Investor Regret and Stock Returns

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Research Questions

1. Can a practical and feasible 'investor regret indicator' be constructed?

- Does this regret indicator have the ability to predict future cross-sectional returns of stocks?

2. Is this predictive ability independent of existing risk factors and characteristics?

3. Does investors' behavior support the regret hypothesis?

Main definition of REG:

- When investors hold a stock and its returns are lower than best performing stocks in the industry, they will experience feelings of regret.
- 'REG' will affect future investment decisions, thus forming a systematic 'regret premium'.

Motivation

Regret is a widely existing behavioral psychological phenomenon

- This emotion is particularly common in investment contexts;
- Regret can affect investors' utility function and future decisions.

Regret theory challenges traditional expected utility theory:

- Classical theory: Investors only care about their actual investment results;
- Regret theory: Investors also compare actual outcomes with "potentially better outcomes".

Regret is difficult to quantify, empirical research is scarce:

- Most studies have not used real trading data to verify whether investors truly adjust their portfolio allocations based on regret.

Contributions

Literature on the role of regret in investor behavior

Prior: Regret leads to irrational behavior(i.e chasing up and killing down).(Qin 2015)

Prior: Through experiments, investors indeed adjust decisions due to regret.(Frydman 2016)

Prior: Regret averse individuals tend to prefer positively skewed risk assets, which explains some investment preferences.(Gollier 2020)

Extend: Introducing ‘regret’ into asset pricing framework (**Mechanism path**).

Extend: Filling the gap between regret theory and empirical asset pricing.

Extend: New dimension for factor models & REG is consistent with investor behavior.

Hypothesis

H1: Stocks with **higher REG** will receive **higher risk adjusted returns** in the future.

High REG → Currently undervalued → High future returns

Low REG → Currently overvalued → Low future returns

H2: REG has an **independent pricing effect**, surpassing the explanatory power of traditional factors.

H3: Investors will **adjust their investment behavior due to regret**.

Core variable: Regret indicator (REG)

Based on Quiggin's (1994) modified utility theory, firm-level regret measure:

$$REG_{i,t} = R_{i,t} - \max_{j \in \text{Industry}(i)} R_{j,t}$$

$R_{i,t}$: The actual return of stock i in month t;

$\max_j R_{j,t}$: Highest monthly return among stocks in same industry (3-digit SIC Ind. code).

- CRSP/COMPUSTAT/Kenneth French/Odean(households)/1963-07~2020-12;

Note: For ease of explanation, $R_{i,t}$ is multiplied by -1.

Larger value of REG indicates stronger regret.

H1: REG is positively correlated with future stock returns

Portfolio construction: **Sorting & Dividing into 5 groups based on REG**

Table 1. Univariate Portfolios of Stocks Sorted by *REG*

Quintile	REG	Mean	CAPM	FF3	FFC	FFCPS	FF5	FF6	FF6PS	Q	Q+
1 (Low)	1.53	0.35	−0.17	−0.22	−0.22	−0.20	−0.33	−0.31	−0.30	−0.32	−0.30
		[2.04]	[−2.61]	[−3.74]	[−3.60]	[−3.19]	[−5.77]	[−5.39]	[−4.92]	[−4.55]	[−4.60]
2	10.13	0.42	−0.05	−0.10	−0.10	−0.08	−0.19	−0.18	−0.17	−0.20	−0.18
		[2.69]	[−1.00]	[−2.04]	[−1.98]	[−1.65]	[−4.15]	[−3.90]	[−3.59]	[−3.35]	[−3.37]
3	18.04	0.56	0.03	−0.02	−0.04	−0.04	−0.14	−0.14	−0.16	−0.16	−0.16
		[3.28]	[0.45]	[−0.37]	[−0.74]	[−0.82]	[−2.86]	[−2.88]	[−2.95]	[−2.78]	[−2.89]
4	28.73	0.71	0.12	0.09	0.08	0.06	0.04	0.03	0.02	−0.03	−0.04
		[3.71]	[2.12]	[1.57]	[1.47]	[1.03]	[0.67]	[0.63]	[0.29]	[−0.47]	[−0.68]
5 (High)	71.68	0.75	0.12	0.17	0.20	0.17	0.27	0.29	0.26	0.28	0.27
		[3.73]	[2.01]	[3.34]	[3.81]	[3.22]	[5.28]	[5.27]	[4.65]	[4.27]	[4.41]
High–Low	70.14	0.40	0.29	0.39	0.41	0.37	0.60	0.60	0.57	0.61	0.58
		[3.66]	[2.59]	[4.10]	[4.36]	[3.79]	[6.52]	[6.30]	[5.67]	[4.95]	[5.15]

Even if using multiple asset pricing models to adjust, **alphas remain significantly positive**.

Control variables: 12 commonly used characteristic indicators (X)

Introducing 12 mainstream charatersitics variables as control variables.

STR, BETA, SIZE, BM, MOM, ILLIQ, COSKEW, IVOL, MAX, OP, IA, SUE

Bivariate sorting: Grouping by X, then sorting by REG within each group;

- Verify whether REG still has predictive power at the control variable level.

Fama MacBeth regression: Observing whether λ_{REG} remains **significantly positive under multiple controls**.

H2: REG is an Independent pricing factor

REG has independent cross-sectional explanatory power(not rely on risk factors).

	1 (Low)	2	3	4	5 (High)	High–Low
BETA	−0.36	−0.30	−0.21	−0.00	0.21	0.56
	[−6.09]	[−5.90]	[−4.10]	[−0.06]	[3.59]	[6.42]
SIZE	−0.46	−0.25	−0.15	−0.00	0.35	0.81
	[−8.98]	[−5.32]	[−3.36]	[−0.06]	[6.70]	[9.34]
BM	−0.40	−0.23	−0.14	0.04	0.23	0.63
	[−7.63]	[−4.69]	[−2.67]	[0.84]	[4.68]	[7.70]
MOM	−0.42	−0.29	−0.17	−0.06	0.18	0.60
	[−7.39]	[−5.14]	[−3.18]	[−1.00]	[3.36]	[7.92]
STR	−0.30	−0.22	−0.10	−0.03	0.22	0.52
	[−5.54]	[−4.53]	[−2.06]	[−0.53]	[4.64]	[6.37]
COSKEW	−0.30	−0.24	−0.15	0.06	0.27	0.57
	[−5.73]	[−4.83]	[−3.01]	[1.26]	[4.82]	[6.46]
ILLIQ	−0.51	−0.25	−0.17	−0.00	0.33	0.84
	[−9.31]	[−5.04]	[−3.55]	[−0.04]	[6.75]	[9.53]
IVOL	−0.38	−0.23	−0.24	−0.02	0.23	0.61
	[−6.90]	[−4.59]	[−4.66]	[−0.36]	[3.93]	[6.83]
MAX	−0.34	−0.20	−0.23	0.01	0.17	0.51
	[−6.48]	[−3.84]	[−4.37]	[0.22]	[2.73]	[5.85]
OP	−0.38	−0.23	−0.20	−0.10	0.24	0.62
	[−6.17]	[−4.28]	[−3.43]	[−1.63]	[4.52]	[6.41]
IA	−0.31	−0.20	−0.16	−0.03	0.25	0.56
	[−5.22]	[−3.87]	[−2.95]	[−0.57]	[4.54]	[5.76]
SUE	−0.28	−0.15	−0.16	−0.06	0.27	0.55
	[−4.59]	[−2.95]	[−2.84]	[−0.92]	[4.43]	[5.40]

H2: FM Cross-Sectional Regression

Table 4. Stock-Level Fama-MacBeth Regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
REG	0.011	0.014	0.014	0.011	0.009	0.008	0.007	0.007	0.007	0.008	0.007	0.006
	[6.44]	[8.23]	[8.18]	[7.15]	[6.70]	[6.60]	[4.19]	[4.94]	[4.85]	[5.62]	[5.65]	[5.13]
STR							−0.023	−0.037	−0.038	−0.024	−0.024	−0.028
							[−6.76]	[−9.53]	[−10.05]	[−5.11]	[−4.59]	[−4.91]
BETA		0.039	−0.005	0.166	0.152	0.173		0.065	0.026	0.117	0.098	0.117
		[0.45]	[−0.07]	[2.05]	[1.70]	[1.86]		[0.69]	[0.29]	[1.45]	[1.10]	[1.29]
SIZE		−0.031	−0.037	−0.100	−0.079	−0.097		−0.029	−0.035	−0.102	−0.081	−0.099
		[−1.08]	[−1.36]	[−3.73]	[−3.10]	[−3.75]		[−0.99]	[−1.26]	[−3.80]	[−3.18]	[−3.85]
BM		0.215	0.209	0.161	0.201	0.108		0.222	0.218	0.171	0.215	0.122
		[3.82]	[3.85]	[3.07]	[3.36]	[1.90]		[3.85]	[3.94]	[3.19]	[3.51]	[2.10]
MOM			0.007	0.007	0.005	0.003			0.007	0.007	0.005	0.003
			[5.73]	[5.71]	[4.34]	[2.92]			[5.68]	[5.72]	[4.29]	[2.78]
ILLIQ				−0.016	−0.020	−0.018				−0.016	−0.019	−0.017
				[−1.32]	[−2.98]	[−2.46]				[−1.26]	[−2.85]	[−2.42]
COSKEW				−0.125	−0.208	−0.226				−0.074	−0.170	−0.188
				[−1.49]	[−2.19]	[−2.23]				[−0.86]	[−1.76]	[−1.82]
IVOL				0.101	0.081	0.116				−0.070	−0.089	−0.082
				[1.85]	[1.90]	[2.83]				[−1.39]	[−1.91]	[−1.67]
MAX				−0.289	−0.270	−0.284				−0.134	−0.109	−0.092
				[−8.03]	[−8.35]	[−9.03]				[−3.18]	[−2.50]	[−2.00]
OP					3.336	1.824					3.631	2.020
					[5.05]	[4.45]					[5.07]	[4.53]
IA					−0.325	−0.221					−0.341	−0.238
					[−5.35]	[−3.64]					[−5.38]	[−3.86]
SUE						0.293						0.299
						[12.98]						[12.99]
Intercept	0.491	0.593	0.550	1.413	1.312	1.571	0.607	0.723	0.684	1.420	1.323	1.540
	[2.28]	[2.36]	[2.27]	[6.09]	[5.54]	[6.34]	[2.77]	[2.80]	[2.74]	[6.23]	[5.59]	[6.35]
Adjusted R^2	0.56%	4.25%	5.16%	6.51%	6.14%	6.25%	1.31%	4.92%	5.77%	7.00%	6.67%	6.80%

REG is not a derivative variable of existing factors such as momentum, scale, value, volatility, etc., but a behavioral driving factor with independent predictive ability.

Is Regret highly consistent with investor behavior?

$$REGINDEX_{i,t} = ret_{i,t} - \max_k [ret_{k,t}]$$

REG(Firm level): Gap between each stock and "winner" in its industry.

- REG: stocks perform poorly in the industry and are despised by investors.

REGINEX(Investor level): Gap between stock held by investors and "winner" in same industry.

- REGINDEX: After comparison, investors feel regretful and decide to rearrange their positions.

1. Using **real portfolio data** from 78000 households to construct **REGINEX**;
2. Observing **whether investors reduce** allocation to the stock **after a high REGINEX**.

H3: REGINEX reveals how retail trading is driven by regret

Quintile	t	$t+1$	$t+2$	$t+3$	$t+4$	$t+5$
1 (Low)	$\boxed{0.0043}$	0.0001	0.0001	0.0001	0.0001	0.0001
2	0.0012	0.0000	−0.0001	−0.0001	0.0000	0.0000
3	0.0006	0.0001	0.0001	0.0001	0.0001	0.0000
4	0.0006	0.0000	0.0002	0.0002	0.0000	0.0001
5 (High)	−0.0021	0.0003	0.0001	0.0001	0.0001	0.0001
High–Low	−0.0060	0.0002	0.0000	0.0000	0.0000	0.0000
	[−12.10]	[0.91]	[0.10]	[0.10]	[−0.04]	[0.15]

- Investors quickly **adjusted positions** after month that **regret** occurs;
- There are no significant adjustments in the following months.

REGINDEX shows same direction in predicting returns as REG

High regret stocks → Abandoned by investors → Current price decline → Possible future premium compensation (regret premium)

Table 6. Regret Index Based on Household Trading Data

	Counterfactual				
Quintile	Two-digit SIC	Three-digit SIC	FF10 industry	State	MSA
1 (Low)	−0.33	−0.25	−0.25	−0.01	−0.04
	[−2.38]	[−2.07]	[−1.71]	[−0.08]	[−0.28]
2	0.03	−0.26	0.01	−0.29	0.00
	[0.34]	[−1.96]	[0.03]	[−1.74]	[0.02]
3	−0.03	0.12	0.08	−0.15	−0.25
	[−0.21]	[0.81]	[−0.05]	[0.06]	[−0.19]
4	0.07	−0.01	−0.05	0.06	−0.19
	[0.45]	[−0.05]	[−0.25]	[0.49]	[−1.32]
5 (High)	0.29	0.28	0.34	0.41	0.49
	[1.57]	[2.17]	[1.37]	[3.67]	[6.73]
High–Low	0.63	0.53	0.58	0.42	0.53
	[2.29]	[2.59]	[2.03]	[2.04]	[3.00]

Regret-driven L-S strategy(long with high regret, short with low regret) **works well**.

研究局限性与未来展望

1. 情境悔恨建模：引入“未实现收益”的心理错失维度

- 当前 REG/REGINDEX 度量只基于“横向比较”(与行业最好股票比较)；
- 而许多投资者悔恨来自“纵向错失”——自己卖早了、买晚了、没买到；
- 可结合 tick 数据与投资者行为建模，引入后悔函数的时间维度。

2. 机构 vs. 散户悔恨反应的差异性分析

- 机构投资者是否也会因为“相对排名”或“基准偏离”而产生悔恨，并进行调仓?
- 使用 13F 数据、基金持仓变化、券商策略回测等，识别机构是否存在“行业错失回避”行为。

3. 引入机器学习探索非线性悔恨反应机制

- 悔恨对定价的影响可能是非线性的：当 REG 较小时影响微弱，超过某阈值后影响陡增；
- 使用机器学习模型（如 random forest, DNN 等）探索 REG 与未来收益的复杂非线性关系；
- 发现更丰富的行为规律，也提高因子构建的预测力。引入机器学习探索非线性悔恨反应机制。

Appendix– Def of Factors

STR: 短期反转，上月收益率（t–1）

BETA: 市场 ，过去 60 个月与市场回报回归的斜率

SIZE: 市值对数，每月底市值对数

BM: 账面市值比，年度账面值 / 市值

MOM: 动量，过去 12 个月收益（跳过最近一个月）

ILLIQ: Amihud 流动性，日收益率 / 成交额，按月平均

COSKEW: 共偏度，与市场回报的三阶矩关系

IVOL: 特质波动率，FF3 残差的标准差

MAX: 彩头收益，每月最高 5 个日收益的平均值

OP: 营运利润率，（营运收入 - 成本） / 总资产

IA: 资产增长率，资产总额年增长

SUE: 意外盈余，标准化季度盈余意外值

Appendix 悔恨溢价与信息摩擦和套利限制相关

结果发现：

REG 溢价在以下股票中更为显著：

小盘股；流动性差；分析师覆盖少；机构持股比例低；

表明悔恨溢价放大于“非理性散户为主”的投资场景。

揭示悔恨溢价的经济根源：不是所有股票都有明显悔恨效应，其形成依赖于市场分割、信息不对称、投资者结构等条件。

Appendix–Long horizon robustness

Table 7. Regret over Longer-Term Investment Horizons

Panel A: Univariate sorts											
	REG based on cumulative returns over the past n months										
	$n = 2$	$n = 3$	$n = 4$	$n = 5$	$n = 6$	$n = 7$	$n = 8$	$n = 9$	$n = 10$	$n = 11$	$n = 12$
1 (Low)	−0.27	−0.29	−0.22	−0.21	−0.16	−0.15	−0.11	−0.11	−0.08	−0.05	−0.08
	[−4.93]	[−5.33]	[−3.92]	[−4.27]	[−3.26]	[−3.15]	[−2.36]	[−2.32]	[−1.77]	[−1.01]	[−1.82]
2	−0.18	−0.08	−0.13	−0.03	−0.09	−0.09	−0.09	−0.11	−0.09	−0.12	−0.10
	[−3.49]	[−1.88]	[−2.59]	[−0.69]	[−1.83]	[−1.73]	[−1.77]	[−2.21]	[−1.82]	[−2.26]	[−1.83]
3	−0.05	−0.13	−0.07	−0.07	−0.02	−0.10	−0.13	−0.00	−0.07	−0.10	−0.12
	[−0.85]	[−2.51]	[−1.42]	[−1.23]	[−0.40]	[−1.79]	[−2.41]	[−0.03]	[−1.35]	[−1.67]	[−2.21]
4	0.12	0.09	0.10	−0.06	−0.09	−0.05	−0.03	−0.13	−0.18	−0.09	−0.04
	[2.31]	[1.61]	[1.81]	[−1.31]	[−1.81]	[−1.06]	[−0.61]	[−2.27]	[−2.71]	[−1.50]	[−0.71]
5 (High)	0.15	0.19	0.14	0.18	0.18	0.21	0.18	0.17	0.24	0.21	0.16
	[2.49]	[3.17]	[2.64]	[3.06]	[3.08]	[3.59]	[3.15]	[3.00]	[3.41]	[3.48]	[2.87]
High–Low	0.42	0.48	0.36	0.39	0.34	0.36	0.29	0.28	0.32	0.26	0.23
	[4.34]	[5.00]	[4.07]	[4.35]	[4.01]	[4.39]	[3.44]	[3.36]	[3.39]	[2.90]	[3.02]