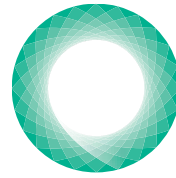


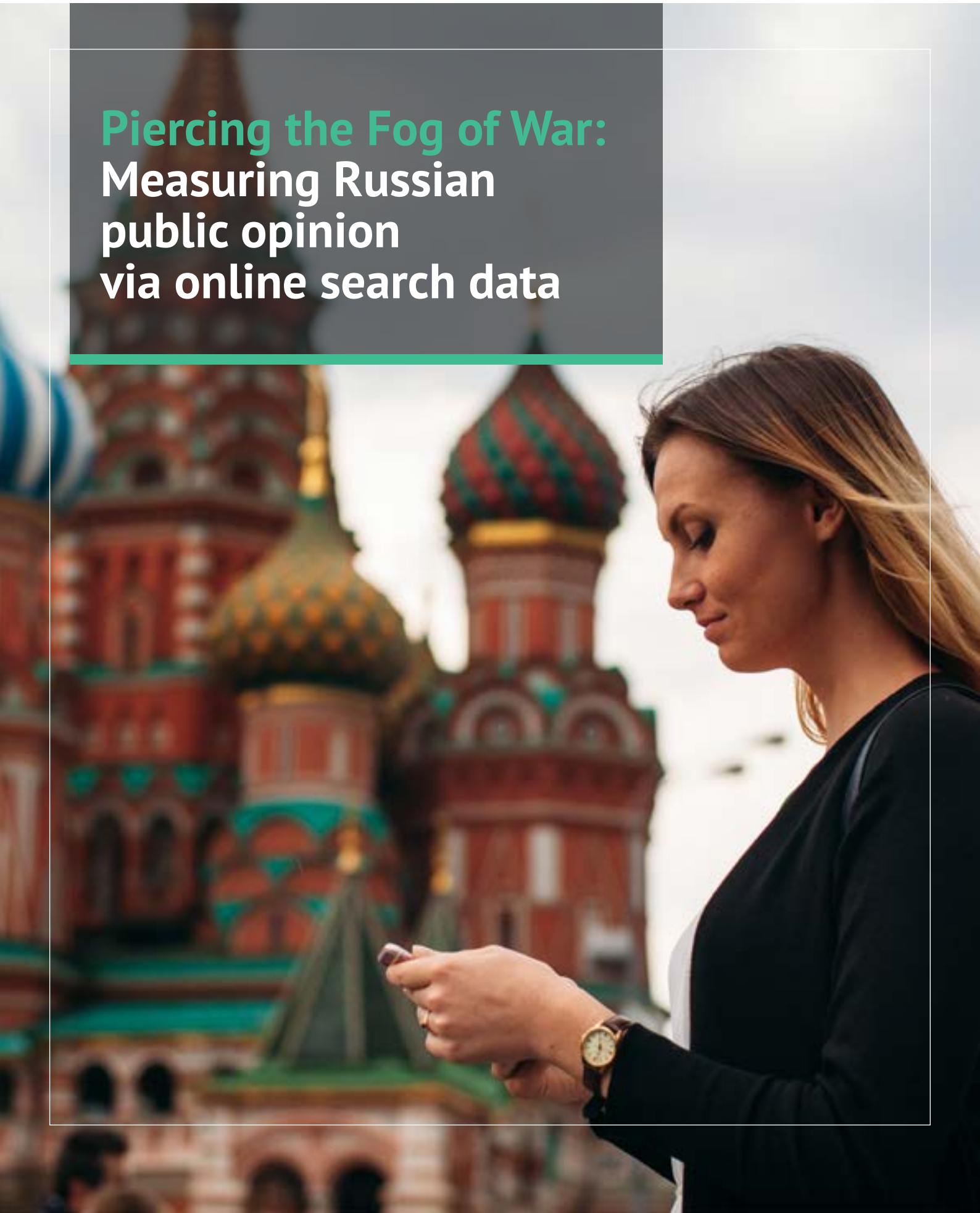


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Cambridge

Piercing the Fog of War:
Measuring Russian
public opinion
via online search data



Executive Summary

As the war in Ukraine continues into its second year, it is critical for policymakers and analysts to obtain accurate assessments of the state of current Russian public opinion. However, existing survey data from within the Russian Federation is widely considered to be unreliable as a result of self-censorship, response bias, and suspected manipulation of survey results.

This report uses web search data collected from within Russia via Google and Yandex in order to proxy for survey measures of Russian public opinion, including political dissent, household financial security, and personal life satisfaction.

Our results suggest that, contrary to official Russian public opinion sources, levels of Russian life satisfaction may be near their lowest levels in a decade, while levels of online dissent have spiked during moments of failure in the prosecution of the war, most notably in response to rising casualties and efforts by the Kremlin at military mobilisation.

In further addition to these observations:

General sentiment (personal wellbeing) among the Russian population has declined almost continuously since the start of the war. Contrary to the findings of Russian polling agencies, we find no evidence of a “war rally” in Russian happiness or life satisfaction, and substantial evidence that the mental health of the Russian population has deteriorated since the decision to invade Ukraine.

Until now, sanctions appear to have had only limited effect upon Russian households. While there was evidence of financial hardship during the first month of sanctions from February to March of 2022, the financial situation of Russian consumers and businesses has stabilised since. Meanwhile, though secondary sanctions on Russian energy exports have likely impacted government revenues, we do not yet see transmission of this effect to ordinary households and consumers.

Tacit questioning of the regime, as measured by searches relating to pacifism or dissident authors, spiked during the initial phase of the war, and again after the partial mobilisation order of September. This suggests that ordinary Russians are not simply passive subjects, but susceptible to critical reflection and opposition to the conflict when it imposes upon everyday lives. However, online dissent has quietened since the third quarter of 2022, when Russia increased reliance upon mercenaries and prison recruits for front-line military operations. These observations are consistent with the view that the regime faces a latent political constraint in its ability to mobilise civilian manpower for offensive operations, due to the extent of tacit domestic dissent produced by ordinary civilian losses.

Piercing the Fog of War: Measuring Russian Public Opinion via Online Search Data^a

Roberto Stefan Foa,^b Roula Nezi^c

In recent decades, public opinion researchers and policymakers have gained valuable insight into the attitudes and opinions of ordinary Russians thanks to regular tracking surveys conducted by polling organisations such as the Levada Center, the Russian Public Opinion Research Center (VCIOM), and FOM. However, since the onset of the war in Ukraine in February 2022, it has become increasingly difficult to attain reliable measures of public opinion in Russia due to growing problems of survey response bias, self-censorship, and doubts concerning the methodology of official state survey organisations. To overcome these difficulties, this paper presents a novel measure using online search data from Google and Yandex to proxy for cognitive mental states in the general population. Comparing such measures to historical and recent surveys, our findings suggest that in reality Russia's public mood is near its lowest level for a decade, while the legitimacy of its regime has been undermined by failure in war. Our results illustrate how political scientists can use online data to shine light on public opinion in difficult-to-survey contexts, and help to assess the dynamics of regime support in non-democratic countries.

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1 Introduction

Since the onset of the war in Ukraine, it has become critical for scholars and analysts to obtain accurate assessments of the state of public opinion in Russia. Unfortunately, however, Russian polling data has been subject to a number of shortcomings (Kalinin, 2016), including potential response bias (Tannenbergh, 2021; Hale, 2022; Yudin, 2022) and changes to survey methodology (Shirokanova, 2020). Sadly, as each of these defects may vary in intensity over time (Frye et al., 2017, 2022), this renders the use of social trends data from the Russian Federation as inherently problematic (Rosenfeld, 2022). For scholars who are interested in analysing contemporary Russian public beliefs and attitudes, therefore, we are left with a conclusion similar to Winston Churchill's pre-World War II prognosis: that Russia is a "riddle wrapped in a mystery inside an enigma" – defying all efforts to analyse or forecast (British Broadcasting Service (BBC), 1939).

This lack of insight also leaves analysts unclear on many of the key questions surrounding Russian public attitudes today. For example, have Russian authorities benefited from a significant "rally-round-the-flag" effect since the start of the war (Mueller, 2022), similar to that which followed the annexation of Crimea (Greene and Robertson, 2022)? Or has the failure of the Putin administration to achieve its stated objectives undermined its legitimacy in the eyes of ordinary Russians? Secondly, have Russian authorities managed to cushion the blow of economic sanctions, or are their citizens now experiencing significant financial hardship that may fuel broader discontent (Harrison, 2022)? And most importantly of all, perhaps, what is the general attitude of Russians towards this war after more than a year of conflict, thousands of casualties, and limited territorial gains (Kizilova and Norris, 2022) – and what might this tell us about the dynamics of popular support for authoritarian regimes more broadly (Gerschewski, 2018)?

This paper proposes answers to these questions via an innovative method for validating and correcting Russian public opinion data, using online search information collected on a daily basis from Russian internet users by Google and Yandex.¹ We show that online

¹ Yandex is the most popular search engine in Russia, with 61% market share, followed by Google (38%).

search data can offer reliable means of cross-checking both short-term (monthly) and long-term (multi-year) variation in Russian public opinion tracking surveys. As a result, such data could also be used to detect moments of alteration or shift in either survey response bias, or unreported changes in methodology by Russian survey institutes. In our study we identify and use these alternations or shifts in public opinion as reference points to correct for suspected biases in official Russian survey data, and provide new and more accurate estimates of Russian public opinion changes. As a final step we examine our new measures to see what they can tell us about how Russian public opinion has evolved over the course of this war, and what this might lead us to expect of Russian policy making in future.

The findings from this analysis have important implications for scholars and policymakers working on both contemporary Russia and authoritarian regimes more broadly. First, contrary to the data released by Russian polling organisations, we find little evidence that the public mood has improved since the invasion. This result not only adds to concerns regarding Russian polling reliability ([Hale, 2022](#); [Buckley, Marquardt, Reuter, and Tertychnaya, 2022](#); [Reisinger, Zaloznaya, and Woo, 2023](#)), but suggests lower legitimacy for the regime than generally acknowledged ([Frye, Gehlbach, Marquardt, and Reuter, 2022](#)). Second, our findings validate the claim that western sanctions had only a limited and temporary impact on Russian households ([Mamonov, Pestova, and Ongena, 2022](#)). This finding feeds into broader concerns regarding the effectiveness of sanctions as a policy tool, both in general ([Oechslin, 2014](#); [Von Soest and Wahman, 2015](#); [Jones, 2015](#)) and regarding Russia specifically ([Dreyer and Popescu, 2014](#)). Finally, our results suggest that ordinary Russians are not merely “passive subjects”, but do show variation over time in their extent of critical thinking regarding the regime. In particular, we find that levels of online dissent are especially sensitive to Russian failures in the war in Ukraine, as well as moves by the government to increase the breadth of military mobilisation. Such findings imply that when authoritarian regimes depend upon civic passivity and disengagement ([Yudin, 2022](#)), they face limits in their capacity for popular mobilisation ([Bernhard and Karakoç, 2007](#)), and confirm the longstanding observation in comparative political science

that military failure constitutes one of the main risk factors for late-stage authoritarian regimes ([Huntington, 1991](#); [Snyder, 2017](#)).

Having laid out the rationale for this research, the rest of this paper proceeds as follows. First, we begin in the next section with a brief review of the literature, including examples of how online search data have been used to validate pre-existing survey measures of public opinion. Then in the second section we outline the data used in this study, together with diagnostic tests to validate our survey indices. After presenting external validation in section three, we then use the indices to address three key question areas – the state of the public mood in Russia following the invasion, the effect of sanctions, and the evolution of cognitive dissent from the regime – before section five concludes.

1.1 Literature review

During its economic and political transition from communism, Russia experienced a rapid flourishing of its survey industry. This began in 1987 with the foundation of the All-Union Center for the Study of Public Opinion, which became the Russian Public Opinion Research Center (VCIOM) in the wake of the Soviet Union's dissolution. Out of VCIOM two further polling agencies emerged: the Public Opinion Foundation (FOM), founded in 1992 as an academic non-profit organisation focused on sociological research, and the Levada Center, which separated in 2003 with a mandate to maintain politically-independent polling research. At the same time Russian academic survey research has also advanced, including via participation in international projects such as the World Values Survey (WVS), the International Social Survey Programme (ISSP), and the European Social Survey (ESS), as well as private polling by agencies such as Gallup, YouGov, and IPSOS.

However in recent years, Russian public opinion polling has been beset by recurring concerns regarding data reliability. Political scientists have questioned the consistently high approval ratings received by the country's president, Vladimir Putin ([Frye, Gehlbach, Marquardt, and Reuter, 2022](#); [Buckley, Marquardt, Reuter, and Tertychnaya, 2022](#)), the high levels of public sentiment that followed the Crimea annexation ([Hale, 2022](#)) and

the independence of Russian polling agencies from state interference. Such concerns have only increased in recent years, not least in the wake of the war in Ukraine and its concomitant censorship of polling organisations, self-censorship by citizens, and media saturation by pro-war propaganda (Kizilova and Norris, 2022).

As a result, this casts doubt on many of the findings reported by Russian polling agencies since February of 2022, which have been almost uniformly supportive of the Kremlin. For example, when Russian citizens have been asked whether they “personally support the actions of Russian military forces in Ukraine,” large majorities are reported to answer in the affirmative, with 70 to 80 per cent responding in agreement (Levada Center, 2022). Similarly, polling agencies such as Levada and VCIOM have registered a large increase in approval ratings for Russian authorities since the start of the war, with Vladimir Putin’s own ratings soaring as high as 80 per cent. This “rally round the flag” effect even extends to assessments of personal wellbeing, with reported life satisfaction reaching close to its highest level on record, according to data from VCIOM (VCIOM, 2023). Meanwhile, official polls support the narrative by Russian authorities that they have insulated their populace from the effect of international sanctions, with household financial satisfaction rising to its highest level in five years. Given the implausibility of some of these findings, it is natural that analysts should ask whether alternative data exists which can either validate or disconfirm their accuracy.

One alternative is that provided by online search data, as in situations where survey results may be considered deficient due to response bias or manipulation, private online activity provides an alternative angle for making inferences about beliefs and attitudes in the general population (Jun, Yoo, and Choi, 2018). In the context of widespread concerns over polling reliability, for example, Google Trends data has been successfully used as a prediction tool for electoral results in political systems as diverse as the United States, Canada and Germany (Polykalas, Prezerakos, and Konidaris, 2013; Martínez, Prado, and Paule, 2019; Prado-Román, Gómez-Martínez, and Orden-Cruz, 2021) and has been validated in heavily polarised referendums (Mavragani and Tsagarakis, 2016) that typically limit the validity of traditional prediction models (Qvortrup, 2016). In

social sciences Google search data has been used to examine how public concern over police violence affects crime rates (Gross and Mann, 2017). Online search data has also proven effective in financial economics as a means of “now-casting” financial sentiment (Choi and Varian, 2012), including in countries where official data may be unreliable, such as in mainland China (Liu, Xu, and Fan, 2018). The same has been shown to be true when forecasting economic conditions, again because negative financial conditions tend to present individuals with very specific informational requirements – concerning bankruptcy law, emergency loans, or mortgage deferral, for example – and this offers researchers a means of constructing and benchmarking consumer and business sentiment indices, which can be cross-validated against historical survey-based measures in these respective areas (Da, Engelberg, and Gao, 2011).

Online search data has also proven an effective means for estimating medical trends in other areas, in particular that of mental health. Because individuals suffering from mental health problems such as anxiety, insomnia or depression tend to search the internet for self-diagnosis, self-help and self-treatment options, this means that a benchmark can be developed of the extent to which such symptoms may be present within the general population at any given point in time (Foa, Fabian, and Gilbert, 2022). Another area in which online search data has proven useful in the context of imperfect information is the global coronavirus pandemic, when search queries were widely used to accurately detect local outbreaks of COVID-19 and search activity relating to its key symptoms (such as loss of taste and smell) proved a reliable tool in pinpointing disease outbreaks (Walker, Hopkins, and Surda, 2020; Mavragani and Gkillas, 2020). Again, such methods were especially useful in countries, such as Iran, where official data was widely considered as inadequate or manipulated (Ayyoubzadeh, Ayyoubzadeh, Zahedi, Ahmadi, and Kalhori, 2020).

As well as proving useful in specific research environments, the use of online search data has also gained broader legitimacy as a more reliable tool for making inferences about public views and behaviour than other “big data” methods such as the scraping of Twitter content, Facebook posts, or information from Amazon (Mellon and Prosser, 2017). Unlike

social media data, search query records are drawn not only from a larger sample but also from a sample that better reflects the entire population, with almost all citizens in developed societies using the internet on a regular basis for the purpose of accessing information. Meanwhile, whereas the “self-presentational” style of social media and traditional surveys inevitably entails a large social desirability bias ([Gayo-Avello, Metaxas, and Mustafaraj, 2011](#)), internet searches are generally perceived by users as anonymous and private. Since users are less influenced by social desirability search data is more amenable for the study of more sensitive topics such as personal health, drug use, or unemployment. As a result online search data can be considered a valid measure of social intentionality in the limited sense that, if a person searches for a given topic, we reasonably can infer them to be seeking genuine information about that subject.

This does not mean that search data is free of potential disadvantages and drawbacks. For example, in 2015 Google discontinued Google Flu Trends (GFT) a service aimed at providing accurate estimates of flu activity by analysing flu-related search queries. At the time, the main limitation of GFT was the overestimation of flu cases due to algorithm updates by Google which affected its search algorithm. These updates typically aimed to improve users’ experience, such as enhancing the relevance of the results they see, but GFT did not control for external factors such as increased media coverage of flu outbreaks – which drove up search volumes regardless of actual flu cases ([Lazer et al., 2014](#)). Potential issues arising from the lack of clarity on algorithm updates have also been highlighted by [Nuti et al. \(2014\)](#), who conducted a systematic review of seventy articles utilizing Google Trends data.

In addition to the above information, it is worth noting that the anonymous and aggregated data made available to researchers by region precludes the possibility of tracking search queries made by specific IP addresses or individuals. Furthermore, issues related to content validity – the extent to which a search query is representative of the concept we aim to measure – may arise since users may search for the same topic but they may enter different words ([Chykina and Crabtree, 2018](#)).

For this reason, best practice in the use of online search data requires extensive validity testing, so as to ensure fit between search activity and user intention - including careful cross-checking of data showing the context in which search terms appear, removal of confounding search terms, testing of multiple search queries, and the application of common sense in results interpretation ([Mellon, 2013](#)).

2 Data and data validation

2.1 Data

In order to construct proxy measures of Russian public opinion against which to benchmark conventional Russian survey measures, data was collected from Google Trends for the Russian Federation during the period from January 1, 2012 up until the most recent available date (May 2023), and cross-validated against Yandex data for the past 12 months. This enables the relative popularity of Google searches to be analysed, as well as a comparison of both search queries and the development of “topics”, in other words of clusters of related queries.

Google Trends, first launched on May 11, 2006, provides a time series index analysing the popularity of search terms entered in Google’s search engine.² As such, the service provides to the public free of charge access to a large sample of terms searched using their platform. To construct an index summarising the popularity of a search term, the total for each is divided by the sum of searches in a specific point in time and location, and this produces an index ranging from zero to a hundred where lower values represent less popular items and higher values those which are more so.

2.2 Keyword selection

For the purpose of the analysis of this paper, we aim at analysing three salient issues that are important to the Russian public and policymakers during the war in Ukraine:

² For further information, see the [Google Trends website](#).

subjective wellbeing; household financial satisfaction; and levels of “cognitive dissent” against the conduct of the war and associated authoritarian drift of Russian institutions. To this avail we construct three search index measures that are designed to proxy for Russian public attitudes and opinions on the above mentioned issues. This allows us to provide an answer to questions of whether Russian authorities benefited from a significant “rally-round-the-flag” effect since the start of the war, whether Russian authorities have managed to cushion the blow of economic sanctions, and whether Russian citizens are beginning to question the legitimacy of the regime in response to its ongoing military failures.

Following similar studies and good practice strategies analysing public opinion with the use of Google Trends ([Mellon, 2014](#); [Böhme, Gröger, and Stöhr, 2020](#); [Nutti, Wayda, Ranasinghe, Wang, Dreyer, Chen, and Murugiah, 2014](#)) we first drew up a “long list” of potential indicators for use in each category, consisting of 15-20 terms in each area; this was then refined in two stages to produce a “shortlist” of indicators after checking their validity using the “related queries” function in Google Trends ([Table 1](#)). This tool returns the top full search queries in which the string appears, and thus, can help confirm or disconfirm whether each is conceptually valid. For example, certain searches may pick up on names of celebrity acts, businesses or other unrelated entities whose name incorporates those words: to give an obvious example, many searches for “credit” were not in relation to attempts to secure financial support, but rather, the names of prominent banks or credit-card companies. By excluding those confounding terms we accounted for issues related to content validity. On the other hand, searches for the term “no downpayment” uncovered individuals without financial means needing to borrow for car loans, white goods or housing. Having filtered term selected by validity according to related queries, we also filtered by search volume (removing terms with too low usage) and excessive sensitivity to news events (terms with spikes in usage unrelated to intention), in order to yield the shorter list that is shown in [Table 1](#) (a full list of terms is given in [Appendix table A.1](#)).

Table 1: Indicators used in search indices

Index	Search Term	Top Related Searches
Subjective Wellbeing (Inverted)	Depression Insomnia Alcoholism Anxiety	Agitated depression What to do if you suffer from insomnia How to cure female alcoholism What areas of life cause the most concern
Financial Satisfaction (Inverted)	Bankruptcy Life Insurance Mortgage Refinance Surrogate Maternity Eviction Kidney Donor	Moratorium bankruptcy 2022 Life and health insurance cost Sber mortgage refinancing Surrogacy price 2022 Law of Russian Federation How much does kidney transplant cost
Cognitive Dissent	“No War” Solzhenitsyn Pacifism Hannah Arendt Authoritarianism Totalitarianism George Orwell Protest	No war with Ukraine Solzhenitsyn about Ukraine Militarism Banality of Evil buy What is democracy Authoritarianism for Dummies 1984 read full content Green ribbon [antiwar] protest

2.3 Search index measures

2.3.1 *Subjective wellbeing*

First, we proxy for subjective wellbeing among Russian internet users by using negative mental health condition symptom searches, such as insomnia, panic attacks, or online tests for depression. Previous studies have found negative mental health search terms to function as effective and reliable proxies for changes in daily surveyed mood states, due to the fact that when individuals experience negative mood conditions they become amenable to searching the internet for self-diagnosis, self-help or self-treatment (Foa, Inglehart, Ponarin, and Karabchuk, 2018; Foa, Fabian, and Gilbert, 2022).³ Items on

³ By contrast, positive mood state terms (e.g. happiness or contentment) have not been found to function effectively for this purpose, as positive moods are non a priori associated with any particular form of online search activity.

negative mood state are used in the diagnosis of depression (Radloff, 1977; Huppert and Whittington, 2003) and individuals who experience mental disorders score lower on measures of subjective wellbeing (Diener, 2012). Meanwhile at the cross-country level, the percentage self-describing as happy has been found to correlate negatively with the suicide rate (Minkov, 2009), while composite measures of subjective wellbeing were found to vary inversely with national means on the Beck depression inventory (Van Hemert, Van De Vijver, and Poortinga (2002) and negatively with national measures of mental ill health (Fischer and Van de Vliert, 2011). For this reason the inverse of negative mental health functions as an effective proxy for life satisfaction, allowing us to use negative mood search terms to develop an alternative subjective wellbeing benchmark. Finally the “related queries” tool in Google Trends allows us to see that most searches for these terms related to self-diagnosis and treatment.

2.3.2 Household financial satisfaction

We proxy for household financial satisfaction among Russian internet users by using term searches that relate to emergency economic needs, such as searching for information about bankruptcy rules or eviction procedures, the availability of short-term lending through non-downpayment loans or mortgage refinance, and indicators of financial desperation such as seeking information about kidney donation or surrogacy. As with subjective wellbeing, we expect greater validity with negative rather than positive term searches: periods of financial security are less associated with any specific online search activity, beyond general spending, whereas periods of emergency need tend to involve specific mechanisms of household support (Vicente, López-Menéndez, and Pérez, 2015). The inverse of this measure of financial distress can then function as a reliable proxy for household financial satisfaction. Again we are able to validate items through the “related queries” tool in Google, which shows that these terms appeared in searches regarding cost saving and prices (Table 1).

2.3.3 *Cognitive dissent*

Our third measure is an index of cognitive dissent, which aims to track the degree of citizen discomfort with the conduct of the war and the “authoritarian drift” of Russian institutions. The logic of the index is that it is based upon term searches which *a priori* would suggest critical reflection on the current political trajectory of the country. We do so by including three categories of terminology: The first are specialised conceptual terms for which searches suggest efforts at self-education arising from such doubts and include concepts such as *totalitarianism*, *authoritarianism*, or *pacifism*. The second relate to specific works or authors whose corpus is associated with resistance to government oppression: for example, Soviet dissidents such as Alexander Solzhenitsyn, or western authors such as George Orwell. Finally, we also include terms that suggest a more active interest in learning about methods to resist government authority: including searches for information about local protests, methods of passive resistance, or specific terminology associated to the antiwar movement (e.g. the slogan, “no war”). In the first round for this index we also considered a range of expressions more overtly associated with the antiwar movement (e.g. “Putler”, “Russia without Putin” or “Putin out”), as well as search terms for contemporary public figures who are associated with the civic opposition (such as activist Alexey Navalny). However these terms were ultimately excluded, as they failed to pass our validity tests. First, they were found to be subject to ephemeral spikes around news events, when search requests are likely to reflect general news interest rather than oppositional sentiment per se. Second, while self-censorship bias did not seem to affect the rate of general informational searches linked to regime-critical concepts or historical authors, we suspect it may affect overtly regime-critical slogans and figures. For this reason, as discussed below, measures of tacit dissent are more reliable for the purpose of making inferences about Russian public opinion, and are relied upon primarily for the index. In order to validate the intuition that our final list of search terms relate to critical ideation, evidence of cognitive dissent can be found in the “related queries” categories from Google Trends: Searches for “George Orwell”, for example, were dominated by requests for Russian-language versions of his dystopian novel *1984*, while leading searches for

Solzhenitsyn, relate to excerpts from *The Gulag Archipelago* calling for Russia to respect Ukraine's autonomy (Table 1).

From here, we then conducted three further analyses to validate our final indicator selection. First, we examined the average internal correlation among items so as to ensure positive covariance between all selected items. We then conducted a confirmatory factor analyses to check that each item used did load correctly within its dimension (see Appendix), and finally sensitivity analyses on the final indices, shown in the diagnostics section below.

2.4 Indices validation and performance

2.4.1 Google vs. Yandex

Having constructed initial indices, we then engaged in an extensive validation exercise in order to ensure that the resultant indices function as reliable, representative, and valid predictors of Russian public attitudes and beliefs. This validation process consisted of a series of stages, each addressing one area of data representativeness, validity, or reliability.

First, a major concern in the use of Google search data from within a country such as Russia is that of sample bias, insofar as internet users opting for Google as their preferred search engine may not accurately represent the general Russian population. Though the proportion of internet users in Russia is high by international comparison (the same as France at 85 per cent of the population, and only five percentage-points behind Israel, Australia, or the United States) a more credible potential source of sampling bias lies in the fact that Google enjoys only a one-third share of the domestic search market, with the remainder dominated by its Russian-origin rival Yandex (Paananen, 2012). While this implies that 28 per cent of all Russians use Google for web search – in statistical inference, an unusually large sample in proportion to total population when trying to estimate a mean – it could, nonetheless, still form a biased sample were the user base of each internet search provider to differ sufficiently in their political beliefs. In order to

verify whether Google search data is representative of the general internet user in Russia, therefore, we also obtained corresponding data from Yandex using the Yandex Wordstat tool, and checked for potential discrepancies. These revealed little difference between the two search engines, and are reported in the Appendix (Figure A.3).

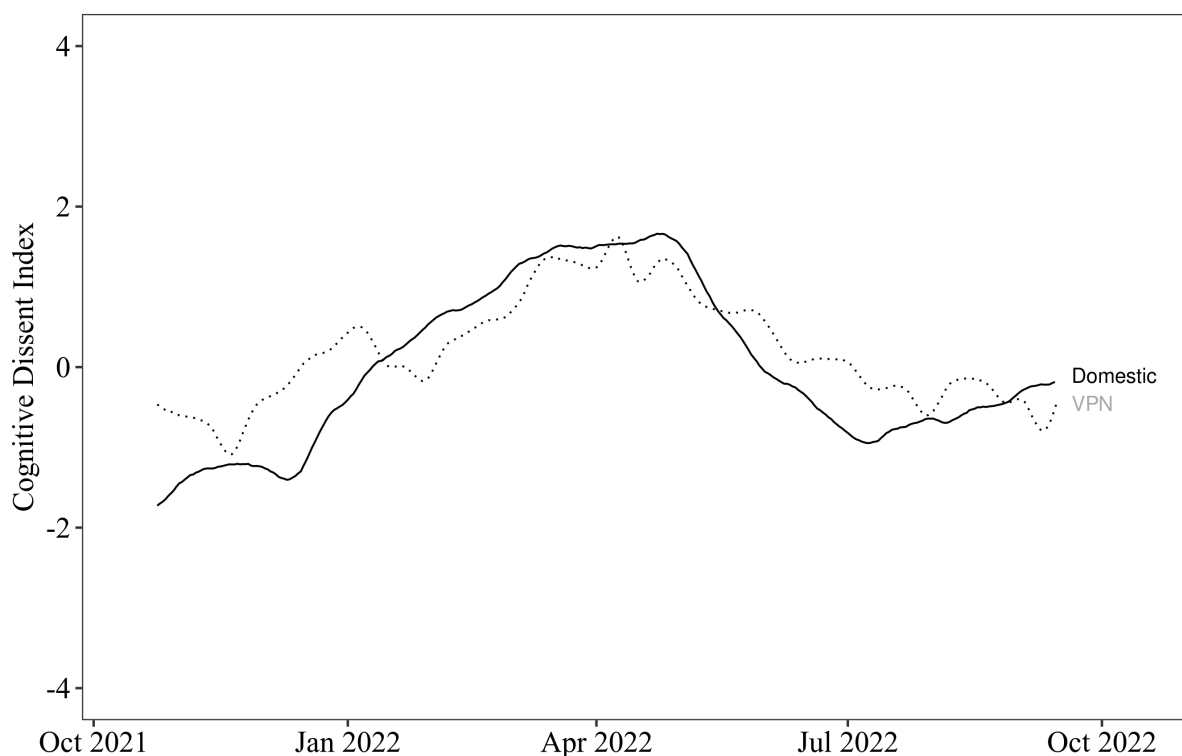
Second, while we may believe web search queries to be less prone to response bias than survey polling, this does not rule out the possibility of self-censorship. Internet usage in Russia is subject to extensive surveillance by domestic security agencies, with a particular focus on the activities of opposition activists and movements (Ermoshina, Loveluck, and Musiani, 2022). In such a climate it is logical that internet users may be circumspect in their search activity in order to avoid the unwanted attention of political authorities (Lokot, 2018). Even more problematic, from an empirical standpoint, is the possibility that the extent of self-censorship bias may have varied over time. Russian laws concerning freedom of expression have become more stringent over time, in particular in 2022 with the passage of the War Censorship law, which made it a criminal offence to attempt to “discredit” the Russian military other Russian state bodies or disseminate any statement that the authorities might consider “unreliable information” concerning the Russian Armed Forces (Galayda, 2022).

2.4.2 Russian vs. foreign Russian language IP

While self-censorship is unlikely to be a great concern for the indicators included in two of our indices (financial satisfaction and mental wellbeing), which are politically neutral in nature, it does present a concern for the “cognitive dissent” index. Though this has led us to avoid the most politically-sensitive topic searches in favour of more neutral ones (e.g. by including canonical authors on authoritarianism such as Orwell or Solzhenitsyn, rather than sensitive contemporary writers such as Anna Politkovskaya), additional validation is required to exclude the possibility that these terms are subject to a similar self-censorship bias. We do this by testing for search response bias by comparing Russian-language searches from IP addresses within Russia (our primary source of data), against searches that were conducted in the Russian language from the IP locations of suspected Russian

VPN users (e.g. in Sweden, Germany or the Netherlands). Due to insufficient sample sizes across most Russian-language queries in Sweden and the Netherlands, Germany was used as the reference country for suspected VPN searches. While a logical concern would be the possibility of accidentally detecting searches by Russian-speaking German residents, we found that within Germany almost all Russian-language search requests originated from western rather than eastern provinces, and of these most were concentrated around major VPN hubs such as Frankfurt. Divergence between these two metrics in 2022 would suggest the existence of self-censorship bias, as the encryption of VPN data between the user and their overseas server should reduce such bias among the users of such services. Fortunately these comparisons suggest little change in levels of self-censorship bias this year, as can be seen from the comparisons in Figure 1, which shows the change in the cognitive dissent index for both domestic and VPN users throughout 2022.

Figure 1: Domestic vs. foreign IP (VPN) Russian-Language Search



Comparison of cognitive dissent index, based on Russian-language searches in Russia and Germany, using 4-month daily moving averages for both measures. Following aggregation of all terms, the overall cognitive dissent index shows little difference over the course of 2022 between Russian-language searches conducted from within Russia (black line) or conducted outside of Russia (dotted line).

2.4.3 Sensitivity analyses

Next, extensive tests were made to ensure the internal validity of indicator groupings within each index, including correlation analysis, confirmatory factor analysis, and single-statistic metrics of index validity. All of the daily search term measures within each conceptual grouping correlate positively with one another, and in factor analysis are revealed as distinctive factor dimensions (Appendix Figure A.1). Following indicator selection, sensitivity analyses were conducted by which each index was recompiled via hundreds of random draws from within its larger indicator pool, and these then plotted to assess the degree of fidelity by each final measure to its potential alternative (equally-valid) variants (shown in Appendix Figure A.2).

3 External validation of indices

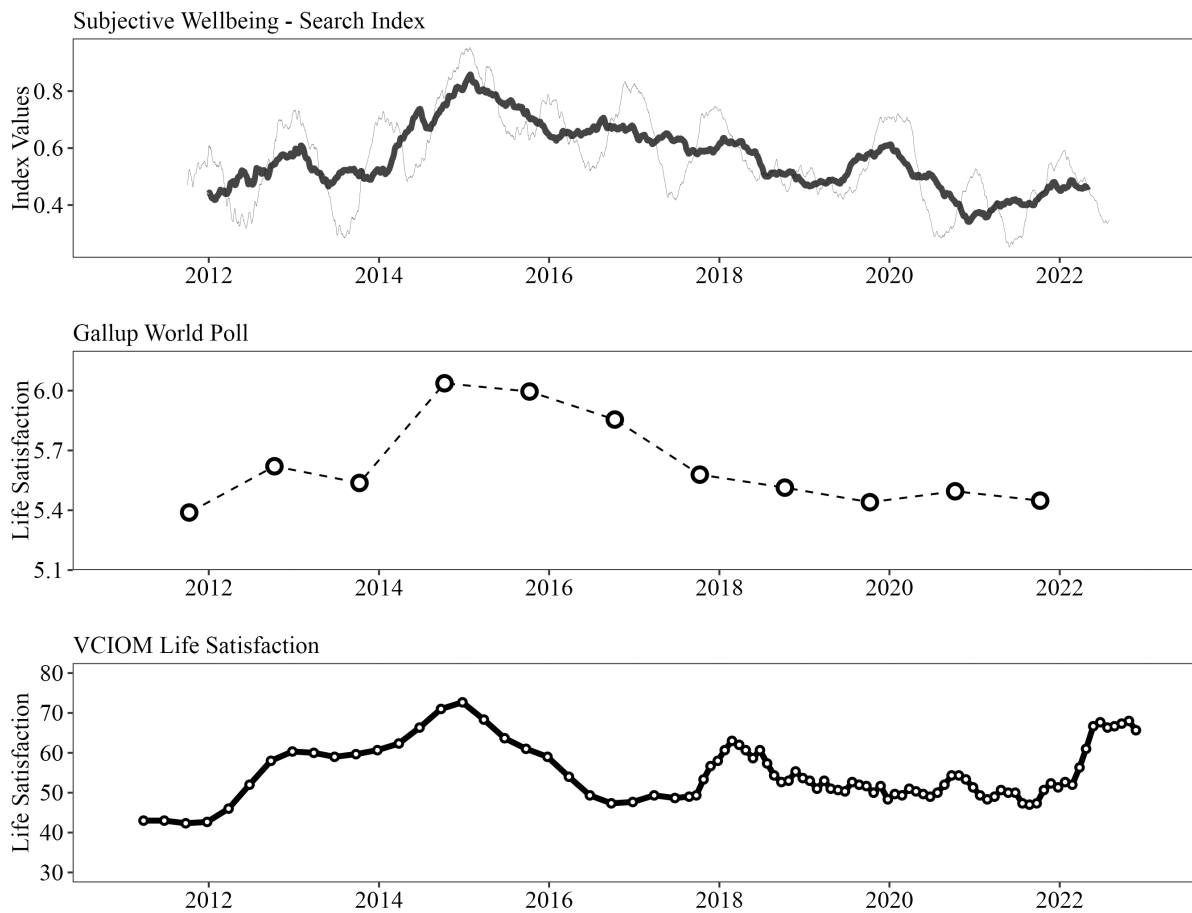
Before presenting empirical results in the next section, in this section we assess the indices' external validity – the extent to which inferences drawn from a given study's sample apply to a broader population (Findley, Kikuta, and Denly, 2021) – by comparing their implied trends in Russian public opinion to the available survey data from within Russia on related topics and issues.

3.1 Subjective wellbeing

First, we can compare the index results for subjective wellbeing to comparable data from survey sources. Since the 1980s, a large number of surveys have asked regarding subjective wellbeing in Russia, though only a few offer regular, repeated sampling (Shirokanova, 2020). One of the most frequently fielded such surveys is that via the VCIOM panel, which since 2004 has asked a nationally-representative sample of Russians regarding their levels of subjective wellbeing (“*To what extent are you satisfied with the life you lead now?*”) The VCIOM data has the advantage of high frequency, with quarterly data until 2017 and monthly data thereafter. Another survey that is fielded regularly in Russia

is the Gallup World Poll, which provides an annual life satisfaction result on a 0-10 scale (Helliwell, Layard, Sachs, De Neve, Aknin, Shun, and Paculor, 2022).

Figure 2: Long term external validation: subjective wellbeing measures, 2012-22



Long-term comparison of three measures of subjective wellbeing in Russia: the subjective wellbeing index based upon online searches; annual results from the Gallup World Poll; and the VCIOM survey index for life satisfaction. Annual rolling average by day used for display of the search index, with 180-day average in light gray. Source: Google Trends, Gallup, VCIOM.

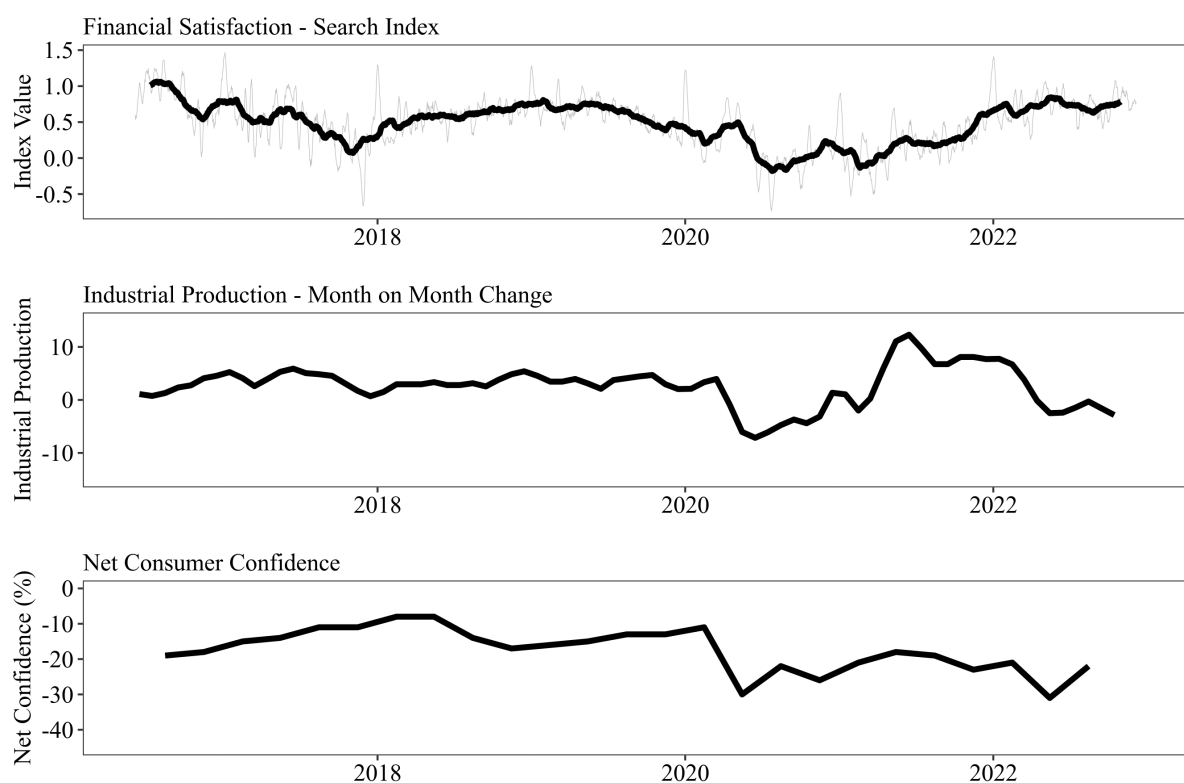
A comparison of both measures to the search index for subjective wellbeing is provided by Figure 2. As can be seen, there is broad agreement between all three measures on the main trends in public sentiment over the course of the last decade: a bump in 2012-3 concurrent with economic recovery; a “rally round the flag” surge in 2014-5 following the annexation of Crimea; a gradual reversion to baseline during the years of economic stagnation; and a jump at the start of the COVID-19 pandemic that was followed by a sharp reversal as the virus began to spread in Russia, culminating with a low at its point

of peak intensity in 2021.

3.2 Household financial satisfaction

Next, we examine how the index of household financial satisfaction compares to other measures of economic wellbeing, such as surveys of consumer sentiment or measures of economic activity. For Russia monthly data on economic activity can be tracked using the index for industrial production, while quarterly data exists for consumer sentiment surveys; data for both measures were extracted from Refinitiv, a global provider of financial market data.⁴

Figure 3: Long term external validation: household financial measures, 2016-22



Long-term comparison of three measures of financial wellbeing in Russia: monthly data for industrial production (month-on-month change); the search index for financial wellbeing; and quarterly consumer sentiment surveys (net positive). Source: Google Trends, Refinitiv.

A comparison of long-term trends on both indicators with the search-based index of financial wellbeing is shown in Figure 3. As each of the indicators taps a slightly different

⁴ For further information see the [Refinitiv](#) website.

aspect of economic activity we should not expect perfect correlation, though in fact there is broad agreement across all three measures. All three for example not only capture the dip at the start of the global COVID-19 pandemic, but also the timing of major coronavirus waves, and the recovery of activity in mid-2021. There is better correspondence between the search index and industrial production, though this may simply be due to the fact that, as a monthly series, the latter captures more short-term variation.

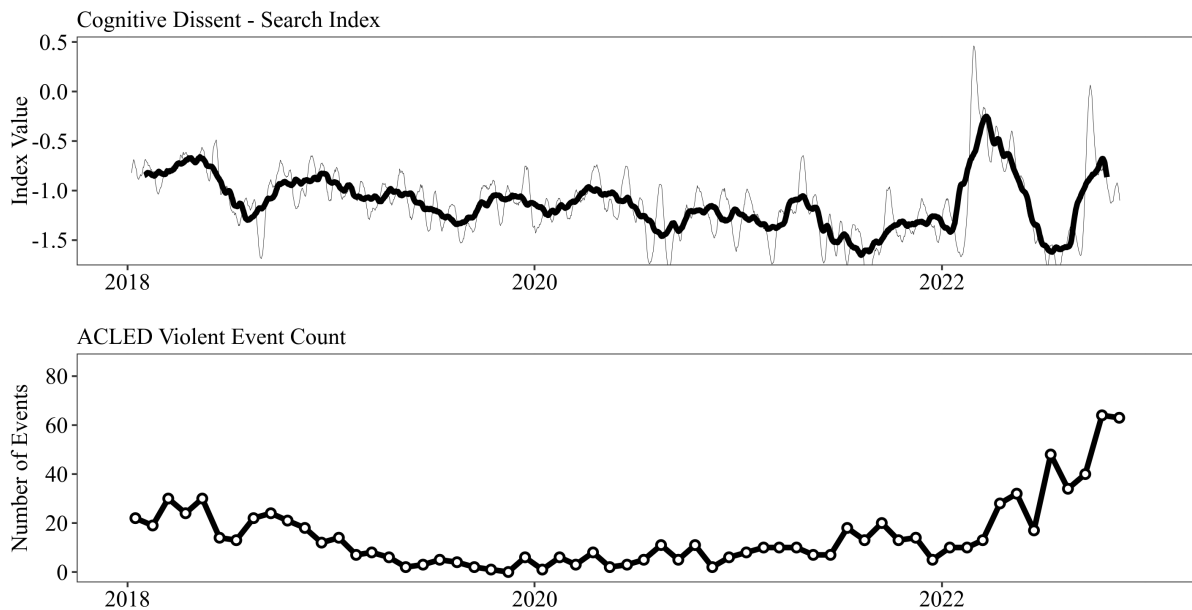
3.3 Cognitive dissent

As external validation for the cognitive dissent measure, it is possible to track the extent of behavioural political dissent in Russia via the number of protests, riots, and recorded acts of political violence occurring each month. While in democratic regimes aggregate data such as tax compliance (Levi, 1997) and voluntary military service (Levi, Sacks, and Tyler, 2009) have been proposed as indicators of legitimacy, in autocratic regimes an alternative measure has been proposed - the extent of mobilized political protest (Gerschewski, 2018). Scholarship on the relationship between mass demonstrations and regime legitimacy has produced empirical evidence suggesting that riots or protests suppressed by political violence indicate declining legitimacy for the regime (Thyen and Gerschewski, 2018).

In our study we obtained information on political dissent in Russia from the ACLED (Armed Conflict and Event Location Dataset),⁵ the latest iteration of which covers the Russian Federation from January 2018 to January 2023. Comparing our index of online dissent with this track record of real-world dissent activities, we can see a broad correspondence between the two measures (Figure 4). Both measures illustrate an initial spike during the 2017-18 anti-corruption protests that was organised by supporters of Alexey Navalny. Then both measures indicate a period of relative quiescence during the global coronavirus pandemic, before mass protests again reinitiated following the 2022 invasion of Ukraine.

⁵ For further information, see the [ACLED](#) website.

Figure 4: Long term external validation: cognitive dissent, 2018-22



Long-term comparison of two measures of dissent in Russia: monthly data on the number of violent events (e.g. riots or protests suppressed by violence); and the cognitive dissent search index measure. Source: Google Trends, ACLED.

4 Results and analysis

Having constructed and validated online search index measures of public opinion and sentiment in Russia, in this section we examine each of three key questions that have arisen for public opinion scholars since the onset of the war in Ukraine.

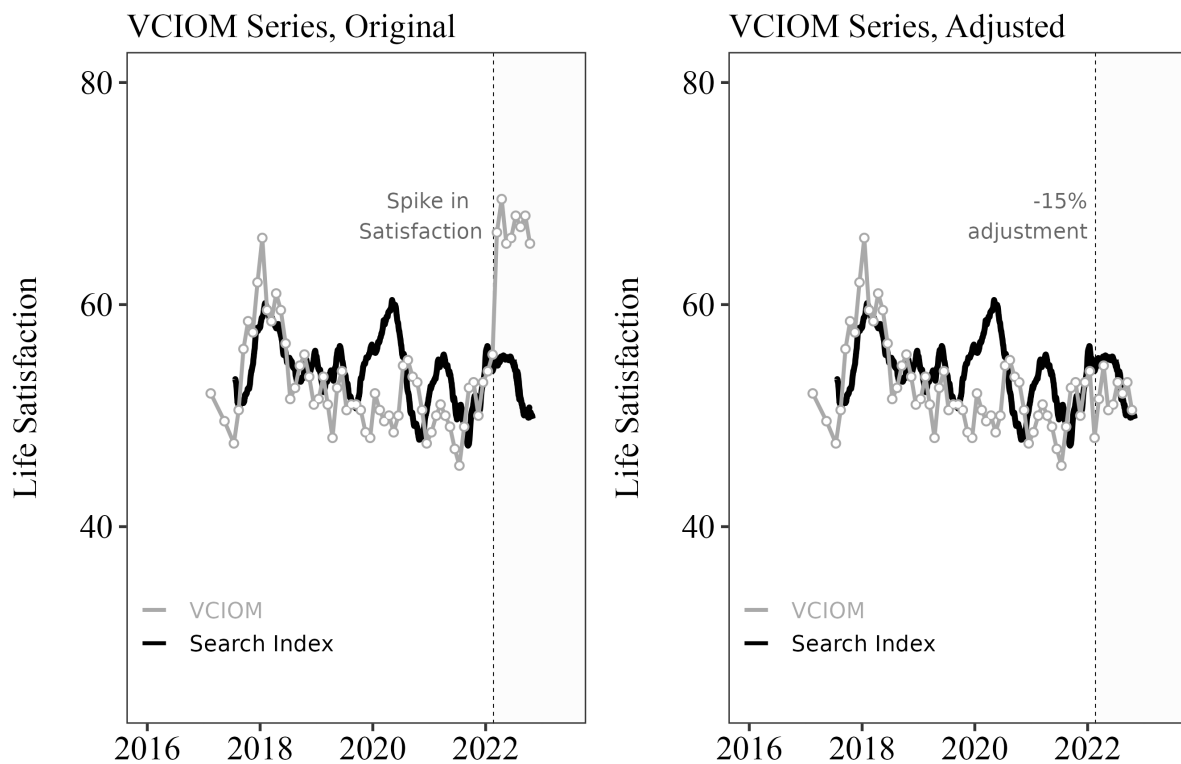
4.1 Re-examining the war rally in public sentiment

First, one of the key debates among public opinion scholars is whether public sentiment in Russia has exhibited a “rally round the flag effect” since the start of the war (Mueller, 2022). While surveys by Russian polling organisations argue that public sentiment has improved since the February invasion (Levada Center, 2022), many scholars consider such findings to lack face validity, given that “while Putin’s popularity skyrocketed following the annexation of Crimea in 2014, there are no signs of similar jubilation in Russia this time” (Timothy Frye, quoted in Project Syndicate 2022). Such debates echo similar

disagreements over the impact of the 2014 annexation of Crimea, which was followed by gains in reported happiness and life satisfaction among many polling organisations – though to varying degrees and extents, depending upon survey item and methodology (Shirokanova, 2020; Hale, 2018; Helliwell, Layard, Sachs, De Neve, Aknin, Shun, and Paculor, 2022; Hale, 2022).

Just as studies have shown that the sentiment boost following the Crimea annexation covered both general mood as well as evaluations of political leaders (Greene and Robertson, 2022), a similar observation has been made from data collected in 2022, and we can cross-validate such general sentiment measures against the online search index of subjective wellbeing. A comparison of this index and the VCIOM monthly series for life satisfaction is shown in Figure 5.

Figure 5: Subjective wellbeing in Russia, 2017–22



Comparison of online search index for subjective wellbeing (inverse mental health searches) and VCIOM survey results for reported life satisfaction. While both measures covary strongly during the years before the war, in 2022 they have undergone a sharp divergence, as can be seen in the left-hand side figure. Yet, making a simple 15-percentage point downward adjustment from the outset of the conflict, they can be brought fully back into alignment.

Comparing both metrics, the most striking observation is that we fail to confirm the apparent sentiment boost in 2022 reported by the VCIOM tracking poll. While the VCIOM level of surveyed life satisfaction jumps by approximately 15 percentage points following the onset of war, the online search metric remains absolutely flat. This discrepancy is especially noteworthy as our long-term comparison of both measures, shown in the previous section, *did* confirm the post-Crimea annexation increase from 2014–16 that was reported by VCIOM, Levada, Gallup and other survey projects.

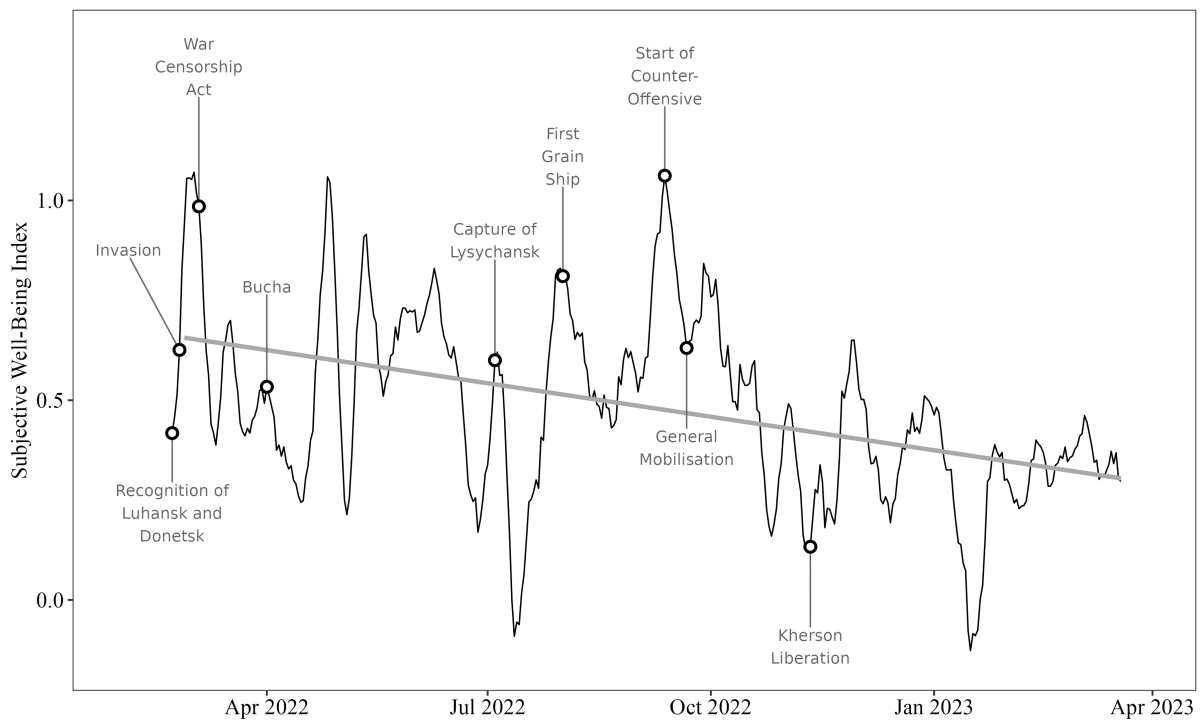
What can account for this disjuncture? The most obvious explanation, recently discussed in a range of scholarly articles, is that some combination of self-censorship bias, response bias and alternation to survey methodology has biased results upwards, supporting claims that contemporary Russian survey results are not anymore as reliable as before the war ([Reisinger, Zaloznaya, and Woo, 2023](#)). We can see from the chart that prior to the war, both measures covaried very well, including a common seasonal pattern whereby subjective wellbeing peaks during the New Year celebration and troughs at the end of the Russian winter, as well as a moderate declining trend in recent years. Yet this synchronous pattern is broken by a major divergence between the two measures in February 2022, when the war started, after which the VCIOM life satisfaction level reaches fifteen percentage points higher than would be expected, based upon our search index values (Figure 5, left-hand side). This also means that by making just one adjustment – namely, subtracting fifteen percentage points from all surveys conducted since February 2022 – the two measures can be brought back into perfect alignment once more (Figure 5, right-hand side).

Beyond the issue of face validity, triangulation of other data should lead us to doubt survey results showing an apparent increase in Russian subjective wellbeing. For example Chestny Znak, a digital labelling system in Russia, has reported that the number of antidepressants sold in the first nine months of 2022 increased by 48 per cent in comparison to the same period in 2021 ([Euronews, 2022](#)). As antidepressants are restricted medications requiring a doctor's prescription, this implies a sharp increase in the number of depression diagnoses. Meanwhile a report by the Russian Psi-Pro psychological

centre found a large increase in levels of anxiety and sleep disturbance following the September mobilisation order, while Russia's YouTalk psychological assistance service reports that requests related to depression increased by 50 per cent ([International Business Times, 2022](#)).

Our initial results also cast doubt on the hypothesis that there was any substantial “rally round the flag” effect upon the general public mood, following the decision to invade Ukraine. However, one of the advantages of our data is that it allows us to explore this hypothesis in much greater detail, by examining daily variation in estimated wellbeing in the period before, during, and after the decision to go to war. We therefore next examine the evolution of the mood of the Russian public with search index measure for subjective wellbeing, setting the rolling average smoothing function to a weekly basis (Figure 6). Key events during the conflict are included by annotation, together with linear regression discontinuity lines either side of the February 21-24 recognition of Luhansk and Donetsk, the Donbas region of Ukraine annexed by Russia, and full-scale invasion.

Figure 6: Russian subjective wellbeing (Imputed), 2022-23



Imputed levels of subjective wellbeing among the Russian public, based on the mental health search index. For ease of trend visualisation a weekly rolling average is used in place of raw daily scores. Contrary to official polling agencies, we find only a brief spike at the start of the war, followed by steady reversion below baseline. Current subjective wellbeing levels are near their lowest levels since the onset of war, and in line with the multi-year lows reached during the final phase of the coronavirus pandemic.

With the benefit of high-frequency, daily estimates, the picture regarding Russian public sentiment at the outset of war becomes suddenly much clearer. At this level of granularity, we are able to detect a – small – “rally” in public sentiment during the first week of the invasion. Yet this boost proved fleetingly short – and as Russian troops became bogged down around Kiev, domestic protests increased, and the government passed the War Censorship Act (March 4), subjective wellbeing reverted fully to its starting point. A somewhat larger rally in public mood had occurred during the weeks prior to invasion – but here the benefit of high frequency data suggests an alternative cause, namely, reversion to the mean following the peak phase of the Omicron coronavirus wave in February.

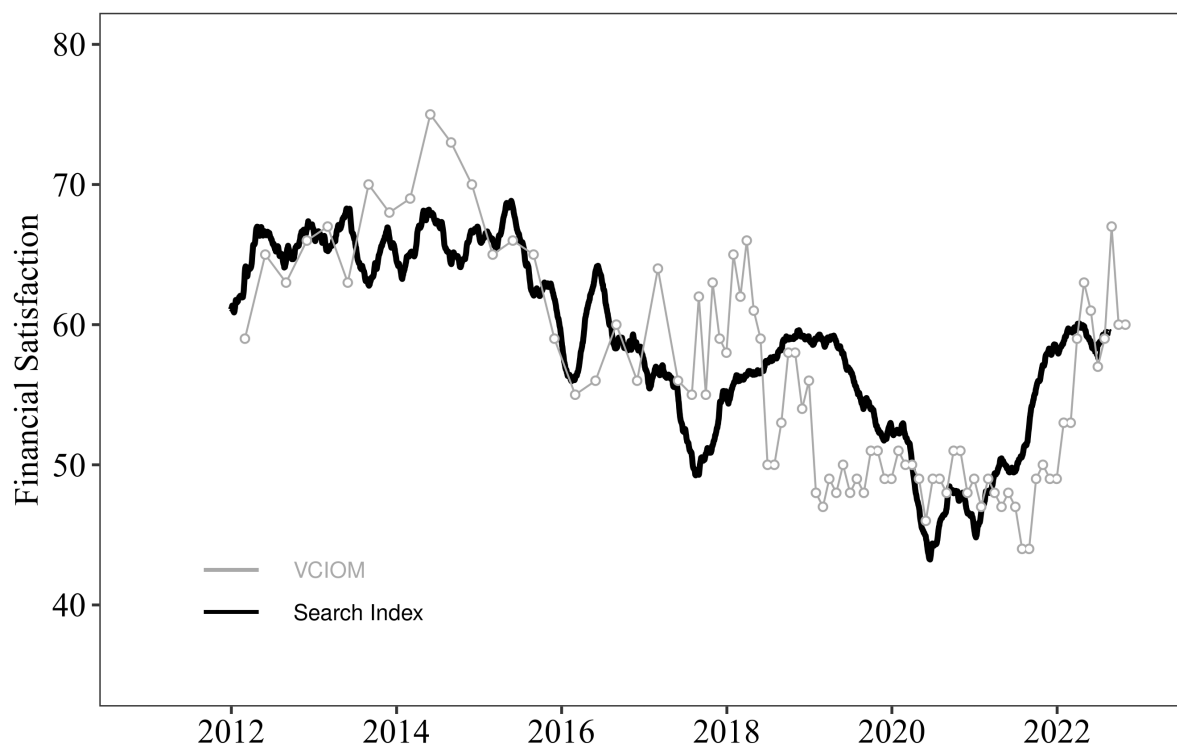
4.2 The effectiveness of sanctions

A second critical issue of debate for analysts and policymakers working on contemporary Russia is obtaining an accurate assessment of how ordinary Russians have responded to the imposition of western sanctions, as well as the informal withdrawal of western investment from the country (Harrison, 2022). While international relations scholars have long debated whether external sanctions either foster discontent against a government (Von Soest and Wahman, 2015) or conversely, consolidate political support in its defence (Pape, 1997; Oechlin, 2014; Jones, 2015), this question is especially salient in the context of the war in Ukraine. At the start of the conflict, unprecedented steps were taken to cut off Russian payment systems and foreign reserves, with scholars asking if “the economic damage for Russia’s war is likely to be felt directly by the Russian people” such that Russia may “come to face severe economic pain and perhaps even collapse” (Mueller, 2022). Moreover, such debates are taking place against the backdrop of longer discussions regarding the effectiveness of the sanctions introduced against Russia following the annexation of Crimea (Frye, 2018), and whether they have deterred the country from pursuing an even more aggressively anti-western foreign policy (Dreyer and Popescu, 2014; Christie, 2016; Alexseev and Hale, 2019). More recently the success of the Russian Central Bank in stabilising the currency and interest rates, together with the preparedness of the Russian financial system to operate without access to foreign payments systems and credit, has led scholars to question the efficacy of the most recent measures (Allen, 2022; Mamonov, Pestova, and Ongena, 2022).

One answer to the question of whether the latest sanctions have affected Russian households is provided by the Levada Center and VCIOM, whose respective tracker panels report current assessments of financial satisfaction and consumer sentiment to be near their highest levels for a decade (VCIOM 2022, Levada 2022). If this is so, then the implication is that neither western sanctions nor the pressure of running a war economy have had any noticeable effect upon Russian households. Yet this has also led many to doubt the authenticity and neutrality of contemporary Russian polling, rather than the

effectiveness of sanctions per se (Rosenfeld, 2022).

Figure 7: Household financial satisfaction in Russia, 2012–23



Comparison of online search index for financial satisfaction (inverse of financial stress, 4-month rolling averages) and VCIOM survey results for reported satisfaction with the state of one's finances. Household financial satisfaction took a sharp drop in Russia during the COVID-19 pandemic – by comparison with which sanctions measures taken since the onset of the war in Ukraine have had a relatively minor impact.

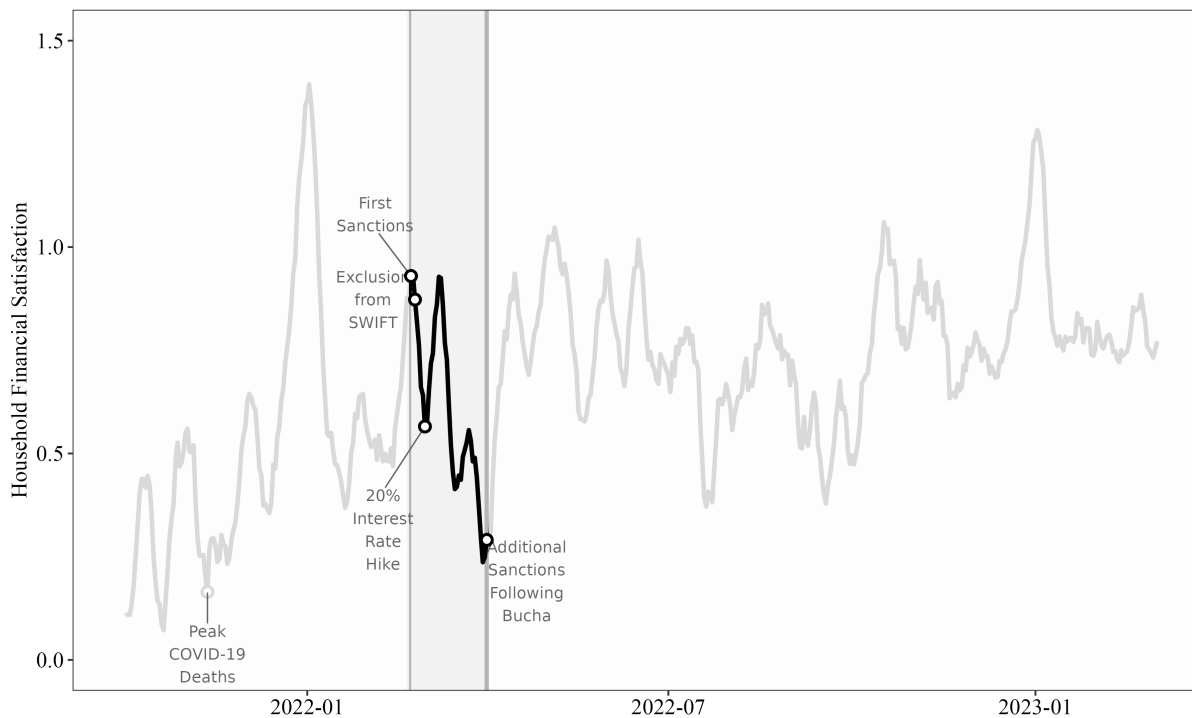
In order to cross-validate the claims made by Russian polling organisations, we can compare their survey results on household financial satisfaction with the results of our financial stress index, which once inverted, serves as a reliable proxy for financial wellbeing. Taking the long-term view (Figure 7), we can see that over the course of the past decade, there is broad covariance between these two metrics. This comparison suggests that, unlike in the case of subjective wellbeing, there is no sudden divergence between the two measures at the outset of war: the increase recorded by VCIOM from 2021 to 2022 is also suggested by the improvement in our online search index proxy measure for household financial wellbeing.

Does this validate claims that sanctions have been ineffective in placing economic

pressure on Russian businesses and consumers? To the extent that a sharp deterioration has failed to materialise, the answer is yes, though additional data also provides insight in to the cause of this outcome. The COVID-19 pandemic affected Russia the most severely during in its final 2021 wave, when it reached its peak intensity as measured by registered COVID-19 fatalities. It was also a major shock event for Russian businesses and households, who did not receive the same degree of economic and financial support extended in western countries (Aslund, 2020). Hence it is from this point forwards that the search measure for financial wellbeing shows a recovery in economic sentiment, and this recovery then ends with the onset of the war in Ukraine. The imposition of sanctions may have failed to derail this recovery in household finances following the shock of the pandemic, but this does not negate the possibility that the restrictions had an effect all the same.

We can study this sequencing more closely by examining the daily data on financial sentiment smoothed on a weekly rolling basis, again, with key economic events being included in the graph Figure 8). This analysis shows that sanctions measures did indeed affect Russian households during the opening (February-March) phase of the war, at which time sanctions were introduced, western companies divested from Russia, the country was excluded from the SWIFT payments system, the rouble underwent rapid devaluation, and the Central Bank raised interest rates from 8 to 20 per cent. The Russian recovery from these measures was, however, relatively rapid, as western subsidiaries acquired new owners, consumers switched to new payments systems, and inflation and interest rates were stabilised.

Figure 8: Financial wellbeing index, 2021-23



Notes: Estimated levels of financial wellbeing among the Russian public, 2021-23, based on online searches for terms relating to economic needs such as loan refinance, bankruptcy or eviction. For ease of trend visualisation the weekly rolling average is used in place of raw daily scores. Financial stress occurred only during the early weeks of the war during the rouble collapse, exclusion from the SWIFT payments network, and withdrawal of foreign investment. A recovery then occurred in April, and since that point levels of estimated financial wellbeing have stabilised.

The benefit of high frequency data allows us to reach a more nuanced conclusion than by examination of polling data alone. Economic sentiment among Russian households was undergoing a recovery in the months prior to the invasion, as the country turned its back on the COVID-19 pandemic and its economy resumed regular activity, and this recovery was suddenly blunted by sanctions measures. Since the onset of war, meanwhile, there has been no net improvement in Russian economic sentiment – contrary to the impression given by official polling data.

4.3 Changing levels of tacit dissent

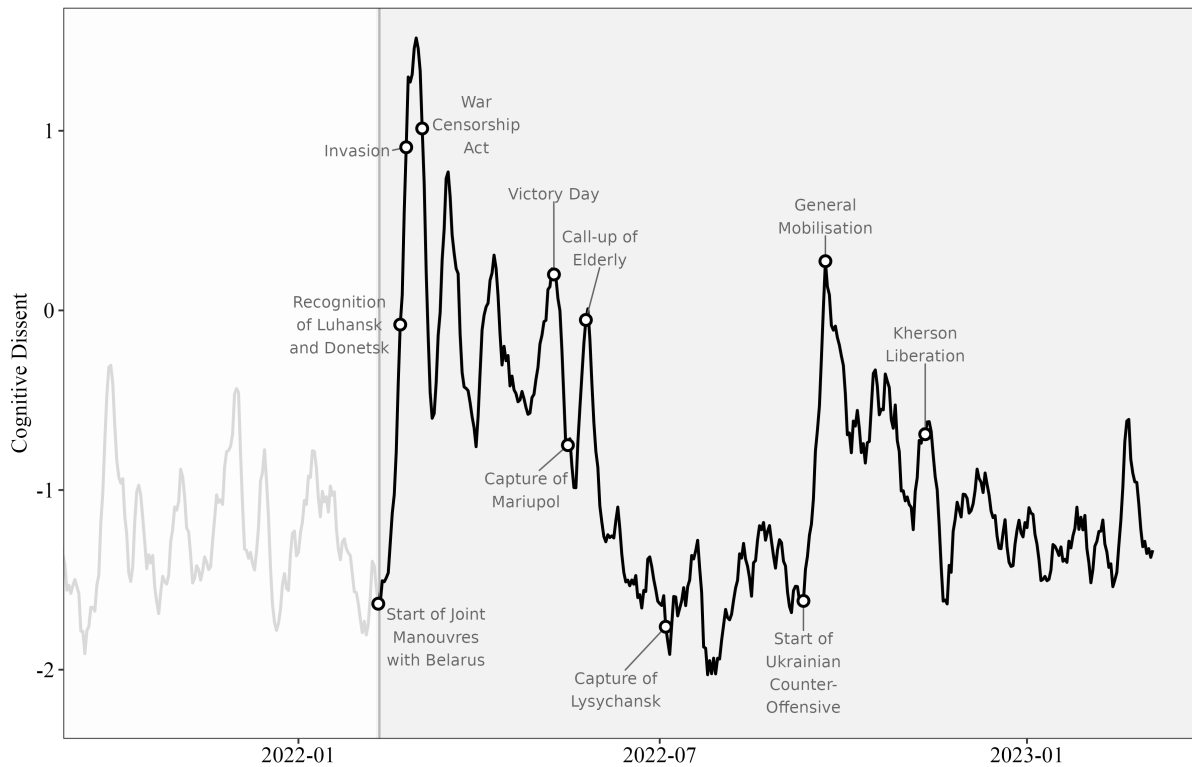
The third area of debate regarding contemporary public opinion in Russia centres around the stance of Russian citizens to the war itself. Are opinion polls showing majority

Russian support for the war to be “treated as genuine signals of Russian public opinion” (Kizilova and Norris, 2022)? Or do levels of response bias and self-censorship hide a latent yet growing discontent with the war, in a way that is further undermining the legitimacy of the regime (Frye, Gehlbach, Marquardt, and Reuter, 2022)? Behind such debates, of course, stands a broader literature on how citizens relate to political authority in authoritarian regimes: and whether this relationship constitutes a two-way interaction (Chapman, 2021), or is merely tacit consent based upon civic withdrawal (Yudin, 2022).

Up to now, however, the main means by which scholars have examined the issue of “tacit dissent” is by tracking non-response rates to survey questions asking ordinary Russians about their degree of support or opposition to the “special military operation” (as it must be described in public opinion surveys). Since the start of the war, for example, the Levada Polling Center has asked representative samples of Russians each month whether they “support the Russian army”, do not do so, or feel discomfort in answering the question, with expressions of discomfort serving as a measure of tacit dissent. While this reveals around one-third of Russians who either withhold their voice or state their opposition, there is speculation that the true rate may be much higher – and that fluctuations from month to month reflect changes in self-censorship, response bias, and entrance or withdrawal from survey panels, rather than genuine opinion shifts (Zvonovsky, 2022).

While these are difficult questions to address using public opinion surveys, they are more amenable to study via online search data: which by nature is conducted in private, with relative anonymity, and without the expression of any particular opinion. An overview of trends in the cognitive dissent index is shown in Figure 9, together with annotation of key events during the conflict.

Figure 9: Cognitive dissent index, 2021-23



Notes: Levels of cognitive dissent among the Russian public, 2021-23, based on online searches for terms indicative of critical thinking towards the regime. For ease of trend visualisation the weekly rolling average is used in place of raw daily scores. Cognitive dissent spikes during both periods of Ukrainian military advance, and points at which the government implements policies of general military mobilisation. Temporary lows also occur on days of Russian military victories (in Mariupol and Lysychansk). A lull occurred in the middle phase of the war during the Donbass advance, but levels have risen again recently.

With the benefit of high-frequency data on Russian online activity, we are able to clarify common misunderstandings surrounding the views and attitudes of ordinary Russians in the current conflict. For example, contrary to the impression that Russian citizens provide unconditional “tacit consent” to Kremlin actions, we do find evidence that cognitive resistance has increased at key phases of the war. This is especially so when there have been efforts at war mobilisation, such as the call-up of elderly reservists in May, and the partial mobilisation order of September. This implies that, even in an environment of extreme pro-regime media saturation, Russians are capable of perceiving governmental failures for what they are, and thinking critically in response. This also suggests that a sufficient accumulation of setbacks would lead to more general public angst at the

progress of the war, and the Kremlin's culpability in any major battlefield failure – and could potentially destabilise the regime, not least given that the two spikes in critical dissent, in March and September, were also periods of heightened anti-governmental protest.⁶

The second and more obvious observation is that the war itself has proven a major catalyst for critical reflection on the regime and political power, with a spike towards record highs following the February invasion. Though there does appear to have been a “hunkering down” of public opinion during the “stalemate” phase of the conflict from April to August, the acknowledgement of failures in the war's prosecution – notably since the start of the Ukrainian counteroffensive in September – has again seen a spike in Russian online dissent. Studies of democratic transition (O'Donnell and Schmitter, 1986; Huntington, 1991) have long emphasised how failure in war constitutes a prime risk factor for late-stage authoritarian regimes (Snyder, 2017), and measures of online dissent may allow us to track this loss of legitimacy “in real time”.

Given the dynamic relationship between the progress of the war and levels of critical dissent, we can explore this link more systematically via time-series models. This also shows a further benefit to having high frequency, daily data on Russian online activity, which allows us to examine public opinion dynamics with greater precision than is possible using monthly or quarterly surveys. As variables that measure how the public is reacting to military failures and setbacks, we are able to include estimates of daily Russian casualty figures, derived from figures released by the Ukrainian Armed Forces and the Ministry of Defence of Ukraine (Ivaniuk, 2023). While these figures may be biased upwards, we have no reason to believe that the magnitude of this bias changes over time, or would be related to shifts in Russian public opinion. Second, we include a range of daily events as measures of Russian success and failure in the prosecution of the war, including legislative moves towards greater mobilisation, days of major military victories (e.g. Lysychansk or Mariupol) and days of military losses (such as the withdrawal from

⁶ It is possible to track the extent of monthly protest using data from [OVD-Info](#), which provides monthly summaries of the numbers of citizens detained by authorities.

the Kiev region or from the city of Kherson). Finally, we also include our daily indices for financial and general wellbeing, the former as a variable for the effectiveness of economic countermeasures in producing anti-regime sentiment, and the latter as a more general control for how public mood influences critical dissent, together with a dummy variable (0/1) for the period since Russia began using prisoners in place of regular conscripts for frontline combat.

These results are shown in Table 2. For ease of interpretation, index values were standardised prior to model estimation: all coefficients therefore show effects upon cognitive dissent in terms of standard deviation shifts. In order to account for potential noise affecting daily oscillation in our search index variables, separate models were estimated using both daily values and weekly rolling averages for the dependent variable, and a range of dependent variable lags.

Table 2: Regression Models: Determinants of Cognitive Dissent

Model	(1)	(2)	(3)	(4)	(5)	(6)
Smoothing	daily	daily	daily	weekly	weekly	weekly
Lag length (days)	7	21	-	7	21	-
Lag Dependent Variable	0.478*** (0.04)	0.416*** (0.05)	-	0.531*** (0.04)	0.470*** (0.04)	-
Financial Satisfaction	-0.038 (0.04)	-0.048 (0.04)	-0.097* (0.04)	-0.025 (0.03)	-0.039 (0.03)	-0.086* (0.04)
Subjective Wellbeing	0.120** (0.04)	0.075 (0.04)	0.213*** (0.05)	0.113** (0.04)	0.080 (0.04)	0.223*** (0.05)
Victory Day	-0.344*** (0.10)	0.034 (0.30)	-0.216 (0.16)	-0.631*** (0.08)	-0.206 (0.27)	-0.475*** (0.14)
Defeat Day	0.603 (0.32)	0.183 (0.15)	0.470 (0.43)	0.385 (0.29)	0.049 (0.22)	0.324 (0.48)
Mobilisation Announcement	1.845*** (0.37)	1.739*** (0.48)	1.496** (0.45)	1.440*** (0.20)	1.275*** (0.36)	1.084*** (0.33)
Log Daily Deaths	0.364** (0.13)	0.396** (0.14)	0.579*** (0.15)	0.303* (0.13)	0.281* (0.12)	0.521** (0.16)
Prisoners as Combatants (0/1)	-0.393*** (0.11)	-0.257* (0.12)	-1.089*** (0.13)	-0.353*** (0.10)	-0.187 (0.11)	-1.154*** (0.13)
Constant	-0.716* (0.29)	-0.951** (0.33)	-0.732* (0.36)	-0.591* (0.29)	-0.715* (0.29)	-0.538 (0.37)
R^2	0.494	0.415	0.346	0.567	0.474	0.383
N	368	354	375	367	353	374

Robust standard errors in parentheses. Lag length specifies lag of the lagged dependent variable.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

These allow for the following inferences. In line with arguments that military defeat represents one of the major risk factors for authoritarian legitimacy, we find that Russian losses on the battlefield are associated with short-term variation in cognitive dissent. In periods when Russian casualties have been highest, ordinary Russians have been the most disposed to explore topics online that are critical towards the regime: learning more about pacifism, the antiwar movement, theories of authoritarianism, or authors writing about these subjects. By contrast, during periods of the conflict when casualties were

lower, online dissent has been significantly reduced. Conversely, days of military victory saw significantly lower levels of dissent, showing a clear link from military success to sustaining the regime's legitimacy.

Second, not only military defeat but also popular mobilisation represents a risk factor for authoritarian regimes whose legitimacy depends upon political non-interference in the lives of their citizens. This can be seen clearly in the Russian case, where moves by the Kremlin to pass laws that extend military mobilisation – whether raising the age of military recruitment in May, or the announcement of partial mobilisation in September – were accompanied by very large spikes in critical thinking among ordinary Russian citizens. Taken together, these two observations confirm a basic proposition: military action by authoritarian regimes is a double-edged sword, with the potential both to extend popular support through foreign policy achievements, yet also to undermine its legitimacy in the event of failures and setbacks. They also confirm that Russians are anxious regarding the human cost of this war, and concerned by the prospect that they, or their loved ones, might become its future victims. The greater that this probability becomes, the more likely Russians begin to think critically of the regime and then perhaps, organise in opposition. For this reason the Kremlin faces a constraint in both the degree to which it can mobilise the general population to fight its war, and the tactics by which the war is conducted – which may help to explain its growing reliance upon artillery and aerial bombardment in place of high risk rapid movement tactics.

Finally, this observation is further confirmed by the estimated effect of the Russian government's decision to delegate mercenaries and prisoners for service in front-line combat in place of regular civilian troops, which since July of 2022 has substantially reduced the probability that ordinary civilian soldiers face injury or fatality during military operations.⁷ According to western intelligence agencies, around 40,000 Russian inmates have thus far been recruited for this role, constituting an important contribution to Russia's

⁷ This delegation of front-line operations is specific to the Bakhmut front, where mercenaries (the Wagner Group) have led combat offensives with the aid of soldiers recruited from the Russian penal system. Elsewhere, the Russian army has continued to be at the forefront of offensive operations; though with generally lower casualty rates than in Bakhmut.

overall military forces ([New York Times, 2023](#)). The regression coefficients show that for observations collected since this decision was taken, there is a large and statistically significant reduction in the baseline rate of cognitive dissent. Again this confirms the limitation that the Kremlin faces in being able to mobilise ordinary civilians for its war effort, and hence, the necessity that it rely upon alternative means to supplement its front line forces. It also implies that, in spite of Russia's vastly greater potential military manpower relative to Ukraine, the country faces much tighter political constraints to its ability to make use of such manpower for offensive purposes, and may struggle to replenish this capacity once prison recruitment diminishes.

5 Conclusion

Since the onset of the war in Ukraine, scholars, policymakers and analysts have sought to attain accurate measures of Russian public opinion in order to assess key questions regarding the conflict: including the drivers and probability of mass protest, the effectiveness of western sanctions, and the feasible policy options facing the Kremlin. Researchers, however, have had to answer these questions via reliance on official Russian polling sources: whose data are beset by concerns regarding self-censorship bias, survey response bias, and suspected official manipulation. In this study, we have sought to overcome such difficulties using internet search data obtained from Google and Yandex. By using such information to proxy for cognitive mental states in the general population, we have been able to audit key survey indicators produced by Russian polling agencies, correct for suspected biases in official data, and provide provisional analysis of the determinants of Russian household financial security, wellbeing, and degree of critical opposition to the regime throughout the course of the war thus far. These results suggest that – contrary to official sources – Russian levels of mental ill health and doubt regarding the legitimacy of the regime are near their highest points for a decade. They also suggest that both are influenced by Russia's progress in the war, and that as the Russian campaign has faltered, ordinary citizens have responded critically towards their government.

In addition, our findings suggest three additional key lessons. First, as an authoritarian regime, the Kremlin faces very tangible limits in the demands it can place upon its citizenry. Announcements of greater military mobilisation are linked to spikes in online dissent, while periods of heightened military casualties are similarly associated with greater search volume around pacifism, protest, and concepts associated with dissent from official propaganda. While this may seem intuitive, our data provide a first empirical confirmation that the Russian people are not merely passive subjects, but rational agents with boundaries regarding the extent of personal sacrifice that can be demanded before questioning the rationale of the conflict and ultimately their government. The Putin administration may be aware of this fact from its own private polling, and if so this would explain its hesitance to introduce partial military mobilisation, or expand further the mobilisation that is now in place.

Second, while western sanctions had measurable impact upon Russian household financial sentiment during the initial months of the war, the West's most effective tools – exclusion from the SWIFT payments network or the freezing of Central Bank assets held overseas – appear to have already played their course. Economic sanctions as a foreign policy tool in most cases do not achieve their primary goal ([Early, 2015](#)). Since March, household financial sentiment has returned the baseline as the Kremlin has managed to stabilise the currency, reduce inflation and interest rates, and implement measures to insulate ordinary Russian households from deeper financial harm. This shows from declining rates of household financial stress, which are now back to pre-war levels; and it seems likely that even with the addition of new policies (such as the price cap on Russian oil exports), the additional stress on Russian households will be limited in the short run, even if this leads to Russian economic stagnation over the longer term.

Finally, the data suggest that, contrary to the results of official polling, there is limited appetite among ordinary Russians for this war. We do not believe – as official surveys imply – that public sentiment in Russia is at multi-year highs, and suspect that it may be nearer to multi-year lows. From online search-based measures of public sentiment, only a mild boost was detected at the outset of war which had already faded by the third week of

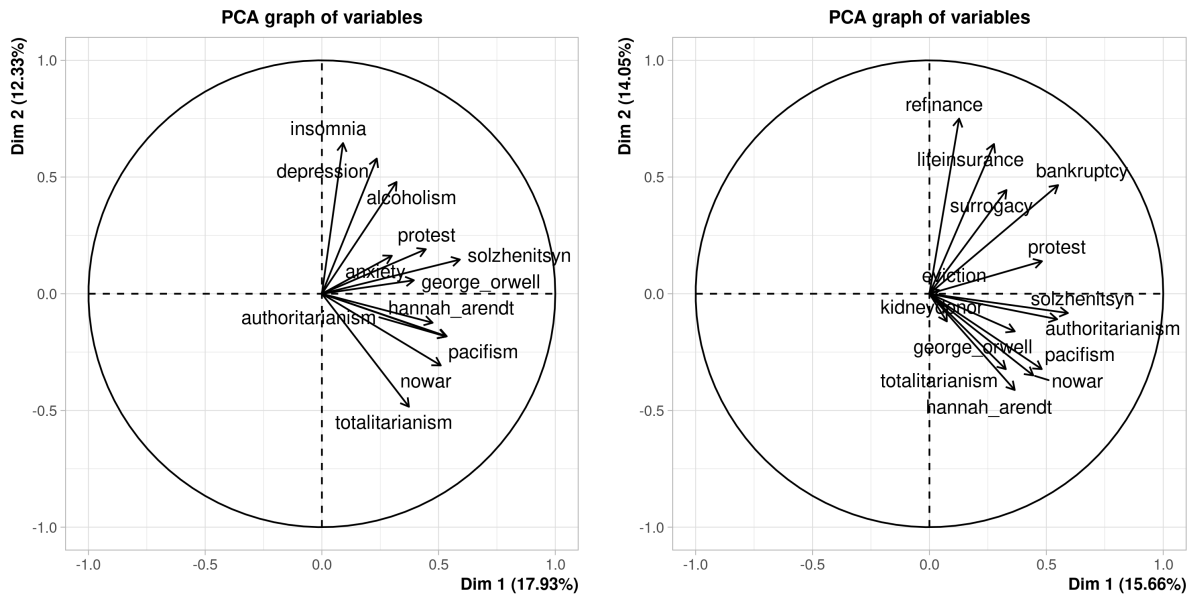
the conflict. Personal wellbeing has continued to deteriorate since then, and we believe the average Russian now has a lower level of life satisfaction than before the decision to invade Ukraine. This weak (and now exhausted) boost in public morale suggests that Russian enthusiasm for the war is low, and that in contrast to the declarations of the Kremlin, there is limited public support for its continuation.

Naturally, these findings are tentative, and our study is not without its limitations. As a measure of public opinion, there is no substitute for reliable, representative, and high quality survey data. Our argument is not that search data can take its place, but only that the addition of such information can help to validate or invalidate survey findings in contexts like Russia, where existing public opinion findings are not always trusted due to widespread response bias, self-censorship, and concerns around polling methodology. As Karl Deutsch once stated, “truth lies at the confluence of independent streams of evidence” (Coppedge, 1999). It is through the combination of such sources that analysts can attain a higher degree of accuracy – and a clearer assessment of public attitudes in authoritarian regimes that lack data transparency, such as contemporary Russia.

Appendix

Confirmatory factor analysis

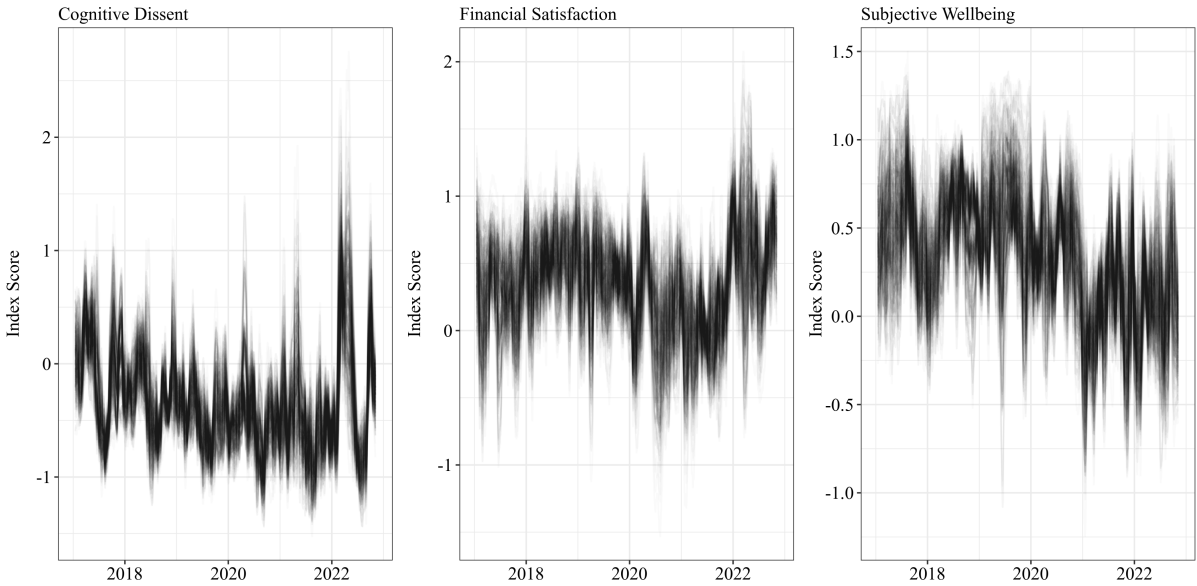
Figure A.1: Visualisation of PCA dimensions



(a) Subjective wellbeing and cognitive dissent (b) Cognitive dissent and financial satisfaction

Notes: Confirmatory PCA factor analyses on items used in indices. The first dimension (x-axis) corresponds to the subjective wellbeing and the financial satisfaction components, respectively, whereas the second dimension (y-axis) corresponds to the cognitive dissent component. The results suggest a high degree of discriminant validity: items used in the wellbeing search index all load positively on the first dimension, but not on the second, whereas items in the cognitive dissent dimension score positively on the second, but not the first.

Figure A.2: Sensitivity analyses



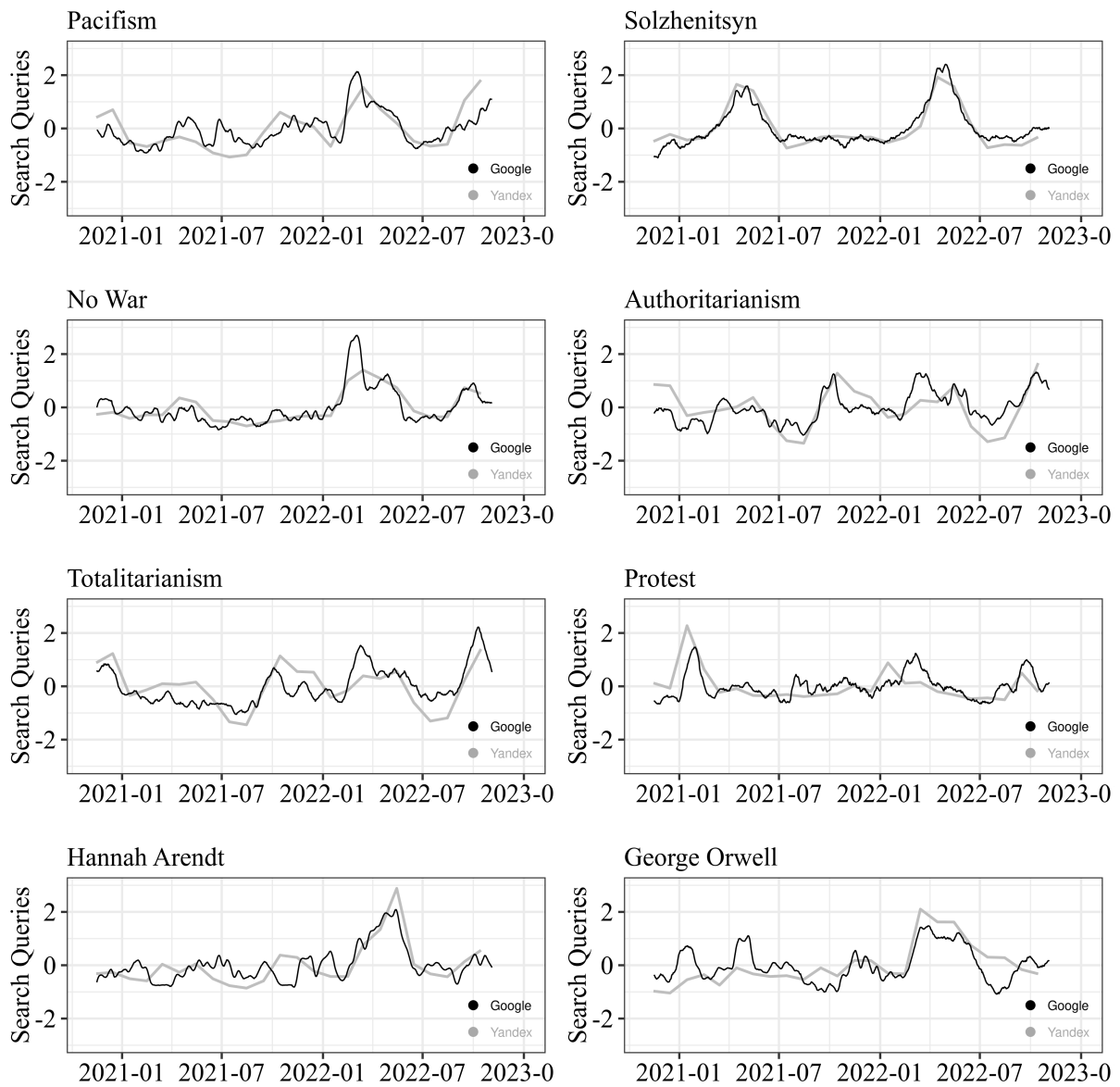
Notes: Sensitivity analyses for the final set of index indicators, taking random draws from half the indicators within an expanded indicator range to construct potential alternative indices.

Table A.1: Indicators tested for use in indices

Round 1	Round 2	Round 3
Subjective Wellbeing		
anxiety	anxiety	anxiety
depression	depression	depression
alcoholism	alcoholism	alcoholism
insomnia	insomnia	insomnia
depression test	depression test	
panic attack	panic attack	
unhappy	unhappy	
how to kill yourself	how to kill yourself	
signs of depression	signs of depression	
how to die		
fear		
psychiatrist		
drug addiction		
sadness		
Financial Satisfaction		
bankruptcy	bankruptcy	bankruptcy
eviction	eviction	eviction
refinance mortgage	refinance mortgage	refinance mortgage
kidney donor	kidney donor	kidney donor
surrogate motherhood	surrogate motherhood	surrogate motherhood
life insurance	life insurance	life insurance
pawn shop	pawn shop	
second hand	second hand	
no downpayment	no downpayment	
unemployment centre		
debt		
credit		
food bank		
homeless shelter		
animal shelter		
loan		
welfare		
Cognitive Dissent		
pacifism	pacifism	pacifism
totalitarianism	totalitarianism	totalitarianism
authoritarianism	authoritarianism	authoritarianism
protest	protest	protest
Solzhenitsyn	Solzhenitsyn	Solzhenitsyn
George Orwell	George Orwell	George Orwell
Hannah Arendt	Hannah Arendt	Hannah Arendt
“no war”	“no war”	“no war”
alternative civil service	alternative civil service	
anarchist’s cookbook	anarchist’s cookbook	
nonviolent resistance	nonviolent resistance	
Boris Nemtsov		
Alexey Navalny		
Anna Politkovskaya		
“Putin out”		
“Putler”		
“Russia without Putin”		

Yandex and Google Cross-Validation

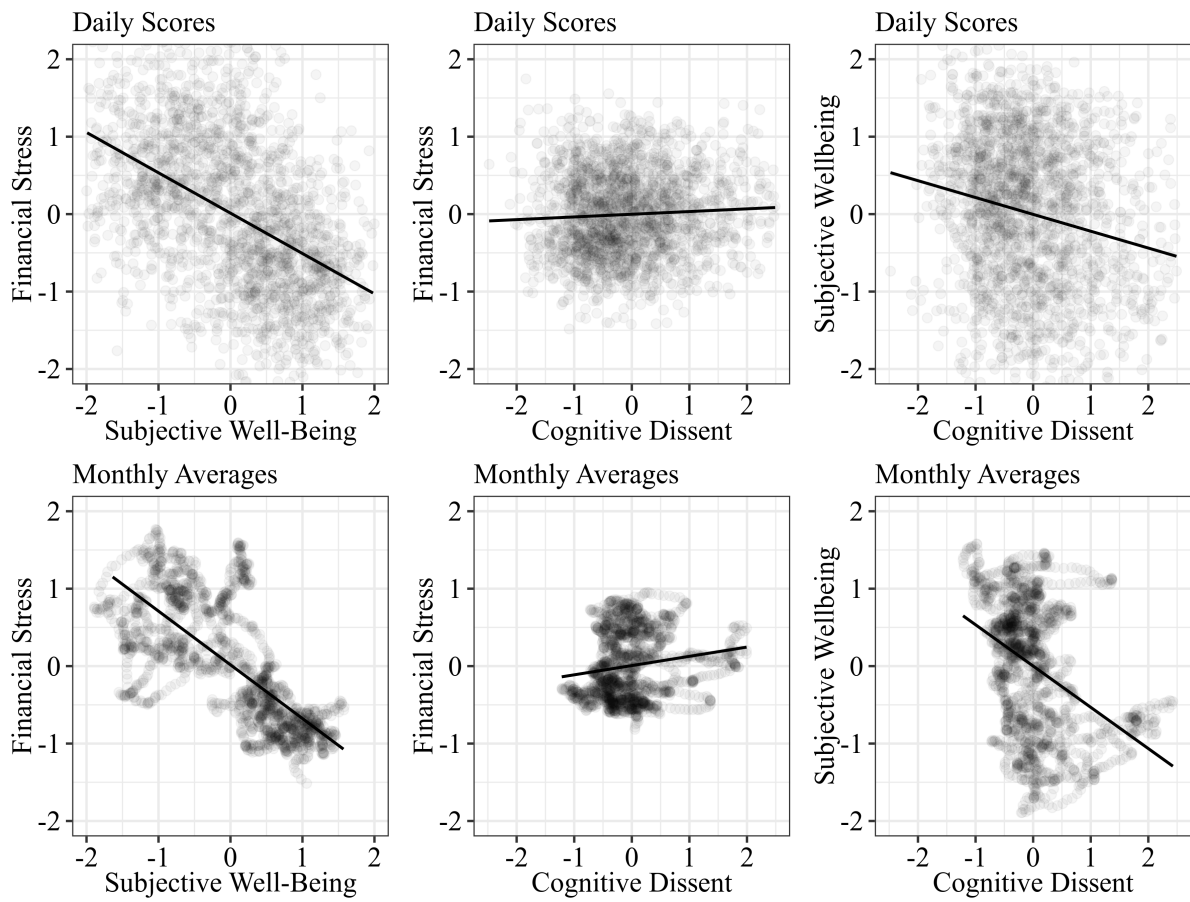
Figure A.3: Google vs. Yandex search trends, by indicator (Cognitive dissent series)



Monthly search data from Yandex, compared with monthly-smoothed daily data from Google Trends. Data for most individual items in the cognitive dissent index varies similarly over time among Google and Yandex users, suggesting that Google data is a valid proxy for the general internet user in Russia.

External validation: covariance among indices

Figure A.4: Correlation Among indices (Standardised scales)



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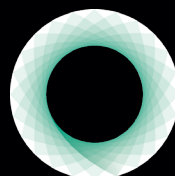
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