Accounting for the Anomaly Zoo: a Trading Cost Perspective

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The views expressed in this presentation are those of the authors and do not necessarily reflect the position of the Board of Governors of the Federal Reserve or the Federal Reserve System.
So many anomalies, so many questions...

- What kind of factor model can explain this zoo? Can such models be rationalized?
- Which anomalies are redundant? Which have synergies?
- What share of these returns is due to data-mining?

We don’t address any of these
Our question is more basic:

How much profit should investors expect (in the future) from investing in anomalies?

(We just want to know the expected return)
Existing literature does not answer the simple question:

<table>
<thead>
<tr>
<th>The Standard Approach</th>
<th>The Problem</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average returns over decades of history</td>
<td>Data mining bias + investor learning =&gt; Can’t expect historical returns to persist into the future (McLean and Pontiff 2016)</td>
</tr>
<tr>
<td>Measure gross returns (before trading costs)</td>
<td>Gross returns are not profits</td>
</tr>
</tbody>
</table>
This Paper:

We study post-publication returns net of costs for 120 anomalies

Costs = effective bid-ask spreads (TAQ/ISSM)

Post-publication net returns are tiny:

Average investor should expect tiny profits from the average anomaly
Related Literature

Many, many papers study trading costs of anomalies

- Stoll and Whaley (1983); Ball, Kothari, and Shanken (1995); Knez and Ready (1996); Pontiff and Schill (2001); Korajczyk and Sadka (2004); Lesmond, Schill, and Zhou (2004); Hanna and Ready (2005); Frazzini, Israel, Moskowitz (2015); Novy-Marx and Velikov (2016) ...

What’s new: by far the most comprehensive set of anomalies (120)

- Allows for inferences regarding short post-publication samples
- Get us much closer to expected profits
Caveats

We do not attempt to study

- Implementation shortfall (Frazzini et al 2015; Briere et al 2019)
- Price impact (Frazzini et al 2015; Briere et al 2019)
- Combining multiple anomalies (DeMiguel et al Forthcoming)

Our goal is a simple benchmark expected return

Our benchmark: uses effective bid-ask spreads for single strategies

- lower bound cost for the average trader, irrespective of portfolio size
- starting point for studying more complex issues
Roadmap

1. Anomalies data and trading cost measures

2. Results
   a) Average published strategy
   b) Average cost-mitigated strategy
   c) Selected cost-mitigated strategies (adjusted for selection bias)
Anomalies data and trading cost measures
Anomalies Data

Begin w/ Chen and Zimmermann’s (2018) 156 replicated characteristics

- Remove 34 that are not continuous
  - Need cost mitigation to understand costs, need continuity for cost mitigation
- Remove 2 that are somewhat hard to call anomalies
  - CAPM beta
  - Tail risk beta (Kelly and Jiang 2014)

Remaining: 120 published anomalies

- 50% focus on Compustat accounting variables
- 30% use purely price data
- 20% use analyst forecasts, institutional ownership, volume, etc

Short post-publication samples require a large number of anomalies
Trading Costs: Basics

Procedure:

1. Track portfolio weights over time
2. Whenever position is entered or exited: assume half the effective bid-ask spread is paid

Effective bid-ask spread:

\[
[\text{Effective Spread}] = 2 \log[\text{Trade Price}] - \log[\text{Quote Midpoint}]
\]

• For buys: trade price > midpoint (pay too much)
• For sells: trade price < midpoint (earn too little)
Interpretation: Lower bound cost to average trader

Lower bound cost

- Omits shorting costs and price impact
- Even the tiny net returns we find are unattainable to many traders

For average trader:

- Technically, a small liquidity demander
- Sophisticated arbitragers may supply liquidity (and bear other costs) (Frazzini, Israel, and Moskowitz 2018; Cont and Kukanov 2017)

Reminder: our goal is a simple benchmark expected return
Trading Costs: Data

Post-publication costs: high-frequency data

• 2003-2016: Daily TAQ (milli/nano-second timestamps)
• 1993-2003: Monthly TAQ (second timestamps)
• 1983-1992: ISSM
  — NASDAQ data starts in 1987

In-sample costs: average 4 low frequency proxies (1926-1982)

• Gibbs (Hasbrouck 2009)
• High-low spread (Corwin and Schultz 2012)
• Volume-over-volatility (Kyle and Obizhaeva 2016)
• Close-high-low (Abdi and Ranaldo 2017)
High-frequency data is important for post-publication samples

Low-Frequency Bias Over Time

- Low-freq spreads are 25-50 bps upward bias in recent data
Our effective spread over time

- Huge spreads in 1930s-1940s
- Spreads rise in 1970s as NASDAQ enters CRSP
- Spreads plummet in 2000s with electronic trading
Is the average published strategy profitable?
Published Strategies

Almost all anomaly publications focus on equal-weighting

• (McLean and Pontiff 2016; Chen and Zimmermann 2018)

And use simple strategies:

• Long/short stocks in extreme quantiles
• Rebalance when signal updates

Same approach here: equal-weighted long-short quintiles + rebalancing when signal updates

• Quick, simple picture of net returns
• Next: cost-mitigated strategies
Result 1: Average investors should expect no profit from the average published strategy

- Standard errors are small
- Net returns are negligible even in-sample
- Decomposition

\[
[\text{Net Return}] \approx [\text{Gross Return}] - [\text{Turnover}] \times [\text{Spread}]
\]

\[
= 30 \text{ bps} - 0.30 \times 111 \text{ bps} = -3 \text{ bps per month.}
\]

<table>
<thead>
<tr>
<th></th>
<th>Average Across 120 Anomalies (%, Monthly)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Gross Return</td>
</tr>
<tr>
<td>In-Sample</td>
<td>0.66</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
</tr>
<tr>
<td>Post-Publication</td>
<td>0.30</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
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Why are trading costs so large post-decimalization?

Decimalization: spread $\approx$ $0.01$, price $\approx$ $20 \Rightarrow$ spread $\approx$ 5 bps.

But 5 bps represents the mode

- Spreads have an extremely long right tail
- Mean spread = 67 bps
- Published strategies require trading across the entire distribution
Recap: is the average published strategy profitable?

No.

• 30% turnover × 111 bps spread wipes out profits

But these strategies completely ignore costs

Can smarter strategies earn profits?
Is the average cost-mitigated strategy profitable?
Cost Mitigation Overview

We combine two techniques

1. Value-weighting: reduces spreads paid
2. Buy/Hold Spreads: reduces turnover

These two together outperform several other cost mitigations

• (Novy-Marx and Velikov 2016, 2018)

Empirical Exercise

1. Optimize two techniques in-sample
2. Re-examine post-publication net returns
The Buy/Hold Spread: mimics optimal trading under trading costs
(Magill-Constantinides 1976; Brandt, Santa-Clara, Valkanov 2009)

**Long-Short Quintiles**

<table>
<thead>
<tr>
<th>Strongest Signal</th>
<th>Buy/Hold 20/30</th>
</tr>
</thead>
<tbody>
<tr>
<td>80th Pct</td>
<td>Hold Long / Enter Long</td>
</tr>
<tr>
<td>70th Pct</td>
<td>Exit / Ignore</td>
</tr>
<tr>
<td>30th Pct</td>
<td>Exit / Ignore</td>
</tr>
<tr>
<td>20th Pct</td>
<td>Exit / Ignore</td>
</tr>
<tr>
<td>Weakest Signal</td>
<td>Hold Short / Enter Short</td>
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</table>
Choose weighting and buy/hold spreads to maximize in-sample net returns

More formally:

\[
\{\{w_i^*\}_{i=1}^N, \{bhs^*(q)\}_{q=1}^4\} = \arg\max \text{ In-Sample Net Return} (w_i, bhs(q(\tau_i)))
\]

where

\[
w_i \in \{\text{equal-weighted, value-weighted}\}
\]

\[
bhs(q) \equiv \text{buy/hold spread as a function of turnover quartile } q
\]

Specification aims to balance performance and robustness
Before cost-mitigation (in-sample)

Average net return

= 5 bps/month
After cost-mitigation (in-sample)

Average net return
= 38 bps/month

Cost-mitigation works well (in-sample)
Result 2: Average investors should expect tiny profits from the average cost-mitigated strategy

- Sizable in-sample net returns plummet around publication
- Average 4-13 bps/month after publication, depending on how you take the average
Selected Cost-Mitigated Strategies
Size, B/M, and momentum are among the better performers

- Consistent with recent papers that measure implementation shortfall
  - Briere et al (2019)
- Are size, value, and momentum special?
- Or are they lucky?
- What about idiovol or distress (FailurePr)?
Final question: Can we expect selected strategies to be profitable?

Tricky question: need to adjust for selection (hindsight) bias

We use two adjustments:

- Forecast post-pub returns using in-sample information
- Empirical-Bayes adjustment
Bias adjustment 1: Forecasting post-pub net returns

Exercise:

1. Sort anomalies on in-sample turnover or net return
2. Examine mean post-publication net returns

<table>
<thead>
<tr>
<th>In-Sample Predictor</th>
<th>Post-Pub Net Returns (% monthly)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Predictor 1 (Worst)</td>
</tr>
<tr>
<td>Turnover</td>
<td>-0.18</td>
</tr>
<tr>
<td></td>
<td>(0.06)</td>
</tr>
<tr>
<td>Net Return</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
</tr>
</tbody>
</table>

Even the best predictors provide only ≈ 20 bps/month

- Excludes shorting costs, price impact
- Shorting costs average 10-20 bps (Cohen et al 2007)
Bias adjustment 2: Empirical Bayes adjustment

Uses empirical Bayes / “big-data” methods (Efron 2010; Azevedo et al 2019; Liu et al Forthcoming)

1. Model unobserved expected return $\mu_i$

2. Estimate $\mu_\mu$ $\sigma_\mu$ by method of moments

3. Bayes formula gives bias adjusted expected return

$$
\bar{r}_i = N(\mu_i, SE_i)
$$

$$
\mu_i \sim N(\mu_\mu, \sigma_\mu)
$$

$$
\mathbb{E}(\mu_i | r_i, SE_i) = s_i \mu_\mu + (1 - s_i) \bar{r}_i
$$

$$
s_i \equiv \frac{SE_i^2}{\sigma_\mu^2 + SE_i^2}
$$
Bias adjustment 2: Empirical Bayes adjustment

<table>
<thead>
<tr>
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<th>Bias-Adjusted Net Return Percentiles (%, monthly)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>50 pct</td>
</tr>
<tr>
<td>Including EW</td>
<td>0.13</td>
</tr>
<tr>
<td>VW only</td>
<td>0.07</td>
</tr>
</tbody>
</table>

Once again:

- Even the best predictors provide only $\approx 20$ bps/month
- Restricted to value-weighting $\Rightarrow 7$ bps

Result 3: average investors should expect only tiny profits from selected, cost-mitigated anomaly strategies.
Intuition: Why is selection bias so large?

Distribution is close to the null of no predictability

- # |t-stats| > 2.0 = 13%
- No predictability => 5%

Most of the heterogeneity can be explained by noise / luck
Conclusion

We study post-publication returns net of costs for 120 anomalies

Post-publication net returns are tiny

Average investor should expect tiny profits from average anomaly

Even the best anomalies provide only tiny net returns