How is Machine Learning Useful for Macroeconomic Forecasting?

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Modelling with Big Data and Machine Learning: Interpretability and Model Uncertainty
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Motivation

- More and more attempts to use ML for macro prediction
  - Neural nets and SVR for inflation and unemployment (Nakamura, 2005; Sermpinis et al. 2014; Smalter and Cook, 2017, Joseph (2019))
  - Random forests / boosting for recessions (Medeiros et al. (2019), Döpke et al. 2015; Ng, 2014)
  - Generalized shrinkage (Stock and Watson, 2012)
  - Lasso forecasts combination (Diebold and Shin, 2018)
  - Horse races (Ahmed et al. 2010; Ulke et al. 2016; Chen et al. 2019)
  - Performance of sparse and dense models (Li and Chen, 2014; Giannone et al. 2018; Kim and Swanson, 2018; Smeekes and Wijler, 2018)

- Result : few progress has been made to *understand* the properties of ML methods when applied to macroeconomic forecasting. That is, the **black box** remains closed.
  - $\rightarrow$ We aim to fill the gap and start opening the box

Our main contribution

- What are the key features of ML modeling that improve prediction?
  - Nonlinearities
  - Shrinkage / Dimensionality Reduction
  - Cross-Validation
  - Funky Loss function

Machine Learning Features

Fixing ideas:

- A very general, time series, prediction setup is

$$\min_{g \in \mathcal{G}} (\hat{L}(y_{t+h}, g(Z_t)) + pen(g; \tau))$$

- Hence, the prediction problem has 4 main aspects
  1. What is $\mathcal{G}$, the space of possible functions? How much non-linearities can we allow for?
  2. What is $pen()$? That is, how do we shrink or reduce dimension in big data setup?
  3. How do we select τ? That is, how do we optimize the hyperparameters of the model?
  4. Finally, what empirical loss function $\hat{L}$ to choose?

Data-poor versus data-rich

Compare the predictive performance of small versus large data sets:

$$H_t^- \equiv \{y_{t-j}\}_{j=0}^{p_y} \quad \textit{and} \quad H_t^+ \equiv \left[\{y_{t-j}\}_{j=0}^{p_y}, \{X_{t-j}\}_{j=0}^{p_f}\right].$$

1. The H_t^- model is the *autoregressive direct* (AR) model, which is specified as:

$$y_{t+h} = c + \rho(L)y_t + e_{t+h}, \quad t = 1, \ldots, T,$$

   where $h \geq 1$ is the forecasting horizon. The only hyperparameter in this model is p_y, the order of the lag polynomial $\rho(L)$.
2. The H_t^+ model is the autoregression augmented with diffusion indices (ARDI) from Stock and Watson(2002):

$$\begin{aligned} y_{t+h} &= c + \rho(L)y_t + \beta(L)F_t + e_{t+h}, \quad t = 1, \ldots, T \\ X_t &= \Lambda F_t + u_t \end{aligned}$$

Disentangling ML features

How do we go at doing that?

- We take these models as two different types of “patients” and administer them one particular ML treatment or combinations of them
- Data : the results from the extensive forecasting exercise that will be described shortly.
- Analysis : design "experiments" to test hypothesis
- Very simple examples of "experiments" for each item:
  1. $\mathcal{G}$: Kernel Ridge Regression vs Ridge Regression
  2. $pen()$: PCA vs LASSO vs Ridge
  3. τ: AR(p) where p is chosen by CV vs AIC vs BIC
  4. $\hat{L}$: Support Vector Regression vs Ridge Regression

Disentangling ML features (made operational)

How do we test hypothesis? A regression!

$$e^2_{t,h,v,m} = \alpha_F + \psi_{t,v,h} + u_{t,h,v,m}$$

- $e^2_{t,h,v,m}$: squared prediction errors of model m for variable v and horizon h at time t
- $\psi_{t,v,h}$: fixed effect term that demean the dependent variable by (t,v,h) "forecasting target"
- $\alpha_F = [\alpha_{\mathcal{G}}, \alpha_{pen()}, \alpha_{\tau}, \alpha_{\hat{L}}]$ terms associated to each feature
- H_0: $\alpha_f = 0 \quad \forall f \in F = [\mathcal{G},\ pen(),\ \tau,\ \hat{L}]$. In other words, the null is that there is no predictive accuracy gain with respect to a base model that does not have this particular feature

Disentangling ML features (made operational)

To get interpretable coefficients, run the regression for pseudo-R^2s:
$R^2_{t,h,v,m} \equiv 1 - \frac{e^2_{t,h,v,m}}{\frac{1}{T}\sum_{t=1}^{T}(y_{v,t+h} - \bar{y}_{v,h})^2}$

$$R^2_{t,h,v,m} = \dot{\alpha}_F + \dot{\psi}_{t,v,h} + \dot{u}_{t,h,v,m}.$$

- Run specific regressions to investigate the heterogeneity of partial effects. For feature f:

$$\forall m \in \mathcal{M}_f : \quad R^2_{t,h,v,m} = \dot{\alpha}_f + \dot{\phi}_{t,v,h} + \dot{u}_{t,h,v,m}$$

where $\mathcal{M}_f$ is defined as the set of models that differs only by the feature under study f.

Creating the experiment: which models?

In order to identify the aspect specific "treatments", we need to create the identifying variations.

- Concretely, this means estimating a bunch of models that differs (almost) only in the specific aspect of ML we wish to study.
- Example: differentiation by $\mathcal{G}$
  - Data-rich patient with linear $\mathcal{G}$ treatment

$$
\begin{aligned}
y_{t+h} &= \alpha + \rho(L)y_t + \beta(L)F_t + \varepsilon_{t+h}, \\
X_t &= \Lambda F_t + u_t
\end{aligned}
$$

  - Data-rich patient with nonlinear $\mathcal{G}$ treatment

$$
\begin{aligned}
y_{t+h} &= c + g(Z_t) + \varepsilon_{t+h}, \\
Z_t &= \left[\{y_{t-0}\}_{j=0}^{p_y}, \{F_{t-j}\}_{j=0}^{p_f}\right]
\end{aligned}
$$

where $g()$ is obtained by kernel trick or by random forests

List of models

Models	Feature 1: function g	Feature 2: regularization	Feature 3: hyperparameters τ	Feature 4: loss function
Data-poor models				
AR,BIC	Linear		BIC	Quadratic
AR,AIC	Linear		AIC	Quadratic
AR,POOS	Linear		POOS CV	Quadratic
AR,K-fold	Linear		K-fold CV	Quadratic
RRAR,POOS	Linear	Ridge	POOS CV	Quadratic
RRAR,K-fold	Lineal	Ridge	K-fold CV	Quadratic
RFAR,POOS	Nonlinear		POOS CV	Quadratic
RFAR,K-fold	Nonlinear		K-fold CV	Quadratic
SVR-AR,Lin,POOS	Linear		POOS CV	$\bar{\epsilon}$-insensitive
SVR-AR,Lin,K-fold	Linear		K-fold CV	$\bar{\epsilon}$-insensitive
SVR-AR,RBF,POOS	Nonlinear		POOS CV	$\bar{\epsilon}$-insensitive
SVR-AR,RBF,K-fold	Nonlinear		K-fold CV	$\bar{\epsilon}$-insensitive
KRRAR,POOS	Nonlinear	Ridge	POOS CV	Quadratic
KRRAR,K-fold	Nonlinear	Ridge	K-fold CV	Quadratic
Data-rich models				
ARDI,BIC	Linear	PCA	BIC	Quadratic
ARDI,AIC	Linear	PCA	AIC	Quadratic
ARDI,POOS	Linear	PCA	POOS CV	Quadratic
ARDI,K-fold	Linear	PCA	K-fold CV	Quadratic
RRARDI,POOS	Linear	Ridge-PCA	POOS CV	Quadratic
RRARDI,K-fold	Linear	Ridge-PCA	K-fold CV	Quadratic
RFARDI,POOS	Nonlinear	PCA	POOS CV	Quadratic
RFARDI,K-fold	Nonlinear	PCA	K-fold CV	Quadratic
KRRARDI,POOS	Nonlinear	Ridge-PCR	POOS CV	Quadratic
KRRARDI,K-fold	Nonlinear	Ridge-PCR	K-fold CV	Quadratic

List of models, cont.

Models	Feature 1: function g	Feature 2: regularization	Feature 3: hyperparameters τ	Feature 4: loss function
$(B_1, \alpha = \hat{\alpha})$,POOS	Linear	EN	POOS CV	Quadratic
$(B_1, \alpha = \hat{\alpha})$,K-fold	Linear	EN	K-fold CV	Quadratic
$(B_1, \alpha = 1)$,POOS	Linear	Lasso	POOS CV	Quadratic
$(B_1, \alpha = 1)$,K-fold	Linear	Lasso	K-fold CV	Quadratic
$(B_1, \alpha = 0)$,POOS	Linear	Ridge	POOS CV	Quadratic
$(B_1, \alpha = 0)$,K-fold	Linear	Ridge	K-fold CV	Quadratic
$(B_2, \alpha = \hat{\alpha})$,POOS	Linear	EN-PCA	POOS CV	Quadratic
$(B_2, \alpha = \hat{\alpha})$,K-fold	Linear	EN-PCA	K-fold CV	Quadratic
$(B_2, \alpha = 1)$,POOS	Linear	Lasso-PCA	POOS CV	Quadratic
$(B_2, \alpha = 1)$,K-fold	Linear	Lasso-PCA	K-fold CV	Quadratic
$(B_2, \alpha = 0)$,POOS	Linear	Ridge-PCA	POOS CV	Quadratic
$(B_2, \alpha = 0)$,K-fold	Linear	Ridge-PCA	K-fold CV	Quadratic
$(B_3, \alpha = \hat{\alpha})$,POOS	Linear	EN-PCR	POOS CV	Quadratic
$(B_3, \alpha = \hat{\alpha})$,K-fold	Linear	EN-PCR	K-fold CV	Quadratic
$(B_3, \alpha = 1)$,POOS	Linear	Lasso-PCR	POOS CV	Quadratic
$(B_3, \alpha = 1)$,K-fold	Linear	Lasso-PCR	K-fold CV	Quadratic
$(B_3, \alpha = 0)$,POOS	Linear	Ridge-PCR	POOS CV	Quadratic
$(B_3, \alpha = 0)$,K-fold	Linear	Ridge-PCR	K-fold CV	Quadratic
SVR-ARDI,Lin,POOS	Linear	PCA	POOS CV	$\bar{\epsilon}$-insensitive
SVR-ARDI,Lin,K-fold	Linear	PCA	K-fold CV	$\bar{\epsilon}$-insensitive
SVR-ARDI,RBF,POOS	Nonlinear	PCA	POOS CV	$\bar{\epsilon}$-insensitive
SVR-ARDI,RBF,K-fold	Nonlinear	PCA	K-fold CV	$\bar{\epsilon}$-insensitive

Creating the experiment: pseudo-out-of-sample setup

- Data: FRED-MD from McCracken and Ng (2016), 134 series
- POOS period starts on 1980M01
- Expanding window
- Forecasting horizons: [1, 3, 9, 12, 24] months
- Forecast of interest:

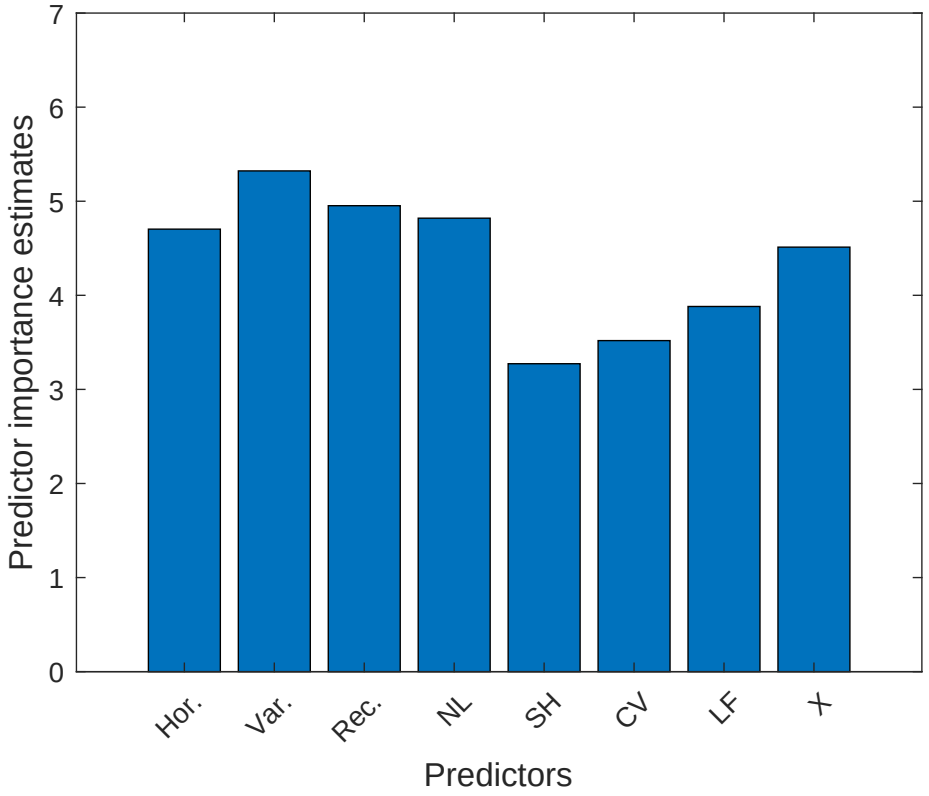
  [if Y_t is I(1)]

$$y_{t+h}^{h} = (1/h)\ln(Y_{t+h}/Y_t)$$

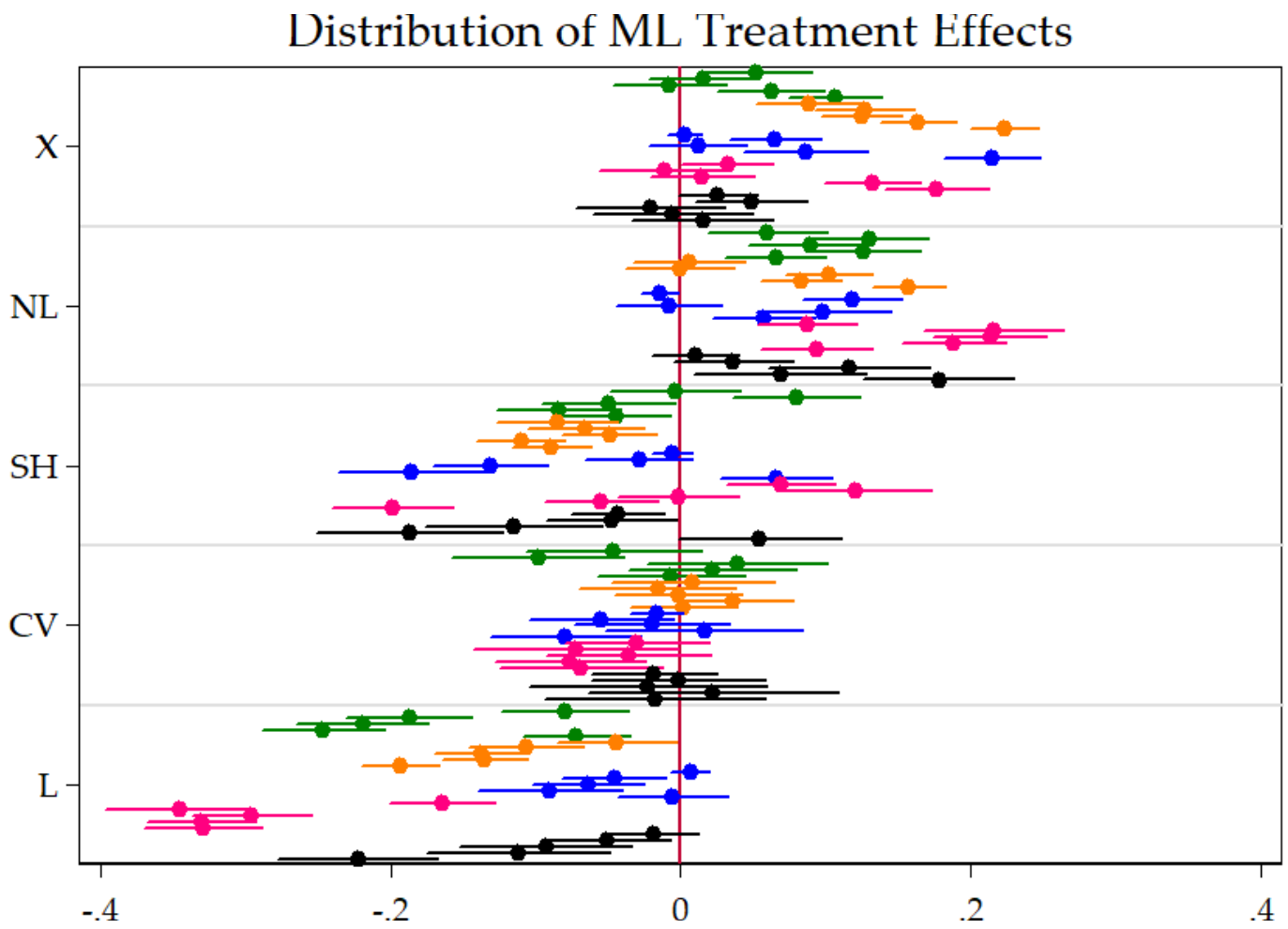
- Variables of interest:
  - I(0) Term spread (SPREAD)
  - I(1) Industrial Production growth (INDPRO), Unemployment Rate change (UNRATE), Inflation (CPIAUCSL), Housing starts (HOUSING)

Results: Disentangling ML Treatment Effects

- Random forest on $R^2_{t,h,v,m}$: report the importance of each features in what is a potentially very non-linear model.
- Let the tree automatically create interactions such as $I(NL = 1) * I(h \leq 12)$

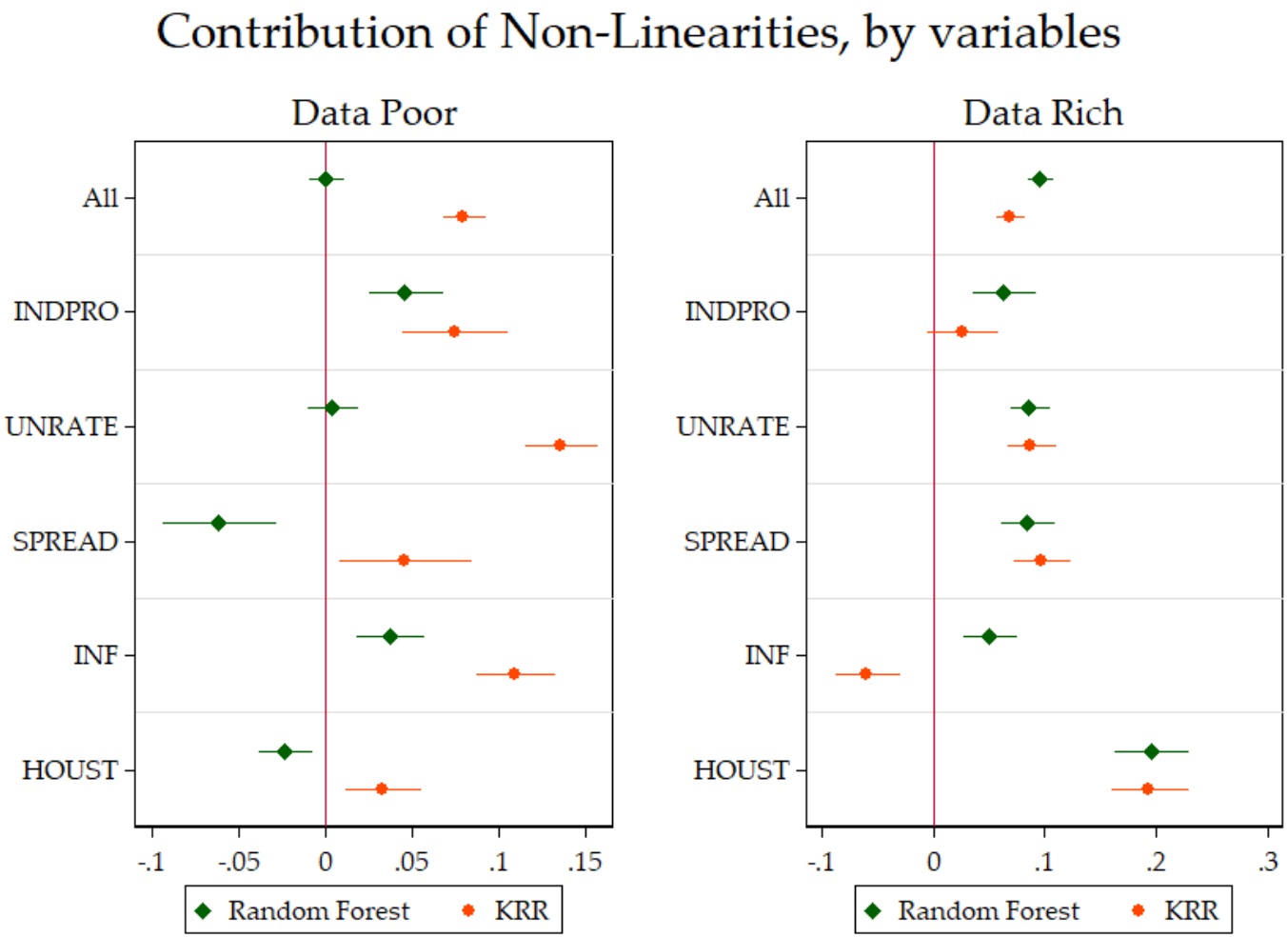


Results: Disentangling ML Treatment Effects



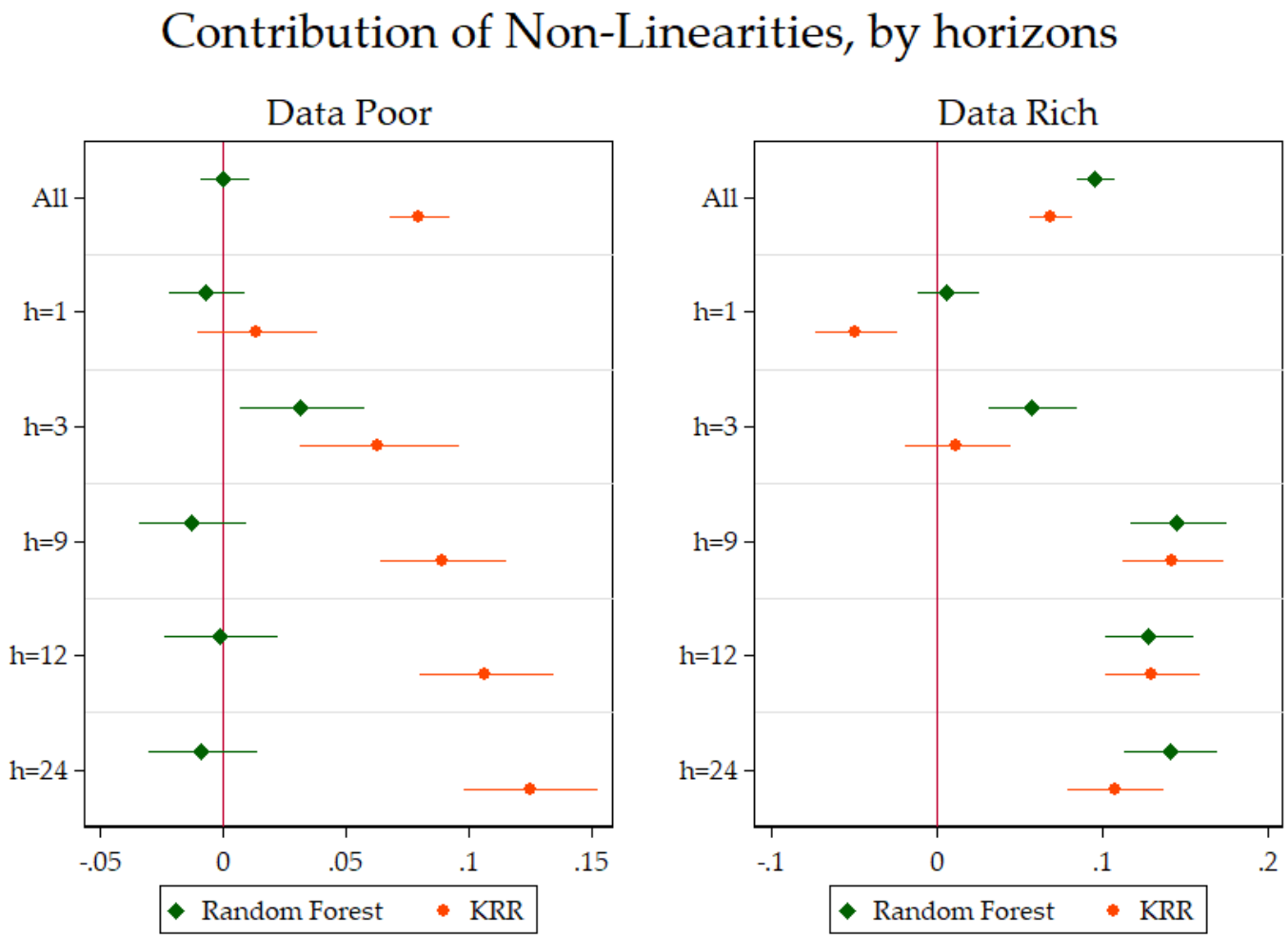
This figure plots the distribution of $\dot{\alpha}_F^{(h,v)}$ by (h,v) subsets. X stands for data-rich. Variables: INDPRO, UNRATE, SPREAD, INF and HOUST. Within a specific color block, the horizon increases from $h = 1$ to $h = 24$ as we are going down. SEs are HAC. These are the 95% confidence bands.

Results: Nonlinearities Effects



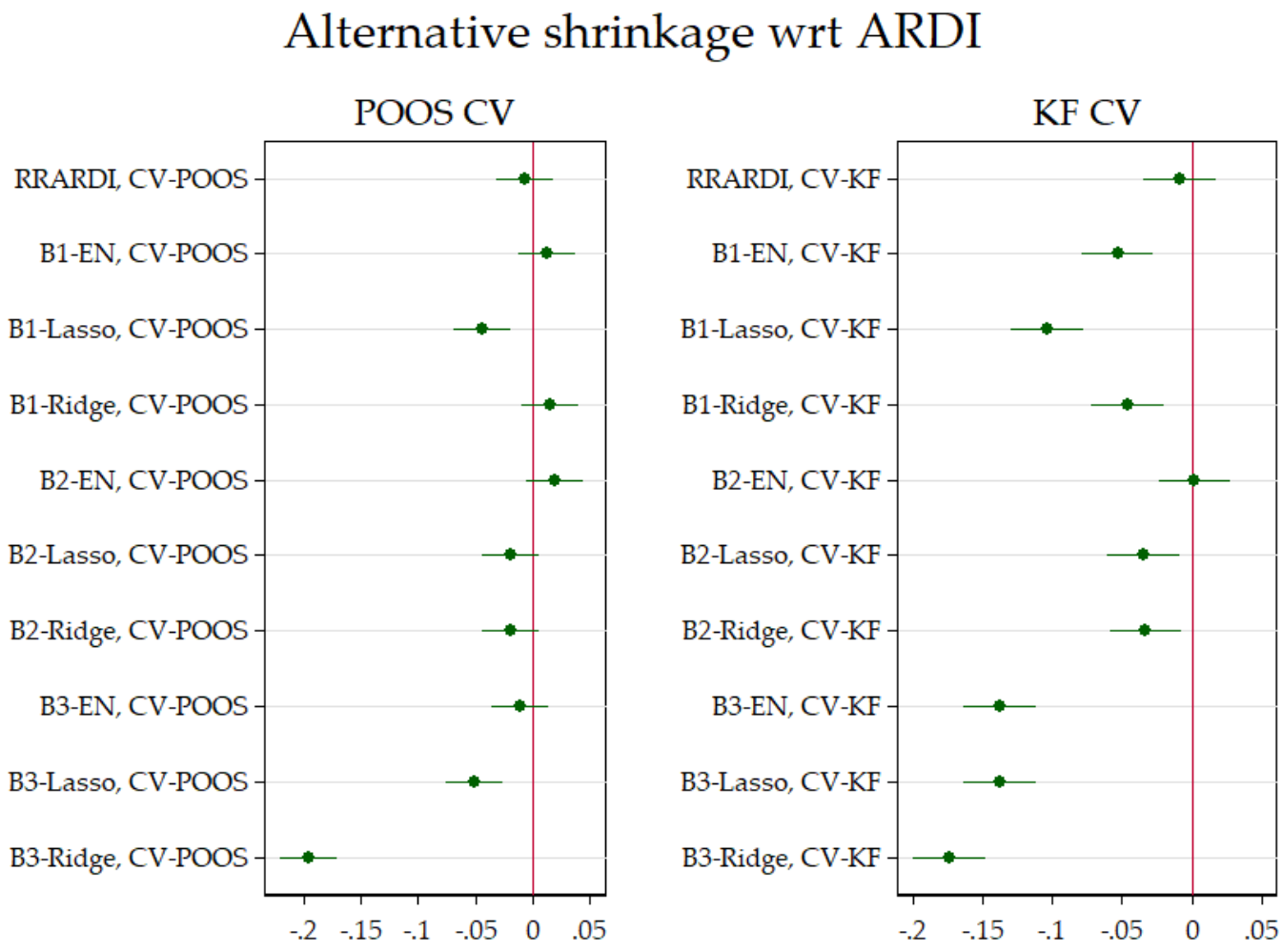
This compares the two NL models averaged over all horizons. The unit of the x-axis are improvements in OOS R^2 over the basis model.

Results: Nonlinearities Effects



This compares the two NL models averaged over all variables. The unit of the x-axis are improvements in OOS R^2 over the basis model.

Results: Alternative Dimension Reduction Effects



This figure compares sparse models averaged over all variables and horizons. The base models are ARDIs specified with POOS-CV and KF-CV respectively.

Results: Hyperparameter Optimization Effects Selection

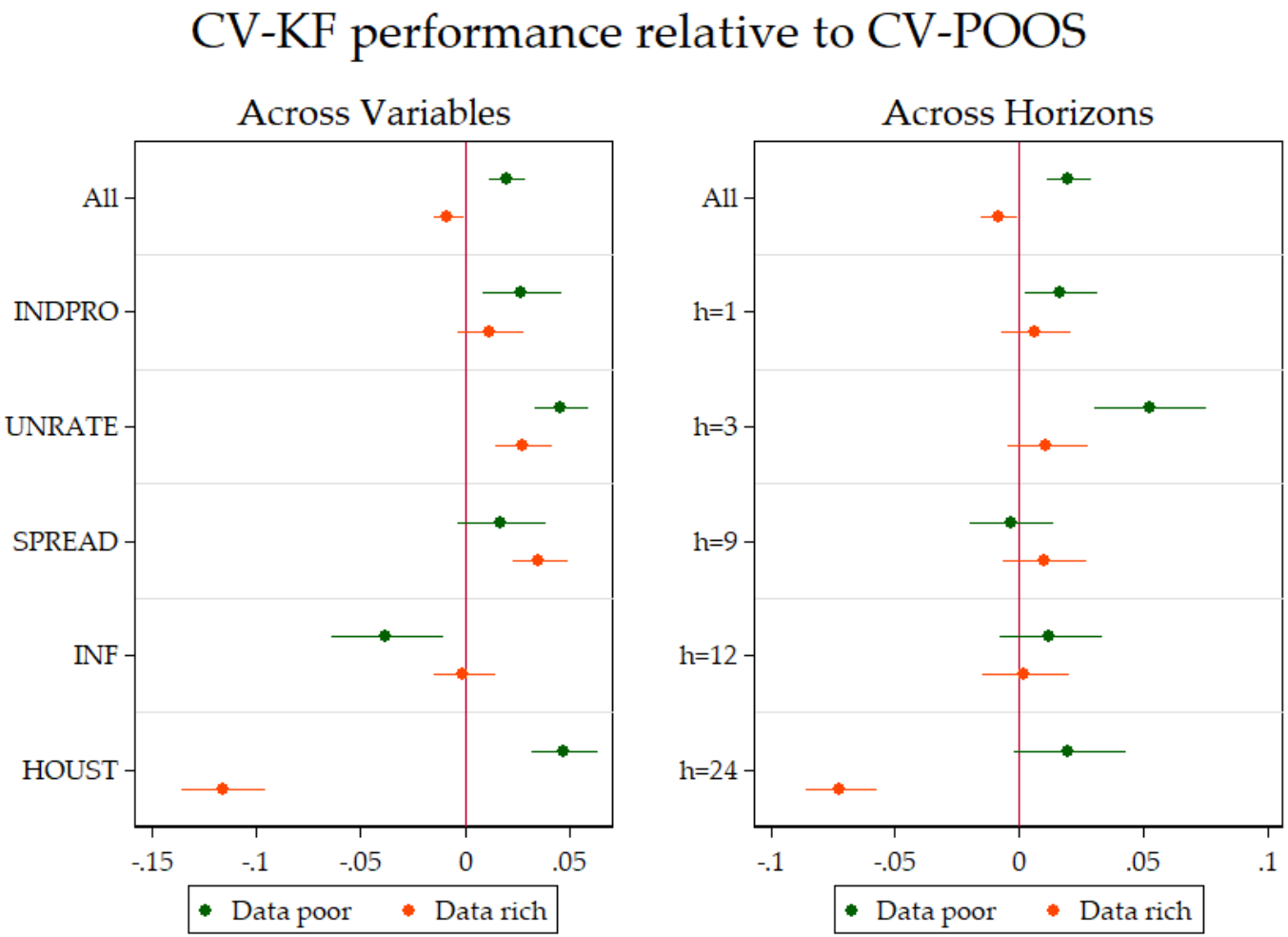
Table: CV comparaison

	(1) All	(2) Data-rich	(3) Data-poor	(4) Data-rich	(5) Data-poor
CV-KF	-0.0380	-0.314	0.237	-0.494	-0.181
	(0.800)	(0.711)	(0.411)	(0.759)	(0.438)
CV-POOS	-1.351	-1.440*	-1.262**	-1.069	-1.454***
	(0.800)	(0.711)	(0.411)	(0.759)	(0.438)
AIC	-0.509	-0.648	-0.370	-0.580	-0.812
	(0.800)	(0.711)	(0.411)	(0.759)	(0.438)
CV-KF * Recessions				1.473	3.405**
				(2.166)	(1.251)
CV-POOS * Recessions				-3.020	1.562
				(2.166)	(1.251)
AIC * Recessions				-0.550	3.606**
				(2.166)	(1.251)
Observations	91200	45600	45600	45600	45600

Standard errors in parentheses

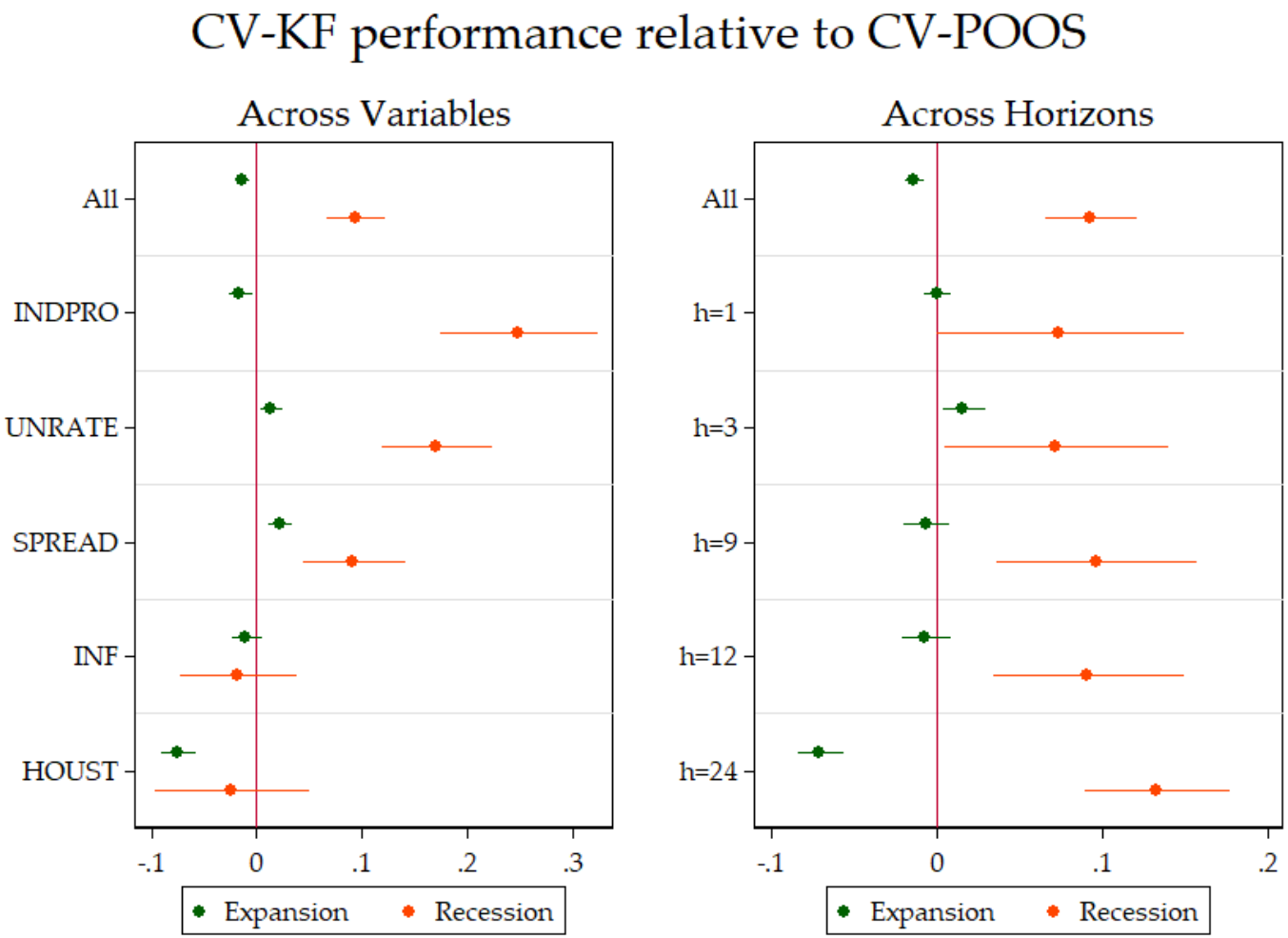
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Results: Hyperparameter Optimization Effects



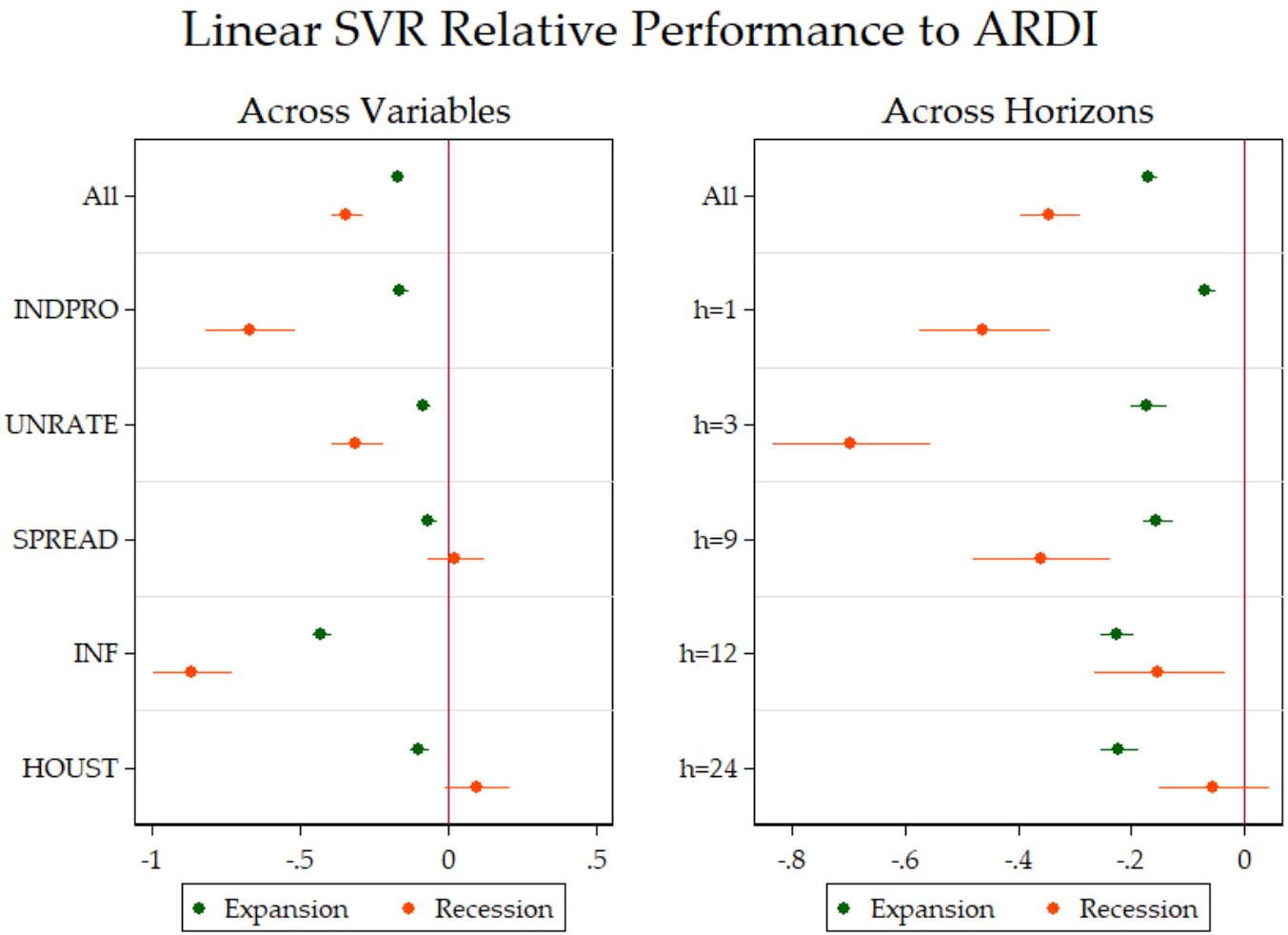
This figure compares the two CVs procedure averaged over all the models that use them. The unit of the x-axis are improvements in OOS R^2 over the basis model.

Results: Hyperparameter Optimization Effects



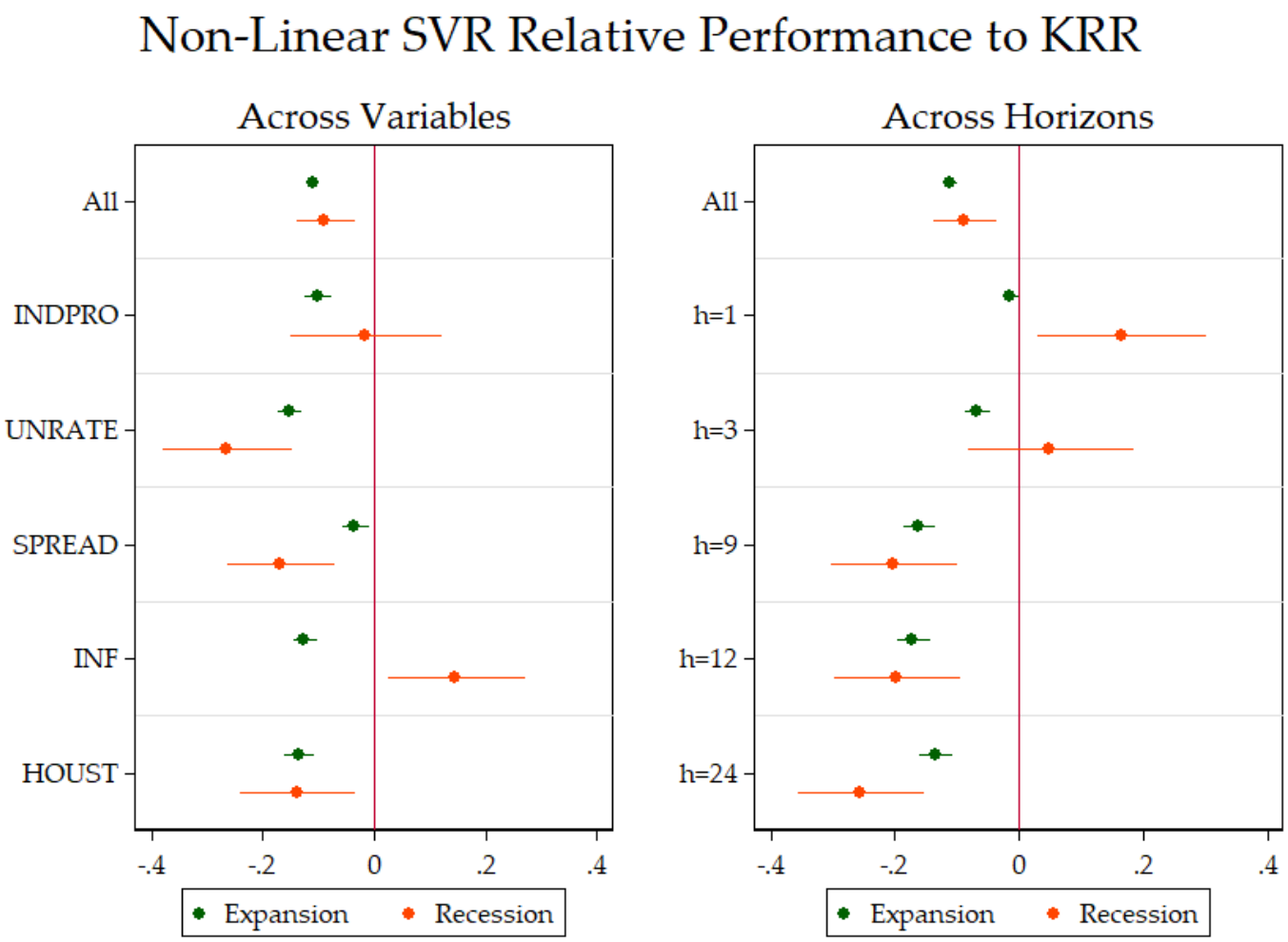
This figure compares the two CVs procedure averaged over all the models that use them. The unit of the x-axis are improvements in OOS R^2 over the basis model.

Results: Loss Function Effects



This graph display the marginal (un)improvments by variables and horizons to opt for the SVR in-sample loss function in both the data-poor and data-rich environments.

Results: Loss Function Effects



This graph display the marginal (un)improvments by variables and horizons to opt for the SVR in-sample loss function in both recession and expansion periods.

Opening the black box

- Interact NL treatment with a vector of macroeconomic variables ξ_{t-h}

$$\forall m \in \mathcal{M}_{NL}: \quad R^2_{t,h,v,m} = \dot{\alpha}_{NL} + \dot{\gamma} I(m \in NL)\xi_{t-h} + \dot{\phi}_{t,v,h} + \dot{u}_{t,h,v,m}$$

  where $\mathcal{M}_{NL}$ is the set of models that differs only by the use of NL.
- **Macro-Finance block** (Adrien et al. 2019; Beaudry et al. 2017, 2019)
  - Adjusted national financial conditions index (Adrien et al. 2019)
  - House price growth

  Uncertainty (Bloom, 2009; Benigno and Benigno 2013; Gorodnichenko and Ng 2017; Carriero et al. 2018)
  - Macroeconomic uncertainty from Jurado et al. 2015

  Sentiments (Angeletos and La'O 2013, Benhabib et al. 2015)
  - UMichigan Consumer Expectations
  - Purchasing Managers Index

  Controls
  - UNRATE, PCE inflation, 1y treasury rate

Opening the black box

Time series of ξ_t

	(1) Base	(2) All Horizons	(3) Data-Rich	(4) Last 20 years
NL	8.998***	5.808***	13.48***	19.87***
	(0.748)	(0.528)	(1.012)	(1.565)
HOUSPRICE	-9.668***	-4.491***	-11.56***	-1.219
	(1.269)	(0.871)	(1.715)	(1.596)
ANFCI	7.244***	2.625	6.803**	20.29***
	(1.881)	(1.379)	(2.439)	(4.891)
MACROUNCERT	17.98***	10.28***	34.87***	9.660***
	(1.875)	(1.414)	(2.745)	(2.038)
UMCSENT	4.695**	3.853**	10.29***	-3.625
	(1.768)	(1.315)	(2.294)	(1.922)
PMI	0.0787	-1.443	-2.048	-1.919
	(1.179)	(0.879)	(1.643)	(1.288)
UNRATE	0.834	2.517**	5.732***	8.526***
	(1.353)	(0.938)	(1.734)	(2.199)
GS1	-14.24***	-9.500***	-17.30***	2.081
	(2.288)	(1.682)	(3.208)	(3.390)
PCEPI	5.953*	6.814**	-1.142	-6.242
	(2.828)	(2.180)	(4.093)	(3.888)
Observations	136800	228000	68400	72300

Standard errors in parentheses, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$

Robustness

- DM tests, Model Confidence Sets INDPRO UNRATE SPREAD INF HOUS
- NBER recessions ($\approx$ 12% of OOS) Recessions
- Last 20 years of data Last 20 Years
- Rolling MSPEs Rolling
- Absolute loss (ex post) Absolute loss
- Quarterly data: GDP, Consumption, Investment, Income, GDP deflator, PCE Quarterly
- Canadian data Canadian

What did we find?

Feature 1: function g

- ML non-linearities are the true game-changer, especially for the data rich environment and when predicting at longer horizons
- NL is important: (i) when uncertainty is high; (ii) during episodes of tighter financial conditions and housing bubble bursts.

Feature 2: regularization with $pen()$

- The factor model will live to see another day

Feature 3: optimization of HPs τ

- CV does not improve significantly upon in-sample criteria
- Best CV practice is the standard K-fold

Feature 4: loss function $\hat{L}$

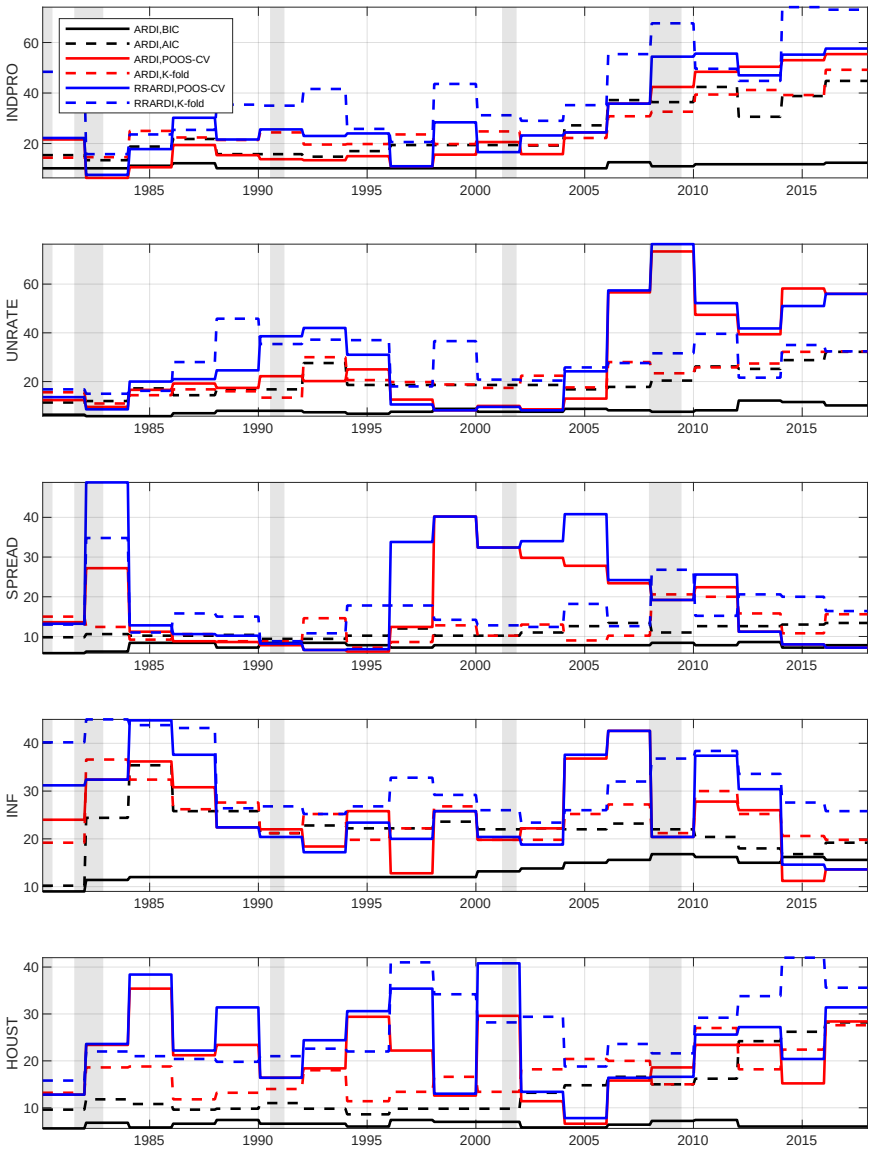
- Stick with the standard L_2 loss function

Where do we go from here?

- A more detailed look at big (macro) data and its interaction with econometrics and ML methods in Leroux, Kotchini and Stevanovic (2019).
- Random Forests seem promising: it combines non-linearities, big data and is computationally tractable.
- Rather than taking RF off the shelf, can we adapt it for time-series/macro data and get better results?
- Answer is *yes* – in fact, a lot better. See Goulet Coulombe (2019)'s Macroeconomic Forests.

Merci pour votre attention.

Number of regressors averaged across horizons back



Results: Industrial Production back

	Full Out-of-Sample					NBER Recessions Periods				
Models	h=1	h=3	h=9	h=12	h=24	h=1	h=3	h=9	h=12	h=24
Data-poor (H_t^-) models										
Data-poor (H_t^-) models										
AR,BIC (RMSPE)	0,0765	**0.0515**	**0.0451**	**0.0428**	**0.0344**	0,127	0,1014	0,0973	0,0898	0,0571
AR,AIC	0.991*	**1.000**	**0.999**	**1.000**	**1.000**	0.987*	1	1	1	1
AR,POOS-CV	0,999	1.021***	**0.985***	**1.001**	1.032*	1,01	1.023***	0.988*	1	1.076**
AR,K-fold	0.991*	**1.000**	**0.987***	**1.000**	1.033*	0.987*	1	0.992*	1	1.078**
RRAR,POOS-CV	1,003	1.041**	**0.989**	**0.993***	**1.002**	1.039**	1.083**	0,991	0,993	1.016**
RRAR,K-fold	0.988**	**1.000**	**0.991**	**1.001**	**1.027**	0,992	1.007**	0,995	1.001**	1.074**
RFAR,POOS-CV	0,995	1,045	**0.985**	**0.955**	**0.991**	1,009	1,073	0.902***	0.890**	0,983
RFAR,K-fold	0,995	**1.020**	**0.960**	**0.930****	**0.983**	0,999	1,013	0.894***	0.887***	0.970*
KRR-AR,POOS-CV	1,023	1,09	**0.980**	**0.944**	**0.982**	1,117	1.166*	0.896**	0.853***	0.903***
KRR,AR,K-fold	**0.947*****	**0.937****	**0.936**	**0.910***	**0.959**	0.922**	0.902**	0.835***	**0.799*****	0.864***
SVR-AR,Lin,POOS-CV	1.134***	1.226***	1.114***	1.132***	**0.952***	1.186**	1.285***	1.079**	1.034***	0.893***
SVR-AR,Lin,K-fold	1.069*	1.159**	1.055**	1.042***	1.016***	1.268***	1.319***	1.067***	1.035***	1.013***
SVR-AR,RBF,POOS-CV	0,999	1.061***	**1.020**	**1.048**	**0.980**	1.062*	1.082***	0.876***	0.941***	0.930***
SVR-AR,RBF,K-fold	**0.978***	**1.004**	1.080*	1.193**	1.017***	0,992	1,009	0,989	1.016***	1.012***
Data-rich (H_t^+) models										
ARDI,BIC	**0.946***	**0.991**	1,037	**1.004**	**0.968**	**0.801*****	**0.807*****	0.887**	0.833***	0.784***
ARDI,AIC	**0.959***	**0.968**	**1.017**	**0.998**	**0.943**	0.840***	**0.803*****	0.844**	**0.798****	**0.768*****
ARDI,POOS-CV	0,994	**1.015**	**0.984**	**0.968**	**0.966**	0.896***	**0.698*****	**0.773*****	**0.777*****	0.812***
ARDI,K-fold	**0.940***	**0.977**	**1.013**	**0.982**	**0.912***	**0.787*****	**0.812*****	0.841**	**0.808****	**0.762*****
RRARDI,POOS-CV	**0.994**	**1.032**	**0.987**	**0.973**	**0.948**	0.908**	**0.725*****	0.793***	**0.778*****	0.861**
RRARDI,K-fold	**0.943****	**0.977**	**0.986**	**0.990**	**0.921**	0.847**	**0.718*****	**0.794*****	**0.796*****	**0.702*****
RFARDI,POOS-CV	**0.948****	**0.991**	**0.951**	**0.919***	**0.899****	0.865**	**0.802*****	0.837***	**0.782*****	0.819***
RFARDI,K-fold	**0.953****	**1.016**	**0.957**	**0.924***	**0.890****	0.889***	**0.864***	0.846***	**0.803*****	**0.767*****
KRR-ARDI,POOS-CV	1,038	**1.016**	**0.921***	**0.934**	**0.959**	1.152*	1,021	0.847***	0.814***	0.886**
KRR,ARDI,K-fold	**0.971**	**0.983**	**0.923***	**0.914***	**0.959**	1,006	0,983	0.827***	**0.793*****	0.848***
$(B_1,\alpha = \hat{\alpha})$,POOS-CV	1,014	**1.001**	**1.023**	**0.996**	**0.946**	1,067	0,956	0,979	0.916**	0.855***
$(B_1,\alpha = \hat{\alpha})$,K-fold	**0.957****	**0.952**	**1.029**	1,046	1,051	0.908**	0.856***	0.874**	**0.816*****	0.890*
$(B_1,\alpha = 1)$,POOS-CV	**0.971***	**1.013**	1.067*	**1.020**	**0.955**	0,991	0,889	1,01	0.935*	0.880**
$(B_1,\alpha = 1)$,K-fold	**0.957****	**0.952**	**1.029**	**1.046**	1,051	0.908**	0.856***	0.874**	**0.816*****	0.890*
$(B_1,\alpha = 0)$,POOS-CV	1,047	1.112**	**1.021**	1,051	**0.969**	1.134*	1.182**	0,997	1,005	0.821***
$(B_1,\alpha = 0)$,K-fold	1,025	1.056*	1,065	1,082	1,052	1,032	0,974	0,923	0,929	0.847***
$(B_2,\alpha = \hat{\alpha})$,POOS-CV	1,061	**0.968**	**0.975**	**0.999**	**0.923****	1,237	0.810***	0.889***	0.904**	0.869**
$(B_2,\alpha = \hat{\alpha})$,K-fold	1,098	**0.949**	**0.993**	**0.974**	**0.970**	1,332	**0.801*****	0.896**	0.851***	**0.756*****
$(B_2,\alpha = 1)$,POOS-CV	**0.973**	1,045	**1.012**	**1.023**	**0.920****	1,034	1,033	0,997	0,957	0.839***
$(B_2,\alpha = 1)$,K-fold	**0.956****	1,022	1,032	**1.025**	**0.990**	0,961	0,935	0,959	0.913**	0.809***
$(B_2,\alpha = 0)$,POOS-CV	**0.933*****	**0.955**	**0.972**	**0.937**	**0.913****	0.902**	**0.781*****	0.904**	0.840***	0.807***
$(B_2,\alpha = 0)$,K-fold	**0.937****	**0.927****	**0.961**	**0.927**	**0.959**	0.871***	**0.787*****	0.858***	**0.775*****	0.776***
$(B_3,\alpha = \hat{\alpha})$,POOS-CV	**0.980**	**0.994**	**1.016**	1,05	**0.952**	1,032	0,95	0,957	0,97	0.861***
$(B_3,\alpha = \hat{\alpha})$,K-fold	**0.973****	**0.946****	1,042	**0.948**	**0.997**	1,016	0.916**	0,938	0.825***	0.827***
$(B_3,\alpha = 1)$,POOS-CV	**0.969***	1,053	1,053	1.080*	**0.956**	0,972	0,946	1,002	1,014	0.906**
$(B_3,\alpha = 1)$,K-fold	**0.946*****	**0.913****	**0.994**	**0.976**	1,01	0.924**	0.829***	0.888*	**0.803*****	0.822***
$(B_3,\alpha = 0)$,POOS-CV	**0.976**	1,049	1,04	1,063	**0.973**	1,034	1,061	0,997	0.932*	0.846***
$(B_3,\alpha = 0)$,K-fold	0,981	1,01	1,03	**1.011**	**0.985**	1,002	0,997	0,95	**0.826*****	0.787***
SVR-ARDI,Lin,POOS-CV	**0.989**	1.165**	1.216**	1.193**	**1.034**	0.915*	0.900**	1,006	0.862**	**0.778*****
SVR-ARDI,Lin,K-fold	1.109**	1.367***	**1.024**	**1.038**	**1.028**	1,129	1,133	**0.776*****	**0.808*****	**0.726*****
SVR-ARDI,RBF,POOS-CV	**0.968***	**0.986**	1.100*	**0.960**	**0.936***	0,958	0.900*	0.873**	**0.760*****	0.820***
SVR-ARDI,RBF,K-fold	**0.951***	**0.946**	**0.993**	**0.952**	**1.001**	0.860**	**0.793*****	**0.806*****	**0.777*****	0.791***

Results: Unemployment rate back

	Full Out-of-Sample					NBER Recessions Periods				
Models	h=1	h=3	h=9	h=12	h=24	h=1	h=3	h=9	h=12	h=24
Data-poor models										
AR,BIC (RMSPE)	1,9578	1,1905	1,0169	1,0058	0,869	2,5318	2,0826	1,8823	1,7276	1,0562
AR,AIC	0,991	0,984	0,988	0.993***	1	0,958	0.960**	0.984*	1	1
AR,POOS-CV	0,988	0,999	1,002	0,995	0,987	0,978	0.980**	0,996	0,998	1,04
AR,K-fold	0,994	0,984	0,989	0.986***	0,991	0.956*	0.960**	0,998	1	1,038
RRAR,POOS-CV	0,989	1	1,002	0.990*	0.972**	0,984	0.988*	0,997	0.991*	1,001
RRAR,K-fold	0,988	0.982*	0.983*	0.989**	0,999	0,963	0.971*	0,992	0,995	1,033
RFAR,POOS-CV	0,983	0,995	0,968	1	1,002	0,989	1,003	0.929**	0.951**	0,994
RFAR,K-fold	0,98	0,985	0,979	1,006	0,99	0,985	0,972	0.896***	0.943*	0,983
KRR-AR,POOS-CV	0,99	1,04	**0.882*****	**0.889*****	0.876***	1,04	1,116	0.843***	0.883***	0.904**
KRR,AR,K-fold	**0.940*****	**0.910*****	**0.878*****	**0.869*****	0.852***	0.847***	0.838***	**0.788*****	**0.798*****	0.908**
SVR-AR,Lin,POOS-CV	1,028	1.133**	1.130***	1.108***	1.174***	1.065*	1.274***	1.137***	1.094***	1.185***
SVR-AR,Lin,K-fold	0,993	1.061**	1.068***	1.045***	1.013***	1.062**	1.108***	1.032**	1,011	1.018***
SVR-AR,RBF,POOS-CV	1,019	1.094*	1,029	1.076**	1,01	1.097**	1.247**	1.047*	1.034***	1.112*
SVR-AR,RBF,K-fold	0,997	1,011	1.078**	1.053*	0,993	1,026	1,009	1,058	1,023	0,985
Data-rich (H_t^+) models										
ARDI,BIC	**0.937****	**0.893****	0,938	0,939	0.875***	**0.690*****	0.715***	**0.798*****	0.782***	**0.783*****
ARDI,AIC	**0.933****	**0.878*****	0,928	0,953	0.893**	**0.720*****	0.719***	**0.798*****	0.799***	**0.787*****
ARDI,POOS-CV	**0.924*****	**0.913***	0,957	0.925*	**0.856*****	**0.686*****	**0.676*****	0.840**	**0.737*****	**0.777*****
ARDI,K-fold	**0.935****	**0.895****	0,929	0,93	0.915**	**0.696*****	0.697***	**0.801*****	0.807***	**0.787*****
RRARDI,POOS-CV	**0.924*****	**0.896***	0,968	0,946	0.870***	**0.711*****	**0.635*****	0.849**	**0.768*****	**0.767*****
RRARDI,K-fold	**0.940****	**0.899****	0,946	0.931*	0.908**	**0.755****	**0.681*****	**0.803*****	0.790***	**0.753*****
RFARDI,POOS-CV	**0.934*****	0,945	**0.857*****	**0.842*****	**0.763*****	**0.724*****	0.769***	**0.718*****	**0.734*****	**0.722*****
RFARDI,K-fold	**0.932*****	**0.897*****	**0.873****	**0.854*****	**0.785*****	**0.749*****	0.742***	**0.731*****	**0.720*****	**0.710*****
KRR-ARDI,POOS-CV	**0.959***	**0.961**	**0.839*****	**0.813*****	**0.804*****	1,01	1,017	**0.748*****	**0.732*****	0.828***
KRR,ARDI,K-fold	**0.938*****	**0.907****	**0.827*****	**0.817*****	**0.795*****	0,925	0,933	**0.785*****	**0.729*****	**0.814*****
$(B_1, \alpha = \hat{\alpha})$,POOS-CV	0,979	**0.945**	0,976	0,953	0.913***	1,049	0.899*	0,933	0.910*	0.871***
$(B_1, \alpha = \hat{\alpha})$,K-fold	0,971	**0.925****	**0.867*****	0.919*	0.925*	0.787***	0.848***	0.840***	0.839***	0.829**
$(B_1, \alpha = 1)$,POOS-CV	0.947***	**0.937***	0,962	0.922**	0.889***	0.857**	0.789***	0.888**	0.860***	0.915*
$(B_1, \alpha = 1)$,K-fold	0,971	**0.925****	**0.867*****	0.919*	0.925*	0.787***	0.848***	0.840***	0.839***	0.829**
$(B_1, \alpha = 0)$,POOS-CV	1.238**	1.319**	1,021	1,07	1,01	1.393*	1.476*	0,979	0,972	**0.764*****
$(B_1, \alpha = 0)$,K-fold	1.246**	0,994	1.062*	1.077*	1,018	1,322	0,963	0,991	0,933	0.802***
$(B_2, \alpha = \hat{\alpha})$,POOS-CV	**0.907*****	**0.918****	0.926*	0.936*	0.911**	**0.756*****	0.767***	0.869**	0.832***	0.808***
$(B_2, \alpha = \hat{\alpha})$,K-fold	**0.917*****	**0.900*****	0.915*	0,931	0,974	**0.728*****	0.777***	0.829***	**0.738*****	**0.713*****
$(B_2, \alpha = 1)$,POOS-CV	**0.914*****	0,955	1,057	1,011	0.883***	0.810***	0.830***	1,029	0,952	0.795***
$(B_2, \alpha = 1)$,K-fold	0,97	**0.901****	0,991	0,983	0.918**	0.837**	0.754***	0,903	0.833***	**0.753*****
$(B_2, \alpha = 0)$,POOS-CV	**0.908*****	**0.893*****	0,991	0.922*	0.889***	0.781**	0.769***	0,915	0.786***	**0.788*****
$(B_2, \alpha = 0)$,K-fold	**0.949****	**0.898*****	0.908**	0.906**	0,967	0,875	0.777***	0.817***	**0.756*****	**0.741*****
$(B_3, \alpha = \hat{\alpha})$,POOS-CV	**0.949****	**0.888*****	0,952	0,943	0.874***	0,933	0.843***	0.886**	0.829***	0.827***
$(B_3, \alpha = \hat{\alpha})$,K-fold	**0.937****	**0.910*****	**0.882****	0.923*	0.921**	0.836*	0.831***	0.868***	0.839***	**0.795*****
$(B_3, \alpha = 1)$,POOS-CV	**0.929*****	**0.921****	0,958	0,983	0.884***	0.812**	0.771***	0.864**	0.851**	0.845***
$(B_3, \alpha = 1)$,K-fold	0,968	0.941*	**0.861*****	0.907*	0,943	0.808**	0.806***	0.832***	0.873**	**0.736*****
$(B_3, \alpha = 0)$,POOS-CV	**0.948****	0,974	0,994	1,066	0.946*	0,979	1,03	0,956	0.877**	**0.799*****
$(B_3, \alpha = 0)$,K-fold	0,969	**0.918*****	0,983	0,998	0.945*	0,963	0.901*	0,957	0.912*	**0.730*****
SVR-ARDI,Lin,POOS-CV	**0.960***	1,041	1,072	0,929	1,028	0,872	0.858*	0,941	0.809***	**0.779*****
SVR-ARDI,Lin,K-fold	0.959*	**0.873*****	**0.838*****	0,926	0,946	0.801**	0.791***	**0.756*****	**0.800****	0.872*
SVR-ARDI,RBF,POOS-CV	**0.966**	**0.995**	1,016	0,957	0.872***	0,938	0.859*	0,937	0.786***	**0.777****
SVR-ARDI,RBF,K-fold	**0.942****	0,958	**0.871****	0.911*	0,920	**0.768*****	0.796***	**0.770*****	**0.763*****	**0.797*****

Results: Term spread back

	Full Out-of-Sample					NBER Recessions Periods				
Models	h=1	h=3	h=9	h=12	h=24	h=1	h=3	h=9	h=12	h=24
Data-poor models										
AR,BIC (RMSPE)	**6.4792**	12,8246	**16.3575**	20,0828	22,2091	**13.3702**	23,16	23,5697	31,597	23,0842
AR,AIC	**1.002***	0,998	**1.053***	1.034**	1.041**	**1.002**	1,001	1,034	0,993	0,972
AR,POOS-CV	**1.055***	1.139*	**1.000**	0,969	1.040**	**1.041**	1,017	0.895*	0.857*	0,972
AR,K-fold	**1.001**	1	**1.003**	0,979	1.038*	**1.002**	0,998	0,911	0.890*	0,983
RRAR,POOS-CV	**1.055****	1.142*	**1.004**	0,998	1,016	**1.036**	1,014	0,899	0,966	0.945**
RRAR,K-fold	**1.044***	0,992	**1.027**	0,96	1,015	**1.024**	0,982	0,959	0.795**	0.957*
RFAR,POOS-CV	**0.997**	0,886	1.125***	1,019	1.107**	**0.906**	**0.816**	1,039	0.747**	1.077**
RFAR,K-fold	**0.991**	0,941	1.136***	1,011	1.084**	**0.909**	0,823	1,023	0.764*	1,038
KRR-AR,POOS-CV	1.223**	0,881	**0.949**	**0.888****	0.945*	**1.083**	**0.702**	**0.788*****	0.758***	0,948
KRR,AR,K-fold	**1.141**	0,983	**1.098****	0,999	1,048	**0.999**	**0.737**	0.833*	**0.663****	**0.924**
SVR-AR,Lin,POOS-CV	1.158**	1.326***	**1.071***	1,045	1,045	1.111*	1,072	0.894*	0.828*	0,967
SVR-AR,Lin,K-fold	1.191**	1,056	**1.018**	0,963	0,993	1,061	1,009	0.886**	0.845**	0.916***
SVR-AR,RBF,POOS-CV	**1.006**	1,039	**1.050***	0,951	0,969	**0.964**	0,902	0.876*	0.761**	**0.864*****
SVR-AR,RBF,K-fold	**0.985**	0,911	**1.038**	0,946	0.933**	**0.990**	**0.737**	0.851**	0.747*	0,968
Data-rich (H_t^+) models										
ARDI,BIC	**0.953**	0,971	**0.979**	0,93	**0.892*****	**0.921**	0,9	**0.790*****	**0.633*****	1,049
ARDI,AIC	**0.970**	0,956	**1.019**	0,944	0.917**	**0.929**	0,867	**0.814*****	**0.647*****	1,076
ARDI,POOS-CV	**0.954**	1,015	**1.067**	0,991	**0.915****	**0.912**	0,92	0,958	0.769**	1,087
ARDI,K-fold	**0.991**	1,026	**1.001**	0,928	0,939	**0.958**	0,967	0.812***	**0.662*****	1,041
RRARDI,POOS-CV	**0.936**	0,994	**1.078**	0,991	0,964	**0.896**	**0.850**	0,952	0.784**	1,092
RRARDI,K-fold	**1.015**	0,992	**1.018**	0,934	0,981	**0.978**	0,899	0.881*	**0.635*****	1.163*
RFARDI,POOS-CV	**0.988**	**0.830***	**0.957**	**0.873****	**0.921****	**0.804**	**0.691**	**0.785*****	**0.606*****	0,985
RFARDI,K-fold	**1.010**	0,883	**0.997**	0,909	0.935**	**0.808**	**0.778**	0.827**	**0.626*****	0,97
KRR-ARDI,POOS-CV	1.355**	0,898	**0.993**	**0.856****	**0.884*****	**0.861**	**0.682***	**0.772*****	**0.621****	**0.905***
KRR,ARDI,K-fold	1.382***	0,96	**0.974**	**0.827****	**0.862*****	**0.858**	**0.684***	**0.754*****	**0.569*****	0.912*
$(B_1,\alpha=\hat{\alpha})$,POOS-CV	1,114	1,06	1.126***	1,021	**0.866*****	**1.009**	0,981	1,02	**0.701****	1,012
$(B_1,\alpha=\hat{\alpha})$,K-fold	**1.089**	1.149**	1.199**	1.106*	0,969	**1.001**	1,041	0,885	0.767**	0,941
$(B_1,\alpha=1)$,POOS-CV	1.125*	1,115	1.172***	1,072	**0.844*****	1,071	1,006	1,033	0,833	0,96
$(B_1,\alpha=1)$,K-fold	**1.089**	1.149**	1.199**	1.106*	0,969	**1.001**	1,041	0,885	0.767**	0,941
$(B_1,\alpha=0)$,POOS-CV	1.173**	1.312**	1.176***	1,088	0,978	1,089	1,065	0,981	0,799	0,966
$(B_1,\alpha=0)$,K-fold	1.163*	1,059	**1.069**	0,929	**0.921****	**1.041**	0,869	**0.810****	0.729**	**0.880***
$(B_2,\alpha=\hat{\alpha})$,POOS-CV	**1.025**	0,993	**1.101****	1,028	**0.897*****	**0.918**	0,908	1,02	**0.651*****	0,989
$(B_2,\alpha=\hat{\alpha})$,K-fold	**0.976**	0,954	**1.098***	1,059	0.935*	**0.931**	0,875	0,938	0.779*	0,952
$(B_2,\alpha=1)$,POOS-CV	1,062	0,968	**1.125****	1,049	0.926***	**0.897**	0,855	1,058	0,79	1,001
$(B_2,\alpha=1)$,K-fold	**0.980**	0,938	**1.130****	1,01	0.950*	**0.948**	0,858	0,976	0.679**	1,001
$(B_2,\alpha=0)$,POOS-CV	1.118*	1,082	**1.097****	1,008	**0.901*****	**1.004**	0,919	1,008	**0.669*****	1,016
$(B_2,\alpha=0)$,K-fold	1,102	0,988	**1.047**	1,041	**0.919****	**0.985**	0,909	0.870*	0.757*	0,986
$(B_3,\alpha=\hat{\alpha})$,POOS-CV	**0.971**	0,964	**1.089****	1,076	0.933*	**0.887**	**0.837**	0,908	0.783*	0.904**
$(B_3,\alpha=\hat{\alpha})$,K-fold	**0.968**	0,944	**1.009**	0,999	**0.898*****	**0.895**	0,872	0.883**	0.744**	**0.907*****
$(B_3,\alpha=1)$,POOS-CV	**1.006**	1,066	**1.059***	1,039	**0.896*****	**0.894**	1,131	0,974	0.764*	0,987
$(B_3,\alpha=1)$,K-fold	**0.994**	0,924	**1.037**	0,96	0,975	**0.934**	0,852	0.834**	0.712**	1,01
$(B_3,\alpha=0)$,POOS-CV	1.181*	0,961	**1.104****	1,056	0.937**	1,215	0,901	1,013	0,825	0.919*
$(B_3,\alpha=0)$,K-fold	**0.999**	0,953	**1.036**	0,94	0,97	**0.897**	0,845	0,923	0.735**	0.925**
SVR-ARDI,Lin,POOS-CV	**1.062**	0,967	**1.164****	1.113*	1,065	1,016	**0.762***	1,117	0.714**	1,097
SVR-ARDI,Lin,K-fold	**0.990**	0,98	**1.011**	**0.922**	**0.909****	**0.935**	0,885	0.825**	**0.667****	0,994
SVR-ARDI,RBF,POOS-CV	**0.972**	0,937	**1.069**	1,039	1,068	**0.875**	**0.741**	**0.796*****	0.707***	1.204*
SVR-ARDI,RBF,K-fold	**1.010**	0,938	**1.122**	**0.914***	**0.923*****	**0.921**	**0.791**	0.859**	0.779*	**0.952***

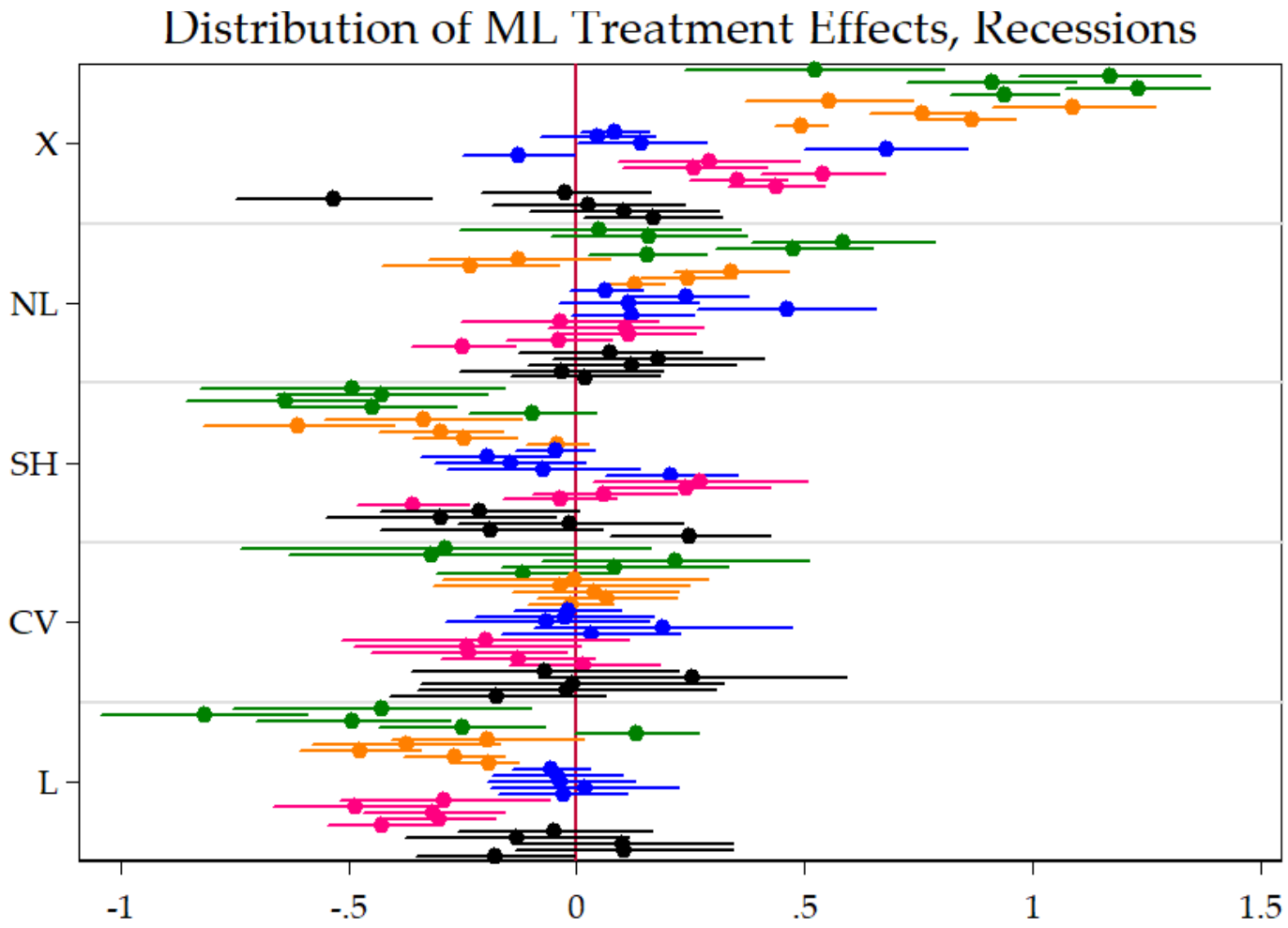
Results: CPI inflation back

	Full Out-of-Sample					NBER Recessions Periods				
Models	h=1	h=3	h=9	h=12	h=24	h=1	h=3	h=9	h=12	h=24
Data-poor models										
AR,BIC (RMSPE)	0,0312	0,0257	0,0194	0,0187	0,0188	0,0556	0,0484	0,032	0,0277	0,0221
AR,AIC	0.969***	0,984	0.976*	0,988	0,995	1	0.970**	0,999	0,992	1,005
AR,POOS-CV	0.966**	0,988	0,997	0,992	1,009	0.961**	0,981	0,995	0,978	1,003
AR,K-fold	0.972**	0.976**	0.975*	0,988	0,987	1,002	0.965***	0,998	0,992	1,005
RRAR,POOS-CV	0.969**	0,984	0,99	0,993	1,006	0.961**	0,982	0,995	0.963*	0,998
RRAR,K-fold	0.964***	0.979**	0.970*	0.980*	0,989	0,989	0.973**	0,996	0,992	0,997
RFAR,POOS-CV	0,983	**0.944***	**0.909***	**0.930**	1,022	1,018	0,998	1,063	1,047	0,998
RFAR,K-fold	**0.975**	**0.927****	**0.909***	**0.956**	0,998	1,032	0,972	1,065	1,103	1,019
KRR-AR,POOS-CV	**0.972**	**0.905****	**0.872****	**0.872****	0.907**	1,023	**0.930****	0,927	0,91	0.852*
KRR,AR,K-fold	**0.931*****	**0.888*****	**0.836****	**0.827*****	0,942	0,965	**0.920****	0,92	0,915	0,975
SVR-AR,Lin,POOS-CV	1.119**	1.291**	1.210***	1.438***	1.417***	1,116	1.196**	1.204**	1,055	1.613***
SVR-AR,Lin,K-fold	1.239***	1.369**	1.518***	1.606***	1.411***	1.159*	1.326*	1.459**	1.501*	1,016
SVR-AR,RBF,POOS-CV	0,988	1,004	1.086*	1.068**	1.127**	0,999	1,004	0,969	1.091**	1.501***
SVR-AR,RBF,K-fold	0,99	1,025	1,025	1,003	1.370***	0,965	0,979	0,996	0.896**	1.553**
Data-rich (H_t^+) models										
ARDI,BIC	0,96	**0.973**	1,024	**0.895***	0.880*	0.919*	**0.906***	0.779*	0.755**	0.713**
ARDI,AIC	**0.954**	**0.990**	1,034	**0.895**	0,884	0,925	**0.898**	0.778*	**0.736****	0.676**
ARDI,POOS-CV	**0.950**	**0.984**	1,017	**0.910**	0,916	0.916*	**0.913***	0.832**	0.781***	**0.669****
ARDI,K-fold	**0.941***	**0.990**	1,028	**0.873***	**0.858***	0.891**	**0.900**	0.784*	**0.709*****	**0.635****
RRARDI,POOS-CV	**0.943***	**0.975**	1,001	**0.917**	0,914	0.905*	**0.912***	0.828**	**0.780*****	**0.666****
RRARDI,K-fold	**0.943****	**0.983**	1,022	**0.875***	**0.882**	0.927*	**0.901**	**0.744****	**0.664*****	**0.613****
RFARDI,POOS-CV	**0.947****	**0.908*****	**0.853****	**0.914***	0,979	0,976	**0.939****	0,988	1,051	0,964
RFARDI,K-fold	**0.936*****	**0.907*****	**0.854****	**0.868****	0.909*	0,962	**0.933****	0,979	0,93	1,003
KRR-ARDI,POOS-CV	1,006	1,043	0,959	0,972	1,067	1,046	1,093	0,952	0,948	0,946
KRR,ARDI,K-fold	**0.985**	0,999	0,983	0,977	0,938	0,998	0,99	1,023	1,022	0,986
$(B_1,\alpha = \hat{\alpha})$,POOS-CV	**0.918****	**0.916***	0,976	0,96	1,026	**0.803*****	**0.900***	0,8	0,848	0,974
$(B_1,\alpha = \hat{\alpha})$,K-fold	**0.908****	**0.921***	1,012	1,056	1.092*	**0.823****	**0.873***	**0.774**	0,836	1,069
$(B_1,\alpha = 1)$,POOS-CV	**0.960**	**0.908****	1,11	1,03	1,076	**0.813****	**0.889***	0,794	0,825	0,989
$(B_1,\alpha = 1)$,K-fold	**0.908****	**0.921***	1,012	1,056	1.092*	**0.823****	**0.873***	**0.774**	0,836	1,069
$(B_1,\alpha = 0)$,POOS-CV	0,971	1,035	1.114*	1,048	1.263**	0.848**	**0.906**	0,935	0,881	0,99
$(B_1,\alpha = 0)$,K-fold	**0.945***	1,057	1.246**	1.289**	1.260***	**0.850*****	**0.939**	0,954	0,944	1,095
$(B_2,\alpha = \hat{\alpha})$,POOS-CV	**0.923****	**0.956****	**0.940**	0,934	0,945	0.871*	0,959	0.803*	0.802*	0.822*
$(B_2,\alpha = \hat{\alpha})$,K-fold	**0.921****	**0.963***	0,995	0,956	1,037	0.868*	0.957*	0.817*	0.778**	0,861
$(B_2,\alpha = 1)$,POOS-CV	**0.942**	**0.959**	1.158*	1.174**	1.151**	0,877	0,927	0,799	0,907	1,087
$(B_2,\alpha = 1)$,K-fold	**0.922****	**0.970**	1,066	0,995	1.168*	0,879	0,929	0,853	0.816*	1,009
$(B_2,\alpha = 0)$,POOS-CV	**0.921****	**0.940**	1,079	0,959	1,071	0.857*	**0.881**	1,129	0,883	0,851
$(B_2,\alpha = 0)$,K-fold	**0.919****	**0.929***	0,997	1,011	1.212**	0.865*	**0.883**	0,825	0,961	0,853
$(B_3,\alpha = \hat{\alpha})$,POOS-CV	**0.935***	**0.941*****	**0.961**	**0.849****	0.901*	0.889*	**0.947****	0.791**	0.785**	0.808**
$(B_3,\alpha = \hat{\alpha})$,K-fold	**0.938***	**0.952****	**0.937**	**0.915**	0,952	0.891*	0.958*	0.801*	0.784**	0,91
$(B_3,\alpha = 1)$,POOS-CV	**0.933***	**0.960**	1,076	1	1,017	**0.856***	**0.917***	**0.755***	**0.769****	0,86
$(B_3,\alpha = 1)$,K-fold	**0.943**	0,978	1,006	**0.894**	1,002	0,889	0,946	0,805	0.806*	0,879
$(B_3,\alpha = 0)$,POOS-CV	**0.946***	**0.939****	**0.896***	**0.871****	1,022	0.894*	**0.931****	0,865	0,875	0,896
$(B_3,\alpha = 0)$,K-fold	**0.921*****	**0.975**	**0.926**	**0.920**	1,106	0.877***	**0.936**	0,839	0,892	1,147
SVR-ARDI,Lin,POOS-CV	1.148***	1.202*	1.251***	1.209***	1.219**	1,068	1,053	0,969	0,969	0,943
SVR-ARDI,Lin,K-fold	1.115***	1.390**	1.197**	1,114	1.177*	1,058	1.295*	0,944	0,954	1,036
SVR-ARDI,RBF,POOS-CV	0,963	1,031	1,002	0,962	0,951	0,922	**0.915**	0,848	0,861	0,996
SVR-ARDI,RBF,K-fold	**0.971****	1,002	0,997	0,945	**0.707*****	0,927	0,964	0,916	0.826**	**0.670****

Results: Housing starts back

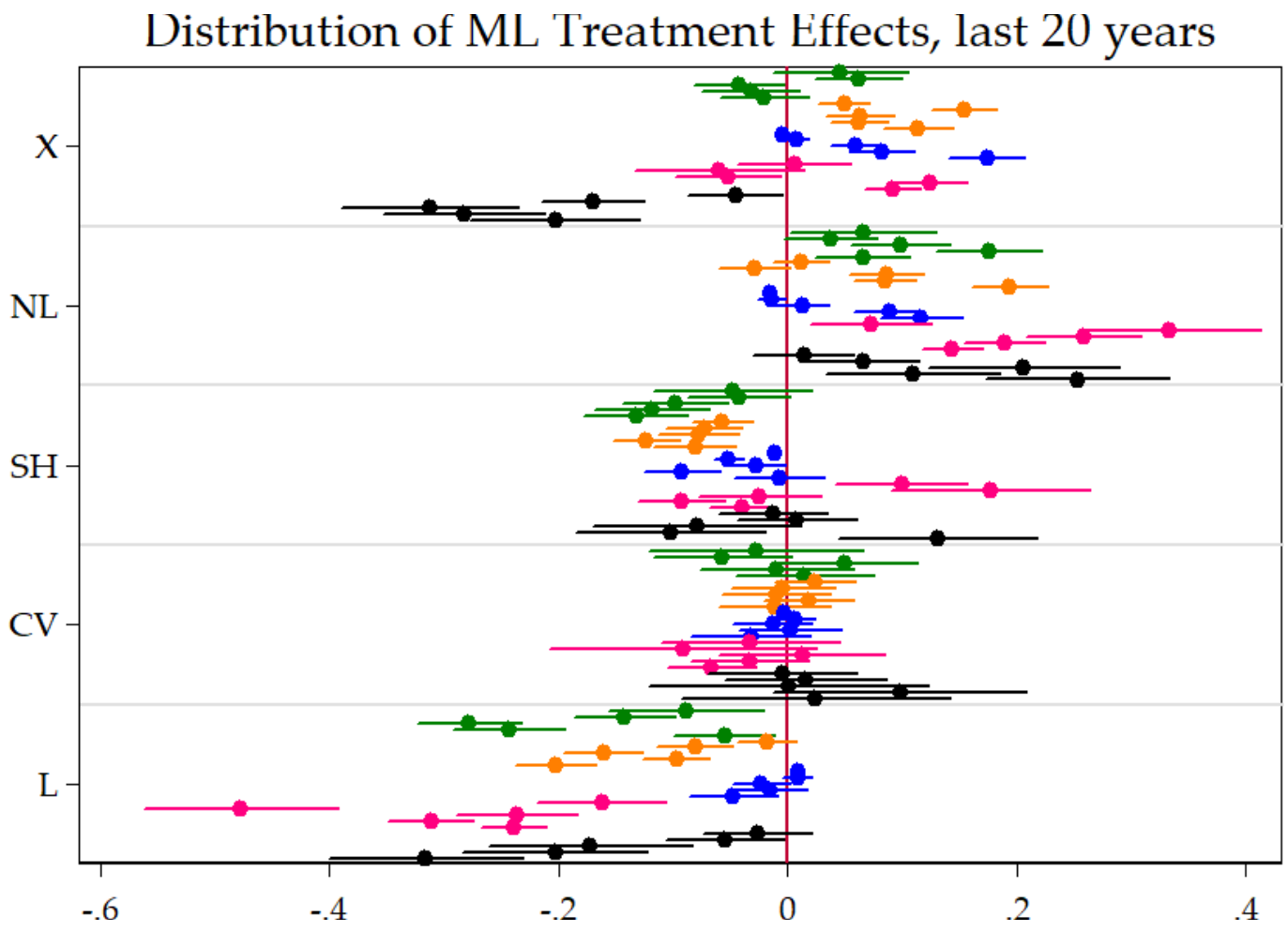
	Full Out-of-Sample					NBER Recessions Periods				
Models	h=1	h=3	h=9	h=12	h=24	h=1	h=3	h=9	h=12	h=24
Data-poor models										
AR,BIC (RMSPE)	**0.9040**	**0.4142**	**0.2499**	0,2198	0,1671	**1.2526**	0,6658	0,4897	0,4158	0,2954
AR,AIC	**0.998**	**1.019**	**1.000**	**1.000**	1	1,01	0.965*	1	1	1
AR,POOS-CV	**1.001**	**1.012**	**1.019***	1,01	1.036**	1,015	**0.936****	1.011*	1,013	1.057**
AR,K-fold	**0.993**	**1.017**	**1.001**	1	1,02	1,01	**0.951****	1	1	1,036
RRAR,POOS-CV	**1.007**	**1.007**	**1.008**	1,009	1.031**	1.027*	**0.939****	1,001	1,013	1.050**
RRAR,K-fold	**0.999**	**1.014**	**0.998**	**0.998**	1.024*	1,013	**0.941****	1.000**	0,999	1.042**
RFAR,POOS-CV	1.030***	**1.026***	**1.028***	1.045**	1,018	1,023	**0.941***	**0.992**	1.048*	1,013
RFAR,K-fold	1.017*	**1.022**	**1.007**	1.031**	1,008	1,02	**0.942***	**0.990**	1,026	1,01
KRR-AR,POOS-CV	**0.995**	**0.999**	**0.969***	1.044*	1.037*	**0.990**	**0.972**	**0.971**	1.050**	0,993
KRR,AR,K-fold	**0.977***	**0.975**	**0.957****	**0.989**	1,001	**0.985**	**0.976**	1,01	1,006	1,004
SVR-AR,Lin,POOS-CV	1.032***	**0.997**	**1.044*****	1.064***	1.223**	1.024*	**0.962***	**0.986***	0,984	**0.957*****
SVR-AR,Lin,K-fold	1.036***	1,031	**1.002**	1,006	1,002	1,013	0,976	1,002	1,009	1,004
SVR-AR,RBF,POOS-CV	**1.008**	1.047**	**1.023**	1.035***	1.060***	**1.014**	0,981	**0.947*****	1,015	1,017
SVR-AR,RBF,K-fold	1,009	**1.011**	**1.012****	1.020***	1.034**	1.021*	0.969*	1.010***	1.017**	1,001
Data-rich (H_t^+) models										
ARDI,BIC	**0.973***	**0.989**	**1.031**	1,051	1,05	**0.946**	1,139	1,048	0,988	0,944
ARDI,AIC	**0.992**	**0.995**	**1.018**	1,06	1,078	**1.000**	1,113	1,025	1,025	0,96
ARDI,POOS-CV	1,01	**1.007**	**1.080**	1,027	0,998	1,023	1,128	1,054	1,015	1,021
ARDI,K-fold	**0.992**	**0.984**	**1.026**	1,061	1,094	**1.011**	1,093	1,027	1,027	0,958
RRARDI,POOS-CV	**0.998**	**1.007**	**1.043**	**0.996**	1,082	1,008	1,119	1,041	0,991	1,022
RRARDI,K-fold	**0.998**	**0.988**	**1.051**	1,064	1,089	1,017	1,118	1,033	0,998	0,941
RFARDI,POOS-CV	**0.997**	**0.944****	**0.930****	**0.920***	0.899**	**0.982**	**0.971**	**0.965**	0,957	0,972
RFARDI,K-fold	**0.994**	**0.962**	**0.939***	**0.914***	**0.838*****	**0.993**	0,985	**0.986**	**0.943**	0.902*
KRR-ARDI,POOS-CV	**0.980**	**0.943*****	**0.915****	**0.942****	**0.884*****	**0.941***	**0.952***	**0.949**	0.964**	0,986
KRR,ARDI,K-fold	**0.982****	**0.949****	**0.928**	**0.933**	**0.889****	**0.973**	**0.973**	**1.003**	1,022	0,994
$(B_1,\alpha=\hat{\alpha})$,POOS-CV	**1.006**	**1.000**	**1.063**	1,016	**0.895****	1,023	1,099	**0.985**	1,026	1,022
$(B_1,\alpha=\hat{\alpha})$,K-fold	1.040*	1.095**	1.250**	1.335**	1.151*	1.096*	1.152**	1,021	1,127	**0.890**
$(B_1,\alpha=1)$,POOS-CV	1.032**	1,039	1,155	1,045	0,949	1,013	1,063	**0.961**	1,025	1,062
$(B_1,\alpha=1)$,K-fold	1.040*	1.095**	1.250**	1.335**	1.151*	1.096*	1.152**	1,021	1,127	**0.890**
$(B_1,\alpha=0)$,POOS-CV	**0.982**	**0.977**	1,084	1.337**	0,959	**0.999**	1,017	1,014	1.152**	0,964
$(B_1,\alpha=0)$,K-fold	**0.982**	**1.006**	1.137*	1.158**	1,007	**0.994**	1,03	**1.017**	1,067	**0.809****
$(B_2,\alpha=\hat{\alpha})$,POOS-CV	1,044	**0.992**	**0.975**	0,988	0,969	1,177	1.126*	1,034	0,989	0,972
$(B_2,\alpha=\hat{\alpha})$,K-fold	**0.988**	**1.003**	**1.069**	1.193**	1,069	1,11	1.188*	1,085	1.133*	0,917
$(B_2,\alpha=1)$,POOS-CV	**1.001**	**1.000**	**0.967**	1,02	0.940*	**0.961**	1,047	**0.943**	0,985	1,006
$(B_2,\alpha=1)$,K-fold	**0.989**	1,095	1.245**	1.203*	1,093	1,007	1.322***	1,1	**0.919**	**0.848****
$(B_2,\alpha=0)$,POOS-CV	1.091*	**0.949**	**0.987**	**0.971**	0,939	1,255	1,027	**0.992**	**0.956**	0,994
$(B_2,\alpha=0)$,K-fold	1,066	**1.068**	1,19	1,044	1,064	1,248	1.332**	1,057	**0.896*****	0,917
$(B_3,\alpha=\hat{\alpha})$,POOS-CV	1,009	**0.951***	**0.935**	0,99	**0.891****	1,028	1,019	**0.958**	**0.963**	0,987
$(B_3,\alpha=\hat{\alpha})$,K-fold	**0.998**	**0.977**	**1.007**	1,055	1,044	1,019	1,115	1,017	**0.979**	**0.882***
$(B_3,\alpha=1)$,POOS-CV	**0.997**	**0.975**	**1.024**	0,996	0.928*	**0.976**	1,001	1,021	**0.940**	1,001
$(B_3,\alpha=1)$,K-fold	1,013	**1.040**	1,071	1,106	1,145	1,042	1.219*	1,036	0,992	1,009
$(B_3,\alpha=0)$,POOS-CV	1.022*	**0.951***	**0.962**	**0.944**	0.932*	1,022	0,981	**0.930**	**0.915****	1,001
$(B_3,\alpha=0)$,K-fold	1.030**	**1.003**	**1.005**	1,011	1,029	**0.986**	1,114	**0.998**	**0.955**	0,934
SVR-ARDI,Lin,POOS-CV	**0.998**	1.078*	1.154*	1.137*	1,142	1,047	1,111	**0.989**	1,009	1,111
SVR-ARDI,Lin,K-fold	**0.992**	**0.971**	**1.017**	1,038	1,11	1,007	1,021	**0.988**	**0.937**	0,959
SVR-ARDI,RBF,POOS-CV	**0.991**	**1.004**	**1.010**	1,044	1,034	**0.987**	1,095	**0.981**	0,969	1,096
SVR-ARDI,RBF,K-fold	**1.002**	**0.998**	**1.045**	1.078*	1.162*	1,023	1,031	1,02	0,984	1,026

Results: Disentangling ML Treatment Effects back



This figure plots the distribution of $\dot{\alpha}_F^{(h,v)}$ by (h,v) subsets. The subsample under consideration are **recessions**. The unit of the x-axis are improvements in OOS R^2 over the basis model. Variables are INDPRO, UNRATE, SPREAD, INF and HOUST.

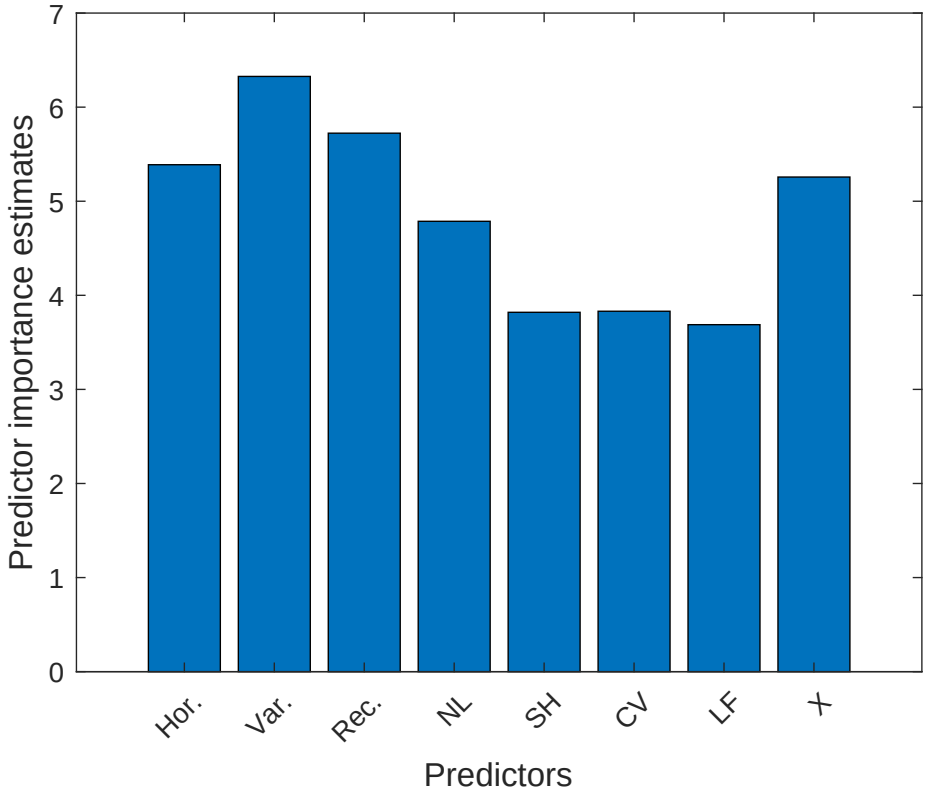
Results: Disentangling ML Treatment Effects back



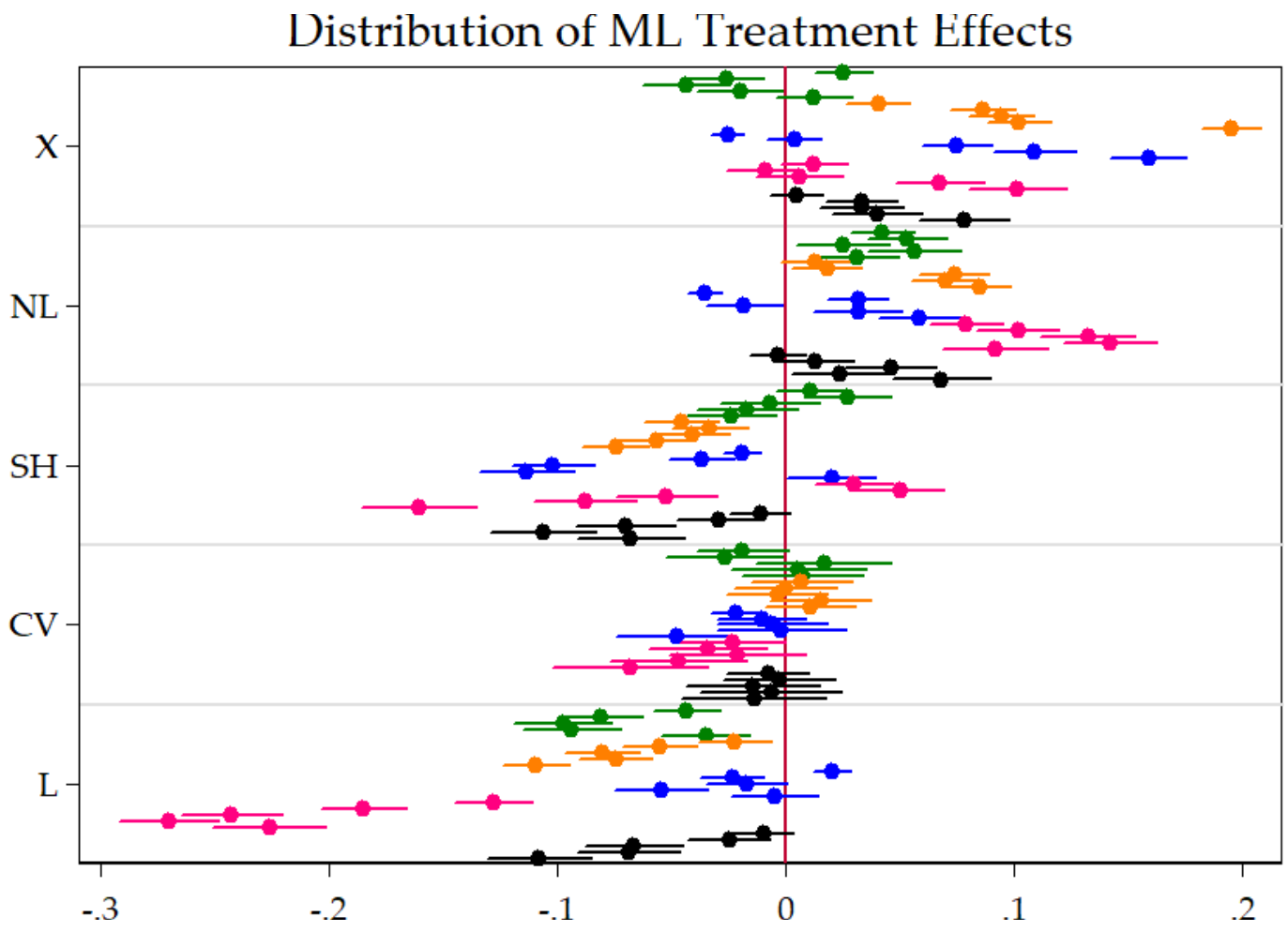
This figure plots the distribution of $\dot{\alpha}_F^{(h,v)}$ by (h,v) subsets. The subsample under consideration are **the last 20 years**. The unit of the x-axis are improvements in OOS R^2 over the basis model. Variables are INDPRO, UNRATE, SPREAD, INF and HOUST.

Results: Disentangling ML Treatment Effects

- Random forest on $R^2_{t,h,v,m}$: report the importance of each features in what is a potentially very non-linear model.
- Let the tree automatically create interactions such as $I(NL = 1) * I(h \leq 12)$

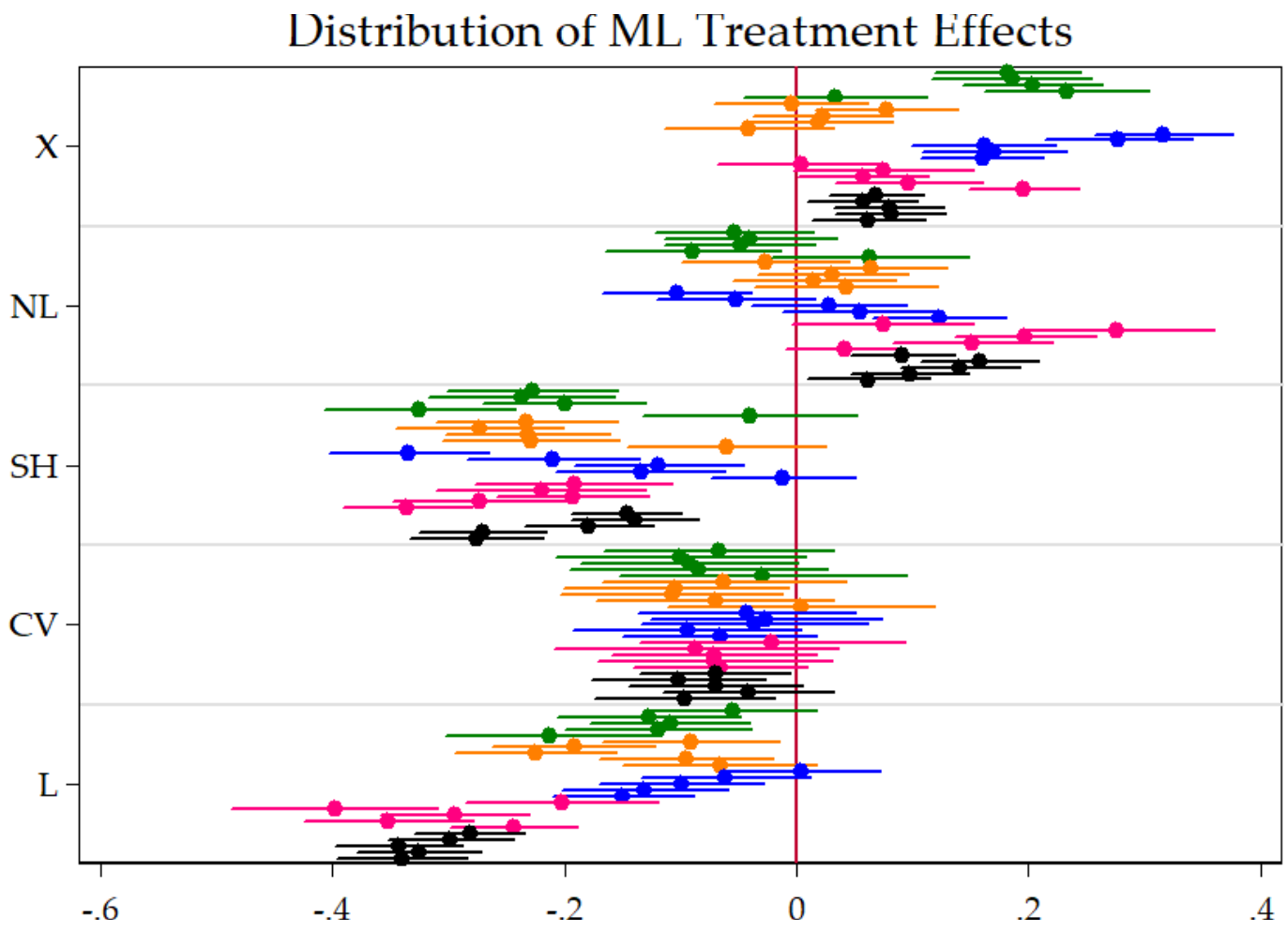


Results: Disentangling ML Treatment Effects back



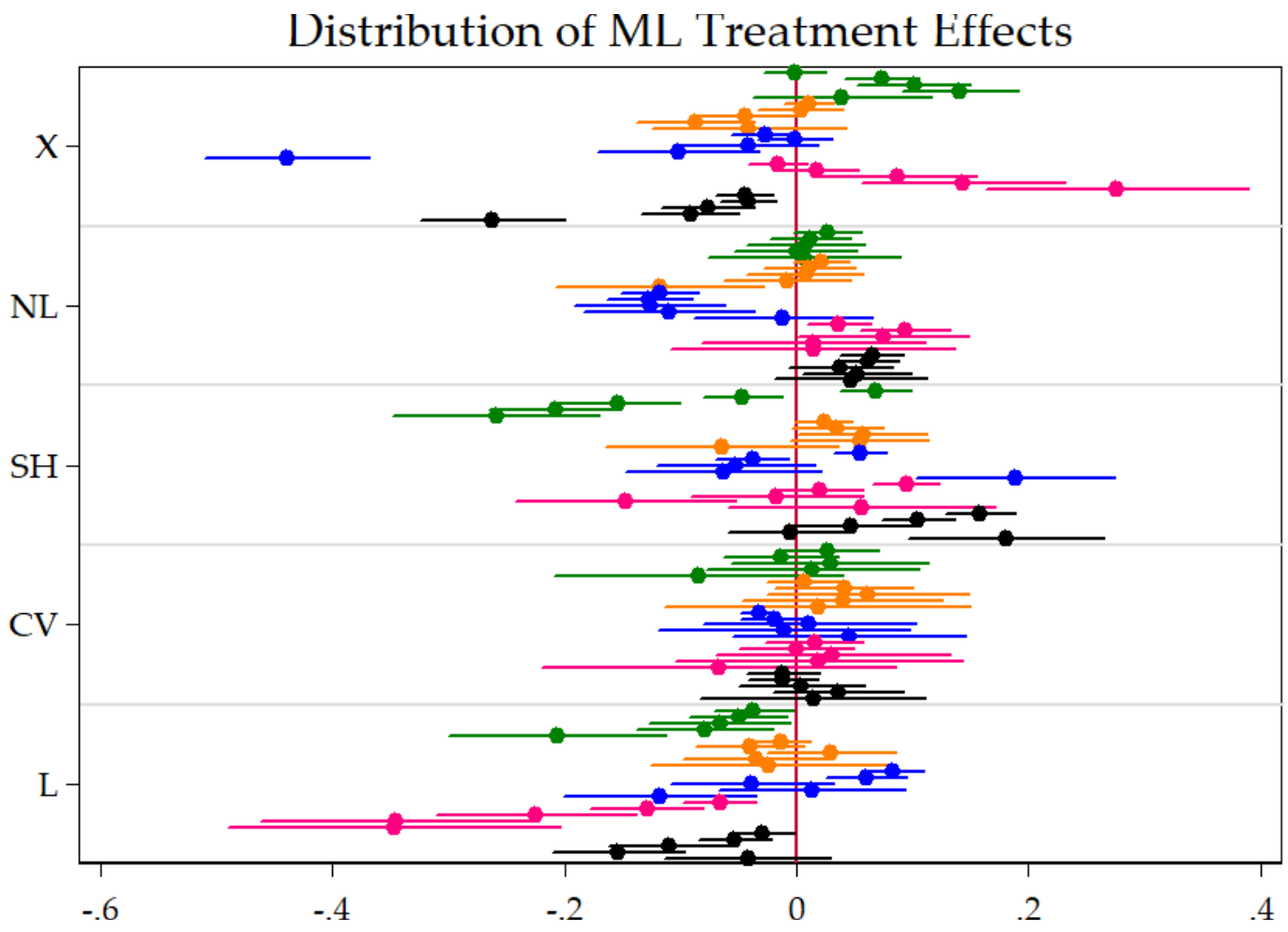
This figure plots the distribution of $\dot{\alpha}_F^{(h,v)}$ by (h,v) subsets. X stands for data-rich. Variables: INDPRO, UNRATE, SPREAD, INF and HOUST. Within a specific color block, the horizon increases from $h = 1$ to $h = 24$ as we are going down. SEs are HAC. These are the 95% confidence bands.

Results: Disentangling ML Treatment Effects back



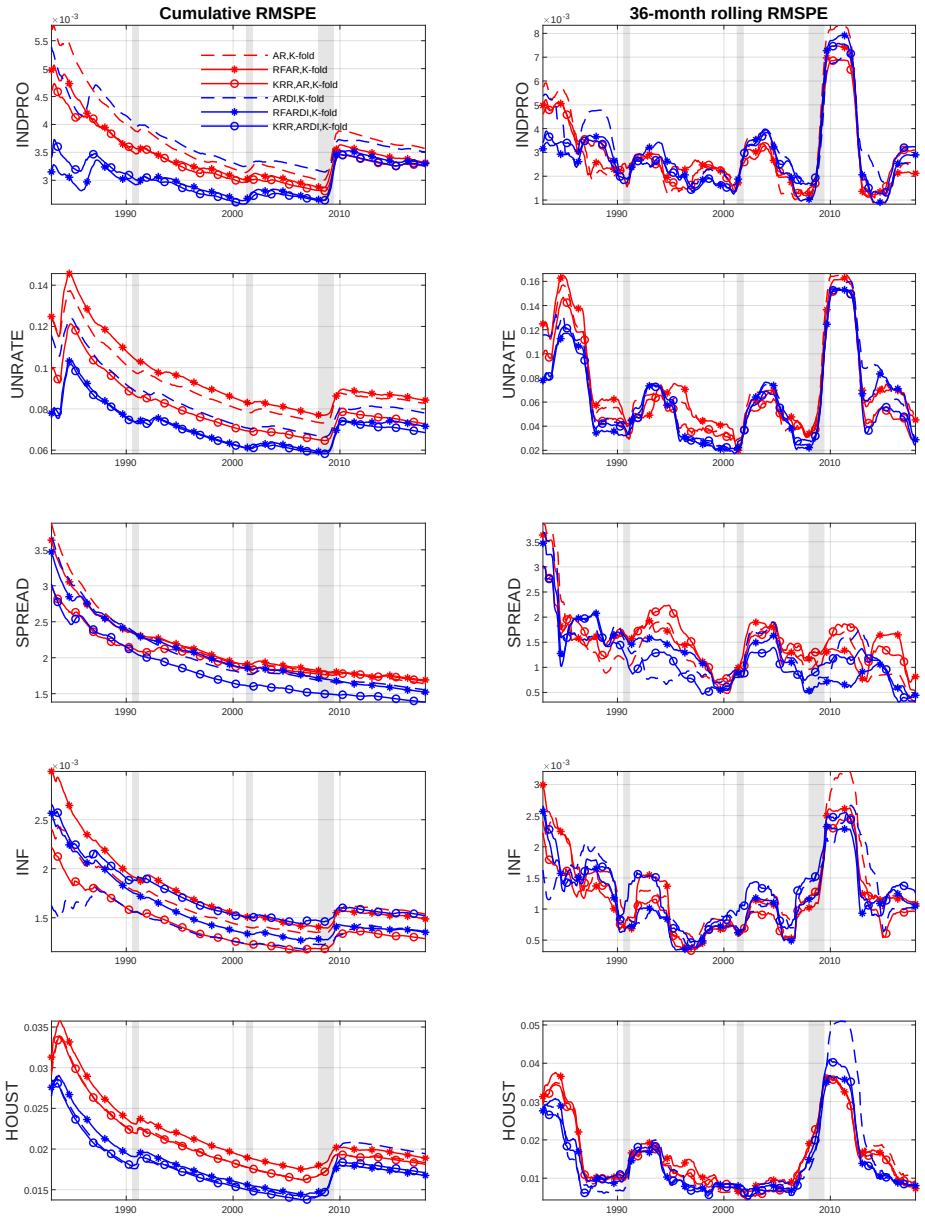
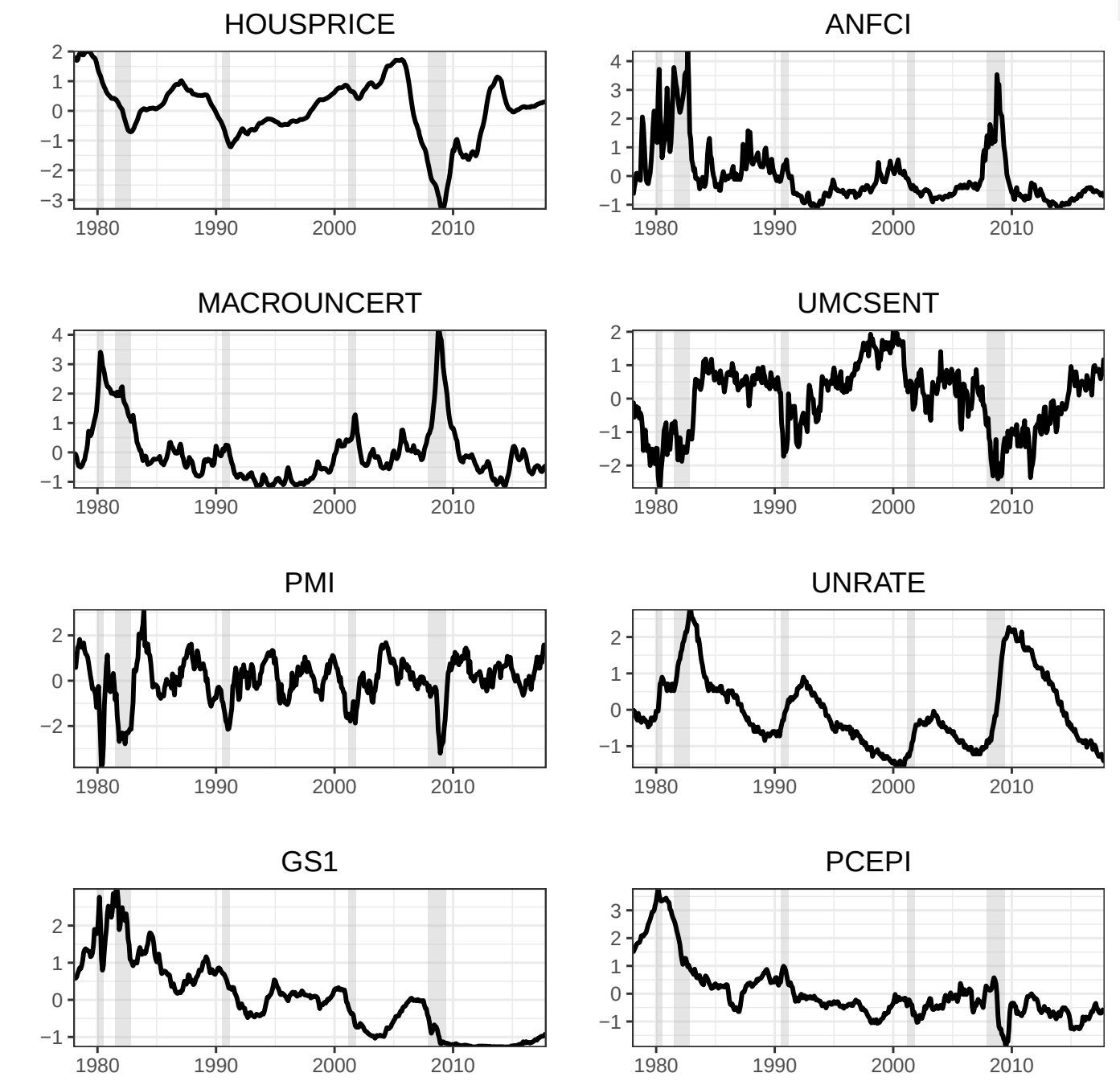
This figure plots the distribution of $\dot{\alpha}_F^{(h,v)}$ by (h,v) subsets. X stands for data-rich. Variables: GDP, CONS, INV, INC and DEF. Within a specific color block, the horizon increases from $h = 1$ to $h = 8$ as we are going down. SEs are HAC. These are the 95% confidence bands.

Results: Disentangling ML Treatment Effects back



This figure plots the distribution of $\dot{\alpha}_F^{(h,v)}$ by (h,v) subsets. X stands for data-rich. Variables: INDPRO, UNRATE, SPREAD, INF and HOUS. Within a specific color block, the horizon increases from $h = 1$ to $h = 8$ as we are going down. SEs are HAC. These are the 95% confidence bands.

Results: TV Nonlinearities and Data-Rich Effects back



Macro variables in ξ_t back