Multivariate crash risk

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1. Introduction

Background & Motivation

- The relation between left tail risk and the cross-section of expected stock returns has received considerable attention in the recent empirical asset pricing literature.
- univariate: crash probability, value-at-risk, or expected shortfall
- bivariate: downside beta, tail beta, lower tail dependence, or option-implied bear beta
- A stock's sensitivity to market crashes and extreme downside realizations of additional risk factors has not been examined yet.
- We fill this gap and investigate the relation between multivariate crash risk and the cross-section of average stock returns

1. Introduction

Question

- Is multivariate crash risk (MCRASH), defined as exposure to extreme realizations of multiple systematic factors, priced in the cross-section of expected stock returns?

- Portfolio sorts
- Fama-MacBeth regression

1. Introduction

Research contents

- In theoretical, there is a positive relation between the pricing errors of the linear model and MCRASH in SDF framework.
- MCRASH cannot be explained by traditional factor betas, firm characteristics and other downside risk measures.

1.Introduction

Related researches

1) Downside risk:

- Roy (1952); Markowitz (1959)
- Ang et al. (2006a); Lettau et al. (2014); Levi and Welch (2020); Bollerslev, Patton, Quaedvlieg, (2021); Kelly and Jiang (2014); Chabi-Yo et al. (2018); Weigert (2016)

2) Crash risk for other asset pricing factors:

- Barroso and Santa-Clara (2015); Daniel and Moskowitz (2016); Ruenzi and Weigert (2018)

3) Nonlinear dependence measures in finance:

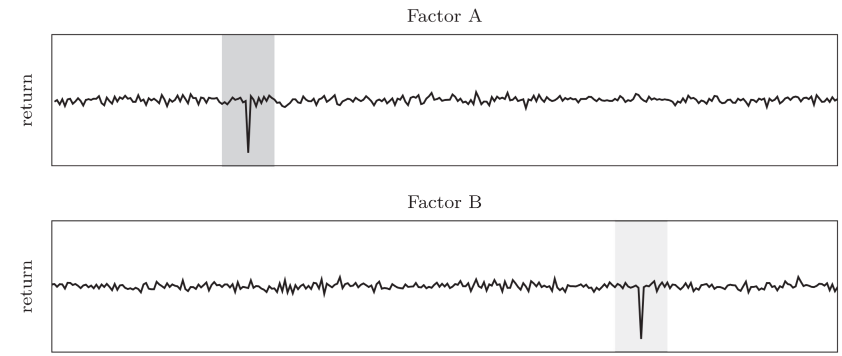
- Longin and Solnik (2001); Poon et al. (2004); Patton (2004); Christoffersen et al. (2012); Christoffersen and Langlois (2013)

1.Introduction

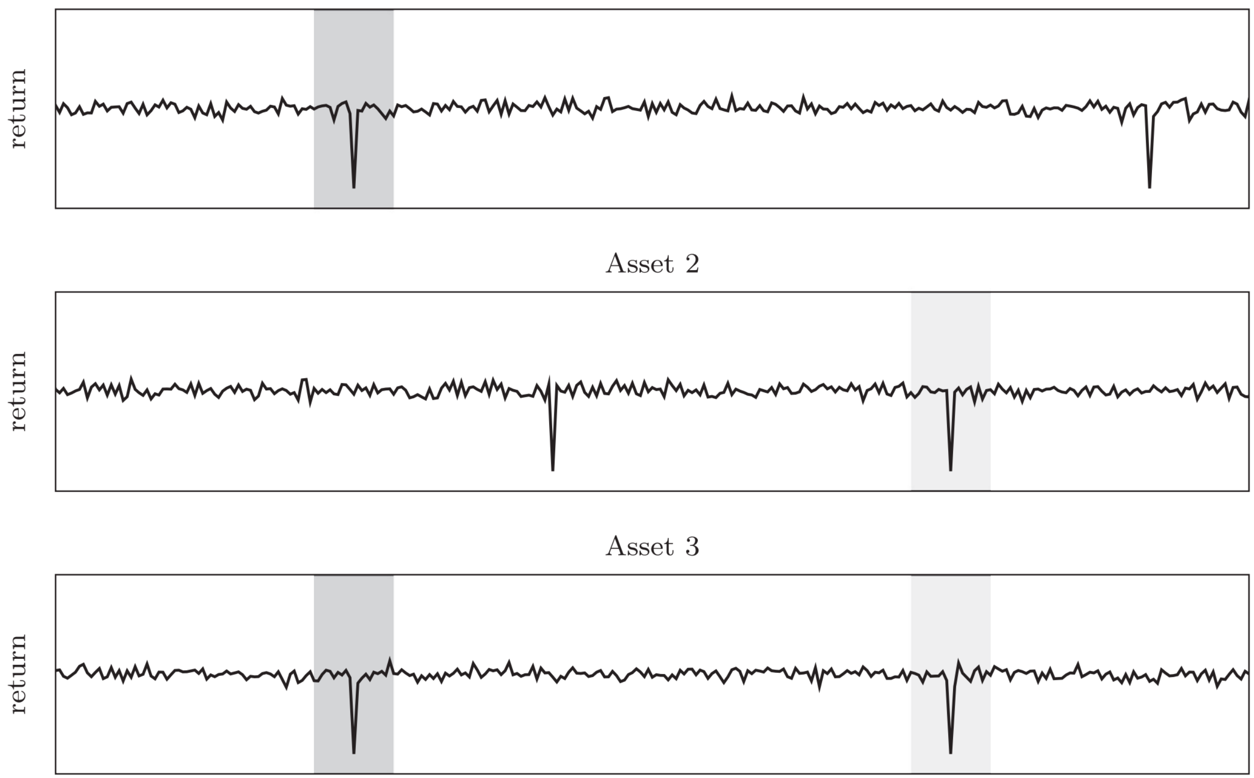
Contribution

- We contribute to the theoretical and empirical literature on downside and crash risk in asset pricing.
- Our paper is the first to study the asset pricing implications of nonlinear dependencies in multifactor models.
- We fill the gap about investigating the relation between multivariate crash risk and the cross-section of average stock returns.

2. Methodology



2.1 Intuition



2. Methodology

2.2 Crash sensitivity in multifactor models

- We apply a quantile-based definition of crash events:

$$T_p[Y] := \{Y \leq Q_p[Y]\} \qquad Q_p[Y] := \sup\{y \in \mathbb{R};\ \mathbb{P}[Y \leq y] \leq p\}$$

- In the following, we investigate systematic crash risk in a model with $N \geq 1$ priced factors and denote the returns of these factors over the period $[t, t+1]$ by $X = (X_1, \ldots, X_N)$.

$$T_p[\boldsymbol{X}] := \bigcup_{j=1}^{N} T_p[X_j] = \bigcup_{j=1}^{N} \left\{X_j \leq Q_p[X_j]\right\}$$

- We define a multivariate systematic tail event denoted by $T_p[X]$ as a realization of X.

2. Methodology

2.2 Crash sensitivity in multifactor models

- we introduce an asset's crash sensitivity in multifactor models as a straight-forward generalization of the well-known bivariate lower tail dependence coefficients.

$$\begin{aligned}\mathrm{MCRASH}_i^{\boldsymbol{X}} :=& \mathbb{P}[T_p[R_i] \mid T_p[\boldsymbol{X}]] \\ =& \mathbb{P}\left[R_i \leq Q_p[R_i] \mid \bigcup_{j=1}^{N} \{X_j \leq Q_p[X_j]\} \right],\end{aligned}$$

- Accordingly, MCRASH measures the probability of asset i to be adversely affected if a crash event occurs for one (or more) of the systematic factors.

2. Methodology

2.3 Multivariate crash risk and expected returns

- If we can replace M by its projection $M^X = E[M \mid X]$, where X is a set of factors or state variables, then we say that X explains the cross-sectional variation in expected stock returns.

$$\mathbb{E}[M(1+R_i)] = 1 \qquad M^{\boldsymbol{X}} = m(\boldsymbol{X})$$

$$\mathbb{E}\left[R_i - R_f\right] = -(1+R_f)\,\mathrm{cov}[m(\boldsymbol{X}), R_i]$$

- We use a first-order Taylor expansion of m (drawbacks)

$$m_L(\boldsymbol{X}) = m(\boldsymbol{x}_c) + \nabla m(\boldsymbol{x}_c) \cdot (\boldsymbol{X} - \boldsymbol{x}_c)$$

$$\nabla m(\boldsymbol{x}_c) := \left(\frac{\partial m}{\partial x_1}(\boldsymbol{x}_c), \ldots, \frac{\partial m}{\partial x_N}(\boldsymbol{x}_c)\right)$$

2. Methodology

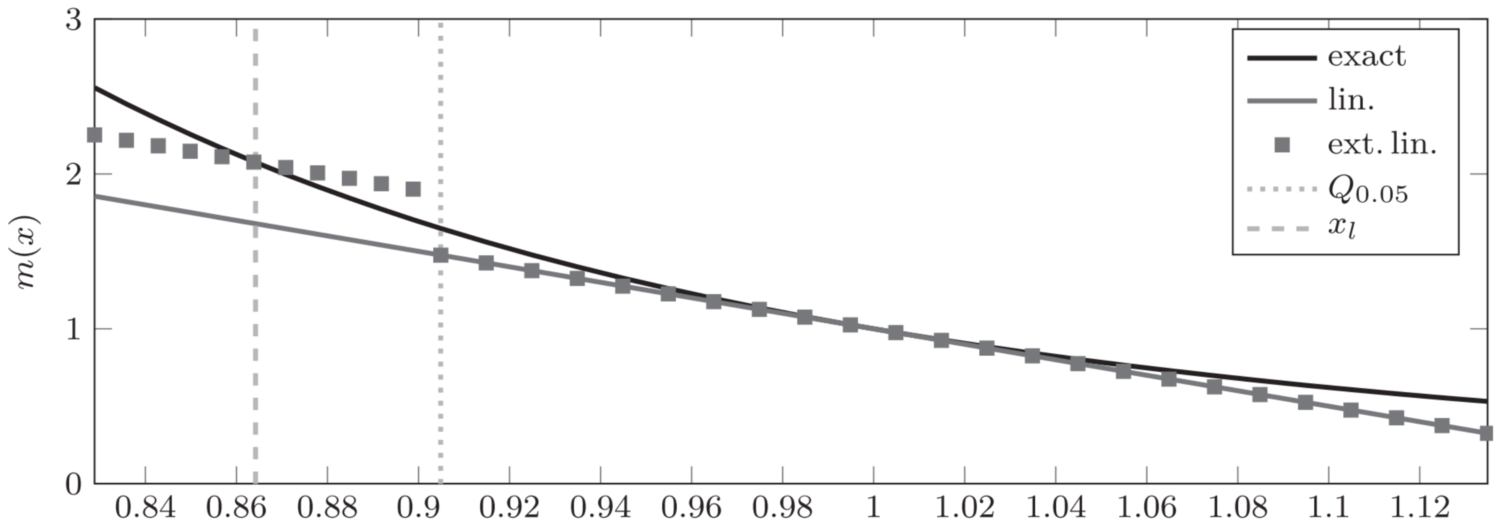
2.3 Multivariate crash risk and expected returns

- We use a first-order Taylor expansion of m (drawback)

$$m_L(\boldsymbol{X}) = m(\boldsymbol{x}_c) + \nabla m(\boldsymbol{x}_c) \cdot (\boldsymbol{X} - \boldsymbol{x}_c)$$

$$m_{L,e}(\boldsymbol{X}) = m_L(\boldsymbol{X}) + \mathbb{1}(T_p[\boldsymbol{X}])\, d_{\text{tail}}(\boldsymbol{X})$$

Panel A: Stochastic discount factor



$$\mathbb{E}\left[R_i - R_f\right] \approx -\,(1 + R_f)\,(\mathrm{cov}[\nabla m(\boldsymbol{x}_c)\cdot \boldsymbol{X}, R_i] + \mathrm{cov}[d_{\mathrm{tail}}\cdot \mathbb{1}(T_p[\boldsymbol{X}]), R_i]) \approx \sum_{j=1}^{N} \beta_i^{(j)}\,\lambda^{(j)} + \mathrm{Tail}_i^{\boldsymbol{X}},$$

2. Methodology

2.3 Multivariate crash risk and expected returns

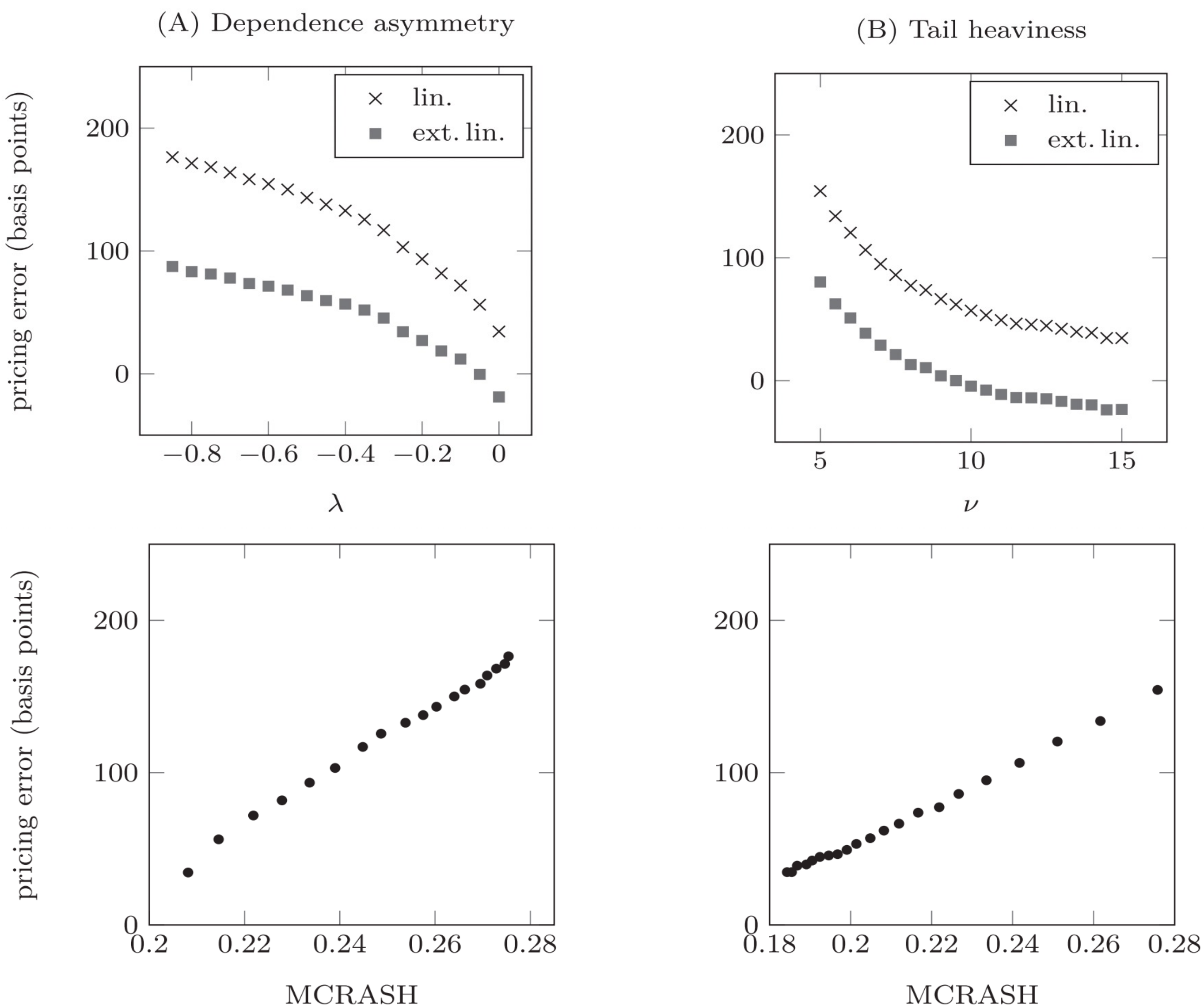
- We derive the extended linear model, where λ_X tail is nonnegative.

$$\mathbb{E}\left[R_i - R_f\right] = \alpha_i + \sum_{j=1}^{N} \beta_i^{(j)}\,\lambda^{(j)} + \left(\mathrm{MCRASH}_i^{\boldsymbol{X}} - p\right)\lambda_{\mathrm{tail}}^{\boldsymbol{X}}$$

$$\beta_i^{(j)} := \frac{\mathrm{cov}\left[X_j, R_i\right]}{\mathrm{var}\left[X_j\right]} \quad \text{and}$$

$$\lambda^{(j)} := -\left(1 + R_f\right)\frac{\partial m}{\partial x_j}(\boldsymbol{x}_c)\mathrm{var}\left[X_j\right]$$

- A1: The univariate distributions of Ri and $X_1, \ldots, X_N$ are continuous with positive densities.
- A2: m is differentiable, decreasing in each argument and convex.


(A) Dependence asymmetry
(B) Tail heaviness
pricing error (basis points)
lin.
ext. lin.
λ
ν
MCRASH
MCRASH

3. Data & Variable

$$\begin{aligned}\mathrm{MCRASH}_i^{\boldsymbol{X}} :=& \mathbb{P}[T_p[R_i] \mid T_p[\boldsymbol{X}]] \\ =& \mathbb{P}\left[R_i \le Q_p[R_i] \mid \bigcup_{j=1}^{N}\{X_j \le Q_p[X_j]\}\right]\end{aligned}$$

3.1 Data

- **Source**： CRSP (stocks with share codes 10 and 11)
- **Time**: from 1964-01 to 2018-12
- **Details**: we require each stock to have at least 200 nonzero return observations over the past 250 trading days and a price of at least USD 2.
- **Factors**: MKT, SMB, HML, RMW, CMA, UMD,BAB

3.1 Estimation of MCRASH

- Parametric GARCH models for the marginal return distributions.
- A nonparametric approach for the dependence modeling.

3. Data & Variable

$$F_{i,s}(y) := \mathbb{P}\left[Y_{i,s} \leq y | \mathcal{F}_{s-1}\right]$$

$$\hat{u}_{i,s} = F_{i,s}(y_{i,s})$$

$$\mathrm{MCRASH}_i^{\boldsymbol{X}} = \mathbb{P}\left[T_p[F_{R_i}(R_i)] \,|\, \bigcup_{j=1}^{N} T_p[F_{X_j}(X_j)]\right]$$

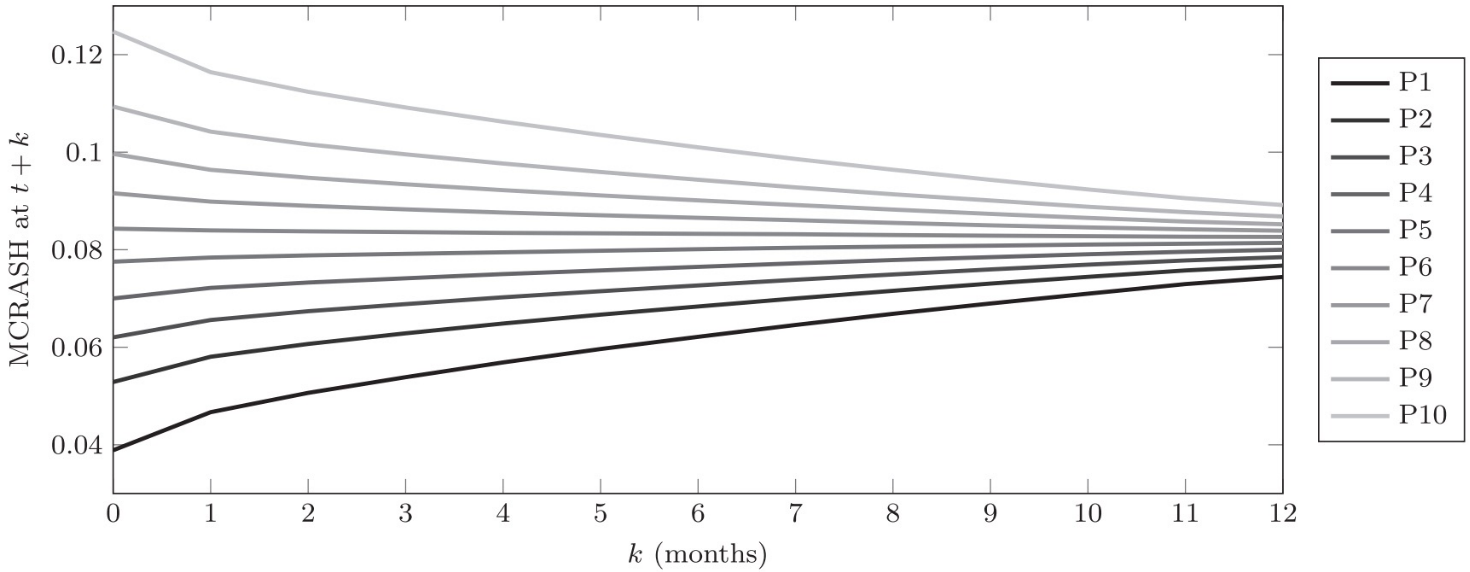
3.1 Estimation of MCRASH

- First, we estimate GARCH(1,1) models for the conditional distributions of the daily asset and factor returns over the last 250 trading days.

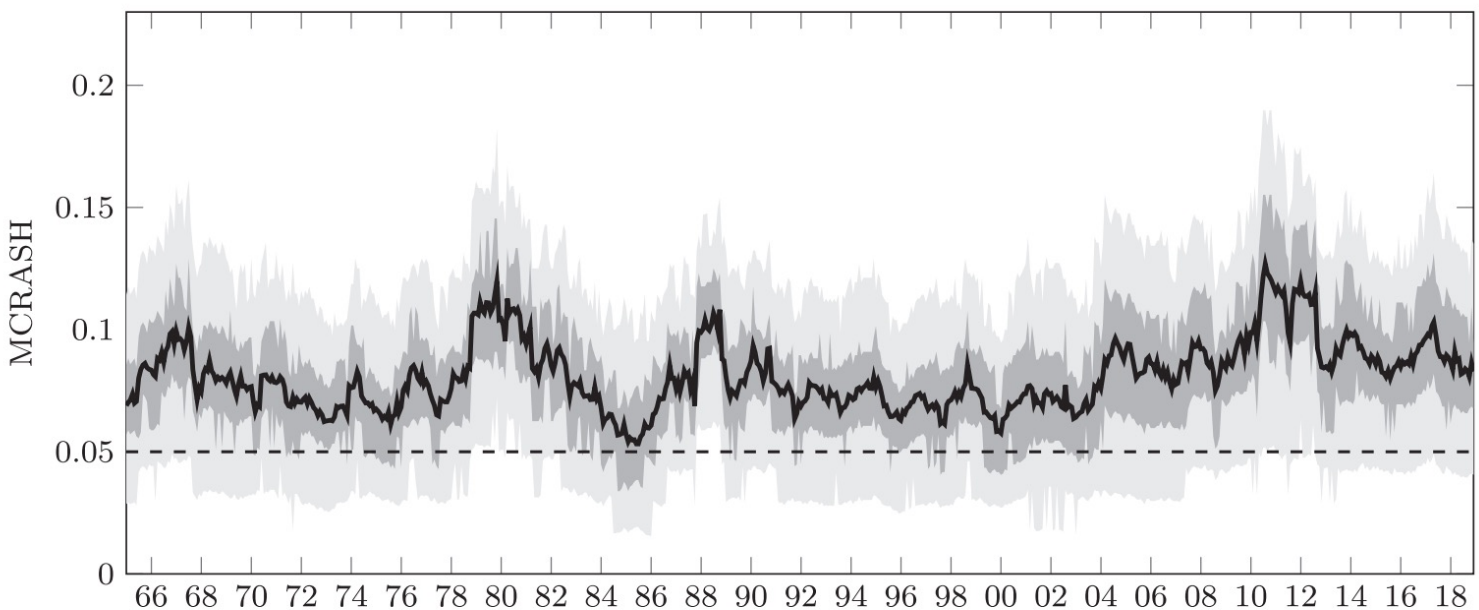
$$Y_{i,s+1} = \mu_i + \sigma_{i,s+1} Z_{i,s+1} \quad \text{and}$$
$$\sigma_{i,s+1}^2 = \omega_{i,0} + \omega_{i,1} (\sigma_{i,s} Z_{i,s})^2 + \omega_{i,2} \sigma_{i,s}^2,$$

- We then apply the resulting marginal cumulative distribution functions to calculate probability integral transforms of the daily returns.

$$\mathrm{MCRASH}_{i|t}^{\boldsymbol{X}} = \frac{\sum_{s \in \mathcal{V}} \mathbb{1}\left(\left\{\hat{u}_{1,s} \leq q_1\right\}\right) \cdot \mathbb{1}\left(\bigcup_{j=2}^{N+1} \left\{\hat{u}_{j,s} \leq q_j\right\}\right)}{\sum_{s \in \mathcal{V}} \mathbb{1}\left(\bigcup_{j=2}^{N+1} \left\{\hat{u}_{j,s} \leq q_j\right\}\right)}$$



MCRASH at $t+k$
0.12
0.1
0.08
0.06
0.04
0
1
2
3
4
5
6
7
8
9
10
11
12
k (months)
P1
P2
P3
P4
P5
P6
P7
P8
P9
P10



MCRASH
0.2
0.15
0.1
0.05
0
66 68 70 72 74 76 78 80 82 84 86 88 90 92 94 96 98 00 02 04 06 08 10 12 14 16 18

4. Empirical results

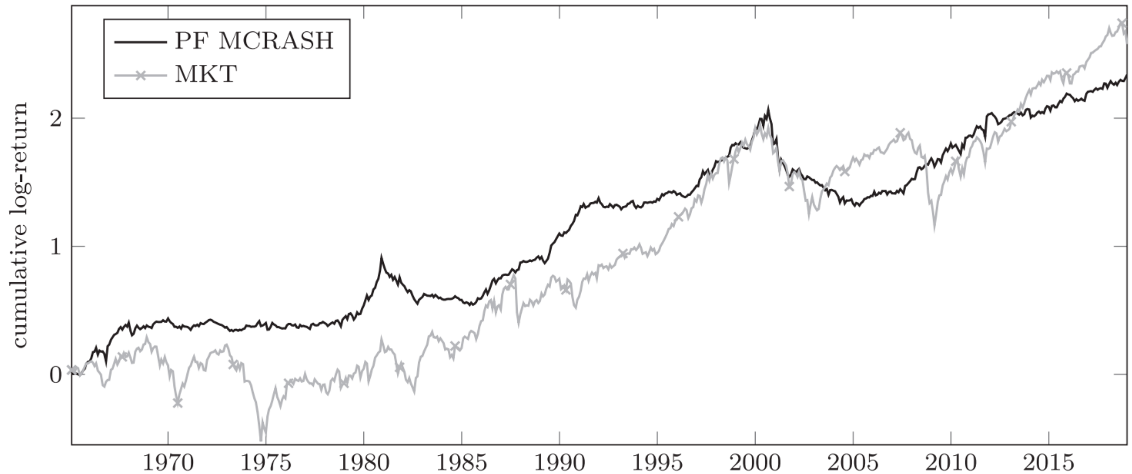
Portfolio sorts (equal-weighted)

Panel A: 1-month holding period

	MCRASH portfolio										
	1	2	3	4	5	6	7	8	9	10	10-1
exret	0.38	0.48	0.53	0.59	0.65	0.68	0.68	0.69	0.73	0.77	0.39
	(1.59)	(1.98)	(2.17)	(2.42)	(2.71)	(2.80)	(2.80)	(2.81)	(2.90)	(3.01)	(3.69)
α 7F	-0.28	-0.17	-0.13	-0.07	-0.02	0.01	0.02	0.05	0.11	0.16	0.44
	(-4.73)	(-3.28)	(-2.56)	(-1.65)	(-0.33)	(0.12)	(0.42)	(0.99)	(1.71)	(2.06)	(4.79)
α 5F	-0.33	-0.25	-0.20	-0.14	-0.08	-0.06	-0.04	-0.01	0.04	0.10	0.43

Panel B: Cumulative risk-adjusted returns

	MCRASH portfolio										
	1	2	3	4	5	6	7	8	9	10	10-1
1 month	-0.28	-0.17	-0.13	-0.07	-0.02	0.01	0.02	0.05	0.11	0.16	0.44
	(-4.73)	(-3.28)	(-2.56)	(-1.65)	(-0.33)	(0.12)	(0.42)	(0.99)	(1.71)	(2.06)	(4.79)
2 months	-0.49	-0.31	-0.25	-0.16	-0.07	-0.04	0.01	0.11	0.19	0.21	0.70
	(-4.28)	(-3.12)	(-2.71)	(-1.98)	(-0.92)	(-0.46)	(0.12)	(1.19)	(1.81)	(1.59)	(4.02)
3 months	-0.66	-0.45	-0.40	-0.27	-0.14	-0.11	-0.04	0.10	0.14	0.15	0.81
	(-3.89)	(-3.04)	(-3.08)	(-2.31)	(-1.20)	(-0.88)	(-0.35)	(0.76)	(0.96)	(0.85)	(3.30)
4 months	-0.87	-0.60	-0.54	-0.45	-0.34	-0.26	-0.14	-0.01	0.01	0.04	0.92
	(-3.97)	(-3.07)	(-3.10)	(-2.80)	(-2.11)	(-1.52)	(-0.82)	(-0.06)	(0.07)	(0.18)	(3.00)
5 months	-1.01	-0.75	-0.74	-0.68	-0.55	-0.40	-0.23	-0.14	-0.19	-0.12	0.89
	(-3.71)	(-3.20)	(-3.50)	(-3.28)	(-2.63)	(-1.93)	(-1.14)	(-0.67)	(-0.79)	(-0.40)	(2.39)
6 months	-1.14	-0.96	-0.99	-0.94	-0.79	-0.60	-0.41	-0.33	-0.38	-0.30	0.84
	(-3.46)	(-3.35)	(-3.79)	(-3.64)	(-3.15)	(-2.42)	(-1.68)	(-1.34)	(-1.35)	(-0.85)	(1.81)



Although surprising at first sight, this is feasible since the latter trading strategy focuses on crashes of the market and nonmarket risk factors (with the market being one risk factor out of seven)

Characteristics

	Control portfolio					
Control	1	2	3	4	5	avg
β^{MKT}	0.19	0.28	0.41	0.48	0.31	0.33
	(2.62)	(3.87)	(5.15)	(5.78)	(2.65)	(6.61)
size	0.44	0.34	0.29	0.11	0.19	0.27
	(3.83)	(3.04)	(3.27)	(1.35)	(2.37)	(4.00)
bm	0.51	0.30	0.17	0.14	0.01	0.22
	(4.47)	(3.03)	(1.81)	(1.80)	(0.11)	(3.53)
mom	0.49	0.21	0.19	-0.03	0.28	0.23
	(4.49)	(2.23)	(2.29)	(-0.36)	(2.94)	(3.65)
rev	0.43	0.31	0.25	0.23	0.36	0.31
	(3.77)	(3.02)	(3.02)	(2.35)	(3.80)	(4.81)
illiq	0.18	0.14	0.38	0.40	0.36	0.29
	(1.96)	(1.55)	(3.66)	(4.35)	(3.63)	(4.25)
max	0.18	0.08	0.25	0.34	0.65	0.30
	(2.74)	(1.19)	(2.82)	(3.14)	(4.87)	(4.98)

Other risk measures

	Control portfolio					
Control	1	2	3	4	5	avg
β^{down}	0.18	0.19	0.33	0.22	0.51	0.29
	(2.81)	(2.69)	(4.76)	(2.47)	(4.30)	(5.54)
β^{tail}	0.42	0.25	0.20	0.14	0.36	0.27
	(3.33)	(2.91)	(2.38)	(1.47)	(3.70)	(3.91)
idiovol	0.05	0.03	0.15	0.14	0.55	0.19
	(0.95)	(0.53)	(2.12)	(1.27)	(3.88)	(3.08)
idioskew	0.29	0.22	0.16	0.40	0.52	0.32
	(3.58)	(2.57)	(1.85)	(4.05)	(5.07)	(4.55)
coskew	0.18	0.39	0.19	0.32	0.28	0.27
	(1.80)	(4.25)	(1.95)	(3.44)	(2.54)	(3.88)
cokurt	0.28	0.24	0.12	0.27	0.23	0.23
	(3.60)	(3.12)	(1.70)	(2.77)	(2.65)	(4.34)
VaR	0.02	0.02	0.11	0.26	0.56	0.19
	(0.31)	(0.40)	(1.57)	(2.70)	(3.88)	(3.60)
β^{bear}	0.29	0.20	0.10	0.28	0.17	0.21
	(1.79)	(1.32)	(0.83)	(1.72)	(0.98)	(1.90)

4. Empirical results

$$R^e_{it+1} = \lambda^0_{t+1} + \lambda^{\text{CRASH}}_{t+1} \cdot \text{MCRASH}_{i|t} + \sum_{j=1}^{K} \lambda^j_{t+1} Y^j_{i|t} + \varepsilon_{it+1}$$

	Future excess returns							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MCRASH	4.33	5.56	5.00	5.41	5.04	4.80	4.45	4.37
	(3.58)	(5.77)	(5.42)	(5.76)	(5.90)	(5.82)	(5.90)	(5.89)
β^{MKT}		-0.25	-0.22	0.04	0.16	0.20	-0.01	0.05
		(-1.54)	(-1.19)	(0.18)	(0.71)	(0.87)	(-0.06)	(0.21)
β^{SMB}			-0.03	-0.04	0.11	0.12	0.15	0.09
			(-0.30)	(-0.32)	(0.87)	(0.97)	(1.21)	(0.73)
β^{HML}				0.20	0.24	0.09	0.00	0.02
				(1.84)	(1.77)	(0.75)	(0.02)	(0.15)
β^{RMW}					0.18	0.21	0.24	0.26
					(2.34)	(2.71)	(3.52)	(3.55)
β^{CMA}						0.14	0.11	0.09
						(1.47)	(1.36)	(1.13)
β^{UMD}							-0.09	0.01
							(-0.36)	(0.05)
β^{BAB}								-0.01
								(-0.09)
Intercept	0.22	0.38	0.42	0.33	0.34	0.34	0.36	0.36
	(0.88)	(1.81)	(2.04)	(1.69)	(1.73)	(1.79)	(1.91)	(2.00)
R^2_{adj} [%]	0.41	3.00	4.12	4.77	5.17	5.45	5.91	6.13
$\bar{n}$	2280	2280	2280	2280	2280	2280	2280	2280

4. Empirical results

Value-weighted and alternative estimation methods

Panel A: Value-weighted sorts risk-adjusted returns

	MCRASH portfolio										
	1	2	3	4	5	6	7	8	9	10	10-1
all	-0.11	-0.03	-0.05	-0.09	0.00	0.05	0.03	-0.01	-0.04	0.05	0.16
	(-1.25)	(-0.46)	(-1.12)	(-2.00)	(-0.01)	(1.29)	(0.86)	(-0.13)	(-0.90)	(0.97)	(1.39)
ex 1%	-0.15	-0.11	-0.10	-0.10	-0.04	0.02	0.01	0.01	0.06	0.11	0.26
	(-1.89)	(-1.95)	(-2.17)	(-2.39)	(-0.84)	(0.45)	(0.28)	(0.22)	(1.17)	(1.80)	(2.47)
ex 5%	-0.16	-0.12	-0.09	-0.07	-0.02	0.01	-0.01	0.02	0.07	0.10	0.26
	(-2.14)	(-1.94)	(-1.66)	(-1.55)	(-0.53)	(0.13)	(-0.25)	(0.40)	(1.23)	(1.58)	(2.79)
ex 10%	-0.19	-0.12	-0.05	-0.03	-0.01	0.02	0.01	0.02	0.05	0.11	0.30
	(-2.75)	(-2.06)	(-0.86)	(-0.59)	(-0.11)	(0.32)	(0.15)	(0.30)	(0.92)	(1.52)	(3.22)
ex 20%	-0.24	-0.15	-0.06	-0.03	-0.01	0.01	0.01	0.02	0.06	0.12	0.37
	(-3.48)	(-2.30)	(-1.12)	(-0.55)	(-0.11)	(0.20)	(0.11)	(0.34)	(1.10)	(1.55)	(3.79)

Panel B: Estimation methods

	(1) base	(2) 10% tail	(3) 2.5% tail	(4) non par.	(5) fully par.	(6) 500d marg	(7) 1000d marg	(8) GJR marg	(9) normal GARCH	(10) DCC
MCRASH	2.69	2.02	1.60	1.86	13.08	2.19	2.21	2.47	2.66	7.51
	(3.96)	(2.17)	(2.92)	(2.58)	(3.07)	(2.97)	(3.08)	(3.76)	(3.85)	(1.89)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2_{adj} [%]	7.29	7.31	7.28	7.30	7.54	7.30	7.30	7.30	7.30	7.55

4. Empirical results

- We now examine the price impact of simultaneous factor crashes:
- 1) Bivariate crash risk measures:

$$\mathrm{CRASH}_i^{X_j} = \mathbb{P}\left[T_p[R_i] \mid T_p\left[X_j\right]\right] = \mathbb{P}\left[R_i \leq Q_p[R_i] \mid X_j \leq Q_p\left[X_j\right]\right]$$

- 2) Simultaneous factor crashes:

$$T_p^{\mathrm{joint}}[X_{j_1}, \ldots, X_{j_M}] = \bigcap_{k=1}^{M} T_p[X_{j_k}]$$

$$\mathrm{JCRASH}_i^{X_{j_1}, \ldots, X_{j_M}} = \mathbb{P}\left[T_p[R_i] \mid T_p^{\mathrm{joint}}\left[X_{j_1}, \ldots, X_{j_M}\right]\right]$$

- We investigate the price impact of $JCRASH$ for selected subsets of the seven factors with $M \leq 5$.

4. Empirical results

CRASH	(1) MKT	(2) SMB	(3) HML	(4) RMW	(5) CMA	(6) UMD	(7) BAB
MCRASH	2.35	2.48	2.99	2.53	2.98	2.76	2.62
	(3.31)	(3.38)	(4.32)	(3.59)	(4.18)	(4.24)	(3.72)
CRASH	0.14	0.06	-0.35	0.17	-0.59	-0.17	-0.01
	(0.73)	(0.25)	(-1.04)	(0.58)	(-1.95)	(-0.50)	(-0.04)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2_{adj} [%]	7.36	7.36	7.35	7.35	7.34	7.38	7.34

JCRASH	(1) MKT SMB	(2) MKT HML	(3) MKT RMW	(4) MKT CMA	(5) MKT UMD	(6) MKT BAB	(7) 3F	(8) 4F	(9) 5F
MCRASH 7F	1.75	2.54	1.91	2.37	1.92	2.50	2.31	2.40	1.88
	(2.82)	(3.99)	(3.02)	(3.65)	(3.06)	(3.61)	(3.60)	(4.11)	(2.84)
JCRASH	1.11	0.44	1.61	0.61	1.10	0.40	0.54	0.35	0.49
	(3.18)	(1.22)	(3.58)	(1.69)	(2.05)	(1.00)	(2.02)	(1.13)	(2.37)
Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2_{adj} [%]	7.59	7.63	7.55	7.65	7.64	7.60	7.62	7.59	7.55
$\bar{n}$	1868	1868	1868	1868	1868	1868	1866	1868	1834

4. Conclusion

- In line with our theoretical results, we find that MCRASH shows a significantly positive impact on average future stock returns.
- The portfolio spread (10-1) is stable when we control for linear risk factor exposure in time-series regressions.
- We also find that the impact of MCRASH on future returns is not explained by factor betas, stock characteristics, or market-based downside risk measures.
- Our results suggest that investors care about the multi-dimensionality of crash risk.
- Capturing nonlinear extreme dependence with well-known factors helps to improve our understanding of the cross-section of expected stock returns.

5. Rep in A Shares

中国市场数据

- 时间：2000-01至2020-12
- 因子：FF5因子+动量因子UMD
- 窗口：过去12个月日滚动窗口
- 样本：剔除过去12个月交易日少于200的股票
- 估计方法：1）GARCH(1,1)模型调整时间序列（skew student分布）；2）使用如下方程估计MCRASH：

$$\mathrm{MCRASH}_{i|t}^{\boldsymbol{X}} = \frac{\sum_{s\in\mathcal{V}} \mathbb{1}(\{\hat{u}_{1,s} \le q_1\}) \cdot \mathbb{1}(\bigcup_{j=2}^{N+1} \{\hat{u}_{j,s} \le q_j\})}{\sum_{s\in\mathcal{V}} \mathbb{1}(\bigcup_{j=2}^{N+1} \{\hat{u}_{j,s} \le q_j\})}$$

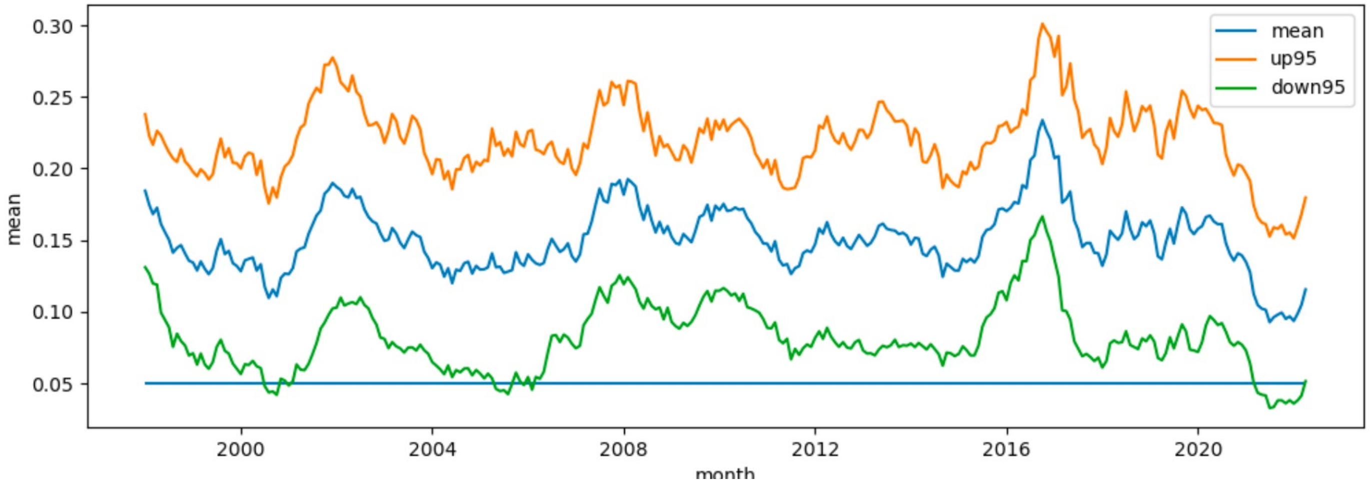
5. Rep in A Shares

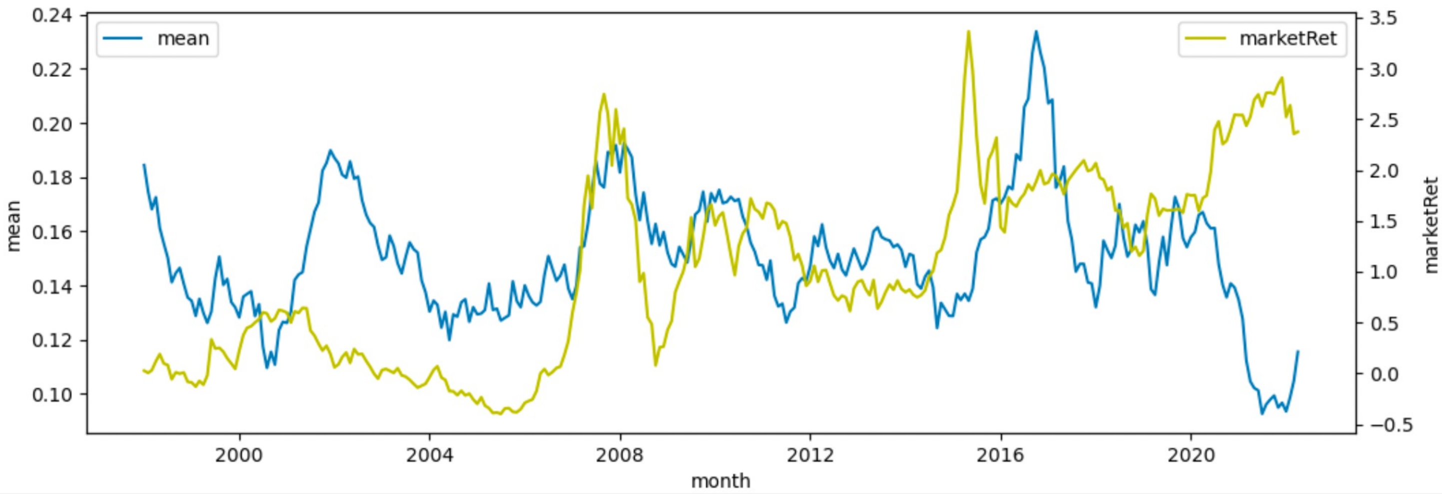
Mean	SD	Min	q25	Med	q75	max
0.1485	0.0435	0.0000	0.1200	0.1489	0.1777	0.3023

Panel A: Summary statistics

	Mean	SD	Skew	Kurt	Min	q5	q25	Med	q75	q95	max
MCRASH	0.08	0.03	0.08	2.81	0.00	0.04	0.06	0.08	0.10	0.13	0.17
β^{MKT}	1.04	0.56	0.45	3.86	-0.99	0.23	0.65	0.98	1.37	2.04	3.42
β^{SMB}	0.42	0.78	0.18	4.31	-2.61	-0.76	-0.10	0.40	0.92	1.73	3.91
β^{HML}	-0.75	0.96	-0.53	5.44	-5.42	-2.50	-1.26	-0.63	-0.13	0.56	3.08
β^{RMW}	-0.38	1.11	-0.42	5.77	-6.29	-2.26	-0.98	-0.32	0.29	1.27	4.30
β^{CMA}	-0.89	1.16	-0.62	6.00	-6.63	-3.01	-1.47	-0.73	-0.16	0.68	3.99
β^{UMD}	0.24	0.71	-0.02	5.44	-2.91	-0.87	-0.18	0.21	0.65	1.40	3.31
β^{BAB}	-1.04	0.98	-0.76	5.57	-5.93	-2.87	-1.54	-0.89	-0.37	0.25	2.85
size	5.86	1.67	0.27	2.90	1.37	3.27	4.65	5.79	6.99	8.73	11.72
bm	0.75	0.94	9.78	253.2	0.02	0.14	0.35	0.60	0.93	1.71	24.62
mom	20.44	56.01	4.00	54.8	-79.92	-38.65	-9.03	11.31	36.48	106.29	862.32
rev	1.35	12.16	2.03	38.73	-51.41	-15.29	-5.06	0.62	6.67	19.96	147.17
illiq	0.37	1.52	11.86	263.28	0.00	0.00	0.02	0.06	0.22	1.57	41.81
max	0.06	0.05	6.15	122.86	0.00	0.02	0.03	0.05	0.07	0.13	1.04

4. Rep in A Shares





4. Rep in A Shares

ticker	ret_mean	ret_t	std_mean	beta	spr	t_CAPM	t_FF3	t_FF5
ew_0	0.123	1.508	0.313	1.061	0.394	0.912	-0.576	-0.365
ew_1	0.143	1.790	0.314	1.073	0.454	1.879	0.163	1.621
ew_2	0.145	1.768	0.319	1.089	0.454	1.817	-0.868	0.224
ew_3	0.145	1.786	0.325	1.093	0.446	1.549	-1.796	0.731
ew_4	0.159	1.960	0.324	1.087	0.490	2.151	-0.287	2.151
ew_HL	0.035	2.045	0.092	0.026	0.383	1.874	0.300	1.232
vw_0	0.088	1.165	0.273	0.927	0.324	-0.247	1.298	0.092
vw_1	0.099	1.369	0.270	0.938	0.366	0.549	1.325	0.910
vw_2	0.107	1.394	0.283	0.986	0.377	0.707	0.329	-0.600
vw_3	0.077	1.056	0.284	0.981	0.273	-1.381	-2.656	-1.560
vw_4	0.109	1.472	0.282	0.962	0.385	0.840	-1.017	-0.518
vw_HL	0.020	0.736	0.151	0.035	0.135	0.609	-1.444	-0.354