Stock Return Predictability: comparing Macro- and Micro-Approaches

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Motivation

- Efficient Market Hypothesis often implies no predictability: $r_{t+1} = \alpha + \beta' \boldsymbol{X}_t + u_{t+1}$
- But aggregate returns may differ from individual ones due to diversification:

"Modern markets show considerable micro efficiency. [But] I had hypothesized considerable macro inefficiency" (Samuelson)

- What would micro-predictability give compared with macro-predictability?
- Interpretation is sensitive, predictability can both come from:
  1. **alpha-predictability**: market inefficiencies
  2. **beta-predictability**: time-varying expected returns

Contribution

- Literature on predictability heavily focuses on **macro-returns**.
- Studies on micro-predictability do not report **time variation** (Rapach et al.,2011) or do not draw **micro-macro comparisons** (Chinco et al., 2019).

Table: Comparison with Literature

	Aggregate	**Individual**
Constant	Campbell and Shiller (1988) Lettau and Ludvigson (2001) van Binsbergen and Koijen (2010)	Avramov (2004) Rapach et al. (2011)
Time-Varying	Goyal and Welch (2008) Dangl and Halling (2012) Kelly and Pruitt (2013) Farmer et al. (2019)	Chinco et al. (2019) **Paper**

Preview: Methodology & Results

1. **Methodology**
    - Three working hypotheses on return predictability.
    - Postwar US monthly excess returns. 23 models estimated.
    - Evaluating first **"raw" micro/macro-predictability** (out-of-sample) in a time-varying manner.
    - Building then a metric of predictability theoretically linked **only with market inefficiencies**: $R^2_{\alpha,t}$.

2. **Results**
    - Raw micro-predictability is **not** structurally lower than macro-predictability ($\neq$ Samuelson).
    - Micro/macro-predictability appear to follow a model where **both** alpha- and beta-predictability are at play.
    - Decomposing return predictability into $R^2_{\alpha,t}$ and $R^2_{\beta,t}$ match the theoretical explanations.

1. Theoretical Background

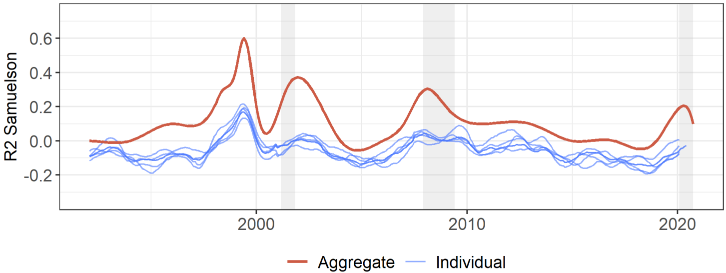
- We build **3 different hypotheses** regarding the behaviour of micro/macro-predictability.
- Remember, return predictability can emerge from alpha-predictability or from beta-predictability
- More formally, following Rapach et al. (2011):

$$\begin{cases} r_{t+1} = \alpha(\boldsymbol{X}_t) + \beta_t' \boldsymbol{f}_{t+1} + \epsilon_{t+1} \\ \boldsymbol{f}_{t+1} = g(\boldsymbol{X}_t) + \boldsymbol{u}_{t+1} \end{cases}$$

- This system constitutes the basis for the 3 hypotheses.

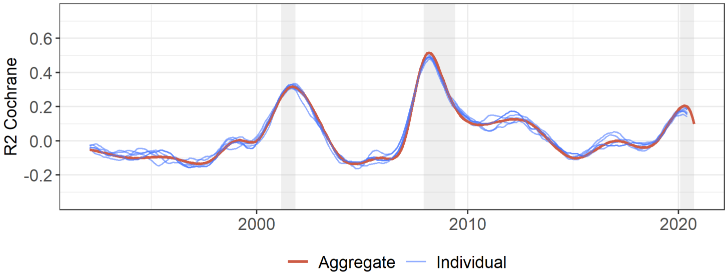
2. H_1, Samuelson's view

- Micro-inefficiencies are **arbitraged away**, and micro-efficient components are **averaged out** in the aggregate.
- Macro-inefficiencies subsist, particularly for aggregate returns.
- Macro-returns should especially be predictable in times of **elevated market inefficiencies** (speculative bubbles or recessions).



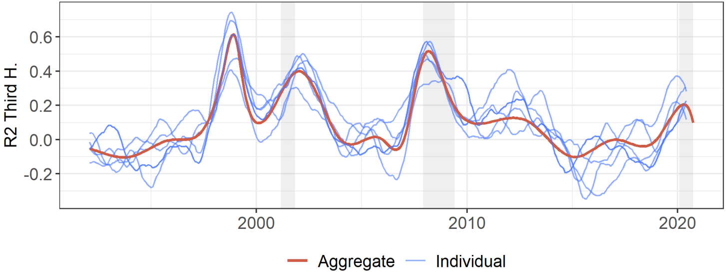
3. H_2, Cochrane's view

- **Markets are efficient**, but micro/macro-predictability persist due to time-variation in expected returns.
- As micro- and macro-predictability emerge from the same phenomenon, **they evolve similarly**.
- The mechanism is especially at play **during recessions** (Henkel et al., 2011).



4. H_3, Third view

- Micro-returns are affected **both** by idiosyncratic efficient and inefficient components that are **averaged out** in the aggregate.
- Macro-returns are affected **both** by alpha- and beta-predictability.
- Consequently: micro-predictability bounces around macro-pred. Strong Macro-predictability during **market booms and recessions**.



Data and Models

Data:

- Postwar US monthly excess returns - K.French website.
- 25 PF returns vs. Aggregate returns.

Models:

- **23 models estimated**. Econometric (DESH, AR...), forecast averaging, ML (ANN), factor models...
- Each period, chosen model is the one with the best previous Out-of-Sample performance.

Methodology:

- Models are estimated on 120-month windows (Timmermann, 2008).
- Raw predictability: **Out-of-Sample R^2** (wrt. prevailing mean)

Disentangling Return Predictability (i)

We first estimate **raw micro/macro-predictability** with:

$$R^2_{os,i,t} = 1 - \sum_{i=t-n}^{t-1} \frac{(r_{i+1} - r^f_{i+1})^2}{(r_{i+1} - \bar{r}_i)^2}$$

We then build a **constrained** return-forecast:

- First by forecasting risk factors $\boldsymbol{f}_{t+1}$
- Then by computing:

$$r^{\beta}_{i,t+1} = \hat{\boldsymbol{\beta}}'_{i,t} \boldsymbol{f}^f_{t+1}$$

All predictability stemming from the risk factors is embedded in $r^{\beta}_{i,t+1}$ (Rapach et al., 2011).

Disentangling Return Predictability (ii)

We can thus build estimates of alpha- and beta-predictability:

$$R^2_{i,\beta,t} = 1 - \sum_{i=t-n}^{t-1} \frac{(r_{i+1} - r^{\beta}_{i+1})^2}{(r_{i+1} - \bar{r}_i)^2}$$

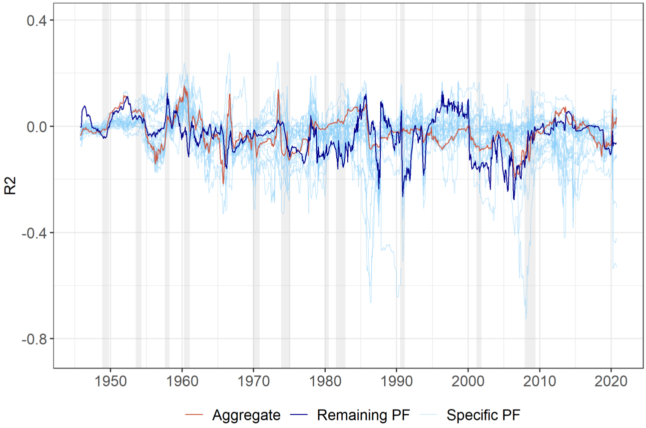
$$R^2_{i,\alpha,t} = 1 - \sum_{i=t-n}^{t-1} \frac{(r_{i+1} - r^{f}_{i+1})^2}{(r_{i+1} - r^{\beta}_{t+1})^2}$$

and show that:

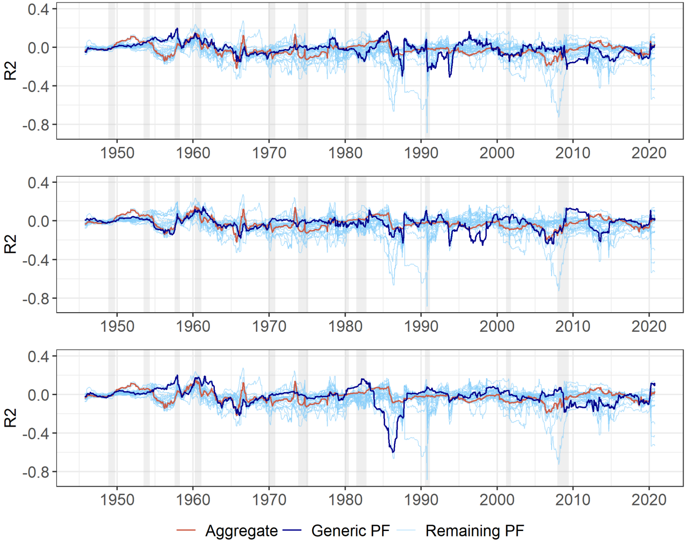
$$R^2_{i,os,t} \sim R^2_{i,\alpha,t} + R^2_{i,\beta,t}$$

$R^2_{i,\alpha,t}$ assesses the **extra-predictability** that can be gained beyond the exposition to predictable risk factors.

1. Raw Pred.: Individual variances > Agg. variance



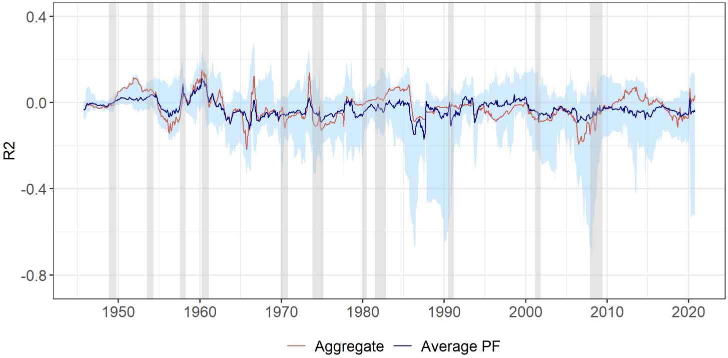
2. Raw Pred.: Micro-pred. isn't lower than macro-pred.



3. Raw Pred.: Aggregating PFs

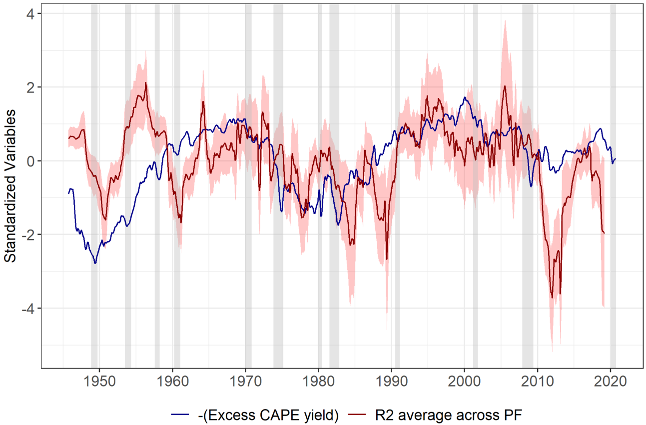
Pooling individual raw predictability series:

- Sharply reduces the variance.
- Increases the **correlation with macro-predictability**.



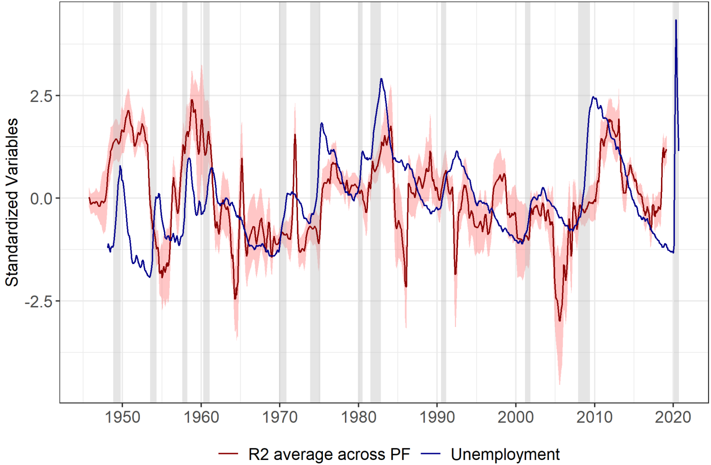
4. Disentangling alpha- and beta-predictability: $R^2_{i,\alpha,t}$

- $\overline{R^2}_{i,\alpha,t}$ high during "Kennedy-Johnson peak" and during the dotcom bubble.
- Relatively strong dispersion along the mean.



5. Disentangling alpha- and beta-predictability: $R^2_{i,\beta,t}$

- $\overline{R^2}_{i,\alpha,t}$ rises during the 1960-61 recession or during the GFC.
- $R^2_{i,\beta,t}$ series are less dispersed, they reflect the same mechanism.



6. Drivers of alpha-Predictability

$$\overline{R^2}_{i,\alpha,t} = c + \gamma'_{IE}\boldsymbol{X}_{IE,t} + \gamma'_{RA}\boldsymbol{X}_{RA,t} + \gamma'_{FC}\boldsymbol{X}_{FC,t} + \epsilon_t$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$-ecy_t$	24.0*** (6.8)	44.3*** (13.0)	24.3*** (6.9)						
pe_t				0.1*** (0.02)	0.1*** (0.01)	0.1*** (0.02)			
$Yale_t$							0.2*** (0.04)	0.2*** (0.03)	0.2*** (0.04)
$-unemp_t$	0.7*** (0.2)	0.6** (0.3)	0.7*** (0.2)	0.8*** (0.2)	1.0*** (0.2)	0.7*** (0.2)	1.3*** (0.4)	1.5*** (0.4)	1.4*** (0.4)
$vol_{1,t}$	−0.001 (0.1)			−0.1 (0.1)			0.3*** (0.1)		
$-LF_t$		0.01 (0.02)			−0.002 (0.02)			0.1* (0.1)	
Baa_t			0.3 (0.8)			−0.4 (0.8)			2.1*** (0.7)
Const.	3.2***	3.2***	3.2***	1.8*	3.3***	1.7*	−10.1***	−5.0*	−11.3***
R^2	0.2	0.3	0.2	0.2	0.2	0.2	0.4	0.4	0.4
Adj.R^2	0.2	0.3	0.2	0.2	0.2	0.2	0.4	0.4	0.4

Note: *p<0.1; **p<0.05; ***p<0.01

7. Drivers of beta-Predictability

$$\overline{R^2}_{i,\beta,t} = c + \gamma'_{IE}\mathbf{X}_{IE,t} + \gamma'_{RA}\mathbf{X}_{RA,t} + \gamma'_{FC}\mathbf{X}_{FC,t} + \epsilon_t$$

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$-ecy_t$	-58.2^{***} (10.1)	-21.4^{*} (12.5)	-59.8^{***} (10.2)						
pe_t				-0.1^{***} (0.03)	-0.04^{***} (0.01)	-0.1^{***} (0.03)			
$Yale_t$							-0.2^{***} (0.05)	-0.2^{***} (0.04)	-0.2^{***} (0.05)
$-unemp_t$	-0.5^{***} (0.2)	-1.1^{***} (0.2)	-0.7^{***} (0.2)	-0.8^{***} (0.2)	-1.3^{***} (0.2)	-0.8^{***} (0.3)	-1.4^{***} (0.3)	-1.7^{***} (0.3)	-1.5^{***} (0.3)
$vol_{1,t}$	-0.02 (0.1)			0.1 (0.1)			-0.1 (0.1)		
$-LF_t$		-0.02 (0.02)			-0.01 (0.02)			-0.1 (0.1)	
Baa_t			-1.3 (0.8)			-0.03 (0.8)			-0.6 (0.9)
Const.	-6.7^{***}	-9.4^{***}	-6.7^{***}	-4.2^{***}	-9.3^{***}	-4.2^{***}	7.3^{*}	2.6	7.6^{**}
R^2	0.2	0.3	0.2	0.1	0.3	0.1	0.4	0.5	0.4
Adj. R^2	0.2	0.3	0.2	0.1	0.3	0.1	0.4	0.5	0.4

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Conclusion

Several findings **corroborate the Third view**. On the raw predictability side:

1. Micro-predictability **is not structurally lower** than macro-predictability, but exhibits a **stronger variance**.
2. Pooling the micro-predictability series yields an index that mimics the macro-predictability estimate (evidence of **diversification**).

And by further disentangling the estimates:

1. Alpha- and beta-predictability **match with their theoretical drivers** (rise during market booms and recessions).
2. Beta-predictability series are less dispersed than alpha-predictability ones as they reflect **the same mechanism**.

The alpha-predictability index appears as a theoretically based and easily updatable metric to spot irrational exuberance.

Estimated Model (i)

Model 1, *Smooth Exponential Smoothing*, Timmermann (2008)

- $p_{t+1} = \alpha p_t + (1-\alpha) r_t$
- With $p_1 = r_1$

Model 2, *Double Exponential Smoothing*, Timmermann (2008)

- $p_{t+1} = \alpha(p_t + \lambda_{t-1}) + (1-\alpha) r_t$
- $\alpha_t = \beta(p_{t+1} - p_t) + (1-\beta)\lambda_{t-1}$
- With $p_1 = 0$, $f_2 = r_2$ and $\lambda_2 = r_2 - r_1$

Model 3, *Autoregressive Model (BIC)*, Timmermann (2008)

- $r_{t+1} = \alpha + \beta(L) r_t + u_t$
- Number of lags chosen with the Bayesian Information Criterion

Model 4, *Autoregressive Model (AIC)*, Elliott and Timmermann (2013)

- $r_{t+1} = \alpha + \beta(L) r_t + u_t$
- Number of lags chosen with the Aikake Information Criterion

Estimated Model (ii)

Model 5, *Smooth Transition Autoregressive Model 1*, Timmermann (2008)

- $r_{t+1} = \boldsymbol{\theta}_0' \boldsymbol{\eta}_t d_t + \boldsymbol{\theta}_1' \boldsymbol{\eta}_t + u_{t+1}$
- $d_t = 1/(1 + exp(\gamma_0 + \gamma_1(r_t - r_{t-6}))$
- With $\boldsymbol{\eta}_t = (1, r_t)'$

Model 6, *Smooth Transition Autoregressive Model 2*, Timmermann (2008)

- $r_{t+1} = \boldsymbol{\theta}_0' \boldsymbol{\eta}_t d_t + \boldsymbol{\theta}_1' \boldsymbol{\eta}_t + u_{t+1}$
- $d_t = 1/(1 + exp(\gamma_0 + \gamma_1 r_{t-3})$
- With $\boldsymbol{\eta}_t = (1, r_t)'$

Model 7, *Neural net model 1*, Timmermann (2008)

- $r_{t+1} = \theta_0 + \sum_{i=1}^{n} \theta_i g(\boldsymbol{\beta}_i' \boldsymbol{\eta}_t) + u_{t+1}$
- With g the logistic function, $\boldsymbol{\eta}_t = (1, r_t, r_{t-1}, r_{t-2})'$ and $n = 2$

Model 8, *Neural net model 2*, Timmermann (2008)

- $r_{t+1} = \theta_0 + \sum_{i=1}^{n_1} \theta_i g(\sum_{j=1}^{n_2} \beta_j g(\boldsymbol{\alpha}_j' \boldsymbol{\eta}_t)) + u_{t+1}$
- With g the logistic function, $\boldsymbol{\eta}_t = (1, r_t, r_{t-1}, r_{t-2})'$, $n_1 = 2$ and $n_2 = 1$

Estimated Model (iii)

Model 9 to Model 18, *Univariate regressions*, Goyal and Welch (2008)

- $r_{t+1} = \theta_0 + \theta_1 x_t + u_{t+1}$
- With x_t (univariate) exogenous regressors

Model 19, *"Kitchen sink" regression*, Goyal and Welch (2008)

- $r_{t+1} = \theta_0 + \boldsymbol{\theta}_1' \boldsymbol{X}_t + u_{t+1}$
- With $\boldsymbol{X}_t$ the exogenous regressors

Model 20, *"Model selection" from* Goyal and Welch (2008)

- With all the potential combinations $\boldsymbol{X}_{i,t}$, we evaluate:
- $r_{t+1} = \theta_{i,0} + \boldsymbol{\theta}_{i,1}' \boldsymbol{X}_{i,t} + u_{i,t+1}$
- At each point in time, we choose the model with we choose the model with the smallest out-of-sample R^2

Estimated Model (iv)

Model 21, *Factor model from*, Kelly and Pruitt (2013)

- Only for aggregate return predictions
- With bm_{it} the book-to-market ratio of portfolio i and F_t the estimated factor, we run the following three regressions:
- $bm_{i,t} = \theta_{i,0} + \theta_{i,1} r_{t+1} + e_{i,t}$ (time series)
- $bm_{i,t} = c_t + F_t \hat{\theta}_{i,1} + u_{i,t}$ (cross section)
- $r_{t+1} = \gamma_1 + \gamma_2 \hat{F}_t + \epsilon_{i,t+1}$ (time series)

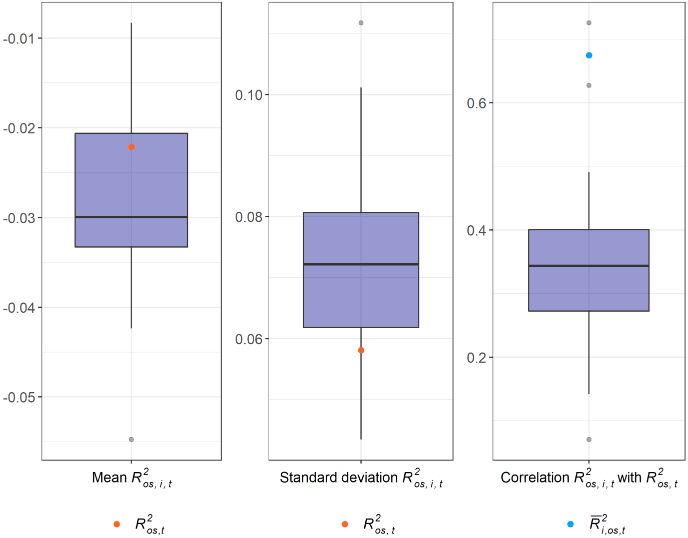
Model 22, *Forecast averaging - equally weighted*, Timmermann (2008)

- Let $p_{j,t+1}$ the forecasts from the J precedent models, we use a simple equally-weighted forecast averaging of the form:
- $p_{t+1} = \sum_{j=1}^{J} p_{j,t+1}$

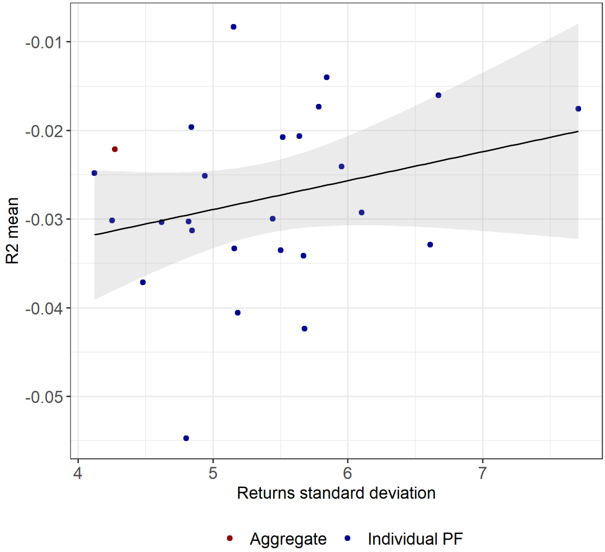
Model 23, *Model selection - in-sample*, Timmermann (2008)

- From the J precedent models (apart from Model 22), we evaluate the in-sample RMSE for each single model and take as a prediction the forecast of the model with the lowest RMSE.

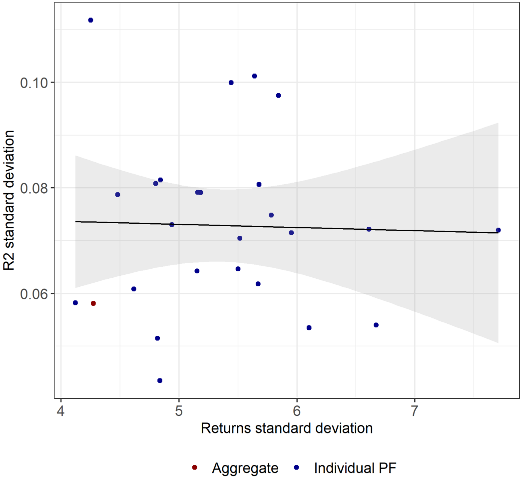
Moments of the raw return predictability series



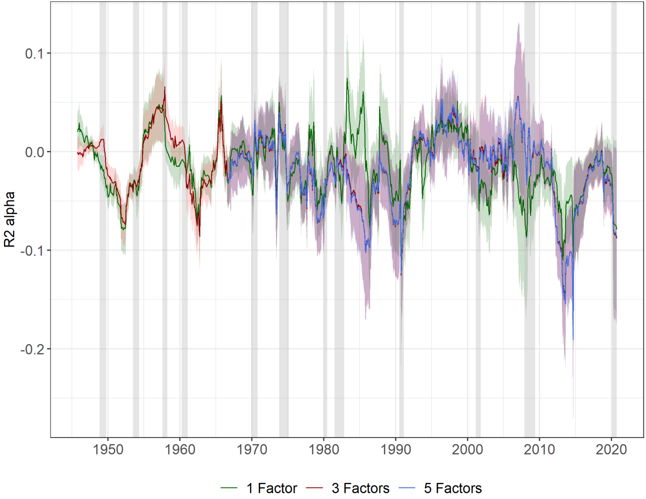
Raw Predictability levels vs. Returns standard deviations



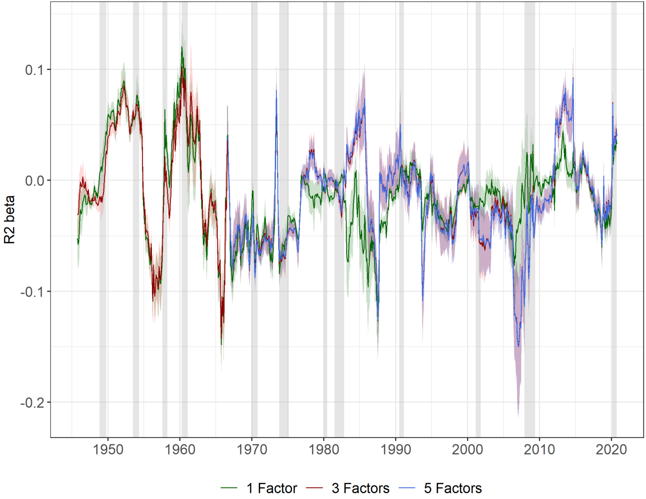
Raw Pred. standard deviations vs. Returns standard deviations



Alternative risk factors: alpha-predictability



Alternative risk factors: beta-predictability



Robustness checks: regressions

	Dependent variable:			
	Alpha-pred.: $\overline{R^2}_{i,\alpha,t}$		Beta-pred.: $\overline{R^2}_{i,\beta,t}$	
	(1)	(2)	(1)	(2)
pe_t	0.001^{**}	0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.0003)	(0.0002)	(0.0002)	(0.0003)
$Michigan_t$	0.0004		-0.001^{***}	
	(0.0003)		(0.0002)	
$-unemp_t$		0.008^{***}		-0.008^{***}
		(0.002)		(0.002)
vol_t	-0.0004		0.0004	
	(0.001)		(0.001)	
$vol_{2,t}$		-0.002		0.002
		(0.002)		(0.001)
Const.	-0.074^{***}	0.017^{*}	0.063^{***}	-0.041^{***}
	(0.026)	(0.010)	(0.022)	(0.016)
Obs.	496	856	496	856
R^2	0.077	0.168	0.086	0.107
Adj. R^2	0.071	0.165	0.086	0.107

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Working Hypothesis Systems

H_1 Samuelson's view:

$$\begin{cases} r_{i,t+1} = \omega_i \alpha(\boldsymbol{X}_t) + \boldsymbol{\beta}'_{i,t}\boldsymbol{f}_{t+1} + \epsilon_{i,t+1} + \delta_i \epsilon_{t+1} \\ r_{t+1} = \alpha(\boldsymbol{X}_t) + \boldsymbol{\beta}'_t \boldsymbol{f}_{t+1} + \epsilon_{t+1} \\ \boldsymbol{f}_{t+1} = \boldsymbol{c} + \boldsymbol{u}_{t+1} \end{cases}$$

H_2 Cochrane's view:

$$\begin{cases} r_{i,t+1} = \boldsymbol{\beta}'_{i,t}\boldsymbol{f}_{t+1} + \epsilon_{i,t+1} + \delta_i \epsilon_{t+1} \\ r_{t+1} = \boldsymbol{\beta}'_t \boldsymbol{f}_{t+1} + \epsilon_{t+1} \\ \boldsymbol{f}_{t+1} = g(\boldsymbol{X}_t) + \boldsymbol{u}_{t+1} \end{cases}$$

H_3 Third view:

$$\begin{cases} r_{i,t+1} = \alpha_i(\boldsymbol{X}_t) + \omega_i \alpha(\boldsymbol{X}_t) + \boldsymbol{\beta}'_{i,t}\boldsymbol{f}_{t+1} + \epsilon_{i,t+1} + \delta_i \epsilon_{t+1} \\ r_{t+1} = \alpha(\boldsymbol{X}_t) + \boldsymbol{\beta}'_t \boldsymbol{f}_{t+1} + \epsilon_{t+1} \\ \boldsymbol{f}_{t+1} = g(\boldsymbol{X}_t) + \boldsymbol{u}_{t+1} \end{cases}$$