Combining Artificial and Expert Intelligence: Using Machine Learning to Improve the World Economic Outlook

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February 4, 2019

Motivation

- Traditional macroeconomic forecasts (e.g. WEO) use country-specific expertise
- Key trade-off: using the past to predict the future...
  - bias $\downarrow$ ...
  - but variance $\uparrow$
- WEO forecasts tend to overfit (Hellwig, 2018) $\rightarrow$ variance $\uparrow$
- **This paper:** explore to what extent Machine Learning (ML) models can improve expert forecasts in WEO
  - without additional data
  - 1- to 5-year horizons
  - full sample of countries

Approach

- Thought experiment:
  - give WEO data to data scientist at time of publication
  - how do predictions of non-expert compare to WEO?
- Goal is not to get most accurate prediction, rather:
  - compare performance of ML models with WEO
  - identify setting in which ML and WEO complement each other
- Study complements Jung et al. (2018) Literature
  - no additional data → minimal information set
  - cover *all* countries

Motivation: Current Approach

WEO forecast errors are consistently higher (r.t. average) in at least three different settings:
→ Ahir & Loungani (2014); Jalles et al. (2015); Eicher et al. (2018); Bluedorn & Leight (2018)

1. During periods of low growth ('optimism') Details
2. In low-income countries Details
3. During recessions Details

Summary of Findings (2013-2016, 1-year)

Can we use ML models to improve macro-economic forecasting?
$\rightarrow$ **14-19% $\downarrow$ RMSE overall**

- Gains are driven by
  1. countries w/ real GDP growth $<$ median
  2. countries w/ real GDP p.c. $<$ median

- ML models are not necessarily better at predicting recessions...
  - ...but help make the role of **(a)symmetric loss function** explicit

Outline

1. Machine Learning Models
   - What, Why, When
2. Method
   - Data
   - Approach
3. Results
   - 3.1 Real economic growth
   - 3.2 Contractions ('recessions')
4. Conclusion

ML Models for Macroeconomic Forecasting

- Algorithms purely focused on predicting y using data from x
- Traditionally used for static, cross-section prediction
  - e.g. customer recommendations, image and speech recognition
- Practical challenges for dynamic forecasts in macroeconomic context
  1. Underlying process more volatile
  2. Lack of large, complete, training datasets
  3. Panel structure
  4. Data revisions are common

Why and When Use ML Models for Macroeconomic Forecasting?

Strengths

1. Generally outperform other quantitative models for prediction
2. Unbiased w.r.t. irrelevant context
3. Use *all* available data
4. Can be tuned to focus on predicting specific events (e.g. recessions)

Weaknesses

1. $\longleftrightarrow$ hard to understand mechanisms ('black box')
2. $\longleftrightarrow$ vulnerable to relevant changes in context
3. $\longleftrightarrow$ reliant on large, high-quality datasets
4. $\longleftrightarrow$ 'dumb' and reliant on model and variable selection by researcher

What Are ML Models?

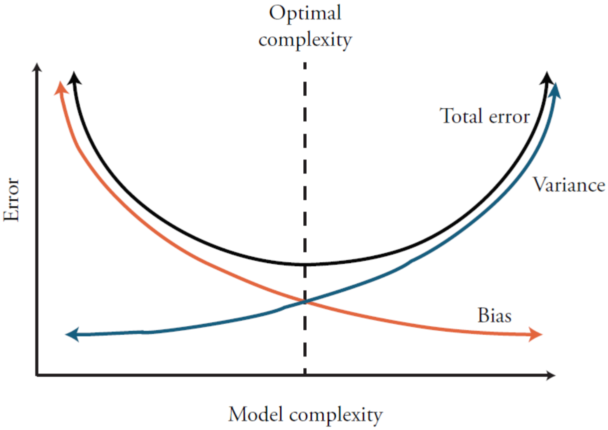
Prediction problem:

- $y_i = f(X_i, \boldsymbol{\beta}) + \epsilon_i$
- $\min_{\boldsymbol{\beta},\boldsymbol{\alpha}} \sum_{i=1}^{N} L(y_i - f(X_i, \boldsymbol{\beta})) \qquad s.t. \quad \boldsymbol{\beta} \in \Theta(\boldsymbol{\alpha})$
  - $\boldsymbol{\beta}$ are parameters that determine specific function
  - $\boldsymbol{\alpha}$ are 'tuning parameters' or 'regularizers' that determine model complexity

Function $\tilde{f}(\boldsymbol{\alpha}, \boldsymbol{\beta}, X_i)$ maps input data (X_i) to prediction (y_i).

Bias-Variance Trade-Off

$$L(z) = z^2 \rightarrow \mathbb{E}[L(\tilde{f}(\cdot) - f(\cdot))] = \text{Bias}[\tilde{f}(\cdot)]^2 + \text{Var}[\tilde{f}(\cdot)] + \text{Var}[\epsilon_i]$$



Source: Smalter Hall (2018)

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  - $\boldsymbol{\beta}$ are parameters that determine specific function
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Function $\tilde{f}(\boldsymbol{\alpha}, \boldsymbol{\beta}, X_i)$ maps input data (X_i) to prediction (y_i).

Estimation (i.e. picking $\tilde{f}(\cdot)$) consists of 3 steps:

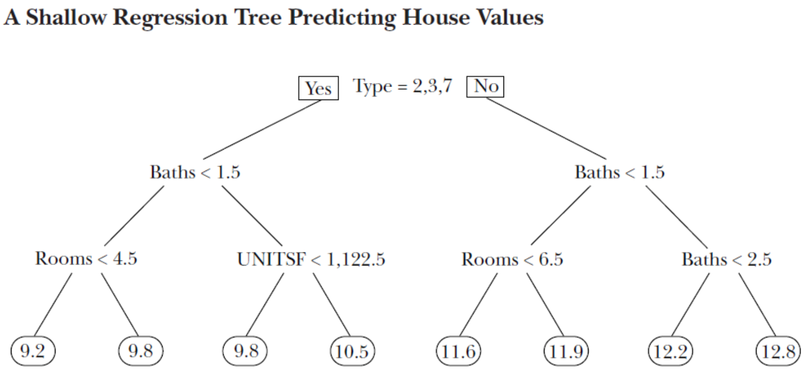
1. Given $\boldsymbol{\alpha}$, pick loss-minimizing $\hat{\boldsymbol{\beta}}$ for subset (training) of data
2. Predict $\hat{y}_i = f(x_i, \hat{\boldsymbol{\beta}})_{|\boldsymbol{\alpha}}$ for remaining (test) data
3. Pick $\boldsymbol{\alpha}$ with lowest loss for test data

Linear Methods (OLS, LASSO, Ridge, Elastic Net)

- $\min_{\beta}\{\sum_{i=1}^{N}(y_i - \beta_0 - \sum_{k=1}^{K}\beta_k x_{ik})^2\}$
    - $s.t. \sum_{k=1}^{K}\gamma|\beta_k| + (1-\gamma)(\beta_k)^2 \leq \lambda$

1. OLS
    - $\lambda \rightarrow \infty$
2. LASSO
    - $\gamma = 1$
3. Ridge
    - $\gamma = 0$
4. Elastic Net
    - $\gamma \in (0,1)$

Decision Trees



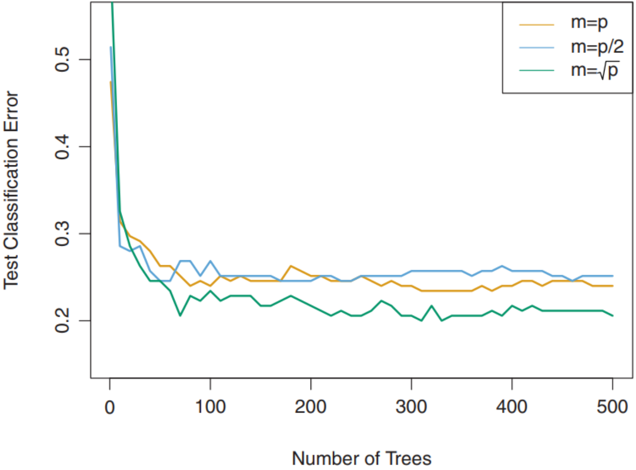
Source: Mullainathan & Spiess (2017)

Random Forest (1)

- Exploits 'wisdom of the crowd' to reduce variance
- Use different trees as building blocks

1. Take bootstrap sample
   - 'experience'
2. At each split, use only randomly chosen m out of p predictors
   - 'expertise'
3. Aggregate predictions of trees for each observation

Random Forest (2)



Source: James et al. (2013). Gene classification with $p = 500$ predictors. Single classification tree has test classification error of 0.457.

Generalizing ML Models

Method	β	**Most common** α
OLS	regression coefficients	-
LASSO	regression coefficients	$\sum_{k=0}^{K} \lvert\beta_k\rvert \leq \lambda_L$
Ridge	regression coefficients	$\sum_{k=0}^{K} (\beta_k)^2 \leq \lambda_R$
Elastic Net	regression coefficients	λ, lasso weight
Decision tree	splits	depth, # of leaves, obs. per leaf
Random forest	aggregation rule	# vars, obs. per bootstrap

Data

Data

- Original 2004-2016 World Economic Outlook (April)
  - Impute missing data using random forests
- Merge w/ real GDP growth from 2018 World Economic Outlook (April)
  - take as actual outcomes

Variable Selection

- Only country-level
- Only variables w/ $> 75\%$ coverage
- Log-level, log-difference, 1-5 year lags

Variables

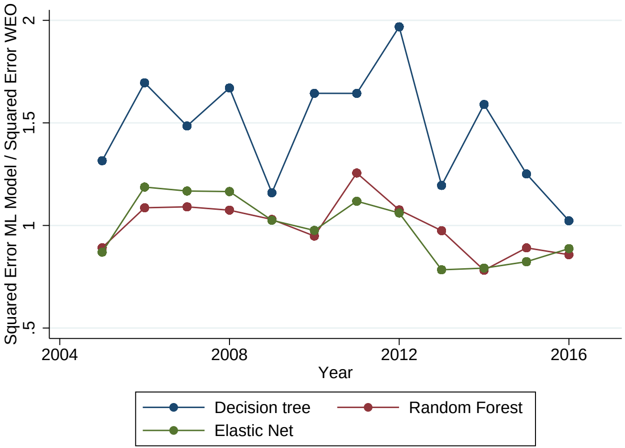
Approach

- $y_{it} = f(x_{i,t-1}, x_{i,t-2}, x_{it,-3}, x_{it,-4}, x_{i,t-5}, \beta) + \epsilon_{it}$
  - y_{it}: y-o-y real GDP growth in %
- Loss function: $L(z) = z^2$ (squared error)
  - in addition, use $L(z) = |z|$ (absolute error)
  - evaluate both mean and median
- Models:
  - Elastic Net
  - Individual decision tree
  - Random forest
- Focus on 2013-2016 period for 1-, 3-, 5-year ahead
  - results qualitatively robust

Learning Rate of ML Models r.t. WEO

All three ML models improve over time r.t. WEO

Extra



1-year Squared Error, 2013-2016

19% and 14% ↓ RMSE for Elastic Net and Random Forest

	WEO	Elastic Net	Decision Tree	Random Forest
RMSE	5.9	4.8	7.7	5.1
RMedSE	1.4	1.4	2.3	1.3
SD SE	248	176	593	198
R-Max.SE	63	60	123	57

RMSE: root-mean-squared error; RMedSE: root-median-squared error; SD SE: standard deviation of squared error; R-Max.SE: root of maximum squared error.

3-year Squared Error, 2013-2016

17% and 13% ↓ RMSE for Elastic Net and Random Forest

	WEO	Elastic Net	Decision Tree	Random Forest
RMSE	5.4	4.5	7.4	4.7
RMedSE	1.5	1.4	2.6	1.5
SD SE	174	126	257	135
R-Max.SE	45	41	64	41

RMSE: root-mean-squared error; RMedSE: root-median-squared error; SD SE: standard deviation of squared error; R-Max.SE: root of maximum squared error.

5-year Squared Error, 2013-2016

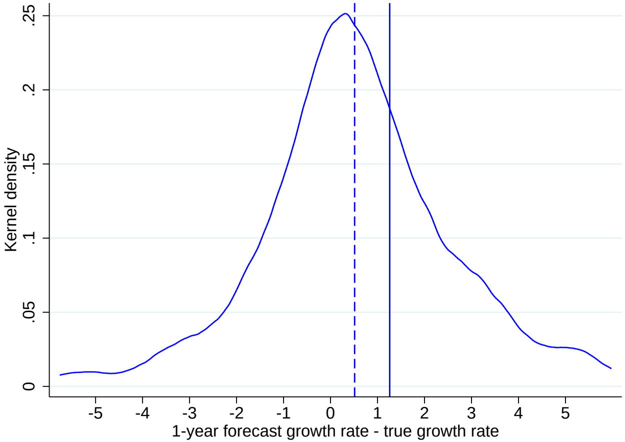
2% and 2% ↓ RMSE for Elastic Net and Random Forest

Extra

	WEO	Elastic Net	Decision Tree	Random Forest
RMSE	5.2	5.1	6.3	5.1
RMedSE	1.7	1.5	2.4	1.5
SD SE	195	182	186	187
R-Max.SE	61	58	58	59

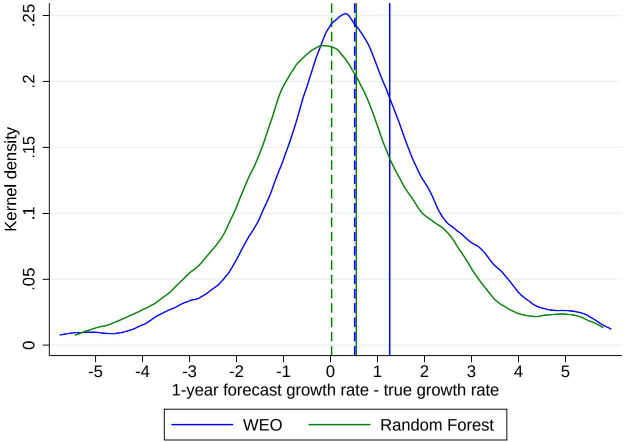
RMSE: root-mean-squared error; RMedSE: root-median-squared error; SD SE: standard deviation of squared error; R-Max.SE: root of maximum squared error.

1-year Error Rate: WEO



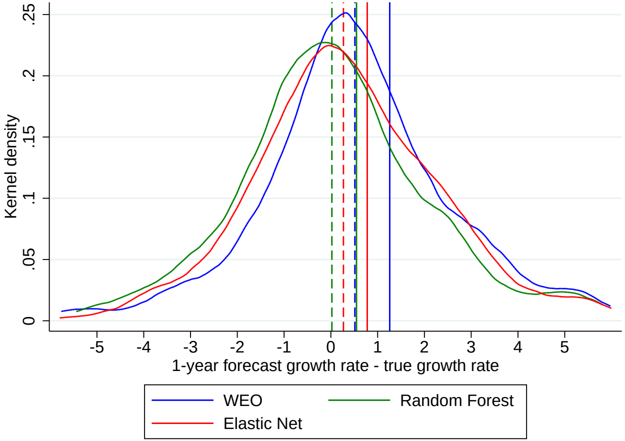
Vertical lines: (a) Solid blue: **mean** WEO error rate; (b) dashed blue: **median** WEO error rate.

1-year Error Rate: WEO and Random Forest



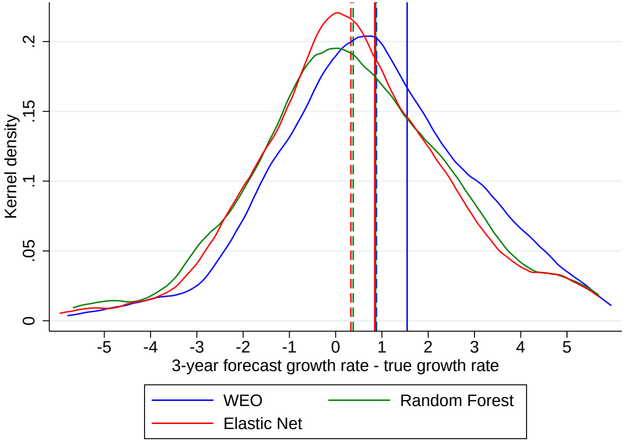
Vertical lines: (a) Solid blue: **mean** WEO error rate; (b) dashed blue: **median** WEO error rate; (c) solid green: **mean** RF error rate; (d) dashed green: **median** RF error rate.

1-year Error Rate: WEO, Random Forest, and Elastic Net



Vertical lines: (a) Solid blue: **mean** WEO error rate; (b) dashed blue: **median** WEO error rate; (c) solid green: **mean** RF error rate; (d) dashed green: **median** RF error rate; (e) solid red: **mean** EN error rate; (f) dashed red: **median** EN error rate.

3-year Error Rate: WEO, Random Forest, and Elastic Net



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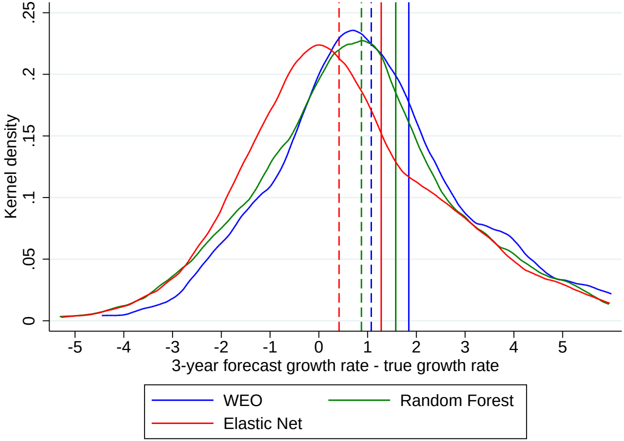
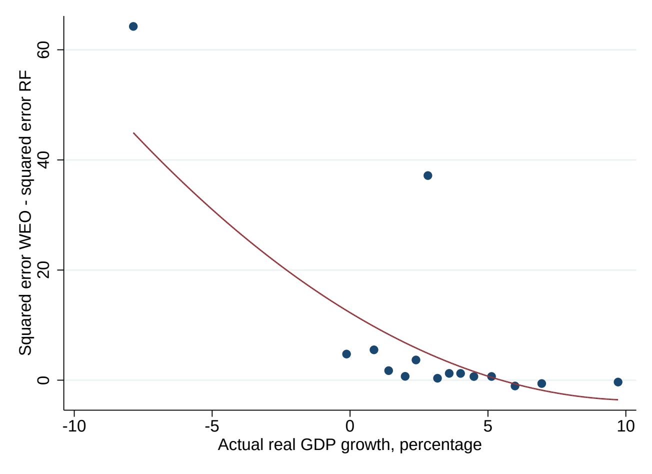
5-year Error Rate: WEO, Random Forest, and Elastic Net



Vertical lines: (a) Solid blue: **mean** WEO error rate; (b) dashed blue: **median** WEO error rate; (c) solid green: **mean** RF error rate; (d) dashed green: **median** RF error rate; (e) solid red: **mean** EN error rate; (f) dashed red: **median** EN error rate.

Performance in low growth years (1)

Random Forest outperforms in periods of low growth ⏩ Extra

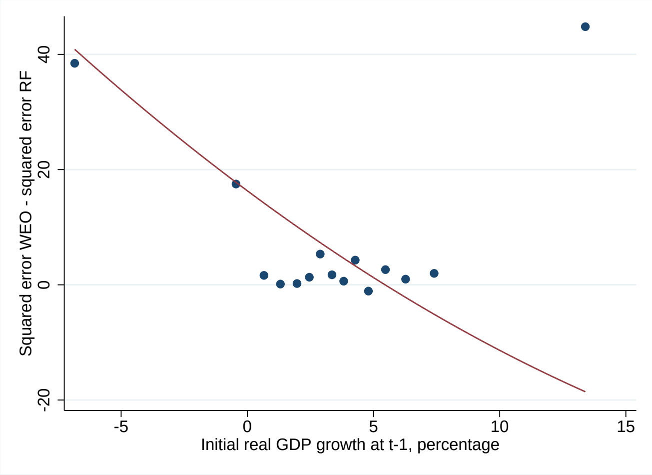


Binned scatter plot; y-variable represents mean value of 15 equally-sized bins.

Performance in low growth years (2)

Random Forest outperforms in *initially* slower growing countries

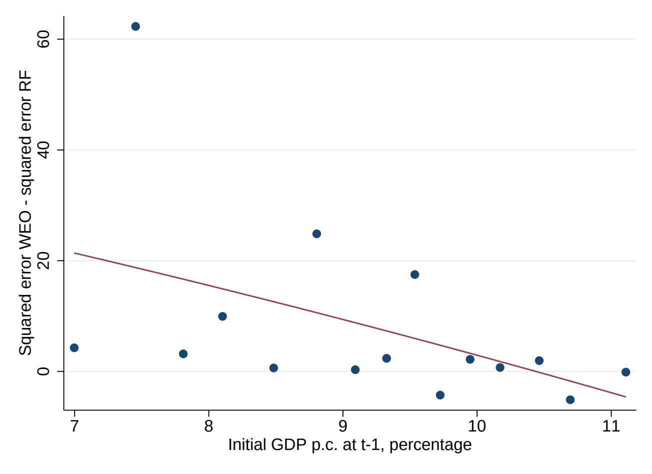
Extra



Binned scatter plot; y-variable represents mean value of 15 equally-sized bins.

Performance and GDP p.c.

Random Forest outperform in *initially* poorer countries ⏩ Extra



Binned scatter plot; y-variable represents mean value of 15 equally-sized bins.

Regression framework

Robust in regression framework (Random Forest)

Extra

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Real GDP growth	-5.654**	-5.982***	-5.994***	-2.902*
	(2.231)	(2.278)	(2.169)	(1.473)
Log GDP p.c., t-1		-9.704*	-6.482*	-0.994
		(4.956)	(3.607)	(2.009)
Africa			18.64	15.48**
			(13.53)	(7.408)
Asia			10.06*	5.738
			(5.874)	(4.806)
Europe			1.458	-2.093
			(6.527)	(3.428)
Latin America			-5.213	0.653
			(6.313)	(2.652)
Year FE	Y	Y	Y	Y
Continent FE	N	N	Y	Y
Observations	741	741	741	2176
Adjusted R^2	0.101	0.118	0.122	0.045

Standard errors in parentheses, clustered at country-level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

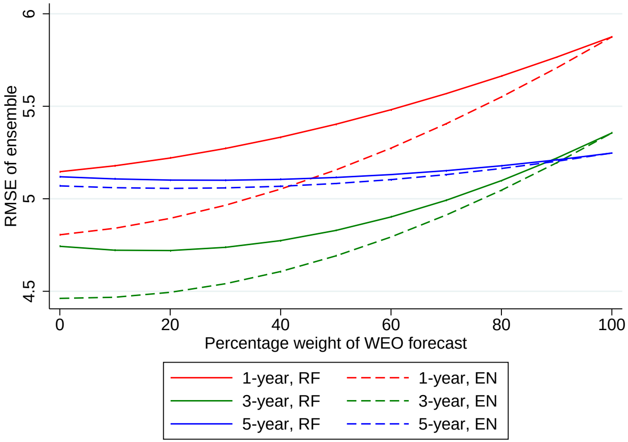
Mean squared error difference between WEO and RF $\approx$ 8.0. Column (4) runs full regression on 2004-2016 sample.

Combining ML and WEO Predictions

- ML models outperform in most settings
- What about a combination of ML models and WEO?
  $\rightarrow$ complementarity between expert and ML expertise
- Combine by taking convex combination (ensemble) predicted growth rates
  - e.g. $y_i^{convex} = 0.5 \cdot y_i^{RF} + 0.5 \cdot y_i^{WEO}$

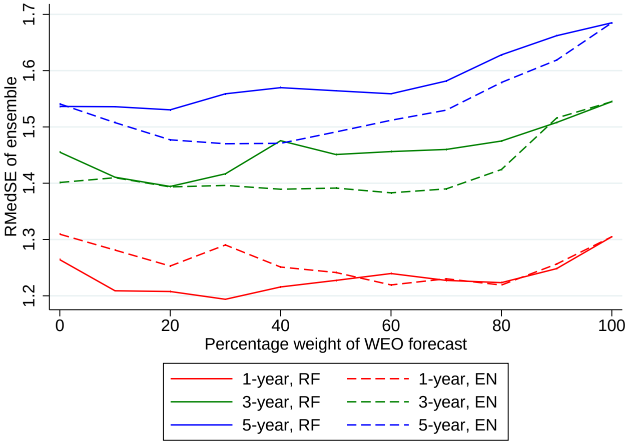
Ensemble of WEO and RF forecasts

WEO adds only little to ensemble in terms of RMSE ⏩ Extra



Ensemble of WEO and RF forecasts

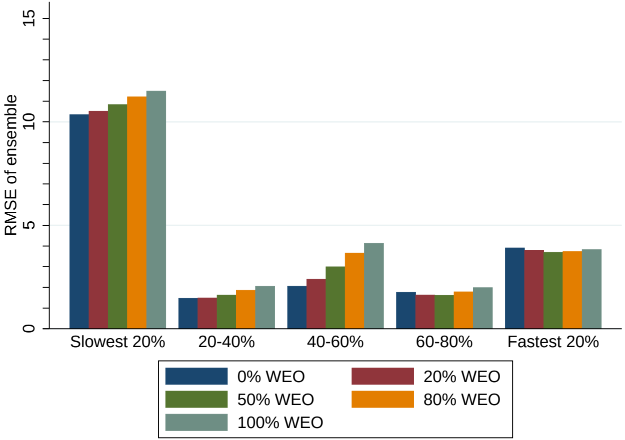
20-30% WEO minimizes RMedSE ⏩ Extra



1-year forecasting gains: actual growth

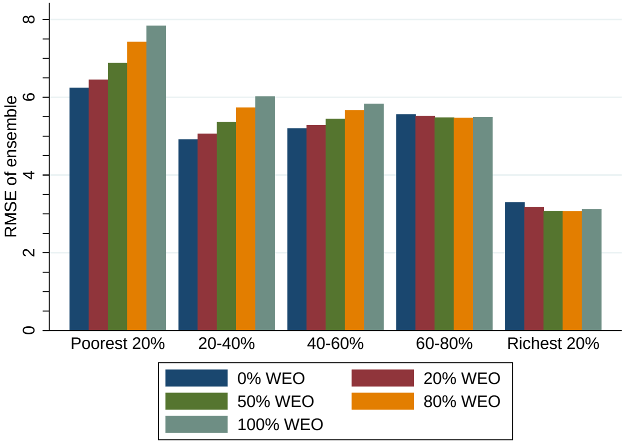
Ensemble slightly improves RMSE for two fastest growing quintiles

Extra

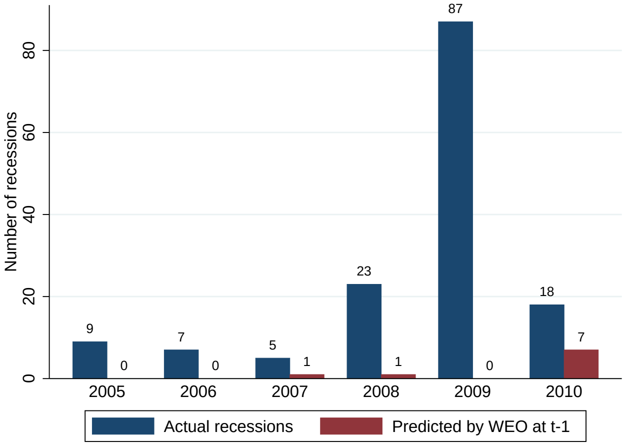


1-year forecasting gains: initial GDP p.c.

Ensemble slightly improves RMSE for two richest quintiles



WEO forecasts miss most recessions



Notes

Formalizing the Asymmetric Loss Function

- WEO: many false negatives $\longleftrightarrow$ few false positives
- Recessions occur only $\approx$ 14 % of years
  $\rightarrow$ need asymmetric loss function to call *any* recessions
- ...at cost of false positives ('can't miss if you don't shoot')
- ML models can help make this trade-off explicit
  - use random forest classification model with variable loss function
  - recession: $y_i = 1$ if $\Delta y_{n,t} < 0$

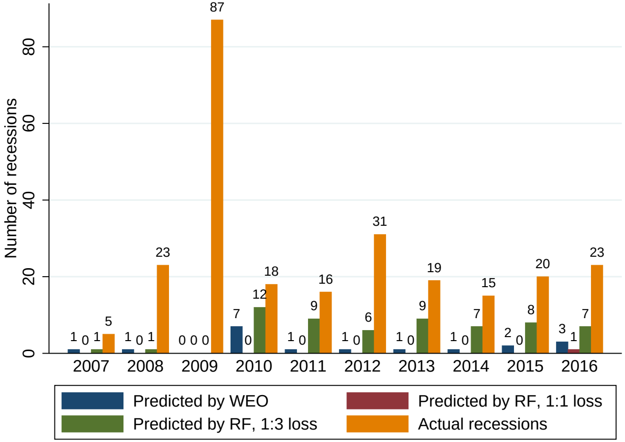
A Loss Function Framework (Elkan, 2001)

	Actual growth	**Actual recession**
Predict growth	0	c_{fn}
Predict recession	c_{fp}	0

- Symmetric loss function: $c_{fp} = c_{fn}$
  - forecasts noisy + recessions infrequent $\rightarrow$ predict growth
- Threshold of $p = P(y_i = 1 | X_i)$ satisfies:
  - $\underbrace{p^* \cdot c_{fn}}_{\text{exp. cost false positive}} = \underbrace{(1 - p^*) \cdot c_{fp}}_{\text{exp. cost false negative}} \rightarrow p^* = \frac{c_{fp}}{c_{fn}+c_{fp}}$
- Intuition:
  - high cost of recession $\rightarrow$ certainty $\rightarrow$ accept false negatives

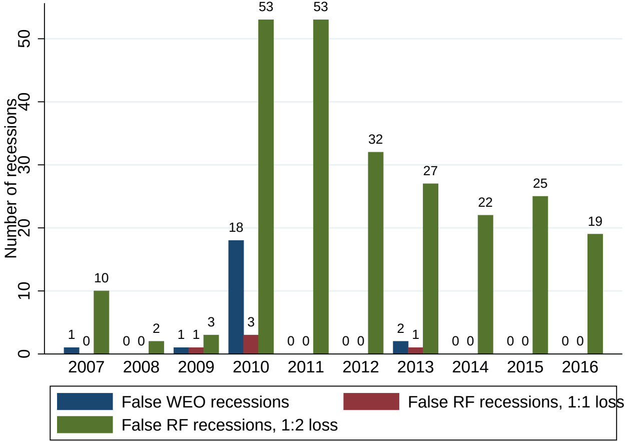
Recessions: 1 Year Ahead (2007-2016)

Random Forest predicts more recessions with 1:3 loss function...

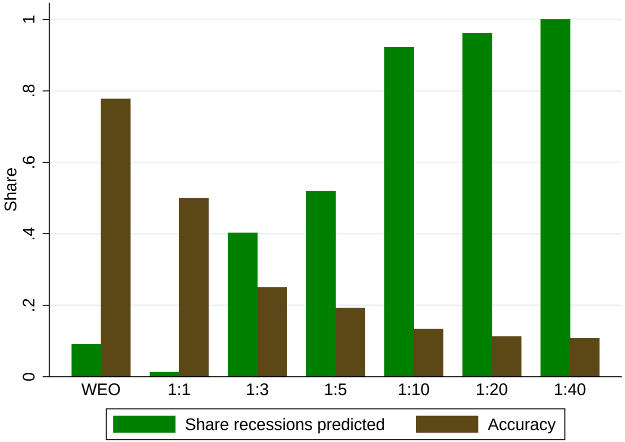


Recessions: False Positives (2007-2016)

...but Random Forest with 1:3 loss function also predicts more false positives



Success Rate and Accuracy of Different Loss Functions (2007-2016)



Conclusion

- Results suggest ML methods can help improve macroeconomic forecasts
- Although not goal of this paper, fine-tuning forecasts could improve prediction further
  - data: country-specific, global macroeconomic data, sentiment surveys, etc.
- However, ML methods are not a panacea:
  - substantial prediction errors remain
  - implementation is still researcher-dependent
- Additional applications
  - macroeconomic aggregates (current account, inflation, etc.)
  - discrete events (e.g. sudden stops)

Appendix, Literature: ML models and macroeconomic forecasting

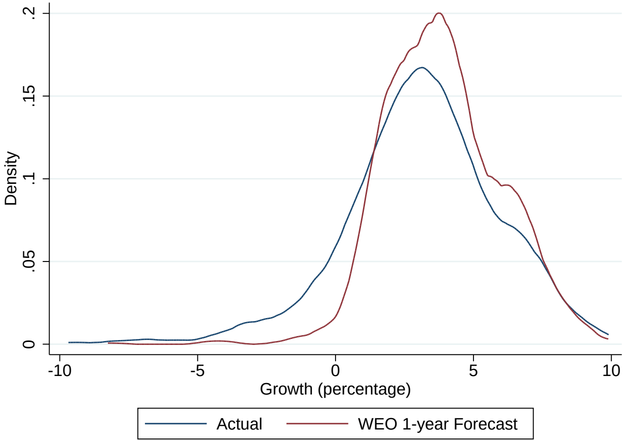
Motivation

- Jung et al. (2018):
  - use ML models and additional data to improve 1-q and 1-y predictions for 7 high- and middle-income countries
- Cook & Smalter Hall (2017); Smalter Hall (2018); Nyman & Ormerod (2016):
  - predict short-run fluctuations macro-economic aggregates in US, UK
- Cepni et al. (2018); Tiffin (2016); Kapetanios & Papailias (2018); Ricardson et al. (2018) ; Fornaro & Luomaranta (2018):
  - use micro-data for GDP nowcasting

Motivation: The World Economic Outlook

Motivation

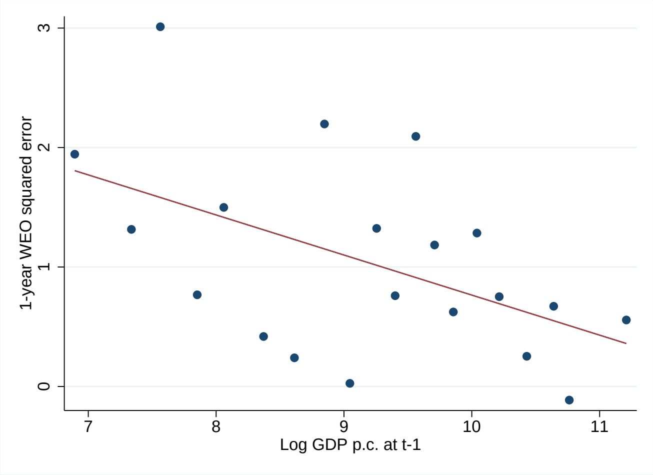
WEO is over-optimistic in its 1-year forecasts



Motivation: The World Economic Outlook

Motivation

WEO forecast errors are higher for low-income countries

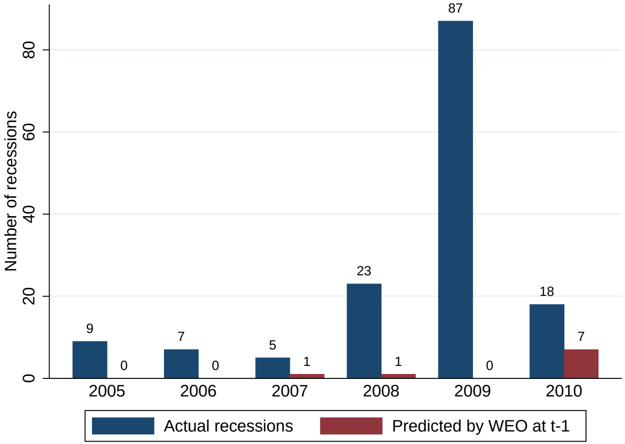


Motivation

Motivation: The World Economic Outlook

◂ Motivation

WEO forecasts miss most recessions



◂ Motivation

Variables

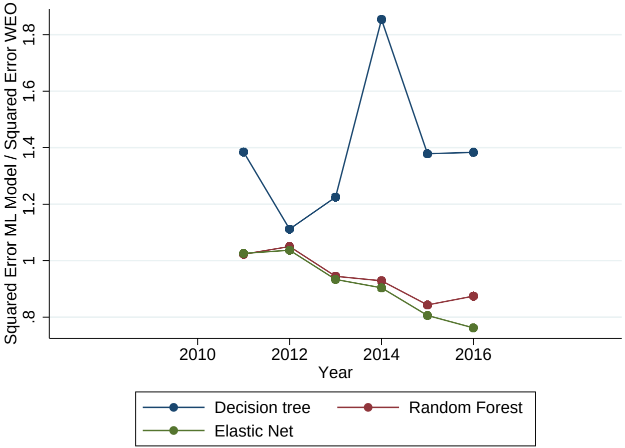
Method

List of variables used from WEO, 2015:

- **GDP measures:** real GDP growth (+ p.c.), GDP at PPP (+ p.c.), GDP at int. (+ p.c.), nominal GDP in USD (+ p.c.), nominal GDP in LCU (+ p.c.), output gap, investment, exports, imports
- **Prices:** GDP deflator, PPP deflator, inflation
- **Government:** government balance, government expenditure, government net debt, government revenue,
- **Other:** current account, employment, libor, population, savings, unemployment

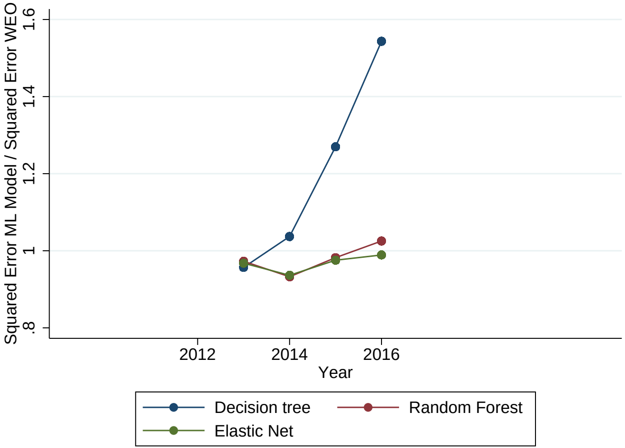
Learning Rate of ML Models r.t. WEO

Results: Growth



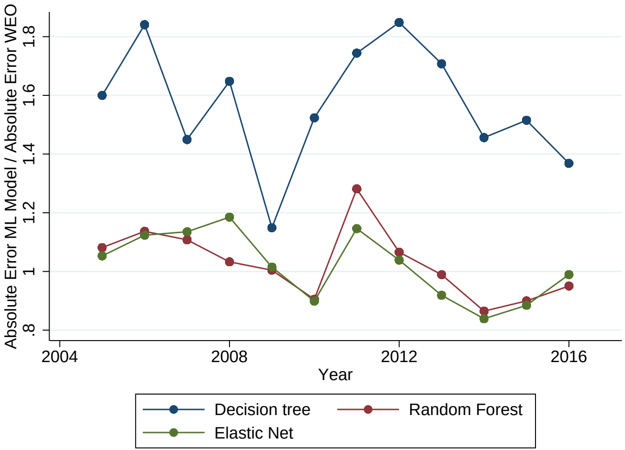
Learning Rate of ML Models r.t. WEO

Results: Growth



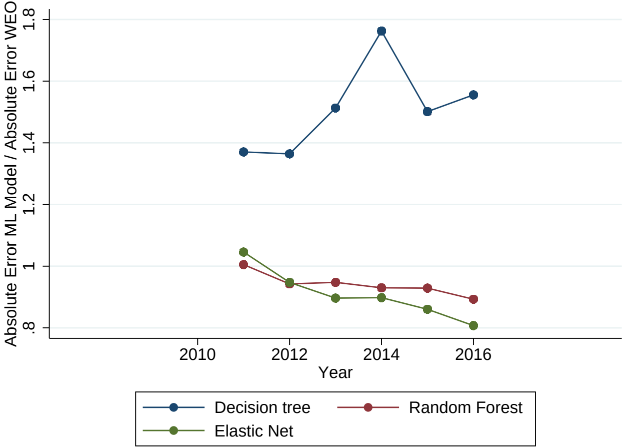
Learning Rate of ML Models r.t. WEO

Results: Growth



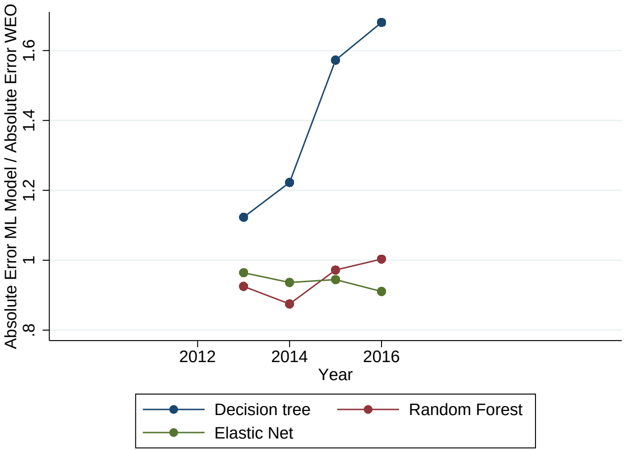
Learning Rate of ML Models r.t. WEO

Results: Growth



Learning Rate of ML Models r.t. WEO

Results: Growth



Results: Growth, Summary 1-year, 2013-2017

Absolute error (EN, RF, 8 %)

	WEO	**Elastic Net**	**Decision Tree**	**Random Forest**
AME	2.5	2.3	3.8	2.3
AMedE	1.3	1.3	2.3	1.3
SD	5.3	4.2	6.7	4.6
A-Max.	63	60	123	57

Results: Growth

Results: Growth, Summary 3-year, 2013-2017

Absolute error (EN 15%, RF 7%

	WEO	**Elastic Net**	**Decision Tree**	**Random Forest**
AME	2.7	2.3	4.2	2.5
AMedE	1.5	1.4	2.6	1.5
SD	4.6	3.8	6.1	4.1
A-Max.	46	41	64	41

Results: Growth

Results: Growth, Summary 5-year, 2013-2017

Absolute error (EN, RF, 7%)

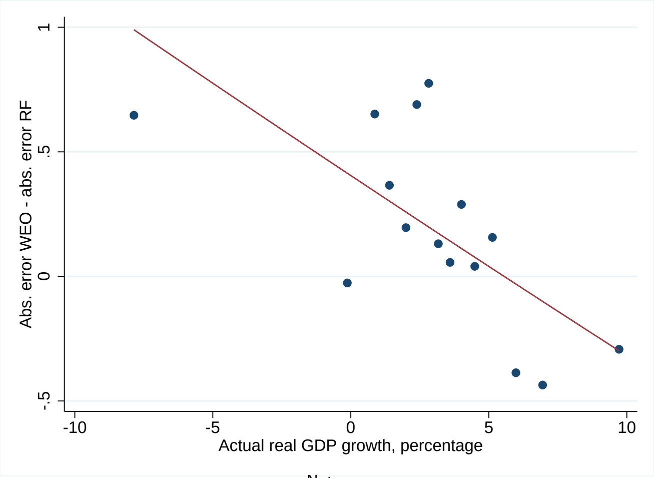
	WEO	Elastic Net	Decision Tree	Random Forest
AME	2.7	2.5	3.7	2.5
AMedE	1.7	1.5	2.4	1.5
SD	4.5	4.4	5.0	4.4
A-Max.	61	58	58	59

Results: Growth

Performance in low growth years

Random Forest outperform in periods of low growth: absolute error

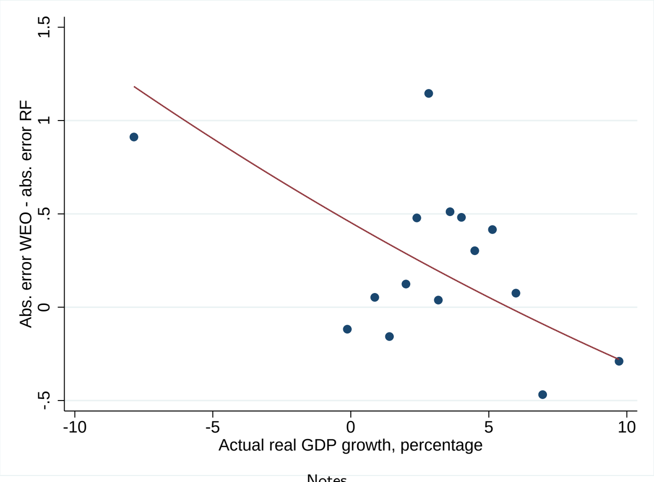
Results: Growth



Performance in low growth years

Elastic Net outperform in periods of low growth: absolute error

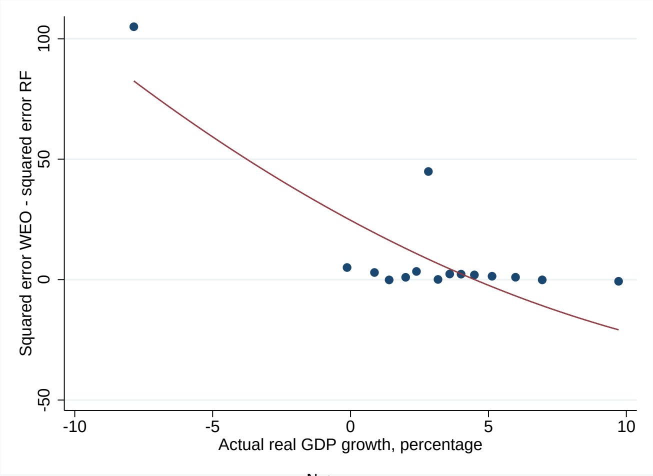
Results: Growth



Performance in low growth years

Elastic Net outperform in periods of low growth: squared error

Results: Growth

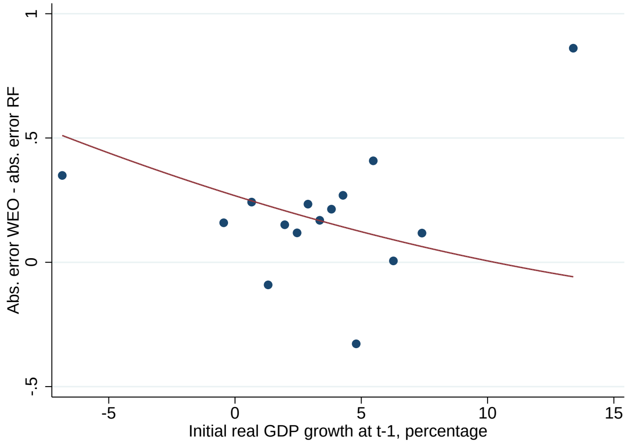


Notes

Performance in low growth years (2)

Random Forest outperforms in *initially* slower growing countries: absolute error

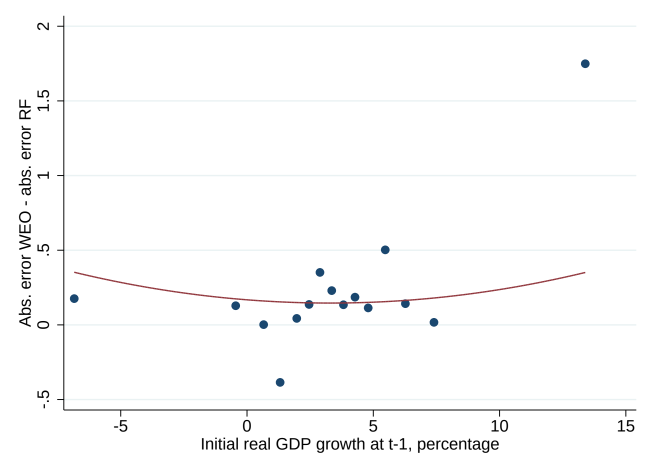
◂ Results: Growth



Notes

Performance in low growth years (2)

Elastic Net outperforms in *initially* slower growing countries: absolute error Results: Growth

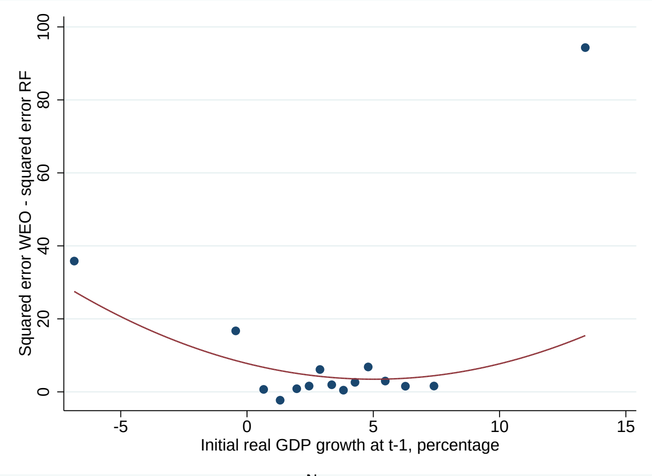


Notes

Performance in low growth years (2)

Elastic Net outperforms in *initially* slower growing countries: squared error

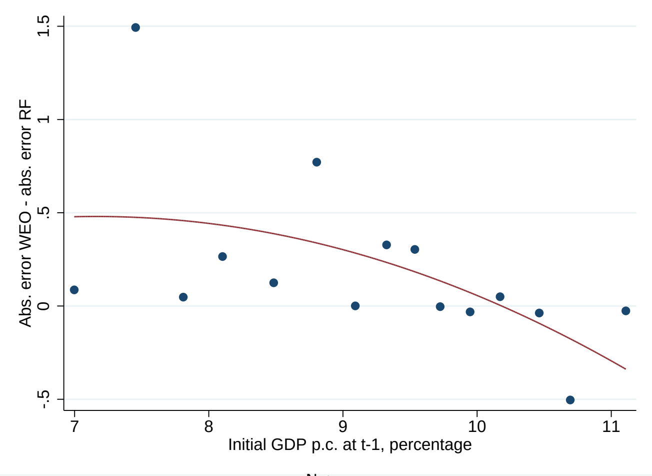
◂ Results: Growth



Performance and GDP p.c.

Random Forest outperform in *initially* poorer countries: absolute error

◂ Results: Growth

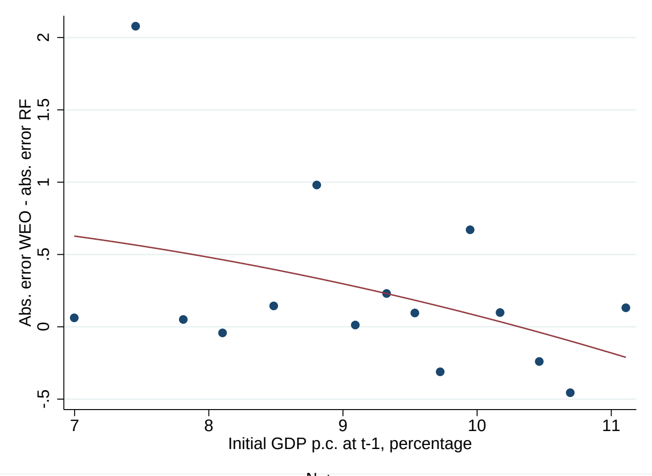


Notes

Performance and GDP p.c.

Elastic Net outperform in *initially* poorer countries: squared error

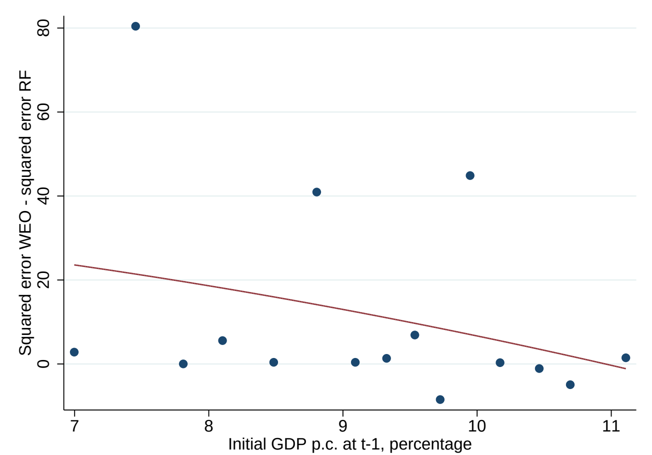
Results: Growth



Performance and GDP p.c.

Elastic Net outperform in *initially* poorer countries: squared error

Results: Growth



Notes

Regression framework

Absolute error, Random Forest

Results: Growth

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Real GDP growth	-0.0760***	-0.0843***	-0.0862***	-0.0660**
	(0.0270)	(0.0281)	(0.0271)	(0.0284)
Log GDP p.c., t-1		-0.246**	-0.217**	-0.107*
		(0.107)	(0.107)	(0.0646)
Africa			0.375	0.340*
			(0.336)	(0.181)
Asia			0.414*	0.157
			(0.230)	(0.152)
Europe			0.155	0.133
			(0.230)	(0.160)
Latin America			0.0633	0.0981
			(0.251)	(0.141)
Year FE	Y	Y	Y	Y
Continent FE	N	N	Y	Y
Observations	741	741	741	2176
Adjusted R^2	0.031	0.050	0.050	0.032

Standard errors in parentheses, clustered at country-level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regression framework

Absolute error, Elastic Net

Results: Growth

	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Real GDP growth	-0.105	-0.114	-0.114*	-0.0675
	(0.0695)	(0.0710)	(0.0664)	(0.0453)
Log GDP p.c., t-1		-0.267*	-0.0973	-0.0146
		(0.148)	(0.148)	(0.0725)
Africa			0.567	0.529**
			(0.484)	(0.252)
Asia			0.169	0.136
			(0.270)	(0.167)
Europe			-0.334	-0.0428
			(0.292)	(0.150)
Latin America			-0.428	0.0254
			(0.276)	(0.140)
Year FE	Y	Y	Y	Y
Continent FE	N	N	Y	Y
Observations	741	741	741	2176
Adjusted R^2	0.032	0.044	0.053	0.026

Standard errors in parentheses, clustered at country-level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Regression framework

Squared error, Elastic Net

Results: Growth

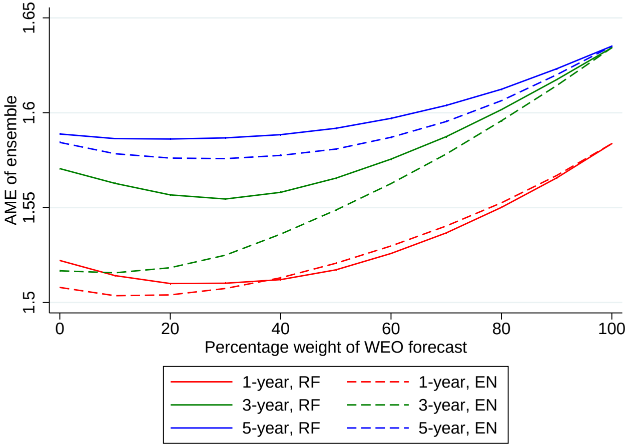
	(1) OLS	(2) OLS	(3) OLS	(4) OLS
Real GDP growth	-9.010*	-9.392*	-9.305*	-4.244
	(5.412)	(5.500)	(5.272)	(2.991)
Log GDP p.c., t-1		-11.29*	-2.574	0.416
		(6.358)	(6.597)	(2.255)
Africa			34.78	23.18*
			(22.84)	(13.28)
Asia			6.673	8.099
			(10.48)	(8.030)
Europe			-9.510	-4.450
			(12.53)	(4.745)
Latin America			-13.80	-0.176
			(10.43)	(3.476)
Year FE	Y	Y	Y	Y
Continent FE	N	N	Y	Y
Observations	741	741	741	2176
Adjusted R^2	0.103	0.112	0.121	0.047

Standard errors in parentheses, clustered at country-level
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Ensemble of WEO and RF forecasts

Mean absolute error

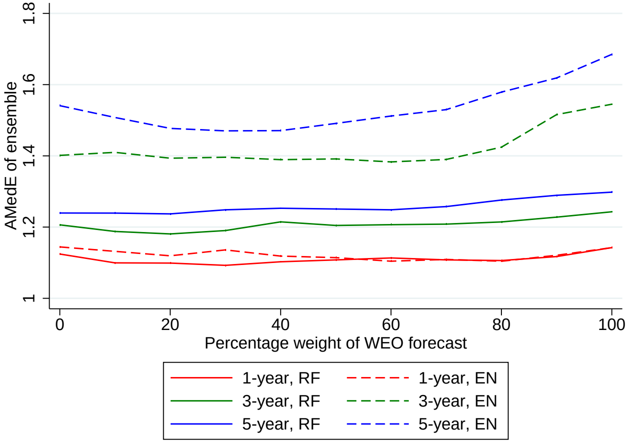
◂ Results: Growth



Ensemble of WEO and RF forecasts

Median absolute error

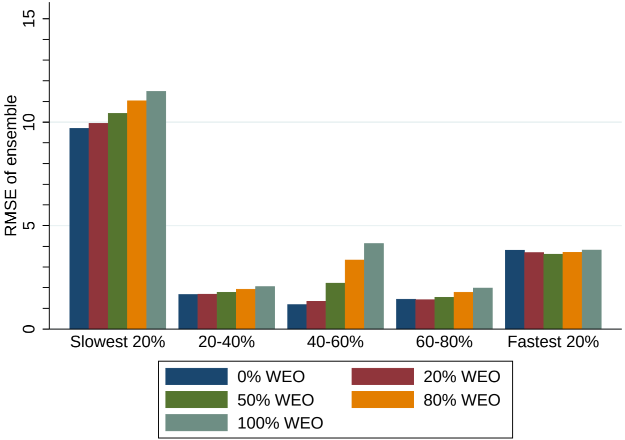
Results: Growth



1-year forecasting gains: actual growth

Elastic Net, RMSE

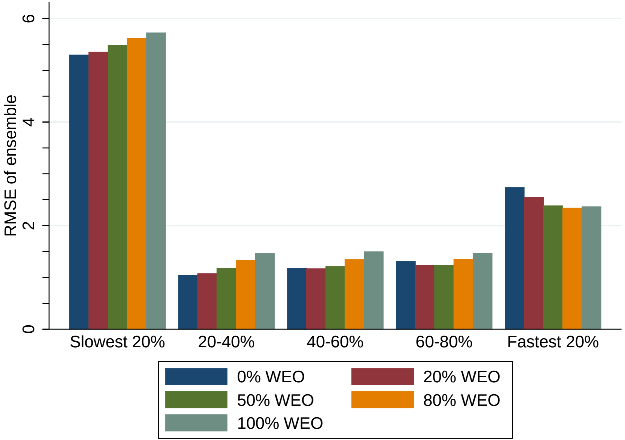
Results: Growth



1-year forecasting gains: actual growth

Random Forest, Mean Absolute Error

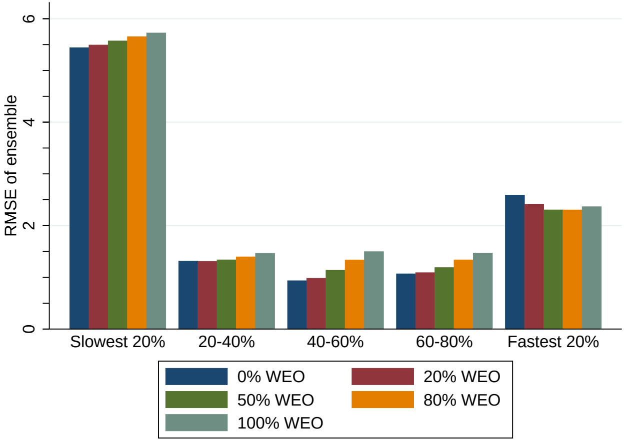
Results: Growth



1-year forecasting gains: actual growth

Elastic Net, Mean Absolute Error

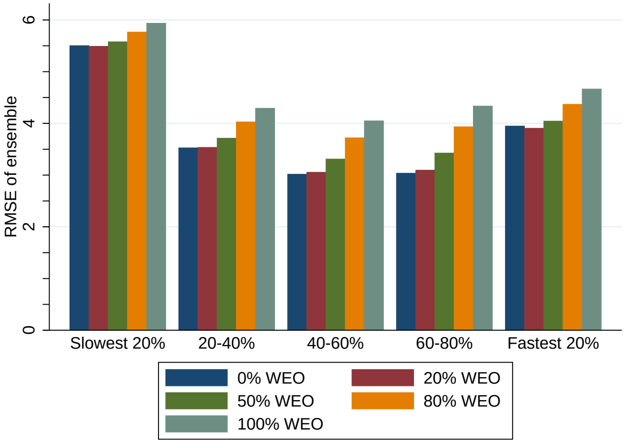
Results: Growth



Forecasting gains: actual growth

Random Forest, RMSE, 3-year

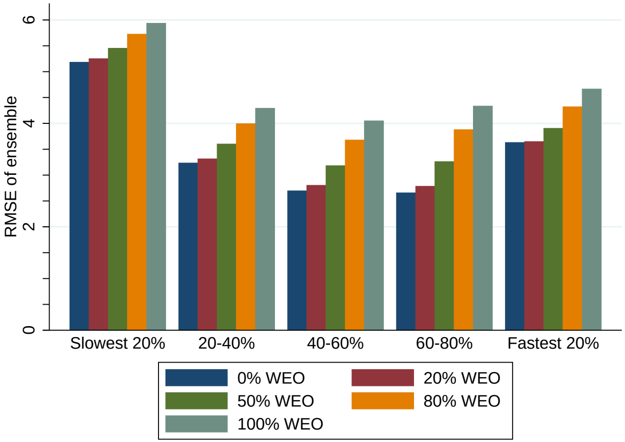
Results: Growth



Forecasting gains: actual growth

Elastic Net, RMSE, 3-year

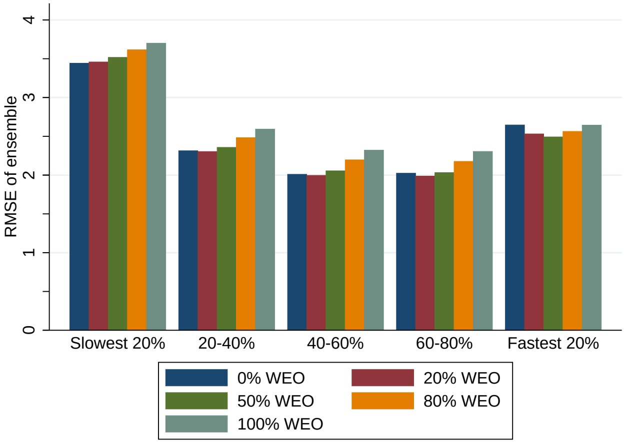
Results: Growth



Forecasting gains: actual growth

Random Forest, MAE, 3-year

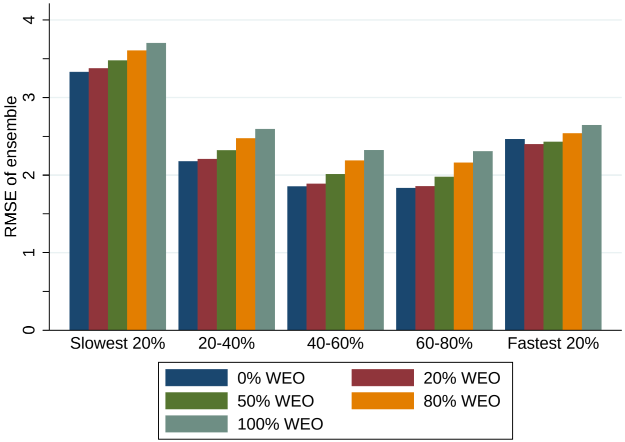
Results: Growth



Forecasting gains: actual growth

Elastic Net, Mean Absolute Error, 3-year

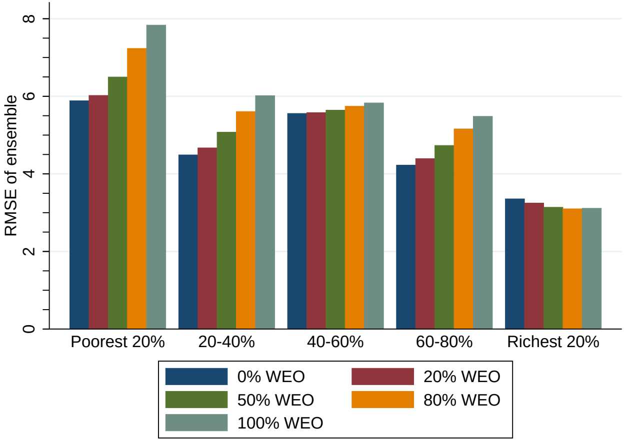
Results: Growth



Forecasting gains: initial GDP p.c.

Elastic Net, RMSE

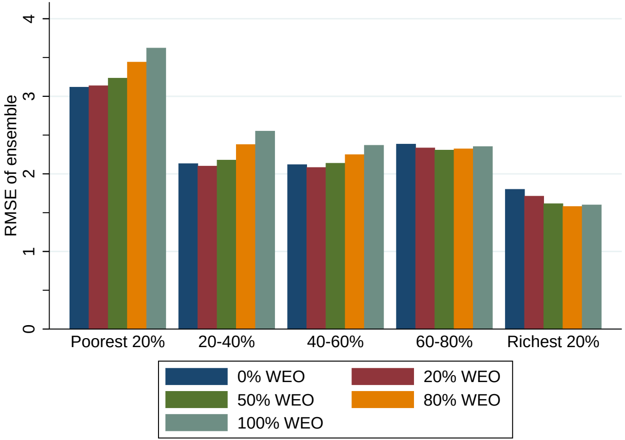
Results: Growth



Forecasting gains: initial GDP p.c.

Random Forest, Mean Absolute Error

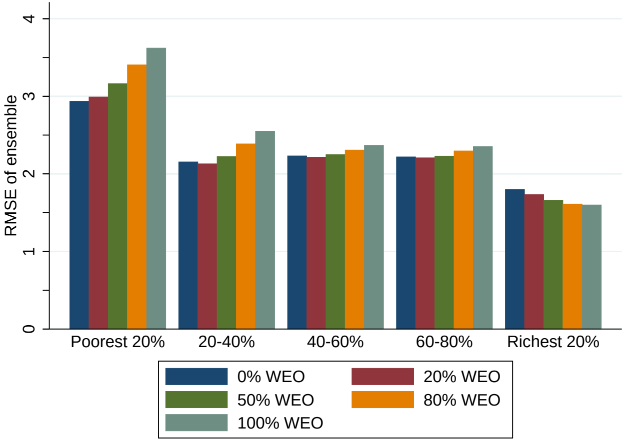
Results: Growth



Forecasting gains: initial GDP p.c.

Elastic Net, Mean Absolute Error

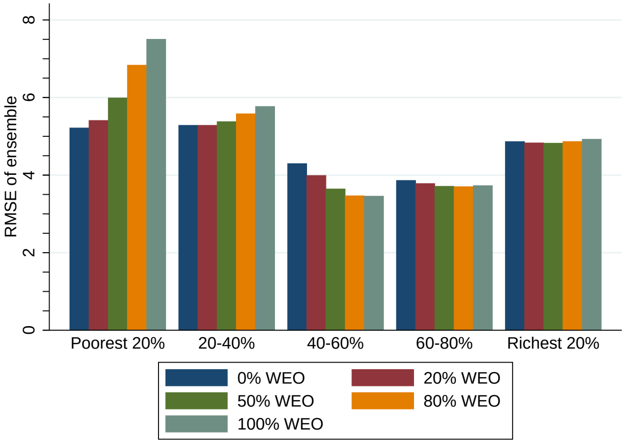
Results: Growth



Forecasting gains: initial GDP p.c.

Random Forest, RMSE, 3-year

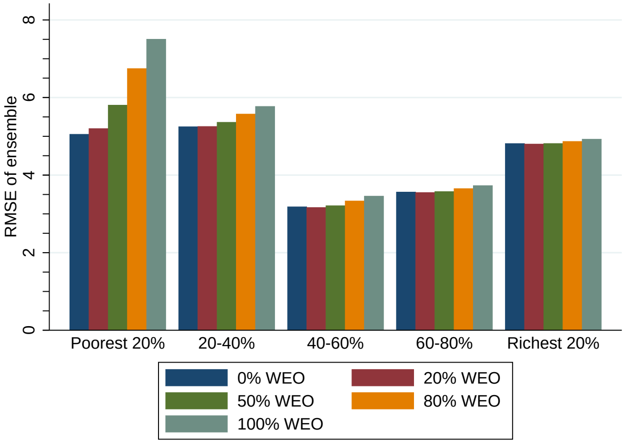
Results: Growth



Forecasting gains: initial GDP p.c.

Elastic Net, RMSE, 3-year

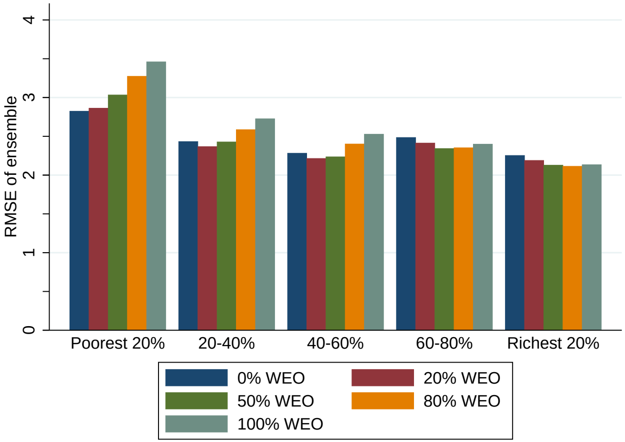
Results: Growth



Forecasting gains: initial GDP p.c.

Random Forest, Mean Absolute Error, 3-year

Results: Growth



Forecasting gains: initial GDP p.c.

Elastic Net, Mean Absolute Error, 3-year

Results: Growth