THE REPORTED SOCIAL UNREST INDEX: A NEW MEASURE OF SOCIAL UNREST IN MIDDLE EAST AND NORTH AFRICAN COUNTRIES, CONSTRUCTION FOR SELECTED COUNTRIES
(ONLINE ANNEX)

Introduction

This annex describes the construction of a new Reported Social Unrest Index (RSU). This is a timely and high-frequency indicator that seeks to consistently quantify social unrest in seven countries: Algeria, Egypt, Jordan, Lebanon, Morocco, Sudan and Tunisia, since 2005.

The RSU is constructed using the monthly count of articles which mention keywords related to protest or social unrest in 17 leading US, U.K. and Canadian newspapers and broadcasting companies. The primary source is Dow Jones' Factiva news aggregator, which contains around 27 million articles from these sources between January 2005 and February 2019. Data is available daily up to the previous day, although we aggregate by month.

The construction of an index based on automated text-searches naturally raises some concerns about the accuracy and the influence of media bias. We address these concerns in several ways. First, by acknowledging directly that this is an index of *reported* social unrest, encouraging the user to account for bias as they see fit. Second, by implementing a human audit process to check that articles captured genuinely do refer to protest. And third, running a broad battery of robustness tests examining alternative specifications for the search terms, language and news sources. We also compare the RSU to other measures of social conflict and mass mobilization, finding broad agreement with alternate measure, but with much-improved coverage and timeliness.

Related Literature

There is a rapidly growing literature on text search methods using newspaper archives to measure several outcomes. We build on this, developing an approach which parallels past work on building similar text-based indices of otherwise hard-to-measure variables.

The seminal paper in this literature is Baker, Bloom and Davis (2016) who construct an index of economic policy uncertainty (EPU) for 12 major economies using 12,000 newspaper articles. They show that policy uncertainty is associated with higher stock price volatility and reduced investment and employment in sectors like defense, health care, finance and infrastructure. Similarly, Ahir et al. (2018) construct a World Uncertainty Index (WUI) for 143 individual countries on a quarterly basis from 1996 onwards. Their index measures the frequency of the word "uncertainty" in the quarterly Economist Intelligence Unit country reports. And in a country-specific setting, Jirasavetakul and Spilimbergo (2018) constructed a news-based economic policy uncertainty (EPU) index for Turkey. The index measures the frequency of news articles about economic policy uncertainty and – similar to our approach – uses Factiva as the primary source.

Uncertainty is not the only concept that text-based indices have been used to measure. For instance, Caldara and Iacoviello (2018) construct a monthly measure of geopolitical risk based on a set of newspaper articles covering geopolitical tensions since 1985. Like us, these authors created an algorithm which counts the frequency of articles that refer to geopolitical risks in leading newspapers published in the US, UK and Canada, using ProQuest Historical Newspapers and ProQuest News stream as the primary sources. To examine the effects that media sentiment has on equity prices, Fraiberger et al, 2018 created a daily news-based sentiment index for 25 advanced and emerging economies between 1991 and 2015. They restrict their sample to articles published by Reuters in English, but develop an algorithm which quantifies tone, counting the number of positive and negative words within financial, political and economic texts. Finally, Hlatshwayo et al. (2018) construct a cross-country news-based flow indexes of corruption and anti-corruption by reviewing 665 million international news articles provided by Factiva. They show that shocks in the corruption index are associated to negative impacts in financial and real variables.

Data and Methodology

We construct a monthly reported social unrest index by counting the number of articles each month in leading English-language newspapers and broadcasting networks that contain keywords relating to social unrest. We collect data from January 2005 to February 2019. The primary source is Dow Jones' Factiva news aggregator, and we restrict our headline search to: the ABC Network, the BBC, the CBS Network, the Canadian Broadcasting Corp, the NBC Network, the Los Angeles Times, the Financial Times, the Boston Globe, the Globe and Mail, the New York Times, the Telegraph U.K., the Times U.K., the Chicago Tribune, the Telegraph, the Guardian U.K., the Wall Street Journal, the Washington Post and the Economist. This list is a very similar set of sources to Caldera and Iacoviello (2018).

We develop a search algorithm that counts articles that reflect discussions on the areas of social unrest, revolutions, social protest and demonstrations. News articles must have at least 99 words and mention at least one of the words listed in Table 1. The articles must be tagged with the subject: "Domestic Politics" or "Civil Unrest" in Factiva. In addition, searches are filtered by geographic coverage to cover only those tagged by Factiva to be related to the country of interest. While searches could be further augmented to explore the mechanisms of social unrest, such as including words related to business and consumer confidence, this is beyond the scope of the current piece. We also include terms that exclude articles related to commemorations of past social unrest episodes, in line with Caldera and Iacoviello (2018). These terms are also listed in Table 1.

Table 1. Search Terms

Search Terms	Search Terms
Factiva's Subject	"Domestic Politics" or "Civil Unrest"
Factiva's Country tag	Country's name only
Include	(Country) **AND** (Protest* **OR** revolution **OR** civil **OR** domestic **near10** unrest)
Exclude	Anniversary **OR** War **OR** Memorial **OR** Movie **OR** Art

Following Jirasavetakul and Spilimbergo (2018), the monthly raw counts of RSU-related articles are normalized by the counts of all news articles in English containing the common and neutral term "today" and have at least 99 words. We normalized the RSU given that the overall volume of articles varies over time. Indeed, an increase in the number of articles that meet the search requirements could simply reflect an increase in the overall volume of articles. Hence, the index indicates the number of newspaper articles that discuss rising social unrest divided by the average total published articles in the anteceding 12 months as calculated in formula 1.

(1)
$$\boldsymbol{RSU_t = \frac{A_t}{\frac{1}{12}\sum_{i=0}^{11} B_{t-i}}}$$

where A_t is the number of news articles that match the search parameter at month t and B_t is the number of total articles in English containing the term "today" at month t.

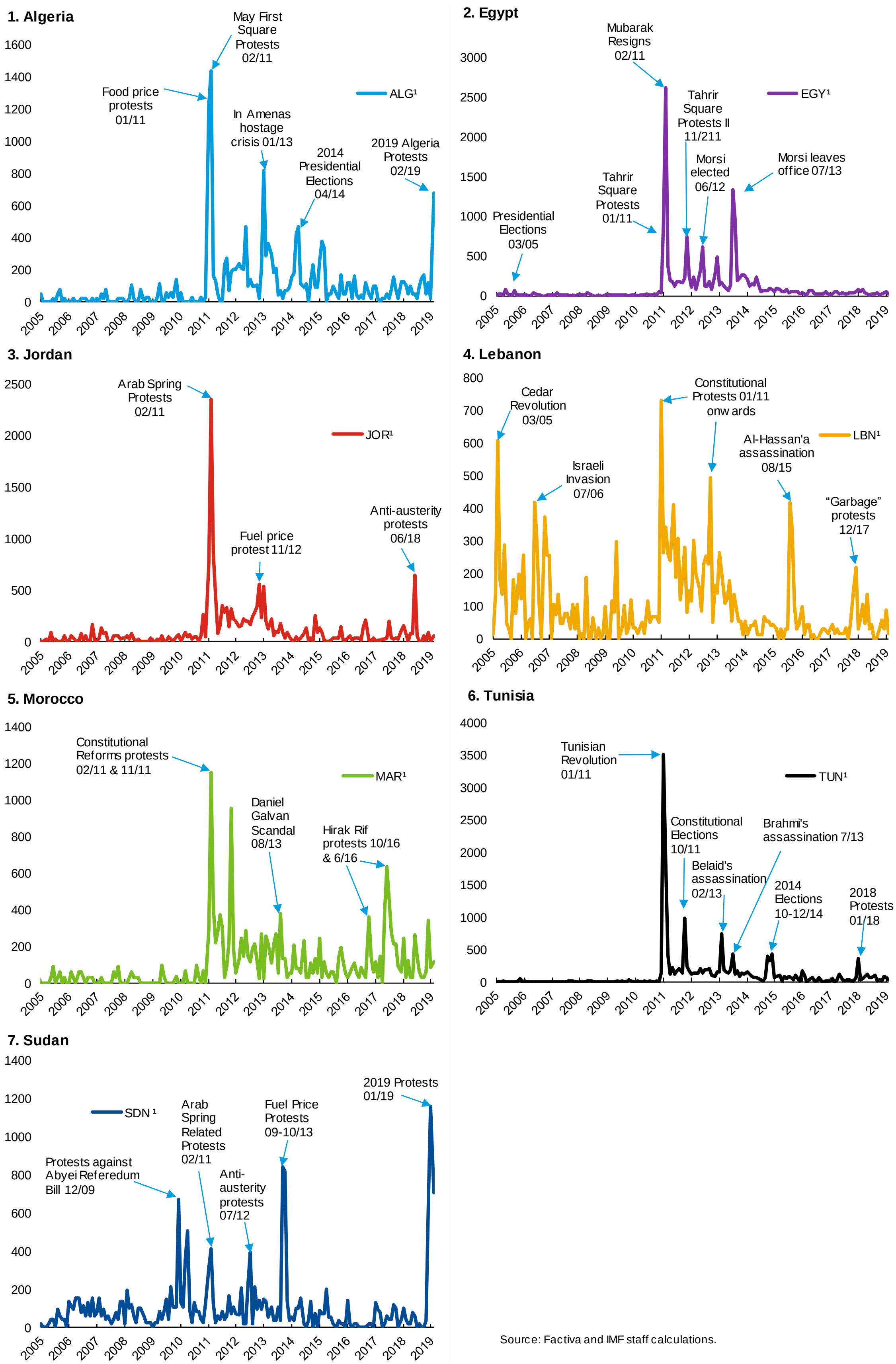
Finally, we have normalized the indices to have a mean of 100 throughout the sample period.

The Reported Social Unrest Index

Figure 1.1. shows that the RSU captures the timing of major episodes of social unrest rather precisely, with major events noted on the charts. For example, the RSU peak in Lebanon during February 2005, immediately following the assassination of Rafik Hariri. And the timing of the Arab Spring related protests are clearly distinguished across countries, with Tunisia and Lebanon peaking in January, and Algeria, Egypt, Jordan, Morocco and Sudan peaking in February 2011, reflecting events on the ground. The precision that the RSU offers in identifying the exact timing of social unrest events makes the tool useful for in-country analysis. A further advantage of this tool is its timeliness, as it can be updated daily it to serve as a surveillance tool. However, the magnitude of the index reflects reported protest, which may be correlated with but not necessarily equivalent to the magnitude of a social unrest episode. For this reason, the RSU should not be used to draw quantitative comparisons among social unrest episodes across countries.

Figure 1.1. The Reported Social Unrest Index, 2005–2019

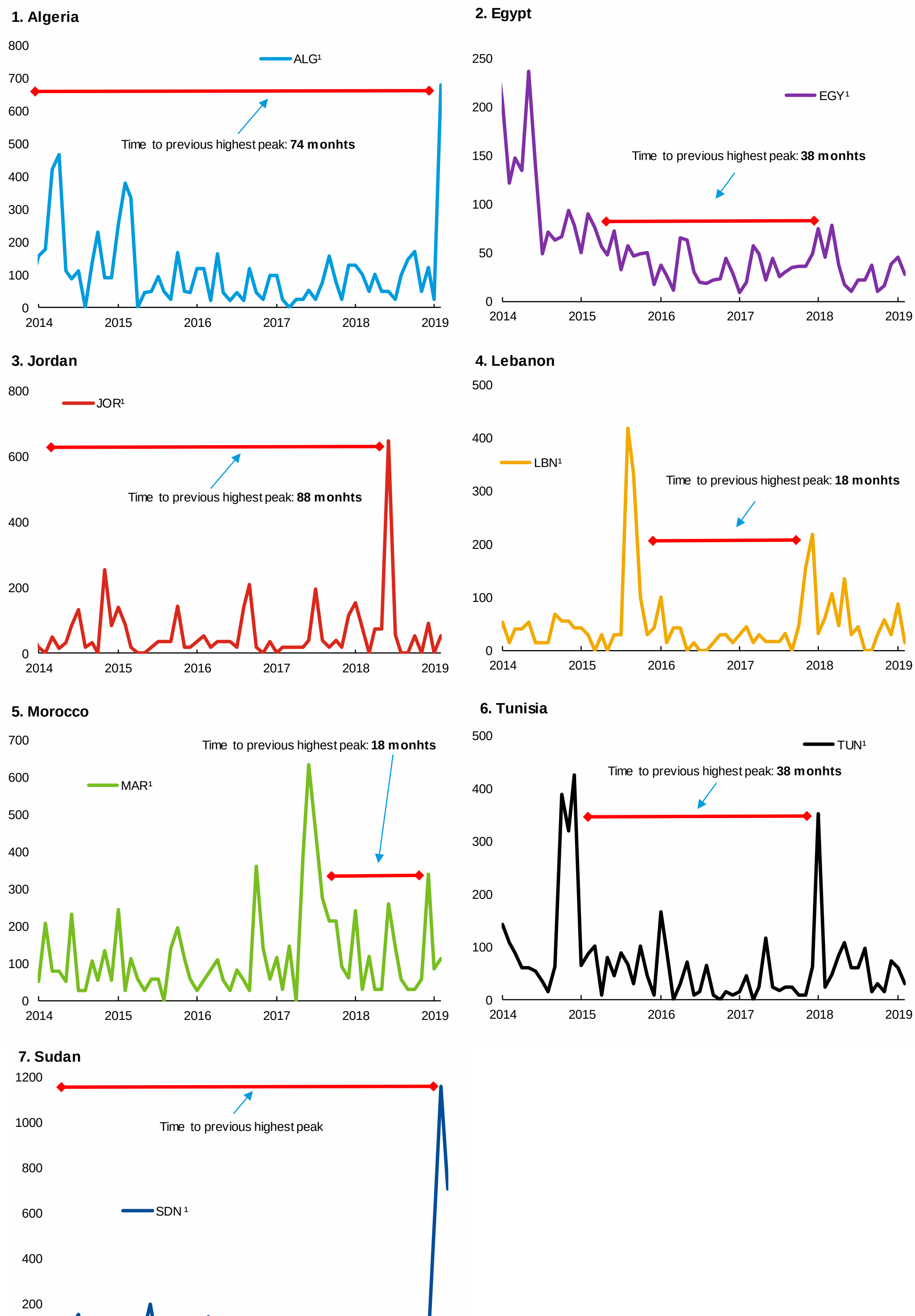
(Index, Jan 2015 = 100, last obs. Feb. 2019)



Source: Factiva and IMF staff calculations.

Figure 1.2. The Reported Social Unrest Index, 2014–2019

(Index, Jan 2015 = 100, last obs. Feb. 2019)



Sources: Factiva and IMF staff calculations.

Note: Feburay 2019 is the highest on record for Sudan since January 2005.

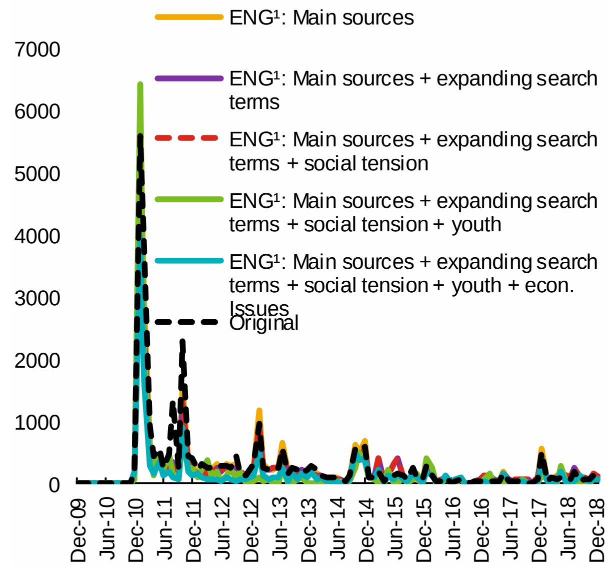
Figure 1.1. shows that RSU for most countries has become more volatile since 2011, reflecting an increase in the frequency of social unrest and protests following the wave of protests from the 2011 Arab Spring. The RSU also shows that incidents of major social unrest appear to have become more frequent towards the end of the sample. After a relatively quiet 2016, social unrest has increased once again (Figure 1.2). Recent protests in Algeria are reflected in five-year record levels of the RSU, and in Sudan the index is at an all-time peak. Indeed, in five of the seven countries considered the RSU has been higher in the last year than at any point since 2015.

Robustness

The construction of an index based on automated text-searches raises concerns about accuracy and bias. We address these concerns by implementing a human audit process and running several robustness tests which examined the effects of alternative specifications of the search terms, language choice and sources selection using Tunisia as a test case.

We used different combinations of terms in the search algorithm. The multiple search algorithms are shown in Table 2. Figure 1.3. shows that adjustments in the search algorithm does not change the identification of major social unrest episodes.

Figure 1.3.
Variations in Search Terms
(Index, Jan 2015 = 100)



Source: Factiva and IMF staff calculations.
Note: ¹These searches exclude terms related to "anniversary", "war", "memorial", "movie" or "art."

Moreover, we wanted to examine whether the choice of using a limited set of 17 leading English-language news sources has an effect in our results. We compared our headline search algorithm against another search using all news sources provided by Factiva. Figure 1.4 shows that, in both cases the search algorithms identified the same major episodes of social unrest during the period 2009-2019.

The choice of the headline search algorithm using 17 leading English-language news sources is important as allowed us to standardize our search for the rest of the countries in the region. Finally, we examined the effect that language variations have on our headline algorithm. This robustness test is important as we wanted to examine the idea that that regional and country-specific media could identify major social unrest events faster than western leading English-language media outlets. We also wanted to examine the effects of political bias that Arabic

and French country-specific sources may have when covering social unrest episodes in this region. In the case of French, we used leading newspaper as well as newswire agencies: Le

Figaro, Le Monde, Libération, Agence France Presse, Reuters, The Associated Press and The Canadian Press.

Particularly, for the Arabic language, a selected set of major international news sources in Arabic did not provided enough coverage through Factiva. An alternative approach was to use all news sources in Arabic language with the goal of removing individual media idiosyncrasies. Table 3 shows the headline search algorithm in French and Arabic.

Table 3. Variations in the Language of Media Outlets

Search Variation	Search Algorithm
"Headline": Original including terms to reduce references to commemoration events	(Tunisia) and (protest* or revolution or ((civil or domestic) near10 unrest)) and wc>99 not (anniversary or war or memorial or movie or art)
Headline search algorithm in French	(Tunisie) and (protest* or revolution* or manifestation* ((civil or domestique) near10 troubles)) and wc>99 not (anniversaire or guerre or commémoratif or film or art)
Headline search algorithm in Arabic	(تونس) and (صراع or تعارض or تضارب or خلاف or نزاع or قتال or كفاح or تلاطم or اصطدام or تصادم or اشتباك or ارتباط or معركة or إختلاف or ثورة or الثورة or انقلاب or قوة ثورية or ((مدني or المنزلي or منزلي or محلي or المحلي or داخلي or الداخلي)) near10 (اضطراب or اضطراب مدني or الاضطرابات الاجتماعية)) and wc>99 not (ذكرى سنوية or الذكرى السنوية or عيد سنوي or العيد السنوي or حرب or حروب or قتال or معركة or عراك or أفلام or فيلم or نصب تذكاري or إحياء الذكرى or إحياء ذكرى or إحتفال بذكرى or فنية or الفن or فن or الفيلم)

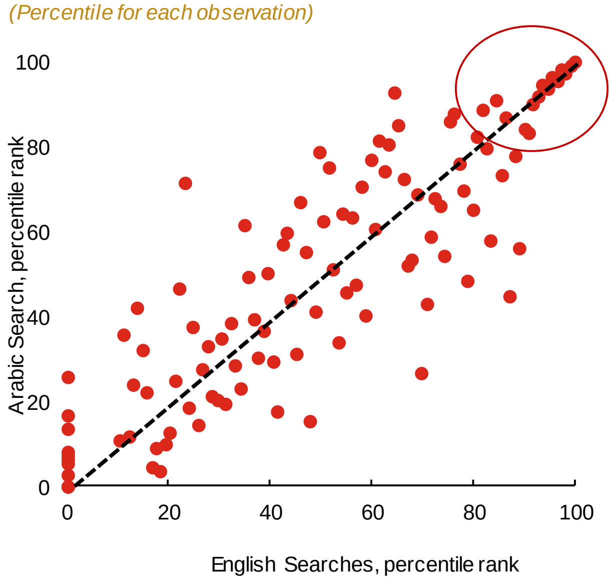
Figure 1.5 shows that the French or Arabic media outlets did not anticipate abrupt episodes of social unrest earlier than English-language news sources. Even though, there are differences in the index, Figures 1.6 and 1.7 show that our headline English search algorithm was able to identify the major social unrest episodes identified by the other two languages.

Agreement of the top ten percent of events is good, confirming our interpretation that the index well-identifies the largest increases in reported social unrest.

Performance Against Other Relevant Indicators

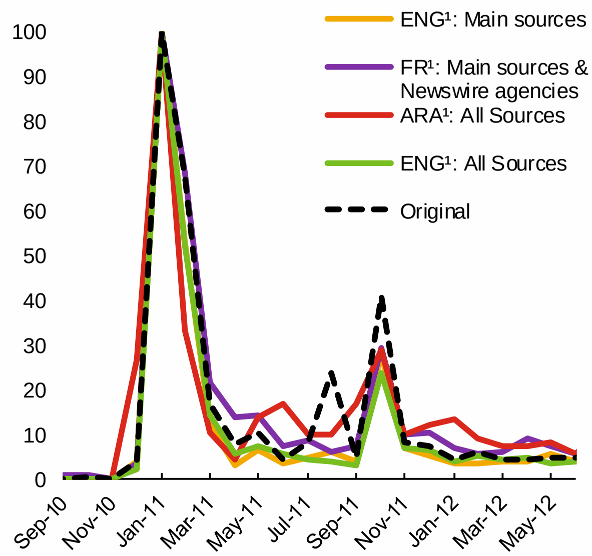
Banks and Wilson (2018) published the Cross-National Time-Series Data (CNTSD) archive which provides annual time series data since 1815 for more than 200 countries until 2017. This dataset is commonly used as a proxy for social unrest and contains domestic conflict event data for the seven countries we examined with the RSU. Figure 1.8 compares the annual average of the RSU to the CNTSD measure of the number anti-government demonstrations. Broadly, these two series match relatively well. Other indicators, including number of riots; number of revolutions, and a weighted conflict measure show little correlation. This suggests that the RSU is picking up actual social unrest, rather than simply reports.

Figure 1.4.
English Broad Search vs. Narrow Search
(Percentile for each observation)



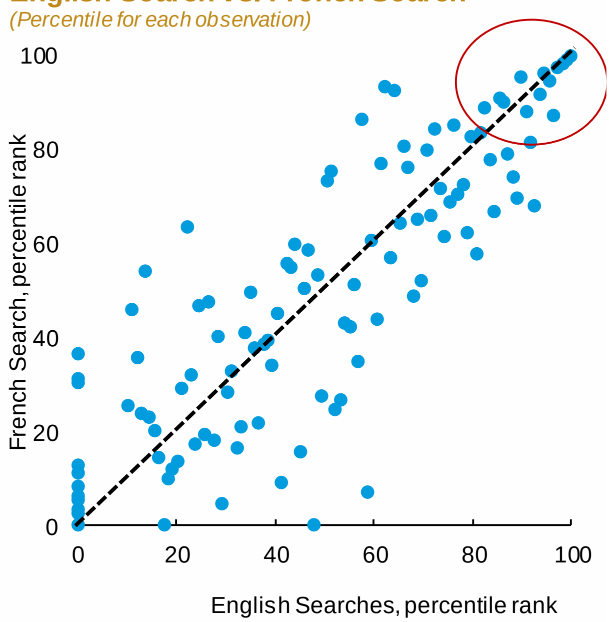
Source: Factiva and IMF staff calculations.

Figure 1.5.
Variations in language, 2010–2012
(Index, Jan 2015 = 100)



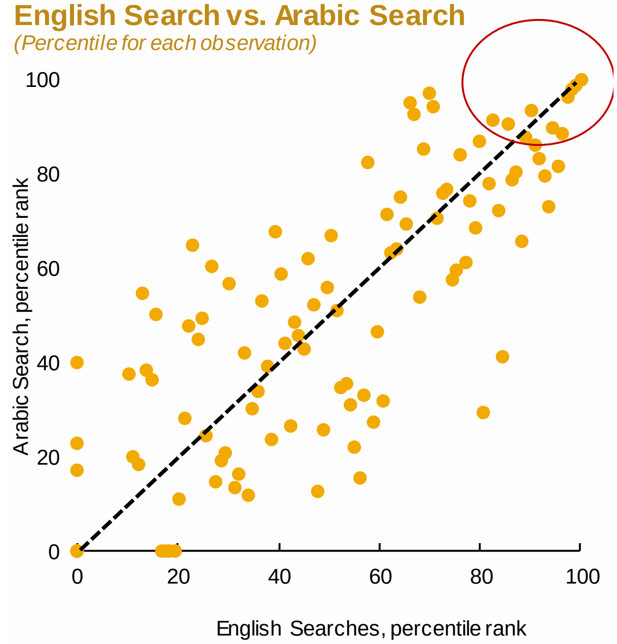
Source: Factiva and IMF staff calculations.
Note: [1]These searches exclude terms related to "anniversary", "war", "memorial", "movie" or "art."

Figure 1.6.
English Search vs. French Search
(Percentile for each observation)



Source: Factiva and IMF staff calculations.

Figure 1.7.
English Search vs. Arabic Search
(Percentile for each observation)



Source: Factiva and IMF staff calculations.

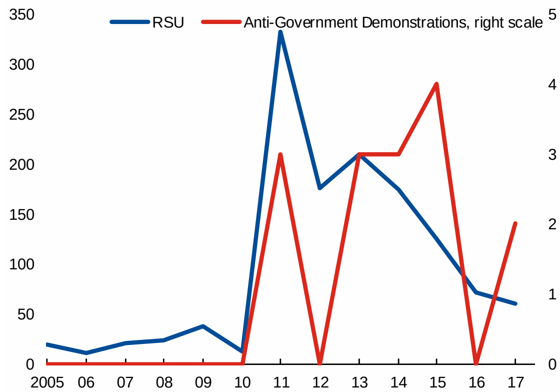
The RSU has three further advantages over this dataset. First, it is high frequency and so can be used to identify periods of social unrest with higher precision than the indicators in the CNTSD. Second, it is available up until the latest month, rather than only until 2017. Third, because the CNTSD identifies only a small number of events per year, errors of only one or two events can have very large relative effects.

Another alternative, is the Mass Mobilization in Autocracies Database (MMAD), presented by Weidmann and Rød (2019). This provides information about individual protest events in a variety of countries and is generated by a combined machine learning and human coding process. Their database covers the period 2005-2012 and is created using information from news articles from three newswire agencies: The Associated Press, the Agence France Press and BBC Monitoring. The database contains data for six of our countries of interest except for Lebanon. Figure 1.9 shows that the RSU is consistent with the number of relevant reports captured by MMAD. The RSU has the advantage that it can be updated daily until March 2019 and that it controls for the changes in media coverage over time.

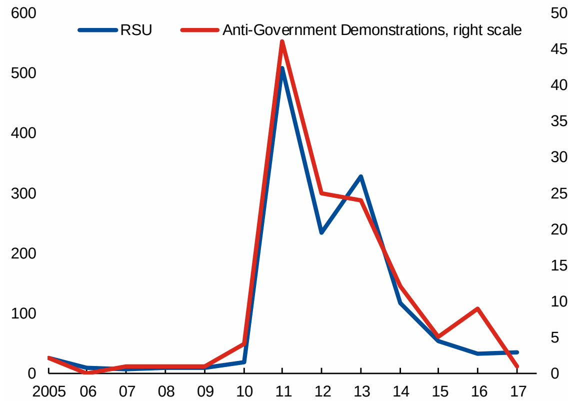
Figure 1.8. The Reported Social Unrest Index and CNTSD's Domestic Conflict Event Indicators

(Index annual averages, and number of demonstrations on right scale)

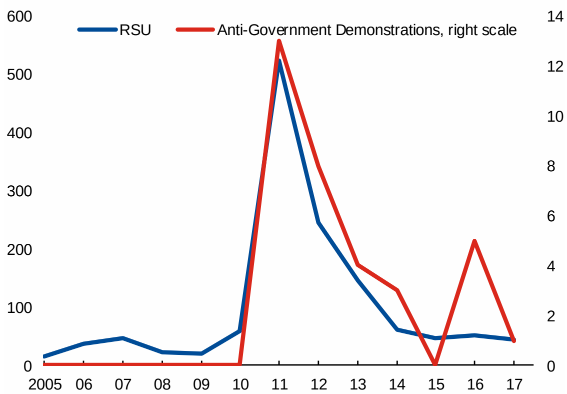
1. Algeria



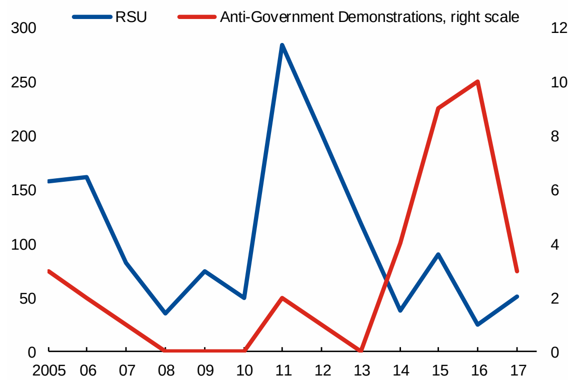
2. Egypt



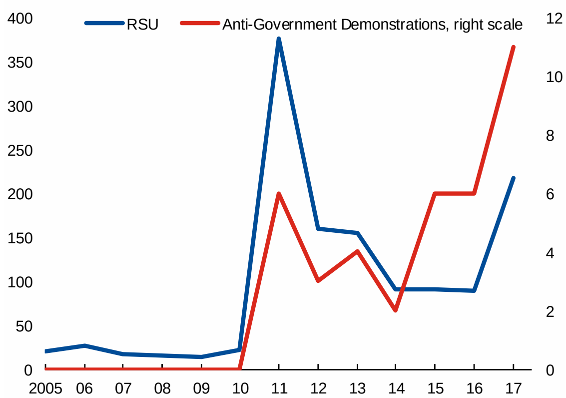
3. Jordan



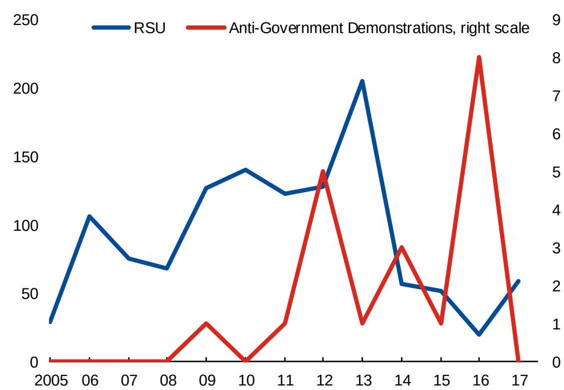
4. Lebanon



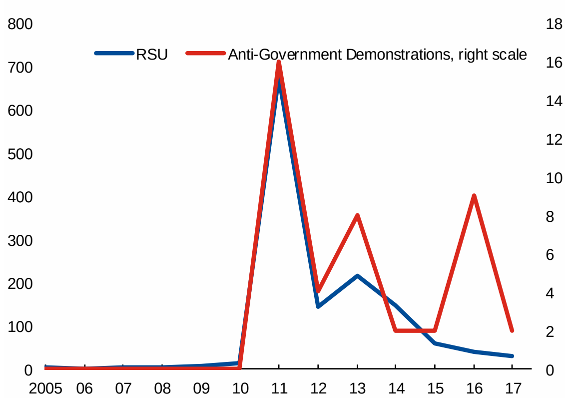
5. Morocco



6. Sudan



7. Tunisia



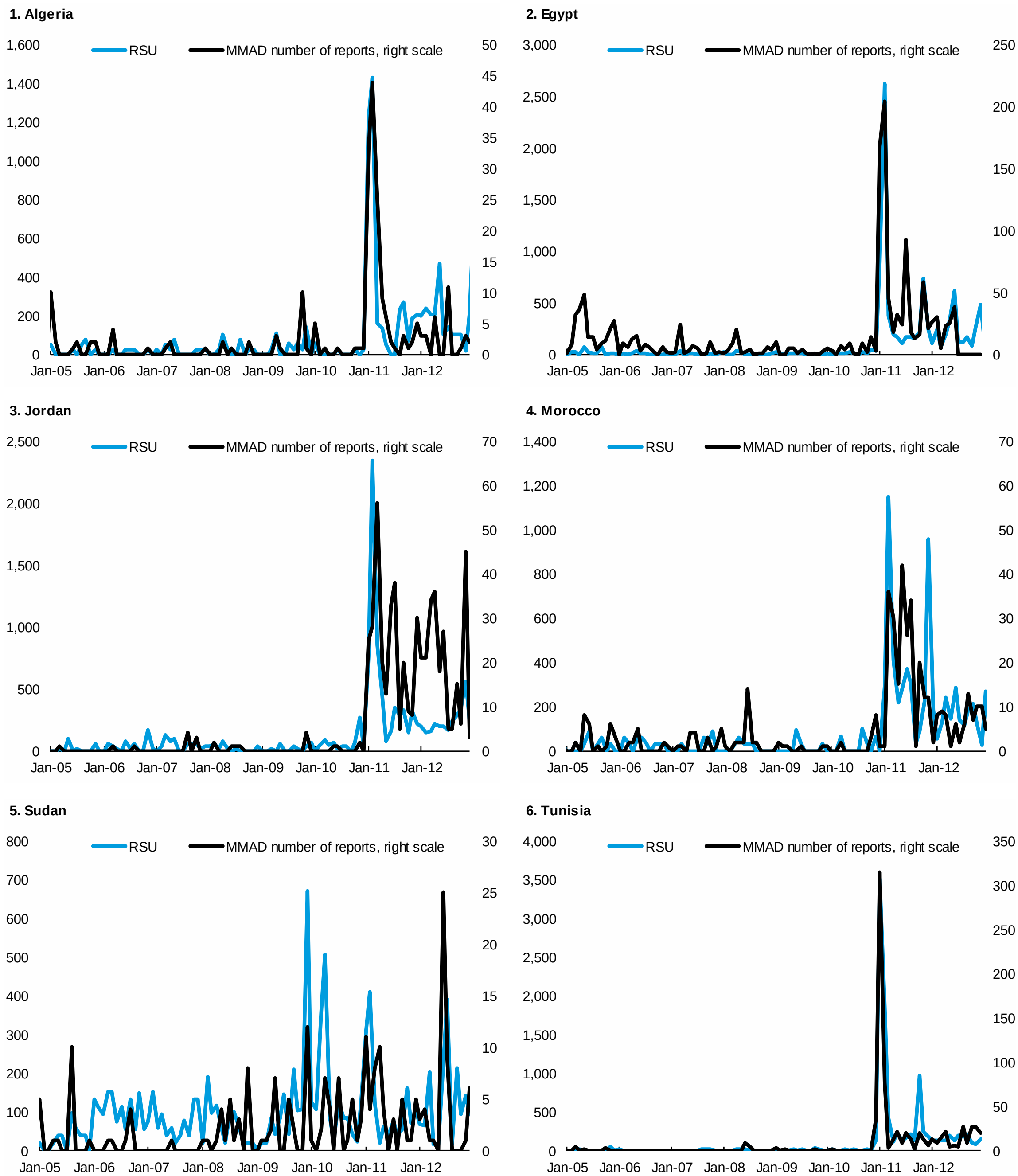
Sources: CNTS Database, Factiva; and IMF staff calculations.

Note: RSU = the reported social unrest index.

CNTSD = cross-national time-series database.

Figure 1.9. The Reported Social Unrest Index and reported Mass Mobilization in Autocracies

(Index and number of reports per month, right scale)



Sources: MMAD Database, Factiva; and IMF staff calculations.

Note: RSU = the reported social unrest index.

MMAD = Mass Mobilization in Autocracies Database.

References

Ahir, H., Bloom, N., and Furceri, D. 2018. "The World Uncertainty Index." *SSRN Electronic Journal.*

Baker, S., Bloom, N., and Davis, S. 2016. "Measuring Economic Policy Uncertainty." *The Quarterly Journal of Economics* 131:4, 1593-1636.

Banks, A., Wilson, K. 2018. "Cross-National Time-Series Data Archive." *Databanks International.*

Caldara, D., and Iacoviello, M. 2018. "Measuring Geopolitical Risk." International Finance Discussion Papers No. 1,222, *Board of Governors of the Federal Reserve System*.

Fraiberger, S., Lee, D., Puy, D., and Romain R. 2018. "Media Sentiment and International Asset Prices." IMF Working Paper, WP/18/274. *International Monetary Fund*.

Hlatshwayo, S., Oeking, A., Ghazanchyan, M., Corvino, D., Shukla, A., and Leigh, L. 2018. "The Measurement and Macro-Relevance of Corruption: A Big Data Approach." IMF Working Paper, WP/18/195. *International Monetary Fund*.

Jirasavetakul, L., and Spilimbergo, A. 2018. "Economic Policy Uncertainty in Turkey." IMF Working Papers 18/272, *International Monetary Fund*.

Weidmann, N. and Rød, E. 2019. "The Internet and Political Protest in Autocracies. Chapter 4." *Oxford University Press.*