Earnings Volatility Timing Around Macro Events

Heming Huang
Carnegie Mellon University
88 Pine St, NY
hemingh@andrew.cmu.edu

Kevin Li
Carnegie Mellon University
88 Pine St, NY
kevinl4@andrew.cmu.edu

Hansen Gan
Carnegie Mellon University
88 Pine St, NY
hgan@andrew.cmu.edu

Laurence Jin
Carnegie Mellon University
88 Pine St, NY
laurencj@andrew.cmu.edu

Abstract

Executive Summary. We examine whether the payoffs to two established cross-sectional equity signals—EPS Forecast Dispersion (FD) and Payout Yield (PY)—vary systematically around recurring earnings-season and fiscal-calendar windows, and whether such regime dependence can be exploited by a transparent timing rule. We interpret earnings seasons as information-intensity regimes in which firm-level cash-flow news and investor attention cluster, while discount-rate sensitivity and macro uncertainty can jointly reshape cross-sectional risk premia. Using monthly long–short factor return series for FD and PY from the OpenSourceAP CrossSection library over 1976–2024, we summarize unconditional performance, test for seasonal shifts in returns by conditioning on earnings-heavy month sets and applying mean-difference and distributional tests, and design a simple switching strategy that allocates to PY in "special" earnings-season months (January and April) and to to a baseline blend. In-sample results indicate that FD tends to weaken while PY strengthens in the special months, and that a calendar-conditioned allocation can improve risk-adjusted performance relative to static exposures. The main limitation is implementability: our analysis relies on pre-constructed long–short portfolio returns rather than a point-in-time security-level reconstruction with explicit universe, lag, and trading-friction assumptions. As future work, we propose a point-in-time replication from WRDS primitives to validate investability and an extension of FD from a level signal to dispersion dynamics (e.g., ΔDispersion or dispersion shocks) to better capture disagreement resolution during earnings-season information bursts.

1 Motivation and Background

Asset prices respond to new information that updates expectations about future cash flows and discount rates. In practice, information does not arrive uniformly over time. Instead, it clusters in recurring windows—most notably around earnings seasons and common fiscal year-end cycles—when a large fraction of firms release earnings, revise guidance, and trigger analyst model updates. Because these windows feature unusually high information intensity and attention, the *pricing mechanism* and the *risk premia* associated with cross-sectional signals can change in predictable ways. This project studies whether two established predictor portfolios exhibit systematic calendar dependence, and whether such seasonality can be exploited by a simple rule-based *switching* strategy.

1.1 Related literature

A first strand of work documents calendar seasonality in equity returns. Early evidence shows that average returns vary across months, including prominent month-of-year patterns [1, 2]. While much of this literature focuses on the market or size-sorted portfolios, it motivates the broader idea that the return-generating process may shift with the calendar.

A second strand links analyst disagreement and short-sale constraints to stock returns. Miller (1977) argues that when pessimistic investors face constraints on short selling, prices can reflect the beliefs of optimists, implying that disagreement can be associated with overpricing and subsequently lower returns [3]. Empirically, Diether, Malloy, and Scherbina (2002) show that dispersion in analyst earnings forecasts is related to the cross-section of stock returns, consistent with disagreement-based mechanisms [4].

A third strand emphasizes that earnings-related information can affect prices with delays. Bernard and Thomas (1989) document post-earnings-announcement drift, in which prices continue to move in the direction of earnings news after announcements, indicating that the market response to earnings information can be gradual [5]. This supports treating earnings seasons as economically meaningful information regimes rather than purely mechanical calendar markers.

A fourth strand focuses on payout policy and the measurement of shareholder distributions. Boudoukh et al. (2007) argue that total payout (dividends plus repurchases) provides a more comprehensive measure than dividends alone for asset-pricing applications [6]. In parallel, evidence on repurchases suggests that buyback-related information can be economically important for returns [7]. Longer-run shifts in payout practice, including the declining propensity to pay cash dividends, further motivate measuring payout broadly rather than focusing on dividend yield alone [8].

Finally, our empirical implementation builds on standardized open-source constructions of cross-sectional predictors and portfolio returns. Chen and Zimmermann (2022) provide data and code to replicate a large set of predictor portfolios, enabling systematic analysis of predictor behavior across regimes [9, 10].

1.2 Forecast dispersion as a disagreement/uncertainty proxy

A large literature links dispersion in analysts' earnings forecasts to differences of opinion and limits to arbitrage. Diether, Malloy, and Scherbina (2002) [4] show that dispersion contains economically meaningful information for the cross-section of stock returns, consistent with disagreement-based mispricing mechanisms. Motivated by this view, we use an earnings-forecast dispersion measure of the form

$$\text{Dispersion}_{i,t} \;=\; \frac{\text{SD}\left(\widehat{EPS}^{(k)}_{i,t}\right)}{\left|\text{Mean}\left(\widehat{EPS}^{(k)}_{i,t}\right)\right|},$$

where $\widehat{EPS}^{(k)}_{i,t}$ denotes analyst k's forecast for firm i at time t. The key economic hypothesis is that dispersion-driven predictability may *weaken* during earnings-heavy months: as firms release synchronized, high-salience information, analysts update from a more common information set and forecasts mechanically converge, compressing dispersion and reducing the effective spread between long and short legs.

1.3 Payout yield as a shareholder-distribution signal

Payout Yield measures total cash distributions to shareholders, typically defined as dividends plus net repurchases scaled by market equity. Boudoukh, Michaely, Richardson, and Roberts (2007)[6] argue that payout yield is a more comprehensive measure of firm payout policy than dividend yield alone and has important implications for empirical asset pricing. We use a canonical definition

$$\text{PayoutYield}_{i,t} \;=\; \frac{\text{Dividends}_{i,t} + \text{Repurchases}_{i,t}}{\text{MarketEquity}_{i,t}}.$$

Around earnings seasons, payout-related information (dividend changes, repurchase authorizations, and post-blackout repurchase activity) can become especially salient, potentially strengthening the signal relative to periods when payout information is less focal.

1.4 Macroeconomic Context

Our empirical "event" is calendar-defined earnings-season intensity. However, we interpret earnings season not merely as a month-of-year anomaly but as a recurring *macro-relevant regime* in which (i) firm-level cash-flow news arrives in concentrated bursts, while (ii) the market's *discount-rate channel* and aggregate risk appetite jointly determine how that cash-flow news maps into prices. In this view, earnings seasons are scheduled "information shocks" whose *price impact* is mediated by macro state variables such as real rates, inflation uncertainty, and policy uncertainty—all of which influence time-varying risk premia and the valuation of long- versus short-duration cash flows [11, 12, 13].

At a high level, equity returns can be viewed as responding to two economically distinct sources of news: updates about expected future cash flows and updates about discount rates (risk premia). Campbell and Vuolteenaho (2004) formalize this decomposition and show why these two channels carry different prices of risk in equilibrium [11]. Earnings seasons are periods when cash-flow-related information flow is mechanically dense (earnings, guidance, segment-level commentary), but the *valuation* of that information depends on the prevailing discount-rate regime. When risk premia are volatile or elevated (e.g., high macro uncertainty, tight policy, or inflation-risk concerns), the same earnings surprise can translate into a materially different price response than in a low-volatility, low-rate environment [12, 13]. This channel-based framing motivates why a calendar proxy can still be macro-relevant: the calendar pins down when information arrives, while macro conditions determine the mapping from information to returns. If the discount-rate channel dominates (e.g., during monetary-policy tightening or heightened policy uncertainty), cross-sectional premia can *rotate* even if the calendar is unchanged. Conversely, when discount-rate variation is muted and cash-flow news is more cleanly priced, predictor payoffs tied to firm-level fundamentals may look more stable.

A useful way to operationalize the discount-rate channel is through *equity duration*: the effective timing of a stock's cash flows. When discount rates rise, long-duration claims (cash flows far in the future) are mechanically hit harder than short-duration claims. Recent asset-pricing evidence shows that many major equity factors—including payout-related factors—can be understood through a duration lens: they load on near-future cash flows and earn premia consistent with compensation for near-term cash-flow risk [14]. Relatedly, monetary policy shocks provide a clean macro experiment: Chen (2022) estimates stock-duration effects around unexpected changes in the federal funds rate and shows that discount rates affect stock prices both directly and indirectly through expected cash-flow growth [15]. Most directly relevant to our "earnings-season regime" concept, Beckmeyer and Meyerhof (2025) study duration-sorted stock returns around *pre-scheduled news announcements* and show a striking state dependence: long-duration stocks earn higher returns around *macroeconomic* news, while short-duration stocks earn significantly elevated returns on *earnings announcement* days [16]. This result supports a concrete macro interpretation for our calendar conditioning: earnings seasons are periods when the market is processing firm-specific cash-flow news at scale, and the relative pricing of short- versus long-duration cash flows (itself a function of the macro discount-rate regime) can tilt the cross-sectional opportunity set.

Payout Yield (dividends plus net repurchases scaled by market equity) is naturally aligned with a short-duration "shareholder distribution" interpretation. In high-rate or high-inflation-uncertainty environments, investors often demand more compensation for long-horizon growth narratives, making near-term distributable cash flows relatively more valuable at the margin. Duration-based factor evidence reinforces this intuition: payout-related factors tilt toward firms whose cash flows arrive sooner, linking their returns to the pricing of near-future cash flows [14]. Earnings seasons can amplify this channel because firms often bundle earnings news with capital allocation communication (dividend decisions, repurchase authorizations, and balance-sheet commentary). Thus, even though our backtest does not explicitly condition on rates or inflation, the macro hypothesis is clear: *PY should be most competitive when discount-rate risk is salient and the market rewards short-duration cash-flow claims*, and earnings seasons are precisely the windows when payout policy becomes especially focal [6, 16]. This also suggests a natural extension beyond fixed "special months": interact the calendar rule with a macro state variable (e.g., real-rate level, inflation uncertainty, or policy uncertainty) to allow the strategy to switch more aggressively into PY when the macro discount-rate channel is dominant [13, 15].

Forecast Dispersion is motivated as a disagreement/uncertainty proxy [4]. Earnings seasons can weaken dispersion-based predictability through an information-mechanics channel: synchronized, high-salience disclosures lead analysts to update from a more common information set, raising *consensus* and reducing cross-sectional dispersion. Barron, Kim, Lim, and Stevens (1998) provide a structural framework linking forecast dispersion to uncertainty and consensus in analysts' information environments, clarifying how dispersion can fall when common information increases [17]. Empirically, Gallo (2017) studies earnings announcements as public signals and documents that disagreement about fundamentals can decrease even when disagreement about *price* does not necessarily fall one-for-one, consistent with the idea that fundamental uncertainty can resolve quickly around earnings [18].

From a macro lens, this dispersion-compression mechanism is likely to be strongest when the information environment is "tight"—i.e., when uncertainty is elevated and investors/analysts place high weight on scheduled disclosures to resolve priors. Macro uncertainty shocks and policy uncertainty are well documented to spike around major events and to affect investment, volatility, and risk premia [12, 19, 13]. In such states, the market's attention to earnings may rise and the speed of belief updating may increase, potentially making *changes* in dispersion (dispersion shocks) more informative than dispersion levels. This provides direct motivation for your proposed extension: shifting FD from a level-sorted signal to a *dynamic* signal such as ΔDispersion or abnormal dispersion changes, which is more tightly linked to belief updating around information arrival [17, 18].

In summary, our calendar-based event sets should be interpreted as proxies for recurring periods of *systematic information intensity* whose return implications depend on macro discount-rate and uncertainty regimes. This framing makes the seasonality tests economically meaningful under the course rubric: we are not merely testing month-of-year patterns, but rather whether two well-known cross-sectional predictors load differently on (i) cash-flow news processing during earnings seasons and (ii) macro-driven discount-rate and uncertainty conditions that vary over time [11, 12, 16]. With this macro interpretation in place, the next section defines the specific calendar regimes used in our diagnostics and the switching strategy implementation.

2 Data and Event Selection

2.1 Data sources

Our empirical inputs come from two complementary sources. First, we rely on Wharton Research Data Services (WRDS) as the underlying data platform for U.S. equity research datasets. WRDS provides centralized access to vendor databases commonly used in academic asset pricing and corporate finance, including CRSP (security-level returns and market equity), Compustat (accounting fundamentals used in payout-related measures), and I/B/E/S (analyst earnings forecasts used to compute forecast dispersion) [20, 21].

Second, we obtain reproducible predictor portfolio return series from the Open Source Asset Pricing ecosystem. Specifically, we use the OpenSourceAP `CrossSection` repository and its associated signal library (Chen and Zimmermann), which provides standardized implementations of many published predictors and their corresponding long–short portfolio returns [10, 9, 22]. This allows us to focus the project on regime dependence and trading design rather than re-implementing every signal from scratch.

2.2 Signal portfolio return data and sampling frequency

The core dataset used in this project is a wide-format CSV of monthly long–short (L/S) returns for cross-sectional predictors (in percent), `PredictorLSretWide.csv`. From this file, we extract the two signals of interest: (i) `ForecastDispersion` and (ii) `PayoutYield`. Returns are sampled at a monthly frequency (end-of-month), and all trading strategies in this paper are implemented as monthly rebalanced allocations across these two L/S portfolios. We restrict the sample to observations from December 1976 onward and evaluate performance through December 2024.

2.3 Event definition: calendar-based earnings-season regimes

The rubric defines events broadly as information shocks or release windows that can induce predictable changes in asset-price dynamics. While canonical examples are macro releases (e.g., CPI or FOMC), the rubric allows earnings-related volatility provided it is connected to broader macro forces (e.g., discount-rate policy regimes or systematic co-movement across assets). Motivated by this guidance, our events are calendar regimes that proxy for earnings-season information intensity and common fiscal cycles.

Concretely, we test two month-based event sets:

1. Fiscal-year-end (FYE) months. We define an indicator for $\{12, 1, 6, 9\}$ (December, January, June, September) to capture common fiscal year-end clustering and related reporting/board cycles.
2. Quarterly reporting-peak months. We define an indicator for months typically associated with peak earnings-season flow for Q1–Q4 reporting, e.g., $\{4, 7, 10, 1\}$ (April, July, October, January).

A key hypothesis is that the efficacy of the two predictors varies around concentrated information periods associated with fiscal-year ends and earnings-season peaks. Figure 1 summarizes the fiscal-year-end (FYE) month distribution by region, highlighting that year-end clustering is substantial (particularly December).

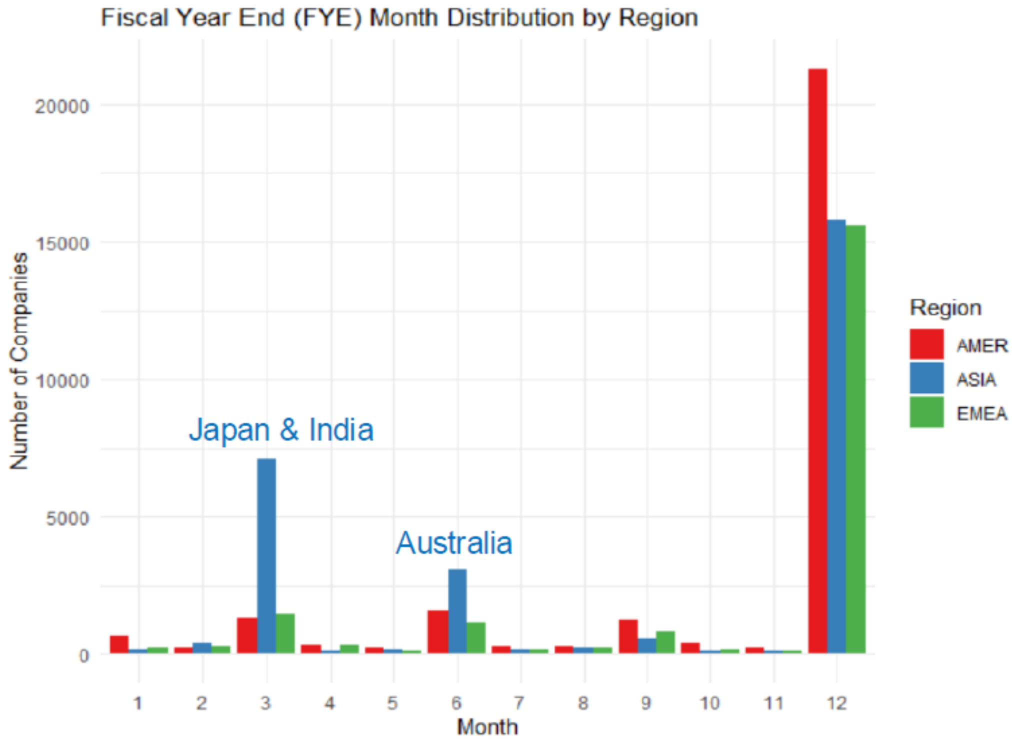

Figure 1: Fiscal year-end month distribution by region.

Figures 2 shows monthly return distributions by calendar month (training sample). The distributions suggest that performance differs materially across months and motivates formal hypothesis testing and conditional portfolio rules. These definitions map the empirical question to a clean event-study style comparison: conditional L/S return distributions in event months versus the remaining months.

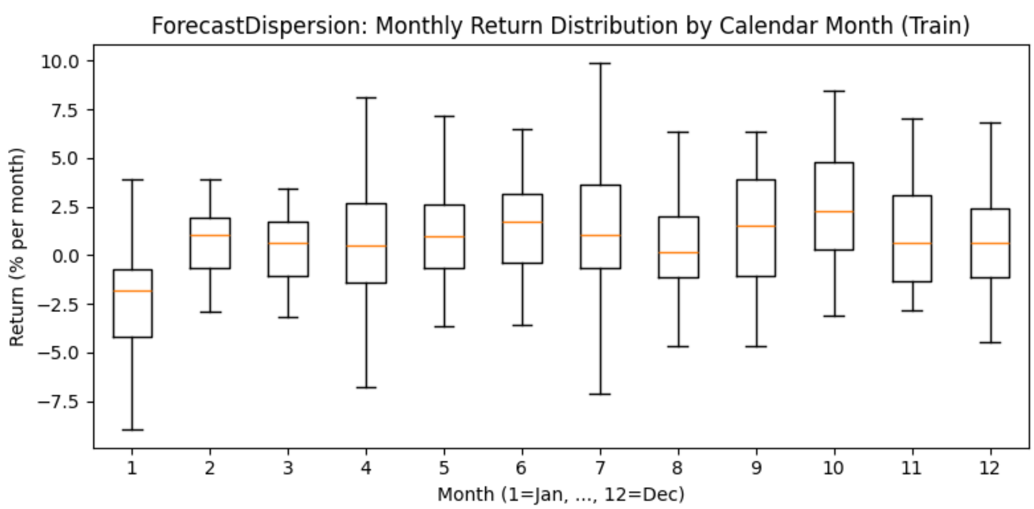

Figure 2: Forecast Dispersion: monthly return distribution by calendar month (training sample).

2.4 Final special-month selection and trading frequency

In the training sample, we compare the conditional return distributions using parametric (Welch) and nonparametric (Mann–Whitney and Kolmogorov–Smirnov) tests. Based on the strongest and most consistent training-sample evidence, the final trading specification treats January and April as special months. The switching rule is:

Use `PayoutYield` in January and April; use `ForecastDispersion` in all other months.

Because the underlying data are monthly, both the event indicators and the trading strategy operate at a monthly horizon, with portfolio selection and rebalancing at month-end.

3 Forward-Looking Discussion

The empirical results in this project are historical. Even if the seasonal patterns we document are statistically meaningful in sample, there is no guarantee they will persist. This section discusses why the return dynamics of Forecast Dispersion and Payout Yield may change going forward, which regimes are most relevant, and how an investor should monitor (and potentially retire) the switching rule.

3.1 Why the past may not repeat

Three broad forces can break a calendar-based effect.

First, the economic environment can shift. Discount-rate dynamics (e.g., inflation and monetary-policy uncertainty) alter how investors price cash-flow news versus risk premia. A high-rate or high-volatility regime can change both the magnitude and sign of factor payoffs, potentially overwhelming any month-of-year pattern. In such environments, an earnings-season month may be dominated by macro shocks rather than firm-level information, reducing the stability of seasonality.

Second, market structure and information processing evolve. Earnings information is disseminated faster today via algorithmic news analytics, alternative data, and tighter analyst guidance loops. If disagreement resolves more quickly, the dispersion signal may compress earlier than it did historically, shifting the timing of any underperformance away from the specific calendar months we label as "special." Conversely, if the signal increasingly reflects persistent uncertainty (e.g., for intangible-heavy firms), its seasonal compression may weaken.

Third, institutional behavior and corporate policy change. Payout Yield depends on dividends and repurchases, which are influenced by regulation, buyback practices (including blackout conventions around earnings), and shifts in corporate capital allocation. If firms structurally alter payout behavior (for example, repurchases becoming less procyclical or more tightly constrained), then the conditional outperformance of Payout Yield in earnings-heavy windows may diminish relative to the historical sample [6].

3.2 Regime dependence for the switching rule

The switching rule is motivated by two mechanisms: (i) forecast disagreement tends to compress around synchronized information arrivals, reducing the effective spread in dispersion-sorted portfolios [4]; and (ii) payout information may be especially salient when firms communicate results and capital-allocation plans, potentially increasing the pricing relevance of shareholder distributions [6]. Both mechanisms are plausibly regime dependent.

We highlight three regimes in which performance could differ:

1. High-volatility or policy-shock regimes. When macro news dominates, cross-sectional predictor returns can become noisier and more correlated, which can reduce the incremental benefit of switching months.
2. Earnings-cycle concentration regimes. If earnings seasons become more "front-loaded" or "stretched" (due to reporting delays, sector concentration, or changes in guidance cadence), then a fixed month set (e.g., January and April) may no longer align with peak information intensity.
3. Buyback/financing regime shifts. If repurchases become structurally less informative (or more mechanically constrained), the Payout Yield leg may lose its edge in the months where it historically performed best.

3.3 Model risk and monitoring plan

Because the switching rule selects a small subset of months, it is exposed to selection risk and structural breaks. To make the approach investable, one should treat the calendar rule as a hypothesis that must be continuously re-validated rather than a permanent law. Practical monitoring steps include:

1. Rolling-window diagnostics: re-estimate the performance gap between special months and other months using a fixed-length rolling window (e.g., 10 or 15 years) and track whether the sign and magnitude remain stable.

2. Stability under alternative month sets: verify that results are not driven by a single outlier month or a small number of extreme observations by repeating the analysis on nearby month definitions (e.g., adding March/May) and checking robustness.
3. Cost and capacity sensitivity: because monthly switching can induce turnover, re-evaluate whether realistic trading costs eliminate the incremental gain from switching.
4. Kill-switch criteria: pre-specify conditions under which the strategy is paused (e.g., rolling Sharpe below zero for K years, or persistent underperformance in special months relative to the baseline factor portfolio).

3.4 Implications for extensions

A natural extension is to replace the fixed calendar indicator with a forward-looking measure of earnings-season intensity, such as the fraction of market capitalization scheduled to report in the next month or an aggregate earnings-announcement count. This would preserve the original intuition while reducing reliance on a static month set. Another extension is to combine the two signals with a continuous allocation rule (e.g., volatility targeting or a simple meta-model) rather than a hard switch, which can reduce sensitivity to small-sample seasonal effects. Finally, the OpenSourceAP framework enables testing the same regime-switching concept across a wider set of predictors to evaluate whether calendar conditioning is a general phenomenon or specific to these two signals [9].

4 Trading Strategy Design

This section translates the seasonality hypothesis into an implementable trading rule. The building blocks are two monthly long–short factor portfolio return series: Forecast Dispersion and Payout Yield, taken from the standardized cross-sectional signal library in OpenSourceAP [10, 9]. Conceptually, Forecast Dispersion proxies for disagreement/uncertainty [4], while Payout Yield captures shareholder distribution policy [6]. Our strategy allocates between these two long–short portfolios as a function of the calendar month.

4.1 Tradable objects and trading horizon

The strategy is implemented at a monthly frequency using factor long–short (L/S) portfolio returns. Each underlying L/S portfolio is dollar neutral by construction (long high-signal stocks, short low-signal stocks), and is intended to be approximately market neutral at the portfolio level (subject to the construction methodology in the source library). Because the inputs are monthly returns, trading decisions occur at month-end and positions are held for one month.

Although our backtest operates on factor return series (research portfolios), the intended real-world implementation would be via a replicated long–short equity book following the same sorting and weighting rules, subject to liquidity and cost constraints. In this project, the focus is on whether a regime-dependent allocation across the two signals improves risk-adjusted performance relative to holding either signal continuously.

4.2 Signal selection rule

Define $m_t \in \{1, \ldots, 12\}$ as the calendar month corresponding to month t. Let r_t^{FD} denote the month-t L/S return of Forecast Dispersion and r_t^{PY} denote the month-t L/S return of Payout Yield. Let $\mathcal{S}$ denote the set of special months that proxy for earnings-season intensity. Based on the training-sample evidence, we set

$$\mathcal{S} = \{1, 4\},$$

corresponding to January and April.

The switching strategy holds Payout Yield in special months and Forecast Dispersion otherwise:

$$r_t^{SW} = \begin{cases} r_t^{PY}, & \text{if } m_t \in \mathcal{S}, \\ r_t^{FD}, & \text{if } m_t \notin \mathcal{S}. \end{cases}$$

Equivalently, define weights

$$w_t^{PY} = \mathbb{1}\{m_t \in \mathcal{S}\}, \qquad w_t^{FD} = 1 - w_t^{PY},$$

so that the strategy return is $r_t^{SW} = w_t^{PY} r_t^{PY} + w_t^{FD} r_t^{FD}$.

4.3 Portfolio construction and exposure controls

The baseline design is a full-switch allocation: each month the strategy assigns 100% of capital to exactly one L/S portfolio return stream (either Payout Yield or Forecast Dispersion). This is attractive for interpretability and aligns directly with the regime story (payout information is most salient in special months; disagreement effects compress in special months).

To improve robustness and reduce sensitivity to month classification, a smoothed variant can be used:

$$r_t^{SM} = \alpha\, r_t^{PY} + (1-\alpha)\, r_t^{FD},$$

with α increased in special months (e.g., $\alpha = \alpha_H$ for $m_t \in \mathcal{S}$ and $\alpha = \alpha_L$ otherwise), where $\alpha_H > \alpha_L$. This reduces turnover relative to a hard switch and can mitigate overfitting.

Because the underlying portfolios are long–short, exposure management focuses on:

1. leverage and volatility: optionally scale returns to a constant target volatility using an ex-ante estimate (e.g., rolling K-month realized volatility),
$$\tilde{r}_t = \frac{\sigma^\star}{\hat{\sigma}_{t-1}} r_t,$$
where $\sigma^\star$ is the target (annualized) volatility and $\hat{\sigma}_{t-1}$ is a lagged estimate to avoid look-ahead bias;
2. concentration limits: in a live replication, impose max weights per name/sector within the long and short books to avoid undue idiosyncratic risk;
3. beta neutrality: if needed, hedge residual market beta using an index future or ETF overlay estimated from historical regressions on market returns.

4.4 Benchmarks

We benchmark the switching strategy against holding each signal continuously (always Forecast Dispersion; always Payout Yield) and against a simple static combination (e.g., 50/50 blend). The central question is whether calendar-conditioned allocation improves risk-adjusted performance out of sample, rather than merely fitting the in-sample seasonality.

5 Simulation and Performance

5.1 Backtest setup and evaluation metrics

We evaluate long–short (L/S) monthly signal returns for two anomaly predictors: Forecast Dispersion (FD) and Payout Yield (PY). The signal return series is the L/S return (in percent per month) provided by the Open Asset Pricing signal library, and we treat it as the strategy return for a unit-notional L/S portfolio.

To reduce the risk of overfitting when selecting seasonal conditioning rules, we split the sample into an in-sample (training) period from 1976-12 to 2014-12 and an out-of-sample (testing) period from 2015-01 to 2024-12.

Performance is summarized using:

- mean and standard deviation of monthly returns;
- annualized mean and volatility (scaled by 12 and $\sqrt{12}$, respectively);
- annualized Sharpe ratio (no cash rate adjustment, consistent with L/S signal returns);
- maximum drawdown (computed on the cumulative equity curve).

5.2 Baseline signal performance

Figure 3 plots cumulative log returns of the two raw signals in the training period. FD exhibits a stronger long-run drift than PY in-sample, motivating the use of FD as the default exposure outside of the targeted “special” months.

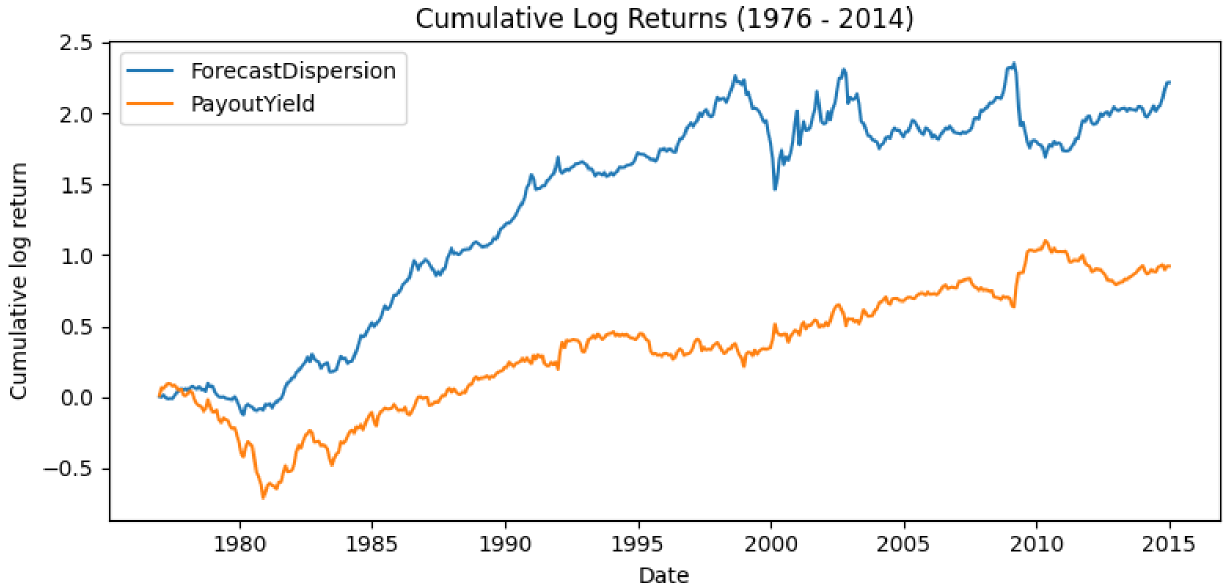

Figure 3: Cumulative log returns of Forecast Dispersion and Payout Yield signal L/S returns in the training sample (1976–2014).

Table 1 reports full-sample summary statistics for each signal. Both signals have positive average returns, with FD exhibiting higher volatility and a higher Sharpe relative to PY.

Table 1: Signal summary statistics (monthly L/S returns, percent).

Signal	N	Mean	Std	t-stat	Ann. Mean	Ann. Vol
Forecast Dispersion	587	0.547	4.128	3.210	6.564	14.300
Payout Yield	858	0.263	3.034	2.536	3.153	10.511

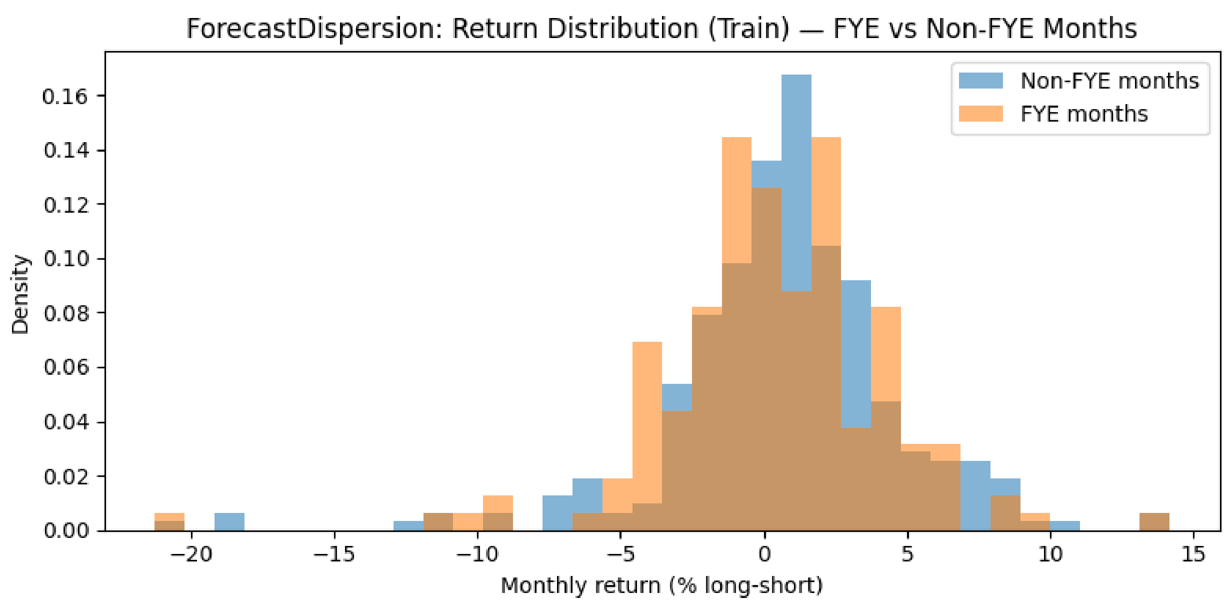

Figure 4: Payout Yield: monthly return distribution by calendar month (training sample).

Finally, Figures 5 and 6 compare the training-period return distributions in FYE months (Jan/Jun/Sep/Dec) versus non-FYE months. These plots serve as distributional diagnostics for whether earnings-heavy windows are associated with a shift in the signal return generating process.

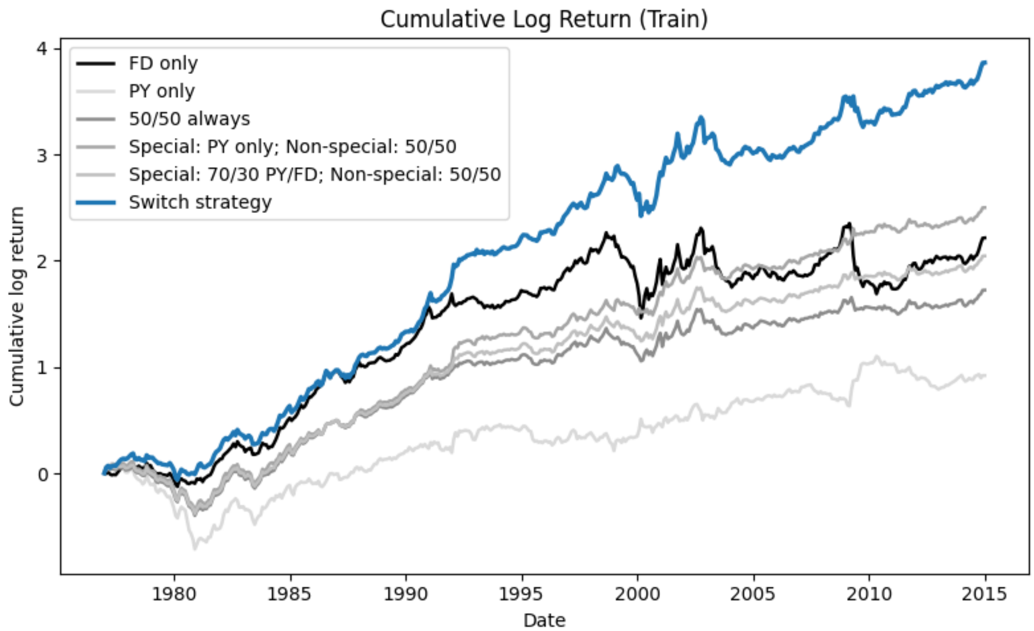

Figure 5: Forecast Dispersion: return distribution in FYE vs non-FYE months (training sample).

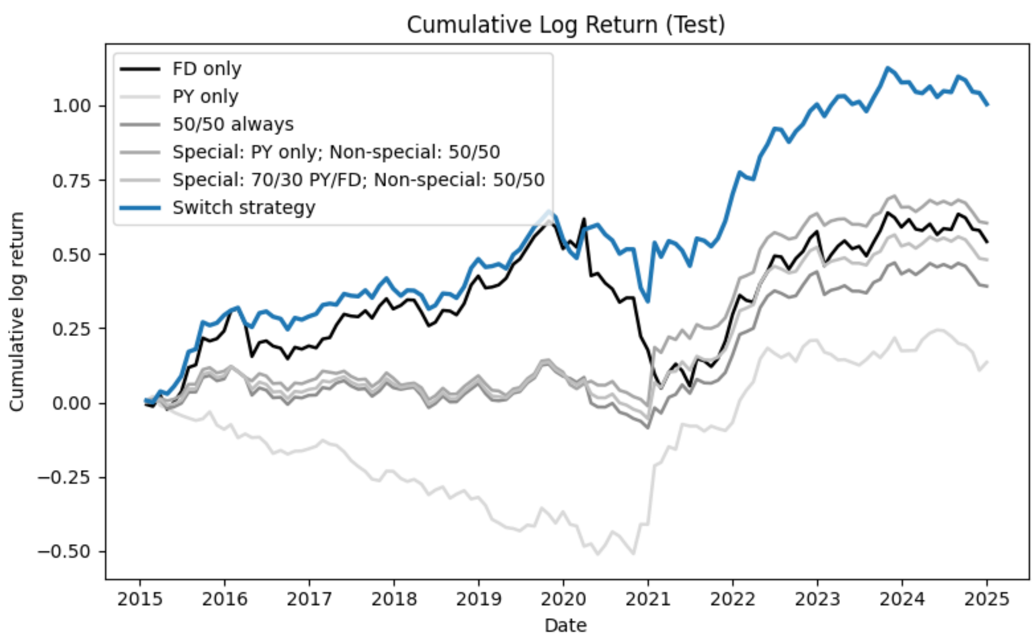

Figure 6: Payout Yield: return distribution in FYE vs non-FYE months (training sample).

5.3 Strategy simulation results

Based on the in-sample seasonality analysis, we designate January and April as the "special" months. We then simulate several simple allocation rules that blend FD and PY depending on whether t is a special month. Let r_t^{FD} and r_t^{PY} denote the monthly L/S returns (in percent) of the two signals. The strategy return is

$$r_t^{strat} = w_t^{FD} r_t^{FD} + w_t^{PY} r_t^{PY}, \qquad w_t^{FD} + w_t^{PY} = 1.$$

We consider the following benchmark strategies:

- FD only: $(w_t^{PY}, w_t^{FD}) = (0, 1)$.
- PY only: $(w_t^{PY}, w_t^{FD}) = (1, 0)$.
- 50/50 always: $(w_t^{PY}, w_t^{FD}) = (0.5, 0.5)$.
- Special: PY only; Non-special: 50/50: $w_t^{PY} = 1$ in special months, else 0.5.
- Special: 70/30 PY/FD; Non-special: 50/50: $w_t^{PY} = 0.7$ in special months, else 0.5.
- Switch strategy: PY only in special months and FD only otherwise.

Table 2 reports the in-sample performance for the strategies that appear in the exported notebook output. The conditional strategy "Special: PY only; Non-special: 50/50" improves the in-sample Sharpe relative to static allocations while keeping drawdowns comparable to the 50/50 baseline.

Table 2: Training-sample strategy performance (1976-12 to 2014-12)

Strategy	CAGR	AnnVol	Sharpe	MaxDD
FD only	5.989	14.121	0.486	-55.211
PY only	2.450	10.595	0.281	-55.380
50/50 always	4.632	8.717	0.564	-36.320
Special: PY only; Non-special: 50/50	6.784	9.230	0.759	-37.153
Special: 70/30 PY/FD; Non-special: 50/50	5.517	8.602	0.669	-36.631
Switch strategy	**10.673**	**12.949**	**0.852**	**-37.615**

The out-of-sample (2015–2024) table shows similar outperformance from our regime shifting strategy.

Table 3: Out-of-sample strategy performance (2015-01 to 2024-12)

Strategy	CAGR	AnnVol	Sharpe	MaxDD
FD only	5.563	15.363	0.431	-43.473
PY only	1.364	12.191	0.169	-41.244
50/50 always	3.990	9.202	0.471	-19.353
Special: PY only; Non-special: 50/50	6.226	10.603	0.621	-14.370
Special: 70/30 PY/FD; Non-special: 50/50	4.922	9.308	0.562	-17.294
Switch strategy	**10.565**	**14.560**	**0.763**	**-26.174**

6 Conclusion

6.1 Summary of findings and economic interpretation

This project evaluates whether the efficacy of two established cross-sectional equity predictors—Forecast Dispersion (FD) and Payout Yield (PY)—varies systematically with the fiscal calendar and earnings-season intensity. Using monthly long–short return series from the Open Source Asset Pricing `CrossSection` library (Chen and Zimmermann, 2022) and WRDS-based dataset foundations (CRSP/Compustat/I/B/E/S access via WRDS), we document that the return distributions of both predictors are not calendar-invariant and that "earnings-heavy" month sets exhibit distinct behavior relative to the rest of the year [9, 10, 20, 21].

The main empirical takeaway is consistent with the regime-switching hypothesis: FD tends to deliver stronger long-run performance as a baseline exposure, while PY becomes relatively more attractive in selected months that proxy for concentrated information arrival and heightened salience of capital-allocation decisions. This pattern aligns with two broad mechanisms emphasized in the literature. First, FD relates to disagreement and limits to arbitrage, where dispersion in analyst forecasts proxies for differences of opinion and associated mispricing channels [3, 4]. Second, PY reflects shareholder distributions (dividends and repurchases), which can become particularly informative when firms communicate results, guidance, and payout intentions around reporting cycles [6]. Viewed through this lens, the proposed calendar-conditioned switching rule (PY in January and April; FD otherwise) is a simple implementation of the idea that the return-generating process for cross-sectional signals can shift with recurring information regimes. A key contribution of the project is not the invention of new predictors, but the demonstration that even well-known signals can exhibit predictable seasonality in their long–short payoffs. In other words, the work shifts emphasis from "which signal is best on average?" to "when is a given signal most reliable?" This perspective is consistent with the broader empirical asset-pricing view that anomalies can be regime dependent, and that predictable variation in information flow (such as earnings-season clustering) can alter both the speed of information incorporation and the pricing of risk premia [5, 4]. At the same time, the project is intentionally narrow in scope: we focus on a small set of months and two signals, and we evaluate a rule-based switching mechanism rather than a fully continuous allocation model. This design makes the economic story transparent and the backtest interpretable, but it increases sensitivity to sample selection and structural change.

6.2 Limitations I: data construction, point-in-time (PiT) realism, and investability

Beyond generic model risk, the most important limitation is *data and implementability risk*. Our empirical exercise directly uses the long–short factor return series provided by the OpenSourceAP signal library rather than reconstructing the underlying long and short portfolios ourselves from raw CRSP/Compustat/I/B/E/S data [9, 10]. While this design is appropriate for testing a research hypothesis (calendar dependence of signal returns), it creates an implementation gap that matters for an investor-facing prospectus.

Concretely, there are two major issues. **(i) Point-in-time availability and timing conventions.** A live strategy requires strict PiT alignment of signal inputs (fundamentals, repurchases, dividends, and analyst forecasts), including explicit information lags and vendor update conventions. Using pre-constructed long–short returns reduces transparency over the precise timing assumptions embedded in the signal formation and portfolio rebalancing pipeline. Even small timing differences can materially change measured performance for signals tied to analyst updates or corporate actions, especially around earnings seasons when information arrival is clustered [4, 6]. **(ii) Universe definition and replicability.** A research factor series is not identical to a tradable strategy. The effective investment universe may include securities that are difficult to short, illiquid, capacity constrained, or subject to time-varying coverage (e.g., entry/exit and survivorship considerations). A practical replication must specify liquid universe screens, exclusion rules, and portfolio constraints (name/sector caps, borrow availability), and then re-evaluate whether the seasonal switching premium survives under those constraints.

These limitations imply that our backtest should be interpreted as *evidence about predictability and regime dependence*, not as a final investable product. The most direct improvement is a "clean-room" replication from WRDS: rebuild FD and PY signals with explicit PiT lags, define a liquid and borrow-feasible universe, and produce net-of-cost performance under transparent portfolio-construction rules.

6.3 Future improvements I: modeling analyst disagreement using Δ-dispersion

A particularly natural extension is to improve the measurement of the disagreement channel by shifting emphasis from the *level* of dispersion to the *change* in dispersion. Conceptually, earnings seasons are periods when information arrives and analysts update. The economically relevant object may therefore be the *resolution (or expansion) of disagreement*, rather than the absolute degree of disagreement at a point in time.

One simple implementation is:

$$\Delta\mathrm{Disp}_{i,t} = \mathrm{Disp}_{i,t} - \mathrm{Disp}_{i,t-1},$$

and the associated cross-sectional trading signal could sort firms on $\Delta\mathrm{Disp}_{i,t}$ each month, forming a long–short portfolio based on large dispersion compressions versus large dispersion expansions. A more robust approach is to define a dispersion "shock" by standardizing changes:

$$\mathrm{Shock}_{i,t} = \frac{\Delta\mathrm{Disp}_{i,t} - \mu(\Delta\mathrm{Disp}_{i,t-12:t-1})}{\sigma(\Delta\mathrm{Disp}_{i,t-12:t-1})},$$

so that the strategy targets *unexpected* disagreement resolution relative to each firm's recent history.

This extension is appealing for three reasons. First, it matches the economic narrative: synchronized information arrivals should mechanically compress disagreement for some firms, and the *magnitude* of that compression may be priced [4]. Second, it may reduce the extent to which the signal is driven by persistent firm types (e.g., structurally high-dispersion firms), improving identification. Third, it naturally integrates with the regime-switching theme: the predictive power of Δ-dispersion can be tested directly in earnings-heavy months versus other months, and potentially across macro regimes (e.g., high-rate or high-volatility periods) where the speed of information diffusion and risk appetite differ.

Operationally, implementing Δ-dispersion requires a fully PiT pipeline for analyst forecasts (I/B/E/S) and careful attention to forecast definition (e.g., horizon, fiscal period, and aggregation across analysts). This strengthens the motivation for the "clean-room" WRDS rebuild described above.

6.4 Future improvements II: modeling earnings season with weighted averages

A second extension is to replace the hard-coded month set with an *earnings-season intensity* proxy—for example, the fraction of market capitalization scheduled to report, the count of earnings announcements, or an aggregate measure of forecast revision activity. While our current approach uses the calendar as a simple regime proxy, an intensity-based measure would align more closely with the economic object of interest (information arrival) and could reduce dependence on a static month definition. This would also help address the structural-break concern: if earnings seasons shift or become more dispersed over time, an intensity proxy can adapt without re-tuning month sets.

Overall, the results support the broader idea that calendar-linked information regimes can be a useful organizing principle for factor timing. However, translating that idea into an investable strategy requires two next steps: (1) a fully transparent, point-in-time reconstruction of the underlying long and short books with explicit universe and friction assumptions; and (2) richer measurement of the disagreement channel using dynamic objects such as Δ-dispersion rather than relying only on the dispersion level [4, 9, 6]. If these improvements preserve the core switching premium out of sample, the strategy would move from an academically motivated regime test toward a robust, implementable long–short allocation framework.

References

[1] Michael S. Rozeff and William R. Kinney. Capital market seasonality: The case of stock returns. *Journal of Financial Economics*, 3(4):379–402, 1976.

[2] Donald B. Keim. Size-related anomalies and stock return seasonality: Further empirical evidence. *Journal of Financial Economics*, 12(1):13–32, 1983.

[3] Edward M. Miller. Risk, uncertainty, and divergence of opinion. *The Journal of Finance*, 32(4):1151–1168, 1977.

[4] Karl B. Diether, Christopher J. Malloy, and Anna Scherbina. Differences of opinion and the cross section of stock returns. *The Journal of Finance*, 57(5):2113–2141, October 2002.

[5] Victor L. Bernard and Jacob K. Thomas. Post-earnings-announcement drift: Delayed price response or risk premium? *Journal of Accounting Research*, 27:1–36, 1989. Supplement.

[6] Jacob Boudoukh, Roni Michaely, Matthew Richardson, and Michael R. Roberts. On the importance of measuring payout yield: Implications for empirical asset pricing. *The Journal of Finance*, 62(2):877–915, April 2007.

[7] David L. Ikenberry, Josef Lakonishok, and Theo Vermaelen. Market underreaction to open market share repurchases. *Journal of Financial Economics*, 39(2–3):181–208, 1995.

[8] Eugene F. Fama and Kenneth R. French. Disappearing dividends: Changing firm characteristics or lower propensity to pay? *Journal of Financial Economics*, 60(1):3–43, 2001.

[9] Andrew Y. Chen and Tom Zimmermann. Open source cross-sectional asset pricing. *Critical Finance Review*, 11(2):207–264, 2022.

[10] OpenSourceAP. Crosssection: Code and data accompanying "open source cross-sectional asset pricing". `https://github.com/OpenSourceAP/CrossSection`. Accessed: 2025-12-13.

[11] John Y. Campbell and Tuomo Vuolteenaho. Bad beta, good beta. *American Economic Review*, 94(5):1249–1275, 2004.

[12] Nicholas Bloom. The impact of uncertainty shocks. *Econometrica*, 77(3):623–685, 2009.

[13] Scott R. Baker, Nicholas Bloom, and Steven J. Davis. Measuring economic policy uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636, 2016.

[14] Niels Joachim Gormsen and Eben Lazarus. Duration-driven returns. *The Journal of Finance*, 78(3):1393–1447, 2023.

[15] Zhanhui Chen. Inferring stock duration around fomc surprises: Estimates and implications. *Journal of Financial and Quantitative Analysis*, 57(2):669–703, 2022.

[16] Heiner Beckmeyer and Paul Meyerhof. The short-duration premium and news announcements. *Journal of Banking & Finance*, 176:107445, 2025.

[17] Orie E. Barron, Oliver Kim, Steve C. Lim, and Douglas E. Stevens. Using analysts' forecasts to measure properties of analysts' information environment. *The Accounting Review*, 73(4):421–433, 1998.

[18] Lindsey A. Gallo. The more we know about fundamentals, the less we agree on the price: Evidence from earnings announcements. Available at SSRN, 2017.

[19] Nicholas Bloom. Fluctuations in uncertainty. *Journal of Economic Perspectives*, 28(2):153–176, 2014.

[20] Wharton Research Data Services (WRDS). Wrds platform overview. `https://wrds-www.wharton.upenn.edu/`. Accessed: 2025-12-13.

[21] Wharton Research Data Services (WRDS). Center for research in security prices (crsp) – wrds vendor page. `https://wrds-www.wharton.upenn.edu/pages/about/data-vendors/center-for-research-in-security-prices-crsp/`. Accessed: 2025-12-13.

[22] Open Asset Pricing. Project code (links to opensourceap/crosssection). `https://www.openassetpricing.com/code/`. Accessed: 2025-12-13.