Predicting Debt Distress in Low-Income Countries

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Motivation: general

- Sovereign debt crises have large economic and social costs
  - Lower growth, productivity, higher poverty (Reinhart and Rogoff 2009, Aguiar and Amador 2021, Farah-Yacoub et al. 2022a)
- Early warning systems for "debt distress" can have large benefits if they enable preventative measures
  - Large literature on predicting debt distress (Badia et. al. (2022) survey)
  - Premise of WB/IMF LIC Debt Sustainability Framework

Motivation: specific WB/IMF policy application

- The WB/IMF Debt Sustainability Framework for Low-Income Countries (LIC DSF)
  - Developed in mid-2000s to provide early warning of debt vulnerabilities
  - Intended to prevent debt re-accumulation post-HIPC/MDRI
  - Used to set borrowing limits, mix of grants and loans from IDA
  - Last reviewed in 2017, new review beginning now
- Core of LIC DSF is an empirical model to predict debt distress
  - Anchored in literature on correlates of external debt servicing difficulties
  - Used to derive country-specific debt thresholds reflecting countries' debt carrying capacity through the "country index"
  - Complex aggregation of predictions from four *ad hoc* probit regressions

Our contributions to literature and policy

1. Refining debt distress outcome measurement to reflect the *onset* rather than *resolution* of episodes of debt servicing difficulties
    - *Median difference of four years between the two*
2. Systematic approach to predictive model selection
    - *Evaluate 559,872 possible models based on J-K-fold cross-validated out-of-sample predictive performance, select best models subject to plausible constraints*
3. Evaluate simple versus sophisticated prediction algorithms
    - *Best simple models strongly dominate more sophisticated alternatives such as Random Forests*
    - *Parsimonious simple models perform almost as well as non-parsimonious ones*
4. Policy implications for LIC-DSF
    - *Scope to improve predictive performance*
    - *Scope to reduce overoptimism bias through k-year-ahead predictions*
    - *Scope to simplify implementation through more streamlined models*

1. Measuring debt distress

1.1 Measuring debt distress: signals

LIC DSF Review 2017 – reflects typical set of debt distress signals in the literature

Defaults on private creditors:
Data from S&P and Catao & Milesi-Ferreti, whenever available

Arrears:
Arrears > 5% of ppg debt stock, for 3 years

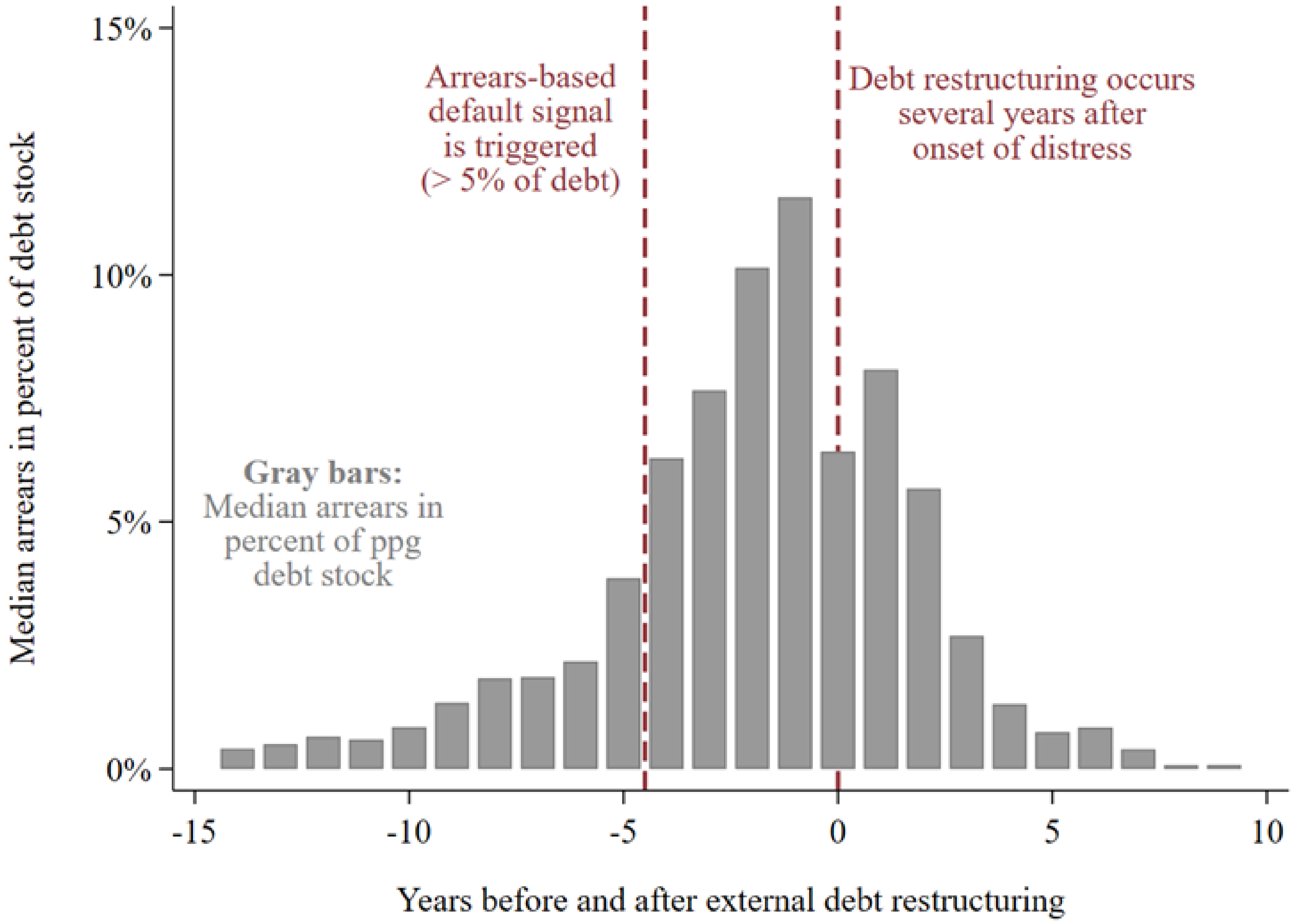
IMF Programs:
Rapid disbursements > 30 % of quota, all program types

Debt restructurings
Default assumed to start 1 year prior:
- Private creditors (Cruces & Trebesch)
- Paris Club creditors (Das et al.)

1.1 Measuring debt distress: signals

LIC DSF Review 2017 – reflects typical set of debt distress signals in the literature		**Our paper:**
Defaults on private creditors: Data from S&P and Catao & Milesi-Ferreti, whenever available	→	**Defaults on private creditors:** Comprehensive new data for all LICs from Farah-Yacoub et al. (2023)
Arrears: Arrears > 5% of ppg debt stock, for 3 years	→	**Arrears:** Arrears > 5% of ppg debt stock, for 3 years
IMF Programs: Rapid disbursements > 30 % of quota, all program types	→	**IMF Programs:** Rapid disbursements > 30 % of quota, only non-concessional programs / no RFI
Debt restructurings Default assumed to start 1 year prior: • Private creditors (Cruces & Trebesch) • Paris Club creditors (Das et al.)	→	**no restructuring signal – key timing point – see next two slides**

1.1 Measuring debt distress: timing of arrears and restructurings



- Restructurings mark conclusion rather than onset of distress (Asonuma & Trebesch 2016)
- Long and variable lags between defaults and restructurings (median of 4 years)

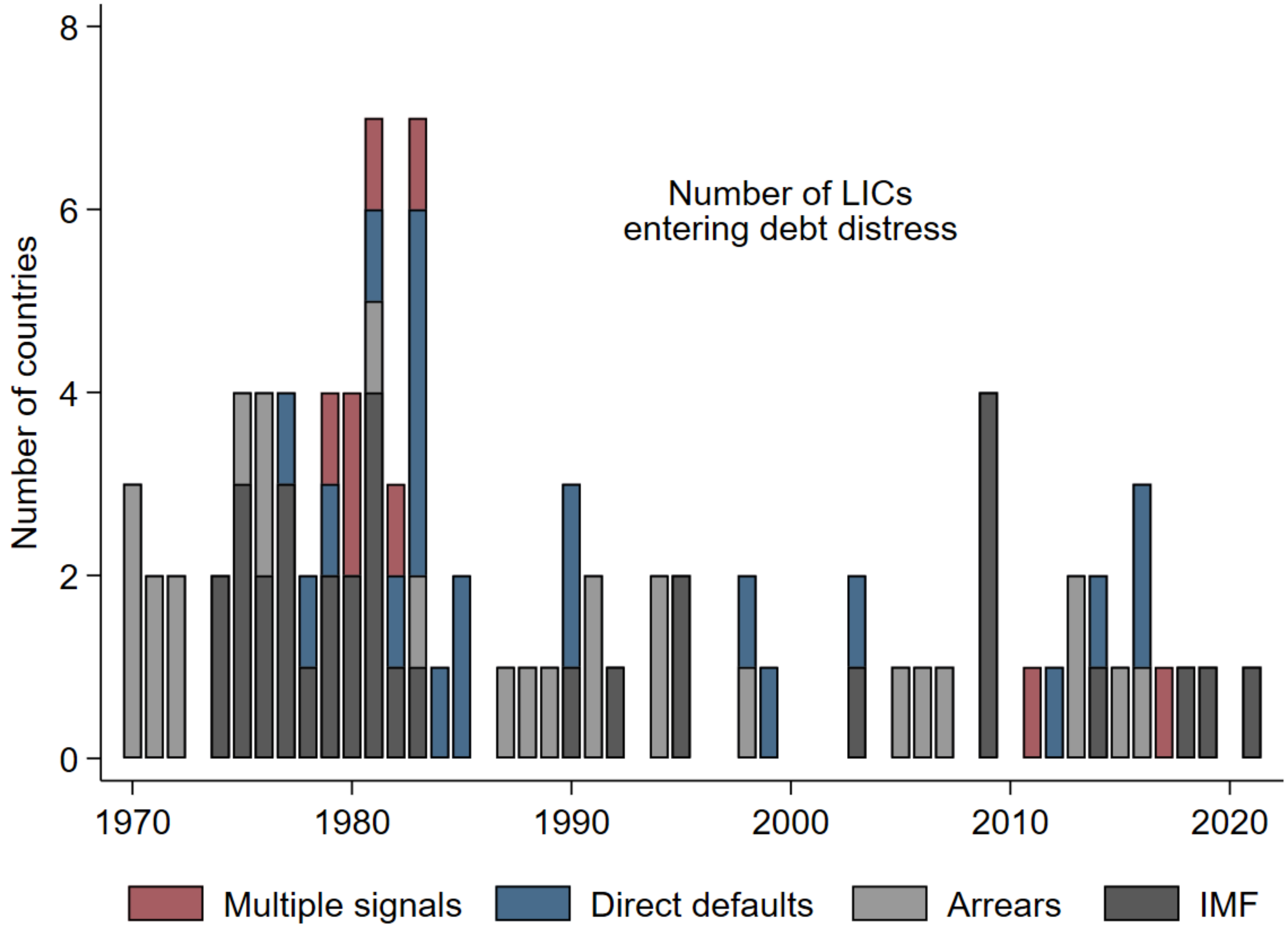
1.2 Measuring debt distress: episodes

- Define distress signal $S_{ct} = 1$ if any one of three distress signals is observed in country c and year t; $S_{ct} = 0$ otherwise
  - (1) defaults, (2) high arrears, (3) large and rapid IMF disbursement

- Define distress episode $Y_{ct+1} = 1$ if:
  - $S_{ct} = S_{ct-1} = S_{ct-2} = 0$: not currently/recently in distress, *and*
  - $S_{ct+1} = 1$: ***distress signal next year***

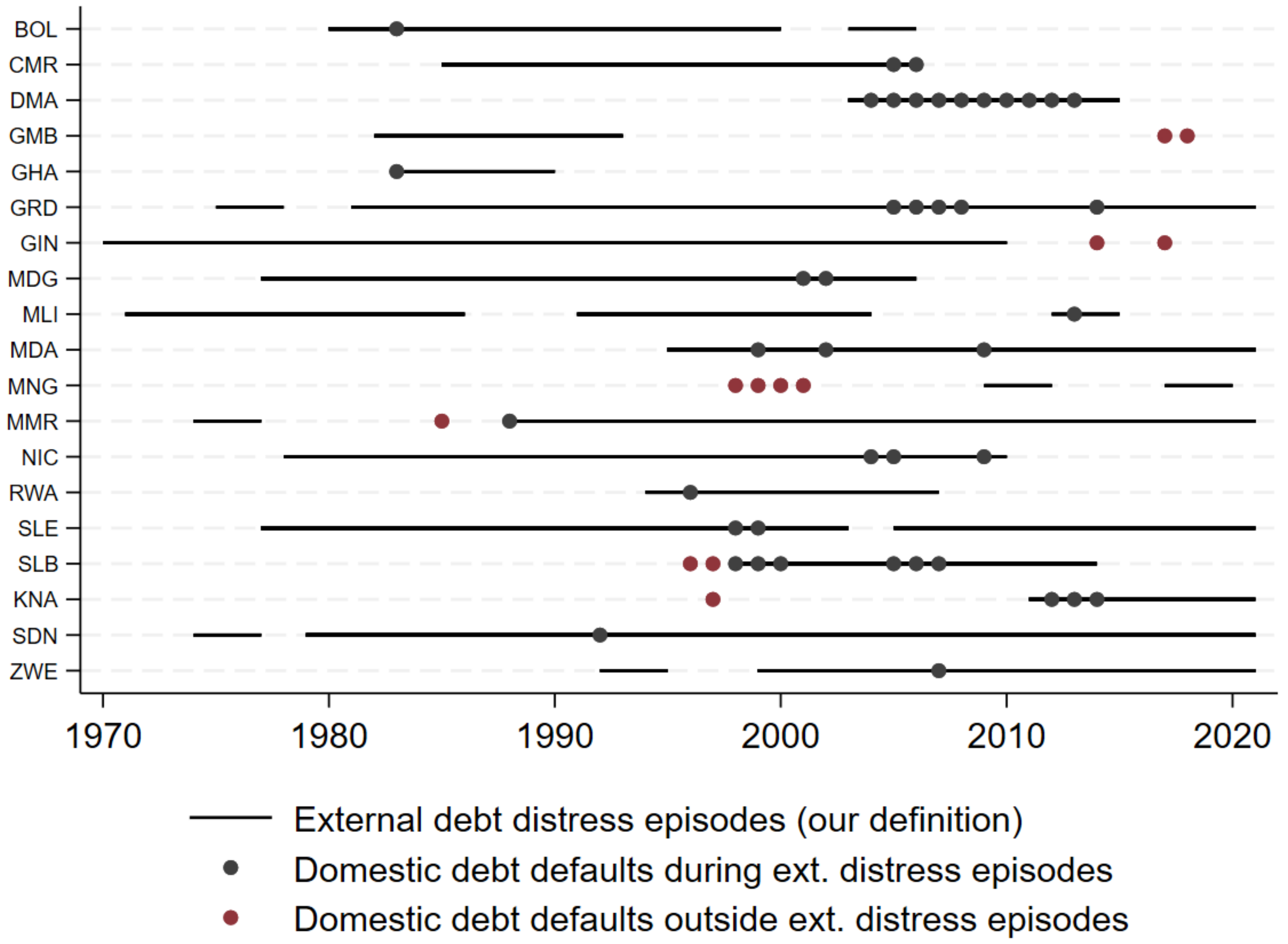
- Define non-distress episodes $Y_{ct+1} = 0$ if:
  - $S_{ct} = S_{ct-1} = S_{ct-2} = 0$: not currently/recently in distress, *and*
  - $S_{ct+1} = 0$: ***no distress signal next year***

1.3 Measuring debt distress: results



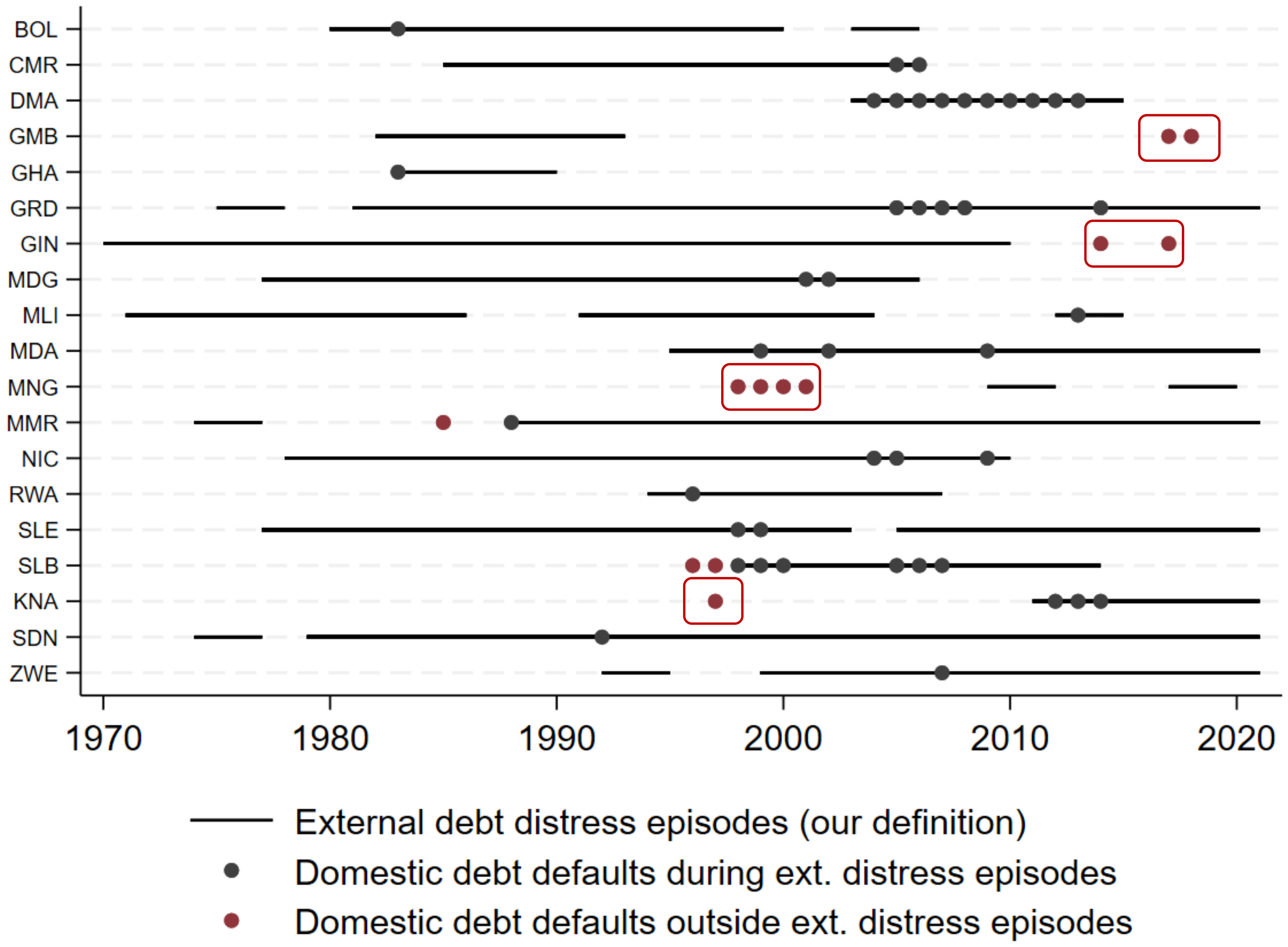
- Sample consists of 1,752 observations covering 80 LIC DSF-eligible countries 1970-2021
- 90 cases of debt distress represent 5.1 percent of sample
- Three signals of roughly equal importance in triggering distress episodes

1.4 Measuring debt distress: domestic debt



- Use data from IMF (2021) to capture 67 domestic debt restructurings in LICs
- No good binary measurement of other forms of default on domestic creditors (inflation, financial repression)
- Strongly correlated with external distress episodes (as expected)

1.4 Measuring debt distress: domestic debt



- Use data from IMF (2021) to capture 67 domestic debt restructurings in LICs (no data on default)
- Strongly correlated with external distress episodes (as expected)
- Yields only 4 new distress episodes

1. Measuring debt distress

2. Predicting debt distress

2.1 Predicting debt distress: probit model

- Estimate <u>predicted probability of distress</u> using probit model:

$$P[Y_{ct+1} = 1] = \Phi(\beta' X_{ct}), \quad \hat{p}_{ct+1} = \Phi(\hat{\beta}' X_{ct})$$

- Cutoff probability p^* generates <u>binary prediction</u> $\hat{Y}_{ct+1} = 1$ when $\hat{p}_{ct+1} > p^*$
  - False positive rate: $FPR = \left(\sum_{ct}(1 - Y_{ct+1})\, \hat{Y}_{ct+1}\right) / \sum_{ct}(1 - Y_{ct+1})$
  - False negative rate: $FNR = \left(\sum_{ct} Y_{ct+1}\left(1 - \hat{Y}_{ct+1}\right)\right) / \sum_{ct} Y_{ct+1}$)

- Select p^* to minimize quadratic mean prediction loss function:

$$L(FNR, FPR) = \sqrt{wFNR^2 + (1 - w)FPR^2}\ , \qquad w = 0.5$$

2.2 Predicting debt distress: standard covariates from **LIC DSF** and literature

- Debt indicators
  - PPG/GDP, PPG/Exports, **NPV/GDP, NPV/Exports, TDS/Exports, TDS/Revenue**, domestic debt/GDP, interest on public debt / Exports
- Policies and institutions
  - **Country Policy and Institutional Assessment (CPIA)**, years since last distress, decaying average of past distress
- Business cycle and level of development
  - **GDP growth**, inflation rate, depreciation rate, log GDP per capita
- Political cycle
  - years in office, years until end of term
- External environment
  - Current account balance, FDI inflows, **remittances**, change in TOT, 10-year US Treasuries rate, **reserves/imports**, trade openness, **world growth**

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  - Current account balance, FDI inflows, **remittances**, change in TOT, 10-year US Treasuries rate, **reserves/imports**, trade openness, **world growth**

2.2 Predicting debt distress: measurement challenges with domestic debt

- Domestic debt levels in LICs are on the rise, but systematic data remains scarce
- We construct series on *total public* (domestic plus external) debt to GDP by combining data from the IMF WEO, Abbas et al. (2010) and Reinhart and Rogoff (2009)
  - Near-complete coverage of country-year observations since 1970 in 2017 LIC DSF database
- Two main shortcomings:
  - Consistency of institutional coverage can not always be ascertained
  - Limited and noisy data on domestic debt *service* which matters most for debt distress in short run – longest available data covers only payments of *interest* not *principal*

2.3 Predicting distress: model space

- "Brute force" approach to model selection – consider models defined by *all* relevant combinations of RHS variables
  - With 28 covariates we would have $2^{28} \approx 268$ million models to study
  - With $(J = 10) \times (K = 10)$ cross-validation, 26 billion probit regressions to estimate
- To limit scope of task to substantively interesting models, we impose a set of restrictions on the model space:
  - CPIA always included (*for LIC DSF policy application, not very binding constraint)*
  - *At least one* debt variable (for LIC DSF policy application)
  - *At most one* debt stock (from PPG/GDP, PPG/Exp, NPV/GDP, NPV/Exp, PD/GDP, PD/Exp)
  - *At most one* debt service (from TDS/Exports, TDS/Revenues, PDI / Exp, PDI / Revenue)
  - *At most one* credit history (from years since distress, decaying average)
  - *At most one* political cycle (from years in office, years until end of term)
  - *At most one* change in value of money (from inflation, depreciation)
- With these restrictions, we consider 559,872 candidate prediction models

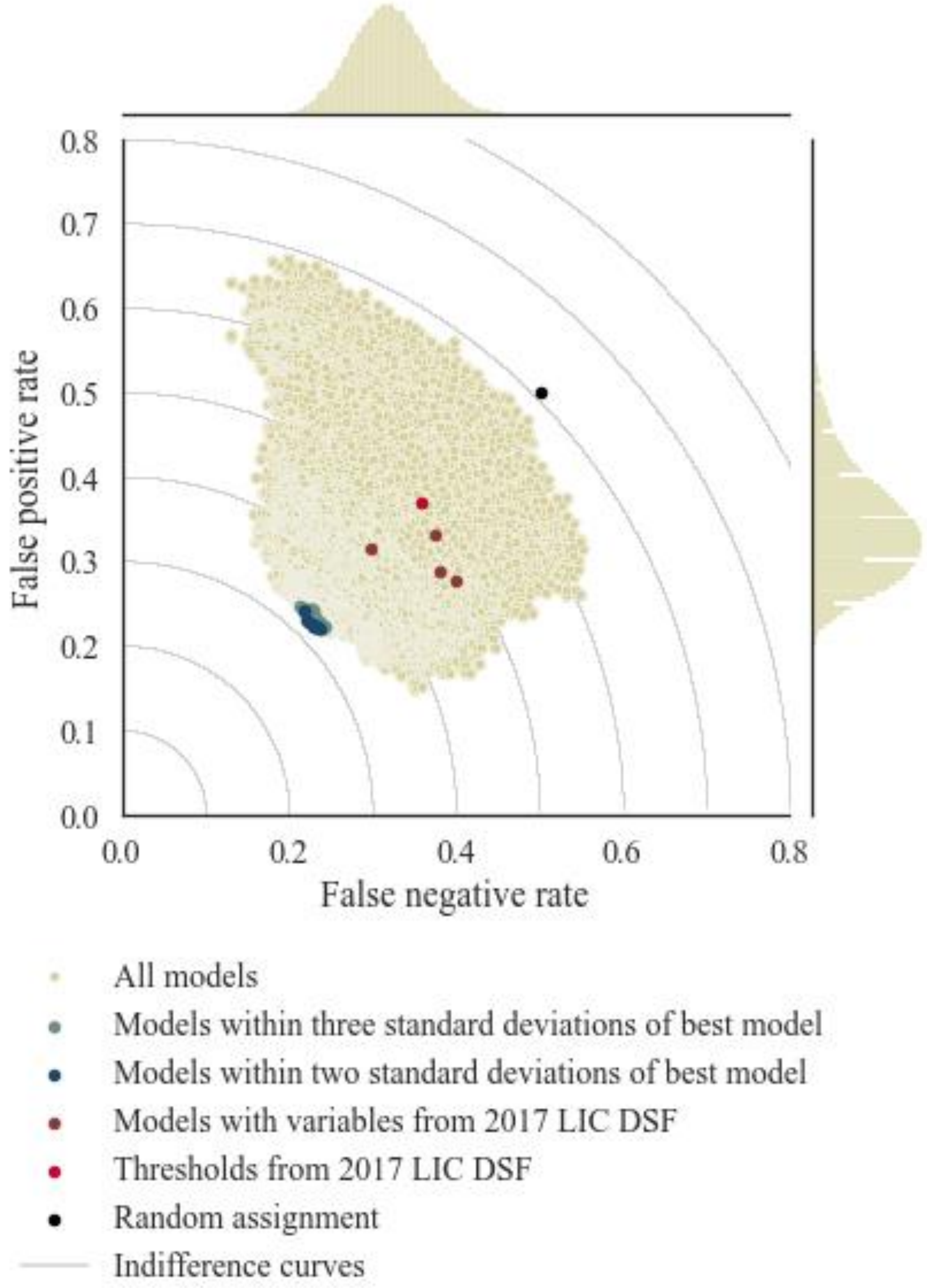
2.4 Predicting distress: cross-validation

- Evaluate models based on out-of-sample predictive performance using J-K-fold cross-validation

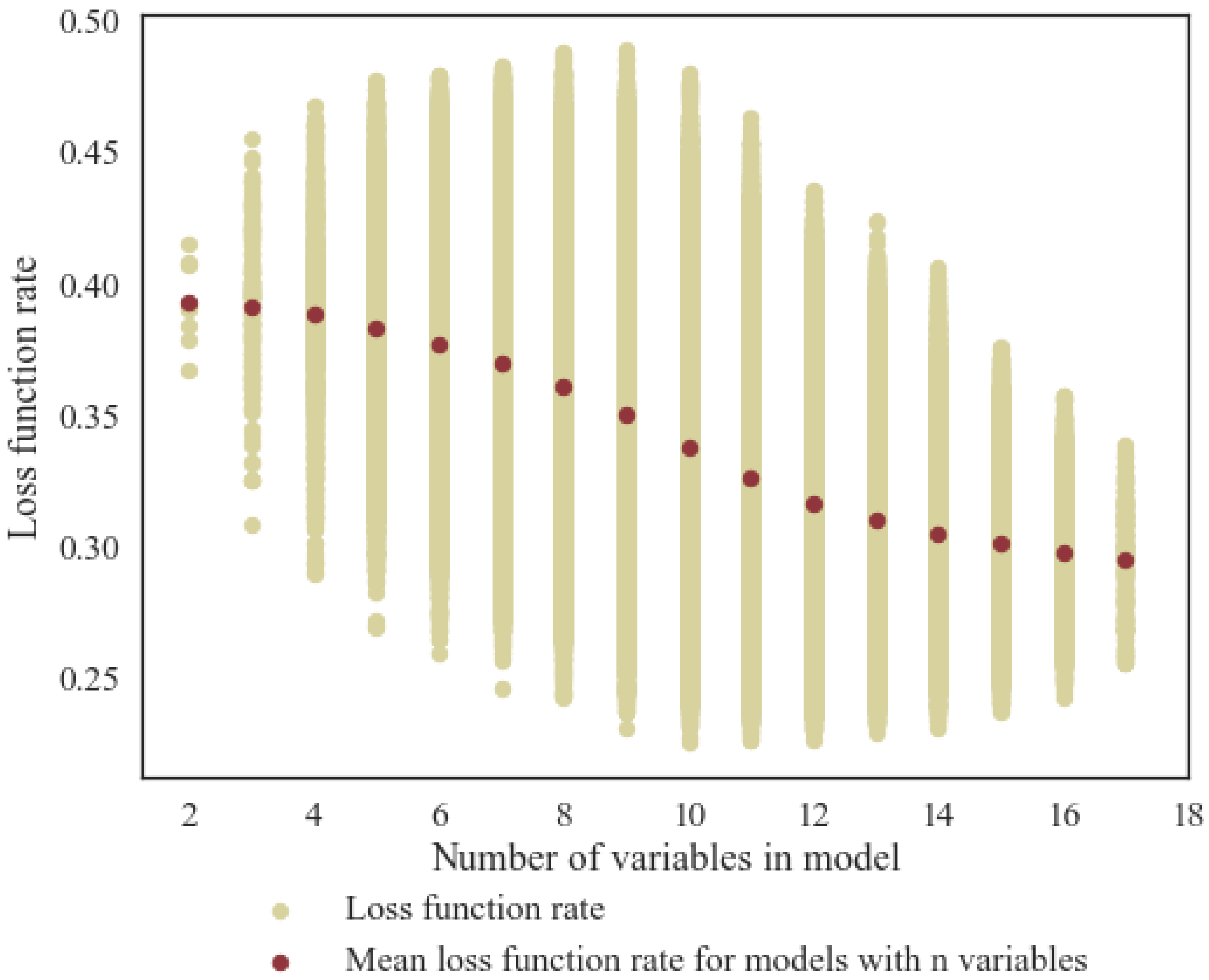
- For each combination of variables that defines a model:
  - Perform K-fold cross-validation for $K = 10$ exhaustive folds
    - *Estimate* probit model in training sample
    - *Select* p^* that minimizes prediction loss function in test sample
  - Repeat $J = 10$ times, retrieving minimized FPR, FNR, and $L(FNR, FPR)$
  - Calculate mean of FPR, FNR, and $L(FNR, FPR)$ across $J = 10$ replications
  - Construct confidence interval for $L(FNR, FPR)$

2.5 Predicting distress: results

- Each point represents the cross-validated loss function (FPR-FNR pair) of a model
- Better models are closer to origin (curves indicate isoquants of prediction loss function)
- Inherent uncertainty about single “best” model, so define set of “good” models shaded blue (L is within 2 or 3 SDs of best model)
- Good models substantially outperform individual probit specifications (dark red dots) and threshold rules (bright red dot) from 2017 LIC DSF



2.6 Predicting distress: parsimony vs. performance



- Some tradeoffs between model size and predictive performance
- Average predictive performance improves modestly with model size (red dots)
- Best model performance conditional on size is U-shaped in model size (lower envelope of yellow points)

2.7 Predicting debt distress: best models

- Our algorithms turn up many (many!) good models that outperform models in 2017 LIC-DSF
    - 431K models (77%) outperform 2017 LIC-DSF mechanical predictions
    - 395K models (71%) outperform best single probit with 2017 LIC-DSF variables

- To guide selection of "best models" we impose three further conditions:
    1. No perverse incentives: $\hat{\beta}_{CPIA} < 0, \hat{\beta}_{DEBT} > 0$
    2. Data availability: *data on all variables in model available for at least 90% of country-year observations since 2000.*
    3. Meaningful effect size: $\beta_x^{marginal}\ \sigma_x / \sigma_y > 0.05$ *(top 20 percent)*

2.7 Predicting distress: selected best models

	Dependent variable: Incidence of external sovereign debt distress in t+1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CPIA	-0.15**	-0.10*	-0.12**	-0.08*	-0.08**	-0.06	-0.11**
Ext. debt service / exports	0.22***	0.19***	0.18***	0.17***	0.17***	0.15***	
Reserves / imports		-0.24***		-0.21***	-0.17***	-0.15**	-0.17*
GDP p.c.			0.18***	0.14***	0.16***	0.13**	0.25***
Inflation			0.11**		0.09**		0.11
GDP growth				-0.09**		-0.09*	
Credit history					-0.07		-0.07
Commodities terms of trade						-0.08*	-0.09
US 10 year yield						0.08*	0.12*
Openness							-0.10
CA balance / GDP							-0.06
Ext. debt stock / exports							0.09
Number of variables	2	3	4	5	6	7	10
Loss function	0.37	0.31	0.29	0.27	0.26	0.27	0.29
False positive rate	0.37	0.32	0.33	0.21	0.25	0.19	0.30
False negative rate	0.36	0.30	0.24	0.32	0.28	0.34	0.27
Data coverage since 2000	0.96	0.94	0.91	0.93	0.91	0.92	0.92
Number of observations	1,002	1,002	1,002	1,002	1,002	1,002	1,002

- Model with only six regressors minimizes prediction loss function ($L = 0.26$)

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- Very parsimonious model with only three predictors does almost as well ($L = 0.31$) – "*Best Parsimonious Model*" *(BPM)*

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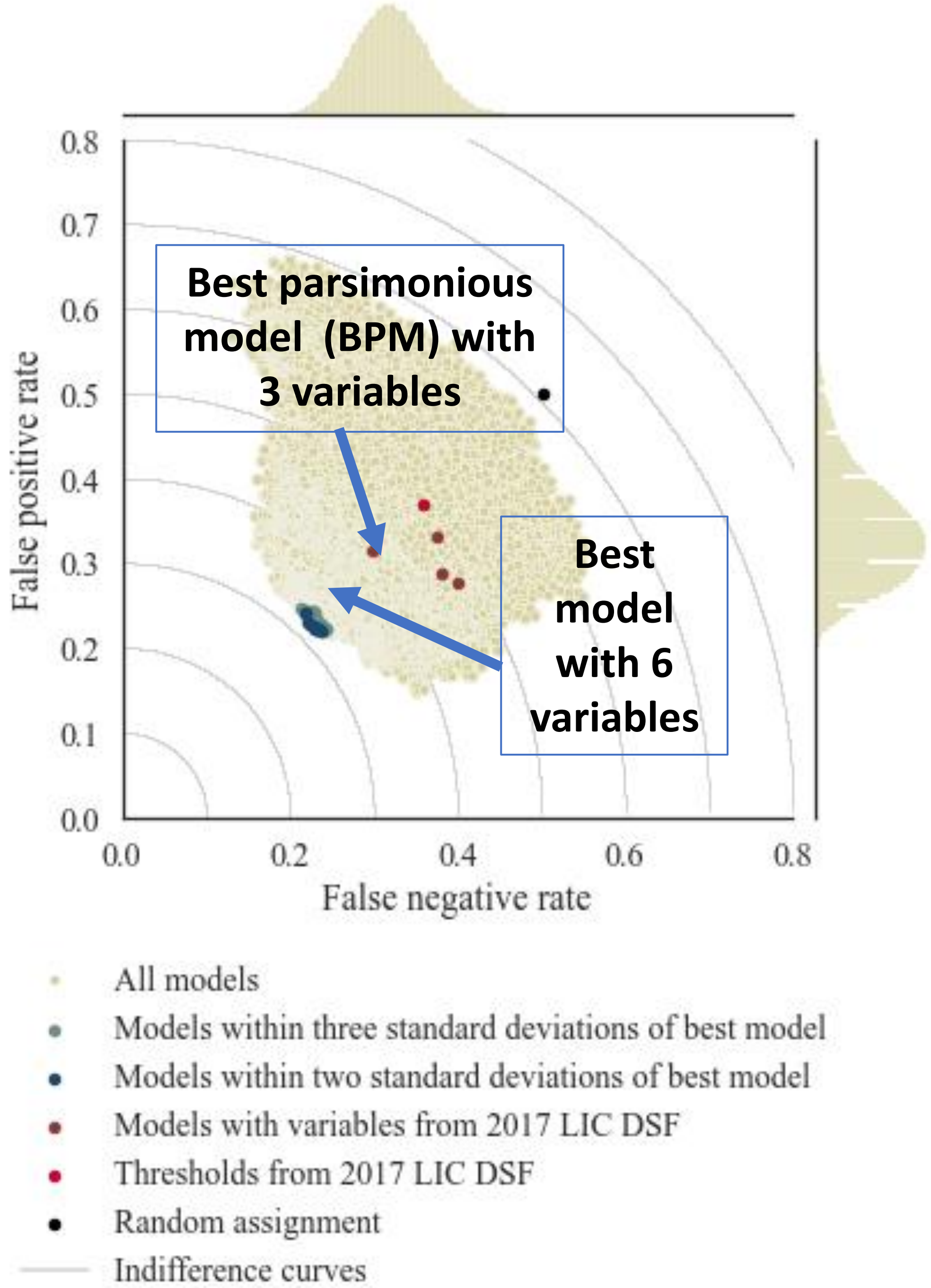
- Very parsimonious model with only three predictors does almost as well ($L = 0.31$) – *"Best Parsimonious Model" (BPM)*
- Total debt service on external debt is only debt indicator that features consistently in best models
- Fairly balanced FPR and FNR (due to choice of quadratic loss function)

2.7 Predicting distress: selected best models

- Best models that satisfy three constraints (no perverse incentives, data availability, economically meaningful effects) are still very good performers



1. Measuring debt distress

2. Predicting debt distress

3. More sophisticated models

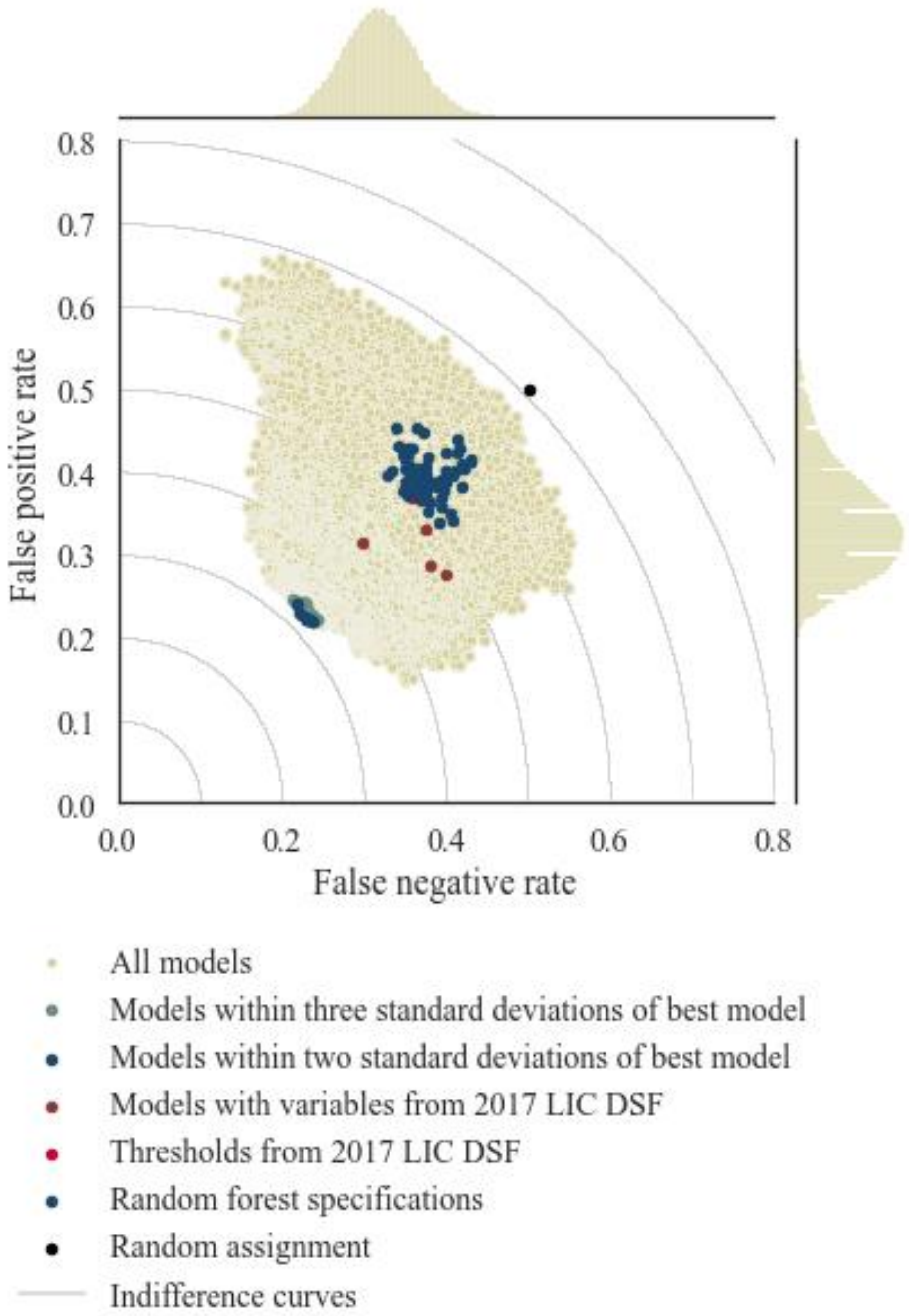
3.1 More sophisticated models: RF

- Probit model is very simple – can more sophisticated prediction algorithms generate better out-of-sample predictions?
- Consider random forest (RF), apply in same sample, with same J-K-fold cross-validation
- Perform grid search over three key tuning parameters to find best RF model:
  - Node purity criterion
  - Number of trees
  - Depth of trees

3.2: More sophisticated models: results

- Best RF does significantly worse in predicting debt distress than simple linear probit models
  - FPR=0.35 (vs. 0.32 in BPM)
  - FNR=0.37 (vs. 0.30 in BPM)

- Suggestive of general principle that more sophisticated ML prediction algorithms add little value in small datasets with small number of predictors



1. Measuring debt distress

2. Predicting debt distress

3. More sophisticated models

4. LIC DSF implications

4.1 LIC DSF implications: better predictions

- Apply old LIC-DSF model to our new sample of events through 2021
  - New model predicts much better than mechanical predictions from LIC-DSF model
  - *Not entirely fair comparison because LIC-DSF model was trained on different sample and a different definition of events*

	Predicted by Best Parsimonious Model		**Predicted by 2017 LIC DSF Model**	
Actual	No distress	Distress	No distress	Distress
No distress	903	394	814	483
Distress	15	44	19	40
False positive rate	0.30		0.37	
False negative rate	0.25		0.32	
Quadratic loss function	0.28		0.35	

4.2 LIC-DSF implications: better predictions

- Re-estimate Best Parsimonious Model in 2017 LIC-DSF sample, with old dependent variable and linear loss function from previous review
  - Pick cutoff probability to match in-sample predictive performance
  - Best parsimonious model does slightly better than more complex 2017 LIC-DSF model
  - *Not entirely fair comparison for BPM because its predictor list was selected in a different sample*

	Predicted by Best Parsimonious Model		Predicted by 2017 LIC DSF Model	
Actual	No distress	Distress	No distress	Distress
No distress	172	156	206	122
Distress	9	54	13	50
False positive rate	0.48		0.37	
False negative rate	0.14		0.21	
Linear loss function	0.25		0.26	

4.3 LIC-DSF implications: optimism bias

- LIC DSF predicts debt distress based on whether projected future debt ratios cross thresholds implied by probit regressions
  - Predicting debt ratios into the future is difficult (numerator and denominator)
  - Risk of optimism bias

- Instead of "*predicting the predictors*" of debt distress, how well can current values of predictors predict distress k periods into the future?

- Define new dependent variable $Y_{ct+k} = 1$ if :
  - $S_{ct} = S_{ct-1} = S_{ct-2} = 0$: not currently/recently in distress, *and*
  - $\max(S_{ct+1}, \dots, S_{ct+k}) = 1$: distress signal **any time in next $\boldsymbol{k = 5}$ years**

4.3 LIC-DSF implications: 5-year predictions

- 5-year-ahead predictions are nearly as good as or even better than one-year-ahead predictions, e.g. for 3-variable model
  - FP=0.30 (compared with 0.32 for one-year-ahead)
  - FN=0.29 (compared with 0.30 for one-year-ahead)
- Suggests scope to improve LIC-DSF by reducing reliance on predicted future debt ratios

	Dep. variable: Incidence of external sovereign debt distress within next five years						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CPIA	-0.41***	-0.41***	-0.36***	-0.37***	-0.31***	-0.32***	-0.33***
Ext. debt service / exports	0.66***	0.72***	0.66***	0.64***	0.55***	0.51***	0.63***
GDP p.c.		0.59***	0.60***	0.64***	0.53***	0.60***	0.57***
Inflation			0.19**	0.18**			
Openness				-0.09		-0.15	-0.17
CA balance / GDP					-0.25***	-0.29***	-0.21***
Credit history					-0.30***	-0.28***	-0.28***
US 10 year yield					0.31***	0.31***	
Reserves / imports							-0.27***
Y.o.y. change in FX rate							-0.24***
Number of variables	2	3	4	5	6	7	8
Loss function	0.40	0.30	0.29	0.29	0.28	0.28	0.28
False positive rate	0.41	0.30	0.30	0.30	0.29	0.26	0.27
False negative rate	0.40	0.29	0.27	0.27	0.28	0.29	0.28
Data coverage since 2000	0.96	0.93	0.91	0.91	0.93	0.93	0.93
Number of observations	899	899	899	899	899	899	899

Summary of Findings

- Improved and simplified definition of debt distress
- Systematic approach to model selection generates better predictions
- Low return to prediction model complexity – probit dominates RF
- Five-year-ahead predictions almost as good as one-year-ahead predictions
- Scope to simplify prediction model to make LIC-DSF more transparent