Concealing the Trading Footprint: Optimal Execution Horizon

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Key Points

- Multiple empirical studies have shown that Order Flow Imbalance has predictive power over the trading range.
- The PIN Theory (Easley et al. [1996]) reveals the Microstructure mechanism by which
  - Market Makers adjust their trading range to avoid being adversely selected by Informed Traders.
  - Informed Traders reveal their future trading intentions when they alter the Order Flow.
  - Consequently, Market Makers' trading range is a function of the Order Flow imbalance.
- **OEH takes into account order imbalance to determine the optimal participation rate.**

SECTION I
Algorithmic Trading is a Pleonasm

Level-III Tick Data on E-Mini S&P500 Futures

Level	Bid	Ask	Sum
0 (match)	64,013,741	64,565,674	128,579,415
1	249,364,228	247,235,292	496,599,520
2	128,454,906	127,845,703	256,300,609
3	67,331,632	69,208,299	136,539,931
4	41,900,084	43,272,263	85,172,347
5	33,916,275	35,021,950	68,938,225
6	36,099,172	36,830,635	72,929,807
7	23,729,230	24,802,513	48,531,743
8	23,776,849	24,698,213	48,475,062
9	21,350,182	22,061,084	43,411,266
10	43,563,079	43,448,671	87,011,750

Level	Bid	Ask	Sum
1	18.56%	18.40%	36.95%
2	9.56%	9.51%	19.07%
3	5.01%	5.15%	10.16%
4	3.12%	3.22%	6.34%
5	2.52%	2.61%	5.13%
6	2.69%	2.74%	5.43%
7	1.77%	1.85%	3.61%
8	1.77%	1.84%	3.61%
9	1.59%	1.64%	3.23%
10	3.24%	3.23%	6.47%

If we process all FIX messages for all E-mini S&P500 Futures contracts active between 11/07/2010 and 11/06/2011, we find that there were:

- 128,579,415 fill messages.
- 496,599,520 BBO messages.
- 1,343,910,260 quote msgs.
- 1,472,489,675 msgs in total.

That is 11.45 msgs for every fill.
Only 36.95% of the messages correspond to changes in the BBO.

Level-III Tick Data on WTI Crude Oil Futures

Level	Bid	Ask	Sum
0 (match)	39,200,716	39,429,463	78,630,179
1	705,620,365	702,582,372	1,408,202,737
2	844,699,996	846,832,348	1,691,532,344
3	64,428,661	66,177,168	130,605,829
4	60,164,108	60,564,964	120,729,072
5	56,691,248	56,529,123	113,220,371
6	47,184,768	47,037,585	94,222,353
7	36,304,942	35,767,771	72,072,713
8	31,526,310	30,672,847	62,199,157
9	28,034,002	27,299,323	55,333,325
10	65,156,228	60,737,872	125,894,100

Level	Bid	Ask	Sum
1	18.21%	18.14%	36.35%
2	21.80%	21.86%	43.66%
3	1.66%	1.71%	3.37%
4	1.55%	1.56%	3.12%
5	1.46%	1.46%	2.92%
6	1.22%	1.21%	2.43%
7	0.94%	0.92%	1.86%
8	0.81%	0.79%	1.61%
9	0.72%	0.70%	1.43%
10	1.68%	1.57%	3.25%

If we process all FIX messages for all WTI Crude Oil Futures contracts active between 11/07/2010 and 11/06/2011, we find that there were:

- 78,630,179 fill messages.
- 1,408,202,737 BBO messages.
- 3,874,012,001 quote msgs.
- 3,952,642,180 msgs in total.

That is 50.27 msgs for every fill! Most of the activity (43.66%) occurs in the second level.

Level-III Tick Data on Gold Futures

Level	Bid	Ask	Sum
0 (match)	13,944,434	14,016,108	27,960,542
1	560,489,837	554,107,482	1,114,597,319
2	504,706,360	505,607,056	1,010,313,416
3	17,716,026	18,196,624	35,912,650
4	21,657,230	22,321,523	43,978,753
5	24,622,971	25,033,098	49,656,069
6	25,198,490	25,221,289	50,419,779
7	23,260,511	23,507,011	46,767,522
8	22,242,995	22,275,941	44,518,936
9	21,397,532	21,193,452	42,590,984
10	29,686,600	29,429,508	59,116,108

Level	Bid	Ask	Sum
1	22.44%	22.18%	44.62%
2	20.21%	20.24%	40.45%
3	0.71%	0.73%	1.44%
4	0.87%	0.89%	1.76%
5	0.99%	1.00%	1.99%
6	1.01%	1.01%	2.02%
7	0.93%	0.94%	1.87%
8	0.89%	0.89%	1.78%
9	0.86%	0.85%	1.71%
10	1.19%	1.18%	2.37%

If we process all FIX messages for all Gold Futures contracts active between 11/07/2010 and 11/06/2011, we find that there were:

- 27,960,542 fill messages.
- 1,114,597,319 BBO messages.
- 2,497,871,536 quote msgs.
- 2,525,832,078 msgs in total.

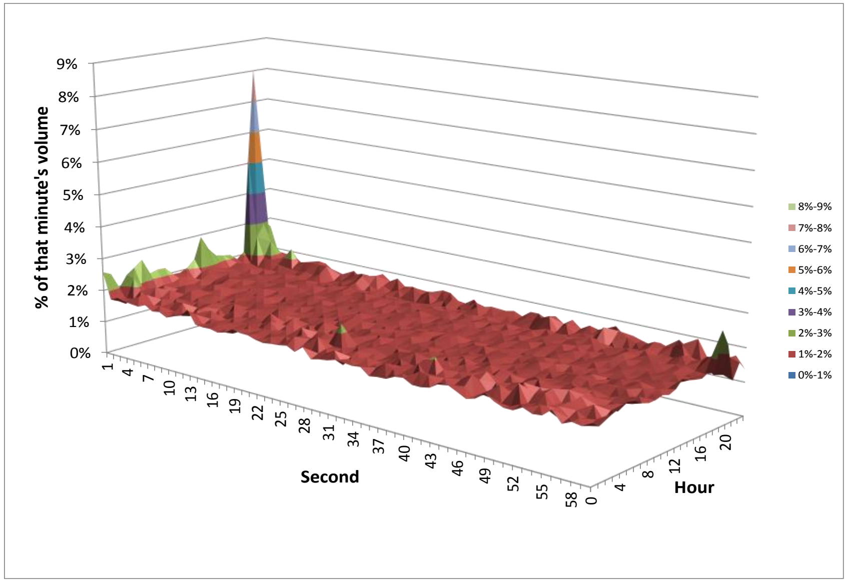
That is 90.34 msgs for every fill!!
Only 44.62% of the messages correspond to changes in the BBO.

SECTION II
Trading Footprint

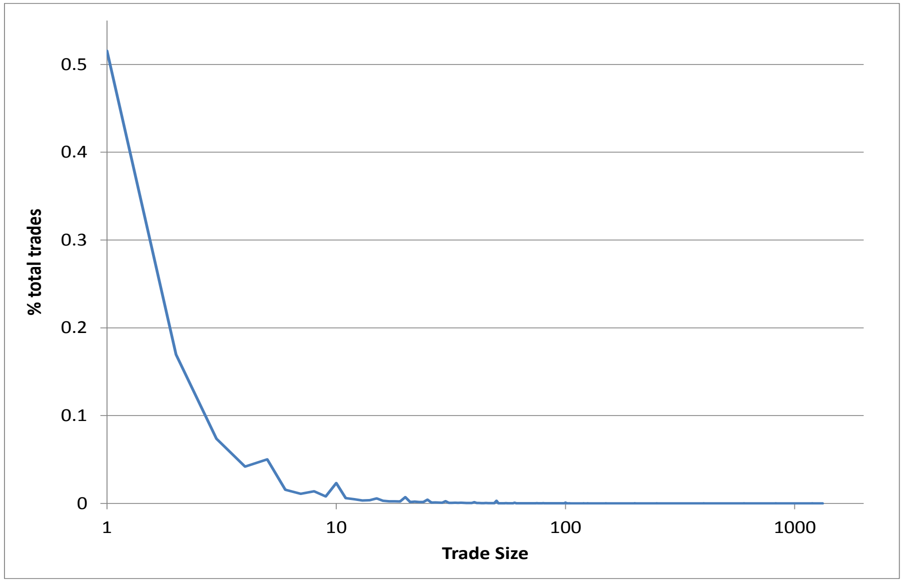
Market Makers and Adverse Selection

- Market makers operate in a Volume Clock:
  - They aim at participating in a certain proportion of the overall market activity, while controlling their inventory.
  - They manage risks by turning their portfolio over (liquidate inventory) after a certain amount of volume.
- When you trade, you “push” trades out of the volume bucket, thus impacting the order imbalance.
- This change in the order imbalance leaks information on your future trading intentions.
- Market makers will adjust their trading ranges accordingly, in an attempt to avoid adverse selection.

It is easy to find trading footprints…

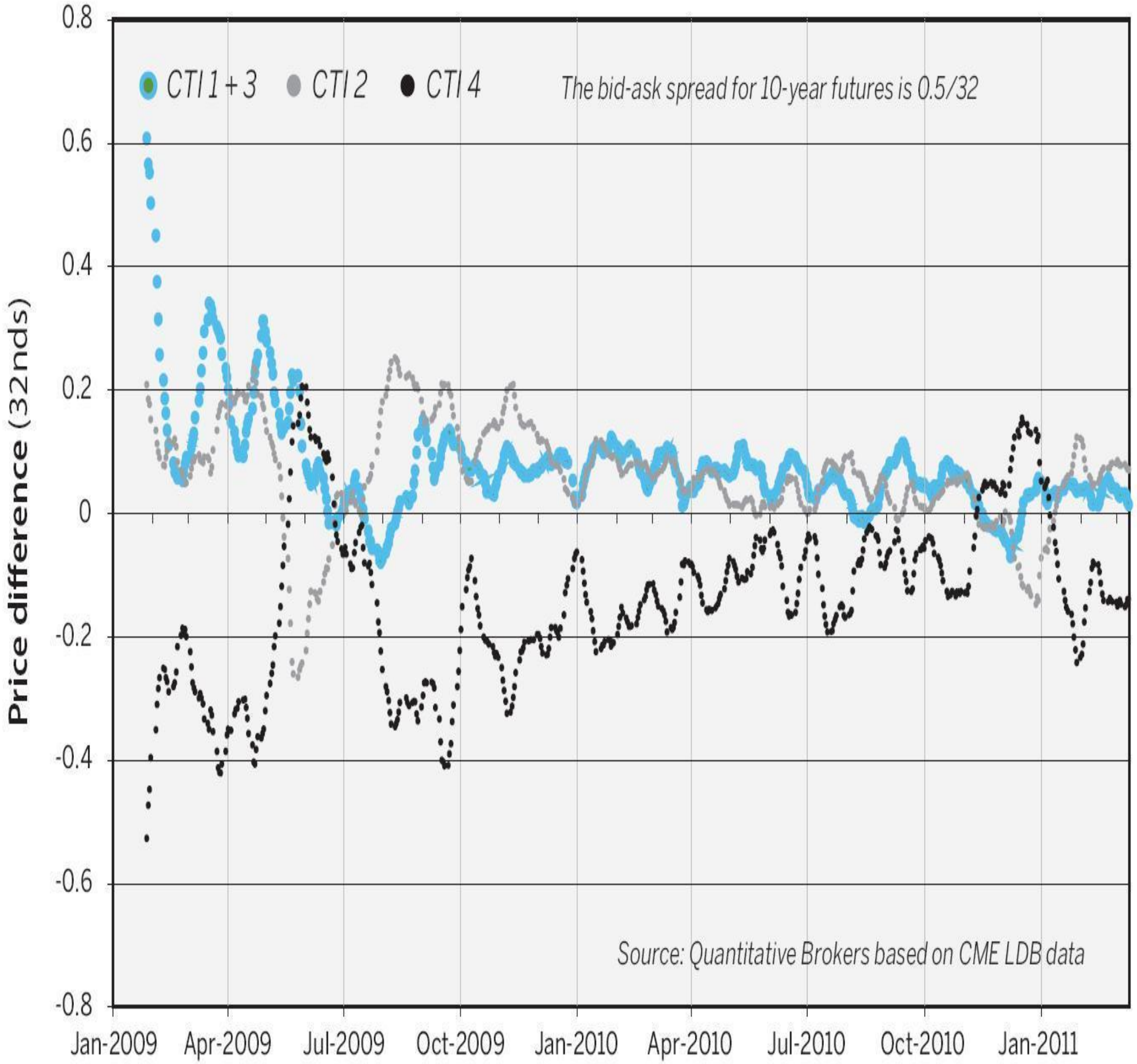


Percentage of volume traded each second of every minute in E-mini S&P500 futures. The spike is the result of LFTs executing TWAPs before close.



Percentage of orders per trade size in E-mini S&P500 futures. GUI traders are easily detectable because of their large, round orders: 5, 10, 50…

… however some traders are improving



Even designated market makers (CT1, CT2, CT3) have seen their gains being “transferred” to liquidity takers (CT4).

Almgren and Burghardt [2011] report the results on this chart.

How does trading leave a footprint? (1/2)

- Let's denote V^B the expected volume associated with buying pressure, and V^S the expected volume associated with selling pressure.
- $V \equiv V^B + V^S$, so the expected Order Imbalance (*OI*) is

$$OI \equiv \frac{V^B - V^S}{V} = 2v^B - 1, \text{ where } v^B = \frac{V^B}{V}$$

- Suppose that you wish to execute a trade of size *m*.
- This means that you hold private information concerning the future value of V^B and V^S.

How does trading leave a footprint? (2/2)

- Given your private information, you expect:

$$\frac{\widetilde{V^B} - \widetilde{V^S}}{V} \equiv \frac{\frac{V^B}{V}(V - |m|) - \frac{V^S}{V}(V - |m|) + m}{V} =$$

$$= (2v^B - 1)\left(1 - \frac{|m|}{V}\right) + \frac{m}{V}$$

- Because *m* leaves a footprint, market makers adjust their expected order imbalance, from OI to:

$$\widetilde{OI} = \varphi[|m|]\left[(2v^B - 1)\left(1 - \frac{|m|}{V}\right) + \frac{m}{V}\right]$$
$$+ (1 - \varphi[|m|])(2v^B - 1)$$

and $\varphi[|m|]$ is the *informational leakage*.

SECTION III
Computing the Order Imbalance

Bulk Volume Classification

- For each volume bucket τ, we can form *J* volume bars of size $\frac{V}{J}$.
- For each bar *j*, *T*% of the volume is classified as buy ***and*** (1-*T*)% as sell (denoted "**bulk classification**"). **Caution: Not all the volume of a single trade or bar is classified as buy *or* sell** (some researchers are confused by this). Then:

$$\hat{V}_\tau^B = \frac{V}{J}\sum_{j=1}^{J} T\left(\frac{P_{\tau,j} - P_{\tau,j-1}}{\sigma_{\Delta P}}, df\right)$$

$$\hat{V}_\tau^S = V\left[1 - \frac{1}{J}\sum_{j=1}^{J} T\left(\frac{P_{\tau,j} - P_{\tau,j-1}}{\sigma_{\Delta P}}, df\right)\right] = V - V_\tau^B$$

where $P_{\tau,j}$ is the last price in bar *j* within bucket τ, *T* is the CDF of the t-distribution with *df* degrees of freedom, and $\sigma_{\Delta P}$ is the estimate of the standard derivation of price changes between bars.

Why should BVC be more informative?

- Eisler et al. [2012] point out that the distinction between informed trader and market maker is no longer obvious in the present electronic markets, where each participant can place both limit and market orders.
- The tick rule attempts to determine the aggressor side.
- However, prices reflect more than aggressor imbalance:
  - Adding a buy limit order induces extra upwards pressure.
  - Cancelling a buy limit order decreases this pressure.
- Following this argument, it may be possible to obtain accurate estimates of order flow imbalance from *the impact that a bulk of trades have on prices*.

Bulk Volume Classification vs. Tick Rule (1/3)

- Market makers adjust to order imbalances, so BVC and TR should have explanatory power over high-low ranges.
- Let's define:
  - $\widehat{OI_\tau} \equiv \frac{\widehat{V_\tau^B} - \widehat{V_\tau^S}}{V_\tau} = 2\frac{\widehat{V_\tau^B}}{V_\tau} - 1$ is the estimated order imbalance.
  - $H_\tau - L_\tau$ is the difference between high and low in volume bucket τ.
- Then, we can fit the following regression model to $\widehat{OI_\tau}$ derived from BVC and TR, and apply the Newey-West HAC correction:

$$H_\tau - L_\tau = \beta_0 + \beta_1 [H_{\tau-1} - L_{\tau-1}] + \gamma \left|\widehat{OI_\tau}\right| + \xi_\tau$$

Bulk Volume Classification vs. Tick Rule (2/3)

Regression Stats for BVC on WTI

Vol. Bar	aR2	NW lags	Coeff(α0)	Coeff(α1)	Coeff(γ)	t-Stat(α0)	t-Stat(α1)	t-Stat(γ)
1000	0.4170	17	5.8920	0.3143	37.8563	36.9490	43.8899	99.0193
2000	0.4656	14	7.5671	0.3310	53.1076	26.6550	35.0893	74.2852
3000	0.5045	13	7.9809	0.3560	65.7965	19.3087	33.5315	67.0455
4000	0.5124	12	8.8928	0.3554	76.2373	18.0799	31.1926	58.1366
5000	0.5186	12	9.4361	0.3648	84.7154	13.8771	25.2215	53.9255
6000	0.5317	11	9.7246	0.3716	93.9735	13.1009	25.3969	49.2206
7000	0.5332	11	9.9700	0.3771	101.8469	11.4000	24.0834	46.4617
8000	0.5319	10	10.5324	0.3711	110.4512	11.2616	23.1319	40.9419
9000	0.5311	10	11.1319	0.3641	119.0141	10.5247	21.5767	40.1135
10000	0.5351	10	11.5727	0.3657	124.8904	10.0351	21.5811	37.8392

Regression Stats for TR on WTI

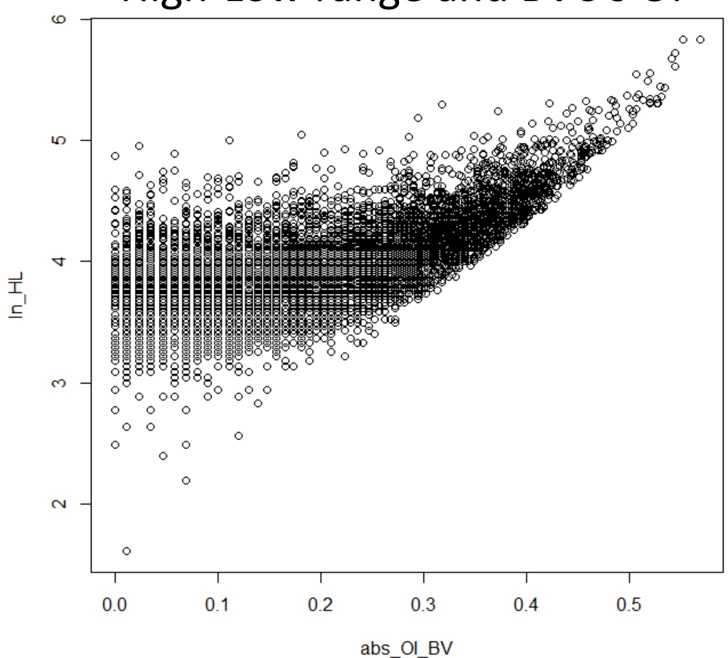
Vol. Bar	aR2	NW lags	Coeff(α0)	Coeff(α1)	Coeff(γ)	t-Stat(α0)	t-Stat(α1)	t-Stat(γ)
1000	0.1971	17	12.7006	0.4174	-5.2172	70.4226	46.7589	-25.5985
2000	0.2110	14	15.3334	0.4558	-2.1625	48.6918	39.7110	-4.5423
3000	0.2414	13	16.5738	0.4927	2.2671	37.1431	36.6620	2.6547
4000	0.2451	12	18.3786	0.4968	6.0838	34.2202	35.5162	4.8603
5000	0.2514	12	19.7551	0.5032	10.6620	25.9718	27.8923	6.3465
6000	0.2634	11	20.5196	0.5134	17.4270	24.2252	28.7296	7.4789
7000	0.2618	11	22.2337	0.5119	19.3449	22.7484	26.9841	6.9339
8000	0.2558	10	23.7416	0.5047	24.6784	21.0508	24.6193	6.8123
9000	0.2524	10	25.2300	0.5026	28.3805	20.9909	24.1256	6.9782
10000	0.2445	10	26.9771	0.4928	30.7460	19.5195	21.7657	6.3642

- BVC's estimation of Order Imbalance has significant explanatory power over high-low ranges (Note: It would be even better with a power specification).
- TR's Order Imbalance has inconsistent explanatory power (note the inconsistent signs associated with TR)
- ***Question: Why does Aggressor-Side Imbalance fail to explain the trading range?***

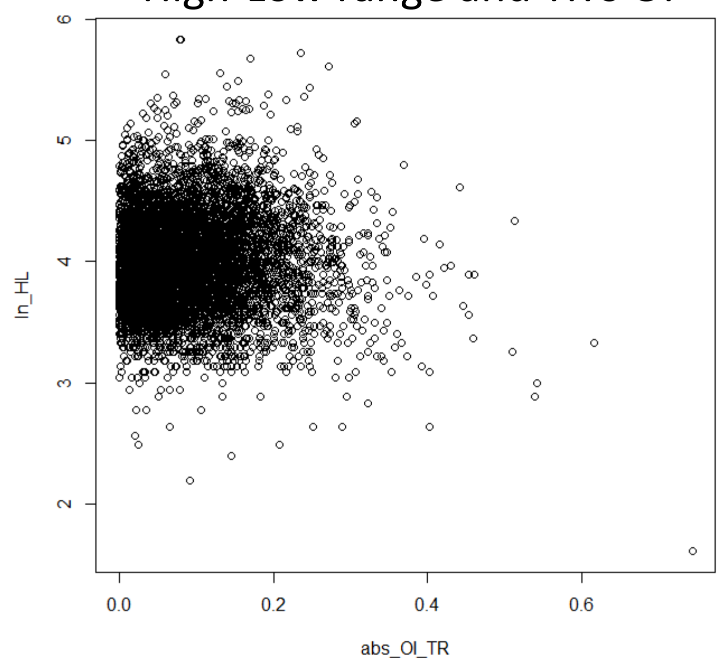
Bulk Volume Classification vs. Tick Rule (3/3)

- ***Answer***: When an informed trader slices and sequentially executes her buy order passively, sell-initiated trades coexist with her persistent buy order flow. ***Informed traders are not necessarily aggressive traders***, thus Aggressor Side-Imbalance is a deficient estimator of Order Imbalance.

High-Low range and BVC's OI



High-Low range and TR's OI

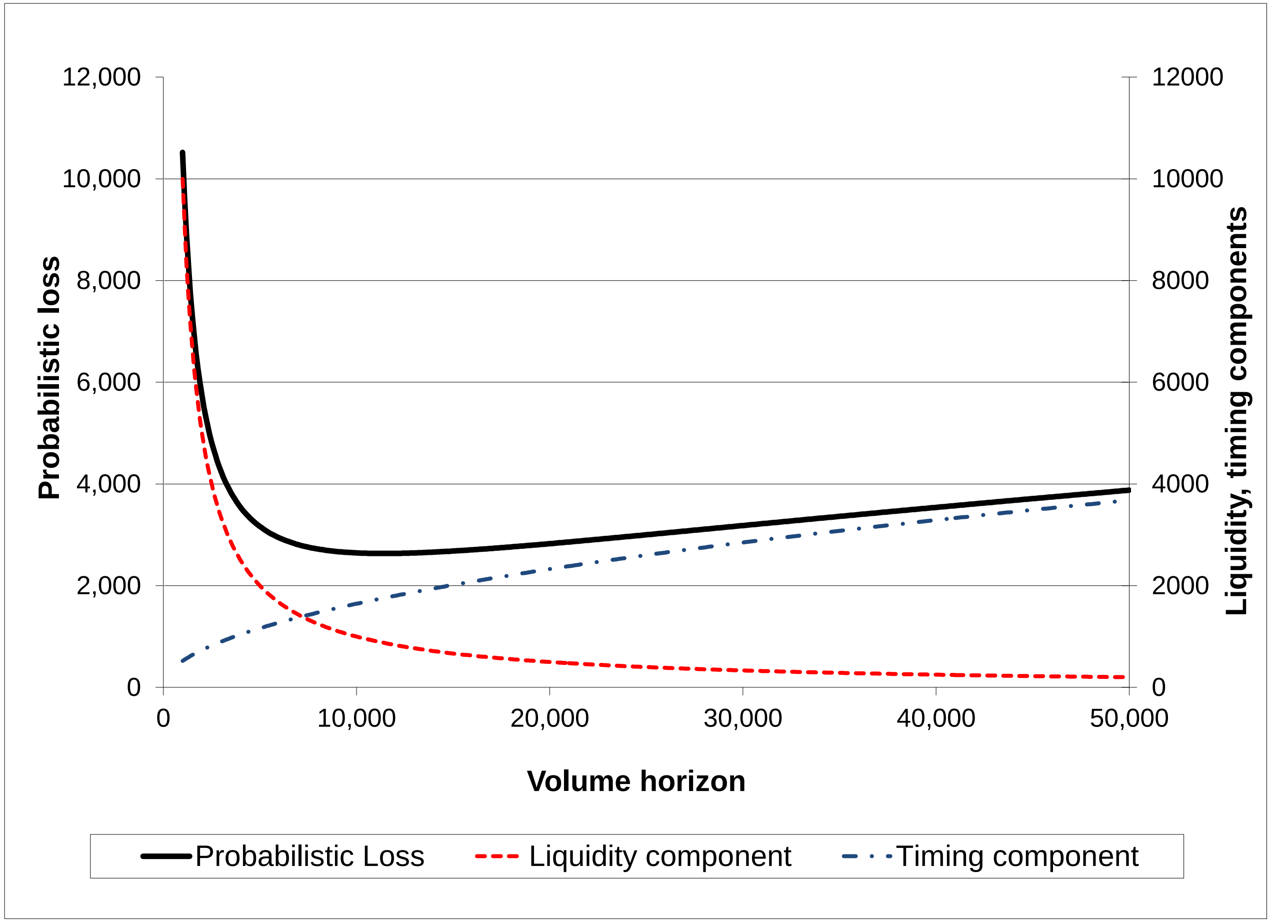


SECTION IV
Optimal Execution Horizon

Smart Execution Algorithms (1/2)

- Smart Execution Algorithms (SEAs) minimize Transaction Costs by computing the optimal:
  a) Slicing of an order.
  b) Execution time.
  c) Aggressiveness.
- Transaction Costs can be divided in components:
  1. Liquidity impact:
     - Temporary: It does not result in information leak.
     - Permanent: Price adjusts to that information leak.
  2. Timing risk: Price may drift during the execution horizon.
- Over the last 10 years, brokers and HFTs have developed SEAs to minimize transaction costs.

Smart Execution Algorithms (2/2)



The more passive execution is, the smaller the liquidity impact (red dashed line), but also the greater the timing risk (blue dashed line).

Optimal Execution Horizon algo

- A key input for execution strategies is the *execution horizon*. This is typically set exogenously, however it would be useful coming up with an estimate.

- Our goal: *To determine the amount of volume needed to "conceal" a trade so that it leaves a minimum footprint on the trading range*.

- The following is an example of a SEA, based in Easley, Lopez de Prado and O'Hara [2012].

Liquidity component (1/2)

- The PIN Theory (Easley et al. [1996]) reveals the Microstructure mechanism by which
  - Market Makers adjust their trading range to avoid being adversely selected by Informed Traders.
  - Informed Traders reveal their future trading intentions when they alter the Order Flow.
  - Consequently, Market Makers' trading range is a function of the Order Imbalance.
- Let $\overline{P}$ be the value of a security at the end of a trading period if good news arrives, and $\underline{P}$ if bad news arrives.
- They define PIN as the *Probability of Informed Trading*.

Liquidity component (2/2)

- For the natural case when the good or bad news are equally likely, they conclude that the bid-ask spread is:

$$\Sigma = PIN\left[\overline{P} - \underline{P}\right]$$

- Easley et al. [2012] show that, in volume time, PIN can be approximated as

$$PIN \approx \frac{E[|V^B - V^S|]}{V} = E[|OI|]$$

- Given our private information on our trade of size *m*,

$$\Sigma = \left|\varphi[|m|]\left[(2v^B - 1)\left(1 - \frac{|m|}{V}\right) + \frac{m}{V}\right] \right.$$
$$\left. + (1 - \varphi[|m|])(2v^B - 1)\right|\left[\overline{P} - \underline{P}\right]$$

Timing risk component

- We can model *P* as an arithmetic random walk in volume time.
- For a security price *P* with St.Dev $\hat{\sigma}$ of price changes over volume buckets of size V_σ, the ΔP over a volume *V* is

$$\Delta P = \hat{\sigma}\sqrt{\frac{V}{V_\sigma}}\xi$$

with IID $\xi \sim N(0,1)$. This is bounded at a significance level λ by

$$Prob\left[Sgn(m)\Delta P > Z_\lambda \hat{\sigma}\sqrt{\frac{V}{V_\sigma}}\right] = 1 - \lambda$$

Footprint minimization

- A probabilistic loss function Π combines both components:

$$\Pi = \underbrace{\left|\varphi[|m|]\left[(2v^B-1)\left(1-\frac{|m|}{V}\right)+\frac{m}{V}\right]+(1-\varphi[|m|])(2v^B-1)\right|\left[\overline{P}-\underline{P}\right]}_{liquidity\ component}$$

$$\underbrace{-Z_\lambda\sqrt{\frac{V}{V_\sigma}}\hat{\sigma}}_{timing\ risk\ component}$$

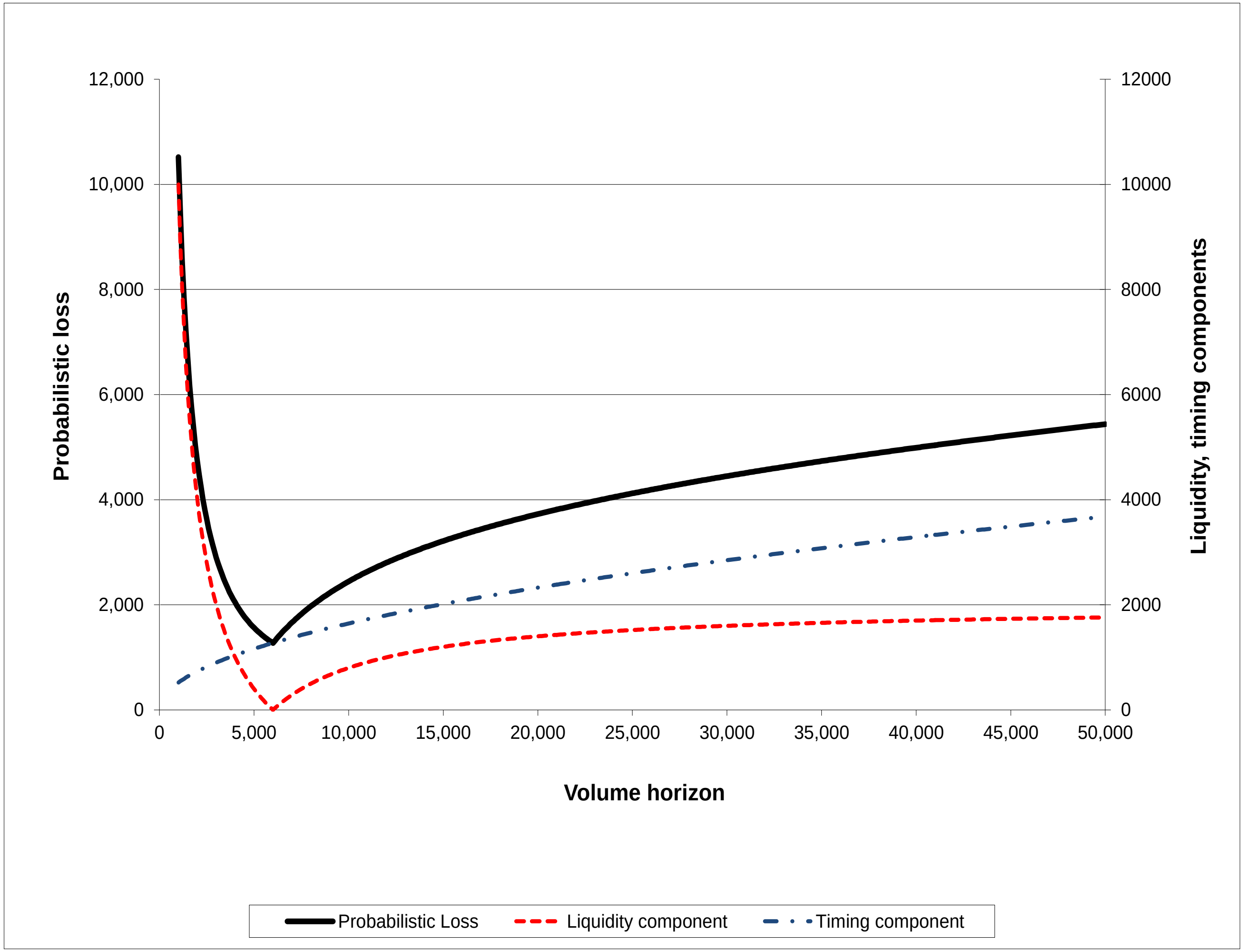
. Π reaches a minimum when V

$$V^* = \begin{cases} \left(\dfrac{Z_\lambda \hat{\sigma}}{2\varphi[|m|]Sgn\left(\widetilde{OI}\right)[(2v^B-1)|m|-m]\left[\overline{P}-\underline{P}\right]\sqrt{V_\sigma}}\right)^{-2/3} & for\ \widetilde{OI} \neq 0 \\ \varphi[|m|]\left(|m|-\dfrac{m}{2v^B-1}\right) & for\ \widetilde{OI} = 0 \end{cases}$$

$$\widetilde{OI} = \varphi[|m|]\left[\frac{m-(2v^B-1)|m|}{V}+(2v^B-1)\right]+(1-\varphi[|m|])(2v^B-1)$$

Scenario 1: $v^B = 0.4$

$\hat{\sigma} = 1{,}000$, $V_\sigma = 10{,}000$, $m = 1{,}000$, $[\overline{P} - \underline{P}] = 10{,}000$, $\lambda = 0.05$ and $\varphi[|m|]$=1.



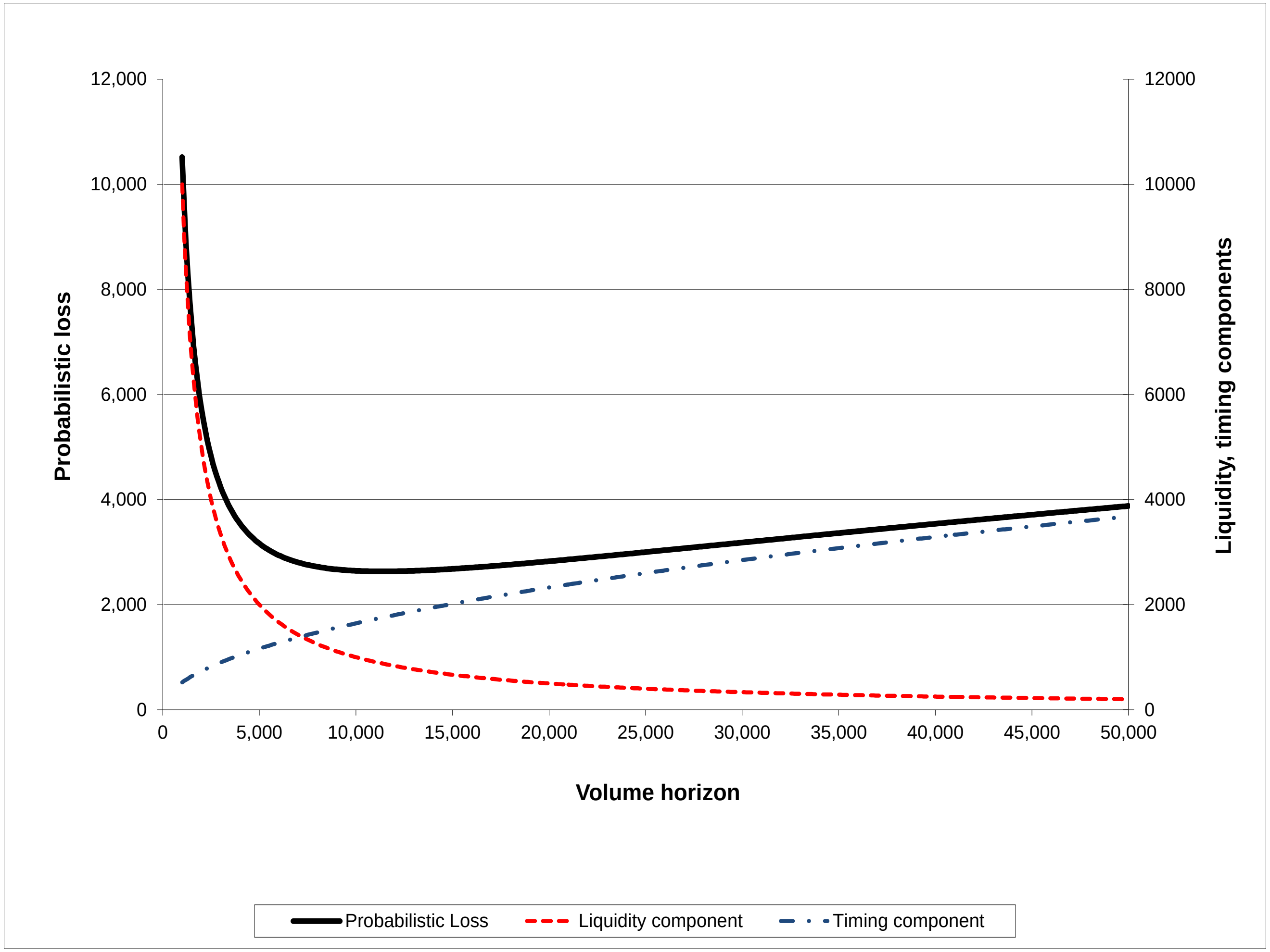
$V^* = 6{,}000$

We are buying in a selling market, thus our order contributes to narrowing the trading spread.

This evidences the fact that order's side, and not only size, determines the execution horizon.

Scenario 2: $v^B = 0.5$

$\hat{\sigma} = 1{,}000$, $V_\sigma = 10{,}000$, $m = 1{,}000$, $[\overline{P} - \underline{P}] = 10{,}000$, $\lambda = 0.05$ and $\varphi[|m|]$=1.

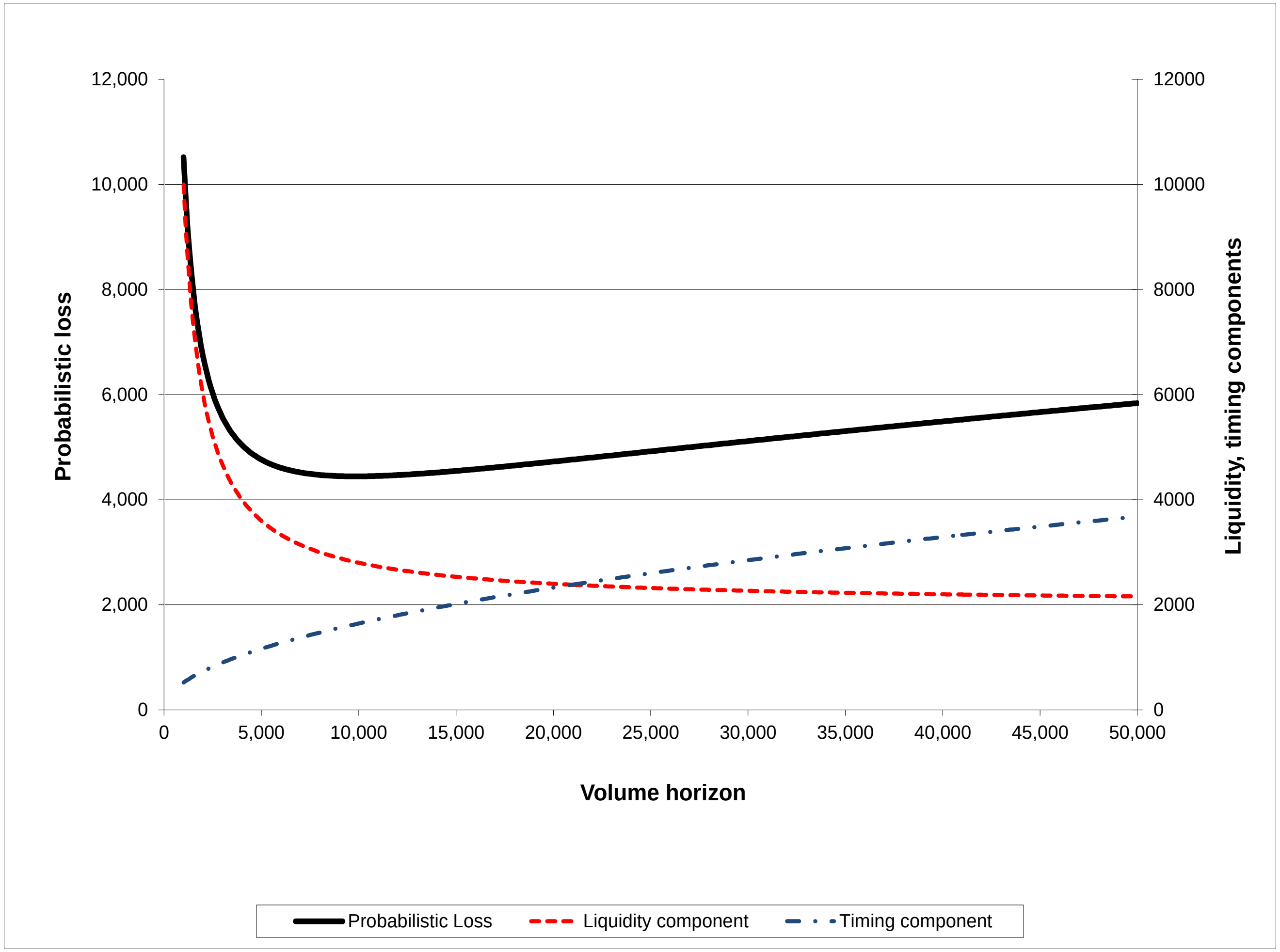


$V^* = 11{,}392$

We are buying in a balanced market. The liquidity component function is now convex decreasing, without an inflexion point, because the market is not leaning against us. The optimal V^* must be larger than in Scenario 1, but limited by greater timing risk with increasing *V*.

Scenario 3: $v^B = 0.6$

$\hat{\sigma} = 1{,}000$, $V_\sigma = 10{,}000$, $m = 1{,}000$, $[\overline{P} - \underline{P}] = 10{,}000$, $\lambda = 0.05$ and $\varphi[|m|]$=1.

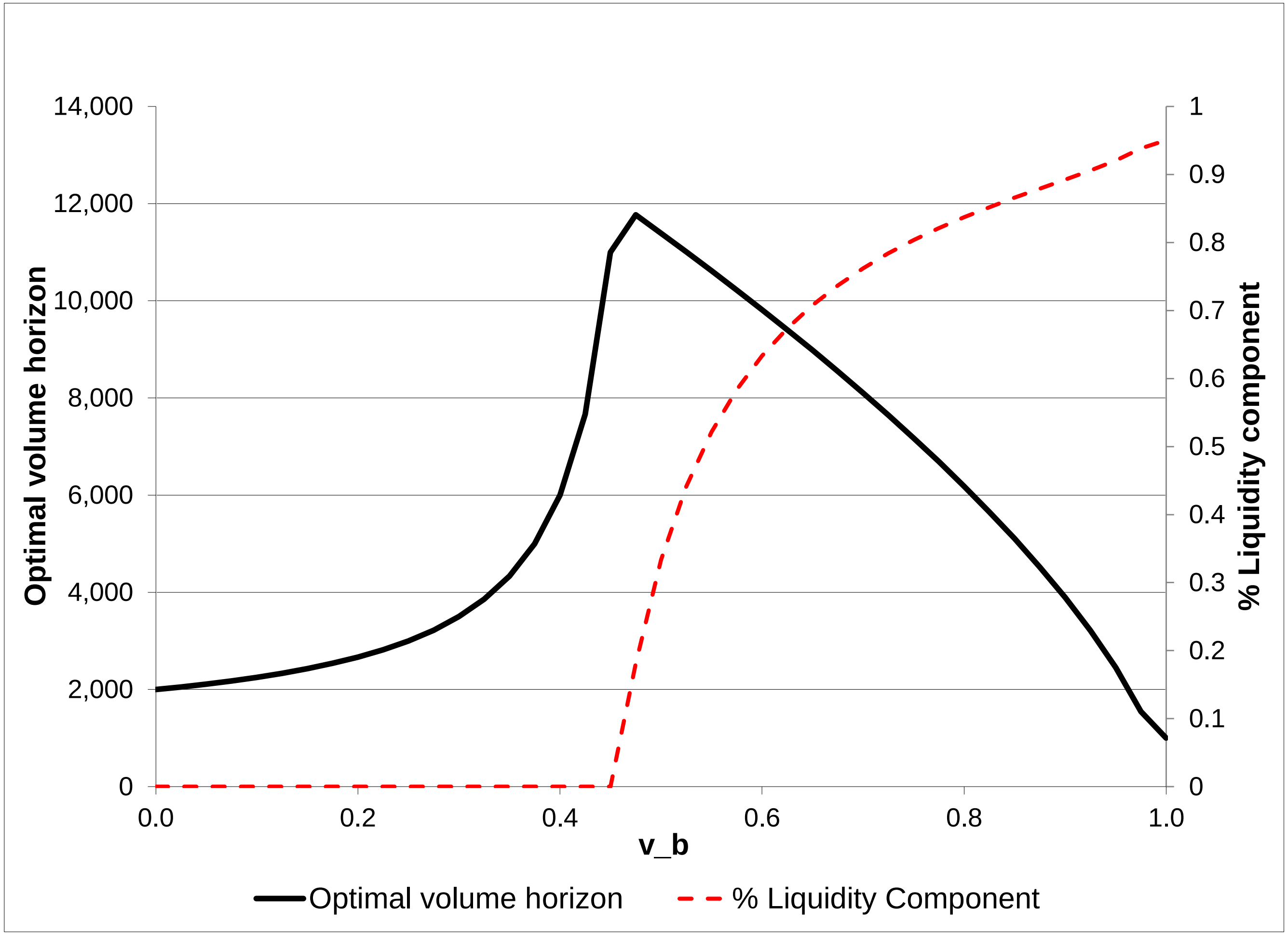


$V^* = 9{,}817$

Two forces contribute to this outcome: First, we are leaning with the market, thus we need a larger volume horizon than in Scenario I. Second, the gains from narrowing Σ are offset by the additional timing risk, and Π eventually cannot be improved further.

For all possible v^B scenarios…

$\hat{\sigma} = 1{,}000$, $V_\sigma = 10{,}000$, $m = 1{,}000$, $[\overline{P} - \underline{P}] = 10{,}000$, $\lambda = 0.05$ and $\varphi[|m|]$=1.

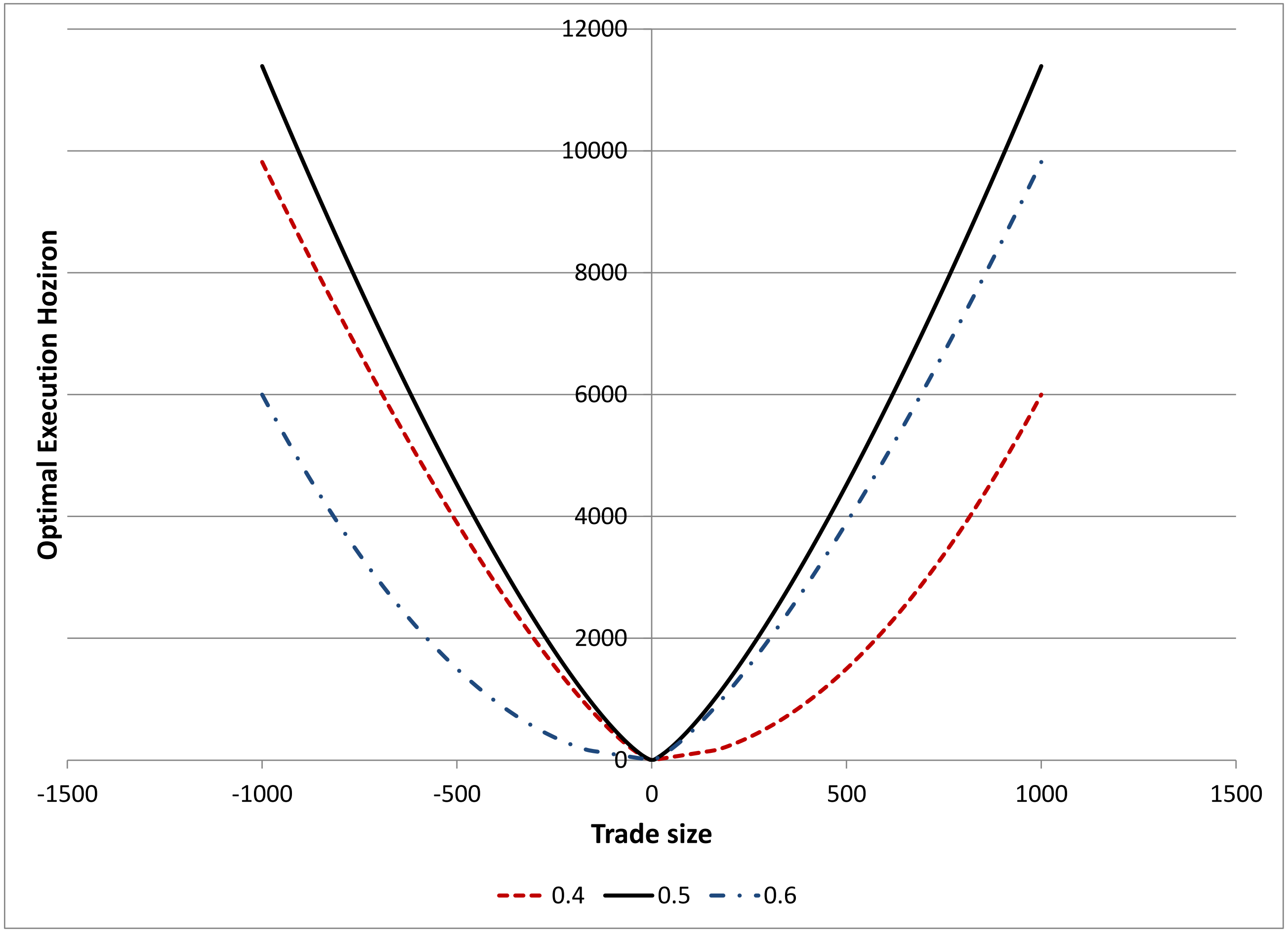


Optimal trading horizon for a buy order depends upon the expected fraction of buy orders in the market. When all orders are buys, v^B is 1, while if all orders are sells v^B is 0.

This explains why extreme order imbalances are typically followed by an increase in trading rates.

For alternative trade sizes and sides …

$\hat{\sigma} = 1{,}000$, $V_\sigma = 10{,}000$, $[\overline{P} - \underline{P}] = 10{,}000$, $\lambda = 0.05$ and $\varphi[|m|]$ linear in m.



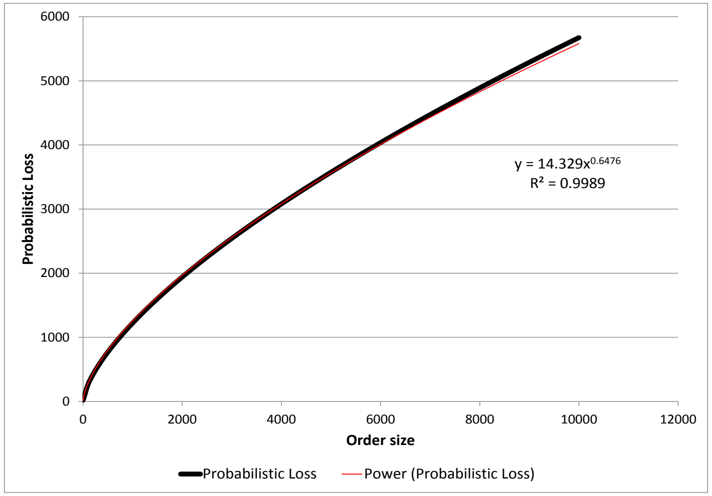
Traditional execution models imply a symmetric execution horizon, regardless of the order imbalance and whether the order leans with or against the market.

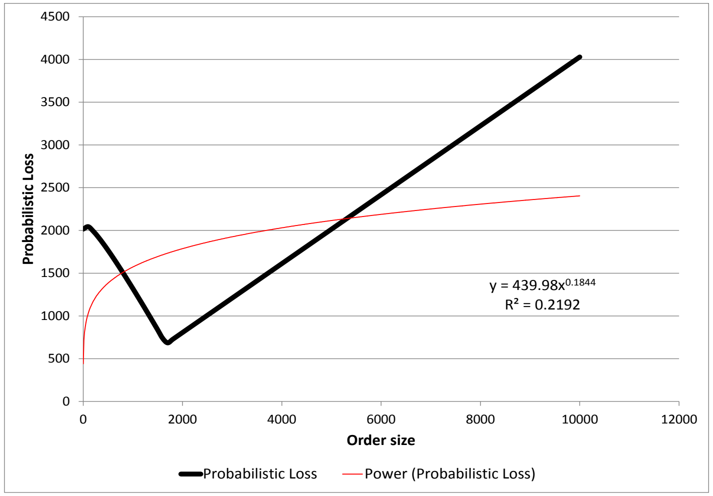
This graph exemplifies the asymmetric OEH response that occurs in the presence of order imbalance ($v^B = \{0.4, 0.5, 0.6\}$).

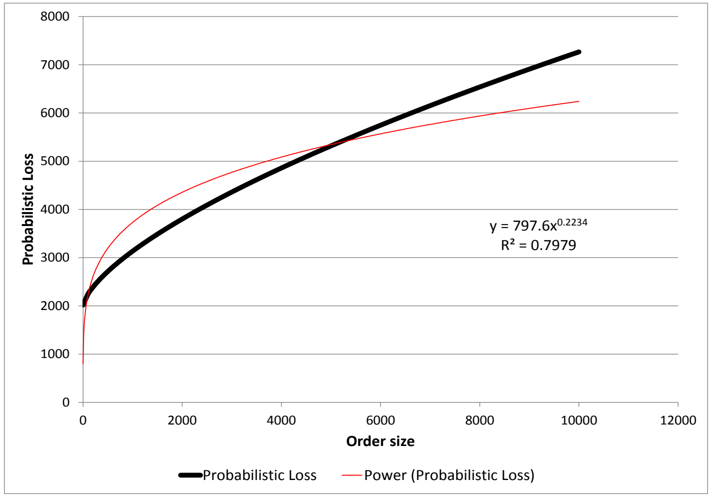
SECTION V
Incorporating OEH into Execution Strategies

The square root rule

$\hat{\sigma} = 1{,}000, V_\sigma = 10{,}000, m = 1{,}000, \left[\overline{P} - \underline{P}\right] = 10{,}000, \lambda = 0.05,$ linear $\varphi[|m|]$.



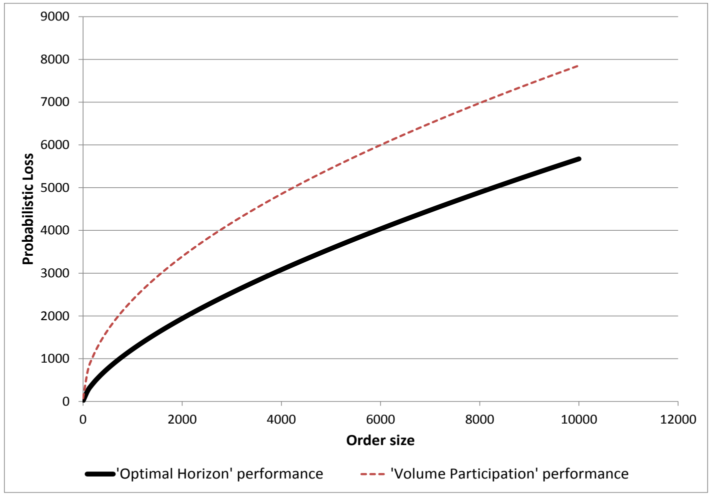


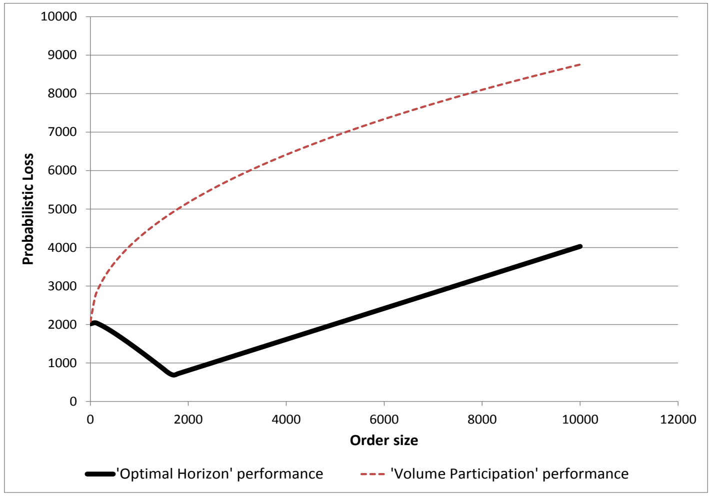


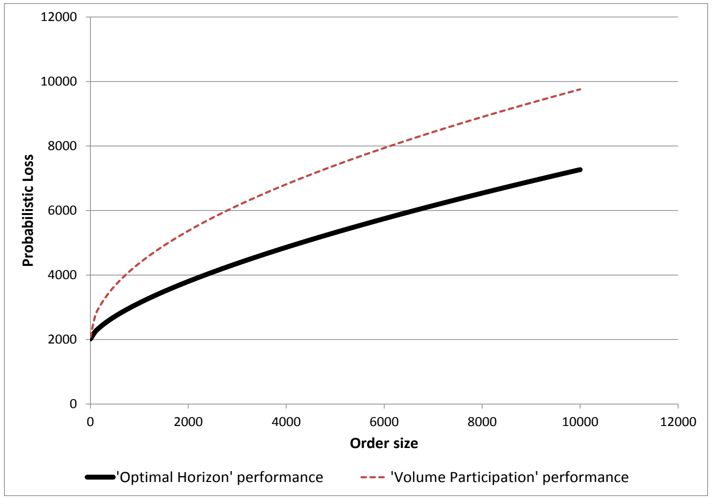
The literature has debated for 30 years whether the market impact function follows a square root, linear or power function. The answer is, square root for $v^B = \frac{1}{2}$ (upper left), linear for $v^B < \frac{1}{2}$ (upper right) and power law for $v^B > \frac{1}{2}$ (bottom left). The reason for the discrepancy is, transaction models didn't account for order imbalance until now!

Volume participation strategies

$\hat{\sigma} = 1{,}000$, $V_\sigma = 10{,}000$, $m = 1{,}000$, $\left[\overline{P} - \underline{P}\right] = 10{,}000$, $\lambda = 0.05$, linear $\varphi[|m|]$.







The probabilistic loss for a buy order takes different functional forms depending on whether $v^B = \frac{1}{2}$ (upper left), $v^B < \frac{1}{2}$ (upper right) or $v^B > \frac{1}{2}$ (bottom left). The dashed red line corresponds to a volume participation strategy that targets a 5% of activity. As expected, it is suboptimal.

Backtested performance for OEH algo (1/3)

We have seen that the liquidity component can be estimated as $\left|\widetilde{OI}_{OEH,\tau}\right|\left[\overline{P}-\underline{P}\right]|m|$. Thus, the total profit during volume bucket τ is

$$PL_{OEH,\tau} = \underbrace{-\left|\widetilde{OI}_{OEH,\tau}\right|\left[\overline{P}-\underline{P}\right]|m|}_{PL^{L}_{OEH,\tau}} + \underbrace{\left(P_{\tau}-\bar{P}_{OEH,\tau}\right)m}_{PL^{T}_{OEH,\tau}}$$

and the analogous expression applies to VWAP. We can then compute the relative outperformance of OEH over VWAP in terms of its information ratio,

$$IR = \frac{E\left[PL_{OEH,\tau}-PL_{VWAP,\tau}\right]}{\sigma\left[PL_{OEH,\tau}-PL_{VWAP,\tau}\right]}\sqrt{n}$$

where $\sqrt{n}$ is the annualization factor, and *n* the number of independent trades per year. We have computed a backtest of OEH's performance relative to VWAP on the following products.

Futures Contract	Exchange	Group	Start	End	Roll	Records	ADV
E-Mini S&P500	CME	Equity	1/1/2007	7/26/2012	12	476,676,009	1,964,844.89
T-Note	CBOT	Rates	1/1/2007	7/26/2012	28	95,091,010	921,056.33
EUR/USD	CME	FX	1/1/2007	7/26/2012	10	188,197,121	233,201.17
WTI Crude Oil	NYMEX	Energy	1/1/2007	7/26/2012	19	164,619,912	194,902.36
Gold	COMEX	Metals	1/1/2007	7/26/2012	27	62,672,073	81,854.96
Corn	CBOT	Softs	1/1/2007	7/26/2012	20	41,833,299	73,860.53
Natural Gas	NYMEX	Energy	1/1/2007	7/26/2012	Volume	50,575,494	61,685.78
Lean Hogs	CME	Meat	1/1/2007	7/26/2012	24	5,499,602	6,544.67
Cotton#2	ICE	Softs	1/1/2007	7/26/2012	20	4,494,294	6,171.32

Backtested performance for OEH algo (2/3)

Futures Contract	Information	Trade Size	Max Profit	OEH Profit (Pts)	Outperf.(Pts)	Outperf.(%)	IR
E-Mini S&P500	Sign	0.01*ADV	12.1428	10.5104	4.3262	35.63%	10.04
T-Note	Sign	0.01*ADV	0.3966	0.3441	0.1322	33.33%	9.18
EUR/USD	Sign	0.01*ADV	0.0074	0.0064	0.0028	37.28%	10.62
WTI Crude Oil	Sign	0.01*ADV	1.3913	1.1949	0.4582	32.93%	10.02
Gold	Sign	0.01*ADV	9.4932	8.1780	3.2875	34.63%	9.68
Corn	Sign	0.01*ADV	8.4173	7.2806	3.1640	37.59%	9.67
Natural Gas	Sign	0.01*ADV	0.1098	0.0945	0.0409	37.26%	9.50
Lean Hogs	Sign	0.01*ADV	0.7451	0.6334	0.2613	35.07%	10.51
Cotton#2	Sign	0.01*ADV	1.3211	1.1358	0.4675	35.38%	7.66

Futures Contract	Information	Trade Size	Max Profit	OEH Profit (Pts)	Outperf.(Pts)	Outperf.(%)	IR
E-Mini S&P500	Sign	0.05*ADV	12.1428	8.2047	2.2770	18.75%	5.63
T-Note	Sign	0.05*ADV	0.3966	0.2682	0.0649	16.37%	4.91
EUR/USD	Sign	0.05*ADV	0.0074	0.0051	0.0015	20.78%	6.51
WTI Crude Oil	Sign	0.05*ADV	1.3913	0.9275	0.2217	15.94%	5.33
Gold	Sign	0.05*ADV	9.4932	6.3202	1.6253	17.12%	5.15
Corn	Sign	0.05*ADV	8.4173	5.6471	1.7222	20.46%	5.73
Natural Gas	Sign	0.05*ADV	0.1098	0.0731	0.0221	20.14%	5.68
Lean Hogs	Sign	0.05*ADV	0.7451	0.4820	0.1230	16.51%	5.32
Cotton#2	Sign	0.05*ADV	1.3211	0.8776	0.2372	17.96%	4.24

Futures Contract	Information	Trade Size	Max Profit	OEH Profit (Pts)	Outperf.(Pts)	Outperf.(%)	IR
E-Mini S&P500	Sign	0.1*ADV	12.1428	6.3551	0.9577	7.89%	2.59
T-Note	Sign	0.1*ADV	0.3966	0.2065	0.0212	5.36%	1.82
EUR/USD	Sign	0.1*ADV	0.0074	0.0039	0.0007	9.18%	3.17
WTI Crude Oil	Sign	0.1*ADV	1.3913	0.7037	0.0600	4.31%	1.58
Gold	Sign	0.1*ADV	9.4932	4.7746	0.5125	5.40%	1.82
Corn	Sign	0.1*ADV	8.4173	4.2081	0.6715	7.98%	2.63
Natural Gas	Sign	0.1*ADV	0.1098	0.0549	0.0091	8.30%	2.57
Lean Hogs	Sign	0.1*ADV	0.7451	0.3580	0.0314	4.22%	1.46
Cotton#2	Sign	0.1*ADV	1.3211	0.6582	0.0869	6.58%	1.72

OEH's outperformance over VWAP for trades equivalent to 1%, 5% and 10% of ADV, with information regarding the side of the price move over the next bucket.

Backtested performance for OEH algo (3/3)

Futures Contract	Information	Trade Size	Max Profit	OEH Profit (Pts)	Outperf.(Pts)	Outperf.(%)	IR
E-Mini S&P500	Sign, Size	0.01*ADV	15.8723	14.1671	6.4076	40.37%	8.52
T-Note	Sign, Size	0.01*ADV	0.5291	0.4721	0.1959	37.03%	6.74
EUR/USD	Sign, Size	0.01*ADV	0.0098	0.0087	0.0039	39.98%	8.74
WTI Crude Oil	Sign, Size	0.01*ADV	1.8682	1.6672	0.6830	36.56%	8.39
Gold	Sign, Size	0.01*ADV	12.5753	11.4060	4.7222	37.55%	6.96
Corn	Sign, Size	0.01*ADV	12.3966	11.0999	5.1200	41.30%	5.77
Natural Gas	Sign, Size	0.01*ADV	0.1380	0.1230	0.0566	40.98%	7.97
Lean Hogs	Sign, Size	0.01*ADV	0.8442	0.7552	0.3348	39.66%	7.92
Cotton#2	Sign, Size	0.01*ADV	1.7879	1.6020	0.7070	39.54%	6.52

Futures Contract	Information	Trade Size	Max Profit	OEH Profit (Pts)	Outperf.(Pts)	Outperf.(%)	IR
E-Mini S&P500	Sign, Size	0.05*ADV	15.8723	11.4107	4.0384	25.44%	7.34
T-Note	Sign, Size	0.05*ADV	0.5291	0.3744	0.1120	21.17%	6.30
EUR/USD	Sign, Size	0.05*ADV	0.0098	0.0071	0.0025	25.40%	8.26
WTI Crude Oil	Sign, Size	0.05*ADV	1.8682	1.3453	0.4091	21.90%	7.25
Gold	Sign, Size	0.05*ADV	12.5753	9.3511	2.9978	23.84%	5.94
Corn	Sign, Size	0.05*ADV	12.3966	8.6294	3.0115	24.29%	6.28
Natural Gas	Sign, Size	0.05*ADV	0.1380	0.0988	0.0358	25.98%	6.91
Lean Hogs	Sign, Size	0.05*ADV	0.8442	0.6141	0.2119	25.11%	7.50
Cotton#2	Sign, Size	0.05*ADV	1.7879	1.2726	0.4329	24.21%	5.46

Futures Contract	Information	Trade Size	Max Profit	OEH Profit (Pts)	Outperf.(Pts)	Outperf.(%)	IR
E-Mini S&P500	Sign, Size	0.1*ADV	15.8723	8.8113	2.2197	13.98%	5.98
T-Note	Sign, Size	0.1*ADV	0.5291	0.2891	0.0546	10.32%	4.69
EUR/USD	Sign, Size	0.1*ADV	0.0098	0.0055	0.0014	14.79%	7.10
WTI Crude Oil	Sign, Size	0.1*ADV	1.8682	1.0389	0.2004	10.73%	5.16
Gold	Sign, Size	0.1*ADV	12.5753	6.7359	1.4143	11.25%	6.36
Corn	Sign, Size	0.1*ADV	12.3966	6.4158	1.5333	12.37%	5.39
Natural Gas	Sign, Size	0.1*ADV	0.1380	0.0768	0.0208	15.11%	5.26
Lean Hogs	Sign, Size	0.1*ADV	0.8442	0.4827	0.1199	14.21%	6.57
Cotton#2	Sign, Size	0.1*ADV	1.7879	0.9576	0.2466	13.79%	4.26

OEH's outperformance over VWAP for trades equivalent to 1%, 5% and 10% of ADV, with information regarding the side and size of the price move over the next bucket.

SECTION VI
Conclusions

Conclusions

- Orders from informed traders impact the order flow imbalance.
- Market makers adjust their trading range accordingly, in order to avoid adverse selection.
- Market makers operate in a Volume Clock, an are particularly susceptible to imbalances in that frequency.
- **The key to optimal execution is to minimize the footprint of your trades on the order flow.**
- The Optimal Execution Horizon algorithm determines the amount of volume needed to conceal the intentions of an informed trader.

THANKS FOR YOUR ATTENTION!

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Bio

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Notice:

The research contained in this presentation is the result of a continuing collaboration with

Prof. Maureen O'Hara
Prof. David Easley

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