The Low Frequency Trading Arms Race: Machines Versus Delays

Alex Dickerson [1] Yoshio Nozawa [2] Cesare Robotti [3]

[1]UNSW Business School

[2]University of Toronto

[3]Warwick Business School

May 2024, ABFER

Motivation

What are the risk factors in the corporate bond market?

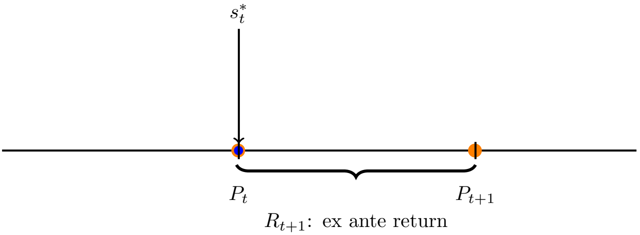
- Bond market CAPM (e.g. Dickerson et al. 2023).
- Duration-adjusted CAPM (e.g. Binsbergen et al. 2023).
- Multifactor models (e.g. Israel et al. 2018; Kelly et al. 2021)

No consensus partly due to **transaction costs**.

Can we apply the empirical methods for stocks to **illiquid assets** and identify factors?

Motivation

Academic research related to **equities** follows a relatively simple portfolio construction framework:



- Signal and trade occur on the last business-day of month t.
- ∞ volume (capacity) is assumed on trade dates (orange dots).
- **Immediate order execution** is assumed and is feasible.

$\Rightarrow$ *Do these portfolio construction methodologies accurately describe the performance of investment strategies and factors as applied to* **illiquid** *assets?*

Motivation

Corporate bonds operate in a fundamentally different **market structure**:

- $>$ 80% of **bonds still trade OTC**, via telephone, with a dealer.
- Immediate order **execution** (via e.g., a LOB) is not always possible.
- In TRACE, '**no-trade**' days comprise $\sim$ 70% of the sample.

When forming their portfolios, bond traders must consider:

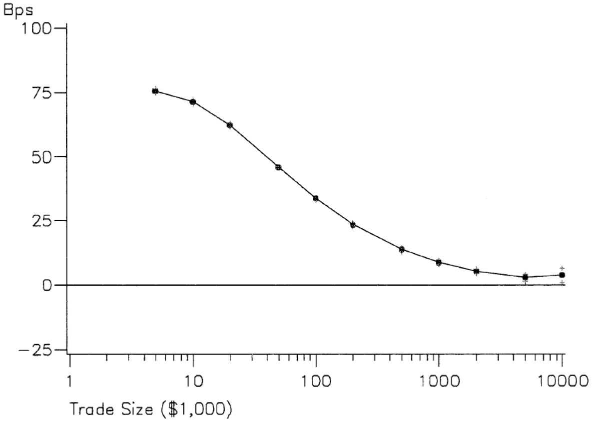
- Search costs
- Dealer inventory constraints and trade sizing
- Bargaining frictions

$\Longrightarrow$ We need an empirical method that accounts for **delays and trade failures**.

Research Questions

1. How do we account for **delays** and **execution failures**?
    - Novel back-testing methodology for corporate bonds
2. Are the **costs of delays** and total costs to trade significant?
    - 200 factors / 9 ML portfolios
    - 3 factors and 0 ML portfolios survive net of costs
3. What **determines** the cost of delays?
    - Time-series/cross-sectional variation
4. How do our **cost estimates differ** from the standard approach?
    - Dependence on gross profits and turnover
    - High turnover $\Rightarrow$ High (low) gross (net) alpha
5. Are our **cost estimates realistic**?
    - Value-added of corporate bond mutual funds
    - Active bond funds lose clients $5mil p.a. relative to passive ETF

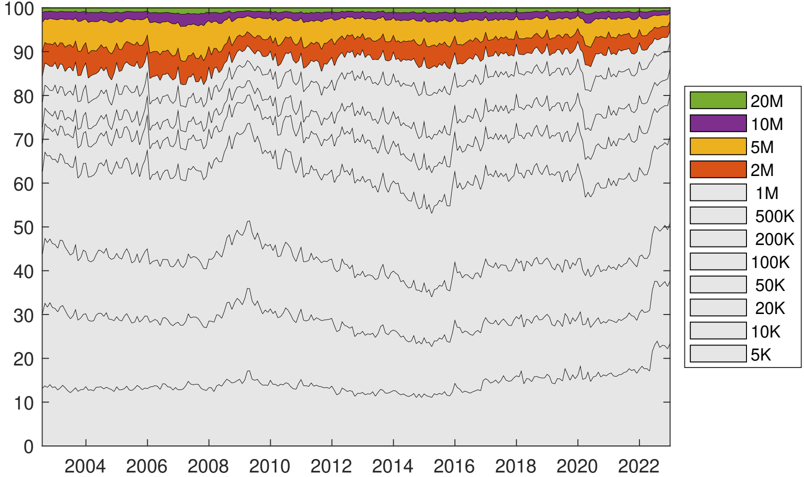
Cost-Trade Size Relationship in OTC Markets



Source: Edwards, Harris, and Piwowar (2007) Figure 1

- '**Size discount**': Bid-ask spreads are a decreasing function of **trade size** (Edwards, Harris, and Piwowar 2007 and Duffie, Gârleanu, and Pedersen 2005).
- Robust to controlling for **client-level fixed effects** (Pinter et al., 2021).

Large Trades Are Rare



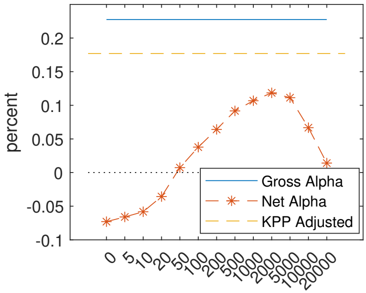
Despite their small costs, the share of large trades is not increasing. Why?

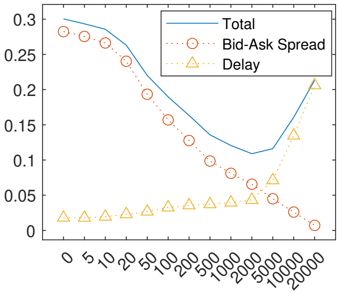
Dealers are supply-side constrained.

Size-Cost Relationship: Delays

⇒ Average α/cost across High-Low portfolio at different trading volumes.

Figure: Effect of Transaction Costs: Example of **Credit Spread-Sorted Portfolio**





- Trading **larger size** results in greater **cost of delay**.
- **Trade-off** between trade size and potential delay costs.
- This **trade-off** has not been explored in the literature.

Trade-offs Between Delays/Execution Failure and Transaction Costs

Assumptions

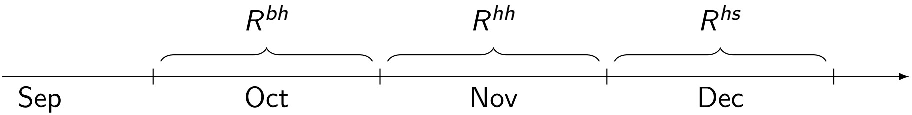
"Researching and backtesting is like drinking and driving. Do not research under the influence of a backtest."
- Marcos Lopez de Prado

1. We take the historical data as 'given', no trade above a given volume target means no action, i.e., the data gives us a single equilibrium outcome. (Simulation results coming next draft)
2. We rebalance monthly. (and quarterly, semi-annually)
3. We allow shorting, and we do not impose additional costs to do this (Markit short-sale costs in next draft).
4. We can only pin down *latent* delay costs as a function of the signal, s, and volume threshold, v. (We also use various simulation methods)
5. The representative investor trades above a given volume threshold, v.

Returns with Execution Delays

Mark-to-market returns:

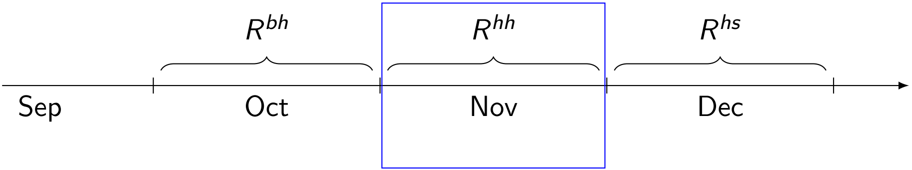
$$R^{hh}_{t+1} = \left(\frac{P^h_{t+1} + AI_{t+1} + C_{t+1}}{P^h_t + AI_t} \right) - 1,$$



Returns with Execution Delays

Mark-to-market returns:

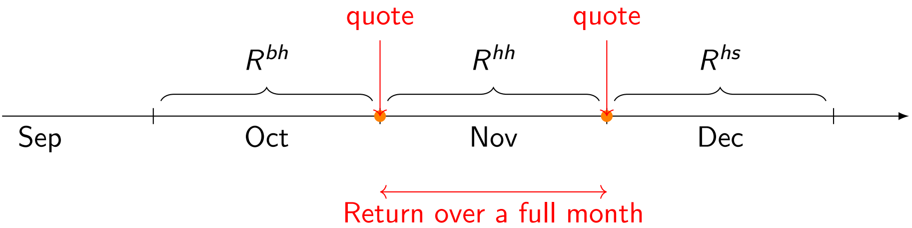
$$R_{t+1}^{hh} = \left(\frac{P_{t+1}^{h} + AI_{t+1} + C_{t+1}}{P_t^{h} + AI_t} \right) - 1,$$



Returns with Execution Delays

Mark-to-market returns:

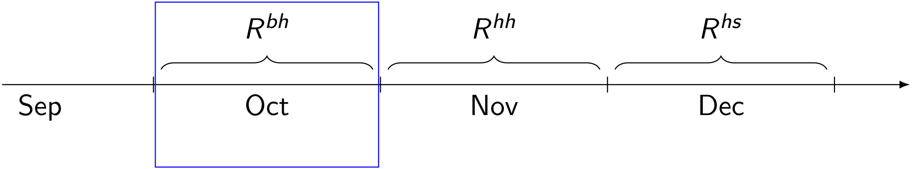
$$R^{hh}_{t+1} = \left(\frac{P^h_{t+1} + AI_{t+1} + C_{t+1}}{P^h_t + AI_t} \right) - 1,$$



Starting a Long Position

$$R_{t+1}^{b(v)h} = \begin{cases} \left(1 + R_{t+1}^{f} \times \frac{d}{Days_{t+1}}\right)\left(\frac{P_{t+1}^{h} + AI_{t+1} + C_{t+1,d}}{P_{t+1,d}^{b(v)} + AI_{t+1,d}}\right) - 1 \text{ if traded,} \\ R_{t+1}^{f} \text{ if not.} \end{cases}$$

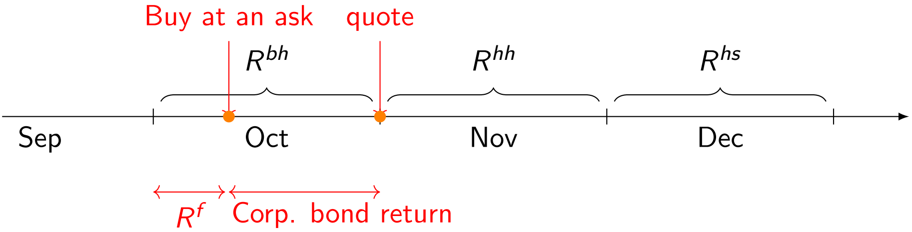
where v is a target trade size for an investor.



Starting a Long Position

$$R_{t+1}^{b(v)h} = \begin{cases} \left(1 + R_{t+1}^{f} \times \frac{d}{Days_{t+1}}\right)\left(\frac{P_{t+1}^{h} + AI_{t+1} + C_{t+1,d}}{P_{t+1,d}^{b(v)} + AI_{t+1,d}}\right) - 1 \text{ if traded,} \\ R_{t+1}^{f} \text{ if not.} \end{cases}$$

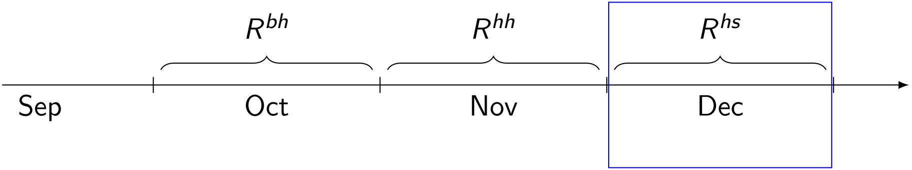
where v is a target trade size for an investor.



Existing from Long Position

$$R_{t+1}^{hs(v)} = \begin{cases} \left(\frac{P_{t+2,d}^{s(v)} + AI_{t+2,d} + C_{t+1} + C_{t+2,d}}{P_t^h + AI_t} \right) \div \left(1 + R_{t+2}^f \times \frac{d}{Days_{t+2}} \right) - 1 \\ \text{if traded,} \\ R_{t+1}^{hh} \text{ if not.} \end{cases}$$

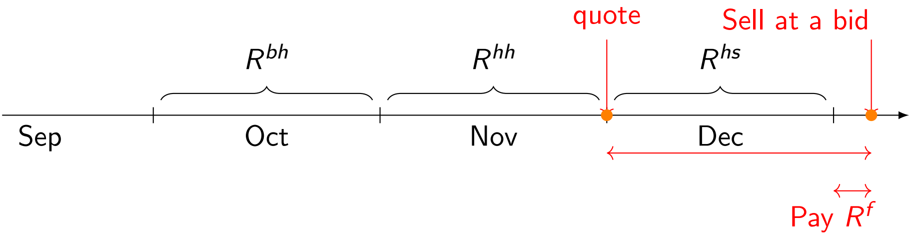
where v is a target trade size for an investor.



Existing from Long Position

$$R_{t+1}^{hs(v)} = \begin{cases} \left(\frac{P_{t+2,d}^{s(v)} + AI_{t+2,d} + C_{t+1} + C_{t+2,d}}{P_t^h + AI_t}\right) \div \left(1 + R_{t+2}^f \times \frac{d}{Days_{t+2}}\right) - 1 \\ \text{if traded,} \\ R_{t+1}^{hh} \text{ if not.} \end{cases}$$

where v is a target trade size for an investor.



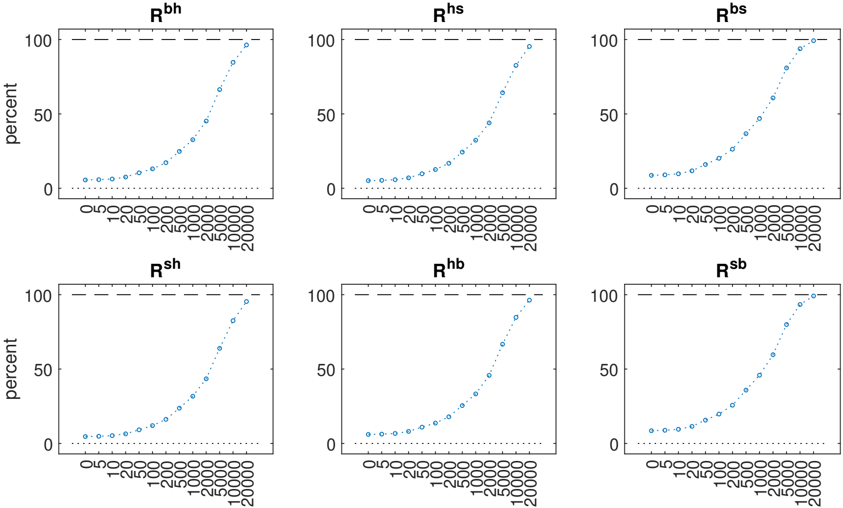
Methodology / Bond Data

1. Combine *daily* TRACE and BAML/ICE bond datasets.
   - Bond characteristics from Mergent.
   - Apply filters (**ex-ante**) to remove extreme price reversals. (+/- 50%)
   - Otherwise, **no winsorization** or **truncation**.
   - Data errors (if any) are immaterial.
2. Compute the simple average of transaction prices separately for bids ($P_{t,d}^{s(v)}$) and asks ($P_{t,d}^{b(v)}$) with volume above v:
   - Size cutoffs of $0, $5,000, $10,000, $20,000, $50,000, $100,000, $200,000, $500,000, $1 million, $2 million, $5 million, $10 million, and $20 million (Edwards et al., 2007).
   - Merge the daily transaction prices in TRACE to the quote prices in ICE.
   - No observation in TRACE but in ICE $\longrightarrow$ no trade.
3. Compute 7 types of possible returns.

Returns exist in our sample even if there is no trade for the bond.

Percentage of No-Trade Observations

$\Longrightarrow$ 6 'types' of net returns, every month t, for each bond i



Methodology / Signal Generation

$\Rightarrow$ Form **quintile** portfolios. Factor is long (Q5) minus short (Q1)

$\Rightarrow$ Sample spans 2002:08–2022:12

We include **200** stock and bond characteristics (**200** factors):

1. **27** 'bond-based' including credit spreads, rating, maturity, and duration.
2. **173** 'equity-based' including most variables from Open Asset Pricing (Chen and Zimmermann, 2022).
3. Covers close to the **entirety of variables** shown to predict future bond returns from the literature.
4. **Missing data**: set to cross-sectional median in month t.
5. **Outliers:** characteristics are cross-sectionally rank demeaned to lie in the interval $[-1,1]$.

Methodology / Machine Learning Models

We estimate **6 ML models** and **3 ensembles**:

1. **Penalized linear** models: Lasso (LASSO), Ridge (RIDGE) and Elastic Net (ENET).
2. **Non-linear regression tree** ensemble methods including random forests (RF), and extreme trees (XT).
3. Feed forward **neural networks** (NN).
4. Linear (LENS), Nonlinear (NENS) and both (ENS) ensembles: $\frac{1}{N}$ averages of the predictions in each month t.

$\Rightarrow$ Trained with expanding window with cross-validation.

Gross and Net Performance – ML Models

Signal	Excess Returns		CAPMB α		Information Ratio			
	Gross	Net Optimal	Gross	Net Optimal	Gross	Net Optimal	Optimal Volume	Turnover (%)
NN	0.531	0.110	0.430	0.039	1.192	0.177	5000	49.10
	(3.69)	(1.71)	(2.97)	(0.67)				
XT	0.548	0.166	0.393	0.042	0.901	0.118	2000	39.71
	(3.40)	(1.39)	(2.48)	(0.40)				
RF	0.387	0.056	0.239	-0.033	0.595	-0.125	10000	32.58
	(3.33)	(0.78)	(2.16)	(-0.49)				
ENET	0.535	0.129	0.422	0.041	0.980	0.121	2000	48.67
	(3.82)	(1.40)	(2.75)	(0.44)				
RIDGE	0.567	0.177	0.504	0.122	1.371	0.425	2000	46.22
	(4.07)	(1.86)	(3.77)	(1.41)				
LASSO	0.517	0.093	0.414	0.019	0.981	0.071	5000	49.92
	(3.08)	(1.04)	(2.21)	(0.20)				
ENS	0.592	0.162	0.476	0.068	1.152	0.215	2000	49.32
	(3.60)	(1.52)	(2.90)	(0.68)				
LENS	0.575	0.159	0.479	0.077	1.226	0.258	2000	49.46
	(3.76)	(1.56)	(3.18)	(0.83)				
NENS	0.562	0.142	0.421	0.029	1.038	0.092	2000	47.67
	(3.45)	(1.33)	(2.58)	(0.30)				

Gross and Net Performance – ML Models

	Excess Returns		CAPMB α		Information Ratio			
Signal	Gross	Net Optimal	Gross	Net Optimal	Gross	Net Optimal	Optimal Volume	Turnover (%)
NN	0.531	0.110	0.430	0.039	1.192	0.177	5000	49.10
	(3.69)	(1.71)	(2.97)	(0.67)				
XT	0.548	0.166	0.393	0.042	0.901	0.118	2000	39.71
	(3.40)	(1.39)	(2.48)	(0.40)				
RF	0.387	0.056	0.239	-0.033	0.595	-0.125	10000	32.58
	(3.33)	(0.78)	(2.16)	(-0.49)				
ENET	0.535	0.129	0.422	0.041	0.980	0.121	2000	48.67
	(3.82)	(1.40)	(2.75)	(0.44)				
RIDGE	0.567	0.177	0.504	0.122	1.371	0.425	2000	46.22
	(4.07)	(1.86)	(3.77)	(1.41)				
LASSO	0.517	0.093	0.414	0.019	0.981	0.071	5000	49.92
	(3.08)	(1.04)	(2.21)	(0.20)				
ENS	0.592	0.162	0.476	0.068	1.152	0.215	2000	49.32
	(3.60)	(1.52)	(2.90)	(0.68)				
LENS	0.575	0.159	0.479	0.077	1.226	0.258	2000	49.46
	(3.76)	(1.56)	(3.18)	(0.83)				
NENS	0.562	0.142	0.421	0.029	1.038	0.092	2000	47.67
	(3.45)	(1.33)	(2.58)	(0.30)				

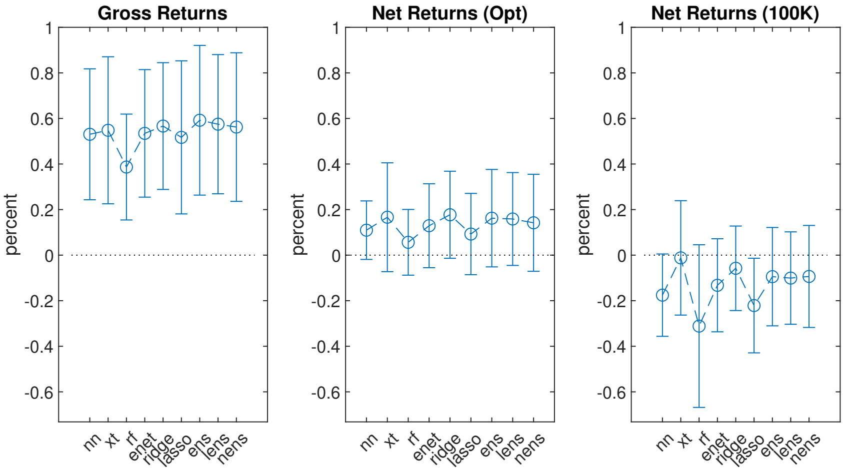
Very Strong Performance Before Costs.

Gross and Net Performance – ML Models

Signal	Excess Returns		CAPMB α		Information Ratio		Optimal Volume	Turnover (%)
	Gross	Net Optimal	Gross	Net Optimal	Gross	Net Optimal		
NN	0.531	0.110	0.430	0.039	1.192	0.177	5000	49.10
	(3.69)	(1.71)	(2.97)	(0.67)				
XT	0.548	0.166	0.393	0.042	0.901	0.118	2000	39.71
	(3.40)	(1.39)	(2.48)	(0.40)				
RF	0.387	0.056	0.239	-0.033	0.595	-0.125	10000	32.58
	(3.33)	(0.78)	(2.16)	(-0.49)				
ENET	0.535	0.129	0.422	0.041	0.980	0.121	2000	48.67
	(3.82)	(1.40)	(2.75)	(0.44)				
RIDGE	0.567	0.177	0.504	0.122	1.371	0.425	2000	46.22
	(4.07)	(1.86)	(3.77)	(1.41)				
LASSO	0.517	0.093	0.414	0.019	0.981	0.071	5000	49.92
	(3.08)	(1.04)	(2.21)	(0.20)				
ENS	0.592	0.162	0.476	0.068	1.152	0.215	2000	49.32
	(3.60)	(1.52)	(2.90)	(0.68)				
LENS	0.575	0.159	0.479	0.077	1.226	0.258	2000	49.46
	(3.76)	(1.56)	(3.18)	(0.83)				
NENS	0.562	0.142	0.421	0.029	1.038	0.092	2000	47.67
	(3.45)	(1.33)	(2.58)	(0.30)				

High Turnover Rate >500% p.a.

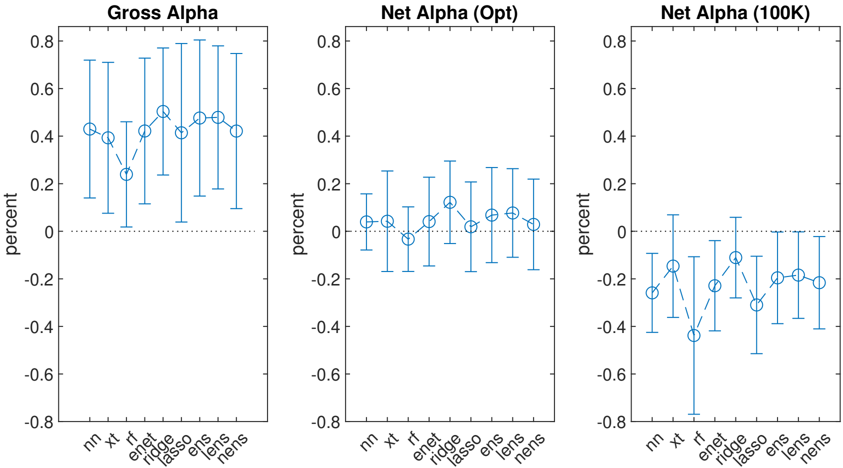
Gross and Net Performance – ML Models – Returns



- Average net portfolio returns at the **100K threshold** all negative.

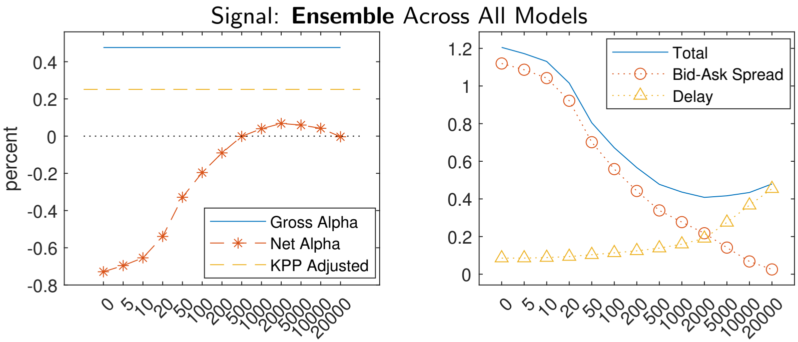
⟶ Fewer delays, but *higher* bid-ask spreads!

Gross and Net Performance – ML Models – Alphas



- **Large gross ML alphas**, >5% per annum.
- Zero and negative net ML alphas at **optimal volume** and **100K**.

Transaction Cost Decomposition



1. Optimal trade size ≈ 2 million.
2. Decomposition:

$$R^{Gross} - R^{Net} = \underbrace{\left(R^{Gross} - R^{DelayOnly}\right)}_{\text{Delay Cost}} + \underbrace{\left(R^{DelayOnly} - R^{Net}\right)}_{\text{Bid-Ask Spread}}$$

Turnover Rate, Gross and Net CAPMB α

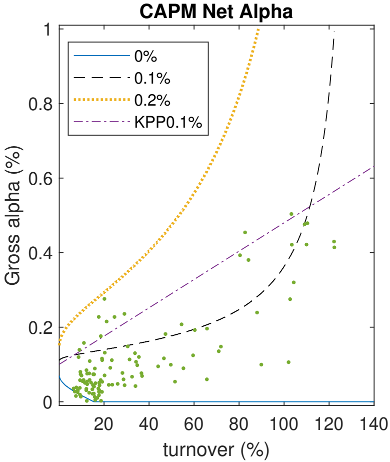
$$\alpha_{Net,s} = -0.079 + 0.040 \log Turn_s + 1.099\alpha_{Gross,s} - 0.254 \log Turn_s \times \alpha_{Gross,s} + \varepsilon_s$$

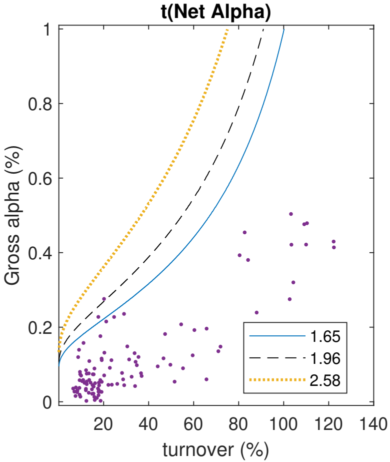
$$\Leftrightarrow \alpha_{StdNet,s} = -0.38\, Turn_s + \alpha_{Gross,s}$$

Turnover Rate, Gross and Net CAPMB α

$$\alpha_{Net,s} = -0.079 + 0.040 \log Turn_s + 1.099\alpha_{Gross,s} - 0.254 \log Turn_s \times \alpha_{Gross,s} + \varepsilon_s$$

$$\Leftrightarrow \alpha_{StdNet,s} = -0.38\, Turn_s + \alpha_{Gross,s}$$



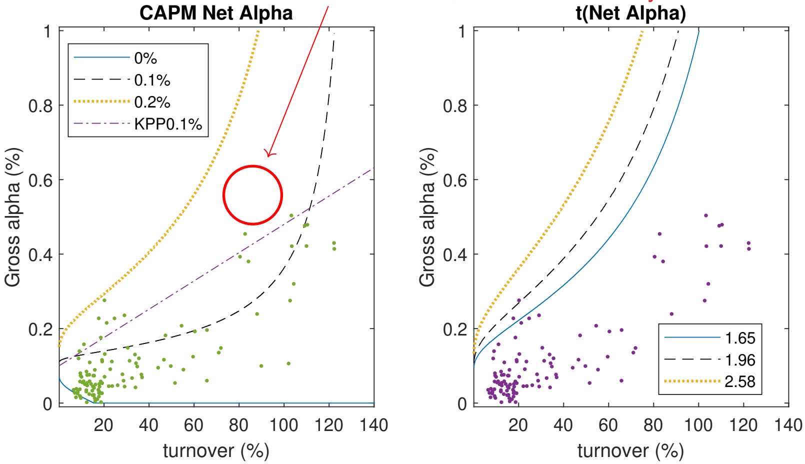


Turnover Rate, Gross and Net CAPMB α

$$\alpha_{Net,s} = -0.079 + 0.040 \log Turn_s + 1.099\alpha_{Gross,s} - 0.254 \log Turn_s \times \alpha_{Gross,s} + \varepsilon_s$$

$$\Leftrightarrow \alpha_{StdNet,s} = -0.38\, Turn_s + \alpha_{Gross,s}$$

Profitable under standard costs, but not after delays.



Conclusion

1. Novel method to compute net returns accounting for **execution delays**.
   - Most bond factors (~99%) fail after costs
2. Trade size is explicitly stated and captures the **trade-offs** between speed and cost.
3. The methods **do not depend on approximation** (e.g. treating prices on the last five business days as the month-end value).
4. Transaction costs vary over time, capturing the impact of changing landscape of bond trading.
5. ML methods are developed based on 200 signals.
6. The cost of delay is large **especially when the signal is profitable.**

References I

Binsbergen, Jules H. van, Yoshio Nozawa, and Michael Schwert, 2023, Duration-based valuation of corporate bonds, Working Paper.

Chen, Andrew Y., and Tom Zimmermann, 2022, Open source cross-sectional asset pricing, *Critical Finance Review* 11, 207–264.

Dickerson, Alexander, Philippe Mueller, and Cesare Robotti, 2023, Priced risk in corporate bonds, *Journal of Financial Economics* 150, article 103707.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, 2005, Over-the-counter markets, *Econometrica* 73, 1815–1847.

Edwards, Amy, Lawrence E. Harris, and Michael S. Piwowar, 2007, Corporate bond market transaction costs and transparency, *Journal of Finance* 62, 1421–1451.

Israel, Ronen, Diogo Palhares, and Scott Richardson, 2018, Common factors in corporate bond returns, *Journal of Investment Management* 16, 17–46.

Kelly, Bryan T., Diogo Palhares, and Seth Pruitt, 2021, Modeling corporate bond returns, *Journal of Finance* forthcoming.

Pinter, Gabor, Chaojun Wang, and Junyuan Zou, 2021, Size discount and size penalty trading costs in bond markets, Discussion Papers 2114, Centre for Macroeconomics (CFM).