What You See is Not What You Get: The Costs of Trading Market Anomalies

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Motivation

- Empirical asset pricing is a "factor zoo" (Cochrane, 2011 *JF*)
- Recent tallies put the number of expected return factors in the several hundreds
  - E.g., Harvey, Liu, and Zhu (2016 *RFS*), Harvey (2017 *JF*), and Hou, Xue, and Zhang (2017 *wp*)
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- The world is probably not so complicated, so what gives?
  - Statistical accidents?
  - Misleading research practices?
  - **Neglected implementation costs?** ← This paper

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$\Longrightarrow$ Unsurprisingly, there is mixed evidence on scalability of anomalies!

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- Advantages:
  - Does not use specialized trading data or parameteric cost functions
  - Does not require the user to take a stand on how factors are traded
  - Applies to a wide range of tradeable factors
- Drawbacks:
  - Provides only a lower bound on real-world costs
  - Requires *some* asset managers to load on the factor(s) considered
  - Cannot speak to costs of counter-factual factor exposures

Main Findings

1. Typical mutual funds face an annual implementation cost of 7.2%–7.6% for momentum, 2.6%–4.1% for value, and approximately zero for market and size factors

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2. By contrast, **small (large)** mutual funds achieve net-of-costs returns to momentum of **3.4% (-2.5%) / year**

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2. By contrast, small (large) mutual funds achieve net-of-costs returns to momentum of 3.4% (-2.5%) / year

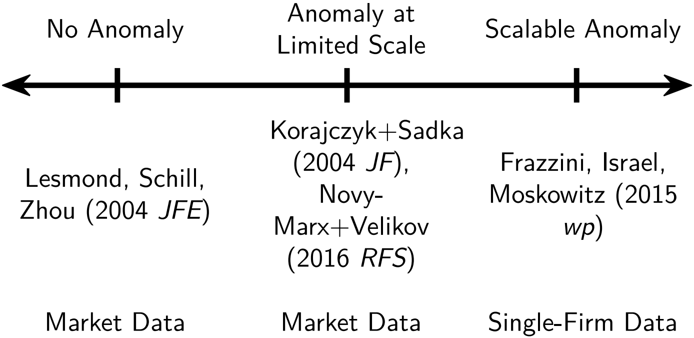
   - We reconcile conflicting results from existing approaches by **differentiating among mutual funds**

3. We **decompose** the implementation costs faced in practice:

   - Short-selling restrictions
   - Restrictions on the investable universe for MFs
   - Departures from academic factors

Selected Related Literature

- Most existing literature on the trading costs of market anomalies focuses on momentum because of its relatively high turnover
  - Jegadeesh and Titman (1993 *JF*, 2001 *JF*) consider, but discard, a trading costs explanation
- Other studies reach different conclusions using different methods and data



Data

- Every existing study in this area uses market or firm-trading data
- Instead, we use CRSP stock and mutual fund data
- After filters, our sample consists of monthly gross returns for:
  - 4,267 unique U.S. domestic equity mutual funds
  - 22,121 unique stock PERMNOs
  - 269 diversified stock portfolios (mostly courtesy Ken French)
- Our sample runs from January 1970 to December 2016
  - A maximum of 564 months, though the median fund has 140 months of data
- Data Filter Details

Summary Statistics

Unit	Funds \#	Lifetime Years	TNA, 1/1970 Million USD	TNA, 7/1993 Million USD	TNA, 12/2016 Million USD
Mean	1286	14.16	128.74	552.87	2590.70
Std. Dev.	917	10.50	302.83	1533.70	13254.00
25%	324	5.75	3.96	37.48	70.93
50%	1023	11.58	23.90	118.36	314.00
75%	2282	19.58	91.18	431.83	1421.30

Fama-MacBeth Estimates of Implementation Costs

Baseline Fama-MacBeth Methodology

1. Run $N_S + N_{MF}$ time-series regressions to obtain factor exposures:

$$r_{it} = \alpha_i + \sum_k f_{kt}\beta_{ik} + \epsilon_{it},\ \ i = 1, \ldots, N_S, N_{S+1}, \ldots, N_S + N_{MF},$$

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2. Run T cross-sectional regressions to obtain compensation for factor exposure for stocks and mutual funds:

$$r_{it} = \sum_k \lambda_{kt}^{S}\hat{\beta}_{ik}1_{i\in S} + \sum_k \lambda_{kt}^{MF}\hat{\beta}_{ik}1_{i\in MF} + \epsilon_{it},\ t = 1, \ldots, T.$$

   Our cross-sectional regressions differ from standard cross-sectional regressions in that **we allow "on-paper" stock portfolios to have different risk compensation from "real-world" mutual funds**

Risk Premia estimates for Stocks and Mutual Funds

	1970 – 2016 (Equal Weighted)				
	N_S	MKT	HML	SMB	UMD
λ^S	100	6.62***	7.09***	3.35***	8.37***
t-stat		(2.75)	(3.91)	(1.70)	(3.59)
λ^S	269	7.23***	5.93***	3.23	10.06***
t-stat		(3.02)	(3.03)	(1.56)	(4.17)
T		564	564	564	564
$\bar{N}_{MF}$		1286	1286	1286	1286

$^{*}p < .10$, $^{**}\ p < .05$, $^{***}\ p < .01$

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λ^{MF}	—	6.98***	2.62	1.01	1.54
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	N_S	MKT	HML	SMB	UMD
λ^{Δ}	100	-0.36	4.47***	2.34**	6.83***
t-stat		(-0.76)	(5.57)	(2.41)	(5.21)
λ^{Δ}	269	0.25	3.31***	2.22**	8.51***
t-stat		(0.5)	(3.58)	(2.05)	(6.19)
λ^{S}	100	6.62***	7.09***	3.35***	8.37***
t-stat		(2.75)	(3.91)	(1.70)	(3.59)
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Risk Premia estimates for Stocks and Mutual Funds

	1970 – 2016 (Value Weighted)				
	N_S	MKT	HML	SMB	UMD
λ^{Δ}	100	-0.38	3.81***	0.26	7.18***
t-stat		(-1.28)	(5.08)	(0.42)	(5.53)
λ^{Δ}	269	-0.21	2.59***	-0.07	7.30***
t-stat		(-0.88)	(3.81)	(-0.14)	(5.54)
λ^{S}	100	6.60***	6.43***	1.27	8.72***
t-stat		(2.75)	(3.51)	(0.75)	(3.74)
λ^{S}	269	6.77***	5.20***	0.94	8.85***
t-stat		(2.82)	(2.84)	(0.56)	(3.80)
λ^{MF}	—	6.98***	2.62	1.01	1.54
t-stat		(2.86)	(1.51)	(0.59)	(0.63)
T		564	564	564	564
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Risk Premia estimates for Stocks and Mutual Funds

		1993 – 2016 (Value Weighted)			
	N_S	MKT	HML	SMB	UMD
λ^{Δ}	100	-0.11	3.12***	-0.24	4.27***
t-stat		(-0.32)	(3.83)	(-0.29)	(2.64)
λ^{Δ}	269	0.28	2.09***	-0.97	5.04***
t-stat		(1.25)	(3.31)	(-1.39)	(2.89)
λ^{S}	100	7.67**	5.43*	1.96	6.01
t-stat		(2.35)	(1.93)	(0.81)	(1.60)
λ^{S}	269	8.06**	4.40	1.23	6.78*
t-stat		(2.49)	(1.54)	(0.51)	(1.83)
λ^{MF}	—	7.78**	2.31	2.20	1.73
t-stat		(2.38)	(0.83)	(0.92)	(0.45)
T		282	282	282	282
$\bar{N}_{MF}$		2123	2123	2123	2123

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Time and Fund Variation in Costs

- Our baseline regression works if mutual fund trading costs are constant across funds and time

- Now generalize to consider the case that mutual funds earn factor returns of
  $$h_{it} = f_t - \eta_{it},$$
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Time and Fund Variation in Costs

- Our baseline regression works if mutual fund trading costs are constant across funds and time
- Now generalize to consider the case that mutual funds earn factor returns of

$$h_{it} = f_t - \eta_{it},$$

  where η_{it} reflects deviations from the academic factor
- The η_{it} term has four components:

$$\eta_{it} = \eta_i + \eta_t \gamma_i + \tilde{\eta}_{it}.$$

  - η_i: fixed, firm-specific costs of trading a factor
  - $\eta_t \gamma_i$: common time-varying liquidity costs η_t, multiplied by fund-specific loadings of factors on these costs γ_i
  - $\tilde{\eta}_{it}$: idiosyncratic costs for firm i and date t

Time and Fund Variation in Costs

- Plugging in our expression for fund returns into our factor model,

$$r_{it} = \alpha_i + h_{it}\beta_i + \epsilon_{it} = (\alpha_i - \eta_i\beta_i) + (f_t - \eta_t\gamma_i)\,\beta_i + (\epsilon_{it} - \tilde{\eta}_{it}\beta_i)$$

- An ideal test compares f_t and h_{it}, and we achieve this ideal if $h_{it} = \bar{h}$

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2. Firms choose factor exposures, and h_{it} is likely correlated with β_i

   $\Longrightarrow$ Omitted variable bias in λ^{MF} estimates
   - Solution: Firms with lower trading costs should invest more aggressively. λ^{MF} is thus **biased up** and so estimated "gaps" are biased down.

Time-Varying Trading Cost Proxies

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- **Approach 1: Principal components**
  - + first PC of market liquidity proxies
    - Amihud illiquidity, Pastor-Stambaugh liquidity, CBOE VIX/VXO, and average Corwin-Schultz (2012 *JF*) bid-ask spreads
  - + first PC of funding liquidity proxies
    - Frazzini and Pedersen's "betting against beta" factor, HKM's intermediary capital ratio, the BAA-10Y spread, and the TED spread

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- **Approach 2: Lasso** (Appendix, very similar results)
  - Use all proxies, and let the data select which factors are most relevant for each mutual fund
  - We use 10-fold cross-validation to choose our penalty parameters

Risk Premia estimates for Stocks and Mutual Funds — Liquidity PCs

		1970 – 2016 (Value Weighted)			
	N_S	MKT	HML	SMB	UMD
λ^{Δ}	100	-0.44	4.07***	0.35	7.49***
t-stat		(-1.45)	(5.17)	(0.57)	(5.71)
λ^{Δ}	269	-0.22	2.83***	-0.02	7.55***
t-stat		(-0.92)	(3.87)	(-0.03)	(5.70)
λ^{S}	100	6.55***	6.71***	1.26	8.77***
t-stat		(2.74)	(3.63)	(0.74)	(3.76)
λ^{S}	269	6.77***	5.47***	0.89	8.84***
t-stat		(2.83)	(2.94)	(0.53)	(3.78)
λ^{MF}	—	6.99***	2.64	0.90	1.28
t-stat		(2.87)	(1.51)	(0.53)	(0.52)
T		564	564	564	564
$\bar{N}_{MF}$		1286	1286	1286	1286

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Risk Premia estimates for Stocks and Mutual Funds — Liquidity Lasso

	1970 – 2016 (Value Weighted)				
	N_S	MKT	HML	SMB	UMD
λ^{Δ}	100	-0.22	4.97***	0.09	8.71***
t-stat		(-0.71)	(6.16)	(0.14)	(6.14)
λ^{Δ}	269	-0.06	3.71***	-0.30	8.57***
t-stat		(-0.24)	(4.88)	(-0.54)	(6.14)
λ^{S}	100	6.70***	6.96***	1.11	8.61***
t-stat		(2.80)	(3.64)	(0.64)	(3.67)
λ^{S}	269	6.86***	5.70***	0.72	8.47***
t-stat		(2.86)	(2.99)	(0.42)	(3.60)
λ^{MF}	—	6.92**	1.99	1.02	-0.10
t-stat		(2.83)	(1.01)	(0.58)	(-0.04)
T		564	564	564	564
$\bar{N}_{MF}$		1286	1286	1286	1286

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Decomposing Implementation Costs

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2. Investability frictions (**no "micro-caps"** constraints)
   - Exclude all stocks in the bottom quintile of market cap (Fama and French, 2008)
3. **Tracking errors** and departures from academic factors
   - Look at performance of funds with high 4-factor R^2 values

The Role of Mutual Fund Shorting Constraints

- What part, if any, of the estimated implementation gap is due to **shorting constraints**?
- We define two variations of the original factors to address this
  1. "**Long** only" factors:

$$HML^{+} \equiv H - R_f$$

  2. "**Tilt**" factors:

$$HML^{\#} \equiv H - MKT$$

    - And the same for SMB and UMD.
- The "tilt" factors: mutual funds have a large baseline market exposure, so increasing exposure to "H" can be financed by reducing market exposure (not actually shorting the market).

Risk Premia Estimates with Long Only Factors

		1970 – 2016 (Value Weighted)			
	N_S	MKT	HML^+	SMB^+	UMD^+
λ^Δ	100	-0.61*	2.56***	0.52	3.09***
t-stat		(-1.94)	(4.05)	(1.00)	(4.52)
λ^Δ	269	-0.29	1.60***	0.02	2.85***
t-stat		(-1.21)	(2.72)	(0.04)	(4.25)
λ^S	100	6.22***	12.25***	9.19***	11.69***
t-stat		(2.59)	(4.33)	(2.85)	(4.11)
λ^S	269	6.54***	11.29***	8.68***	11.46***
t-stat		(2.73)	(3.95)	(2.68)	(4.02)
λ^{MF}	—	6.83***	9.69***	8.66***	8.60***
t-stat		(2.81)	(3.25)	(2.60)	(2.85)
T		564	564	564	564
$\bar{N}_{MF}$		1286	1286	1286	1286

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Risk Premia Estimates with Tilt Factors

	N_S	1970 – 2016 (Value Weighted) MKT	$HML^{\#}$	$SMB^{\#}$	$UMD^{\#}$
λ^{Δ}	100	-0.61*	3.17***	1.13*	3.70***
t-stat		(-1.94)	(4.34)	(1.77)	(5.08)
λ^{Δ}	269	-0.29	1.89***	0.31	3.15***
t-stat		(-1.21)	(3.06)	(0.58)	(4.81)
λ^{S}	100	6.22***	6.03***	2.97*	5.47***
t-stat		(2.59)	(4.19)	(1.94)	(4.57)
λ^{S}	269	6.54***	4.75***	2.15	4.92***
t-stat		(2.73)	(3.28)	(1.42)	(4.18)
λ^{MF}	—	6.83***	2.86*	1.83	1.77
t-stat		(2.81)	(1.92)	(1.17)	(1.47)
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Risk Premia Estimates with No Microcaps

		1970 – 2016 (Value Weighted)			
	N_S	*MKT*	*HML*	*SMB*	*UMD*
λ^{Δ}	80	-0.37	2.85***	0.70	6.14***
t-stat		(-1.39)	(3.84)	(1.24)	(4.66)
λ^{S}	80	6.61***	5.47***	1.71	7.68***
t-stat		(2.74)	(3.03)	(1.07)	(3.31)
λ^{S}	100	6.60***	6.43***	1.27	8.72***
t-stat		(2.75)	(3.51)	(0.75)	(3.74)
λ^{MF}	–	6.98***	2.62	1.01	1.54
t-stat		(2.86)	(1.51)	(0.59)	(0.63)
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Risk Premia Estimates by Four-Factor Model R^2

			Value Weighted		
	$\bar{R}^2$	*MKT*	*HML*	*SMB*	*UMD*
λ_5^{MF}	94.2%	6.50***	3.60**	1.78	4.59*
t-stat		(2.69)	(1.99)	(1.04)	(1.68)
λ_4^{MF}	89.9%	6.91***	2.93*	2.67	0.73
t-stat		(2.82)	(1.70)	(1.57)	(0.26)
λ_3^{MF}	86.0%	7.31***	3.00*	0.09	3.23
t-stat		(2.96)	(1.68)	(0.05)	(1.20)
λ_2^{MF}	79.9%	7.29***	2.66	1.15	-0.81
t-stat		(2.98)	(1.48)	(0.64)	(-0.31)
λ_1^{MF}	55.4%	7.00***	2.93	-0.98	2.08
t-stat		(2.80)	(1.52)	(-0.49)	(0.72)
λ^{MF}	81.1%	6.98***	2.62	1.01	1.54
t-stat		(2.86)	(1.51)	(0.59)	(0.63)
λ_5^{Δ}	–	0.27	1.60**	-0.84	4.26***
t-stat		(1.17)	(2.02)	(-1.45)	(2.80)
$\lambda = 0$		0.00***	0.41	0.00***	0.02**
$\lambda =$		0.00***	0.83	0.00***	0.01***
$\Delta\lambda \lessgtr 0$		0.27	0.08*	0.79	0.68

Decomposing Implementation Costs

- Our baseline results suggested approximately zero costs for MKT and SMB, and so we focus on HML and UMD.

	Baseline	No shorts	No micros	Track error	TOTAL
HML	3.81	1.25	0.96	2.21	4.42
UMD	7.18	4.09	1.04	2.92	8.05
HML	100%	33%	25%	58%	116%
UMD	100%	57%	14%	41%	112%

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- The largest sources of costs for the average mutual fund are:
  - **HML**: Tracking error. MFs may deviate from the academic value factor and instead pursue an alternative, worse performing, version.
  - **UMD**: Short sales constraints. Momentum profits accrue roughly equally from both the long and short positions (Israel and Moskowitz, 2013, *JF*).

Cost Estimates Across Funds and Time

Selected Versus Representative Mutual Funds

- **We can also examine subsets of the mutual fund universe**. Just slice the cross-sectional regression into parts:

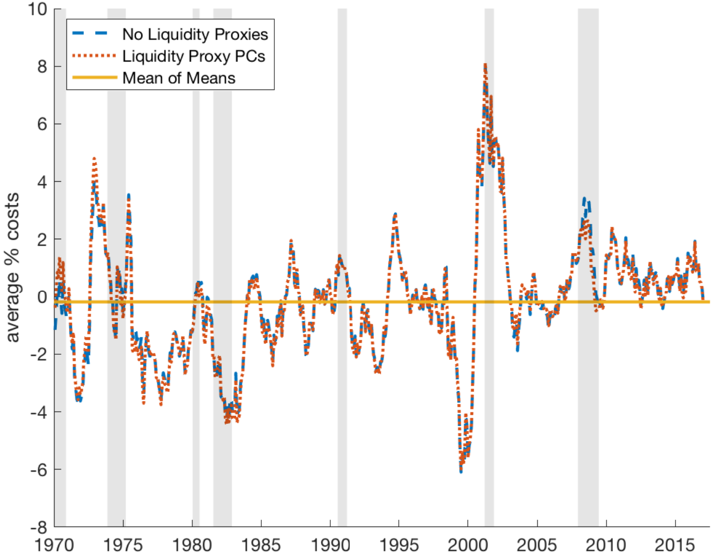
$$r_{it} = \sum_k \lambda_{kt}^{MF,g} \hat{\beta}_{ik} + \epsilon_{it}, \ t = 1, \ldots, T, \ g = 1, \ldots, 5.$$

- This allows us to distinguish between
  - "Special" asset managers (Frazzini, Israel, Moskowitz (2015 *wp*))
  - "Representative" asset managers (Lesmond, Schill, Zhou (2004 *JFE*) and Korajczyk, Sadka (2004 *JF*))
- We split funds into total net asset (TNA) groups for an initial examination because size matters for α
  - Berk and Green (2004 *JPE*), Pastor, Stambaugh, and Taylor (2015 *JFE*), Berk and van Binsbergen (2015 *JFE*)

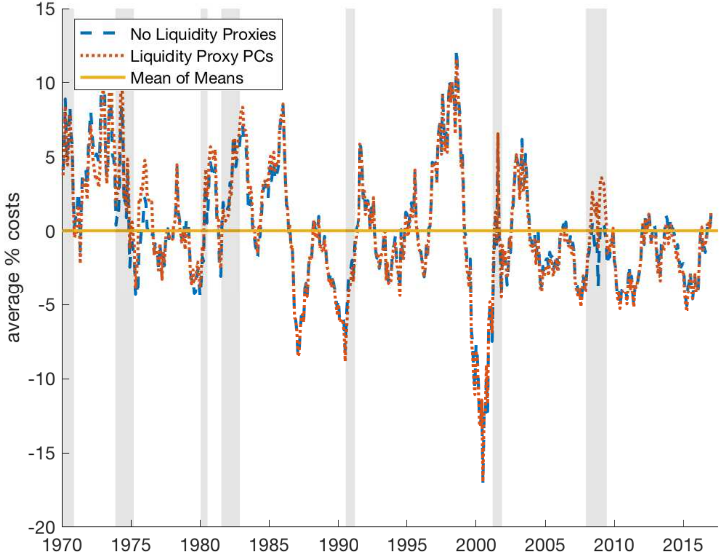
Slopes for Stocks and Mutual Funds — TNA Splits

	Value Weighted			
	MKT	*HML*	*SMB*	*UMD*
λ^{MF}_{mega}	6.66***	3.11*	1.89	-2.53
t-stat	(2.74)	(1.67)	(1.05)	(-0.75)
λ^{MF}_{large}	6.85***	2.78	0.90	0.86
t-stat	(2.78)	(1.54)	(0.52)	(0.31)
λ^{MF}_{medium}	7.02***	2.45	0.90	2.36
t-stat	(2.87)	(1.41)	(0.52)	(0.92)
λ^{MF}_{small}	7.36***	2.94	1.20	3.40
t-stat	(2.98)	(1.64)	(0.72)	(1.25)
λ^{MF}_{micro}	7.18***	2.60	-2.68	-0.24
t-stat	(2.94)	(1.11)	(-1.32)	(-0.06)
λ^{Δ}_{small}	-0.59	2.26**	-0.26	5.45***
t-stat	(-1.59)	(2.22)	(-0.34)	(3.32)
λ^{MF}	6.98***	2.62	1.01	1.54
t-stat	(2.86)	(1.51)	(0.59)	(0.63)
$\lambda = 0$	0.01***	0.46	0.56	0.11
$\lambda =$	0.13	0.81	0.46	0.13
$\Delta\lambda \not\lessgtr 0$	0.01***	0.28	0.20	0.01***

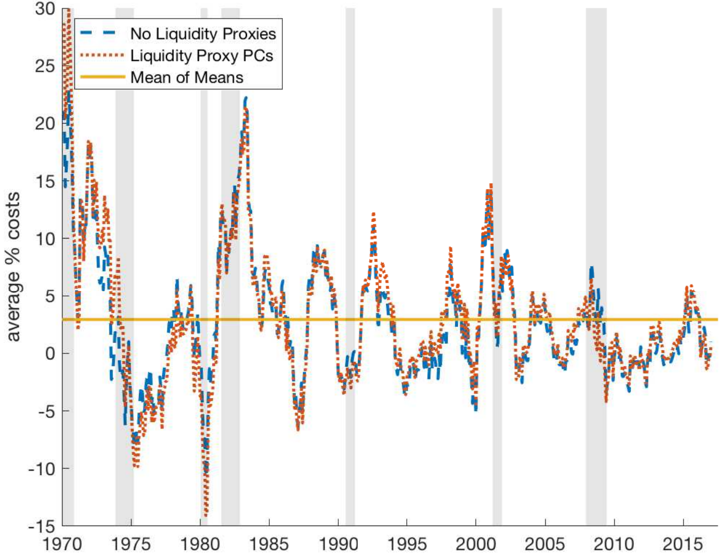
Rolling performance diff b/w stocks and MFs: MKT



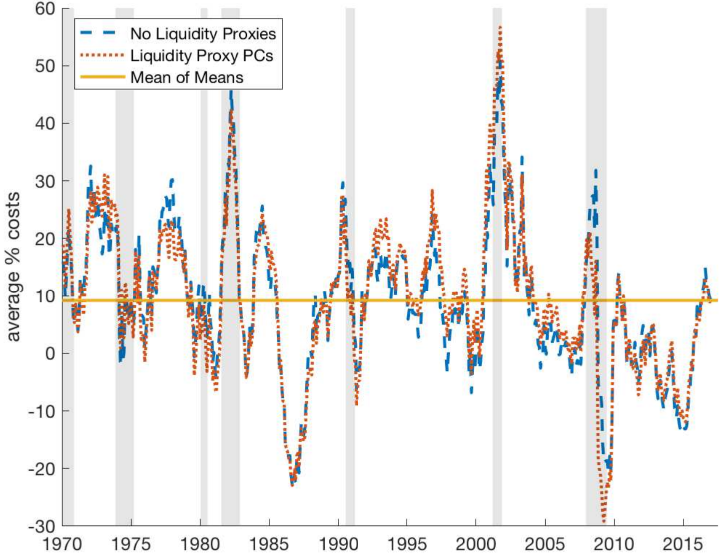
Rolling performance diff b/w stocks and MFs: SMB



Rolling performance diff b/w stocks and MFs: HML



Rolling performance diff b/w stocks and MFs: UMD



Conclusion

- We develop new tools to **estimate the costs of factor investing.**
- Our approach is distinguished by its:
  1. **Generality:** applicable to any tradable factor.
  2. **Light data requirements:** only CRSP, and public, data required. No proprietary or hard-to-handle microstructure data needed.
  3. **No parametric models:** no parametric transaction costs models (though FMB is parametric, of course).
- For typical mutual funds, real-world implementation costs:
  - Do not affect the returns to holding the market or size factors
  - Eliminate returns to momentum
  - Sharply reduce returns to value

$\Longrightarrow$ **Major anomalies are less anomalous!**

Data Filters ▸ Back

1. Fill missing names with the same fund number group. Drop funds without defined fund names
2. Fill missing expense ratios with the nearest values. Set to missing expense ratios $>$50%. Convert fees from net to gross by adding expense ratios / 12
3. Linearly interpolate log TNA values. Set to missing TNAs less than \$0 or exceeding \$1T
4. Drop observations with absolute returns exceeding 100%
5. Drop ETFs, ETNs, VAU funds
6. Value-weight returns within a fund group using lagged TNA
7. Drop observations before a fund reaches a TNA of \$10M
8. Filter non-US domestic equity funds

Comparison with Profitability Estimates from Prior Work

		HML	*SMB*	*UMD*
Cross-Sectional Slopes w/ PCA 1970–2016	λ^{MF}	2.64	0.90	1.28
	t-stat	(1.51)	(0.53)	(0.52)
	λ^{MF}_{small}	2.55	1.37	2.62
	t-stat	(1.37)	(0.82)	(0.97)
Korajczyk and Sadka (2004) 1967–1999	α_{gross}			6.84***
	t-stat			(4.54)
	$\alpha^{espr.}_{net}$			5.40***
	t-stat			(3.59)
	$\alpha^{qspr.}_{net}$			4.80***
	t-stat			(3.17)
Lesmond et al. (2004) 1980–1998	r_{gross}			7.83***
	t-stat			(6.22)
	r^{LDV}_{net}			0.13
	t-stat			(0.07)
	r^{direct}_{net}			2.24
	t-stat			(1.22)

* $p < .10$, ** $p < .05$, *** $p < .01$

Comparison with Profitability Estimates from Prior Work

		HML	*SMB*	*UMD*
Cross-Sectional Slopes w/ PCA	λ^{MF}	2.64	0.90	1.28
1970–2016	t-stat	(1.51)	(0.53)	(0.52)
	λ^{MF}_{small}	2.55	1.37	2.62
	t-stat	(1.37)	(0.82)	(0.97)
Frazzini et al. (2015)	r_{gross}	4.86	7.98***	2.26
1986–2013	t-stat	(1.12)	(3.01)	(0.40)
	r_{net}	3.51	6.52**	-0.77
	t-stat	(0.80)	(2.48)	(-0.14)
Novy-Marx and Velikov (2016)	r_{gross}	5.64***	3.96*	15.96***
1963–2013	t-stat	(2.68)	(1.66)	(4.80)
	r_{net}	5.04**	3.36	8.16**
	t-stat	(2.39)	(1.44)	(2.45)

*$p < .10$, ** $p < .05$, *** $p < .01$