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Delayed-Information Accounting Pressure and Geometry as a State Organizer in Cross-Sectional Return Ranking

Lucian Kai Chiang

Jinan New Channel-JUTES High School, Jinan, China

congressus@icloud.com

Abstract. This paper reconstructs tradable accounting signals from raw quarterly statements under a conservative delayed-information protocol. Using 23,343 accounting-statement files and 6,871 daily-price files, it rebuilds six core accounting variables, converts cumulative flows into single-quarter quantities, and maps each report to the first trading day after a 60-day delay. On the resulting sample of 23,458 firm-quarter observations for 1,712 firms across 40 rolling test windows, the paper studies whether future cross-sectional return ranking is better described by a smooth linear backbone or by a peer-relative inactive-band mechanism that gates local laws. OLS and Ridge deliver mean quarterly Spearman information coefficients around 0.022. A geometry-gated local-law specification reaches 0.025, but the lift over Ridge is not statistically decisive. Relative to alternative state constructors, geometry yields the highest observed coefficient-path compression of the effective accounting law, but its edge over quantile gating is small and likewise not statistically decisive. The contribution is therefore bounded: in this delayed-information setting, geometry is most useful as a sparse and interpretable organizer of state-dependent coefficient drift, not as a universally stronger predictor.

Keywords: accounting pressure, delayed information, cross-sectional return ranking, state dependence, return prediction

1. Introduction

Quarterly accounting disclosures are informative, but they do not translate mechanically into tradable cross-sectional return-ranking signals. Classic studies establish the information content of earnings and show that market adjustment can be delayed around accounting news [1-5]. More recent work on return prediction reaches a second stylized fact: disciplined linear characteristic models are difficult to displace consistently out of sample [6-9]. These two observations motivate the central question of this paper: once quarterly accounting information is rebuilt from raw statements and aligned to conservative availability dates, what empirical map best links accounting dynamics to subsequent return ranking?

A second strand of the literature shows why accounting variables remain relevant even after one moves beyond short-window announcement studies. Early financial-statement prediction papers connect composite statement information to subsequent returns and future earnings [10-13]. Related

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portfolio-sorting work demonstrates that statement-based diagnostics can separate stronger from weaker firms within value and growth segments [14, 15], while broader quality and conservatism measures also carry return implications [16, 17]. This paper is closest to that tradition in spirit, but it imposes a stricter delayed-information design and asks whether the empirical map should be interpreted as globally smooth or locally state dependent.

A third strand clarifies the accounting mechanisms that can make such signals persistent or mispriced. Earnings-return links depend on timeliness, cash-flow content, and the relative persistence of accrual components [18-21]. The accrual and balance-sheet anomaly literature then shows that investors can misread the implications of accrual quality, asset growth, and net operating asset accumulation for future profitability and returns [22-26]. These findings justify treating the present signal as a pressure operator built from quarter-to-quarter accounting reconfiguration rather than as a single-period levels predictor.

On the asset-pricing side, the paper also speaks to the literature on parsimonious factor structures, characteristic models, and flexible cross-sectional maps. Standard benchmark models remain central reference points [27, 28], and recent work shows both the power and the fragility of characteristic-based prediction once one accounts for regularization, covariance structure, and nonlinearities [29, 30]. The present contribution is deliberately narrower: it does not claim a new dominant factor model, but instead tests whether a geometry-defined inactive band helps organize how accounting pressure enters a ranking rule.

The paper treats that question as a pressure-to-ranking problem. First, raw statements are quarterized and aligned to delayed trading dates, producing a panel designed to reflect what could plausibly have been known when positions were formed. Second, six accounting variables are transformed into a compact multi-quarter pressure operator. Third, competing maps from pressure to ranking are compared. The benchmark is a smooth six-feature linear backbone. The structured alternative compresses pressure into three economic blocks, defines a peer-relative inactive band, and allows the local linear law to change only when a cluster state exits that band.

This framing matters because it prevents the geometry line from being treated as a generic nonlinear add-on. Geometry is instead introduced as a structural hypothesis about how accounting pressure becomes rank-relevant. If small or balanced changes are absorbed within an inactive band, then geometry should first appear empirically as a state organizer; only after that should one ask whether it supports a different local law. That is the logic followed here.

The contribution is deliberately narrow and threefold. First, the paper delivers a transparent delayed-information reconstruction from raw statements and prices. Second, it formulates a compact pressure-to-ranking problem and evaluates it against a strong linear backbone rather than against a weak strawman. Third, it subjects a theory-motivated geometric state hypothesis to a restrictive test: geometry must earn its place by explaining conditional coefficient drift, not by being presumed to dominate unconditional prediction. On that test, the evidence is bounded. A disciplined linear backbone remains the strongest unconditional benchmark, while geometry contributes mainly by organizing conditional ranking regimes. Additional comparisons against quantile-, k-means-, and random-state gates indicate that geometry is not mechanically dominant over simpler alternatives for average rank improvement, and its observed edge over quantile gating in path compression is small and not statistically decisive.

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2. Raw reconstruction and delayed-information design

2.1. From raw archives to a delayed-information panel

The raw source universe contains 23,343 accounting-statement files and 6,871 daily-price files. Ticker recovery from the accounting archive identifies 5,620 unique firms, and intersecting those identifiers with the price archive leaves 5,115 firms with both accounting and price coverage. A recommended delayed-information panel contains 171,248 firm-quarter rows for 4,686 firms. Restricting the sample to the 2012-2024 period, six-feature complete cases, and firms with at least four admissible prior quarters yields the final estimation sample of 23,458 firm-quarter observations for 1,712 firms across 48 availability quarters.

Table 1. Sample construction from raw archives to the final estimation panel

Stage	Count
Raw accounting statement files	23,343
Raw daily price files	6,871
Tickers with both archives	5,115
Recommended delayed-information rows (+60d)	171,248
Recommended delayed-information firms (+60d)	4,686
Rows with complete six-feature coverage	42,406
Final estimation rows after four-lag history filters	23,458
Final firms in the estimation panel	1,712
Availability quarters in 2013Q1-2024Q4	48
Rolling test windows	40

The accounting archive mixes first-quarter, half-year, third-quarter, and annual filings. Flow variables are therefore quarterized before use. Let $X^{cum}_{y,q}$ denote a cumulative flow for fiscal year y and quarter q. Single-quarter flows are reconstructed by the standard within-year differencing rule,

$$x_{y,1} = X^{\mathrm{cum}}_{y,1}, \qquad x_{y,2} = X^{\mathrm{cum}}_{y,2} - X^{\mathrm{cum}}_{y,1} \tag{1}$$

$$x_{y,3} = X^{\mathrm{cum}}_{y,3} - X^{\mathrm{cum}}_{y,2}, \qquad x_{y,4} = X^{\mathrm{cum}}_{y,4} - X^{\mathrm{cum}}_{y,3}$$

Stock variables are taken as quarter-end levels. The six final features are basic EPS, net profit, quarterly ROE, free cash flow, total assets, and a negatively signed debt ratio. The sign convention for debt ratio is chosen so that larger values correspond to more favorable balance-sheet structure.

The panel does not treat fiscal quarter-end dates as if the underlying information were immediately tradable. In the absence of filing timestamps for the full archive, each report is mapped to a conservative availability date,

$$avail_{i,t} = FTD(end\_date_{i,t} + 60\ calendar\ days) \tag{2}$$

where FTD(.) denotes the first trading day on or after the stated date. The future target uses the same delayed-information convention two fiscal quarters ahead,

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$$y_{i,t} = \frac{P(avail_{i,t+2}) - P(avail_{i,t})}{P(avail_{i,t})} \tag{3}$$

The object studied below is therefore a map from delayed-information accounting pressure to future delayed-information cross-sectional returns.

2.2. Accounting pressure and the competing maps

Net profit, free cash flow, and total assets are transformed by $x \mapsto \mathrm{sgn}(x)\log(1+|x|)$; basic EPS, quarterly ROE, and the negatively signed debt ratio remain on native scale. Within each availability quarter, every transformed feature is winsorized at the 1st and 99th percentiles and standardized cross-sectionally to produce $z_{i,j,t}$. Multi-quarter accounting pressure is then defined by a four-quarter exponentially weighted first-difference operator,

$$p_{i,j,t} = \sum_{k=1}^{4} \omega_k \left(z_{i,j,t-k+1} - z_{i,j,t-k}\right) \tag{4}$$

$$\omega_k = \frac{e^{-0.5(k-1)}}{\sum_{l=1}^{4} e^{-0.5(l-1)}}$$

The benchmark map is a smooth six-feature linear backbone,

$$F_{i,t}^{(0)} = b^{\top} p_{i,t} \tag{5}$$

with $p_{i,t} \in R^6$ estimated in a rolling Ridge specification. The structured line compresses pressure into three interpretable blocks,

$$u_{i,t} = Mp_{i,t},\ M = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \tag{6}$$

so that u^Q summarizes quality/profitability pressure, u^C captures cash-flow pressure, and u^B captures balance-sheet pressure. To make the state local rather than global, each firm-quarter is centered against the coordinate-wise median of its k = 25 nearest neighbors in block space. Denoting the peer center by $c_{i,t}$, the centered state is $\tilde{u}_{i,t} = u_{i,t} - c_{i,t}$.

Only the three cluster directions are retained,

$$c_Q = \left(1, -\tfrac{1}{2}, -\tfrac{1}{2}\right) \tag{7}$$

$$c_C = \left(-\tfrac{1}{2}, 1, -\tfrac{1}{2}\right)$$

$$c_B = \left(-\tfrac{1}{2}, -\tfrac{1}{2}, 1\right)$$

Each direction is normalized by a quotient-width function,

$$h_\rho(v) = \|v\|_1 + \rho\|B\Pi v\|_1,\ \rho \geq 0 \tag{8}$$

leading to standardized projections

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$$q_{i,t}^{r} = \frac{\langle \tilde{u}_{i,t}, c_r \rangle}{h_\rho(c_r)} \tag{9}$$

Let $r^{*}_{i,t}$ = arg $\max_{r \in \{Q,C,B\}} |q^{r}_{i,t}|$. A single threshold $\tau_C > 0$, constrained to the 70th, 80th, or 90th percentile of training-window $|q|$, defines the cluster state

$$s_{i,t} = \begin{cases} 0, & |q_{i,t}^{r^*}| \le \tau_C, \\ r^{*+}, & q_{i,t}^{r^*} > \tau_C, \\ r^{*-}, & q_{i,t}^{r^*} < -\tau_C. \end{cases} \tag{10}$$

The most structured specification is then a geometry-gated local law,

$$F_{i,t}^{(1)} = b^{\top} p_{i,t} + \sum_{r \in \{Q\pm, C\pm, B\pm\}} 1\{s_{i,t} = r\} \Delta b_r^{\top} p_{i,t} \tag{11}$$

When $s_{i,t} = 0$, the model collapses exactly to the backbone. Geometry therefore enters empirically as a state hypothesis first and as a local-law switch only afterwards.

3. Empirical results

3.1. A disciplined backbone remains the dominant unconditional map

Table 2 reports the main unconditional ranking results. The strongest unconditional predictor is still a linear backbone: OLS and Ridge deliver mean quarterly Spearman ICs of 0.0218 and 0.0213, respectively. Elastic Net and Lasso remain positive but weaker. The geometry-gated local law raises the point estimate to 0.0250, but the increment over Ridge is only 0.0037 and is not statistically decisive. The result therefore does not support the claim that geometry robustly supersedes a strong linear benchmark.

Table 2. Main unconditional ranking performance on the final delayed-information sample

Model	Windows	Mean IC	Median IC	IR	Pos. share	NW t	NW p	Q5-Q1
OLS	40	0.0218	0.0228	0.294	0.575	1.652	0.099	-0.0020
Ridge backbone	40	0.0213	0.0238	0.288	0.575	1.622	0.105	-0.0011
Elastic Net	36	0.0149	0.0197	0.211	0.583	1.055	0.291	0.0149
Lasso	40	0.0190	0.0230	0.262	0.600	1.431	0.153	-0.0034
Cluster state only	40	0.0008	-0.0104	0.010	0.425	0.058	0.954	-0.0252
Geometry-gated local law	40	0.0250	0.0102	0.332	0.625	1.823	0.068	-0.0004

Newey-West statistics use lag two. Q5-Q1 is the mean top-minus-bottom quintile return spread across test quarters.

Two implications follow immediately. First, the accounting backbone is doing most of the unconditional predictive work. Second, any role claimed for geometry has to be stated relative to that backbone rather than as a wholesale replacement. The point estimate of the gated law is the largest among the tested models, but the lack of statistical separation from Ridge forces a narrower interpretation.

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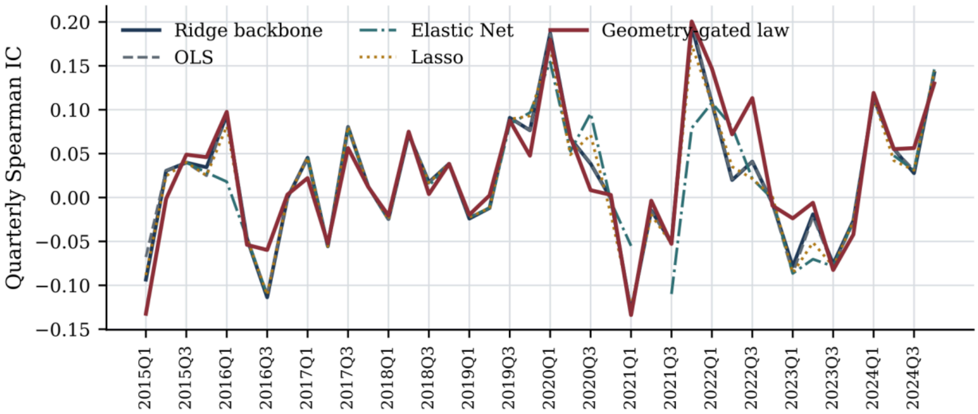

Figure 1. Rolling quarterly information coefficients. The geometry-gated local law tracks the Ridge backbone closely and occasionally exceeds it, but the gap remains small relative to window-to-window variation

3.2. Geometry matters first as a state organizer

The geometry line becomes much clearer when evaluated as a state hypothesis rather than as a standalone score. Figure 2 reports the estimated threshold and active share in the upper panel and the dominant-state composition in the lower panel. On average, the gated specification is active in roughly 30% of firm-quarter observations, with a mean threshold around 0.088. Q-dominant states are the most frequent, followed by C-dominant and B-dominant states. This is exactly what one would expect from a sparse inactive-band mechanism: geometry is not always on, but neither is it degenerate.

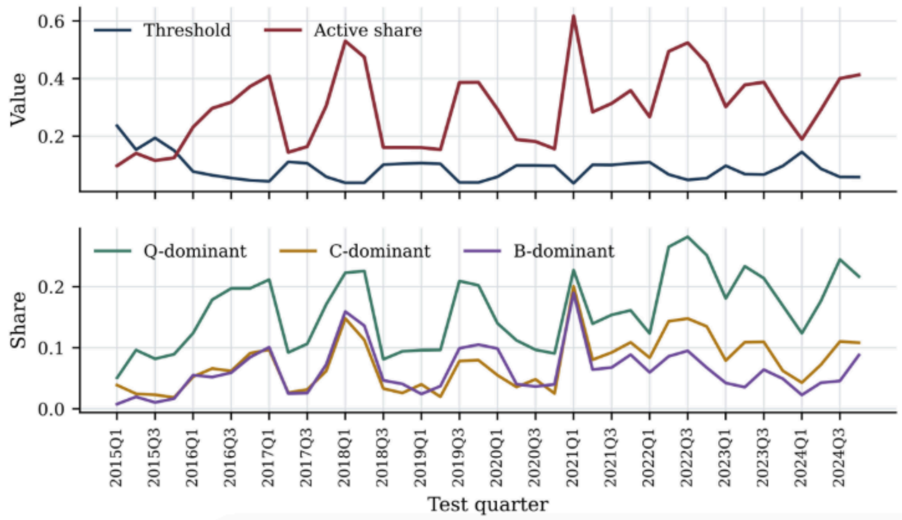

Figure 2. State diagnostics for the geometry line. The upper panel reports the estimated inactive-band threshold and the share of active observations. The lower panel reports the composition of active states by dominant cluster. Geometry enters empirically as a sparse and nondegenerate state structure

By contrast, the pure state score on its own is almost useless: its mean IC is 0.0008. Geometry therefore is not an unconditional score in its own right. It becomes relevant only when the state is used to determine whether the backbone should continue to apply globally or switch to a different local law. This is the most important structural result of the paper. Geometry behaves like a regime organizer first and a predictor only indirectly. To assess that role where geometry should matter most, the paper also compares geometry against quantile-, k-means-, and random-state gates on coefficient-path compression: how well a sparse state representation explains the time variation of the effective accounting law implied by the rolling backbone.

Table 3. Geometry-state diagnostics and law-compression evidence

Diagnostic	Value
Mean active share	0.298
Mean threshold tau_C	0.088
Mean Q-dominant share	0.161
Mean C-dominant share	0.075
Mean B-dominant share	0.063
Mean IC of state-only score	0.0008
Mean IC of gated local law	0.0250
Mean IC lift over Ridge	0.0037
NW p for lift over Ridge	0.420
Adj. R^2 of path compression (geometry)	0.352
Adj. R^2 of path compression (quantile)	0.345
Paired p for geometry > quantile	0.422

3.3. Local laws do change, but not enough to dominate the backbone

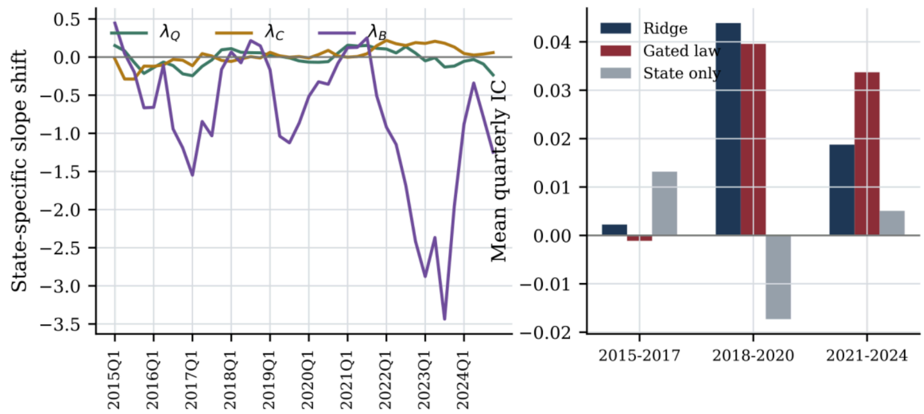

Figure 3. Local-law evidence. Left: paths of the state-specific slope shifts. Right: subperiod mean ICs for the Ridge backbone, state-only score, and geometry-gated local law. The local-law effect is strongest in higher-activation periods, especially through the balance-sheet channel

Figure 3 combines two pieces of evidence. The left panel tracks the state-specific slope shifts. The balance-sheet channel shows the largest and most persistent negative deviations, especially in the higher-activation part of the sample; the cash-flow channel is mildly positive, and the quality

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channel fluctuates around zero. The right panel shows subperiod mean ICs for Ridge, the state-only score, and the gated law. The gated law becomes most useful in the high-activation 2021-2024 subperiod, but it does not dominate in earlier periods.

This pattern supports a restrained conclusion. Geometry does appear to organize when the effective law changes and which block drives that change, especially in balance-sheet-dominated states. But these local-law shifts do not aggregate into a statistically decisive unconditional gain over the backbone. The additional state-constructor comparison sharpens the point: geometry does not dominate quantile gating mechanically for unconditional rank improvement, and its observed edge in compressing the time variation of the effective accounting law is small and not statistically decisive. In other words, the empirical role of geometry is conditional and organizational rather than universally additive.

4. Discussion

Two conclusions are worth separating. The first is predictive: a disciplined accounting backbone remains the strongest unconditional map from delayed-information pressure to subsequent cross-sectional return ranking. The second is structural: geometry enters the data more plausibly as a sparse state organizer than as a universal nonlinear enhancement. This distinction matters because the same theoretical object can play very different empirical roles. A geometric state that changes local ranking laws need not dominate a global linear benchmark in average IC to be informative. In particular, the direct comparison against quantile gating indicates that geometry's observed edge lies not in mechanical gains in average prediction, but in a slightly more interpretable state construction with marginally higher path compression; that edge is small in magnitude and not statistically decisive.

Three limitations should be explicit. First, the incremental gain over Ridge is not statistically decisive, so the paper does not establish universal nonlinear superiority. Second, the observed advantage of geometry over quantile gating in path compression is small and not statistically decisive, so claims of geometric uniqueness would be unwarranted. Third, the study holds fixed the delayed-information target and a largely linear benchmark family; richer targets and stronger nonlinear baselines remain for future work. These limits do not erase the positive result, but they bound it tightly: the present evidence supports geometry as an interpretable regime variable layered on top of a strong backbone, not as a replacement for it.

This interpretation also clarifies why the negative evidence is informative rather than discouraging. The geometry line was evaluated in nested form: block compression, peer-relative centering, state detection, and finally gated local laws. That sequence shows where structure begins to matter and where it stops earning additional complexity. In the present sample, the balance-sheet block carries the most stable state-dependent slope shifts, while the quality block contributes less consistently. Relative to quantile, k-means, and random state gates, geometry does not provide the strongest local reranking or residual-spread evidence. Its most consistent contribution is a sparse, interpretable state construction with modest path compression. Future work should therefore treat the geometry line primarily as a regime variable - potentially valuable for conditional ranking or portfolio overlay rules - rather than as a generic nonlinear score meant to replace a strong backbone everywhere.

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5. Conclusion

This paper reconstructs quarterly accounting pressure from raw statements, aligns that pressure to conservative delayed-information dates, and studies how the resulting signal maps into cross-sectional return ranking. The evidence supports a bounded conclusion. A disciplined linear backbone remains the strongest unconditional predictor in average out-of-sample ranking performance. Geometry becomes empirically relevant only after pressure is compressed into peer-relative block states and interpreted through an inactive-band mechanism, where it helps identify when local laws change and which margin drives the change, especially on the balance-sheet side.

The contribution is therefore not a claim of universal nonlinear superiority. It is, first, a transparent delayed-information design built directly from raw statements and prices and, second, a restrictive empirical test of a theory-motivated geometric state hypothesis. In this sample, geometry earns its place mainly as a sparse and interpretable organizer of conditional coefficient drift, not as a reliable replacement for a strong linear backbone. That bounded result is still useful: it narrows the plausible pressure-to-ranking map and indicates where additional model complexity begins to matter and where it does not.

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