Advances in cross-sectional asset pricing: Taming the Factor Zoo

Empirical Asset Pricing

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A zoo of factors

As Jonas descibed a couple of weeks ago

- The finance literature has constructed an enormous amount of factors that apparently all are priced in the cross-section of U.S. stocks
- A substantial part of the analysis is to evaluate the new proposed risk factor by existing risk factors
- A typical saying is something like: "The findings cannot be explained by existing risk factors"
- ... or "The findings cannot be explained by standard risk factors"
- However, as we will see; this is done in a bit ad-hoc manner traditionally...

The standard approach of evaluating risk factors

The Review of Financial Studies

Short-term Momentum

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significant average return of +16.4% per annum (Figure 1, right bar). We show that both strategies generate significant abnormal returns relative to the standard factor models currently applied in the literature. We also show that short-term momentum persists for 12 months and is strongest among the largest and most liquid stocks. Finally, we show that our main findings extend to 22 developed markets outside the United States.

The standard approach of evaluating risk factors

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Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns☆

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Table 2
Univariate portfolio analysis.

This table presents return comparisons between equity deciles formed monthly based on VaR1 between 1962 and 2014. Portfolio 1 is the portfolio of stocks with the lowest value-at-risk and Portfolio 10 is the portfolio of stocks with the highest value-at-risk. The table reports the one-month-ahead excess returns and five-factor alphas for each decile. The last column shows the differences of monthly excess returns and alphas between deciles 10 and 1. Alphas are calculated after adjusting for the market, size, value, and momentum factors of Fama and French (1993) and Carhart (1997) and the liquidity factor of Pastor and Stambaugh (2003). Panel A presents results for value-weighted portfolio returns. Panel B presents results for equal-weighted portfolio returns. VaR1 is defined in Table 1. Newey-West (1987) adjusted *t*-statistics are presented in parentheses.

Panel A: Value-weighted returns	Port1	Port2	Port3	Port4	Port5	Port6	Port7	Port8	Port9	Port10	High-Low
Excess return	0.47	0.61	0.58	0.56	0.57	0.57	0.62	0.51	0.31	−0.31	−0.78
	(3.28)	(3.59)	(3.14)	(2.72)	(2.49)	(2.20)	(2.25)	(1.70)	(0.90)	(−0.77)	(−2.34)
Alpha	0.07	0.09	0.02	−0.07	−0.05	−0.08	−0.01	−0.16	−0.39	−0.87	−0.94
	(0.92)	(1.62)	(0.35)	(−0.99)	(−0.56)	(−0.88)	(−0.12)	(−1.34)	(−3.16)	(−5.02)	(−4.42)

Panel B: Equal-weighted returns	Port1	Port2	Port3	Port4	Port5	Port6	Port7	Port8	Port9	Port10	High-Low
Excess return	0.71	0.81	0.85	0.88	0.92	0.89	0.88	0.68	0.52	0.05	−0.66
	(4.73)	(4.65)	(4.42)	(4.20)	(4.01)	(3.59)	(3.37)	(2.36)	(1.64)	(0.15)	(−2.34)
Alpha	0.25	0.25	0.21	0.19	0.19	0.13	0.11	−0.09	−0.22	−0.56	−0.80
	(2.99)	(3.63)	(3.19)	(3.11)	(3.07)	(1.99)	(1.93)	(−1.36)	(−2.85)	(−5.50)	(−5.20)

The standard approach of evaluating risk factors

A Market-Based Funding Liquidity Measure

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We construct a traded funding liquidity measure from stock returns. Guided by a model, we extract the measure as the return spread between two beta-neutral portfolios constructed using stocks with high and low margins, to control for their sensitivity to the aggregate funding shocks. Our measure of funding liquidity is correlated with other funding liquidity proxies. It delivers a positive risk premium that cannot be explained by existing risk factors. A model augmented by our funding liquidity measure has superior pricing performance for various portfolios. Despite evident comovement, this measure contains additional information that is not subsumed by market liquidity. (*JEL* G10, G11, G23)

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The standard approach of evaluating risk factors

	(0.22)	(1.28)	(0.5)	(1.29)	(2.28)	(2.27)
F. Average across five margin-sorted portfolios [1/1965–10/2012][a]						
Exret	0.32	0.55	0.52	0.73	1.21	0.90
	(2.30)	(3.87)	(3.73)	(4.98)	(6.97)	(5.77)
Alpha	0.12	0.25	0.17	0.34	0.76	0.64
	(0.97)	(1.92)	(1.31)	(2.38)	(3.31)	(2.93)

This table presents BAB portfolio returns conditional on the five margin proxies and the average portfolio returns across five margin proxies. Size refers to a stock's market capitalization. Idiosyncratic volatility is calculated following Ang et al. (2006). The Amihud illiquidity measure is calculated following Amihud (2002). Institutional ownership refers to the fraction of common shares held by institutional investors. Analyst coverage is the number of analysts following a stock. Stocks are sorted into five groups based on NYSE breaks, where 1 indicates the low-margin group and 5 indicates the high-margin group. The high-margin group includes stocks that have small market cap, large idiosyncratic volatility, low market liquidity, low institutional ownership, and low analyst coverage. "Diff" indicates the return difference between two BAB portfolios constructed with high-margin and low-margin stocks. We report raw excess returns (indicated by "Exret") and risk-adjusted alphas. Alphas are calculated using a five-factor model: the Fama-French (1993) three factors, the Carhart (1997) momentum factor, and a liquidity factor proxied by the returns of a long-short portfolio based on stocks' Amihud measures. Returns and alphas are reported as a percentage per month. The Newey-West five-lag adjusted *t*-statistics are in parentheses. [a] 5, no coverage; 4, one analyst; for the rest, divided into 1–3.

Taming the factor zoo

- Traditionally, when proposing a new factor, the authors choose some benchmark model (FF3, FF5, FF3+UMD, etc...) to examine whether existing factors can explain the anomaly...
- ... meaning that the 300 other anomalies are not taken into account when evaluating a new factor

  $\rightarrow$ Today, we will examine how machine learning algorithms can help us to determine whether a new factor is truly new or redundant
- We will focus on whether a new factor contains a marginal contribution when explaining the cross-section of returns

A wonderful example...

- Heston and Sadka (2008) introduce a seasonality factor: a univariate sort based on past performance for the given month
- Against the FF3, the risk factor is highly significant but not if including the UMD
- $\rightarrow$ the seasonality factor is, hence, redundant when controlling for momentum...
- On the other hand, Heston and Sadka (2008) proposes several different seasonality factors while Feng et al. (2020) do not mention which one they use...

Taming the factor zoo

Objective

- We are interested in a framework to systematically examine the contribution of a risk factor(s), g_t, relative to existing risk factors using appropriate inference
- More specifically, we are interested in estimating and testing the marginal contribution of g_t conditional on existing risk factors h_t
- h_t is probably a high-dimensional set of factors in which some is probably redundant...

  $\rightarrow$ can you feel the smell of model selection (LASSO)?

Recap of SDF

- First, we need to specify our target
- From the SDF lecture, the expected return of some asset is given as

$$\mathbb{E}_t[r_{i,t+1}] - r_{f,t+1} = -(1 + r_{f,t+1})\text{Cov}_t[M_{t+1}, r_{i,t+1}] \tag{1}$$

- The covariance between the stochastic discount factor and the returns explains differences in expected returns!
- The SDF is typically assumed to be linear in some factors

The setting

- We will consider the following model/SDF:

$$M_t = \gamma_0^{-1} - \gamma_0^{-1}\lambda_v' v_t \equiv \gamma_0^{-1}(1 - \lambda_g' g_t - \lambda_h' h_t) \tag{2}$$

  λ's are the SDF loadings, g_t is the test factors, and h_t is the potentially confounding factors

- Note that we do not assume that h_t all are useful factors. They might have a 0 loading in the SDF
- Meaning that the expected return (not measured as excess)

$$\mathbb{E}_t[R_{t+1}] = \iota_n \gamma_0 + C_g \lambda_g + C_h \lambda_h \tag{3}$$

- Our objective is related to estimate and test λ_g controlling for h_t

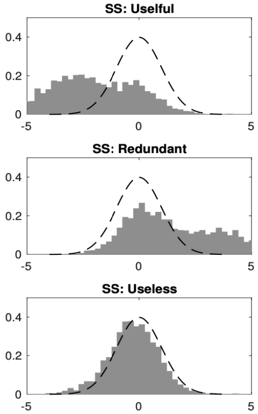
Issue with standard LASSO?

Denote by h_t a (likely high-dimensional) set of observable factor (candidate) controls, and (still) g_t the factor(s) of interest.

- The traditional LASSO is constructed with the aim of predictions
- For any finite sample, we cannot ensure that the method selects the true model
- But if important factors are excluded from the set of controls, h_t, inference about the factors of interest are erroneous

Issue with standard LASSO?

- As Feng et al. (2020) show in their appendix:



- Unless the factor is useless, using a standard LASSO for model selection, the estimates are not normally distributed

Solution to standard LASSO

- The two-pass variable selection of Belloni et al. (2014)
- This implies that a second step is added to capture missed factors from the LASSO that might introduce an OVB
- The factors not included in the two steps have minimal SDF loadings and minimal relation to the factors we want to test!

The double-selection method

- First selection: Search for factors in h_t that are useful for explaining the cross-sectional variation in expected returns. This can be done using classical
- Second selection: Search for factors in h_t that are useful for explaining the cross-sectional variation in exposures to the risk factor g_t (covariances Cov$[g_t, r_{i,t}]$). This can also be done using classical LASSO

Relationship OVB 101

- Remember that the bias of a coefficient in the present of an omitted variable is given as

$$\mathbb{E}[\hat{\beta}|X] = \beta + (X'X)^{-1}\mathbb{E}[X'Z|X]\delta. \tag{4}$$

- In the first step, we search for factors in which δ is not 0
- In the second step, we (roughly) search for factor for which $\mathbb{E}[X'Z|X]$ is non-zero

  $\rightarrow$ Using the double selection method, the two sources are minimized!

1st step

- In the first step, we run the following cross-sectional LASSO regression

$$E(R_t) = \gamma_0 + C_h \lambda_h + \varepsilon \tag{5}$$

  where C_h still is the covariance between h_t and R_t

- The Regression selects the factors being most important for explaining cross-sectional variation in expected returns

- Denote the selected factors as I_1

2nd step

- In the second step, we estimate the relationship between C_g and C_h by the following LASSO regression

$$C_{g,j} = \xi_j + C_h \chi_j' + \eta \tag{6}$$

- The second step identifies the factors whose SDF exposures are highly correlated with those of g_t
- Hence, factors that might be missed, and related to g_t, from the first step might be picked up in the second step
- Denote the union of factors from step two as I, i.e., $I_2 = \cup_{j=1}^{d} I_{2,j}$

3rd step

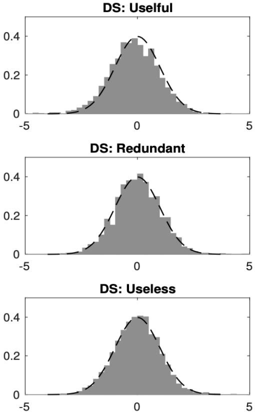
- In the third step, we run a simply cross-sectional OLS regression

$$E(R_t) = \gamma_0 + C_h\lambda_h + C_g\lambda_g + \varepsilon \tag{7}$$

- In which we restrict all factors **not** in the joint union of I_1 and I_2 to have a 0 SDF loading

Simulation results

- The simulation plot from the appendix is now given as:



- In the tables, they show that the bias is many times larger when applying a single selection relative to the double selection!

Methodology

A small note:

- Feng et al. (2020) adopt a weighting to λ_h by operator norm of the univariate betas for the factors in h_t... In other words the normalized squared betas...
- This ensures a larger penalty to variables smaller univariate betas –> helps remove spurious factors
- In practice, this can be implemented by multiplying the covariances in steps 1 and 2 by their squared mean beta across test portfolios which we normalize in the cross-section of factors

  $\rightarrow$ this implies that penalties on the coefficients are effectively smaller for high beta factors

Inference

- Feng et al. (2020) show that under some assumptions (see the appendix)

$$\sqrt{T}(\hat{\lambda}_g - \lambda_g) \xrightarrow{\mathcal{L}} N_d(0,\Pi) \tag{8}$$

  where Π is the assymptotic covariance matrix, and $\xrightarrow{\mathcal{L}}$ simply means convergence in probability (note that d is taken as the dimension of g_t)...

- The formula for the estimate of the covariance matrix is fairly long and can be seen on page 1341 in the article.
- The formula is incorporated in the Matlab script
- In the authors' replication file, they do not apply the HAC type of estimator as they write in the paper. You can easily extend the Matlab formula in our script to take this into account
- Note, that the inference procedure is valid even if we suffer from an OVB

Relationship to the three-pass estimator

- The *taming the factor zoo approach* is very much related to the three-pass estimator
- One could also use βs in Step 1 and 2 above to estimate risk premia and not SDF loadings
- This will, however, change the object such that we examine whether a new risk factor generates an adjusted return that cannot be explained by existing factors (This is written in many papers)
- $\rightarrow$ This is of course also something you can investigate!

Tuning hyperparameters

- Remember that when performing a LASSO, we have to choose how large a penalty to give coefficients. A higher λ, a more sparse model
- Gu et al. (2020) split their training sample into two: a training and a validation
- Given the in-sample focus, this does not seem like a natural way of doing things
- Instead, Feng et al. (2020) consider a K-fold cross-validation

The K-fold cross-validation

- In the K-fold cross-validation, we construct K different random subsamples
- We then perform the following steps for each subsample k:

  1. For each possible value of the hyperparameters:

     1. Train the model the K-1 other subsamples
     2. Use subsample k as "test" sample using some evaluation metric (SSE, for instance)

- The optimal choice of the hyperparameters is the one minimizing the sum (or mean) of the evaluation metric across all K subsamples
- In this way, we mimick the out-of-sample exercise, and the approach does not require the same time-series dimension as the

The K-fold cross-validation

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Discussion of approach

Existing attepts...

- Feng et al. (2020) are not the first to examine the marginale contribution of introduced factors given a high dimensional
- Kozak et al. (2018) consider PCA to approximate the SDF, Kozak et al. (2020) ENet, Gu et al. (2021) autoencoder (corresponds to nonlinear PCA)
- All correspond to the first step...

  $\rightarrow$ The first step is motivated by the "oracle property" of LASSO which suggests that LASSO will recover the true model when $T \rightarrow \infty$

- As shown above this is probably not true in finite samples...
- The double-selection method can, however, can be used with the other methods such that a PCA is, for instance, used instead of LASSO

SDF loadings vs. risk premia

- The object of our exercise is to examine whether a factor can explain the cross-sectional variation
- Most of our course has examined whether a given factor is priced in the cross-section
- The two measures have, however, different economic interpretations
- The SDF loading is related to the marginal utility of investors, whereas the risk premia are related to the compensation to investors for taking some risk
- Only the SDF loading can tell us whether a factor is useful in pricing the cross-section of returns
- A nonzero risk premium can, for instance, come from correlation with the true underlying risk factors

A survey

- See Kelly and Xiu (2021) for a survey on ML in finance

Drawback

- The main drawback of the procedure is that it requires data on *all* relevant factors as opposed to just a large set of portfolios as in Giglio and Xiu (2021), which is much easier to obtain
- We still have to specify the functional form of the SDF... See Chen et al. (2020) for how to apply deep learning

Empirical findings of Giglio et. al

Data

- They consider 150 different factors from the literature constructed using the Kenneth French approach
- They consider 750 portfolios as test assets
- They consider the most recently proposed 15 factors as test factors

  $\rightarrow$ They investigate whether the 15 proposed factor has a marginal contribution to explaining cross-sectional variation in the 750 portfolios conditional on the 135 other factors

The first step

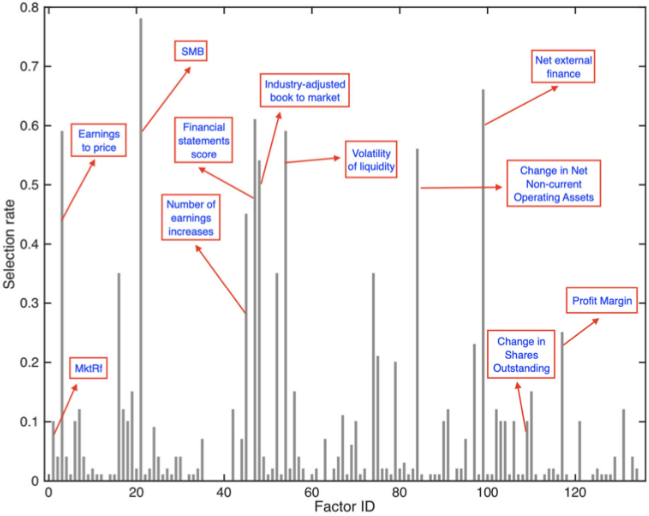
- Feng et al. (2020) identifies four factors in the linear SDF: SMB, net external finance, change in shares outstanding, and profit margin
- The question is naturally how robust the results are towards sample selection in the CV step?

Robustness first step

- To tune the hyperparameters, Feng et al. (2020) consider a cross-validation method which randomly generates K (in their case 10) subsamples
- The choice of the optimal hyperparameters, hence, depends on how the computer allocate observations into the subsamples, i.e., the random number generator
- To examine the robustness towards the random number generator, Feng et al. (2020) consider 200 different seedings
- If LASSO is perfect at selecting the true model, the output would be the same for all seedings

Robustness first step

- The following plot shows the inclusion frequency for the various factors in the first step



Robustness first step

- The LASSO is not perfect!
- Most factors is selected between 1% to 20% of the different seedings

Testing for newly introduced factors

- The table below shows their results:

id	Factor Description	(1) DS λ_s (bp)	(1) DS tstat (DS)	(2) SS λ_s (bp)	(2) SS tstat (SS)	(3) FF3 λ_s (bp)	(3) FF3 tstat (OLS)
136	Cash holdings	−34	−0.42	15	0.17	10	0.54
137	HML Devil	54	1.04	−13	−0.25	−100	−2.46**
138	Gross profitability	20	0.48	3	0.06	23	2.00**
139	Organizational Capital	28	0.92	−1	−0.03	20	1.91*
140	Betting Against Beta	35	1.45	38	1.50	36	2.25**
141	Quality Minus Junk	73	2.03**	4	0.11	39	3.10***
142	Employee growth	43	1.36	−4	−0.12	−12	−0.89
143	Growth in advertising	−12	−1.18	0	0.03	12	1.32
144	Book Asset Liquidity	40	1.07	5	0.12	20	1.59
145	RMW	160	4.45***	15	0.41	20	1.80*
146	CMA	38	1.10	0	0.01	3	0.28
147	HXZ IA	51	2.11**	5	0.21	21	1.94*
148	HXZ ROE	77	3.37***	23	0.83	33	2.92***
149	Intermediary Risk Factor	112	2.21**	60	1.19	4	0.08
150	Convertible debt	−15	−1.36	−39	−3.22***	26	3.32***

$\rightarrow$ Only a handful of the factors are significant when controlling for existing factors

- Applying the FF3 model as benchmark delivers opposite conclusions for a handful of the factors

Conclusion

- The findings are robust towards changes in the tuning parameters even though the benchmark model changes substantially
- The authors suggest examining the marginal contribution when proposing a new factor
- They see this as a way to bring discipline when proposing new factors

Empirical illustration

Object

- Let us try to use the methodology to examine whether macroeconomic uncertainty exposure is priced in the cross-section of US stocks when controlling for existing factors
- Meaning whether Macroeconomic uncertainty exposure has a marginal contribution to explain cross-sectional variation relative to existing factors

Data

- We will consider the sample period from 1991 to 2019 as examined in the previous mlx file
- The test assets consist of the 202 portfolios examined in the three-pass estimator
- The confounding factor will consist of the 153 factors from the global factor data constructed by Jensen et al. (2021) in addition to the market factor from Kenneth French (I am unsure on whether the market is included in Jensen et al. (2021)). The factors are constructed as capped value-weighted
- To ease the computational burden, we will consider a 5-fold CV and only include a single seed. The code is, however, written such that you can easily change these choices

Factor construction

- Remember, from **?** that the MU exposure was estimated using the following equation using 60 months of rolling window

$$
\begin{aligned}
R^e_{i,t} = {} & \alpha_i + \beta_{MU,i} MU_t + \beta_{MKT,i} MKT_t + \beta_{SMB,i} SMB_t \\
& + \beta_{HML,i} HML_t + \beta_{UMD,i} UMD_t + \beta_{LIQ,i} LIQ_t \\
& + \beta_{IA,i} R_{IA,t} + \beta_{ROE,i} R_{ROE,t} + \varepsilon_{i,t}
\end{aligned} \tag{9}
$$

Factor construction

- We then construct the factor following the ones from the Kenneth French data library:
- We independently sort stocks based on size (ME) and Macroeconomic uncertainty exposure (MU), where we consider two size groups determined using the median NYSE size as the breakpoint and three momentum groups using breakpoints determined from the 30th and 70th NYSE percentiles
- The intersections provide us with six portfolios: Big Low exposure (BL), Big Neutrals (BN), Big High exposure (BH), Small Low exposure (SL), Small Neutrals (SN), and Small high exposure (SH)
- The macroeconomic uncertainty factor is then constructed from the six portfolios as follows

$$MU = \frac{1}{2}\left[SH + BH\right] - \frac{1}{2}\left[SL + BL\right], \tag{10}$$

Standard approaches

- The table below presents the alphas for different standard asset pricing benchmark models:

	FF3	FF3+UMD	FF5
α	-0.25	-0.31	-0.14
	[-2.19]	[-2.40]	[-1.25]

$\rightarrow$ whether or not the anomaly can be explained by existing risk factors crucially depends on the benchmark model!

First step

- Of the 154 factors, the first step LASSO estimator selects 6
- Implying that the LASSO estimator choose a relatively sparse model
- This results depend on the choice of factors, test assets, the K in K-fold CV, and the seeding

Second step

- The second step LASSO estimator selects three different factors: market, ivol from ff3 residuals, and the ami 126 day
- The number for the second step is substantially lower than in Feng et al. (2020)
- This might be due to either:
  1. The cross-section of factors do not span the entire factor cross-section
  2. The MU factor is substially different from the rest of the factors
  3. The covariance between MU factor and the test assets is more or less completely spanned by existing factors
- To examine the last point, we can run the post-LASSO regression for the second step

	Intercept	ami	ivol	mkt	R^2
T-stat	[5.23]	[-9.84]	[-15.13]	[-9.20]	76.01%

Third step

- The test delivers a t-statistic of roughly 0 suggesting that the marginal contribution of the MU factor is nearly non-existing
- The SDF loadings are of the MU factor is, hence, spanned by existing factors
- You should, however, note that this result is probably highly dependent on many choices that I made for you

About projects

The website of Jensen et. al

- The empirical illustration from before applied the factors from Jensen et al. (2021)
- The website https://jkpfactors.com contains 153 factors for a widely selection of countries

  $\rightarrow$ The factor can be applied in many different asset pricing studies!
- You can, for instance, examine
  1. The findings of Dong et al. (2022) in an international context
  2. Whether the difference in factor performance across countries can forecast exchange rates
  3. Is there a lead-lag relationship in factor performance as examined by Rapach et al. (2013) for market returns?
  4. etc...

About projects

- Estimate and test the risk premia on one or more new risk factors, robust to OVB and measurement errors, possibly comparing to existing methods.
- Revisit fundamental risk factors, testing them and estimating their risk premia using the three-pass methodology.
- Estimate and test risk premia in other asset classes, for instance within the bonds or currency sphere.
- Estimate and test risk premia in international markets using global factors and returns (see e.g. Kenneth French's website for some data or Bryan Kelly's website for awesome data).
- Perform the study of Feng et al. (2020) for another country. For instance, Kenneth French has 150+ portfolios for European and Japanese stocks

About projects

- Adjust the analysis of Feng et al. (2020) for the publication lag. For instance, examining whether the conclusion from the 14 newly discovered factors changes if applied to the in-sample period of the 14 studies. Feng et al. (2020) has published their data on the Journal of Finance site for the article if you want to examine this
- Test the strength of existing or new risk factors via $\hat{W}$ and R_g^2. Maybe do it over different subsamples or on a rolling bias?
- The risk compensation of momentum is, for instance, given as the following over different macroeconomic states:

	Low	Normal	High
MOM	-0.61	1.10	1.45

$\Rightarrow$ Last, you can simply be creative

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