FORECASTING SOCIAL UNREST: A MACHINE LEARNING APPROACH

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FORECASTING SOCIAL UNREST: A ML APPROACH

What we do

- Develop ML based forecasting model of unrest events of Barret et al. (2020)
- Shed light on predictors, produce risk index.

Why do this?

- We know relatively little about the data generating process.
- Risk index driven by forecast performance.

Results:

- AUC and Balanced Accuracy of 66%, significantly better than chance.
- Relatively modest role for predictors in lit.: Inflation, contagion from neighbors, digital media.

SOCIAL UNREST EVENTS

(a) Number of Unrest events





(b) Unrest and per capita GDP growth



SOCIAL UNREST EVENTS

(a) Number of Unrest events



Barret et al (2021), authors' calculations

(b) Impact of increases in unrest on output



LITERATURE

Drivers of unrest:

- Food prices (Bellemare 2015), inequality (Acemoglu and Robinson 2000), competition between elites (Turchin and Korotayev 2020), social media (Enikolopov et. al 2020), social media + weak growth (Manacorda and Tesei 2020)
- \rightarrow Useful if we can give forewarning of events

 \rightarrow We contribute to the literature by considering a wide range of drivers over a large set of countries.

implications. Social offices and ma	SIGDIIIY···
can induce changes in political shifts.	Acemoglu and Robinson (2000), Aidt and Frank (2015), Aidt and Leon (2016)
reduces investment (and increases government consumption)	Alesina & Tabellini (1989); Hossain and Chowdhury (1998); Darby, Li, and Muscatelli (2004); Leduc & Liu (2016)
prompts capital flight and depresses financial market returns	Alesina & Tabellini (1989); Bernhard and Leblang (2006); Abdelbaki (2013); Acemoglu et al. (2017); Bondar & Barrett (2020)
pauses firm labor market actions	Leduc & Liu (2016)
lowers household consumption	Leduc & Liu (2016)
reduces growth	Barro (1991); Asteriou et al. (2000); Saadi Sedik and Xu (2020); Hadzi-Vaskov, Pienknagura, and Ricci (2020)

mplications, Social uprost and instability

DATA: MEASURING (MAJOR) SOCIAL UNREST

Data:

• Newspaper-based Boolean indicator of Barrett, et al. (2020) - Reported Social Unrest Index (RSUI)

- "protest" or "riot" or "revolution" within 10 words of "unrest" & excludes terms that generate obvious false positives
- Based on article counts from Dow Jones Factiva (only major news media in USA, CAN, and UK), leverage Factiva's tags (e.g., on country and subject)
- Normalized to address variation in media coverage
- 120+ countries (36 LICs, 56 EMs, 33 AEs), 1995-2020



DATA: PREDICTORS

- Fiscal crisis model database (Hellwig 2020): growth, fiscal, inflation, ToT, remittances, governance, elections, income level, commodity exporting status...
- ICRG, CNTS, Polity IV: Internet, television, schooling, religious frictions, legislative effectiveness, regime type...
- Natural disasters: Extreme temperature, floods, epidemics, ...
- World Uncertainty Index of Ahir et. al (2020)
- World bank: Inequality, unemployment, poverty, access to basic services
- IMF: CPI, structural reforms
- Target is unrest event 1 year ahead.
- \rightarrow Over 340 features (including lags, etc.)

MODEL EVALUATION

TimeSeriesSplit Testing set 0 Training set 1 2 3 CV iteration 4 5 6 7 1995..2005 ->2006 ..2019 ->2020

RESULTS BY MODEL TYPE



**significant at 5%, * at 10% for DeLong test. Horizontal bars show mean AUC over the test set with the error bars representing standard errors.



Receiver operating characteristic: Social Unrest

RESULTS: OVER TIME & ACROSS TYPE



(b) Mean balanced accuracy by type of unrest



PROBABILITIES OF UNREST

(a) Average probability of unrest



RISK INDEX COUNTRY EXAMPLES

UNITED KINGDOM

UNITED STATES



RISK INDEX COUNTRY EXAMPLES

EGYPT



THAILAND



DRIVERS: SHAPLEY VALUES



DRIVERS: SHAPLEY VALUES

(b) Time variation in selected Shapley values



CONCLUSIONS

Social unrest raises financial, economic and political risks.

- We combine a new text-based measure of unrest with a large data set to explore the predictors for such events.
- Tree-based models perform best and can achieve a balanced accuracy and AUC around 66% - i.e. are "right, two thirds of the time".
- Some evidence for the predictors highlighted in the literature, what matters most is recent unrest.
 - Inflation (esp. food), unrest in neighbors, economic growth, digital media.
- Future work to focus on high frequency data, e.g. twitter, google search, etc.

THANKS

EXTRA SLIDES

TYPES OF UNREST

Unnest type Key words		Share of events	
Unrest type	Key words	(percent)	
Government	political, anti-government, government, anti-president, president,	17.5	
	coalition, opposition, resignation, resigns, impeachment		
Democratic-reform related	Arab Spring, journalist, journalists, freedom, lawyer, democracy,		
	Tahir Square, law, independence, anti-police, constitution,	0.4	
	anti-corruption, corruption, reform, anti-segregation,	9.4	
	constitutional, suffrage, women, referendum, fraud, civil society		
Global issues	occupy, anti-WEF, anti-Davos, anti-U.N.,	3.6	
	anti-US, intervention, foreign, anti-globalization, G20,		
	climate, environment, environmental, immigration, Brexit		
	migration, migrant, refugee, human rights, summit, anti-war		
Religious	anti-blasphemy, Mosque, Quran	0.6	
Elections	candidates, vote, electoral, poll	14.0	
Basic needs	anti-austerity, austerity, electricity,		
	energy, yellow vests, gas, strike, union, healthcare,	8.3	
	education, school, land, agriculture		
Coup/Sudden End to Tenure	ousted, assassination, assassinated, military	5.7	
Violence	deadly, riots, violent, civil war, burning	4.9	
Unknown		36.0	

RESULTS BY UNREST TYPE

(b) Mean balanced accuracy by type of unrest

