Determinants of PTA Design

Insights from Machine Learning

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Midwest International Trade

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  - consistently **important determinants**: interdependence, geography, governance

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determinants of PTA formation

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APPLYING MACHINE LEARNING (ML) TO PTA CONTEXT

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Applying machine learning (ML) to PTA context

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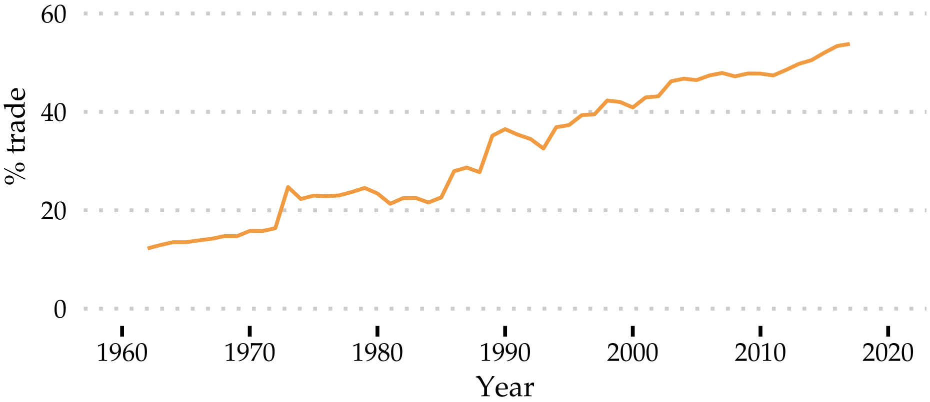
- **This Paper:** random forest to identify factors important for provisions included in PTA

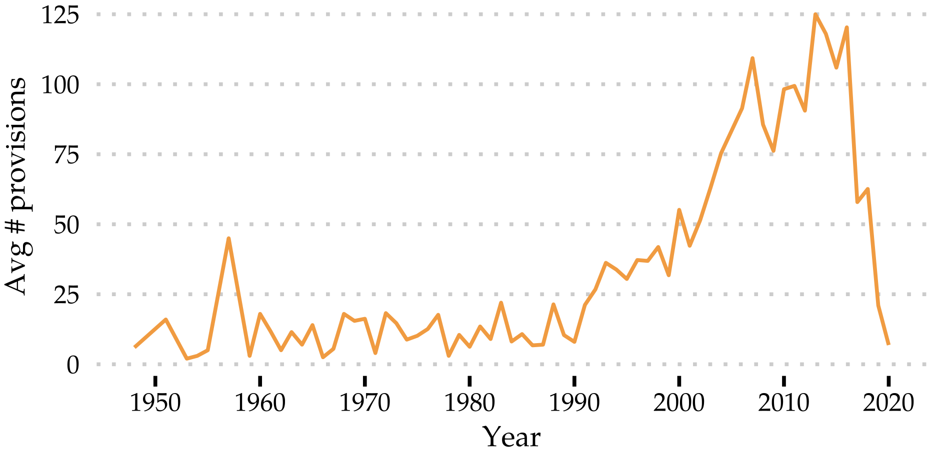
Background

of PTAs Has Skyrocketed



share of global trade happening between PTA members (data: EIA)

PTA Design Has Become More Complex



average number of provisions in a PTA over time (data: DESTA)

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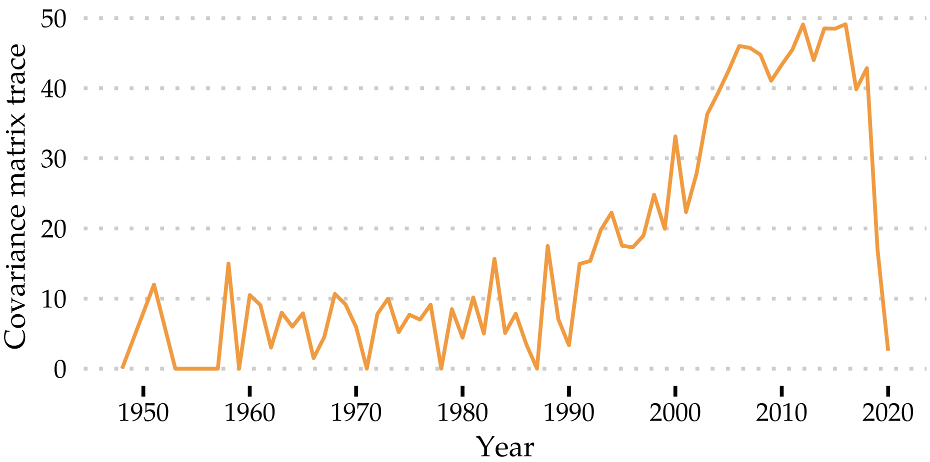

variance of provisions included in PTAs over time (data: DESTA)

Understanding PTA Design Complexity

- estimated effects of PTAs on trade $\gg$ effects explainable by trade costs reductions
  - $\rightarrow$ inclusion of non-tariff provisions more important for boosting trade
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  - $\rightarrow$ understand determinants of design to better understand the breadth of outcomes signatories are seeking
- understanding determinants of provisions matters for understanding their effects
  - – estimation of PTA effects suffers from their endogenous formation
  - – literature has instrumented for PTA formation with determinants exogeneous to studied outcome
  - $\rightarrow$ identify a wide range of design determinants to serve as IVs later

Empirical Approach

- which country-pair characteristics are highly predictive of...

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  2. country pair's **PTA design** (inclusion of a particular provision in a PTA)?

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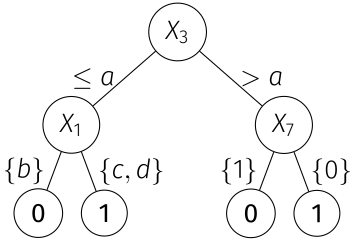

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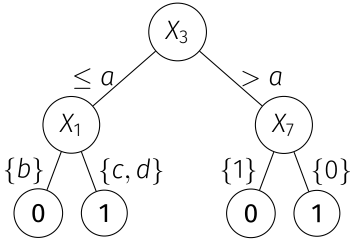

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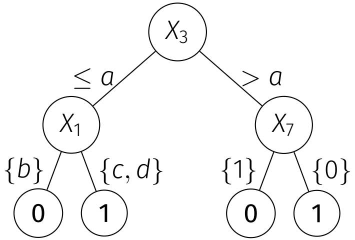

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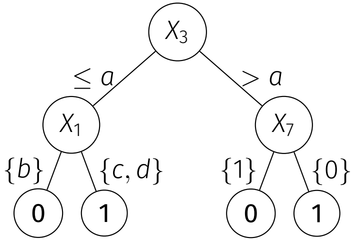
- to classify an observation: all trees classify it, majority wins



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- variable is an "important" predictor if Altmann permutation importance p-value $< 1\%$

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   - **proximity, culture**: CEPII Gravity, CEPII Language, GeoDist, UNCTADstat
   - **trade, FDI**: UN Comtrade, WITS, IMF CDIS, BACI
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   - factors found to be important determinants of overall PTA formation
     - e.g. macroeconomic variables, PTA contagion, domestic politics
   - factors related to particular PTA provision policy areas
     - e.g. innovation, energy use, labor markets, sectoral variables
2. collect and merge data on potential determinants
   - **economy, society**: Penn World Tables, World Development Indicators
   - **proximity, culture**: CEPII Gravity, CEPII Language, GeoDist, UNCTADstat
   - **trade, FDI**: UN Comtrade, WITS, IMF CDIS, BACI
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   - **country**-level **factor** variables: same or not, combination
     - e.g. combination of political regimes within pair

Results: PTA Formation

Determinants of PTA Formation

- country-pair characteristics most predictive of PTAs:
  - **geographic proximity**: distance, continents
  - **contagion**: competition from third countries for export markets
  - **domestic politics**: executive and legislative composition, features, tenure
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▶ *modifications & performance*

Most Likely New PTAs

- country pairs that are most likely to have a PTA according to RF, but don't

	Country Pair	PTA Probability
1	Dominican Republic, Panama	0.47
2	Colombia, Costa Rica	0.46
3	Bosnia & Herzegovina, Slovenia	0.45
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5	Norway, Russia	0.45
6	Albania, Greece	0.45
7	Ecuador, Panama	0.44
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Results: PTA Design

Predictive Performance

- compare performance of RF models for each provision with alternative models
  - 2/3 training sample, 1/3 test sample
  - RF outperforms a single tree and conventional logistic regression

	Full Sample			Non-NA Sub-Sample		
	Random Forest	Tree	Logit	Random Forest	Tree	Logit
25th %-ile	0.123	0.212	0.432	0.055	0.107	0.079
median	**0.164**	**0.277**	**0.456**	**0.079**	**0.145**	**0.114**
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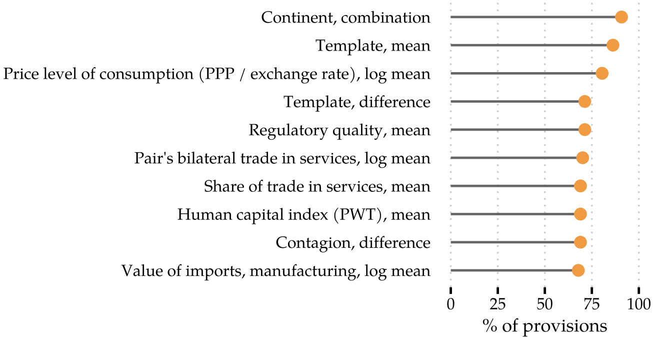
- rank country-pair characteristics by % of provisions each is a significant predictor of



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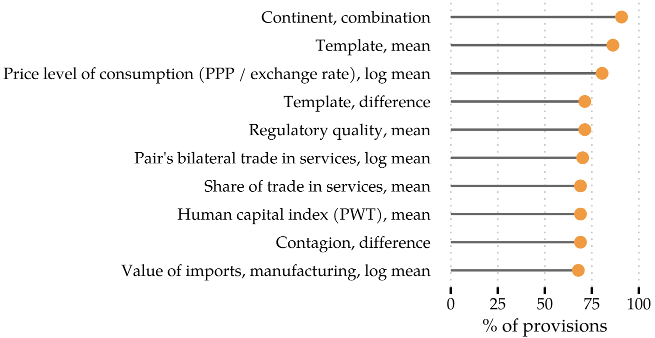

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▶ *alternative variable sets* ▶ *distribution of determinants* ▶ *DTA*

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    - but can't provide a single coefficient summarizing a variable's effect
    - → motivate future research to focus on individual mechanisms related to identified determinants

RF Tuning

- parameters
  - N (number of trees): 500
  - M_{try} (number of variables to consider at each split), *nodesize* (number of obs in terminal node): k-fold cross-validation

back

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- parameters
  - N (number of trees): 500
  - M_{try} (number of variables to consider at each split), *nodesize* (number of obs in terminal node): k-fold cross-validation
- splitting statistic: **AUC-ROC**
  - prob. that a random “true 0” and “true 1” are both classified correctly
  - due to imbalanced data, outperforms standard **misclassification rate**
    - even when overall performance measured with misclassification rate

back

RF Implementation: Missings

- **problem**: most observations have at least some missing predictors
  - collect hundreds of potential determinants from dozens of datasets
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    - $\rightarrow$ throw away almost all data
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- *Tang, Ishwaran (2017)*: "on-the-fly imputation" for RFs
  - at each node, only non-missing data is used to come up with a split, then missings are split randomly
  - $\rightarrow$ uses all data without imputation
    - variables with many missings naturally get lower VIM values

back

Contagion

- large literature documents contagion/interdependence of PTAs

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- likely mechanism:
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$$\text{Contagion}_{p,ij,t} = \left(\frac{\text{bilateral exports}_{ij}}{\text{total exports}_i}\right) \sum_{k \neq i,j} \left(\frac{\text{bilateral exports}_{kj}}{\text{total imports}_j}\right) 1_{p,jkt}$$

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Formation Details & Performance

- 480,738 country-pair-5yr observations $\rightarrow$ computational simplifications
  - 10 (rather than all) random splitting points considered at each node
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OOB Misclassification			
Overall	0 (Absent)	1 (Present)	Share of 1s
0.255	0.264	0.021	0.035

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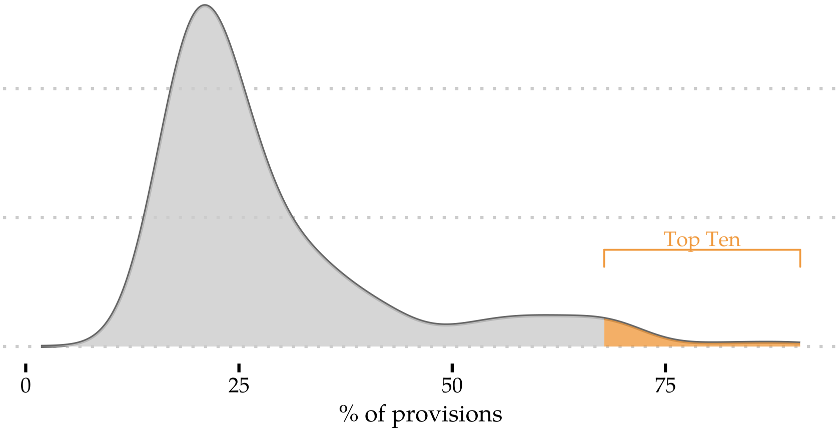
	OOB Misclassification			
	Overall	0 (Absent)	1 (Present)	Share of 1s
25th %-ile	0.120	0.000	0.390	0.148
median	**0.160**	**0.006**	**0.702**	**0.212**
75th %-ile	0.226	0.034	0.948	0.359

back

Results: Distribution of Determinant Importances

- distribution of variables by the % of provisions each is a significant predictor of



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Results: Alternative Variable Sets

- alternative way to isolate important variables: run RFs with subsets of country-pair characteristics

All	Excluding Top 10	Economy	Geography	History, Culture	Interdependence	Politics	Trade
0.160	0.186	0.191	0.148	0.210	0.137	0.179	0.187

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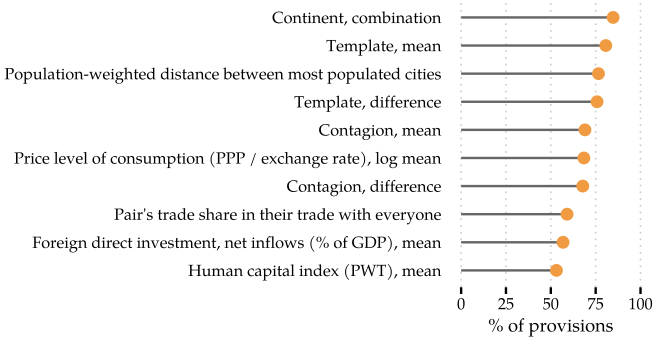
All	Excluding Top 10	Economy	Geography	History, Culture	Interdependence	Politics	Trade
0.160	0.186	0.191	0.148	0.210	0.137	0.179	0.187

- **interdependence**, **geography** again have highest predictive power
  - even outperform the original RF with complete set of variables

back

Results: Top 10 Determinants of Overall Design, DTA



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