

Week 6: Trading Costs

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Keim and Madhavan (1997)

- Explicit costs
 - Commissions
 - We don't worry about them too much
- Implicit costs
 - Quoted bid-ask spread
 - Market maker's compensation for providing liquidity; price of immediacy
 - Effective spread
 - “True” spread, since many traders trade within the quoted spread
 - Price impact
 - Larger trades move prices
 - Opportunity cost



Roll (1984)

- The bid-ask spread complicates research, since we don't observe the true price.
 - We have three prices: bid, P_b , ask, P_a , and true price, P^*
 - The true price is often between P_a and P_b , although it need not be.
 - How do we define returns: From P_a to P_a , P_b to P_b , P_b to P_a ...?
 - How is $P_a - P_b$ determined?
- Roll (1984) provides a simple model of how the bid-ask spread might impact the time-series properties of returns.
 - Provides most of the intuition and the framework on how we think about the bid-ask spread.

Roll (1984)

- The observed market price is

$$P_t = P_t^* + q_t \frac{s}{2}$$

- P_t^* : fundamental price in a frictionless economy
- s : bid-ask spread (independent of the P_t level)
- q_t : i.i.d index variable - takes values of 1 with prob. 0.5 (buy)
- takes value of -1 with prob. 0.5 (sell)
- q_t is unobservable. But, with the assumptions, $E[q_t] = 0$ and $Var(q_t) = 1$
- For simplicity assume that P_t^* does not change - $Var(\Delta P_t^*) = 0$
- The change in price is (define the *cost* $c = s/2$):

$$\Delta P_t = \Delta P_t^* + q_t \frac{s}{2} - q_{t-1} \frac{s}{2} = \Delta P_t^* + c \Delta q_t$$



Roll (1984)

- Its variance and autocovariance are:
 - $Var(\Delta P_t) = Var(\Delta P_t^*) + c^2 Var(I_t) + c^2 Var(I_t) = 2c^2 (= s^2/2)$
 - $Cov(\Delta P_t, \Delta P_{t-1}) = -c^2$
- Note:
 - The fundamental value is fixed, but there is variation from c .
 - The bid-ask spread induces negative correlation in returns even in the absence of other fluctuations.
 - The variance and covariance depend on the magnitude of the bid-ask spread.
 - In this particular example, it induces a 1st-order serial correlation.

Roll (1984)

- We can also express the cost (aka half-spread) as a function of the covariance:
 - $c = [-Cov(\Delta P_t, \Delta P_{t-1})]^{-1/2}$
- In practice, we can find $Cov(\Delta P_t, \Delta P_{t-1}) > 0$
- To avoid this problem, Roll (1984) defines the cost as
$$c = -[|Cov(\Delta P_t, \Delta P_{t-1})|]^{-1/2}$$
- Roll calls $s(= 2 \times c)$ the “effective spread,” which is estimable.

Hasbrouck (2009)

- Takes the Roll (1984) model:

$$\Delta P_t = c\Delta q_t + \epsilon_t$$

- ... generalizes it by adding a market factor:

$$\Delta P_t = c\Delta q_t + \beta_m r_{mt} + \epsilon_t$$

- ... makes a few assumptions ^{σ_ϵ^2}
 - $\epsilon_t \sim N(0, \sigma_\epsilon^2)$ & *i.i.d.*
 - Priors for the unknowns $\{c, \sigma_\epsilon^2, q_1, \dots, q_T\}$
- ... and sequentially draws the parameter estimates using a Gibbs sampler to characterize the posterior densities



Hasbrouck (2009)

- The Gibbs measure achieves the highest correlation (96.5%) with high-frequency TAQ data estimates

Table III

Correlations between Liquidity Measures for the Comparison Sample

The comparison sample consists of approximately 150 NASDAQ firms and 150 NYSE/Amex firms selected in a capitalization-stratified random draw in each of the years from 1993 to 2005. Definitions of the liquidity measures are given in Table I. Partial correlations are adjusted for log (end-of-year price) and log (market capitalization).

	c_{it}^{TAQ}	c_{it}^{Gibbs}	c_{it}^{Moment}	$PropZero_{it}$	λ_{it}	I_{it}
Pearson correlation						
c_{it}^{TAQ}	1.000	0.965	0.878	0.611	0.513	0.612
c_{it}^{Gibbs}	0.965	1.000	0.917	0.579	0.450	0.589
c_{it}^{Moment}	0.878	0.917	1.000	0.451	0.378	0.504
$PropZero_{it}$	0.611	0.579	0.451	1.000	0.311	0.252
λ_{it}	0.513	0.450	0.378	0.311	1.000	0.668
I_{it}	0.612	0.589	0.504	0.252	0.668	1.000



Novy-Marx and Velikov (2016)

- Apply the Gibbs measure to 23 anomalies and create a taxonomy of anomalies
 - Useful rules of thumb for anomalies & whether they survive trading costs based on their turnover
 - Typical value-weighted anomaly $\sim 50\text{bps}$
 - If turnover more than 50% per month, net returns are negative
- Several new methods
 - “Generalized alpha”
 - Buy/hold spread trading cost mitigation technique
- Price impact estimation



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Novy-Marx and Velikov (2016)

- Trading cost calculation procedure
 - Track portfolio weights over time
 - Whenever a position is entered or exited, assume half of the effective spread (i.e., Hasbrouck's effective cost) is paid
- Interpretation: lower bound cost for average trader using market orders
- Note: lots of missing observations in Hasbrouck for small stocks
 - Creates look-ahead bias (excluding stocks with missing data)
 - Thus, we fill in 29% of stock-months (4% of market cap) in based

on $\sqrt{(rankME_i - rankME_j)^2 + (rankME_i - rankME_j)^2}$



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Trading costs formulas from DNMV (2022)

- Net returns for month t are given by:

- Long side:

$$f_t^{net} = f_t^{gross} - TC_t^f$$

- Short side:

$$f_t^{S,net} = -f_t^{gross} - TC_t^f$$

- Trading cost calculation procedure

- Turnover (TO) for a factor f in month t defined as:

$$TO_t^f = \frac{1}{2} \sum_{i=1}^{N_t} |w_{i,t} - \tilde{w}_{i,t-}|$$

- Trading costs (TC) defined as:

$$TC_t^f = \sum_{i=1}^{N_t} |w_{i,t} - \tilde{w}_{i,t-}| \cdot c_{i,t}$$

where $c_{i,t}$ is the one-way transaction cost (i.e., effective half-spread)



Novy-Marx and Velikov (2016)

- Problem with performance evaluation: we can't regress net anomaly strategy returns on net factor returns
 - If a loading is negative, the alpha from this regression effectively assumes you “earn” the trading costs

- Solution: Generalized alpha (α^*):

$$\frac{MVE_{\{X,y\}}}{w_{y,MVE\{X,y\}}} = \alpha^* + \beta^* MVE_X + \epsilon^*$$

- Does the mean-variance efficient portfolio of the factors and the strategy under evaluation improve the investment opportunity set for an investor who has access to the MVE of the factors only
- $w_{y,MVE\{X,y\}}$ terms ensures it's the same as alpha when there is no trading costs



Novy-Marx and Velikov (2016): Taxonomy

Table 3
Value-weighted returns

Panel A: Low-turnover strategies						
Anomaly	$E[r_{gross}^e]$	α_{FF4}^{FF4}	TO	T-costs	$E[r_{net}^e]$	α_{FF4}^{FF4}
Size	0.33 [1.66]	-0.14 [-1.77]	1.23	0.04	0.28 [1.44]	
Gross profitability	0.40 [2.94]	0.52 [3.83]	1.96	0.03	0.37 [2.74]	0.51 [3.77]
Value	0.47 [2.68]	-0.17 [-1.76]	2.91	0.05	0.42 [2.39]	-0.02 [-0.17]
ValProf	0.82 [5.18]	0.50 [4.01]	2.94	0.06	0.77 [4.82]	0.49 [3.93]
Accruals	0.27 [2.14]	0.27 [2.15]	5.74	0.09	0.18 [1.43]	0.19 [1.55]
Asset growth	0.37 [2.52]	0.07 [0.58]	6.37	0.11	0.26 [1.75]	0.03 [0.21]
Investment	0.56 [4.44]	0.35 [2.90]	6.40	0.10	0.46 [3.60]	0.31 [2.62]
Piotroski's F-score	0.20 [1.04]	0.31 [1.75]	7.24	0.11	0.09 [0.45]	0.24 [1.37]
Panel B: Mid-turnover strategies						
Net issuance	0.57 [3.70]	0.58 [4.10]	14.4	0.20	0.37 [2.43]	0.41 [2.93]
Return-on-book equity	0.71 [2.96]	0.84 [4.41]	22.3	0.38	0.33 [1.38]	0.59 [3.18]
Failure probability	0.85 [2.52]	0.94 [4.89]	26.1	0.61	0.24 [0.73]	0.70 [3.55]
ValMomProf	1.43 [7.41]	0.68 [5.52]	26.8	0.43	0.99 [5.18]	0.68 [5.22]
ValMom	0.93 [4.81]	-0.12 [-1.31]	28.7	0.41	0.51 [2.67]	
Idiosyncratic volatility	0.63 [2.13]	0.83 [5.14]	24.6	0.52	0.11 [0.37]	0.41 [2.57]
Momentum	1.33 [4.80]	0.35 [3.04]	34.5	0.65	0.68 [2.45]	0.40 [3.12]
PEAD (SUE)	0.72 [4.52]	0.58 [4.31]	35.1	0.46	0.26 [1.60]	0.29 [2.21]
PEAD (CAR3)	0.91 [6.54]	0.87 [6.39]	34.7	0.57	0.34 [2.41]	0.38 [2.85]
Panel C: High-turnover strategies						
Industry momentum	0.93 [3.97]	0.83 [3.52]	90.1	1.22	-0.29 [-1.20]	
Industry relative reversals	0.98 [5.72]	1.05 [6.66]	90.3	1.78	-0.80 [-4.73]	
High-frequency combo	1.61 [11.21]	1.48 [9.93]	91.0	1.45	0.16 [1.11]	0.05 [0.35]
Short-run reversals	0.37 [1.71]	0.45 [2.22]	90.9	1.65	-1.28 [-6.02]	
Seasonality	0.84 [5.21]	0.82 [5.03]	91.1	1.46	-0.62 [-3.88]	
Industry relative reversals (low volatility)	1.25 [9.36]	1.17 [8.96]	94.0	1.06	0.19 [1.41]	0.07 [0.57]



Novy-Marx and Velikov (2016)

- Mean-variance efficient weights with no costs given by:

$$\omega_{MVE} = \frac{\Sigma^{-1} \mu_e}{1 \Sigma^{-1} \mu_e}$$

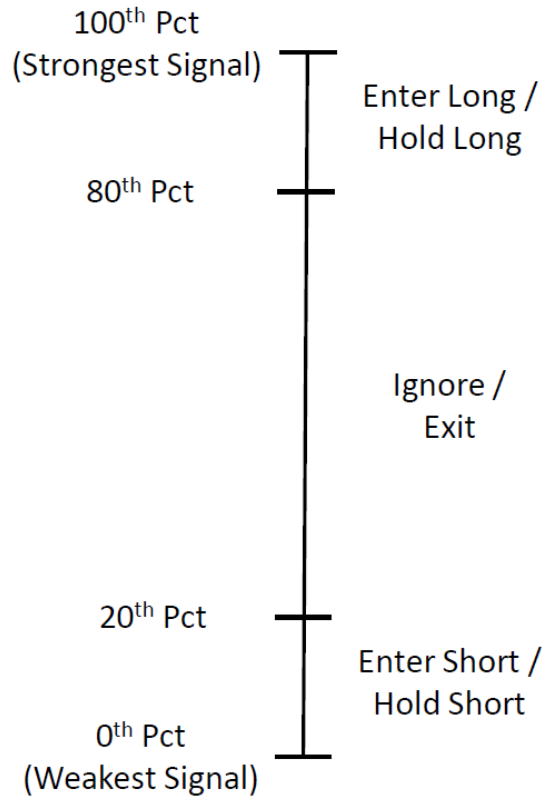
- we can estimate with ex-post vector of average returns & variance-covariance matrix
- However, with costs, we can't just apply the formula with net returns
 - Need to do a numerical optimization



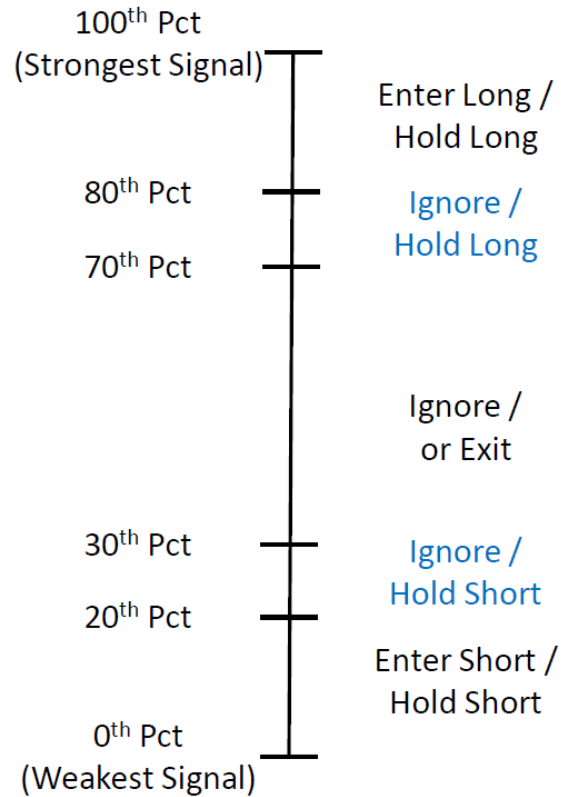
Novy-Marx and Velikov (2016)

- Buy/hold spreads: a simple trading cost mitigation technique

Long-Short Quintiles



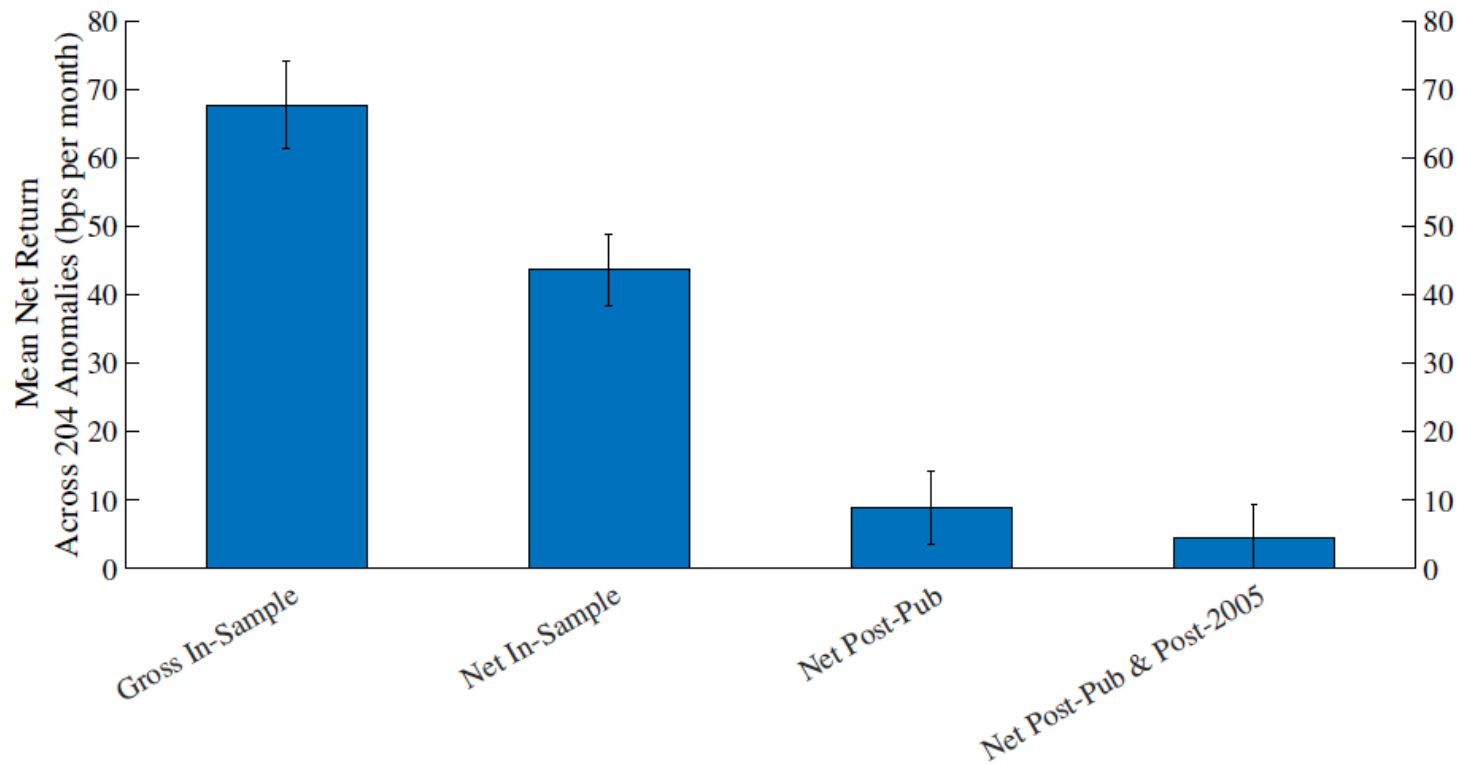
Buy/Hold 20/30



Chen and Velikov (2022)

- Main goal: “zero in” on the average anomaly

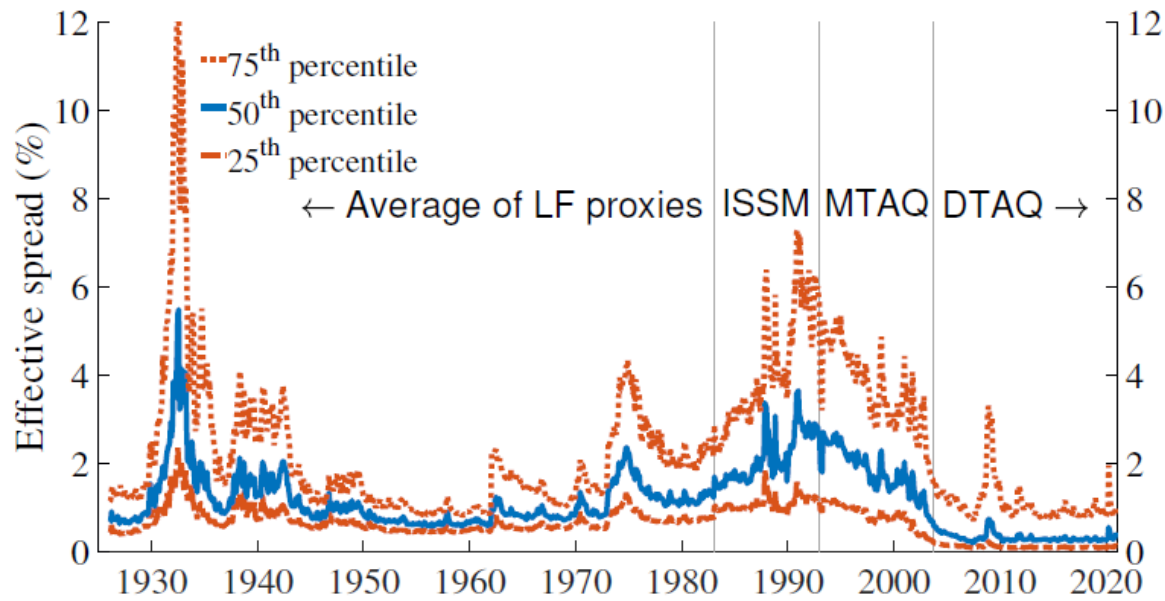
Figure 1: Anomaly Mean Long-Short Returns. Error bars show two standard errors.



Chen and Velikov (2022)

- Main (in my opinion) contribution: a new trading cost measure that combines what's in the literature

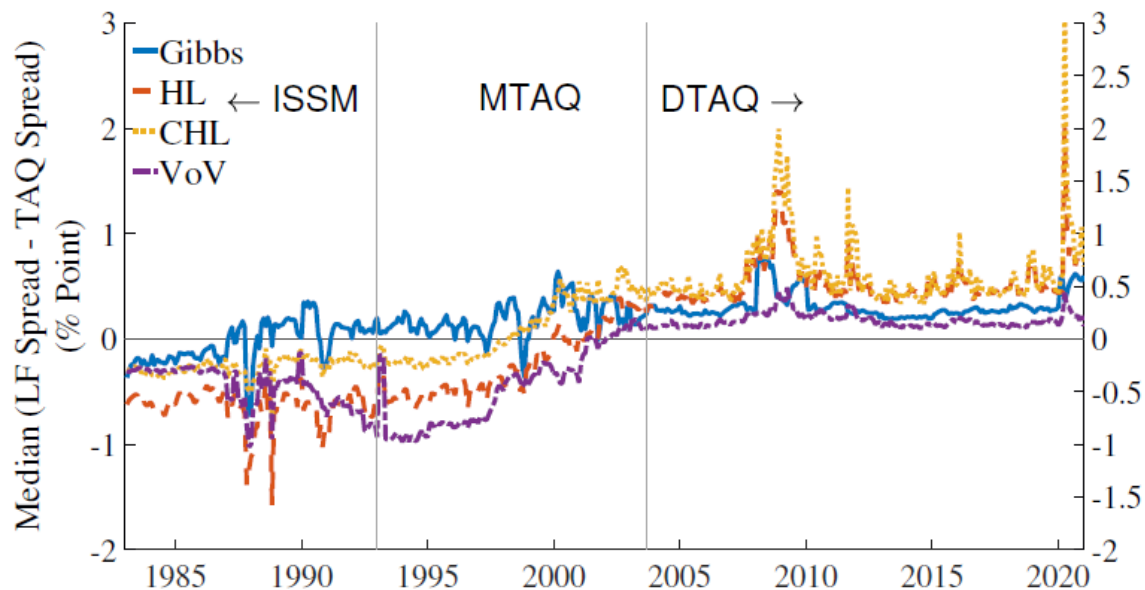
Figure 3: Combined Effective Spreads Over Time. Spreads combine high-frequency and low-frequency data. We use high-frequency Daily TAQ (DTAQ), Monthly TAQ (MTAQ), and ISSM when available. Otherwise, we use the average of four low frequency proxies: Gibbs (Hasbrouck (2009)), HL (Corwin and Schultz (2012)), CHL (Abdi and Rinaldo (2017)), and VoV (Kyle and Obizhaeva (2016)). The combined spread tracks well-known structural changes like the entry of NASDAQ (early 1970s) and decimalization (early 2000s).



Chen and Velikov (2022)

- Why do we need the new measure?
 - Severe bias in low-frequency measures post-decimalization
- Especially important for post-publication results

Figure 2: The Bias in Low-Frequency Effective Spread Proxies. We take the difference between low-frequency effective spreads and TAQ effective spreads at the firm-month level and then take the median across firms to calculate the median error in each month. Low-frequency spreads are from Hasbrouck (2009) (Gibbs), Corwin and Schultz (2012) (HL), Abdi and Rinaldo (2017) (CHL), and Kyle and Obizhaeva (2016) (VoV). Post-decimalization, low-frequency proxies are biased upward by roughly 25-50 bps. LF spread data are found at <https://sites.google.com/site/chenandrewy/>, HF spread code is at <https://github.com/chenandrewy/hf-spreads-all>, and replication code is at <https://github.com/velikov-mihail/Chen-Velikov>.



Chen and Velikov (2022)

- Combination “back-cast”
 - Stronger correlation of combined measure with high-frequency data
 - Simple average outperforms individual measures
 - Errors “average out”

Table 1: Correlations Between Low-Frequency Proxies and High-Frequency Effective Bid-Ask Spreads

Correlations are pooled. We examine four low frequency proxies: Gibbs is Hasbrouck's (2009) Gibbs estimate of the Roll model, HL is Corwin and Schultz's (2012) high-low spread, CHL is Abdi and Rinaldo's (2017) close-high-low, and VoV (volume-over-volatility) is Fong et al.'s (2017) implementation of Kyle and Obizhaeva (2016) microstructure invariance hypothesis. LF_Ave is the equal weighted average of the four low frequency proxies. TAQ and ISSM are computed from high-frequency data. The low frequency measures are imperfectly correlated, suggesting that they contain distinct information. LF_Ave has the highest correlation with high-frequency spreads. HF spread code is found at <https://github.com/chenandrewy/hf-spreads-all> and <https://github.com/velikov-mihail/Chen-Velikov>. LF spread data is at <https://sites.google.com/site/chenandrewy/>.

Panel A: LF spread correlations (1926-2020)						
	Gibbs	HL	CHL	VoV		
Gibbs	1.00					
HL	0.63	1.00				
CHL	0.74	0.86	1.00			
VoV	0.74	0.53	0.73	1.00		

Panel B: Correlations with TAQ (1993-2020)						
	TAQ	Gibbs	HL	CHL	VoV	LF_Ave
TAQ	1.00					
Gibbs	0.84	1.00				
HL	0.64	0.60	1.00			
CHL	0.79	0.72	0.85	1.00		
VoV	0.84	0.72	0.53	0.74	1.00	
LF_Ave	0.90	0.89	0.82	0.93	0.86	1.00

Panel C: Correlations with ISSM (1983-1992)						
	ISSM	Gibbs	HL	CHL	VoV	LF_Ave
ISSM	1.00					
Gibbs	0.88	1.00				
HL	0.77	0.74	1.00			
CHL	0.83	0.78	0.88	1.00		
VoV	0.86	0.81	0.62	0.74	1.00	
LF_Ave	0.92	0.94	0.88	0.93	0.87	1.00



Chen and Velikov (2022)

- Depending on data availability, we either:
 - Calculate monthly realized spreads from high-frequency data
 1. Calculate effective spreads for all eligible trades, k , in ISSM & TAQ
$$[Effective\ Spread]_k = 2|\log(P_k) - \log(M_k)|$$
where
 - P_k is the price of the k th trade
 - M_k is the prevailing midpoint of the matched NBBO quotes
 2. For each stock-day, take a share-weighted average across all trades
 3. For each stock-month, take an equal-weighted average across all days
 - Use average of up to four low-frequency estimators from the literature
 - Gibbs (Hasbrouck, 2009)
 - High-low spread (Corwin and Schultz, 2012)
 - Close-high-low (Abdi and Ranaldo, 2017)
 - Volume-over-volatility (Kyle and Obizhaeva, 2016)



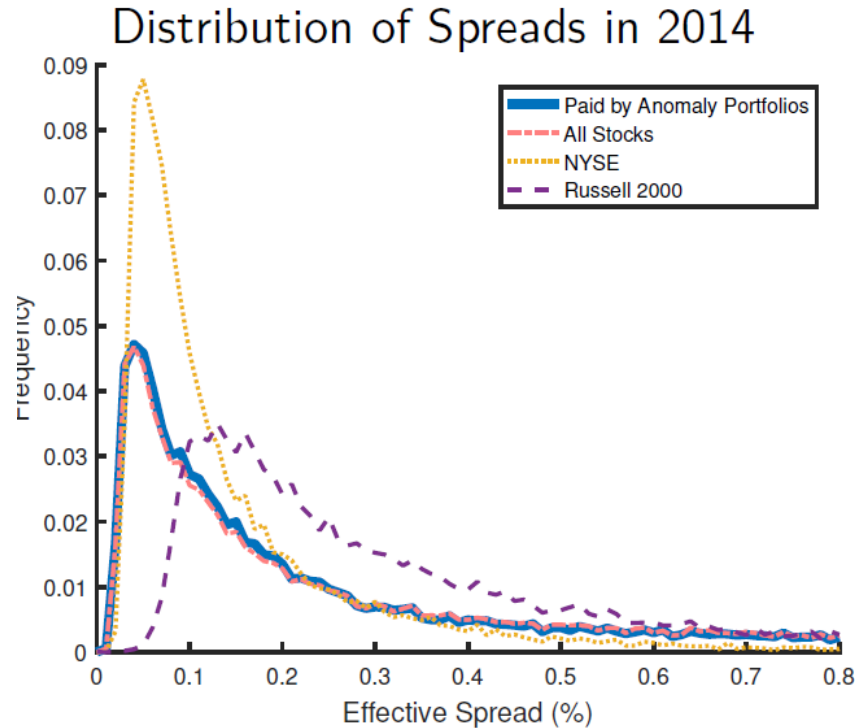
Chen and Velikov (2022)

- Trading cost hierarchy
 1. Daily TAQ (2003 – 2020)
 2. Monthly TAQ (1993 – 2003)
 3. ISSM (1983 – 1992)
 - NASDAQ data missing prior to 1987 and sporadically between 1987 and 1991
 4. Low-frequency average (1926 – 2020)
 - Require at least one of the four measures
 5. Match based on closest distance in market capitalization and idiosyncratic volatility rank space (1926 – 2020)
$$d = \sqrt{(rankME_i - rankME_j)^2 + (rankIVOL_i - rankIVOL_j)^2}$$
 6. Match based to nearest stock based on market capitalization (1926 – 2020)



Chen and Velikov (2022)

- Long right tail of the effective spread distribution

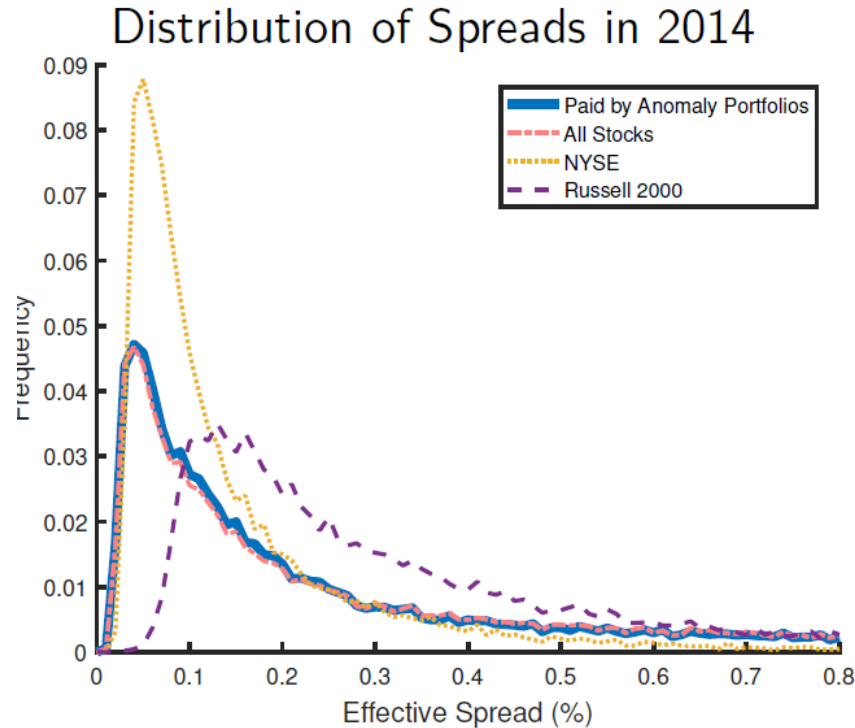


- Decimalization: spread \approx \$0.01, price \approx \$20 \Rightarrow spread \approx 5 bps
 - But that's the mode! 20% of NYSE stocks have spreads $>$ 20 bps



Chen and Velikov (2022)

- Long right tail of the effective spread distribution



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 - But that's the mode! 20% of NYSE stocks have spreads $>$ 20 bps

