Does History Repeat Itself? The Evolution of Market Efficiency Over the Past Century

Lezgin Ay
Ivy College of Business
Iowa State University
lezgin@iastate.edu

Abstract

I combine a hand-collected sample of earnings announcements from the *Wall Street Journal* over the years, 1934-1971, with more recent data from Compustat, and document a striking U-shaped pattern in the evolution of market efficiency over the extended period, 1934-2018. In terms of investors' response to both firm-specific and market-wide news, markets are more efficient during the early and late years in this extended sample, while they become less efficient in the middle decades. I argue that this U-shaped pattern in the degree of market efficiency over time has been driven by two distinct economic dynamics. While the recent evolution in information-processing technology has led to more efficient markets in the later periods, the surprisingly high degree of market efficiency in the 1930s and 1940s reflects the greater relative importance of earnings announcements as a critical source of information that commanded investor attention, at a time when there was less overall information to process and fewer alternative information venues to consider. Overall, these results highlight that the evolution of market efficiency has not followed a linear path, but rather, divergent economic forces have caused the U-shaped pattern in market efficiency over time.

Key Words: market efficiency, underreaction, post-earnings announcement drift, PEAD, price delay.

JEL Classifications: G12, G14, G18

This is a preliminary draft. Please do not cite or circulate without permission. I want to thank Kelley Anderson, Ginka Borisova, James Brown, Tony Cookson, Arnold Cowan, Donna Dudney (discussant), Yunhui Han, Diane Janvrin, Tyler Jensen, Tingting Liu, Christine Parlour, Jeffrey Pontiff, Andy Puckett, Billy Xu, and seminar participants at the Financial Management Association 2021 and Iowa State University for helpful comments and suggestions.

I. Introduction

Evolution in the market's ability to efficiently price assets over time depends critically on the interplay between the continually growing amount and complexity of information arriving, and the capacity to process this information. In the current era of big data, the collection and analysis of large datasets are essential to making effective, forward-looking investment decisions. However, recent developments in data processing capacity and the new data-intensive trading strategies it has generated have been blamed for occasional setbacks and shocks involving market volatility, illiquidity, and inefficiency.[1] This observation raises questions about whether the recent evolution in the structure of capital markets, the big data era, and the accompanying advanced financial practices are likely to spawn continuing improvement, or perhaps periodic deterioration, in market efficiency.

The recent literature documents a steady, significant trend toward greater market efficiency over the most recent four decades.[2] However, this literature typically covers a limited sample period involving CRSP and Compustat data since 1970s, which is characterized by unique dynamics involving the amount and complexity of information arrival, as well as information processing capabilities. In contrast to the recent period analyzed in this literature, the prior evolution in these ongoing market dynamics involving information arrival and processing technology has been neither smooth nor continuous.

Over the past century, there has been substantial evolution in regulations involving firm-specific disclosure requirements of new information, as well as technological advances in the ability to process this information. As a result, the market has faced episodes of periodic

---

[1] For example, see Farboodi and Veldkamp (2020), Beggs, Brogaard, and Hill-Kleespie (2021), Weller (2017), Menkveld and Yueshen (2019), and Baldauf and Mollner (2020).
[2] McLean and Pontiff (2016), Bai, Philippon, and Savov (2019).

mismatches in the availability of information and the ability to process that information.[3] In this light, while the prevailing view seems to be that market efficiency has improved continuously over time and should continue to improve steadily into the foreseeable future, this view may be misleading. Serious consideration of how the market is likely to behave in the future requires a thorough analysis of longer historical periods that cover more heterogeneous periods for information arrival and processing ability.

This paper examines the evolution of market efficiency over 1934 - 2018 to better understand the ebbs and flows in the historical journey toward the market's current environment so that we may hope to better understand the market's future prospects. In particular, I analyze evolution in the market's ability to efficiently incorporate firm-specific news as measured by the reaction to earnings announcements and market-wide news as measured by Hou and Moskowitz (2005) price delay measure. Earnings announcements offer an ideal setting to examine the evolution of market efficiency since these events generate a dramatic market response immediately. One impediment to this analysis is that earnings announcement data are only available since 1972 through Compustat. I resolve this problem by hand-collecting earnings announcement data for all firms with earnings releases published in the Digest of Earnings Reports section of the daily *Wall Street Journal* over the years, 1934 – 1971, until Compustat data become widely available. I then combine this early sample with Compustat earnings announcement data over the years 1972 - 2018.[4]

[3] For example, the period immediately following the Securities Exchange Act of 1934 witnessed a dramatic increase in the amount of information disclosed to the public. However, at such times, the capacity to process such immense growth in the body of information has not kept pace with the rising amount and complexity of information arriving, until the financial services industry was first able to use computing technology on a large scale in the 1980s.
[4] The WSJ began publishing earnings reports in June 1930. However, the coverage in 1930 and 1931 is fairly small but it improves afterward. My analysis begins in 1934 because of this coverage issue and the fact that the earnings surprise measure (standardized unexpected earnings, or SUE) requires eight previous quarterly observations. Another important reason is that the standardization of accounting reports and audit mandate began with the Securities Exchange Act of 1934.

Figure I provides a first glance at the main findings, which indicate an inverted U-shaped pattern in the degree of market inefficiency across the 10-year periods that span the extended sample period, 1934 - 2018. Panel A of Figure I plots evolution in the market's average post-earnings announcement drift (PEAD) over days +2 through +61 following the firm's earnings release (on day 0) for a long-short hedge portfolio based on the firm's standardized unexpected earnings (SUE), averaged across all announcements made during each 10-year period. Panel A shows that the market's underreaction to earnings news (i.e., the magnitude of PEAD) increases steadily over the first half of the sample, from 1.8% in the first 10-year period (1934-1943) to 5.00% in the middle of the sample (1984-1993). Then PEAD declines steadily across subsequent decades, from its peak in the 1980s toward 1.24% in the last five-year period, 2014 – 2018.

Similarly, Panel B of Figure I plots analogous evolution in the market's overall inefficiency in responding to market-wide information, as measured by the average Hou and Moskowitz (2005) price delay measure, for each 10-year period in the extended sample. Once again, while the market is more efficient (i.e., there is a smaller average price delay) in the early decades, this measure of inefficiency increases towards the 1980's before dropping again in the later decades. Surprisingly, Figure I indicates that the market reveals a smaller delay in responding to both firm-specific earnings news and market-wide information in the first few decades of this sample. This evidence suggests a relatively high degree of efficiency in processing value-relevant information in the 1930s and 1940s, which deteriorated steadily toward less efficient markets until the middle decades of the sample, before reversing back toward greater efficiency in the last few decades. To the best of my knowledge, this is the first study that examines the evolution of market efficiency over such a long historical period and reveals this U-shaped pattern in the degree of market efficiency over the past century.

These results indicate that the evolutionary trend in market efficiency has not followed a consistent linear path towards steady improvements in the market's pricing of new information. Rather, I conjecture that the interplay between divergent economic forces over time has led to this U-shaped pattern in the market's ability to process information efficiently. Theoretically, these findings are consistent with the implications of bounded rationality for the evolution of market efficiency over time. Unlike the common assumption of pure rationality in most asset pricing models, a more realistic assertion is that investor rationality is bounded by limits to both the available information and investors' capacity to process that information (Simon (1982), Gilovich, Griffin, Kahneman (2002)).

Therefore, continued growth in the amount of information available does not necessarily push the market steadily toward greater efficiency in processing that information over time, especially when limits to investors' rationality prevent them from processing the growing body of information in a timely fashion. By the same token, in Martin and Nagel's (2021) model, investors can forecast asset prices efficiently when the number of firm attributes (i.e., the complexity of information) is sufficiently small relative to the number of firms. Consequently, the harmony between the amount and complexity of available information and the information processing capacity of investors becomes critical for the degree of market efficiency achieved over time.[5]

In line with the theoretical arguments based on bounded rationality, I conjecture that the surprisingly high degree of efficiency in the 1930s and 1940s likely reflects a greater ability for investors to focus on the more limited amount and complexity of public information available at

[5] See Brunnermeier and Oehmke (2009) for a discussion of the implications of complexity in financial markets.

the time.[6] The information produced by the investment industry and firms in this early portion of the sample period was substantially less voluminous and complex. As a result, investors were better able to process the limited information available and react more quickly to its arrival. On the other hand, as time passed toward the middle decades of the sample, I conjecture that tremendous growth in compelled firm-specific information disclosure flooded the market with value-relevant information at a greater pace than investors could keep up with, given the prevailing technology. Then finally, in more recent decades, major advances in technology have vastly increased the speed with which investors can process the growing amount and complexity of information.

A notable development in the recent literature on market efficiency is that, within the cross-section of stocks, the informativeness of large firms is significantly greater than that of small firms (Farboodi, Veldkamp, and Venkateswaran (2021)). One explanation for this behavior is that investors generally have access to more and better data about large firms than small firms. During the early decades of the extended sample period, this differential amount of data for large versus small firms was more significant. Under bounded rationality, the resulting mismatch between the amount of information available and the capacity to process that information during this early period could have had a differential impact on the degree of efficiency for large versus small firms. As a result, the evolution of price efficiency for large firms may have followed a different path than that for small firms.

I examine this conjecture by analyzing large and small firms separately and find that, while large firms are consistently priced more efficiently than small firms, the evolution in this inefficiency follows a similar inverted U-shaped pattern for both large and small firms. However,

[6] Barinov and Yildizhan (2020) and You and Zhang (2008) document that investor underreaction is stronger for more complex firms and firms with more complicated 10-K reports.

it is noteworthy that price inefficiency for large firms peaks earlier and subsequently improves faster over time, relative to that for small firms. In contrast, inefficiency for small firms takes longer to evolve, as the information growth for small firms has progressed at a slower rate. Hence, small firm inefficiency peaks later and then takes longer to reach more efficient levels.

Among the several explanations that have been proposed to help understand investor underreaction embodied in PEAD and the Hou and Moskovitz (2005) price delay measure, the most prominent is that the market tends to underreact to both firm-specific and market-wide news. However, the more efficient pricing that prevails during the earlier periods in the sample appears to be incompatible with common explanations of investor underreaction based on market impediments such as the cost of trading (liquidity), short-selling constraints, or trading frictions, which were generally greater during these early periods.[7]

In addition, the recent literature on PEAD finds that the drift begins promptly after the earnings release (i.e., immediately after days 0 and +1). However, Hirshleifer, Lim, and Teoh (2009) argue that boundedly rational investors should not necessarily begin to update their beliefs immediately following the earnings release. Instead, they suggest a bounded rationality argument in which the drift should begin with a significant *delay* following the earnings release, since meaningful new firm-specific information may not be expected to arrive until the next earnings announcement approaches.[8] In other words, investors subject to bounded rationality are likely to focus their attention on publicly available news. As a result, after the initial response to earnings announcements, prices should continue to adjust only later, when more information

[7] See Ke and Ramalingegowda (2005), Zhang, Cai, and Keasey (2013), and Ng, Rusticus, and Verdi (2008) for transaction costs, Mendenhall (2004) for arbitrage risk, Chordia, Goyal, Sadka, Sadka, and Shivakumar (2009) for illiquidity, and Zhang (2006) for information uncertainty.
[8] For example, Zhang (2008) finds the average response time for analysts to update their forecasts with the latest earnings release is 12 days, using data from 1996 to 2002. See also Abarbanell and Bernard (1992), Bagnoli, Levin, and Watts (2005), Ivkovic and Jegadeesh (2004), Easterwood and Nutt (1999), and Stickel (1989).

arrives. This argument provides a testable implication for the bounded rationality argument, to help understand the U-shaped pattern in market efficiency over the sample period: the structure of inefficiencies such as PEAD should be different in the early and later sample periods, when information arrives and can be processed at different rates.

I explore this argument by focusing on investors' response to firm-specific news provided in earnings announcements. Post-earnings announcement drift is one of the earliest and most robust empirical anomalies documented in the literature, which represents "the evidence most damaging to the naïve and unwavering belief in market efficiency" (Lev and Ohlson, 1982, p. 284, Fama, 1998).[9] Most importantly, unlike the Hou and Moskowitz (2005) price delay measure, analysis of the market's response to earnings news benefits from the fact that earnings announcement dates are well-publicized events. As a result, the market's reaction to the arrival of this new firm-specific information can be vigorously analyzed using stock returns and trading volume around the event.

During the 1930s and 1940s, investors observed fewer information signals about firm-specific performance outside the realm of earnings announcements compared to more recent decades. In the 1930s and 1940s, the primary source of information was financial newspapers, and there were fewer sources of firm-specific, industry, or macroeconomic news. Managers typically did not issue guidance to investors, and there were fewer financial analysts. In this environment, the *Wall Street Journal* made regular calls to firm executives, urging them to reveal more information to their potential shareholders.[10] In this environment, when a firm's earnings information was released, investors were likely to be intensely focused on this disclosure of the

[9] Ball and Brown (1968) first documented evidence of PEAD for a sample of 261 firms between 1957 and 1965. See also Foster, Olsen, and Shevlin (1984), Bernard and Thomas (1989), and Livnat and Mendenhall (2006) for early contributions in this area.
[10] For example, see the *Wall Street Journal* Display Ad from 1949, reproduced in Figure II.

limited information available. After the announcement, they would need to wait until much later to adjust their beliefs further, when meaningful new information would arrive at the next earnings announcement. This environment suggests a significant delay between the immediate response to an earnings release and the beginning of the subsequent drift when substantive new information begins to arrive around the next earnings release. In contrast, in more recent years since the 1970s, since the publication of Ball and Brown (1968), investors are increasingly aware of PEAD and the consequent implications of current earnings for future earnings (Bernard and Thomas, 1988, 1989). Furthermore, changes in regulations have compelled more timely disclosure of other firm-specific information since the 1930s. As a result, in more recent years, the market's delayed price response to earnings news is more likely to begin immediately after the announcement, and this speed of adjustment should accelerate over time, resulting in smaller PEAD and greater efficiency (McLean and Pontiff, 2016).

In line with this view, I show that in the 10-year periods since 1974, the drift in the SUE hedge portfolio return consistently begins immediately after the announcement and continues steadily through day +60, peaking only after this period. In contrast, in the four earlier decades prior to 1974, there is little or no substantive drift in the first month following the earnings release. For example, in the first decade between 1934-1943, there is a one-month delay before the drift begins to swell, with just 3.93% of the total 60-day drift occurring in the first month after the earnings release (i.e., over days +2 to +21). Then, in each subsequent decade, the percentage of the total drift that is realized in the first month increases steadily, as the drift comes to begin immediately after the earnings release (on day +2) in more recent decades, and with more than 20% of the total 60-day drift occurring in the first month. This evidence of a delayed drift during the early era is consistent with an explanation for PEAD based on underreaction in the presence of boundedly rational investors.

Another implication of the boundedly rational investor argument is that, during the early years of the sample period, if the arrival of value-relevant information was more limited but more impactful, then more resources should have been devoted to earnings announcements at the time. In this light, the surprisingly greater efficiency around earnings announcements during the early decades of the sample period is likely due to investors allocating more attention and resources towards analyzing such firm-specific earnings news. I label this conjecture the 'early earnings attention hypothesis,' which argues that earnings announcements conveyed relatively more important information to investors in the early sample periods, in comparison to later sample periods when other information sources became more abundant.

I conduct several tests to explore this 'early earnings attention hypothesis' and find consistent supporting evidence. First, I document that average abnormal trading volume on the two days around the earnings announcement (AVOL[0,+1]) is relatively high during the 1930s, before declining steadily until the 1970s, and then subsequently increasing again over the last few decades. This U-shaped pattern in AVOL[0,+1] over time suggests that investors paid greater attention to the release of earnings information both early and late in the extended sample period, and less attention in the middle decades. This outcome is consistent with the view that, in the early years, earnings announcements were a more important source of firm-specific information, which attracted greater attention by investors and thus contributed to the lower underreaction to earnings news and greater market efficiency at the time.

Second, I examine the proportion of total 62-day announcement returns (CAR[0,+61]) that is realized immediately (CAR[0,+1]), for the subset of stocks each quarter that attract the greatest investor attention. I find that the subset of stocks with high AVOL[0,+1] in any given quarter tend to realize a greater proportion of total announcement returns immediately (i.e., CAR[0,+1] / (CAR[0,+61]) is greater). This evidence also supports the 'early earnings attention hypothesis,' indicating that the subset of stocks that investors focus most on around earnings announcements reveals less underreaction to the earnings news and greater price efficiency.

Third, I examine evolution in the relative information content of earnings news over the extended sample period, to explore the extent of total variation in a firm's quarterly stock return that is explained by quarterly earnings announcement returns (i.e., CAR[0,+1]). In particular, I use the R^2 from a regression of a firm's quarterly return on the firm's quarterly 2-day announcement return (CAR[0,+1]) in that quarter, as a proxy for the relevant information contained in earnings announcements (Ball and Shivakumar, 2008). Yet again, I find that the relative importance of earnings announcements was higher during both the early and late years in the sample period. Together with the analogous U-shaped pattern in AVOL[0,+1] over time, this evidence suggests that investors placed greater weight on earnings announcements both early and late in the sample period, relative to the middle decades. The greater importance placed by investors on earnings news (i.e., the higher R^2 measures) in the early decades further corroborates the 'early earnings attention hypothesis,' suggesting that firm-specific earnings news was relatively more important at the time. The similarly high R^2 documented in recent decades also suggests that investors have again recently increased their focus on earnings news, perhaps due to the introduction of Reg-FD and other regulations compelling more timely and public disclosure of firm-specific earnings information.[11]

[11] Reg-FD became effective in 2000, and prohibited firms from sharing non-public information to select investors.

II. Literature Review

Other scholars have also compiled panels with long time series of stock characteristics and returns to examine whether data-snooping has impacted the documentation of many market anomalies.[12] For example, Linnainmaa and Roberts (2018) show that many accounting-based anomalies fail to hold up or have smaller magnitudes out of sample. On the other hand, while PEAD continues to be the subject of much impactful research, the vast majority of studies on price efficiency around earnings announcements relies on Compustat data since 1972.[13] This paper contributes to this dialogue on the robustness of research on market efficiency by examining a novel sample of earnings announcements that has not been studied before.

Several other studies also find that the immediate reaction to earnings news (CAR[0,+1]) and subsequent drift (CAR[+2,+61]) differ across various groups of stocks and time periods. For example, several characteristics of stocks have been shown to affect PEAD including firm size, return volatility, transaction costs, analyst coverage, and institutional ownership. Likewise, other attributes of the marketplace also impact PEAD, including investor type, investment style, day of the week, the number of same-day announcements, social interactions, and more.[14] However, all of these studies are published after Ball and Brown (1968), and most use data for later periods when investors were aware of the profit opportunities associated with PEAD, which complicates inferences from their analysis.

---

[12] For example, see Harvey et al. (2016), Hou et al. (2017), Linnainmaa and Roberts (2018), and Wahal (2018).

[13] For recent studies of PEAD, see Yifan, Nekrasov, and Teoh (2020), He and Narayanamoorthy (2020), Beaver, McNichols and Wang (2020), Ali, Chen, Yao, and Yu (2020), Thomas, Zhang, and Zhu (2021), Li and Lytvynenko (2021), Meursault, Liang, Routledge, and Scanlon (2021).

[14] Among others, see Odean (1999), Barber and Odean (2000), Bartov (1992), Bartov, Krinsky, and Radhakrishnan (2000), Hirshleifer and Teoh (2003), Mendenhall (2004), Hirshleifer, Myers, Myers and Teoh (2008), Campbell, Ramadorai, and Schwartz (2009), Baker et al (2010), Ke and Ramalingegowda (2005), Taylor (2010), Ayers et al (2011), Hirshleifer, Lim, and Teoh (2009), DellaVigna and Pollet (2009), Ng, Rusticus, and Verdi (2008), and Hirshleifer, Peng, and Wang (2019).

Moreover, the magnitude of the drift documented in this body of research has diminished over time, as the market has become more aware of new research on this phenomenon (McLean and Pontiff, 2016), and liquidity has improved (Chordia, Subrahmanyam, and Tong, 2016). On the other hand, the substantial body of important work on PEAD since Ball and Brown (1968) consistently documents that the drift begins immediately after the earnings release (i.e., on day +2). While evidence on the magnitude of PEAD varies somewhat across stocks and sample periods since 1972, the recent evidence that PEAD has decayed since the beginning of the Compustat sample, and that the drift begins immediately on day +2, remains largely unchanged until this study. In contrast, this study provides novel evidence that, in the early years (before Compustat), there was less underreaction to earnings news and a one-month delay before the drift begins.

III. The Environment for Corporate Disclosure and Financial News Prior to the 1970s

The crash of 1929 and the Great Depression led to major reforms with the Securities Act of 1933 and the Securities Exchange Act of 1934. Both acts placed a new emphasis on corporate disclosure to help prevent financial manipulation and provide investors with the information needed to make informed decisions. For example, the 1934 act required public firms to file detailed balance sheet and income statements annually within 120 days after the fiscal year-end (10Ks), as well as less detailed reports semiannually within 45 days after the first half of the fiscal year (9Ks), and a current report within ten days of the end of any month when a significant event occurred (8Ks).[15]

However, the NYSE had already been leading these efforts to improve disclosure practices long before the regulators stepped in. As early as 1895, the NYSE required all listed

[15] See Benston (1973) and Zarb and Kerekes (1970, p. 38).

companies to submit annual reports that included balance sheet and income statement data, and distribute these to stockholders.[16] The NYSE similarly mandated the filing of quarterly reports in 1926.[17] By 1929, all stocks listed on the NYSE reported their net income regularly.[18] Furthermore, the NYSE's mandate also compelled firms to immediately share any value-relevant information with the newspapers in New York that publish financial news.[19] Figure III in Appendix A shows a timeline documenting notable changes in regulations, which directly or indirectly affected the corporate disclosure practices over the past century.

At the beginning of the 1900s, financial news was being disseminated fairly efficiently, with the help of technological developments such as the telegraph, telephone, and stock ticker, as well as newspapers and newswires. These developments contributed to help open the world of trading to the general public. The available technology also allowed investors to submit and execute orders within a relatively short period of time, typically within the same day.[20] Competition among newswires, in particular, helped enhance the timely reporting of financial news.[21] The *Wall Street Journal* has been the premier financial newspaper reporting financial news consistently. The *New York Times* and the *Tribune* were the other regular daily newspapers popular in the New York district. However, while these outlets also provide general financial news, they are not regarded as reliable or comprehensive in their coverage compared to the WSJ. Baker, Bloom, Davis, and Sammon (2019, p. 6) emphasize that the WSJ has "the most thorough coverage of financial news and has the most complete and consistent archive back to 1900."

[16] Sobel, R. (1968, p. 177).
[17] See Reilly (2004, p. 11). Karmel (2001) states that companies agreed to disclose reports quarterly in 1932, while Mahoney (1997) reports that NYSE began pushing companies to report quarterly in 1920s.
[18] Benston (1969).
[19] Zarb and Kerekes (1970, p. 38 and p. 99).
[20] See New York Stock Exchange (1936) for details about the inner workings of the exchange during the 1930s.
[21] https://archive.org/details/0474_Nations_Market_Place_01_11_58_00

IV. Data and Variables

IV. A. Wall Street Journal Data on Earnings Announcements, and CRSP Coverage since 1934

I wish to generate a continuous dataset that contains all available earnings announcements, extending as far back in time as possible. Compustat coverage of earnings announcements does not begin until the second half of 1971, and its initial coverage is incomplete for the second half of 1971. Thus, I require another source for earnings announcement data prior to 1972.

I resolve this problem by hand-collecting earnings announcement data from the *Wall Street Journal* (WSJ) archives from 1934 through 1971, and combining this sample with Compustat data since 1972. In June 1930, the daily WSJ began publishing earnings figures released by firms on the previous day in a table with the heading, "Current Earnings Reports." I use the Proquest search engine to download these daily earnings reports for the period between June 1930 and December 1971, from the digital archive containing pdf files of the WSJ. This search yields fairly small samples for 1930 and 1931, but the coverage expands greatly in 1932. Since I require 8 quarters of data to compute the firm's earnings surprise (i.e., standardized unexpected earnings, or SUE), my final sample begins in 1934 and extends through 2018.

Figure III provides an example of this WSJ earnings report published on April 14, 1937. This example is indicative of the quality of the pdf files available, which varies considerably over the sample period, 1934 - 1971. In many cases, the Proquest search engine cannot detect the earnings report in the WSJ, even though the table heading and keywords match. Thus, I manually check each daily WSJ with a missing earnings report to ensure that my coverage is complete.

For each earnings announcement, my primary variables of interest from Figure III include the company name, earnings announcement date, period end date, net income for the current quarter, and corresponding net income from the same quarter in the previous year. In these WSJ earnings reports, losses are not recorded as negative numbers. Instead, a symbol beside the earnings number points to a footnote in each table, if that number represents a net loss. I check all footnotes in each earnings report to ensure that losses are recorded properly. In cases where I cannot read the company name or the reported earnings numbers due to low quality of the pdf files, I exclude these observations from my final sample of announcements.

I collect this information for all quarterly earnings announcements reported in the WSJ, and match these data with CRSP using the company name. On average, my sample from 1934 to 1971 covers 58% of the CRSP universe.[22] Table I compares the summary statistics for characteristics of the firms in this WSJ sample with the average firm in the CRSP universe during the same period. I present monthly time-series averages of the cross-sectional means across all firms in my sample. The average firm in my sample is slightly larger and more liquid than the average CRSP firm. This outcome is likely due to the WSJ not reporting earnings for the smallest companies.[23] The other attributes of the firms in my sample are similar to the typical CRSP stock, including share turnover, market beta, idiosyncratic volatility, and book-to-market.

IV. B. Descriptive Statistics and Control Variables

All variables are defined in Table II. I construct the standardized unexpected earnings surprise (SUE) measure as in Foster, Olsen, and Shevlin (1984), and sort the cross section of all announcing stocks into quintiles (0 to 4) each calendar quarter, based on SUE. Next, I divide this quintile rank by four to obtain the adjusted SUE rank (Adj_SUE), which ranges from 0 to 1. Note

[22] I compare the number of firms in my final sample, which consists of the subset of these announcements with non-missing data for all variables required for my analysis, with the analogous restricted sample from CRSP.
[23] Frazzini and Lamont (2007) point to this issue as the reason behind Compustat's low coverage of earnings announcements for small firms, since the WSJ is one of the main sources for Compustat earnings dates.

that a one-unit increase in Adj_SUE moves from the lowest SUE quintile to the highest SUE quintile, which is analogous to a hedge portfolio that compares these extreme portfolios.

Investors who had access to the WSJ at the time were able to compare the earnings performance of the announcing firm for the most recent quarter with the corresponding quarter from the previous year, as reported by the WSJ. According to Livnat and Mendenhall (2006), Compustat periodically updates their earnings data over time as firms restate their earnings. Thus, there is a discrepancy between the earnings data seen by investors and the Compustat data used in many recent studies, which might result in understating or inflating the magnitude of the market's response to earnings news. Since I analyze the numbers that were actually reported in the WSJ as they became available to investors, I overcome this potential bias.

I obtain daily stock return data from CRSP and exclude observations with a share price less than $1. To ensure the timeliness of the announcements in my sample, I delete announcements appearing more than 90 calendar days after the quarter-end date provided in the WSJ earnings report. I use historical book-to-market data from Kenneth French's library and complement these data with Compustat annual data after 1950.[24] The control variables for my main analysis include the adjusted rank of SUE, lagged SUE rank, firm size in month *t-1*, the number of earnings announcements on the same day (Hirshleifer, Lim, and Teoh, 2009), the most recent publicly available book-to-market ratio,[25] the compounded daily returns and standard deviation across returns over the previous two weeks (i.e. days *t-11* to *t-2*), average daily stock illiquidity over month *t-1*, average daily turnover between days *t-11* and *t-2*, and the firm's

[24] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[25] Book equity data in Kenneth French website are collected from Moody's Industrial Manuals, which were published every year in June. If the earnings announcement date is after June, then I divide the current year's book-equity with the previous month's firm size. If the announcement is on or before June, then I use the previous year's book-equity data and divide this by the previous month's firm size.

market beta estimated over months *t-36* to *t-1* (from regressions of the firm's monthly stock return on the CRSP value-weighted market return). I also obtain the size and book-to-market cut off values from Kenneth French's website.

In Table III, I provide summary statistics for the main variables during each decade from my complete dataset. The average firm size increases over time, from $70 million between 1934 and 1943, to $7.9 billion between 2014 and 2018. The average firm has a beta of 1.41 and SUE of 0.155 between 1934-1943, while the corresponding values are 1.13 and 0.172 for 2014-2018 period. The average share turnover over the ten days prior to the announcement is 0.10% for the first five decades, which subsequently increases to 0.8% for the most recent decades, while the average volatility varies less over time.

V. Portfolio Analysis: Earnings Announcement Returns for Quintiles based on SUE

My analysis begins with a portfolio approach. Every quarter, I sort the cross-section of stocks into quintiles based on the firm's standardized unexpected earnings (SUE). For each SUE quintile portfolio, I then calculate the cross-sectional mean cumulative abnormal returns (CARs) for various time frames around the earnings announcement. Next, I average these mean CARs across all quarters during each 10-year span over the sample period, 1934 – 2018, and report the average return on the hedge portfolio that is long the top SUE quintile and short the bottom quintile. The results are presented in Table IV, for each 10-year period. I focus on the returns measured over four time frames: the initial announcement return on days (0,+1), and three post-announcement time frames covering days (+2,+61), (+2,+120), and (+2,+180).[26]

[26] In the following analysis, I mainly focus on the drift that occurs over the next 60 days after the earnings announcement, since longer horizons may encompass the next quarterly announcement and confound my results.

In the four columns of Table IV, I document both a significant initial response to earnings news (CAR(0,+1)) and post-announcement drift (PEAD) during every decade of my extended sample period. The first column reveals a tilted U-shaped pattern in the initial response to earnings news (CAR(0,+1)) across these nine decades. This initial response is larger in magnitude during the early and late periods, and smallest during the middle periods. For example, in the first decade (1934-43), the mean CAR(0,+1) is 2.92%, before declining over subsequent periods to 2.21% in the middle decade (1974-83), and then increasing again toward 4.02% for the most recent years, 2014-2018.

The remaining columns in Table IV provide the analogous evidence for the average post-announcement drift (PEAD) over three different time frames following the earnings release on day 0. This evidence reveals an *inverted* U-shaped pattern for PEAD over time, which is smaller in magnitude during the early and late periods, and largest during the middle periods. The implications of this *inverted* U for PEAD over time are consistent with the U-shaped pattern for the initial announcement returns, CAR(0,+1), in the first column. Together, these four columns indicate that the stock market was *more efficient* during the *early and late* portions of my sample, and *less efficient* during the *middle* decades. That is, there was less underreaction to earnings news (i.e., a larger initial response, CAR(0,+1), and smaller PEAD, CAR(2,+61)) both early and late in my sample period, while there was greater underreaction (i.e., a smaller initial response and larger PEAD) in the middle of my sample. For example, the second column of Panel A reveals that the 60-day PEAD, CAR(+2,+61), is 1.80% during the first decade of the sample, 1934-1943. Then over time, the magnitude of this drift increases steadily until it reaches 5.00% during 1984-1993, before declining from this peak back toward 1.24% in the last five-year period, 2014-2018.

This evidence reveals a striking U-shaped pattern of evolution in the degree of market efficiency throughout my extended sample period, indicating that markets were more efficient at incorporating earnings news in the early and late years of the sample, and less efficient in the middle years. The recent trend toward increasing market efficiency over the last three decades (i.e., toward larger initial returns and smaller drift) is commonly explained by dramatic increases in information production and processing technology, as well as investor sophistication, along with declining market frictions.[27] In sharp contrast, the opposite trend toward declining market efficiency over the first few decades of the sample (i.e., toward smaller initial returns and larger drift), prior to Compustat, is surprising for two reasons.

First, the prevailing literature typically argues that the market's underreaction to earnings news is due to information uncertainty and trading frictions such as illiquidity, transaction costs, information processing costs, etc.[28] Therefore, any scholar attempting to examine the evolution of PEAD prior to the availability of Compustat data would naturally expect less efficient markets (i.e., a smaller initial response and larger drift) in the pre-Compustat era, when these market impediments were much more prevalent. However, surprisingly, the results documented here point to the opposite conclusion.

Second, McLean and Pontiff (2012) document a general decline in anomaly returns after investors learn about anomalies through academic publications. Thus, one would expect greater underreaction to earnings news (i.e., a smaller initial reaction and larger PEAD) in the pre-

[27] For recent studies of PEAD, see Yifan, Nekrasov, and Teoh (2020), He and Narayanamoorthy (2020), Beaver, McNichols and Wang (2020), Ali, Chen, Yao, and Yu (2020), Hirshleifer, Peng, and Wang (2019), Thomas, Zhang, and Zhu (2021), Li and Lytvynenko (2021), Meursault, Liang, Routledge, and Scanlon (2021). In addition, see Odean (1999), Barber and Odean (2000), Bartov (1992), Bartov, Krinsky, and Radhakrishnan (2000), Hirshleifer and Teoh (2003), Mendenhall (2004), Hirshleifer, Myers, Myers and Teoh (2008), Campbell, Ramadorai, and Schwartz (2009), Baker et al (2010), Ke and Ramalingegowda (2005), Taylor (2010), Ayers et al (2011), Hirshleifer, Lim, and Teoh (2009), DellaVigna and Pollet (2009), and Ng, Rusticus, and Verdi (2008).
[28] For example, see Chordia et. al. (2009) and Ng et al. (2008) for evidence regarding transaction costs, Bartov, Radhakrishnan, and Krinsky (2000) and Vega (2006) regarding investor sophistication.

Compustat period, before there was wide-spread knowledge of this anomaly. However, the lower underreaction documented here in the decades prior to Compustat is inconsistent with this learning argument as well.

I argue that the evidence of greater market efficiency during the pre-Compustat era is a result of the generally lower amount and complexity of information that was available to investors in the early years of the sample period. While the technology to process information was more limited prior to the 1970s, the amount and complexity of information that investors needed to process were also much lower. For example, there was much less firm-specific information disclosure required or rendered, and there were fewer alternative information sources available to investors. Consequently, the periodic release of earnings information likely took on even greater importance at the time, so that investors were even more likely to focus their limited attention to the information contained in the WSJ earnings report and, as a result, prices reflected the available information more quickly. Later, towards the 1970s, the amount and complexity of value-relevant information increased dramatically, while the technology for processing this explosion of information lagged, leaving investors with information overload. Subsequently, as advances in information technology evolved into the 1980s and beyond, the ability of investors to process information overcame the vast growth and complexity of this information, which helped to reverse the trend in evolution toward more efficient markets.

VI. Regression Analysis of Earnings Announcement Returns

This section estimates a pooled regression model to further examine the evolution in market efficiency over time. This model analyzes the determinants of SUE hedge portfolio returns following earnings announcements, within each decade between 1934 and 2018, while controlling for other potential determinants of investor's reaction to earnings news, as follows:

$$\begin{aligned} CAR(a,b)_{it} = \beta_0 &+ \beta_1 Adj\_SUE_{it} + \beta_2 Lagged\_SUE_{it-1} + \beta_3 \#Ann_{it} + \beta_4 Ret[-11,-2]_{it} \\ &+ \beta_5 BM_{it} + \beta_6 Beta_{it} + \beta_7 Size_{it} + \beta_8 IVOL_{it} + \beta_8 Turnover_{it} \\ &+ \beta_9 Illiq_{it} + \delta_d + \gamma_m + \nu_y + \varepsilon_{it}\,. \qquad (1) \end{aligned}$$

$CAR(a,b)_{it}$ measures the cumulative abnormal return over days *a* to *b* following the earnings announcement for firm *i* during quarter *t* (on day 0). I focus on two time frames, the initial 2-day reaction, CAR(0,+1), and the subsequent 60-day drift, CAR(+2,+61). All variables are defined in Table II. In all regression analysis, I include fixed effects for day, month, and year (δ_d, γ_m, and ν_y), and I adjust standard errors for heteroscedasticity and cluster by day of the announcement.

The key regression result from Equation (1) is the coefficient of the adjusted rank of SUE (Adj_SUE, β_1), which is analogous to the return on a hedge portfolio that is long the highest SUE quintile and short the lowest SUE quintile. To understand this result, note that the relation between the Adj_SUE and returns implied by this model is given by the partial derivative, $\frac{\partial CAR(a,b)_{i,t}}{\partial Adj\_SUE_{i,t}} = \beta_1$. This derivative shows that a one-unit increase in Adj_SUE, from 0 to 1 (which moves from the bottom to the top SUE decile), is associated with a "hedge portfolio" return ($CAR(a,b)_{it}$) of β_1 percent.

I estimate Equation (1) across all earnings announcements during each decade of the extended sample, and provide the results in Table V. Panel A presents the evidence for the initial announcement returns (CAR(0,+1)), while Panel B gives the analogous results for the post-announcement drift (CAR(+2,+61)). In the first row of Panel A, the evidence indicates a statistically significant SUE hedge portfolio return (β_1) across all nine decades of the sample period, after controlling for other firm attributes that have also been shown to predict returns. The magnitude of this initial reaction remains fairly stable during the pre-Compustat period (i.e., up to the 1980s), and then subsequently increases after the 1980s, indicating a stronger initial reaction to earnings news during the era since Compustat data are available.

Panel B of Table V similarly indicates significant post-announcement drift (CAR(+2,+61)) that reveals evolution over time similar to the behavior of PEAD in Figure I and Table IV. That is, while the coefficient of Adj_SUE (β_1) is statistically significant for all nine decades, the magnitude of this coefficient follows an inverted U-shaped pattern across decades. The implied hedge portfolio return (β_1) is 1.8% for the first decade (1934-43), but this drift increases monotonically over the first five decades of the sample, to 5.2% in the middle decades (1974-83 and 1984-93), before reversing back to 1.6% in the most recent period (2014-18). Together, these regression results corroborate the portfolio analysis in Figure I and Table IV, indicating more efficient pricing of earnings news during the early and late years in the sample.

VII. The Trend in Market Efficiency from 1934 to 2018

VII.A. Firm-Specific News

The above analysis documents a non-linear trend in the evolution of price efficiency over the past century, whereby the market's incorporation of earnings news consistently became less efficient over the first few decades, from the 1930s to the 1980s, before reversing to become more efficient in the last few decades since the 1980s. In this section, I further examine this non-linear trend in the evolution of market efficiency by using trend regression to analyze the entire sample of earnings announcements from 1934 to 2018. I accomplish this task by expanding Equation (1) to include a quarterly time trend, along with a trend-squared term, as well as their interactions with Adj_SUE, as follows:

$$\begin{aligned} CAR(a,b)_{it} = {} & \beta_0 + \beta_1 Adj\_SUE_{it} + \beta_2 Trend_{it} + \beta_3 Adj\_SUE_{it} \text{ x } Trend_{it} \\ & + \beta_4 Trend^2_{it} + \beta_5 Adj\_SUE_{it} \text{ x } Trend^2_{it} \end{aligned}$$

$$+ \beta_6 \text{Lagged\_SUE}_{it-1} + \beta_7 \#\text{Ann}_{it} + \beta_8 \text{Ret}[-11,-2]_{it} + \beta_9 \text{BM}_{it} + \beta_{10} \text{Beta}_{it}$$

$$+ \beta_{11} \text{Size}_{it} + \beta_{12} \text{IVOL}_{it} + \beta_{13} \text{Turnover}_{it} + \beta_{14} \text{Illiq}_{it} + \delta_d + \gamma_m + \nu_y + \varepsilon_{it}, \quad (2)$$

where Trend is a quarterly time trend.

Once again, the key variable of interest is the coefficient of Adj_SUE (β_1), which is analogous to the return on the SUE hedge portfolio, after controlling for other factors that may also predict returns. In this specification, the interaction between Adj_SUE and Trend^2 (i.e., β_5) accounts for a possible nonlinear trend in this hedge portfolio return (β_1). The U-shaped trend for the immediate response to earnings news (CAR(0,+1)), documented in Tables IV and V, implies a significant positive coefficient for the interaction term, (Adj_SUE x Trend^2), β_5. In contrast, the inverted U-shaped trend for PEAD (CAR(+2,+61)) points to a negative coefficient, β_5.

Table VI presents the results from estimating Equation (2). The left three columns provide the evidence for CAR(0,+1), while the right three columns share the evidence for CAR(+2,+61). In the first three columns of Table VI, the coefficient of the interaction term, Adj_SUE x Trend^2 (β_5) is positive and significant, which renders further support for the U-shaped trend in the market's initial reaction to earnings news (CAR(0,+1)), documented in Tables IV and V. In contrast, the last three columns of Table VI reveal a significant negative coefficient (β_5), which similarly supports the inverted U-shaped trend in the post-announcement drift (CAR(+2,+61)). Together, this evidence reinforces the finding of a nonlinear path indicating that the extended sample period begins with a relatively high degree of market efficiency, which deteriorates over the next few decades until the 1970s and 1980s, before reversing that trend to steadily become more efficient over the last half of the sample period.

VII.B. Market-Wide News

The evidence presented thus far establishes that the degree of market efficiency embodied in investors' response to firm-specific news follows a non-linear path throughout the extended sample period. In this section, I assess the analogous evolution of a broader aspect of market efficiency, reflected in the timing of the stock market's response to market-wide news. A potential concern regarding the evidence presented so far is that my hand-collected sample of early earnings announcements may not represent the entire stock market, since the *WSJ* does not provide exhaustive data on earnings announcements for all firms over this period. Furthermore, since I gather these earnings data from the *WSJ*, it is also possible that the announcements in my sample received relatively more attention from investors at the time, which could influence this evidence of higher efficiency during the early decades.

For these reasons, I consider an alternative measure of price efficiency that reflects more than just the market's response to earnings information. Following Hou and Moskowitz (2005), I construct a measure of the delay with which stock prices respond to market-wide information. Every calendar quarter, I estimate following two regressions for each firm in the CRSP universe:

$$R_{iT} = \beta_0 + \beta_1 R_{m,T} + \varepsilon_{iT}, \tag{3}$$

$$R_{iT} = \beta_0 + \beta_1 R_{m,T} + \beta_2 R_{m,T-1} + \beta_3 R_{m,T-2} + \beta_4 R_{m,T-3} + \beta_5 R_{m,T-4} + \varepsilon_{iT}, \tag{4}$$

where the dependent variable, R_{iT}, is the return of stock *i* on day T, while $R_{m,T}$ is the CRSP value-weighted market return on day T. The measure of price delay for firm *i* in quarter *t* is one minus the ratio of the R^2 measures from Equation (3) versus Equation (4). A higher measure of price delay indicates greater price delay, such that more of the total variation in the firm's daily stock return is explained by past daily market returns. I aggregate the resulting data on this firm-level price delay measure across all stocks every quarter, to obtain a measure of the market's aggregate price delay in responding to market-wide information (labeled Price_Delay).

Next, I analyze the concave nature of the evolution in this aggregate price delay measure over time, using a nonlinear time series trend regression, as follows:

$$\begin{aligned} \text{Price\_Delay}_t = \alpha_1 &+ \beta_1 \text{Trend}_t + \beta_2 \text{Trend}^2_t + \beta_3 \text{Aggregate\_Returns}_t \\ &+ \beta_4 \text{Aggregate\_Volatility}_t + \beta_5 \text{Aggregate\_Turnover}_t \\ &+ \beta_6 \text{Aggregate\_Illiquidity}_t + \beta_7 \text{Aggregate\_Disagreement}_t + \varepsilon_t, \quad (5) \end{aligned}$$

where the dependent variable is the quarterly cross-sectional average Price_Delay measure, and the control variables include several measures of aggregate stock market behavior. These measures include the cumulative monthly market return (Aggregate Return), daily market return volatility (Aggregate Volatility), the mean daily aggregate stock turnover (Aggregate Turnover), Amihud illiquidity (Aggregate Illiquidity), and the mean monthly stock return volatility (Aggregate Disagreement) averaged during *quarter t*.

Table VII presents the results from estimating Equation (5). The specification in the first column only includes the trend and trend-squared terms, while the second column includes the above controls. Once again, the results establish the concave nature of the evolution in market efficiency over time. In both columns, the trend is positive and significant while the trend-squared term is negative and significant, indicating an inverted U-shaped pattern whereby the market is more efficient (i.e., has a lower price delay) in both the early and late portions of the sample period, but less efficient (i.e., has a greater price delay) in the middle periods. I conclude that my main results throughout this paper are not an artifact of selection bias associated with my hand-collected sample of earnings announcements, but instead they are generalizable to broader aspects of price efficiency that apply to the entire stock market.

VIII. The Amount of Available Information for Large vs. Small Firms

It is conceivable that the information environment of different firms varies substantially in the cross-section, as well as over time. Indeed, the prevailing literature shows that the recent trend for the aggregate market to become more efficient over time is concentrated among larger firms (Farboodi, Veldkamp, and Venkateswaran, 2021). The main reason proposed for this behavior is that more information is available for large firms, so that as information processing capacity has increased over time, the prices of large firms have become more efficient relative to small firms. As a result, large firms have driven the recent trend toward greater aggregate efficiency observed in the past few decades.

Motivated by this observation, I argue that the difference in the amount and complexity of information across large versus small firms was more prevalent in the early years of the extended sample. Furthermore, over time, the amount and complexity of information available for large firms increase earlier and faster relative to that for small firms. Therefore, the U-shaped path of evolution in market efficiency, due to mismatches between the amount and complexity of information and the capacity to process that information, should be different for large versus small firms under bounded rationality.

Panel A of Figure IV plots the magnitude of PEAD (CAR[2,61]) over each decade for large versus small firms, separately. Every quarter, I group stocks into terciles based on firm size, and compute the average PEAD for subsets of stock in the upper and lower terciles of size across the 10-year periods between 1934 and 2018. Panel A shows that, while the evolution in investor underreaction (i.e., PEAD) follows an inverted U-shaped pattern across decades for both large and small firms, large firms consistently display less underreaction and greater efficiency than small firms for most decades. Furthermore, the peak in the evolution of investor underreaction appears earlier for large firms than for small firms, and subsequently declines faster. That is, large firms reach their peak of displaying the greatest inefficiency earlier, and subsequently become more efficient faster, relative to small firms. On the other hand, the analogous inefficiency for small firms takes longer to reach its peak, as the information environment for small firms improves later more slowly over time. This finding supports the view that differences in the information environment for large versus small firms has significantly affected the evolution of price efficiency for different firms in the cross-section.

In Panel B of Figure IV, I present the analogous results for the Hou and Moskowitz (2005) measure of price delay. In this analysis, every quarter I sort stocks into terciles based on market capitalization and compute the average Price_Delay for large firms (top tercile) and small firms (bottom tercile), separately. Similar to the results in Panel A, the delay in the price response to market-wide news exhibits an inverted U-shaped pattern over time, for both large and small firms. Moreover, large firms reveal a lower price delay than small firms for all decades, and large firms reach their peak delay earlier than small firms. Overall, the evidence in this section establishes the importance of the mismatch between the amount and complexity of information available and the capacity to process that information, when investors are subject to bounded rationality.

IX. The Speed of Adjustment and the Delayed Response to Earnings Announcements

The weaker PEAD and lower price delay during the early years of the sample appear contrary to the typical explanations for investor underreaction that are based on trading frictions, since these frictions were more prevalent during the early years. For example, according to the underreaction argument for PEAD, investors do not understand the implications of current earnings for future earnings and they update their views slowly as new information arrives. In this context, while the prevailing evidence on PEAD indicates that substantial drift begins immediately after the earnings release, Hirshleifer, Lim and Teoh (2009) argue that investors with bounded rationality should update their beliefs only later, with a significant delay, when substantive new information eventually arrives near the firm's next earnings announcement.

In this section, I further explore this underreaction argument behind the delayed response to earnings news, by analyzing how the structure of price delay embodied in PEAD has evolved over time. Since Ball and Brown (1968), investors have known about PEAD. Thus, it is difficult to discern whether the recent evidence for PEAD based on data since the 1970s indicates that investors simply adjust slowly to the earnings news on day 0, or instead, perhaps investors only respond later to new information about persistent earnings that eventually arrives near the next announcement. An advantage of my extended sample is that I can explore the existence, nature, and structure of PEAD prior to the 1970s, to explore whether the post-announcement drift begins to accumulate immediately after the earnings release (on day +2), or after a substantial delay.

Table VIII provides evidence regarding evolution in the speed of price adjustment to earnings news, for each 10-year period over the extended sample. In particular, this table reports the proportion of the total cumulative 62-day market response to earnings news (CAR[0,+61]) that occurs over three different time frames around the earnings announcement: (i) the initial 2-day response, CAR[0,+1], (ii) the subsequent one-month drift, CAR[+2,+21], and the entire subsequent three-month drift, CAR[+2,+61]. These three proportions take into account the magnitude of the total market response to earnings news, and thus reveal a clearer picture of the changing dynamics over time, regarding whether post-announcement drift commences immediately following the earnings release (i.e., on day +2), or only later, as the next earnings announcement approaches.

First, consider the top row of Table VIII, which provides the proportion of the total 62-day return realized immediately (i.e., CAR[0,+1] / CAR[0,+61]). This evidence once again indicates a U-shaped pattern over time in the market's initial response to earnings news, which is higher during the early and later decades of the sample period, and lowest during the middle years. Specifically, while 61.84% of the total 62-day announcement return is realized on days 0 and +1 in the first decade, 1934-1943, this proportion declines monotonically to 30.92% of returns in 1984-1993, before increasing back toward 76.44% in the last 5-year period. At the same time, the third row of Table VIII shows that the 60-day drift (CAR[+2,+61]) is 38.16% of the total 62-day announcement return in the first decade, and this proportion increases to 69.08% between 1984-1993, before declining back toward 23.56% in the most recent period. These complimentary shifting proportions of the immediate response, CAR[0,+1], versus the PEAD, CAR[+2,+61] once again reveals the U-shaped pattern in the degree of efficiency over time.

Next, I provide novel evidence supporting the underreaction argument as an explanation for PEAD during the pre-Compustat era, prior to the 1970s. The second row of Table VIII shows the proportion of total returns realized over the first month following the earnings announcement, across all 10-year periods during the extended sample. The percentage of the total announcement return realized during the first month (CAR[+2,+21] / CAR[0,+61]) increases steadily across most of the extended sample. In particular, while just 3.93% of the total 61-day PEAD occurs during the first month between 1934 and 1943, this proportion increases to roughly 20% over the last few decades.[29] This evidence further illuminates support for the underreaction argument.

[29] Figure A.I and A.II in Appendix A provide the evolution of the 60-day PEAD and the cumulative abnormal returns for each SUE quintile portfolio, for every 10-year period between 1934 and 2018. These graphs also reveal that, during the first half of the sample, there is little drift over the first month following the announcement, and the subsequent drift is concentrated later, just before the next earnings announcement when new information arrives.

X. Evolution in the Relative Importance of Earnings Announcements over Time

My analysis so far documents strong evidence of a U-shaped pattern in the evolution of market efficiency over the past century. Next, I explore the economic mechanism behind this surprisingly high degree of market efficiency for the early years, or in other words, the remarkably large inefficiency over the middle years. I propose an 'early earnings attention hypothesis,' which conjectures that the greater efficiency in the pricing of earnings news prior to the 1970s, documented above, likely reflects an early environment in which investors paid greater attention to earnings announcements. At the time, the amount and complexity of other types of information were relatively scarce, so investors were forced to rely more on earnings news to make their trading decisions. Moreover, due to the lack of other information sources, earnings announcements were richer in terms of relative information content during the early decades.

X.A. Evolution in the Average Abnormal Volume around Earnings Announcements

The existing literature commonly relies on abnormal trading volume around the earnings release to proxy for the heightened investor attention paid to earnings announcements.[30] In this section, I examine how the degree of investor attention placed on earnings news has evolved over time, by plotting the average abnormal volume on the two days around earnings announcements, for every decade of the extended sample period.

Panel A of Figure V provides evidence regarding evolution in the average abnormal volume that occurs on the two days around earnings announcements (AVOL[0,+1]), for subsets of stocks with a large earnings surprise, across the 10-year periods between 1934 and 2018. Abnormal trading volume on days 0 and +1 is defined as the difference between the log dollar

[30] For example, see Frazzini and Lamont (2007), Barber and Odean (2008), DellaVigna and Pollet (2009), Yuan (2015), and Chapman (2018).

volume for each stock and its average log dollar volume over days -60 to -11 prior to the earnings announcement. Every quarter, I compute the mean AVOL[0,1] for all stocks that appear in either the top or bottom quintile portfolios ***based on SUE***. (i.e., stocks with a large earnings surprise). Then I compute the average of these AVOLs across all quarters within each decade of the sample period, and plot this average AVOL[0,+1] for every decade.

Panel A of Figure V indicates that the amount of investor attention devoted to earnings news (proxied by average AVOL[0,+1]), follows a U-shaped pattern similar to those appearing in other contexts, in Figures I and IV. Here, the mean abnormal volume is largest in the first decade of my sample between 1934 and 1943, and subsequently declines over the next three decades. This result is consistent with the early earnings attention hypothesis, in which I conjecture that investors focused relatively more attention on earnings announcements during the early portion of my sample.

In Panel A of Figure V, it is noteworthy that this early focus on earnings news (i.e., AVOL[0,+1]) declines across the first four decades of the sample, as disclosure regulation expands so that the sources and amount of information other than earnings announcements become more widely available. Then, beginning in the middle decade, 1974-1983, AVOL[0,+1] increases again over the next few decades as the market becomes more accessible to investors, while major advances appeared in information processing technology, along with the growing availability and complexity of information. I further note that the mean quarterly AVOL[0,+1] has increased in recent decades, presumably due to fewer impediments to stock market participation, until it is comparable to that during the first two decades of the sample.

X.B. Evolution in the Initial versus Total Market Reaction to Earnings Announcements

Next, I examine additional implications of the early earnings attention hypothesis, by analyzing how the immediate versus delayed response to earnings news has evolved since the 1930s, for subsets of stocks with either low or high attention paid to the earnings release. Each quarter, I first sort the cross-section of earnings announcements into terciles based on my proxy for investor attention focused on the earnings release, AVOL[0,+1]. For the stocks subject to either low or high investor attention (i.e., the bottom or top tercile by AVOL[0,+1]), I then compute the mean SUE hedge portfolio returns across decades over two periods: days 0 and +1 (CAR[0,+1]), and days 0 through +61 (CAR[0,+61]). Finally, for these two subsets of high attention stocks, I calculate the mean ratio of the initial 2-day announcement return to the total return, CAR[0,+1] / CAR[0,+61], and report this mean ratio for every decade of the sample.

Panel B of Figure V plots the resulting mean ratio of returns, CAR[0,+1] / CAR[0,+61], for the two subsets of stocks in either the top or bottom tercile by AVOL[0,+1], for every decade of the sample. The **blue** bars present the ratio, CAR[0,+1] / CAR[0,+61], for stocks subject to high investor attention (i.e., with high AVOL), while the **orange** bars provide the analogous results for stocks subject to low attention (i.e., with low AVOL).

First, consider the evidence for the subset of stocks subject to high attention around the earnings release (i.e., the **blue** bars in Panel B of Figure V). This plot indicates a U-shaped pattern in this mean ratio over time, which indicates that the subset of high attention stocks displays a larger proportion of the total 62-day announcement return that is realized immediately on days 0 and +1, during both the early and late decades of the sample. In contrast, the middle decades of the sample reveal less efficient markets, in the form of a smaller initial reaction to earnings news relative to total announcement returns, for stocks subject to high attention.

Once again, this evidence in the **blue** bars from Panel B of Figure V indicates that, among firms with high AVOL[0,+1], more efficient pricing of earnings news (i.e., higher initial reaction versus lower drift) is concentrated in the early and late decades of the sample. Furthermore, in all decades up until the most recent five year period, stocks in the high AVOL tercile (i.e., the **blue** bars) realize a higher proportion of total 62-day announcement returns immediately, relative to stocks in the low AVOL tercile (i.e., the **blue** bars are above the **orange** bars). For example, between 1934-1943, almost 80% of total announcement returns are realized immediately for high AVOL stocks, while this proportion is around 20% for low AVOL stocks.

This discussion draws us to the evidence for the alternative subset of stocks subject to low investor attention around the earnings release (i.e., the **orange** bars in Panel B of Figure V). This plot indicates that, for low attention stocks, the initial 2-day reaction comprises less than 30 percent of the total 62-day announcement return for most of the sample period, up to the new millennium. Only in the most recent 5-year period, 2014-18, does the initial 2-day reaction to earnings news for low attention stocks (the **orange** bars) rise to a similar level to that for high attention stocks (the **blue** bars). This evidence indicates that, for most of the sample period, there is less efficient pricing around earnings announcements (i.e., a smaller initial reaction relative to post-announcement drift) for stocks that are subject to low attention. Altogether, the evidence in Figure V is consistent with the early earnings attention hypothesis, which argues that the greater efficiency in the pricing of earnings news prior to the 1970s reflects an early environment in which investors paid greater attention to earnings announcements, compared to recent times.

X.C. Evolution in the Information Content of Earnings Announcements

Another related aspect of the higher market efficiency around earnings announcements that I document during the early portion of the sample is the relatively large proportion of all firm-specific information that was contained in earnings announcements at the time. According to the 'early earnings attention hypothesis,' prior to the 1970s, earnings information accounted for most of the value-relevant information accessible to investors. Over the decades, new regulations compelling greater and more timely corporate disclosure have led to the proliferation of additional sources of firm-specific information, including 10Ks, 9Ks, 8Ks, 10Qs, etc.

In this historical light, I suggest that the relative amount of new information released by companies through earnings announcements was significantly greater during the early portion of the sample period. Ball and Shivakumar (2008) quantify the relative amount of new information provided through earnings announcements, using the R^2 in a regression of stock returns on earnings announcement returns. In this section, I employ their measure to document the evolution in the relative amount of new information provided to investors through earnings announcements, over the sample period.[31] Every calendar quarter, I estimate the following model:

$$R_{iq} = \beta_0 + \beta_1 CAR[0,1]_{iq} + \varepsilon_{iq}, \tag{6}$$

where the dependent variable, R_{iq}, is the cumulative monthly return for stock *i* over the three months during quarter *q*, while $CAR[0,1]_{iq}$ is the initial 2-day earnings announcement return for firm *i* in quarter *q*. Ball and Shivakumar (2008) propose that the R^2 from a quarterly regression such as Equation (6) measures the information content of the earnings announcement during each quarter (which I label as $Information\_Content_q$). Next, I relate this R^2 measure to a time trend, the trend squared, and other control variables calculated over the same quarter, as follows:

[31] Ball and Shivakumar (2008) regress annual returns on four quarterly earnings announcement returns, CAR(0,+1)s, realized during the year. I lose a significant portion of my observations in the early years of my sample when I require four earnings returns during the year. Therefore, I regress quarterly returns on the announcement returns realized during the same quarter to obtain a modified version of their information content measure.

$$\text{Information\_Content}_q = \alpha_1 + \beta_1 \text{Trend}_q + \beta_2 \text{Trend}^2_q + \beta_3 \text{Aggregate\_Returns}_q$$
$$+ \beta_4 \text{Aggregate\_Volatility}_q + \beta_5 \text{Aggregate\_Turnover}_q$$
$$+ \beta_6 \text{Aggregate\_Illiquidity}_q + \beta_7 \text{Aggregare\_Disagreement}_q + \varepsilon_q, \quad (7)$$

where the dependent variable is the quarterly average Information_Content measure, and the control variables include several measures of aggregate stock market behavior as defined in Equation (5).

The results from estimating Equation (7) are presented in Table IX. The specification in the first column of Table IX only includes the trend and trend squared trend terms, while the second column also includes controls for various aggregate stock market conditions. In both columns, the coefficient of the trend is negative and significant, while that of the trend squared term is positive and significant. These results establish the convex nature of the information content of earnings announcements over the extended sample period, showing that this measure of information content was greater during both the early and late parts of the sample.

On the one hand, the higher information content of earnings news (i.e., a higher quarterly R^2 from Equation (6)) during the early periods suggests that a relatively high proportion of all firm-specific information that was accessible to investors at the time appeared in earnings announcements. Over time, as additional sources of information became available, the market's initial announcement return ($CAR[0,+1]_{iq}$) lost some of its explanatory power, until the middle of the sample period.

On the other hand, the subsequent return toward a higher information content of earnings news in the latter periods is consistent with the evolution in regulations toward requiring more timely corporate disclosure of more information (such as Reg FD).[32] Combined with Figure V,

[32] See Figure III in Appendix A for a timeline delineating changes in the regulation of corporate disclosure.

the evidence in Table IX offers more insights into the potential drivers of the greater efficiency in the pricing of earnings news both before and after the 1970s. This evidence renders more support for the early earnings attention hypothesis, suggesting that earnings announcements played a relatively more important role as an information source early in the sample period, as investors paid more attention to earnings announcements at the time.

XI. Conclusion

I analyze the evolution of market efficiency over the past century by combining a novel hand-collected sample of earnings announcements published in the *Wall Street Journal* between 1934 and 1971, with Compustat data on earnings announcements since 1972. Surprisingly, I show that the market is more efficient (i.e., prices reflect firm-specific and market-wide news with less delay) during both the early and late parts of the sample, but less efficient in the 1970s and 1980s. I argue that this U-shaped pattern in the evolution of market efficiency over time reflects the changing dynamics between the amount and complexity of information and the capacity to process this information.

My analysis uncovers two potential dynamic mechanisms behind the U-shaped pattern of market efficiency over the past century. First, I argue that investors with bounded rationality had few information sources other than earnings announcements in the early years, which increased the attention and resources dedicated to processing the information released through earnings announcements. As a result, the higher relative importance of earnings announcements at the time contributed to more efficient prices.

Second, during the early years, earnings announcements played a relatively more important role in the firms' disclosure of value-relevant information to the public. The lack of other information venues increased the relative information content of earnings announcements at the time, which resulted in more timely adjustment of prices to earnings news. Combined with the increased attention paid by investors to earnings announcements, markets were more efficient during the early periods. However, over time, the increasing amount and complexity of information available to investors were not accompanied by concomitant technological progress in information processing until the 1980s. As a result, following the early decades of the extended sample, investors with limited resources and processing capacity couldn't keep up with the vast amount of information, and markets became less efficient until the late 1970s, after which prices became more efficient again.

In addition, I document a major structural shift in the nature of PEAD during the early periods, compared with more recent times. Most prior studies of PEAD analyze recent Compustat data on earnings announcements since the 1970s, and find that substantial post-announcement drift begins to accumulate immediately during the first month after the earnings release. However, the earlier years in my extended sample reveal a substantial delay before this drift begins, indicating no substantial drift over the first month following the earnings release, after which prices finally begin to adjust more rapidly as the next quarterly announcement approaches. This finding provides strong support for an explanation behind PEAD based on investor underreaction. In the early years of this extended sample period, investors were not yet aware of academic work that eventually documented the implications of current earnings for future earnings and stock prices. As a result, prior to the 1970s, substantial post-announcement drift did not begin accumulating until later in the quarter, when new information about the firm's subsequent earnings likely began to arrive.

My findings have important implications for future dynamic behavior of price efficiency in financial markets. This evidence suggests that markets may not necessarily continue their recent trend toward consistently becoming more efficient over time. My surprising results for the early decades over the past century emphasize the importance of studying longer time series that involve several evolutionary phases of the information environment in financial markets. With the ever-increasing amount and complexity of data available to investors, the prospects for potential information overload become a critical phenomenon that should capture the attention of scholars interested in market efficiency. The continually evolving amount and complexity of information and its implications for price efficiency also represent an important concern for regulators that compel disclosure of such information, and regulate the form of such disclosure. Recent initiatives by the SEC to simplify and clarify disclosure demonstrates the attention paid by regulators to this critical issue.[33]

[33] SEC issued a rule regarding "Disclosure Update and Simplification" effective November 15, 2018. The rule can be found here: https://www.sec.gov/rules/final/2018/33-10532.pdf

References

Abarbanell, J., and Bernard, V. (1992). Tests of Analysts' Overreaction/Underreaction to Earnings Information as an Explanation for Anomalous Stock Price Behavior. *The Journal of Finance*, 47(3), 1181-1207.

Adrian, T., Etula, E., and Muir, T. (2014). Financial Intermediaries and the Cross-Section of Asset Returns. *The Journal of Finance*, 69(6), 2557-2596.

Akbas, F. (2016). The Calm before the Storm. *The Journal of Finance*, 71(1), 225-266.

Amihud, Y., (2002). Illiquidity and Stock Returns: Cross-Section and Time-Series Effects. *Journal of Financial Markets* 5: 31–56.

Ashiq, A., Xuanjuan, C., Tong, Y. and Tong, Y. (2020). "Can Mutual Funds Profit from Post Earnings Announcement Drift? The Role of Competition." *Journal of Banking & Finance* 114: 105774. Web.

Ayers, B. C., Li, O. Z., and Yeung, P. E. (2011). Investor trading and the post-earnings-announcement drift.(Report). *Accounting Review*, 86(2), 385-416.

Bagnoli, M., Levin, S., and Watts, S. G. (2005). Analyst estimate revisions clusters and corporate events, Part I. *Annals of Finance* 1, 245-265.

Bai, J., Philippon, T. and Savov, A. (2016): "Have Financial Markets Become More Informative?," Journal of Financial Economics, 122 35), 625–654.

Baker, S., Bloom N., and Davis S. J. (2019). What triggers stock market jumps? Working paper.

Baker, M., and Wurgler, J. (2006). Investor sentiment and the cross section of stock returns. *Journal of Finance* 61 (No. 4), 1645-1680.

Baker, M., Litov, L., Wachter, J., and Wurgler, J. (2010). Can Mutual Fund Managers Pick Stocks? Evidence from Their Trades Prior to Earnings Announcements. *Journal of Financial and Quantitative Analysis*, 45(5), 1111-1131.

Baldauf, M. and Mollner, J. (2020) High-Frequency Trading and Market Performance. The Journal of Finance. 75.3: 1495-526. Web.

Ball, R., and Brown P. (1968). An empirical evaluation of accounting income numbers. Journal of *Accounting Research* 6 (No. 2), 159-178.

Ball, R., and Shivakumar, L. (2008). "How Much New Information Is There in Earnings?" Journal of Accounting Research 46.5: 975-1016. Web.

Ball, R., Kothari S. P., and Watts, R. L. (1993). Economic determinants of the relation between earnings changes and stock returns. *The Accounting Review* 68 (No. 3), 622-638.

Barber, B., and Odean, T. (2000). Trading Is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors. *The Journal of Finance*, 55(2), 773-806.

Barber, B. M., and Odean, T. (2008). "All That Glitters: The Effect of Attention and News on the Buying Behavior of Individual and Institutional Investors." *The Review of Financial Studies* 21.2 (2008): 785-818. Web.

Barberis, N., Shleifer, A., and Vishny, R. (1998). A model of investor sentiment, *Journal of Financial Economics* 49, 307–43.

Barinov, A., Shawn S. P., and Celim Y. (2016). Firm Complexity and Post Earnings Announcement Drift, Working paper.

Bartov, E., Radhakrishnan, S., and Krinsky, I. (2000). Investor sophistication and patterns in stock returns after earnings announcements. *The Accounting Review*, 75(1), 43-63.

Bartov, E. (1992). Patterns in Unexpected Earnings as an Explanation for Post-Announcement Drift. *The Accounting Review*, 67(3), 610-622.

Beggs, W. and Brogaard, J. and Hill-Kleespie, A. (2021). Quantitative Investing and Market Instability. Available at SSRN: https://ssrn.com/abstract=3281447.

Benston, G. (1973). Required disclosure and the stock market: An evaluation of the Securities Exchange Act of 1934. *American Economic Review* 63 (No. 1), 132-155.

__________. (1969). The value of the SEC's accounting disclosure requirements. *The Accounting Review* 44 (3), 515-32.

Berkman, H., V. Dimitrov, P. C. Jain, P. D. Koch, and S. Tice. (2009). Sell on the news: Differences of opinion, short sales constraints, and returns around earnings announcements, *Journal of Financial Economics* 92, 376–399.

Bernard, V. and Thomas, J. (1989). Post-earnings announcement drift: Delayed price response or risk premium? *Journal of Accounting Research* 27 (No. 1), 1-36.

__________. (1990). Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics* 13 (December), 305-340.

Blume, M. E., Crockett J., and Friend, I. (1974). Stockownership in the United States: Characteristics and Trends. Survey of Current Business (November 1974), 16-40.

Brunnermeier, M. K., and Oehmke, M. (2009). Complexity in Financial Markets. N. pag. Print.

Campbell, J. Y., Ramadorai, T. and Schwartz, A. (2009). Caught on tape: Institutional trading, stock returns, and earnings announcements. *Journal of Financial Economics* 92: 66–91.

Chen, S., Defond, M., and Park, C. (2002). Voluntary disclosure of balance sheet information in quarterly earnings announcements. *Journal of Accounting and Economics* 33 (No. 2), 229-251.

Chordia, T., Goyal, A., Sadka, G., Sadka, R., and Shivakumar, L. "Liquidity and the Post-Earnings-Announcement Drift." Financial Analysts Journal 65.4 (2009): 18-32. Web.

Chordia, T., Subrahmanyam, A., and Tong, Q. (2014). Have capital market anomalies attenuated in the recent era of high liquidity and trading activity? *Journal of Accounting and Economics*, 58(1), 41-58.

Daniel, K., Hirshleifer D., and Subrahmanyam, A. (1998). Investor psychology and security market under- and over-reactions, *Journal of Finance* 53, 1839–85.

Easterwood, J. C., and Nutt, S. R. (1999). Inefficiency in analysts' earnings forecasts: Systematic misreaction or systematic optimism? *Journal of Finance* 54 (5), 1777-1797.

Farboodi, M., and Veldkamp, L. (2020). Long-Run Growth of Financial Data Technology. The American Economic Review 110.8 (2020): 2485-523. Web.

Farboodi, M., Matray, A., Veldkamp, L., and Venkateswaran, V. (2021). Where Has All the Data Gone? Conditionally Accepted at Review of Financial Studies.

Foster, G., Olsen, C. and Shevlin. T. (1984). Earnings releases, anomalies, and the behavior of security returns. *The Accounting Review* 59 (No. 4), 574-603.

Frazzini, A., and Lamont, O. (2007). The earnings announcement premium and trading volume, NBER Working paper 13090.

Gilovich, T., Griffin, D., and Kahneman, D. (Eds.). (2002). Heuristics and biases: The psychology of intuitive judgment. Cambridge, UK: Cambridge University Press.

Garfinkel, J. A., and Sokobin, J. (2006). Volume, opinion divergence, and returns: A study of post-earnings announcement drift. *Journal of Accounting Research*, 44(1), 85-112.

Grinblatt, M., & Han, B. (2005). Prospect theory, mental accounting, and momentum. *Journal of Financial Economics*, 78(2), 311-339.

Gurun, Umit G., & Coskun, Ali. (2012). Do funds follow post-earnings announcement drift? *Journal of Derivatives & Hedge Funds* 18 (No. 3), 236-253.

Harvey, C. R., Liu, Y., Zhu, H. (2016) … and the Cross-Section of Expected Returns, *The Review of Financial Studies*, Volume 29, Issue 1, January 2016, Pages 5–68, https://doi.org/10.1093/rfs/hhv059

Hirshleifer, D., Lim, S. and Teoh, S. H. (2009). Driven to distraction: Extraneous events and underreaction to earnings news. *Journal of Finance* 64 (No. 5), 2289-2325.

__________. (2011). Limited investor attention and stock market misreactions to accounting information. *Review of Asset Pricing Studies* 1 (No. 1), 35-73.

Hirshleifer, D., Myers, J. N., Myers, L. A., and Teoh, S. H. (2008). Do Individual Investors Cause Post-Earnings Announcement Drift? Direct Evidence from Personal Trades. *The Accounting Review*, 83(6), 1521-1550.

Hirshleifer, D., and Sheng, J. (2019). The attention trigger effect: Macro news and efficient processing of micro news. (September 4, 2019). Available at SSRN: https://ssrn.com/abstract=2890864 or http://dx.doi.org/10.2139/ssrn.2890864.

Hirshleifer, D., and Teoh, S. H. (2003). Limited investor attention and stock market misreactions to accounting information. *Review of Asset Pricing Studies* 1 (No. 1), 35-73.

Hong, H., and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets, *Journal of Finance*, vol. 54(6), pages 2143-2184, December.

Hou, K., and Moskowitz, T. J. (2005). "Market Frictions, Price Delay, and the Cross-Section of Expected Returns." The Review of Financial Studies 18.3 (2005): 981-1020. Web.

Hou, K., Xue, C., Zhang, L. (2015). Digesting Anomalies: An Investment Approach, *The Review of Financial Studies*, Volume 28, Issue 3, March 2015, Pages 650–705, https://doi.org/10.1093/rfs/hhu068

Ivkovic, Z., and Jegadeesh, N. (2004). The timing and value of forecast and recommendation revisions. *Journal of Financial Economics* 73 (3), 433-463.

Karmel, R. S. (2001). The future of corporate governance listing requirements. *SMU Law Review* 54 (No. 1), 356.

Ke, B., & Ramalingegowda, S. (2005). Do institutional investors exploit the post-earnings announcement drift? *Journal of Accounting and Economics*, 39(1), 25-53.

Kross, W. (1981). Earnings and announcement time lags. *Journal of Business Research* 9 (No. 3), 267-281.

Li, Y., Nekrasov, A., and Teoh, S. H. (2020). "Opportunity Knocks but Once: Delayed Disclosure of Financial Items in Earnings Announcements and Neglect of Earnings News." Review of Accounting Studies 25.1: 159-200. Web.

Li, Z. & Lytvynenko, I. P. (2021). "Currency fluctuations and the post-earnings announcement drift," Finance Research Letters, Elsevier, vol. 40(C).

Linnainmaa, J. T., and Roberts, M. R. (2018). The History of the Cross-Section of Stock Returns. *The Review of Financial Studies*, 31(7), 2606-2649.

Lev, B., and Ohlson, J. A. (1982). "Market-Based Empirical Research in Accounting: A Review, Interpretation, and Extension." Journal of Accounting Research 20: 249-322. Web.

Livnat, J., and Mendenhall, R. R. (2006). Comparing the post-earnings-announcement drift for surprises calculated from analyst and time series forecasts. *Journal of Accounting Research* 44 (1), 177–205.

Livnat J. and C. Petrovits. (2009). Investor sentiment, post-earnings announcement drift, and accruals, Working Paper.

Mahoney, P. G. (1997). The Exchange as Regulator. *Virginia Law Review* 83, 1453.

Martin, I., and Nagel, S. (2021) Market efficiency in the age of big data. Journal of Financial Economics. Forthcoming.

Mclean, R. D., and Pontiff, J. (2016). Does academic research destroy stock return predictability? *Journal of Finance* 71 (No. 1), 5-31.

Mendenhall, R. R. (2004). "Arbitrage Risk and Post-Earnings-Announcement-Drift." *Journal of Business* 77: 875-94.

Menkveld, A. and Yueshen, B. Z. (2019). The Flash Crash: A Cautionary Tale About Highly Fragmented Markets. *Management Science*, vol. 65, issue 10, 4470-4488.

Meursault, V. and Liang, P. J., Routledge, B. R., and Scanlon, M. PEAD.txt: Post-Earnings-Announcement Drift Using Text (April 9, 2021). Available at SSRN: https://ssrn.com/abstract=3778798 or http://dx.doi.org/10.2139/ssrn.3778798

Mian, G., & Sankaraguruswamy, S. (2012). Investor sentiment and stock market response to earnings news. *Accounting Review*, 87(4), 1357-1384.

New York Stock Exchange. (1936). New York Stock Exchange: Its functions and operations. Committee on Public Relations, New York Stock Exchange.

Ng, J., Tjomme O. R., Rodrigo S. V. (2008). Implications of transaction costs for the post-earnings announcement drift. *Journal of Accounting Research* 46 (No. 3), 661-696.

Odean, T., (1999). Do investors trade too much? *American Economic Review* 89 (No. 5, December), 1279-1298.

Patton, A., and Verardo, M. (2012). Does Beta Move with News? Firm-Specific Information Flows and Learning about Profitability. *The Review of Financial Studies,* 25(9), 2789-2839.

Reilly, K. S. (2004). Corporate stories: 'Fortune' magazine and modern managerial culture. Doctoral Dissertations, available from Proquest.

Rytchkov, O. (2014). Asset Pricing with Dynamic Margin Constraints. *The Journal of Finance,* 69(1), 405-452.

Santa-Clara, P., and Saretto, A. (2009). Option strategies: Good deals and margin calls. *Journal of Financial Markets,* 12(3), 391-417.

Sadka, R. (2006). Momentum and post-earnings-announcement drift anomalies: The role of liquidity risk. *Journal of Financial Economics* 80, 309-349.

Simon, C. J. (1989). The Effect of the 1933 Securities Act on Investor Information and the Performance of New Issues. *The American Economic Review*. Jun., 1989, Vol. 79, No. 3 (Jun., 1989), pp. 295- 318

Simon, H. A. (1982). Models of bounded rationality. Cambridge, MA: MIT Press.

Sobel, R. (1968). The Big Board: A history of the New York stock market / by Robert Sobel. Foreword by Broadus Mitchell. New York: Free Press.

Stickel, S. E. (1989). The timing of and incentives for annual earnings forecasts near interim earnings announcements. *Journal of Accounting and Economics* 11 (2), 275-292.

Shuoyuan, H. and Narayanamoorthy, G. (2020) "Earnings Acceleration and Stock Returns." Journal of Accounting & Economics 69.1: 101238. Web.

Taylor, D. (2010). Individual investors and corporate earnings. Working paper

Tetlock, P. (2007). Giving Content to Investor Sentiment: The role of media in the Stock Market. *Journal of Finance* 62 (No. 3), 1139-1168.

Watts, R. (1978). Systematic 'abnormal' returns after quarterly earnings announcements. *Journal of Financial Economics, 6* (2), 127-150.

Weller, B. M. (2018). Does Algorithmic Trading Reduce Information Acquisition?, The Review of Financial Studies, Volume 31-6.

William, B. H., McNichols, M. F., and Wang, Z. Z. (2020) "Increased Market Response to Earnings Announcements in the 21st Century: An Empirical Investigation." Journal of Accounting & Economics 69.1: 101244. Web.

You, H., and Zhang, X. (2009). Financial reporting complexity and investor underreaction to 10-K information. Rev Account Stud 14, 559–586. https://doi.org/10.1007/s11142-008-9083-2

Zarb, F., and Kerekes, G. (1970). The stock market handbook; reference manual for the securities industry. Edited by Frank G. Zarb and Gabriel T. Kerekes. Assisted by Lynne Craft and John Johnsrud. Homewood, Ill.: Dow Jones-Irwin.

Zhang, Q., Cai, C. X., and Keasey, K. (2012) "Market Reaction to Earnings News: A Unified Test of Information Risk and Transaction Costs." Journal of Accounting & Economics 56.2-3: 251-66. Web.

Zhang, X. F. (2006). Information Uncertainty and Stock Returns. *Journal of Finance*, 61(1), 105-137.

Zhang, Y. (2008). Analyst responsiveness and the post-earnings-announcement drift. *Journal of Accounting and Economics* 46 (1), 201-215.

Zolotoy, L. (2011). Earnings news and market risk: Is the magnitude of the post-earnings announcement drift underestimated? *Journal of Financial Research* 34 (No. 3), 523-535.

Figure I. Price Delay to Firm-Specific and Market-wide News from 1934 to 2018

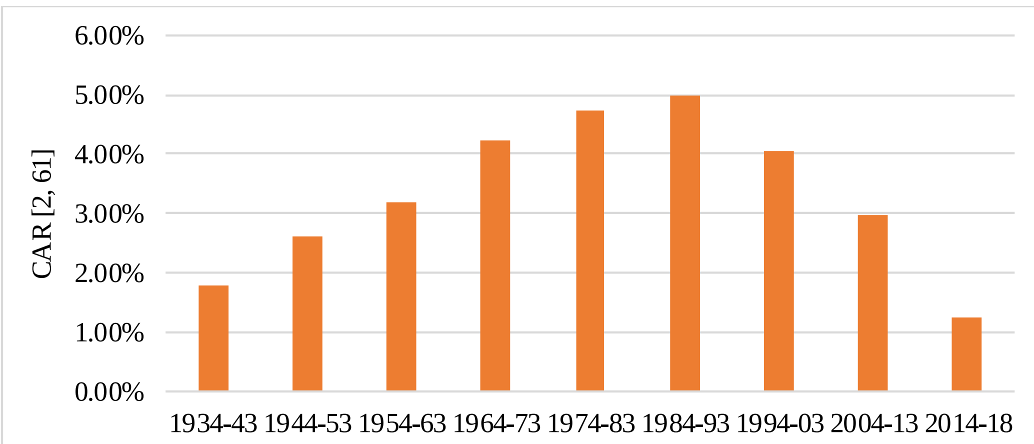
Panel A compares the mean cumulative abnormal returns (CARs) for the high minus low SUE quintile hedge portfolio measured over two time frames around earnings announcements, covering days (2, 61) averaged over each decade from 1934 to 2018. SUE is based on the definition of Foster, Olsen and Shevlin (1984): SUE = $(EPS_{i,q} - EPS_{i,q-4}) / \sigma_{q-8,q-1}$ where $EPS_{i,q}$ and $EPS_{i,q-4}$ are firm *i*'s earnings per share in quarters *q* and *q-4*, and $\sigma_{q-8,q-1}$ is the standard deviation of $EPS_{i,q} - EPS_{i,q-4}$ over the past eight quarters. Abnormal returns are the differences between daily cumulative returns to each stock and a size and book-to-market matched portfolio. The **orange** bars present CAR(2,61) averaged across all announcements made each decade. Abnormal returns are computed as the difference between the cumulative returns to each stock and a size and book-to-market matched portfolio. In Panel B, I provide the average price delay for the entire CRSP universe for each decade over the extended sample period, from 1934 to 2018. I measure the market's delay in incorporating market-wide information, based on Hou and Moskowitz (2005). Each calendar quarter (*q*), I first estimate the following two regression models:

$$R_{iT} = \beta_0 + \beta_1 R_{m,T} + \varepsilon_{iT}, \quad (3)$$

$$R_{iT} = \beta_0 + \beta_1 R_{m,T} + \beta_2 R_{m,T-1} + \beta_3 R_{m,T-2} + \beta_4 R_{m,T-3} + \beta_5 R_{m,T-4} + \varepsilon_{iT}, \quad (4)$$

where the dependent variable, R_{iT}, is the return on stock *i* during day *T*, while $R_{m,T}$ is the CRSP value-weighted market return on day *T*. For each quarter (*q*), the Hou and Moskowitz (2005) measure of price delay for each firm (*i*) is one minus the ratio of the R^2 from Equation (3) to the R^2 from Equation (4). I then aggregate these firm-specific price delay measures across all stocks (*i*) during each quarter (*q*), and report the average aggregate price delay measure for each decade.

Panel A. Price-Delay to Firm-Specific News



Panel B. Price-Delay to Market-Wide News

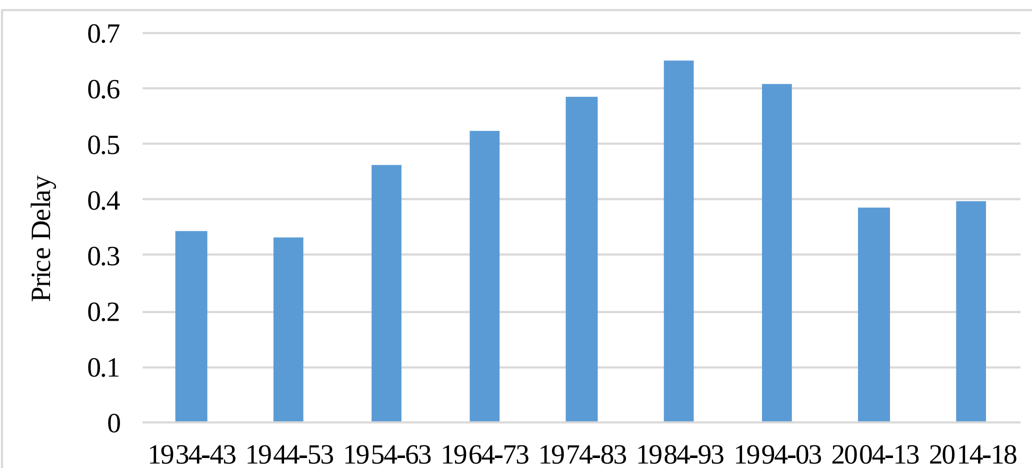
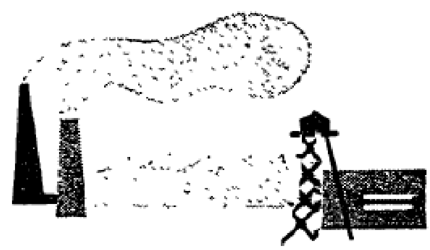


Figure II. The *Wall Street Journal*'s call for more information from corporate executives

Display Ad 59 -- No Title
Wall Street Journal (1923 - Current file); Nov 28, 1949;
ProQuest Historical Newspapers: The Wall Street Journal
pg. 10

More should be known about your Company than the goods or services it produces

More than ever, corporation officers realize the need for going beyond the sales of products and services . . . They know they must "sell" their companies, too, and the needs they fill, to:



- Stockholders who may or may not read the pamphlet report that arrives among a flood of mail . . .
- Moneyed people who must some day replace present stockholders (or their estates) who sell . . .
- People who, as leaders in their communities, influence the thinking of millions...
- People who make and shape the investment opinions of other people . . .
- Customers and prospective customers who should know more of your company . . .

. . . Many of them are not on your mailing lists . . .

. . . but all should be informed more fully than can any news article of your company's assets, of earnings (and why they are good or not good), of future possibilities.

Many thousands of these people are numbered among the 225,000 readers of the 135,000 copies of The Wall Street Journal.

Hence many companies publish in The Wall Street Journal: all pertinent information in the report that should have wider distribution than the mailing list can give . . . other companies confine themselves to the balance sheet, income account, and profit and loss account.

We will be glad to publish your figures in a suitable space: or to send you a folder showing specimen reports. May we hear from you?

THE WALL STREET JOURNAL, *published at 44 Broad Street, New York 4; 415 Bush Street, San Francisco 8; Young & Poydras Streets, Dallas 2.*

Figure III. Current Earnings Report from the April 14, 1937 issue of the *Wall Street Journal*

Current Earnings Reports

Following is Dow-Jones summary of earnings reported by various companies, giving the net income after federal taxes, common share earnings for the period indicated and annual dividend rate on common stocks. When profit is before federal taxes, no calculation of share earnings is made. If stock is listed on the New York Stock Exchange the tape symbol is given in parentheses after name of company:

Tuesday, April 13, 1937:

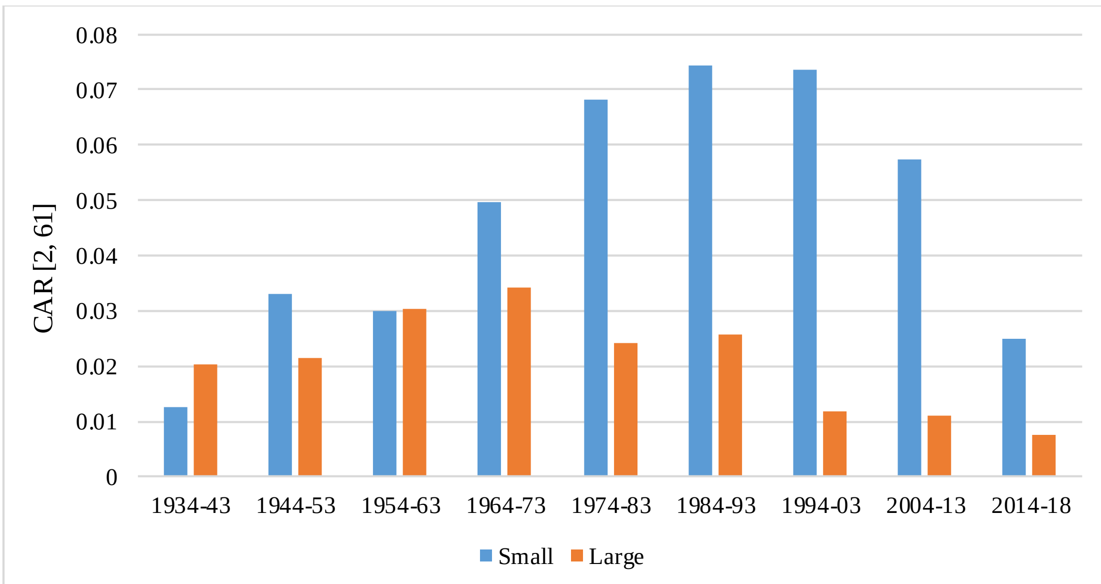
Company:	Annual dividends	Net income 1937	Net income 1936	Common share earnings 1937	Common share earnings 1936	Surplus after dividends 1937	Surplus after dividends 1936
Allen Industries, Inc.:							
March 31 quarter	§$1.00	$177,496	$162,415	h$.70	h$.66	*.....	*.....
Barker Bros. Corp. (BKR):							
March 31 quarter	f...	173,694	67,814	h.72	h.15	......	......
Bridgeport Machine Co.:							
March 31 quarter	1.00	‡175,897	‡77,878	....	....	......	......
Cleveland-Cliffs Iron Co.:							
March 31 quarter	f...	108,499	†72,180	....	....	......	......
Collins & Aikman Corp. (CK):							
Year, February 27	w.50	4,991,659	3,974,687	8.15	6.28	$1,775,997	$2,973,911
General Finance Corp.:							
February 27 quarter	f...	138,742	83,587	h.16	h.12	......	......
Goldblatt Bros., Inc.:							
x Thirteen months, January 31	2.40	1,947,414	1,114,226	h3.07	h1.86	......	......
Hoe & Co., R.:							
Six months, March 31	f...	182,695	†43,518	....	....	......	......
International Great Northern R. R.:							
Two months, February 28	....	†494,916	†479,412	....	....	......	......
Kimberly-Clark Corp. (KMB):							
March 31 quarter	1.00	t451,561	t204,282	.93	.42	......	......
Twelve months, March 31	1.00	t1,106,763	t536,668	2.27	1.10	......	......
Nash-Kelvinator Corp. (NSK):							
February 28 quarter	1.00	709,563	63,731	....	....	......	......
Pacific Finance Corp. of Calif.:							
March 31 quarter	§1.80	392,789	412,463	.70	.79	......	......
Parker Rust Proof Co. (PRK):							
March 31 quarter	§1.50	329,850	250,393	.76	.58	......	......
Pittsburgh & West Virginia Ry. (PW):							
Two months, February 28	f...	101,234	56,463	.33	.18	......	......
Transue & Williams Steel Forging Corp. (TU):							
March 31 quarter	w.15	‡78,349	‡33,515	....	....	......	......
		1936	1935	1936	1935	1936	1935
American Pneumatic Service Co.:							
Year, December 31	f...	†$130,458	†$210,247	....	....	......	......
Chicago & North Western Rwy. System (NW):							
Year, December 31	f...	†9,388,038	†11,448,630	....	....	......	......
Cleveland Automatic Machine Co.:							
Year, December 31	f...	31,269	†13,800	p$1.94	....	......	......
Continental Diamond Fibre Co. (CDM):							
Year, December 31	k$2.00	596,060	167,677	1.30	$.37	d$317,340	d$311,738
Crowell Publishing Co.:							
Year, December 31	3.00	2,923,118	2,399,639	2.81	2.12	612,826	1,026,931
Imperial Oil, Ltd.:							
Year, December 31	k1.25	25,628,285	20,220,860	.95	.98	d8,078,062	d8,467,427
Kansas Gas & Electric Co.:							
Twelve months, December 31	....	1,257,971	1,003,791	....	....	......	......
Kildun Mining Corp.:							
Year, December 31	f...	†90,702	†17,061	....	....	......	......
Massachusetts Utilities Assoc.:							
Year, December 31	f...	1,470,741	1,441,866	....	....	......	......
Montana Power Co.:							
Twelve months, December 31	....	3,306,006	2,608,406	....	....	......	......
Nebraska Power Co.:							
Twelve months, December 31	....	1,825,026	2,048,966	....	....	......	......
Smith (L. C.) & Corona Typewriters, Inc. (SLT):							
December 31 quarter	§1.00	279,141	......	1.36	....	......	......

*Not available. †Net loss. ‡Profit before federal income taxes. §Plus extras. d Deficit. f No common dividend. h On shares outstanding at close of respective periods. k Paid in year 1936. p On preferred stock. t Surplus available for common stock, after preferred dividends. w Last dividend declared; period not announced by company. x Thirteen months ended January 31, 1937, compared with year ended December 31, 1935.

Figure IV. Price Delay to Firm-Specific and Market-wide News: Small vs. Large Stocks

Panel A plots the magnitude of post-earnings announcement drift (CAR [2,61]) for large and small firms across decades. Each calendar quarter, I group stocks into terciles based on their size and compute the average CAR[2,61] for the subset of stocks in top and bottom terciles of size across quarters over each decade. Blue bars represent CAR[2,61] for small stocks, while orange bars represent the analogous results for large stocks. In Panel B, I provide the average Hou and Moskowitz (2005) price delay measure by repeating the analysis in Panel B of Figure I for subsets of stocks in the top and bottom terciles of firm size each quarter. I then aggregate these firm-specific price delay measures across all small and large stocks separately and report the average price delay measure over each decade.

Panel A. Price-Delay to Firm-Specific News: Small vs. Large Stocks



Panel B. Price-Delay to Market-Wide News: Small vs. Large Stocks

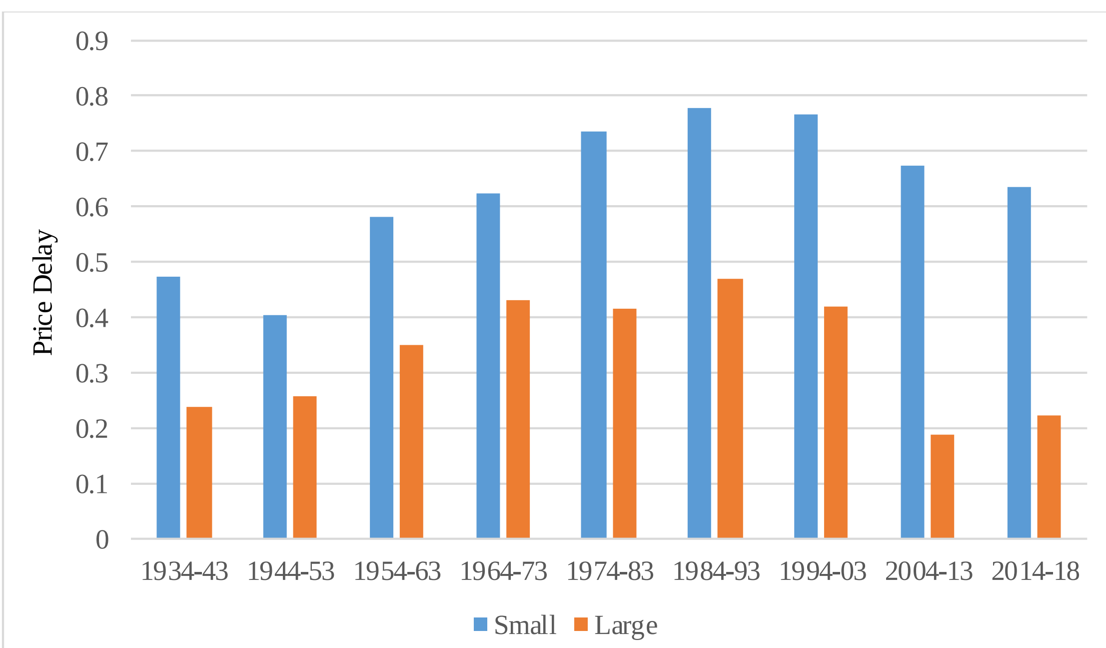
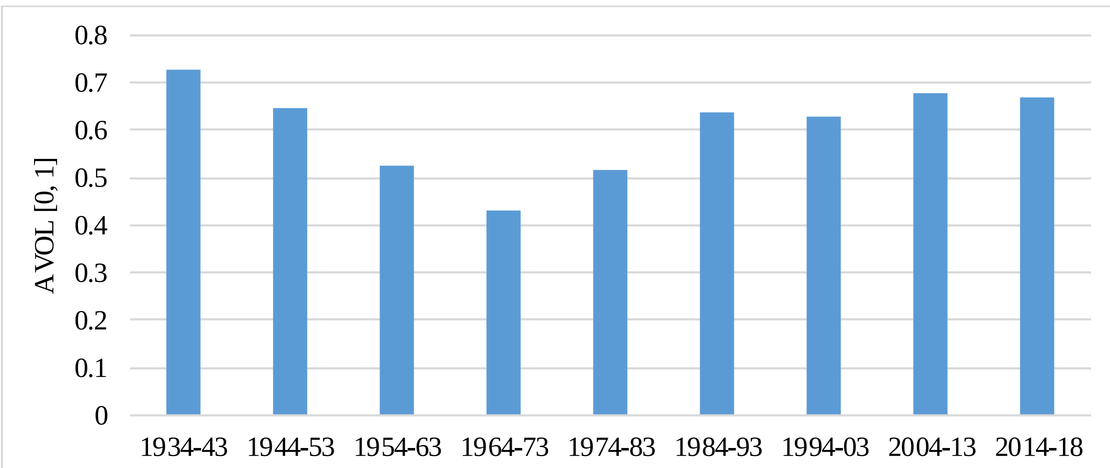


Figure V. Average Abnormal Trading Volume around Earnings Announcements

Panel A documents evolution in the average quarterly abnormal volume that occurs on the two days around earnings announcements (AVOL[0,+1]), for subsets of stocks with a large earnings surprise, across all 10-year periods between 1934 and 2018. Abnormal trading volume on days 0 and +1 is defined as the difference between the log dollar volume for each stock and its average log dollar volume over days -60 to -11 prior to the earnings announcement. Every quarter, I compute AVOL[0,+1] for all stocks in either the top or bottom quintile portfolios ***based on SUE***. Then, I plot the average of these AVOLs across all quarters over each decade.

Panel B documents evolution in the proportion of the market's total response to earnings announcements that is realized on the first two days around the earnings release (i.e., days 0 and +1), for the two subsets of stocks with either low or high investor attention focused on the earnings news, across all 10-year periods between 1934 and 2018. Each quarter, I group stocks into tercile portfolios ***based on AVOL[0,+1]*** and compute the average 2-day announcement return (CAR[0,+1]) and the total 62-day announcement return (CAR[0,+61]) for top and bottom tercile of AVOL across quarters over each decade. I then plot the proportion of these averages, CAR[0,+1] / CAR[0,+61], each decade. The **blue** bars present the proportion of averages for the stocks in the High AVOL tercile, while the **orange** bars provide the analogous results for the stocks in the Low AVOL tercile.

Panel A. Average AVOL(0,+1) around Earnings Announcements, for Each Decade



Panel B. Proportion of Average 62-Day Announcement Return Earned on Days 0 and +1, CAR[0,+1] / CAR[0,+61]), for Each Decade

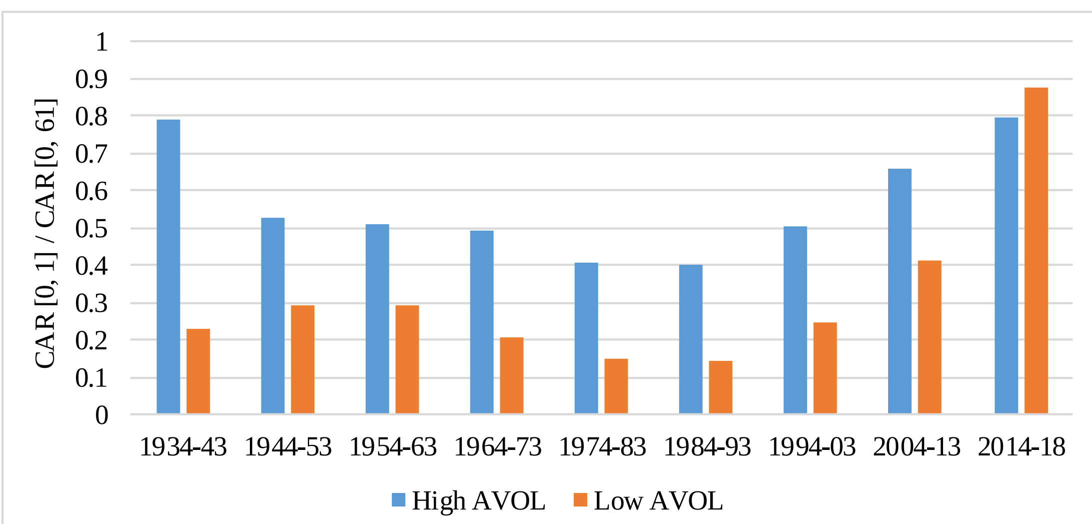


Table I. Summary Statistics for my Sample Firms versus the CRSP Sample over 1934-1971

This table compares firm characteristics for my final sample of announcing firms versus the CRSP sample over 1934 and 1971. I provide time-series averages of the monthly cross-sectional means for all variables. All variables are defined in Table II.

Variables	WSJ Sample	CRSP Sample
Market Capitalization (Millions of $)	129.66	111.65
Share Turnover (%)	2.61%	2.62%
Market beta	1.241	1.220
IVOL	2.15%	2.21%
Illiquidity	0.079	0.118
Book-to-market	1.63	1.70

Table II. Variable Definitions

	Dependent Variables
CAR $[a, b]_{i,t}$	Cumulative abnormal return for stock *i* from day $d = a$ to b, following the earnings announcement in quarter t. Abnormal returns are calculated as the difference between compounded daily returns for stock *i* (Ret_{id}) and the size and book-to-market matched portfolio ($MatchRet_{md}$) between days a and b. Each stock is matched to one of six portfolios based on median market capitalization and 30th and 70th percentile of book-to-market based on cutoffs provided by Kenneth French. $\prod_{d=a}^{d=b}(1 + Ret(i,d)) - \prod_{d=a}^{d=b}(1 + MatchRet(m, d))$
	Independent Variables
SUE	Standardized unexpected earnings (SUE) is based on the definition of Foster, Olsen, and Shevlin (1984). SUE = $(EPS_{i,q} - EPS_{i,q\text{-}4})\ /\ \sigma_{q-8,q\text{-}1}$ where $EPS_{i,q}$ and $EPS_{i,q\text{-}4}$ are firm *i*'s earnings per share in quarters *q* and *q-4*, and $\sigma_{q-8,q\text{-}1}$ is the standard deviation of $EPS_{i,q} - EPS_{i,q\text{-}4}$ over the past eight quarters.
Adj_SUE	Adjusted Rank of SUE, constructed by sorting the cross-section of earnings announcements each quarter into quintiles (0 – 4), and then dividing each quintile rank by 4. The adjusted rank ranges from 0 for the lowest SUE quintile to +1 for the top SUE quintile.
# Ann	The logarithm of the number of same-day announcements.
Ret [-11, -2]	The cumulative return for stock *i* over days *t-11* to *t-2*.
IVOL	The standard deviation of returns for stock *i* over days *t-11* to *t-2*.
Illiquidity	The average daily Amihud illiquidity measure, computed as the ratio of the daily absolute return to the dollar trading volume for stock *i* in month *t-1*, multiplied by 10^4.
Trend	The quarterly time trend divided by 1000.
$Trend^2$	The quarterly squared time trend divided by 1000.
Turnover	The logarithm of average daily turnover for stock *i* over days *t-11* to *t-2*.
BM	The logarithm of the book-to-market ratio for firm *i* for the most recent period prior to day *t*.
Size	The logarithm of the market capitalization for stock *i* in the month prior to day *t*.
Beta	The market beta of stock *i*, estimated by regressing monthly returns for stock *i* against the CRSP value-weighted market index over months *t-36* to *t-1*.
AVOL [0, 1]	Average abnormal trading volume on the earnings announcement day and the next day, where abnormal volume for stock *i* on day *t* and day *t+1* is the difference between log dollar volume for stock *i* and its average log dollar volume over days *t-60* to *t-11*.

Table III. Summary Statistics

This table provides summary statistics for the variables in my main analysis over each decade. All variables are defined in Table II. The sample period covers January 1934 through December 2018.

	Period	SUE	Size	Beta	BM	Ret[11,02]	Ivol	Turnover	Illiquidity
Mean	1934-43	0.155	69.73	1.413	2.178	0.006	0.028	0.001	0.217
	1944-53	0.237	102.40	1.276	1.346	0.003	0.017	0.001	0.036
	1954-63	0.131	318.94	0.995	1.071	0.006	0.016	0.001	0.012
	1964-73	0.387	529.00	1.294	0.848	0.005	0.020	0.001	0.013
	1974-83	0.336	465.04	1.230	1.329	0.012	0.024	0.001	0.052
	1984-93	0.077	935.44	1.092	0.886	0.006	0.027	0.003	0.036
	1994-03	0.126	2344.62	0.968	0.777	0.011	0.033	0.005	0.027
	2004-13	0.065	4148.70	1.229	0.809	0.005	0.026	0.008	0.036
	2014-18	0.172	7935.85	1.131	0.733	0.001	0.020	0.008	0.026

	Period	SUE	Size	Beta	BM	Ret[11,02]	Ivol	Turnover	Illiquidity
Std	1934-43	1.177	253.43	0.627	4.770	0.088	0.022	0.002	0.822
	1944-53	1.430	370.40	0.531	2.009	0.053	0.010	0.001	0.109
	1954-63	1.144	1202.27	0.461	1.574	0.052	0.009	0.002	0.047
	1964-73	1.590	2041.51	0.560	0.707	0.072	0.012	0.002	0.041
	1974-83	1.691	1779.15	0.581	0.871	0.088	0.015	0.002	0.173
	1984-93	1.819	3320.77	0.586	0.883	0.091	0.020	0.004	0.256
	1994-03	1.823	11666.77	0.899	0.859	0.115	0.026	0.009	0.154
	2004-13	1.813	17646.27	0.895	1.468	0.092	0.020	0.012	0.465
	2014-18	1.851	31052.85	0.851	1.543	0.082	0.018	0.019	0.633

	Period	SUE	Size	Beta	BM	Ret[11,02]	Ivol	Turnover	Illiquidity
Median	1934-43	0.108	11.79	1.365	1.191	0.003	0.023	0.001	0.034
	1944-53	0.158	21.86	1.230	0.962	-0.001	0.015	0.001	0.012
	1954-63	0.112	71.92	0.977	0.798	0.001	0.014	0.001	0.003
	1964-73	0.333	112.29	1.232	0.704	-0.001	0.017	0.001	0.002
	1974-83	0.245	90.99	1.174	1.173	0.004	0.021	0.001	0.004
	1984-93	0.124	129.27	1.062	0.732	0.000	0.021	0.002	0.001
	1994-03	0.122	194.17	0.821	0.577	0.002	0.026	0.003	0.001
	2004-13	0.093	467.47	1.081	0.589	0.003	0.022	0.005	0.000
	2014-18	0.117	971.53	1.068	0.516	0.001	0.016	0.005	0.000

Table IV. Earnings Announcement Returns for SUE Hedge Portfolio Returns

This table presents the mean cumulative abnormal returns (CARs) on the hedge portfolio that is long the top SUE quintile and short the bottom quintile over four time frames covering days (0, 1), (2, 61), (2, 120), and (2, 180). I report average CARs across quarters during each decade between 1934 and 2018.

Period	CAR [0, 1]	t Value	CAR [2, 61]	t Value	CAR [2, 120]	t Value	CAR [2, 180]	t Value
1934-43	2.92%	15.33	1.80%	3.00	5.40%	5.88	7.67%	6.76
1944-53	2.46%	23.28	2.60%	7.42	5.28%	11.2	6.25%	9.61
1954-63	2.32%	26.56	3.20%	11.08	6.42%	14.23	8.38%	12.98
1964-73	2.77%	32.29	4.24%	16.16	6.15%	14.72	7.37%	13.79
1974-83	2.21%	35.59	4.73%	22.17	7.63%	24.88	9.67%	23.39
1984-93	2.24%	34.91	5.00%	24.82	7.90%	25.22	9.94%	24.99
1994-03	2.95%	35.72	4.04%	14.67	6.17%	15.54	7.55%	14.28
2004-13	3.98%	45.53	2.97%	13.52	4.06%	12.76	4.96%	12.39
2014-18	4.02%	33.48	1.24%	4.23	1.91%	4.33	1.80%	3.25

Table V. Earnings Announcement Returns, Controlling for Firm Attributes

This table presents the results from estimating Equation (1): Return $[a, b]_{it} = \alpha + \beta_1$ Adj_SUE$_{it}$ + Controls + ε_{it}. The dependent variable is the cumulative abnormal return for stock *i*, compounded over days *a* to *b* following the earnings announcement in quarter *t* (on day 0) over each decade from 1934 to 2018. The coefficient of Adj_SUE is analogous to the return on a hedge portfolio that is long the top SUE quintile and short the bottom SUE quintile. Panel A provides the results for CAR [0,1], while Panel B presents the results for CAR [2,61]. Control variables are defined in Table II, and include the lagged SUE, the number of same-day announcements, lagged return over days -11 to -2, book-to-market, beta, size, standard deviation of returns over days -11 to -2, turnover for these same days, and illiquidity. All models include fixed effects for day of the week, month, and year. Standard errors are adjusted for heteroscedasticity and clustered by the day of the announcement. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A. Initial Announcement Returns: CAR [0, 1]

Variables	CAR [0, 1]								
	34-43	44-53	54-63	64-73	74-83	84-93	94-03	04-13	14-18
Adj_SUE	0.027***	0.025***	0.023***	0.032***	0.027***	0.029***	0.037***	0.049***	0.047***
	(16.70)	(25.53)	(27.60)	(36.45)	(41.54)	(42.64)	(45.19)	(56.45)	(39.75)
Lagged SUE	0.001***	-0.000	0.000	-0.000***	-0.000***	-0.001***	-0.001***	-0.002***	-0.002***
	(2.67)	(-0.05)	(0.31)	(-5.27)	(-6.42)	(-10.86)	(-13.43)	(-24.38)	(-14.54)
#Ann	0.000	-0.000	-0.000	-0.001**	-0.001***	-0.001	-0.002***	-0.001**	-0.000
	(0.25)	(-0.04)	(-0.96)	(-2.39)	(-2.77)	(-1.43)	(-4.33)	(-2.57)	(-0.61)
Ret [-11, -2]	-0.046***	-0.035***	-0.035***	-0.047***	-0.043***	-0.030***	-0.048***	-0.028***	-0.014**
	(-4.08)	(-4.69)	(-5.13)	(-8.98)	(-9.57)	(-7.55)	(-13.77)	(-6.05)	(-2.00)
BM	-0.001	0.001*	0.001*	0.004***	0.003***	0.003***	0.004***	0.003***	0.002***
	(-0.56)	(1.89)	(1.82)	(8.80)	(8.48)	(8.69)	(12.55)	(8.79)	(4.61)
Beta	0.002	0.001	-0.000	-0.001*	-0.001***	-0.001**	-0.002***	-0.000	0.000
	(1.23)	(1.65)	(-0.39)	(-1.83)	(-2.72)	(-2.18)	(-4.48)	(-1.01)	(0.20)
Size	-0.000	0.000	0.000**	-0.000	-0.000***	-0.001***	-0.000***	-0.000	0.000
	(-0.18)	(0.02)	(2.18)	(-0.24)	(-3.62)	(-5.11)	(-2.62)	(-1.37)	(0.48)
IVOL	-0.054	0.012	-0.087*	-0.086**	0.051**	0.050***	0.063***	-0.010	-0.006
	(-0.96)	(0.24)	(-1.77)	(-2.29)	(2.04)	(2.77)	(2.97)	(-0.44)	(-0.10)
Turnover	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000**	-0.001***	-0.001
	(-1.27)	(-0.40)	(-0.73)	(-0.21)	(-1.19)	(-1.05)	(2.08)	(-3.34)	(-1.49)
Illiquidity	0.010	-0.000	0.019*	0.014*	0.005***	0.001	0.014***	0.001	0.000
	(1.35)	(-0.08)	(1.71)	(1.70)	(2.93)	(0.88)	(4.77)	(0.77)	(0.16)
Constant	-0.023**	-0.014***	-0.020***	-0.008*	0.001	-0.002	0.007*	-0.007	-0.015*
	(-2.48)	(-4.30)	(-5.71)	(-1.87)	(0.23)	(-0.61)	(1.80)	(-1.57)	(-1.91)
Observations	7,310	9,293	14,078	30,543	71,864	102,595	148,511	130,510	54,024
Adjusted R-squared	0.083	0.096	0.079	0.072	0.041	0.029	0.028	0.036	0.036

Table V, continued

Panel B. Post-Earnings Announcement Returns: CAR [2, 61]

Variables	CAR [2, 61]								
	34-43	44-53	54-63	64-73	74-83	84-93	94-03	04-13	14-18
Adj_SUE	0.018***	0.026***	0.034***	0.047***	0.052***	0.052***	0.046***	0.033***	0.016***
	(3.25)	(8.01)	(12.47)	(18.25)	(24.42)	(25.94)	(18.20)	(16.14)	(6.04)
Lagged SUE	-0.000	-0.001***	-0.000	-0.001***	-0.001***	-0.000	-0.001**	-0.000	-0.000
	(-0.55)	(-2.62)	(-0.63)	(-3.14)	(-3.61)	(-0.78)	(-2.52)	(-0.59)	(-0.97)
#Ann	0.005*	0.003*	0.000	0.003*	0.002	-0.004**	-0.001	0.003**	0.001
	(1.65)	(1.88)	(0.06)	(1.65)	(1.28)	(-2.31)	(-0.32)	(2.15)	(0.86)
Ret [-11, -2]	-0.027	-0.031	0.036	-0.018	-0.045***	-0.006	0.008	-0.022	-0.025
	(-1.09)	(-1.25)	(1.64)	(-1.12)	(-4.35)	(-0.66)	(0.67)	(-1.37)	(-1.06)
BM	0.003	0.003	0.002	0.002	0.002*	0.003**	-0.001	0.009***	0.002*
	(1.21)	(1.19)	(1.25)	(1.03)	(1.69)	(2.27)	(-0.39)	(7.34)	(1.83)
Beta	0.001	0.009***	-0.000	-0.007***	0.000	-0.001	0.002	0.000	-0.006***
	(0.14)	(2.78)	(-0.17)	(-2.70)	(0.03)	(-0.42)	(1.06)	(0.39)	(-3.97)
Size	0.001	-0.000	-0.002***	-0.001	-0.000	-0.001**	-0.004***	-0.000	0.003**
	(0.94)	(-0.35)	(-2.65)	(-0.74)	(-0.97)	(-2.51)	(-6.02)	(-0.01)	(2.04)
IVOL	0.080	-0.023	-0.323**	-0.015	0.013	-0.151***	-0.021	0.138	0.037
	(0.59)	(-0.12)	(-2.09)	(-0.14)	(0.18)	(-3.00)	(-0.31)	(1.63)	(0.12)
Turnover	0.000	-0.001	0.000	0.002*	0.001	0.002***	0.003***	0.003***	-0.003*
	(0.75)	(-1.06)	(0.39)	(1.72)	(0.95)	(5.23)	(5.84)	(4.83)	(-1.84)
Illiquidity	0.003	0.020**	-0.017	-0.026	0.017***	-0.001	0.014*	-0.003**	0.034***
	(0.32)	(2.22)	(-0.57)	(-1.21)	(2.78)	(-0.36)	(1.95)	(-2.37)	(9.71)
Constant	-0.029	-0.013	0.017	0.007	-0.018	0.015	0.047***	-0.009	-0.063*
	(-1.18)	(-0.94)	(1.34)	(0.47)	(-1.33)	(1.44)	(3.73)	(-0.76)	(-1.92)
Observations	7,310	9,293	14,078	30,543	71,864	102,595	148,511	130,510	54,024
Adjusted R-squared	0.008	0.020	0.018	0.021	0.016	0.012	0.007	0.008	0.032

Table VI. The Nonlinear Trend in Market Efficiency from 1934 to 2018

This table presents the results from estimating Equation (2):
$CAR[a, b]_{it} = \alpha + \beta_1 Adj\_SUE_{it} + \beta_2 Trend + \beta_3 Adj\_SUE_{it} x Trend + \beta_4 Trend^2 + \beta_5 Adj\_SUE_{it} x Trend^2 + Controls + \varepsilon_{it}$. The dependent variable is the cumulative abnormal return for stock *i* compounded over days (0, +1) or (+2,+ 61) following the earnings announcement of firm *i* during quarter *t*. The coefficient of Adj_SUE (β_1) is analogous to the return on a hedge portfolio that is long the top SUE quintile and short the bottom SUE quintile. The variable, Trend, indexes the period of the observation. Across models, I include different subsets of controls. In columns (1) and (4), I estimate Equation (2) with only the trend terms, without the controls, while columns (2) and (5) add the control variables included in Table V. Columns (3) and (6) add the interactions of all the control variables with Trend and $Trend^2$ (these interaction coefficients are omitted here for brevity). Table II provides variable definitions. All models include fixed effects for day of the week, month, and year. Standard errors are adjusted for heteroscedasticity and clustered by the day of the announcement. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Variables	CAR [0, 1]			CAR [2, 61]		
	(1)	(2)	(3)	(4)	(5)	(6)
Adj_SUE	0.032***	0.034***	0.029***	-0.006	-0.005	-0.003
	(22.64)	(23.96)	(19.37)	(-1.33)	(-1.02)	(-0.63)
Trend	1.105***	-0.036	0.123	8.898***	8.813***	10.037***
	(2.72)	(-0.09)	(0.29)	(6.46)	(6.29)	(6.85)
Adj_SUE x Trend	**-0.158*** **	**-0.105*** **	**-0.094*** **	**0.578*** **	**0.602*** **	**0.590*** **
	(-9.82)	**(-6.43)**	**(-5.45)**	**(12.12)**	**(12.59)**	**(11.71)**
$Trend^2$	-0.002***	-0.002***	-0.003***	-0.004*	-0.004*	-0.007***
	(-3.47)	(-2.77)	(-3.78)	(-1.73)	(-1.70)	(-2.87)
Adj_SUE x $Trend^2$	**0.001*** **	**0.0004*** **	**0.0005*** **	**-0.002*** **	**-0.002*** **	**-0.002*** **
	(14.24)	**(10.75)**	**(11.01)**	**(-13.18)**	**(-13.63)**	**(-12.76)**
Lagged SUE		-0.001***	0.000		-0.000***	-0.001
		(-31.59)	(1.28)		(-4.06)	(-1.12)
#Ann		-0.001***	0.001		0.001*	0.004*
		(-5.37)	(1.50)		(1.80)	(1.84)
Ret [-11, -2]		-0.037***	-0.024**		-0.009	-0.079***
		(-18.90)	(-2.18)		(-1.46)	(-2.81)
BM		0.003***	-0.002**		0.003***	0.007***
		(19.62)	(-2.35)		(5.02)	(2.68)
Beta		-0.001***	0.005***		0.000	-0.000
		(-5.29)	(4.08)		(0.46)	(-0.11)
Size		-0.000***	0.001***		-0.001***	0.004***
		(-5.21)	(2.66)		(-2.84)	(2.99)
IVOL		0.039***	-0.087		0.006	0.019
		(3.31)	(-1.36)		(0.14)	(0.09)
Turnover		-0.000***	-0.001**		0.002***	-0.000
		(-3.61)	(-2.33)		(6.68)	(-0.45)
Illiquidity		0.001*	0.009		0.013*	0.015
		(1.65)	(1.37)		(1.71)	(1.60)
Constant	-0.016***	-0.009***	-0.037***	-0.005	0.012	-0.060***
	(-6.33)	(-3.10)	(-5.91)	(-0.53)	(1.07)	(-2.72)
Trend x Controls	N	N	Y	N	N	Y
$Trend^2$ x Controls	N	N	Y	N	N	Y
Observations	568,728	568,728	568,728	568,728	568,728	568,728
Adjusted R-squared	0.024	0.032	0.033	0.007	0.009	0.009

Table VII. Price Delay to Market-Wide Information

This table presents the results from relating the quarterly time trend and squared time trend to the average price delay across all stocks measured over the same quarter, based on Hou and Moskowitz (2005). Each calendar quarter (q), for every firm (i), I begin by estimating the following two regression models:

$$R_{iT} = \beta_0 + \beta_1 R_{m,T} + \varepsilon_{iT}, \tag{3}$$

$$R_{iT} = \beta_0 + \beta_1 R_{m,T} + \beta_2 R_{m,T-1} + \beta_3 R_{m,T-2} + \beta_4 R_{m,T-3} + \beta_5 R_{m,T-4} + \varepsilon_{iT}, \tag{4}$$

where the dependent variable, R_{iT}, is the return on stock i during day T, while $R_{m,T}$ is the CRSP value-weighted market return during day T. For quarter (q), the measure of price delay for each firm (i) is one minus the ratio of the R^2 from Equation (3) to the R^2 from Equation (4). I then aggregate these firm-specific price delay measures across all stocks (i) during quarter (q), and relate this average measure of price delay (Average_Price_Delay) to the time trend, squared time trend, and other control variables calculated over the same quarter, as follows:

$$\text{Average\_Price\_Delay}_q = \alpha_1 + \beta_1 \text{Trend}_q + \beta_2 \text{Trend}^2_q + \text{Controls} + \varepsilon_q. \tag{5}$$

In column (2), I account for different aspects of stock market conditions average during quarter t. These include the cumulative monthly market returns (Aggregate Returns), daily market return volatility (Aggregate Volatility), the mean daily aggregate stock turnover (Aggregate Turnover), Amihud illiquidity (Aggregate Illiquidity), and the mean monthly stock return volatility (Aggregate Disagreement) averaged during *quarter t*. The dependent variable is the cross-sectional average price delay measure of Hou and Moskowitz (2005) during quarter (q). The sample period covers January 1934 through December 2018. Robust t-ratios are provided in parentheses beneath the parameter estimates (Newey and West, 1987). *, **, and *** indicate significance at the .10, .05, and .01 levels, respectively.

Variables	(1)	(2)
Trend	**4.030*** **	**3.748*** **
	(9.99)	**(8.73)**
Trend^2	**-0.010*** **	**-0.010*** **
	(-9.60)	**(-6.55)**
Aggregate Returns		-0.056
		(-1.04)
Aggregate Volatility		-15.038***
		(-7.44)
Aggregate Turnover		-0.299
		(-1.03)
Aggregate Illiquidity		0.241***
		(4.72)
Aggregate Disagreement		1.218***
		(6.91)
Constant	0.197***	0.173***
	(6.03)	(5.58)
Adjusted R^2	0.539	0.788

Table VIII. Proportion of Announcement SUE Hedge Portfolio Returns

This table presents the evolution in the average magnitude of the immediate response to earnings announcements (CAR [0,+1]), the subsequent response over the first month (CAR [+2,+21]) and the PEAD (CAR [+2,+61]), each measured as a proportion of total 62-day cumulative announcement returns (CAR [0,+61]), for every 10-year period in the extended sample, 1934 - 2018.

SUE Hedge Portfolio Return	As % of CAR [0, +61]								
	1934-43	1944-53	1954-63	1964-73	1974-83	1984-93	1994-03	2004-13	2014-18
CAR [0, +1]	61.84%	48.60%	42.03%	39.53%	31.81%	30.92%	42.19%	57.23%	76.44%
CAR [2, +21]	3.93%	8.27%	8.73%	12.31%	19.02%	20.38%	18.75%	25.02%	18.06%
CAR [2, +61]	38.16%	51.40%	57.97%	60.47%	68.19%	69.08%	57.81%	42.77%	23.56%

Table IX. Information Content of Earnings Announcements

This table presents the results from relating the quarterly time trend and squared time trend to the information content of earnings announcements measured over the same quarter, based on Ball and Shivakumar (2008). Each calendar quarter (*q*), I begin by estimating the following regression model:

$$R_i = \beta_0 + \beta_1 CAR[0,1]_i + \varepsilon_i, \quad (6)$$

where the dependent variable, R_i, is the cumulative return on stock *i* during quarter *q*, while $CAR[0,1]_i$ is the earnings announcement return for stock *i* during quarter *q*. For quarter (*q*), the measure of information content of earnings announcements is the R^2 from Equation (6). I then relate this measure of information content of earnings announcements (Information_Content) to the time trend, squared time trend, and other control variables calculated over the same quarter, as follows:

$$Information\_Content_q = \alpha_1 + \beta_1 Trend_q + \beta_2 Trend^2_q + Controls + \varepsilon_q. \quad (7)$$

In column (2), I account for different aspects of stock market conditions average during quarter *t*. These include the cumulative monthly market returns (Aggregate Returns), daily market return volatility (Aggregate Volatility), the mean daily aggregate stock turnover (Aggregate Turnover), Amihud illiquidity (Aggregate Illiquidity), and the mean monthly stock return volatility (Aggregate Disagreement) averaged during *quarter t*. The dependent variable is the information content of earnings announcements measure of Ball and Shivakumar (2008) during quarter (*q*). The sample period covers January 1934 through December 2018. Robust t-ratios are provided in parentheses beneath the parameter estimates (Newey and West, 1987). *, **, and *** indicate significance at the .10, .05, and .01 levels, respectively.

Variables	(1)	(2)
Trend	-0.694***	-0.627**
	(-4.82)	(-2.26)
$Trend^2$	0.003***	0.003***
	(8.02)	(3.39)
Aggregate Returns		-0.012
		(-0.32)
Aggregate Volatility		-2.464***
		(-2.62)
Aggregate Turnover		0.080
		(0.46)
Aggregate Illiquidity		0.012
		(0.37)
Aggregate Disagreement		-0.255**
		(-2.22)
Constant	0.086***	0.122***
	(6.76)	(5.89)
Adjusted R^2	0.397	0.459

Internet Appendix A

Does History Repeat Itself?

The Evolution of Market Efficiency over the Past Century

Figure A.I illuminates a dramatic structural change in PEAD from my early sample to the more recent years analyzed in the bulk of the literature. Since 1974, the drift in the SUE hedge portfolio return begins immediately after the announcement and continues steadily through day +60 and peaks after the period as shown in Panel A. In contrast, during the four decades before 1974, there is little drift for roughly one month after the earnings release.

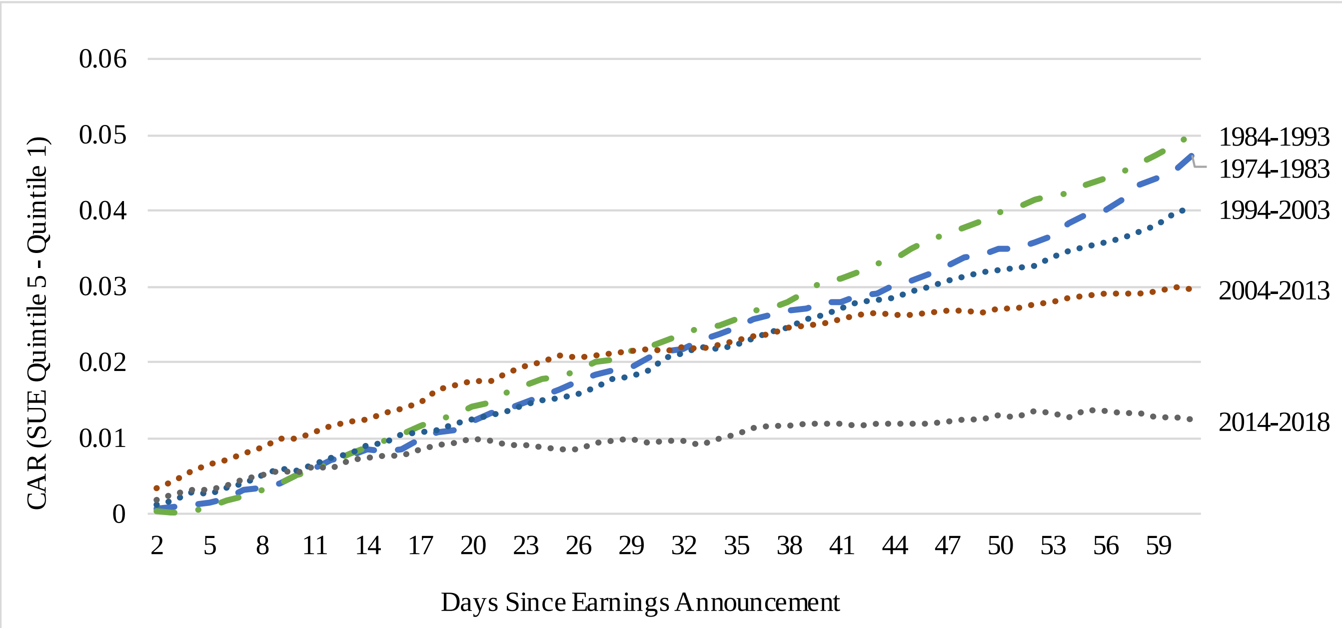
Figure A.II shows the cumulative abnormal returns to SUE quintile portfolios over each decade between 1934-2018. Starting from 1970s, the drift starts immediately after the earnings announcement. The returns drift upward (downward) following good (bad) news until the next announcement. However, during the first four decades, there is little drift over the first month after the announcement and the drift is more concentrated before the next earnings announcement, when new information arrives. Together with Figure I, this graph illustrates novel evidence supporting the underreaction argument.

Figure A.III lists the regulatory milestones over the past century that directly or indirectly had an impact on the corporate disclosure requirements and practices.

Figure A.I. Post Earnings Announcement Drift: 1934 - 2018

These figures plot the cumulative abnormal returns (CARs) for the high minus low quintile SUE (standardized unexpected earnings) hedge portfolio between day +2 to day +61 after earnings announcements (on day 0) over each decade between 1934 and 2018. SUE is based on the definition of Foster, Olsen and Shevlin (1984): SUE = $(EPS_{i,q} - EPS_{i,q-4}) / \sigma_{q-8,q-1}$ where $EPS_{i,q}$ and $EPS_{i,q-4}$ are firm i's earnings per share in quarters q and q-4, and $\sigma_{q-8,q-1}$ is the standard deviation of $EPS_{i,q} - EPS_{i,q-4}$ over the past eight quarters. Abnormal returns are the differences between daily cumulative returns to each stock and a size and book-to-market matched portfolio. Panel A plots the CARs over 1974 to 2018, i.e. Compustat sample, while Panel B. plots the entire sample period from 1934 to 2018.

Panel A: PEAD over 1974 and 2018



Panel B: PEAD over 1934 and 2018

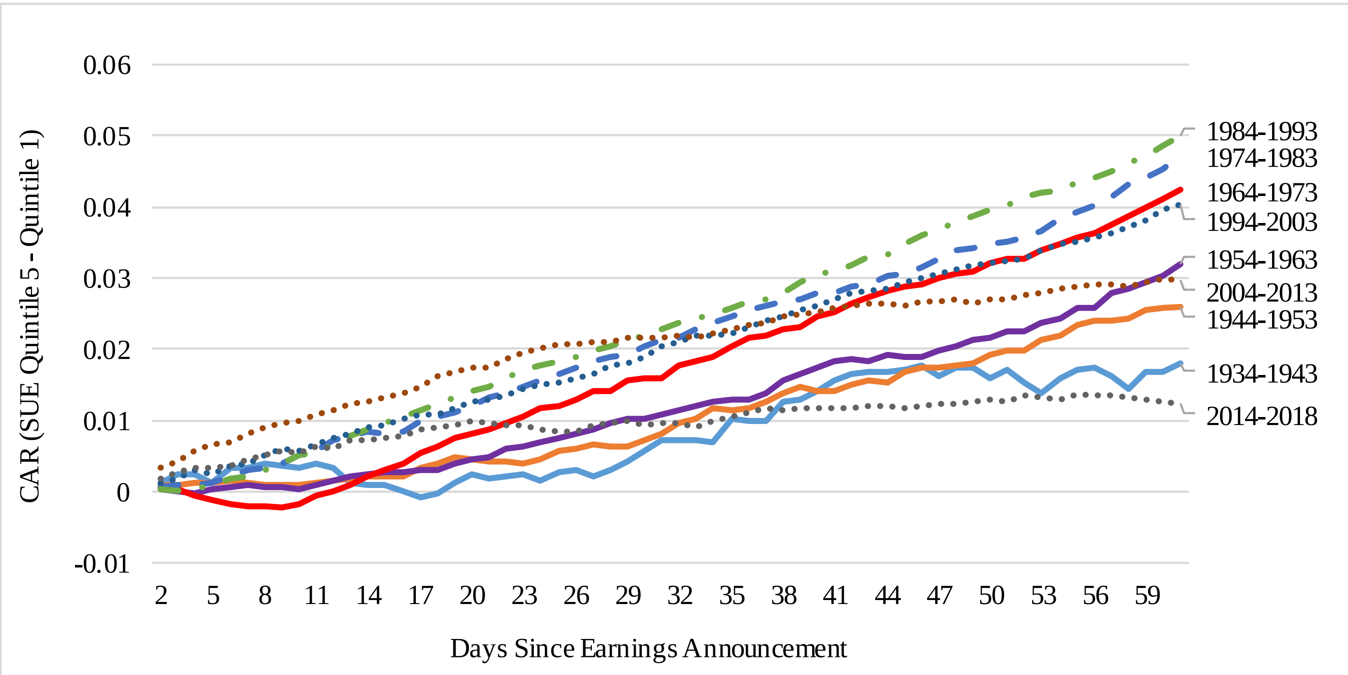
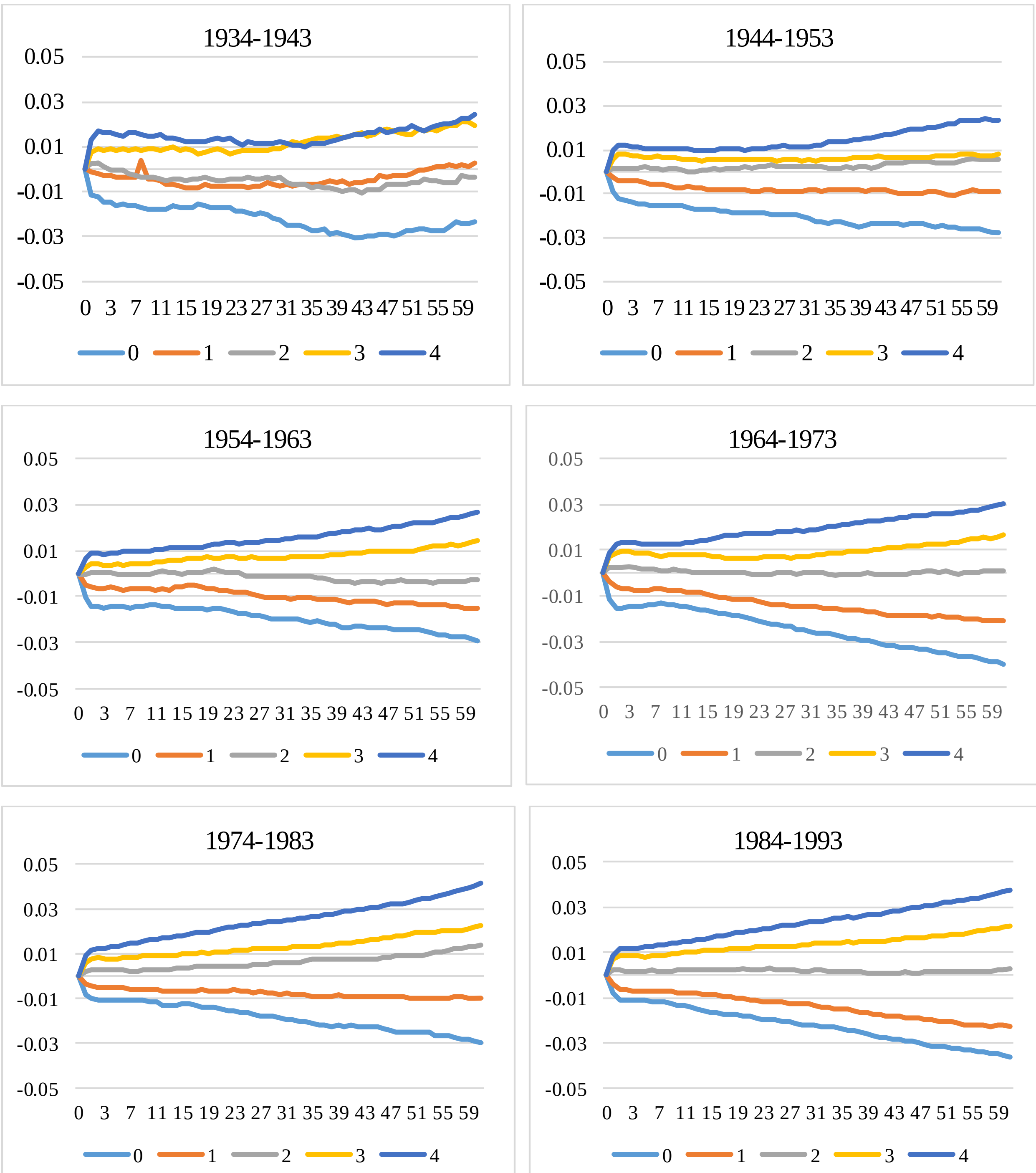
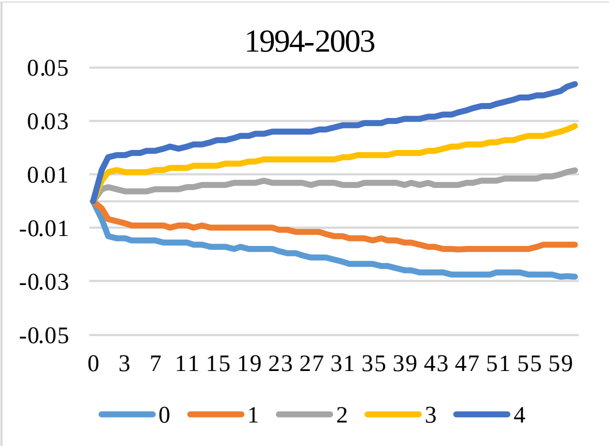
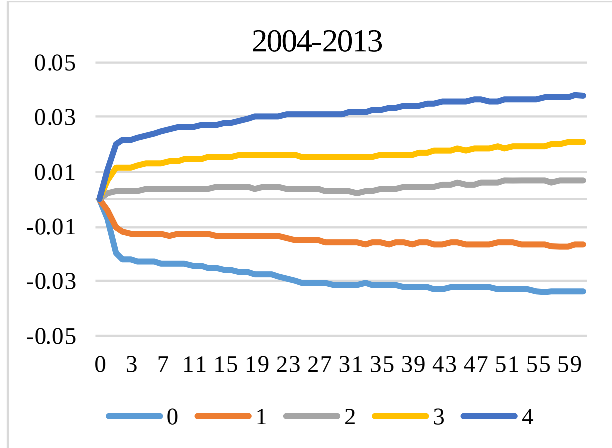


Figure A.II. Cumulative Abnormal Returns Around Earnings Announcements

This figure plots the cumulative abnormal returns (CARs) to SUE (standardized unexpected earnings) quintile ranked portfolios between day 0 to day +61 around earnings announcements (on day 0) over each decade between 1934 and 2018. SUE is based on the definition of Foster, Olsen and Shevlin (1984): SUE = $(EPS_{i,q} - EPS_{i,q-4}) / \sigma_{q-8,q-1}$ where $EPS_{i,q}$ and $EPS_{i,q-4}$ are firm *i*'s earnings per share in quarters *q* and *q-4*, and $\sigma_{q-8,q-1}$ is the standard deviation of $EPS_{i,q} - EPS_{i,q-4}$ over the past eight quarters. Abnormal returns are the differences between daily cumulative returns to each stock and a size and book-to-market matched portfolio, where compounding starts on day 0 and ends on day +61.




1994-2003
0.05
0.03
0.01
-0.01
-0.03
-0.05
0 3 7 11 15 19 23 27 31 35 39 43 47 51 55 59
0
1
2
3
4


2004-2013
0.05
0.03
0.01
-0.01
-0.03
-0.05
0 3 7 11 15 19 23 27 31 35 39 43 47 51 55 59
0
1
2
3
4

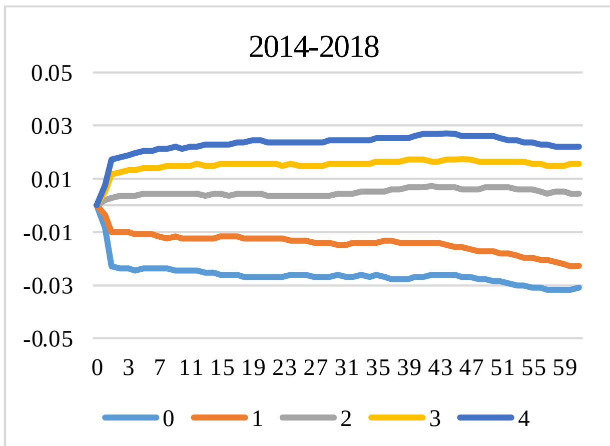

2014-2018
0.05
0.03
0.01
-0.01
-0.03
-0.05
0 3 7 11 15 19 23 27 31 35 39 43 47 51 55 59
0
1
2
3
4

Figure A.III. Timeline of Disclosure Requirements by NYSE and the Regulators

This figure provides the dates and content of the disclosure requirements by NYSE and the regulators. I provide the timeline of significant disclosure milestones. * indicates a requirement by the NYSE and are provided by Simon (1989).

Year	Requirement
1869*	Committee on Stock List Requires Disclosure of Financial Conditions.
1870-1880*	Committee on Stock List Requires Statement of Condition and List of Corporate Officers.
1910*	NYSE closes its unlisted department. Most firms apply for listing on the exchange.
1910s*	Committee on Stock List requests periodic financial statements and Initial Offering Disclosure Reports.
1924*	Quarterly earnings statements become common in listing agreements of NYSE.
1926*	Increased detail in financial reporting required by NYSE.
1928*	Independent audits are required.
1911-1933	47 states adopted Blue Sky Laws to prevent fradulent security sales.
1933	Securities Act of 1933.
1934	Securities Exchange Act of 1934 created SEC (Securities Exchange Commission). The act required public firms to file detailed balance sheet and income statements annually within 120 days after the fiscal year-end (10K), as well as a less detailed report semiannually within 45 days after the first half of the fiscal year (9K), and a current report within ten days of the end of any month when a significant event occurred (8K). SEC also required financial statements to be audited by independent CPAs.
1964	SEC extended mandated disclosure requirements to large firms traded Over-the-counter (OTC).
1970	SEC mandated quarterly reporting for all publicly traded U.S. companies.
2000	Regulation Fair Disclosure became effective and prohibited firms from sharing non-public information to select investors.
2002	Sarbanes Oxley Act of 2002 required firms to disclose any material changes in their financial condition or operations urgently to the public.
2018	The SEC has launched recent initiatives to simplify disclosure, “Disclosure Update and Simplification,” effective November 15, 2018.