# Algorithmic Trading and Information Dynamics Around Unscheduled Corporate Events

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**Abstract**

Prior work establishes that algorithmic trading (AT) deters information acquisition around scheduled events, but whether this extends to unscheduled corporate events is unknown. Using a sample of unexpected special dividend announcements, we find that abnormal AT activity (measured as deviations from firm-specific baselines) widens pre-announcement informational gaps. To measure the informational asymmetries, we develop a standardized price jump measure which allows us to preserve over 50% of observations that would be discarded using prior price jump approaches. Our findings indicate that aggregate AT activity declines for approximately 20 trading days following special dividend announcements, persisting longer than that observed around regular dividend benchmarks. This withdrawal pattern suggests that AT strategies profit from information asymmetry rather than information processing; when information asymmetries are publicly resolved, AT activity appears to decline.

**JEL Codes:** G10, G14

**Keywords:** Algorithmic Trading, Corporate Announcements, Price Jump, Event Study, Special Dividends, Abnormal Returns

# 1 Introduction

Technological advancements continuously introduce new dynamics into the trading process in financial markets. For example, algorithmic trading (AT) has transformed market dynamics by influencing liquidity, volatility, and price discovery. Although some studies argue that AT enhances market efficiency by accelerating the impounding of available information into prices (Brogaard et al., 2014), others suggest that it may deter information acquisition by diminishing the incentives for informed traders to produce new information (Korajczyk and Murphy, 2019; Yang and Zhu, 2020). The dual role of AT, facilitating rapid price adjustment to readily available information while potentially stifling the acquisition of new information (Weller, 2018), raises questions about its broader impact on market dynamics.

How AT affects the price discovery process surrounding corporate signals remains an open question. Signaling theory predicts that informed agents use costly signals to transmit private information to the market when the benefits exceed the costs (Akerlof, 1978; Spence, 1973; Ross, 1977). Dividends are a natural example of such a signal. Firms may pay dividends to bind managers and reduce the cash flow available for wasteful spending, thus providing information to the market (Easterbrook, 1984; Jensen, 1986). Alternatively, firms may pay dividends to signal managers' private information regarding firms' future earnings (Bhattacharya, 1979; John and Williams, 1985; Miller, 1985). Regardless of the reason for the dividend signal, dividends are costly as they are double taxed and reduce available investment opportunities for firms.

To explore the intersection of AT and corporate signaling events, we investigate the information dynamics surrounding special dividends. Special dividends are unscheduled and should be unexpected, as opposed to earnings announcements or regular dividend payments which occur on a fixed schedule. Other unexpected corporate events may have a more ambiguous signal such as a merger or acquisition. Announcement returns from mergers and acquisitions contain information about the bidder, the target, and the deal (Fuller et al., 2002). Our empirical framework requires an unexpected corporate signal that has an unambiguous expected return such that informed traders will desire to generate private information and trade on this information.[1] Previous research consistently finds that special dividends are a valuable unexpected corporate signal as they are typically associated with a positive market reaction (Howe et al., 1992; Jayaraman and Shastri, 1988). By observing AT activity around special dividends, we gain insight into how AT can detect informed trading activity (and potentially deter it), devoid of any calendar-based strategies.

We leverage the empirical framework of Weller (2018) to determine if AT is related to pre-announcement information acquisition and extend it to test if AT increases the speed at which prices reflect the information disseminated by a special dividend announcement. Weller (2018) develops a price jump measure that reflects information incorporation into stock prices before an earnings announcement. This measure can produce uninformative values when returns in the pre- and post-announcement windows are similar in magnitude but opposite in sign (reversals) and Weller (2018) truncates the sample to exclude these observations. Our measure can accommodate all return patterns, retaining 50% more observations than we would retain under Weller's truncation. We show these observations are statistically different from the retained sample, characterized by higher volatility, higher volume, tighter spreads, and larger announcement returns. The standardized price jump is a tool that researchers may use for studying return dynamics around any corporate event.[2]

Using a sample of 865 unexpected special dividends announced between 2012 and 2024 and four proxies for AT using data from SEC MIDAS, we find AT is positively associated with the standardized price jump at the announcement of an unexpected special dividend. This finding implies that AT in

[1] An expected return direction is required for our setting. We leverage the tension between informed trader activity in the pre-event window and the market response in the contemporaneous event window. There needs to be an information asymmetry which is resolved for us to measure the proportion of information that was acquired and incorporated by informed traders. If the corporate signal is ambiguous and does not resolve an asymmetry, we would be measuring aggregate speculation activity as opposed to informed trading activity.

[2] The unstandardized price jump measure while relatively new has been used in top finance and accounting journals, and we hope that researchers will elect to use our measure to improve estimation accuracy and retain a larger sample of observations (McClure et al., 2025; Brogaard and Pan, 2022).

the pre-announcement window of an unexpected special dividend can deter traders from acquiring private information on a firm pre-announcement. While this is consistent with the findings of Weller (2018), our setting critically removes any calendar-based timing strategies. Our findings are stable across industry and year fixed effects specifications and robust to placebo tests, permutation tests, bootstrapped standard errors, and alternative baseline AT windows. A crucial component to our analysis is that there must be an information asymmetry resolved by the special dividend. We motivate this notion by providing evidence of an information gap in the pre-announcement window, as hidden trading levels are higher in the pre-announcement window and significantly higher on the days directly preceding the announcement.

The literature has found that AT can be beneficial for markets as it is associated with incorporating information into prices (Brogaard et al., 2014). Our paper corroborates this with the finding that AT increases the immediate incorporation of information following a special dividend announcement. Despite this positive attribute of AT activity, we find that AT activity sharply declines following the announcement of a special dividend. To benchmark this finding, we compare the decline in AT activity to regular dividend increases, and find the decline is stronger and more persistent around special dividends as opposed to regular increases. Since AT is found to detect informed trading activity (Weller, 2018) and erode the economic rents of the informed traders, AT profits from an information asymmetry. A possible mechanism for the decline in AT when a special dividend is announced is that once the information gap is tightened by the dissemination of the signal, this eliminates any asymmetry and may deter AT activity.

Although special dividends are infrequent, they are well-suited to our setting: they are one of the few truly unexpected corporate events, they remain large in size (consistently 5 to 10 times larger than regular dividends (Figure 1, Panel B)), and they are associated with large positive abnormal returns. The market reaction is strongest in firms that are not regular-dividend payers, consistent with the signal being more valuable for firms that are more opaque.

The remainder of this paper is organized as follows. Section 2 reviews the related literature. Section 3 describes our data. Section 4 develops our hypotheses and describes our empirical methodology. Section 5 presents our results. Section 6 discusses robustness tests. Section 7 concludes.

# 2 Related Literature

## 2.1 Dividend Signaling

Lintner (1956) lays the foundation for the dividend signaling literature with his observation that firms are reluctant to cut dividends and only gradually increase dividends if firms believe they can sustain the dividends. Miller and Modigliani (1961) argue dividend irrelevance yet concede that with irrational participants in the market, dividends may act as a signal of higher future earnings from the firm. Bhattacharya (1979) models how tax rate differences between dividends and capital gains can generate investor preferences and shows that dividends serve as a costly but credible signal of future cash flows. Miller (1985) demonstrates that dividends are a costly signal as dividends reduce the firms' internal financing (slack). Alternatively, Easterbrook (1984) suggests that paying dividends reduces informational asymmetries and agency costs. Jensen (1986) also hypothesizes that managers pay dividends to reduce their free cash and align managers' and shareholders' interests. Our analysis is agnostic about the specific information being signaled (increased future earnings or reduction of free cash) as what matters is that dividends contain information that is a valuable signal to the market.

Empirically, Allen and Michaely (2003) note that despite the absence of a clear consensus on whether dividends signal future earnings or a reduction of free cash, there is information content in dividends. Sant and Cowan (1994) find that following dividend omissions, firms' future earnings become more unpredictable. Fuller and Goldstein (2011) present evidence that dividend-paying stocks outperform non-dividend paying stocks in declining markets, demonstrating that dividend payments provide investors with information.

Fuller (2003) finds that informed traders possess private information about the firm before it is publicly conveyed through the signal. Therefore, in the presence of more informed traders the reaction to a dividend will be less pronounced as the information is already incorporated leading up to the announcement despite the announcement itself being unknown. In our study we examine whether in the presence of higher AT, informed traders are unable to extract economic rents from their private information. Without economic incentives, traders are not enticed to pursue private information and this reduction in informed trading leading up to the special dividend announcement would cause a greater market reaction to the announcement as information is not incorporated into the price.

## 2.2 Special Dividends

Special dividends are unexpected one-time payments that firms make to shareholders. DeAngelo et al. (2000) examine special dividends announced between 1926 and 1995 to find that special dividends were once commonplace but have become more infrequent, and the occurrence of large special dividends has increased. Special dividends are associated with positive market reactions ranging from 1.85% to 3.44% cumulative abnormal returns (Brickley, 1983; Jayaraman and Shastri, 1988; Howe et al., 1992; Gombola and Liu, 1999; Lie, 2000). Jayaraman and Shastri (1988) find that recurring special dividends command a lower market reaction than non-recurring. Lie (2000) finds that firms which declare a special dividend have accumulated excess funds but generate fewer funds ex-post. The literature reaches a consensus that special dividends provide a sufficient informational shock. We contribute to the special dividend literature by investigating the impact of AT on the information dynamics of the signal originating from the special dividend, and whether insiders or sophisticated traders influence the return dynamics surrounding the unexpected announcements.

### 2.3 Algorithmic Trading

AT or High-Frequency Trading (HFT) plays an increasingly important role in how information is incorporated into asset prices (Brogaard et al., 2014; Weller, 2018; Zhang, 2018). In this study, we focus on the broad set of AT strategies, which encompass any type of trading that relies on computerized execution.[3] AT increases the incorporation of readily available information into prices, which discourages participants from acquiring private information (Weller, 2018). This finding is corroborated by the theoretical model of Yang and Zhu (2020) who demonstrate that traders who only trade on past order flows and who possess no innate trading motivations can erode the profits of a trader who is trading on private information by trading in the same direction as the informed trader's order.[4] If the profits of the informed trader are decreased, this reduces the incentive for a trader to "become informed." Weller (2018) relies on proxies to detect overall market level AT activity, but Korajczyk and Murphy (2019), as well as Van Kervel and Menkveld (2019) find direct evidence of computerized traders trading in the same direction as institutional traders while using data with trader identities. The key distinction of our setting, compared to prior work, is that the unscheduled nature of a special dividend announcement allows us to disentangle calendar-based strategies from continuous order flow monitoring.

## 3 Data

### 3.1 Special Dividends

We use Center for Research in Securities Pricing (CRSP) data to identify all special dividends paid from 1996–2024 by common stocks (share code 10 or 11). We start at 1996 as 1995 is the final year of DeAngelo et al. (2000). We identify special dividend amounts, regular dividend amounts, declaration

[3] HFT and AT are commonly used interchangeably, however, HFT is a subset of AT, with participants primarily acting as market makers (Menkveld, 2013).

[4] The process of trading in the same direction as an inferred institutional (informed) trade is known as back-running.

dates, and ex-dividend dates.[5] From CRSP we also collect stock information; daily price, volume, returns, market capitalization (price × shares outstanding), daily ask close and daily bid close. We use the daily return series for a symbol to construct a volatility measure which is the 40-day rolling standard deviation of daily returns. We construct a liquidity proxy denoted as *spread* which is the daily closing ask minus the bid. Summary statistics are presented in Table 2, Panel B; summary statistics are computed over days $[-250, +40]$ relative to the announcement and ex-dividend dates.[6] For computing abnormal returns surrounding special dividends we estimate the Fama and French (2015) five-factor model and include momentum (Jegadeesh and Titman, 1993).[7]

In Figure 1, panel A we plot yearly special dividend frequency along with the percentage of special dividend payers relative to firms which pay a regular dividend (or a special). We find that among firms which pay a regular dividend, specials appear to remain rare, with the percentage of firms which pay a regular dividend paying a special dividend in the same year ranging from 5–18%. The changes in this percentage appear to be driven by increases in special dividend frequency, not a change in the composition of dividend paying firms who pay a special as well. There was an influx in special dividend frequency in 2012 as a response to changes in individual tax rates (Hanlon and Hoopes, 2014).[8]

Special dividends have also remained large in size. Table 1 follows DeAngelo et al. (2000) and tabulates the number of special dividends for each four-year bin along with how many special dividends meet distribution thresholds of 5%, 10%, and 18.6% of equity value. DeAngelo et al. (2000) choose 18.6% as the final threshold as Dann (1981) finds that repurchases are 18.6% of pre-announcement

[5] Regular dividend codes are 1222, 1232, 1242, 1252 and special dividends are 1262 and 1272.

[6] Volatility has fewer observations as we require a minimum of 10 previous trading dates to compute the standard deviation of returns. We do not use these early event window dates in regressions; they are simply to describe the firms in our sample.

[7] We use the factor data provided by Dr. Kenneth French on his website and thank Dr. French for providing the data: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[8] The Jobs and Growth Tax Relief Reconciliation act had lowered the personal tax rate on dividends but was set to expire on December 30, 2010. It was extended for two years and set to expire on December 30, 2012, in addition, there was a 3.8% raise from the Patent Protection and Affordable Care Act of 2012. Therefore, an increase in special dividends was a mechanism for firms to distribute their earnings before the higher tax rates took effect in 2013.

equity value. While we still find that special dividends are rare, their cash distribution is large in value, suggesting that these distributions convey a strong signal. Figure 1, panel B plots the time series of special dividend size relative to a firm's most recent regular dividend conditional on the regular dividend occurring in one year before the special announcement. Special dividends are consistently 5 to 20 times larger than their regular counterparts, which is suggestive that market participants will interpret a special dividend as a stronger signal than a regular dividend increase or maintenance.

### 3.2 Algorithmic Trading

Weller (2018) constructs four proxies to measure algorithmic trading activity. These proxies are constructed using the Market Information Data Analytics System (MIDAS), provided by the U.S. Securities and Exchange Commission (SEC). MIDAS offers summary statistics at the stock-day-exchange level. Since Weller (2018) states that a higher cancel-to-trade ratio and odd-lot ratio indicate an increase in AT activity, whereas a lower trade-to-order ratio and trade size indicate more AT activity, we construct the same four proxies to measure AT activity:

- Trade-to-order ratio (TTO): Total trade volume divided by order volume.
- Cancel-to-trade ratio (CTT): Number of cancellations divided by the number of trades.
- Odd-lot ratio (OLR): Odd-lot (trades which execute in a quantity less than the round-lot size, which is typically 100 shares) volume divided by round-lot volume.
- Trade Size (TS): Total trade volume divided by number of trades.

Since the SEC began reporting this data in 2012, we construct our AT proxies using data from 2012 to 2024. For our analysis of AT trading in relation to special dividends, we limit our sample of special dividends to those announced between July 1, 2012 and October 21, 2024. We begin on July 1, 2012 as we require an estimation period of the AT proxies before announcement date to construct the abnormal AT proxies. We also run placebo tests before the event window. We end our sample on October 21, 2024 as we need enough trading days in the post-announcement window. As shown in

Table 3 we started with 1,778 special dividends announced between 2012 and 2024 for common stocks. We remove 680 special dividends which are "expected" based on the firm's history of paying special dividends.[9] We exclude 11 events coinciding with other non-dividend corporate announcements on the same date, 80 events lacking sufficient CRSP and MIDAS data over the event window $[-253, +40]$, and 135 events due to zero trading volume on one or more days. We also require that symbols have at least 287 out of 290 trading days populated in both CRSP and MIDAS; all firms satisfy this criterion. After removing 7 additional events for miscellaneous reasons such as ticker changes, we are left with a final sample of 865 special dividend events.

## 4 Hypothesis Development and Methodology

### 4.1 Standardized Price Jump

The price jump measure of Weller (2018) – hereafter referred to as Weller's PJ – captures the information incorporation into the stock price before an event. Intuitively it is the ratio of the information revealed around the event relative to the total information of the event which includes the pre- and post-announcement windows. The price jump ratio is formally defined as:

$$PJ_{i,t}^{(a,b)} = \frac{CAR_{i,t}^{(T-1,\,T+b)}}{CAR_{i,t}^{(T-a,\,T+b)}} \tag{1}$$

where $CAR_{i,t}$ is the cumulative abnormal return for stock i at time t, T is the event date, a is the length of the pre-announcement window, and b is the length of the post-announcement window. The price jump ratio can be interpreted as the percentage of the total information revealed at announcement relative to the total information that was acquirable. In the presence of an informed trader with perfect

[9] Our method for determining whether a special dividend is "expected" is based on whether a firm paid a special dividend within two of the three prior calendar years, if so, the dividend is expected. Our results are robust to an alternative decay-based surprise filter where we keep a count for each firm and increment it by one every time a firm pays a special dividend, the count is decreased by one every 400 calendar days, special dividends where the count is below 2 are classified as a surprise.

private information trading without detection (Kyle, 1985) there would be a smooth incorporation of the information and no price jump.

Weller (2018) bounds his price jump ratio between 0 and 1. A price jump of 0 implies all information that was acquirable has been incorporated and a price jump of 1 implies that no information which was acquirable was incorporated pre-announcement. This metric is subject to limitations pertaining to CARs in the pre- and post-announcement windows being similar in magnitude but opposite in sign (reversals). The price jump can yield values that are informative, but lie outside of (0,1).[10] We contend that observations lying outside of (0,1) can be valuable and present tail cases, that when not included can distort estimations and confound inference.

We propose a more robust price jump measure which can accommodate all return dynamics. Before presenting the measure, we identify five desirable properties that any generalized price jump measure should satisfy:

1. *Universal domain.* The measure should be defined for all return patterns, including reversals where pre- and post-announcement CARs have opposite signs, and near-zero denominator cases.
2. *Monotonicity.* The measure should be monotonically increasing in the magnitude of the informational gap resolved at announcement. Events where less information is incorporated pre-announcement should produce larger price jumps.
3. *Concordance.* In the well-behaved region where both measures are defined, the generalized measure should be concordant with the original price jump, preserving the economic interpretation.
4. *Continuity.* The measure should vary continuously with the underlying return dynamics; it should not require sample truncation that introduces a discontinuity between retained and discarded observations.
5. *Non-negativity.* The measure should be bounded below by zero, as a price jump of zero has a natural interpretation: all acquirable information was incorporated pre-announcement.

Weller's price jump satisfies properties (2), (3), and (5) within its admissible domain $[0, 1]$, but fails properties (1) and (4): Any observations outside $[0, 1]$ must be discarded, and this truncation is

[10] Consider a stock which has a significant information asymmetry between the firm and the market. Assume there is a CAR of -2% in the days leading up to an event (days T-a to T-1). Now assume that the firm has positive information but has not been able to convey this through a signal. The firm then conveys this information through a costly signal and the market reacts extremely positively and surrounding the event window there is a CAR of 2.1% (days T-1 to T+b). The unstandardized price jump would be computed as $PJ = \frac{0.021}{0.021+(-0.020)} = 2.1$. Therefore, this observation would be excluded. Similarly, if the signs of the two windows were reversed, the PJ would be computed as $PJ = \frac{-0.021}{-0.021+0.020} = -2.1$, also excluded. Examples from the data are provided in Appendix A.

non-random (Appendix A.1). However, the standardized price jump, defined below, satisfies all five properties.

Formally:

$$PJ_{i,t}^{stan} = \frac{\left| kCAR_{i,t}^{(T-1,\,T+b)} - kCAR_{i,t}^{(T-a,\,T-2)} \right| \cdot \left( kCAR_{i,t}^{(T-1,\,T+b)} \right)^2}{\left( kCAR_{i,t}^{(T-a,\,T-2)} \right)^2 + \left( kCAR_{i,t}^{(T-1,\,T+b)} \right)^2} + \left| \frac{CAR_{i,t}^{(T-1,\,T+b)}}{CAR_{i,t}^{(T-a,\,T+b)}} \right| \tag{2}$$

We follow the notation of Weller (2018) but also introduce $k$, where $k = 100$ and expresses cumulative abnormal returns in percentage points.[11] Intuitively, the first term measures the magnitude of the announcement surprise, weighted by the announcement window's dominance in total return variation. The second term captures the relative share of pre-announcement price movement, ensuring the measure remains informative when pre- and announcement-window returns are similar in magnitude. Critically, the standardized price jump allows us to retain 50% of observations that would be cut if we were to employ the regular price jump instead. $PJ^{stan}$ can still produce large values around events with particularly unusual return dynamics; we therefore winsorize at the 99% level. For $PJ^{stan}$ we validate properties (1)–(3) empirically in Figures 2–3 and Appendix A. Properties (4) and (5) are satisfied by the construction of the measure, as the standardized PJ cannot produce negative values and any return dynamics will produce an informative value which measures the information disseminated surrounding an announcement.

We prefer the use of the standardized price jump for several reasons. First, Figure 2 displays the distributions of both Weller's price jump and the standardized price jump. The raw distribution of Weller's measure (Panel A) exhibits a considerable amount of observations residing outside the $[0, 1]$ range, making it necessary to truncate the sample to obtain a well-behaved measure; we also remove observations which are extreme outliers for presentability. This truncation discards nearly

[11] $k$ is not a tuned constant, it converts returns to percentage points to manage interactions with the squared terms. Our main estimates hold under a log-transformation of $PJ^{stan}$.

half the observations, reducing the sample from $N = 865$ to $N = 433$ (Panel C). In contrast, the raw standardized measure (Panel B) is right-skewed but naturally bounded, the events which lie toward the right tail represent considerable asymmetries resolved by the signal from the special dividend (Panel D).

Second, in Figure 3 we rank observations by each measure and overlay the other to illustrate their correspondence and divergence. In Panel A, events are ranked by the standardized price jump, with Weller's price jump measure overlaid where it lies in $[0, 1]$. The two measures track each other closely for "market non-events" where both windows exhibit similar return patterns. However, the standardized measure assigns meaningfully different values for events with return reversals. Events associated with large standardized price jumps are not quantified significantly differently using the regular price jump. In Panel B when the truncated sample is ranked by the regular price jump, the standardized price jump generally increases as well. However, there is some disagreement towards the right tail, which are events with a large asymmetry, often accompanied with a reversal. Panel C shows the ranking for standardized price jumps again with the untruncated regular price jump where red markers indicate observations where Weller's untruncated measure falls outside $[0, 1]$, yet the standardized measure produces informative values for these events. Panel D clearly shows that the tails of the regular price jump metric are unable to effectively quantify the informational asymmetry resolved, whereas the standardized can.

Third, Panel A of Table 2 reports the distributional properties of both measures. Weller's unrestricted price jump has a mean of $-0.302$ and a standard deviation of 17.031, reflecting the extreme values generated by near-zero denominators. When restricted to $[0, 1]$, the sample is reduced to 433 observations – a loss of 49.9% of the sample. The standardized price jump, after winsorizing, has a mean of 3.743 and a standard deviation of 5.556 across all 865 observations.

### 4.2 Information Acquisition

We contend that while AT and its relation to information dynamics around scheduled events has been studied, our setting is fundamentally different due to the unexpected nature of special dividends. In an event such as an earnings announcement (Weller, 2018) where the content is unknown, but the timing is known, AT can prepare or alter behavior ex-ante. In the case of an unexpected special dividend, the timing and the content are both unknown variables. Weller (2018) finds that AT deters information acquisition; the mechanism is that AT detects informed trading, trades in the same direction, and lowers the extractable rents that informed traders can generate from their private information. If the deterioration of economic rents of informed traders exceeds the cost of acquiring the information, then sophisticated traders are not incentivized to acquire this information. This causes there to be a price jump at announcement date as there was no private information incorporated into prices beforehand.

Where our study differs is that, by removing calendar timing effects, we test whether informed traders are still detected by ATs and are deterred from acquiring information preceding an unexpected event, or whether informed traders may better capitalize on their private information when there is no predetermined date of information dissemination. A critical component of our hypothesis is that the private information must be acquirable; the event cannot be so unexpected that no market participant can obtain inside information. Special dividends are well-suited to this setting. Though Lie (2000) finds that prior to special dividend announcements, firms have a buildup of funds, this connection is ambiguous. Opler et al. (1999) suggest that firms with strong growth opportunities and riskier cash flows have greater holdings of cash. These are the exact firms that do not pay dividends (Fama and French, 2001).

We state that an impending special dividend may be ambiguous, for our hypothesis it is not essential that an informed trader "predict" a special dividend. Rather our setting requires that there is an information asymmetry between the firm and the market, and whether or not a trader collects costly information without the knowledge that there is an impending announcement that will reconcile the information asymmetry. In Figure 4 we plot the hidden volume (HVR) and hidden trade ratios (HTR) along with the pre and post mean levels of the two metrics. A sophisticated trader can use hidden trades for a variety of strategies, such as concealing private information. Hidden trading activity is elevated in the pre-event period as opposed to the post-event period. While the figure is somewhat noisy, we also find that the days immediately preceding the announcement have statistically significantly higher hidden trading activity, as displayed in Table IA1. While it is possible that the increased hidden trading could reflect other trading strategies (such as market making) besides concealing private information, it seems unlikely there would be a statistically significant spike in the days immediately prior to an unscheduled announcement from any other source besides informed trading. In summary, the figure provides suggestive evidence of an informational asymmetry that is unexpectedly resolved by the special dividend announcement, along with the footprints of informed trading.

This leads to our formal hypothesis: if algorithms are always active in detecting informed trading order flow, this will deter traders from collecting private information prior to an unscheduled event. Stated formally as:

*H1: Abnormal algorithmic trading activity is associated with wider informational gaps before special dividend announcements, consistent with AT detecting and deterring informed trading.*

### 4.3 Information Incorporation

Fama (1970) proposed that in an efficient market, prices should fully reflect all available information, and new information should be rapidly incorporated into prices. Yet, violations of market efficiency are found, as the market frequently overreacts or underreacts to new information (De Bondt and Thaler, 1985; Jegadeesh and Titman, 1993; La Porta, 1996; Hirshleifer et al., 2009). Baldauf and Mollner (2020) demonstrate that high-frequency traders (HFTs) can deter information acquisition through their rapid incorporation of already available information. The finding that AT reduces information acquisition is typically viewed in a negative light. To our knowledge, no paper has investigated whether the presence of elevated AT can facilitate a more complete price response to the signal originating from an unexpected corporate event. Thus, the market may interpret the signal content of a special dividend more efficiently in the presence of higher AT activity.[12]

*H2: Algorithmic trading accelerates the speed at which the market interprets and incorporates the signal from a special dividend announcement.*

In summary, our setting is an event in which there is an information asymmetry, which is partially or fully resolved by the signal transmitted by an unexpected corporate announcement. The informational asymmetry is supported by Figure 4. We are effectively testing if AT activity deters informed traders from resolving this information asymmetry despite there being no public knowledge of an impending announcement, as well as whether or not AT activity allows the market to process the signal at a faster rate.

### 4.4 Abnormal Algorithmic Trading

Algorithmic trading intensity varies across firms due to structural factors such as liquidity, institutional ownership, and index membership. These cross-sectional differences are orthogonal to event-specific information dynamics and, if left unaddressed, may confound inference. To isolate whether AT *changes* around a specific special dividend announcement, we construct abnormal AT measures by differencing each firm's event-window AT from its own baseline, analogous to the construction of abnormal returns in standard event studies.

[12]The direction of the market reaction to a special dividend is irrelevant in our paper. It could be the firm is signaling positive information (e.g., excess earnings) or be signaling negative information (e.g., lack of investment opportunities). We test whether the market reaches a conclusion about its reaction faster in the presence of high AT activity or whether AT delays the formation of market consensus regarding the event.

Formally, for each AT proxy $j$ and firm $i$, we define abnormal AT as:

$$AbnormalAT_{j,i} = AT_{j,i}^{\text{[T-21, T-1]}} - AT_{j,i}^{\text{[T-61, T-22]}} \tag{3}$$

where $AT_{j,i}^{\text{[T-21, T-1]}}$ is the mean of the AT proxy $j$ for firm $i$ over the 21 trading days preceding the announcement and $AT_{j,i}^{\text{[T-61, T-22]}}$ is the mean over a 40-day baseline window sufficiently distant from the event to avoid contamination. The baseline window remains within the same quarter, balancing the stability of the estimate against proximity to the event.[13]

This within-firm differencing approach is analogous to the construction of abnormal returns in standard event studies and is a natural way to remove the endogenous cross-sectional variation in AT activity. If a firm structurally attracts high AT due to omitted variables, this level effect is differenced out; the remaining variation captures whether AT activity deviates from the firm's own norm in the period surrounding the announcement. As an empirical validation, we conduct placebo tests in which we randomly assign pseudo-announcement dates drawn from outside the event window and calculate abnormal AT using identical methodology. All placebo coefficients are statistically insignificant (Table 7, Panel A), confirming that our measure captures event-specific dynamics rather than persistent firm characteristics.[14]

# 5 Results

## 5.1 Signal Content of Special Dividends

This subsection confirms that special dividends generate sufficient informational shocks to test AT dynamics. We document market reactions and their cross-sectional determinants before turning to

[13]We examine robustness to alternative baseline windows of $[-80, -41]$ and $[-120, -61]$ in Table IA10 and the results are qualitatively similar.

[14]Firm fixed effects and time fixed effects could potentially control for this; however, for most firms we only have one observation. Furthermore, if a firm's baseline AT activity varies through time differently than that of other firms, time fixed effects would fail to capture this. Our abnormal measure effectively de-means AT activity for both time and firm-varying effects. We also estimate placebo tests without fixed effects in Table IA14.

AT analysis.

In Table 4 we compute abnormal returns and cumulative abnormal returns centered on the special dividend declaration date. We find no evidence of significant information leakage before the announcement, as abnormal returns are statistically insignificant in the pre-event period. On the announcement date (day 0), abnormal returns are significantly positive at 0.64%, and CARs reach 3.67% over the 11-day window $[-5, +5]$, significant at the 1% level. The magnitude of these returns confirms that special dividends convey economically meaningful information to the market.

We partition the sample into firms that also pay regular dividends (dividend-paying firms, $N = 647$) and those that do not (non-dividend-paying firms, $N = 218$). Non-dividend-paying firms exhibit substantially larger announcement returns: a day 0 abnormal return of 1.28% compared to 0.42% for dividend payers. This difference is consistent with the signal of the special dividend being more informative for firms that are more opaque to the market. For firms that regularly pay dividends, the market already has a periodic information channel but a special dividend from a non-dividend-paying firm reveals more information. Cumulative abnormal returns centered around the ex-dividend date are positive in the pre-event window, but become insignificant by the end of the window.

Since we seek to identify which aspect of the special dividend incites the market response, we estimate cross-sectional regressions of the form:

$$CAR_i^{[-1,+5]} = \alpha + \beta_1\, divamt_i + \beta_2\, ratio_i + \beta_3\, (ratio_i \times divamt_i) + \gamma\, \mathbf{X}_i + \varepsilon_i \tag{4}$$

where *divamt* is the special dividend amount per share, *ratio* is the special-to-regular dividend ratio of the firm's most recent regular dividend, and **X** is a vector of firm-level controls (*price*, *volume*, *volatility*, *size*, *spread*), all in log units and measured as event-window averages over $[-21, -1]$.

Table 5 reports the cross-sectional regressions of cumulative abnormal returns on special dividend characteristics and firm controls. The dollar amount of the special dividend is positively and significantly associated with CARs ($\hat{\beta} = 0.0167$, $p < 0.01$), indicating that larger distributions elicit stronger market reactions. The ratio of the special dividend to the most recent regular dividend is significant in a univariate specification but is subsumed by the dollar amount in multivariate models. The interaction between dollar amount and ratio is statistically insignificant. The key takeaway is that it is the absolute size of the distribution, not the relative size, that drives the market response. Among the control variables, price is negatively associated with CARs, consistent with smaller firms generating larger announcement reactions, while volatility is positively associated with CARs.

Having established that special dividends generate economically significant and persistent market reactions, we now examine whether algorithmic trading affects the information dynamics surrounding these events.

### 5.2 Information Acquisition

First we examine whether abnormal AT activity widens the informational gap preceding the announcement. To do so, we estimate cross-sectional regressions of the pre-announcement price jump on AT proxies, first using raw AT levels (Panel A of Table 6), then using abnormal AT measures (Panel B of Table 6), followed by placebo validation (Table 7).

The baseline specification takes the form:

$$PJ_i = \alpha + \beta\, AT_i^j + \gamma\, \mathbf{X}_i + \delta_t + \delta_k + \varepsilon_i \tag{5}$$

where $PJ_i$ is either Weller's price jump (restricted to $[0, 1]$) or the standardized price jump for firm $i$, $AT_i^j$ is one of four AT proxies $j \in \{TS, OLR, TTO, CTT\}$ averaged over the pre-announcement window $[-21, -1]$, $\mathbf{X}_i$ is a vector of firm-level controls (log price, log volume, log market capitalization, volatility, and spread), and $\delta_t$ and $\delta_k$ denote year and Fama–French 12 industry fixed effects, respectively. Each

AT proxy is entered separately to avoid multicollinearity among the four measures.[15] In Panel B, we replace $AT_i^j$ with $AbnormalAT_i^j$, the abnormal AT measure constructed as described in Equation 3.

#### 5.2.1 Raw AT Levels

Panel A of Table 6 reports estimates of Equation 5 using raw AT levels. With Weller's price jump as the dependent variable ($N = 433$), only TTO is marginally significant ($p < 0.10$). Using the standardized price jump ($N = 865$), the coefficients are larger in magnitude but remain statistically insignificant across all four proxies. The lack of explanatory power is unsurprising: raw AT levels largely reflect persistent structural characteristics – liquidity, institutional ownership, index membership – rather than event-specific dynamics. A firm with structurally high AT will register as "high AT" regardless of whether an information event is imminent. We estimate placebo tests of Equation 5 without fixed effects in Table IA14 and find three of the four AT proxies are statistically significant while none of the abnormal measures are, implying that a firm's baseline AT outside of the event window is correlated with price dynamics, but the abnormal AT activity in the event window does capture event dynamics and is not a spurious relation.

#### 5.2.2 Abnormal AT Levels

Panel B of Table 6 re-estimates the same specification replacing AT levels with abnormal AT. The results sharpen considerably. For the standardized price jump, the abnormal coefficients are estimated as follows: Abnormal TS a coefficient of $-3.32$ ($p < 0.05$), Abnormal OLR a coefficient of 2.90 ($p < 0.01$), Abnormal TTO a coefficient of $-1.35$ ($p < 0.05$), and Abnormal CTT a coefficient of 1.11 ($p < 0.10$). The coefficient signs are internally consistent: proxies that increase with AT activity (OLR, CTT) enter positively, while proxies that decrease with AT activity (TS, TTO) enter negatively. All four proxies point in the direction of higher abnormal AT in the pre-announcement being associated

[15] We report a horse race specification with all four proxies entered simultaneously in Table IA6; no individual proxy retains significance due to high variance inflation.

with a larger price jump at announcement, indicating a wider informational gap.

To put these estimates in economic terms, a one-standard-deviation increase in Abnormal OLR is associated with a 0.60-unit increase in the standardized price jump ($0.11\sigma$), equivalent to 44% of the median price jump. Across all four proxies, the estimated effect of a one-standard-deviation change ranges from 25% to 44% of the median, with internally consistent signs. This magnitude is economically meaningful and suggests that the deterrence of information acquisition documented by Weller (2018) for scheduled earnings announcements extends to settings where there is no publicly known event date.

For Weller's price jump restricted to $[0, 1]$, the abnormal AT measures likewise improve relative to Panel A: Abnormal OLR, Abnormal TTO, and Abnormal CTT are each statistically significant ($p < 0.10$), though the sample is limited to the 433 observations satisfying the $[0, 1]$ bound. The weaker results likely reflect Weller's price jump not effectively capturing the information dynamics of our sample, where a significant asymmetry is resolved and return patterns often involve large magnitudes or reversals. The central takeaway from Panel B is that it is abnormal AT — not the level of AT — that predicts pre-announcement information gaps and within-firm deviations isolate event-specific dynamics that cross-sectional levels cannot capture.

#### 5.2.3 Placebo Tests

Table 7 reports placebo tests designed to validate that the Panel B results capture announcement-specific dynamics. We randomly assign pseudo-announcement dates drawn uniformly from $[-120, -60]$ days before the actual event. At these pseudo-dates, we calculate AT and abnormal AT at the placebo window, and use price jump from the true window. If the relationship in Table 6 were driven by omitted firm characteristics that are correlated with both AT and return dynamics, these correlations would appear at non-event dates as well.

Panel B of Table 7 reports the placebo results. All abnormal AT coefficients are small in magnitude and statistically insignificant across both price jump measures. The placebo tests confirm that the abnormal AT–price jump relationship is specific to the actual announcement window and not an artifact of persistent firm characteristics.

### 5.3 Information Incorporation

Second, we examine whether AT accelerates the incorporation of information following the announcement. To do so, we estimate cross-sectional regressions of post-announcement price dynamics on AT proxies, using three complementary dependent variables: an information incorporation ratio (Panel A of Table 8), the post-announcement standardized price jump (Panel B of Table 8), and a return reversal indicator (Panel C of Table 8).

The baseline specification takes the form:

$$Y_i = \alpha + \beta\, AT_i^j + \gamma\, \mathbf{X}_i + \delta_t + \delta_k + \varepsilon_i \tag{6}$$

where $Y_i$ is one of three dependent variables defined below, $AT_i^j$ is one of four AT proxies $j \in \{TS, OLR, TTO, CTT\}$ averaged over the post-announcement window $[0, +2]$, $\mathbf{X}_i$ is the same vector of firm-level controls as in Equation 5 (log price, log volume, log market capitalization, volatility, and spread), and $\delta_t$ and $\delta_k$ denote year and Fama–French 12 industry fixed effects, respectively. As before, each AT proxy is entered separately, and we estimate the specification using both raw AT levels and post announcement abnormal AT measures. A distinction we make in this setting is that abnormal AT is defined differently. Formally, for each AT proxy $j$ and firm $i$, we define abnormal AT as:

$$AbnormalAT_i = AT_i^{\text{[T, T+2]}} - AT_i^{\text{[T-61, T-22]}} \tag{7}$$

where $AT_i^{\text{[T, T+2]}}$ is the mean of one of the four AT proxies for firm $i$ over the event date and the two trading days following the announcement and $AT_i^{\text{[T-61, T-22]}}$ is the mean over the 40-day baseline window. In this specification, we examine whether AT activity following the special dividend signal is associated with faster price adjustment, thus we measure abnormal AT using observed AT on days (0,2) as opposed to (-21,-1).

#### 5.3.1 Incorporation Ratio

Panel A of Table 8 reports estimates of Equation 6 where the dependent variable is the incorporation ratio, defined as $CAR_{[0,+2]}/CAR_{[0,+5]}$. This ratio captures the fraction of the five-day post-announcement cumulative abnormal return that is incorporated within the first two trading days. If the incorporation ratio is close to one, there is rapid information incorporation. No AT proxy whether measured in raw levels or as abnormal is significantly associated with the incorporation ratio ($N = 865$). However, the incorporation ratio suffers from similar issues as does Weller's price jump measure since it is mechanically unstable when $CAR_{[0,+5]}$ approaches zero, as small denominator values amplify noise. Thus, we estimate another incorporation ratio with an alternative window, specifically $CAR_{[0,+2]}/CAR_{[0,+10]}$. The results are stronger, but the extended window may capture dynamics beyond information incorporation, therefore we lean on the original (0,5) window for our main inference (Table IA11).

#### 5.3.2 Post-Announcement Standardized Price Jump

Panel B of Table 8 re-estimates Equation 6 using the post-announcement standardized price jump as a complementary dependent variable. This measure, computed as the standardized price jump over $[0, +2]$ relative to $[0, +5]$, captures how much of the total five-day price discovery is concentrated in the initial two-day window without the denominator instability of the incorporation ratio.

Using raw AT levels, no proxy is statistically significant. However, replacing AT levels with abnormal AT sharpens the results considerably. The abnormal coefficients are estimated as follows: Abnormal TS a coefficient of $-1.71$ ($p < 0.05$), Abnormal TTO a coefficient of $-0.62$ ($p < 0.05$), and Abnormal CTT a coefficient of 0.55 ($p < 0.05$). The coefficient signs are internally consistent: proxies that decrease with AT activity (TS, TTO) enter negatively, while the proxy that increases with AT activity (CTT) enters positively. All three significant proxies indicate that higher abnormal AT corresponds to a larger fraction of the total five-day response being concentrated in the initial $[0, +2]$ window.

Our results suggest that only abnormal measures combined with the standardized price jump are valid for estimating any relation between AT and information incorporation. This parallels the information acquisition results in Table 6, where the distinction between raw and abnormal AT proved decisive.

#### 5.3.3 Return Reversals

Panel C of Table 8 estimates a linear probability model of Equation 6 where the dependent variable is a return reversal indicator, equal to one if the sign of $CAR_{[0,+2]}$ differs from the sign of $CAR_{[0,+5]}$, and zero otherwise. A return reversal indicates that the market's initial interpretation of the announcement was subsequently revised; approximately 15% of events in our sample exhibit such reversals. If the signal was processed efficiently then the signal should theoretically be processed completely on the event date. The (0,+2) window allows for a buffer.

Using raw AT levels, no proxy is significantly associated with the probability of a reversal. With abnormal AT, the TTO ratio ($-0.083$, $p < 0.01$) and CTT ratio (0.090, $p < 0.01$) significantly predict reversal probability, suggesting that AT accelerates the initial price response but does not necessarily improve its accuracy. However, the abnormal AT and reversal windows are contemporaneous, making reverse causality difficult to rule out.

Overall, the incorporation results suggest that abnormal AT activity can increase the incorporation of information originating from a corporate event into prices. While taken together with the finding that AT deters information acquisition, the overall welfare becomes nuanced. Firms which have significant internal private information may need to consider the AT levels in their common stock. A firm with a large information asymmetry and high levels of AT activity may have more motivation to engage in a signaling event as AT levels will deter traders from pursuing this private information on their own, as well as accelerate the market interpretation of the signal.

### 5.4 Algorithmic Trading Withdrawal

Our most striking finding is that aggregate AT activity declines following special dividend announcements and remains depressed for approximately 20 trading days. This pattern is documented in Figure 5 and formally tested in Table IA8. This creates a tension: AT facilitates information incorporation, yet withdraws precisely when new information arrives.

Figure 5 plots abnormal AT proxies in event time $[-20, +20]$ for both special dividends and regular dividend increases announced by the same firms. We include regular dividend increases as a reference, as they can also be used as corporate signals. For special dividends, all four AT proxies exhibit a sharp shift at the announcement date: TS increases (less AT), OLR declines (less AT), TTO increases (less AT), and CTT declines (less AT). The direction of each proxy consistently indicates a reduction in AT activity. This decline persists for approximately 20 trading days before reverting toward baseline levels. The same pattern exists with regular dividends but the magnitude and persistence of the withdrawal is not as large.[16]

Table IA8 formalizes this visual evidence. For each day in $[0, +20]$, we compute the cross-sectional mean of abnormal AT and test whether it differs from zero. All four proxies show statistically significant declines on the announcement day and this significant decline persists through day 20 for most proxies. The decline is strongest in the first two days and gradually attenuates.

The AT withdrawal pattern is puzzling: AT has been found to accelerate the incorporation of available information in the empirical literature and in our study (Table 8, Panel B). Yet we find that

[16] We run a difference-in-differences analysis in Table IA4 which confirms that the AT response to special dividends is statistically different from the response to regular dividends.

aggregate AT declines post-announcement (Table IA8). We reconcile these findings as AT strategies profit from information asymmetry, specifically, from detecting and trading alongside informed order flow. When a special dividend publicly reveals previously private information, the profitable edge from order flow detection dissipates. Algorithms withdraw until normal information asymmetries re-establish.

To our knowledge, this sustained post-announcement withdrawal of AT activity around an unscheduled corporate event has not been previously documented. The pattern has implications for understanding the economic function of AT: rather than serving as a pure information-processing technology that should activate more intensely when new information arrives, AT activity decreases when the information asymmetry is resolved.

## 6 Robustness

We subject our main findings to a battery of robustness tests that we will summarize here. A detailed discussion of each test is provided in Appendix B.

**Fixed effects and window sensitivity.** The information acquisition results are stable across four fixed effects specifications (none, year only, industry only, both; Table IA2). Results are also robust to alternative baseline windows ($[-80, -41]$, $[-120, -61]$) and shorter pre-event windows, though shorter windows reduce statistical significance (Table IA10).

**Statistical inference.** Bootstrap confidence intervals (10,000 replications) exclude zero for three of four AT proxies, and permutation $p$-values are uniformly smaller than OLS $p$-values (Table IA3). Power analysis confirms adequate power for Abnormal OLR; the remaining proxies are individually underpowered, though permutation and placebo tests argue against spurious inference.

**Instrumental variables.** Following Weller (2018), we estimate 2SLS using log price as an instrument (Table IA5). The instrument captures structural cross-sectional variation in AT related to price.

Our abnormal AT construction already isolates event-specific variation by demeaning across firms. Instrumenting abnormal AT directly yields weak first stages, confirming the price-level instrument does not generate useful variation beyond what our abnormal measure already captures.

**Cross-event gradient.** A gradient analysis across four event types (surprise specials, non-surprise specials, regular increases, regular decreases) confirms the strongest AT–price jump relationship for surprise special dividends (Table IA9).

**Multiple testing and multicollinearity.** After Benjamini-Hochberg correction at 5%, three of four proxies (Abnormal TS, OLR, TTO) remain significant (Table IA7). A horse race regression with all four proxies entered simultaneously yields no individual significance due to high VIFs (3.02–8.89), consistent with the proxies capturing overlapping variation (Table IA6).

**Additional tests.** Abnormal hidden trading ratios (HTR, HVR) are insignificant when substituted for AT proxies, implying that AT activity rather than informed trading activity drives results. Information incorporation regressions are robust to dropping fixed effects and to logistic estimation of the reversal indicator (Table IA15). Higher AT is associated with the probability but not the magnitude of return reversals (Table IA12).

## 7 Conclusion

This paper investigates whether algorithmic trading affects information dynamics around unscheduled corporate events. Using a sample of 865 special dividend announcements from 2012 to 2024 and four AT proxies constructed using SEC MIDAS data, we examine whether AT deters pre-announcement information acquisition and accelerates post-announcement information incorporation.

We find that aggregate AT activity declines for approximately 20 trading days following a special dividend announcement and remains depressed relative to firm-specific baselines. This withdrawal persists longer and with greater magnitude than the AT response to regular dividend increases by the same firms. The pattern is inconsistent with a view of AT as a pure information-processing technology that becomes more active when new information arrives. Instead, it suggests that AT strategies profit from information asymmetry; when a special dividend publicly resolves that asymmetry, algorithms withdraw.

We also find that abnormal AT activity measured as deviations from firm-specific baselines is positively associated with the pre-announcement price jump. Higher abnormal AT in the weeks preceding a special dividend predicts a wider informational gap at announcement, consistent with AT detecting and deterring informed traders from incorporating private information into prices before the event. This finding extends the literature demonstrating that the information deterrence channel operates even when there is no publicly known event date for algorithms to target. Since AT incorporates information into prices in the pre-event period, we test if it accelerates the signal processing ability of the market in the post-event window. The evidence for post-announcement information incorporation is weaker: abnormal AT is associated with faster initial price convergence as measured by the standardized price jump, but not by a raw incorporation ratio. Higher abnormal AT also relates to a greater probability of reversals, with the possibility of reverse causality being high.

As a methodological contribution, we develop a standardized price jump measure that accommodates all return patterns, including events where pre- and post-announcement returns are similar in magnitude but opposite in sign. The regular price jump measure (Weller, 2018) requires truncating observations outside of $[0, 1]$, which would eliminate approximately 50% of our sample. The standardized price jump retains these observations and is applicable to any corporate event study in which researchers wish to measure pre-announcement information incorporation.

Our findings carry practical implications. The 20-day AT decline suggests a temporary period of reduced liquidity provision from algorithmic traders following major announcements, which may be relevant for timing subsequent corporate actions. The widening of an informational gap preceding non-scheduled corporate signaling announcements suggests that firms may need to assess their AT levels when considering engaging in a costly signal. For regulators, the results underscore that while AT's positive social value is attributed to improving price discovery, if AT withdraws its participation when it is not favorable, there could be adverse social effects. For investors, abnormal patterns in AT proxies and hidden trading activity can provide inference on information asymmetry between a firm and the market.

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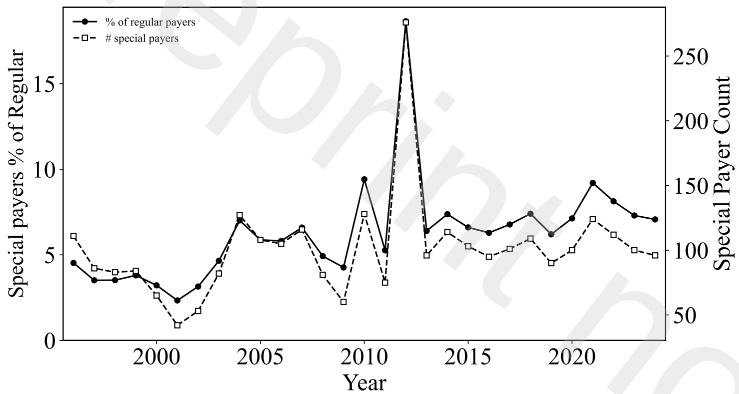
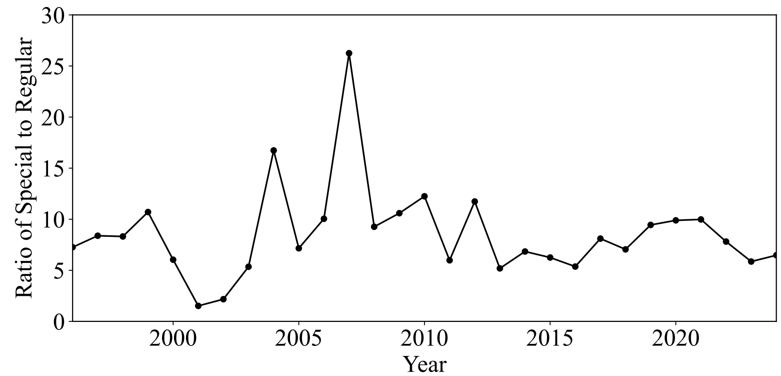
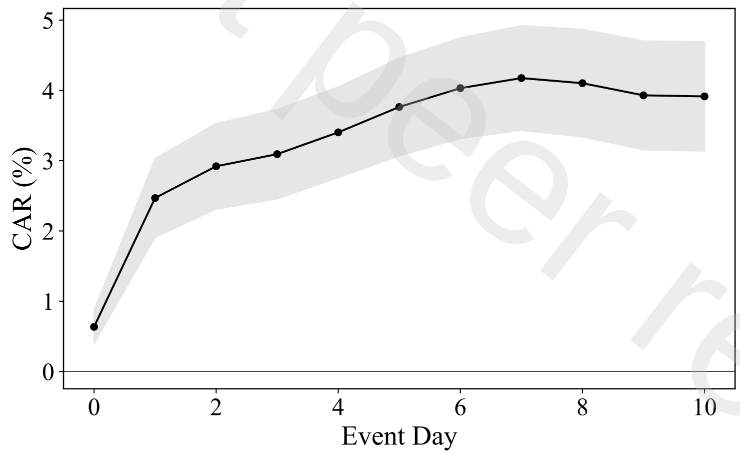
# Figures




(a) Special Dividend Frequency

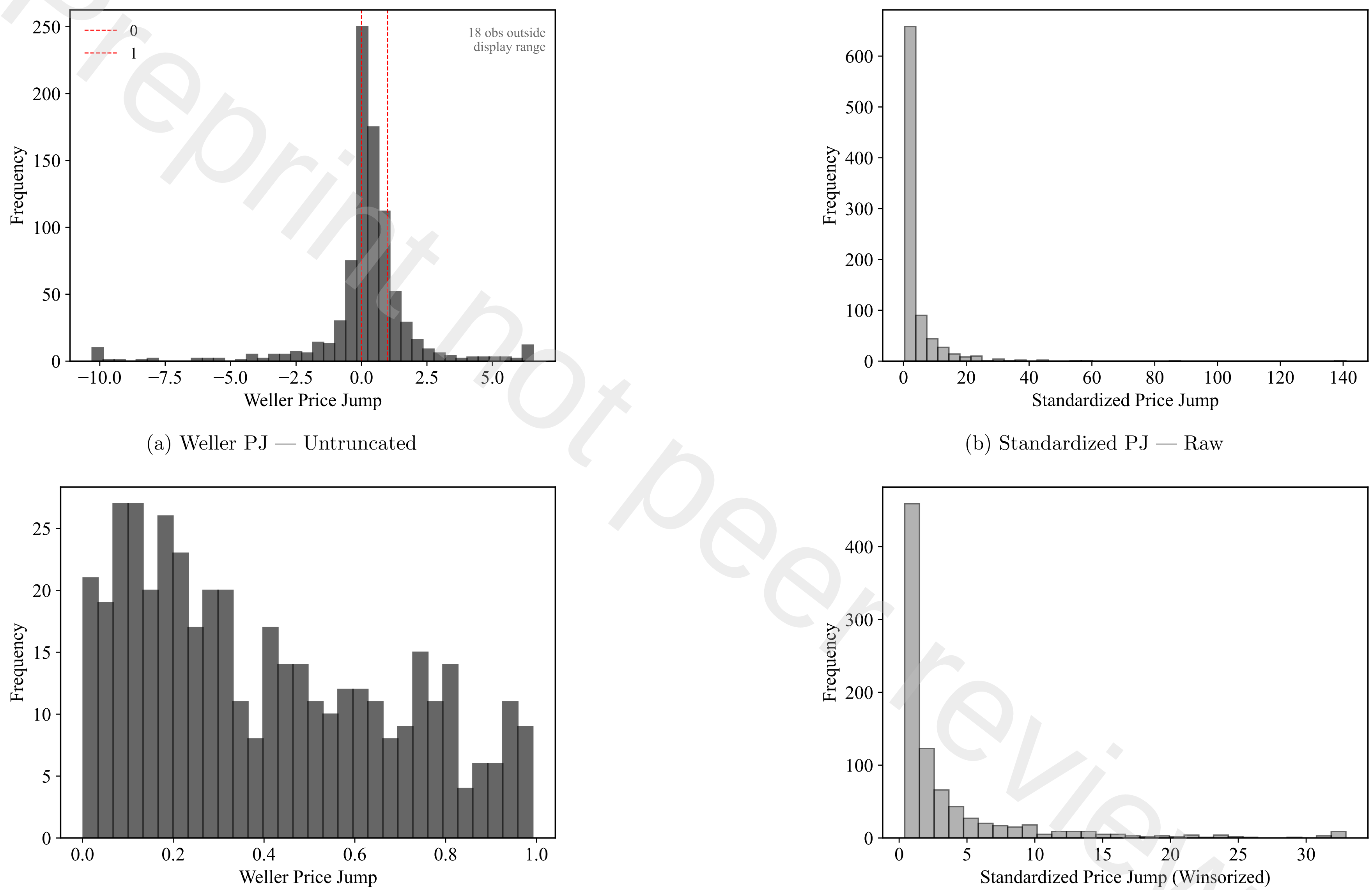



(b) Special-to-Regular Dividend Ratio




(c) Cumulative Abnormal Returns

Figure 1: **Descriptive Overview: Special Dividends and Market Reaction.** Panel (a) plots the number of firms paying special dividends (dashed line, right axis) and special dividend payers as a percentage of regular dividend payers (solid line, left axis) for each year from 1996 to 2024. The 2012 spike reflects the anticipated increase in dividend tax rates under the American Taxpayer Relief Act. Panel (b) plots the mean ratio of the special dividend amount to the most recent regular dividend amount for each year; special dividends are consistently 5–10 times larger than the corresponding regular dividend. Panel (c) plots mean cumulative abnormal returns (CARs) from event day 0 through day 10 relative to the special dividend declaration date; the shaded region denotes the 95% confidence interval.



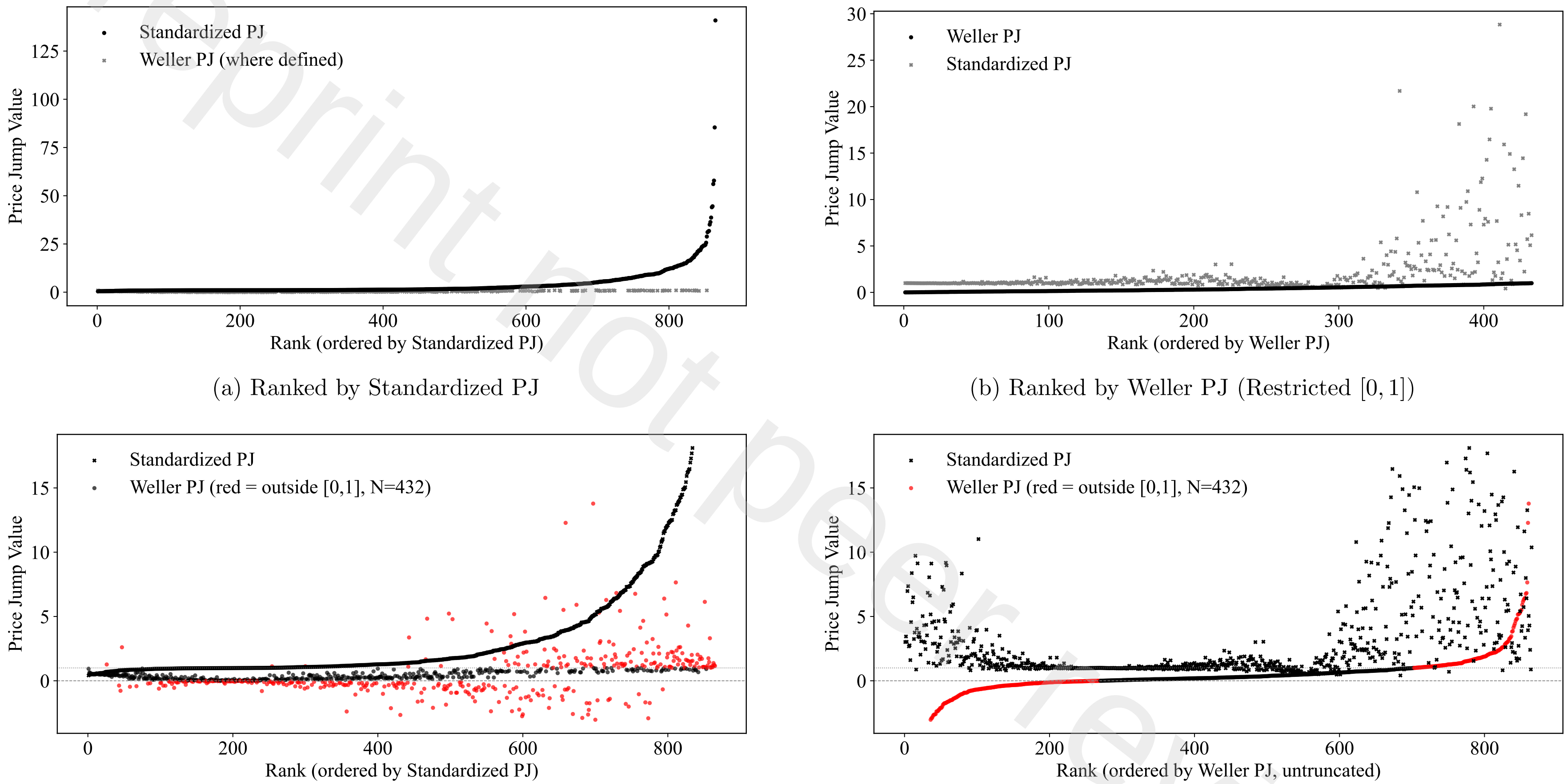

(a) Weller PJ — Untruncated

(b) Standardized PJ — Raw

(c) Weller PJ — Restricted $[0, 1]$

(d) Standardized PJ — Winsorized 1%/99%

Figure 2: **Price Jump Measure Distributions.** This figure compares the distributional properties of Weller's (2018) price jump ratio and our standardized price jump measure across special dividend events. Panel (a) shows Weller's PJ untruncated, we omit some of the large outlier variables for interpretability and scaling. Panel (b) shows the raw standardized PJ. Panel (c) restricts Weller's PJ to the unit interval $[0, 1]$. Panel (d) shows the standardized PJ winsorized at the 1st and 99th percentiles.



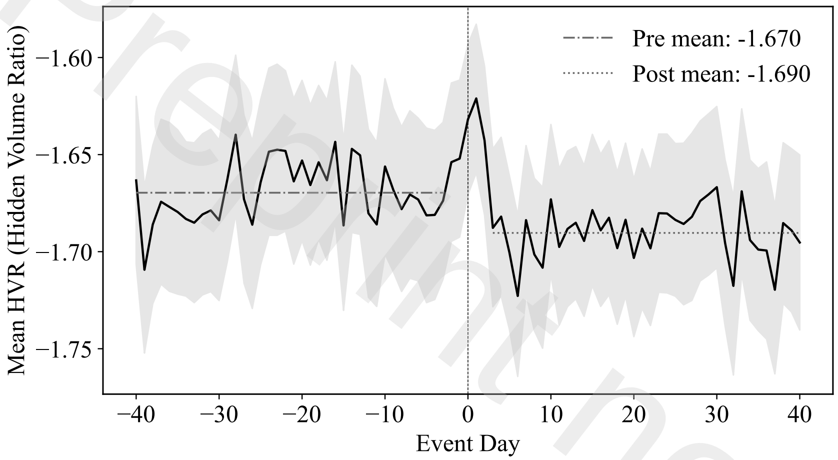

(a) Ranked by Standardized PJ

(b) Ranked by Weller PJ (Restricted $[0, 1]$)

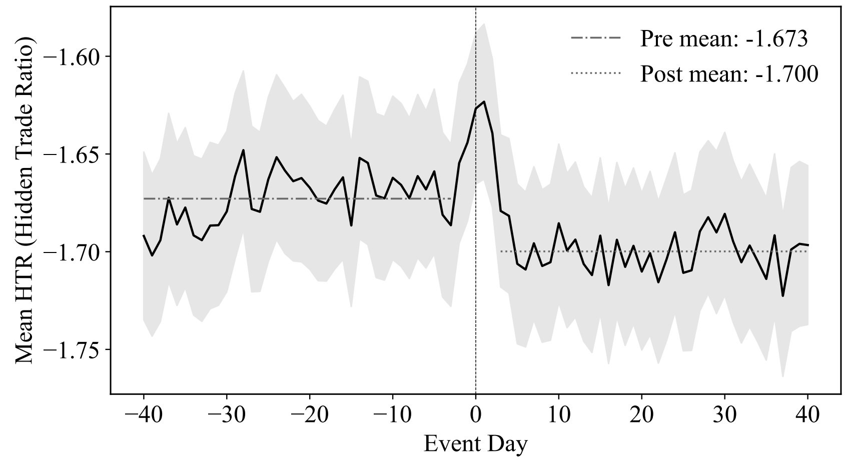
(c) Full Sample Ranked by Standardized PJ (Weller Uncensored)

(d) Full Sample Ranked by Weller PJ (Untruncated)

Figure 3: **Ranked Comparison of Price Jump Measures.** Panel (a) orders all events by their standardized price jump value (filled circles) and overlays Weller's PJ (crosses) where defined in $[0, 1]$. Panel (b) orders the subset of events with valid Weller PJ by that measure and overlays the standardized PJ. Panel (c) ranks all events by standardized PJ and overlays the full (uncensored) Weller PJ; red markers indicate Weller values outside $[0, 1]$. Panel (d) ranks by the full untruncated Weller PJ.

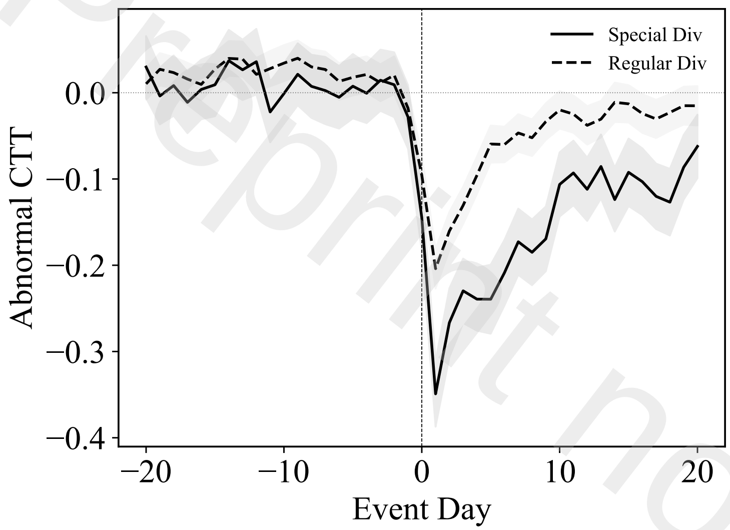



(a) Hidden Volume Ratio (HVR)

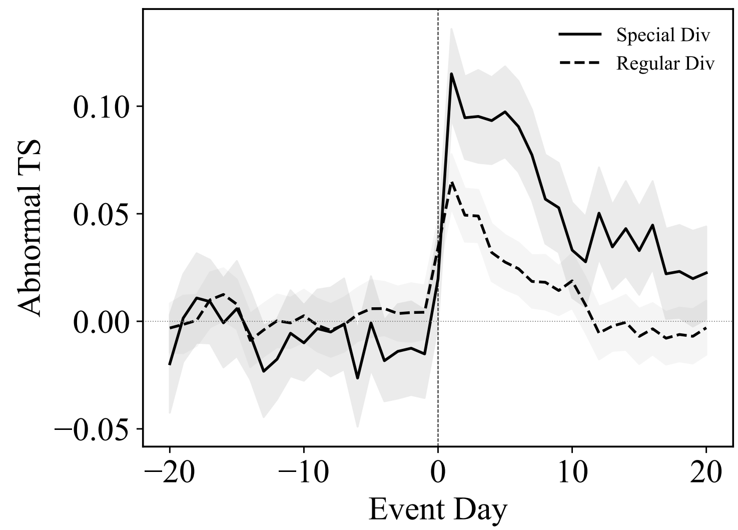



(b) Hidden Trade Ratio (HTR)

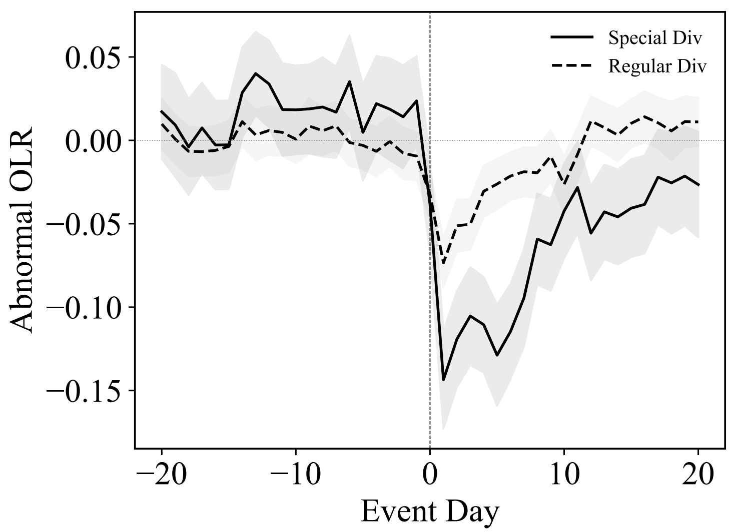
Figure 4: **Hidden Trading Activity in Event Time.** Each panel plots the mean daily level of a hidden trading measure over event days $[-40, +40]$ relative to the special dividend declaration date. The solid line is the cross-sectional mean; the shaded region denotes the 95% confidence interval. Horizontal lines represent the pre-event mean (dash-dot) and post-event mean (dotted). HVR is the log ratio of hidden order volume to total volume for hidden-eligible trades. HTR is the log ratio of hidden trades to total hidden-eligible trades.



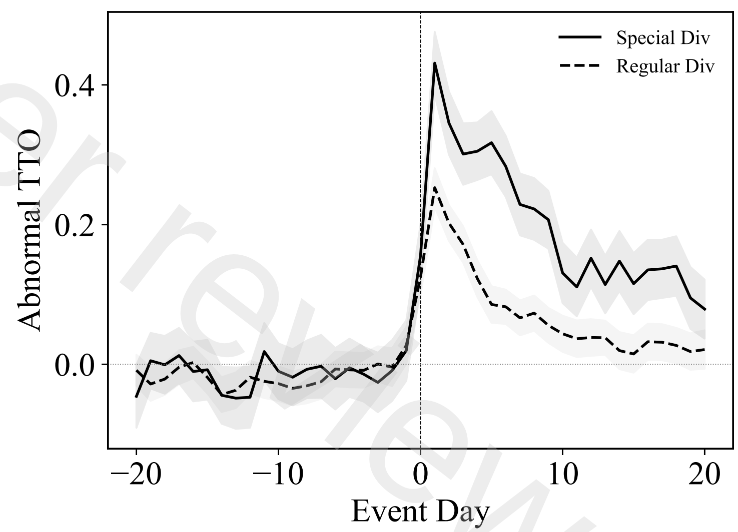

(a) Cancel-to-Trade Ratio (CTT)




(b) Trade Size (TS)




(c) Odd-Lot Ratio (OLR)




(d) Trade-to-Order Ratio (TTO)

Figure 5: **Algorithmic Trading Response: Special vs. Regular Dividends.** Each panel compares mean daily abnormal AT around special dividend announcements (solid line) vs. regular dividend increase announcements (dashed line) by the same firms over event days $[-20, +20]$. Abnormal AT is computed as the daily value minus the firm-specific baseline mean over $[-61, -22]$. Shaded regions denote 95% confidence intervals.

## Tables

**Table 1: Size Classification of Special Dividends by Period**

| | | Count Exceeding | | | Percent Exceeding | | |
|---|---|---|---|---|---|---|---|
| Period | $N$ | 5% | 10% | 18.6% | 5% | 10% | 18.6% |
| 1996–1999 | 363 | 76 | 60 | 43 | 20.94 | 16.53 | 11.85 |
| 2000–2003 | 260 | 46 | 30 | 24 | 17.69 | 11.54 | 9.23 |
| 2004–2007 | 525 | 134 | 88 | 52 | 25.52 | 16.76 | 9.90 |
| 2008–2011 | 398 | 144 | 69 | 33 | 36.18 | 17.34 | 8.29 |
| 2012–2015 | 682 | 212 | 99 | 53 | 31.09 | 14.52 | 7.77 |
| 2016–2019 | 464 | 109 | 55 | 30 | 23.49 | 11.85 | 6.47 |
| 2020–2024 | 680 | 170 | 60 | 32 | 25.00 | 8.82 | 4.71 |
| Total | 3,372 | 891 | 461 | 267 | 26.42 | 13.67 | 7.92 |

*Notes:* This table reports the number and percentage of special dividends exceeding various thresholds of the firm's equity value. Special dividends are identified from CRSP (distribution codes 1262 and 1272) for common stocks (share codes 10 and 11) over 1996–2024. The thresholds of 5%, 10%, and 18.6% follow DeAngelo et al. (2000). The 18.6% corresponds to the average value of repurchases from Dann (1981).

**Table 2: Summary Statistics**

| Variable | $N$ | Mean | Std. Dev. | Min | P1 | P25 | Median | P75 | P99 | Max |
|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Price Jump Measures* | | | | | | | | | | |
| Weller PJ (Full) | 865 | −0.302 | 17.031 | −472.936 | −10.293 | −0.084 | 0.238 | 0.784 | 6.561 | 90.038 |
| Weller PJ [0,1] | 433 | 0.396 | 0.278 | 0.001 | 0.006 | 0.153 | 0.326 | 0.622 | 0.970 | 0.992 |
| Standardized PJ | 865 | 4.023 | 8.096 | 0.414 | 0.538 | 0.993 | 1.361 | 3.730 | 32.929 | 140.874 |
| Std. PJ (Winsorized) | 865 | 3.743 | 5.556 | 0.414 | 0.538 | 0.993 | 1.361 | 3.730 | 32.165 | 32.929 |
| *Panel B: Event and Firm Characteristics* | | | | | | | | | | |
| Special Dividend ($) | 865 | 2.011 | 3.851 | 0.003 | 0.020 | 0.250 | 1.000 | 2.000 | 20.000 | 43.400 |
| Log Price | 262,354 | 3.183 | 1.064 | −1.619 | 0.470 | 2.573 | 3.155 | 3.820 | 6.185 | 7.590 |
| Log Volume | 262,354 | 12.145 | 2.082 | 0.000 | 7.159 | 10.760 | 12.154 | 13.573 | 16.744 | 19.747 |
| Log Market Cap | 262,354 | 13.846 | 1.767 | 7.770 | 10.049 | 12.544 | 13.737 | 14.969 | 18.119 | 19.616 |
| Log Volatility | 254,569 | −3.857 | 0.489 | −6.805 | −4.878 | −4.186 | −3.877 | −3.561 | −2.553 | −0.399 |
| Log Spread | 262,354 | −3.587 | 1.283 | −9.211 | −4.606 | −4.605 | −3.912 | −2.996 | 0.507 | 3.042 |
| *Panel C: Algorithmic Trading Proxies* | | | | | | | | | | |
| Trade Size (TS) | 244,802 | 4.287 | 0.636 | 0.000 | 2.414 | 3.944 | 4.381 | 4.650 | 5.867 | 8.915 |
| Odd-Lot Ratio (OLR) | 244,443 | −1.780 | 0.917 | −9.722 | −4.505 | −2.312 | −1.663 | −1.101 | −0.163 | 0.000 |
| Trade-to-Order (TTO) | 244,802 | −3.655 | 0.772 | −12.145 | −6.025 | −4.041 | −3.585 | −3.181 | −2.013 | 0.961 |
| Cancel-to-Trade (CTT) | 244,802 | 3.009 | 0.726 | −0.757 | 1.571 | 2.531 | 2.922 | 3.391 | 5.227 | 10.138 |
| Hidden Volume Ratio (HVR) | 243,999 | −1.699 | 0.635 | −9.603 | −3.284 | −2.103 | −1.689 | −1.267 | −0.283 | 0.000 |
| Hidden Trade Ratio (HTR) | 244,001 | −1.706 | 0.625 | −5.282 | −3.128 | −2.147 | −1.704 | −1.265 | −0.311 | 0.000 |

*Notes:* This table reports summary statistics for the special dividend sample. Panel A compares price jump measures. Weller PJ (Full) is the unrestricted price jump ratio from Weller (2018); Weller PJ [0,1] restricts to observations with values in the unit interval. Standardized PJ is our proposed measure that accommodates all return patterns including reversals; Std. PJ (Winsorized) clips at the 99th percentile. Panel B presents event-level and firm-level characteristics computed across all firm-day observations within the estimation and event windows. Panel C reports daily algorithmic trading proxy values from MIDAS. All AT proxies are log-transformed ratios. TS is average trade size (tradevol/trades), OLR is odd-lot volume ratio, TTO is trade-to-order ratio, CTT is cancel-to-trade ratio, HVR is hidden volume ratio, and HTR is hidden trade ratio.

**Table 3: Sample Construction**

| Step | Description | Removed | Remaining |
|---|---|---|---|
| 1 | Special dividends (2012–2024, SHRCD 10/11) | — | 1,778 |
| 2 | Surprise-spacing filter | 680 | 1,098 |
| 3 | Same-day non-dividend announcement exclusion | 11 | 1,087 |
| 4 | Edge-day completeness filter | 80 | 1,007 |
| 5 | Minimum observations (>287 days) | 0 | 1,007 |
| 6 | Zero-volume exclusion | 135 | 872 |
| 7 | Manual ticker exclusions | 7 | 865 |

*Notes:* This table details the sequential filters applied to construct the final sample of special dividend events. The initial universe comprises all special dividends (CRSP distribution codes 1262 and 1272) declared between July 1st 2012 and December 31st 2024 by common stocks (share codes 10 and 11). Step 2 removes events that fail the surprise-spacing filter, which excludes firms with recurring special dividends within the prior calendar year. Step 3 drops events coinciding with other non-dividend corporate announcements on the same day. Step 4 requires complete MIDAS data on the boundary days of the event window. Step 5 requires the CRSP data be present and nonmissing for at least 287 out of the 290 days; we allow a slight buffer to retain observations given the small sample size. Step 6 excludes firm-days with zero trading volume. Step 7 removes manually identified tickers with data anomalies such as duplicate tickers and share code switches. The final sample contains 865 special dividend events.

## Table 4: Abnormal Returns Around Special Dividend Events

| | *Declaration Date* | | | | | | *Ex-Dividend Date* | |
|---|---|---|---|---|---|---|---|---|
| | All Events | | Dividend Payers | | Non-Dividend Payers | | All Events | |
| Day | AR (%) | CAR (%) | AR (%) | CAR (%) | AR (%) | CAR (%) | AR (%) | CAR (%) |
| $-5$ | 0.07 | 0.07 | 0.12 | 0.12 | $-0.05$ | $-0.05$ | $0.36^{***}$ | $0.36^{***}$ |
| $-4$ | 0.06 | 0.13 | 0.05 | 0.17 | 0.06 | 0.01 | $0.30^{***}$ | $0.66^{***}$ |
| $-3$ | $-0.02$ | 0.11 | $-0.04$ | 0.13 | 0.04 | 0.05 | $0.16^{*}$ | $0.81^{***}$ |
| $-2$ | $-0.14^{**}$ | $-0.03$ | $-0.06$ | 0.07 | $-0.38^{**}$ | $-0.33$ | $0.22^{***}$ | $1.03^{***}$ |
| $-1$ | $-0.06$ | $-0.10$ | $-0.09$ | $-0.02$ | 0.01 | $-0.33$ | $0.23^{***}$ | $1.27^{***}$ |
| 0 | $0.64^{***}$ | $0.54^{***}$ | $0.42^{***}$ | $0.40^{**}$ | $1.28^{***}$ | $0.95^{*}$ | 0.05 | $1.32^{***}$ |
| 1 | $1.83^{***}$ | $2.37^{***}$ | $1.57^{***}$ | $1.97^{***}$ | $2.63^{***}$ | $3.58^{***}$ | $-0.18^{*}$ | $1.13^{***}$ |
| 2 | $0.45^{***}$ | $2.83^{***}$ | $0.41^{***}$ | $2.38^{***}$ | 0.57 | $4.15^{***}$ | $-0.43^{***}$ | $0.70^{***}$ |
| 3 | $0.17^{*}$ | $3.00^{***}$ | 0.14 | $2.52^{***}$ | 0.28 | $4.42^{***}$ | $-0.24^{***}$ | $0.47^{*}$ |
| 4 | $0.31^{***}$ | $3.31^{***}$ | $0.28^{***}$ | $2.80^{***}$ | $0.39^{*}$ | $4.81^{***}$ | $-0.01$ | $0.46^{*}$ |
| 5 | $0.36^{***}$ | $3.67^{***}$ | $0.28^{***}$ | $3.08^{***}$ | $0.60^{**}$ | $5.41^{***}$ | $-0.09$ | 0.37 |
| $N$ | 865 | | 647 | | 218 | | 865 | |

*Notes:* This table reports mean daily abnormal returns (AR) and cumulative abnormal returns (CAR) around special dividend events. The first six columns use the announcement date as the event date; we report separately for all events, firms that also pay regular dividends (Dividend Payers), and firms that do not (Non-Dividend Payers). The last two columns report returns around the ex-dividend date for all events. Abnormal returns are computed using the Fama and French (2015) five-factor model plus momentum (Jegadeesh and Titman, 1993), estimated over days $[-250, -41]$ relative to each event date. $^{***}$, $^{**}$, and $^{*}$ denote significance at the 1%, 5%, and 10% levels based on cross-sectional $t$-tests.

**Table 5: Cross-Sectional Regressions of Cumulative Abnormal Returns**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Intercept | 0.2431*** | 0.1297** | 0.2224*** | 0.2224*** |
| | (0.0539) | (0.0571) | (0.0852) | (0.0853) |
| divamt | 0.0167*** | | 0.0250** | 0.0250** |
| | (0.0028) | | (0.0099) | (0.0099) |
| ratio | | 0.0133*** | −0.0064 | −0.0064 |
| | | (0.0022) | (0.0074) | (0.0074) |
| ratio×divamt | | | | −0.0000 |
| | | | | (0.0010) |
| price | −0.0374*** | −0.0308*** | −0.0504*** | −0.0504*** |
| | (0.0086) | (0.0091) | (0.0151) | (0.0151) |
| volume | −0.0080 | −0.0150*** | −0.0119*** | −0.0119*** |
| | (0.0055) | (0.0045) | (0.0044) | (0.0044) |
| volatility | 0.0252*** | 0.0191** | 0.0174* | 0.0174* |
| | (0.0091) | (0.0094) | (0.0090) | (0.0091) |
| size | 0.0101 | 0.0180*** | 0.0165*** | 0.0165*** |
| | (0.0067) | (0.0051) | (0.0050) | (0.0050) |
| spread | 0.0106** | 0.0060 | 0.0089** | 0.0089** |
| | (0.0044) | (0.0044) | (0.0044) | (0.0045) |
| Observations | 865 | 647 | 647 | 647 |
| $R^2$ | 0.113 | 0.104 | 0.137 | 0.137 |

*Notes:* This table reports OLS cross-sectional regressions of cumulative abnormal returns (CAR$[-1,+5]$) on special dividend and firm characteristics. Abnormal returns are estimated using the Fama and French (2015) five-factor model plus momentum (Jegadeesh and Titman, 1993) over the estimation window $[-250,-41]$. divamt is the special dividend amount per share. ratio is the special-to-regular dividend ratio (available only for firms that also pay regular dividends; $N = 647$ in columns 2–4). price, volume, size, volatility, and spread are in log units and measured as event-window averages [-21,-1]. Column (4) includes an interaction term between ratio and divamt. Heteroskedasticity-robust (HC1) standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table 6: Information Acquisition: Algorithmic Trading and Pre-Announcement Price Jumps**

| | TS | OLR | TTO | CTT | TS | OLR | TTO | CTT |
|---|---|---|---|---|---|---|---|---|
| ***Panel A: AT Levels*** | | | | | | | | |
| *DV: Weller's Price Jump* | | | | | *DV: Standardized Price Jump* | | | |
| AT Proxy | 0.0678 | −0.0483 | −0.0558* | 0.0562* | 0.4107 | 0.2256 | −0.3483 | 0.2601 |
| | (0.0649) | (0.0393) | (0.0322) | (0.0327) | (1.1923) | (0.6367) | (0.4408) | (0.4536) |
| $N$ | 433 | 433 | 433 | 433 | 865 | 865 | 865 | 865 |
| $R^2$ | 0.065 | 0.066 | 0.070 | 0.069 | 0.133 | 0.133 | 0.133 | 0.133 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year & Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ***Panel B: Abnormal AT*** | | | | | | | | |
| *DV: Weller's Price Jump* | | | | | *DV: Standardized Price Jump* | | | |
| Ab. AT Proxy | −0.1151 | 0.1163* | −0.0834** | 0.0820* | −3.3159** | 2.8945*** | −1.3541** | 1.1112* |
| | (0.0938) | (0.0627) | (0.0380) | (0.0441) | (1.4539) | (0.9520) | (0.6297) | (0.6481) |
| $N$ | 433 | 433 | 433 | 433 | 865 | 865 | 865 | 865 |
| $R^2$ | 0.066 | 0.071 | 0.072 | 0.070 | 0.140 | 0.143 | 0.139 | 0.136 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year & Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table reports OLS regressions of price jump measures on algorithmic trading (AT) proxies around special dividend announcements. Each column represents a separate regression with one AT proxy as the independent variable. Panel A uses AT levels averaged over the pre-announcement window $[-21, -1]$. Panel B uses abnormal AT, constructed as the difference between the pre-event mean ($[-21, -1]$) and the baseline mean ($[-61, -22]$). Weller's Price Jump is the price jump ratio from Weller (2018), restricted to $[0, 1]$. Standardized Price Jump is our proposed measure, winsorized at the 99th percentile. AT proxies are: TS (log trade size), OLR (log odd-lot ratio), TTO (log trade-to-order ratio), and CTT (log cancel-to-trade ratio). Controls include log price, log volume, log market capitalization, volatility, and spread. All specifications include Fama–French 12 industry and year fixed effects. HC1 standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table 7: Placebo Tests: Algorithmic Trading at Non-Event Dates**

| | TS | OLR | TTO | CTT | TS | OLR | TTO | CTT |
|---|---|---|---|---|---|---|---|---|
| ***Panel A: AT Levels*** | | | | | | | | |
| *DV: Weller's Price Jump* | | | | | *DV: Standardized Price Jump* | | | |
| AT Proxy | 0.1015* | −0.0714** | 0.0137 | −0.0065 | 1.1064 | −0.6551 | 0.2376 | −0.1555 |
| | (0.0563) | (0.0351) | (0.0319) | (0.0313) | (1.0077) | (0.6372) | (0.3925) | (0.3995) |
| $N$ | 433 | 433 | 433 | 433 | 864 | 864 | 864 | 864 |
| $R^2$ | 0.069 | 0.071 | 0.063 | 0.063 | 0.135 | 0.135 | 0.133 | 0.133 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year & Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ***Panel B: Abnormal AT*** | | | | | | | | |
| *DV: Weller's Price Jump* | | | | | *DV: Standardized Price Jump* | | | |
| Ab. AT Proxy | 0.0057 | 0.0307 | −0.0118 | 0.0044 | −2.4030 | 0.2720 | −0.0919 | −0.3146 |
| | (0.1056) | (0.0668) | (0.0396) | (0.0439) | (1.9426) | (1.1014) | (0.6294) | (0.6167) |
| $N$ | 433 | 433 | 433 | 433 | 862 | 862 | 862 | 862 |
| $R^2$ | 0.063 | 0.063 | 0.063 | 0.063 | 0.136 | 0.133 | 0.133 | 0.133 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Year & Industry FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table reports placebo tests using pseudo-announcement dates drawn uniformly from $[-120, -60]$ relative to the actual special dividend declaration date. The dependent variables are the actual price jump measures computed at the true event date. Panel A uses AT levels averaged over $[\text{pseudo} - 21, \text{pseudo} - 1]$. Panel B uses abnormal AT, constructed as the difference between the pseudo pre-event mean and the pseudo baseline mean ($[\text{pseudo} - 61, \text{pseudo} - 22]$). Weller's Price Jump is restricted to $[0, 1]$. Standardized Price Jump is winsorized at the 99th percentile. AT proxies are: TS (log trade size), OLR (log odd-lot ratio), TTO (log trade-to-order ratio), and CTT (log cancel-to-trade ratio). Controls include log price, log volume, log market capitalization, volatility, and spread. All specifications include Fama–French 12 industry and year fixed effects. HC1 standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table 8: Information Incorporation and Post-Announcement Dynamics**

| | TS | OLR | TTO | CTT |
|---|---|---|---|---|
| ***Panel A: Incorporation Ratio*** | | | | |
| *AT Levels, days* $[0, +2]$ | | | | |
| AT Proxy | $-0.3786$ | 0.2436 | $-0.0430$ | 0.0995 |
| | (0.3181) | (0.1818) | (0.1927) | (0.2012) |
| *Abnormal AT, days* $[0, +2]$ | | | | |
| Ab. AT Proxy | 0.0922 | $-0.2930$ | $-0.1363$ | 0.2927 |
| | (0.3765) | (0.2976) | (0.1743) | (0.2024) |
| $N$ | 865 | 865 | 865 | 865 |
| Controls | Yes | Yes | Yes | Yes |
| Year & Industry FE | Yes | Yes | Yes | Yes |
| ***Panel B: Post-Announcement Standardized Price Jump*** | | | | |
| *AT Levels, days* $[0, +2]$ | | | | |
| AT Proxy | $-0.0080$ | 0.0982 | $-0.3358^{*}$ | $0.4710^{**}$ |
| | (0.4875) | (0.2790) | (0.2025) | (0.2101) |
| *Abnormal AT, days* $[0, +2]$ | | | | |
| Ab. AT Proxy | $-1.7091^{**}$ | 0.5523 | $-0.6198^{**}$ | $0.5524^{**}$ |
| | (0.7011) | (0.4051) | (0.2552) | (0.2451) |
| $N$ | 865 | 865 | 865 | 865 |
| Controls | Yes | Yes | Yes | Yes |
| Year & Industry FE | Yes | Yes | Yes | Yes |
| ***Panel C: Post-Announcement Return Reversals (LPM)*** | | | | |
| *AT Levels, days* $[0, +2]$ | | | | |
| AT Proxy | 0.0100 | $-0.0248$ | $-0.0538^{**}$ | $0.0726^{**}$ |
| | (0.0538) | (0.0315) | (0.0262) | (0.0282) |
| *Abnormal AT, days* $[0, +2]$ | | | | |
| Ab. AT Proxy | $-0.0872$ | 0.0500 | $-0.0831^{***}$ | $0.0903^{***}$ |
| | (0.0608) | (0.0455) | (0.0267) | (0.0289) |
| $N$ | 865 | 865 | 865 | 865 |
| Controls | Yes | Yes | Yes | Yes |
| Year & Industry FE | Yes | Yes | Yes | Yes |

*Notes:* This table examines whether AT accelerates post-announcement information incorporation and or is associated with return reversals, with Fama–French 12 industry and year fixed effects. Each column represents a separate regression with one AT proxy. Panel A uses the incorporation ratio, CAR$[0, 2]$/CAR$[0, 5]$, as the dependent variable. Panel B uses the standardized price jump computed over the post-announcement window. Panel C reports linear probability model (LPM) regressions where the dependent variable equals one if the sign of CAR$[0, 2]$ differs from the sign of CAR$[0, 5]$ (approximately 15% of events). AT proxies are measured over $[0, +2]$ for levels or differenced from $[-61, -22]$ for abnormal measures. Controls include log price, log volume, log market capitalization, log volatility, and log spread. All specifications include Fama–French 12 industry and year fixed effects. Heteroskedasticity-robust standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

# Appendix A Standardized Price Jump: Worked Examples and Sample Comparison

This appendix provides additional support for the standardized price jump measure introduced in Section 4. First, we present four worked examples from the sample that illustrate the step-by-step computation of both measures under different return dynamics. Second, we characterize the observations that Weller's $[0, 1]$ truncation discards and show that they differ systematically from the retained sample. Third, we present a subsample regression comparison that isolates the effects of the measure choice versus the sample restriction.

## A.1 Worked Examples

We illustrate the computation of both price jump measures using four observations from our sample. In each case, $CAR^{[-21,-2]}$ denotes the pre-announcement cumulative abnormal return and $CAR^{[-1,+1]}$ the announcement-window cumulative abnormal return, both in percentage points.

**Example 1: Normal Agreement — AEO (September 12, 2012)**

American Eagle Outfitters announced a special dividend with $CAR^{[-21,-2]} = 3.14\%$ and $CAR^{[-1,+1]} = 2.15\%$. Both windows have the same sign, so Weller's measure is well-behaved:

$$PJ^{Weller} = \frac{2.15}{2.15 + 3.14} = \frac{2.15}{5.29} = 0.406.$$

The standardized price jump is computed in two parts. The first term captures the announcement surprise weighted by the announcement window's dominance:

$$\text{First term} = \frac{|2.15 - 3.14| \times 2.15^2}{3.14^2 + 2.15^2} = \frac{0.99 \times 4.62}{9.86 + 4.62} = 0.316.$$

The second term captures the relative share of pre-announcement movement:

$$\text{Second term} = \frac{|3.14|}{|3.14| + |2.15|} = \frac{3.14}{5.29} = 0.593.$$

Thus $PJ^{stan} = 0.316 + 0.593 = 0.910$. Both measures agree: there was a moderate informational gap but a majority of information was acquired and incorporated pre-announcement. This example illustrates the baseline correspondence between the two measures.

**Example 2: Reversal — COST (January 30, 2015)**

Costco's special dividend announcement was preceded by a negative drift, with $CAR^{[-21,-2]} = -2.98\%$ and $CAR^{[-1,+1]} = 4.41\%$. The opposite signs create a reversal:

$$PJ^{Weller} = \frac{4.41}{4.41 + (-2.98)} = \frac{4.41}{1.43} = 3.082 \;\notin [0,1],$$

so this observation would be discarded under Weller's truncation. The standardized measure handles the reversal:

$$\text{First term} = \frac{|4.41 - (-2.98)| \times 4.41^2}{2.98^2 + 4.41^2} = \frac{7.39 \times 19.45}{8.88 + 19.45} = 5.07,$$

$$\text{Second term} = \frac{|-2.98|}{|-2.98| + |4.41|} = \frac{2.98}{7.39} = 0.403,$$

yielding $PJ^{stan} = 5.07 + 0.40 = 5.48$. The negative pre-event drift was reversed by a positive announcement reaction – consistent with a meaningful information asymmetry being resolved by the signal. The standardized measure captures this moderate asymmetry; Weller's measure discards it entirely.

**Example 3: Magnitude — SIGA (March 12, 2024)**

SIGA Technologies announced a special dividend with $CAR^{[-21,-2]} = 3.00\%$ and $CAR^{[-1,+1]} = 32.01\%$ — a massive announcement-window reaction. Both CARs are positive, so Weller's measure is well-defined:

$$PJ^{Weller} = \frac{32.01}{32.01 + 3.00} = \frac{32.01}{35.01} = 0.914 \ \in [0, 1].$$

A value near 1 suggests a large informational gap. However what it does not account for is the magnitude of the informational gap. This same value of 0.914 could be acheived by a minor return pattern with a similar ratio. The standardized measure, however, reflects the event's magnitude:

$$\text{First term} = \frac{|32.01 - 3.00| \times 32.01^2}{3.00^2 + 32.01^2} = \frac{29.01 \times 1024.64}{9.00 + 1024.64} = 28.76,$$

$$\text{Second term} = \frac{|3.00|}{|3.00| + |32.01|} = \frac{3.00}{35.01} = 0.086,$$

yielding $PJ^{stan} = 28.76 + 0.09 = 28.84$. Where Weller's ratio compresses this into $[0, 1]$ alongside far smaller events, the standardized measure recognizes the substantial informational gap that was resolved at announcement. This distinction matters for cross-sectional regressions: the standardized measure allows the econometric specification to differentiate between events with large and small information asymmetries, even when both have Weller values near unity.

**Example 4: Denominator Collapse — AMSF (February 27, 2014)**

Amerisafe Inc. experienced a near-symmetric reversal, with $CAR^{[-21,-2]} = -9.71\%$ and $CAR^{[-1,+1]} = 9.82\%$. The denominator of Weller's measure approaches zero:

$$CAR^{[-1,+1]} + CAR^{[-21,-2]} = 9.82 + (-9.71) = 0.11 \approx 0,$$

$$PJ^{Weller} = \frac{9.82}{0.11} = 90.04.$$

This value is economically meaningless and would be discarded. The standardized measure uses a sum-of-squares denominator that is bounded away from zero whenever either CAR is nonzero:

$$\text{First term} = \frac{|9.82 - (-9.71)| \times 9.82^2}{9.71^2 + 9.82^2} = \frac{19.53 \times 96.43}{94.28 + 96.43} = 9.87,$$

$$\text{Second term} = \frac{|-9.71|}{|-9.71| + |9.82|} = \frac{9.71}{19.53} = 0.497,$$

yielding $PJ^{stan} = 9.87 + 0.50 = 10.37$. The pre-event price drift was almost entirely offset by the announcement reaction, indicating a substantial resolution of information asymmetry. Weller's denominator collapse produces 90.04 – nearly ninety times the theoretical maximum – while the standardized measure assigns a moderate value that correctly reflects the magnitude of the reversal.

## A.2 Characteristics of Dropped Observations

Weller's $[0, 1]$ truncation discards nearly half the sample: 432 of 865 observations fall outside the admissible range. Table A1 compares the mean characteristics of the retained and dropped subsamples. Dropped observations have significantly higher trading volume, marginally higher volatility, tighter spreads, and larger absolute announcement-window CARs. The last difference is especially consequential: the events discarded by Weller's truncation are precisely those with the strongest announcement reactions, meaning the truncation systematically removes the most informative observations from the cross-section. Size, price, dividend amount, and absolute pre-announcement CARs do not differ significantly between the two groups. These results indicate that the $[0, 1]$ restriction does not remove observations at random; rather, it selectively eliminates higher-activity, higher-information events, which may bias cross-sectional regressions that rely on the truncated sample.

**Table A1: Characteristics of Observations Dropped by Weller's $[0, 1]$ Truncation**

| Variable | Kept ($N$=433) | Dropped ($N$=432) | Diff (D–K) | $t$-stat | $p$-value | |
|---|---|---|---|---|---|---|
| Size (log mktcap) | 13.848 | 13.967 | 0.119 | −0.989 | 0.323 | |
| Price (log) | 3.265 | 3.209 | −0.055 | 0.764 | 0.445 | |
| Volume (log) | 11.920 | 12.197 | 0.276 | −1.991 | 0.047 | ** |
| Volatility (log) | −3.955 | −3.895 | 0.060 | −1.933 | 0.054 | * |
| Spread (log) | −3.447 | −3.612 | −0.165 | 2.097 | 0.036 | ** |
| Dividend Amt. ($) | 2.137 | 1.886 | −0.251 | 0.957 | 0.339 | |
| $\|CAR^{[-21,-2]}\|$ (%) | 6.523 | 7.005 | 0.483 | −0.880 | 0.379 | |
| $\|CAR^{[-1,+1]}\|$ (%) | 3.995 | 5.414 | 1.419 | −2.723 | 0.007 | *** |

*Notes:* This table compares mean characteristics of events retained vs. discarded by Weller's $[0, 1]$ price jump restriction. "Kept" observations ($N = 433$) have $PJ^{Weller} \in [0, 1]$; "Dropped" ($N = 432$) fall outside this range. Diff is Dropped minus Kept. Welch Satterthwaite $t$-statistics are presented. *, **, *** denote significance at the 10%, 5%, and 1% levels.

## A.3 Subsample Regression Comparison

A natural question is whether the stronger results in our main analysis arise because the standardized price jump is a mechanically different measure or because it retains the 432 observations that Weller's truncation discards. To disentangle these two channels, Table A2 reports three parallel regressions for each abnormal AT proxy: (1) Weller's price jump on the truncated subsample ($N = 433$), (2) the standardized price jump on the same truncated subsample ($N = 433$), and (3) the standardized price jump on the full sample ($N = 865$). Comparing rows (1) and (2) isolates the effect of the measure while holding the sample constant; comparing rows (2) and (3) isolates the effect of restoring the dropped observations while holding the measure constant.

On the truncated subsample, switching from Weller's measure to the standardized price jump does not materially improve inference. Weller's measure yields marginal significance for Abnormal OLR ($p = 0.064$) and Abnormal CTT ($p = 0.063$), while the standardized price jump on the same 433 observations produces no significant coefficients. The key improvement comes from restoring the full sample. Moving from row (2) to row (3), Abnormal OLR strengthens from insignificant to highly significant ($p = 0.002$), Abnormal TS from insignificant to significant ($p = 0.023$), and Abnormal TTO from insignificant to significant ($p = 0.032$), with Abnormal CTT becoming marginally significant ($p = 0.086$). This pattern indicates that the statistical power of our main results derives primarily from retaining the observations that Weller's truncation discards – the higher-activity, higher-information events documented in subsection A.2 – rather than from a mechanical difference between the two measures themselves. The standardized price jump's contribution is not that it rescales the dependent variable, but that it produces well-defined values for all return patterns, thereby preserving the full cross-section for estimation.

**Table A2: Subsample Regression Comparison: Weller PJ vs. Standardized PJ**

| Sample | IV | Coef. | SE | $t$ | $p$ | $N$ |
|---|---|---|---|---|---|---|
| Weller N=433 | aolr | 0.1163 | 0.0627 | 1.855 | 0.0636* | 433 |
| StdPJ N=433 | aolr | 1.1658 | 0.7159 | 1.628 | 0.1035 | 433 |
| StdPJ N=865 | aolr | 2.8945 | 0.9520 | 3.040 | 0.0024*** | 865 |
| Weller N=433 | ats | -0.1151 | 0.0938 | -1.228 | 0.2196 | 433 |
| StdPJ N=433 | ats | -1.1042 | 1.0161 | -1.087 | 0.2772 | 433 |
| StdPJ N=865 | ats | -3.3159 | 1.4539 | -2.281 | 0.0226** | 865 |
| Weller N=433 | atto | -0.0834 | 0.0380 | -2.192 | 0.0284** | 433 |
| StdPJ N=433 | atto | -0.5490 | 0.3800 | -1.445 | 0.1485 | 433 |
| StdPJ N=865 | atto | -1.3541 | 0.6297 | -2.150 | 0.0315** | 865 |
| Weller N=433 | actt | 0.0820 | 0.0441 | 1.859 | 0.0630* | 433 |
| StdPJ N=433 | actt | 0.3496 | 0.4587 | 0.762 | 0.4459 | 433 |
| StdPJ N=865 | actt | 1.1112 | 0.6481 | 1.715 | 0.0864* | 865 |

*Notes:* Each row reports the coefficient on the abnormal AT proxy from a univariate PJ regression with controls (log price, volume, volatility, size, spread) and year and Fama–French 12 industry fixed effects. "Weller N=433" uses $PJ^{Weller}$ as the DV on the $[0, 1]$-restricted subsample. "StdPJ N=433" uses $PJ^{stan}$ (winsorized) on the same subsample. "StdPJ N=865" uses $PJ^{stan}$ (winsorized) on the full sample. *, **, *** denote significance at the 10%, 5%, and 1% levels.

# Appendix B Detailed Robustness Discussion

This appendix provides extended discussion of the robustness tests summarized in Section 6.

## B.1 Fixed Effects Specifications

Table IA2 re-estimates the information acquisition regressions (Table 6, Panel B) under four fixed effects specifications: no fixed effects, year fixed effects only, industry fixed effects only (Fama–French 12 industries), and both year and industry fixed effects. The coefficients on abnormal AT are stable across specifications. In Tables IA13 and IA14 we report the information acquisition and placebo regressions without fixed effects; the results are similar across specifications.

## B.2 Window Sensitivity

To address concerns that our estimations using abnormal AT depend on the baseline and pre-event window specifications, Table IA10 presents a matrix of results across five pre-event windows ($[-21,-1]$, $[-15,-1]$, $[-10,-1]$, $[-5,-1]$, $[-3,-1]$) and three baseline windows ($[-61,-22]$, $[-80,-41]$, $[-120,-61]$). The results are not particularly sensitive to the baseline window, but shorter pre-event windows reduce statistical significance while the coefficient signs remain similar.

## B.3 Bootstrap, Permutation, and Power Analysis

Table IA3 addresses concerns about the distributional assumptions underlying OLS inference. The first panel reports alternative inference based on 10,000 paired bootstrap replications and 10,000 permutation iterations in which abnormal AT is randomly reassigned across events. Three of four AT proxies produce bootstrap 95% confidence intervals that exclude zero – Abnormal CTT's interval narrowly includes it ($[-0.026, 2.648]$) – reinforcing the OLS significance levels. The permutation $p$-values are uniformly smaller than the OLS $p$-values (e.g., 0.003 vs. 0.004 for Abnormal OLR; 0.005 vs. 0.015 for Abnormal TS), indicating that the observed associations are unlikely to arise from chance reassignment of AT across events.

The second panel evaluates statistical power. At 80% power and a 5% two-sided significance level, the minimum detectable effect (MDE) for Abnormal OLR (2.62) falls below the observed coefficient (2.71), confirming adequate power for this proxy. For Abnormal TS, TTO, and CTT, the MDEs exceed the observed effects (e.g., 4.03 vs. 3.50 for TS), indicating that the sample is underpowered for these measures individually. Importantly, the permutation and placebo tests both argue against spurious inference: the permutation $p$-values confirm that the AT–price jump associations are non-spurious, and the placebo regressions show no relation between abnormal AT and pre-announcement returns at non-event dates.

### B.4 Instrumental Variables

Following Weller (2018), we estimate 2SLS regressions using log price over $[-42, -22]$ as an instrument for AT activity (Table IA5). The instrument captures structural cross-sectional variation in AT related to price. Our abnormal AT construction already isolates event-specific variation by demeaning across firms, effectively serving as its own identification strategy. Instrumenting abnormal AT directly yields weak first stages, confirming that the price-level instrument does not generate useful variation beyond what our abnormal measure already captures. We therefore rely on our placebo tests (Table 7), cross-event gradient analysis (Table IA9), and bootstrap and permutation inference (Table IA3) for identification.

### B.5 Cross-Event Gradient and Additional Tests

Table IA9 compares the AT–price jump relationship across four event types: surprise special dividends, non-surprise special dividends, regular dividend increases, and regular dividend decreases. Special dividends exhibit the largest effect, consistent with conveying the strongest signal. Regular dividend increases show a relation to abnormal TTO and CTT, but the magnitudes are smaller.

Abnormal hidden trading ratios (HTR, HVR) are insignificant when substituted for AT proxies in the information acquisition specification, implying that it is AT activity rather than informed trading activity driving results. After Benjamini-Hochberg FDR correction at 5% (Table IA7), Abnormal TS, OLR, and TTO remain significant while CTT does not. A horse race regression with all four proxies entered simultaneously (Table IA6) yields no individual significance due to high variance inflation factors (VIFs range from 3.02 to 8.89), consistent with the four AT proxies capturing overlapping variation from MIDAS data.

Table IA15 reports the information incorporation regressions without fixed effects, as well as estimating the reversal indicator using logistic regression. The results are qualitatively consistent with Table 8. Table IA12 examines whether AT predicts the magnitude of return reversals among reversal events ($N = 150$). No significant relationship emerges, suggesting that while AT predicts the *probability* of a reversal, it does not predict its severity.

# Internet Appendix Tables

**Table IA1: Daily Abnormal Hidden Trading Around Special Dividend Announcements**

| | Ab. HVR | | Ab. HTR | |
|---|---|---|---|---|
| Day | Mean | $t$-stat | Mean | $t$-stat |
| $-5$ | 0.001 | 0.08 | $0.027^{**}$ | 2.16 |
| $-4$ | 0.001 | 0.07 | 0.005 | 0.41 |
| $-3$ | 0.007 | 0.50 | 0.000 | 0.03 |
| $-2$ | $0.030^{*}$ | 1.93 | $0.033^{***}$ | 2.66 |
| $-1$ | $0.030^{**}$ | 2.05 | $0.043^{***}$ | 3.41 |
| 0 | $0.049^{***}$ | 3.19 | $0.057^{***}$ | 4.51 |
| 1 | $0.061^{***}$ | 4.11 | $0.062^{***}$ | 4.81 |
| 2 | $0.039^{**}$ | 2.46 | $0.047^{***}$ | 3.78 |
| 3 | $-0.007$ | $-0.41$ | 0.005 | 0.43 |
| 4 | $-0.001$ | $-0.04$ | 0.002 | 0.18 |
| 5 | $-0.019$ | $-1.29$ | $-0.021$ | $-1.61$ |

*Notes:* This table reports mean daily abnormal hidden trading measures for event days $-5$ through $+5$ relative to the special dividend declaration date. Abnormal hidden trading is computed as the daily hidden trading proxy minus the firm-specific baseline mean over $[-61, -22]$. HVR is the log hidden volume ratio (hidden volume relative to total volume). HTR is the log hidden trade ratio (hidden trades relative to total trades). Both measures are constructed from SEC MIDAS data. Significance is assessed via cross-sectional $t$-tests. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA2: Robustness: Fixed Effects Specifications**

| | None | Year FE | Industry FE | Year + Industry FE |
|---|---|---|---|---|
| Ab. OLR | $2.7130^{***}$ | $2.7133^{***}$ | $2.7854^{***}$ | $2.8952^{***}$ |
| | (0.9366) | (0.9453) | (0.9500) | (0.9519) |
| Ab. TS | $-3.4998^{**}$ | $-3.1416^{**}$ | $-3.6433^{**}$ | $-3.3162^{**}$ |
| | (1.4394) | (1.4448) | (1.4538) | (1.4538) |
| Ab. TTO | $-1.5090^{**}$ | $-1.2461^{*}$ | $-1.6076^{**}$ | $-1.3543^{**}$ |
| | (0.6579) | (0.6495) | (0.6461) | (0.6297) |
| Ab. CTT | $1.2834^{*}$ | 1.0475 | $1.3528^{**}$ | $1.1113^{*}$ |
| | (0.6815) | (0.6707) | (0.6652) | (0.6481) |
| $N$ | 865 | 865 | 865 | 865 |
| Controls | Yes | Yes | Yes | Yes |

*Notes:* This table re-estimates the Table 6 Panel B specification (standardized price jump on abnormal AT) under alternative fixed effects structures. Each cell reports the coefficient on the indicated abnormal AT proxy from a separate regression. Column 1 reproduces the baseline with no fixed effects. Columns 2–4 add year fixed effects, Fama–French 12 industry fixed effects, and both, respectively. Controls include log price, log volume, log market capitalization, log volatility, and log spread. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA3: Robustness: Bootstrap, Permutation Inference, and Statistical Power**

| | *Bootstrap and Permutation Inference* | | | | | | *Statistical Power* | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| AT Metric | Coef. | OLS $p$ | Boot. SE | Bootstrap 95% CI | Perm. $p$ | $N$ | MDE (80%) | Obs. Effect | Detectable? | $N$ |
| Ab. OLR | $2.7130^{***}$ | 0.004 | 0.9338 | [0.905, 4.578] | 0.003 | 865 | 2.624 | 2.713 | Yes | 865 |
| Ab. TS | $-3.4998^{**}$ | 0.015 | 1.4599 | [−6.362, −0.613] | 0.005 | 865 | 4.033 | 3.500 | No | 865 |
| Ab. TTO | $-1.5090^{**}$ | 0.022 | 0.6530 | [−2.800, −0.243] | 0.005 | 865 | 1.843 | 1.509 | No | 865 |
| Ab. CTT | $1.2834^{*}$ | 0.060 | 0.6794 | [−0.026, 2.648] | 0.033 | 865 | 1.909 | 1.283 | No | 865 |

*Notes:* This table combines alternative inference (left panel) and statistical power analysis (right panel) for the information acquisition regressions (standardized price jump on abnormal AT). *Left panel:* Coefficients from an OLS regression and OLS $p$ reproduce the baseline estimates. Bootstrapped SE and Bootstrap 95% CI are from 10,000 paired bootstrap replications. Perm. $p$ is from a permutation test that randomly shuffles the abnormal AT variable across events (10,000 iterations). *Right panel:* The minimum detectable effect (MDE) at 80% power and a 5% two-sided significance level is computed as $2.802 \times \text{SE}$. Controls include log price, log volume, log market capitalization, log volatility, and log spread. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$ based on OLS $p$-values.

**Table IA4: Difference-in-Differences: AT Response to Special vs. Regular Dividends**

| | Pooled OLS | | | Event FE | |
|---|---|---|---|---|---|
| | SD ($\hat{\beta}_1$) | Post ($\hat{\beta}_2$) | SD×Post ($\hat{\beta}_3$) | Post ($\hat{\beta}_2$) | SD×Post ($\hat{\beta}_3$) |
| TS | 0.1987*** | 0.0010 | 0.0352*** | −0.0002 | 0.0363*** |
| | (8.51) | (0.38) | (5.56) | (−0.07) | (5.75) |
| OLR | −0.2821*** | −0.0010 | −0.0497*** | 0.0007 | −0.0491*** |
| | (−9.04) | (−0.28) | (−5.74) | (0.20) | (−5.74) |
| TTO | 0.1090*** | 0.0506*** | 0.1011*** | 0.0514*** | 0.1003*** |
| | (4.84) | (7.61) | (7.11) | (7.71) | (7.05) |
| CTT | −0.0356 | −0.0479*** | −0.0789*** | −0.0494*** | −0.0774*** |
| | (−1.61) | (−8.18) | (−6.34) | (−8.43) | (−6.22) |
| $N$ | | | 246,503 | | |

*Notes:* This table reports difference-in-differences regressions comparing AT dynamics around special vs. regular dividend announcements by the same firms. The specification is: $AT_{it} = \alpha + \hat{\beta}_1 SD_i + \hat{\beta}_2 Post_{it} + \hat{\beta}_3 (SD_i \times Post_{it}) + \varepsilon_{it}$. $SD_i = 1$ for special dividends, 0 for regular dividend increases. $Post_{it} = 1$ for event days $[0, +40]$, 0 for $[-40, -1]$. The coefficient of interest is $\hat{\beta}_3$, which captures the differential AT response to special dividends. Event FE absorbs $SD_i$. $t$-statistics from event-clustered standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA5: Instrumental Variables (2SLS) Estimates**

| | *Raw AT Levels* | | | | *Abnormal AT* | | | |
|---|---|---|---|---|---|---|---|---|
| | TS | OLR | TTO | CTT | Ab. TS | Ab. OLR | Ab. TTO | Ab. CTT |
| ***Panel A: First Stage*** | | | | | | | | |
| Log Price (IV) | $-0.3186^{***}$ | $0.5321^{***}$ | $-0.0472$ | $0.0418$ | $0.0167^{*}$ | $-0.0342^{**}$ | $0.0721^{***}$ | $-0.0710^{***}$ |
| | (0.0269) | (0.0413) | (0.0322) | (0.0341) | (0.0095) | (0.0140) | (0.0209) | (0.0182) |
| First-stage $F$ | 241.22 | 173.16 | 70.94 | 53.84 | 4.86 | 4.66 | 5.88 | 4.69 |
| ***Panel B: Second Stage (DV: Standardized PJ)*** | | | | | | | | |
| $\widehat{\text{AT}}$ | $2.9321^{**}$ | $-1.7555^{**}$ | $19.8069$ | $-22.3721$ | $-55.9844$ | $27.3550^{*}$ | $-12.9591^{**}$ | $13.1663^{**}$ |
| | (1.3096) | (0.7842) | (16.3948) | (20.6572) | (36.9687) | (14.1945) | (6.2933) | (6.2196) |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| $N$ | 865 | 865 | 865 | 865 | 865 | 865 | 865 | 865 |

*Notes:* This table reports two-stage least squares (2SLS) estimates following Weller (2018). The instrument for algorithmic trading activity is the log of the average stock price over event days $[-42, -22]$. *Left panel:* Raw AT levels are instrumented directly. *Right panel:* Abnormal AT proxies (event-window AT minus pre-event baseline) are instrumented with the same price-level instrument. Controls include log market cap, log volume, volatility, and bid-ask spread (log price excluded from second stage). HC1 standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA6: Horse Race: Joint Regression and Multicollinearity Diagnostics**

| | *Joint Regression* | | | *Diagnostics* |
|---|---|---|---|---|
| Variable | Coef | SE | $t$-stat | VIF |
| ***Panel A: AT Proxies*** | | | | |
| Ab. OLR | −0.3641 | (3.0677) | −0.119 | 3.02 |
| Ab. TS | −5.3741 | (6.6415) | −0.809 | 4.37 |
| Ab. TTO | 0.0541 | (2.9786) | 0.018 | 8.89 |
| Ab. CTT | 1.8983 | (2.8890) | 0.657 | 7.06 |
| ***Panel B: Controls*** | | | | |
| Log Price | $-1.4656^{**}$ | (0.6035) | −2.429 | 4.09 |
| Log Mkt Cap | 0.1651 | (0.3556) | 0.464 | 9.63 |
| Log Volume | −0.2838 | (0.3606) | −0.787 | 8.60 |
| Volatility | $2.6768^{***}$ | (0.6597) | 4.058 | 1.32 |
| Spread | −0.0589 | (0.3844) | −0.153 | 3.36 |
| $N$ | | 865 | | |

*Notes:* This table reports a single OLS regression of the standardized price jump (winsorized) on all four abnormal AT proxies simultaneously and standard controls (columns 1–3), together with variance inflation factors (VIF, column 4). Controls include log price, log volume, log market capitalization, log volatility, and log spread. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA7: Benjamini–Hochberg FDR Correction: Information Acquisition (Abnormal Activity)**

| AT Metric | DV | Coef | Raw $p$ | BH $p$ | Sig (BH) |
|---|---|---|---|---|---|
| Ab. TS | PJ Stan | $-5.3744^{**}$ | 0.0224 | 0.0448 | Yes |
| Ab. TS | PJ Stan (wins) | $-3.4998^{**}$ | 0.0150 | 0.0448 | Yes |
| Ab. OLR | PJ Stan | $3.2033^{**}$ | 0.0145 | 0.0448 | Yes |
| Ab. OLR | PJ Stan (wins) | $2.7130^{***}$ | 0.0038 | 0.0448 | Yes |
| Ab. TTO | PJ Stan | $-2.4504^{**}$ | 0.0189 | 0.0448 | Yes |
| Ab. TTO | PJ Stan (wins) | $-1.5090^{**}$ | 0.0218 | 0.0448 | Yes |
| Ab. CTT | PJ Stan | $2.1136^{**}$ | 0.0406 | 0.0697 | No |
| Ab. CTT | PJ Stan (wins) | $1.2834^{*}$ | 0.0597 | 0.0895 | No |
| Ab. HVR | PJ Stan | 2.0519 | 0.1989 | 0.2386 | No |
| Ab. HVR | PJ Stan (wins) | 1.6475 | 0.1460 | 0.1946 | No |
| Ab. HTR | PJ Stan | −0.4739 | 0.7445 | 0.7445 | No |
| Ab. HTR | PJ Stan (wins) | −0.5276 | 0.6408 | 0.6990 | No |

*Notes:* This table applies the Benjamini and Hochberg (1995) false discovery rate (FDR) correction to the information acquisition tests from Table 6 Panel B regressions. Each row reports the coefficient on one abnormal activity variable from a separate regression, using either the raw standardized price jump (PJ Stan) or the winsorized version (PJ Stan wins) as the dependent variable. The BH $p$-value is the adjusted $p$-value controlling the FDR at 5%. Controls include log price, log volume, log market capitalization, log volatility, and log spread. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$ (based on raw $p$-values).

**Table IA8: Post-Announcement Decline in Algorithmic Trading Activity**

| Day | Ab. TS | Ab. OLR | Ab. TTO | Ab. CTT |
|---|---|---|---|---|
| 0 | 0.020* | −0.038** | 0.156*** | −0.145*** |
| 1 | 0.115*** | −0.144*** | 0.431*** | −0.349*** |
| 2 | 0.095*** | −0.119*** | 0.345*** | −0.267*** |
| 3 | 0.095*** | −0.105*** | 0.301*** | −0.230*** |
| 4 | 0.093*** | −0.111*** | 0.305*** | −0.239*** |
| 5 | 0.097*** | −0.129*** | 0.317*** | −0.239*** |
| 6 | 0.091*** | −0.115*** | 0.283*** | −0.209*** |
| 7 | 0.077*** | −0.095*** | 0.229*** | −0.173*** |
| 8 | 0.057*** | −0.059*** | 0.222*** | −0.185*** |
| 9 | 0.053*** | −0.063*** | 0.207*** | −0.169*** |
| 10 | 0.033*** | −0.042*** | 0.131*** | −0.106*** |
| 11 | 0.028** | −0.028** | 0.111*** | −0.093*** |
| 12 | 0.050*** | −0.056*** | 0.152*** | −0.112*** |
| 13 | 0.035*** | −0.043*** | 0.114*** | −0.086*** |
| 14 | 0.043*** | −0.046*** | 0.148*** | −0.124*** |
| 15 | 0.033*** | −0.041*** | 0.115*** | −0.092*** |
| 16 | 0.045*** | −0.038** | 0.135*** | −0.103*** |
| 17 | 0.022** | −0.022 | 0.137*** | −0.120*** |
| 18 | 0.023** | −0.025 | 0.141*** | −0.127*** |
| 19 | 0.020* | −0.021 | 0.095*** | −0.086*** |
| 20 | 0.023** | −0.027 | 0.079*** | −0.062*** |

*Notes:* This table reports mean daily abnormal algorithmic trading activity for event days 0 through 20 relative to the special dividend declaration date. Abnormal AT is computed as the daily AT proxy value minus the firm-specific baseline mean over $[-61, -22]$. Significance is assessed via cross-sectional $t$-tests against the null of zero abnormal AT. AT proxies are: TS (trade size), OLR (odd-lot ratio), TTO (trade-to-order ratio), and CTT (cancel-to-trade ratio) all in log units. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA9: Gradient Analysis: Abnormal AT Across Dividend Event Types**

| | Ab. OLR | Ab. TS | Ab. TTO | Ab. CTT |
|---|---|---|---|---|
| Surprise Specials | $2.7130^{***}$ | $-3.4998^{**}$ | $-1.5090^{**}$ | $1.2834^{*}$ |
| | (0.9366) | (1.4394) | (0.6579) | (0.6815) |
| Non-Surprise Specials | $-0.0690$ | 0.6174 | $-0.2298$ | 0.2449 |
| | (1.0081) | (1.0590) | (0.4067) | (0.4264) |
| Dividend Increases | 0.2072 | $-0.6039$ | $-0.4786^{***}$ | $0.6340^{***}$ |
| | (0.3322) | (0.3681) | (0.1809) | (0.2169) |
| Dividend Decreases | $-1.5618$ | 1.3560 | $-0.1482$ | 0.6866 |
| | (1.1867) | (1.6830) | (0.7303) | (0.8672) |

*Notes:* This table reports the coefficient on each abnormal AT proxy from separate regressions of the standardized price jump (winsorized) on abnormal AT and controls across four dividend event samples. Surprise specials are the main sample from Table 6 Panel B. Non-surprise specials are special dividends by firms with recurring special dividend history. Controls include log price, log volume, log market capitalization, log volatility, and log spread. Dividend increases and decreases are regular dividend changes by the same firms. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA10: Robustness: Alternative Pre-Event and Baseline Windows**

| | **Ab. TS** | | | **Ab. OLR** | | |
|---|---|---|---|---|---|---|
| Pre-Event Window | [−61, −22] | [−80, −41] | [−120, −61] | [−61, −22] | [−80, −41] | [−120, −61] |
| [−21, −1] (Main) | $-3.4998^{**}$ | $-2.1964^{*}$ | $-1.7940$ | $2.7130^{***}$ | $1.6040^{*}$ | $1.0347$ |
| | (1.4394) | (1.2789) | (1.2109) | (0.9366) | (0.8718) | (0.7455) |
| [−15, −1] | $-3.6150^{**}$ | $-2.5880^{**}$ | $-2.2543^{**}$ | $2.9720^{***}$ | $2.0774^{**}$ | $1.4947^{*}$ |
| | (1.4408) | (1.2825) | (1.1296) | (1.0344) | (0.9513) | (0.8001) |
| [−10, −1] | $-3.3663^{**}$ | $-2.6787^{**}$ | $-2.3611^{**}$ | $2.8238^{***}$ | $2.1552^{**}$ | $1.6139^{**}$ |
| | (1.3298) | (1.2470) | (1.0867) | (0.9632) | (0.8859) | (0.7712) |
| [−5, −1] | $-2.2331^{*}$ | $-1.7968^{*}$ | $-1.6077^{*}$ | $1.6852^{**}$ | $1.3156^{*}$ | $0.9621$ |
| | (1.1608) | (1.0584) | (0.9578) | (0.8564) | (0.7729) | (0.7121) |
| [−3, −1] | $-1.1833$ | $-0.9120$ | $-0.7777$ | $0.5192$ | $0.2748$ | $0.0755$ |
| | (1.2146) | (1.1182) | (1.0263) | (0.7146) | (0.6880) | (0.6149) |

| | **Ab. TTO** | | | **Ab. CTT** | | |
|---|---|---|---|---|---|---|
| Pre-Event Window | [−61, −22] | [−80, −41] | [−120, −61] | [−61, −22] | [−80, −41] | [−120, −61] |
| [−21, −1] (Main) | $-1.5090^{**}$ | $-1.3817^{***}$ | $-0.8563^{**}$ | $1.2834^{*}$ | $1.1661^{**}$ | $0.7317$ |
| | (0.6579) | (0.5073) | (0.4321) | (0.6815) | (0.5216) | (0.5228) |
| [−15, −1] | $-1.2196^{*}$ | $-1.1953^{**}$ | $-0.7521^{*}$ | $0.8296$ | $0.8290^{*}$ | $0.4851$ |
| | (0.6285) | (0.4933) | (0.4171) | (0.6370) | (0.4951) | (0.4999) |
| [−10, −1] | $-1.1370^{*}$ | $-1.1283^{**}$ | $-0.7508^{*}$ | $0.7533$ | $0.7541$ | $0.4637$ |
| | (0.5931) | (0.4775) | (0.4135) | (0.5952) | (0.4681) | (0.4659) |
| [−5, −1] | $-0.6604$ | $-0.7061$ | $-0.4356$ | $0.2566$ | $0.3122$ | $0.0984$ |
| | (0.5721) | (0.4613) | (0.4105) | (0.5529) | (0.4327) | (0.4276) |
| [−3, −1] | $-0.3364$ | $-0.4070$ | $-0.1995$ | $0.0263$ | $0.1010$ | $-0.0768$ |
| | (0.5341) | (0.4437) | (0.4097) | (0.4852) | (0.4032) | (0.3998) |
| $N$ | 865 | 865 | 865 | 865 | 865 | 865 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table reports the coefficient on each abnormal AT proxy from regressions of the standardized price jump (winsorized) on abnormal AT and controls. Each cell represents a separate regression. Rows vary the pre-event window over which AT activity is averaged; columns vary the baseline window used to construct abnormal AT. The main specification uses a pre-event window of [−21, −1] and a baseline of [−61, −22]. Controls include log price, log volume, log market capitalization, log volatility, and log spread. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA11: Alternative Information Incorporation Regressions**

| AT Metric | Coef | SE | $t$-stat | $p$-value |
|---|---|---|---|---|
| Ab. TS | $0.8276^{***}$ | (0.3056) | 2.708 | 0.0068 |
| Ab. OLR | $-0.5351^{**}$ | (0.2350) | $-2.277$ | 0.0228 |
| Ab. TTO | $0.2240^{*}$ | (0.1185) | 1.890 | 0.0587 |
| Ab. CTT | $-0.1828$ | (0.1267) | $-1.443$ | 0.1491 |

*Notes:* This table reports OLS regressions where the dependent variable is the ratio CAR$[0,2]$/CAR$[0,10]$, which captures the fraction of the total 10-day post-announcement return that is realized within the first two trading days. Each row represents a separate regression of the CAR fraction on one abnormal AT proxy and the standard controls. Abnormal AT is computed as the pre-event mean $[-21,-1]$ minus the baseline mean $[-61,-22]$. Controls include log price, log volume, log market capitalization, log volatility, and log spread. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA12: Reversal Magnitude Regressions (Reversal Firms Only)**

| AT Metric | Coef | SE | $t$-stat | $p$-value |
|---|---|---|---|---|
| *Raw AT Levels* | | | | |
| TS | −0.0103 | (0.0064) | −1.605 | 0.1085 |
| OLR | 0.0075* | (0.0039) | 1.896 | 0.0580 |
| TTO | −0.0044 | (0.0041) | −1.081 | 0.2798 |
| CTT | 0.0047 | (0.0044) | 1.055 | 0.2915 |
| HVR | 0.0026 | (0.0058) | 0.450 | 0.6527 |
| HTR | 0.0048 | (0.0059) | 0.802 | 0.4228 |
| *Abnormal AT* | | | | |
| Ab. TS | −0.0124 | (0.0133) | −0.933 | 0.3510 |
| Ab. OLR | 0.0034 | (0.0073) | 0.470 | 0.6382 |
| Ab. TTO | −0.0044 | (0.0050) | −0.875 | 0.3817 |
| Ab. CTT | 0.0044 | (0.0053) | 0.835 | 0.4035 |
| Ab. HVR | −0.0082 | (0.0075) | −1.101 | 0.2710 |
| Ab. HTR | −0.0111 | (0.0104) | −1.068 | 0.2855 |

*Notes:* This table restricts the sample to events exhibiting price reversals (where the pre-event and event-window CARs are opposite in sign, $N = 150$) and regresses the absolute magnitude of the reversal on AT proxies and controls. Each row represents a separate regression. The upper panel uses raw AT levels; the lower panel uses abnormal AT. Controls include log price, log volume, log market capitalization, log volatility, and log spread. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA13: Information Acquisition Without Fixed Effects**

| | TS | OLR | TTO | CTT | TS | OLR | TTO | CTT |
|---|---|---|---|---|---|---|---|---|
| ***Panel A: AT Levels*** | | | | | | | | |
| *DV: Weller's Price Jump* | | | | | *DV: Standardized Price Jump* | | | |
| AT Proxy | $-0.0430$ | 0.0208 | $-0.0310$ | 0.0013 | $-1.8721^{***}$ | $1.4557^{***}$ | $-0.1368$ | $-0.7278^{*}$ |
| | (0.0384) | (0.0262) | (0.0280) | (0.0252) | (0.5813) | (0.3745) | (0.3786) | (0.3765) |
| $N$ | 433 | 433 | 433 | 433 | 865 | 865 | 865 | 865 |
| $R^2$ | 0.010 | 0.008 | 0.009 | 0.007 | 0.082 | 0.086 | 0.067 | 0.071 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ***Panel B: Abnormal AT*** | | | | | | | | |
| *DV: Weller's Price Jump* | | | | | *DV: Standardized Price Jump* | | | |
| Ab. AT Proxy | $-0.1085$ | $0.1106^{*}$ | $-0.0669^{*}$ | $0.0704^{*}$ | $-3.4993^{**}$ | $2.7122^{***}$ | $-1.5087^{**}$ | $1.2833^{*}$ |
| | (0.0873) | (0.0592) | (0.0354) | (0.0403) | (1.4394) | (0.9366) | (0.6579) | (0.6815) |
| $N$ | 433 | 433 | 433 | 433 | 865 | 865 | 865 | 865 |
| $R^2$ | 0.010 | 0.014 | 0.013 | 0.013 | 0.075 | 0.076 | 0.075 | 0.071 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table replicates Table 6 without fixed effects. OLS regressions of price jump measures on algorithmic trading (AT) proxies around special dividend announcements. Each column represents a separate regression with one AT proxy as the independent variable. Panel A uses AT levels averaged over the pre-announcement window $[-21, -1]$. Panel B uses abnormal AT, constructed as the difference between the pre-event mean ($[-21, -1]$) and the baseline mean ($[-61, -22]$). Weller's Price Jump is the price jump ratio from Weller (2018), restricted to $[0, 1]$. Standardized Price Jump is our proposed measure, winsorized at the 99th percentile. Controls include log price, log volume, log market capitalization, volatility, and spread. No fixed effects are included. HC1 standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

## Table IA14: Placebo Tests Without Fixed Effects

| | TS | OLR | TTO | CTT | TS | OLR | TTO | CTT |
|---|---|---|---|---|---|---|---|---|
| ***Panel A: AT Levels*** | | | | | | | | |
| *DV: Weller's Price Jump* | | | | | *DV: Standardized Price Jump* | | | |
| AT Proxy | −0.0204 | 0.0042 | 0.0152 | −0.0324 | $-1.4675^{***}$ | $0.9599^{**}$ | 0.4751 | $-1.0126^{***}$ |
| | (0.0384) | (0.0248) | (0.0286) | (0.0240) | (0.5496) | (0.3935) | (0.3567) | (0.3383) |
| $N$ | 433 | 433 | 433 | 433 | 864 | 864 | 864 | 864 |
| $R^2$ | 0.007 | 0.007 | 0.007 | 0.010 | 0.076 | 0.077 | 0.069 | 0.076 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ***Panel B: Abnormal AT*** | | | | | | | | |
| *DV: Weller's Price Jump* | | | | | *DV: Standardized Price Jump* | | | |
| Ab. AT Proxy | 0.0450 | 0.0102 | −0.0001 | −0.0055 | −2.4976 | 0.4305 | −0.2034 | −0.1628 |
| | (0.1004) | (0.0629) | (0.0384) | (0.0434) | (2.0373) | (1.2195) | (0.6559) | (0.6260) |
| $N$ | 433 | 433 | 433 | 433 | 862 | 862 | 862 | 862 |
| $R^2$ | 0.007 | 0.007 | 0.007 | 0.007 | 0.071 | 0.067 | 0.067 | 0.067 |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

*Notes:* This table replicates Table 7 without fixed effects. Placebo tests using pseudo-announcement dates drawn uniformly from $[-120, -60]$ relative to the actual special dividend declaration date. The dependent variables are the actual price jump measures computed at the true event date. Panel A uses AT levels averaged over $[\text{pseudo} - 21, \text{pseudo} - 1]$. Panel B uses abnormal AT, constructed as the difference between the pseudo pre-event mean and the pseudo baseline mean ($[\text{pseudo} - 61, \text{pseudo} - 22]$). Controls include log price, log volume, log market capitalization, volatility, and spread. No fixed effects are included. HC1 standard errors in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

**Table IA15: Information Incorporation and Post-Announcement Dynamics Without Fixed Effects**

| | TS | OLR | TTO | CTT |
|---|---|---|---|---|
| ***Panel A: Incorporation Ratio*** | | | | |
| *AT Levels, days* $[0, +2]$ | | | | |
| AT Proxy | $-0.1337$ | 0.0994 | 0.0010 | 0.0474 |
| | (0.2236) | (0.1449) | (0.1984) | (0.1969) |
| *Abnormal AT, days* $[0, +2]$ | | | | |
| Ab. AT Proxy | 0.0435 | $-0.2876$ | $-0.0549$ | 0.1566 |
| | (0.3614) | (0.2900) | (0.1838) | (0.2068) |
| $N$ | 865 | 865 | 865 | 865 |
| Controls | Yes | Yes | Yes | Yes |
| ***Panel B: Post-Announcement Standardized Price Jump*** | | | | |
| *AT Levels, days* $[0, +2]$ | | | | |
| AT Proxy | $-0.6861^{**}$ | $0.4541^{**}$ | $-0.3488^{**}$ | 0.2111 |
| | (0.2807) | (0.1866) | (0.1735) | (0.1828) |
| *Abnormal AT, days* $[0, +2]$ | | | | |
| Ab. AT Proxy | $-1.6201^{**}$ | 0.6883 | $-0.6569^{***}$ | $0.6482^{***}$ |
| | (0.7161) | (0.4317) | (0.2322) | (0.2164) |
| $N$ | 865 | 865 | 865 | 865 |
| Controls | Yes | Yes | Yes | Yes |
| ***Panel C: Post-Announcement Return Reversals (Logistic)*** | | | | |
| *AT Levels* | | | | |
| AT Proxy | $-0.0917$ | 0.0188 | $-0.3368^{*}$ | $0.3761^{**}$ |
| | (0.2492) | (0.1608) | (0.1730) | (0.1753) |
| *Abnormal AT* | | | | |
| Ab. AT Proxy | $-0.7156$ | $0.4993^{*}$ | $-0.6566^{***}$ | $0.7199^{***}$ |
| | (0.4701) | (0.3017) | (0.1898) | (0.2063) |
| $N$ | 865 | 865 | 865 | 865 |
| Controls | Yes | Yes | Yes | Yes |

*Notes:* This table examines whether AT accelerates post-announcement information incorporation and/or is associated with return reversals. Each column represents a separate regression with one AT proxy. Panel A uses the incorporation ratio, $\text{CAR}[0, 2]/\text{CAR}[0, 5]$, as the dependent variable. Panel B uses the standardized price jump computed over the post-announcement window. Panel C reports logistic regressions where the dependent variable equals one if the sign of $\text{CAR}[0, 2]$ differs from the sign of $\text{CAR}[0, 5]$ (approximately 15% of events). AT proxies are measured over $[0, +2]$ for levels or differenced from $[-61, -22]$ for abnormal measures. Controls include log price, log volume, log market capitalization, log volatility, and log spread. Standard errors are in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.