# The Evolving Efficiency of Price Discovery in Extended Market Hours: Evidence from Short-Term Extended Market Post-Earnings Announcement Drift (STEM-PEAD)

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*Carey Reed Blackstone, Jr.*

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# The Evolving Efficiency of Price Discovery in Extended Market Hours: Evidence from Short-Term Extended Market Post-Earnings Announcement Drift (STEM-PEAD)

by

Carey Reed Blackstone, Jr.

A Dissertation Submitted in Partial Fulfillment of the Requirements for the Degree

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## ACCEPTANCE

This dissertation was prepared under the direction of the CAREY REED BLACKSTONE, JR. Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Business Administration in the J. Mack Robinson College of Business of Georgia State University.

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**ABSTRACT**

The Evolving Efficiency of Price Discovery in Extended Market Hours:
Evidence from Short-Term Extended Market Post-Earnings Announcement Drift (STEM-PEAD)

by
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June 2025

Committee Chair: Welsey J. Johnston
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I examine how the efficiency of price discovery in the U.S. stock market's extended market hours (EMH) has changed over time, focusing on the speed at which prices incorporate new information during the after-market-close (AMC) and before-market-open (BMO) sessions. Using tick-level data, I analyze how S&P 1500 stock prices respond to earnings surprises (ESs) in two periods: a Base Period (2004–2012), chosen to enable comparison with Li (2016A), and a Post-Li Period (2017–2021), which follows Li's publication.

Consistent with prior EMH price discovery literature, I construct an event window that begins at the time of the ES and ends at the close of the next regular trading session. I divide the window into two segments: an initial price adjustment (IPA) segment of 15 minutes followed by a short-term extended market post-earnings announcement drift (STEM-PEAD) segment that runs through the end of the event window. I measure the total price adjustment over the full window and the share that occurs within each segment.

I find strong evidence that EMH price discovery has become faster in the Post-Li period -- a greater proportion of the total adjustment now occurs during the IPA segment, and a smaller proportion during the STEM-PEAD segment. I also document meaningful differences between

AMC and BMO. Prices respond more quickly during AMC in the initial minutes following an ES. However, by the end of both sessions, BMO accounts for a greater share of the total price adjustment than AMC. The crossover point varies by session (AMC vs. BMO), pricing instrument (trades vs. mid-quotes), and period (Base vs. Post-Li).

In other analyses, I re-examine Gregoire & Martineau (2022)'s finding that quote prices adjust more quickly than trade prices in EMH in the initial minutes after an ES. I find similar results for BMO ES events, and opposite results for AMC ES events.

By disaggregating EMH into separate AMC vs. BMO sessions and analyzing both trade and quote data, my study contributes new insights to the EMH price discovery and PEAD literatures and has practical implications for investors, executives, and regulators.

INDEX WORDS: Price Discovery, Market Efficiency, Post-Earnings Announcement Drift, After-Hours Market, Extended-Hours Market

# I INTRODUCTION

The U.S. stock market's extended market hours (EMH) trading sessions are important and increasingly relevant. Much of the news that impacts prices (*e.g.*, earnings announcements, macroeconomic reports, geopolitical news, etc.) becomes public during EMH, significant price discovery takes place during EMH (*e.g.*, Gregoire & Martineau 2022, Levi et al. 2018, Li 2016A[1], Jiang et al. 2012, Barclay & Hendershott 2008), EMH volume increased substantially over the past half-decade[2], and plans are underway to expand EMH sessions from 9.5 hours per day to as many as 16.5 hours per day (SEC 2024A, SEC 2024B).

The EMH sessions' contributions to price discovery are a public good. The efficiency of price discovery *within EMH* and over *short-horizons* -- especially in the first few minutes after new information becomes known -- matters to market participants and others. In times of crisis, policymakers and corporate decision-makers need to act quickly, and benefit greatly from accurate, up-to-date information outside of the market's regular trading hours (RTH). In response to new information that arrives outside of RTH and that impacts their investments' value, investors may want to act immediately to adjust their portfolio or implement hedging strategies[3]. Efficiency outside of RTH (*i.e.*, within EMH) and over short horizons may bolster confidence and trust in the market over longer horizons and during RTH[4].

A large and growing body of literature examines the efficiency of RTH price discovery and concludes that it has become increasingly efficient[5]. Given the importance and increasing

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1 Li (2016A) is a chapter in Li's PhD dissertation, an update to his 2014 unpublished work (Li 2014); a less detailed version (Li 2016B) appears in *Journal of Trading*.

2 According to FINRA (2024, pg. 40, fig. 3.1.1.4), EMH dollar-volume was ~7% of total volume in 2024, up from the 3% reported by Gregoire & Martineau (2022) for 2011- 2015. According to *NYSE Data Insights*, EMH volumes were ~7% of total volume for Q3-2021 (Bazinas 2021) and 11% as of January 2025 (Bazinas 2025).

3 Consider, for example, a stock where negative news becomes public at 6pm, during EMH hours. While it may be difficult to immediately sell the stock (*i.e.*, if there is insufficient liquidity during EMH), hedging might be possible by placing an order in an open futures market or an open foreign stock market.

4 Efficient EMH price discovery also creates value for market participants by leading to a more efficient RTH opening price, Barclay & Hendershott 2008).

5 See, for example, Akbas et al. (2023), Martineau (2022), Chordia & Miao (2020), McLean & Pontiff (2016), and Chordia et al. (2014).

relevance of the EMH sessions, it is somewhat surprising that very few studies examine the *evolution* of the efficiency of price discovery *in EMH*.

In fact, I am aware of only one such study, a recent paper by Christensen et al. (2025)[6]. My study differs from theirs in several ways. First, there are two EMH sessions every day -- a 4pm to 8pm after-market-close (AMC) session that follows the RTH session[7], and a 4am to 9:30am before-market-open (BMO) session that precedes the RTH session -- and their study examines only the AMC portion of EMH hours. My study examines both the AMC and BMO sessions. Second, their study focuses on only the 50 stocks that have the largest AMC trading volume on earnings announcement (EA) days. My study focuses on a much broader set of stocks, the members of the S&P 1500[8]. Finally, the focus of their paper is on developing a new jump ratio to examine price movements in EMH; their focus on the efficiency of price discovery is secondary, and as noted above, limited to 50 stocks during AMC.

* * * * *

In this paper, I examine how the efficiency of price discovery in EMH has evolved. As price adjustment speed is one of the central measures of market efficiency (Fama 1991)[9], I analyze the speed with which prices incorporate new information to assess the efficiency of EMH price discovery. I use earnings surprises (ESs) during the AMC and BMO sessions as news events.

The studies most closely related to mine include Gregoire & Martineau (2022), Jiang et al. (2012), and Li (2016A). My research differs from those in several key respects. I analyze changes over time, whereas those studies focus on a single period. Gregoire & Martineau (2022) pooled AMC and BMO events without distinguishing between the sessions; I examine them

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6 Akbas et al. (2023) and Martineau (2022) also examines the evolution of the efficiency of price discovery. However, their studies examine the efficiency of *RTH* price discovery *over daily or monthly horizons*.

7 When the market is open a half-day, RTH ends at 1pm and AMC runs from 1pm to 5pm. I have adopted the AMC and BMO acronyms from Jiang et al. (2012).

8 To qualify for inclusion in my sample, a stock had to be a member of the S&P 1500 as of the date of their EA.

9 Other dimensions of efficiency include informativeness and accuracy.

separately and test for differences. Jiang et al. (2012) studied price adjustment over the entire AMC/BMO session -- I focus on adjustment *within* the sessions, during the first 1 to 60 minutes after an ES. Li (2016A) examined only AMC and framed the post-ES price adjustment primarily as a potentially tradable capital market anomaly, and secondarily as a study contributing to the PEAD literature. My study includes both BMO and AMC and I analyze how price adjustment speed changes over time to evaluate shifts in the efficiency of EMH price discovery, designing my study to contribute primarily to the EMH price discovery literature and secondarily to the PEAD literature.

Price discovery is the process by which prices adjust to incorporate new information (O'Hara 2003). PEAD (post-earnings announcement drift) is the tendency for stock prices to adjust gradually in response to ESs, drifting in the direction of the ES over an extended horizon that begins after the ES -- slowly enough that it is possible, *after* the ES has occurred, to predict more reliably than random-chance whether the stock is likely to generate future excess returns (Ball & Brown 1968). PEAD has long been considered one of the most persistent challenges to market efficiency (Fama 1998, Martineau 2022), and measures incorporating PEAD are a common proxy for price adjustment speed (Blankespoor et al. 2020), and thus efficiency.

Although most studies that examine PEAD analyze its drift over monthly horizons (*e.g.*, 90 days, 30 days, etc.), some studies focus on daily horizons (*e.g.* Martineau 2022, Hirshleifer & Sheng 2022, Kottimukkalur 2019), and some studies, such as mine, examine PEAD over horizons of less than 24 hours (*e.g.*, Li 2016A, Jiang et al. 2012).

To distinguish this short-horizon PEAD from longer-horizon "regular" PEAD, I use the acronym STEM-PEAD (short term extended market PEAD).

I construct a sample of S&P 1500 ES events and compare post-ES price adjustment speed across two periods. The first is a "Base Period" (2004-2012), designed to closely mirror Li (2016A)'s sample[10]. The second is the "Post-Li Period" (2017-2021), which follows the publication of Li's study.

I designed the Post-Li period to begin after Li's publication so that I could incorporate McLean & Pontiff's (2016) post-publication decay theory (*i.e.*, the publication of an anomaly spurs arbitrage activity, thereby increasing market efficiency) as one of several foundations supporting my hypothesis (developed in Section II) that the efficiency of price discovery in EMH has increased in the Post-Li period relative to the Base Period[11].

*My Research Questions*

I investigate the efficiency of price discovery in EMH by examining the speed at which prices adjust to earnings news during the first few minutes following an ES. I use STEM-PEAD to measure price adjustment speed. My study focuses on three research questions:

1. Has the efficiency of price discovery within EMH improved since Li's study?
2. Does it vary with factors associated with regular PEAD?
3. Does it differ between BMO and AMC?

Over the next few subsections of this introduction, I briefly review (a) efficient price discovery and the speed of price adjustment, (b) PEAD, and (c) the EMH landscape and EMH price discovery.

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[10] My Base Period sample differs from Li (2016A)'s in that it does not include 2002-2003 due to data availability limitations. My Base and Post-LI Period samples also differ from Li in that do not apply what I refer to as his "three minute rule" for excluding ES events from my sample. Li excluded from his final sample those ES events which had no trade within the first three-minutes after an ES; his stated purpose was to remove events with trading halts in place around the time of an ES. I do not apply Li's "three-minute rule when constructing my sample for several reasons. First, the "three-minute" rule does not accurately identify trading halts; it severely over-estimates the number of trading halts (see Appendix C). Second, I retain events with no trades within the first three-minutes after an ES to preserve completeness -- the absence of trading or quoting activity in EMH is itself an informative outcome.

[11] As discussed in Section II, and elsewhere, other foundations supporting this hypothesis include declines in trading costs (Chordia et al. 2014), technology-driven growth in algorithmic low-latency trading (LLT) (Chordia & Miao 2020) and increases in arbitrage activity and skill (Chordia et al. 2014; Akbas et al. 2023) not related to McLean & Pontiff (2016)'s post-publication decay theory.

## I.1 Efficient Price Discovery: the Speed at which Prices Adjust to News

In an efficient market, asset prices always incorporate all available information, providing "accurate signals" for resource-allocation and decision-making (Fama 1970, pg. 383). Price discovery is the process by which prices adjust to incorporate new information (O'Hara 2003).

The more efficient the price discovery process, the faster prices adjust to incorporate new information. When price discovery is sufficiently efficient, prices adjust at rates that make it impossible to subsequently predict and act upon trading opportunities that reliably generate excess returns[12] (Fama 1991, Jensen 1978). Return predictability and the price adjustment speed are therefore central measures of market efficiency (Fama 1991)[13].

A growing body of research finds that stock prices incorporate new information more rapidly in recent years -- *i.e.*, price discovery during has become more efficient (*e.g.*, Akbas et al. 2023, Martineau 2022, Chordia & Miao 2020, McLean & Pontiff 2016, Chordia et al. 2014). The increased efficiency is attributed to factors such as declines in trading cost (Chordia et al. 2014), increases in arbitrage activity (Chordia et al. 2014) and skill (Akbas et al. 2023), arbitrage in response to the publication of academic research on anomalies (McLean & Pontiff 2016), and technology-enabled increases in algorithmic low-latency trading (LLT) (Chordia & Miao 2020).

Such studies commonly evaluate the efficiency of price discovery by examining the speed with which stock prices adjust to earnings news after it becomes public -- analyzing both the initial price adjustment (IPA) as well as the subsequent drift (*i.e.*, PEAD) that follows the IPA[14]. Although the studies cited in the prior paragraph typically define the IPA window to run from the

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[12] Excess returns are returns that exceed expected market returns, adjusted for risk and net of all costs (*e.g.*, transaction costs, information acquisition costs, information processing costs, etc.) (Jensen 1978).

[13] Price adjustment speed and return predictability have been used as market efficiency measures since at least Ball & Brown (1968) and Fama et al. (1969).

[14] This is not to imply that such studies focus exclusively on how stock prices respond to earnings news. For example, McLean & Pontiff's (2016) study examines 97 variables found to predict anomalous returns, 2 of which are associated with earnings news. At a macro level, however, McLean & Pontiff's (2016) study is, in a sense, focused on how stock prices respond to new information -- they find that once the existence of a given anomaly becomes public information (due to the publication of academic research about the anomaly), the anomaly's excess returns decay, indicating an improvement in market efficiency.

day of the news event through the first trading day after the event and the PEAD window to run from the first trading day after the event and to end one or two months later, research examining short-horizon windows (such as my study) also use make use of the IPA and PEAD as measures, adjusting them to cover windows no longer (and often much shorter) than the first 24 hours following the news event (*e.g.*, Beschwitz et al. 2020, Chordia et al. 2018, Li 2016A).

## I.2 Post-Earnings Announcement Drift (PEAD)[15]

PEAD is the subject of a voluminous body of finance and accounting literature. PEAD-related papers continue to be of academic interest, garnering publication in top-tier journals. Martineau (2022) found that over the five-year period ending October 2020, 58 PEAD-related studies were published in the "top 11" journals in finance and accounting[16]. Using the same search methodology as Martineau (2022)[17], I find an additional 41 PEAD-related papers were published by those same journals over the subsequent four-year period ending December 2024.

### *I.2.1 PEAD and IPA Event Windows*

PEAD is typically measured as the excess (or abnormal) returns[18] measured over the second part of an event window that starts and ends at times $t_0$ and $t_{end}$, where $t_0$ is the time of the ES event. Most PEAD-related studies specify an event window that spans several months, where $t_0$ indicates the day (but not the specific time) of the ES event and $t_{end}$ indicates the (but not the specific time) of the window's end. The event window following an ES event is typically

[15] For a recent review article on PEAD, see Fink (2021).

[16] The 11 journals searched by Martineau (2022) included 5 finance journals: Journal of Finance (JF), Journal of Financial Economics (JFE), Review of Financial Studies (RFS), Journal of Financial and Quantitative Analysis (JFQA), and The Review of Finance (RF); plus 5 accounting journals: Journal of Accounting & Economics (JAE), Journal of Accounting Research (JAR), The Accounting Review (TAR), Review of Accounting Studies (RAS), Contemporary Accounting Research (CAR); plus Management Science (MS). Martineau (2022) searched those journals using the Web of Science database, and the topic search phrase "(post-earnings announcement drift OR announcement drift OR price formation) AND earnings".

[17] See prior footnote for Martinuea's (2022) methodology. My search was performed in January 2025.

[18] Among those studies that have examined PEAD over event windows of 24 hours or less (*e.g.*, Gregoire & Martineau 2022, Beshwitz et al. 2020, Chordia et al. 2018, Li 2016A, Jiang et al. 2012), it is typical for PEAD to be measured using raw returns, rather than excess or abnormal returns. As Fama (1998, pg. 283) noted, "because daily expected returns are close to zero, the model for expected returns does not have a big effect on inferences about abnormal returns" when an event-window is a few days or less.

divided into two parts, the IPA (initial price adjustment) window from $t_0$ to $t_1$, and the PEAD windowfrom $t_1$ to $t_{end}$. It is typical for $t_1$ to be first day (day 1) after the ES event.

As an example, a typical PEAD study might examine IPA[0, 1] and PEAD [1, 60], where IPA[0, 1] represents the return from RTH close on day of the ES through RTH close on the first trading day after the ES, and PEAD [1, 60] represents the return from RTH close on the first trading day after the ES through RTH close on the 60th 60 after the ES. Studies that measure IPA and PEAD in this manner include Martineau (2022) or Hirshleifer et al. (2009).

### *I.2.2 Earnings Surprises (ESs) -- Random-Walk v. Analyst Estimates / EPS and Revenue*

As noted by Fink (2021), Martineau (2022), and others, ESs are typically defined as the standardized difference between actual earnings per share (EPS) and estimated EPS, where estimated EPS figures are calculated using one of two methods: (a) economic modeling that assumes a random-walk of asset prices (*e.g.*, time-series predictions), or (b) analyst estimates (*e.g.*, the median of analysts' estimates, commonly referred to as "consensus estimates")[19].

PEAD has been found to have a stronger, more persistent relationship with ESs based on analyst estimates than with ESs based on a random-walk model (Martineau 2022, Livnat & Mendenhall 2006).

Following Jegadeesh & Livnat (2006), Li (2016A) defined ESs to include not only EPS, but also revenue. Jegadeesh & Livnat (2006) found that PEAD was stronger when revenue and EPS were either both PSs or both NSs (*i.e.*, when both measures were ESs in the same direction); they conjectured that an unexpected change in a firm's most recently reported revenues could be

[19] A substantial amount of earnings-related news becomes public when a company issues an EA -- this includes not only the firm's actual EPS figures, but also news about other actual financial metrics (revenue, margins, etc.), operations, customer-relationships, sales activity, acquisitions and divestitures, strategy and plans, future financial targets (i.e., guidance), and so on. In addition to the information in the EA, many firms also hold conference calls immediately following the EA's release, where they provide additional information and answer questions from analysts. To capture more of this broad set of information in their definition of an ES, a small number of studies define ESs as excess or abnormal returns during a short window around time of the ES; examples include Levi et al. (2018), Zhou & Zhu (2012), Kishore et al. (2008), and Chan et al. 1996). Note that Kishore et al. (2008) is sometimes cited as Brandt et al. (2008). However, most studies define ESs based on one of the two methods in this sentence – using a random-walk model or analyst estimates (see Martineau 2022).

expected to have a more enduring impact on a firm's future EPS growth than an unexpected change in the firm's most-recently reported EPS.

*I.2.3 Portfolio vs. Individual Stock-level Examinations of PEAD*

Some studies examine PEAD using a long-short portfolio approach (*i.e.*, by constructing a portfolio that buys stocks with extreme PSs and that sells-short stocks with extreme negative NSs) and some at an individual stock level. In his review of PEAD-related papers published in the "top 11" finance and accounting journals between 1999 and 2020, Martineau (2022) found that the studies examined PEAD at the individual stock level. In line with Martineau's (2022) findings, Li (2016A) examined STEM-PEAD at the individual stock level.

*I.2.4 Factors Associated with PEAD*

PEAD's drift and corresponding excess returns are often explained as being due investor underreaction (Hirshleifer et al. 2009, Fama 1998, Bernard & Thomas 1990)[20], and its magnitude and persistence are commonly attributed to market frictions (arbitrage inhibitors) such as transaction costs (Bhushan 1994), illiquidity (Chordia et al. 2009, Sadka 2006), limited arbitrage capital (Lasser et al. 2010), short-sale constraints (Boehmer & Wu 2013, Diamond & Verrecchia 1987), investor inattention (DellaVigna & Pollet 2009, Hirshleifer et al. 2009), and differences in opinion (Garfinkel and Sokobin 2006, Vega 2006).

PEAD's magnitude and direction are associated with the magnitude and direction of ESs (Livnat & Mendenhall 2006, Bernard & Thomas 1989). Returns tend to be positive following good news and negative following bad news, with stronger responses to more extreme surprises. IPA exhibits a similar relationship with ESs (Hirshleifer et al. 2009, DellaVigna & Pollet 2008).

[20] Fama (1998, pg. 286) referred to PEAD as the "granddaddy of underreaction events".

Theory (Hong & Stein 1999, Diamond & Verrecchia 1987) and empirical evidence (Reed 2007, Hong et al. 2000) suggest that prices adjust more slowly to bad news than to good news[21]. Consistent with this, both the magnitude of PEAD and the ratio of PEAD returns to total post-news returns (IPA + PEAD) tend to be larger following bad news (Bird et al. 2014, Reed 2007).

*I.2.5 The attenuation or disappearance of regular PEAD in recent years*

The excess returns associated with regular PEAD have recently attenuated or disappeared when measured at *monthly* horizons (Abkas et al. 2023, Martineau 2022, Chordia et al. 2014).

Furthermore, Martineau (2022) examines PEAD at a *daily* horizon and finds that in recent years, excluding microcap stocks, PEAD's abnormal returns have disappeared by the close of the second RTH session after the ES event[22]. Martineau (2022) recommends that future PEAD-related studies examine price discovery over intraday horizons, as Li's (2016A) study did and which my study does.

Meursault et al. (2023) construct an ES measure based on a machine-learning analysis of earnings call transcripts (ES.txt) and find that the PEAD associated with ES.txt (PEAD.txt) is larger than regular PEAD (*e.g.*, PEAD based on ES derived from analyst estimates or random-walk models). Measuring regular PEAD and PEAD.txt over daily and monthly horizons that start on the first day after an ES, Meursault et al. (2023) examine the years 2010-2019 and find that, although regular PEAD has all but disappeared, PEAD.txt has not.

**[Subsection I.3 begins on next page]**

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21 Hong & Stein (1999) propose the theory that information gradually-diffuses through the marketplace, with bad news spreading more slowly than good news; Hong et al. (2000) test this hypothesis. Diamond & Verrecchia (1987) propose a theory that short-sale constraints slow the speed with which bad news is incorporated into prices; Reed (2007) tests this hypothesis.

22 Martineau finds that prices have adjusted to fully reflect the ES news by the end of day 0 and that the return from day 0 to day 1 is "approximately martingale" (Martineau 2022). Martineau (2022) knew only the dates, but not the times, of ES events before 1996. To account for ESs that occur after the closing of RTH, he defined day 0 to include both the ES date as well the following day. Accordingly, for ESs announced during AMC, his day 0 price is the closing price at the end of the first RTH session after the ES, whereas for ESs announced during BMO, his day 0 price is the closing price at the end of the second RTH session after the ES.

## I.3 Price Discovery During Extended Market Hours (EMH)

### *I.3.1 The EMH Landscape*

The overwhelming majority of EAs are made during EMH. Michaely et al. (2014) found that more than 95% of EAs occur outside RTH during 2004-2009, and Gregoire & Martineau (2022) found that 99.1% of EAs occur outside RTH during 2011-2016.

My findings (discussed in subsection III.3 and shown in Table 6) are consistent with theirs. In my sample of S&P 1500 stocks, I found that 92.7% and 98.2% occurred during EMH during 2004-2012 and 2017-2021, respectively. BMO EAs are slightly more common than AMC EAs during 2004-2012, and vice versa during 2017-2021. The vast majority of EAs are announced between 4pm and 6pm during AMC or 6am and 9:30am during BMO.

The EMH trading landscape differs from RTH in several ways. EMH has substantially less trading activity and is less liquid, with higher volatility and wider spreads; furthermore, it is not mandatory for liquidity providers to participate during EMH (Gregoire & Martineau 2022).

Retail investors/traders are generally discouraged from participating in EMH (Barclay & Hendershott 2003). Brokerages are required to warn clients of risks associated with EMH trading -- reduced liquidity, higher volatility and wider spreads (FINRA 2024, FINRA 2014)[23].

There is less trading activity during BMO (Gregoire & Martineau 2022); several EMH price discovery papers that focus on only AMC provide this as a key reason why they chose to exclude BMO from their study (*e.g.*, Christensen et al. 2025, Cui & Gozluklu 2024, Li 2016A).

Another structural difference between BMO and AMC lies in the fact that the RTH open occurs immediately after the end of BMO -- there is less time for post-ES price discovery to occur during EMH for BMO ESs than for AMC ESs.

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[23] Based on data from Robinhood (an online brokerage that caters to retail investors/traders), Cui & Gozluklu (2024) find some evidence of a recent (post-2018) increase in retail trading during the AMC session of EMH following scheduled news releases where the news is positive (*e.g.*, a positive earnings surprise).

*I.3.2 The EMH Price Discovery Literature*

A growing body of research on EMH price discovery examines how trade and quote prices adjust to incorporate new information during EMH. Several studies find that meaningful price discovery occurs during EMH (Santosh 2019, Jiang et al. 2012; Barclay & Hendershott 2003), despite its lower volumes and thinner liquidity as compared to RTH. Using an event window that spans from the time of an ES through the next RTH close, Jiang et al. (2012) find that for BMO ES events, about 36% of the event-window adjustment occurs during the BMO session in which the ES was announced (with the remaining 64% occurring during the first RTH session after the ES). For AMC ES events, they find that about 42% of the total event-window adjustment occurs during the AMC session in which the ES was announced (with the remaining 58% occurring during the next day's BMO and RTH sessions).

Some EMH price discovery studies focus exclusively (Christensen et al. 2025, Li 2016A) -- or nearly exclusively (Santosh 2019) -- on the AMC sessions, whereas others examine AMC and BMO as separate sessions (Jiang et al. 2012; Barclay & Hendershott 2008, 2003) or as part of a unified pool of EMH events without testing for differences between the sessions (Gregoire & Martineau 2022). As noted in the prior paragraph, Jiang et al. (2012) documented that for the typical ES event, the AMC session's contribution to AMC ES price discovery was slightly higher than the BMO session's contribution to BMO ES price discovery.

Trades and quotes each contribute to price discovery, interacting with one another in a dynamic process (Hasbrouck 1991) -- current quotes are influenced by new information and information revealed by contemporaneous trades and prior quotes and trades, and current trades are influenced by new information and information revealed by prior quotes and trades. Accordingly, several EHM price discovery studies examine both trades and quotes when analyzing price adjustment dynamics (Gregoire & Martineau 2022, Li 2016A, Jiang et al. 2012, Barclay & Hendershott 2008, 2003). Gregoire & Martineau (2022) find that, following ES events, quote prices adjust more quickly than trade price in EMH -- theory suggests that market frictions (*e.g.*, thin liquidity, high trading costs, arbitrage constraints, etc.) impedes trade price adjustment more than quote price adjustment, and market makers and traders (especially low-latency and algorithmic traders) may adjust quotes either as a price signaling mechanism or seeking trades that never materialize. Based on their findings that quotes make significant contributions to price discovery during EMH (even, or especially in the absence of trading and consistent with Biais et al. 1999), Gregoire & Martineau recommend that EMH price discovery studies not discard events for which there are no trades, as quote transactions by themselves can reveal valuable information about price discovery.

Although Li (2016A) found no relationship between the post-ES speed of price discovery and factors found to have a relationship with PEAD, other studies have found evidence of such a relationship -- which is not unexpected as the market frictions theorized to influence PEAD are theorized to do so because they are believed to slow down the speed of price discovery. For example, Gregoire & Martineau (2022) and Jiang et al. (2012) found a relationship between post-ES price adjustment speed and liquidity, proxied by market cap.

I am aware of only one study that examines changes in EMH price discovery over time, a recent paper by Christensen et al. (2025). My study differs from theirs in several ways. They only examine AMC; I examine BMO as well as AMC. They analyze only 50 large stocks, whereas I construct a sample of the full S&P 1500. Finally, their study's primary focus is on developing and testing a new jump ratio to examine price movements in EMH; only secondarily do they focus on the changes in efficiency of price discovery over time.

The EMH studies most closely related to mine are Gregoire & Martineau (2022), Jiang et al. (2012), and Li (2016A). However, my research differs from those in several key respects. I analyze changes over time, whereas they all focus on a single period. In contrast to Gregoire & Martineau, I examine and separately analyze AMC and BMO to test for differences. Whereas Jiang et al. (2012) studied price adjustment over the entire AMC/BMO session, I focus on adjustment *within* the sessions, during the first 1 to 60 minutes after an ES. While Li (2016A) examined only AMC and positioned his study primarily as a potentially tradable capital market anomaly, I investigate BMO and AMC and design my study to contribute primarily to the EMH price discovery literature (and secondarily, like Li, to the PEAD literature).

### I.4 Overview of Findings and Contributions

To examine how the efficiency of price discovery in EMH has changed over time, I construct a sample of ESs by S&P 1500 stocks for 2004-2012 (the Base Period) and 2017-2021 (the Post-Li Period). For each ES event, I obtain TAQ tick-level trade and quote data.

I follow Li (2016A)'s approach closely in constructing my sample, with one exception: I do not apply his "three-minute rule," which excludes events with no trades within the first three minutes after an ES. I explain and justify this decision in subsection III.2.4 and Appendix C.

Consistent with prior EMH price discovery research (Gregoire & Martineau 2022; Jiang et al. 2012; Barclay & Hendershott 2008, 2003), I construct an event window that begins at the time of the ES and ends at the close of the next regular trading session. I divide this window into two segments: an IPA (initial price adjustment) window, which spans from the ES to between 1 and 60 minutes later, and a STEM-PEAD (short-term extended market post-earnings announcement drift) window, which begins immediately after the IPA window and continues through the end of the event window.

I measure price discovery speed by measuring the proportion of the total event window return that occurs during each of the IPA and STEM-PEAD windows. Smaller STEM-PEAD values and larger IPA values indicate faster price adjustment during the IPA window.

Although I examine IPA/STEM-PEAD windows of varying lengths, I focus most of my analysis on an IPA window that spans from the time of an ES through 15 minutes after an ES -- or, equivalently, a STEM-PEAD window that begins 15 minutes after an ES. Focusing on the first 15 minutes after an event is common in the price discovery literature -- see, for example, Patell & Wolfson (1984) and Busse & Green (2002), which found that RTH prices incorporate news within 15 minutes or less. Furthermore, the longest EMH IPA window examined by Li (2016A) was 15 minutes.

I find that price discovery is faster in the Post-Li period -- that a greater share of total price adjustment occurs in the first 15 minutes following an ES as compared to the Base Period. This pattern is robust across sessions (AMC and BMO), pricing instruments (trades and quotes), and IPA windows ranging from 1 to 60 minutes in duration.

In the Post-Li Period, measured using Barclay & Warner (1993)'s weighted price contribution (WPC), around 20% of the total adjustment is completed in the first 15 minutes for AMC trades and quotes, and for BMO quotes (though BMO trade prices lag at around 13%).

I also find that price discovery speed differs materially between AMC and BMO. In the first few minutes after an ES, both trades and quotes adjust more quickly during AMC. However, by the end of the sessions, a greater share of post-ES price adjustment has occurred during BMO.

The increase in price adjustment speed from the Base to Post-Li period differs by session. During BMO, quotes adjust more quickly than trades, consistent with the findings of Gregoire & Martineau (2022). However, during AMC, trades adjust more quickly than quotes.

In contrast to Li (2016A), I find several PEAD-linked factors influence short-horizon post-ES price adjustment speed -- especially proxies for liquidity and investor attention. I conjecture that Li did not observe these relationships due to differences in his measures of speed and mine.

My study contributes to the EMH price discovery literature in several ways. It provides new evidence that EMH price discovery speed has increased since Li (2016A) and uncovers differences in trade vs. quote dynamics between AMC and BMO -- differences that are obscured when EMH is treated as a unified session, as in Gregoire & Martineau (2022). My study contributes to the PEAD literature by shedding additional light on the characteristics of the STEM-PEAD variant of "regular" PEAD.

In addition, my study offers insights for market participants such as investors and traders, and public-company executives responsible for engaging with investors analysts and the media. As EMH price discovery becomes faster at incorporating new information, it provides earlier signals of how prices are likely to evolve in response to material news that becomes public outside of RTH. Market participants who monitor these signals can begin developing plans and taking action sooner than those who wait for signals from RTH.

Finally, regulators may my study's findings on AMC vs. BMO differences in quote and trade dynamics relevant in light of the ongoing growth in EMH activity and the recent regulatory approvals that allow the exchanges to offer extended EMH trading hours.

The remainder of my paper is organized as follows. Section II presents my hypotheses. Section III describes my data sources, sample construction and variable definitions. Section IV reports my results, including graphical, tabular, and regression analyses. Section V contains supplemental analysis regarding the economic magnitude of STEM-PEAD during the Base and Post-Li periods. Section VI concludes.

## II HYPOTHESES

To address my research questions -- whether price adjustment speed (price discovery efficiency) in EMH has increased since Li (2016A)'s study, whether it differs between BMO and AMC, and whether it varies based on factors associated with regular PEAD -- I test the three hypotheses described below and summarized in Table 1 at the end of this section.

Hypothesis 1 (H1): The speed of price discovery in EMH has increased since Li (2016A)

The speed at which prices adjust to new information during RTH has been increasing, attributable to factors such as declines in trading cost (Chordia et al. 2014), increases in arbitrage activity (Chordia et al. 2014) and skill (Akbas et al. 2023), arbitrage in response to the publication of academic research on anomalies (McLean & Pontiff 2016), and technology-enabled increases in algorithmic low-latency trading (LLT) (Chordia & Miao 2020).

Li (2016A) framed his findings, in part, as having identified an exploitable (although economically small) market anomaly. Accordingly, McLean & Pontiff (2016)'s post-publication anomaly decay hypothesis might, by itself, be sufficient reason to expect that EMH stock prices would adjust more quickly to EMH ESs following the publication of Li (2016A). However, one need not rely solely on McLean & Pontiff (2016A). The other factors that have led to an increase in RTH price discovery speed -- declining trading costs, increased algorithmic LLT activity, and general increases in arbitrage activity and skill -- would be expected to have also increased the efficiency of price discovery during EMH.

Furthermore, the EMH sessions have become more active since the time of Li (2016A)'s study. Prior literature finds a positive relationship between trading activity and market efficiency (Chordia et al. 2011), including during EMH (Barclay & Hendershott 2008). Prior literature has also found that initial post-ES price discovery during EMH is faster when measured using quote prices, which are less subject to trading frictions, than when measured using trade prices (Gregoire & Martineau 2022).

For the foregoing reasons, I expect to find that post-ES EMH price discovery efficiency has increased since Li (2016A). *More specifically, I define the price adjustment from the time of an AMC/BMO ES through the next RTH close as the "total" price adjustment and test the following sub-hypotheses:*

- **H1a:** In the Post-Li period, a larger proportion of the total price adjustment occurs in the 15-minute initial price adjustment (IPA) window, suggesting that EMH price discovery has become faster.
- **H1b:** The effects described in H1a are smaller when price adjustment is measured using quote prices rather than trade prices.

<u>Hypothesis 2 (H2): The speed of price discovery in EMH differs between AMC and BMO</u>

In their study examining post-EA price discovery during AMC/BMO, Jiang et al. (2012) focused on price adjustment over the same event window as my study (*i.e.*, from time of ES through the next RTH close). Based on a sample of EAs by S&P 500 stocks during 2004-2008 and measuring the proportion of price adjustment that occurs during AMC/BMO relative to the price adjustment over their event window, they found the following. For AMC EAs, 42% of the price adjustment occurred during AMC, and for BMO EAs, 36% occurred during BMO.

Upon first reading, Jiang et al. (2012)'s results suggest that AMC price discovery is faster than BMO price discovery. However, they also found that the average price adjustment per trade was higher during BMO than AMC. Also, their study's average post-EA AMC event window (time of a given event's EA to end of AMC) was longer than their average post-EA BMO event window (time of a given event's EA to end of BMO), which could account for their findings that a greater proportion of price adjustment occurs during AMC than BMO[24].

Unlike Jiang et al. (2012), my focus is not on price change over the entire post-event portion of AMC/BMO event windows of varying length, but rather on the change over an IPA (initial price adjustment) window of fixed length (*i.e.*, the first 15 minutes after an ES).

Since the time of Jiang et al. (2012), as well as since the publication of Li (2016A), there has been an increase in EMH trading and quoting activity, especially after an ES announcement and the increases differ between AMC and BMO. This can be seen in the mean and median number of trades and quotes per ES event reported in Table 6.

Given the differences between AMC and BMO -- such as differences in trading and quoting activity (as shown in Table 6) and the fact that AMC occurs at the end of the workday and after RTH and before the overnight non-trading hours, whereas BMO occurs at the start of the workday and before RTH (all of which lead to differences in AMC vs. BMO market participants and their motivations and trading-risks, etc.) -- one would expect there to be differences in the speed of price discovery during BMO vs. AMC. Whether they are faster or slower during BMO vs. AMC, and whether those speed differences have changed since the publication of Li (2016A), I treat as an empirical question. I only predict that there will be differences.

*More specifically, I define the price adjustment from the time of an AMC/BMO ES through the next RTH close as the "total" price adjustment and test the following hypothesis:*

[24] Jiang et al. (2012) defined the AMC window to run from 4pm to 6:30pm and the BMO window from 7am to 9:30am. Based on their sample's distribution of EAs by time of day (Jiang et al. 2012, pg. 1307, Fig. 1), the typical AMC event in their sample had a longer post-EA AMC event window as compared to the typical BMO event's post-EA BMO event window.

- **H2:** The proportion of total price adjustment that occurs in the 15-minute initial price adjustment (IPA) window differs between AMC and BMO, reflecting differences in the speed of price discovery.

Hypothesis 3 (H3): Post-ES price discovery speed in EMH is influenced by PEAD-linked factors

The magnitude and persistence of PEAD are commonly attributed to market frictions (arbitrage inhibitors) that slow the rate of price discovery -- frictions such as, illiquidity (Chordia et al. 2009, Sadka 2006), short-sale constraints (Boehmer & Wu 2013, Diamond & Verrecchia 1987), investor inattention (DellaVigna & Pollet 2009, Hirshleifer et al. 2009), differences in opinion (Garfinkel and Sokobin 2006, Vega 2006), and slower information diffusion rates for bad news relative to good news (Bird et al. 2014, Reed 2007).

As those factors have been found to influence PEAD *because they slow down the speed of price discovery,* one would expect them to also influence post-ES price discovery speed in EMH.

That is why it was somewhat surprising that Li (2016A) did not find a relationship between any of those factors and post-ES price adjustment speed in the AMC session. I conjecture that Li (2016A) did not find the expected relationships because the study's adjustment speed measures were not well designed to capture cross-sectional variations.

Li (2016A) constructed two adjustment speed measures, both of which measured the elapsed time after a stock's ES when its price first became equal to or greater than its final price at the end of the measurement-window. The first measure's measurement-window ended two hours after an event's ES, and the second one's window ended at the conclusion of AMC (*e.g.*, 8pm). These measures are not conventional (not found in other literature) and are constructed to measure how quickly a stock arrives at its final price during the measurement window, rather than how fast it adjusts over the IPA portion of the price adjustment curve.

Most studies that examine post-ES price adjustment speed -- including PEAD studies explicitly or implicitly measure price adjustment speed over the IPA stage of the price adjustment curve. For example, in a typical "regular" PEAD study, the IPA window accounts for less than 2% of the total event window (*e.g.*, 1 day divided by 60 days = ~1.7%). If PEAD's drift and associated returns are taken to be the result of incomplete price adjustment during the IPA window, then measuring the relationship between variations in PEAD returns and factors that slow the price discovery process is effectively a measure of the speed of price adjustment during the IPA window.

While some studies use PEAD and/or IPA returns as standalone measures of adjustment speed, others construct ratios -- such as PEAD / (IPA + PEAD) or IPA / (IPA + PEAD) -- to capture the relative speed of adjustment across each window, where a higher IPA-based ratio (or a lower PEAD-based ratio) indicates faster adjustment. Studies that use ratio-based measures include Jiang et al. (2012), Barclay & Hendershott (2003), DellaVigna & Pollet (2009), Beschwitz et al. (2020), and Chordia et al. (2018).[25]

Unlike Li (2016A), prior EMH studies that have focused on measuring price adjustment speed during the IPA window have found post-ES price discovery speed in EMH to be related to PEAD-linked factors: having a positive relationship with liquidity (Greogire & Martineau 2022, Jiang et al. 2012) and investor attention (Jiang et al. 2012), and a negative relationship with bad news (Gregoire & Martineau 2022, 2019). Jiang et al. (2012) also find a positive relationship between surprise magnitude and post-ES price adjustment speed[26].

[25] Jiang et al. (2012) and Barclay & Hendershott (2003) use Barclay & Warner (1998)'s Weighted Price Contribution (WPC) measure. DellaVigna & Pollet (2009) use DellaVigna & Pollet (2009)'s Delayed Response Ratio (DRR) measure, and Beschwitz et al. (2020) and Chordia et al. (2018) use Beschwitz et al. (2020)'s Speed of Price Response measure, which they characterize as "similar in spirit" to DellaVigna & Pollet (2009)'s DRR.

[26] Li (2016A) also found a relationship between post-ES AMC price adjustment speed and surprise magnitude for PSs but not for NSs and conjectured that short-sale constraints might explain the lack of a relationship in the case of NSs.

Because my study focuses on the speed of price discovery during the IPA window, and because I construct adjustment speed measures in accordance with Jiang et al. (2012), I expect to find that post-ES price discovery speed in EMH is influenced by PEAD-linked factors. *More specifically, I define the price adjustment from the time of an AMC/BMO ES through the next RTH close as the "total" price adjustment and test the following sub-hypotheses:*

- **H3:** The proportion of the total price adjustment occurs in the 15-minute initial price adjustment (IPA) window is associated with PEAD-linked factors as follows:
    - positively related to surprise magnitude, liquidity, and investor attention, and
    - negatively related to bad news, short-sale constraints, and differences of opinion,

  suggesting that these factors influence the speed of EMH price discovery.

* * * * *

Table 1 on the following page summarizes my hypotheses, and the relationships tested. It also notes the tests used to evaluate the hypotheses, and the subsections in Section IV in which the results are reported.

**[Turn to next page for Table 1]**

**Table 1 Hypotheses Summary**

| Hypothesis | Expected Direction | Tests | Results Subsection |
|---|---|---|---|
| H1a: Post-Li, a larger proportion of total price adjustment occurs in IPA window | (+) | Graphical Analysis<br>Tabular Analysis<br>Regressions Analysis | IV.1<br>IV.2<br>IV.3.1 |
| H1b: The H1a effects will be smaller when price adjustment measured by quotes vs. trades | (-) | Tabular Analysis<br>Regressions Analysis | IV.2<br>IV.3.1 |
| H2: The proportion of total price adjustment that occurs in IPA window differs for AMC vs. BMO | ? | Graphical Analysis<br>Tabular Analysis<br>Regression Analysis | IV.1<br>IV.2<br>IV.3.2 |
| H3: The proportion of total price adjustment that occurs in IPA window is associated with:<br>• surprise magnitude, liquidity, investor attention<br>• NSs, short-sale constraints, opinion differences | <br><br>(+)<br>(-) | Regression Analysis | IV.3.1 and IV.3.2 |

**[Section III begins on next page]**

# III DATA

When assembling and analyzing the data for my study, I divided it into four subsamples. Each subsample covered one of two time-periods (Base: 2004-2012 or Post-Li: 2017-2021) and one of two ES announcement times (AMC or BMO), as illustrated in Table 2.

**Table 2 The Four Subsamples in My Study**

| | (2004 – 2012) Base Period | (2017 – 2021) Post-Li Period |
|---|---|---|
| Time of ES Announcement | AMC | AMC |
| | BMO | BMO |

The Base period covers the years examined by Li, excluding 2002-2003 as I was unable to obtain tick-level data for those years. The Post-Li period covers the years after Li published his dissertation (Li 2016A) and accompanying paper in the *Journal of Trading* (Li 2016B).

## III.1 Data Sources

I obtained a day-by-day list of S&P 1500 stocks from Bloomberg, and data on quarterly EAs by those stocks from the academic-research version of the Refinitiv Institutional Broker's Estimate System (IBES) datasets available at Wharton Data Research Services (WRDS).

From that set of EAs, I identified the subset that qualified as ES events. As previously discussed, I defined ESs as EAs where actual revenue and actual EPS (a) both exceed consensus (a positive surprise or PS), or (b) both fall short of consensus (a negative surprise or NS).

For the ES events, I obtained tick-level trade and quote data from the New York Stock Exchange's (NYSE's) Trade and Quote (TAQ) datasets available at WRDS. I also obtained data to construct variables associated with each stock's characteristics (*e.g.*, market capitalization, short-interest, etc.) as of its ES event, from the following datasets available at WRDS: (i) the annual-update version of the Center for Securities Research's (CRSP) Daily Stock File, and (ii) the daily-update version of Compustat's Supplemental Short Interest File.

## III.2 Sample Construction

### *III.2.1 Earnings Announcements (EAs) by S&P 1500 Stocks*

As shown in Table 3, I found 53,631 Base Period / 29,638 Post-Li EA events where IBES had a record containing a non-missing value of the announcing stock's actual EPS.

I initially classified an EA as having occurred during (a) BMO if its timestamp was greater than or equal to 4am and less than 9:30am, and (b) AMC if its timestamp was greater than or equal to 4pm (1pm on half-days) and less than or equal to 8pm (5pm on half-days).

I found that 49,710 (92.7%) and 29,090 (98.2%) occurred during EMH (AMC or BMO) during 2004-2012 and 2017-2021, respectively. BMO EAs were slightly more common than AMC EAs during 2004-2012, and vice versa during 2017-2021. The vast majority of EAs are announced between 4pm and 6pm during AMC or 6am and 9:30am during BMO.

Following Li (2016A) and supported by the findings of Hu & Stephan's (2022), I excluded from my final sample of AMC/BMO EAs those EAs timestamped exactly at the 4pm close of RTH (1pm on half-days)[27]. This filter eliminated 2,440 Base Period and 436 Post-Li Period EAs, leaving 47,270 Base Period and 28,654 Post-Li AMC/BMO EAs.

[27] Hu & Stephan (2022) noted that although the RTH session closes (*i.e.*, ends) at 4pm (1pm on half-days), in practice it can take several tenths of a second to a few minutes for the exchanges to complete the closing auction for a given stock. Hu & Stephan (2022) found evidence that the Nasdaq and NYSE-Arca exchanges, with average "closing delay's" of 2.3 and 0.37 seconds, respectively, appear to allow traders to enter RTH orders into the RTH central order limit book (CLOB) between the official RTH close and the completion of the closing auction, and that such orders can get executed as part of the closing auction. Furthermore, Hu & Stephan (2022) found evidence that traders were able to execute RTH trades, during the short window between the official RTH close and the completion of the closing auction, by acting on earnings news released exactly at the official close. Hu & Stephan (2020) also note that, in response to a February 6, 2014 *Wall Street Journal (WSJ)* article that reported on this phenomenon ("Ulta's December 5, 2013 EA"), the stock exchanges and SEC subsequently issued guidance that directed publicly-traded companies to delay their AMC EAs until either 5 minutes after the official close or until the completion of the closing auction for their stock. Finally, Hu & Stephan (2022) found evidence of a drop in the number of EAs released exactly at the close after the WSJ article was published.

**Table 3 S&P 1500 EAs during Base & Post-Li Periods by Market Session and Announcement Time**

**Panel A: Summary by Market Session**

| | 2004-2012 Base Period | | 2017-2021 Post-Li Period | |
|---|---|---|---|---|
| | # of EAs | % | # of EAs | % |
| BMO | 26,694 | 49.8% | 13,920 | 47.0% |
| AMC | 23,016 | 42.9% | 15,170 | 51.2% |
| EMH Total | 49,710 | 92.7% | 29,090 | 98.2% |
| RTH | 2,445 | 4.6% | 283 | 1.0% |
| Closed | 1,476 | 2.8% | 265 | 0.9% |
| **Totals** | **53,631** | **100.0%** | **29,638** | **100.0%** |

**Panel B: Summary by Announcement-Window for BMO Session and for AMC Session**

**EAs announced during BMO**

| Window[(3)] | | 2004-2012 Base Period | | 2017-2021 Post-Li Period | |
|---|---|---|---|---|---|
| From | To | # of EAs | % | # of EAs | % |
| 4:00 AM | 4:30 AM | 54 | 0.2% | 12 | 0.1% |
| 4:30 AM | 5:00 AM | 44 | 0.2% | 4 | 0.0% |
| 5:00 AM | 5:30 AM | 247 | 0.9% | 56 | 0.4% |
| 5:30 AM | 6:00 AM | 216 | 0.8% | 165 | 1.2% |
| 6:00 AM | 6:30 AM | 2,808 | 10.5% | 2,027 | 14.6% |
| 6:30 AM | 7:00 AM | 2,255 | 8.4% | 4,114 | 29.6% |
| 7:00 AM | 7:30 AM | 6,561 | 24.6% | 3,031 | 21.8% |
| 7:30 AM | 8:00 AM | 5,130 | 19.2% | 1,994 | 14.3% |
| 8:00 AM | 8:30 AM | 5,131 | 19.2% | 1,434 | 10.3% |
| 8:30 AM | 9:00 AM | 2,940 | 11.0% | 730 | 5.2% |
| 9:00 AM | 9:30 AM | 1,308 | 4.9% | 353 | 2.5% |
| **BMO Totals** | | **26,694** | **100.0%** | **13,920** | **100.0%** |

**EAs announced during AMC**

| Window[(3)] | | 2004-2012 Base Period | | 2017-2021 Post-Li Period | |
|---|---|---|---|---|---|
| From | To | # of EAs | % | # of EAs | % |
| 4:00 PM | 4:00 PM | 2,440 | 10.6% | 436 | 2.9% |
| >4:00 PM | 4:30 PM | 11,572 | 50.3% | 10,151 | 66.9% |
| 4:30 PM | 5:00 PM | 2,918 | 12.7% | 2,255 | 14.9% |
| 5:00 PM | 5:30 PM | 2,748 | 11.9% | 1,504 | 9.9% |
| 5:30 PM | 6:00 PM | 1,138 | 4.9% | 334 | 2.2% |
| 6:00 PM | 6:30 PM | 774 | 3.4% | 275 | 1.8% |
| 6:30 PM | 7:00 PM | 692 | 3.0% | 103 | 0.7% |
| 7:00 PM | 7:30 PM | 404 | 1.8% | 73 | 0.5% |
| 7:30 PM | 8:00 PM | 330 | 1.4% | 39 | 0.3% |
| **AMC Totals** | | **23,016** | **100.0%** | **15,170** | **100.0%** |

Notes:
1. EA dates and times are from IBES; figures above do not include EAs where IBES had non-missing EPS values.
2. 8 EAs occurred on days the market was open a half-day -- 5 during BMO, 1 during RTH (10:45am), 1 during AMC (4:05pm), and 1 when the market was closed (5:36pm).
3. Announcement windows start at the time under the "To" column and end just before the time under the "From" column, except for the first two rows under "EAs announced during AMC", where the first row (from 4:00 PM to 4:00 PM) represents EAs announced exactly at 4pm, and the second row (from >4:00 PM to 4:30 PM) represents EAs announced just after 4pm through EAs announced just before 4:30pm.

### *III.2.2 Earnings Surprises (ESs) by S&P 1500 stocks*

To construct my sample of AMC/BMO ES events, I started with the 47,270 Base Period / 28,654 Post-Li AMC/BMO EAs described above and retained only those events where (a) IBES had non-missing values not only for actual EPS, but also for actual revenues, consensus EPS and consensus revenue, and (b) actual results for EPS and revenue were announced simultaneously. After applying this filter, there were 45,372 Base Period and 28,519 Post-Li EAs from which to construct my sample of ES events.

From that set of EAs, I identified the subset that qualified as ESs -- EAs where revenue and EPS both exceeded consensus or both fell short of consensus. I defined a positive surprise (PS) as an ES where revenue and EPS both exceeded consensus and a negative surprise (NS) as an ES where both fell short. I identified 26,878 Base Period and 18,566 Post-Li ESs; I refer to this as my *raw* sample of ES events. Table 4 provides the breakdown of my raw sample by time-period, ES type (PS or NS), and the trading session during which the ES occurred.

**Table 4 Raw Sample of ES Events by Time-Period, ES Type, and the Trading Session during which the ES occurred**

| | (2004 – 2012) Base Period | | | (2017 – 2021) Post-Li Period | | |
|---|---|---|---|---|---|---|
| Trading Session | PS Events | NS Events | Total ES Events | PS Events | NS Events | Total ES Events |
| AMC | 8,560 | 3,156 | 11,716 | 7,391 | 2,208 | 9,599 |
| BMO | 10,800 | 4,362 | 15,162 | 6,970 | 1,997 | 8,967 |
| Total | 19,360 | 7,518 | 26,878 | 14,361 | 4,205 | 18,566 |
| | Memo: 45,372 EA Events in Sample | | | Memo: 28,519 EA Events in Sample | | |

As shown in Table 4, my raw sample of ESs included 11,716 AMC events for 2004-2012, not counting ESs that occurred exactly at 4pm (1pm on half-days), of which 8,560 were PSs (73.1% of 11,716) and 3,156 were NSs (26.9% of 11,716). As Li (2016A) noted, citing Chan, Karceski, and Lakonishok (2007) and Gennotte and Trueman (1996), that fact that the majority of ESs were PSs is consistent with previous studies.

I next checked the reasonableness of my ES counts at this stage of the construction of my sample by comparing my counts to Li (2016A). At what I believe to be the same stage in the construction of his sample, Li (2016A) found 10,417 ESs for 2002-2012, of which 7,776 (74.6% of 10,417) were PSs and 2,641 were NSs (25.4% of 10,417).

After discovering that my raw sample's ES counts for 2004-2012 were materially greater than Li's (2016A) counts for 2002-2012 (a longer period), I examined 864 alternative combinations of rules that Li (2016A) might have used to initially identify the number of ESs in the initial version of his sample of ES events (*e.g.*, initially include days the market was closed or not, include ES events announced exactly at 4pm (1pm on half-days) or not, require the announcements of revenue and EPS to have occurred simultaneously or not, etc.).[28]

Although I could not exactly match Li's (2016A) ES counts for 2002-2012, I was able to come within 0.13% of his ES counts (10,403 vs. 10,417) -- within 0.12% of his PS counts (7,785, or 74.8% ESs vs. 7,776 or 74.6% of ESs) and 0.87% of his NS counts (2,618, or 25.2% of ESs vs. 2,641, or 25.4% ESs) -- if I modified my sample selection rules to (a) include PSs and NSs announced on days the market was closed, (b) not require actual Revenues to have been announced simultaneously with actual EPS, and (c) require the announcing stock to have been a member of the S&P 1500 not only on the day of the EA, but also on December 31, 2012[29].

Based on the foregoing, I concluded that my rules for constructing my raw sample of ES events were acceptably consistent with Li's (2016A), and that where my rules differed -- *i.e.*, by including ES events by stocks that were an S&P 1500 members as of their EA date, regardless of whether they were an S&P 1500 member as of December 31, 2012, and excluding ES events that

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[28] Additional documentation with extensive details on sample construction, including SAS code, is available from the author upon request.

[29] I also note that Li (2016A) stated that he defined PSs and NSs using what I label the "OR" Rule -- defining an EA as a PS when either actual revenue or EPS exceeds consensus and neither falls short, and as an NS as when either falls short of consensus and neither exceeds. In other words, he defined a PSs and NSs as follows:

PS = (Actual EPS > Consensus and Actual Revenue is not less than Consensus) OR (Actual Revenue > Consensus and Actual EPS not less than Consensus)

NS = (Actual EPS < Consensus and Actual Revenue not greater than Consensus) OR (Actual Revenue < Consensus and Actual EPS not greater than Consensus)

However, as detailed extensively in additional documentation available from the author upon requestion, I believe Li (2016A) actually defined PSs and NSs, as I have defined them, using what I label the "AND" Rule:

PS = Actual EPS > Consensus AND Actual Revenue > Consensus NS = Actual EPS < Consensus AND Actual Revenue < Consensus

I could find no combination of other rules for selecting and counting PS/NS events for the period 2002-2012 that, when using Li's (2016A) stated "OR" Rule definition of PSs and NSs, resulted in PS/NS counts and that differed from Li's reported counts (2016A) by less than 3.65%/14.56%.

The main reason the "OR" Rule leads to a much larger number of PSs and NSs than the "AND" Rule is because, during 2002-2012, there were a large number of EAs where actual EPS was equal to consensus while revenue either exceeded (a PS under the "OR" Rule, but not the "AND" Rule) or fell short (an NS under the "OR" Rule, but not the "AND" Rule). During that period, there were very few EAs where Revenue was equal to consensus while EPS either exceeded or fell short.

Because I believe Li (2016A) used the "AND" Rule, and because the "AND" Rule provides a much cleaner signal for a PSs and NSs than does the "OR" Rule (*i.e.*, an EA where a stock exceeds or falls short of consensus on both EPS and Revenue is a stronger, cleaner signal of positive or negative news than an EA where a stock exceeds or falls short on only one of the two measures), I chose to use the "AND" Rule to identify PS and NS events in my study. Furthermore, given that most of the additional PS/NS events identified by the "OR" Rule are EAs where Actual EPS equals consensus, because, as Li (2016A) notes (citing Graham, Harvey & Rajgopal (2005)), it is easier for companies to manage their actual EPS (*e.g.*, by cutting expenses during a quarter), one could argue (a) that merely achieving consensus EPS during a quarter when revenues exceed could be a sign of weakness (negative news) rather than strength (positive news), and (b) that being able to achieve consensus EPS during a quarter when revenues fall short could be a sign of strength (positive news) rather than weakness (negative news).

occurred on days the market was closed and/or where actual revenues were not announced simultaneously with actual EPS results -- the differences were appropriate.

Next, I examined my raw sample of ESs to review cases where a given stock issued multiple EAs on the same day. Of the 26,878 Base- Period and 18,566 Post-Li Period ESs in my raw sample, I removed 32 Base Period (0.12% of 26,878) and 9 Post-Li (0.05% of 18,566) "stale and/or ambiguous" ESs -- events where the ES was for a stock that made other EAs that day and either (a) of all the EAs the stock made that day, the ES was not the EA for the most-recently announced quarter (*i.e.*, the ES was "stale"), and/or (b) other EAs made by the stock that day provided a contradictory signal -- some of the EAs were PSs while others were NSs (*i.e.*, the ES was "ambiguous"). After removing those 32 Base Period and 9 Post-Li events, 26,846 Base Period and 18,557 Post-Li ES events remained in my sample.

For each remaining ES event in my sample, I attempted to obtain TAQ trade and quote data for (i) the last trading day prior to the ES, (ii) the day of the ES, and (iii) the trading day that included the first RTH session after the ES (*i.e.*, the day of the ES for BMO events, and the next trading day after the ES for AMC events).

Of the 26,846 Base Period and 18,557 Post-Li ESs that remained in my sample at this stage, I obtained TAQ data for the required days for 26,786 (99.8% of 26,846) Base Period and 18,532 (99.9% of 18,557) Post-Li ES events[30]. I confirmed that for each event for which I obtained data for the required days that I was also able to obtain (a) the last trade prior to the EA, (b) the first trade after the EA, and (c) the opening and closing trades during the next RTH session following the EA (*i.e.*, in the case of BMO events, the opening and closing trades were during the

[30] Of the 26,846 Base Period and 18,557 Post-Li ES events in my sample of ES events at this stage of its assembly, I was unable able to obtain TAQ trade and quote data for the required days for 60 Base Period and 25 Post-Li events. In all but one case, the reason why I was unable to obtain the TAQ trade and quote data was because there were data mapping issues (*e.g.*, mapping the stock ticker associated with the data I obtained from Bloomberg to the stock ticker used by IBES, mapping the stock ticker associated with the data I obtained from IBES to the stock ticker used by TAQ, etc.) which required manual research to resolve and which I did not discover until after I no longer had access to the TAQ datasets. In the one remaining case, the stock associated with an AMC event was suspended from trading, after the ES event, before the opening of the market on the following trading day (the ES event was Dean Foods' 11/12/19 EA of its results for the quarter ended 09/30/19). Additional documentation with extensive details on sample construction is available from the author upon request.

announcement day's RTH session, and in the case of AMC events, those trade were during the next day's RTH session). Table 5 provides the breakdown of my preliminary sample of ES events by period (Base vs. Post-Li), ES type, and the session during which the ES occurred.

**Table 5 Final Sample of ES Events by Period, ES Type, and the Trading Session during which the ES occurred**

| | (2004 – 2012) Base Period | | | (2017 – 2021) Post-Li Period | | |
|---|---|---|---|---|---|---|
| Trading Session | PS Events | NS Events | Total ES Events | PS Events | NS Events | Total ES Events |
| AMC | 8,522 | 3,121 | 11,643 | 7,369 | 2,201 | 9,570 |
| BMO | 10,789 | 4,354 | 15,143 | 6,968 | 1,994 | 8,962 |
| Total | 19,311 | 7,475 | 26,786 | 14,337 | 4,195 | 18,532 |

*III.2.3 Trade and Quote Data*

When constructing my sample of TAQ trade data, like Li (2016A) I followed Huang & Stoll (1996), Hasbrouck (2010), Lee & Ready (1993) and applied standard tick-level data cleaning procedures to clean the raw TAQ trade data. Specifically, I excluded the following from my cleaned sample of TAQ trade data: trades flagged as incorrect, trades where the price or number of shares traded was zero, trades with non-standard settlement conditions, out-of-sequence, trades, earlier obligation trades, prior reference price trades, and/or bunched-solds trades, and/or trade records that were informational messages that did not represent an actual trade[31].

When constructing my sample of TAQ quote data, like Li (2016A), I followed Lee & Ready (1993) and Holden & Jacobsen (2014) and applied standard tick-level data cleaning procedures to clean the raw TAQ quote data. I constructed a set of NBBO quotes by excluding quotes that were NBBO-ineligible quotes, locked (bid = ask), or crossed quotes (ask < bid), and by treating quotes with zero or negative prices or shares-quoted as withdrawn quotes[32].

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31 Additional documentation with extensive details on sample construction, including SAS code, is available from the author upon request.
32 Additional documentation with extensive details on sample construction, including SAS code, is available from the author upon request.

Unlike Li (2016A) -- and unlike Holden & Jacobsen (2014), who examine trades during RTH rather than AMC or BMO -- I did not classify quotes with spreads greater than $5.00 as NBBO-ineligible. Instead -- in accordance with Gregoire & Martineau (2022) who recommend adjusting the threshold for classifying outlier spreads because spreads larger than $5.00 are common during AMC and BMO -- I excluded quote observations where the absolute value of the bid-ask spread was greater than 20% of the mid-quote. For brevity, from here forward, unless otherwise noted, when I use the terms trades and quotes (including mid-quotes, bids, offers or asks), I am referring to trades and quotes that remained in my sample after applying the cleaning and outlier exclusion rules discussed in this subsection III.2.3. Also, from here forward, unless otherwise specified, I sometimes use the term quote by itself as a shorthand for mid-quote.

*III.2.4 Retaining ESs with No Trades in First 3 Minutes after an EA (diverging from Li 2016A)*

Li (2016A) also excluded from his final sample those ES events where no trades were observed during the first three minutes after the event's EA. His stated reason was to remove events where a trading halt *might have been* in place during his post-ES event window.

I diverged from Li (2016A) and did not apply his "three-minute rule" to remove events from my final sample for the reasons that follow (also see Appendix C for additional details).

First, I found Li's three-minute rule to severely over identify the number of ES events that had an actual halt in place during the first three minutes after an ES announcement. Li's three-minute rule classified an estimated 43.5% as his preliminary sample of ESs, as having had a trading halt in effect during the initial three-minute window after an ES. Directly examining TAQ data for the codes that indicate a trading halt, and focused on the 11,643 events in my Base Period AMC subsample (*i.e.*, my subsample that corresponds to Li's sample), I found that (a) only 33 events -- less than 0.3% -- had a trading halt in place during the entire three-minute window following an ES announcement, and (b) no events had a trading halt in place for the entire AMC session following the ES announcement. My finding that the incidence rate of actual trading halts is relatively low is consistent with prior literature (Jiang et al. 2012).

The second reason I diverge from Li (2016A) is because Li provides no justification for removing events where halts were (or might have been) in effect during a portion of the event window after an EA, and studies investigating EMH price discovery do not typically exclude events with halts[33]. Furthermore, Gregoire & Martineau (2022) specifically recommend not excluding events where little or no EMH trading occurs, arguing that excluding such events "leads to a selection bias to toward larger, more liquid stocks, and events with larger news shocks" (Gregoire & Martineau 2022, pg. 293).

## III.3 Descriptive Statistics for Trade and Quote Activity around ES Events

### *III.3.1 Trade and NBBO Quote Update Statistics on a Per-Event Basis*

Table 6 provides the number of ES events in my final sample, categorized by the presence or absence of trades and NBBO quote updates during the AMC/BMO session in which the ES was announced: (i) events with post-ES trades and quotes, (ii), events with post-ES trades, but no quotes, and (iii) events with post-ES quotes, but no trades, and (iv) events with no post-ES trades or quotes. Table 6 also provides statistics on the mean and median number of Trades and NBBO quote updates per-ES event. Panel A provides the statistics for the full AMC/BMO session in which the ES was announced, and Panel B provides the statistics for the post-ES portion of the AMC/BMO session in which the ES was announced.

[33] Within the EMH price discovery literature, I found only one paper that excluded events where halts were in effect, a study by Christensen et al. (2025) in which the authors develop and analyze a market microstructure jump test, a context where including events with halts might have led to misleading inferences. Unlike Li (2016A), Christensen et al. (2025) identify actual (vs. potential) halts by examining TAQ data for codes indicating halts and trading resumptions.

**Table 6 ES Events in Final Sample with and without Post-ES Trades and NBBO Quote Updates and Per-Event Trade & NBBO Quote Update Statistics**

| | Base Period | | | Post-Li | | | Total | | |
|---|---|---|---|---|---|---|---|---|---|
| | AMC | BMO | Total | AMC | BMO | Total | AMC | BMO | Total |
| **PANEL A: Full EMH Session Statistics (Pre- and Post-ES)** | | | | | | | | | |
| **Number of ES Events with and without Trades and NBBO Quote Updates during initial AMC/BMO Session** | | | | | | | | | |
| Trades and Quotes | 11,453 | 10,460 | 21,913 | 9,533 | 7,749 | 17,282 | 20,986 | 18,209 | 39,195 |
| Trades, but no Quotes | 94 | 92 | 186 | 25 | 80 | 105 | 119 | 172 | 291 |
| Quotes, but no Trades | 94 | 3,895 | 3,989 | 12 | 845 | 857 | 106 | 4,740 | 4,846 |
| No Trades or Quotes | 2 | 696 | 698 | - | 288 | 288 | 2 | 984 | 986 |
| Final Sample | 11,643 | 15,143 | 26,786 | 9,570 | 8,962 | 18,532 | 21,213 | 24,105 | 45,318 |
| **Percentage ES Events with and without Trades and NBBO Quote Updates** | | | | | | | | | |
| Trades | 99.2% | 69.7% | 82.5% | 99.9% | 87.4% | 93.8% | 99.5% | 76.3% | 87.1% |
| Quotes | 99.2% | 94.8% | 96.7% | 99.7% | 95.9% | 97.9% | 99.4% | 95.2% | 97.2% |
| No Trades or Quotes | 0.0% | 4.6% | 2.6% | 0.0% | 3.2% | 1.6% | 0.0% | 4.1% | 2.2% |
| **Number of Trades per-Event during initial AMC/BMO session** | | | | | | | | | |
| Mean per Event | 762 | 236 | 464 | 1,509 | 570 | 1,055 | 1,099 | 360 | 706 |
| Median per Event | 15 | 5 | 9 | 31 | 24 | 28 | 22 | 9 | 15 |
| **Number of NBBO Quote Updates per-Event during initial AMC/BMO session** | | | | | | | | | |
| Mean per Event | 987 | 579 | 756 | 982 | 1,093 | 1,035 | 985 | 770 | 870 |
| Median per Event | 22 | 56 | 43 | 41 | 85 | 58 | 33 | 65 | 49 |
| **PANEL B: Post-ES Statistics** | | | | | | | | | |
| **Number of ES Events with and without Post-ES Trades and NBBO Quote Updates during initial AMC/BMO Sessio** | | | | | | | | | |
| Trades and Quotes | 8,607 | 10,349 | 18,956 | 6,986 | 7,631 | 14,617 | 15,593 | 17,980 | 33,573 |
| Trades, but no Quotes | 1,063 | 97 | 1,160 | 1,394 | 135 | 1,529 | 2,457 | 232 | 2,689 |
| Quotes, but no Trades | 780 | 3,912 | 4,692 | 343 | 853 | 1,196 | 1,123 | 4,765 | 5,888 |
| No Trades or Quotes | 1,193 | 785 | 1,978 | 847 | 343 | 1,190 | 2,040 | 1,128 | 3,168 |
| Final Sample | 11,643 | 15,143 | 26,786 | 9,570 | 8,962 | 18,532 | 21,213 | 24,105 | 45,318 |
| **Percentage ES Events with and without Post-ES Trades and NBBO Quote Updates** | | | | | | | | | |
| Trades | 83.1% | 69.0% | 75.1% | 87.6% | 86.7% | 87.1% | 85.1% | 75.6% | 80.0% |
| Quotes | 80.6% | 94.2% | 88.3% | 76.6% | 94.7% | 85.3% | 78.8% | 94.4% | 87.1% |
| No Trades or Quotes | 10.2% | 5.2% | 7.4% | 8.9% | 3.8% | 6.4% | 9.6% | 4.7% | 7.0% |
| **Number of Post-ES Trades per-Event, during initial AMC/BMO session** | | | | | | | | | |
| Mean per Event | 708 | 231 | 438 | 1,376 | 552 | 978 | 1,009 | 350 | 659 |
| Median per Event | 9 | 5 | 6 | 16 | 23 | 19 | 11 | 9 | 10 |
| **Number of Post-ES NBBO Quote Updates per-Event, during initial AMC/BMO session** | | | | | | | | | |
| Mean per Event | 887 | 556 | 700 | 884 | 894 | 889 | 885 | 682 | 777 |
| Median per Event | 6 | 54 | 28 | 12 | 79 | 40 | 8 | 62 | 33 |

The statistics in Table 6 show that after an EMH ES, it is quite common for post-ES trades and quotes to take place during the AMC/BMO session in which the ES was announced. Across all four subsamples, ~90% (or more) of events have at least one post-ES trade or quote during the ES announcement session, with ~69% to ~88% having at least one post-ES trade and ~77% to ~95% having at least one post-ES quote. The statistics suggest it has become more common for ESs to have post-ES trades since the Base Period, especially during BMO.

Across all four subsamples, although the mean number of post-ES trades and quotes per-event ranges from several hundred to over a thousand, the median numbers show that the typical ES event has a much more modest number of post-ES trades and quotes. The median number of post-ES trades appears to have increased since the Base Period, especially during BMO.

The statistics also indicate heightened quoting activity during BMO compared to AMC, during both the Base and Post-Li periods. Compared to AMC ESs, a greater proportion of BMO ESs have at least one post-ES quote. The median number of post-ES quotes for BMO ESs is substantially larger than both (a) the median number of post-ES quotes for AMC ESs, and (b) the median number of post-ES trades for BMO ESs.

*III.3.2 Trade and NBBO Quote Update Statistics on a Per-Hour Basis*

Table 7 provides trade and NBBO quote update statistics, on a per-hour basis, for the EMH session in which the ES was announced and, for comparison, for the preceding RTH session. Panel A provides the statistics for the full AMC/BMO session in which the ES was announced, and Panel B provides the statistics for only the post-ES portion of that session.

The statistics in Table 7 are for 2004 and 2021, the years at the beginning and end of my sample. The reason for including only those years is to reduce the risk that changes in how odd-lot trades (trades of less than 100 shares) were reported to TAQ (my data source) could lead to incorrect inferences regarding changes in the per-hour trade and quote statistics over time.

Prior to December 9, 2013, only some (*i.e.*, not all) odd-lot trades were included in the TAQ datasets (O'Hara et al. 2014). This means that my Post-Li (2017-2021) sample contains the complete set of odd-lot trades, whereas my Base (2004-2012) period sample does not. Odd-lot trades were far less common in 2004 -- they accounted for just ~1.25% of NYSE RTH dollar volume (O'Hara et al. 2014, pg. 2203, fig. 1). Only since the growth in low latency trading and algorithmic trading -- i.e., since 2004 -- have odd-lot trades become relatively common (odd-lot trades were also common prior to the 1970s).

Since odd-lot trades were not common in 2004, restricting Table 7 to 2004 and 2021 reduces the risk that changes in how odd-lot trades were reported to TAQ could lead to incorrect inferences regarding changes in the per-hour trade and quote statistics over time.

**[Turn to next page for Table 7]**

**Table 7 Number of Trades and NBBO Quote Updates Around ES Events for 2004 and 2021**
**Per-Hour Statistics for AMC/BMO Announcement Session and Preceding RTH Session**

| | | Year = 2004 | | | | | | Year = 2021 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | AMC Announcements | | | BMO Announcements | | | AMC Announcements | | | BMO Announcements | | |
| ***Transactions During-->*** | | AMC | Prior RTH | AMC / RTH | BMO | Prior RTH | BMO / RTH | AMC | Prior RTH | AMC / RTH | BMO | Prior RTH | BMO / RTH |
| **PANEL A: Full EMH Session Statistics (Pre- and Post-ES)** | | | | | | | | | | | | | |
| Number of ES Events | | | | | | | | | | | | | |
| Total | | 1,142 | 1,142 | 100.0% | 1,553 | 1,553 | 100.0% | 2,203 | 2,203 | 100.0% | 2,042 | 2,042 | 100.0% |
| -- with Trades | | 1,133 | 1,142 | 99.2% | 795 | 1,553 | 51.2% | 2,202 | 2,203 | 100.0% | 1,947 | 2,042 | 95.3% |
| -- with Quote Updates | | 1,107 | 1,142 | 96.9% | 1,300 | 1,553 | 83.7% | 2,203 | 2,203 | 100.0% | 2,009 | 2,042 | 98.4% |
| Trades per Hour | Mean | 115 | 680 | 16.9% | 8 | 330 | 2.5% | 460 | 3,179 | 14.5% | 147 | 3,479 | 4.2% |
| | Median | 4 | 228 | 1.9% | 0.2 | 221 | 0.1% | 10 | 1,337 | 0.8% | 9 | 1,976 | 0.4% |
| Quote Updates per Hour | Mean | 114 | 2,450 | 4.7% | 13 | 1,307 | 1.0% | 256 | 20,607 | 1.2% | 250 | 28,184 | 0.9% |
| | Median | 4 | 921 | 0.4% | 2 | 907 | 0.3% | 17 | 6,811 | 0.3% | 23 | 9,622 | 0.2% |
| Shares per Trade | Mean | 1,763 | 442 | 398.9% | 388 | 539 | 72.1% | 630 | 76 | 824.5% | 114 | 80 | 141.9% |
| | Median | 799 | 338 | 236.1% | 292 | 415 | 70.3% | 214 | 67 | 318.8% | 60 | 70 | 85.0% |
| **PANEL B: Post-ES Statistics** | | | | | | | | | | | | | |
| Number of ES Events | | | | | | | | | | | | | |
| Total | | 1,142 | 1,142 | 100.0% | 1,553 | 1,553 | 100.0% | 2,203 | 2,203 | 100.0% | 2,042 | 2,042 | 100.0% |
| -- with Trades | | 875 | 1,142 | 76.6% | 788 | 1,553 | 50.7% | 1,941 | 2,203 | 88.1% | 1,937 | 2,042 | 94.9% |
| -- with Quote Updates | | 746 | 1,142 | 65.3% | 1,269 | 1,553 | 81.7% | 1,896 | 2,203 | 86.1% | 1,927 | 2,042 | 94.4% |
| Trades per Hour | Mean | 99 | 680 | 14.5% | 25 | 330 | 7.7% | 426 | 3,179 | 13.4% | 331 | 3,479 | 9.5% |
| | Median | 2 | 228 | 0.9% | 0.3 | 221 | 0.1% | 6 | 1,337 | 0.4% | 19 | 1,976 | 0.9% |
| Quote Updates per Hour | Mean | 92 | 2,450 | 3.7% | 40 | 1,307 | 3.0% | 234 | 20,607 | 1.1% | 459 | 28,184 | 1.6% |
| | Median | 1 | 921 | 0.1% | 7 | 907 | 0.7% | 10 | 6,811 | 0.1% | 48 | 9,622 | 0.5% |
| Shares per Trade | Mean | 1,148 | 442 | 259.7% | 387 | 539 | 71.8% | 366 | 76 | 479.2% | 121 | 80 | 150.8% |
| | Median | 546 | 338 | 161.5% | 288 | 415 | 69.3% | 70 | 67 | 104.8% | 61 | 70 | 86.4% |

Notes:
Source: TAQ. Odd-lot trades (< 100 shares) were not typically included in TAQ before 12/09/13 (O'Hara et al. 2014). However, this table's lack of odd-lot data for 2004 might not lead to misleading inferences because odd-lots were far less common in 2004 -- they accounted for just ~1.25% of NYSE RTH dollar volume (O'Hara et al. 2014, pg. 2203, fig. 1). Only since the growth in low latency trading and algorithmic trading (i.e., since 2004) have odd-lot trades become relatively common (odd-lots were also common prior to the 1970s).

## III.4 Variable Definitions

### *III.4.1 Measures for Price Discovery Speed*

I define an event window that begins at the time of an ES and ends at the subsequent RTH close[34]. I refer to the price adjustment over the event window as either the total price adjustment or the total return. I measure price discovery speed during the event window using several complementary approaches.

[34] Martineau (2022) finds that, for S&P 1500 stocks since 2005, post-ES price discovery is substantially complete as of the first RTH.

In my initial graphical analysis in subsection IV.1, I plot the mean cumulative return over the course of the event window and visually interpret the shape and slope of the return curves as a measure of speed.

For the remainder of my analysis, I divide the event window into two parts -- an IPA window and a STEM-PEAD window. The IPA window begins at the time of an ES and ends 15 minutes later. The STEM-PEAD window begins at the end of the IPA and ends at the next RTH close.

In my tabular analysis in subsection IV.2, I follow Jiang et al. (2012) and Barclay & Hendershott (2008, 2003) and employ Barclay & Warner (1993)'s Weighted Price Contribution (WPC) as another measure of speed.

I use WPC to measure the percentage of total price adjustment that occurs during the IPA window and during the STEM-PEAD window. By construction, the WPC values for the two windows adds up to 1. Smaller WPC-STEM-PEAD and larger WPC-IPA values indicate faster price discovery during the IPA window and vice versa.

In my regression analysis in subsection IV.3, I employ a modified version of the WPC regressions used by Jiang et al. (2012) and Jain et al. (2019). As further discussed in subsection III.4.1.3, I use the log return over the STEM-PEAD window as the dependent variables in my regressions and include the log return over the full event window, and its interactions, as a control. Increases (decrease) in STEM-PEAD returns, holding event window returns constant, are indicative of slower (faster) price discovery during the IPA window.

III.4.1.1 The Cumulative Return Measure for My Initial Graphical Analysis

$Cumulative\_Return_{i,0\ to\ t}$ is the cumulative return for event *i* from time *0* to time *t,* where time *0* is the time of event *i*'s ES announcement and time *t* denotes the number of elapsed seconds since the announcement. I calculate $Cumulative\_Return_{i,0\ to\ t}$ using equation (1), assuming a strategy of buying on a PS and shorting on an NS.

$$Cumulative\_Return_{i,0\ to\ t} = \left(\frac{Price_{i,t}}{Price_{i,0}} - 1\right) * SurpriseDirection_i \tag{1}$$

$Price_{i,0}$ and $Price_{i,t}$, are, respectively, the most recent prices for event *i*'s stock as its ES announcement, and as of time *t* (where $t=0$ is the time of the announcement). $SurpriseDirection_i$ is +1 if the event was a PS and -1 if the event was an NS. When calculating $Return_{i,0\ to\ t}$ based on mid-quote prices, I use trade prices for the price as of the time of the ES announcement ($Price_{i,0}$) and the prices as of the next RTH open ($Price_{i,Open}$) and close ($Price_{i,Close}$). I calculate two variants of the $Cumulative\_Return_{i,0\ to\ t}$ measure -- one based on trading prices and the other based on mid-quote prices.

In subsection IV.1, I plot the mean of $IPA\_Return_{i,0\ to\ t}$ for various subsamples (*e.g.*, Base Period BMO events, etc.) -- from $t=0$ to $t=Close$ -- and interpret the return curve's slope as an indicator of average adjustment speed (*i.e.*, a steeper slope indicates faster price discovery).

III.4.1.2 The Weighted Price Contribution (*WPC*) Measure

As discussed above, I use WPC to measure the percentage of total price adjustment that occurs during the IPA and STEM-PEAD partitions of the event window. Following Jiang et. al (2012), I construct WPC for a given partition using equations (2) through (6):

$$LogReturn_{p,i} = \log(Price_{i,p(end)} / Price_{i,p(start)}) \tag{2}$$

$$LogReturn_i = \log(Price_{i,Close)} / Price_{i,0}) \tag{3}$$

$$PC_{p,i} = \left(\frac{LogReturn_{p,i}}{LogReturn_i}\right) \tag{4}$$

$$Weight_i = \left(\frac{|LogReturn_i|}{\sum_{i=1}^{I} |LogReturn_i|}\right) \tag{5}$$

$$WPC_p = \sum_{i=1}^{I} [Weight_i * PC_{p,i}] = \sum_{i=1}^{I} [(\frac{|LogReturn_i|}{\sum_{i=1}^{I} |LogReturn_i|}) * (\frac{LogReturn_{p,i}}{LogReturn_i})] \qquad (6)$$

$WPC_p$ is the WPC from partition *p* (where *p* = IPA or STEM-PEAD), and represents the weighted average price contribution of all events, *i*, in the sample or subsample under evaluation -- the sample or subsample consisting of events *i* through *I*. $Price_{i,p(start)}$ and $Price_{i.p(end)}$ denote the most recent price of event *i*'s stock as of the beginning and end of partition *p*, respectively. $Price_{i,0}$ and $Price_{i,Close}$ denote the most recent price of event *i*'s stock as of the time of the ES announcement and as of the next RTH close, respectively. $LogReturn_{p,i}$ is, therefore, the log return for event *i* during partition *p* and $LogReturn_i$ is the log return for event *i* over the full event window (*i.e.*, time of the ES announcement through the next RTH close).

The ratio $LogReturn_{p,i}$ to $LogReturn_i$ is defined as the price contribution of partition *p* to event *i*'s total price change over the event window, and is denoted as $PC_{p,i}$. The ratio of (i) the absolute value of $LogReturn_i$ for event *i* to (ii) the sum of the absolute values of $LogReturn_i$ across all events *i*=1 to *I*, is defined as the weighting factor for event *i*, and is denoted as $Weight_i$.

I construct two variants of the PC and WPC measures -- one based on trade prices and another based on mid-quote prices. When calculating the PC and WPC measures based on mid-quote prices, I use trade prices for the prices as time of the ES announcement ($Price_{i,0}$) and as of the next RTH open ($Price_{i,Open}$) and close ($Price_{i,Close}$).

I denote the PC and WPC measures for the IPW and STEM-PEAD windows as $PC_{IPA}$, $PC_{STEM\text{-}PEAD}$, $WPC_{IPA}$ and $WPC_{STEM\text{-}PEAD}$, respectively.

In my tabular analysis in subsection IV.2, I report $WPC_{IPA}$ and $WPC_{STEM\text{-}PEAD}$ by subsample (*e.g.,* Base-Period BMO events, etc.).

III.4.1.3 Changes in STEM-PEAD Log Returns as Measured via Regression Analysis

I construct my third measure of price discovery speed from a regression incorporating variables that capture, for each event, *i*, the total price adjustment over the full event window, $EW\_Rtn_i$, and the portion of such adjustment that occurs during the STEM-PEAD window, $STEM\_PD\_Rtn_i$. The $STEM\_PD\_Rtn_i$ and $EW\_Rtn_i$ variables are the log returns defined in equations (2) and (3), respectively.

I use regression analysis to examine how *STEM_PD_Rtn* varies by period (Base vs. Post Li), session (AMC vs. BMO), pricing instrument (trades vs. quotes), and PEAD-linked factors (*e.g.*, liquidity, investor attention, etc.).

In the regressions, I control for *EW_Rtn.* This control is required because changes in *STEM_PD_Rtn* can reflect (i) a shift in price discovery from the STEM-PEAD window to the IPA window or vice versa, (ii) changes in the magnitude of total price adjustment over the full event window, or (iii) both. Controlling for *EW_Rtn* enables the regressions to distinguish *STEM_PD_Rtn* changes due to IPA/STEM-PEAD price discovery shifts from those due to changes in the magnitude of event window returns.

Decreases (increases) in *STEM_PD_Rtn,* holding *EW_Rtn* constant, indicate faster (slower) price discovery during the IPA window.

The regressions I use to measure price discovery speed are a modified form of the WPC regressions used in Jiang et al. (2012) (the "Jiang WPC regression"). The Jiang WPC Regressions attempted to capture changes in the proportion of price discovery during the IPA / STEM-PEAD windows by using the ratio *(STEM_PD_Rtn)* / (*EW_Rtn*) -- otherwise known as $PC_{STEM\text{-}PEAD}$ as defined in equation (4) -- as a dependent variable[35].

[35] The notation used in Jiang et al. (2012) indicates that WPC was the dependent variable; however, for an individual stock, the WPC equation (equation (6)) resolves to the PC measure (equation (4)). Based on email correspondence with Jiang et al. (2012) co-author T. Likitapiwat, I believe I am accurately interpreting the Jiang WPC Regression equations. In their study, although they did not use the IPA and STEM-PEAD labels, their IPA period was from the time of an ES

The ratio *(STEM_PD_Rtn)* / (*EW_Rtn*) captures the proportion of total price adjustment that occurs during the STEM-PEAD window, consistent with my study's requirements.

However, using ratios such as *(STEM_PD_Rtn)* / (*EW_Rtn*) as the dependent variable in a regression can be problematic -- if *EW_Rtn* for a given event *i* is close to 0, the ratio becomes quite large (*i.e.*, as the denominator approaches 0, the ratio approaches infinity), leading to extreme outliers and creating challenges for regression analysis. This problem is sometimes referred to as "the small denominator" problem.

To avoid the small denominator problem issues, I modify the Jiang WPC Regression equation. I use their regression equation (Jiang et al. 2012, pg. 1317) as the starting point:[36]

$$\frac{STEM\_PD\_Rtn_i}{EW\_Rtn_i} = \alpha + \beta' \cdot IVs'_i + \varepsilon_i \tag{7}$$

The $STEM\_PD\_Rtn_i$ and $EW\_Rtn_i$ variables are as defined above and $IVs'$ and $\beta'$ are the vectors of independent variables (*e.g.*, SUE, firm size, etc.) and corresponding coefficients, respectively. To remove the denominator from the dependent variable, I multiply both sides of equation (7) by $EW\_Rtn_{,i}$ and simplify the result as shown in equation (8):

$$(EW\_Rtn_i) \cdot \left(\frac{STEM\_PD\_Rtn_i}{EW\_Rtn_i}\right) = (\alpha + \beta' \cdot IVs'_i + \varepsilon_i) \cdot (EW\_Rtn_i) \tag{8}$$

*…which simplifies to…*

$$STEM\_PD\_Rtn_i = \alpha \cdot EW\_Rtn_i + \beta' \cdot (IVs'_i \cdot EW\_Rtn_i) + \varepsilon_i \cdot EW\_Rtn_i$$

Finally, I revise equation (8) to make it a suitable regression equation. Specifically, I add to the equation the un-interacted main effects (the $IVs'_i$), a new intercept, and an updated error term.

through the subsequent RTH open, and their STEM-PEAD period was from the RTH open to the RTH close. Although they did not specify whether they used (*STEM_PD_Rtn / EW_Rtn*) or (*IPA_Rtn /EW_Rtn*) as their DV, because the two measures sum to 1 [*i.e.*, (*STEM_PD_Rtn / EW_Rtn*) = 1 - (IPA_Rtn / *EW_Rtn*)], either measure could serve as a substitute for the other as the DV in a regression.

[36] As noted in above and in the prior footnote, for a single event *i*, the WPC measure used as the dependent variable in the Jiang WPC Regressions resolves to the ratio *STEM_PD_Rtn / EW_Rtn*.

I then relabel the coefficients for clarity and drop the term $\varepsilon_i \cdot EW\_Rtn_i$ because it will be absorbed by the updated error term.

$$STEM\_PD\_Rtn_i = \alpha + \beta_1 \cdot EW\_Rtn_i + \beta_2' \cdot IVs'_i + \beta_3' \cdot (IVs'_i \cdot EW\_Rtn_i) + \varepsilon_i \qquad (9)$$

Equation (9) preserves the core logic of the Jiang WPC Regression, while avoiding the small denominator problem. It provides a tool for estimating how the STEM-PEAD window's share of price discovery varies by period (Base vs. Post Li), session (AMC vs. BMO), pricing instrument (trades vs. quotes), and PEAD-linked factors (*e.g.*, liquidity, investor attention, etc.).

Although my approach addresses the small denominator issue, it introduces a different concern. The dependent variable $STEM\_PD\_Rtn_i$ is a component of the independent variable $EW\_Rtn_i$, since $EW\_Rtn_i = STEM\_PD\_Rtn_i + IPA\_Rtn_i$. This could lead to high correlation levels among the independent variables -- that is, multicollinearity. High multicollinearity tends to inflate standard errors (making it harder to detect statistically significant results) and reduce the stability of regression coefficients across models and samples (making them less reliable).

To assess whether multicollinearity posed serious risks to my regressions, I examined the variance inflation factors (VIFs) for the regression of *STEM_PD_Rtn* on *EW_Rtn* and indicator variable specifying whether a given ES event was during the Base or Post_Li periods (the variable *Post_Li*, as defined in subsection III.4.2) and its interaction with *EW_Rtn*. The VIF for *EW_Rtn* is 1.72 and 1.71 for *EW_Rtn* and its interaction with *Post_Li*. I also examined the VIFs for the regressions reported in Tables 9, 10, 11, 12, and 13 in subsections IV.3.1 through IV.3.3. Most VIFs were in the range of 1 to 3. The VIFs associated with the *SUE* (see definition in subsection III.4.2) and *SUE x EW_Rtn* were elevated in some of the models run on BMO samples (in the 9.5 to 10.5 range). In one model (the Trades model for Table 11) where the VIF for *EW_Rtn* was 5.31. The higher VIFs associated with *SUE* are consistent with expectations based on prior literature.

Taken as a whole, these results suggest that multicollinearity does not pose a serious risk to my regression analysis. In subsection IV.3, I present the full regression specification and report my results.

*III.4.2 Measures Hypothesized to Be Related to EMH Price Discovery Speed*

I constructed variables to indicate the period (Base or Post-Li) and trading session (AMC or BMO) during which a given ES event was announced, to indicate whether price discovery speed was measured using trading prices or mid-quote prices, and to measure other factors that I hypothesized would be related to EMH price discovery speed -- investor attention, short-sale constraints, liquidity, differences of opinion, and surprise direction and magnitude.

$Post\text{-}Li_i$ is a dummy variable that indicates the period during which event *i* occurred; it is set equal to 1 for Post-Li (2017-2021) events and equal to 0 for Base Period (2004-2012) events.

$BMO_i$ is a dummy variable that indicates the trading session during which event *i's* ES was announced; it is set equal to 1 for BMO announcements and equal to 0 for AMC announcements.

$Quote_i$ is a dummy variable that indicates whether the WPC price discovery measures for event *i* were calculated using trading prices or mid-quote prices; it is set equal to 1 if mid-quote prices were used and equal to 0 if trading prices were used.

$SUE_i$, a proxy for surprise magnitude, is the standardized unexpected earnings for event *i*'s ES. $SUE_i$ is computed by (i) calculating the difference between (x) the most recent consensus (mean) EPS estimate for event *i's* stock prior to its ES announcement and (y) the actual EPS reported in event *i*'s ES announcement, and then dividing the resulting difference by (ii) event *i*'s stock price as of the RTH close on the day prior to the ES announcement.

*$NS_i$* is dummy variable that indicates the surprise direction for event *i*; it is set equal to 0 for PSs and equal to 1 for NSs.

*$Analyst\_Coverage_i$*, a proxy for investor attention, is the number of analysts that were covering event *i*'s stock as of the ES announcement date[37].

*$Competing\_EAs_i$*, another proxy for investor attention, is the number of other S&P 1500 EAs that were announced on the same day and session (AMC or BMO) as event *i*'s announcement. Larger values for *$Competing\_EAs_i$* are taken as a measure of investor distraction, and thus decreased investor attention.

*$Short\_Ratio_i$*, a proxy for short-sale constraints, is the short-ratio for event *i*'s stock as the ES announcement date. The short-ratio is calculated as the (i) percentage of the stock that was reported to have been sold short as of the ES announcement date, divided by (ii) the number of shares that were reported to have been outstanding as the date the short interest was reported. Short interest is typically reported on a bi-monthly basis.

*$Log\_MarketCap_i$,* a proxy for liquidity, is the log of the market capitalization of event *i*'s stock as of the RTH close on the day prior to the event's ES announcement.

*$Analyst\_Dispersion_i$*, a proxy for differences of opinion, is the standard deviation of the most recent set of analysts' EPS estimates prior to event *i*'s ES announcement.

**[Section IV begins on next page]**

[37] To be more precise, *$Analysts_i$* is the number of analysts that contributed an EPS estimate to the most recent IBES consensus (mean) EPS estimate as of event *i*'s ES announcement date, based on data obtained from the NUMEST field in WRDS' IBES STATSUM datasets.

# IV RESULTS

## IV.1 Graphical Evidence on the Speed of Price Discovery in EMH

I begin my analysis by presenting a series of graphs of the mean of $CumulativeReturn_{i,0\ to\ t}$, across all events, from ES announcement time through the end of each event's AMC/BMO announcement session and including data points for the following RTH open and close.

I calculate $CumulativeReturn_{i,0\ to\ t}$ values for each event at successive one-second intervals after the time of an ES, using the most recent price as of each elapsed second[38]. I refer to the graphed results as the "price adjustment curves".

Figures 1 reports a series of four graphs, each of which provides a comparison of the Base period price adjustment curves (the blue lines) vs. the Post-Li curves (the red lines). AMC results are in Panels A (trade-price results) and B (quote-price results). BMO results are in Panels C and D.

All four panels provide graphical evidence that prices adjust more rapidly in the Post-Li period, whether measured using trade prices or quote prices. In each case, the Post-Li price adjustment curve (the red lines) approaches its RTH open/close ending price (the red squares) more quickly than the Base curve (the blue lines) approaches its ending price (the blue Xs).

I note that the mean cumulative returns as of the post-ES RTH open and close are lower in the Post-Li period (shown by the red squares) as compared to the Base period (shown by the blue Xs). This suggests the magnitude of the total post-ES price adjustment is lower in the Post-Li period -- perhaps more of the new information in an ES announcement is incorporated into prices

[38] For events announced after the start of AMC/BMO, the elapsed seconds on the right-hand side of the graphs represent times after the AMC/BMO session has ended. For example, for a BMO ES event announced at 9:00am, there are only 1,800 elapsed seconds until the 9:30am end of BMO. To avoid issues associated with right-censored data, for each event, I calculate a value of cumulative returns for each second represented on the graphs. For example, in the case of the BMO ES event announced at 9:00am, I calculate cumulative return values for elapsed seconds beyond 1,800, even though such seconds are, for that event, after the end of the BMO session; for all such observations, I set the cumulative return equal to the cumulative return as of the end of BMO. In other words, I construct the graphs of cumulative return using a balanced panel of data. If I did not use a balanced panel of data, the graphs of the cumulative mean would show a spike in cumulative returns near the end of AMC/BMO; the spike is not real; it is an artifact of "attrition bias" due to right-censored panel data.

before the ES is announced. However, that is not the focus of this study, so I leave an investigation of the difference in total post-ES price adjustment magnitude to future research.

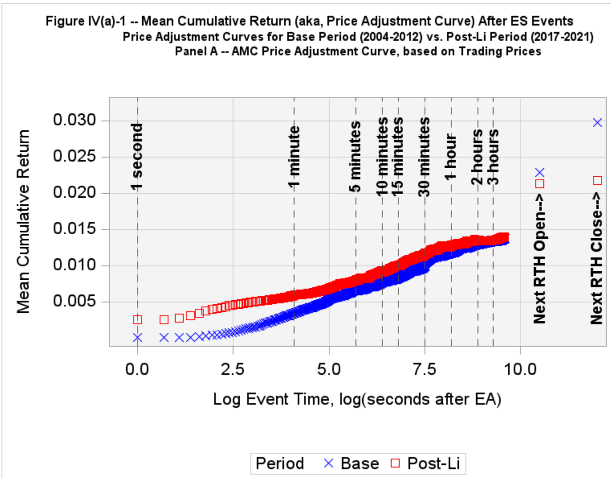
That said, I do take those differences into account in my analysis and tests. For example, when analyzing the price adjustment curves in Figure 1, I do not base my inference that price discovery speed has increased simply because the red Post-Li line is higher than the blue Base line; instead I visually examined how quickly each line approached its RTH open/close ending price, thereby using the graph to measure the total proportion of adjustment that occurred at each point along the curve. Furthermore, in my tabular analysis (subsection IV.2) and regression analysis (subsection IV.3), I measure IPA price adjustment speed by capturing the proportion of the total post-ES adjustment that occurs within each segment of the event window -- the IPA window and the STEM-PEAD window.

Focusing on the first 15 minutes of each Panel, I find the results consistent with H1a (Post-Li, a larger portion of total adjustment occurs in the IPA window) and H2 (the proportion of total adjustment that occurs in the IPA window differs for AMC vs. BMO).

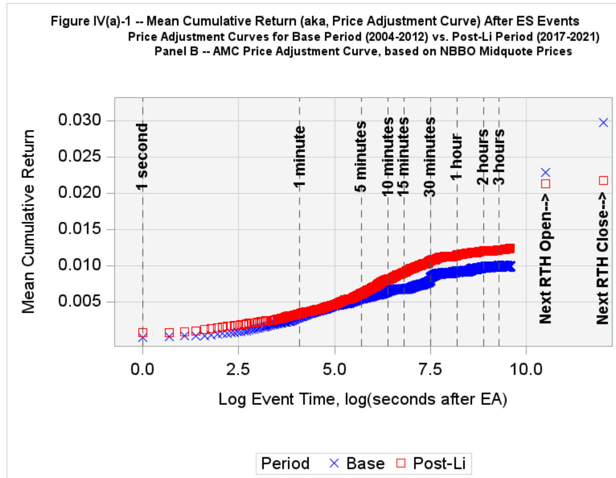
**[Turn to next page for Figure 1]**

## Figure 1 Mean Cumulative Return (aka, Price Adjustment Curve) after ES Events: <u>Price Adjustment Curves for Base Period (2004-2012) vs. Post-Li Period (2017-2021)</u>

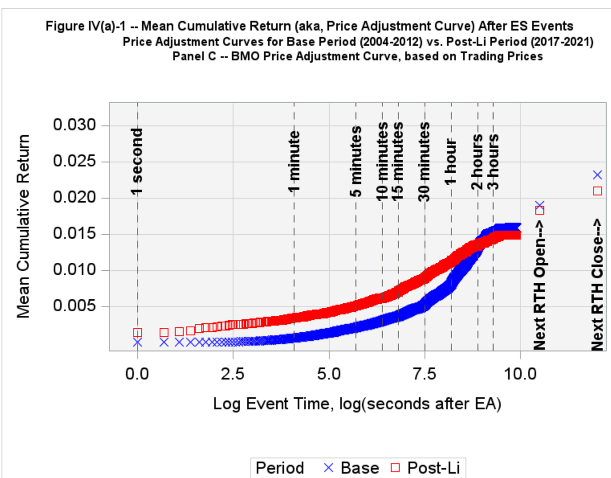
### Panel A
### AMC Session, Based on Trading Prices



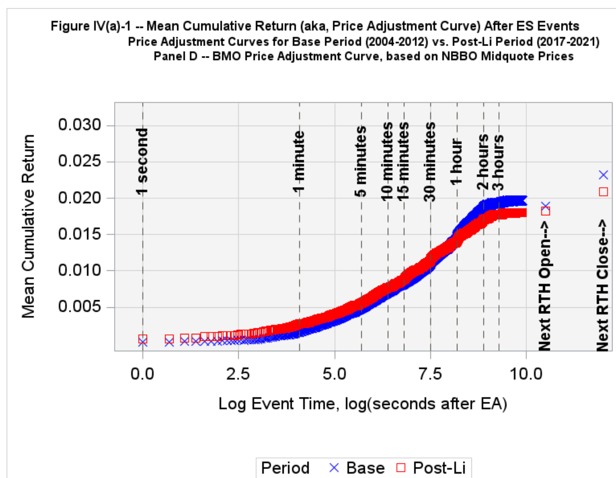

### Panel B
### AMC Session, Based on Midquote Prices




### Panel C
### BMO Session, Based on Trading Prices




### Panel D
### BMO Session, Based on Midquote Prices




The x-axis depicts the number of elapsed seconds after an ES announcement and is displayed in log(seconds). The y-axis depicts the mean cumulative return across all ES events in the plotted subsample (*e.g.*, Base Period AMC ESs; Post-Li Period AMC ESs, etc.). Cumulative returns are calculated using the following equation, which assumes a strategy of buying a PS and shorting an NS: $CumulativeReturn_{i,0\ to\ t} = ((Price_{i,t} / Price_{i,0}) - 1) * SurpriseDirection_i$. $CumulativeReturn_{i,0\ to\ t}$ denotes the cumulative return for event *i* from the time of the event's ES announcement through time *t* seconds after the announcement. $Price_{i,t}$ is the most recent price for event *i*'s stock as of time *t* seconds after the event's ES announcement. To ensure a balanced panel and avoid right-censoring bias, when *t* elapsed seconds for event *i* is after the end of the AMC/BMO during which the event's ES was announced, an observation for $Price_{i,t}$ is recorded using the event's stock price as of the end of the AMC/BMO announcement session. $SurpriseDirection_i$ is +1 if the event was a PS and -1 if the event was an NS. When calculating $Return_{i,0\ to\ t}$ using NBBO mid-quote prices, trading prices are used for the price as of the ES announcement ($Price_{i,0}$) and the prices as of the next RTH open ($Price_{i,RTH\ Open}$) and close ($Price_{i,\ RTH\ Close}$).

Figure 2's four graphs provide a comparison of AMC (blue lines) vs. BMO (red lines) price adjustment curves. Base period results are in Panels A (trade-price results) and B (quote-price results), and Post-Li results are in Panels C and D.

All four panels provide graphical evidence that post-ES price discovery speed differs between AMC and BMO, whether measured using trade prices or quote prices. Focusing on the first 15 minutes of each Panel, I find the results consistent with H2 (the proportion of total adjustment that occurs in the IPA window differs between for AMC vs. BMO).

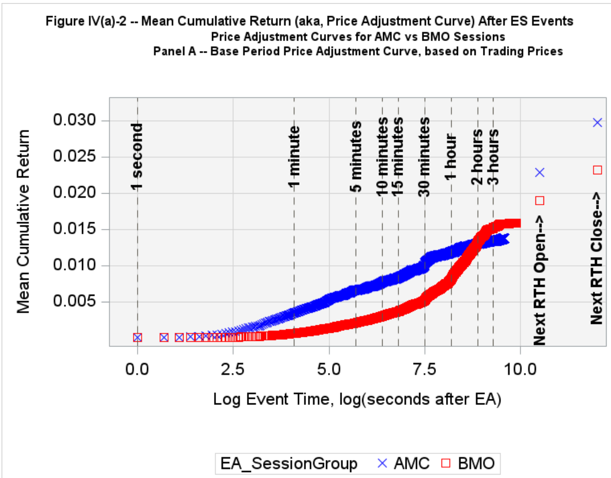
It is interesting that for the Base period (Panels A and B), the total price adjustment as of the next RTH close was larger for AMC announcements (blue Xs) than BMO announcements (red squares), but for the Post-Li period (Panels C and D) the difference had nearly disappeared. This is consistent with Martineau (2022)'s finding that in recent years the post-ES price discovery process is substantially complete as of the first RTH close after an ES.

The price adjustment curves in Panels C and D suggest that, Post-Li, the speed of post-ES price discovery is faster during BMO as compared to AMC (the BMO price adjustment curves converge more quickly to the ending RTH closing price), especially quote-based prices.

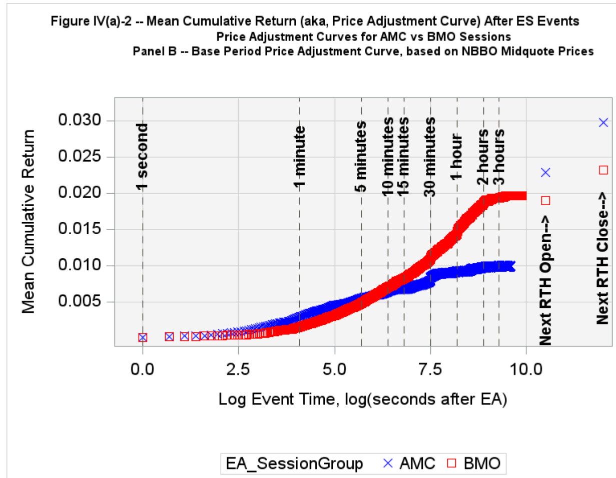
**[Turn to next page for Figure 2]**

## Figure 2 Mean Cumulative Return (aka, Price Adjustment Curve) after ES Events: Price Adjustment Curves for AMC vs BMO Sessions

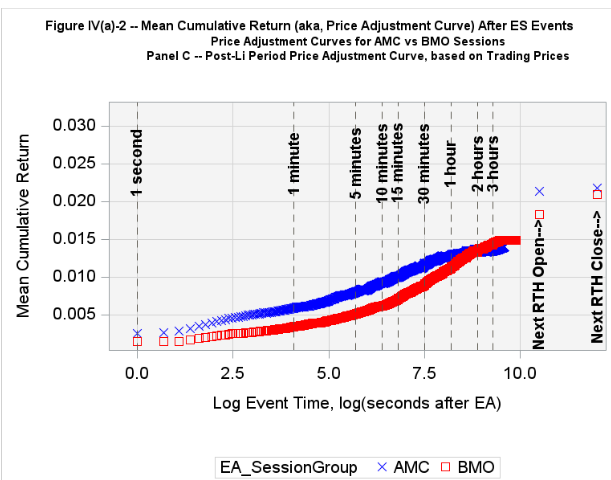
### Panel A
### Base Period, Based on Trading Prices



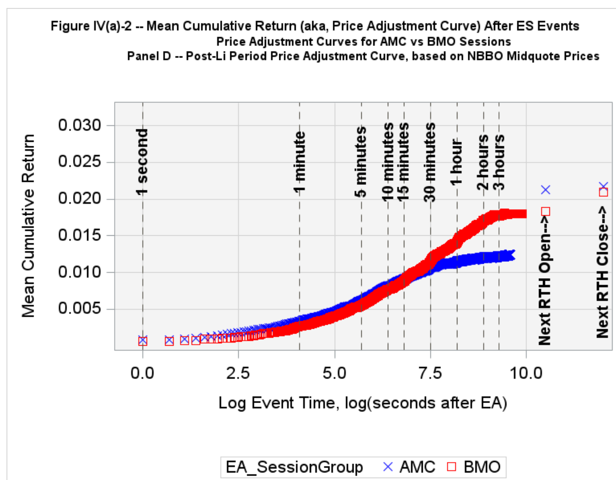

### Panel B
### Base Period, Based on Midquote Prices




### Panel C
### Post-Li Period, Based on Trading Prices




### Panel D
### Post-Li Period, Based on Midquote Prices




The x-axis depicts the number of elapsed seconds after an ES announcement and is displayed in log(seconds). The y-axis depicts the mean cumulative return across all ES events in the plotted subsample (*e.g.*, Base Period AMC ESs; Post-Li Period AMC ESs, etc.). Cumulative returns are calculated using the following equation, which assumes a strategy of buying a PS and shorting an NS: $CumulativeReturn_{i,0\ to\ t} = ((Price_{i,t} / Price_{i,0}) - 1) * SurpriseDirection_i$. $CumulativeReturn_{i,0\ to\ t}$ denotes the cumulative return for event *i* from the time of the event's ES announcement through time *t* seconds after the announcement. $Price_{i,t}$ is the most recent price for event *i*'s stock as of time *t* seconds after the event's ES announcement. To ensure a balanced panel and avoid right-censoring bias, when *t* elapsed seconds for event *i* is after the end of the AMC/BMO during which the event's ES was announced, an observation for $Price_{i,t}$ is recorded using the event's stock price as of the end of the AMC/BMO announcement session. $SurpriseDirection_i$ is +1 if the event was a PS and -1 if the event was an NS. When calculating $Return_{i,0\ to\ t}$ using NBBO mid-quote prices, trading prices are used for the price as of the ES announcement ($Price_{i,0}$) and the prices as of the next RTH open ($Price_{i,RTH\ Open}$) and close ($Price_{i,\ RTH\ Close}$).

In Figures 3 and 4, I report supplementary analysis, not to test my hypotheses, but to assess whether my results are consistent with Gregoire & Martineau (2022)'s finding that, over an 59 minute event window that starts one minute after an ES event, EMH mid-quote prices adjust more quickly than EMH trade prices after an ES.

The graphs in Figures 3 and 4 provide a comparison of trade (blue Xs) vs. quote (red squares) price adjustment curves. Figure 3 provides AMC results in Panels A (Base period) and B (Post-Li); BMO results are in Panels C and D. Figure 4 shows the results for EMH as a whole -- providing a consolidated view of AMC and BMO, which is how Gregoire & Martineau (2022) examined EMH sessions -- with Base period results in Panel A and Post-Li results in Panel B.

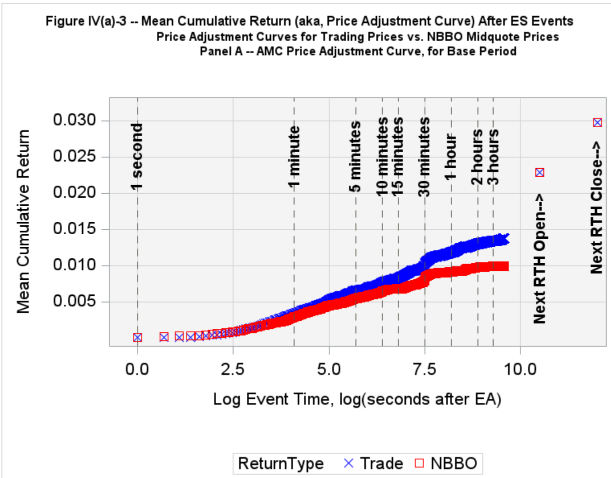
Panels C and D of Figure 3 provide evidence that BMO mid-quote prices adjust more quickly after an ES than do BMO trade prices, consistent Gregoire & Martineau (2022)'s findings. However, Panels A and B of Figure 3 provide evidence of the opposite behavior during AMC, evidence that AMC mid-quote prices adjust more slowly after an ES than do BMO prices (especially during the Base period), which at first read appears contrary to Gregoire & Martineau (2022)'s findings.

However, as can be seen in Figure 4, my results for the EMH session as a whole are consistent with Gregoire & Martineau (2022).

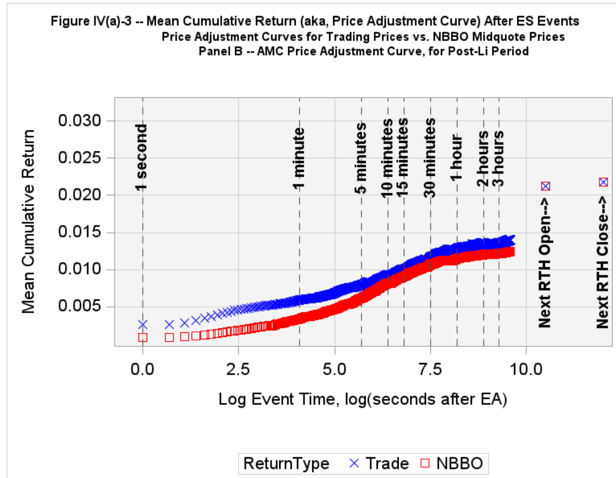
**[Turn to next page Figure 3]**

## Figure 3 Mean Cumulative Return (aka, Price Adjustment Curve) after ES Events: Price Adjustment Curves Trading Prices vs. NBBO Midquote Prices

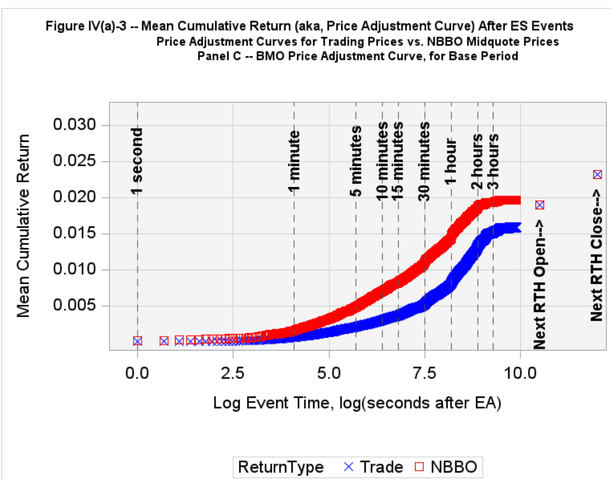
### Panel A
### AMC Session, Base Period



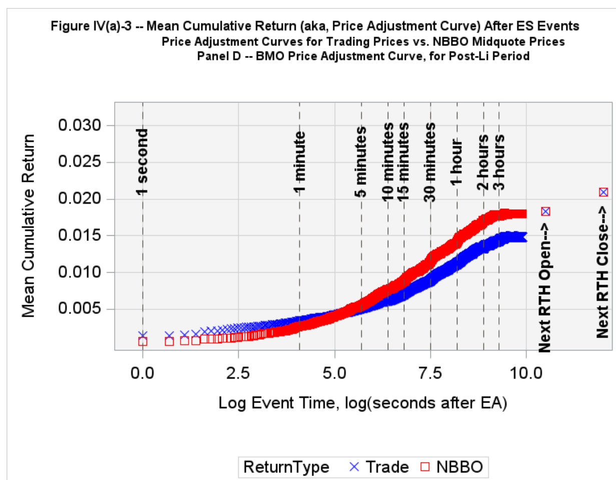

### Panel B
### AMC Session, Post-Li Period




### Panel C
### BMO Session, Base Period



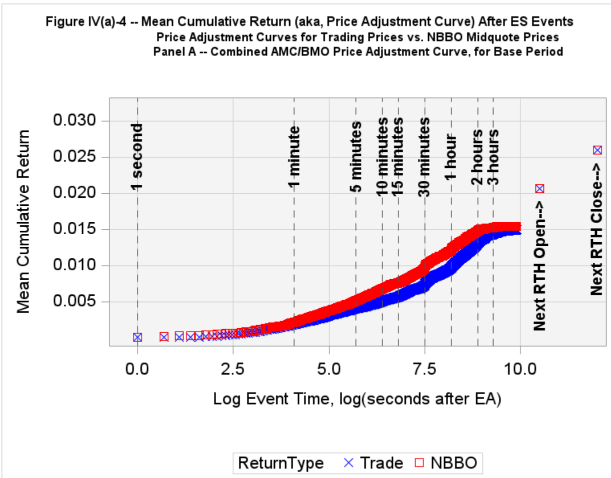

### Panel D
### BMO Session, Post-Li Period



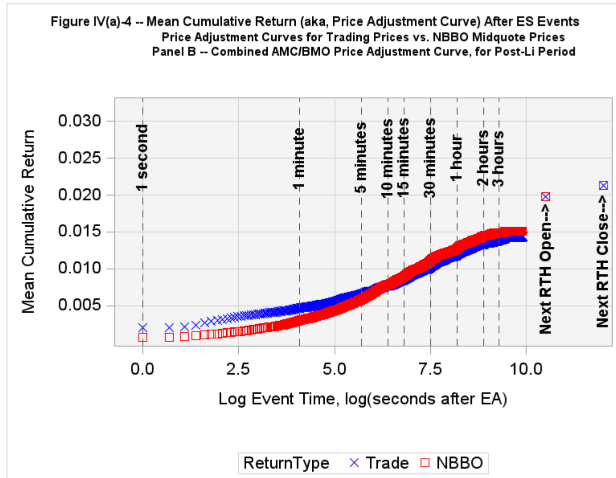

The x-axis depicts the number of elapsed seconds after an ES announcement and is displayed in log(seconds). The y-axis depicts the mean cumulative return across all ES events in the plotted subsample (*e.g.*, Base Period AMC ESs; Post-Li Period AMC ESs, etc.). Cumulative returns are calculated using the following equation, which assumes a strategy of buying a PS and shorting an NS: $CumulativeReturn_{i,0\ to\ t} = ((Price_{i,t} / Price_{i,0}) - 1) * SurpriseDirection_i$. $CumulativeReturn_{i,0\ to\ t}$ denotes the cumulative return for event *i* from the time of the event's ES announcement through time *t* seconds after the announcement. $Price_{i,t}$ is the most recent price for event *i*'s stock as of time *t* seconds after the event's ES announcement. To ensure a balanced panel and avoid right-censoring bias, when *t* elapsed seconds for event *i* is after the end of the AMC/BMO during which the event's ES was announced, an observation for $Price_{i,t}$ is recorded using the event's stock price as of the end of the AMC/BMO announcement session. $SurpriseDirection_i$ is +1 if the event was a PS and -1 if the event was an NS. When calculating $Return_{i,0\ to\ t}$ using NBBO mid-quote prices, trading prices are used for the price as of the ES announcement ($Price_{i,0}$) and the prices as of the next RTH open ($Price_{i,RTH\ Open}$) and close ($Price_{i,\ RTH\ Close}$).

# Figure 4 Mean Cumulative Return (aka, Price Adjustment Curve) after ES Events: Price Adjustment Curves Trading Prices vs. NBBO Midquote Prices -- Combined EMH Session (includes AMC and BMO events)

**Panel A**
**Base Period**




**Panel B**
**Post-Li Period**




The x-axis depicts the number of elapsed seconds after an ES announcement and is displayed in log(seconds). The y-axis depicts the mean cumulative return across all ES events in the plotted subsample (*e.g.*, Base Period AMC ESs; Post-Li Period AMC ESs, etc.). Cumulative returns are calculated using the following equation, which assumes a strategy of buying a PS and shorting an NS: $CumulativeReturn_{i,0\ to\ t} = ((Price_{i,t} / Price_{i,0}) - 1) * SurpriseDirection_i$. $CumulativeReturn_{i,0\ to\ t}$ denotes the cumulative return for event *i* from the time of the event's ES announcement through time *t* seconds after the announcement. $Price_{i,t}$ is the most recent price for event *i*'s stock as of time *t* seconds after the event's ES announcement. To ensure a balanced panel and avoid right-censoring bias, when *t* elapsed seconds for event *i* is after the end of the AMC/BMO during which the event's ES was announced, an observation for $Price_{i,t}$ is recorded using the event's stock price as of the end of the AMC/BMO announcement session. $SurpriseDirection_i$ is +1 if the event was a PS and -1 if the event was an NS. When calculating $Return_{i,0\ to\ t}$ using NBBO mid-quote prices, trading prices are used for the price as of the ES announcement ($Price_{i,0}$) and the prices as of the next RTH open ($Price_{i,RTH\ Open}$) and close ($Price_{i,\ RTH\ Close}$).

**[Turn to next page for Subsection IV.2]**

### IV.2 Tabular Evidence on the Speed of Price Discovery in EMH

Table 8 presents the WPC measure for IPA and STEM-PEAD windows of different lengths. In all cases, the IPA windows start at the time of an ES. Different rows in the table provide the WPC results for IPA windows that end 1, 5, 10, 15, 30, or 60 minutes after an ES announcement, or at the end of AMC/BMO. In all cases, the STEM-PEAD windows start at the end of the IPA window and end at the next RTH close.

The table provides the WPC results for the IPA window (*WPC_IPA*) and STEM_PEAD window (*WPC_STEM_PEAD*) for each of my four subsamples (*e.g.*, Base period AMC events, etc.). Column headings indicate whether WPC was calculated using trade prices or quote prices.

The layout of Panel A facilitates a comparison of the WPC measures for the Post-Li vs. Base periods, and the layout of Panel B facilitates a comparison of AMC vs. BMO.

Examining Panel A, the results are consistent with H1a (Post-Li, a larger portion of total adjustment occurs in the IPA window). The *WPC_IPA* values, whether based on trade-prices or quote-prices, are larger in the Post-Li period than Base period for both AMC and BMO. This is the case not only for the 15-minute IPA window specific to my hypotheses, but also for all other IPA window lengths reported in Table 8.

The results for AMC tend to contradict H1b (the H1a effect will be smaller when price adjustment is measured via quotes vs. trades), whereas the results for BMO tend to support it. For AMC events -- for each IPA window length, except for the window that ends 1 minute after an ES -- the Post-Li vs. Base period percentage increase in *WPC_IPA* (shown in columns 5 and 8) is larger when *WPC_IPA* is measured via quote prices, the opposite of what H1b predicts. For BMO events, and for each IPA window length, the Post-Li vs. Base increase in *WPC_IPA* is smaller when measured using quote prices, consistent with H1b's prediction.

One possible explanation could be the degree to which Reg NMS rules are honored differs between AMC and BMO. Reg NMS rules impose a legal requirement that, during RTH, trades must occur (unless certain exceptions apply) at NBBO quote prices. The legal requirement does not apply during AMC and BMO, even though market participants may choose to honor the requirement to execute trades at NBBO prices. There may be structure differences in the degree to which market participants honor those requirements during AMC vs. BMO. These differences could be why -- contrary to what one would expect based on Gregoire & Martinea (2022), as discussed in subsection IV.1 -- AMC trade prices tend to adjust more quickly than AMC mid-quote prices after an ES event. Changes in the degree to which the Reg NMS rules are honored in practice during AMC vs. BMO could be evolving over time, and if so, that might explain why the Post-Li increase in AMC *WPC_IPA* is larger when WPC is measured using quote prices, contrary to H1b's prediction. This is an interesting avenue to explore for future research but is beyond the scope of my current study.

Turning to Panel B, the results are consistent with H2 (the proportion of total adjustment that occurs in the IPA window differs for AMC vs. BMO). I highlight two interesting observations from the results. First, the absolute differences between AMC and BMO WPC_IPA are smaller when WPC is measured using quote prices, and larger when measured using trade prices, except when the IPA window is defined to end at the conclusion of AMC/BMO. Second, the results suggest that post-ES price discovery is faster during AMC vs. BMO during the first hour after an ES announcement. However, BMO catches up as the end it nears the end of the session, which is not surprising as one would expect prices to adjust more rapidly near the RTH open.

Finally, not to test my hypotheses, but to assess whether my results are consistent with Jiang et al.'s (2012) reported figures for *WPC_IPA*, I report the following. In their study, their sample was comprised of S&P 500 EAs during 2004-2008. They obtained the following *WPC_IPA* values, when measuring *WPC_IPA* from the time of an EA through the end of the AMC/BMO announcement session. Their *WPC_IPA* for that IPA window was 0.42 for AMC and 0.36 for BMO. In untabulated results, the results from an analogous subsample of my sample (*i.e.*, S&P 500 ESs during 2004-2008), my WPC_IPA measures are 0.40 for AMC and 0.38 for BMO. I believe the differences between my results and theirs can be attributed to the fact that they included all EA events in their sample, whereas my sample included only those EAs that were earnings surprises (*i.e.*, ESs). Also, their sample included only the 4:00pm to 6:30pm portion of the AMC session and the 7:00am to 9:30 portion of the BMO session, whereas my sample included the full sessions.

**[Turn to next page for Table 8]**

## Table 8 Mean WPC during IPA and STEM-PEAD Windows

### Base vs. Post-Li Periods / AMC vs. BMO Sessions / Trade Prices vs. Mid-Quote Prices

**PANEL A: Base vs. Post-Li Measures for AMC and BMO**

| *( t minutes after ES* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | WPC -- IPA Window | | | | | | WPC -- STEM-PEAD Window | | | |
| End of IPA WIndow | No. of Events | | Trade Prices | | | Mid-Quotes | | | Trade Prices | | Mid-Quotes | |
| | Base Period | Post-Li Period | Base | Post-Li | *Delta* | Base | Post-Li | *Delta* | Base | Post-Li | Base | Post-Li |
| **AMC ES Events** | | | | | | | | | | | | |
| 1 | 11,614 | 9,569 | 0.059 | 0.086 | *46%* | 0.056 | 0.067 | *19%* | 0.941 | 0.914 | 0.944 | 0.933 |
| 5 | 11,606 | 9,569 | 0.127 | 0.145 | *15%* | 0.111 | 0.132 | *20%* | 0.873 | 0.855 | 0.889 | 0.868 |
| 10 | 11,582 | 9,567 | 0.157 | 0.192 | *22%* | 0.129 | 0.181 | *40%* | 0.843 | 0.808 | 0.871 | 0.819 |
| **15** | **11,562** | **9,563** | **0.179** | **0.211** | ***18%*** | **0.141** | **0.200** | ***42%*** | **0.821** | **0.789** | **0.859** | **0.800** |
| 30 | 11,487 | 9,547 | 0.223 | 0.253 | *13%* | 0.179 | 0.240 | *34%* | 0.777 | 0.747 | 0.821 | 0.760 |
| 60 | 11,281 | 9,505 | 0.272 | 0.290 | *7%* | 0.211 | 0.270 | *28%* | 0.728 | 0.710 | 0.789 | 0.730 |
| AMC End | 11,643 | 9,570 | 0.311 | 0.328 | *6%* | 0.231 | 0.300 | *30%* | 0.689 | 0.672 | 0.769 | 0.700 |
| **BMO ES Events** | | | | | | | | | | | | |
| 1 | 15,138 | 8,961 | 0.011 | 0.053 | *387%* | 0.030 | 0.057 | *90%* | 0.989 | 0.947 | 0.970 | 0.943 |
| 5 | 15,097 | 8,951 | 0.036 | 0.088 | *143%* | 0.088 | 0.110 | *25%* | 0.964 | 0.912 | 0.912 | 0.890 |
| 10 | 15,050 | 8,940 | 0.055 | 0.114 | *108%* | 0.125 | 0.153 | *22%* | 0.945 | 0.886 | 0.875 | 0.847 |
| **15** | **14,958** | **8,916** | **0.070** | **0.132** | ***89%*** | **0.148** | **0.178** | ***20%*** | **0.930** | **0.868** | **0.852** | **0.822** |
| 30 | 14,433 | 8,750 | 0.103 | 0.177 | *72%* | 0.212 | 0.231 | *9%* | 0.897 | 0.823 | 0.788 | 0.769 |
| 60 | 12,846 | 8,295 | 0.160 | 0.234 | *46%* | 0.286 | 0.303 | *6%* | 0.840 | 0.766 | 0.714 | 0.697 |
| BMO End | 15,143 | 8,962 | 0.382 | 0.431 | *13%* | 0.477 | 0.500 | *5%* | 0.618 | 0.569 | 0.523 | 0.500 |

**PANEL B: AMC vs. BMO Measures for Base and Post-Li Periods**

| *( t minutes after ES* | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | WPC -- IPA Window | | | | | | WPC -- STEM-PEAD Window | | | |
| End of IPA WIndow | No. of Events | | Trade Prices | | | Mid-Quotes | | | Trade Prices | | Mid-Quotes | |
| | AMC | BMO | AMC | BMO | *Delta* | AMC | BMO | *Delta* | AMC | BMO | AMC | BMO |
| **Base Period** | | | | | | | | | | | | |
| 1 | 11,614 | 15,138 | 0.059 | 0.011 | *-82%* | 0.056 | 0.030 | *-46%* | 0.941 | 0.989 | 0.944 | 0.970 |
| 5 | 11,606 | 15,097 | 0.127 | 0.036 | *-71%* | 0.111 | 0.088 | *-20%* | 0.873 | 0.964 | 0.889 | 0.912 |
| 10 | 11,582 | 15,050 | 0.157 | 0.055 | *-65%* | 0.129 | 0.125 | *-4%* | 0.843 | 0.945 | 0.871 | 0.875 |
| **15** | **11,562** | **14,958** | **0.179** | **0.070** | ***-61%*** | **0.141** | **0.148** | ***5%*** | **0.821** | **0.930** | **0.859** | **0.852** |
| 30 | 11,487 | 14,433 | 0.223 | 0.103 | *-54%* | 0.179 | 0.212 | *19%* | 0.777 | 0.897 | 0.821 | 0.788 |
| 60 | 11,281 | 12,846 | 0.272 | 0.160 | *-41%* | 0.211 | 0.286 | *36%* | 0.728 | 0.840 | 0.789 | 0.714 |
| EMH End | 11,643 | 15,143 | 0.311 | 0.382 | *23%* | 0.231 | 0.477 | *106%* | 0.689 | 0.618 | 0.769 | 0.523 |
| **Post-Li Period** | | | | | | | | | | | | |
| 1 | 9,569 | 8,961 | 0.086 | 0.053 | *-39%* | 0.067 | 0.057 | *-15%* | 0.914 | 0.947 | 0.933 | 0.943 |
| 5 | 9,569 | 8,951 | 0.145 | 0.088 | *-40%* | 0.132 | 0.110 | *-17%* | 0.855 | 0.912 | 0.868 | 0.890 |
| 10 | 9,567 | 8,940 | 0.192 | 0.114 | *-41%* | 0.181 | 0.153 | *-15%* | 0.808 | 0.886 | 0.819 | 0.847 |
| **15** | **9,563** | **8,916** | **0.211** | **0.132** | ***-37%*** | **0.200** | **0.178** | ***-11%*** | **0.789** | **0.868** | **0.800** | **0.822** |
| 30 | 9,547 | 8,750 | 0.253 | 0.177 | *-30%* | 0.240 | 0.231 | *-4%* | 0.747 | 0.823 | 0.760 | 0.769 |
| 60 | 9,505 | 8,295 | 0.290 | 0.234 | *-19%* | 0.270 | 0.303 | *12%* | 0.710 | 0.766 | 0.730 | 0.697 |
| EMH End | 9,570 | 8,962 | 0.328 | 0.431 | *31%* | 0.300 | 0.500 | *67%* | 0.672 | 0.569 | 0.700 | 0.500 |

**[Table 8 continues on next page]**

This table reports the WPC values for the IPA and STEM-PEAD windows (*WPC_IPA* and *WPC_STEM_PEAD*, respectively), by subsample (Base-Period AMC events, Post-Li Period AMC events, Base-Period BMO events, Post-Li Period BMO events), for IPA window ending (STEM-PEAD windows starting) from 1 minute after an ES to 60 minutes after an ES. All IPA windows start at the time of an ES announcement. All STEM-PEAD windows start at the end of the IPA window and end at the close of the first RTH after the ES announcement. Column labels indicate whether a given WPC measure was calculated based on trade prices or mid-quote prices.

The WPC for a given partition *p* (IPA or STEM-PEAD) is calculated using the formulas below, in accordance with Barclay & Hendershott (2008) and Jiang et al. (2012):

$$LogReturn_{p,i} = \log(Price_{i,p(end)} / Price_{i,p(start)}) \qquad LogReturn_i = \log(Price_{i,Close} / Price_{i,0}) \qquad PC_{p,i} = \left(\frac{LogReturn_{p,i}}{LogReturn_i}\right) \qquad Weight_i = \left(\frac{|LogReturn_i|}{\sum_{i=1}^{I} |LogReturn_i|}\right)$$

$$WPC_p = \sum_{i=1}^{I} [Weight_i * PC_{p,i}]$$

The number of events (N) in each sub-sample are indicated in columns (1) and (2). The number of events in a given sub-sample declines as the time after an ES event increases for the following reason. For a given ES event, when the number of minutes after the event's announcement occurs after the end of the AMC/BMO session during which the announcement was made, that event is dropped from the sample. For example, an BMO ES event announced at 9:15am would be dropped from samples where the IPA window ends (the STEM-PEAD window starts) at a time greater than or equal to 15 minutes after the ES announcement, as such times would be on or after the 9:30am end of BMO for that event. As such, that event would no longer be subject to any further price movements during BMO and including it in WPC calculations for subsamples for which it could not make price contributions would bias downwards those subsamples WPC estimates.

**[Turn to next page for Subsection IV.3]**

**IV.3 Regression Evidence on the Speed of Price Discovery in EMH**

To test my hypotheses, I regress *STEM_PD_Rtn* on variables indicating each ES event's period (Base or Post-Li) and session (AMC or BMO), the pricing instrument used to calculate returns (trades vs. quotes), proxies for PEAD-linked factors (*e.g.*, liquidity, investor attention, etc.), and *EW_Rtn* (included as a control).

As discussed in subsection III.3.1.3, my regression models are modified versions of the WPC regressions used by Jiang et al. (2012). All models start with the specification shown in equation (10), which is used to test H3 (PEAD-linked factors influence post-ES price discovery speed in EMH). To test other hypotheses, I add additional terms to the model, as detailed in the relevant subsections below.

$$STEM\_PD\_Rtn_i = \alpha + \beta_1 \cdot EW\_Rtn_i + \beta'_2 \cdot (PEAD\_Factors_i) + \beta'_3 \cdot (PEAD\_Factors_i \cdot EW\_Rtn_i) + \alpha_{Firm} + \varepsilon_i \quad (10)$$

$STEM\_PD\_Rtn_i$ and $EW\_Rtn_i$ are as defined in subsection III.4.1.3. $PEAD\_Factors_i$ denotes a vector of variables used as proxies for the factors hypothesized to influence the post-ES speed of price discovery in EMH. This vector includes $NS_i$, $SUE_i$,, $Analyst\_Coverage_i$, $Competing\_EAs_i$, $Short\_Ratio_i$, $Log\_MarketCap_i$, and $Analyst\_Dispersion_i$, each of which is defined in subsection III.4.2. All *PEAD_Factors* variables are standardized to have a mean of 0 and a standard deviation of 1, except for the binary indicator variable $NS_i$. All regressions include firm fixed effects and use standard errors clustered by firm and date.

In the subsections below, I identify the specific regression terms -- referred to as "hypothesis testing terms" -- used to test each hypothesis. The sign of a statistically significant coefficient on a hypotheses testing term is interpreted as follows. A decrease (increase) in *STEM_PD_Rtn* (controlling for *EW_Rtn*) indicates faster (slower) price discovery.

Negative coefficients indicate that the term is associated with a shift in the timing of price adjustment, with the STEM-PEAD window accounting for a smaller share of the total post-ES adjustment and the IPA window accounting for a larger share -- suggesting faster price discovery. Positive coefficients, therefore, are interpreted as faster price discovery.

I first report the regression results testing the influence of PEAD-linked factors on post-ES price discovery speed in EMH (H3). I begin with that analysis because I include the PEAD-linked factors as controls in subsequent regressions testing for speed differences between the Base and Post-Li periods (H1a and H1b) and between AMC and BMO (H2).

*IV.3.1 The Influence of PEAD-linked Factors*

To test the influence of PEAD-linked on the post-ES speed of price discovery in EMH (H3), I estimate the regression model specified in equation (10) and examine the vector of coefficients ($\beta'_3$) on the interaction terms $PEAD\_Factors_i \cdot EW\_Rtn_i$. Table 9 reports the regression results for each of the four primary subsamples. Each primary subsample is further divided into trades and quotes subsamples, yielding a total of eight subsamples analyzed.

The coefficients on *Log_MarketCap x EW_Rtn* are negative and statistically significant at the 1% level across all subsamples, except for Post-Li BMO events, where they are significant at the 5% level, and for Base Period AMC quotes, where they are statistically significantly *positive* at the 1% level. The negative coefficients are consistent with H3's prediction of a positive relationship between liquidity (proxied by stock size) and the price discovery speed.

However, the positive coefficient for Base Period AMC quotes is unexpected; it suggests that greater liquidity was associated with slower quote-based price discovery during Base Period AMC sessions. One possible explanation is that, during Base Period AMC sessions, price

# Table 9 Regression Results on Post-ES Price Discovery Speed in EMH: The Influence of PEAD-Linked Factors

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Trade Prices | | | | Quote Prices | | | |
| | Base Period | | Post-Li Period | | Base Period | | Post-Li Period | |
| | AMC | BMO | AMC | BMO | AMC | BMO | AMC | BMO |
| **PEAD_Factors x EW_Rtn** | | | | | | | | |
| *SUE* | 0.012 | -0.010 | 0.018 | 0.106*** | 0.007 | -0.011 | 0.026 | 0.085*** |
| | (0.019) | (0.009) | (0.020) | (0.030) | (0.017) | (0.009) | (0.019) | (0.027) |
| *NS* | 0.040** | -0.007 | 0.017 | -0.047** | 0.063*** | 0.016 | 0.022 | -0.041* |
| | (0.019) | (0.012) | (0.025) | (0.022) | (0.018) | (0.014) | (0.023) | (0.022) |
| *Analyst_Coverage* | -0.043*** | -0.024** | -0.009 | -0.064*** | -0.048*** | -0.017* | 0.027 | -0.058*** |
| | (0.010) | (0.010) | (0.020) | (0.014) | (0.011) | (0.010) | (0.020) | (0.014) |
| *Competing_EAs* | 0.045*** | 0.025*** | 0.043*** | 0.052*** | 0.012 | 0.035*** | 0.028*** | 0.060*** |
| | (0.009) | (0.005) | (0.008) | (0.012) | (0.010) | (0.006) | (0.008) | (0.012) |
| *Short_Ratio* | -0.017** | -0.010** | -0.047*** | -0.030*** | -0.016** | -0.007 | -0.033*** | -0.028*** |
| | (0.008) | (0.005) | (0.010) | (0.009) | (0.008) | (0.005) | (0.012) | (0.009) |
| *Log_MarketCap* | -0.035*** | -0.022*** | -0.075*** | -0.030** | 0.039*** | -0.040*** | -0.081*** | -0.036*** |
| | (0.012) | (0.008) | (0.020) | (0.013) | (0.013) | (0.009) | (0.020) | (0.013) |
| *Analyst_Dispersion* | 0.029* | 0.001 | 0.027** | 0.009 | 0.052*** | 0.004 | 0.015 | 0.011 |
| | (0.015) | (0.005) | (0.013) | (0.009) | (0.013) | (0.005) | (0.013) | (0.009) |
| **EW_Rtn and Intercept** | | | | | | | | |
| *EW_Rtn* | 0.799*** | 0.932*** | 0.761*** | 0.903*** | 0.876*** | 0.865*** | 0.777*** | 0.867*** |
| | (0.012) | (0.006) | (0.016) | (0.009) | (0.011) | (0.007) | (0.016) | (0.010) |
| Intercept | -0.002** | -0.002*** | -0.005*** | -0.005*** | -0.001 | -0.005*** | -0.004*** | -0.008*** |
| | (0.001) | (0.000) | (0.001) | (0.001) | (0.001) | (0.000) | (0.001) | (0.001) |
| *N* | 10,994 | 14,286 | 9,165 | 8,606 | 10,994 | 14,286 | 9,165 | 8,606 |
| *Adj.* $R^2$ | 0.829 | 0.929 | 0.800 | 0.881 | 0.859 | 0.835 | 0.789 | 0.815 |

This table reports results from the regression model shown in Equation (10). *STEM_PD_Rtn* is calculated based on trade prices in the subsample results reported in columns (1) through (4), and on quote prices in the subsamples results reported in columns (5) through (8).

To reduce complexity, only the interaction terms relevant to hypotheses H3 are reported, along with *EW_Rtn* and the Intercept. All independent variables are standardized to have a mean of 0 and a standard deviation of 1, excluding *EW_Rtn* and the binary indicator variables. All models include firm fixed effects and standard errors clustered by firm and date. Standard errors are reported in parentheses beneath coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Note: the number of observations, N, included in the regression results differs from the total number of ES events each subsample for the following reasons. First, ES events for BMO announcements on or after 9:15am and ES events for AMC announcements on or after 7:45pm (4:45pm on days the market was open a half-day) are dropped from the analysis because the end of their 15-minute IPA window occurs after the conclusion of the BMO/AMC announcement session. After dropping those events, there were 11,552 events in the Base Period AMC subsample, 14,958 in the Base Period BMO subsample, 9,563 in the Post-Li AMC subsample, and 8,916 in the Post-Li BMO subsample. The remaining differences between those figures and *N* reflects other observations which were dropped (*e.g.*, observations where the fixed effects group contained only a single observation and/or observations with missing PEAD-linked Factor variables).

**[Subsection IV(c).1 continues on the next page]**

discovery may have occurred primarily through trades, rather than quotes -- especially for larger, more liquid stocks.

The coefficients on *Competing_EAs x EW_Rtn* are positive and statistically significant at the 1% level across all subsamples, except for Base Period AMC, where they are positive but not statistically significant  Because *Competing_EAs* proxies for investor inattention -- lower values indicate greater attention -- the sign of the coefficient must be reversed to assess the effect of attention.  The positive coefficients, therefore, suggest that increased attention is associated with faster price discovery, consistent with H3.

*Analyst_Coverage* is another proxy for investor attention -- larger values indicate increased attention.  The coefficients onr *Analyst_Coverage x EW_Rtn* are negative and statistically significant for all subsamples, except for the Post-Li AMC subsamples.  I note that the Base Period BMO quote subsample is only significant at the 10% threshold.  The negative coefficients are consistent with H3.

*Short_Ratio* is used as a proxy for short-sale constraints.  The coefficients on *Short_Ratio* x *EW_Rtn* are negative and statistically significant across all subsamples, except for Base Period BMO quotes.  The negative coefficients suggest that higher short ratios are associated with faster price discovery, contrary to H3's prediction.

I included *Short_Ratio* as direct poxy for short-sale constraints based on its use in Li (2016A).  However, it might not be a valid proxy for short-sale constraints.  Prior literature (Chen et al. 2002) notes that a stock can have a low short ratio because it is difficult or costly to short.  If so, *Short_Ratio* would function as inverse indicator of short-sale constraints, which could help explain the negative coefficients observed in my analysis.

For the remaining PEAD-linked variables -- *SUE* (a poxy surprise magnitude), *NS* (a proxy for bad news vs. good news), and *Analyst_Dispersion* (a proxy for differences of opinions) -- the results are mixed, but mostly not supportive of H3.

For *SUE* x *EW_Rtn*, the only coefficients that are statistically significant are for the Post-Li BMO trades and quotes subsamples; the coefficients are positive, which suggests slower post-ES price discovery speed, the opposite of what H3 predicts.

For *NS* x *EW_Rtn*, the coefficients are statistically significant for Base Period AMC trades and quotes, and for Post-Li BMO trades and quotes. The coefficients are positive for Base AMC, suggesting slower post-ES price discovery speed, consistent with H3. However, the coefficients are negative for Post-Li BMO, the opposite of what H3 predicts.

For *Analyst_Dispersion* x *EW_Rtn,* the coefficients are statistically significant only for Base Period AMC trades and quotes and Post-Li AMC trades. The significance for Base Period AMC trades is at only the 10% level. The coefficients are all positive, consistent with H3.

*IV.3.2 Base vs. Post-Li Period Differences*

In this subsection, I report the results of regression tests of H1a (Post-Li, a larger portion of total adjustment occurs in the IPA window) and H1b (the H1a effect will be smaller when price adjustment is measured via quotes vs. trades).

To test hypothesis H1a, I modified the regression specification in equation (10) to include the period indicator variable, $Post\_Li_{i,}$ and its interaction with $EW\_Rtn_i$. The *PEAD_Factors* and their interactions with *EW_Rtn* are retained as controls. The revised specification is:

$$STEM\_PD\_Rtn_i = \alpha + \beta_1 \cdot EW\_Rtn_i + \beta_2 \cdot Post\_Li_i \qquad (11)$$

$$+ \beta_3 \cdot (Post\_Li_i \cdot EW\_Rtn_i)$$

$$+ \beta'_4 \cdot (PEAD\_Factors_i) + \beta'_5 \cdot (PEAD\_Factors_i \cdot EW\_Rtn_i) + \alpha_{Firm} + \varepsilon_i$$

Table 10 reports the regression results for AMC, BMO, and AMC/BMO combined, for trades and for quotes. To reduce complexity, the table reports only the interaction of interest, $Post\_Li_i \cdot EW\_Rtn_i$, along with $EW\_Rtn_i$ and the Intercept.

The results provide support for H1a. The coefficient on $Post\_Li_i \cdot EW\_Rtn_i$ are negative and statistically significant at the 1% threshold across all subsamples.

**Table 10 Regression Results on Post-ES Price Discovery Speed in EMH: Changes from Base to Post-Li Period**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Trade Prices | | | Quote Prices | | |
| | AMC | BMO | AMC + BMO | AMC | BMO | AMC + BMO |
| **Post_Li x EW Rtn** | | | | | | |
| *Post_Li x EW Rtn* | -0.059*** | -0.067*** | -0.069*** | -0.083*** | -0.039*** | -0.071*** |
| | (0.013) | (0.013) | (0.010) | (0.015) | (0.013) | (0.011) |
| **EW_Rtn and Intercept** | | | | | | |
| *EW_Rtn* | 0.805*** | 0.944*** | 0.871*** | 0.852*** | 0.879*** | 0.865*** |
| | (0.013) | (0.008) | (0.008) | (0.013) | (0.008) | (0.008) |
| Intercept | -0.003*** | -0.003*** | -0.003*** | -0.002*** | -0.006*** | -0.004*** |
| | (0.001) | (0.000) | (0.000) | (0.001) | (0.000) | (0.000) |
| *N* | 20,260 | 22,985 | 43,678 | 20,260 | 22,985 | 43,678 |
| *Adj. $R^2$* | 0.816 | 0.910 | 0.857 | 0.826 | 0.826 | 0.826 |

This table reports results from the equation (11) regression model. The model was run on subsamples where *STEM_PD_Rtn* was calculated using trade prices (columns (1) through (3)) and quote prices (columns (4) through (6)); and where only AMC events where included (columns (1) and (2)), only BMO events (columns (2) and (5)) were included, and both AMC and BMO events were included (columns (3) and (6)).

To reduce complexity, only the interaction term relevant to hypotheses H1a is reported, along with *EW_Rtn* and the Intercept. All models include firm fixed effects and standard errors clustered by firm and date. Standard errors are reported in parentheses beneath coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Note: The full sample included 45,318 events, of which 21,213 were AMC events and 24,105 were BMO events. The number of observations, *N*, included in the regression results differs from the total number of events in the full sample, for the following reasons. First, ES events for BMO announcements on or after 9:15am and ES events for AMC announcements on or after 7:45pm (4:45pm on days the market was open a half-day) are dropped from the analysis because the end of their 15-minute IPA window occurs after the conclusion of the BMO/AMC announcement session. After dropping those events, 44,999 ES events remained in the sample to be analyzed, of which 21,125 were AMC events and 23,874 were BMO events. The difference between those figures and *N* reflects other observations which were dropped (*e.g.*, observations where the fixed effects group contained only a single observation and/or observations with missing PEAD-linked Factor variables).

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To test hypothesis H1b, I modified the regression specification in equation (11) by adding the pricing instrument indicator variable, $Quote_i$, and its interactions with $Post\_Li_i$ and $EW\_Rtn_i$. The *PEAD_Factors* and their interactions with *EW_Rtn* are retained as controls. The revised specification is:

$$STEM\_PD\_Rtn_i = \alpha + \beta_1 \cdot EW\_Rtn_i + \beta_2 \cdot Post\_Li_i + \beta_3 \cdot Quote_i \qquad (12)$$
$$+ \beta_4 \cdot (Post\_Li_i \cdot Quote_i)$$
$$+ \beta_5 \cdot (Post\_Li_i \cdot EW\_Rtn_i)$$
$$+ \beta_6 \cdot (Quote_i \cdot EW\_Rtn_i)$$
$$+ \beta_7 \cdot (Post\_Li_i \cdot Quote_i \cdot EW\_Rtn_i)$$
$$+ \beta'_8 \cdot (PEAD\_Factors_i) + \beta'_9 \cdot (PEAD\_Factors_i \cdot EW\_Rtn_i) + \alpha_{Firm} + \varepsilon_i$$

Table 11 reports the regression results for AMC trades and quotes, BMO trades and quotes, and the full sample of AMC and BMO trades and quotes. To reduce complexity, the table reports only the interactions of interest, $Post\_Li_i \cdot EW\_Rtn_i$, $Quote_i \cdot EW\_Rtn_i$, and $Post\_Li_i \cdot Quote_i \cdot EW\_Rtn_i$, as well as $EW\_Rtn_i$, and the Intercept.

For the separate AMC and BMO results, the coefficients are all statistically significant at the 1% threshold, except the coefficient on $Post\_Li_i$ x $Quote_i$ x $EW\_Rtn_i$ for AMC, which is significant at the 5% threshold.

For BMO, the coefficient on $Post\_Li_i$ x $EW\_Rtn_i$ is negative (-0.063), consistent with H1a. The coefficient on $Post\_Li_i$ x $Quote_i$ x $EW\_Rtn_i$ is positive (+0.20), indicating that the increase in price discovery speed from the Base to the Post-Li periods is smaller for quotes than trades, as predicted by H1b.

For AMC, the coefficient on $Post\_Li_i$ x $EW\_Rtn_i$ is negative (-0.058), consistent with H1a. The coefficient on $Post\_Li_i$ x $Quote_i$ x $EW\_Rtn_i$ is also negative (-0.027), indicating that that the increase in price discovery speed from the Base to the Post-Li periods is larger for quotes than trades, the opposite of what H1b predicts.

When the EMH sessions are examined as a unified session (*i.e.*, making no attempt to distinguish AMC events from BMO events), as shown in column (3) of Table 11, the coefficient on $Post\_Li_i$ x $Quote_i$ $x$ $EW\_Rtn_i$ is not statistically significantly different than zero.

**Table 11 Regression Results on Post-ES Price Discovery Speed in EMH: Changes from Base to Post-Li Period -- Trade vs. Quote Differences**

| | (1) | (2) | (3) |
|---|---|---|---|
| | Trade & Quote Prices Combined | | |
| | AMC | BMO | All |
| **Primary Results** | | | |
| *EW_Rtn* | 0.806*** | 0.943*** | 0.871*** |
| | (0.012) | (0.008) | (0.008) |
| *Post_Li* x *EW_Rtn* | -0.058*** | -0.063*** | -0.069*** |
| | (0.013) | (0.013) | (0.010) |
| *Quote* x *EW_Rtn* | 0.044*** | -0.062*** | -0.006 |
| | (0.009) | (0.004) | (0.005) |
| *Post_Li* x *Quote* x *EW_Rtn* | -0.027** | 0.020*** | -0.002 |
| | (0.011) | (0.006) | (0.007) |
| Intercept | -0.002*** | -0.004*** | -0.003*** |
| | (0.001) | (0.000) | (0.000) |
| *N* | 41,060 | 46,554 | 87,614 |
| *Adj.* $R^2$ | 0.826 | 0.872 | 0.844 |

This table reports results from the equation (12) regression model. The model was run on subsamples including only AMC events (column (1), only BMO events (column (2), and all events (column (3)). In all subsamples, there were two observations for each ES event, one where trade prices were used to calcualte *STEM_PD_Rtn*, and another where quote prices were used.

To reduce complexity, only the interaction term relevant to hypotheses H1a and H1b are reported, along with *EW_Rtn* and the Intercept. All models include firm fixed effects and standard errors clustered by firm and date. Standard errors are reported in parentheses beneath coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Note: The full sample included 45,318 events, of which 21,213 were AMC events and 24,105 were BMO events. The following events were dropped from the subsamples. ES events for BMO announcements on or after 9:15am and ES events for AMC announcements on or after 7:45pm (4:45pm on days the market was open a half-day) were dropped from the analysis because the end of their 15-minute IPA window occurs after the conclusion of the BMO/AMC announcement session. After dropping those events, 44,999 ES events remained in the sample to be analyzed, of which 21,125 were AMC events and 23,874 were BMO events.

Because the subsamples in this table included two observations for each ES event (one observation for trade prices, the other for quote prices), the number of events in the subsamples after the adjustments described above were as follows: 89,998 total observations, 42,250 AMC observations, and 23,874 BMO observations. The differences between those figures and the number of observations, *N*, included in the regression results reflect other observations which were dropped (*e.g.*, observations where the fixed effects group contained only a single observation and/or observations with missing PEAD-linked Factor variables).

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As an alternative way to test H1b, I used the coefficients and standard errors reported for $Post\_Li_i \cdot EW\_Rtn_i$ that were reported in Table 10 (*i.e.*, the table reporting the results for the regressions used to test H1a).

For BMO, the difference between the trade- and quote-derived coefficients is -0.028 and the standard error for the difference is 0.018, yielding a z-score of -1.523[39]. The interpretation of this is as follows. The quote-derived coefficients are smaller than the trade-derived coefficients, consistent with H1b, and the one-tailed p-value (*i.e.*, the CDF of -1.523) is 0.064; H1b is supported at a statistical significance threshold of 10%, but not at 5%, using this alternative test. Thus, the results of this alternative test for BMO are consistent with my primary test based on equation (12) and as reported in Table 11 above.

For AMC, the difference between the trade- and quote-derived coefficients is 0.024 and the standard error for the difference is 0.020, yielding a z-score of 1.209[40]. The interpretation of this is as follows. There is not statistically significant support for the hypothesis that quote-derived coefficients are smaller than the trade-derived coefficients, thus, H1b is rejected. Furthermore, the difference between the quote- and trade-derived coefficients is positive, indicating that that the increase in price discovery speed from the Base to the Post-Li periods is larger for quotes than trades, the opposite of what H1b predicts. The p-value for a one-tailed test of the null hypothesis that the increase is larger for quotes than trades (*i.e.*, for the opposite of what H1b predicts) is 0.113 (*i.e.*, 1 minus the CDF of 1.209). Thus, the results of this alternative test for AMC are consistent with my primary test based on equation (12) and as reported in Table 11 above, although -- unlike my primary test -- this alternative test does not find statistically significant support for the opposite of H1b (i.e., that the change in quote adjustment speed has been greater than the change in trade adjustment speed) during BMO.

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[39] The difference between the coefficients is: -0.067 coefficient for BMO trades minus -0.039 coefficient for BMO quotes = -0.028. The standard error for the difference between the two coefficients is calculated as follows: the square-root of the sum of each coefficient's squared standard error, which is equal to the square root of (0.13^2 + 0.13^2) = 0.01838. The z-score is equal to the difference divided by the standard error of the difference, or -0.028 / 0.01838 = -1.523.

[40] The difference between the coefficients is: -0.059 coefficient for AMC trades minus -0.083 coefficient for BMO quotes = 0.024. The standard error for the difference between the two coefficients is calculated as follows: the square-root of the sum of each coefficient's squared standard error, which is equal to the square root of (0.15^2 + 0.13^2) = 0.01985. The z-score is equal to the difference divided by the standard error of the difference, or 0.024 / 0.01985 = 1.209.

For EMH as a whole, the difference between the trade- and quote-derived coefficients is 0.002 and the standard error for the difference is 0.015, yielding a z-score of 0.135[41]. The interpretation of this is as follows. There is not statistically significant support for the hypothesis that quote-derived coefficients are smaller than the trade-derived coefficients, thus, H1b is rejected. I also note that the one-tailed p-value (*i.e.*, the CDF of 0.135) is 0.554. Thus, the results of this alternative test for EMH as a whole are consistent with my primary test based on equation (12) and as reported in Table11 above.

*IV.3.3 AMC vs. BMO Session Differences*

In this subsection, I report the results of regression tests of H2 (the proportion of total adjustment that occurs in the IPA window differs for AMC vs. BMO). To test H2, I started with the initial regression specification from equation (10) and modified it to include the session indicator variable, $BMO_i$, and its interactions with $EW\_Rtn_i$. The revised specification is:

$$\begin{aligned} STEM\_PD\_Rtn_i = \alpha + \beta_1 \cdot EW\_Rtn_i + \beta_2 \cdot BMO_i \\ + \beta_3 \cdot (BMO_i \cdot EW\_Rtn_i) \\ + \beta'_4 \cdot (PEAD\_Factors_i) + \beta'_5 \cdot (PEAD\_Factors_i \cdot EW\_Rtn_i) + \alpha_{Firm} + \varepsilon_i \end{aligned} \tag{13}$$

Table 12 reports the regression results for separate subsamples of Base Period trades, Post-Li trades, and Base Period quotes, and Post-Li quotes. To reduce complexity, the table reports only the interaction of interest, $BMO_i \cdot EW\_Rtn_i$, along with $EW\_Rtn_i$ and the Intercept.

The coefficients on $BMO_i \cdot EW\_Rtn_i$ are positive and statistically significant at the 1% threshold across all subsamples, except for Base Period quotes. The results suggest the following, when the IPA window is defined to be 15 minutes long:

41 The difference between the coefficients is: -0.069 coefficient for AMC trades minus -0.071 coefficient for BMO quotes = 0.002. The standard error for the difference between the two coefficients is calculated as follows: the square-root of the sum of each coefficient's squared standard error, which is equal to the square root of (0.11^2 + 0.10^2) = 0.01487. The z-score is equal to the difference divided by the standard error of the difference, or 0.002 / 0.01487 = 0.135.

- Trade-based price discovery is faster during AMC than BMO, in both the Base and Post-Li Periods, consistent with H2.
- Quote-based price discovery is also faster during AMC than BMO, but only in the Post-Li Period, consistent with H2.
- Quote-based price discovery speed does not differ between AMC and BMO in the Base Period, contrary to H2's prediction.

**[Turn to next page for Table 12]**

**Table 12 Regression Results on Post-ES Price Discovery Speed in EMH: Differences Between AMC and BMO Sessions**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | Trades | | Quotes | |
| | Base Period | Post-Li Period | Base Period | Post-Li Period |
| **Primary Results** | | | | |
| *BMO x EW_Rtn* | 0.118*** | 0.124*** | 0.008 | 0.064*** |
| | (0.010) | (0.016) | (0.011) | (0.017) |
| **EW_Rtn and Intercept** | | | | |
| *EW_Rtn* | 0.804*** | 0.767*** | 0.857*** | 0.784*** |
| | (0.010) | (0.015) | (0.010) | (0.015) |
| Intercept | -0.002*** | -0.005*** | -0.002*** | -0.005*** |
| | (0.001) | (0.001) | (0.000) | (0.001) |
| *N* | 25,652 | 17,968 | 25,652 | 17,968 |
| *Adj.* $R^2$ | 0.880 | 0.835 | 0.847 | 0.798 |

This table reports results from the equation (13) regression model. The model was run on subsamples including AMC and BMO events where *STEM_PEAD_Rtn* was calculated based on trade prices (columns (1) and (2)) and quote prices (columns (3) and (4)), for Base Period (columns (1) and (3)) and Post-Li (columns (2) and (4)) events.

To reduce complexity, only the interaction term relevant to hypotheses 2 is reported, along with *EW_Rtn* and the Intercept. All models include firm fixed effects and standard errors clustered by firm and date. Standard errors are reported in parentheses beneath coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Note: The full sample included 45,318 events, of which 26,786 were Base Period events and 18,532 were Post-Li events. The following events were dropped from the subsamples. ES events for BMO announcements on or after 9:15am and ES events for AMC announcements on or after 7:45pm (4:45pm on days the market was open a half-day) were dropped from the analysis because the end of their 15-minute IPA window occurs after the conclusion of the BMO/AMC announcement session. After dropping those events, 44,999 ES events remained in the sample to be analyzed, of which 26,520 were Base Period events and 18,479 were BMO events. The differences between those figures and the number of observations, *N*, included in the regression results reflect other observations which were dropped (*e.g.*, observations where the fixed effects group contained only a single observation and/or observations with missing PEAD-linked Factor variables).

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As previously noted, Gregoire & Martineau (2022)'s found that, over the first 59 minutes following an ES, mid-quote prices adjust more quickly than trade prices in EMH. In the closing paragraphs of subsection IV.1, I noted that the graphical evidence is consistent with their findings for BMO and for EMH (AMC and BMO combined), but not for AMC alone.

To further investigate the foregoing AMC vs. BMO differences, I performed additional regression analysis. I started with the initial regression specification from equation (10) and modified it to include the pricing instrument indicator variable, $Quote_i$, and its interactions with $EW\_Rtn_i$. The revised specification is:

$$STEM\_PD\_Rtn_i = \alpha + \beta_1 \cdot EW\_Rtn_i + \beta_2 \cdot Quote_i + \beta_3 \cdot (Quote_i \cdot EW\_Rtn_i) + \beta'_4 \cdot (PEAD\_Factors_i) + \beta'_5 \cdot (PEAD\_Factors_i \cdot EW\_Rtn_i) + \alpha_{Firm} + \varepsilon_i \tag{14}$$

Table 13 reports the regression results on separate subsamples broken down by period and session. The Panel A subsamples include all ES events, whereas the Panel B subsamples exclude S&P 500 events. To reduce complexity, the table reports only the interaction of interest, $Quote_i \cdot EW\_Rtn_i$, along with $EW\_Rtn_i$ and the Intercept.

In Panel A, for BMO events during the Base and Post-Li periods, the coefficients on $Quote_i \cdot EW\_Rtn_i$ are negative and statistically significant, consistent with Gregoire & Martineau (2022)'s finding that mid-quote prices adjust faster than trade prices.

However, for AMC events -- during both the Base and Post-Li periods -- the coefficients are negative and statistically significant, suggesting that during AMC, mid-quote prices are slower to adjust than trade prices. For EMH during both the Base and Post-Li periods, the coefficients were not statistically significantly different than zero, indicating no evidence of speed differences between mid-quotes and trades.

Gregoire & Martineau (2022) also noted that the trade vs. mid-quote speed differences they observed were influenced by stock size -- that the speed difference was more pronounced for S&P 400 and S&P 600 stocks, and de minimis for S&P 500 stocks (and not statistically different from zero for stocks in the top size quintile). Panel B of Table 13 reports the results of regression analysis on subsamples that exclude S&P 500 stocks. The coefficients on *Quote* x *EW_Rtn* for the EMH subsamples (both Base Period and Post-Li) that exclude S&P 500 stocks are negative and statistically significant, suggesting that for EMH as a whole, mid-quote prices adjust more quickly than trade prices, consistent with Gregoire & Martineau (2022).

## Table 13 Regression Results on Post-ES Price Discovery Speed in EMH: Trade vs. Quote Differences Between AMC and BMO Sessions

### Panel A -- All ES Events

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Base Period | | | Post-Li Period | | |
| | AMC | BMO | AMC + BMO | AMC | BMO | AMC + BMO |
| **Primary Results** | | | | | | |
| *Quote x EW_Rtn* | 0.044*** | -0.062*** | -0.006 | 0.017** | -0.041*** | -0.008 |
| | (0.009) | (0.004) | (0.005) | (0.008) | (0.005) | (0.005) |
| **EW_Rtn and Intercept** | | | | | | |
| *EW_Rtn* | 0.816*** | 0.929*** | 0.865*** | 0.761*** | 0.906*** | 0.819*** |
| | (0.011) | (0.006) | (0.007) | (0.016) | (0.009) | (0.011) |
| Intercept | -0.001 | -0.003*** | -0.002*** | -0.005*** | -0.007*** | -0.005*** |
| | (0.001) | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) |
| *N* | 22,468 | 29,060 | 51,528 | 18,592 | 17,494 | 36,086 |
| *Adj.* $R^2$ | 0.850 | 0.886 | 0.864 | 0.803 | 0.855 | 0.820 |

### Panel B – Excludes S&P 500 ES Events

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Base Period | | | Post-Li Period | | |
| | AMC | BMO | AMC + BMO | AMC | BMO | AMC + BMO |
| **Primary Results** | | | | | | |
| *Quote x EW_Rtn* | 0.021** | -0.058*** | -0.013** | 0.008 | -0.043*** | -0.012** |
| | (0.010) | (0.005) | (0.006) | (0.008) | (0.006) | (0.006) |
| **EW_Rtn and Intercept** | | | | | | |
| *EW_Rtn* | 0.835*** | 0.917*** | 0.861*** | 0.767*** | 0.905*** | 0.819*** |
| | (0.015) | (0.012) | (0.010) | (0.020) | (0.014) | (0.015) |
| Intercept | 0.021** | -0.058*** | -0.013** | 0.008 | -0.043*** | -0.012** |
| | (0.010) | (0.005) | (0.006) | (0.008) | (0.006) | (0.006) |
| *N* | 16,490 | 16,486 | 32,976 | 13,330 | 9,886 | 23,216 |
| *Adj.* $R^2$ | 0.854 | 0.895 | 0.869 | 0.813 | 0.876 | 0.833 |

This table reports results from the equation (14) regression model. The model was run on subsamples of Base Period events (columns (1) through (3)) and Post-Li Period events (columns (4) through (6)), consisting of AMC-only events (columns (1) and (4), BMO-only events (columns (2) and (5)), and both AMC and BMO events (columns (3) and (6)). All subsamples included two observations for each event, one using trade prices to calculate *STEM_PD_Rtn*, the other using quote prices. The Panel B subsamples exclude S&P 500 events.

To reduce complexity, only the interaction of interest (*Quote* x *EW_Rtn*) is reported, along with *EW_Rtn* and the Intercept. All models include firm fixed effects and standard errors clustered by firm and date. Standard errors are reported in parentheses beneath coefficient estimates. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively, based on two-tailed tests.

Note: The full sample included 45,318 events, broken down as follows: 26,786 Base Period events (11,643 AMC / 15,143 BMO) and 18,532 Post-Li events (9,570 AMC / 8,962 BMO). The following events were dropped from the subsamples. ES events for BMO announcements on or after 9:15am and ES events for AMC announcements on or after 7:45pm (4:45pm on days the market was open a half-day) were dropped from the analysis because the end of their 15-minute IPA window occurs after the conclusion of the BMO/AMC announcement session. After dropping those events, 44,999 ES events remained in the sample to be analyzed, broken down as follows: 26,520 Base Period events (11,562 AMC / 14,958 BMO) and 18,479 Post-Li events (9,563 AMC / 8,916 BMO). For Panel A, the differences between those figures and the number of observations, *N*, included in the regression results reflects other observations which were dropped (*e.g.*, observations where the fixed effects group contained only a single observation and/or observations with missing PEAD-linked Factor variables). For Panel B, the differences also include the exclusion of S&P 500 events from the subsamples.

## V SUPPLEMENTAL ANALYSIS: MAGNITUDE OF STEM-PEAD RETURNS

In this section, I provide supplemental analysis regarding the economic magnitude of STEM-PEAD returns during the Base and Post-Li periods. Specifically, I examine the trade returns over the STEM-PEAD segment of the event-window, where the STEM-PEAD segment begins 15 minutes after an ES and ends at the close of the next RTH session.

I measure the trade return for each ES event assuming the following trading strategy. The initial trade is a buy if ES is a PS, and a short sale if the ES is an NS. The trade is unwound at the end of the event window, that is, at the close of the first RTH session after the ES.

For the entry trade, I use the price of the first actual trade that occurs during the STEM-PEAD window (*i.e.*, the first trade where the elapsed time after the ES is more than 15 minutes after the ES)[42]. For AMC ES events, the first trade could occur during the AMC session in which the AMC ES was announced, during the subsequent BMO session or RTH open. For BMO ES events, the first trade could occur during the BMO session in which the BMO ES was announced or during the subsequent RTH open. For the exit trade, I use the price at the close of the first RTH session after the ES (*i.e.*, as of the end of the event window).

In his analysis, Li (2016A) estimated that the transaction costs were \$0.005 per trade transaction, or \$0.010 in total including the entry and exit trade. I calculate trade returns before transaction costs (*i.e.*, gross returns) as well as after transaction costs (*i.e.*, net returns). I use Li's transaction cost estimates when calculating net returns.

Li found that the mean trade return remained "significantly positive even beyond a 15-minute response" (Li 2016A, pg. 2). By performing the supplemental analysis described above on my

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[42] I note that using the first trade that occurs more than 15 minutes after the ES event is a different approach than I use in my primary analysis. For my primary analysis, for the price as of X minutes after an ES (*i.e.*, 15 minutes in this case), I use the most recent price as of X minutes, consistent with other literature on price discovery. However, as my supplemental analysis is designed to examine the potential trading returns that could be generated by an investor or trader who places an order 15 minutes after an ES, for this supplemental analysis it is more appropriate to use the first trade that occurs after the 15 minute mark -- because it would not be possible for the investor or trader to purchase or sell-short the stock at the price of a trade that occurred before the 15 minute mark.

four primary subsamples (Base Period AMC, Post-Li AMC, Base Period BMO, Post-Li BMO), I examine whether there are differences in the trading returns between AMC and BMO and between the Base and Post-Li period.

Based on the results from my primary analysis (reported in Section IV), one might expect the mean STEM-PEAD return -- or the ratio of the mean STEM-PEAD return to the mean Event Window return -- to have declined in the Post-Li Period as compared to the Base Period.

The results for my supplemental analysis regarding the economic magnitude of STEM-PEAD returns are reported in Table 14.

For AMC ES events, the mean STEM-PEAD net return (after trading costs) has declined from 1.53% (0.524 of the mean event window return) in the Base Period to 0.75% (0.353 of the mean event window return). There has also been a decrease in the percentage of STEM-PEAD net returns that are positive, decreasing from 59.2% in the Base Period to 54.3% in the Post-Li Period. Finally, there has been a decrease in the percentage of ES events where the first trade to occur more than 15 minutes is the RTH Open trade, decreasing from 13.6% in the Base Period to 10.1% in the Post-Li Period -- this indicates that more AMC ESs experience trades more than 15 minutes after an ES in the Post-Li period as compared to the Base Period.

For BMO ES events, the mean STEM-PEAD net return (after trading costs) has declined from 0.58% (0.254 of the mean event window return) in the Base Period to 0.52% (0.251 of the mean event window return). There has also been a decrease in the percentage of STEM-PEAD net returns that are positive, decreasing from 52.9% in the Base Period to 52.0% in the Post-Li Period. Finally, there has been a substantial decrease in the percentage of ES events where the first trade to occur more than 15 minutes is the RTH Open trade, decreasing from 33.3% in the Base Period to 15.3% in the Post-Li Period -- this indicates that substantially more BMO ESs experience trades more than 15 minutes after an ES in the Post-Li period as compared to the Base Period.

I conjecture that the substantial increase in EMH trading for BMO ES events can explain the relatively small decrease in the ratio of the mean STEM-PEAD return to mean event window return. Given the evidence in my primary results (reported in Section IV) indicate that price discovery is faster in the Post-Li period for both AMC and BMO ES events, one would expect the ratio of mean STEM-PEAD returns to mean event window returns to have meaningfully declined from the Base to the Post-Li period. However, because BMO ES events in the Post-Li period are more likely to experience a BMO trade during the STEM-PEAD window (that is, sooner than the next RTH open, earlier in the price discovery process), for BMO ES events, the average post-15-minutes trade takes place earlier in the Post-Li Period than in the Base Period. That is, for BMO events, the average post-15-minutes trade takes place earlier in the price discovery process during the Post-Li Period than during the Base Period. This could explain why, even if price discovery is faster in the Post-Li Period, the ratio of mean STEM-PEAD returns to event window returns has not meaningfully declined for BMO ES events in the Post-Li period.

**[Turn to next page for Table 14]**

## Table 14 STEM-PEAD Returns for Base vs. Post-Li Periods: <u>Assuming a Strategy of Buying a PS / Shorting an NS</u>

*note: Inspired by Table 1.2 of Li (2016A)*

| | Base Period | | | | Post-Li Period | | | | Post-Li vs. Base Delta | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Count | Mean Return | Percent Positive | Entry @ Next RTH Open % | Count | Mean Return | Percent Positive | Entry @ Next RTH Open % | Mean Return | Percent Positive | Entry @ Next RTH Open % |
| **Panel A -- Gross Returns (i.e., before trading costs)** | | | | | | | | | | | |
| **AMC** | | | | | | | | | | | |
| Event Window (EW) Returns | 11,643 | 2.97% | 65.4% | | 9,570 | 2.18% | 61.5% | | -0.80% | -3.87% | |
| STEM-PEAD Returns | 11,643 | 1.58% | 59.5% | 13.6% | 9,570 | 0.79% | 54.5% | 10.1% | -0.79% | -4.94% | 3.50% |
| *Ratio of STEM-PEAD / EW Rtns* | | *0.533* | | | | *0.364* | | | *(0.169)* | | |
| **BMO** | | | | | | | | | | | |
| Event Window (EW) Returns | 15,143 | 2.32% | 65.2% | | 8,962 | 2.09% | 61.7% | | -0.23% | -3.48% | |
| STEM-PEAD Returns | 15,143 | 0.62% | 53.2% | 33.3% | 8,962 | 0.55% | 52.1% | 15.3% | -0.07% | -1.13% | 18.03% |
| *Ratio of STEM-PEAD / EW Rtns* | | *0.269* | | | | *0.263* | | | *(0.006)* | | |
| **Panel B -- Net Returns (After Estimated Trading Costs of $0.005 per trade)** | | | | | | | | | | | |
| **AMC** | | | | | | | | | | | |
| Event Window (EW) Returns | 11,643 | 2.92% | 65.1% | | 9,570 | 2.14% | 61.3% | | -0.78% | -3.74% | |
| STEM-PEAD Returns | 11,643 | 1.53% | 59.2% | 13.6% | 9,570 | 0.75% | 54.3% | 10.1% | -0.77% | -4.95% | 3.50% |
| *Ratio of STEM-PEAD / EW Rtns* | | *0.524* | | | | *0.353* | | | *(0.171)* | | |
| **BMO** | | | | | | | | | | | |
| Event Window (EW) Returns | 15,143 | 2.27% | 64.9% | | 8,962 | 2.06% | 61.6% | | -0.21% | -3.36% | |
| STEM-PEAD Returns | 15,143 | 0.58% | 52.9% | 33.3% | 8,962 | 0.52% | 52.0% | 15.3% | -0.06% | -0.90% | 18.03% |
| *Ratio of STEM-PEAD / EW Rtns* | | *0.254* | | | | *0.251* | | | *(0.003)* | | |

This table reports the mean of the STEM-PEAD returns, and the Event Window Returns, for the Base Period AMC, Post-Li AMC, Base Period BMO, and Post-Li BMO subsamples. The returns are calculated assuming a strategy of buying upon a PS and selling-short upon an NS. The event window returns are calculated assuming the entry price is the price of the last trade before the EA event. The STEM-PEAD returns are calculated assuming that the entry price is the price of the first trade that occurs more than 15 minutes after the ES event (*i.e.*, the IPA window is defined to be 15 minutes). For both the event window and STEM-PEAD returns, the exit prices are assumed to be the closing price from the first RTH session after the ES event.

Panel A reports the mean returns assuming no trading costs. Panel B reports the mean returns assuming a cost of $0.005 per trade, which yields a total cost of $0.010 for each round-trip trade (*i.e.*, inclusive of the trade to enter the position and the trade to unwind the position).

Because the mean event window returns differ by period, this table reports not only the mean STEM-PEAD returns, but also the ratio of the mean STEM-PEAD returns to the mean Event Window returns.

The column labeled "Percent Positive" reports the percent of events where the "buy a PS / sell an NS strategy" yields a positive return. The column labeled "Entry @ Next RTH Open %" reports the percentage of events where entry trade for the "buy a PS / sell an NS strategy" does not occur until the RTH open (*i.e.*, it does not occur during the EMH sessions).

**[Section VI begins on next page]**

# VI CONCLUSIONS

In an efficient market, prices quickly incorporate new information, providing timely and accurate signals for decision-makers. Although short-horizon inefficiencies may be less relevant to long-term capital allocation decisions, rapid price adjustment matters to investors, managers, and policymakers who often need to act in real time. Moreover, short-horizon inefficiencies can erode public trust in the market's fairness and reliability.

Most studies on the U.S. stock market's efficiency examine regular trading hours (RTH). However, a growing body of research has begun to analyze the before market open (BMO) and after market close (AMC) trading sessions, collectively known as extended market hours (EMH).

These sessions are important and increasingly relevant. Much of the news that impacts asset prices becomes public during their hours. EMH trading volume has increased substantially over the past half-decade, and plans are underway to lengthen EMH to as many as 16.5 hours per day. Although EMH sessions are less active and less liquid than RTH, prior studies have shown that they make significant contributions to price discovery (Gregoire & Martineau 2022, Li 2016A, Jiang et al. 2012, Barclay & Hendershott 2008, 2003).

Although it is well established that RTH price discovery has become more efficient in recent years (*e.g.*, Akbas et al. 2023; Martineau 2022; Chordia & Miao 2020; McLean & Pontiff 2016; Chordia et al. 2014) -- due in part to declining trading costs, the rise of low-latency algorithmic trading, and increases in arbitrage activity and skill (including arbitrage in response to published papers) -- whether EMH sessions have undergone a similar evolution has been an open question.

My study addresses that question by examining whether the speed of price adjustment in EMH has increased over time. I also explore three related questions. Is that speed influenced by factors commonly associated with post-earnings announcement drift (PEAD)? Does it differ between AMC and BMO sessions? And, as a secondary focus, does it vary between trade-based and quote-based measures of price discovery? These are timely questions -- with implications for both the price discovery and PEAD literatures, as well as for researchers, investors, managers, and policymakers seeking to understand how efficient today's extended trading environment has become.

Using the tick-level trade and quote data for a full set of earnings surprises (ESs) -- subject to data availability, and as defined in this study -- by S&P 1500 firms during 2004–2012 (Base Period) and 2017–2021 (Post-Li Period), I find clear evidence in support of H1a: price discovery during EMH is more efficient in the Post-Li period. Following an ES, prices adjust more quickly, incorporating a greater proportion of the post-ES adjustment during the initial price adjustment (IPA) window. This pattern is robust across sessions (AMC and BMO), pricing instruments (trades and quotes), and IPA windows ranging from 1 to 60 minutes in duration.

In the Post-Li Period, I find that around 20% of the total adjustment is completed in the first 15 minutes for AMC trades and quotes, and for BMO quotes (BMO trades lag at around 13%).

I also find strong evidence consistent with H2: price discovery speed differs materially between AMC and BMO. In the first few minutes after an ES, prices -- both trades and quotes -- adjust more quickly during AMC. However, by the end of the sessions, a greater proportion of the post-ES price adjustment has occurred during BMO, for both trades and quotes. The crossover occurs around 15 minutes after an ES for quotes in the Base Period, around 30 minutes for quotes in the Post-Li Period, and more than 60 minutes for trades in both periods.

To investigate other trade-quote adjustment speed differences, I examine whether the increase in price discovery speed from the Base to Post-Li period (per H1a) is greater for trades than quotes (H1b). I find mixed results: the evidence supports H1b for BMO but contradicts it for AMC. This asymmetry may reflect between-session differences in (i) the extent to which Reg NMS rules are voluntarily honored[43] and (ii) the composition of market participants (*e.g.*, institutional investors, algorithmic traders, retail participants). These differences may also be evolving over time. This could help explain why H1b is supported in BMO but not AMC -- a direction worth exploring in future research.

Some of my results initially appeared inconsistent with Gregoire & Martineau (2022), who find that quote prices adjust more quickly than trade prices in EMH, particularly when larger stocks are excluded. More specifically, my findings align with theirs for BMO, but not AMC (where I observe the opposite behavior). However, when I exclude S&P 500 stocks and follow their approach by analyzing EMH without distinguishing AMC from BMO, my results reconcile with theirs. By separately analyzing AMC and BMO, I uncover meaningful differences in price adjustment behavior that are obscured when EMH is treated as a unified session.

One possible explanation for the AMC vs. BMO differences is as follows. As can be seen in Panel B of Table 6, during both the Base and Post-Li periods, there are stark differences between AMC and BMO in terms of the level of quoting activity relative to the level of trading activity. The ratios of (a) the median NBBO quote updates per event to (b) the median trades per event are as follows: (i) 6/9 for AMC Base period, (ii) 12/16 for AMC Post-Li period, (iii) 54/5 for BMO Base period, and (iv) 79/23 for BMO Post-Li period. In other words, the typical AMC ES event experiences more trades than NBBO quote updates. This could potentially explain why trade prices adjust more quickly than quotes during AMC.

I also re-examine Li (2016A)'s finding that short-horizon post-ES price discovery speed in EMH is not influenced by factors that PEAD studies have linked to price adjustment speed over

[43] The legal requirement to follow Reg NMS rules apply only to RTH, although anecdotal evidence (including FINRA rules) suggests that broker-dealers and market makers often adhere to them voluntarily during EMH.

longer horizons. Whereas Li measures how long it takes prices to reach their final price as of the end of a two-hour post-ES event window -- or, alternatively, their highest/lowest post-ES price during the AMC session) -- I instead construct measures in accordance with the PEAD and EMH price discovery literatures. Specifically, I divided the event window into an IPA segment and a PEAD segment (which I refer to as the short-term extended market PEAD, or STEM-PEAD, segment) and capture the proportion of the post-ES adjustment that occurs during each segment to measure price discovery speed.

In contrast to Li (2016A), and consistent with H3, I find that several PEAD-linked factors -- particularly proxies for liquidity and investor attention -- are significantly associated with short-horizon post-ES price discovery speed in EMH. However, I also find mixed evidence for other PEAD-linked factors, such as good-news vs. bad-news asymmetries and differences of opinion.

*Contributions to Literature*

My study makes several contributions to the EMH price discovery and PEAD literatures. First, it provides new evidence that price discovery speed in EMH has increased since Li (2016A). Second, by disaggregating EMH into BMO and AMC sessions, the study uncovers meaningful differences in how price adjustment unfolds across the two sessions -- differences that are obscured when EMH is treated as a unified session, as in Gregoire & Martineau (2022). Third, I find that several PEAD-linked factors influence EMH price discovery speed -- consistent with Gregoire & Martineau (2022)'s findings regarding liquidity, and supportive of the view that frictions that impede long-horizon adjustment also affect price discovery over short horizons.

*Contributions to Practice*

My study also offers several insights for (i) investors and traders, (ii) public-company CEOs, CFOs, and their investor relations (IR) teams, and (iii) regulators. As EMH price discovery becomes faster at incorporating new information, it provides earlier signals of how prices are likely to evolve in response to material news that becomes public outside of RTH. Market participants who monitor these signals can begin developing plans and taking action sooner than those who wait for signals from RTH. This advantage may be even more pronounced for those who monitor both trade and quote prices, as quotes may move more quickly than trades, particularly during BMO. Investors and traders who monitor EMH can respond more quickly, such as by executing hedging trades in other markets that may be open at the time. CEOs, CFOs, and IR teams who monitor EMH activity can better anticipate how the upcoming trading day is likely to unfold and gain valuable time to develop messaging and to proactively shape the day's narrative. In light of the ongoing increase in EMH activity and recent regulatory approval for stock exchanges to extend AMC by 3.5 hours (to end at 11:30 p.m.) and BMO by 2.5 hours (to start at 1:30 a.m.), regulators may find relevant the cross-session differences in quote and trade behavior documented in my study -- such as quote prices responding more slowly, on average, than trades during AMC.

*Avenues for Future Research*

My study raises several avenues for future research. First, while I find that EMH price discovery speed has increased, future work could investigate whether this trend has continued beyond 2021, or whether it varies systematically with market conditions, macroeconomic cycles, or firm characteristics. Second, future studies could examine EMH price discovery by focusing on other dimensions of efficiency, such as informativeness and accuracy. Third, investigating the causes of the between session differences observed in my study presents an interesting avenue for future research.

# APPENDICES

## Appendix A: Extended Literature Review: Price Discovery in EMH

This appendix provides an extended literature review on price discovery in the U.S. stock market's extended market hours (EMH). While a brief review of this literature is provided in subsection I.3 of this dissertation, the material presented here offers a more detailed account that some readers may find helpful as additional background.

### *A.1. Quotes and Price Discovery in EMH*

Trades and quotes each contribute to price discovery, interacting with one another in a dynamic process (Hasbrouck 1991) -- current quotes are influenced by new information and information revealed by contemporaneous trades and prior quotes and trades, and current trades are influenced by new information and information revealed by prior quotes and trades.

As discussed earlier, there is less trading activity (per-session and per-hour) during EMH than RTH. EMH trading activity does increase substantially, *on average*, during the brief window immediately following an EA. Yet, even after an EA is released, most stocks experience very few EMH trades during EMH and many experience zero EMH trades. Furthermore, prior to 1994, there was virtually no trading on the Nasdaq market during BMO hours -- but Nasdaq market participants could and did post non-binding quotes as a mechanism for engaging in price discovery prior to the opening of RTH (Barclay & Hendershott 2008).

For the foregoing reasons, several EMH price discovery studies have focused on discovery via quotes (*e.g.*, Christensen 2025, Gregoire & Martineau 2022, Biais et al. 1999). Biais et al.

(1999) found that, in the absence of trading activity, EMH price discovery can occur solely through quotes[44].

Christensen (2025), Gregoire & Martineau (2022) and Li (2016A) all found that post-ES EMH price discovery is faster when measured using mid-quotes or against-trend quotes rather than trade prices.

Mid-quotes are the midpoint of national best bid (NBB) quote and the national best offer (NBO) quote. For brevity, from here forward, I refer to NBBO mid-quotes as mid-quotes, NBBs as bids and NBOs as offers or asks. As shown below against-trend quotes are asks after a PS (it would be "against-trend" to post an offer to sell a stock whose price is expected to increase due to the good news), and as bid quotes following an NS (it would be "against-trend to post an offer to buy a stock whose price is expected to decline due to the bad news)[45]. With-trend quotes represent the opposite side of against-trend quotes -- bids after a PS and asks after an NS.

**With-Trend and Against-Trend Quotes**

| Surprise Type | With-Trend Quotes | Against-Trend Quotes |
|---|---|---|
| PS | Bids | Asks |
| NS | Asks | Bids |

The three studies by Christensen et al. (2025), Gregoire & Martineau (2022), and (Li 2016A) all find that against-trend quote prices respond immediately after an ES, and that with-trend quote prices respond more slowly. Because against-trend quotes respond immediately whereas

[44] Biais et al.'s (1999) study examined EMH price discovery on a non-U.S. stock market -- the Paris Bourse exchange (now known as Euronext Paris). However, I consider their study relevant to my research because, during the period they studied, the Bourse BMO session was similar to the pre-1994 Nasdaq market in that no trading took place, but market participants could and did post cancelable / revisable quote orders to buy or sell shares upon the opening of RTH. Furthermore, Biais et al. (1999) is commonly cited by, and their "unbiasedness regression" methodology is often used is, research investigating price discovery in the U.S. stock market (see, for example, Martineau 2022, Jiang et al. 2012, Barclay & Hendershott 2008, Barclay & Hendershott 2003).

[45] I credit Li (2016A) for the names "against-trend quotes and "with-trend quotes". Gregoire & Martineau (2022) use the term "best quotes" to refer to against-trend quotes, and Christensen et al. (2025) use the term "BBO" (best bid and offer).

with-trend quotes respond more slowly, mid-quote prices also respond immediately and spreads widen (Christensen et al. 2025, Gregoire & Martineau 2022, Li 2016A).

Based on their findings, which are consistent with Christensen et al. (2025) and Li (2016A), Martineau (2022, pg. 292) note that "the use of trade prices to compute returns when trading is sparse causes price adjustments to be measured with a delay compared to using quote prices", and recommend incorporating mid-quotes into one's analysis when investigating price discovery during times where trading is relatively sparse (*i.e.*, during EMH) over horizons of more than one-hour (such as is the case in my study)[46].

*A.2. Trades and Price Discovery in EMH*

Even though trading is still relatively sparse during EMH, trades are important to EMH price discovery (Barclay & Hendershott 2008, Barclay & Hendershott 2003) and EMH studies typically examine trading prices -- some evaluate price discovery speed based solely on trade prices (*e.g.*, Cui & Gozluklu 2024, Lyle et al. 2024, Santosh 2019, Levi et al. 2018, Jiang et al. 2012, Barclay & Hendershott 2008, Barclay & Hendershott 2003), others based on both trade and quote prices (*e.g.*, Christensen et al. 2025, Gregoire & Martineau 2022, Li 2016A).

Barclay & Hendershott (2008) find that increased BMO trading activity increases the speed of BMO price discovery (as well as the signal-to-noise ratio) vs. price discovery solely via quotes, and that price discovery is faster (albeit noisier) when there is new information (proxied by increases in unexpected BMO trading volume) to be incorporated into prices.

Broadly examining price discovery (*i.e.*, with no particular focus on price discovery following earnings news), Barclay & Hendershott (2003) find that individual trades convey more

[46] Based on the following logic, Gregoire & Martineau (2022) recommend using against-trend quotes for horizons shorter than one-hour. Because with-trend-quotes adjust more slowly than against-trend quotes, mid-quotes to adjust more slowly than against-trend quotes. So Gregoire & Martineau (2022) recommend using against-trend quotes when examining horizons of less than one-hour. However, as time proceeds after an EA, spreads narrow, as the result of not only with-trend quotes catching up to against-trend quotes but also as the result of reversals in against-trend quote prices. Gregoire & Martineau (2022) find that the reversal in against-trend quotes persists for a longer time, so they recommend using mid-quotes when analyzing horizons greater than one-hour.

information per trade during EMH than during RHT. Focused on price discovery following ESs, Jiang et al.'s (2012) results are consistent with Barclay & Hendershott's (2003), finding that individual post-ES trades convey more information per trading during the initial EMH session than during the subsequent RTH session.

For my study, I am not focused on dissecting the information incorporated into prices following an ES into its public information vs. private information components. Even so, it may be useful to briefly discuss how the price discovery literature has traditionally viewed the respective contributions that trades and quotes make to public information vs. private information. The traditional model (Hasbrouck 1991) assumes that the public information incorporated into prices can be identified by unexpected changes (innovations) in quote prices (where expected changes in quote prices are derived from prior quotes and contemporaneous and prior trades), and that public information, and that the private information can be identified by unexpected changes in trade prices (where expected changes in trade prices are derived from prior quotes and prior trades). The unexpected changes in trade and quote prices are commonly referred to as "innovations" (Hasbrouck 1991).

To summarize, the traditional view is that public information is conveyed exclusively through quote-price innovations and that private information is conveyed exclusively through trading-price innovations. Note that the traditional view does not say that the discovery of public information cannot be observed by examining trading prices, nor does it say that the discovery of private information cannot be observed by examining quote prices. Trading prices are influenced by quote prices and vice versa (Hasbrouck 1991). Therefore, even if one accepts the traditional view that public information first gets incorporated into prices via quotes, the public information would thereafter be reflected in trading prices. Likewise, even if one takes the view that private information first gets incorporated into prices via trades, it would thereafter be reflected in quote prices. Accordingly, studies that investigate price discovery following public news (such as ESs) can observe the total information (both public and private) incorporated into prices by examining either quotes or prices or both.

As Hasbrouck (1991) notes, the distinction between public and private information is not as clear in practice as econometric models, such as his, take it to be.

Furthermore, several studies challenge the traditional view that public information is initially incorporated into prices via quotes and private information initially via trades. Brugler & Hendershott (2024) find, contrary to the traditional view, public information can be first be incorporated via trades (rather than via quotes), and private information can first be incorporated via quotes (rather than via trades) -- specifically, they find that approximately 40% of price discovery from trades is from public information (60% from private information) and that approximately 40% of price discovery from quotes is from private information (60% from public information). In other words, they find that trades and quotes contribute roughly equally to the discovery of each type of information.

Another study that argues that trades are important to the price discovery of public information is Santosh (2019). He finds that post-EA EMH price adjustment speed is more closely related to the elapsed number of trades after an EA (“trade time”) than to the elapsed “clock time”, and that the cross-sectional adjustment speed is more homogenous when measured by trade time vs. clock time.

*A.3. Impact of Earnings Surprise Magnitude and Direction*

As noted earlier, regular IPA and PEAD returns have been found to be related to the direction and magnitude of ESs (Livnat & Mendenhall 2006, Bernard & Thomas 1989, Hirshleifer et al. 2009, DellaVigna & Pollet 2008). Several studies provide evidence suggestive of a similar relationship between ESs and short-window versions of IPA and PEAD where one or both measures span a window that starts during the EMH session when an ES occurred and that ends no later than the close of the subsequent RTH session.

For example, Cui & Gozluklu (2024) found their measures for short-window IPA returns (window = start to end of initial AMC session) and PEAD returns (window = open to close of subsequent RTH session) to be related to the direction and magnitude of RavenPack-constructed earnings news sentiment scores, suggestive of a similar relationship between short-horizon IPA and PEAD returns, and ES measures derived from EPS (and revenue) figures.

In their study of 50 S&P 500 stocks having the highest EA-day AMC transaction volumes, Christensen et al. (2025) analyzed IPA returns measured over a one-minute window that started at the time of an AMC EA and found them to be related to the direction and magnitude of ESs.

Gregoire & Martineau examined windows that started at the time of an EMH EA and that ended one-hour later. Their study provides graphical evidence (but not statistical evidence) that short-horizon IPA and PEAD returns are both related to the direction and magnitude of ESs (Gregoire & Martineau 2022, pg. 275, fig. 3).

Although their study focused on macroeconomic announcement surprises and did not include EMH hours, Chordia et al. (2018) constructed IPA windows that spanned 500 milliseconds before an announcement to 5 minutes after an announcement and found their short-window IPA return to be related to surprise magnitude.

Examining price discovery through the lens of Barclay & Warner (1993)'s weighted price contribution (WPC) measure, rather than through the lens of IPA or PEAD returns, Jiang et al. (2012) analyze an event window from the time of an EMH ES through the subsequent RTH close. They find a relationship between ES magnitude and the proportion of ES-to-subsequent-RTH-close price discovery that takes place during the initial EMH session. Although not a direct test of a relationship between ES magnitude and EMH price adjustment speed when measured via short-window IPA or PEAD, Jiang et al.'s (2012) results suggest such a relationship.

Li (2016A) found a relationship between post-ES AMC price adjustment speed and surprise magnitude for PSs but not for NSs. He conjectured that short-sale constraints might explain the lack of a relationship in the case of NSs. However, as I discuss in Appendix B, Li's variables for measuring price adjustment speed were not well designed to capture cross-sectional variations. As a result, Li's cross-sectional regression tests were mis-specified and may have lacked statistical power.

*A.4. Effects of Market Frictions on EMH Price Discovery*

As discussed earlier, the speed of price discovery, as measured by PEAD, has been found to be related to market frictions such as illiquidity (Chordia et al. 2009, Sadka 2006), limited arbitrage capital (Lasser et al. 2010), short-sale constraints (Diamond & Verrecchia 1987), investor inattention (DellaVigna & Pollet 2009, Hirshleifer et al. 2009), and differences in opinion (Garfinkel and Sokobin 2006, Vega 2006).

Gregoire & Martineau (2022) find that the post-ES short-horizon EMH IPA returns vary as a function of liquidity (proxied by a stock's market cap).

Jiang et al. (2012) evaluate EMH post-ES price discovery over windows that run from the time of an ES to the subsequent RTH close, using WPC as their measure, and find a relationship between (a) the proportion of price discovery that takes place during the initial EMH session and (b) various market frictions found to have a relationship with PEAD. Specifically, they find a relationship with information asymmetry (proxied by analyst coverage[47]), liquidity (proxied by a stock's market cap), and investor attention (proxied by the number of EAs that occurred on the same day, and during the same session AMC or BMO, session as a given ES).

Using WPC as a measure and windows that run from the RTH close immediately preceding an ES to the subsequent RTH close, Barclay & Hendershott (2008) find a relationship between the proportion of EMH that takes place during the initial EMH session and variables commonly used as proxies for liquidity -- average daily trading dollar volume, and market capitalization. Interestingly, they find a positive relationship for dollar volume and a negative relationship for market capitalization (Barclay & Hendershott 2008), which they leave unexplained.

Santosh (2019) develops his own measure of price discovery[48] and, using windows that start at the RTH close immediately preceding an AMC ES and end at the subsequent RTH close, and when measuring price discovery by elapsed "clock time"[49], finds a relationship between the proportion of price discovery that occurs during the initial EMH session[50] and liquidity (proxied by a stock's market capitalization) and information asymmetry (proxied by analyst coverage)[51].

Li (2016A) analyzed the relationship between post-ES AMC price adjustment speed and various market frictions including investor attention (proxied by analyst coverage, and the number of same-day same session EAs), limited arbitrage capital (proxied by the short-to-float ratio, and by the number of earlier or concurrent same day same session surprises), liquidity

[47] Some studies use size-adjusted analyst coverage as a proxy for information-asymmetry (Cao & Narayanamoorthy 2012).

[48] Santosh's (2019) measure involves a two-stage OLS regression where the first stage regresses the return over the full horizon by which time a stock's price is assumed to have fully adjusted to the ES, such as a horizon from the time of the EMH ES event through the close of the subsequent RTH session. Rather than using the actual return, the second stage uses the coefficient from stage one to estimate the expected return over the full-horizon and then regresses (a) the return over a measurement-window that starts at the time of the ES and that ends before the end of the full horizon (such as from the time of the EMH ES event through end of the EMH session), on (b) the expected return over the full-horizon. Conceptually, Santosh's second stage is related to Biais et al.'s (1999) "unbiasedness regression", which regresses the actual (rather than expected) return over the full-horizon on the return over the measurement-window. Said another way, Santosh's (2019) second stage reverses the dependent and independent variables of Biais et al.'s (1999) "unbiasedness regression" using the expected, rather than actual, value of the full-horizon return. The main regression coefficients from Santosh's (2019) second-stage equation and Biais et al.'s (1999) equation are the variables of interest, representing the proportion of the full-horizon price discovery that takes place during the measurement-window; the coefficients from each equation approach the value 1 as the end of the measurement-window approaches the end of the full horizon.

[49] As noted earlier, Santosh also measures price discovery by "tick time" (the number of elapsed trades after an EA); when measuring price discovery by "tick time", Santosh (2019) finds no relationship with either liquidity or information asymmetry.

[50] The EMH session includes the AMC session during which the ES occurred, non-trading overnight hours, and the BMO session prior to the next day's RTH open).

[51] Santosh (2019) also labels analyst coverage as a proxy for investor sophistication, which is conceptually related to, but not the same as, information-asymmetry.

(proxied by a stock's market capitalization), and differences of opinion (proxied by the standard deviation of analyst estimates).

Li (2016A) did not find any of the market frictions he examined to be related to adjustment speed at the 5% significance level. However, as noted earlier (and as I discuss in Appendix B) Li's cross-sectional regression tests were mis-specified and may have lacked statistical power because they relied on unconventional variables that were not well designed to capture cross-sectional variations in adjustment speed.

*A.5. Asymmetric Price Adjustment to Positive vs. Negative News*

Prior studies have found that the *magnitude* of price adjustment to be greater, and the *speed* of price adjustment to be slower, in response to bad news vs. good news. I first discuss papers that focused on RTH before turning to ones that focused on EMH.

Johnson & So (2018) attribute the magnitude asymmetries to a systemic upward bias in prices prior to news announcements that subsequently reverses post announcement, where the pre-announcement upward bias is caused by liquidity providers rationally charging asymmetrically higher costs to share sellers than share buyers prior to announcements because liquidity providers seek to limit their inventory positions (to reduce their risk) prior to an announcement. Kothari et al. (2009) explain magnitude asymmetries as being the result of company managers being quicker to reveal good news than bad news -- withholding the release of bad news, until required to release it -- which leads prices to impound more news into prices prior to mandatory public announcements (such as an EA) if the news is good rather than bad; as a result, for a given level of news, the post-announcement price adjustment will be greater for bad news than good news.

Diamond & Verrecchia (1987) attribute the adjustment speed asymmetries to short-sale constraints that interfere with prices adjustment in response to negative news, and Hong et al. (2000) attribute it to the theory that the diffusion of information to the investing public occurs gradually rather than instantaneously and that slow news diffuses more slowly than good news leading to a slower price adjustment process following bad news.

Turning to studies that have investigated EMH price discovery, Gregoire & Martineau (2022) examine PS vs. NS price adjustment during a window (*i.e.*, the IPA window) that runs from 1 minute prior to an EA to 60 minutes after an EA and present visual evidence that, during their IPA window and adjusted for variations in ES magnitude, the *magnitude* of post-ES EMH price adjustment is greater for NSs than PSs. Li (2016A) examines STEM-PEAD (measured over horizons starting 0 to 15 minutes after an EA and ending at the closing of AMC session) and provides tabular evidence that, during his STEM-PEAD window, the *magnitude* of post-ES AMC price adjustment is greater for PSs than NSs.

Santosh (2019) examines PS vs. NS price adjustment during an IPA window that runs from the first trade after an EA through the thirtieth trade (the median elapsed time of which is four minutes in his broad sample of stocks) and presents visual evidence that suggests the *speed* of post-EA AMC price discovery during the IPA window is slower for NSs than PSs (Santosh 2019, Fig. 5a, pg. 21); however, Santosh (2019) does not test whether the differences suggested by his visual evidence are statistically significant.

*A.6. Comparing Price Discovery in AMC and BMO Sessions*

Only a small number of studies have included data from both EMH sessions (AMC & BMO) in their analysis, and even fewer have separately examined AMC vs. BMO price discovery.

Examining the 250 Nasdaq stocks with the highest trading dollar volume, Barclay & Hendershott (2003) found that, on average and including days with and without earnings news, more information is incorporated into prices during BMO than AMC. They also found a positive relationship between EMH price discovery and EMH trading dollar volume. They did not test, but their results would also be consistent with, a similar relationship between EMH price discovery and the number of EMH trades (see Barclay & Hendershott 2003, Panel B of Table 5).

Barclay & Hendershott (2008)'s findings are consistent with Barclay & Hendershott (2003). Although Barclay & Hendershott (2008)'s focus is on examining the impact of increases in Nasdaq BMO trading on the efficiency of the subsequent RTH session's opening price, their tabulated results (Barclay & Hendershott 2008, Tables 2 and 5) suggests that once trading during BMO became less rare, on average and including days with and without earnings news, more information is incorporated into prices during BMO than AMC.

Jiang et al. (2012) examine post-ES EMH price discovery for S&P 500 stocks and separately analyze price discovery after ESs announced during AMC from those announced during BMO.

They analyze price discovery over a horizon that starts with the last trade prior to an ES and ends at the close of the next day's RTH session. They divide the horizon into three windows: (a) AMC hours (which are only relevant to AMC announcements), (b) BMO hours, and (c) RTH hours. They find the percentage of price discovery during each of those three windows to be as follows. For AMC announcements, AMC accounts for 42%, BMO for 14%, and RTH for 40% (the overnight hours between AMC and BMO account for the remaining 4%). For BMO announcements, BMO accounts for 36% and RTH for 64%.

Although Santosh (2019)'s primary focus is on price discovery following AMC announcements, his paper includes a brief section examining post-ES price discovery for BMO announcements. He finds that for both BMO and AMC ES announcements, approximately 75% of the price discovery is completed by the RTH open following the announcement. Interestingly, he also finds that after the first 30 minutes of RTH, there is a divergence in the amount of cumulative post-ES price discovery for AMC vs. BMO announcements, such that by the close of the RTH session, about 90% of post-ES price discovery has been completed for BMO announcements, whereas about 95% has been completed for AMC announcements (Santosh 2019, pg. 30, fig. 10). He notes that the differences are statistically significant.

Santosh (2019)'s results are consistent with Lyle et al. (2010), who find that post-ES price discovery is slower for BMO ES announcements relative to AMC ES announcements. Lyle et al. (2019) examine price adjustment over 24-hour windows following an ES, but although they do include EMH trades within their analysis as their 24-hour windows begin and end during EMH, they do not examine the portion of price discovery that takes place during EMH vs. the portion that takes place during RTH.

Gregoire & Martineau (2022) analyze AMC and BMO data as a single sample, without investigating whether price discovery differs between the sessions.

## Appendix B: Detailed Overview of Li (2016A)

This appendix provides a detailed overview of Li (2016A), whose study of post-earnings price adjustment during extended market hours serves as one of the primary foundations for my research. While a brief review of Li's study is included in the main body of this dissertation as part of subsection I.3's summary overview of the EMH price discovery literature, the material presented here offers a more detailed account that some readers may find helpful.

### *B.1. Overview and Positioning of Li (2016A)*

Examining the market's AMC session, Li investigated how stock prices adjust in response to ESs announced during AMC. He found that after an AMC ES, a stock's trading and mid-quote[52] prices tend to drift in the direction of the surprise over the remainder of AMC and that the drift continues through the next day's RTH opening. As notedin the main body of this dissertation, I refer to this short-term extended market post-earnings drift as STEM-PEAD to distinguish it from regular PEAD.

While Li secondarily positioned his research as contributing to the price discovery literature, he mainly positioned it as contributing to the literature on capital markets (including market anomalies in general and PEAD in particular) and as contributing to practitioners by providing "guidance on a valuable trading opportunity" (Li 2016A, pg. 5). He focused much of his investigation on the abnormal returns associated with implementing a rules-based trading strategy to exploit STEM-PEAD. For example, in both his abstract and his introduction he said that for 2002-2012, he identified "5,881 rule-based trading opportunities generate an average

[52] Li (2016A) did not expressly state that he observed the drift in mid-quote prices; however, Li documented finding that after an ES, against-trend quote prices immediately jump while with-trend quote prices adjust more slowly. Therefore, one can infer that Li found that after an ES, mid-quote prices tend to drift in the direction of the ES. Gregoire & Martineau (2022) also observe the post-ES drift in mid-quote prices during EMH, and they credit Li (2016A) with having also identified the mid-quote price drift (Gregoire & Martineau 2022, pg. 263, footnote 2). As noted, against-trend quotes are defined as ask quotes following a PS and as bid quotes following an NS.

return of 1.53% within four[53] hours." (Li 2016A, pg. ii; see also pg. 1) and "[a]fter costs…an investor who properly exploits the slow adjustment beats the market by 11.5% per year." (Li 2016A, pg ii; see also bottom of pg. 2 and top of pg. 3). Also, the first sentence in his conclusion reads "[m]y paper quantifies after-hours trading profitability…" (Li 2016A, pg. 32).

*B.2. Li's Sample and Rules-Based Trading Strategy for Calculating STEM-PEAD Returns*

Li's sample was comprised of quarterly ESs announced by S&P 1500 stocks during AMC between 2002-2012. He excluded from his sample ESs that were announced prior to 4:01pm, and events where the first post-ES trade did not occur within the first three minutes after the ES.

He classified each ES as either a PS or an NS. I infer that he defined a PS as an ES where reported revenues and EPS for the quarter both exceeded analyst consensus, and an NS as one where both measures fell short of consensus[54]. He found that 78.2% of the ESs in his sample were PSs and 21.8% were NSs (which, as he noted, is consistent with other studies).

Li calculated the raw returns (before and after estimated transaction costs of $0.0050 per share; but not adjusted for market returns) associated with STEM-PEAD by assuming a strategy of initiating a trade after an ES and unwinding the trade at the end of AMC. He assumed the entry trade would entail going buying after a positive ES and selling short after a negative ES.

Li calculated the STEM-PEAD returns over several different trading horizons -- varying the starting time of the entry trade from 0 to 15 minutes after the EA. For his primary analysis, he

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[53] As the AMC runs from 4pm to 8pm, four hours would be the maximum duration of an event for an ES announced at 4pm. Events where the ES was announced after 4pm would have a shorter duration. For example, for an ES announced at 5:30pm, the event window would be only 2.5 hours.

[54] Li states that he defined a PS as an ES "in which neither the top line (revenue) nor the bottom line (earnings per share, EPS) misses, and at least one of them beats, the corresponding consensus estimate" (Li 2016A, pg. 2) and an NS as an ES "in which neither the top line nor the bottom line beats, and at least one of them misses, the corresponding consensus estimate" (Li 2016A, pg 2). I label his stated definition as the "OR" rule (*i.e.*, a PS is one where actual revenue >= consensus OR actual EPS >= consensus; an NS is one where actual revenue <= consensus OR actual EPS <= consensus).

However, as discussed in subsection III.2.2, my analysis strongly suggests that he actually used the rule described in the sentence to which this footnote refers, which I label the "AND" rule (*i.e.*, a PS is one where actual revenue > consensus AND actual EPS > consensus; an NS is one where actual revenue < consensus and actual EPS < consensus).

Under any scenario where If I applied the "OR" rule, I identified a much larger number of PSs and NSs than reported by Li for AMC ESs during 2002-2012, whereas when I applied the "AND" rule, I was able to identify scenarios where my 2002-2012 AMC PS and NS counts were within 0.12% and 0.87% of Li's counts.

The reason the "OR" rule leads to a much larger number of PSs and NSs than the "AND" rule is because, for AMC EAs during 2002-2012, there were a large number of EAs where actual EPS was equal to consensus while revenue either exceeded (a PS under the "OR" rule, but not the "AND" rule) or fell short (an NS under the "OR" rule, but not the "AND" rule). During that period, there were very few EAs where Revenue equaled consensus while EPS exceeded or fell short.

assumed the exit trade occurred at the end of AMC. However, he also provided graphical evidence of STEM-PEAD returns (Li 2016A, pg. 11, Fig. 1.1) that assumed the exit trade return occurred at the opening of the next trading day's RTH.

*B.3. Li's Event Window and its Two Partitions (i.e., the STEM-PEAD and IPA windows)*

In choosing to calculate STEM-PEAD's as described above, Li effectively defined an event window that started at the time of an ES and ended (except in the case of Li's Fig 1.1) at the end of AMC -- a window divided into two parts: (i) a STEM-PEAD window beginning 0 to 15 minutes after the ES and ending at the end of the event window, and (ii) an IPA window beginning at the start of the event window (*i.e.*, the time of the ES and ending at the start of the STEM-PEAD window (*i.e.*, 0 to 15 minutes after the ES).

Although his analysis and findings were focused on the STEM-PEAD window, given the construction of his event window, they also provide insights into the IPA window. By structuring his event windows as described above, Li placed the partition between the IPA and STEM-PEAD window early in the post-ES price adjustment process, effectively positioning his study as an examination of the early stage of the price adjustment curve.

*B.4. Li's Findings Regarding STEM-PEAD and Its Associated Returns*

Examining price adjustment speed for trades and quotes and calculating STEM-PEAD returns -- based on trading prices and against-trend quote prices, and, except as noted, for the window *t* minutes after the ES through the end of AMC -- Li reported the following results:

- Trading prices begin to adjust immediately after an ES, but the drift is slow enough that STEM-PEAD returns (before and after transaction costs) remain significantly positive even when the start of the STEM-PEAD return window (*i.e.*, the entry trade) is 15 minutes after the ES announcement.

- Against-trend quote prices adjust more quickly than trading prices; the jump in the first minute is such that a trader who bought at the ask following a PS or sold short at the bid following an NS would not generate a positive return. In other words, STEM-PEAD returns calculated using against-trend quotes are not positive when the start of the STEM-PEAD window (*i.e.*, the entry trade) is one minute or more after the ES announcement[55].
- Quote prices adjust asymmetrically -- after an ES, against-trend quote prices immediately jump while with-trend quote prices adjust more slowly; as a result, mid-quote prices tend to drift after an ES.
- The magnitude of returns associated with NSs are greater than the magnitude associated with PSs (*i.e.*, prices respond more strongly to NSs than PSs).
- Of the post-ES price discovery that occurs from the time of the ES through the next day's RTH open, on average, approximately 72% occurs during the AMC session in which the ES was announced and 28% occurs during the next day's BMO session prior to RTH[56].

Table 1 of Appendix B provides a summary of the STEM-PEAD returns reported by Li for the windows that began 0, 1, and 15 minutes after an ES and that ended at the end of AMC[57].

[55] Although Li did not comment on the matter, the table reporting his return calculations for against-trend quote prices (Li 2016A, pg. 21, Table 1.5) indicates that against-trend quote prices tend to overreact to ES news (the returns in his table are significantly negative for all of the reported STEM-PEAD return windows that begin one minute or more after the ES announcement). That against-trend quote prices tend to overreact is consistent with the findings of Gregoire & Martineau (2022, pg. 279). Gregoire & Martineau conjecture that the overreaction is the due to liquidity providers setting high against-trend prices to "protect themselves from opportunistic traders that are more sophisticated or quicker at processing public news" (Gregoire & Martineau 2022, pg. 279).

[56] The 72% estimate is calculated as follows: 1.53% return from time of ES through close of AMC (as reported in Li 2016A, pg. 13, Table 1.2) divided by 2.1% return from time of ES through the next RTH open (as visually estimated from the graph reported in Fig 1.1 of Li 2016A on page 11). In both cases, the returns in the prior sentence are calculated based on trading prices before transaction costs.

[57] Li also reported returns for times t = 2, 3, 5, and 10 minutes.

**Table 1 of Appendix B**
**STEM-PEAD Returns Reported by Li (2016A)**

| | Returns from *t* minutes after an ES through end of AMC | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | PSs | | | NSs | | | Overall | | |
| | 0 Min(*). | 1 Min. | 15 Min. | 0 Min(*). | 1 Min. | 15 Min. | 0 Min(*). | 1 Min. | 15 Min. |
| **Returns Based on Trading Prices** (from Table 1.2 of Li 2016, pg. 13) | | | | | | | | | |
| Before costs | 1.11% | 0.52% | 0.20% | 3.02% | 1.46% | 0.48% | 1.53% | 0.72% | 0.26% |
| After costs | 1.04% | 0.46% | 0.15% | 2.94% | 1.37% | 0.42% | 1.46% | 0.66% | 0.21% |
| **Returns Based on Against-Trend Quote Prices** (from Table 1.5 of Li 2016, pg. 15) | | | | | | | | | |
| Before costs | -0.06% | -0.87% | -1.10% | 1.74% | 0.01% | -1.22% | 0.33% | -0.68% | -1.12% |
| After costs | -0.12% | -0.93% | -1.15% | 1.67% | -0.07% | -1.28% | 0.27% | -0.75% | -1.18% |

(*) For quotes, the returns in the "0 Minutes" column are from the first quote after the ES announcement through the end of AMC

### *B.5. Li's Findings Regarding the Post-ES Price Adjustment Speed and Factors Commonly Found to have a Relationship with PEAD*

Through regression analysis, Li examined the relationship between a stock's post-ES price adjustment speed and factors commonly found to be related to PEAD. His findings were somewhat surprising; of the factors he examined, with one exception, he found none to have a relationship with the post-ES price adjustment speed when setting the statistical significance threshold to 5%. The one exception was that he found post-ES price adjustment speed to be statistically significantly related to the surprise magnitude for PSs, but not NSs when using standardized unexpected earnings (*SUE*)[58] to measure of surprise magnitude[59].

Listed below are the factors commonly found to be related to PEAD that Li examined for a relationship between a stock's post-ES price adjustment speed:

- Investor attention (Hirshleifer et al. 2009, DellaVigna & Pollet 2009) as proxied by (i) the number of analysts covering the stock (*Analyst_Coverage*), and (ii) the number of EAs issued by other S&P 1500 stocks on the same day during the same AMC session as the announcing stock (*Competing_EAs*).

[58] For a given stock's quarterly ES, *SUE* is calculated as (*EPS_Consensus* - *EPS_Reported*)/*Price*, where *EPS_Consensus* is the mean of analysts EPS estimates for the quarter, *EPS_Reported* is the reported EPS, and *Price* is the stock's RTH closing price on the day prior to the ES.

[59] Li also found post-ES price adjustment speed to be related to a stock's short-to-float ratio (*Short_Ratio*) for NSs, but not for PSs, at the 10% significance level.

- Short-sale constraints (Boehmer & Wu 2013, Lasser et al. 2010, Diamond & Verrecchia 1987) as proxied by the stock's short-to-float ratio (*Short_Ratio*)[60].
- Liquidity (Chordia et al. 2009, Sadka 2006) as proxied by the stock's size as measured by the log of its market capitalization (*Log_MarketCap*)[61].
- Differences of opinion (Garfinkel and Sokobin 2006, Vega 2006) as proxied by the standard deviation of analyst estimates for the stock's EPS prior to the ES announcement (*Analyst_Dispersion*).
- Surprise magnitude (Livnat & Mendenhall 2006) as proxied by the stock's standardized unexpected earnings (*SUE*)[62].

Li also examined the relationship between post-ES price adjustment speed and a stock's historical 30-day volatility, but I am aware of no studies that find a relationship between PEAD and historical 30-day volatility[63].

### *B.6. My Conjecture re: Why Li did not find relationships between Post-ES Price Adjustment Speed and Factors Commonly Found to have a Relationship with PEAD*

I conjecture that Li did not find relationships between the PEAD-associated factors he examined and post-ES price adjustment speed because the cross-sectional regression tests may have been mis-specified and lacked statistical power.

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[60] Li (2016A) also used the number of other PSs/NSs announced by S&P 1500 stocks on the same day, during the same AMC session, and at the same time or an earlier time as the announcing stock (*Competing_PSs*, *Competing_NSs*) as a proxy for limits on arbitrage capital. I am aware of no other studies that use those measures as a proxy for limits on arbitrage capital.

[61] Li (2016A) conjectured that insufficient liquidity on the with-trend side of quotes was responsible for the slow price drift associated with STEM-PEAD, and documented that there was an increase in the percentage of against-trend orders that were intermarket sweep orders (ISOs) -- a liquidity-demanding type of order to buy or sale shares -- during the AMC session on the day of an ES announcement as compared to the prior day's AMC session. However, Li did not test whether there was a relationship between the proportion of against-trend orders that were ISO orders and the speed of post-ES price adjustment. Neither did he test whether there was an increase in the proportion of with-trend orders that were ISO orders.

[62] For a given stock's quarterly ES, *SUE* is calculated as (*EPS_Consensus* - *EPS_Reported*)/*Price*, where *EPS_Consensus* is the mean of analysts EPS estimates for the quarter, *EPS_Reported* is the reported EPS, and *Price* is the stock's RTH closing price on the day prior to the ES. Li (2016A) also used absolute unexpected earnings (*EPS_Consensus* - *EPS_Reported*) and the interaction of absolute unexpected earnings and the stock's price-to-earnings ratio (*Price* / *EPS_Reported*) as proxies for surprise magnitude. The use of absolute unexpected earnings as a proxy for surprise magnitude is not common in the literature, and I am aware of no other studies that use the interaction between absolute unexpected earnings and the price-to-earnings ratio as a proxy for surprise magnitude.

[63] I note, however, that Mendenhall (2004) found a positive relationship between PEAD returns and arbitrage risk as proxied by a stock's historical *idiosyncratic* volatility; however, subsequent studies call challenge those results. Chordia et al. (2009) find idiosyncratic volatility to be subsumed by factors measuring size (and liquidity) and Brav & Heaton (2010) find Mendenhall (2004)'s controls insufficient to disentangle size-related effects from idiosyncratic volatility effects.

The variables Li used to measure adjustment speed were unconventional (not found in prior literature) and appear conceptually flawed, as they focus on later stages of the adjustment process. However, as discussed below, because Li's study is positioned as an examination of the early stages of the adjustment process -- and because prior literature on price adjustment also typically focuses on the early stages -- the adjustment speed variables would have better aligned with the study's focus and prior literature if they had been designed to capture the early stages.

Furthermore, there tends to be less cross-sectional variation across ES events in later stages of the adjustment process compared to early stages. Regression models in which the dependent variable exhibits insufficient cross-sectional variability tend to lack statistical power.

By placing the partition between the IPA and STEM-PEAD windows early in the post-ES price adjustment process (*i.e.*, 0 to 15 minutes after the ES), Li positioned his study as an examination of the early stage of the price adjustment curve.

Focusing on the early part of the price adjustment curve is consistent with the literature that examines how prices adjust to new information, including PEAD studies[64] and it is common to measure post-news price adjustment speed by constructing variables based on the returns over the PEAD and/or IPA windows (Blankespoor et al. 2020) -- higher PEAD and lower IPA returns indicate slower adjustment, whereas lower PEAD and higher IPA returns indicate faster adjustment (Blankespoor et al. 2020). While some studies use abnormal PEAD and/or IPA returns as standalone measures of adjustment speed, others construct ratios -- such as PEAD / (IPA + PEAD) or IPA / (IPA + PEAD) -- to capture the relative speed of adjustment across each window, where a lower PEAD-based ratio indicates faster adjustment. Studies that

[64] For example, it is common in PEAD studies (e.g., Martineau 2022, Hirshleifer et al. 2009) to partition the event window such that the partition between the IPA and PEAD windows at the end of day 1 of an event window that spans from the end of day 0 through the end of day 60, thereby resulting in an IPA window that accounts for ~1.7% (1/60) of the event window and a PEAD window that accounts for 98.3% (59/60) of the event window.

use ratio-based measures include Jiang et al. (2012), Barclay & Hendershott (2003), DellaVigna & Pollet (2009), Beschwitz et al. (2020), and Chordia et al. (2018).[65]

However, although Li (2016A) positioned his study as an examination of the early stage of the price adjustment curve, for reasons unexplained, the adjustment speed variables examined only the later stages of the price adjustment curve. Li's adjustment speed variables were constructed via the following algorithms:

- First Hit Time (FHT) -- the number of seconds after an ES when a stock first trades at the FHT-trigger price (at or above for a PS; at or below for an NS), where the FHT-trigger price is the last trading price as of the end of the two-hour post-ES window.
- Time to Highest Return (THR) -- the number of seconds after an ES when a stock first trades at the THR-trigger price (at or above for a PS; at or below for an NS), where the THR-trigger price is the last trading price as of the end of AMC.

The following example illustrates how Li's two variables work, assuming a positive earnings surprise.

| Time | Price | Seconds since ES | Comment |
|---|---|---|---|
| 4:30pm | $100.00 | 0 | Time of Earnings Announcement |
| **5:00pm** | **$101.50** | **1,800** | **FHT = 1,800** (1st time price hits price as of end of 2-hour window) |
| 5:25pm | $101.25 | 3,300 | |
| 6:28pm | $101.50 | 7,080 | Last trade as of the end of the 2-hour post-ES window (FHT-trigger price = $101.50) |
| **7:00pm** | **$102.00** | **9,000** | **THR = 9,000** (1st time price hits THR-trigger price) |
| 8:00pm | $101.95 | 12,600 | End of AMC Session (THR-trigger price = $101.95) |

[65] Jiang et al. (2012) and Barclay & Hendershott (2003) use Barclay & Warner (1998)'s Weighted Price Contribution (WPC) measure. DellaVigna & Pollet (2009) use DellaVigna & Pollet (2009)'s Delayed Response Ratio (DRR) measure, and Beschwitz et al. (2020) and Chordia et al. (2018) use Beschwitz et al. (2020)'s measure similar in spirit to DellaVigna & Pollet (2009)'s DRR.

In summary, the FHT measure focuses on the end of the process over a two-hour window, and the THR measure focuses on the end of the process ending at the end of AMC. As discussed in the main body of this dissertation, I hypothesize that price adjustment speed will be found to vary with PEAD-linked factors when measured using variables that capture the early stages of the adjustment process.

**Appendix C: Li's (2016A) Three-Minute Rule to Identify Potential Trading Halts**

Li (2016A) excluded from his final sample those ES events where no trades were observed during the first three minutes after the event's EA. His stated reason was to remove events where a trading halt might have been in place during his post-ES event window.

For the following reasons, I diverged from Li (2016A) and did not remove such ES events from my final sample -- I did not apply Li's "three-minute rule".

- Li provided no justification for removing events where halts were (or might have been) in effect during some portion of the event window following the event's EA.
- Most studies on EMH price discovery do not typically exclude events with halts, unless their research question requires them to do so. For example, among EMH price discovery studies, I found only one -- Christensen et al. (2025) -- that excluded events where halts were in effect. Furthermore, Gregoire & Martineau (2022) specifically recommend not excluding events where little or no EMH trading occurs, arguing that excluding such events "leads to a selection bias to toward larger, more liquid stocks, and events with larger news shocks" (Gregoire & Martineau 2022, pg. 293).
- I found Li's three-minute rule to be severely mis-specified for identifying halts. The overwhelming majority of events it removes do not involve halts. As discussed below, there are more direct ways to identify halts, and their incidence rate is several orders of magnitude lower than Li's three-minute rule would suggest.

There are two types of halts (Chakrabarty et al. 2011): (a) regulatory halts where all venues are required to halt, and (b) non-regulatory halts where the halt applies only to the venue that declared the halt. Although Li (2016A) does not indicate whether he intended to define halts to include both regulatory and non-regulatory halts, because his three-minute rule classified an event as having a halt only if there was a lack of trading on *all* venues, it is reasonable to assume that he intended to exclude only those events where regulatory halts were in effect.

Of the 10,417 events in Li (2016A)'s preliminary sample of AMC ES events, his three-minute rule classified 4,536 (43.5% of 10,417) as ES events where a halt was in effect during the first three-minutes after the event's EA. Li removed all 4,536 such events from his final sample of ES events. Although Li did not indicate how many EA events were in the starting sample from which he constructed his sample of ES events, I estimate it would have been approximately 18,500 EAs[66], which suggests that his three-minute rule classified at least 24.5% of EAs (4,536 divided by 18,500) as having a halt in place during the first three minutes after the EA.

Prior literature suggests that the incidence of halts is nowhere near that high. For example, Marshall et al. (2023)'s findings suggest that halts *within one day* of an EA event occur in about 1.2% of EA events[67] and Jiang et al. (2012)'s findings suggest that halts *on the same day* as an EA event occur in about 0.9% of EA events[68].

As noted in Chakrabarty et al. (2011), Marshall et al. (2023), and Jiang et al. (2016), there are more direct ways to identify halts than Li's (2016A) three-minute rule. The initiation of a halt is directly signaled via the issuance of a quote with a "halt" condition code[69] and the lifting of a halt is signaled via the subsequent issuance of non-zero quote with a "normal" condition code[70].

To provide additional evidence that the incidence rate of halts is several orders of magnitude lower than Li's three-minute rule would suggest, I examined TAQ raw quote data (*i.e.*, before

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[66] A precise estimate is 18,523 ESs, which assumes that Li (2016A)'s sample included only EAs where the announcing stock was an S&P 1500 member not only on the EA date, but also on 12/31/12 *(consistent with the discussion in subsection III.2.1 of this document)*. Additional documentation with extensive details on sample construction, including SAS code, is available from the author upon request.

[67] Marshall et al. (2023) identify 7,914 trading halts in their sample, of which they indicate that approximately 10% -- or about 791 -- occurred within one day of an EA. 791 trading halts within one-day of an EA, out of the 66,460 firm-quarters in their sample (a proxy for firm-EAs), equals ~1.2%.

[68] Jiang et al. (2012) examined EAs by S&P 500 stocks during 2004-2008 and found 90 trading halts that occurred on the same day as the EA in their sample of 10,238 EA events (90 / 10,238 = 0.88%).

[69] For example, in the Monthly TAQ Quote datasets, the start of a regulatory halt is signaled via quotes with condition code 4 (news dissemination), 9 (non-firm quote regulatory halt), 11 (news pending), or 27 (regulatory halt where additional information has been requested by the exchange).

[70] For example, in Monthly TAQ Quote datasets, a regulatory halt's end is signaled via a subsequent non-zero quote with condition code 1, 2, 6, 10, 12, 23, or 29. Codes 3 or 8 can also be used to signal the lifting of a halt, but they also indicate that trading is closing for an exchange (code 3) or market maker (code 8).

applying the cleaning and outlier-exclusion filters discussed in subsection III.2.3 in the main body of this dissertation) for each of the 11,643 ES events in the AMC Base Period subsample of my preliminary sample. I focused on the AMC Base Period subsample because it is essentially the same sample as Li's (2016A), except that, as previously discussed, it does not include data for 2002 and 2003. For each of the 11,643 AMC Base Period ES events in my preliminary sample, I examined raw TAQ quote data to determine if a halt was in effect during any portion of the AMC session following the event's EA. I defined a halt to start when a "halt" quote was posted, and to end upon the posting of the next "normal" quote whose timestamp was at least 10 seconds after the halt started. I used the 10 second rule to allow for the possibility that it could take a few seconds for all venues to implement a regulatory initiated by another venue.

Of the 11,643 Base Period AMC ESs in my final sample, only 33 (< 0.3%) had a halt in effect for the full three-minute window after the EA, and none had a halt in effect for the entire time between the EA and the end of AMC. In total, I found only 129 ESs (out of 11,643) where a halt was in effect for even a portion of time from the EA through the end of AMC[71].

If I had applied Li (2016A)'s three-minute rule, it would have classified 5,612 of the 11,643 ES events, or 48%, as having had a halt in place during the three minutes following the event's EA, and it would have eliminated them from my final sample.

Based on the above, I concluded that Li (2016A)'s three-minute rule was severely mis-specified for its intended purpose. Having confirmed that the incidence rate of halts was very low, and in accordance with Gregoire & Martineau (2022) and others (*e.g.*, Jiang et al. 2012, Barclay & Hendershott 2003, etc.), I determined that it would be appropriate to not eliminate ES events with halts from my final sample of ES events[72].

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[71] The mean portion of the post-ES AMC window (*i.e.*, the time from the EA through the end of AMC) subject to a halt was 3.5%; the maximum portion was 25%.

[72] I also note that Li indicated that not applying his 3-minute rule "only helps finding the slow price adjustment [*i.e.*, STEM-PEAD]" (Li 2016A, pg. 8, footnote 14).

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