight Rate Diff_t	-1.268**	(0.616)	-1.269**	(0.626)	-1.236**	(0.616)	-1.261**	(0.630)
Banxico US$ Sales_t	0.078	(0.064)	0.065	(0.067)	0.076	(0.063)	0.061	(0.064)
US Presidential Election_t	-1.557	(1.070)	-1.602	(1.088)	-1.556	(1.070)	-1.629	(1.065)
US Presidential Election_{t-1}	8.395***	(1.171)	8.469***	(1.170)	8.374***	(1.142)	8.413***	(1.108)
Trump Primary Candidate_t	0.059	(0.089)	-0.003	(0.107)	0.061	(0.087)	-0.023	(0.102)
Trump GOP Nominee_t	0.101	(0.152)	0.167	(0.167)	0.095	(0.144)	0.123	(0.157)
President-Elect_t	0.267	(0.184)	0.194	(0.177)	0.269	(0.178)	0.156	(0.174)
Trump Presidency_t	-0.112	(0.089)	-0.099	(0.109)	-0.105	(0.088)	-0.110	(0.102)
NAFTA Rounds_t	0.198	(0.153)	0.210	(0.152)	0.196	(0.152)	0.203	(0.154)
$\text{Tweet}_t \times \text{Pre-Candidate}_t$			-0.063	(0.157)			-0.106	(0.153)
$\text{Tweet}_t \times$ Primary Candidate_t			0.120	(0.095)			0.075	(0.091)
$\text{Tweet}_t \times$ GOP Nominee_t			-0.133	(0.221)			-0.196	(0.219)
$\text{Tweet}_t \times \text{President-Elect}_t$			0.407	(0.369)			0.617	(0.383)
$\text{Tweet}_t \times \text{Presidency}_t$			-0.106	(0.091)			-0.090	(0.093)
Constant	0.260	(0.161)	0.292*	(0.177)	0.237	(0.147)	0.251*	(0.150)
$\text{ARCH-in-Mean}_{t-1}$	-0.453*	(0.264)	-0.478*	(0.276)	-0.414*	(0.228)	-0.368*	(0.214)
Variance Equation								
ARCH(1)	0.054**	(0.026)	0.043*	(0.025)	0.048**	(0.023)	0.038*	(0.020)
GARCH(1)	0.824***	(0.059)	0.844***	(0.051)	0.838***	(0.048)	0.864***	(0.040)
Tweet_t	-0.257	(0.494)			-0.580	(0.638)		
Trump Primary Candidate_t	0.019	(0.228)			0.028	(0.220)		
Trump GOP Nominee_t	0.406	(0.281)			0.408	(0.277)		
President-Elect_t	0.120	(0.385)			0.116	(0.376)		
Trump Presidency_t	-0.089	(0.220)			-0.081	(0.218)		
$\text{Tweet}_t \times \text{Pre-Candidate}_t$			-0.266	(0.936)			-0.601	(1.004)
$\text{Tweet}_t \times$ Primary Candidate_t			-0.287	(0.667)			-1.173	(0.980)
$\text{Tweet}_t \times$ GOP Nominee_t			0.962**	(0.431)			0.758	(0.514)
$\text{Tweet}_t \times \text{President-Elect}_t$			1.119*	(0.605)			1.025	(0.737)
$\text{Tweet}_t \times \text{Presidency}_t$			-0.528	(0.569)			-0.817	(0.799)
S&P 500_{t-1}	-0.300	(0.233)	-0.403**	(0.168)	-0.343	(0.209)	-0.483***	(0.163)
Bond Spread_{t-1}	0.332***	(0.089)	0.339***	(0.077)	0.329***	(0.087)	0.346***	(0.079)
Constant	-2.738***	(0.435)	-2.879***	(0.414)	-2.756***	(0.359)	-2.944***	(0.362)
AIC	1891.57		1890.43		1890.55		1889.56	
Ljung Box-Q of $\frac{\varepsilon_t}{h_t}$	0.57		0.71		0.56		0.79	
Ljung Box-Q of $(\frac{\varepsilon_t}{h_t})^2$	0.23		0.83		0.28		0.49	

Note: Dependent variable is daily percentage change in USD/MXN exchange rate. $T = 804$. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Supplemental Information to "Does the @realDonaldTrump Really Matter to Financial Markets?"

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Contents

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1 Unit Root Tests

The results of four unit root tests on the main dependent variable, the percentage change in the USD-MXN exchange rate, are shown in Table 1. The Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test is based on the null hypothesis that the series is stationary, while the Augmented Dicky-Fuller (A-DF) and Dickey-Fuller with a Generalized Least Squares transformation (DF-GLS) are based on the null hypotheses that the series contains a unit root. Ten augmenting lags were included in all tests to mitigate issues from residual autocorrelation. As is clear from Table 1, taking the percentage change in the USD/MXN exchange rate renders the series stationary, which is what we use in our analysis.

Table 1: Unit Root Tests Suggest % Change in Peso is Stationarity

Test	Peso Ex. Rate	% Change
Augmented Dickey-Fuller	-2.06	-7.98*
KPSS	4.87*	0.18
DF-GLS (w/ trend)	-1.68	-6.67*
DF-GLS (w/o trend)	-0.23	-7.99*

Note: $T = 795$, $*:\ p < 0.05$. KPSS has a null hypothesis of stationarity; all others have a null of a non-stationary series. Test statistics include 10 augmenting lags in order to purge autocorrelation.

2 Summary Statistics

Summary statistics are available in Table 2.

2.1 Data Sources

Our data sources are as follows:

- Data on the Mexican peso are from https://www.investing.com/currencies/usd-mxn-historical-data. As a robustness check, we also compare these exchange rate data to those from the Federal Reserve Economic Database (FRED) below.

- Tweet data (including information such as likes, retweets, and the timing of tweets) are from the Trump Twitter Archive: http://www.trumptwitterarchive.com and https://github.com/bpb27/trump_tweet_data_archive.

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	N
Pct. Peso	0.032	0.847	804
Tweet (dummy)	0.297	0.457	804
Tweet (0, 1, 2+ tweets)	0.415	0.693	804
Tweet (ln(retweet))	2.445	3.914	804
Tweet (ln(favorite)	2.676	4.361	804
Tweet (7:00-21:00 UTC)	0.299	0.458	804
Tweet (12:00-16:00 UTC)	0.29	0.454	804
Tweet (negative sentiment)	0.236	0.644	804
Tweet (positive sentiment)	0.27	0.697	804
S&P 500	0.043	0.768	804
Bond Spread	0.04	1.362	804
Δ ln(Banxico US$ Stock)	0	0.002	804
Δ Overnight rate Difference	0.004	0.048	804
Banxico US$ Sales	0.303	0.46	804
President-Elect	0.066	0.248	804
Presidency	0.336	0.473	804
Primary Candidate	0.353	0.478	804
GOP Nominee	0.101	0.301	804
NAFTA Rounds	0.024	0.152	804

- Data on the S&P 500 are from https://www.investing.com/indices/us-spx-500-historical-data.
- Data on NAFTA hearings, announcements, and rounds are from the US Trade Representative website's press releases: https://ustr.gov/about-us/policy-offices/press-office/press-releases.
- Data used to calculate the Δ overnight rate difference are from Mexico's central bank (http://www.banxico.org.mx) and the US Federal Reserve (https://www.federalreserve.gov).
- Bond spread data are calculated from Mexican (https://www.investing.com/rates-bonds/mexico-10-year-historical-data) and US (https://www.investing.com/rates-bonds/u.s.-10-year-bond-yield-historical-data) bond yields.
- Data on Mexico central bank operations (Δ ln(Banxico US$ Stock), Banxico US$ Sales) are from Mexico's central bank: http://www.banxico.org.mx.

3 Details on Retweets and Favorites Variables

In Figure 1, we plot the interaction between tweets and the log number of times a tweet is retweeted in each of the US electoral cycle periods. There is a substantial amount of variation in retweets across time: Trump's Mexico-related tweets received an average of 8.2 logged retweets, with a minimum of 2.3 and maximum of 11.4. While it appears that there are many more tweets occurring in the Primary Candidate and President periods, both of these periods encompass approximately one year, while others, such as the President-Elect or GOP Nominee periods, encompass only a few months.

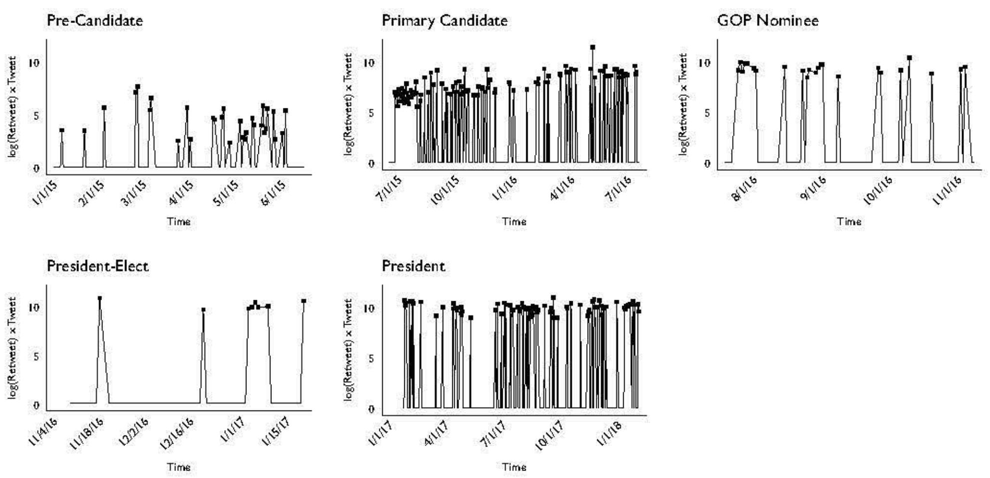

Figure 1: Main Independent Variable: Tweet $\times$ log(Retweets)

In Figure 2, we show a time series plot of the interaction between tweets and the log of the number of times a tweet is liked/favorited. Although the two plots look similar—the two measures are extremely highly correlated at 0.98—in general other Twitter users tend to be more likely to favorite one of Donald Trump's tweets rather than retweet it. Similar to retweets, there is a substantial amount of variation: Mexico-related tweets receive an average of 9.2 logged favorites, with a minimum of 2.9 and maximum of 12.2.

4 Details on Creating Simulated Predictions

In the main paper, we present several plots of simulated expected values of the heteroskedastic error variances. These figures were created in a manner similar to the popular `Zelig` and Clarify packages (Tomz, Whittenberg and King 2003; Imai, King and Lau 2009)—as well as others

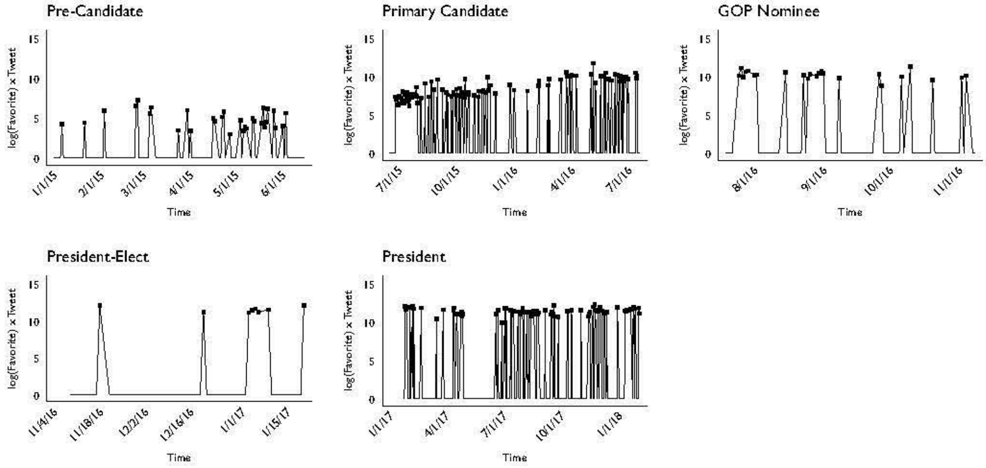

Figure 2: Main Independent Variable: Tweet $\times$ log(Favorites)

developed specifically for time series applications (e.g., Williams and Whitten 2011; Jordan and Philips 2018*a*,*b*)—all of which involve using stochastic simulation techniques to assess both statistical and substantive significance. As King, Tomz and Wittenberg (2000) point out, these approaches involve no new assumptions beyond those needed to estimate the original model (e.g., the model is correctly specified, the error term is well-behaved). However, to the best of our knowledge, we are the first to incorporate this approach for ARCH/GARCH models.[1]

After estimating the model, we generated 6000 simulated parameter estimates for both the mean and variance equations, drawn from a multivariate normal with means equal to the original model estimates, and variance from the estimated variance covariance matrix.[2] This incorporates estimation uncertainty (each of the 6000 parameter estimates will differ slightly from one another), while remaining consistent with the underlying estimated model (King, Tomz and Wittenberg 2000).

With these 6000 simulated model estimates, the next step is to set our covariates in the variance equation to substantively interesting values and generate expected values of the outcome. Recall that the variance equation is given as:

$$\sigma_t^2 = \omega\varepsilon_{t-1}^2 + \alpha\sigma_{t-1}^2 + exp(\mathbf{z}_t\boldsymbol{\gamma}) \tag{1}$$

[1]This approach is not dissimilar to the post-estimation `predict, variance` in Stata, although we also incorporate the heteroskedastic variance component (which can be obtained in Stata using `predict, het`), as well as calculate measures of uncertainty surrounding these predictions through stochastic simulation.

[2]King, Tomz and Wittenberg (2000, p. 353) suggest drawing from the entire variance-covariance matrix to minimize the potential for error; we do this in our simulations, since both the mean and variance equations are simultaneously estimated using a single variance-covariance matrix.

We set our independent variables in the variance equation (the $exp(\mathbf{z}_t\boldsymbol{\gamma})$ part) to the following for the first several values: the lagged percent change in the S&P 500 and bond spreads were set to sample means, and the political dummy variables (if present) were set to zero except for "Trump as Primary Candidate". All tweet variables and/or interactions were set to zero, and we also assume that the ARCH term (ε^2_{t-1} in Equation 1) is zero throughout the entire period. The value of the GARCH term (σ^2_{t-1}) is set to its previous value. Thus, at each subsequent time point, the previous value of the expected error variance is used as the prior value. Note that since the previous value of the expected error variance at the first time point does not exist, it is necessary to perform a "burn-in"—we choose 30 time points—such that the expected error variance converges on a stable value before any shocks occur. Such burn-ins are common in other stochastic simulations of dynamic models (c.f., Jordan and Philips 2018*a*,*b*). Such a period can be seen in Figure 3, which shows a plot of all 30 burn-in periods in the left plot. The right plot shows the type of figure we present in the main paper, which starts after the burn-in period (the start point is shown by the dashed vertical line in the left plot). At $t = 3$ in the right-hand plot in Figure 3, the tweet variable takes on a value of one (or whatever value described for the alternative tweet operationalizations such as favorites or retweets). At $t = 4$, the contemporaneous tweet variable reverts back to zero. For $t = 5$ to $t = 12$, the tweet variable remain at zero, but due to the GARCH term, some persistence of the tweet shock is still felt in the system even after $t = 4$.

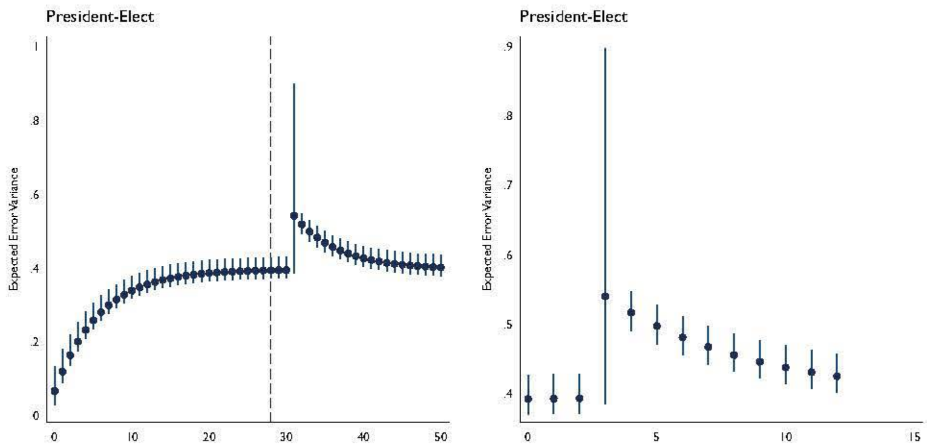

Figure 3: Graphical Illustration of the "Burn-In" Period Necessary to Produce Stable Pre-Shock Values

We plot the mean of the expected values, along with 95 percent confidence intervals created using percentiles of the 6000 estimates at each point in time. Note too that since the heteroskedastic variance terms all enter into the variance equation via the exponential link—the $exp(\mathbf{z}_t\boldsymbol{\gamma})$ term in Equation 1—not only will this produce positive values by construction (which makes sense given that σ_t^2 must be strictly positive), confidence intervals will skew upwards away from zero. This can be seen in Figure 3, where the mean expected error variance tends to be lower than the midpoint distance between the upper and lower confidence intervals.

4.1 A Note on Modeling Strategy

Much of our analysis involves GARCH models, which are notorious for their convergence problems in estimating the maximum likelihood. The most common issue with convergence in our estimates centered around "rare" events such as each of the NAFTA rounds (forcing us to combine them into a single NAFTA variable).

Our analysis was conducted in Stata. All GARCH models in our analyses use the observed information matrix for calculating the standard errors, rather than the less-common outer product of the gradient. While most models converged after several iterations without issue, with some we had to set priming values of the ARCH terms to zero, rather than computing priming values based on the expected unconditional variance, in order to achieve convergence. We did not change the convergence tolerance or iteration methods from the default in Stata.[3]

5 Robustness Checks

5.1 A Re-Examination of When Tweets Matter

Although the results in the main paper support our argument, it could be said that Trump's propensity to send Mexico-related policy tweets might have been affected by his perceived chance of winning. Moreover, investors may have paid more attention to his tweets based on his probability of winning, rather than based on what they knew about his policy goals and resolve and when they knew it (e.g., GOP primary candidate, GOP nominee, president-elect...).

To address this possibility, we incorporate a measure of Trump's chances of winning from the University of Iowa's Iowa Electronic Markets (IEM) website into the models.[4] We employ a winner-take-all measure (i.e., the expected popular vote plurality winner in the 2016 presidential

[3]The only exception is for some of the sentiment analysis models in Table 4 below.

[4]https://iemweb.biz.uiowa.edu/markets/data_Pres16.html.

election). It is available from 1 January, 2015 until 10 November, 2016. The series is shown in the left plot in Figure 4. Trump's probability of winning started around 50 percent and tended to slowly decrease as the election neared, with substantial volatility near the election in November 2016. Since this series clearly contains a downward linear trend across time, in the right plot in Figure 4 we show the de-trended series, which is what we use in the analysis below through the inclusion of a time trend. Each of the vertical slashes shows important dates; when Trump announced his presidential bid (in June 2015), and when he formally won the GOP nomination (in July 2016).

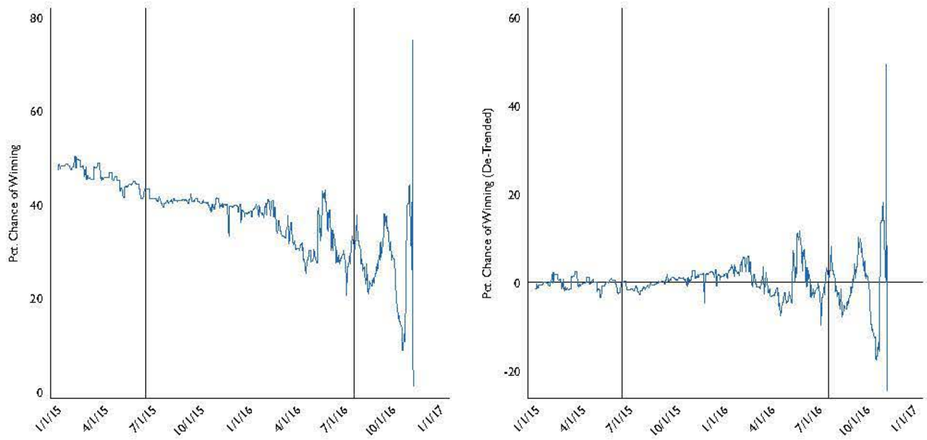

Figure 4: Trump's Likelihood of Winning According to Prediction Markets (Left) and De-Trended Series (Right)

Note: Raw series (left) and de-trended series (right). Left-most vertical slash indicates when Trump announces presidential bid (June 16, 2015). Right-most slash indicates when he won the GOP nominee (July 19, 2016).

In Table 3 we show the results of Trump's Mexico-related tweets, now including the prediction market data instead of the political dummies. Our sample is much shorter since the prediction market data stop after the 2016 presidential election; a number of the variables in our other models cannot be estimated in this sample since they come after the election (e.g., NAFTA negotiations). Last, since the prediction market series is clearly trending across time—we find that the series is trend-stationary—we add linear time trends to both the mean and variance equations.[5] The results are quite similar to those in the main paper. Tweets do not appear to affect changes in the peso, as evidenced by the lack of statistical significance in the mean equation in both Models 1 and 2. In contrast, increases in the probability that Trump would win tend to lead to devaluations in the value of the peso (meaning positive increases in the percent

[5] The Dickey-Fuller GLS test indicated that the series was trend-stationary out to 13 augmenting lags, thus we choose to add a linear time trend rather than take the first difference.

change in the peso) relative to the dollar. In Model 1, there appears to be no effect of prediction markets on volatility, nor do tweets affect volatility, a similar finding in the main paper.

Table 3: Robustness: Prediction Markets

	(1)		(2)	
Mean Equation				
Pct. Peso$_{t-1}$	0.066	(0.055)	0.045	(0.055)
Tweet Dummy$_t$	0.036	(0.077)	0.439	(0.477)
Pct. Prediction Mkt$_t$	0.022**	(0.011)	0.014	(0.010)
Tweet$_t$ $\times$Pct. Prediction Mkt$_t$			-0.008	(0.012)
S&P 500$_{t-1}$	0.063	(0.051)	0.034	(0.048)
Bond Spread$_{t-1}$	0.002	(0.030)	0.020	(0.029)
Δ ln(Banxico US$ Stock$_t$)	17.019	(18.334)	5.577	(19.211)
Δ Overnight Rate Difference$_t$	-2.065*	(1.135)	-2.827**	(1.114)
Banxico US$ Sales$_t$	0.082	(0.089)	0.186*	(0.095)
US Presidential Election$_t$	-2.468**	(1.106)	-2.230	(2.535)
US Presidential Election$_{t-1}$	9.003***	(0.981)	7.605***	(2.530)
Time Trend	0.002***	(0.001)	0.001	(0.001)
Constant	-0.753	(0.530)	-0.902*	(0.513)
ARCH-in-Mean$_{t-1}$	-0.850**	(0.355)	0.240	(0.202)
Variance Equation				
ARCH(1)	0.006	(0.022)	0.028	(0.044)
GARCH(1)	0.837***	(0.047)	0.796***	(0.104)
Tweet Dummy$_t$	0.066	(0.319)	6.307***	(1.324)
Pct. Prediction Mkt$_t$	0.009	(0.018)	0.093***	(0.024)
Tweet$_t$ $\times$Pct. Prediction Mkt$_t$			-0.175***	(0.034)
S&P 500$_{t-1}$	-0.177	(0.121)	-0.511**	(0.241)
Bond Spread$_{t-1}$	0.511***	(0.106)	-0.342*	(0.189)
Time Trend	0.002**	(0.001)	0.004***	(0.001)
Constant	-3.459***	(1.026)	-6.747***	(1.360)
N	483		483	

Note: Dependent variable is daily percentage change in USD/MXN exchange rate. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Model 2 in Table 3, we interact the tweet measure with the prediction market variable. While the interaction is not statistically significant in terms of the value of the exchange rate, it is statistically significant and negative in the variance equation. Moreover, the coefficient on tweets themselves in the variance equation is positive, quite large in magnitude, and statistically significant. This indicates that tweets increased volatility, and tended to have the greatest effect when it was less certain that Trump would win, according to prediction markets. As evidenced by Figure 4, this tended to be closer to the election (i.e., in the GOP nominee period). This echoes the findings in the main paper, in that tweets in the GOP nominee period tended to affect volatility of the USD/MXN exchange rate the most.

5.2 Additional Sentiment Analysis Results

In the main paper, we used dichotomous measures of either negative or positive tweet sentiment, coded using the `syuzhet` package by Jockers (2017), which uses the syuzhet sentiment dictionary (or lexicon) developed by the Nebraska Literary Lab. Words in each tweet are assigned a positive, negative, or neutral sentiment, and these are added together to produce a net positive, negative, or neutral tweet overall. We then turned these into dichotomous positive or negative tweets in the main paper. We chose this dichotomous measure because continuous measures were sparse and created substantial convergence difficulties in the ARCH/GARCH models.

In this section, we show several additional results using an alternative package, `sentimentr` (Rinker 2019).[6] Unlike `syuzhet`, `sentimentr` incorporates valence shifters that magnify positive or negative sentiment; for instance, "is *very* bad" is more negative than "is bad". Thus, `sentimentr` amplifies or deamplifies (or even negates) sentiment based on the surrounding words and context. In Table 4, Models 1 and 2, we show the same positive and negative dichotomous tweet codings using `sentimentr`.[7] The results are quite similar to those using `syuzhet` in the main paper; tweets with either positive or negative sentiment affect volatility in the peso—largely at similar magnitudes—but only during the GOP Nominee and Primary Candidate periods.

In Models 3 through 5 we create continuous measures of sentiment to test whether more negative (or positive) tweets affect volatility to a greater extent. As is clear from the sometimes-large coefficients and standard errors, these models faced considerable convergence issues. In fact, we were not able to get the continuous negative sentiment model using `sentimentr` to converge at all. However, Models 3, 4, and 5 do shed some light on whether more negative or positive tweets influence exchange rates. In Model 3, the tweet variable now takes on the sentiment value given by the `syuzhet` package, where higher values indicate more negative sentiment. Tweets that are coded as net positive or neutral are set to zero. It appears that although the coefficients tend to be in the expected direction, more negative tweets have a statistically significant positive effect on volatility only in the GOP Nominee period. In Models 4 and 5 we test whether more positive tweets affect exchange rates, using both `syuzhet` and `sentimentr`, respectively. The findings are quite similar to the continuous negative sentiment results; volatility increases when tweets are more positive in sentiment, but only during the

[6] https://github.com/trinker/sentimentr.

[7] Due to convergence issues, the likelihood function in Model 2 was maximized via the Broyden-Fletcher-Goldfarb-Shanno algorithm instead of Stata's default settings.

Table 4: Additional Sentiment Analysis

	(1)		(2)		(3)		(4)		(5)	
	Negative Dummy sentimentr		Positive Dummy sentimentr		Continuous Negative syuzhet		Continuous Positive syuzhet		Continuous Positive sentimentr	
Mean Equation										
Pct. Peso_{t-1}	0.010	(0.039)	0.014	(0.039)	-0.003	(0.041)	0.013	(0.039)	0.010	(0.040)
$\text{Tweet}_t \times$Pre-Candidate_t	0.045	(0.211)	-0.018	(0.164)	0.083	(0.425)	-0.183	(0.179)	-0.297	(0.840)
$\text{Tweet}_t \times$Primary Candidate_t	0.014	(0.099)	0.031	(0.104)	0.236***	(0.091)	0.008	(0.139)	-0.092	(0.526)
$\text{Tweet}_t \times$GOP Nominee_t	0.267	(0.261)	0.116	(0.300)	-0.000	(0.254)	0.081	(0.275)	0.314	(1.180)
$\text{Tweet}_t \times$President-Elect_t	0.801	(0.655)	0.490	(0.385)	1.255	(2.678)	0.157	(0.261)	0.598	(0.965)
$\text{Tweet}_t \times \text{Presidency}_t$	-0.100	(0.118)	-0.223**	(0.105)	0.126	(0.085)	-0.050	(0.072)	-0.112	(0.359)
S&P 500_{t-1}	0.065	(0.042)	0.067	(0.043)	0.035	(0.040)	0.065	(0.044)	0.065	(0.045)
Bond Spread_{t-1}	0.029	(0.023)	0.033	(0.023)	0.028	(0.023)	0.030	(0.023)	0.032	(0.024)
Δ ln(Banxico US$ Stock_t)	11.695	(16.575)	12.526	(16.691)	11.814	(15.513)	12.468	(16.630)	12.240	(16.615)
Δ Overnight Rate Difference_t	-1.319**	(0.625)	-1.248**	(0.626)	-1.322**	(0.603)	-1.242**	(0.624)	-1.251**	(0.626)
Banxico US$ Sales_t	0.051	(0.065)	0.056	(0.066)	0.067	(0.062)	0.083	(0.064)	0.082	(0.066)
US Presidential Election_t	-1.457	(1.140)	-1.582	(1.085)	-1.581	(1.068)	-1.586	(1.016)	-1.580	(1.028)
US Presidential Election_{t-1}	8.502***	(1.244)	8.413***	(1.171)	8.433***	(1.122)	8.366***	(1.098)	8.364***	(1.102)
Trump Primary Candidate_t	0.039	(0.093)	0.033	(0.097)	-0.029	(0.082)	0.059	(0.093)	0.054	(0.095)
Trump GOP Nominee_t	0.096	(0.158)	0.056	(0.140)	0.094	(0.140)	0.060	(0.136)	0.043	(0.130)
President-Elect_t	0.219	(0.166)	0.171	(0.172)	0.187	(0.142)	0.229	(0.174)	0.216	(0.172)
Trump Presidency_t	-0.097	(0.088)	-0.074	(0.094)	-0.120	(0.085)	-0.100	(0.087)	-0.108	(0.089)
NAFTA Rounds_t	0.194	(0.155)	0.209	(0.152)	0.214	(0.160)	0.208	(0.155)	0.199	(0.155)
Constant	0.276**	(0.122)	0.223*	(0.127)	0.199*	(0.115)	0.255**	(0.128)	0.232	(0.143)
ARCH-in-Mean	-0.461**	(0.202)	-0.360*	(0.190)	-0.318**	(0.158)	-0.439**	(0.219)	-0.392*	(0.238)
Variance Equation										
ARCH(1)	0.048**	(0.022)	0.049*	(0.026)	0.101**	(0.039)	0.051**	(0.026)	0.052*	(0.028)
GARCH(1)	0.852***	(0.041)	0.855***	(0.052)	0.653***	(0.120)	0.838***	(0.055)	0.831***	(0.073)
$\text{Tweet}_t \times$Pre-Candidate_t	-1.148	(3.133)	-1.919	(5.763)	-135.190	(968.227)	-5.124	(16.139)	-6.739	(15.883)
$\text{Tweet}_t \times$Primary Candidate_t	-0.961	(1.071)	-1.399	(1.498)	-4.504	(4.374)	-0.244	(0.941)	-2.763	(11.407)
$\text{Tweet}_t \times$GOP Nominee_t	1.293***	(0.456)	1.276**	(0.557)	0.835***	(0.323)	1.118**	(0.517)	4.159**	(1.736)
$\text{Tweet}_t \times$President-Elect_t	1.605**	(0.713)	1.481*	(0.812)	4.796	(5.834)	0.501	(0.898)	1.368	(4.007)
$\text{Tweet}_t \times \text{Presidency}_t$	-0.559	(1.076)	-1.461	(2.061)	-0.862	(1.074)	-0.503	(0.866)	-5.000	(7.311)
S&P 500_{t-1}	-0.457***	(0.164)	-0.476***	(0.179)	0.167	(0.328)	-0.350**	(0.169)	-0.330	(0.218)
Bond Spread_{t-1}	0.348***	(0.080)	0.348***	(0.083)	0.324***	(0.073)	0.369***	(0.074)	0.364***	(0.075)
Constant	-3.014***	(0.340)	-2.993***	(0.385)	-1.967***	(0.415)	-2.890***	(0.391)	-2.808***	(0.483)
N	804		804		804		804		804	

Note: Dependent variable is daily percentage change in USD/MXN exchange rate. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

GOP nominee period. Overall these additional sentiment results indicate that positive and negative tweets tend to affect the USD/MXN exchange rate in a similar way, and more positive or negative tweets raise volatility further during the GOP nominee period.

5.3 Disaggregating Tweet Subjects

In the main paper, we created an aggregate measure of all of Trump's Mexico-related tweets based off 17 relevant keywords: peso, Nieto, Peña, deport, Latino, trade deficit, NAFTA, TPP, Mexican, immigrant, Hispanic, trade, Mexico, wall, immigration, illegal, and border. While all of these topics could potentially be seen as negative in the eyes of investors—a wall may discourage US-Mexico trade—it could be the case that investors are only paying attention to trade-related tweets. In order to test this we split up our tweets into two categories:

- **Trade-relevant**: all tweets containing at least one mention of the following: peso, trade, trade deficit, NAFTA, or TPP
- **Immigration-relevant**: all tweets containing at least one mention of the following: deport, Latino, Mexican, immigrant, Hispanic, wall, immigration, illegal, border

Since Nieto, Peña, and Mexico could be referring either trade or immigration, we excluded these terms. 62 days in our sample contained a tweet with relevance to trade, while 194 contained a mention of immigration. The results for the trade- and immigration-relevant tweets are shown in Table 5. In Model 1, which shows trade-only tweets, there is no evidence that tweets pertaining to trade affect either the level or the volatility of the exchange rate across the entire sample period, similar to the findings in the main paper. In Model 2, which shows the interactions between trade tweets and the political time period dummies, there is evidence of increased volatility in the period in which Trump was the GOP nominee. Because there were no tweets pertaining to trade when he was president-elect, we omit the $\text{Tweet}_t \times \text{President-Elect}_t$ variable. The pre-candidate, primary candidate, and president interactions are not statistically significant, which is the same as the findings in the main paper.

For immigration-specific tweets, shown in Models 3 and 4, results are similar to those for trade. The non-interactive model (Model 3) shows no evidence that immigration-relevant tweets across the entire sample affect either changes in the exchange rate or volatility. In contrast, in Model 4 in Table 5 there appears to be evidence that tweets increase volatility in the GOP

Table 5: Separating Trade- and Immigration-Specific Tweets

	(1) Trade Only		(2) Trade Only		(3) Immigration Only		(4) Immigration Only	
Mean Equation								
Pct. Peso_{t-1}	0.008	(0.040)	0.011	(0.042)	0.004	(0.040)	0.012	(0.039)
Tweet_t	-0.015	(0.100)			-0.066	(0.062)		
S&P 500_{t-1}	0.068	(0.043)	0.064	(0.041)	0.067	(0.043)	0.069	(0.043)
Bond Spread_{t-1}	0.030	(0.023)	0.039*	(0.023)	0.031	(0.023)	0.029	(0.023)
Δ ln(Banxico US$ Stock_t)	12.266	(16.598)	17.587	(17.111)	13.398	(16.692)	10.314	(16.773)
Δ Overnight Rate Difference_t	-1.210**	(0.614)	-0.884	(0.618)	-1.264**	(0.611)	-1.317**	(0.625)
Banxico US$ Sales_t	0.079	(0.065)	0.145**	(0.067)	0.088	(0.064)	0.058	(0.066)
US Presidential Election_t	-1.564	(1.053)	-1.623**	(0.784)	-1.561	(1.060)	-1.624	(1.057)
US Presidential Election_{t-1}	8.402***	(1.160)	8.520***	(0.751)	8.396***	(1.154)	8.369***	(1.141)
Trump Primary Candidate_t	0.057	(0.091)	0.046	(0.089)	0.076	(0.091)	0.014	(0.100)
Trump GOP Nominee_t	0.108	(0.152)	0.079	(0.126)	0.124	(0.150)	0.103	(0.155)
President-Elect_t	0.268	(0.188)	0.160	(0.137)	0.283	(0.189)	0.229	(0.166)
Trump Presidency_t	-0.120	(0.089)	-0.063	(0.092)	-0.105	(0.090)	-0.072	(0.104)
NAFTA Rounds_t	0.198	(0.153)	0.198	(0.171)	0.209	(0.153)	0.224	(0.153)
$\text{Tweet}_t \times \text{Pre-Candidate}_t$			-0.104	(0.211)			0.011	(0.192)
$\text{Tweet}_t \times$ Primary Candidate_t			0.001	(0.156)			0.050	(0.096)
$\text{Tweet}_t \times$ GOP Nominee_t			-0.133	(0.494)			-0.022	(0.232)
$\text{Tweet}_t \times \text{President-Elect}_t$							0.106	(0.484)
$\text{Tweet}_t \times \text{Presidency}_t$			-0.030	(0.219)			-0.207**	(0.094)
Constant	0.286**	(0.146)	0.178	(0.159)	0.283*	(0.145)	0.278	(0.181)
$\text{Arch-in-Mean}_{t-1}$	-0.494**	(0.243)	-0.360	(0.234)	-0.490**	(0.232)	-0.448*	(0.269)
Variance Equation								
ARCH(1)	0.052**	(0.024)	0.085	(0.060)	0.051**	(0.024)	0.047*	(0.027)
GARCH(1)	0.840***	(0.056)	-0.287	(0.193)	0.823***	(0.055)	0.835***	(0.062)
Tweet_t	-0.365	(1.044)			-0.391	(0.469)		
Trump Primary Candidate_t	-0.030	(0.235)			0.060	(0.229)		
Trump GOP Nominee_t	0.404	(0.287)			0.419	(0.276)		
President-Elect_t	0.071	(0.416)			0.151	(0.376)		
Trump Presidency_t	-0.111	(0.226)			-0.072	(0.218)		
$\text{Tweet}_t \times \text{Pre-Candidate}_t$			-0.115	(0.291)			-0.196	(1.127)
$\text{Tweet}_t \times$ Primary Candidate_t			-0.081	(0.207)			-0.645	(0.706)
$\text{Tweet}_t \times$ GOP Nominee_t			1.042*	(0.544)			0.891*	(0.491)
$\text{Tweet}_t \times \text{President-Elect}_t$							1.269*	(0.700)
$\text{Tweet}_t \times \text{Presidency}_t$			0.109	(0.368)			-0.854	(0.690)
S&P 500_{t-1}	-0.337	(0.217)	0.075	(0.062)	-0.299	(0.208)	-0.395**	(0.167)
Bond Spread_{t-1}	0.350***	(0.094)	0.050	(0.033)	0.322***	(0.086)	0.324***	(0.082)
Constant	-2.897***	(0.432)	-0.337	(0.207)	-2.704***	(0.403)	-2.775***	(0.466)
N	804		804		804		804	

Note: Dependent variable is daily percentage change in USD/MXN exchange rate. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

nominee and president-elect periods. In the mean equation in Model 4, results also suggest that tweets when Trump is president result in reduced changes in the USD/MXN exchange rate. Taken together, the results in Table 5 are very similar to those found in the main paper; tweets—either relevant to trade or immigration—appear to have the same effect on increasing volatility in the exchange rate, but only in the GOP nominee and president-elect periods.

5.4 Robustness of Coding the USD/MXN Exchange Rate

In this section we explore the robustness of our findings to the use of other measures for the percentage change in the USD/MXN nominal exchange rate, the results of which are shown in Table 6. In Models 1 and 2, we examine the percentage change in the daily low of the USD/MXN exchange rate. In Model 1, there is no evidence that tweets across the entire time period affect either changes in this exchange rate or its volatility, similar to previous findings. In Model 2, we interact the tweet variable with the political period dummies. While the tweet-political dummy interactions are not statistically significant in the mean equation, in the variance equation tweets produce a statistically significant increase in volatility in the GOP nominee period. The other time periods are in the same direction and of similar magnitude as previous findings as well.

In Models 3 and 4, we use the percentage daily change in the daily high of the USD/MXN exchange rate. Interestingly, both the percentage change in the daily high and daily volatility seem to be affected by tweets during the president-elect period. For most of the models in the main text and SI, we find that tweets only affect volatility—not value—during this period. We thus suspect that tweets may generate more extreme losses (or highs in this coefficient) in the value of the peso relative to the dollar, instead of greater losses in its average daily value. Last, in Models 5 and 6 we use an alternative measure of the USD/MXN exchange rate provided by the US Federal Reserve Economic Database (FRED). The results using this alternative source are nearly identical to those in the main paper, since they suggest that tweets do not matter across the entire sample and only in the GOP nominee and president-elect periods (and, here, in the GOP primary period, although this effect is only weakly statistically significant).

Table 6: Alternative Codings of the Peso

	(1) Daily Low		(2) Daily Low		(3) Daily High		(4) Daily High		(5) FRED		(6) FRED	
Mean Equation												
Pct. Peso_{t-1}	0.079**	(0.039)	0.081**	(0.039)	0.040	(0.041)	0.062	(0.040)	0.023	(0.039)	0.023	(0.039)
Tweet Dummy_t	-0.015	(0.047)			0.027	(0.056)			0.023	(0.060)		
S&P 500_{t-1}	-0.144***	(0.032)	-0.151***	(0.031)	-0.103***	(0.036)	-0.090**	(0.036)	-0.002	(0.042)	0.007	(0.041)
Bond Spread_{t-1}	0.039*	(0.021)	0.038*	(0.021)	0.082***	(0.021)	0.072***	(0.021)	0.041*	(0.024)	0.044*	(0.024)
Δ ln(Banxico US$ Stock_t)	6.203	(13.180)	6.230	(12.795)	8.945	(16.110)	8.172	(15.009)	-2.190	(17.737)	-2.152	(17.727)
Δ Overnight Rate Difference_t	-1.381***	(0.525)	-1.174**	(0.473)	0.578	(0.577)	0.359	(0.631)	0.167	(0.631)	0.370	(0.624)
Banxico US$ Sales_t	0.065	(0.051)	0.075	(0.051)	0.095*	(0.058)	0.075	(0.057)	0.081	(0.067)	0.089	(0.069)
US Presidential Election_t	-0.840	(0.730)	-0.813	(0.806)	0.295	(1.214)	0.376	(2.169)	-0.795	(0.918)	-0.751	(0.938)
US Presidential Election_{t-1}	-0.734	(0.620)	-0.699	(0.664)	11.793***	(1.174)	11.613***	(4.291)	7.093***	(0.954)	7.261***	(0.954)
Trump Primary Candidate_t	-0.006	(0.065)	-0.060	(0.078)	0.203*	(0.110)	0.133	(0.093)	0.171	(0.129)	0.039	(0.123)
Trump GOP Nominee_t	0.033	(0.110)	0.012	(0.118)	0.232	(0.171)	0.069	(0.146)	0.279	(0.197)	0.191	(0.199)
President-Elect_t	0.146	(0.143)	0.094	(0.126)	0.365*	(0.214)	0.141	(0.145)	0.664**	(0.326)	0.473*	(0.263)
Trump Presidency_t	-0.116*	(0.066)	-0.142*	(0.078)	-0.018	(0.077)	0.014	(0.087)	-0.207*	(0.111)	-0.289**	(0.126)
NAFTA Rounds_t	0.091	(0.135)	0.088	(0.137)	0.226	(0.141)	0.196	(0.134)	0.289*	(0.153)	0.263*	(0.146)
$\text{Tweet}_t \times$ Pre-Candidate_t			-0.127	(0.118)			0.079	(0.130)			-0.162	(0.159)
Tweet $\text{Dummy}_t \times$ Primary Candidate_t			0.041	(0.075)			0.047	(0.090)			0.158	(0.105)
Tweet $\text{Dummy}_t \times$ GOP Nominee_t			-0.009	(0.229)			0.164	(0.195)			0.178	(0.225)
Tweet $\text{Dummy}_t \times$ President-Elect_t			-0.184	(0.328)			0.566*	(0.339)			0.465	(0.395)
Tweet $\text{Dummy}_t \times \text{Presidency}_t$			-0.025	(0.074)			-0.003	(0.080)			-0.093	(0.085)
Constant	0.099	(0.068)	0.122	(0.075)	0.154	(0.132)	0.009	(0.095)	0.534***	(0.173)	0.681***	(0.176)
Arch-in-Mean_{t-1}	-0.127	(0.089)	-0.112	(0.078)	-0.587*	(0.350)	-0.200	(0.155)	-1.054***	(0.326)	-1.167***	(0.286)
Variance Equation												
ARCH(1)	0.031	(0.023)	0.032	(0.024)	0.070**	(0.033)	0.106***	(0.040)	0.014	(0.014)	0.008	(0.009)
GARCH(1)	0.539***	(0.090)	0.576***	(0.100)	0.429	(0.265)	0.732***	(0.065)	0.849***	(0.061)	0.920***	(0.029)
Tweet Dummy_t	0.084	(0.189)			0.201	(0.166)			0.131	(0.202)		
Trump Primary Candidate_t	0.152	(0.174)			0.510***	(0.183)			0.145	(0.189)		
Trump GOP Nominee_t	0.677***	(0.225)			0.688***	(0.235)			0.431**	(0.215)		
President-Elect_t	0.562*	(0.298)			0.837***	(0.292)			0.424	(0.322)		
Trump Presidency_t	-0.006	(0.175)			0.114	(0.182)			-0.229	(0.176)		
Tweet $\text{Dummy}_t \times$ Pre-Candidate_t			-0.314	(0.488)			-3.571	(19.031)			0.572	(0.440)
Tweet $\text{Dummy}_t \times$ Primary Candidate_t			0.074	(0.279)			0.407	(0.456)			0.417*	(0.231)
Tweet $\text{Dummy}_t \times$ GOP Nominee_t			1.320***	(0.310)			0.804	(0.728)			1.232***	(0.314)
Tweet $\text{Dummy}_t \times$ President-Elect_t			0.098	(0.942)			1.379**	(0.661)			0.900**	(0.456)
Tweet $\text{Dummy}_t \times \text{Presidency}_t$			-0.091	(0.289)			-0.574	(0.692)			-0.580	(0.531)
S&P 500_{t-1}	0.029	(0.108)	0.077	(0.110)	0.229*	(0.134)	-0.469**	(0.239)	-0.266**	(0.135)	-0.407***	(0.112)
Bond Spread_{t-1}	0.523***	(0.072)	0.592***	(0.063)	-0.038	(0.079)	-0.353**	(0.154)	0.286***	(0.085)	0.398***	(0.061)
Constant	-2.153***	(0.322)	-2.173***	(0.347)	-1.860***	(0.558)	-2.589***	(0.252)	-2.776***	(0.481)	-3.588***	(0.483)
N	804		804		804		804		773		773	

Note: Dependent variable is daily percentage change in the daily lows of the USD/MXN exchange rate for Models 1 and 2, the daily percentage change in the daily high of the USD/MXN exchange rate for Models 3 and 4, and the daily percentage change in the average exchange rate for Models 5 and 6. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Additional Results

6.1 Placebo Tweets

It might be that Trump's Mexico-related tweets coincide with some other factor that is affecting the value of the USD/MEX exchange rate. Or that his tweets in general—Mexico-related or not—spur movements in either dollar or peso value or volatility or both. To test whether this is occurring, we created a set of five "placebo" tweets equal to one if Trump tweeted about Bernie Sanders, Hillary Clinton, Ted Cruz, China, or Europe.[8] Table 7 shows the number of times a subject was mentioned and the total number of days in our sample for which a particular subject was mentioned. Mexico and the 14 other related subjects in our analysis were mentioned 676 times, for a total of 239 days in the analysis. Clinton and Cruz were mentioned an astonishing 628 and 925 times, respectively; about half of all days in our sample contained at least one tweet about Ted Cruz. Tweets about Bernie Sanders, China, and Europe were far less common.

Table 7: Number of Occurrences Across Subjects

Subject	Raw Number of Occurrences in Sample	Number of Days in Sample
Mexico Only	65	48
Mexico and Related	676	239
Bernie Sanders	60	37
Hillary Clinton	628	256
Ted Cruz	925	454
China	60	47
Europe	11	10

Note: Raw number of occurrences in sample are the total number of times a subject was mentioned. Number of days in sample are the number of days in which a subject was mentioned at least once. The subject "Mexico and Related" is the one used in the main analysis. Number of observations in sample = 806.

We next ran our core model specifications on these placebo subjects. We could not include Europe in the results since its low number of mentions caused the model to fail to achieve convergence. We could not estimate the interactive models for Bernie Sanders or China due to similar convergence issues caused by a lack of tweets on these subjects. Still, as is clear from Table 8, none of the tweet or lag tweet variables for the four subjects are statistically significant for the non-interactive models (Models 1, 2, 4, and 6), in either the mean or variance equation.

For the interactive models (Models 2 and 5), the only statistically significant interaction is

[8] For China, the search terms were "China" and "Chinese". For Europe, "European", "EU", "Europe" and "Euro".

Table 8: Placebo Subjects

	(1) Bernie Sanders		(2) Hillary Clinton		(3) Hillary Clinton		(4) Ted Cruz		(5) Ted Cruz		(6) China	
Mean Equation												
Pct. Peso$_{t-1}$	0.003	(0.040)	0.008	(0.040)	-0.004	(0.063)	0.003	(0.040)	-0.004	(0.040)	0.005	(0.040)
Tweet$_t$	0.004	(0.134)	-0.014	(0.064)			0.042	(0.055)			-0.171	(0.106)
S&P 500$_{t-1}$	0.065	(0.044)	0.069	(0.043)	0.069^{*}	(0.042)	0.068	(0.043)	0.067	(0.043)	0.068	(0.043)
Bond Spread$_{t-1}$	0.031	(0.023)	0.030	(0.023)	0.047^{**}	(0.023)	0.031	(0.023)	0.031	(0.024)	0.029	(0.023)
Δ ln(Banxico US$ Stock$_t$)	12.078	(16.673)	12.688	(16.594)	17.052	(17.077)	13.469	(16.592)	13.993	(16.785)	16.144	(17.261)
Δ Overnight Rate Difference$_t$	-1.235^{**}	(0.606)	-1.263^{**}	(0.607)	-0.683	(0.629)	-1.205^{*}	(0.617)	-1.151^{*}	(0.604)	-1.039	(0.686)
Banxico US$ Sales$_t$	0.090	(0.065)	0.085	(0.063)	0.146^{**}	(0.065)	0.082	(0.064)	0.081	(0.065)	0.086	(0.065)
US Presidential Election$_t$	-1.544	(1.045)	-1.540	(1.071)	-1.595^{**}	(0.786)	-1.581	(1.016)	-1.559	(1.016)	-1.552	(0.971)
US Presidential Election$_{t-1}$	8.408^{***}	(1.150)	8.428^{***}	(1.174)	8.434^{***}	(0.748)	8.352^{***}	(1.079)	8.370^{***}	(1.063)	8.318^{***}	(1.074)
Trump Primary Candidate$_t$	0.062	(0.093)	0.058	(0.093)	0.055	(0.097)	0.069	(0.092)	0.043	(0.156)	0.103	(0.118)
Trump GOP Nominee$_t$	0.112	(0.151)	0.126	(0.153)	0.074	(0.199)	0.129	(0.149)	0.151	(0.210)	0.203	(0.213)
President-Elect$_t$	0.280	(0.191)	0.266	(0.186)	0.163	(0.145)	0.304	(0.191)	0.199	(0.223)	0.446	(0.418)
Trump Presidency$_t$	-0.117	(0.091)	-0.123	(0.090)	-0.098	(0.095)	-0.106	(0.090)	-0.127	(0.155)	-0.098	(0.099)
NAFTA Rounds$_t$	0.205	(0.154)	0.203	(0.154)	0.207	(0.161)	0.196	(0.153)	0.217	(0.150)	0.173	(0.162)
Tweet$_t$ ×Pre-Candidate$_t$					-0.090	(0.182)			0.048	(0.155)		
Tweet$_t$ ×Primary Candidate$_t$					-0.026	(0.097)			0.062	(0.095)		
Tweet$_t$ ×GOP Nominee$_t$					0.021	(0.218)			-0.024	(0.197)		
Tweet$_t$ ×President-Elect$_t$					-0.094	(0.267)			0.114	(0.236)		
Tweet$_t$ ×Presidency$_t$					0.078	(0.110)			0.022	(0.082)		
Constant	0.289^{**}	(0.143)	0.298^{**}	(0.136)	0.079	(0.129)	0.261^{*}	(0.141)	0.290	(0.192)	0.391	(0.273)
Arch-in-Mean$_{t-1}$	-0.516^{**}	(0.235)	-0.512^{**}	(0.214)	-0.183	(0.170)	-0.518^{**}	(0.214)	-0.532^{**}	(0.210)	-0.744	(0.545)
Variance Equation												
ARCH(1)	0.053^{**}	(0.025)	0.050^{**}	(0.023)	0.113^{*}	(0.059)	0.044^{*}	(0.023)	0.045^{*}	(0.025)	0.029	(0.033)
GARCH(1)	0.820^{***}	(0.061)	0.832^{***}	(0.050)	-0.255	(0.289)	0.836^{***}	(0.046)	0.830^{***}	(0.054)	0.900^{***}	(0.095)
Tweet$_t$	-0.579	(1.105)	0.295	(0.286)			-0.360	(0.292)			-1.842	(3.769)
Primary Candidate$_t$	0.056	(0.236)	-0.104	(0.243)			-0.017	(0.211)			0.032	(0.222)
GOP Nominee$_t$	0.411	(0.277)	0.230	(0.313)			0.325	(0.275)			0.431	(0.286)
President-Elect$_t$	0.120	(0.383)	0.100	(0.391)			0.077	(0.370)			0.346	(0.497)
Presidency$_t$	-0.105	(0.216)	-0.066	(0.217)			-0.135	(0.214)			-0.014	(0.226)
Tweet$_t$ ×Pre-Candidate$_t$					0.093	(0.236)			-0.213	(0.305)		
Tweet$_t$ ×Primary Candidate$_t$					0.168	(0.148)			-0.344	(0.366)		
Tweet$_t$ ×GOP Nominee$_t$					0.508^{**}	(0.200)			0.305	(0.453)		
Tweet$_t$ ×President-Elect$_t$					0.157	(0.381)			-1.001	(1.258)		
Tweet$_t$ ×Presidency$_t$					-0.450^{*}	(0.234)			-0.901^{*}	(0.507)		
S&P 500$_{t-1}$	-0.257	(0.241)	-0.368^{*}	(0.194)	0.097	(0.073)	-0.360^{**}	(0.177)	-0.294	(0.211)	-0.412	(0.265)
Bond Spread$_{t-1}$	0.333^{***}	(0.090)	0.352^{***}	(0.090)	0.061^{*}	(0.034)	0.346^{***}	(0.086)	0.384^{***}	(0.111)	0.298^{***}	(0.100)
Constant	-2.746^{***}	(0.430)	-2.915^{***}	(0.391)	-0.436	(0.288)	-2.630^{***}	(0.380)	-2.581^{***}	(0.354)	-3.378^{***}	(1.005)
N	804		804		804		804		804		804	

Note: Dependent variable is daily percentage change in the USD/MXN exchange rate. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

that during the GOP nominee period, tweets that included mentions of Hillary Clinton also increased variance. Part of this may be because Trump is tweeting about both Clinton and Mexico in the same tweet; of the 256 days in our sample that contained a Clinton tweet, 92 of those days also contained a Mexico-related tweet. No tweets for Ted Cruz were statistically significant at conventional levels (although the tweet-presidency interactions are negative and significant at the 10 percent level for both Clinton and Cruz). Moreover, for the interactive models, none of the interactions are statistically significant in the mean equation in Table 8. Taken together, these placebo results provide further evidence that Trump's Mexico-related tweets are what affect the peso, rather than his general tweets or some other tweet subject.

6.2 Trump's Mexico-Related Tweets and the Mexican Stock Market

In this section, we examine whether Trump's Mexico-related tweets affect the MSCI Mexican Stock market index. Table 9 shows how tweets (*Tweet Dummy*) affect the percentage change in the MSCI Mexican stock market index. As shown in Models 1 and 2, tweets do not affect changes in the stock market index. To see if Trump's Mexico-related tweets affect Mexican stock market volatility, in Models 3 and 4 we add *Tweet Dummy* to the variance equation. While there appears to be evidence of volatility in Model 3, as suggested by the statistically significant ARCH and GARCH effects, *Tweet Dummy* is not statistically significant.

Last, in Model 4 we show interaction between tweets and the political period dummies. In the mean equation, tweets appear to lead to positive and then negative changes in the Mexican stock market index in the pre-candidate and primary candidate periods, respectively, although these effects are only weakly statistically significant. Turning to volatility, the Trump presidency in Model 4 is statistically significant at the 0.10 level and negative, which indicates that volatility decreases in response to a tweet during this period (relative to the other periods). No other periods are statistically significant; again indicating that tweets do not affect the Mexican stock market. Thus, the results here show only weak evidence that Mexico-related tweets are having any effect on either the value or volatility of the Mexican stock market.

Table 9: Mexican Stock Market Index

	(1)		(2)		(3)		(4)	
Mean Equation								
MSCI Mexico$_{t-1}$	-0.115**	(0.047)	-0.143***	(0.046)	-0.126***	(0.047)	-0.071	(0.046)
Pct. Peso$_{t-1}$	-0.622***	(0.069)	-0.551***	(0.063)	-0.531***	(0.064)	-0.535***	(0.067)
Tweet Dummy$_t$	-0.038	(0.096)	0.008	(0.085)	0.018	(0.085)		
S&P 500$_{t-1}$	0.053	(0.066)	0.079	(0.067)	0.063	(0.071)	0.020	(0.072)
Bond Spread$_{t-1}$	-0.013	(0.036)	-0.039	(0.035)	-0.019	(0.037)	0.012	(0.038)
Δ ln(Banxico US$ Stock$_t$)	12.130	(27.518)	13.610	(27.625)	8.610	(28.213)	10.005	(27.646)
Δ Overnight Rate Difference$_t$	0.610	(0.893)	-0.034	(0.907)	-0.141	(0.892)	-0.119	(0.905)
Banxico US$ Sales$_t$	-0.202*	(0.106)	-0.035	(0.102)	-0.032	(0.101)	-0.086	(0.107)
US Presidential Election$_t$	0.248	(1.234)	0.392	(1.660)	0.352	(1.630)	0.052	(1.376)
US Presidential Election$_{t-1}$	-9.884***	(1.228)	-10.083***	(1.784)	-10.151***	(1.691)	-9.965***	(1.355)
Trump Primary Candidate$_t$	-0.051	(0.135)	-0.043	(0.128)	-0.191	(0.161)	0.032	(0.191)
Trump GOP Nominee$_t$	-0.108	(0.187)	0.031	(0.194)	-0.180	(0.232)	0.052	(0.257)
President-Elect$_t$	-0.158	(0.212)	-0.153	(0.216)	-0.194	(0.265)	-0.015	(0.265)
Trump Presidency$_t$	-0.019	(0.142)	0.159	(0.146)	0.259	(0.189)	0.370*	(0.205)
NAFTA Rounds$_t$	-0.363	(0.290)	-0.303*	(0.176)	-0.329*	(0.190)	-0.384	(0.234)
Tweet Dummy$_t$×Pre-Candidate$_t$							0.427*	(0.245)
Tweet Dummy$_t$×Primary Candidate$_t$							-0.269*	(0.161)
Tweet Dummy$_t$×GOP Nominee$_t$							-0.179	(0.314)
Tweet Dummy$_t$×President-Elect$_t$							-0.280	(0.481)
Tweet Dummy$_t$×Presidency$_t$							0.175	(0.133)
Constant	0.160	(0.128)	-0.271	(0.207)	-0.475	(0.309)	-0.952***	(0.314)
Arch-in-Mean$_{t-1}$			0.213**	(0.102)	0.378**	(0.189)	0.631***	(0.190)
Variance Equation								
ARCH(1)			0.062***	(0.018)	0.030	(0.020)	0.011	(0.017)
GARCH(1)			0.926***	(0.022)	0.901***	(0.036)	0.826***	(0.037)
Tweet Dummy$_t$					-0.328	(0.372)		
Trump Primary Candidate$_t$					0.350	(0.290)		
Trump GOP Nominee$_t$					0.644*	(0.375)		
President-Elect$_t$					-0.020	(0.433)		
Trump Presidency$_t$					-0.283	(0.268)		
Tweet Dummy$_t$×Pre-Candidate$_t$							-0.091	(0.504)
Tweet Dummy$_t$×Primary Candidate$_t$							0.187	(0.204)
Tweet Dummy$_t$×GOP Nominee$_t$							0.514	(0.356)
Tweet Dummy$_t$×President-Elect$_t$							-0.087	(0.894)
Tweet Dummy$_t$×Presidency$_t$							-0.743*	(0.387)
S&P 500$_{t-1}$					-0.439***	(0.152)	-0.450***	(0.088)
Bond Spread$_{t-1}$					0.337***	(0.112)	0.304***	(0.058)
Constant			0.020	(0.013)	-2.628***	(0.633)	-1.666***	(0.257)
N	804		804		804		804	

Note: Dependent variable is daily percentage change in MSCI Mexico Stock Market Index. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6.3 Trump's Mexico-Related Tweets and the Mexican Bond Market

Table 10 examines the impact of Trump's Mexico-related tweets on the percentage change in the interest rate spread between 10-year Mexican and US government bonds. Similar to the results for the Mexican stock market, there is no evidence that tweets across the entire sample affect the bond spread in the mean equation, as shown in Models 1, 2, and 3. There appears to be some evidence that tweets have a positive and statistically significant effect on the percentage change in bond spreads in the president-elect period, and a negative effect in the GOP nominee period, although this is statistically significant at the 10 percent level.

Table 10: Bond Spreads

	(1)		(2)		(3)		(4)	
Mean Equation								
Bond Spread$_{t-1}$	-0.032	(0.038)	-0.029	(0.039)	-0.034	(0.040)	-0.027	(0.040)
Pct. Peso$_{t-1}$	0.463***	(0.064)	0.397***	(0.067)	0.352***	(0.063)	0.378***	(0.064)
Tweet Dummy$_t$	0.134	(0.103)	0.076	(0.094)	0.091	(0.096)		
S&P 500$_{t-1}$	0.208***	(0.067)	0.168**	(0.065)	0.156**	(0.068)	0.172**	(0.070)
Δ ln(Banxico US$ Stock$_t$)	83.021***	(29.501)	75.295***	(28.758)	72.560**	(30.057)	67.323**	(28.842)
Δ Overnight Rate Difference$_t$	-1.165	(0.958)	-1.032	(1.052)	-0.724	(0.945)	-0.976	(0.965)
Banxico US$ Sales$_t$	0.095	(0.114)	-0.028	(0.114)	-0.021	(0.110)	-0.051	(0.108)
US Presidential Election$_t$	-1.742	(1.318)	-1.724	(3.596)	-1.913*	(1.082)	-1.959	(1.244)
US Presidential Election$_{t-1}$	5.778***	(1.319)	3.580*	(2.037)	4.182***	(1.427)	5.527***	(1.213)
Trump Primary Candidate$_t$	0.042	(0.145)	0.015	(0.154)	-0.388	(0.311)	-0.045	(0.195)
Trump GOP Nominee$_t$	0.055	(0.200)	-0.073	(0.211)	-0.585	(0.374)	0.034	(0.251)
President-Elect$_t$	0.172	(0.227)	0.264	(0.258)	0.841	(0.609)	0.089	(0.283)
Trump Presidency$_t$	-0.004	(0.152)	-0.124	(0.173)	-0.878**	(0.374)	-0.242	(0.212)
NAFTA Rounds$_t$	0.220	(0.311)	0.125	(0.252)	0.150	(0.251)	0.156	(0.249)
Tweet Dummy$_t\times$Pre-Candidate$_t$							0.304	(0.308)
Tweet Dummy$_t\times$Primary Candidate$_t$							0.230	(0.159)
Tweet Dummy$_t\times$GOP Nominee$_t$							-0.527*	(0.291)
Tweet Dummy$_t\times$President-Elect$_t$							1.346**	(0.661)
Tweet Dummy$_t\times$Presidency$_t$							-0.037	(0.140)
Constant	-0.076	(0.137)	0.467	(0.309)	1.666***	(0.606)	0.666**	(0.300)
Arch-in-Mean$_{t-1}$			-0.273**	(0.139)	-0.756***	(0.269)	-0.349***	(0.128)
Variance Equation								
ARCH(1)			0.074***	(0.028)	0.043*	(0.022)	0.027	(0.022)
GARCH(1)			0.859***	(0.062)	0.600***	(0.106)	0.749***	(0.075)
Tweet Dummy$_t$					-0.048	(0.126)		
Trump Primary Candidate$_t$					-0.328*	(0.169)		
Trump GOP Nominee$_t$					-0.434**	(0.220)		
President-Elect$_t$					0.244	(0.253)		
Trump Presidency$_t$					-0.701***	(0.173)		
S&P 500$_{t-1}$					-0.081	(0.102)	-0.273**	(0.136)
Bond Spread$_{t-1}$					0.165***	(0.058)	0.361***	(0.062)
Tweet Dummy$_t\times$Pre-Candidate$_t$							0.540	(0.361)
Tweet Dummy$_t\times$Primary Candidate$_t$							-0.076	(0.250)
Tweet Dummy$_t\times$GOP Nominee$_t$							-0.129	(0.536)
Tweet Dummy$_t\times$President-Elect$_t$							0.787*	(0.467)
Tweet Dummy$_t\times$Presidency$_t$							-1.028**	(0.487)
Constant			0.110	(0.068)	-0.238	(0.333)	-1.176***	(0.380)
N	804		804		804		804	

Note: Dependent variable is daily percentage percentage change in the interest rate spread between 10-year Mexican and US government bonds. Standard errors in parentheses. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Tweets also do not appear to affect volatility in bond spreads across the full sample, as shown by the lack of statistical significance on the *Tweet* coefficient in the variance equation in Model 3. Model 4 shows that tweets are not statistically significantly different from zero during much of the election process, with the exception that they appear to increase volatility in the president-elect period (though this effect is only weakly statistically significant), while reducing volatility during the Trump presidency.

7 Asymmetric Shocks to the Peso

In all models with conditional heteroskedasticity, we saw that covariates affect not only changes in the USD/MXN exchange rate (the "mean equation") but also the conditional variance. We also found evidence that unexpected shocks affect volatility (the "ARCH" term) as well as the lagged value of volatility itself (the "GARCH" term). All of our models assumed that any shocks not modeled in the conditional variance had a uniform effect, no matter their sign. In other words, if the error term in one period was positive, and of the same magnitude as a negative error in another period, our models assumed that these shocks had equivalent effects on the conditional variance.[9]

However, a large literature exists on how unexpected news tends to have asymmetric effects on markets. "Bad" unexpected economic news (unexpected innovations that depreciate the peso relative to the dollar) may have a different effect than "good" unexpected news (unexpected innovations that appreciate the peso relative to the dollar). A series of asymmetric ARCH/GARCH models have thus been developed to model and test for this phenomenon. In this section we estimate three types of GARCH models that allow for asymmetries in the error. Because these models are more difficult to estimate than the GARCH models above and in the main paper, we could not include covariates in the conditional variance equation, since these models could not achieve convergence. Still, the results in Table 11 show some interesting things.

In Model 1, we specify a simple asymmetric—or SAARCH—model (Engle 1990), which appears as follows:

$$\sigma_t^2 = \omega_0 + \omega_1 \varepsilon_{t-1}^2 + \omega_2 \varepsilon_{t-1} + \omega_3 \sigma_{t-1}^2 \tag{2}$$

[9]This occurs in standard ARCH models due to the fact that the lagged error—i.e., the ARCH term—is squared: ε_{t-1}^2.

In other words, we add $\omega_2\varepsilon_{t-1}$ to the model, which allows the conditional variance to be affected differently if ε_{t-1} is positive or negative, as opposed to the standard ARCH(1) term, $\omega_1\varepsilon_{t-1}^2$. As shown in Model 1 in Table 11, the ARCH term is positive and statistically significant as is the GARCH term, similar to the findings above and in the main paper. The SAARCH term is also positive and statistically significant, which suggests that more positive errors tend to increase the error variance. There thus appears to be some amount of asymmetry taking place based on whether the error is positive or negative.

Table 11: Asymmetric ARCH/GARCH Models

	(1) SAARCH		(2) EGARCH		(3) APARCH	
Mean Equation						
Pct. Peso_{t-1}	0.013	(0.042)	0.023	(0.040)	0.015	(0.042)
Tweet_t	0.012	(0.058)	0.022	(0.058)	0.014	(0.058)
Bond Spread_{t-1}	0.030	(0.023)	0.031	(0.023)	0.031	(0.023)
S&P 500_{t-1}	0.054	(0.041)	0.061	(0.041)	0.058	(0.042)
Δln Banxico US$ Stock_t	10.163	(15.939)	10.057	(16.446)	9.633	(15.932)
Δ Overnight Rate Difference $_t$	-1.191**	(0.600)	-1.158*	(0.620)	-1.133*	(0.594)
Banxico US$ Sales_t	0.142**	(0.066)	0.139**	(0.066)	0.139**	(0.067)
US Presidential Election_t	-2.090	(1.347)	-2.405***	(0.895)	-2.294*	(1.172)
US Presidential Election_{t-1}	7.448***	(1.279)	8.836***	(1.010)	7.260***	(1.053)
Trump Primary Candidate_t	0.038	(0.078)	0.028	(0.080)	0.032	(0.079)
Trump GOP Nominee_t	-0.012	(0.117)	-0.004	(0.112)	-0.016	(0.116)
Trump President-Elect_t	0.186	(0.129)	0.208	(0.127)	0.191	(0.130)
Trump Presidency_t	-0.047	(0.083)	-0.061	(0.084)	-0.056	(0.084)
NAFTA Rounds_t	0.205	(0.160)	0.193	(0.170)	0.198	(0.162)
Constant	-0.022	(0.075)	-0.015	(0.075)	-0.017	(0.075)
Variance Equation						
ARCH(1)	0.078**	(0.034)				
SAARCH(1)	0.055**	(0.027)				
GARCH(1)	0.851***	(0.075)				
EARCH(1)			0.055	(0.035)		
Asy. EARCH(1)			0.163***	(0.062)		
EGARCH(1)			0.921***	(0.050)		
PARCH(1)					0.082**	(0.038)
Asy. PARCH(1)					0.318	(0.257)
PGARCH(1)					0.844***	(0.076)
Power					1.599**	(0.637)
Constant	0.046	(0.029)	-0.039	(0.027)	0.055	(0.035)
N	804		804		804	

Note: Regression with standard errors in parentheses. Dependent variable is daily percent change in the USD/MXN exchange rate. Two-tailed tests. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In Model 2, we present the results from an EGARCH model (Nelson 1991), which appears as:

$$\ln(\sigma_t^2) = \omega_0 + \omega_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \omega_2 \left(|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}| - \sqrt{\frac{2}{\pi}} \right) + \omega_3 \ln(\sigma_{t-1}^2) \tag{3}$$

As the results indicate, the EARCH(1) term ($\omega_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$) is positive but not statistically significant, while both the asymmetric EARCH(1) ($\omega_2 \left(|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}| - \sqrt{\frac{2}{\pi}} \right)$) and EGARCH(1 ($\omega_3 \ln(\sigma_{t-1}^2)$) terms are.

Last, in Model 3 we show an asymmetric power ARCH, or APARCH model (Ding, Granger and Engle 1993):

$$(\sigma_t^2)^{\zeta/2} = \sigma_t^{\zeta} = \omega_0 + \omega_1 (|\varepsilon_{t-1}| + \omega_2 \varepsilon_{t-1})^{\zeta} + \omega_3 \sigma_{t-1}^{\zeta} \tag{4}$$

The results are difficult to interpret, but the power term, ζ, is about 1.6 and statistically significant. While the PARCH(1) term is positive and statistically significant, its asymmetric counterpart is not. Last, the power GARCH term is positive and statistically significant.

To better show how asymmetry is taking place, it is common to show a "news response function" of the expected conditional error variance given a positive or negative shock. Each of the three models from Table 11 is shown in Figure 5.[10] As is clear from the figure, negative shocks appear to raise expected conditional variance to a lesser extent than positive shocks. Since a positive shock signifies the peso experienced a percent increase towards depreciation relative to the dollar, this aligns with expectations about how unexpected bad news contributes to greater volatility than unexpected good news. This effect holds across all three asymmetric models from Table 11. Unfortunately, since we could not add predictors to the heteroskedastic variance in these models, these shocks could be due to *any* form of unexpected news—including tweets—that affect the USD/MXN exchange rate. Still, these results show that "bad" news (unexpected innovations that depreciate the peso relative to the dollar) affect volatility more than appreciations ("good" news), which is in line with our findings in the main text.

[10]For these predictions, we have to assume a expected variance when the error is zero; we assume 0.5, which is near the average from the predictions in the main paper.

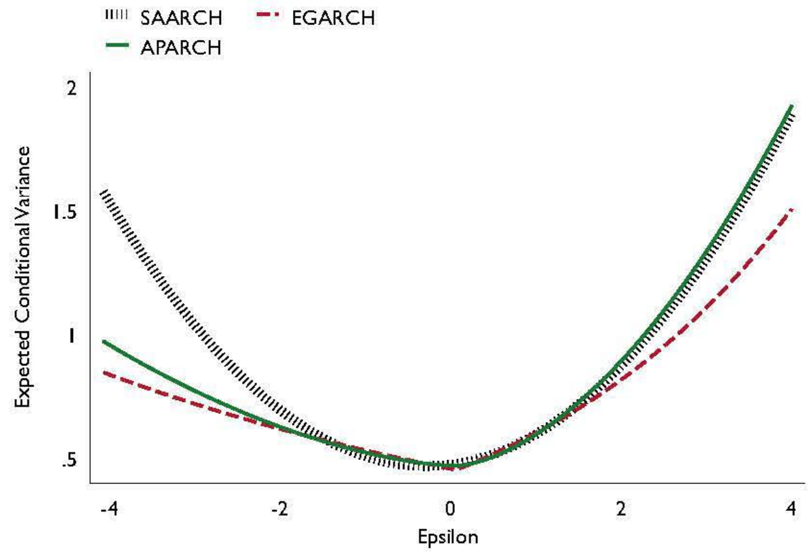

Figure 5: Asymmetric News Response Function

8 VECM Analysis of the Mexican and US Stock Markets

In the main paper we chose to use the US S&P 500 stock market indicator rather than the MSCI Mexican stock market indicator. This was done for several reasons. First, since the peso is such a commonly traded currency, a lot of its movement depends on not just the Mexican economy but also the health of the US and global economy more broadly. Second, the two indicators (the percentage change in each respective stock market index) are correlated at 0.51. Third, while we do not find any evidence that the stationary, percentage change in the two series have any causal relationship between one another, we do find evidence that in the raw series, movements in the S&P 500 are driving changes in the Mexican Index.[11]

As evidence of this, we present a vector error correction model (VECM) in Table 12. We included three lags for each model, as well as a deterministic linear trend. Tests indicate that there is a cointegrating relationship between the two series. Moreover, as Table 13 shows, Granger causality block exogeneity tests on the lagged first-differences indicate that, at least in the short-run, movements in the S&P 500 drive changes in the Mexican stock market, not the other way around. Last, in Figure 6 we show orthogonalized impulse response functions, which depict (moving clockwise from top left) a shock in the Mexican stock market index on itself, Mexican stock market on the S&P 500, the S&P 500 on itself, and the S&P 500 on the

[11]We used a vector autoregressive model (VAR) for the percentage change series (not reported here) and, using Granger-causality tests, find no evidence that the previous value of one series appears to be driving the other.

Mexican stock market. As is clear from Figure 6, shocks to the S&P 500 cause movements in the Mexican stock market, not the reverse. Thus, we are fairly confident that the most important stock market index to include is the S&P 500.

Table 12: VECM Results Show the S&P 500 Drives the Mexican Stock Market

	S&P 500 Index		Mexican Index	
Cointegrating Equation	0.001	(0.005)	0.050^{**}	(0.021)
ΔS&P 500_{t-1}	-0.021	(0.042)	0.339^{*}	(0.186)
ΔS&P 500_{t-2}	-0.093^{**}	(0.042)	-0.351^{*}	(0.186)
ΔS&P 500_{t-3}	-0.014	(0.042)	0.172	(0.186)
ΔMexican Index_{t-1}	0.004	(0.009)	0.121^{***}	(0.041)
ΔMexican Index_{t-2}	0.009	(0.009)	-0.013	(0.041)
ΔMexican Index_{t-3}	-0.002	(0.009)	-0.101^{**}	(0.041)
Trend	0.004	(0.002)	-0.000	(0.011)
Constant	-0.369	(1.155)	-0.042	(5.144)
N	801			

VECM with standard errors in parentheses. Two-tail tests.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Granger Causality Tests

Test:	χ^2
S&P 500 Index $\rightarrow$ Mexican Index	8.30^{**}
Mexican Index $\rightarrow$ S&P 500 Index	1.39

Note: Block exogeneity tests using contemporaneous coefficients of VECM. H_0: Granger non-causality. $*$=0.10, $**$=0.05, $***$=0.01.

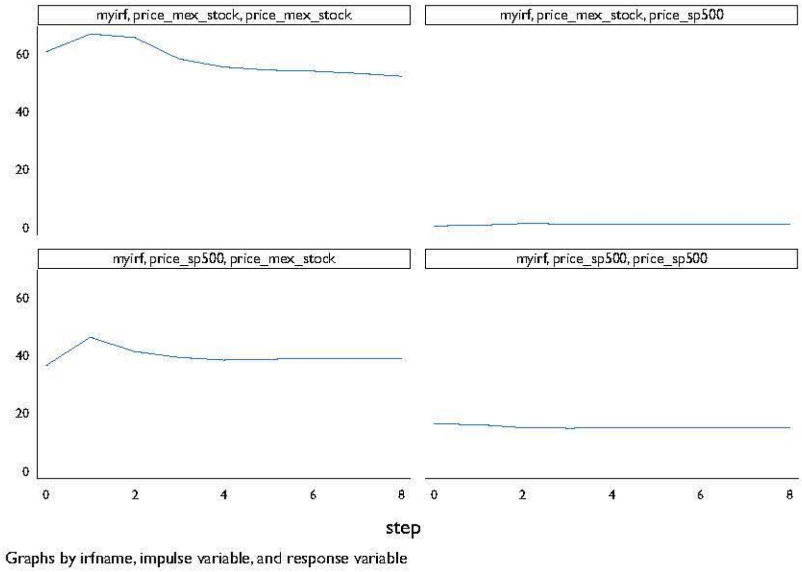

Figure 6: Orthogonalized Impulse Response Function

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