How Autocrats Manipulate Economic News: Evidence from Russia's State-Controlled Television

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Journal of Politics, forthcoming

Conventional wisdom says that autocrats manipulate news through censorship. But when it comes to economic affairs – a highly sensitive topics for modern autocrats – the government's ability to censor information effectively is limited, because citizens can benchmark the official news against their incomes, market prices, and other observables. We propose that instead of censoring economic facts, the media tactically frames those facts to make the government appear as a competent manager. Using a corpus of daily news reports from Russia's largest state-owned television network, we document extensive evidence supporting this prediction. Bad news is not censored, but it is systematically blamed on external factors, whereas good news is systematically attributed to domestic politicians. Such selective attribution is used more intensely in politically sensitive times (elections and protests) and when the leadership is already enjoying high popular support – consistent with the existing theories of information manipulation.

Keywords: propaganda, economy, authoritarianism, Russia[1]

[1]Replication materials are available at JOP's dataverse: https://doi.org/10.7910/DVN/2CS1VF. For financial support, we are grateful to the Jordan Center for the Advanced Study of Russia at New York University. Thanks to Georgy Egorov, Scott Gehlbach, Jason Guo, Chistopher Li, Nikolay Marinov, Margaret Roberts, Sergey Sanovich, Maria Snegovaya, Alessandro Vecchiato, seminar participants at University of California at Los Angeles, Stanford University, Harriman Institute at Columbia University, Rice University, and Yale University, as well as three anonymous reviewers.

Electronic copy available at: https://ssrn.com/abstract=3023254

Economic hardships threaten survival of democratic as well as autocratic governments (e.g., Bueno de Mesquita et al., 2003). However, autocrats enjoy one comparative advantage – they can directly control how the media covers economic affairs. In 2014, when its economy was on the verge of a crash, the Russian government allegedly banned television networks from using the word 'crisis' in relation to its economy. The television did cover stories about depreciation of the national currency, price inflation, and troubles in the financial markets, but officially these events did not represent a systemic crisis. According to the news narrative, "there was an anti-crisis government committee, there was an anti-crisis government plan, but crisis there was not."[2]

To survive in office, instead of repression or ideology, modern autocrats increasingly employ information manipulation to create a perception that they are competent economic managers who should stay in office on that merit (Guriev and Treisman, 2015). This growing breed of rulers is particularly vulnerable to any public information that makes them appear incompetent. So how do modern autocrats deal with the eventuality of bad economic news? Common sense suggests the straightforward answer is to either censor bad news or distort it. Yet, the fact that such capacious regimes like Russia or China permit critical information in the public sphere (King, Pan and Roberts, 2013; Lorentzen, 2014; Lipman, 2005) indicates that we should look beyond censorship and distortion to better understand how governments manipulate media.

We argue that despite being especially vulnerable to bad economic news, autocrats often are not in a position to censor or distort it *effectively*. Citizens can benchmark the official economic news against multiple observables – private incomes, lines at unemployment offices, market prices, and so on. Large discrepancies between these observables and the 'official' narrative might render the state media completely non-credible. Economic news is quite distinct from, say, domestic politics or international affairs, on which hard external information is typically more difficult to obtain. Thus, instead of censorship, the government is more likely to incentivize the media to report economic facts as they are, but frame them in a way that shifts the blame for bad news

[2] Aleksandr Baklanov, "The word 'crisis' was banned on Russian television" (in Russian), snob.ru, Jan 16, 2015.

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to external factors and awards credit for good news to the actions of the government. At least with economic news, selective attribution should dominate censorship.

We test these theoretical intuitions on the case of Russia, an ideal setting to assess how modern autocrats manipulate media. Russia's government is very concerned with upholding its reputation as an effective economic manager (Treisman, 2011). Thus, the methods of news manipulation in Russian media are not accidental, but tactically crafted and tested by time (Arutunyan, 2009). Furthermore, Russia is currently seen as an innovator in matters of information manipulation, both in terms of how it handles the media domestically and how it uses informational campaigns to achieve its policy goals abroad (van Herpen, 2016). The lessons we learn from the Russian case are likely to apply in other regimes that are either structurally similar to Russia or directly emulate its media manipulation strategies.

Using a corpus of news reports from Russia's largest state-owned television station *Channel 1* from 1999 to 2016, we document two novel empirical regularities. First, the state media does not appear to censor negative economic facts. Using two independent designs, we show that the coverage of good and bad economic news is highly symmetric. Second, the media systematically employs selective attribution – it attributes bad news to the actions of foreign governments or global economic processes and good news to the actions of Russia's political elites, especially president Vladimir Putin. These attributions are constructed either by invoking an explicit causal narrative (good/bad news caused by a specific actor) or by association (a specific actor is mentioned in the context of good/bad news, without a causal argument). The use of selective attribution intensifies during elections and popular protests, but also during times when the country's leadership is already widely supported by the population. This is consistent with what political economy models of government manipulation of media predict (Gehlbach and Sonin, 2014).

These findings expand our understanding of *how* media manipulation works. The extant literature has focused on how media distorts or hides economic facts. We show how the media attempts to manipulate the *beliefs about the causes* of those facts – without distorting or hiding the facts themselves.[3] This method of information manipulation has deep historical roots,[4] but it has been surprisingly overlooked in the scholarship.[5] We advance the literature by providing a theoretical rationale for the use of selective attribution and empirical evidence of its systematic use in an important case.

To be clear, our findings do not question that censorship remains an important strategy of information manipulation, especially when it comes to collective action by the citizens. Consistent with what researchers find in China (King, Pan and Roberts, 2013), the Russian government routinely censors information about political events like popular protests (Mikhailov, 2011). Rather, our findings suggest that governments are likely to use domain-specific strategies of information-manipulation; that is, they can switch between censorship and selective attribution depending on how easy it is to hide bad news or frame it in a way that actually benefits the government.

This paper contributes to the literature on state propaganda (Geddes and Zaller, 1989; Huang, 2015*a*,*b*), by focusing on its supply side. Thus, in a more general sense, it relates to the research on information and political accountability. Literature on accountability argues that citizens evaluate economic performance of incumbents relative to the context (Kayser and Peress, 2012). We extend these ideas to show how a government can strategically 'contextualize' economic information to avoid being sanctioned for economic underperformance. The manipulation of news through selective attribution presents one channel through which governments can undermine the widely hypothesized link between economic performance and political survival.

Finally, this paper contributes to the case-specific literature on Putin's model of media manipulation and its political effects (Arutunyan, 2009; Gehlbach, 2010; Peisakhin and Rozenas, 2018). To our knowledge, there is no study about how the media – in Russia or elsewhere – manipulates *economic news*. Many non-democratic regimes

[3]The distinction between a first oder fact ('unemployment is falling') and its causal attribution ('unemployment is falling because of X') is standard in the literature (Miller and Ross, 1975).

[4]Lenin wrote: "The propagandist dealing with, say, the question of unemployment, must explain the capitalist nature of the crisis, the causes of its inevitability in modern society" (Kenez, 1985, p. 7). For Joseph Goebbels, propaganda was primarily about showing how given facts justify a specific ideology ('theory'): "The goal of propaganda is to make what the theorists have discovered clear to the broad masses" (Goebbels, 1931).

[5]One exception is analysis of the media 'slant' in China by Roberts, Stewart and Airoldi (2016).

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ground their legitimacy in good economic performance and so they are likely to face similar incentives and constraints as in Russia. In that sense, our findings carry potential implications outside of Russia. This paper develops a battery of methodological tools and empirical findings, on which further comparative debate can be built.

STRATEGIES OF NEWS MANIPULATION

Negative economic news primarily hurts a government by creating a common knowledge among citizens that they are ruled by an incompetent government. Upon hearing bad news, every citizen learns that his private misery is shared by others, which enables them to coordinate on removing the government (Egorov, Guriev and Sonin, 2009). There are multiple reasons why a government would allow bad news in the public domain. Extensive censoring makes citizens less willing to consume the media, making it difficult to reach a broad audience. Thus, to retain any credibility, the media must at least sometimes disclose negative information (Gehlbach and Sonin, 2014).

It might be particularly risky to censor news topics on which citizens can acquire independent information. The economic news clearly falls into this category. Citizens obtain information about economic fundamentals from their private incomes, employment opportunities, prices at grocery stores, and so on. Large discrepancies between these private perceptions of the state of the economy and the official news may deem the media non-credible (Shadmehr and Bernhardt, 2015; Guriev and Treisman, 2015).

The literature suggests that reporting facts is just one avenue among many through which the media shapes the beliefs of the population. Laski (1948, p. 670) famously noted that the power of the press lies not only in presenting facts but also in "its ability to surround these facts by an environment of suggestion which, often half-consciously, seeps its way into the mind of the reader and forms his premises." Ultimately, bad economic news per se cannot hurt the government unless citizens draw a causal connection between the nature of the news and the government's competence. The economy can be underperforming for many reasons. However, as long as citizens believe that the underperformance was not caused by government incompetence, negative economic facts alone will not lead to an increased mobilization against the regime.

Citizens might be well aware of specific economic facts even without the media, which makes this domain of news particularly difficult to manipulate. However, citizens are less likely to be strongly cognizant of the *causes of those economic facts*. When information on economic facts cannot be censored effectively, the state can instead incentivize the media to frame those facts in a way that makes a government appear as a competent economic manager. Studies show that people's attitudes about causal attributions are indeed manipulable (Iyengar, 1990). Thus, it is reasonable to expect that when the state's ability to censor news successfully is limited – as is the case with economic news – selective attribution would be used. Good economic news would be attributed to government actions, whereas bad economic news would be attributed to external factors such as foreign government or global financial processes.

Just how precisely causal attributions are constructed is an empirical question, for which we do not have strong theoretical priors. We would expect that at least two methods could be employed. First, the news could invoke an explicit argument that the domestic government causes good economic news and external factors cause bad economic news. We refer to this form of attribution as *direct*. Second, the attribution might also be *associational*: the media might mention domestic politicians in the context of good news and external factors in the context of bad news without explicitly drawing a causal connection.

Based on this discussion, we hypothesize the following: First, the media reports bad economic news, at least on topics where external information exists. Second, the media draws explicit causal connections between good news and the domestic government, and bad news and external factors (direct attribution). Third, the media mentions domestic politicians more in the context of good news, whereas it mentions external factors more in the context of bad news (attribution by association).

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Data and Measurements

Our analyses are based on the daily news reports from *Channel 1* – Russia's largest state-owned television station. Since early 2001, a majority of *Channel 1*'s shares are owned by the state, and the rest is controlled by an oligarch loyal to President Putin, and a company close to the president. The Kremlin exerts tight control over the network's editorial policy through regular weekly meetings with its editors (Vardanyan, 2017).

The entire corpus of news includes 305,061 reports spanning from January 1999 to July 2016, which we obtained from the channel's online archive.[6] Of these, we took all news reports on Russia's domestic economy, identified using the channel's classification tags (N = 13,173).[7]

Measuring Censorship

Censorship is fundamentally unobservable and can be measured directly only in rare situations (King, Pan and Roberts, 2014). We propose an indirect method of measuring censorship by testing whether the media covers economic events that are bad news at lower rates than the events that are good news. The idea is that if we can measure specific economic events 'objectively' (without relying on the media reports that can be tainted by censorship), we can then check whether those events are covered asymmetrically depending on whether they are good or bad news.

Implementing this measurement strategy requires information about economic events that can be measured objectively at a high frequency. We obtained data on four economic indicators that fit these requirements: (1) daily returns in the Moscow stock exchange (RTS) obtained from `moex.com`, (2) daily returns in Russian ruble vs the U.S. dollar exchange rate (RUB/USD) from `investing.com`, (3) daily returns in the spot

[6]Technically, we can treat *Channel 1* as state-owned only starting with February, 2001. However, the state influence on the channel was strong even before the acquisition of the majority share. The results remain virtually identical if we only use post-acquisition data.

[7]*Channel 1* did not tag reports before November 2000, so for that period we used an L1-regularized (lasso) logistic regression model to identify reports on Russia's domestic economy using lemmatized words (unigrams) as predictors.

price of Brent crude oil from the U.S. Energy Information Administration, and (4) monthly changes in the consumer price index (CPI) from the Russian Federal State Statistics Service (*Rosstat*). Since we are focusing on the short-term changes in these indicators, we sometimes refer to them as 'economic shocks.'

Even though only a tiny fraction of Russian citizens have stock investments, it is generally understood that a weak market performance is perceived as bad news, and Russia's political elites are known to be sensitive to this fact.[8] As Russia's economy is highly reliant on oil, low oil price is commonly perceived to be an adverse event for Russia's economic outlook (Public Opinion Foundation, 2017) . Public opinion surveys consistently show that the value of Russia's national currency and consumer price inflation are highly important topics for a great majority of Russians (Levada Center, 2004, 2008, 2014).

To identify whether the news about the performance of a given indicator are reported, we use the following queries: 'stock market' or 'RTS' for RTS index, 'dollar' in conjunction with 'ruble' or 'currency' for RUB/USD exchange rate, 'oil' in conjunction with 'price' for oil price, and 'inflation' for the consumer price index. In Appendix B.3, we provide evidence validating this simple measurement strategy.

Measuring Selective Attribution

Our analyses of censorship ask the question 'Which economic events are reported in the media?' In contrast, when we analyze selective attribution, we ask 'How is the news that ends up being reported framed?' To answer the latter question, we consider all economic news reports on *Channel 1*, a small fraction of which are on the four indicators used in our analysis of censorship.

To measure selective attribution, we extract two types of information from each news report: whether the report contains information that is good or bad news for the Russian economy and to whom the event is attributed. The key challenge is that a

[8]After Russia's largest independent radio news network was taken over by a pro-Kremlin management, the journalists were instructed to provide more positive news. Stock performance was listed as an example of good news: "If the stock market is up, that is positive" (Kramer, 2007).

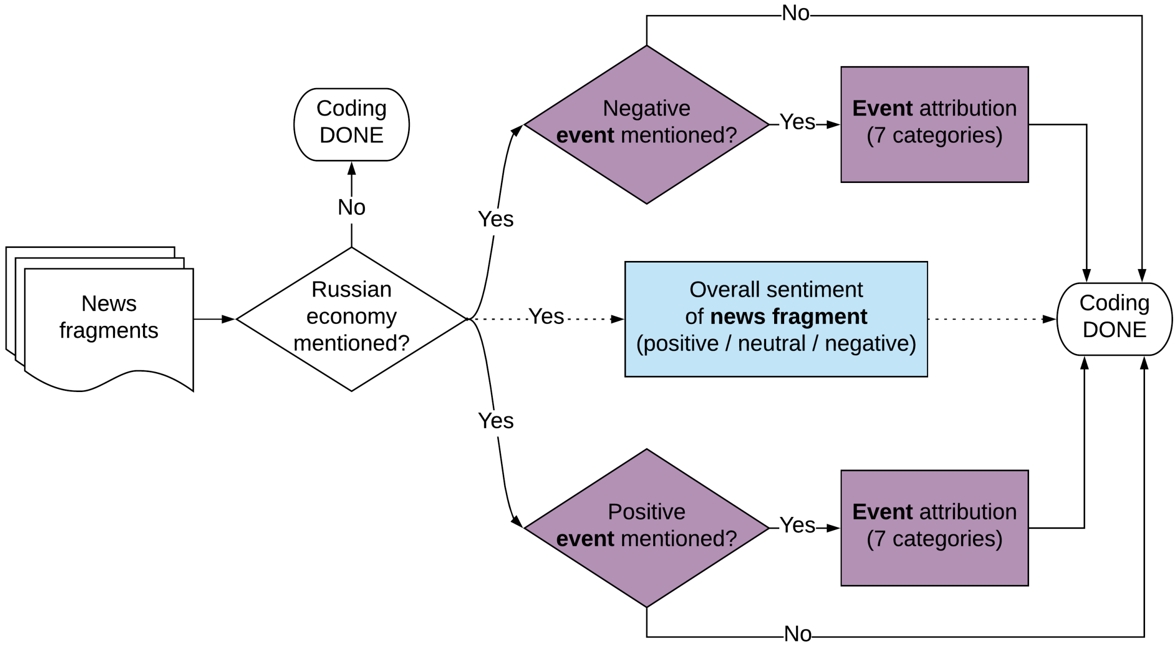

Figure 1: THE CODING PROCESS IN THE *CrowdFlower* WORKFLOW.

news report typically mentions multiple events or processes, some of which is good news, whereas others are bad news. This complexity inhibited the use of automated methods of natural language processing. We employed the crowd-sourcing method that has been shown to work well in political science applications (Benoit et al., 2016). The coding was performed on the *CrowdFlower* platform where online 'workers' were given fragments of news texts and tasked to code them according to our set of rules. We employed 544 Russian-speaking coders who were able to perform the job by the *CrowdFlower* standards based on an entrance quiz and hidden test questions.

We first split each news report into smaller fragments ranging from three to ten sentences with the modal length of seven sentences. Longer fragments lead to low inter-coder reliability because they typically mention many events with overlapping attributions. Shorter fragments create a sparsity problem since they rarely describe both an event and its attribution. We then took a random sample of 6,706 news fragments, stratified by year and month to have an approximately balanced temporal coverage, which we then submitted for coding.

The coding process in the *CrowdFlower* workflow is displayed in Figure 1. After

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a coder identifies a fragment on the Russian economy, the coding process splits into two arms. In the first arm (solid arrows), the coder identifies whether the fragment describes an event (or process) that is good news or bad news for the Russian economy; then, the coder is asked to which of the following seven categories the event is attributed. The seven categories are: (1) Vladimir Putin, (2) Russian authorities and officials, except Putin, (3) Russian business companies, (4) foreign authorities, (5) foreign business companies, (6) foreign economy, (7) other. The same event could be attributed to multiple categories, but in practice, this occurred in less than 11% of events. Note that the data generated by this arm are at the level of *event*. We use the data produced by this arm to analyze direct attribution that links the sentiment of an event (positive or negative) with the likelihood of that event being attributed to a specific category.

Our inspection indicated that coders distinguished poorly between references to foreign businesses and foreign economy. Hence, we collapsed these two categories into a single 'foreign economy' category. The direct attribution of events to 'Russian business' also turned out to be problematic. If a fragment mentioned that Russian business is doing poorly/well, the coders were automatically attributing the news to Russian businesses. Thus, we exclude 'Russian business' from the set of attribution categories as well as the residual 'Other' category, which leaves us with four categories of attribution. The exclusion of these two categories does not affect the inferences we make concerning the remaining categories.

In the second arm of the coding process (dashed arrows in Figure 1), we ask coders to evaluate the overall sentiment (negative, neutral, or positive) of a given news fragment. We use the data produced by this arm to analyze the attribution by association. Here, the unit of analysis is a news fragment, which might describe one or more events with various sentiments. We ask whether a specific agent (person, officials, foreign government, etc.) is more likely to be *mentioned* in a news fragment with a positive vs a negative sentiment. To measure whether a specific agent is mentioned in a given fragment, we designed four search queries that identify references to Vladimir Putin, other Russian officials, foreign economy, and foreign powers. For Russian officials, we queried the last names of all Russian prime-ministers and major ministers (except Putin) between 1999 and 2016. For foreign economies, we used references to the dollar, the euro, and oil. For foreign powers, we used references to the country and capital city names for the U.S., Britain, Germany, France, Italy, and European Union, and the names of their leaders.

For every news fragment, we collected judgments of at least three coders. Text fragments that produced disagreement among coders received additional coding from up to two other people. In aggregating coder judgments, we use the weighted majority rule with weights proportional to the coders' overall 'trust' score on the platform. Appendix A provides a more detailed description of the coding workflow and the judgment aggregation procedure.

From the set of coded fragments, 4,744 discussed the Russian economy. These fragments describe 3,323 positive events and 994 negative events; 72% of the fragments have an overall positive sentiment, and 18% have negative sentiment. Since the Russian economy grew substantially during the time covered by our study, these marginal percentages do not tell us much about potential asymmetries in the coverage of good versus bad news. To measure the latter, we have to consider the coverage of positive versus negative economic news *conditional* on the occurrence of such news, as we do now.

Analysis of Censorship

One would expect large economic shocks – whether they are good or bad news – to deserve greater attention from the media than minor economic shocks. Thus, if the media reports are not censored, we would expect the relationship between the size of an economic shock and its coverage to either follow a symmetric U-shaped form or to be asymmetric in a very specific direction – events that are bad news are covered at higher rates than events that are good news. If we find that bad news is covered at similar or even higher rates than good news, it would serve as evidence against the hypothesis of censorship.

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To test this empirical implication, let $y_t(k)$ denote the *coverage* of economic indicator $k \in \{\text{RTS}, \text{RUB/USD}, \text{Oil}, \text{CPI}\}$ at time t, where t represents days (for the first three indicators measured by day) or months (for CPI, which is measured by month). For the daily measured indicators, y_t is the binary variable that takes a value equal to one if the television talks about the respective event on day t. For the CPI, y_t refers to a proportion of days per month on which inflation is covered (we rescale this measure to have a maximum value equal to one for comparability with the coverage).[9]

Let $\Delta_t(k)$ denote the value of the economic shock k at time t. For RTS, RUB/USD, and Oil, we use the daily log returns (in percentages), $\Delta_t = 100 \ln(x_t/x_{t-1})$, where x_t is the value of the indicator on day t. For CPI, we use month-to-month changes, $\Delta_t = 100(x_t - x_{t-1})$. We then estimate the following semi-parametric regression:

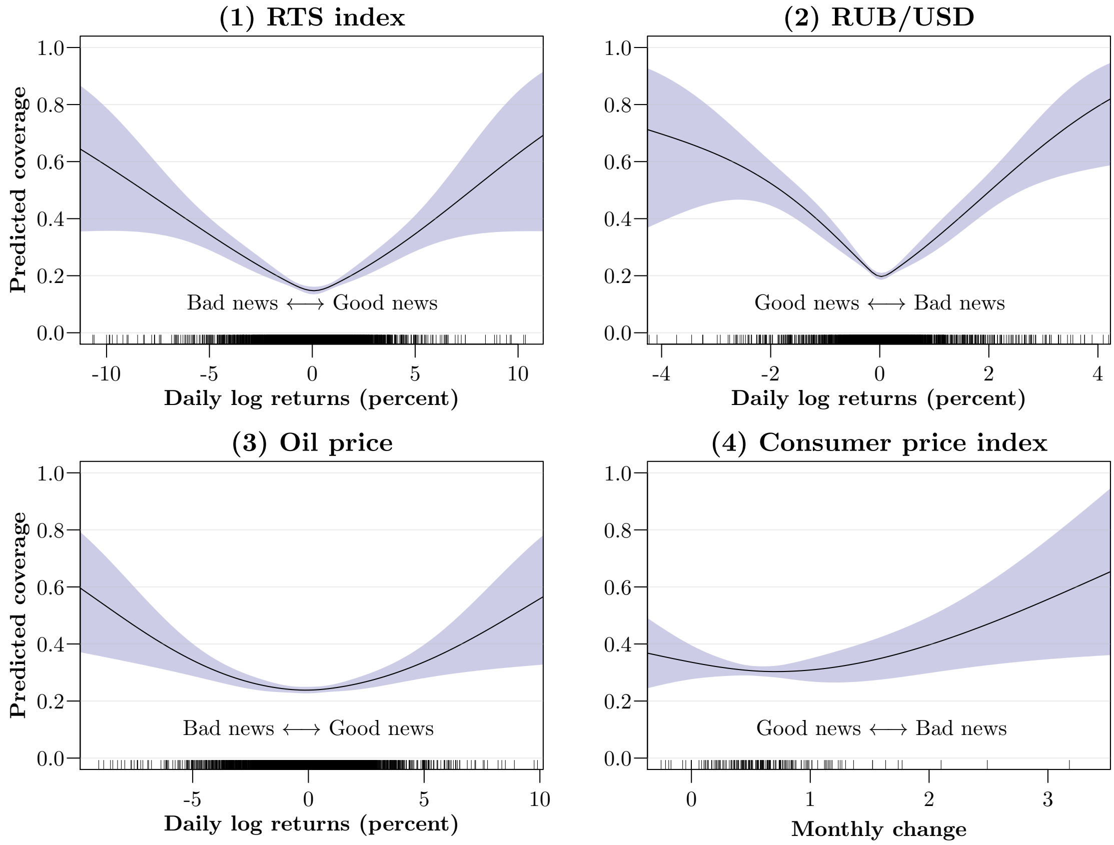
$$\mathbb{E}[y_t(k)] = F_k\left(g_k(\Delta_t(k))\right), \tag{1}$$

where the left-hand-side is the expected coverage, F_k is the inverse link function which we specify depending on the support of the outcome variable $y_t(k)$, and g_k is an unknown smooth function approximated by regression splines using tensor product smooths (Wood, 2011).

Our goal is to evaluate whether there is an asymmetric relationship between $\Delta_t(k)$ and $\mathbb{E}[y_t(k)]$, for each k. For the first three outcomes, which are binary, we set F_k to be the standard normal cumulative function resulting in probit regressions. For the CPI, the outcome variable is continuous, so we set F_k to be the identity function resulting in a normal linear model. To reduce the impact of extreme values, we exclude the shocks that are above or below five standard deviations above or below their mean. In Appendix B.2, we show that our conclusions remain the same if we do not exclude extreme values or if we exclude them using more stringent criteria.

Figure 2 shows estimated relationships between the economic shocks, $\Delta_t(k)$, and their expected coverage, $\mathbb{E}[y_t(k)]$. In all cases, we see that the predicted coverage in-

[9] In Appendix B.1, we measure coverage using the counts of reports (per day or month depending on the indicator), and arrive at identical conclusions.



Note: Predicted coverage of events with 95% confidence bounds. In graphs 1-3, the y-axis represents the predicted probability that the event is covered on a given day. In graph 4, the y-axis represents the fraction of days per month (rescaled to have maximum equal to one) on which inflation was covered.

Figure 2: COVERAGE OF ECONOMIC EVENTS ON *Channel 1*.

creases with the absolute magnitude of the shock: a 'big news' is covered more than a 'small news,' which makes sense. Importantly, we do not observe events that are bad news to be covered at lower rates compared to events that are good news. In plots 1–3, one can see a highly symmetric U-shaped relationship between the size of the shock and the coverage intensity. For example, as the RTS index grows by five percentage points, the probability that this event is covered increases by about 0.2 points, which is about the same as when the RTS index decreases by five percentage points. Similar symmetric U-curves are clearly seen in plots 2 and 3. Plot 4 indicates that inflation receives more coverage on television as consumer prices rise at a high as opposed to a low rate. Given that price inflation is continuously cited by Russian citizens among the most important issues facing the country (Levada Center, 2004, 2008, 2014), this is not what we would expect to see if the media were censoring bad news on inflation.

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It is entirely possible that *Channel 1* reports news on an economic indicator even when the indicator is performing poorly, but the reports themselves are 'incorrect.' For example, when the stock market underperforms, the media could downplay the severity of the news or even misreport the event by stating that the market actually performed well. To investigate this possibility, we used our search queries to extract the set of news mentioning the four indicators and measured three additional features of the extracted texts on the *CrowdFlower* platform. Specifically, we measured whether the report mentions a given indicator in a negative/positive context, whether it mentions an increase/decrease in a given indicator, and whether the overall sentiment of a given text is negative/positive. We find that on all three dimensions, the nature of the news report corresponds closely to the nature of the event, which indicates no evidence that *Channel 1* actually distorts the news (see Appendix B.3 for details).

We also investigated the possibility of a more subtle version of censorship. The performance of economic indicators often is evaluated relative to specific benchmark values. For example, an increase in the price of the US dollar from 49.8 to 50.1 rubles can be perceived as a far more negative event than an increase of the same magnitude from 49.5 to 49.8, because the former crosses the benchmark of 50. Such benchmarks are 'psychological barriers' in the evaluation of economic information (Monroe, 1990). We exploit this idea by drawing and testing the following hypothesis: If the news were censored, we should observe a discontinuous drop in the coverage of 'bad' relative to 'good' news right around a benchmark. Consider the earlier example: if the news is censored, then the coverage of currency rates should drop discontinuously when RUB/USD value is right above 50 or another benchmark point.

We test this hypothesis with respect to the RTS index, RUB/USD, and oil price.[10] We select benchmarks for each economic indicator relative to its scale. The RTS Index ranges from about 130 points to 2,300 points, and so we use digits divisible by 100 as benchmarks (100, 200, 300, and so on). The price of the USD varies between 23 to 86 rubles and the price of Brent oil futures ranges from 16 to 144 USD per barrel (this is

[10]Unfortunately, the data on inflation are too coarse for such analysis.

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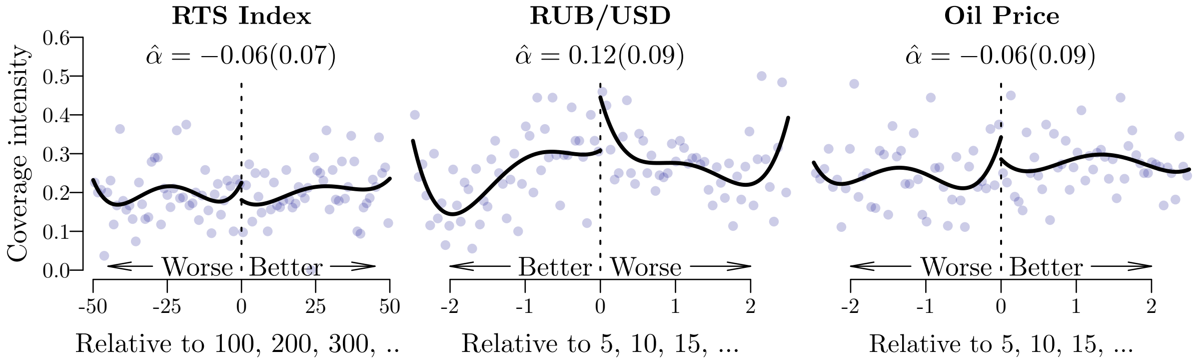

Note: The figure shows binned coverage probabilities with RD curves and the estimated bias-corrected discontinuity effects with robust standard errors in parentheses. A zero value on the x-axis means that an indicator is at a benchmark value (e.g., RTS = 1,500 or RUB/USD = 45).

Figure 3: COVERAGE INTENSITY AROUND MARKET BENCHMARKS.

how oil price is reported in Russia). For these two indicators, we use digits divisible by five as benchmarks (e.g., 25, 30, 35, and so on).

For each of the three indicators, we create a variable $d_t(k)$ measuring the deviation of the value of indicator k on day t from the nearest benchmark. For example, if the value of RUB/USD on day t is 39.7, then $d_t(\text{RUB/USD}) = -0.3$ and if the value of RTS on day t is 1,620 points, then $d_t(\text{RTS}) = 20$. We then estimate the following regression discontinuity (RD) model:

$$\mathbb{E}[y_t(k)] = f(d_t(k)) + \alpha_k \cdot D_t(k), \tag{2}$$

where f is an unknown continuous function, and $D_t(k)$ is an indicator equal to one if $d_t(k) > 0$, and zero otherwise. Under the hypothesis of censorship, the α coefficients for RTS and Oil should be positive (because high values in the RTS Index and oil prices are good news). The α coefficient for RUB/USD should be negative because an increase in the RUB/USD ratio is bad news. Note that at the discontinuity point where $d_t(k) = 0$ we are effectively comparing the coverage of news that is equivalent in its actual economic content, but potentially different in its sentiment.

Figure 3 displays RD plots that use data-driven bin selection (Calonico, Cattaneo and Titiunik, 2015) with bias-corrected estimates of the discontinuity effects with robust standard errors (Calonico, Cattaneo and Titiunik, 2014). In all cases, the estimated discontinuity effects are in the opposite direction to what we would expect if bad news were censored – the coverage of negative events increases, rather than decreases, around the benchmarks. The estimates are too noisy to draw strong conclusions (the discontinuity effect is significant at 90% confidence level only in the case of the RUB/USD), but they clearly do not support the hypothesis that good news is reported more than bad news.

Overall, our analyses indicate no evidence that Russian television is censoring information on economic events that are bad news. Obviously, this evidence is insufficient to conclude that *Channel 1* does not censor any economic news; proving such a negative is most impossible. One could argue that the government cannot be impacted negatively by bad news on the four topics we are analyzing here. Since very few Russians have investments in the stock market or are directly affected by oil prices, it could be that the media truthfully reports events on these topics, because by doing so it can provide information to investors without antagonizing citizens. This conjecture would not explain why *Channel 1* reports bad news on the currency value and the CPI, both of which are important for a significant majority of Russians (Levada Center, 2004, 2008, 2014). Furthermore, *Channel 1* news is not geared towards investors (who most likely learn about the market before it gets covered on TV), but towards ordinary citizens.

The above results also do not imply that Russian television covers the economy in the same way as the media in Western democracies. Due to market concerns, the commercial media tends to over-report negative events as as part of a revenue-maximizing strategy (Ju, 2008; Soroka, 2006). If we use independent revenue-driven media as our benchmark, then *Channel 1* appears somewhat biased because it does not over-report bad news relative to good news. However, a theoretically relevant benchmark is a media that does disclose bad news, not the media that over-reports it. On that count, *Channel 1* appears to be within the bounds of the benchmark.

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Analysis of Selective Attribution

We now test the proposition that the state-controlled media manipulates information by providing a specific interpretation of the economic news that it reports. More precisely, we consider whether the media selectively attributes the responsibility for bad news to external economic and political causes and good news to domestic politicians. One way to construct such selective attribution is by arguing directly that external factors caused bad economic news and domestic political elites were behind good economic news. For example, in late 2000, after a crash in the Russian stock market, *Channel 1* reported the following:

> *Today, due to the sharp decline in market quotes, trading in the Russian trading system was stopped. In the US, George Bush and Al Gore continue the battle in the courts. Democrats believe that the process will continue until December 18, when the Electoral College will meet. [...] The uncertainty about the outcome of the U.S. presidential election, after all, was reflected in the stock markets. Indeed, not so much in the American markets, as in the Russian ones.*

The fragment suggests an external cause behind an evidently negative economic event – the uncertainty created by the contested presidential election in the United States. If citizens believe that this bad news was indeed caused by the outside actor, then the news itself should not negatively impact how Russian citizens view their government's economic competence. However, in the case of good news, the government's reputation can be improved if the media attributes this news to the government. Here is an example of this strategy:

> *Cabinet ministers responsible for socio-economic issues gathered in Vladimir Putin's office in the Kremlin. [...] On the previous day, the president [...] heard many complaints that working retirees receive low pensions. The president promised to sort out the situation. And now we have a result. Working pensioners will receive higher payments. In the coming month, the president will issue a decree to raise pensions for working retirees.*

This fragment describes two events: a negative event not attributed to anyone (pensions are low), and a positive event attributed directly to Putin's actions (pensions are going to increase as a result of a presidential decree).

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Instead of arguing directly that the reported news was caused by a specific actor, the media could also employ a less conspicuous attribution method: it could avoid mentioning domestic politicians in a negative context and mention them in a positive context only. In this case, the attribution would be constructed by association. As an example, consider the following announcement:

> *In 2009, the inflation will be 13 percent lower than the previous estimate. The news was announced by the head of the Central Bank Sergey Ignatiev in a meeting with the prime-minister Vladimir Putin.*

The fragment would carry exactly the same *economic* content without mentioning Putin. Yet, a positive event (decrease in the inflation rate) is mentioned in association with Putin, but without explaining how Putin precipitated that event.

We now test whether the above examples of selective attribution are representative of a systematic pattern. In our censorship analyses, we studied whether an event (measured independently of the media reports) gets reported. In contrast, here we focus on how the attribution of economic news that were actually reported – those news include, but are not limited to, the news on the four indicators used in our censorship analysis. As discussed in the section 'Data and Measurement,' we analyze selective attribution at two levels: for direct attribution, the unit of analysis is an event, whereas for attribution by association, the unit of analysis is news fragment. Thus, the term 'news' in the context of direct attribution refers to events, whereas it refers to 'fragment' in the context attribution by association.

Consider Figure 4, which shows the proportion of good and bad news attributed directly to one of the four categories. The left panel shows proportions of news attributed directly. About twenty percent of news that coders identified as good is directly attributed to Putin, but the proportion of bad news directly attributed to Putin is statistically indistinguishable from zero. A less drastic, but similar pattern appear with respect to Russian government officials to whom *Channel 1* attributed about 65 percent of good news and 50 percent of bad news. Remarkably, when it comes to foreign economy and foreign powers, the pattern reverses. Bad news are about ten times more likely to be directly attributed to foreign economic factors than good news.

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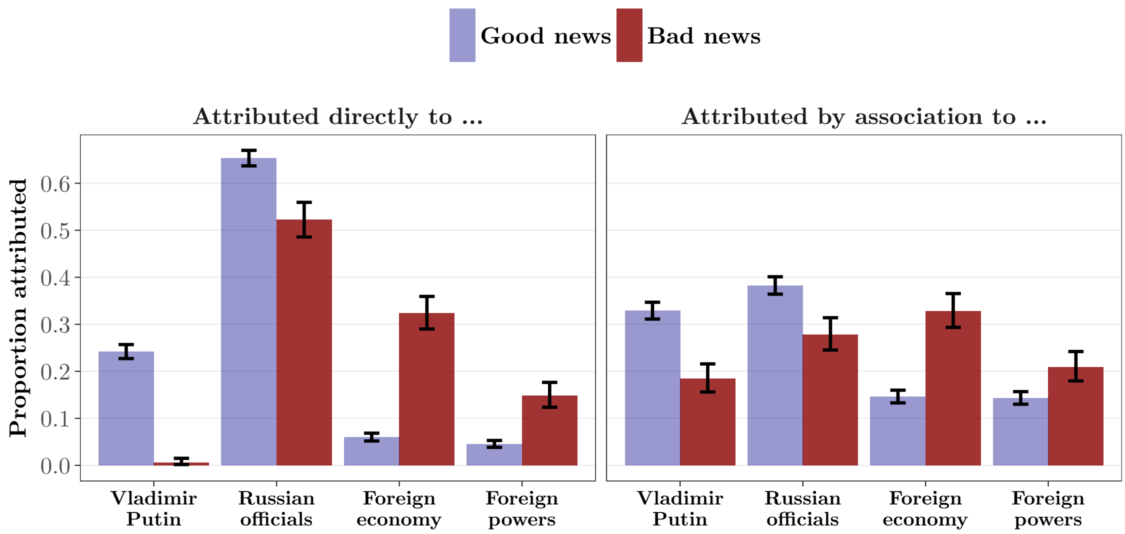


Note: The figure shows the proportion of news attributed to each of the categories with 95 percent confidence intervals – events on the left (N = 4,317) and news fragments on the right (N = 4,104). Since attribution to multiple categories is possible, the proportions do not sum up to one.

Figure 4: ATTRIBUTIONS OF GOOD VS. BAD ECONOMIC NEWS.

Foreign governments are about three times more likely to be directly blamed for bad economic news than to be credited for good news.

The right panel of Figure 4 shows very similar patterns with respect to attribution by association. Putin and other government officials are significantly more likely to be mentioned in news fragments with a positive sentiment than in news fragments with a negative sentiment. The pattern however reverses when it comes to foreign economic factors and foreign powers.

The above descriptive statistics do not account for several important factors. First, it could be that good news is concentrated in the same periods of time when the Russian government and Putin were politically active, thereby confounding the relationship between the type of news and its attribution. Second, we need to take into account potential seasonal and weekday effects: high-economic performance seasons or days could coincide with increased government activity. To address these issues, we fit the following binary probit regression:

$$\Pr\{a_i(j) = 1 | Z_i, \boldsymbol{x}_i\} = \Phi\left(\beta_j \cdot Z_i + \text{Year}_i + \text{Month}_i + \text{Weekday}_i\right), \tag{3}$$

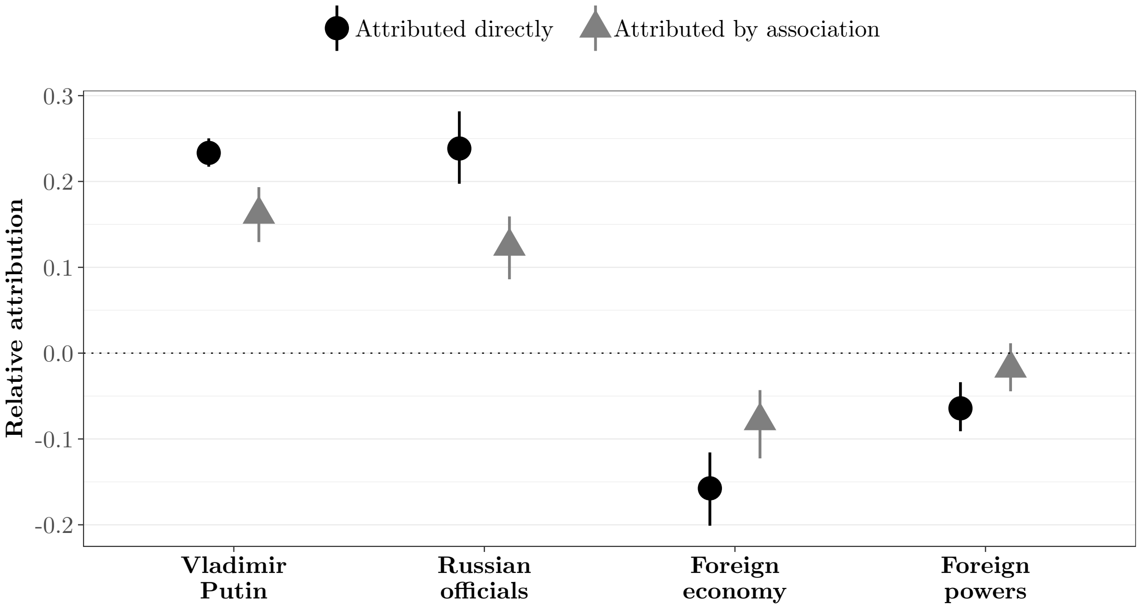
where i refers to the unit of analysis (event for direct attribution and fragment for associational attribution) and j refers to one of the four attribution categories. The indicator variable $a_i(j)$ takes the value equal to one if the news i is attributed to category j, and zero otherwise. The indicator variable Z_i is equal to one if the news i is good (event i is good news or fragment i has an overall positive sentiment) and equal to zero otherwise. If the parameter β_j is positive (negative), it means that good (bad) news is more likely to be attributed to category j than bad (good) news. The variable *Year* stands for year fixed effects, which control for time trends. The variables *Month* and *Weekday* are fixed effects for month and weekday, respectively. We estimate the above probit regression separately for each attribution category and for each attribution type. To account for serial correlations, we cluster standard errors by year-months.

For easier interpretation, we focus on the sample-averaged *relative attribution* defined as

$$R(j) = \frac{1}{N}\sum_{i=1}^{N} \Pr\{a_i(j) = 1 | Z_i = \text{Good}, \boldsymbol{x}_i\} - \Pr\{a_i(j) = 1 | Z_i = \text{Bad}, \boldsymbol{x}_i\}. \tag{4}$$

In words, for each observation in the dataset, we calculate the difference in the predicted probability of good news versus bad news being attributed to category j, and then take their average. If $R(j)$ is positive (negative), then good (bad) news is more likely to be attributed to category j than bad (good) news.

Figure 5 shows predicted relative attributions. Focusing on direct attribution, we see that good news is attributed at about 0.2 points higher rate to Putin and Russian officials than bad news. The pattern is reversed once we consider foreign factors – bad news is attributed at about 0.15 higher rate to foreign economy than good news and foreign powers are attributed bad news at about 0.05 higher rate than good news. These contrasts are slightly weaker when it comes to associational attribution, but they point to the same direction: First, Putin and Russian officials are about 0.12 to 0.17 points more likely to be mentioned in the news fragments with overall positive compared to negative context. Second, foreign economic factors and foreign governments are about 0.03 to 0.07 points more likely to be mentioned in the context of bad



Note: The figure shows sample-averaged estimates of relative predicted attributions (defined in the text) from probit regressions with year, month, and weekday fixed effects. The vertical bars represent the 95 percent bootstrapped confidence intervals.

Figure 5: PREDICTED RELATIVE ATTRIBUTIONS OF ECONOMIC NEWS.

news than in the context of good news. All of these these effects, except attribution by association to foreign powers, are significant at the 99 percent confidence level.

We see strong evidence suggesting that *Channel 1* does engage in systematic selective attribution, but several alternative interpretations of these results are possible. Russia's economy is highly dependent on oil. Moreover, it was also deeply impacted by the economic sanctions from the West in response to Crimea annexation in 2014. Therefore, attribution of bad news to foreign factors could be driven exclusively by sanctions and oil prices, and so would not constitute evidence of a politically motivated strategy. However, this alternative explanation cannot account for why good news is disproportionately attributed to Putin or Russian officials. Just because some bad news is objectively driven by foreign factors, it does not imply that good news must be disproportionately caused by domestic politicians. Furthermore, to rule out this alternative explanation, we conduct a series of robustness checks reported in Appendix C.1. Our results remain very similar if we exclude reports on oil and sanctions, if we exclude years 2008-2009 when Russia was hit by the global financial crisis, or if

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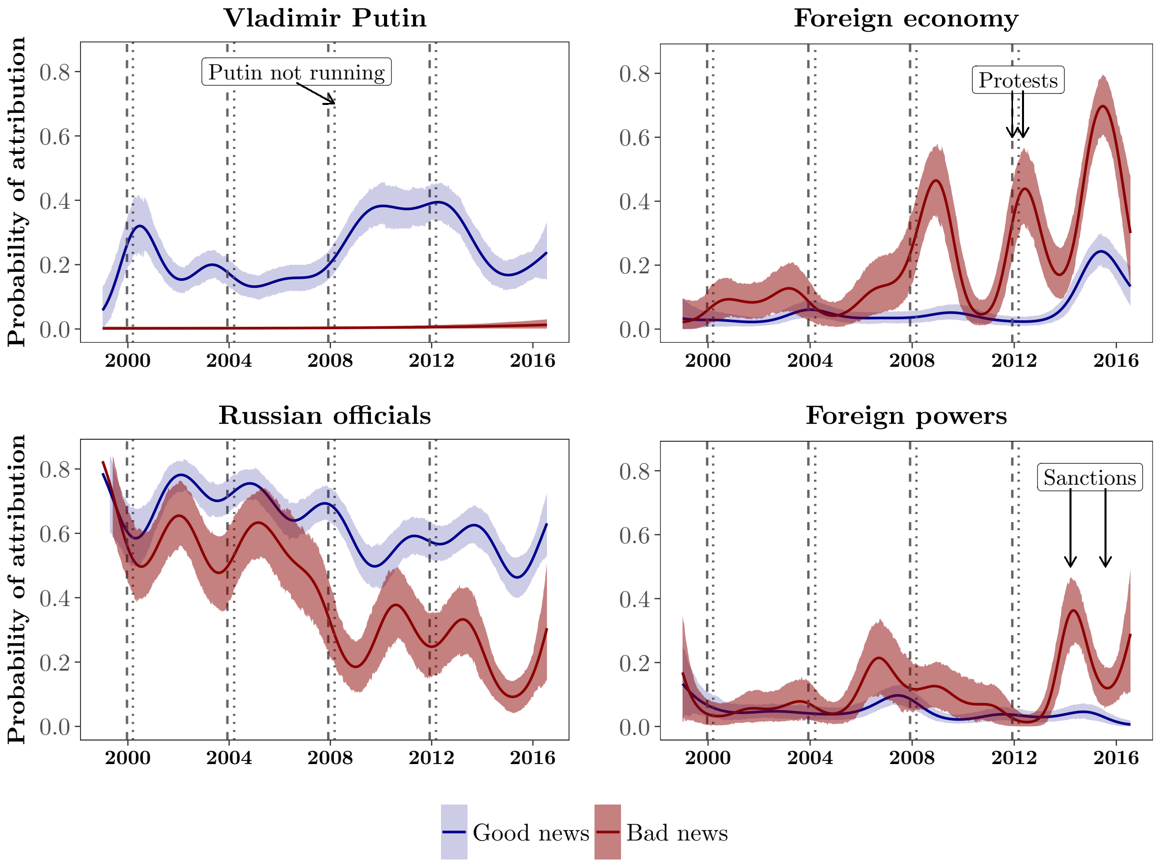
we use data only from before or after the Crimea annexation.

Biases of the coders could also drive the results. Conceivably, a coder could perceive a report as good news simply because it mentions the domestic government or bad news if it mentions foreign actors. We rule out this possibility in the following way: instead of relying on coders to determine the sentiment of the news and its attribution, we only used coding information on the sentiment of news. We then use the structural topic model (Roberts, Stewart and Airoldi, 2016) to predict how the prevalence of topics varies in news fragments depending on whether those fragments report negative or positive economic events. The procedure and its results are discussed in Appendix C.2, but the key message is this: when a news report mentions only positive economic event, it is more likely to talk about Putin, budget planning or the meetings of government officials. However, when the report contains only negative events, it is more likely to talk about topics related to housing issues, teacher salaries, global crises, oil prices, and the stock market. Thus, the findings are not likely to be an artifact of biases in the coding process.

The Dynamics of News Manipulation

The previous sections documented how Russia's state-owned television employs selective attribution to manipulate economic news. In this section, we analyze the dynamics of the intensity with which the economic news is manipulated using this method. Does the intensity of selective attribution vary in ways that are consistent with the existing theories of information manipulation?

The political economy models draw several predictions as to when the government-controlled media would engage in more news manipulation (Gehlbach and Sonin, 2014). We should observe more news manipulation when the government needs to mobilize citizens to turn out in elections or to demobilize protests. We should also observe more news manipulation when the government already enjoys extensive support in the population. As Gehlbach and Sonin (2014) explain, "when citizens need less persuasion to vote for the incumbent [...], then the incumbent government has greater



Note: The figures show predicted probabilities of direct attribution of events, with 95% CI's. The vertical dashed and dotted lines show parliamentary and presidential elections, respectively.

Figure 6: DIRECT ATTRIBUTION OF ECONOMIC NEWS OVER TIME.

latitude to skew reporting in its favor without discouraging citizens from watching the news" (p. 166). We now subject these predictions to an empirical test.

The first prediction suggests an electoral cycle effect: the degree of selective attribution should be higher around the time of elections compared to other periods. Before elections, news manipulation would presumably be used to mobilize turnout and pro-government support. However, since elections often serve as focal points for protests (Tucker, 2007), news manipulation should also be high in the immediate aftermath of elections, when citizens need to be persuaded *against* participating in protests.

To evaluate the effects of the electoral cycle, we analyze how the degree of selective attribution varied across time. If we observe selective attribution to peak around the time of elections, it would indicate evidence for the electoral cycle effect.[11] We fit

[11]During the period of our study, Russia's national presidential and parliamentary elections followed a fixed four-year cycle and so the timing of elections can be treated as exogenous, in the short

a flexible probit regression model of the form $\Pr\{a_i(j) = 1\} = \Phi(g_j(Z_i, t_i))$, where $a_i(j) = 1$ refers to event i attributed to category j, t_i refers to a day in which event i is reported, Z_i is an indicator for good ($Z_i = 1$) versus bad ($Z_i = 0$) news, and g_j is an unknown smooth function approximated by thin-plate regression splines (Wood, 2011). The model is estimated separately for each attribution category j using the same degree of smoothing. We then calculate the predicted probabilities of attribution of good news, $\Phi(\hat{g}_j(1, t))$, and bad news, $\Phi(\hat{g}_j(0, t))$, for each attribution category j and each day t, and plot them against time in Figure 6.

Consider first the two left-most graphs showing the predicted probabilities of attribution to Putin and Russian officials. Obviously, many factors could be behind these dynamics, but we do observe some moderate evidence of the electoral cycle effect. The attribution of good news to Putin peaked right after 2000, right before 2004, and right after 2012 presidential elections when Putin was running. However, no comparable peak occurred in the vicinity of the 2008 presidential election when Putin was not running. We also see an indication of the electoral cycle effect in the graph for 'Russian officials' – bad news is attributed to Russian officials at consistently lower rates right around the time of elections. Note that this evidence of the electoral cycle effect emerges in a purely inductive way as our models do not contain any information about the actual timing of elections.

The evidence for the electoral cycle effect with respect to foreign actors is more ambiguous. There were three peaks of negative attribution to 'Foreign economy.' The first is most likely attributable to the global financial crisis (though the wave clearly began prior the crisis hit in September 2008). The second peak occurred after the 2012 parliamentary elections when there was no objective reason to attribute Russia's economic mishaps to external causes. Interestingly, this second wave peaked right around the time of large scale anti-government protests in May 2012. The third peak in negative attribution most likely was precipitated by the Western economic sanctions following Russia's annexation of the Crimea in 2014.[12] Finally, there is no evidence that

run at least.

[12]We also see an uptick in positive attribution towards foreign economy as of 2014. These reports

attribution of bad news to 'Foreign governments' would intensify around the time of elections. The only moderate evidence to that effect is that the largest wave of negative attribution started building up right after the post-election protests in 2012 – well before the Western sanctions were put in place.

Overall, we find moderate support for the hypothesis that the degree of news manipulation increases when the government needs to mobilize the population to participate in elections or when it needs to persuade them against participating in protests – that often takes place after elections. The evidence to this effect is stronger with respect to Russia's domestic political actors than with respect to foreign actors, which makes sense as it is the reputation of the domestic actors that is most at stake during the time of elections.[13]

To test the second prediction that selective attribution should increase when the leader's support is high we study how selective attribution varies depending on the popular support for Putin. Specifically, we replicate the regression analyses from the previous section interacting the indicator for *Good news* with the variable *Support* that measures Putin's popular approval during the month *before* time t. The data on Putin's popular approval is from (Levada Center, 2018). According to the earlier discussion, we should observe more good news attributed to Putin and Russian officials and more bad news attributed to foreign actors when Putin's support is high relative to when it is low. As in our earlier regressions, we include fixed effects for year, month, and weekday, and cluster standard errors by year-month.

The results are summarized in Figure 7, which shows simulated predicted *relative* attribution rates for each of the four categories conditional on Putin's approval during the prior month being low (sample minimum) versus high (sample maximum). In the figure, we also report bootstrapped p-values for the null hypothesis that there is more positive attribution to domestic actors and more negative attribution to external actors when Putin's support is low compared to when it is high.

We see that good news is attributed to Putin at similar rates irrespective of his

are mainly about how foreign sanctions created positive externalities in Russia's economy.

[13]In Appendix D.1, we discuss evidence for the electoral cycle effect on attribution by association.

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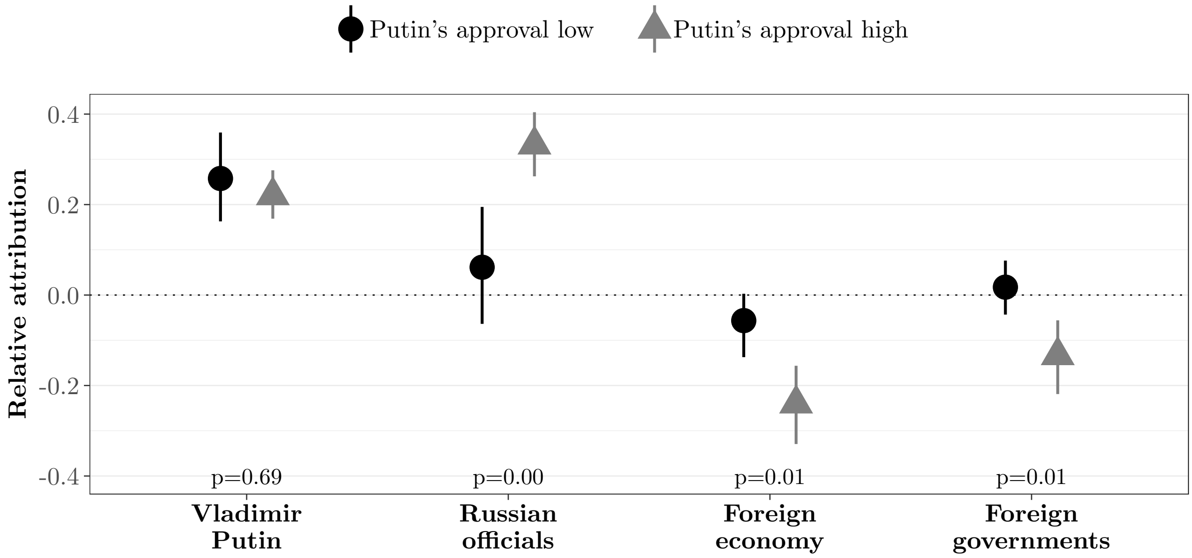

Note: The figure shows predicted relative attribution rates with 95% CI's when Putin's approval in the prior month is low versus high. The p-values are for one-sided null hypothesis that there is more positive attribution to domestic actors and more negative attribution to external actors when Putin's support is low compared to when it is high. The CI's and p-values are clustered by year-month.

Figure 7: RELATIVE DIRECT ATTRIBUTION CONDITIONAL ON PUTIN'S APPROVAL.

prior support. However, good news is attributed to Russian officials and bad news is attributed to a foreign economy and foreign governments at significantly higher rates when Putin's support is high compared to when it is low. For the latter three categories, we can reject the null hypothesis that there is more news manipulation in favor of Russian regime when Putin's support is low at the 95 percent confidence level.[14]

Intuition suggests that we should see more news manipulation when the leader's popular approval is low. The evidence is more consistent with the political economy models of media manipulation than the intuition. We do not find any support for the proposition that the news is manipulated more when the leader's support is weak;

[14]Why do results for Putin differ from other categories? One possibility is that Putin's approval is endogenous to the degree of selective attribution towards him (even though we use Putin's approval lagged by one month). Admittedly, Putin's approval should be more sensitive to selective attribution with respect to him than with respect other three categories. Thus, the endogeneity problem is less likely to affect these other results. Another possibility is that most good news were attributed to Putin when he was the prime minister in 2008–2012 – the period that also coincided with a brief political liberalization in Russia under President Medvedev and an increase in citizens' protest sentiment (Golosov, 2012).

instead, at least on some dimensions, the opposite appears to be the case.[15]

CONCLUSIONS

The conventional wisdom presumes that autocrats censor bad news or distort it in order to preserve their reputation. We document evidence from an important case that challenges this view. In Russia, where the incumbent is highly sensitive to bad economic news and is also capable of manipulating the media, the state-controlled media does not censor bad news on a number of politically salient economic issues. Instead, the media routinely reports both good and bad economic news, but it does so in the way that implicates the domestic government when the news is good and foreign factors when the news is bad. Selective attribution, not outright censorship or distortion, appears to be the key tool used by such modern autocratic regimes as Russia, at least when it comes to the economy.

The underlying assumption behind the thinking about information manipulation in autocracies seems to be that bad news is *per se* detrimental to the government's reputation. Our findings suggest that an autocrat is not as concerned about whether certain facts are *reported*, but is more concerned about how those facts will be *interpreted*. To impose a specific interpretation that benefits the government requires the media to frame facts in a certain way. If the media is successful at persuading citizens that external factors are culpable for economic failures while the domestic government is responsible for economic accomplishments, then the facts themselves – without the underlying interpretation – cannot directly hurt or benefit the government.

These findings also have wider implications for understanding the link between economic performance and autocratic survival (Reuter and Gandhi, 2011). Autocrats who effectively manage to shift the blame for economic under-performance on external factors will be less vulnerable to removal from office. Of course, this can only be the case if the strategy of selective attribution is effective at swaying the beliefs of the

[15] We also do not find evidence for the null hypothesis when we use prior changes in Putin's support (see Appendix D.3).

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citizens. Whether that is the case is an important question for future research.

Our study builds on one case, but the mechanism of information manipulation that we document might be at work in other contexts. There are good reasons to expect that other authoritarian regimes that ground their legitimacy in economic performance would also heavily engage in selective attribution. For instance, the Chinese government often aims to preemptively set the agenda for coverage of bad news to "emanate great voices at crucial moments" by using coordinated social media postings (Huang, 2017). Selective attribution might potentially play an integral part in this type of agenda setting. It is also possible that selective attribution is a strategy used by highly partisan media in democracies. Even though there is some anecdotal evidence to support this claim (James, 2017), it remains to be seen whether such intuition would hold up to a rigorous empirical scrutiny. The methods developed in this paper are easily transportable to the study of information manipulation in other environments (other regimes and languages), which will hopefully be useful in building further comparative debate on this topic.

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ONLINE APPENDIX
How Autocrats Manipulate Economic News: Evidence from Russia's State-Controlled Television

CONTENTS

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A. Coding Process

A.1. CrowdFlower *Workflow*

To make use of our text data, we employ the crowd-sourcing method, which has been shown to perform well in various tasks were human input is needed to extract information from text (Benoit et al., 2016). In our case, we needed to extract three types of information: First, whether a given news fragment talks about positive or negative events or processes related to Russian economy (extracting event types). Second, whether those events are attributed to certain actors or processes (extracting direct attribution). Third, whether the segment has an overall positive, neutral, or negative sentiment (extracting sentiment).

The coding was performed on the *CrowdFlower*, a popular platform for collecting crowd-sourced data. We trained human coders to detect news attribution and their overall sentiment. We employed coders with the knowledge of Russian and selected only those coders who were able to perform the job by using the standard CrowdFlower procedure of an entrance quiz and hidden test questions. Overall, we employed over 544 coders who coded over $6,706$ news fragments, randomly sampled from the Channel 1 corpus.

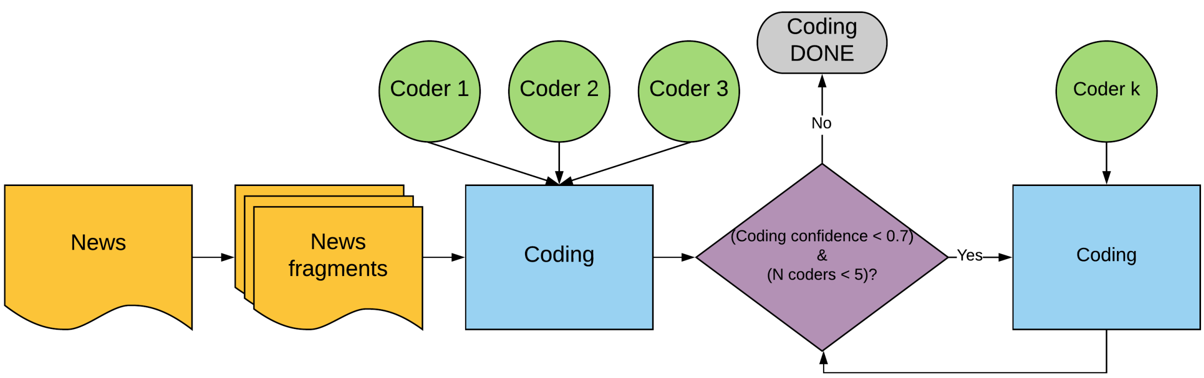

Figure 1: *CrowdFlower* coding process.

Our *CrowdFlower* workflow is shown in Figure 1. We split each news report into smaller fragments (ranging from three to ten sentences with the modal length of seven sentences) in order to make the coding task easier. For every news fragment, we collected judgments of at least 3 coders. Text fragments that produced disagreement among coders received additional codings from up to two other coders.

Table 1 presents the questionnaire for *Crowdflower* coders. As Figure 1 shows, each coder was first asked if the news fragment mentions Russian economy at all. If so, she received three additional questions. First, to whom the news fragment attributes economic events/processes that are negative for the Russian economy. The attribution categories were "personally V.Putin", "Russian authorities and officials" (excluding V.Putin), "large Russian business companies", "foreign authorities", "large foreign business companies", and "general tendencies of world / foreign economy". There was also a separate category "Not mentioned" for news fragments that do not mention a negative event or process. The same for positive events. Second, a similar question about positive economic events and processes. Finally, a question about the overall sentiment of the news fragment (optimism about the Russian economy, a neutral tone, or pessimism).

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A.2. Questionnaire

1. Are any events/processes in Russian economy mentioned here?
- Yes (1)
- No (0)

2. NEGATIVE events/trends in Russian economy:
- are not mentioned in this fragment (1)
- are attributed (explicitly or implicitly) to V.Putin personally (2)
- are attributed (explicitly or implicitly) to RUSSIAN authorities/officials (3)
- are attributed (explicitly or implicitly) to large RUSSIAN business companies (4)
- are attributed (explicitly or implicitly) to FOREIGN governments (5)
- are attributed (explicitly or implicitly) to FOREIGN large business companies (6)
- are attributed (explicitly or implicitly) to the general trends in the world / foreign economies (7)
- none of the above applies (999)

3. POSITIVE events/trends in Russian economy:
- are not mentioned in this fragment (1)
- are attributed (explicitly or implicitly) to V.Putin personally (2)
- are attributed (explicitly or implicitly) to RUSSIAN authorities/officials (3)
- are attributed (explicitly or implicitly) to large RUSSIAN business companies (4)
- are attributed (explicitly or implicitly) to FOREIGN governments (5)
- are attributed (explicitly or implicitly) to FOREIGN large business companies (6)
- are attributed (explicitly or implicitly) to the general trends in the world / foreign economies (7)
- none of the above applies (999)

4. The dominant sentiment of this news fragment is:
- positive / optimistic with respect to Russian economy (1)
- negative / pessimistic with respect to Russian economy (-1)
- neutral / objective description of events / processes in Russian economy (0)

Table 1: *CrowdFlower* questionnaire.

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B. CENSORSHIP ANALYSIS: ADDITIONAL TESTS

B.1. *Alternative Measure of Coverage Intensity*

In the paper, the coverage intensity was measured using a binary indicator equal to one if a keyword pertaining to economic outcome k was mentioned on a given day (for the three daily indicators). We use this approach as our baseline because most of the variation is between days when the indicator is not covered at all or covered once – the distribution of the number of reports that cover indicators is quite skewed. While focusing on the binary outcome (covered at least once vs not covered) seems plausible, one should also admit a reasonable possibility that the media could talk about good news much more than bad news, on the intensive margin.[1]

To consider this possibility, we estimate negative binomial count regression models. For the three financial daily indicators, the outcome variable is the number of news segments in which the indicator is mentioned. For the monthly inflation indicator, the outcome is the number of days (in a given month) that the indicator is mentioned.

The results are displayed in Figure 2 below. We see that the patterns are roughly similar to the ones reported in the paper. There is a slight asymmetry towards very good RTS index performance being reported at somewhat higher rates than very bad performance, but the confidence intervals at the end points are too wide to warrant this conclusion. Very large downward shocks in oil price (bad news) are also reported at slightly higher rates than very large upward shocks (good news), but, again, no strong conclusions about asymmetric coverage can be drawn from these analyses.

[1] We are grateful to an anonymous reviewer for this observation.

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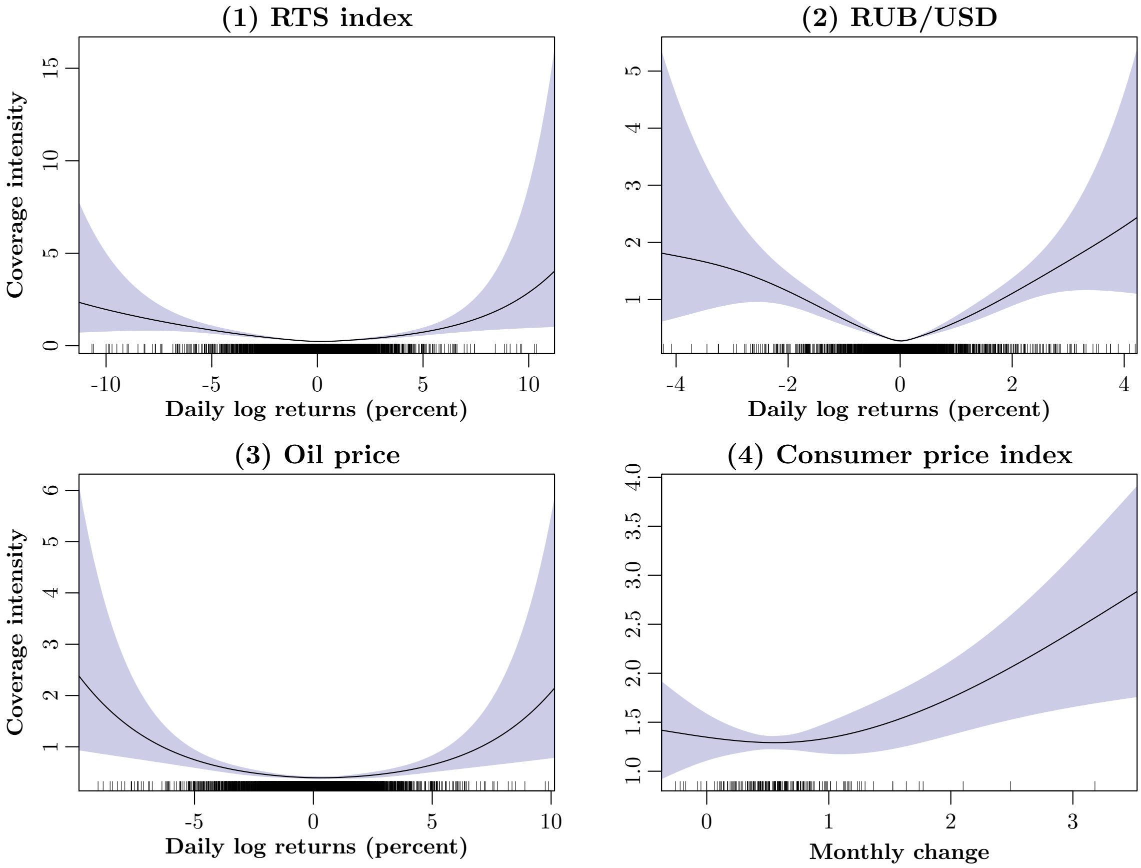

Figure 2: Censorship analysis using counts of reports with outcome-specific keyword (negative binomial regressions). Dependent variable: number of news segments mentioning the economic indicator. Independent variable: change in the economic indicator. Grey bounds are 95% confidence intervals for predicted outcome.

B.2. Sensitivity to outliers

In our main analyses, we removed from the analysis extreme values of economic indicators. We did so to avoid the situation where few extreme values drive the behavior of the estimated curves. Does this exclusion work in favor of delivering specific results? Below we show the results of analyses that are identical to ones reported in the paper, only without any removal of outliers.

We observe that the only tangible difference is that – as expected – the confidence intervals 'blow up' at the end points of the scales because of the lack of data. Otherwise, the plots indicate that bad news is covered with similar rates as good news.

It is also possible that our analysis does not exclude sufficiently many extreme

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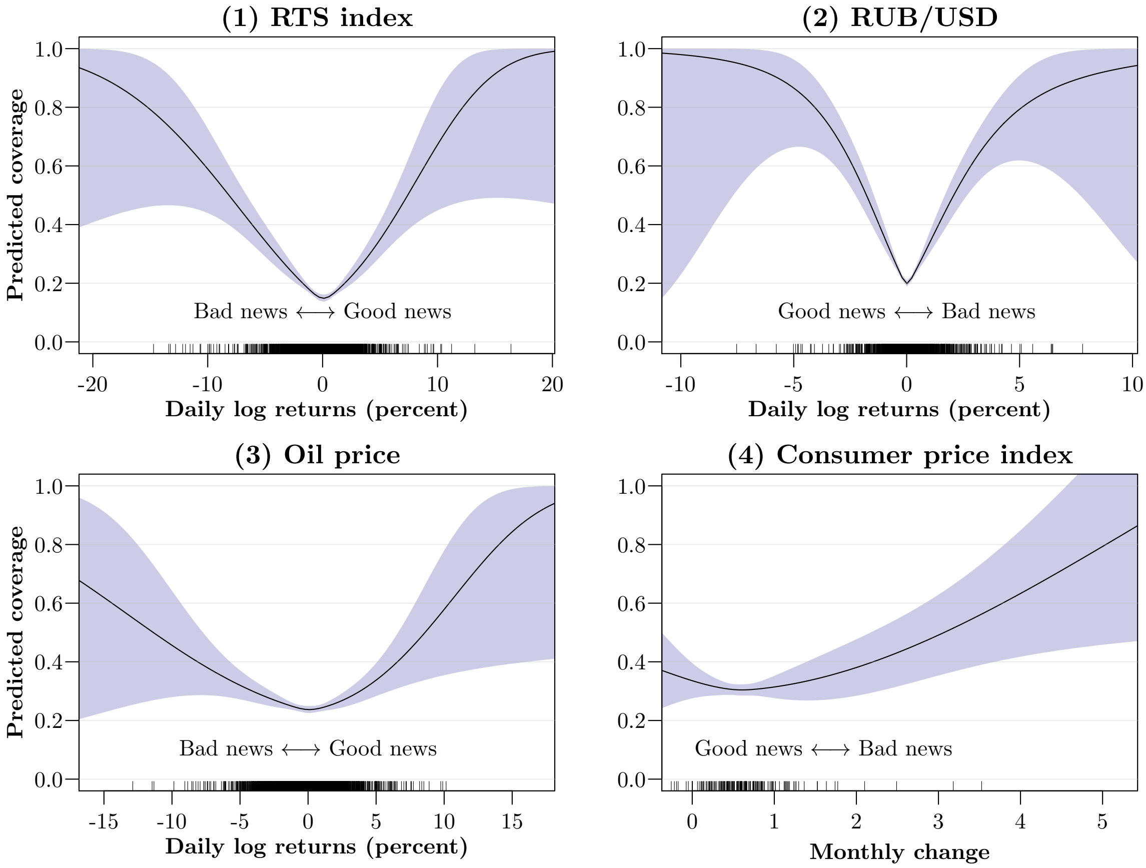

Figure 3: Censorship analysis without outlier exclusion. Dependent variable: binary variable for whether news segments mention the economic indicator. Independent variable: change in the economic indicator. Grey bounds are 95% confidence intervals for predicted outcome.

values. The figure below shows results of analysis restricted to values of economic indicators within two standard deviations from their means. There is no indication that bad news is covered at lower rates than good news even at this scale.

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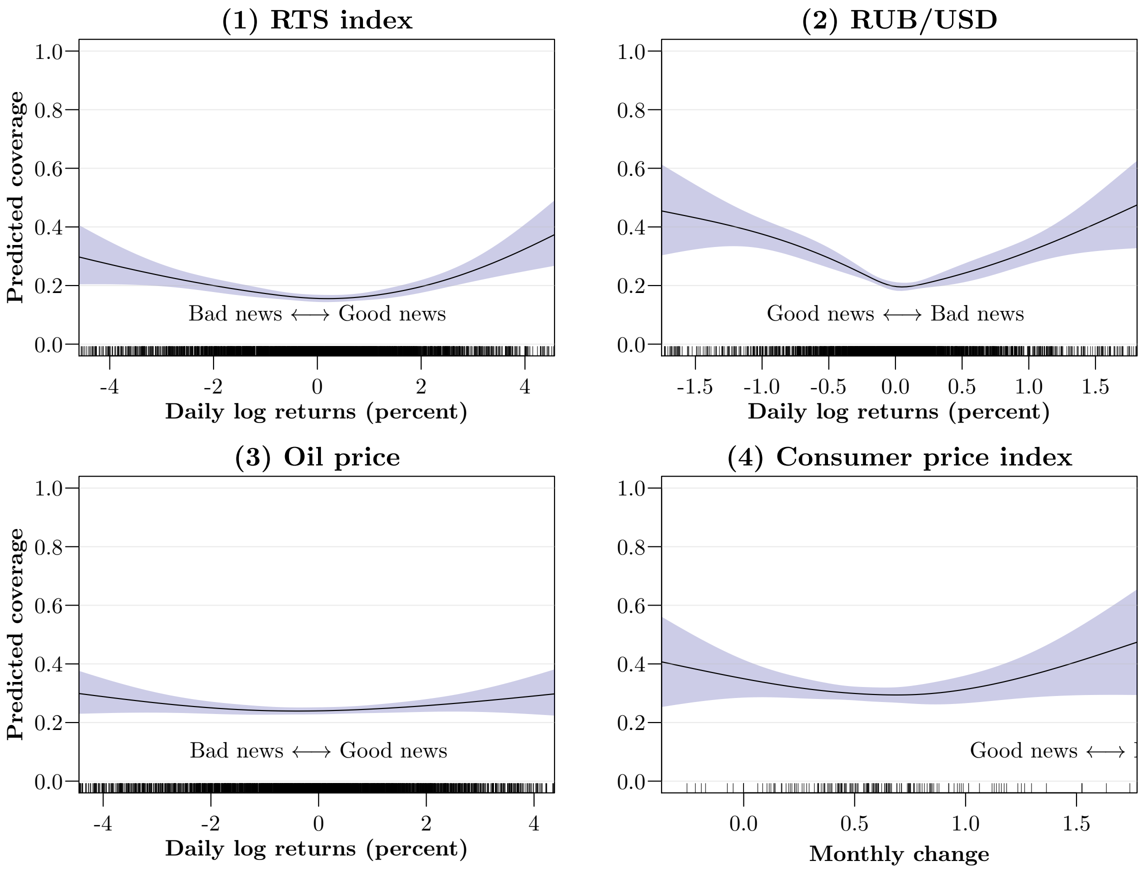

Figure 4: Censorship analysis with economic indicators restricted to two standard deviations from their means. Dependent variable: binary variable for whether news segments mention the economic indicator. Independent variable: change in the economic indicator. Grey bounds are 95% confidence intervals for predicted outcome.

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B.3. Distortion Tests

In this section, we investigate whether television engages in distorting bad economic news. This is important because our tests of censorship reported in the paper only determine that Chanel One does report on an economic indicator x even when x is performing poorly. However, it is possible that although the news is reported, it is actually *misreported*. The media could directly lie that the indicator has improved even when it has actually deteriorated; it could also report that the indicator has in fact deteriorated but spin that as good news for the Russian economy.

To investigate the possibility of news distortion, we look into how the content of economic news *that do get reported* is related to the values of the four economic indicators. We extract the news texts where the keywords for each of the four economic indicators were mentioned (this was our measure of coverage in the censorship tests). We then split these texts into smaller chunks, following the same procedures and the *Crowdflower* platform as in the coding of news attribution discussed in Appendix A, to evaluate different aspects of news sentiment. We asked three coders to evaluate each news fragment and extracted the response that obtained the weighted majority of coders' votes, while removing responses with fewer than two coders in agreement.

For each of our four economic indicators, we ask three sets of questions.

1. We ask coders whether the news fragment discusses a given indicator in a *positive or negative context*.

2. We ask coders whether the news fragment reports *an increase or decrease in a given economic indicator*. This question allows us to identify the specific dynamics of the indicators as reported in the news. It also serves as a sanity check for our keyword strategy of identifying texts that actually talk directly about the values of indicators, since the coders can also code a news fragment as mentioning the indicator in a different context, or not mentioning it at all.

3. Finally, the media could also misinform citizens about the economic performance of the regime without censoring bad news by embedding bad news in an otherwise positive narrative about the national economy. Hence, we also ask a question on *the overall sentiment of the news fragment* as it pertains to the Russian economy: Is it optimistic, neutral, or pessimistic?

Our overall expectation is that if the news is not distorted, its negativity/positivity (as measured by the three questions above) should correlate respectively with the negativity/positivity of the values of the respective economic indicators. We conduct two sets of tests to evaluate whether this is indeed the case. In the first set of tests, we estimate the following type of probit regressions:

$$\mathbb{E}[y_{it}(k)] = \Phi\left(\alpha_{0k} + \alpha_{1k} \cdot \Delta_t(k)\right), \tag{1}$$

where k denotes one of the four economic indicators, $y_{it}(k)$ denotes one of the three measures of news negativity/positivity for a news fragment mentioning a keyword for economic indicator k at time t, and $\Delta_t(k)$ is the value of the indicator k at time t.

The independent variables in these analyses are the same as in the censorship analysis of the paper. The only difference we make is that we express those variables in terms of z-scores so that their magnitudes are comparable across different indicators. We estimate the above probit model separately for each of the three measures of news positivity/negativity, and for each of the four economic indicators.

The results are shown in Table 2. In Panel A, we show how the value of each economic indicator is related to the probability that the indicator is reported in a *negative* context (the references category is the indicator reported in a positive context). As one can see, all for economic indicators tend not to be mentioned in a negative news context when the Russian economy performs well. In particular, higher values of the first two indicators (RTS index and oil prices) correspond to better economic outcomes and are negatively associated with the probability of being mentioned in a bad context. On the other hand, higher values of the other

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	High value - good news		High value - bad news	
	RTS index	Oil price	RUB/USD	CPI
Panel A: Dependent variable: indicator reported in a negative context				
scale(change)	-0.71^{***}	-0.18^{*}	1.27^{**}	2.95^{***}
	(0.10)	(0.09)	(0.45)	(0.63)
N	212	278	166	403
Log Likelihood	-61.97	-157.05	-68.02	-176.99
Panel B: Dependent variable: increase in indicator's value mentioned				
scale(change)	0.92^{***}	0.42^{*}	5.36^{***}	7.50^{***}
	(0.18)	(0.18)	(1.30)	(1.46)
N	104	146	89	204
Log Likelihood	-36.16	-98.53	-43.89	-109.91
Panel C: Dependent variable: sentiment of the news chunk is positive				
scale(change)	0.88^{***}	0.92^{***}	-3.21^{***}	-4.77^{***}
	(0.14)	(0.17)	(0.86)	(1.13)
N	182	240	125	340
Log Likelihood	-58.54	-110.35	-52.57	-141.87

Table 2: Probit regression coefficients with standard errors in parentheses. Significance levels: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$. The independent variable in each specification is the z-score of a given economic indicator.

two indicators point at economic problems and are indeed positively related to the probability of appearing in a bad news context.

In Panel B, the dependent variable is equal to one if the news fragment mentions an increase in the value of the indicator (e.g., mentions increase in oil prices or Russian stock market value). The reference category here is the news that mentions a decrease in a value of a given indicator. We exclude the news fragments that were coded as not mentioning either an increase or decrease of a given economic indicator directly. We see that the coefficients for all indicators are statistically significant and in the expected direction. An increase in the actual value of an economic indicator is associated with an increase reported in the news, no matter whether it is good or bad for the national economy.

In panel C, the dependent variable is equal to one if the news has overall positive sentiment. Here again, all coefficients are statistically significant, and their signs

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align with the economic meaning of the indicators. Larger values of RTS index and oil prices signal good economic performance and tend to appear in overall positive news, whereas the other two indicators have the opposite signs, since their larger values indicate economic hardship.

Our second batch of tests uses a more flexible, semi-parametric probit specification of the form

$$\mathbb{E}[y_{it}] = \Phi(g(\Delta_t)), \tag{2}$$

where, as before, y_{it} represents one of the three measures of news positivity/negativity, Φ is the standard normal cumulative distribution function, g is unknown smooth function and Δ_t is a value of one of the four economic indicators at time t. Here, we pool data from all four economic indicators and use the inverted exchange rate and inflation, as above. Thus, higher values of all indicators point to better economic performance.

We then transform each indicator into z-scores, so that they are all on the same scale. We pool data across four indicators because we can only analyze events that actually got reported. Credibly estimating the above semi-parametric probit model separately for each indicator is quite unrealistic given the relatively small amount of data.

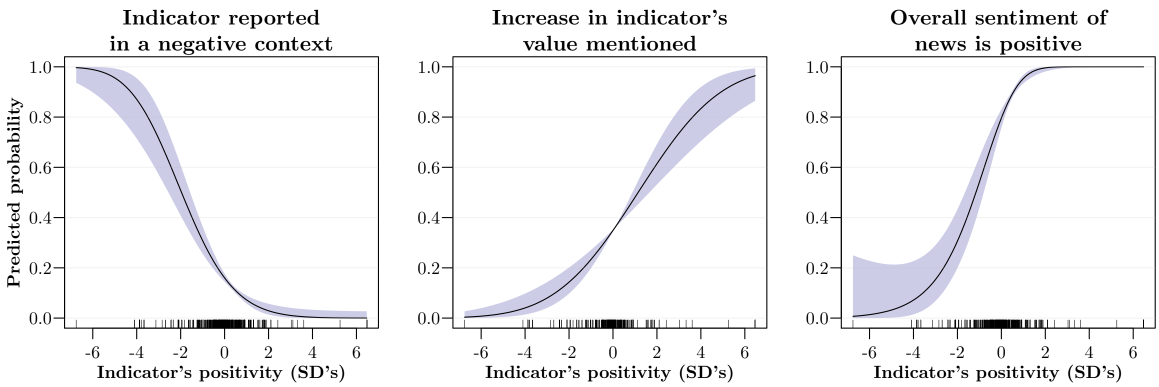

Figure 5: Positivity of indicator (across all four economic indicators, in z-scores) vs predicted positivity/negativity of news reports across three measures.

The results are shown in Figure 5. The left figure shows how the predicted probability that a news report on an indicator on day t varies with the indicator's positivity on day t. We see that when the indicator takes large negative values (e.g., RTS index falls by several standard deviations or more, or CPI index increases by several standard deviations), the predicted probability that the indicator is going to be reported in a negative context is large. This predicted probability decreases as the positivity of the indicator increases. The figure in the middle shows the predicted probabilities for mentioning that a given indicator has increased in value (relative to decreasing in value). When an indicator is highly negative, the news reports that it is negative with a large probability (or positive with the probability close to zero). Finally, the right-most figure shows that when the indicator is performing poorly, the sentiment of the news tends to be overwhelmingly negative, and vice versa.

Overall, all of the analyses above suggest no evidence that reports on the four economic indicators would be distorting information either by misreporting the facts or spinning them in artificially positive light.

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C. Attribution Analysis: Additional Results

C.1. Data Subsets

	Vladimir Putin	Russian officials	Foreign economy	Foreign powers	Observations
Panel A: All sample					
Direct	2.02***	0.65***	−0.87***	−0.48***	4,317
	(0.18)	(0.06)	(0.10)	(0.09)	
Associational	0.62***	0.40***	−0.32***	−0.08	4,104
	(0.07)	(0.06)	(0.08)	(0.07)	
Panel B: Excluding reports on oil and sanctions					
Direct	2.03***	0.55***	−0.78***	−0.42***	3,655
	(0.21)	(0.06)	(0.10)	(0.10)	
Associational	0.58***	0.43***	−0.12	−0.04	3,493
	(0.08)	(0.07)	(0.09)	(0.08)	
Panel C: Excluding recession years 2008 and 2009					
Direct	1.92***	0.54***	−0.75***	−0.32***	3, 805
	(0.18)	(0.07)	(0.12)	(0.10)	
Associational	0.61***	0.45***	−0.22**	−0.07	3,621
	(0.09)	(0.07)	(0.10)	(0.08)	
Panel D: Pre-Crimean annexation					
Direct	2.08***	0.56***	−0.88***	−0.23**	3,648
	(0.20)	(0.07)	(0.12)	(0.10)	
Associational	0.61***	0.40***	−0.12	−0.03	3,448
	(0.08)	(0.07)	(0.09)	(0.08)	
Panel E: Post-Crimean annexation					
Direct	1.65***	1.12***	−0.68***	−1.80***	669
	(0.36)	(0.15)	(0.14)	(0.23)	
Associational	0.48**	0.41*	−0.77***	−0.49***	618
	(0.19)	(0.22)	(0.17)	(0.16)	

Significance levels: ***$p < .001$; **$p < .01$; *$p < .05$

Table 3: Probit regression coefficients (with standard errors clustered by year-months) for the binary variable *Good news*. All regressions adjust for year, month, and weekday fixed effects.

C.2. *Analysis of Attributions with Structural Topic Models*

The previous results on the selective attribution of Russian TV news are based on coding news fragments using a predefined set of attribution categories. Even though we ask coders to consider as many as seven possible attributions of good/bad events, one could be reasonably concerned about the extent to which our results might be driven by the choice of attribution categories. In this section, we employ an agnostic unsupervised approach to show that the selective attribution of the news is not an artefact of our coding scheme.

We use the Structural Topic Model (hereinafter – STM), a modern method of topic modeling that summarizes texts in terms of a small number of topics and identifies the effects of text covariates on the topic structure (Roberts, Stewart and Airoldi, 2016). This is done in an unsupervised way by estimating a Bayesian hierarchical generative model of text that models the probabilistic process of text generation via, first, sampling a topic for a given word place in a text, and then sampling a specific word for that word place from the chosen topic. Thus, a topic is defined within this framework as a probability distribution over all words in the corpus, and every document is represented as a mixture of topics.

Unlike earlier topic models that assumed no variation in the prior distributions across different texts (Blei, Ng and Jordan, 2003; Blei and Lafferty, 2007), STM makes use of text-level covariates in the prior distributions to allow texts to have different *a priori* proclivity to different topics. This is a strong advantage of STM, given our interest in uncovering dissimilarities between positive and negative news.

Mathematically, the document-level topic proportions $\vec{\theta}_d = (\theta_d^{(1)}, ..., \theta_d^{(K)})$, where d indexes documents, and K is the number of topics, is modeled with a logistic normal distribution as a two-step process. First, draw normal quantities:

$$\vec{\eta}_d \sim N_{K-1}(\Gamma' x'_d, \Sigma),$$

where x'_d is a vector of document-level covariates that affect topic prevalence in a document, Γ is a coefficient vector, and Σ is a covariance matrix. Notice, that for identifiability purposes, $\vec{\eta}_d$ is sampled from a $(K-1)$-dimensional normal distribution, and η_d^K is set to zero.

Then, map these normal quantities to a simplex to make sure they add up to one and represent valid topic proportions:

$$\theta_d^{(k)} = \frac{exp(\eta_d^{(k)})}{1 + \sum_j exp(\eta_d^{(j)})}$$

Due to the complexity of the model and the nonconjugacy arising from the use of the logistic normal distribution, model parameters are estimated with an approximate variational EM algorithm (Roberts, Stewart and Airoldi, 2016), assuming the number of topics K is known. We use the algorithm proposed by Lee and Mimno (2014) and implemented in *stm* R-package for automatic selection of the number of topics, and repeat the process 10 times to make sure the results are numerically stable and imply a consistent substantive interpretation.

In order to summarize topical differences of the news chunks that describe negative vis-a-vis positive events, we estimate STMs with a vector x_d' including two dummy variables for news chunks that describe positive and negative events (these are not redundant, since a chunk can also describe both events or neither event), and a 10-degree B-spline for time. We then compute average marginal topic distributions for chunks with only positive and only negative events, as well as their confidence intervals using 1000 simulated Γ coefficients and manipulated values of the covariates.

Figure 6 shows that positive events mentioned in TV news are largely related to the activities of the President or the members of the government (topics "Kremlin meetings", "Putin", "Government discussions", "Government discussions (2)"). The news fragments devoted to these topics draw public attention away from the actual economic facts to the efforts of the Russian officials to improve the economic performance of the regime. Alternatively, the positive news focuses on macro-

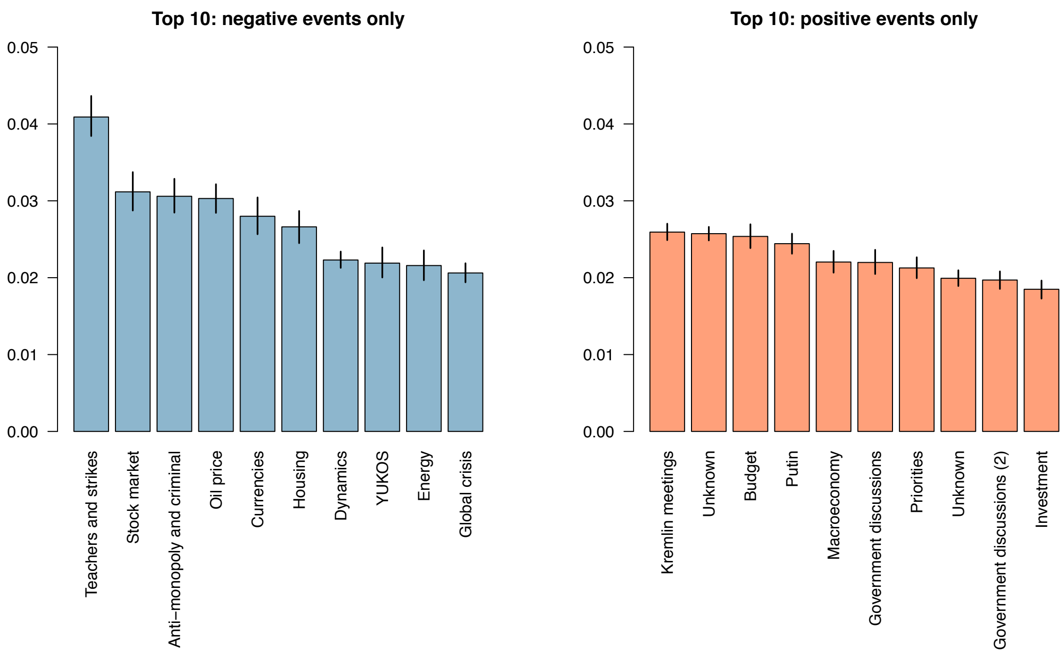

Figure 6: Top 10 topics by event-sentiment.

indicators of the national economy (topics “Budget”, “Macroeconomy”, “Priorities”, and “Investment”) rather then issues more closely related to the well-being of the citizens.

On the other hand, news with negative topics are more related to citizens’ well-being (“Teachers and strikes” and “Housing”). These topics also often allude to the causes of the economic hardship (“Stock market”, “Oil price”, “Global crisis”, “Anti-monopoly and criminal”) and, importantly, often mention external factors and the global economy as the driving force behind the bad news.

Thus, instead of broadcasting ‘alternative facts’ about the national economy, Russian TV news focuses on building hopes for a better future associated with the efforts of the government, and attributing economic hardship to external factors – which are the categories employed for the main analyses in this paper.

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D. Dynamics of Attribution: Additional Results

D.1. Electoral Cycle Effect in Associational Attribution

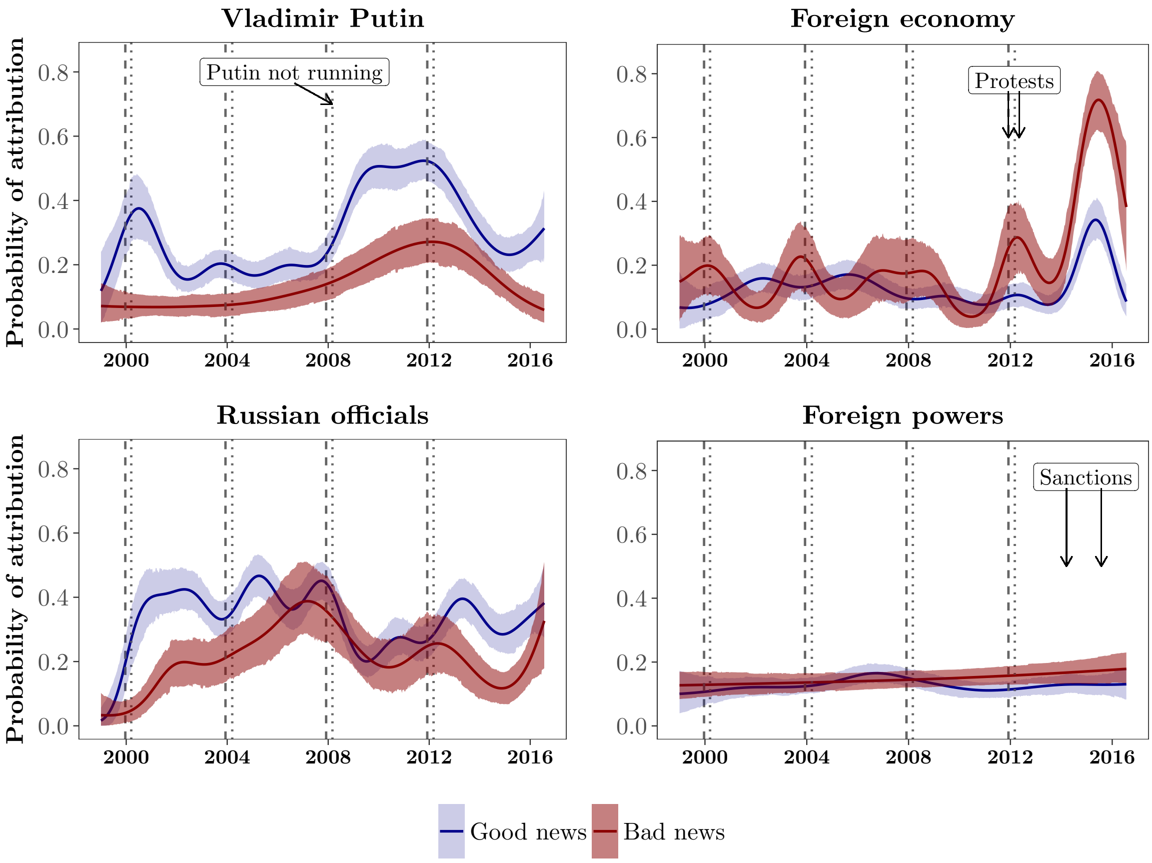

Figure 7: Temporal variation in the associational attribution.

Figure 6 in Section presents evidence of electoral cycles as one of the driving forces behind the dynamics of news manipulation in Russia by focusing on direct attribution. Here, we explore electoral cycles in associational attribution, the other manipulation technique this paper highlights.

The two left panels in Figure 7 are in line with the findings from analyzing direct attribution. Here, selective attribution peaks for Putin around the times of elections, except the 2008 presidential election when Putin was not running. One can also see a substitution effect for Russian officials around the 2004 and 2012 elections. As expected, there is no such an effect in 2008. The fact that one does not find any substitution in 2000 might due to the peculiarities of Putin's first electoral campaign when he was running for president as a new prime minister who has just formed a new government, and any critique against Russian officials could have been perceived as an attack at Putin himself.

The two right panels present mixed results. The top panel for foreign economy provides clear evidence of electoral cycles with negative attribution peaking around every election. However, we find null results for foreign powers. This could partly be due to the fact that an active and explicit anti-Western foreign policy is a relatively new turn in Russian politics that started after the Euromaidan protests in Ukraine. Russian television was not portraying Europe and the U.S. as its enemies before that, which explains no need for state-controlled TV to emphasize the subversive role of foreign governments during electoral campaigns. null results.

Interestingly, we can neither find spikes in negative attribution to foreign governments after the introduction of sanctions. Although this is not directly related to the electoral cycles, it is worth mentioning that after the U.S. and E.U. imposed sanctions on Russia, Channel One has been often mentioning foreign governments to emphasize both the willingness and ability of European businesses to invest in Russian economy despite political decisions of the respective governments. Thus, foreign governments do appear in news with an overall positive sentiment, although for contrasting effects. However, our analysis of associational attribution cannot distinguish those cases.

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D.2. *Heterogeneity Conditional on Putin's Approval: Coefficient Estimates*

The table below reports probit regression coefficients for the results underlying Figure 7 in section of the paper. All four regressions control for year, month, and weekday fixed effects. All four interactive coefficients are in the direction that is consistent with the predictions from the literature: positive for Vladimir Putin and Russian officials, and negative for Foreign economy and Foreign powers. Note, however, that the significance of these coefficients does not necessarily correspond with the existence of significantly heterogeneous effects shown in Figure 7 in the paper.

	Vladimir Putin	Russian officials	Foreign economy	Foreign powers
	(1)	(2)	(3)	(4)
Good news	1.81^{***}	0.18	-0.71^{*}	0.22
	(0.52)	(0.20)	(0.35)	(0.29)
Approval	-0.53	-1.19^{***}	1.24^{**}	0.86
	(0.91)	(0.30)	(0.46)	(0.52)
Good news×Approval	0.36	0.77^{**}	-0.24	-1.06^{*}
	(0.91)	(0.28)	(0.46)	(0.42)

Significance levels: $^{***}p < .001$; $^{**}p < .01$; $^{*}p < .05$

Table 4: Regression coefficients for probit models with interactions. All specifications include year, month, and weekday fixed effects (N = 4,234). Standard errors (in parentheses) clustered by year-month.

Notably, the interactive coefficient for Foreign economy is not significant, even though the differences between the estimates sampled averaged relative attribution rates are quite obvious from the figure in the graph and the bootstrapped p-value of those differences is small. Such discrepancy between the significance of the interactive coefficients and the significance of other relevant quantities (like marginal effects on probabilities) has been noted as a common phenomenon in binary regression models (Berry, DeMeritt and Esarey, 2010).

D.3. *Heterogeneity Conditional on the Change in Putin's Approval*

In section of the paper, we study how the relative attribution of good vs bad news depends on Putin's prior popular approval. Here, we conduct an alternative analysis where we instead use the change in Putin's approval in the prior month. In other words, if the outcome variable is measured at month t, the variable *Support* is equal to $(x_{t-1} - x_{t-2})/x_{t-2}$. We then, again, estimate the specified probit regressions that interact the indicator for *Good news* with the variable *Support*, and control for year, month, and weekday fixed effects.

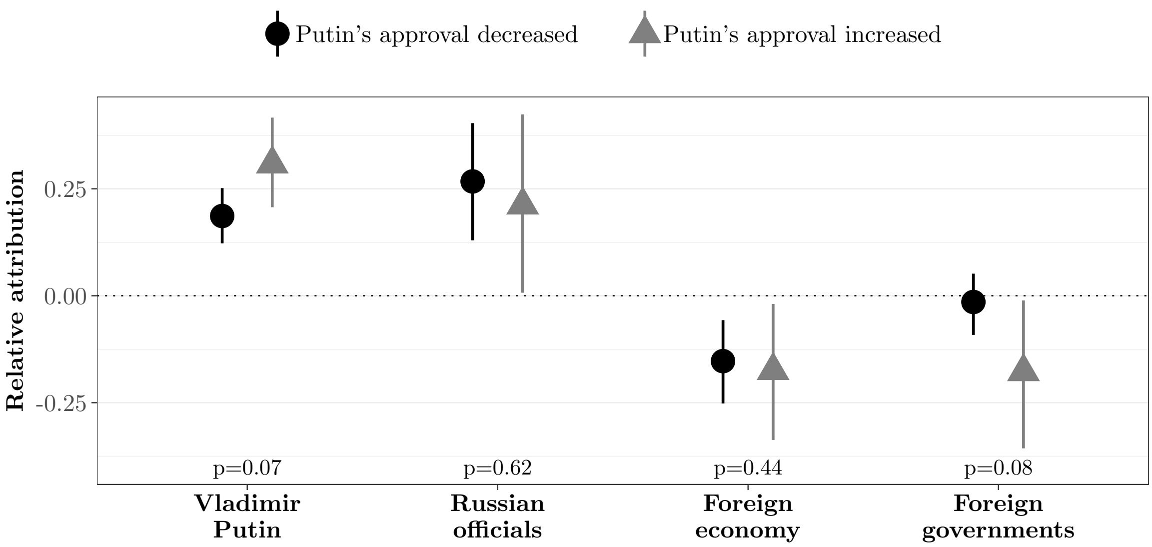

Figure 8: Relative direct attribution depending on the change in Putin's approval in prior month.

The results are shown in Figure 8. First, here we observe that there is more attribution of good news to Putin when his approval has *increased* during the prior month. The null hypothesis that there is more selective attribution when Putin's prior support has been decreasing is rejected at 90 percent confidence level. This is consistent with the second prediction made in the paper. Second, we do not observe significant differences in how the news are attributed to Russian officials or foreign economy depending on the prior changes in Putin's approval. Third, bad news are attributed to foreign governments at higher rates after Putin's approval has increased relative to when it has decreased.

There are some inconsistencies between the results in the above figure and the ones reported in the paper: the effect for Putin is significant here, but not in the paper, whereas the effects for Russian officials and Foreign economy are not significant here, though they are significant in the paper. However, none of these results – either here or in the paper – go against the prediction that there is more selective attribution of news (positive with respect to Russian actors and negative with respect to foreign actors) when the leader's support is high relative to when it is low.

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