Discussion of:

Market Efficiency in the Age of Big Data

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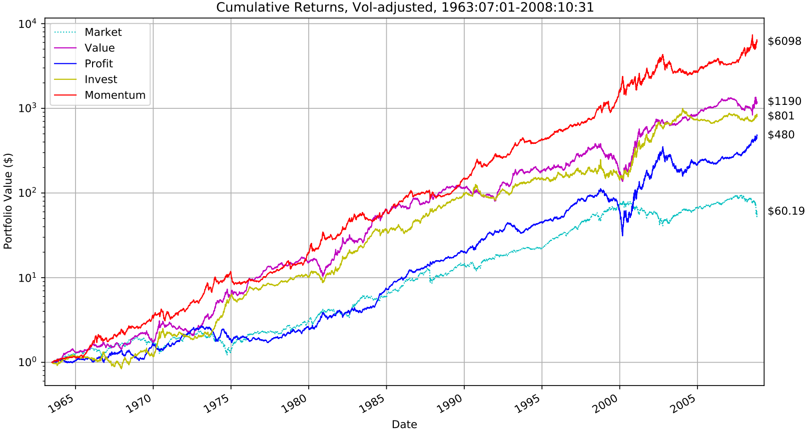
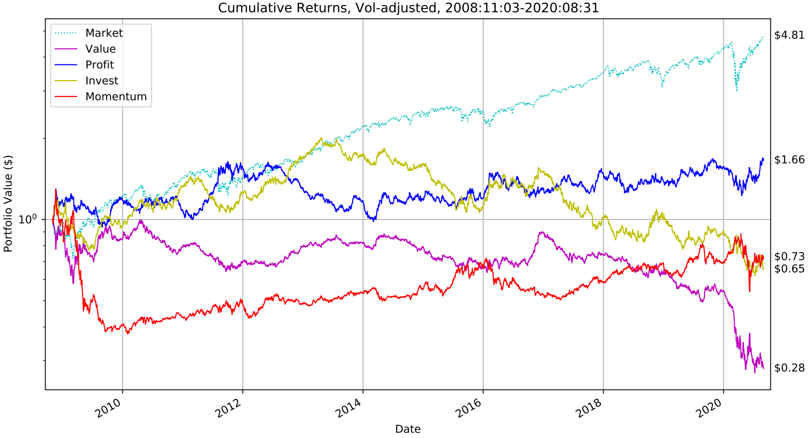
FF (2015) factors, cumulative returns

- Each FF(2015)-based strategy's leverage is adjusted to equalize volatilities
  - at $\sigma = \sigma_{\mathrm{Mkt}}$ =14.9%
- Time period is 1963:07–2008:11



FF (2015) factors, cumulative returns

- Time period here is 2008:11–2020:08



Value performance 1926-2020

10-year rolling returns – Fama-French "Value" strategy.

Summary

- In the 45 years leading up to the financial crisis, systematic value factors produced high returns and high SRs.
- In the 12 years since, they have been a disaster.

	1963:07–2008:10			2008:11–2020:08		
	$\overline{R}$	σ	SR	$\overline{R}$	σ	SR
Market-R_f	4.64%	14.9%	0.31	14.28%	20.0%	0.72
Value (HML)	5.45%	7.4%	0.75	-5.55%	11.7%	-0.47
Profit (RMW)	3.63%	5.9%	0.61	1.25%	6.0%	0.26
Invest (CMA)	4.14%	6.0%	0.69	-0.42%	5.1%	-0.08
Mom (UMD)	9.92%	10.0%	0.99	-1.03%	16.4%	-0.06
R_f	5.53%	—	—	0.48%	—	—

Basic Idea

- Many anomalies were really strong until they were “discovered”, and then have “disappeared”.
- This could be because:
  1. They were never there in the first place
     - e.g., Harvey, Liu, and Zhu (2016), Harvey (2017)
  2. Once they were discovered they were, partially or fully, arbitraged away.
     - e.g., McLean and Pontiff (2016).
- This paper instead argues that apparent predictability could result from agents’ need to learn the underlying parameters governing the cashflow generating process.
  - Timmermann (1993), Lewellen and Shanken (2002), Collin-Dufresne, Johannes, and Lochstoer (2016, 2017), Johannes, Lochstoer, and Mou (2016)
- This is the first paper I am aware of that explores the effect of learning on cross-sectional anomalies.

The Model

- The model features a representative risk-neutral investor who sets prices.
- A key feature of the model is that, to estimate value, the agent needs to estimate cashflow growth rates, which is inherently slow in a noisy environment.
- How well is a new asset (e.g., SPACs) going to perform?
- Value is PV of future dividends $\mathbf{y}_t$
- investors look at a set of predictive variables $\mathbf{X}$, and need to estimate $\mathbf{g}$ in:

$$\boldsymbol{\Delta}\mathbf{y}_t = \mathbf{X}\mathbf{g} + \mathbf{e}_t$$

- Investors have a prior on $\mathbf{g}$

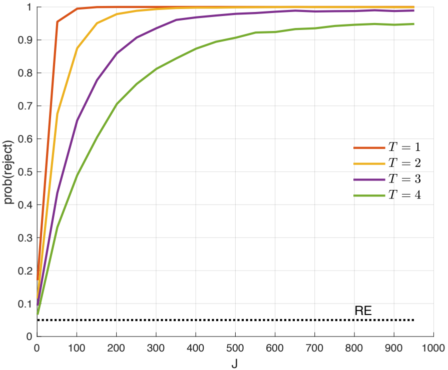
$$\mathbf{g} \sim \mathcal{N}\left(\mathbf{0}, \Sigma_g\right)$$

  and update, using Bayes' rule, based on new cashflow realizations.
- Thus, for of $\mathbf{g}$ that saw a large update, a characteristic-portfolio will have a high realized return
  - as investor's posterior changes the price changes.

Key Findings

- For reasonable *J*s, the probability of rejecting the null by an econometrician who doesn't understand the learning that is going on his high:

(B) Rejection probability of no-return-predictability null



Key Findings

- *Persistence*: In-sample predictability. *No* out-of-sample predictability.
    - And, as J grows, the in-sample SR's $\rightarrow \infty$.
- *No forward or backward predictability*
    - The return predictability in and *past* or *future* time sample is uncorrelated with the predictability in a non-overlapping sample.

Modeling Declining Anomaly Performance

- I'm going to talk a little about some of the challenges to an explanation of declining anomaly performance based solely on learning.
- This is more than a little unfair, as the authors are not arguing that learning explains all x-sectional anomalies
  - However, I would think that the ultimate objective of this line of research would be to understand how learning, data mining, and arbitrage drive time-variation in anomaly returns.
    - e.g, how could we estimate a nested model with these three features?
  - or perhaps in thinking through issues involved in more concretely modeling learning
    - e.g., is learning faster today than it was pre-information era?

Momentum

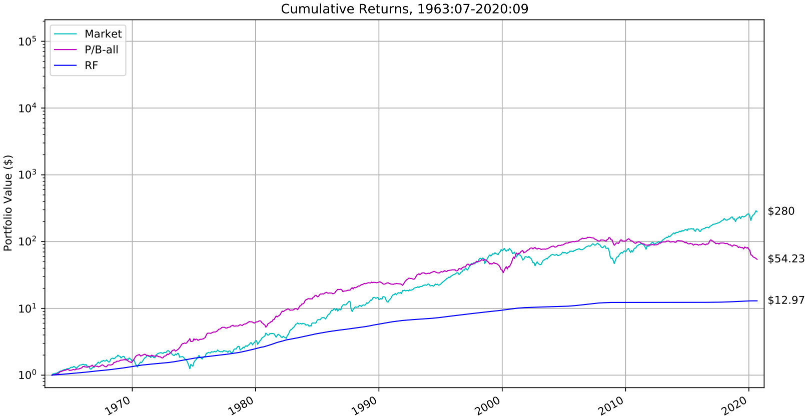
- At least for Value and Momentum, there is fairly strong evidence that effects are consistent across many distinct time periods and asset classes
  - See, e.g., Asness, Moskowitz, and Pedersen (2013)
- A batch of fairly recent papers have argued that, not only the premium, but the nature of the time-variation (Daniel and Moskowitz, 2016) is consistent across time periods and geographies:
  - Chabot, Remy, and Jagannathan (2009): “Momentum Trading . . . ” (UK, 1867-1907)
  - Geczy and Samonov (2015): “Two Centuries . . . ” (US, 1801-1926)
  - Goetzmann and Huang (2018): “Momentum in Imperial Russia” (Russia, 1865-1914)

Discrimiinating between Learning and Arbitrage

- If learning is what is going on, the anomalies should disappear among all stocks at about the same rate.
    - That is, this shouldn’t be dependent on arbitrage costs.

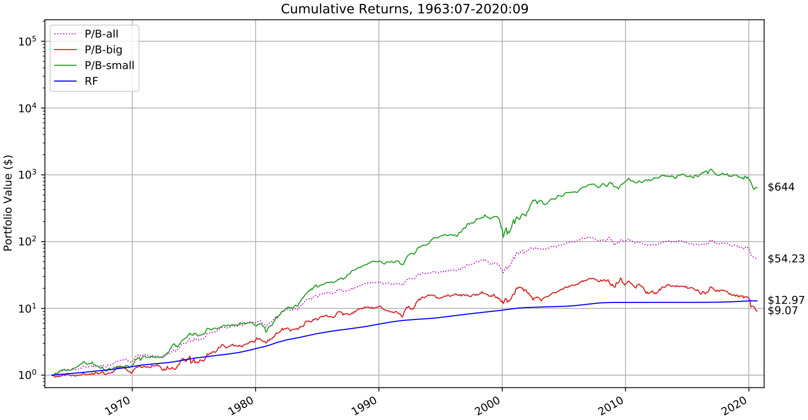
Cumulative Returns of Value Portfolios

FF-Value Only



Cumulative Returns of Value Portfolios

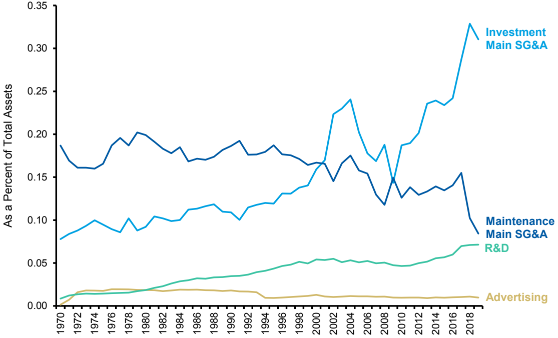
Small- & Large-Cap Components of FF-Value



Inattention? — *Intangible Capital*

Intangible assets have become increasingly important component of firm value.[1]

Exhibit 3: Components of Selling, General, and Administrative (SG&A) Costs, 1970-2019



Source: O'Shaughnessy Asset Management based on Luminita Enache and Anup Srivastava, "Should Intangible Investments Be Reported Separately or Commingled with Operating Expenses? New Evidence," Management Science, *Vol. 64, No. 7, July 2018, 3446-3468.*

Measuring Intangible Captial

- New evidence suggests that markets have not rationally incorporated the value of intangible assets into prices.
  - This is perhaps evidence of slow (ie., not rational Bayesian) learning.

Measuring Intangible Captial

- Park (2019) follows Peters and Taylor (2017) and each fiscal year t calculates *Organizational Capital* K_t^O and *Knowledge Capital* K_t^K as:[2]

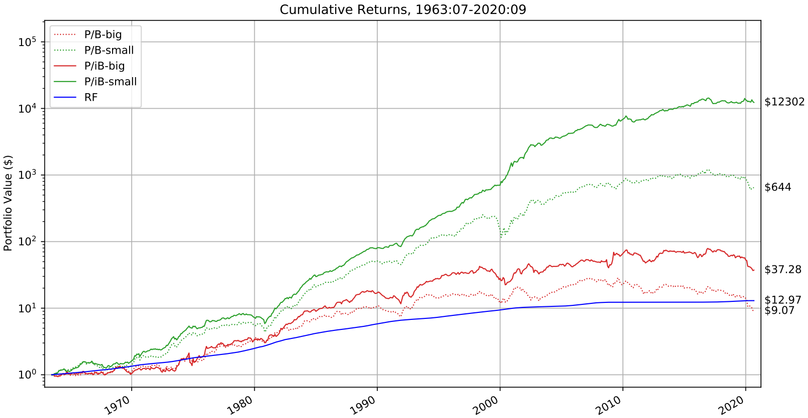
$$\begin{aligned} K_t^O &= (1-0.2) \times K_t^O + 0.3 \times \text{SG\&A}_t \\ K_t^K &= (1-\delta^{RD}) \times K_t^K + \text{R\&D}_t \end{aligned}$$

  where the industry-specific R&D depreciation rate δ^{RD} is taken from Li and Hall (2020).

- To calculate the *intangible-Adjusted Book Equity*, iBE, she adds K_t^O and K_t^K to standard book-equity (Fama and French, 2015), and subtracts goodwill.

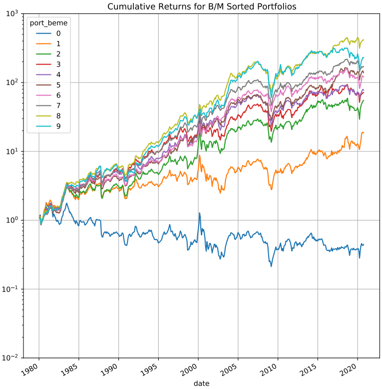
intangible-Value Portfolios

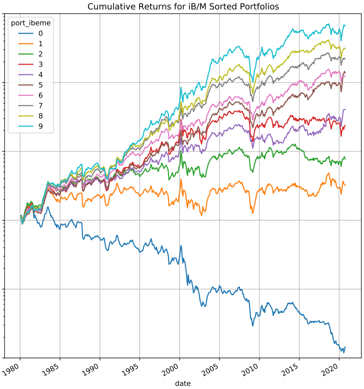
Intangible-Adjusted Value (iHML), from Park (2019)



Bottom Size Decile Firms

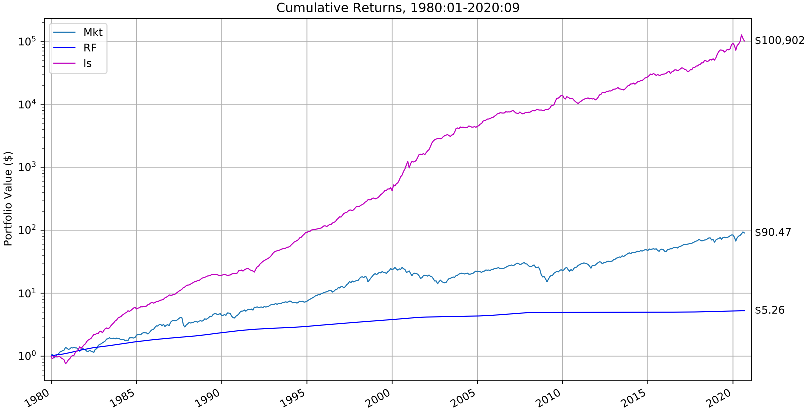
- The improvement in performance is particularly strong in very small firms.
  - again suggesting that limits to arbitrage affects portfolio performance





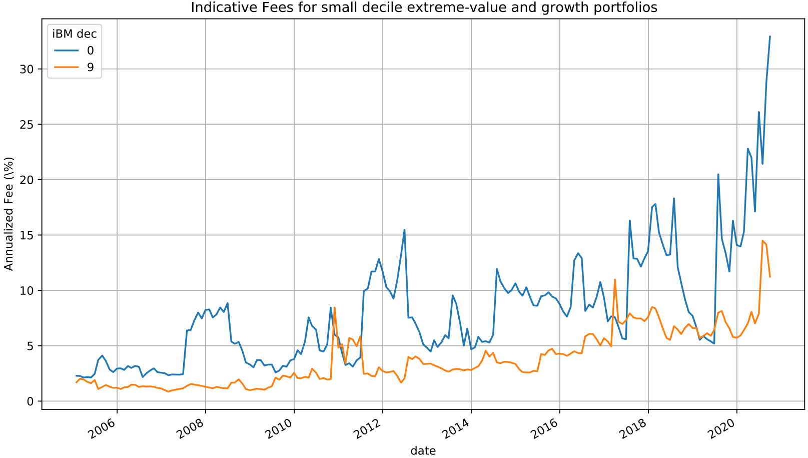
Long-short Returns—Bottom Size Decile

- Moreover, for a value-minus-growth portfolio, based on intangible-adjusted-book values, consisting only of bottom-size-decile firms, there has been no decline in performance over the last decade:



Fees —Bottom Size Decile Firms

- Indicative fees for bottom-decile iValue and iGrowth firms based on Markit data.



Generalized Learning

- For asset managers, learning is at least perceived as being really important.
  - Cliff Asness & 2007 quant-crisis: learning about flows
- There is a fascinating analysis in Brunnermeier and Nagel (2004):
  - In the late-1990s “technology bubble” hedge funds were long tech stocks.
  - Apparently based (predictable) investor sentiment, they reduced these positions in advance of the collapse in prices starting in March 2004.
  - *How did these agents learn about forecasting shifts in sentiment?*
- Recent price moves in GME, BTC suggest that this is a difficult problem in some environments!
- A model which integrates learning into an environment with sentiment, conditional on the environment, would be fascinating.

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