Do the texts of bilateral trade agreements influence its effectiveness?

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Introduction

- Trade agreements have been progressively becoming longer
- Typically, trade agreements are studied on a case-by-case basis
- There have been papers studying the role texts of trade agreements on their outcome (e.g. Seiermann, 2018)

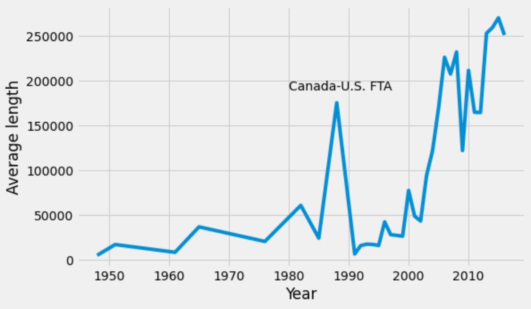


Figure: Average length of trade agreements over time

Data sources

- Corpus built from the WTO Regional Trade Agreement Information System (Alschner et al., 2017)
  - *Date, Parties, Region, WTO membership...*
- The CEPII Gravity Database (Conte et al., 2021)
  - *GDP, Distance, Common language, Colonial relationship, Legal origins, Population, RTA coverage, Trade flow, Start-up costs...*

Sample trade agreement


```
...
<wto_rta_id>11</wto_rta_id>
<treaty_identifier>10</treaty_identifier>
<status>In Force</status>
<notification>GATT Art. XXIV &amp; GATS Art. V...
<date_signed>2006-03-01</date_signed>
<date_into_force>2006-07-24</date_into_force>
<date_notification>2007-04-04</date_notification>
<end_implementation>2016-12-30</end_implementation>
<date_inactive/> ...
<body>
    <chapter name="Preamble" chapter_identifier="128">
        <article article_identifier="1016">
...
```

Theories of trade

- Trade agreements aim to reduce barriers and promote trade
- Theories suggest there are net benefits to opening up to trade
- The Gravity Model
- $F_{ij} = G\frac{M_i M_j}{D_{ij}}$

Our hypotheses

- H1: The effectiveness of a trade agreement increases as it becomes longer.
- H2: The effectiveness of a trade agreement increases as it becomes more detailed.
- H3: The effectiveness of a trade agreement increases if it is written with nicer language.

Methodology

Stage 1: Data cleaning

- Converting text and other metadata from XML to Python-readable format
- Removing undesirable trade agreements (multilateral, non-English, between countries that ceased to exist)
- Merging trade agreement data with socioeconomic variables during its lifespan

Stage 2: Feature extraction

- Descriptive statistics directly extracted from trade agreement text
  - *Total words, Unique words, Length of articles...*
- Unsupervised topic modelling on trade agreement articles with K-means using a tf-idf setting
- Supervised classification on the niceness of trade agreement preambles using ULMFiT transfer learning

Stage 3: Regression and Prediction

- **Regression**
- Panel data regression, controlling for relative GDP, the existence of RTA, and time fixed effects
- Aimed to establish causality

$$log\_tradeflow_{it} = \beta_0 + \sum_{j=1}^{N} \beta_j extracted\ feature_{jit}$$
$$+relativeGDP_{it} + RTA_{it} + \sum_{t=1}^{T} a_t + \epsilon_{it}.$$

Stage 3: Regression and Prediction

- **Prediction**
- Predicted variable: change in trade flows
- Predictors: Gravity variables and features from the text
- Random forests for prediction
- Shapley values to understand feature importance and direction of impact

Results

Summary Statistics

	Total words	Total articles	Unique words
Min	4852	1	362
25%	19364	27	937.25
Median	31720.5	41	1189.5
75%	171747.5	155	4131.5
Max	491979	310	8815
Mean	97372.9	87.1	2383.9
Std deviation	120630.8	85.7	2165.4

Table: Descriptive statistics of trade agreements

Summary Statistics

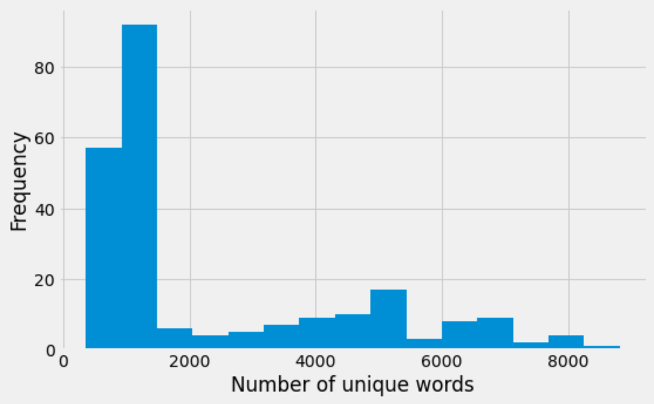


Figure: Distribution of unique words in trade agreements

Topic Modelling

- Cluster 1: Generic legal text
  - *shall, party, agreement, trade, measure...*
- Cluster 2: Investment agreements
  - *service, supplier, financial, investment, investor...*
- Cluster 3: Rules of origin
  - *good, custom, duty, originating, product...*
- Clusters 2 and 3 potentially indicates how specific and detailed a trade agreement is

Topic Modelling

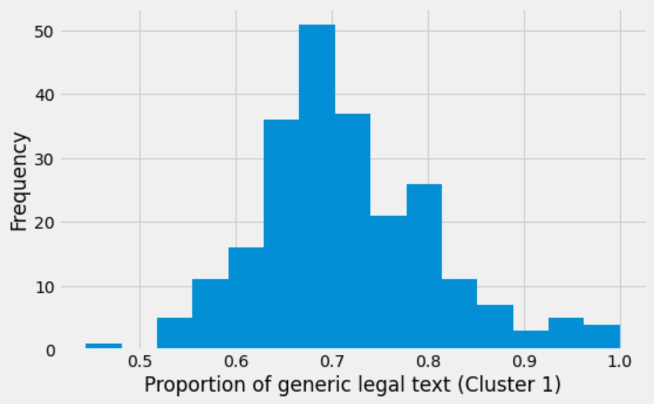


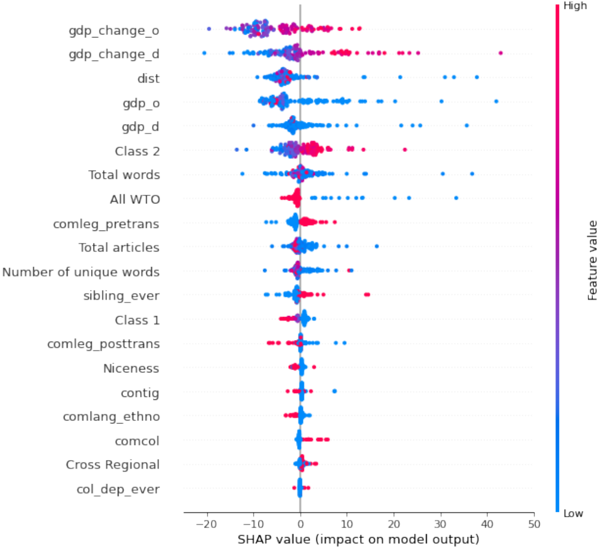
Figure: Distribution of trade agreement genericity

Regression results

Variable	**log_tradeflow**		**log_manuf_tradeflow**	
Unique words	0.00065***	0.00068***	0.00061***	0.00065***
	(0.000087)	(0.000086)	(0.000090)	(0.000088)
Niceness	-0.4061	-0.2981	-0.4319	-0.4282
	(0.4069)	(0.4059)	(0.4203)	(0.4175)
Generic legal text	7.0002***	7.3697***	6.0020***	6.4995***
	(2.1279)	(2.0642)	(2.1979)	(2.1230)
Relative GDP		1.5649***		0.6558**
		(0.2911)		(0.3011)
RTA		-0.1921		-0.4686
		(0.2208)		(0.2288)
cons	4.9979***	3.6499**	5.3299***	4.5318***
	(1.6673)	(1.6561)	(1.7228)	(1.7039)
R^2	0.2086	0.2939	0.2009	0.2601

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Predictive powers



Robustness

- Regression:
  - Relatively robust to addition of controls (see previous table)
- Prediction:
  - Low value of R^2 on the validation set
  - Concerns of overfitting as there is not much data

Conclusion

- H1 is partially supported by significant positive estimated coefficients and some predictive power.
- There is no sufficient evidence in support of H2. Regression results showed that having generic legal text improved trade flow.
- There is no sufficient evidence in support of H3. Regression results were null and the predictive power of niceness was minuscule.
- Overall, these features of the text of trade agreements are likely to only have had a limited impact on trade flows.

Discussion

Limitations of research question

- Complexity of trade
- Choice of features extracted
- Labelling of 'niceness' could be improved

Possible future research questions

- Analysing the appendix of rules of origin and Harmonised System codes to investigate the effects of restrictions on specific goods
- Would require industry/product level data on bilateral trade flows

Q&A

Any questions?