Columbia | SIPA
Center for Environmental Economics and Policy

CEEP WORKING PAPER SERIES
WORKING PAPER NUMBER 12

OCTOBER 2020

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https://ceep.columbia.edu/sites/default/files/content/papers/n12.pdf

Russian Holidays Predict Troll Activity 2015-2017*

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October 29, 2020

Abstract

While international election interference is not new, Russia is credited with "industrializing" trolling on English-language social media platforms. In October 2018, Twitter retrospectively identified 2.9 million English-language tweets as covertly written by trolls from Russia's Internet Research Agency. Most active 2015-2017, these Russian trolls generally supported the Trump campaign (Senate Intelligence Committee, 2019) and researchers have traced how this content disseminated across Twitter. Here, we take a different tack and seek exogenous drivers of Russian troll activity. We find that trolling fell 35% on Russian holidays and to a lesser extent, when temperatures were cold in St. Petersburg. More recent trolls released by Twitter do not show any systematic relationship to holidays and temperature, although substantially fewer of these that have been made public to date. Our finding for the pre-2018 interference period may furnish a natural experiment for evaluating the causal effect of Russian trolling on indirectly-affected outcomes and political behaviors – outcomes that are less traceable to troll content and potentially more important to policymakers than the direct dissemination activities previously studied. As a case in point, we describe suggestive evidence that Russian holidays impacted daily trading prices in 2016 election betting markets.

Keywords: Russian trolling, natural experiment, holidays, Presidential elections

*We thank Joseph Doyle, Olle Folke, Parijat Lal, Bhashkar Mazumder, and Koleman Strumpf for helpful comments and Solveig Asplund for proof reading. We thank Suresh Naidu for suggesting we look at online betting markets in related work. All errors are our own.

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Professional Russian trolling is malevolent and murky. The February 2018 US grand-jury indictment states that the Internet Research Agency (IRA) in St. Petersburg conducted "information warfare against the United State of America" by using "fictitious U.S. personas on social media platforms...." (US Department of Justice, 2018). These fake personas communicated with "unwitting" members of the public to sow distrust in the US political system, discourage minorities from voting, make assertions of voter fraud, organize political rallies, stoke racial divisions,[1] assist the Trump campaign,[2] and other illicit activities.[3] Employees used an Internet proxy service to conceal their I.P. addresses (Chen, 2015) and "covering tracks" was a goal of the IRA operation (US Department of Justice, 2018). As has been widely reported, Russian interference is believed by many to continue during the current election cycle.

In October 2018, Twitter released 2.9 million English-language tweets from 3,841 accounts as "affiliated with the IRA", which we refer to as "Wave 1" tweets. Twitter's stated goal was to "enable independent academic research and investigation". Since January 2019, Twitter has blocked an additional 770,000 English-language tweets of surreptitiously Russian origin, without explicitly attributing them to the IRA. What caused Twitter's suspicions of particular accounts and tweets they have flagged was not disclosed.[4] Nevertheless, Twitter's disclosure of the suspicious Twitter accounts and tweets they think are tied to professional Russian trolling provides the requisite data for our empirical analysis.[5]

Empirically, Russian trolling activity is correlated with the timing of other legitimate activities, including breaking news stories[6] and overall internet traffic levels. Additionally, trolling activity exhibits time trends, seasonality, and the influence of the day of the week. This can make it difficult to ascribe time-series variation in trolling intensity and its effects to the work of trolls *per se*, as opposed to other factors.

Here we explore factors behind Russian trolling activity in the US that are likely specific to Russia. This forensic exercise may be useful for shedding light on the production function of Russian trolling (Zitzewitz, 2012). To the extent they are indeed coordinated in Russia, this would be consistent with Twitter's identification of particular English-language tweets as of surreptitiously Russian-origin. Furthermore, it might

[1]According to the Senate Intelligence Committee's bipartisan report in 2019, "The Committee found the IRA targeted African-Americans more than any other group or demographic. Through individual posts, location targeting, Facebook pages, Instagram accounts, and Twitter trends, the IRA focused much of its efforts on stoking divisions around hot-button issues with racial undertones."

[2]The Senate Intelligence Committee's bipartisan report stated: "The Committee found that the IRA sought to influence the 2016 U.S. presidential election by harming Hillary Clinton's chances of success and supporting Donald Trump at the direction of the Kremlin. The Committee found that IRA social media activity was overtly and almost invariably supportive of then-candidate Trump to the detriment of Secretary Clinton's campaign."

[3]The Federal Election Campaign Act "prohibits foreign nationals from making any contributions, expenditures, independent expenditures, or disbursements for electioneering communications" (US Department of Justice, 2018).

[4]In June 2019, Twitter stated: "...we employ a range of open-source and proprietary signals and tools to identify when attempted coordinated manipulation may be taking place, as well as the actors responsible for it."

[5]Twitter blocking occurs *after* a substantial period of unchecked online activity, which is what we analyze.

[6]For example, Russian troll accounts "respond to shifts in political circumstances", e.g. "the well-known faint/stumble by Hillary Clinton leaving a 9/11 commemoration event, followed by her pausing the campaign with an announcement of pneumonia." (Linvill and Warren, 2020)

help social media, cybersecurity firms, and government agencies to identify ongoing interference activities. Finally, and most important for future research, our approach might allow researchers to isolate exogenous drivers of trolling activity in the US – neglected by research to date – and thereby its true and full effect.

We find that Russian holidays decrease trolling by 35% in the corpus of Twitter's primary data release on October 2018 of 2.9 million tweets. The decrease in overall holiday tweeting is largest for original tweets, which may be more impactful than retweets. To a lesser extent, warmer temperatures in St. Petersburg also increased trolling.

From January 2019 to June 2020, Twitter released another 770,000 English language tweets as of surreptitiously Russian origin, but without explicitly attributing them to the IRA in St. Petersburg.[7] The reduced number of recently-released trolls could indicate: 1) less trolling recently on Twitter by Russians, 2) that Twitter is holding on to this "wave 5" information so as not to compromise its defensive methods in the run-up to the 2020 election, or 3) Russians have gotten better at "covering their tracks". Indeed, following the glare of publicity their trolling received around the February 2018 US indictment of the IRA, Russians may have adopted new methods of interference. While we have less statistical power to detect effects in the 2018-2020 period because there are far fewer suspicious tweets to analyze, we see no relationship between Russian holidays or St. Petersburg's temperature in the most recent period. Power issues aside, this null finding is consistent with Russia getting better at "'covering its tracks".

Despite its importance and popular interest, little is known about the causal effects of Russian trolling on outcomes politicians and policymakers actually care about, such as campaign donations or election probabilities. Arguably, these outcomes are more important than the direct observed dissemination of troll content itself that has previously been studied. Such indirect effects would include the downstream impact of Russian trolls on unwitting internet users who do not retweet the (surreptitiously) Russian tweet or its content and how they and their US compatriots behave when off Twitter. This is where exogenous variation in Russian trolling could be useful in forging a link. To the extent local Russian factors drive English-language trolling, this may provide a natural experiment for considering impacts on higher-stakes, election-related behaviors.

Instead, previous research has focused on persons who had direct interactions with Russian trolls and automated bots and how trolling content disseminated. Importantly, this direct dissemination can and has been observed.

Bail *et al.* (2020) surveyed Twitter users in the fall of 2017 and observed in longitudinal data whether they directly accessed content from IRA accounts, the true IRA identities of which had not been disclosed to the public at that time. Bail *et al.* (2020) note that prior to their paper:

> *Yet, to our knowledge, no studies have examined whether these efforts actually impacted the attitudes and behaviors of the American public.*

At follow-up, Bail *et al.* (2020) found "no evidence that interacting with these accounts substantially impacted 6 political attitudes and behaviors." They reason that IRA activity may not show its intended effect because it was accessed disproportionately

[7]For waves 2 and 4, Twitter noted: "We cannot render definitive attribution to the IRA for these (418) accounts, although most appear to originate in Russia", and "accounts are associated with Current Policy, engaging in state-backed political propaganda within Russia". See link1, link2.

by (US) Twitter users who were already polarized. Bail *et al.* (2020) also note that "[s]tudies of political communications and campaigns, for example, have repeatedly demonstrated that it is very difficult to change people's views". In contrast, a working paper by Dutta *et al.* (2020) analyzes Twitter behavior of those users who were actively contacted by IRA bots and provide "some of the first evidence that contacted Twitter users' behavior underwent significant changes...following interactions with Russia's Internet Research Agency." They characterize their working paper's findings of changes in tweeting frequency and tweet sentiment as correlational: "The intent of this paper is not to establish causality" (Dutta *et al.*, 2020). Focussing on Russian bots, Gorodnichenko *et al.* (2018) find that "diffusion of information on Twitter is largely complete within 1-2 hours" and have a "tangible effect on the tweeting activity of humans". A working paper by Im *et al.* (2020) builds a machine learning algorithm to predict the likelihood that an account is a Russian troll, unbeknownst to other Twitter users. They then see to what extent these likely-troll accounts diffuse content to journalists.[8]

All of these findings are for observed and direct links to trolling content. For social media content more broadly, impacts on "downstream" political outcomes like street protests or voter turnout have been shown using natural experiments, e.g. within Russia itself (Enikolopov, Makarin, and Petrova, 2020). In terms of content dissemination via social media, Zhuravskaya, Petrova, and Enikolopov (2020) note: "As immediate reactions are often based on emotions rather than reason, fake news, which evokes fear or anger, may spread faster than real news, which is often less emotionally charged."

For Russian trolling specifically, we know of no natural experiment-based evidence that it has affected the more important downstream outcomes that may not be directly linkable with tweet- or account-level trolling data. To capture the full downstream impacts of trolling, such outcomes also need to be considered alongside the more "traceable" ones. As a case in point, we describe suggestive evidence that Russian holidays impacted daily trading prices in 2016 election betting markets in the Discussion section.

1 Methods and Research Design

1.1 Data

1.1.1 Russian Tweets

According to the federal indictment, IRA began its interference in the US around 2014 with its English-language "translator project" (US Department of Justice, 2018).[9] This English-language group was "elite and secretive" (Chen, 2015). In July 2016, more than eighty IRA employees were assigned to this covert effort.

In October 2018, Twitter announced:

> *[W]e are releasing the full, comprehensive archives of the Tweets and media that are connected with these two previously disclosed and potentially state-backed operations on our service. We are making this data available with the goal of encouraging open research and investigation of these behaviors from*

[8]Anecdotally, the Washington Post noted that Eric Trump, Donald Trump Jr., and Kellyanne Conway all posted information from a likely Russian troll @TEN_GOP in the run-up to the 2016 presidential election.

[9]Bail *et al.* (2020) cite a US Senate Intelligence Committee that IRA has been active since 2013. Twitter blocked suspicious tweets posted back to 2009.

researchers and academics around the world. These large datasets comprise 3,841 accounts affiliated with the IRA, originating in Russia, and 770 other accounts, potentially originating in Iran. They include more than 10 million Tweets and more than 2 million images, GIFs, videos, and Periscope broadcasts, including the earliest on-Twitter activity from accounts connected with these campaigns, dating back to 2009.

Among these were 2.9 million English-language tweets from the 3,841 IRA-affiliated accounts. Since October 2018, Twitter has been detecting and suspending accounts with known state-backed information operations. As of October 2020, Twitter released 418, 4 and 1,152 blocked accounts linked with Russia in January 2019, June 2019 and June 2020, respectively. We refer to these releases as "waves" 2-4. Unfortunately, the date/time at which the individual account was blocked or removed is not disclosed by Twitter.[10] Nor do we know whether the suspect accounts disclosed in the same blocking announcement were blocked simultaneously or separately. We focus on English tweets on the "day shift": 9am-9pm Russia time.[11] Finally and descriptively, Linvill and Warren (2020) document "enormous heterogeneity in theme and approach across IRA accounts". For example, some tweets appear targeted at right-wing followers and others to sow discord on the left.

The time series of Russian trolling activities by wave is shown in Figure 1. We see very little (unmasked) trolling activity after the fall of 2018. Also, the vast majority of English tweets – some 80% – come from wave 1, which were most active from late 2014 through the end of 2017.

1.1.2 Downstream outcomes

According to February 2018 indictment, IRA sought to develop "certain fictitious U.S. personas into "leader[s] of public opinion in the United States" (US Department of Justice, 2018). Therefore, we look at the Hedonometer, a summary, widely-referenced[12] metric of "average happiness" of English tweets on Twitter. Hedonometer notes on its website: "Our Hedonometer is based on people's online expressions, capitalizing on data-rich social media, and we're measuring how people present themselves to the outside world". Dodds *et al.* (2011) provide detailed information on their scoring algorithm. An advantage to analyzing these downstream data is that they are available for all the initial posting dates of the subsequently-blocked accounts and tweets. As only 1,702 tweets posted before 2012 were subsequently blocked, we use 2012 as the start year of our study period.

Rhode and Strumpf (2004) note there have been "large and well-organized markets for betting on presidential elections" stretching back to at least 1868. 2020 Election odds come from BetData, which tracks odds for 105 potential candidates beginning in

[10] See supplementary material section 4 for an attempt at analyzing inferred blocking dates. We thank Joe Doyle for a conversation that spurred this RD-style investigation.

[11] Chen (2015) notes that IRA work shifts began at 9am and finished at 9pm. Linvill and Warren (2020) likewise note: "IRA employees tasked with making social media posts are reported to have been organized into 12-hour shifts, a day shift and night shift, and instructed to make posts at times appropriate to U.S. time zones."

[12] On October 3, Google scholar showed 680 citations of Dodds *et al.* (2011). The popular press has also frequently invoked the Hedonometer, e.g. *The Washington Post* in August 2019 and *The New York Times* in February 2015.

November 2016. Because the identified trolls were most active before the November 2016 election, we have less overlap between our election odds data and observed troll activity. 2016 Presidential election betting data come from Iowa Election Markets (IEM) and PredictIt, which both begin in November 2014. Since we observe daily price for 2016 Election odds and hourly price for 2020 Election odds, we use the daily closing price for 2016 election odds and hourly price at 2pm EST (9pm Russian time) for 2020 odds. We use the implied probability of winning for Republican's and Democrat's candidates as outcome variables. A key difference of these markets is that PredictIt only allows traders in the US, BetData (Betfair) forbids US traders.[13] IEM is open to traders worldwide.[14]

1.2 Research Design

1.2.1 Russian Holidays

We define Russian holidays using the eight Federal holidays enumerated within the Labor Code of the Russian Federation. The eight Russian holidays are:

New Years (January 1)
Eastern Orthodox Christmas (January 7)
Defender of the Fatherland Day (February 25)
International Women's Day (March 8)
Labor Day (May 1)
Victory Day (May 9)
Russia Day (June 12)
Unity Day (November 4).

We do not use January 1 because it coincides with a US holiday (which we also control for).

We are not the first to notice a relationship between Russian holidays and Russian malfeasance in the US. In 2015, a cybersecurity firm in California was studying "an advanced persistent threat group that we suspect the Russian government sponsors", which they referred to as APT29. Their focus was not on Russian trolling by the IRA, but instead non-public actions by Russian intelligence itself. Released in July 2015, the "Hamertoss" threat intelligence report by Fireeye Inc. noted in passing that "APT29 appeared to cease operations on Russian holidays....". They did not present any additional details or empirical evidence. To our knowledge, this holiday effect has not been picked up in the academic literature studying Russian interference. And fortunately for us, Russian holidays differ from US holidays, which may have distinct effects on outcomes of interest.

[13]From Betfair: "You will not bet or attempt to bet with us if you are located in the United States of America or in any other country with a comparable legal situation. These countries will be determined by Betfair from time to time."

[14]From the IEM Trader's Manual: "Participation in the IEM is open to students, faculty, and staff at colleges and universities worldwide; IEM political markets are also open to non-academic participants."

1.2.2 Ambient Temperature

Daily temperature data is from the National Climatic Data Center Global Summary of the Day (GSOD) dataset.[15] We use mean temperature from weather stations in St. Petersburg 2012-2019 for the main result, and add London and other cities in U.S. in Supplementary Material Section 1.3.

1.2.3 Wave-specific Factors

Figure 1 shows that the level of tweeting differs markedly by wave of release. Additionally, Wave 1 was specifically attributed to the Internet Research Agency, while subsequent waves of blocked Russian tweets were not. Trolling tactics and practices evolved over time and it is possible that different groups of actors in differing locations within Russia were involved in different waves. For these reasons, our regression specifications include wave-specific fixed effects and allow the effect of temperature and holiday to vary by wave:

$$\begin{aligned} Y_{wt} = \sum_{w=1}^{4} \beta_w Holiday\_RU_t \times Wave_w + \sum_{w=1}^{4} \gamma_w Temperature_t \times Wave_w \\ + \theta_t Holiday\_US_t + DOW_t + (Wave * Year)_{wt} + (Wave * Month)_{wt} + \varepsilon_{wt} \end{aligned} \quad (1)$$

where $\mathrm{Y_{wt}}$ denotes the number of wave w tweets posted 9am-9pm Russian time on day t.[16] Coefficients β_1 to β_4 capture wave-specific impacts of Russian holidays, and γ_1 to γ_4 capture temperature impacts. We also include a $\mathrm{Holiday\_US_t}$ dummy and day of week fixed effects that are common across waves. $(Wave * Year)_{wt}$ and $(Wave * Month)_{wt}$ denote year and month FE that are interacted with the wave dummies.

2 Results

2.1 Wave by Day Results

In Table 1, we analyze how Russian holidays and temperature in St. Petersburg affect the total number of suspect (i.e. subsequently-blocked) tweets at the wave-day level. To isolate the holiday effect, we control for day-of-week fixed effects (FE), wave by year FE, and wave-specific seasonality (wave by calendar month FE). The number of blocked tweets released in the first wave during Russian holidays decreases by 0.29 standard deviations or 35.1% relative to the mean, as compared with non-holidays. The .29 point estimate is fairly precise, with a standard error of .09 to .10. Also on the first wave, a one standard deviation increase in temperature more modestly increases blocked tweets by 0.056 standard deviations, or 6.8% relative to the mean. Holiday and temperature estimates appear driven by the subset of original tweets (Panel B), which

[15] https://www.ncei.noaa.gov/access/search/data-search/global-summary-of-the-day

[16] We drop tweets with blank tweet_text for further analysis. Among non-blank tweets, we consider pure retweets without comments as retweets, non-retweets or retweets with comments as original tweets. In practice, we label tweet as retweet if it starts with "RT" and its field is_retweet is true. In Appendix Section 6, we add back blank tweets and only use field is_retweet to label retweets. Results are very similar to main results without blank tweets.

might be expected to have a greater impact on downstream outcomes than retweets (Panel C).

In Column (2)-(4), we add linear, quadratic, and cubic day trends in the regression to allow for the nonlinear time trend in Russian trolling activity. Since we already control for wave by year FE, we assume the same within-year trends for the four waves after controlling wave-specific seasonality. R^2s are similar in Column (1)-(4), indicating a poor explanatory contribution from the time trends. Estimates on holidays and temperature remain stable with these additional controls. In Column (5) and (6), we conduct a more aggressive control strategy, leveraging within year-by-month-by-wave comparisons. Adding these fixed effects increases the R^2 from .36 to .5.[17] The impact estimate for Russian holidays is highly robust, the point estimate remaining at -.29 standard deviations. Though estimates on temperature are not significant, we think seasonality of temperature in St. Petersburg is sufficiently controlled with calendar month FE and we will only use Column (1)-(4) estimates to gauge the impact of local temperature fluctuations. Adding year-month FE may absorb temperature fluctuations that last for several days and are registered by the year by month FE.

In contrast to the first wave, the impact of holiday or temperature on tweets released in other three waves is not significantly different from 0. As mentioned above, the latter three releases together contain 20% of the total English-language troll tweets Twitter has tied to Russia to date.

2.2 Wave 1 Event Study

We show the holiday impact on the first wave "mother lode" of tweets in Figure 2. Over the 2012-2017 activity period for wave 1 accounts, we use 42 holidays for original tweets and 44 holidays for retweets. Without any control variables, the number of tweets decreases by roughly 200 on day 0 and the magnitude is very similar to our point estimates in Table 1 Panel A, which includes a more extensive set of controls. In the event that holidays coincide with weekends or are otherwise correlated with the day of the week, we add day-of-week FE (only, no other control variables) in the middle panel. The pattern is quite similar and the trough on day 0 (the holiday itself) is more obvious.

In addition to day of the week FE, Appendix Table S6 adds additional control variables and shows that the holiday effect is robust and statistically significant. These regression controls include year and month FE, and even year by month FE, thereby restricting comparisons to be within the same month. The bottom panel of Figure 2 displays the same-month comparisons. Residuals with day-of-week and year-month FE decrease by 85 original tweets and 70 retweets on day 0.

Figure 3 focusses on the sub-period of the 2016 election campaign: November 2014-November 2016. The holiday pattern is if anything more pronounced during these two years, this despite using only 11 holidays for original tweets and 15 holidays for retweets. Again, this pattern is highly robust to regression controls.

[17] R^2s are higher for the retweeting operations than original tweets.

2.3 Robustness

First stage estimates are robust when we drop the top 10 busiest days for each wave 2012-2019 (SI Section 1.2). The magnitude of holiday effect is somewhat smaller than that in Table 1. Although very busy trolling days contribute some to the estimated holiday effect, we still see a qualitatively-similar decrease in the number of tweets on holidays as compared with the non-busiest days.[18] Dropping the temperature in St. Petersburg variable, i.e. only focussing on holiday, also yields similar first stage estimates (SI Section 1.1). We also control for daily temperature in other major American/English cities: London, New York, Los Angeles, and Washington DC (SI Section 1.3). The first stage point estimates have slightly larger magnitudes with the inclusion of temperature controls in the four Western cities.

2.4 First Stage Mechanism

Holiday timing is an intuitive and common natural experiment in economics. For example, avoidance by physicians of holiday deliveries creates a pronounced dip in induced deliveries, which can be used to evaluate health impacts of induction on surrounding days (Jacobson *et al.*, 2020). Part of the reason is that the shadow cost of leisure increases markedly on holidays. This is a fairly straight-forward mechanism for reduced Russian trolling activity on Russian holidays.

Turning to temperature, St. Petersburg is cold. In July, the average daily high temperature is 72 °F and daily high temperatures in January are typically below freezing. IRA work has been characterized as occurring indoors and concentrated for a time at an office building at 55 Savushkina Street in St. Petersburg. In an office environment, task productivity peaks around 72 °F (Seppänen *et al.*, 2006; Heal *et al.*, 2017). To the extent that indoor climate control is imperfect at trolling workplaces, warmer ambient temperatures may bring the indoor temperature closer to the productivity optimum. Alternatively, it could be that cold experienced outside of work has a persistent effect on productivity while at work. Finally, colder temperatures may be associated with factors like ice that make it more difficult to get to work.

For completeness, we note factors that did not appear to affect trolling activity. Domestic Russian protests may have distracted IRA workers from the US-interference operation. Motivated by the observation that "Employees were mostly in their 20s" (Chen, 2015), we considered the schedule of local hockey games. Neither appeared to affect the intensity of English-language trolling activity. Finally, increased Brexit trolling did not appear to decrease non-Brexit trolling (through a trolling supply constraint).

3 Discussion

International political interference is anything but new. Britain interfered in the 1940 U.S. election to support Roosevelt. The CIA covertly placed ideological content in East German media (Yaffa, 2020) and orchestrated the overthrow of Iran's democratically-elected prime minister Mohammad Mossadeqin in 1953. The CIA also interfered in the 1996 Russian election. Scott Shane (*The New York Times*) noted in a 2018 interview:

[18] Busiest days may also be an outcome of the Russian holiday schedule.

But we have certainly put our thumb on the scales in elections once in Russia, trying to prevent the election of a communist in 1996 who was leading in the polls against Boris Yeltsin. And so we, you know, we intervened in a significant way to help Yeltsin's re-election.

What is more novel about election interference by the IRA is that it "industrialized the art of trolling" (Chen, 2015). Indeed, a former IRA employee relayed to the *Washington Post*: "Your first feeling, when you ended up there, was that you were in some kind of factory that turned lying, telling untruths, into an industrial assembly line...."

The null findings in Bail *et al.* (2020) resonate with a broader suspicion that while salacious, Russian trolling does not have important "downstream" effects, say to election outcomes. As the *New Yorker* recently put it, the impactful IRA narrative may be an "overly convenient" explanation for our home-grown problems and:

What if, to borrow an old horror-movie trope, the call is coming from inside the house? (Yaffa, 2020)

That is, domestic election interference by the President, news media disinformation, domestic conspiracy theories, etc. may be more consequential. President Trump himself has repeatedly questioned the integrity of mail-in voting and the Director of the US Postal Service has been accused of deliberately slowing mail deliveries. Switching to COVID-19, Bursztyn *et al.* (2020) attribute higher mortality to watching Sean Hannity on Fox, who has consistently downplayed the risks of infection. These culprits are all domestic.

Our novel approach to trolling attempts to isolate variation in disinformation coming from abroad. We find that Russian holidays and temperatures in St. Petersburg help predict daily variation in Russian trolling activity. That is, we argue a phone call is indeed also coming from "outside the house".

Moreover, if Russian holidays and temperature are exogenous, then they may help address the issue for causal inference posed by endogenous selection into who accesses (Bail *et al.*, 2020) or is the target of (Dutta *et al.*, 2020) IRA content. And if additional exogenous factors can be identified, this could be a powerful approach for assessing trolling impacts. As troll tweets include a time stamp, this might include utilizing variation at a higher frequency than the daily variation we consider.[19] When Twitter discloses more recent Troll activity – perhaps after the November 2020 election – these again can be explored for their relationship to exogenous drivers and thereby their potential causal effect on recent election-related outcomes. Twitter accounts from Turkey, China, Iran, and Venezuela have also been blocked by Twitter alongside those from Russia, so our approach could be extended to consider other source country-specific factors behind trolling.

To illustrate both "proof of concept" as well as some limitations, the appendix sections 2.2, 3.2, and 3.3 consider two downstream outcomes: daily Hedonometer and election odds. The Hedonometer measures sentiment and inferred happiness of English-language tweets. Reduced form impacts for Russian holidays are not distinguishable from 0, implying no detectable impact on happiness. Standard errors are similar to point estimates. If we take double the point estimates, we can reject impacts of around .01. For comparison, we see that the Hedonometer increases .056 on US holidays, fell 0.06 when Brett Kavanaugh was confirmed for the Supreme Court, and fell .2 on the

[19] For example, election odds are available from BetData by the hour.

day of the mass shooting in Dayton (SI Table S16). Analyzing the Hedonometer has the advantage of leveraging daily variation across the full time period of wave 1 tweets.

We can also consider daily presidential election odds as inferred from betting markets. A drawback in considering election odds is that we are forced to analyze a shorter time period, which renders our reduced form (but not the first stage) noisier. Considering the 2016 election odds, Iowa Election Markets data began November 17, 2014 and ended November 10, 2016. This means we can analyze 2016 odds around just 15 holiday events[20] and 315 betting days in total.[21] The reduced form event study figures are shown in Figures S1. Democratic odds peak on Russian holidays, while Republican odds hit their nadir. Unadjusted event study estimates (top panel, Figure S1) are very similar to the regression-adjusted ones (middle and bottom panels, Figure S1). Tables S13 and S14 show a statistically significant increase in 2016 Democratic odds on Russian holidays when trolling fell by around a third (Figure 3).[22] Conversely, odds for Republicans fell by a similar amount on the 15 Russian holidays. Notably, the reduced form estimates do not change *at all* with alternative sets of control variable in Tables S13 and S14 – including month by year fixed effects – suggesting a robust relationship.

We repeat the analysis of 2016 election odds using data from the PredictIt betting market.[23] While newer, the PredictIt market is likely thicker than the Iowa Election Market.[24] Additionally, only US Citizens may bet on the PredictIt market for presidential candidates,[25] appealing for a reason we note below. The unadjusted reduced form for 2016 again shows a Democratic peak in odds on Russian holidays and a Republican minimum (Figure S2). This basic pattern persists with regression adjustment.[26] The reduced form effect of holidays is distinguishable from 0 at the 5% significance level, as show in Table S15. Effect magnitudes are around .01. If in Instrumental-Variables fashion one is willing to scale this by the first stage to extrapolate to the elimination of Russian trolling (see Footnote 28), 2016 odds move by around .03. In contrast, US holidays show no impact on election odds (Table S15). Finally, we note Russian holidays have similar-sized effects in the Iowa and PredictIt data.[27]

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[20]There are 16 Russian holidays over this period. The last holiday, Nov 4, 2016, is dropped due to incomplete "post" betting data.

[21]Using a 21 day window around each holiday. If we drop the busiest trolling days and events, we analyze only 11 holidays and 231 days for all and original tweets, and 15 holidays and 315 days for retweeted tweets.

[22]Appendix Table S11 shows first stage in tables for the November 2014-November 2016 period. If anything, the holiday-indued reduction is more obvious than in the full sample.

[23]We sum prices from the candidate-specific market as it permits analysis of more holidays and more betting days (315 betting days, same as with the the Iowa data). The candidate-specific PredictIt market is substantially thicker than the political party PredictIt market, the former having nine times more trading volume over our sample period.

[24]Indeed, the trading volume over our 315 day period is two orders of magnitude higher on PredictIt than Iowa Election Markets. We thank Koleman Strumpf for flagging the differences in thickness/liquidity across exchanges.

[25] PredictIt's Parker Howell emailed us on October 19, 2020: "All traders on PredictIt have to be American citizens who have passed ID verification. Anyone trying to trade from a Russian IP address would have been blocked in 2016. If ever we suspect a trader of fraud their account is frozen until they can upload a US-issued photo ID."

[26]The vertical scale makes the regression-adjusted pattern appear noisier than the unadjusted reduced form (Figure S2).

[27]The Democrats' probability increases by 2.5% on Russian holidays in the Iowa data (Table S14) and increases 2.1% in the PredictIt data (Table S15). Conversely, Republicans' probability decreases by 1.7% on

Our 2020 election odds data begin in November 2016. Wave 1 tweets stop at the end of 2017. This permits a reduced form analysis of just 168 betting days (and 8 holiday events in total) that are, moreover, *extremely early* in the 2020 campaign. While holidays if anything matter more for the first stage in original tweets from late 2016 through 2017, in the reduced form we detect no impact on 2020 election odds that is distinguishable statistically from zero.

The above reduced form estimates for holidays can be interpreted causally if the conditional independence assumption is satisfied (Angrist and Pischke, 2009).[28] While that seems likely enough to us, the noise in the reduced form figures is a reason for caution. But even if Russian holidays are conditionally independent of potential outcomes, this does not imply that the reduced form impacts are attributable to Russian trolling. One obvious threat is that Russian holidays might have a direct effect on US election odds or internet happiness, e.g. through non-trolling Russians living in the US. Unfortunately we have been unable to find information on the number of undisguised Russians or Russian-Americans placing election bets or tweeting in English, let alone the effect of Russian holidays on their betting behavior or happiness (as expressed in English on Twitter). For the Hedonometer null result, our prior is that this is very small relative to the roughly 59 million non-Russian Twitter users in the US. To the extent that only US citizens can bet on the PredictIt market, we are less concerned about direct effects of Russian holidays on 2016 election odds, although US citizens who observe Russian holidays could still exert a direct effect on election odds. That US holidays appear to have no effect on US election odds (*cf.* the Hedonometer increase on US holidays) may suggest the *direct* effect of Russian holidays on betting behavior by Russian-Americans in PredictIt markets might also be modest.

Our reduced form approach readily generalizes to the analysis of other high-frequency US outcomes that may be of interest to researchers and are believed to impact elections, such as time-series variation in political campaign donations, street protests, etc. Our analysis here can be viewed as initial "proof of concept" for future analyses that emphasize:

1. Exogenous drivers of Russian trolling activity – neglected by the existing literature.
2. Trolling's causal effect on indirectly-affected outcomes of interest, i.e. outcomes where the precise path of content sharing, dissemination, and downstream impacts cannot be traced.

These indirect channels may be the most challenging <u>and</u> important ones to understand.

Russian holidays in the Iowa data (Table S14), and decreases by 2.8% in the PredictIt data (Table S15).

[28]We do not conduct an instrumental variables (IV) analysis that predicts subsequently-exposed trolling activity on Twitter from Russian holidays and St. Petersburg's weather. There would be some familiar reasons to take such IV estimates with a grain of salt. Most obvious is that Twitter was not the only online platform the IRA has targeted. Part of the effect, assuming there is one, could be coming from variation in trolling on platforms like Facebook or Instagram, which would not be captured by the endogenous variable Twitter provided. Similarly, Russian Twitter accounts that were not blocked could be undetected Trolls and follow a similar (unobserved) first stage on Twitter. These omissions would violate the exclusion restriction for the blocked suspected-IRA tweets (endogenous variable) we can observe and analyze. And as always, the strength of the instruments in the first stage for the particular outcome of interest would need to be assessed (Staiger and Stock, 1997; Lee *et al.*, 2020).

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Figure 1: Time series of tweet activity by wave of public release.

(We drop top 10 busiest days for wave 1, 2, 4 2012-2019 and calculate monthly sum of all tweets.)

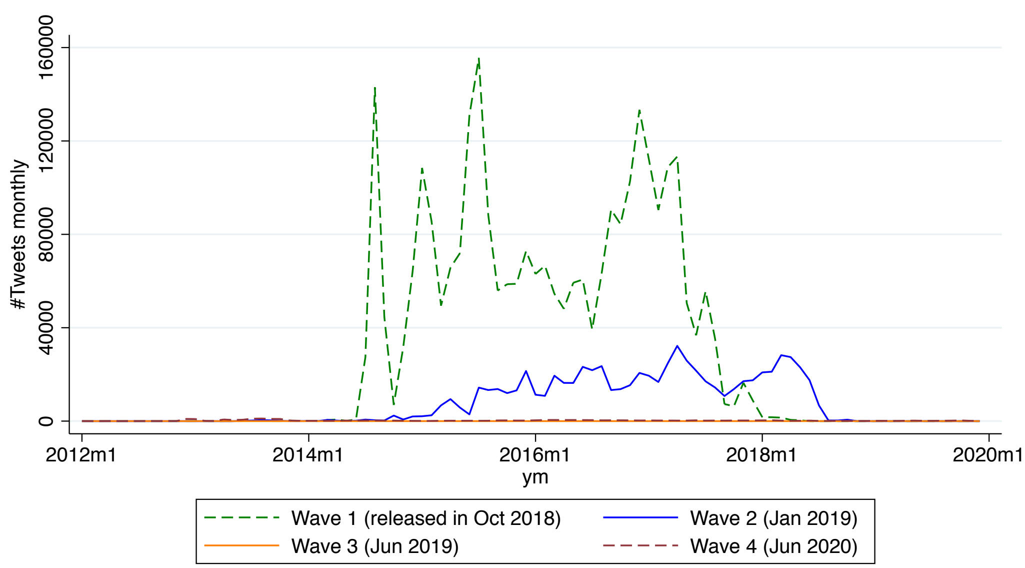
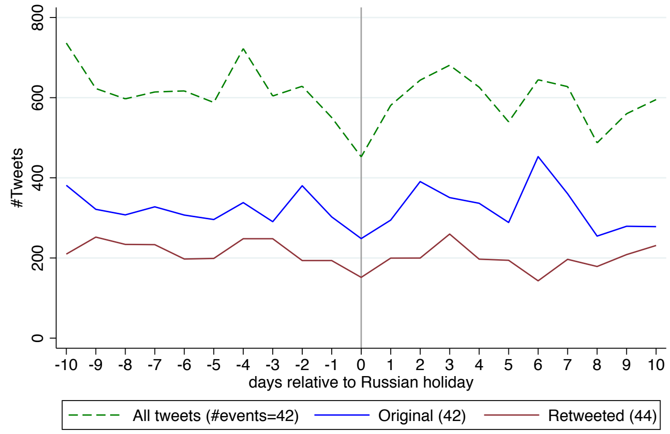


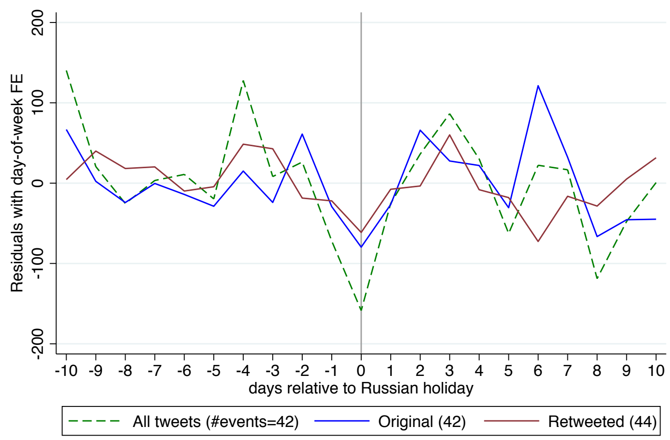
Figure 2: Event Study of Wave 1 tweets (day shift) around Russian holidays 2012-2017

(We drop top 10 busiest days for each category (all, original, retweeted tweets) 2012-2017, and only keep holiday events with complete data over the 21-day window. This results in a smaller number of events than 48 (8 events per year over 6 years) and a different number of events for each category, reported in parentheses. For Panel A, we calculate the simple average of tweets on each event day. For Panel B and C, we add day-of-week FE and year-month FE and calculate the average of predicted residuals.)

Panel A: Raw data



Panel B: Residuals with day-of-week FE



Panel C: Residuals with day-of-week and year by month FE

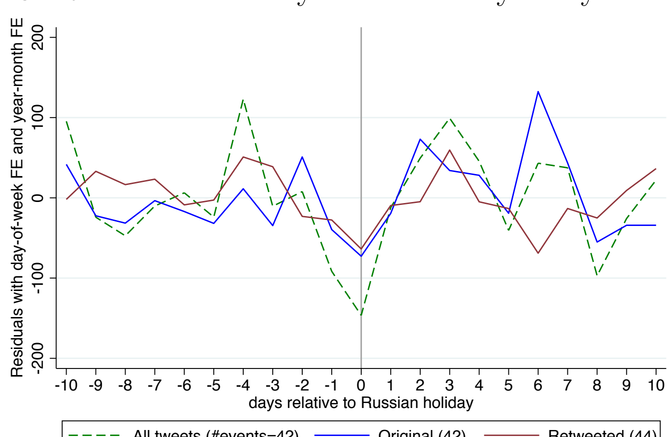
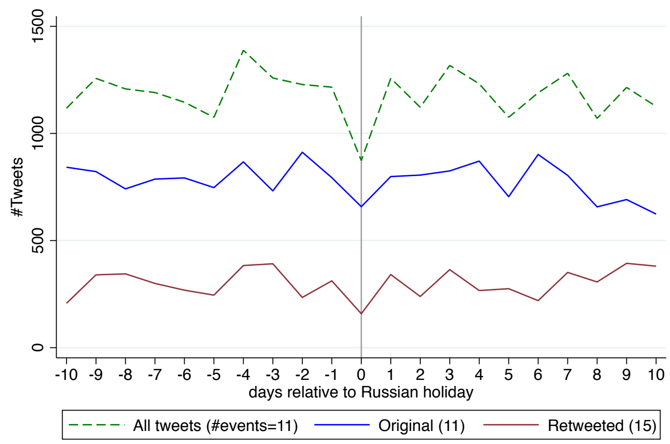


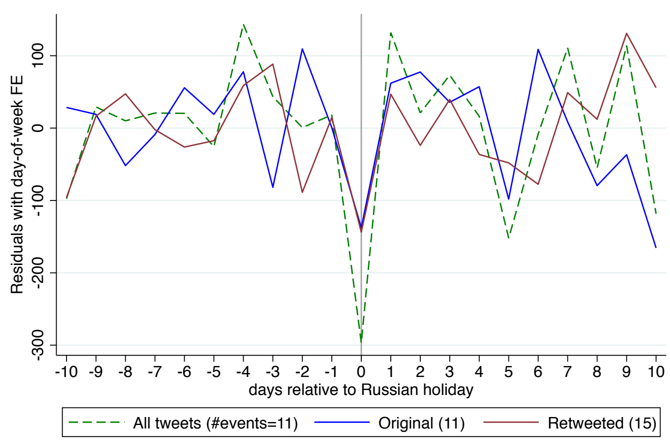
Figure 3: Wave 1 tweets (day shift) around Russian holidays **Nov. 2014-Nov. 2016**

(Similar to Figure 2, we drop top 10 busiest days for each category (all, original, retweeted tweets) 2012-2017, and only keep holiday events with complete data over the 21-day window. This results in a smaller number of events than 15 (8 events per year over 2 years, minus Unity Day (Nov 4) 2016 with incomplete betting data) and different number of events for each category, reported in parentheses.)

Panel A: Raw data



Panel B: Residuals with day-of-week FE



Panel C: Residuals with day-of-week and year by month FE

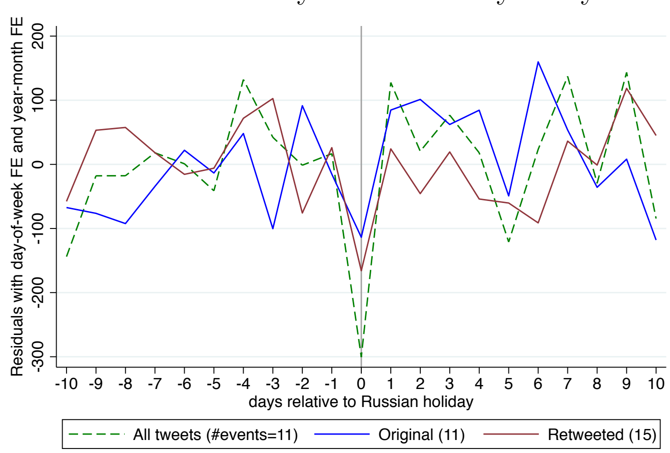


Table 1: First stage: Russian holiday and temperature on blocked tweets on the day shift

	Panel A: #All tweets (z)					
	(1)	(2)	(3)	(4)	(5)	(6)
Holiday_RU × Wave=1	-0.292***	-0.291***	-0.291***	-0.291***	-0.293***	-0.293***
	(0.103)	(0.103)	(0.103)	(0.103)	(0.092)	(0.093)
Holiday_RU × Wave=2	-0.040	-0.039	-0.039	-0.039	-0.039	-0.039
	(0.103)	(0.103)	(0.103)	(0.103)	(0.092)	(0.093)
Holiday_RU × Wave=3	-0.007	-0.006	-0.006	-0.006	-0.007	-0.007
	(0.103)	(0.103)	(0.103)	(0.103)	(0.092)	(0.093)
Holiday_RU × Wave=4	-0.009	-0.008	-0.008	-0.008	-0.009	-0.009
	(0.103)	(0.103)	(0.103)	(0.103)	(0.092)	(0.093)
Temp × Wave=1 (z)	.0564*	.0564*	.0555*	.0544*	.00092	.000867
	(.0323)	(.0323)	(.0323)	(.0323)	(.0332)	(.0332)
Temp × Wave=2 (z)	-.0148	-.0148	-.0157	-.0168	.00442	.00436
	(.0323)	(.0323)	(.0323)	(.0323)	(.0332)	(.0332)
Temp × Wave=3 (z)	.00115	.00114	.000221	-.000862	.00171	.00165
	(.0323)	(.0323)	(.0323)	(.0323)	(.0332)	(.0332)
Temp × Wave=4 (z)	-.000871	-.000874	-.0018	-.00288	.000357	.000304
	(.0323)	(.0323)	(.0323)	(.0323)	(.0332)	(.0332)
Holiday_US	.0119	.012	.0118	.012	.0129	.0129
	(.0474)	(.0475)	(.0474)	(.0474)	(.0426)	(.0426)
Days ($\times 10^{-3}$)		.121	.646	.881		-.014
		(.853)	(.861)	(.876)		(2.28)
Days^2 ($\times 10^{-6}$)			-.186***	-.428**		.306
			(.0421)	(.172)		(1.8)
Days^3 ($\times 10^{-9}$)				.0553		-.103
				(.0382)		(.398)
Observations	11560	11560	11560	11560	11560	11560
R-square	0.362	0.362	0.363	0.364	0.500	0.500
Y-mean	166.8	166.8	166.8	166.8	166.8	166.8
Y-std.dev.	687.8	687.8	687.8	687.8	687.8	687.8
Y-mean Wave1	568.4	568.4	568.4	568.4	568.4	568.4
Y-std.dev. Wave1	1283.1	1283.1	1283.1	1283.1	1283.1	1283.1
Y-mean Wave2	93.16	93.16	93.16	93.16	93.16	93.16
Y-std.dev. Wave2	159.1	159.1	159.1	159.1	159.1	159.1
Y-mean Wave3	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
Y-std.dev. Wave3	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416
Y-mean Wave4	5.801	5.801	5.801	5.801	5.801	5.801
Y-std.dev. Wave4	19.38	19.38	19.38	19.38	19.38	19.38

	Panel B: #Original tweets (z)					
	(1)	(2)	(3)	(4)	(5)	(6)
Holiday_RU × Wave=1	-0.266**	-0.265**	-0.265**	-0.265**	-0.267***	-0.266***
	(0.109)	(0.109)	(0.109)	(0.109)	(0.100)	(0.100)
Holiday_RU × Wave=2	-0.016	-0.015	-0.015	-0.015	-0.016	-0.016
	(0.109)	(0.109)	(0.109)	(0.109)	(0.100)	(0.100)
Holiday_RU × Wave=3	-0.006	-0.005	-0.005	-0.005	-0.006	-0.006
	(0.109)	(0.109)	(0.109)	(0.109)	(0.100)	(0.100)
Holiday_RU × Wave=4	-0.008	-0.007	-0.007	-0.007	-0.008	-0.008
	(0.109)	(0.109)	(0.109)	(0.109)	(0.100)	(0.100)
Temp × Wave=1 (z)	.0957***	.0957***	.0951***	.0916***	.0293	.0293
	(.0342)	(.0342)	(.0342)	(.0342)	(.0358)	(.0358)
Temp × Wave=2 (z)	.00619	.00619	.0056	.00216	.00942	.0094
	(.0342)	(.0342)	(.0342)	(.0342)	(.0358)	(.0358)
Temp × Wave=3 (z)	.000539	.000536	-.0000525	-.0035	.000916	.000892
	(.0342)	(.0342)	(.0342)	(.0342)	(.0358)	(.0358)
Temp × Wave=4 (z)	-.00182	-.00182	-.00241	-.00585	-.000759	-.000783
	(.0342)	(.0342)	(.0342)	(.0342)	(.0358)	(.0358)
Holiday_US	.0267	.0268	.0266	.0272	.0289	.029
	(.0502)	(.0502)	(.0502)	(.0502)	(.046)	(.046)
Days ($\times 10^{-3}$)		.12	.454	1.2		.136
		(.903)	(.912)	(.927)		(2.46)
Days^2 ($\times 10^{-6}$)			-.119***	-.889***		.123
			(.0446)	(.182)		(1.94)
Days^3 ($\times 10^{-9}$)				.176***		-.0514
				(.0404)		(.43)
Observations	11560	11560	11560	11560	11560	11560
R-square	0.283	0.283	0.284	0.285	0.415	0.415
Y-mean	98.98	98.98	98.98	98.98	98.98	98.98
Y-std.dev.	563.6	563.6	563.6	563.6	563.6	563.6
Y-mean Wave1	370.4	370.4	370.4	370.4	370.4	370.4
Y-std.dev. Wave1	1081.3	1081.3	1081.3	1081.3	1081.3	1081.3
Y-mean Wave2	21.04	21.04	21.04	21.04	21.04	21.04
Y-std.dev. Wave2	55.05	55.05	55.05	55.05	55.05	55.05
Y-mean Wave3	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
Y-std.dev. Wave3	0.0416	0.0416	0.0416	0.0416	0.0416	0.0416
Y-mean Wave4	4.449	4.449	4.449	4.449	4.449	4.449
Y-std.dev. Wave4	18.92	18.92	18.92	18.92	18.92	18.92

	Panel C: #Retweeted tweets (z)					
	(1)	(2)	(3)	(4)	(5)	(6)
Holiday_RU × Wave=1	-0.178*	-0.178*	-0.177*	-0.178*	-0.179**	-0.180**
	(0.103)	(0.103)	(0.103)	(0.102)	(0.085)	(0.085)
Holiday_RU × Wave=2	-0.065	-0.065	-0.064	-0.065	-0.063	-0.064
	(0.103)	(0.103)	(0.103)	(0.102)	(0.085)	(0.085)
Holiday_RU × Wave=3	-0.005	-0.004	-0.004	-0.004	-0.004	-0.005
	(0.103)	(0.103)	(0.103)	(0.102)	(0.085)	(0.085)
Holiday_RU × Wave=4	-0.006	-0.006	-0.006	-0.006	-0.006	-0.007
	(0.103)	(0.103)	(0.103)	(0.102)	(0.085)	(0.085)
Temp × Wave=1 (z)	-.0535*	-.0535*	-.0546*	-.0503	-.056*	-.0561*
	(.0322)	(.0322)	(.0321)	(.0321)	(.0304)	(.0304)
Temp × Wave=2 (z)	-.0481	-.0481	-.0492	-.0449	-.00802	-.0081
	(.0322)	(.0322)	(.0321)	(.0321)	(.0304)	(.0304)
Temp × Wave=3 (z)	.0017	.0017	.000639	.00486	.00231	.00223
	(.0322)	(.0322)	(.0321)	(.0321)	(.0304)	(.0304)
Temp × Wave=4 (z)	.0015	.0015	.000433	.00466	.00237	.00229
	(.0322)	(.0322)	(.0321)	(.0321)	(.0304)	(.0304)
Holiday_US	-.0242	-.0241	-.0244	-.0251	-.0263	-.0264
	(.0472)	(.0472)	(.0472)	(.0471)	(.039)	(.039)
Days ($\times 10^{-3}$)		.0542	.659	-.26		-.304
		(.849)	(.857)	(.871)		(2.08)
Days^2 ($\times 10^{-6}$)			-.214***	.73***		.496
			(.0419)	(.171)		(1.65)
Days^3 ($\times 10^{-9}$)				-.216***		-.147
				(.038)		(.364)
Observations	11560	11560	11560	11560	11560	11560
R-square	0.373	0.373	0.374	0.376	0.584	0.584
Y-mean	67.87	67.87	67.87	67.87	67.87	67.87
Y-std.dev.	285.6	285.6	285.6	285.6	285.6	285.6
Y-mean Wave1	198.0	198.0	198.0	198.0	198.0	198.0
Y-std.dev. Wave1	532.7	532.7	532.7	532.7	532.7	532.7
Y-mean Wave2	72.11	72.11	72.11	72.11	72.11	72.11
Y-std.dev. Wave2	128.2	128.2	128.2	128.2	128.2	128.2
Y-mean Wave3	0	0	0	0	0	0
Y-std.dev. Wave3	0	0	0	0	0	0
Y-mean Wave4	1.351	1.351	1.351	1.351	1.351	1.351
Y-std.dev. Wave4	2.663	2.663	2.663	2.663	2.663	2.663
DOW FEs	Y	Y	Y	Y	Y	Y
Wave-Month FEs	Y	Y	Y	Y		
Wave-Year FEs	Y	Y	Y	Y		
Wave-Year-Month FEs					Y	Y

Notes: The smaller sample size than four times #days 2012-2019 is due to 32 days with no temperature data. * significant 10% level; ** significant at 5% level; *** significant at 1% level.