Credit Shocks and Populism

Discussed by: Tho Pham

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Research question and methodologies

- Examine the impacts of lending shocks on the electoral support for populist parties in Germany
- Identification strategy: DiD with continuous treatment (exposure to lending cut)
- Textual analysis: Use semi-supervised ML approach to identify the degree of populism in the parliamentary speeches of each party

Results

Higher exposure to the credit shock increases support for parties that are:

- populist
- adopt a populist rhetoric
- discuss bank-related topics more frequently

Measurement error: Treatment indicator

- Commerzbank dependence (in 2006):
  $\frac{\text{no of relationship banks that are CB branches}}{\text{total no of relationship banks}}$
- Strong assumption: **"the local banking market is somewhat stable, and there are negligible differences between the relationship banks in 2006 and the latest recorded ones"**
  - Unclear what are the dates (years) of the latest records
  - New relationship lending could be established
  - Likewise, relationship in 2006 could have been recorded as no relationship in this data
- Suggestion: Create the histogram of CB dependence and show that it is similar to Panel B of Figure 3 in Huber (2018)

Topic modelling

- Thoroughly done, but...
- Is it necessary/suitable?
  - The top 20 tokens obtained via seeded LDA are almost identical to (or are variants of) the seeded (stemmed) words
  - Except "crisis" and "ecb" topics: there are words/tokens which do not seem to "fit in", e.g., jahr (year), kolleg (college), kollegen (colleagues)
- Suggestion: Perhaps you can use other NLP tools (e.g., StanfordNLP, ConceptNet) to expand the list of seed words and use the expanded list to measure populism

Complementary story

- How's about:
  - Voters could be more attracted to the parties of which speeches "stood out", e.g., talking about the same issues like others but expressing those issues in a different way
  - Would voters still be attracted if a party keeps talking about banking crisis (hence, a high score of "how much") but offering no new info (e.g., the same or similar statements are repeated)?
- One could use Google's BERT to extract word/sentence embeddings and measure the cosine similarity across speeches
  - Don't need pre-defined topics. Similarity is measured solely based on the semantics of speeches
  - Smaller (average) similarity (compared to speeches of other parties) = more "unique" (Point 1 above)
  - Smaller pairwise similarity across speeches of the same party = more "diverse" (Point 2 above)

DiD with continuous treatment (Callaway et al., 2021)

- Causal effects arising in DiD with continuous treatment:
  - Level effect (ATT): average effect of dose d relative to untreated, specific to the group that actually experienced this dose
  - Slope effect (ACRT): causal response of a marginal change in dose d, specific to the group that actually experienced this dose
- Long story short: comparing ATTs across different doses and identifying ACRT (this paper) would be tricky because of selection bias
- Keep an eye on this evolving literature
- In the meantime: Acknowledge the assumption required to interpret β as ACRT + discuss limitations

Other comments/questions

- Data inconsistency/outliners
  - Individuals at least **16** yrs old in 2006 (Page 9)
  - Max birth year in full sample is *1998* (Table 1) = only **8!** yrs old in 2006
  - Max birth year in pre-shock sample is *1989* (Table 2)
  - Negative income?

- Very interesting paper and I really enjoyed reading it!