The Certification Effect: Stamp of Approval or Just Another Anomaly?

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A Thesis

In the Department of Finance

Presented in Partial Fulfillment of the Requirements

For the Degree of

Master of Science (Finance)

at Concordia University

Montreal, Quebec, Canada

July 2024

CONCORDIA UNIVERSITY

School of Graduate Studies

This is to certify that the thesis is prepared

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Entitled: The Certification Effect: Stamp of Approval or Just Another Anomaly?

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Master of Science (Finance)

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Abstract

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The relation between analyst publications and their effects on the underlying stocks is a well-researched field of finance. However, none go so far as to identify the fundamental effect of a firm receiving its first recommendation from an analyst beyond standard recommendation effects. We examine a sample of 6168 analyst initiation of coverage events, separated into a positive subsample and negative subsample to determine the abnormal returns generated in the two days after, one-month after, and one year after event windows using an event study methodology. In addition, we compare these abnormal returns to those generated by a respective control subsample of mid-caps to calculate the certification effect. Finally, we study the relationship the different event window certification effects have with firm-level variables. We find that the abnormal returns generated by the small-caps are consistently different than those generated by the respective control subsample of mid-caps, and that the certification effects are significantly non-zero values. We also find that the short certification effect has no relationship with firm level variables, while mid and long certification effects have a relationship with Board Size. We fail to establish a relationship between the mid and long certification effects and the change of stock volatility of the underlying firm. We conclude that while the certification effect does exist in the short-term, its effect is lost in the long-term as new events take place and confound the results.

Acknowledgements

I would like to thank my dear supervisors, Dr. Denis Schweizer and Dr. Juliane Proelss, for their guidance, advice, and suggestions throughout all the stages of writing my thesis. Your responses were always insightful, I can't imagine completing this journey without you.

To my mom, dad, and brother you have always been on my side, through thick and thin you all helped me find the light when I couldn't see it. I'm the luckiest person in the world with a family like us. You are my motivation to do better and to reach higher, my pillars of strength and wisdom, and my shoulders to cry on. Distance will never stop me from feeling your warmth.

To my friends both near and far, thank you for companionship and understanding during this time. Even our shortest conversations have left me with a smile on my face on my gloomiest of days. My life is only just beginning, and I can't wait to spend more of it with all of you. My cheerleaders, my comfort zone, my inspiration, with your encouragement I can do anything.

To everyone that has supported me through my journey, thank you from the bottom of my heart. Your contributions, no matter how small, have been invaluable in helping me reach this milestone.

To Lebanon, my home, this thesis is a testament to what you make happen, the experiences and education you have offered me are the foundations of my achievement.

I am who I am because of all of you.

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Introduction

In the last month of 2023, Franklin Templeton published an online article expressing reserved optimism for small-cap equities specifically after the challenges the market faced during the COVID pandemic (Gannon, 2023). This optimism resonates with other industry experts as they believe that multiple factors, such as, the segment's undervaluation, could contribute to the possible recovery of the market segment (Hansen, 2024). Additionally, the possibility of the Federal Reserve cutting interest rates is also poised to benefit small-cap companies as it encourages investors to search for viable riskier ventures (Moleux, 2024). Consequently, this growing interest in the small-cap sector creates an incentive to understand the macroeconomic factors that would affect it as well as the impact of market participants, particularly analysts whose recommendations could mean the difference between an investment in this segment over another.

Analysts are cornerstones of the financial markets as their main function is to provide information and thus promote market efficiency. They offer crucial guidance to all stakeholders of the markets, from the largest institutions to the independent investors. Their publications and reports hold sway as evidenced by management research. For example, Puffer and Weintrop (1991) highlighted the impact of analyst reports on CEO succession, correlating underperformance in achieving estimated earnings per share with increased CEO turnover. Similarly, Gentry and Shen (2013) found that unmet earnings per share forecasts results in firms cutting research and development costs. However, they also showed that, in the presence of high analyst coverage, which indicates extensive monitoring, managers are incentivized to restrain cost-cutting efforts as they fear potential investor backlash.

Moreover, financial literature stresses the importance of analysts in the markets. Chung and Jo (1996) drew attention to the significantly positive relationship of analyst following improving the value of companies (measured in Tobin's Q). In highlighting analysts' function as information intermediaries, Kim, Ryu, and Yang (2021) found their recommendations to be more valuable to investors during instances of high information uncertainty and Frankel & Li (2004) supported the result that a greater analyst following reduces information asymmetry as measured by a profitability and intensity of insider trading. Meanwhile, Hong, Lim, and Stein (2000) found an inverse relationship between momentum and analyst coverage suggesting stronger momentum effects in markets with less analyst coverage. Such markets exist within the Unites States' stock exchanges as Bhushan (1989) showed a direct, strong, and significant relationship between firm size and analyst coverage. Consequently, smaller companies on the exchanges, all else equal, would be found to be covered by less analysts than larger companies. This disparity leads to observations such as that of Heikkilä (2016) who showed that investors of stocks covered by a single analyst tend to react more to publications by that analyst, particularly when the information is positive. The limited analyst coverage of smaller firms creates an environment that allows for studying a specific aspect of analyst reporting: their initiation of coverage events.

The initiation of coverage event is generally defined as the first time an analyst or a brokerage begins coverage of a particular company (Demiroglu & Ryngaert, 2010; Crawford, Roulstone, and So, 2012). Such an event was found to result in liquidity improvements and a +4.86% positive abnormal returns on the announcement date (Demiroglu & Ryngaert, 2010), and was shown to increase stock return synchronicity (Crawford, Roulstone, and So, 2012). Similarly, initiations were found to have an incremental impact even when other analysts already covered the stock (Irvine, 2003). While the literature has provided several results on the consequences of initiations, research has yet to delve into the fundamental aspect of the initiation beyond the recommendation. Specifically, the gap in the literature is that there is no answer to the question: does the initiation of coverage, isolated from other effects, hold value reflected in the prices of these stocks?

Therefore, this study proposes the following questions to address this gap. Is a stock covered for the first time by an analyst a unique event such that it is significantly different from standard recommendation announcements by analysts? Also, does this event have a consistent effect for all firms in the small-cap market and does this effect reduce stock volatility in the long-term?

We argue that the first analyst recommendation announcement of a small-cap company creates a consistent effect known as a certification effect. This effect is defined as the improvement of a stock's return due to the first analyst recommendation announced such that the effect is independent of firm level characteristics. Therefore, it is calculated as the difference of cumulative abnormal returns of the stock with the average cumulative abnormal returns of a control group of mid-cap stocks with an announcement period around the same time as the initiation[1]. The expected result of the certification effect in the long-term is that the small-cap stocks become more efficient, more liquid, and hence, less risky.

Using a sample of 6,186 distinct small-cap recommendation announcements – occurring at least one trading year after the company's IPO event – in addition to financial and managerial information, we find evidence that the act of initiating coverage does cause a shock to a stock's price and this influence is independent of firm level characteristics. Event study analysis reveals that on average there is a consistent difference between the first recommendation announcement for a small-cap firm and standard recommendation announcements released for mid-cap stocks within the same quarter. We also note that significant relationships between the mid-term and long-term difference with various firm-level variables indicating that the announcement's effects do not extend to the mid-term nor the long-term.

The rest of this paper is organized as follows. Section two discusses the past literature on the topic of analyst coverage and then develops testable hypotheses for the effect of the first recommendation announcement of analysts on small-cap equities. Section three reveals the sample data and methodology employed to test the hypotheses. Section four shows and discusses the results of the tests performed with contextualization from literature within the field. Section five concludes the study.

[1] Justification for selecting mid-cap stocks for the control sample is provided in section 3.1 of the study.

Literature & Hypotheses

2.1 Short-Term Analyst Coverage Effects

The primary function of analysts within the financial markets is to mitigate information asymmetry through their forecasts, publications, and recommendations. However, the searching and collecting of information required to accomplish this task is itself a cost and an investment of resources as Bloomfield (2002) recognized in the Incomplete Revelation Hypothesis (IRH) which states that "Statistics that are more costly to extract from public data are less completely revealed by market prices". Engelberg, Ozoguz, and Wang (2018) found that stocks listed on the NYSE, AMEX, and NASDAQ with higher industry clustering tended to have more earnings estimates published which suggests that analysts release more information for firms within the same industry. This explains a solution the industry uses to manage the cost of extracting information mentioned previously, as the spillover hypothesis provided reduces the difficulty, and subsequently, the cost of finding information for analysts which allows them to publish more information.

Although, even with such a solution, analysts tend to favor firms that voluntarily release strategic and non-financial disclosures, as demonstrated by Hamrouni et al. (2017). Their study found a positive and significant (1% level) association between the number of voluntary disclosures and the number of analysts following the stock. Similarly, they observed a positive and significant (1% level) relationship between the publication of strategic information and the number of analysts tracking the stock. This furthers the implication that analysts prefer to cover more transparent firms and firms with more readily available information. Moreover, this conclusion is also corroborated with the evidence from Xie (2013). Her study of stock inclusions in the S&P indices revealed that with greater media coverage, small-cap stocks received more analyst attention along with recommendation upgrades. Within the same market segment, the evidence also points to more analysts covering firms with better corporate governance and less agency costs since they would have a higher quality of disclosures (Fortin, & Roth, 2010). Specifically, under all model specifications used (OLS, and Negative Binomial), the significance of the relationship was at the 0.05 level or better, but directional causality was not established.

Taking the Efficient Market Hypothesis (EMH) into account, the notion that analyst recommendations would result in a significant change in returns is a contraindication of the hypothesis since, in general, recommendations are made with publicly available information that should already be incorporated into the price of the stock. Sharda (2022)'s analyst recommendations for companies in the BSE 100 corroborate this efficiency as the average abnormal returns generated with a magnitude of 0.824% were only significant on the event date. Nevertheless, this does not imply that it is impossible for analyst recommendations to have an impact. As mentioned previously in the IRH, if searching for information is costly enough (Bloomfield, 2002) then by the hypothesis as well, the analyst recommendation should generate an effect that includes said cost into the stock price. This conjecture is proven consistently both nationally and internationally. For the latter, Murg, Patchler, and Zeitlberger (2014) show regular abnormal returns and losses ranging from -1.534% (change from buy to sell recommendation) to 1.232% (change from sell to buy recommendation) generated in the short-term by analyst recommendation changes for 24 firms in the Austrian market across 14 years through their use of an ARMA-market-GARCH model. Similarly, Guagliano, Linciano & Contento (2013) found significant positive abnormal returns – ranging from 0.98% to 2.19% depending on the sampling criteria – for the announcements of upgrades and initiations in the Italian small-cap market. As for the former, in the United States, Loh & Stulz (2011) found that analyst recommendations are likely to be impactful for small firms with their evidence being from their base sample of 154,134 recommendation changes as well as more robust and stricter samples and definitions. Likewise, short-term abnormal returns were found with Cremers, Pareek and Sautner (2021), where upgrades were found to create a positive abnormal return and downgrades were inversely showing an abnormal loss within the event window [-1, +1] around the announcement event window with their sample of US stocks. Moreover, Demiroglu & Ryngaert (2010) found a similar positive reaction in the short-term window for initiation of coverage events such that their sample generated positive abnormal returns of 4.86%; however, their sample only contained Hold, Buy or Strong Buy initiation recommendations.

Therefore, due to the consistent trend of analyst recommendations having an impact on small-cap returns in the short-term this study poses the following hypothesis for the first recommendation given to small-cap firms within the US stock markets.

Hypothesis 1a: *The first recommendation for a firm being a buy/strong buy (sell/hold/underperform) recommendation will result in significant positive (negative) abnormal* *returns for small-cap stocks in the short term due to the positive (negative) sentiment generated within the period.*

2.2 Long-term Analyst Coverage Effects

Extending the observations past the immediate impact of an analyst's recommendation, the literature finds several impactful patterns within the market in general and small-cap segment in particular. One of the earliest studies into longer event windows is Womack (1996). His study found abnormal stock return drifts in the months after the recommendation announcement. More specifically, his findings were that an upgrade had an average positive drift of 2.4% and were significant up to one month after the announcement while a downgrade has an average negative drift of -9.1% and were significant for up to six months after the announcement. His results also showed the effects were more impactful for small-caps than large-caps. The comparative lack of effects for large-caps is corroborate with evidence from Panchenko (2007) who identified a trend in U.S large-caps within the [-30,30] event window period around analyst recommendation upgrades and downgrades. Their results within the period of 1997 to 2003 are also similar to Sharda (2022)'s conclusions such that upgrades exhibit a positive abnormal return roughly equal to a recommendation downgrade's abnormal loss and only exhibiting significance on the event date. On the other hand, Womack (1996)'s evidence of drift in the small-cap market, i.e. less liquid market and segments is supported by Hong et al. (2000)'s work. Their study found that environments with low analyst coverage admit a slower information diffusion time, particularly for negative news. This also justifies the works of Demiroglu and Ryngaert (2005) and their observations on the firms with no previous analyst coverage. Their sample consisted solely of neutral to positive recommendations – Hold, Buy, and Strong Buy – with the majority being the latter two recommendations. They found that the positive abnormal returns continue up to 3 months after the announcement at an average of 8% each month. Similar results followed from Bolster, Tahran, & Ebrahimi (2017)'s investigation of stocks across the market segments. They observed that upgrades and downgrades of Morningstar analysts provided an abnormal positive return – cumulative abnormal return of up to 0.85% with an upgrade to 5 stars – and abnormal losses – cumulative abnormal return of -0.98% with a downgrade to 1 star – respectively with both being significant in the month following the announcement. Therefore, this study shall expect similar results to those that were found before:

However, this study also wishes to explore the effects further than one month after the announcement. Studies such as Ertimur, Muslu, & Zhang (2011) provide insight into this extended long-term period. They found evidence that analyst recommendation initiations[2] are optimistically biased and underperform in the long-run compared to their non-initiated counterparts – particularly the "Strong Buy" recommendation underperforms annually by 4% comparatively. Their reasoning points to what they referred to as the "reporting explanation", the conflict-of-interest analysts face where their reports are optimistically biased to generate investment banking business. This is corroborated with evidence of how automated/Robo-Analysts issue less optimistic recommendations compared to traditional analysts and have better long-run performance for their positive recommendations (Coleman, Merkley, & Pacelli, 2022). These results contradict Brooks & Wang (2004) that utilized event windows extending to [0, 109] (around half a year). They found that, following the Private Securities Litigation Reform Act and the Securities Litigation Uniform Standards act, analyst recommendation upgrades produced long-term upward drifts across the event windows resulting in buy and hold abnormal returns — in their model — of up to 8.31%. However, their results seem to be the outlier, rather than the norm, as the effects of analyst optimism seem to extend as well beyond just the recommendations. Cusatis (2008) found an optimism bias within analyst earnings per share growth forecasts for the one-year and the three-to-five-year period. Similarly, Cook & Wang (2010) show evidence of analysts' long term growth forecasts to be more optimistically biased and potentially face a second conflict of interest in that they wish to maintain positive relations with the management of the firms they are observing. Moreover, Jegadeesh et al. (2004) finds that adherence to analyst recommendations would result in losses rather than gains as analysts tend to recommend higher growth and more expensive stocks rather than stocks with better value and fundamentals. There also exist relationships governed by the time shortly after IPOs. Das, Guo & Zhang (2006) found that higher amounts of residual analyst coverage points towards analysts being more confident about the potential of the company and found that such companies outperform companies with lower residual analyst coverage over the three-year period after the IPO. Hence, this points to a predictive power for analysts where they will tend to provide coverage quickly for companies they believe to meet their expectations. This also implies the

[2] As defined by Irvine (2003) refers to the first time an analyst announces a recommendation on a company, not the first recommendation recorded for the company.

contrapositive statement that if a company won't meet their expectations, then there would be little residual analyst coverage during the period after the IPO. Therefore, there is a reasonable amount of evidence that would point towards small-caps underperforming in the long-term particularly after positive or optimistic recommendations. Hence, the following hypothesis to be observed for the study:

Hypothesis 1b: *The effect of the first recommendation within at least the month post the announcement will be consistent with the short-term effect. That is if the recommendation is a Buy/Strong Buy (Hold/ Sell/ UnderPerform) the abnormal return of the within the following month will be positive (negative). After one month, the long-term window will reveal underperformance and abnormal loss for the first recommendation when it is a positive recommendation, while the negative recommendation will remain consistent with its abnormal loss.*

2.3 Recommendation Effect Depends on Firm Size

In addition to the effect analyst recommendations have on stock returns, there is evidence to extend the relation that the analyst recommendations are more likely to have inversely proportional effects depending on the size of the firm, i.e. holding all else constant, the smaller the firm, the more impactful the analyst's recommendation will have on it. Loh & Stulz (2009)'s work with I/B/E/S recommendations from 1993-2006, points to exactly this conclusion. Moreover, their work also highlights that there is greater influence when there are lower numbers of prior earnings forecasts published on the stock. A possible justification for such results can be found through Lim (2001) whose results show an optimism bias towards the forecasts of smaller companies due to their more volatile and less transparent nature. Likewise, Brown, Feigin, and Ferguson (2013)'s study focusing on a single Australian star analyst and his announcements in a niche market shows how a singular analyst can generate abnormal trading volumes and alter perceptions in a small market. On top of that, Irvine (2003) shows how a new analyst beginning coverage on a stock that already has coverage can have an incremental impact on the stock price, as well as a noticeable effect on the stock's liquidity. Hence, there are several factors that play into the expectation of the following hypothesis within this study.

The difference of impact based on firm size has even more extensive evidence. Jha, Lichtblau, & Mozes (2003) found that analyst recommendations are more informative within environments with more uncertainty, such as with smaller firms. Therefore, their results point to recommendations having a greater impact on prices for small-caps rather than larger firms. Results from Devos et al. (2015) also show that there is a difference between analyst recommendations within different information environments. Their observation solidifies the results that analyst recommendations are more impactful in less informative environments. Meanwhile Lo (2017) — like Lim (2001) — found that analysts are generally more optimistic towards small-cap stocks and release more positive recommendations with the expectation of positive performance in the future, which is realized since the difference of returns between the small and large firm size samples is statistically significant with an average of up to 0.48% depending on the model used to estimate the returns.

However, this study aims to compare small-caps to mid-caps. Therefore, it is important to note that mid-caps are often neglected and overlooked in both the literature as well as in investing discourse as Ge (2018) pointed out; this limitation extends itself in the analyst coverage literature. Hence, this study is one of the very few that explicitly compares effects between small-caps and mid-caps. Despite that, a line of reasoning does exist within the literature that would show that analyst recommendation announcements could be more impactful for specifically mid-cap stocks than for small-cap stocks. Bhushan (1989) reported a proportional relationship between analyst coverage and firm size, measured using market value. That is, as a firm's market value increases, ceteris paribus, the firm should have a larger amount of analyst coverage. Secondly, Branson, Guffey, and Pagach (2010) found that the impact of an initiation of analyst coverage[3] has a concave shape based on the amount of analyst coverage a company already has. That is, a company that already has a light amount of coverage will show a greater price impact by an analyst publishing their first recommendation on the firm compared to a firm with no analyst coverage receiving its first and a firm with an existing high level of analyst coverage. Therefore, since mid-caps would have a light amount of coverage then if there are more initiations than upgrades or reversals or reiterations by existing analysts, there is the potential for the study to observe that analyst recommendations are more impactful for mid-caps than small-caps. On the other hand, since this study does not limit the type of recommendation

[3] As defined by Irvine (2003) refers to the first time an analyst announces a recommendation on a company, not the first recommendation recorded for the company.

within the mid-cap sample, then the expectation is to observe effects like the comparisons between small-caps and large-caps previously mentioned:

Hypothesis 2: *There is a significant positive difference between the cumulative abnormal returns (buy and hold abnormal returns) of small-cap stocks and the cumulative abnormal returns (buy and hold abnormal returns) of mid-cap stocks with similar recommendations. This difference will exist in all event windows and is known as the certification effect (mid certification effect/long certification effect).*

2.3 Certification Effect

Analyst coverage lends itself to more benefits for the stock being followed, for example, He, Bai, and Ren (2019) show that the resiliency of a stock to crashes is proportional to the amount of transparency and coverage the stock receives from analysts. Additionally, Li & You (2015) show how under their definition of analysts initiating coverage – the definition put forward by Irvine (2003) – investor recognition improves for the stock under observation. Sun and Liu (2010) discuss the future performance of the stock after initiations of coverage and found that initiations provide incremental information about the underlying stock's future performance to investors, particularly in the one-month period after the initiation. Meanwhile, Doukas, Kin, and Pantzalis (2005) show a double-sided argument that pushes for a "goldilocks zone" for the number of analysts covering a particular firm. Firstly, if there are too many analysts covering a firm, they found that on average the firms will be overvalued by investors. On the other hand, if there are too little analysts covering a firm then the stock will, according to their findings, be undervalued due to the opaqueness of the underlying firms and possible agency problems associated with such a lack of transparency. Therefore, there is an incentive for public firms to attract analysts, but not too many that it may hinder long-term performance; and, within such a conclusion lies a question: what prompts analysts to begin the initial coverage of stocks? And what are the effects that originate from the initiation of coverage?

The focus on the former question primarily began with Bhushan (1989)'s connection between analyst coverage and firm size, as mentioned previously. In addition, a proportional relationship was also established between analyst coverage and the amount of intangible assets where intangible assets were measured in research and development expenditure and marketing expenses (Barth, Kasznik, & McNichols 2010). Meanwhile, more recently, Martineau and

Zoican (2023) found a causal relationship between the volume of uninformed trading and the number of analysts covering the stock. Specifically, they found that “a one standard deviation increase in retail investing causes an increase of 0.6 in analysts covering the stock”.

Meanwhile, the latter question is addressed partially through Demiroglu and Ryngaert (2010)’s study of neglected stock. The study determined that the reaction analysts had on this unique sample of stocks were notable improvements with stock prices and liquidity. The importance of this result is because a portion of their sample follows their first definition of neglected stocks which is stocks that received an announcement of an analyst recommendation without ever prior receiving an analyst recommendation. Although, their sample also included firms that had a gap of one year between recommendation announcement as well; this limitation was addressed by Dhiensiri and Sayrak (2010)’s study. They found similar improvements to stock prices and liquidity in a sample consisting solely of beginning of coverage announcements. Moreover, their results also showed that there is a lack of a relationship between the cumulative abnormal returns generated for the sample within the beginning of coverage announcement event window and the analyst firm’s reputation, the exchange listing or if the analyst firm was also the underwriter for the IPO. Additionally, the event windows extended to over three months before and after the announcement (70 trading days) indicating the longevity of such results.

However, no study seemed to discuss the possibility of firm-level characteristics impacting the effect of an initiation of coverage. In fact, Farooq (2023) found, in France, that analysts preferred to observe market information as opposed to firm specific information for their analysis to be able to cover a larger number of firms. Another limitation is that studies that observed the initiation of coverage events also did not specify whether such effects found were tied to the recommendation or if it is the initiation itself. In addition, while studies such as Hong et al. (2000) discussed the persistence of negative news in less transparent market environments, no study discusses the persistence of the initiation effects. This study poses the following hypotheses given both the possibility of initiation of coverage being an exogenous effect of the stock and the importance of analyst coverage on the visibility of small firms in the long-term:

Hypothesis 3a: *The short-term certification effect is independent of firm-level characteristics, and stock volatility prior to the event date.*

Hypothesis 3b: *certification effects beyond the short-term will have a significant and positive relation with the short-term certification effect, but no relationship with firm-level variables.*

2.4 Certification Effect & Volatility

Finally, it is important to define precisely potential consequences of the certification effect on the stock as there are several potential avenues to explore, a particular effect frequently discussed is the relationship between analysts and stock volatility. For instance, an inverse relationship between analyst coverage and the stock return volatility of French firms was found by Sahut, Gharbi and Gharbi (2021); while Bond and Cummins (2004) observed a significant positive relationship between analyst disagreements and stock volatility with US firms.

Analyst recommendations were also shown to influence liquidity and volatility of the underlying stock. Chen, Jung, and Ronen (2017) focused on analyst reiterated recommendations. Their results pointed to reiterations of the same recommendation having a market impact by reducing uncertainty which was measured as the implied volatility of 30-day in the money option contracts. Hence, reiterations were found to be proxies for informational content and could be essentially considered as a “confirmation effect”. In a similar vein, Devos et al. (2015) uncovered that analyst upgrades/downgrade recommendations were seen as influential and impacted abnormal volumes and volatility. Particularly, their results were in greater magnitude for stocks in lower quality information environments, which were described as segments where stocks were observed to have lower measures of stock synchronicity, since such environments are found to be more challenging for investors to assess the firms’ policies.

With respect to initiation of analyst coverage, Dhiensiri and Sayrak (2010) found no relation between the event and the change of volatility of the underlying stock. Although, such a conclusion contests Schutte & Unlu (2009)’s observations. They determined that initiations of coverage – with a definition in-line with the neglected stocks definition by Demiroglu and Ryngaert (2010), but more restrictive (no estimate or revision in the past two years instead of one year) – have noise reducing effects for the year after the initiation for the underlying stock. However, such differences could be due to the difference of definitions used to describe stock return volatility and uncertainty. Nevertheless, this study proposes the conjecture that the certification effect – the effect of an initiation of coverage sans the recommendation effect – is an effect that reduces stock return volatility. The reasoning is that the initiation is an information improving effect, and as such should be a factor that reduces the riskiness of the stock. Hence, the following hypothesis:

Hypothesis 4: *Stock volatility on average decreases after the first recommendation announcement of an analyst on IBES and should be negatively correlated with the long certification effect as risk reduction should be seen across a long horizon.*

Data & Methodology

3.1 Sample Construction and Distribution

The initial sample of first-time recommendation announcements on small-cap stocks was obtained by merging the CRSP and IBES databases on the stock's CUSIP ID. CRSP is the database that contains all stock market information dating back to 1960, while IBES contains analyst information dating back to 1976. For a stock to be eligible for the sample, it had to meet the following criteria: it must have been classified as a small-cap by FINRA[4] at the time of its first IBES announcement, it must be traded in the United States, and it must be specifically coded as a common share (excluding mutual funds, REITs, ETFs, and financial institutions).

The sample was divided into two subsamples, depending on the type of first-time recommendation, the positive subsample and the negative subsample. If the recommendation were a "Buy" or "Strong Buy" then the stock was placed in the positive recommendation subsample; otherwise, the stock was placed in the negative subsample. This gave us an initial sample of 6,168 stocks spanning the years 1993 to 2024, of which 4,579 are in the positive subsample and 1,589 are in the negative subsample. This was the sample on which the event study was carried out to determine the cumulative abnormal return and the buy and hold abnormal return required for subsequent analysis.

To include accounting information, the sample was merged with COMPUSTAT to retrieve the firm size, return on assets, and leverage of the firm for the fiscal year the announcement took place. This resulted in a sample of 5,306 firms where 4,009 were within the positive subsample and 1,297 were a part of the negative subsample. The loss of sample size was due to missing variable information from COMPUSTAT. Additionally, the sample was merged with BoardEx to retrieve the managerial variables; this resulted in a sample of 1,171 companies where 889 were in the positive subsample and the remaining 282 were in the negative subsample. The managerial variables included were executive gender, executive age, and board size. In cases where unique identifiers were lacking, the Ticker and company name were used to merge BoardEx data, which may have led to imperfect matching.

[4] The stock must have a market capitalization between $250 million and $2 billion

The event study was performed using an estimation period minimum of 250 trading days and a maximum of 400 trading days, this estimation period was chosen to avoid the IPO effects as discussed by Ritter (1991) as with a large enough estimation window, and high minimum, this would exclude all young firms that had their IPO within the year. Hence, the entire sample shrank due to this requirement as the number of firms that were eligible after this requirement was 2,495 firms of which 1,622 were in the positive subsample and 873 were in the negative subsample. Consequently, the sample containing only accounting information was reduced to 2,049 firms (1,361 positive, 688 negative), and the sample containing both accounting and executive variables was reduced to 297 firms (204 positive, 93 negative). Table 1 summarizes the construction process and its effects on sample size, while Table 2 shows the distribution of announcements per year along the sample construction.

As a control sample for calculating the abnormal returns generated by a "standard analyst recommendation announcement", a sample of mid-cap stocks was constructed once again by merging the CRSP and IBES databases. To be eligible to be part of the control, the announcement had to occur at least one calendar year after the firm's first coverage announcement, coincide with at least one of the original sample stocks' announcement year, quarter and industry[5], and the stock must be a mid-cap according to FINRA's[67] definition. This control sample comprised over 100,000 unique announcements from 1993 to 2024. The control events were then divided by industry, announcement year, announcement quarter, and recommendation type. This was considered the "standard recommendation effect" for that period and industry. Using mid-caps as the control was deemed a compromise, as large-cap stocks are too different from small-cap stocks to serve as a viable control and using future small-cap announcements raised endogeneity concerns. Nonetheless, using mid-cap announcements as the control assumes a certain level of similarity between the two segments, such that they are affected similarly by market dynamics.

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[5] First digit SIC code

[6] The stock must have a market capitalization between $2 billion and $10 billion.

[7] The use of the FINRA definition for both the sample and control were for simplicity; however, it does not account for the possible effect of inflation during the 30-year period of announcements. While controlling for time-fixed effects may alleviate the bias or sample loss, another alternative could be to account for inflation by augmenting the definition of FINRA with an inflation multiplier to more accurately define the boundaries within the year of the announcement, or to separate the stocks based on percentile sizes and observing which percentiles contain each market segment.

3.2 Methodology & Variables

3.2.1 Variable Calculation and Definitions

Table 3 provides a summary of all variables, their sources, and calculation method. This section will discuss the use of these variables.

Size

The size variable in financial studies is often a choice between the natural log of total assets or the natural log of the market capitalization of the company. The latter is used well in defining and separating firms based on size in papers such as Demiroglu and Ryngaert (2010), as well as was found to be related to analyst coverage as a whole (Bhushan, 1989). The former, however, was used in the study for several reasons. Firstly, the market cap of the firms was already considered twice in the study, in sample construction and in expected return estimation (see following sections). Hence, market-cap as a factor was already controlled for. Second, total assets provided an estimate of all resources the underlying firm has available (Dang, Li, and Zhang, 2018), which seemed relevant to analysts aside from market cap.

Leverage

The Leverage variable measured is the debt-to-equity ratio (total debt divided by book value of equity) was viewed as one of the most significant ratios for understanding the long-term risk and financial health of a firm (Gibson, 1987). Due to its forward-facing nature, this study viewed it as relevant for the upcoming analysis as it would be relevant for analysts to consider in their recommendations.

Return of Assets

Return on assets (ROAs) were used in this study as a measure of profitability. It is calculated as the earnings before interest, taxes, depreciation, and amortization divided by total assets. The reasoning for its use is similar to leverage, analysts require information on how efficient and profitable a firm is with respect to the resources it has available. Therefore, it’s relevant for this study’s analysis as analysts would favor firms with greater ROAs than firms with lower ROAs.

Age

The age variable refers to the age of the CEO of the underlying company. It proxies for several characteristics as different aged CEOs manage firms differently. Navaretti, Castellani, and Pieri (2022) found that younger CEOs drive firms to grow faster, however, this did not necessarily translate to the firms being more profitable. There was also evidence found that analysts favored “glamour stocks” which includes high growth stocks (Jegadeesh et. al, 2004). Hence, a potential underlying relationship between the variables exists.

Gender

The gender variable refers to the gender of the CEO of the underlying company. Evidence to consistent patterns between CEO announcements and analyst reactions have already shown that women CEO receives more muted responses as opposed to men when earnings forecasts are announced by the firm (Cook et. al, 2019).

Board Size

Board size is a variable that measures the number of members on the board of directors of the underlying firm. Generally, it is a measure meant to proxy for potential agency problems within the company. Jiraporn, Chintrakarn, and Kim (2012) found that a staggered board, which also leads to larger boards, encourages greater analyst following as they reduce information asymmetry and make it easier for analysts to retrieve information. Hence a relationship could be found within this study’s analysis.

$\frac{S_a - S_b}{S_b}$

The change of stock return volatility, measured as the difference of the geometric standard deviations of the period after the analyst recommendation announcement and the period before the recommendation announcement, over the geometric standard deviation of the period before the recommendation announcement. The before period is the period [-30, -1] and the after period is either [1,30] or [1,250] depending on the event window under analysis. Section 2.4 provided evidence for the potential relationship between stock return volatility and the initiation of coverage as analyst recommendations seem to be related to liquidity and risk. This study utilized this measure to capture whether the change in volatility is related to the initiation or not.

The variable is similar to the *Δ*Volatility variable from Dhiensiri and Sayrak (2010), but their calculation of the variable utilized the residual of the stock return volatility instead.

3.2.2 Methodology Framework and Assumptions

Event Studies

This study utilized the event study methodology to determine the impact of the initial analyst recommendation announcement on the different subsamples across various event windows. The objective is to utilize this methodology to prove or disprove H1a and H1b.

The methodology began with the pivotal paper by Fama, Fisher, Jensen and Roll (1969), which has reframed the methods in which information is observed to affect the market. The application of the methodology is far reaching in finance as practically every type of announcement can be observed using the methodology: Mergers and Acquisitions (Fama & Malkie, 1970), Stock splits (Fama et al., 1969), Dividend announcements (Suwanna, 2012), to name a few, and most relevant to this study, analyst recommendation announcements (Murg et. al, 2014; Guagliano et. al 2013; Demiroglu & Ryngaert, 2005; Demiroglu & Ryngaert, 2010; Panchenko, 2007). The methodology can be reduced to a few simple steps (Kothari & Warner, 2007):

1. Identify the announcement event and the date of the announcement.
2. Estimate the expected/predicted returns of the stock using a particular estimation model and period.
3. Calculate the abnormal returns as the actual returns on the event date *t* less the expected returns generated by the model used.
4. Aggregate the abnormal returns across the event window and perform the relevant statistical tests

The major points of contention for the methodology reside in steps 1,2, and 4.

For step 1, the major limitations were identifying what constitutes an event and sampling the correct dates. As Berkman and Truong (2009) identified, if an announcement was made in the after-trading hours, dates may be mis-specified, and results may be shifted in the event window. For the announcements, this study uses the announcement dates posted in the IBES database for analyst recommendations.

For step 2, a large portion of literature discusses how expected returns should be modeled. Anderson (2013) for example noted the limitations of the mean-adjusted model, market adjusted model and equity valuation models in markets with missing stock return data. Similarly, Hitchen (2024) described several issues with the approach of time-series regressions suggesting transitioning out of methodologies that relied on the capital asset pricing model completely. Be that as it may, the prevailing literature utilizes either the mean-adjusted, market adjusted, market, Fama and French three factor or Carhart four factor model approach.

The mean-adjusted and market-adjusted models suffer from the lack of considering market risk (Brown & Warner, 1985), although their performance is comparable to the market (CAPM) model. The Fama and French three factor (FF3F) model adds on to the CAPM model two additional explanatory factors *SMB* and *HML* which correspond to the anomaly that smaller companies generally outperform bigger companies and the anomaly that value stocks outperform growth stocks respectively (Fama & French, 1993). While the Carhart model – also known as the Carhart four factor model (C4F) – adds one more factor to the Fama and French model, *UML*, a factor describing the anomaly in the stock market known as momentum (Carhart, 1997). Since both FF3F and C4F models use the same factors, they make similar assumptions such as factor independence[8] and factor stability[9]. Also, analysis of both shows that both contain bias (Ahern, 2009). Griffin (2002) pointed out that the factors are country specific and international evidence shows a lack of significant difference between the two under statistical testing (Khoa & Huynh, 2023).

Dhiensiri and Sayrak (2010) utilized the market-adjusted model. Irvine (2003) and Demiroglu and Ryngaert (2010) utilized a Buy and Hold abnormal return approach comparing the returns to a size index indicating the importance of the size factor in their studies. Meanwhile, Panchenko (2007)'s methodology focused on the market model to estimate returns. Therefore, there doesn't seem to be much consistency in what is considered the best model. However, it is important to note that analyst coverage does seem interrelated with momentum

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[8] Assumes that the Market Risk, Size, Value, and Momentum (if included) factors are all independent of each other.
[9] Assumes that factor premiums are relatively stable over time.

factors (Ali & Hirshleifer, 2020), and thus incorporating the momentum factor could raise endogeneity concerns. Hence, this study will pursue the estimation of expected returns using the FF3F model approach but will also show graphically the results of the market model[10].

$$R_{it} - R_f \; = \; \alpha_i \; + \; \beta_i \cdot \left(R_{Mt} - R_f\right) + \; s_i \cdot \; SMB_t \; + h_i \cdot \; HML_t + \varepsilon_{it} \qquad (1)$$

R_{it} indicates the expected returns of stock i on event date t, R_f indicates the risk-free rate, R_{Mt} indicates the market rate of return on the event date t where the market is the CRSP full market index. SMB_t is the Fama and French small minus big factor on the event date t and similarly HML_t is the Fama and French high minus low factor on the event date t.

As mentioned previously, the estimation period for the expected returns calculation must exceed at least 250 trading days to ensure that the firm had been trading on the stock market for at least one year after its IPO and prior to receiving its first analyst recommendation.

Step 3 defines the remaining procedure to calculate abnormal returns through equation (2):

$$AR_{it} = R_{it} - ER_{it} \qquad (2)$$

AR_{it} indicates the abnormal return of stock i at event date t, R_{it} indicates the actual return of stock i on event date t and ER_{it} indicates the expected return of stock i on event date t calculated through equation (1).

Finally, for step 4, determining the event window and the aggregation method for the abnormal returns – cumulative abnormal returns vs buy and hold abnormal returns – are the prevailing points of contention. One suggestion is to report on the event windows for which abnormal returns are significant (Armitage, 1995). Another possible action is to observe the results of past literature and gauge the relevance of past event windows. Dhiensiri and Sayrak (2010) and Demiroglu and Ryngaert (2010) reported short event windows around the event date [-1,1]. Panchenko (2007) reported on an event window of [-30, 30]. Womack (1996) observed results up to six months after the announcement date. However, the main drawback of long windows within an event study methodology is the potential for confounding events and

[10] Rit-Rf = i + i·(Rmt-Rf)

overlapping events which raise doubts about causality and drawing meaningful conclusions as to the actual effects of the events in question.

This study reported 3 different event windows, the short-term, mid-term and long-term periods. The short-term period is [-2, 2] following the guideline of reporting the event dates for which the abnormal return is significant (Armitage, 1995). The mid-term period is the window [-2, 30] following similarly to Panchenko (2007)'s event window and their volatility analysis, as well as Womack (1996)'s one month period. Additionally, the study reported the long window of [-2,250] as a one-year after announcement to observe the long-term effects of the recommendation announcement and to observe if optimism effects like Cusatis (2008) or Ertimur et al. (2011) could be observed. The reasoning of the two days prior to the event date was to possibly capture any potential leakage effect as noted by Panchenko (2007) as well as avoid missing the event due to problematic announcement dates (Berkman & Truong, 2009). Eq. (3) and (4) show the aggregation methods. For the short window [-2, 2] cumulative abnormal returns were calculated as is standard for the short term; however, for the mid and long-term windows, Buy and Hold abnormal returns were utilized as it is more insightful for longer term windows (Kothari & Warner, 2007).

$$CAR[t-2; t+2]_i = \sum_{t-2}^{t+2} AR_{it} \tag{3}$$

$$BHAR[t-2; t+k]_i = \prod_{t-2}^{t+k}(1+R_{it}) - \prod_{t-2}^{t+k}(1+ER_{it}) \tag{4}$$

The event study was performed through SAS using code from WRDS customized and corrected to suit the need of this study in addition to being verified through the WRDS Daily event study online software and the EVENTUS software. It was carried out with the base sample of small-cap stocks, split into its subsamples, along with the mid-cap control sample split into similar positive and negative announcement subsamples. The small-cap stocks' returns are the main variables of interest while the mid-cap stocks' returns were for comparison in the calculation of the certification effects following. For more details of the procedure and testing of event studies Eckbo (2008)'s Handbook of Corporate Finance provides greater in-depth insight into the procedure.

H1a would be considered supported if we observe significant positive abnormal returns for the positive subsample and significant negative abnormal returns for the negative subsample.

H1b would be considered supported if we observe positive abnormal returns in the mid-term then negative abnormal returns in the long term for the positive subsample and significant negative abnormal returns for the negative subsample across all event windows.

Calculating the Certification Effect & Testing for Significance

After both sample event studies, the certification effect was calculated for the different periods studied to test for the hypothesis H2 and to proceed for further analysis. To calculate the certification effect, the average quarterly cumulative abnormal return, $QCAR^{11}_{syqn}$, and average quarterly buy and hold abnormal return, $QBHAR^{12}_{syqn}$, of the mid-cap stocks were calculated.

To calculate $QCAR_{syqn}$, the cumulative abnormal returns (CAR) of the control mid-cap stock announcement events with the same recommendation type[13] *s*, announcement year *y*, announcement quarter *q*, and industry *n* were averaged.

To calculate $QBHAR_{syqn}$, the buy and hold abnormal returns (BHAR) of the control mid-cap stock announcement events with the same recommendation type *s*, announcement year *y* and announcement quarter *q* and industry *n* were averaged.

After their calculation, the certification effect (CE), Mid certification effect (MCE), and long certification effect (LCE) of a stock *i* can be defined and calculated as the difference of the *CAR* of a stock *i* with a recommendation type *s*, announcement year *y* and announcement quarter *q* with the *QCAR* belonging to the same recommendation type *s*, announcement year *y* and announcement quarter *q*, the difference of the *BHAR* of the window [-2, 30] of the stock *i* with a recommendation type *s*, announcement year *y* and announcement quarter *q* with the *QBHAR* of event window [-2, 30] of the same recommendation type *s*, announcement year *y* and announcement quarter *q* and the difference of the *BHAR* of the window [-2, 250] of the stock *i* with a recommendation type *s*, announcement year *y* and announcement quarter *q* with the

[11] QCAR is calculated for the event window [-2,2]

[12] QBHAR is calculated twice, once for event window [-2,30] and once for event window [-2,250]

[13] Recommendation type is defined as either “positive” for a Buy or a Strong Buy recommendation, or “negative” for a Sell, Hold or Underperform recommendation, that is, the averages are calculated for the positive recommendation subsample and the negative recommendation subsample separately.

QBHAR of event window [-2, 250] of the same recommendation type *s*, announcement year *y* and announcement quarter *q* respectively. All calculations can be seen in equations (5), (6), and (7) respectively.

$$CE_i = CAR_{isyqn} - QCAR_{syqn} \tag{5}$$

$$MCE_i = BHAR_{isyqn[-2,30]} - QBHAR_{syqn[-2.30]} \tag{6}$$

$$LCE_i = BHAR_{isyqn[-2,250]} - QBHAR_{syqn[-2.250]} \tag{7}$$

Additionally, an independent sample t-test was performed. The objective of this test is to conclude that the difference between the small-cap subsamples and their equivalent mid-cap subsamples is significant and non-zero, and therefore, accepting or failing to accept H2.

The two sample t-test, also known as the independent samples t-test, is a powerful test used to reject the null hypothesis that the means of two independent populations are the same (Gio & Rosmaini, 2018).

$H_0: \mu_x = \mu_y$

$$t = \frac{\bar{x} - \bar{y}}{s_p\sqrt{\frac{1}{n_x} + \frac{1}{n_y}}} \tag{8}$$

$$S_p = \sqrt{\frac{(n_x - 1)s_x^2 + (n_y - 1)s_y^2}{n_x + n_y - 2}} \tag{9}$$

Where x, y are independent normally distributed samples, $\bar{x}$ and $\bar{y}$ are their respective sample means, S_p is the pooled standard error of the two samples, s_x and s_y are their respective sample standard deviations and n_x and $n_y$are their respective sample sizes.

It does rely on several assumptions that must be upheld for the results to be meaningful. The primary assumption held, as the t-test is a parametric test, is the assumption of the samples having normal distributions. Additionally, the samples must be independent of each other, and there must be homogeneity of variances, as is standard in parametric tests (Gio & Rosmaini, 2018).

H2 will be considered supported if there is evidence to reject the null hypothesis of the t-test.

Linear Regression Relationship Analysis

This study used the linear regression model to identify the relationship between the certification effects calculated, and the variables described in section 3.2.1. The objective of the regression models was to conclude on H3a and H3b

Multiple linear regression models provide information determining potential relationships between variables. Its use is prevalent in financial and economics literature, particularly in cross-sectional analysis. The fundamental assumptions of the linear regressions are the following: linearity in the relationship between the independent variables and the dependent variable, homoscedasticity, independence of error, and zero-mean residuals.

$$\hat{y} = b_0 + b_1x_1 + b_2x_2 + b_3x_3 + \cdots \tag{10}$$

Testing within regression models revolve around determining whether coefficients are significant indicating a relationship between the independent variable and the dependent variable, but it is important to note that this significance does not imply causality.

This study follows in parallel with the methodology from Dhiensiri and Sayrak (2010). The below equations (11) – (22) represent all models that are analyzed and reported upon

$$CE_i = b_0 + b_1\frac{D}{E}_i + b_2 ln(AT)_i + b_3ROA_i + b_4S_{bi} + b_5IND_i \tag{11}$$

$$\begin{aligned} CE_i = b_0 + b_1\frac{D}{E}_i + b_2\, ln\,(AT)_i + b_3ROA_i + b_4S_{bi} + b_5IND_i + b_6Age_i \\ + b_7Gender_i + b_8Board\ Size_i \end{aligned} \tag{12}$$

$$\begin{aligned} MCE_i = b_0 + b_1\frac{D}{E}_i + b_2\, ln\,(AT)_i + b_3ROA_i + b_4IND_i + b_5CE_i \\ + b_6\frac{S_a - S_b}{S_b}_{i[-30,30]} \end{aligned} \tag{13}$$

$$MCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_4 IND_i + b_5 CE_i + b_6 \frac{S_a - S_b}{S_b}_{i[-30,30]} + b_7 BD_i + \overrightarrow{Interaction_{ik}} \tag{14}$$

$$MCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_4 IND_i + b_5 \frac{S_a - S_b}{S_b}_{i[-30,30]} + b_6 BD_i + \overrightarrow{Interaction_{ik}} \tag{15}$$

$$MCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_4 IND_i + b_5 CE_i + b_6 \frac{S_a - S_b}{S_b}_{i[-30,30]} + b_7 Age_i + b_8 Gender_i + b_9 Board\ Size_i \tag{16}$$

$$MCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_4 IND_i + b_5 \frac{S_a - S_b}{S_b}_{i[-30,30]} + b_6 Age_i + b_7 Gender_i + b_8 Board\ Size_i + b_9 BD_i + \overrightarrow{Interaction_{ik}} \tag{17}$$

$$MCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_4 IND_i + b_5 CE_i + b_6 \frac{S_a - S_b}{S_b}_{i[-30,30]} + b_7 Age_i + b_8 Gender_i + b_9 Board\ Size_i + b_{10} BD_i + \overrightarrow{Interaction_{ik}} \tag{18}$$

$$LCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_4 IND_i + b_5 CE_i + b_6 \frac{S_a - S_b}{S_b}_{i[-30,250]} \tag{19}$$

$$LCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_4 IND_i + b_5 CE_i + b_6 \frac{S_a - S_b}{S_b}_{i[-30,250]} + b_7 BD_i + \overrightarrow{Interaction_{ik}} \tag{20}$$

$$LCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_4 IND_i + b_5 CE_i + b_6 \frac{S_a - S_b}{S_b}_{i[-30,250]} + b_7 Age_i + b_8 Gender_i + b_9 Board\ Size_i \tag{21}$$

$$LCE_i = b_0 + b_1 \frac{D}{E_i} + b_2 \, ln\,(AT)_i + b_3 ROA_i + b_4 IND_i + b_5 CE_i + b_6 \frac{S_a - S_b}{S_b}_{i[-30,250]} + b_7 Age_i + b_8 Gender_i + b_9 Board\ Size_i + b_{10} BD_i + \overrightarrow{Interaction_{ik}} \quad (22)$$

D/E is the debt-to-equity ratio calculated by calculating total debt and dividing it by Book value of equity. *ln (AT)* is the measure of firm size; it is the natural log of total assets (*AT*). *ROA* is the return on assets as the measure for profitability found by dividing *EBITDA* (earnings before interest taxes and depreciation) over total assets (*AT*). *IND* is the variable for industry fixed effects. *Age* is the CEO of the company's age at the time of the announcement, *Gender* is a dummy variable that represents the CEO's gender, and *Board Size* is the variable for the size of the board of directors. In the regression *CE* will be used within the regression of *MCE* and *LCE* to determine if the short-term effect plays a role in the long-term effect, and $\frac{s_b - s_a}{s_b}$ represents the change of volatility of a stock measured as the change in the standard deviation of returns. *BD* represents a dummy variable (buy dummy) where *BD = 1* if the stock belongs to the positive subsample (i.e. has a buy/strong buy recommendation) and 0 otherwise and $\overrightarrow{Interaction}$ is a 3x1 vector representing the interaction variables between *BD* and $\frac{s_b - s_a}{s_b}$, *BD* and *firm size* and the *BD* and *CE* along with their respective coefficients. Table (4) lists all variables used, their sources, calculations, and definitions. Additionally, for robustness, the analyses were performed using winsorized variables at the 5% and 95% levels.

H3a will be considered supported if this study finds no relationship between the independent variables in equations (11) and (12) and the dependent variable CE.

H3b will be considered fully supported if this study finds a significant and positive relationship between CE and MCE in equations (13), (14), (16), and (18) and no relationship with the other independent variables within the equations; in addition to the same holding for LCE and CE in equations (19) – (22). If some other variables are found to be significant in the models, they will be discussed in context, however, support for the hypothesis would be withdrawn.

MCE LCE & Volatility Relationship Analysis and Sample Testing

This study explored the relationship between the mid/long term certification effect and the respective change of stock return volatility described in section 3.2.3. The relationships were explored with linear regression models; in addition, one sample testing was performed to provide additional clarity to the change of stock return volatility variable. The objective of this exploration was to conclude on H4.

The standard hypothesis testing procedure determines whether to reject or fail to reject a null hypothesis under a particular significance level. The t-test statistic is sufficient drawing conclusions on the mean of a population. However, similar to the independent test, relies on the assumption of normality as it is a parametric test (Ross & Willson, 2017).

H_0: $\mu=0$

$$t = \frac{\bar{x} - \mu}{\frac{s}{\sqrt{n}}} = \frac{\bar{x}}{\frac{s}{\sqrt{n}}} \tag{23}$$

Where μ is the population mean $\bar{x}$ is the sample mean, *s* is the sample standard deviation and *n* is the sample size.

This allowed us to test for both the existence of the change of stock return volatility and its direction. The tests were done with the samples and subsamples created after the event study, since the variable were under observation in relation to *MCE* and *LCE* as well.

For testing the relationship with *MCE* and *LCE* the following regression equations were utilized using the same samples used in the previous regressions:

$$MCE_i = b_0 + b_1 \frac{s_b - s_a}{s_b}_{i[-30,30]} \tag{24}$$

$$MCE_i = b_0 + b_1 \frac{s_b - s_a}{s_b}_{i[-30,30]} + b_2 BD_i + b_3 BD * \frac{s_b - s_a}{s_b}_{i[-30,30]} \tag{25}$$

$$LCE_i = b_0 + b_1 \frac{s_b - s_a}{s_b}_{i[-30,250]} \tag{26}$$

$$LCE_i = b_0 + b_1 \frac{s_b - s_a}{s_b}_{i[-30,250]} + b_2 BD_i + b_3 BD * \frac{s_b - s_a}{s_b}_{i[-30,250]} \tag{27}$$

$$\frac{s_b - s_a}{s_b}_{i[-30,30]} = b_0 + b_1 MCE_i \tag{28}$$

$$\frac{s_b - s_a}{s_b}_{i[-30,30]} = b_0 + b_1 MCE_i + b_2 BD_i + b_3 BD * MCE_i \tag{29}$$

$$\frac{s_b - s_a}{s_b}_{i[-30,250]} = b_0 + b_1 LCE_i \tag{30}$$

$$\frac{s_b - s_a}{s_b}_{i[-30,250]} = b_0 + b_1 LCE_i + b_2 BD_i + b_3 BD * LCE_i \tag{31}$$

With the variables MCE_i, LCE_i, $\frac{s_b - s_a}{s_b}_i$, and BD_i being as defined previously for a stock i, the mid certification effect, long certification effect, change of stock return volatility and the Buy Dummy variable indicating whether the stock received a positive recommendation (*BD* = 1) or a negative recommendation (*BD* = 0) respectively. While $BD * \frac{s_b - s_a}{s_b}_i$ and $BD * LCE_i$ represent the interactions between the recommendation being positive or negative with the change of stock return volatility and the recommendation type with the long certification effect for a particular stock *i*. Additionally, for robustness, the analyses were performed using winsorized variables at the 5% and 95% levels.

H4 is accepted if we note a negative t-score in the sample testing, and if there existed a relationship within the linear regression equations (24) – (31).

Results & Discussion

4.1 Event Study Results

4.1.1 Short Window Analysis

H1a referred to the effect of a recommendation announcement on the small-cap stock returns. The objective was to observe if a positive (negative) abnormal return was generated in both the short-term and mid-term for a positive (negative) recommendation – where positive refers to a Buy/Strong Buy recommendation and negative refers to a Sell/Hold/Underperform recommendation. This was under the assumption that the different recommendations within the same type create the same effect – a strong buy is on average equivalent in effect to a buy recommendation; sell, hold, and underperform provide equivalent negative recommendation effects.

Results of the short window analysis can be viewed through Tables (5) and (6) along with Figures (1) through (4). For the positive subsample, significant abnormal returns were found along with cumulative abnormal returns that spanned for longer than the event date for both the small-caps and the mid-caps. As table (5) shows, the positive subsample admits an average cumulative abnormal return of 1.3% on the event date significant at the 1% level with abnormal returns of the same date at 0.83% significant at the 1% level. CAR remained significant post the event date, while abnormal returns trailed off and were no longer significant past the first date after the event. The positive mid-cap announcements followed the same pattern, although with lower abnormal returns and CAR respectively at 0.76% and 0.81% on the event date, with both being significant at the 1% level, the abnormal returns did become insignificant past the day t+1. This is consistent with the results of Murg et al. (2014) and Loh and Stulz (2011) and provides evidence for the significant and more impactful effect of the analyst recommendations on the small-cap stock as compared to the mid-cap stocks in the positive instances.

The results are also consistent between the different estimation models used to calculate expected returns and were similar to the results of Dhiensiri and Sayrak (2010) with their market adjusted model. With this consistency, this study concludes that a positive recommendation does create a positive shift in stock returns in the short term as investors react to the news and the market absorbs the added information as suggested by the incomplete revelation hypothesis (Bloomfield, 2002). The consistency of this reaction exists across all market segments and firm sizes, the only difference seems to be the magnitude of the adjustment, and the speed at which the market reacts to the news.

For the sample of Sell/Hold/Underperform, we noted the significant abnormal loss and cumulative abnormal loss presented in the mid-cap events found in Panel (b) of Table (6), with significance at the 1% level. The mid-caps exhibited a very close, but opposite result by t+2 with a CAR of -0.98% compared to the 1% CAR at the end of the period for the positive subsample, consistent with our H1a. However, not only did the small-caps exhibit a lack of significance on the event date, but also, according to the results of Panel b in Table (5) and Figure (3), the subsample exhibited positive abnormal returns on the date t-1, contrary to expectations. It appears that the results for the negative news are more in line with Panchenko (2007) as their downgrade subsample displayed similar leakage results or announcements preceding reporting dates within the database, while the lack of significance of the movement could be explained with justifications like the reasonings of Heikkilä (2016) which showed that investors don't tend to react as intensely with negative news; which would explain the delayed significance and the abnormal losses that occur on the dates t+1 and t+2 rather than on the event date itself.

Another possible justification for the positive abnormal returns observed at t-1 is that the data was subject to an incorrect date posted in IBES as Berkman and Truong (2009) warned could be possible. If the actual announcements happened after closing hours, or close to closing hours causing IBES to move the announcement one day forward. This is a reasonable reality since, if an analyst were to want to release bad news, they would be incentivized to avoid the trading hours of the day. However, such a theory would raise a particularly curious question. Why would a sell-side analyst announce a "Sell/Underperform/Hold" recommendation as the first ever recommendation for the stock in the first place? Sell-side analysts have an incentive to promote stocks to the benefit of their brokerage, it is one of the main conflicts of interests discussed in the literature of this subtopic as it leads to a bias towards optimism (Hayward & Boeker, 1998; Hirsch & Pozner, 2005; Jegadeesh, Kim, Krische, & Lee 2004; Malmendier & Shanthikumar, 2007). This is not the first study to raise such a question, Demiroglu & Ryngaert (2005) raises it with their "Hold" recommendations alone as their study did not contain "Sell/Underperform" recommendations. Their reasoning for the neutral recommendation was that it is used in order to avoid the use of the more negative recommendations, but when the years under observation are expanded large enough the negative recommendations appear, albeit not as commonly as the positive recommendations, but still frequent enough that they can't be ignored since as Table (1) shows eligible announcements within the negative subsample make up almost 35% of the sample after the event study; more than 1 in 3 initiations were given a non-positive recommendation. This study leaves the question for future research, but there is another point to question about the result as well. If the announcement date was indeed a day late in the database and the actual announcement happened on t-1 then, why does it generate positive abnormal returns?

The news was negative, and the abnormal returns quickly turn to abnormal losses on the dates t+1, and t+2. The only point towards there being no issue is the lack of significance according to the test statistic, but as mentioned previously Panchenko (2007) also noted the same results, only in the correct direction. If the information were leaked, then the direction of the abnormal returns is wrong, the investors would sell, causing returns to drop (Panchenko, 2007) not rise. The only conclusion within this line of thinking that is consistent would be that if this is not an endogeneity issue and information is leaked then not all the information is leaked, rather, only the fact that there would be an announcement was released. On the other hand, if the information was not leaked and the event date is truly mis specified, that still fails to explain the positive returns on exactly the "correct" event date alone and the immediate abnormal loss afterwards as this contradicts rationality. Finally, the results could not be due to an issue with the software used as different event study software was used and the results remained consistent, in addition to the control sample displaying the expected behavior as shown in Fig. (4) and Table (6). Therefore, this study puts forward the following timeline of events as a possibility:

- On day t-2 trading of the stock is proceeding as expected.
- On day t-1, or between day t-2 and t-1, information is leaked that an analyst will be issuing a report and recommendation on the stock, anticipation causes return to increase, but the analyst does not release the information until the end of the day.
- On day t, investors react to the negative news and correct the past anticipation.
- On days t+1 and t+2, investors continue to react to the negative news as information moves slowly (Hong et al., 2000).

This would be consistent with the certification effect, as the news of the announcement is isolated from the recommendation, in essence, this abnormal return could be precisely what the effect defines.

All things considered, even with the anomalous results at t-1, the study finds the negative abnormal returns on dates t+1 and t+2, along with the significant results of the positive subsample as sufficient evidence to accept H1a.

4.1.2 One Month Window and Long Window Analysis

H1b referred to the effect the recommendation announcement would have in the mid/long-term. The objective was to observe consistency for the negative recommendations between the mid/long-term while observing a positive effect in the mid-term and a downward shift in the long-term for the positive recommendations. The assumptions being held are that the initial announcement is the only significant announcement for initiations and that the mid/long-term performance is not affects by other events within the event window.

One-month and one-year windows' results were summarized in Table (7) and figures (5) to (12). Overall, the one-month results met expectations. We note that the positive buy and hold abnormal returns in the positive subsample were consistently larger in magnitude to the control counterpart. Moreover, we also observe the continuing buy and hold abnormal loss generated in the negative subsample carries forward after the date t+2.

The positive subsample admits a 0.59% buy and hold abnormal return at the end of the event period while its respective control sample seems to trail downwards into a loss of -0.186% with only the latter being significant at the 1% level. This is most likely due to the fact that they share similar downward trending graphs as the one-year period would show their abnormal losses. Aside from this pattern, the positive result across the entire period is consistent with the literature in the less transparent markets (Womack, 1996; Demiroglu & Ryngaert, 2005), with the difference of magnitudes between this study and past results could be due to the different models used.

The negative subsample admitted a buy and hold abnormal loss of -2.09% with its respective control sample having an abnormal loss of -1.39%. Both sample results were significant at the 1% level. This downward drift follows Hong et al. (2000)'s conclusion of slow information diffusion for negative news.

Long window results were summarized in Table (7), and Figures (5) to (8) displayed the results over the event window. We observed the consistent negative trend one trading year after the event date across all subsamples. However, for both the positive small-cap events and the positive mid-caps we also noticed that the buy and hold abnormal loss does not begin until after 29-30 trading days. The significant results remained however, with the positive small-cap subsample admitting the largest loss of 32.48%, significant at the 1% level under the cross-sectional t-test. The results deviating after the 30-day mark could be due to several factors. The study did not consider recommendation upgrades, downgrades or reiterations during this period as these are factors that would be occurring during this event window and had also been shown to affect the underlying stock (Chen et al., 2017; Devos et al., 2015); hence are confounding factors that could affect the long-term results. Additionally, when calculating the factor coefficients for the models, the outlier estimates were winsorized at the 5% and 95% level, but there still exist companies with outlier BHAR values that could have weighed the data down. Moreover, in a similar reasoning, around one-third of the events (particularly those used for the regression analysis in this study) have their event windows across crisis periods[14] which could alter the results as well (Corbet, Dowling, and Cummins, 2015). On the other hand, this result could also be evidence of the analysts being wrong and the effects were due to investor optimism as has been shown to be a possible result in previous studies (Ertimur, 2011; Cusatis, 2008; Jegadeesh et al., 2004; Cook & Wang, 2011). Alternatively, the general underperformance could be caused by a bad firm bias within the sample as analysts tend to initiate coverage for firms they are more confident in, closer to the firms' IPO date (Das et al., 2006).

The negative long window found buy and hold abnormal losses as expected. Both the sample in question and the control sample are significant at 1% with losses of -21.8% and -12.63% respectively. Both are also noticeably at less of a loss compared to the positive subsample and its control. In this case, this points to analysts issuing this recommendation to be more accurate, Coleman et al. (2022) showed that automated analysts issued less optimistic recommendations and were found to be more accurate, this could be a sign of a better analyst. As

[14] Crisis years being considered are 2000-2001, 2008-2009, 2020-2021.

mentioned previously, analysts are incentivized to provide positive recommendations. Moreover, analysts are more inclined to pick up a stock closer to its IPO date if they are more confident in the underlying firm's performance (Das et al., 2006). Therefore, to not have a recommendation within the stock's debut year, and subsequently, to pick-up the stock only to issue a recommendation against incentives, should be indicative of the analyst's discipline.

All in all, while there is the potential that the certification effect does not extend so far ahead due to confounding events within the long event window, there is evidence of its existence in the market in at least the short-term as the difference between the subsamples and their corresponding control samples remains across periods. These results meet the expectations of H1b and therefore, this study fully accepts H1.

4.2 Certification Effects

H2 discussed the difference between the cumulative abnormal returns and the buy and hold abnormal returns between the small-cap equities and their respective mid-cap control sample. This was under the assumption that industry, recommendation, and time fixed effects similarly affect the small-cap and mid-cap equities.

Findings in Table (4) showed there was a significant difference between the cumulative abnormal return and buy and hold abnormal returns of small-caps compared to the average CAR and BHAR of mid-caps with similar announcements within the same relative time periods. The table shows the average certification effect (CE) for the positive subsample to be 0.70%, the average mid certification effect (MCE) to be 0.77%, and the long certification effect (LCE) to be -10.86%, while CE, MCE, and LCE for the negative subsample to be respectively, 0.57%, -0.70%, and -9.17%; moreover, all subsample certification effects are significant at the 1% level except for MCE which is significant at the 10% level for the positive subsample and insignificant for the negative subsample.

The negative average LCE and the negative MCE for the negative subsample were unexpected. Potential justifications follow similarly from the long window analysis in section 4.1.2 as buy and hold abnormal losses observed include extreme negative weighted outliers. However, it should be noted as well that mid-cap stocks did observe similar results following the same methodology. Another possible reason is the existence of a trend of negative news following positive recommendation announcements, as Bandopadhyaya & Jones (2006) demonstrated that investor sentiment affects short-term pricing and international evidence from Dash & Maitra (2018) showed that investor sentiment has causal effects on small-caps and mid-caps in both the short and long term. Other possibilities are that events simply affect small-caps in greater absolute magnitude compared to larger companies. Kothari and Warner (2007) do warn that firm size does play a role in the influence of events on firm prices. The limitation here falls under the lack of a perfect control group to accurately extract the exact duration for the certification effect from the "standard recommendation effect".

Regardless, the significant differences still existed and hence provided evidence that there is a difference between the results of the small-cap sample and the control samples; hence supporting H2, at least for the short-term period.

4.3 Relationship Analysis

H3 explained the main predictions of this study and refers to the assertion that the certification effect (mid/long certification effect) observed were exogenous to firm level characteristics, the volatility (change of volatility) of the stock return and industry fixed effects. This is underlined with the assumption that if the relationship does not exist within a linear system as shown through a linear regression, it also does not exist in a non-linear system.

4.3.1 CE and firm level characteristics

The short-window regression results in Table (9) showed the lack of significance with firm-level variables except for leverage in column (1) at the 1% level, which is lost with the introduction of managerial variables, additionally, the coefficient of leverage being 0.00016 did lend itself to being an extremely weak to non-existent effect. Additionally, there were differences between the base case of the stock's industry being within Agriculture, Forestry, and Fishing[15] and Services[16] in column (1) as the industry effect is significant at the 10% level and positive. However, this does not hold for the model in column (2) nor for any other industry. This indicates weak evidence that the certification effect could be industry dependent, as the industry fixed effects proxy for risk, investor sentiment and competition within the company's respective subdomains, so there is reason to observe different magnitudes of the effect for different

[15] SIC Code starting with the digit 0.
[16] SIC Code starting with the digit 8.

industries. In fact, it was shown that on average the analyst that initiates coverage of a stock provides more industry related information than firm specific predictions (Crawford, Roulstone, and So, 2012) and this result may be representing such an effect. On the other hand, the overall evidence of all other industries being insignificant and significance only reaching the lowest threshold of significance does point more to the opposite conclusion, and that industry effects were controlled effectively through the control sample. These results also parallel Dhiensiri and Sayrak (2010)'s lack of significant relationship between the cumulative abnormal returns with any factor save liquidity. Thus, the results support that the announcement is exogenous to the firm level characteristics along with the volatility of the stock return prior to the announcement date. In addition, the winsorized results further support the conclusion that CE is exogenous of firm-level characteristics since, according to Table 14, all variables are insignificant.

4.3.2 MCE and firm level characteristics

The mid-length window regressions results were provided in Table (10). Similarly to the short-window regression, industry effects showed very weak relationships, only appearing when CE was removed from the regression equation as in column (5) and column (10). Otherwise, we note the significance of firm size at the 1% level until the inclusion of managerial variables at which point gender becomes significant before interaction terms are added at the 10% level. Once the interaction terms are added, in the full model Board Size becomes significant at the 5% level. Additionally, the interaction term between the Buy Dummy variable and the change of stock return volatility was significant at the 5% level in the same models, column (8) and column (9). CE is possibly the most important variable as removing it causes the explanatory power of the model to reduce drastically, and the significance of the variable is consistent at the 1% level. The significance of CE was expected as CE does represent the initial announcement effect in the short-term, so as the announcement effect increases, then on average it should be expected that MCE would increase.

The explanatory power of firm size is lost with the inclusion of the managerial variables. The variables may be interrelated; however, untabulated correlation and collinearity analysis revealed that is not the case within the sample. Also, the sign of its coefficient is positive, while the managerial variables have negative coefficients, indicating that they do not affect MCE in the same way. The firm size coefficient alludes to MCE increasing as firm size increases, or more specifically, firms with greater total assets, all else equal, seem to have larger MCE within the larger sample. Potential justification could be that since they were small-cap firms, the larger book valued firms were undervalued, or more positive reactions were portrayed towards larger companies, as they were viewed as comparatively safer. The gender variable showed in column (6) and (7) that on average MCE decreased when the CEO is a man. However, out of the sample of 297 firms, 288 are men; hence, due to the imbalance, even slight variations in values within the women led firms could cause false positives in significance, a limitation caused by the lack of executive data available. Also, significance only reached 10%, and was completely lost with the inclusion of the interaction variables, further supporting the possibility of sample imbalance. The Board size variable refers to the number of members on the board of directors. Its negative significant coefficient implies that, on average, as the board increases MCE decreases. As mentioned previously, larger boards are generally preferred by analysts as they reduce information asymmetry and make it easier for information to be released into the market (Jiraporn et al., 2021). The negative sign could therefore be evidence of the contrapositive incomplete revelation hypothesis (Bloomfield, 2002), since, if statistics are more completely revealed by market prices, i.e. if information is more readily available and priced in, then there is less need for dedicated individuals to retrieve information and thus reduces the impact of the initiation of coverage. Therefore, contrary to expectations, firm level effects seem to relate to the longer windows as multiple factors seem to influence and interconnect with the analyst recommendation announcement. Additionally, the winsorized results support this conclusion as Table 15 shows similar significance patterns, with the exceptions being ROA showing significance in all models along with Gender, while Board Size loses its significance. This points towards a preference of larger and mor profitable firms as MCE increases as both ROA and firm size increase. On the other hand, Gender's consistent significance rather than Board Size induces similar effects; however, this could once again be simply due to the unbalanced nature of the sample between Male and Female CEOs.

4.3.3 LCE and firm level characteristics

The long certification effect results were provided in Table (11). We observed that our expectation of the significance of CE was met for all models except the final full model that included all firm, managerial, industry and interaction variables (significance decreasing from 1% level to 10% and finally no significance in the final model in column (8)). The CE variable also possessed a consistent positive coefficient indicating the proportional relationship between CE and LCE similar to its relationship with MCE.

The significance of the relationship between the change of volatility and LCE differed compared to the same relationship with MCE. The change of volatility did not have a significant relationship in Table 10 with MCE except through the interaction term (5% significance) in column (5) when excluding CE from the model. The relationship with LCE was consistent in several models (3), (4), (7) and (8), i.e. the models that included the interaction terms. These relationships will be focused on in more detail in section 4.4.

The significance of the Board Size variable, and varying significance of firm size were not initially accounted for but were consistent with the results for MCE in the previous section, including the sign of the relationships. The significance and negative nature of Board Size implies that, all else held constant, as the Board Size of a firm increases LCE will decrease. Analysts seem to prefer more transparent firms (Fortin, & Roth, 2010), particularly when it comes to smaller companies. Hence, this result could potentially be justified with agency costs being incorporated to the value of the long certification effect, as the greater the size of the board, the increase probability for independent board members, the lower the agency cost, and once again by the incomplete revelation hypothesis (Bloomfield, 2002) the less LCE is generated.

Firm size, on the other hand, was significant insofar that the managerial variables are excluded (in columns (1) to (4)), and only became significant at the 10% level in the full model (column (8)). Therefore, the explanatory power of firm size seems to diminish when managerial information and type of recommendation are studied, similar to MCE. As mentioned previously, this could be due to the undervaluation of the book value of assets causing the analyst recommendation announcement to allow investors to look more closely at the firm since the evidence in the literature already points to liquidity improvements for the stock in the time after analyst recommendation announcements (Demiroglu & Ryngaert, 2010; Irvine, 2003; Dhiensiri and Sayrak, 2010).

The winsorized results of Table 16 follow similarly to the results of Table 15 for MCE. Firm size and ROA are both positive and significant, and gender remains as the only significant managerial variable. In addition, leverage becomes significant and negative indicating an aversion to firms with larger amounts of debt. Overall, the consistent trend within winsorized results seems to indicate a preference for safer firms.

Therefore, this study accepts H3a, as no significant relationship could be established. However, the study cannot accept H3b as the longer windows seem to confound effects that reflect in the relationship with the longer certification effects MCE and LCE.

4.4 Change of Volatility, MCE & LCE

H4 discussed further possible effects of the long certification effect. The objective is to determine if stock volatility decreased after the recommendation announcement. With respect to the variables of this study, the aim was to observe a negative change of volatility of stock return, with a significant linear relation existing between the mid/long certification effect and the change of volatility. This hypothesis held the same assumptions as H3.

Table 12 provided detailed results for the change of stock return volatility variable. Panel a. revealed that, contrary to expectations, stock return volatility seems to increase significantly after the recommendation announcement date since all samples had a positive and significant t-stat except for the smallest subsample – negative subsample with all variables after event study – in the mid window [-30, 30].

We noted as well the difference of magnitudes between the positive and negative subsamples after each step of the sample construction procedure for the long window [-30,250]. The negative subsample seems to be comparatively less volatile than the positive subsample. In the mid window, there seems to be no particular difference. This could point to the optimistic sentiments raising risk for the positive subsample (Cho & Kim, 2020).

Panel b. showed the relationship analysis between MCE and the change of stock volatility. The relationship was viewed in both directions where columns (1), (5) refer to equation (24) in the two regression samples used previously, (2), (6) refer to equation (25), columns (3), (7) refer to the equation (28), and columns (4) and (8) refer to equation (29). Panel c. is designed identically, but for equations (26), (27), (30), and (31) for the respective column pairings. A noteworthy observation is that the signs of the coefficients are consistent between the short term and the long-term. Additionally, they shared the same significance pattern such that column (6) in both panels was more significant than the rest, although less so for MCE compared to LCE. The results of the column suggest that there is a significant relationship such that if the recommendation were positive (BD = 1) then MCE observes a reducing effect due to the interaction term with the change of volatility variable having a negative coefficient (-1.309) that is greater in magnitude than the coefficient of the change of volatility variable (0.1696). Therefore, this indicates that when the recommendation effect is positive, the volatility tends to reduce MCE on average. However, there is only extremely weak evidence for the reverse relationship as column (8) shows that the interaction between the recommendation being positive and MCE is significant at the 10% level. This implies that when the recommendation is positive, the larger the MCE the lower the change of volatility becomes.

However, column (6) of Panel c. observed a greater effect from the positive recommendation (coefficient equal to 1.3) than the change in volatility (coefficient is -2.62, but since recommendation is positive then, with the interaction coefficient 2.64 added this implies an overall effect of 0.02) while the change of volatility is particularly significant on its own when the recommendation is negative (BD = 0). On the other hand, the relationship is insignificant in the opposite direction as it seems that LCE has no impact on the change of volatility.

A possible justification for such an occurrence is the unequal time periods used for the before period (30 trading days) and the after period (250 trading days) resulting in the after period covering various confounding events such as recommendation changes and firm level announcements which would affect volatility while are being controlled for through the calculation of LCE. However, this justification does not explain the lack of a relationship with MCE. Dhiensiri and Sayrak (2010) also failed to observe significance between their Δvolatility variable and the short-term cumulative abnormal returns. However, both they and this study used linear regressions as the model of choice. And given that there are other studies that did find risk reducing results, this creates a particular line of reasoning. Either the model or the variable of stock return volatility or both are not accurate representations of the relationship, or the risk metric involved. Besides the limitations of the model, there is the chance that simply one announcement was not enough to create a noticeable impact on stock return volatility. Schutte and Unlu (2009) found that the more recommendations are published, the less risky the stock becomes. Chen et al. (2017)'s findings reported the loss of risk effect is in the reiteration, while Devos et al. (2015) showed it to also exist for upgrades and downgrades. Moreover, there's also the possibility again of confounding effects, a particularly noteworthy one is Bond and Cummins (2004)'s disagreement effect. Their study brought up evidence that if analysts' recommendations disagreed with each other, then stock volatility increases instead. Pairing this result with the fact that this market segment is less transparent and, thus, more difficult to navigate by participants, then disagreements could be consistent within the segment. This reasoning is consistent with Lin, Chen and Chen (2010) where it was shown that analyst herding characteristics are proportional to firm size and thus analysts tended to herd less in markets with smaller firms.

Moreover, the winsorized results show the same consistent pattern in all panels, with the significance of the relationships in panel b and panel c of Table 17 deteriorating further and solidifying the conclusion that there does not appear to be a relationship between MCE / LCE and their respective change of volatility variable.

Therefore, this study is unable to accept H4 as this study is unable to provide reasonable results to objectively reach the conclusion that a relationship between the certification effects and the change of volatility exists.

Conclusion

Interest in the small-cap market is improving after a period of lackluster performance due to the pandemic, and the inflationary period that followed. In this study we set out to investigate the implications of a stock in a generally less transparent market segment receiving its first analyst recommendation through the use of event study and linear regression procedures.

Similar to the past literature, we observed positive and significant short-term returns for positive recommendations while also observing abnormal losses in the short-term for negative recommendations after the announcement date, and possible leakage on the day before the announcement. We also found that these abnormal returns and losses differ significantly from standard recommendations made in more liquid markets, and that this difference is neither correlated nor explained by firm level variables or erratic stock movements in the short-term. However, the mid to long-term difference seems to be explained more by a couple of variables, particularly, Board Size which could be due to the improvement to information asymmetry larger boards tend to promote. Therefore, while there is reasonable evidence that a certification effect does exist, its longevity seems predicated on information diffusion time and the absence of confounding factors such as other announcements or releases.

The implications of these results are substantial. Firstly, they show that even individual analysts hold influence in the market with their recommendations, particularly in less transparent segments such as with the small-caps as the results parallel Heikillä (2016). The significance of the short-term abnormal returns and the lack of significance of firm level variables, both point to how analysts are viewed as information intermediaries with their role of presenting information and promoting market efficiency. This study could also be seen as a continuation of Dhiensiri and Sayrak (2010) as it adds further to the results of their study. This is also the first study to relate underlying firm characteristics with initial analyst recommendation announcements and effects. This study therefore also pushes forward the literature to better understand the relationship between analysts and the firms they choose to provide recommendations for and the value this brings those firms.

Nevertheless, this study isn't without its flaws, most notable of which is the limitation and compromise required in the selection of the control sample. As mentioned in section 3.1, the mid-caps are the compromise between the extreme differences between the large-caps and the small-caps as well as the endogeneity concerns of using small-cap recommendations to determine the “standard recommendation effect”. However, mid-caps are still significantly different from small-caps. In addition, the study only considered the strictest definition of an initiation of coverage which limits sample size; and often, a recommendation announcement of a particular analyst is followed in a few days by other analyst recommendation announcements, a fact that could influence the stock through effects such as herding, or disagreements. Consequently, as well, the use of this definition potentially promoted a bad firm bias within the sample such that the firms did not receive a recommendation sooner since analysts could have lacked confidence in their long term performance (Das et al., 2006). Additionally, the larger event windows are subject to the periodic review of analysts, so recommendation upgrades/downgrades and reiterations would also be occurring within the event window; this limits the accuracy of the long-window results. Similarly, this study did not consider if company releases or media publications were occurring during the trading windows. These confounding effects limit the extent of long-term analysis. In a similar vein, the study assumed all analyst recommendation announcements as equal and did not consider the brokerage, or the analyst’s reputation which could impact the results as international evidence provides (Brown et al., 2014). Additionally, the study suffered from a limitation of scope as the United States small-cap market, while less-transparent that its larger equivalents, sees much more movement than its international counterparts, and one solution to generalize this study is to open this research into other markets, both emerging and developed.

Future research could look to alleviate these limitations, more generalized and non-parametric tests could solidify conclusions and provide deeper insights into the data. Alternative samples for controls and comparison analysis to determine better control portfolios could be performed. Methodologies involving time series analysis may better represent and deal with the confounding factors, and other sampling methodologies could be employed to reduce the impact of close analyst announcements such as averaging the recommendation if there is a disagreement and propensity score matching to develop potentially more statistically viable control groups. Future research can also build off of this topic since an intuitive question arises from this study. What are the effects of an initiation of coverage event on the rivals of the stock within the same market segment and industry that have yet to have any recommendation? Is there some sort of ripple effect within the segment, does it cause losses elsewhere within the sector? Perhaps, another branch from this study could be in the decision making that causes an analyst to issue a recommendation announcement, what influences an analyst to initiate a recommendation on a particular stock over another; future research could investigate using machine learning algorithms to study informal media networks such as forums, news outlets and comment sections, and determine their relationship with analyst coverage and recommendations, or if information within them influences the market as well and in what ways. Lastly, future inquiries could look into more comparative analyses between the market segments and the differing behaviors of the market participants within them as a means of bridging the understanding between the well-known and highly visible stocks and their less transparent counterparts.

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Appendix A: List of Tables

This table reports the process of sample construction. The starting point is the base sample from CRSP and IBES. It comprises all first-time coverage announcements within the period of 1993 to 2024 such that the sample is split between the positive or negative subsample depending on if the recommendation were a buy/strong buy recommendation or not.

Table 1 Detailed Overview of Sample Construction

Construction Step	N	% of base sample
Base Sample from CRSP and IBES Before Event Study	6168	100.00%
Positive Recommendation Base Subsample	4579	74.24%
Negative Recommendation Base Subsample	1589	25.76%
Sample with COMPUSTAT Variables Before Event Study	5306	86.02%
Positive Recommendation Subsample with COMPUSTAT Variables Before Event	4009	65.00%
Negative Recommendation Subsample with COMPUSTAT Variables Before Event Study	1297	21.03%
Sample with COMPUSTAT & BoardEx Variables Before Event Study	1151	18.66%
Positive Recommendation Subsample with COMPUSTAT & BoardEx Variables Before Event Study	877	14.22%
Negative Recommendation Subsample with COMPUSTAT & BoardEx Variables Before Event Study	274	4.44%
Sample After Event Study	2495	40.45%
Positive Recommendation Subsample After Event Study	1622	26.30%
Negative Recommendation Subsample After Event Study	873	14.15%
Sample with COMPUSTAT Variables After Event Study	2049	33.22%
Positive Recommendation Subsample with COMPUSTAT Variables After Event Study	1361	22.07%
Negative Recommendation Subsample with COMPUSTAT Variables After Event Study	688	11.15%
Sample with COMPUSTAT & BoardEx Variables After Event Study	294	4.82%
Positive Recommendation Subsample with COMPUSTAT & BoardEx Variables After Event Study	202	3.31%
Negative Recommendation Subsample with COMPUSTAT & BoardEx Variables After Event Study	92	1.51%

This table reports the distribution of the first recommendation announcements based on the year of the announcement. The table is separated based on the sample and subsamples defined in Table 1. The announcements are distributed between the years 1993 – 2024. The entries in years 1993-1999 are excluded when BoardEx is considered.

Table 2 Announcement Year Distribution

	Base Sample Before Event Study	Positive Recommendation Base Subsample	Negative Recommendation Base Subsample
1993	972	624	348
1994	195	150	45
1995	160	122	38
1996	230	195	35
1997	188	160	28
1998	213	172	41
1999	312	279	33
2000	273	248	25
2001	105	81	24
2002	132	94	38
2003	118	70	48
2004	222	118	104
2005	183	119	64
2006	171	109	62
2007	209	154	55
2008	94	66	28
2009	105	65	40
2010	127	84	43
2011	125	87	38
2012	145	99	46
2013	158	111	47
2014	181	143	38
2015	162	114	48
2016	102	75	27
2017	126	93	33
2018	148	116	32
2019	168	121	47
2020	192	165	27
2021	400	345	55
2022	153	120	33
2023	97	78	19
2024	2	2	0
N	**6168**	**4579**	**1589**

	Sample with COMPUSTAT variables before Event Study	N. Obs. Lost	Positive Subsample with COMPUSTAT Variables Before Event Study	N. Obs. Lost	Negative Subsample with COMPUSTAT Variables Before Event Study	N. Obs. Lost
1993	852	120	542	82	310	38
1994	146	49	111	39	35	10
1995	135	25	105	17	30	8
1996	197	33	169	26	28	7
1997	159	29	135	25	24	4
1998	179	34	148	24	31	10
1999	269	43	242	37	27	6
2000	238	35	216	32	22	3
2001	91	14	71	10	20	4
2002	114	18	80	14	34	4
2003	91	27	57	13	34	14
2004	166	56	101	17	65	39
2005	150	33	96	23	54	10
2006	138	33	88	21	50	12
2007	175	34	129	25	46	9
2008	66	28	49	17	17	11
2009	71	34	51	14	20	20
2010	105	22	71	13	34	9
2011	111	14	82	5	29	9
2012	124	21	92	7	32	14
2013	142	16	101	10	41	6
2014	167	14	137	6	30	8
2015	145	17	103	11	42	6
2016	96	6	75	0	21	6
2017	122	4	90	3	32	1
2018	138	10	109	7	29	3
2019	158	10	117	4	41	6
2020	185	7	161	4	24	3
2021	367	33	318	27	49	6
2022	139	14	109	11	30	3
2023	69	28	53	25	16	3
2024	1	1	1	1	0	0
N	**5306**		**4009**		**1297**	

	Sample with COMPUSTAT & BoardEx Variables Before Event Study	N. Obs. Lost	Positive Subsample with COMPUSTAT & BoardEx Variables Before Event Study	N. Obs. Lost	Negative Subsample with COMPUSTAT & BoardEx Variables Before Event Study	N. Obs. Lost
2000	15	258	13	235	2	23
2001	13	92	9	72	4	20
2002	20	112	15	79	5	33
2003	24	94	18	52	6	42
2004	52	170	28	90	24	80
2005	44	139	31	88	13	51
2006	46	125	24	85	22	40
2007	62	147	48	106	14	41
2008	27	67	21	45	6	22
2009	17	88	12	53	5	35
2010	53	74	36	48	17	26
2011	57	68	46	41	11	27
2012	76	69	60	39	16	30
2013	87	71	66	45	21	26
2014	87	94	71	72	16	22
2015	57	105	44	70	13	35
2016	44	58	39	36	5	22
2017	67	59	50	43	17	16
2018	76	72	58	58	18	14
2019	94	74	74	47	20	27
2020	105	87	92	73	13	14
2021	11	389	9	336	2	53
2022	6	147	6	114	0	33
2023	11	86	7	71	4	15
2024	0	2	0	2	0	0
N	**1151**		**877**		**274**	

	Sample After Event Study	N. Obs. Lost	Positive Subsample After Event Study	N. Obs. Lost	Negative Subsample After Event Study	N. Obs. Lost
1993	861	111	531	93	330	18
1994	72	123	45	105	27	18
1995	68	92	44	78	24	14
1996	56	174	38	157	18	17
1997	67	121	54	106	13	15
1998	95	118	67	105	28	13
1999	79	233	60	219	19	14
2000	57	216	43	205	14	11
2001	51	54	36	45	15	9
2002	69	63	46	48	23	15
2003	70	48	40	30	30	18
2004	70	152	36	82	34	70
2005	48	135	27	92	21	43
2006	50	121	22	87	28	34
2007	61	148	43	111	18	37
2008	49	45	35	31	14	14
2009	56	49	30	35	26	14
2010	43	84	27	57	16	27
2011	49	76	37	50	12	26
2012	45	100	24	75	21	25
2013	27	131	11	100	16	31
2014	38	143	25	118	13	25
2015	56	106	34	80	22	26
2016	30	72	20	55	10	17
2017	34	92	22	71	12	21
2018	37	111	26	90	11	21
2019	57	111	35	86	22	25
2020	61	131	53	112	8	19
2021	76	324	59	286	17	38
2022	63	90	52	68	11	22
2023	0	97	0	78	0	19
2024	0	2	0	2	0	0
N	**2495**		**1622**		**873**	

	Sample with COMPUSTAT Variables After Event Study	N. Obs. Lost	Positive Subsample with COMPUSTAT Variables After Event Study	N. Obs. Lost	Negative Subsample with COMPUSTAT Variables After Event Study	N. Obs. Lost
1993	758	214	462	162	296	52
1994	57	138	38	112	19	26
1995	54	106	36	86	18	20
1996	44	186	31	164	13	22
1997	60	128	49	111	11	17
1998	73	140	52	120	21	20
1999	66	246	50	229	16	17
2000	50	223	37	211	13	12
2001	45	60	32	49	13	11
2002	54	78	36	58	18	20
2003	46	72	28	42	18	30
2004	56	166	31	87	25	79
2005	42	141	27	92	15	49
2006	30	141	12	97	18	44
2007	40	169	26	128	14	41
2008	23	71	18	48	5	23
2009	28	77	21	44	7	33
2010	30	97	19	65	11	32
2011	40	85	32	55	8	30
2012	31	114	17	82	14	32
2013	23	135	10	101	13	34
2014	32	149	23	120	9	29
2015	47	115	29	85	18	30
2016	26	76	19	56	7	20
2017	32	94	20	73	12	21
2018	32	116	22	94	10	22
2019	51	117	34	87	17	30
2020	56	136	51	114	5	22
2021	66	334	52	293	14	41
2022	57	96	47	73	10	23
2023	0	97	0	78	0	19
2024	0	2	0	2	0	0
N	**2049**		**1361**		**688**	

	Sample with COMPUSTAT & BoardEx Variables After Event Study	N. Obs. Lost	Positive Recommendation Subsample with COMPUSTAT & BoardEx Variables After Event Study	N. Obs. Lost	Negative Recommendation Subsample with COMPUSTAT & BoardEx Variables After Event Study	N. Obs. Lost
2000	5	268	3	245	2	23
2001	6	99	4	77	2	22
2002	10	122	7	87	3	35
2003	10	108	8	62	2	46
2004	17	205	5	113	12	92
2005	13	170	10	109	3	61
2006	10	161	2	107	8	54
2007	18	191	11	143	7	48
2008	15	79	13	53	2	26
2009	9	96	5	60	4	36
2010	13	114	10	74	3	40
2011	22	103	19	68	3	35
2012	13	132	8	91	5	41
2013	9	149	7	104	2	45
2014	17	164	13	130	4	34
2015	17	145	11	103	6	42
2016	7	95	5	70	2	25
2017	12	114	7	86	5	28
2018	15	133	9	107	6	26
2019	26	142	18	103	8	39
2020	28	164	26	139	2	25
2021	1	399	0	345	1	54
2022	1	152	1	119	0	33
2023	0	97	0	78	0	19
2024	0	2	0	2	0	0
N	**294**		**202**		**92**	

Defines all variables used within the regression equations. Where D/E is leverage, Ln (AT) is firm size, ROA is return on assets as a measure for profitability, IND is a 10 category dummy variable representing industry fixed effects, Age defines the age of the CEO, gender is a dummy variable representing the gender of the CEO, Board Size indicates the number of directors on the board of directors, Sb-Sa/Sb indicates the change of volatility of the stock, Sb indicates the volatility of the dates prior to the announcement and Buy Dummy (BD) is a dummy variable indicating whether the recommendation was a buy/strong buy or not.

Table 3 Variable Definitions

Variable	Source	Source Variables	Equation	Description
D/E	COMPUSTAT	total_debt; bv_equity	total_debt / bv_equity	Debt-to-equity ratio from COMPUSTAT calculated as total debt over book value of equity where total debt is the maximum value chosen between the COMPUSTAT variable DT or the sum of the COMPUSTAT variables DLC and DLTT and Book value of equity is the sum of the COMPUSTAT variables SEQ, TXDITC, and -1* the max between PSTKRV and PSRK1
LN(AT)	COMPUSTAT	AT	log(at)	Natural log of total assets calculated using COMPUSTAT's variable AT for total assets, used a representative of firm size
ROA	COMPUSTAT	ebitda; at	ebitda/at	Return on assets from COMPUSTAT calculated as the earnings before interest taxes and depreciation over total assets using the COMPUSTAT variables ebitda and at
IND	CRSP	HSICCD	INT(HSICCD/1000)	Industry fixed effects from CRSP calculated as the first integer of the CRSP variable HSICCD used a dummy variable with 10 categories representing the 10 possible starting digits for the SIC code 0 to 9

Variable	Source	Source Variables	Equation	Description
AGE	BOARDEX	dob; annualreportdate		Age of the CEO calculated as the difference between their date of birth and the closest report date within the year to the announcement date
GENDER	BOARDEX	GENDER		Gender of the CEO from BoardEx retrieved from the variable of the same name, Dummy variable indicating 1 if the CEO is male and 0 if female
BOARD SIZE	BOARDEX	DEP; INDEP	DEP + INDEP	Size of the board of directors of the company from BoardEx measured as the sum of dependent and independent directors from BoardEx where independent directors have the role name "Independent", and the dependents are connected to the CEO and do not.
S_b	CRSP	ret	$\sqrt{\frac{\sum_{t=-30}^{-1}(r_{it} - \bar{r})^2}{30 - 1}}$	Volatility of a stock from CRSP measured as the geometric standard deviation of returns before the first recommendation announcement. The before period utilized to measure this variable is the period [-30, -1], log returns were for the calculation.
$\frac{S_a - S_b}{S_b}$	CRSP	ret	$\frac{S_a - S_b}{S_b}$	Change of volatility of a stock from CRSP measured as the difference of geometric standard deviations of returns before and after the first recommendation announcement over the standard deviation of the before period where the before period is the period [-30, -1] and the after period is the period [1,250] for the window [-2,250] and [1,30] for the window [-2,30].

Buy Dummy (BD)	IBES	IRECCD	Type of recommendation from IBES retrieved from the variable IRECCD where BD = 1 if IRECCD was 1 or 2 indicating a strong buy or buy respectively and 0 if IRECCD was 3, 4, or 5 which indicate hold, sell, and underperform respectively.

Shows the calculation of CE, MCE, and LCE. The calculation is done for each individual stock within the sample, using the CAR and BHARs estimated with the Fama and French three factor model. The table presents a two-sample difference test that shows that CE and LCE are statistically significant values. In this table $\overline{CE} = \overline{CAR} - \overline{QCAR}$, $\overline{MCE} = \overline{BHAR} - \overline{QBHAR}$ of the one month window, and $\overline{LCE} = \overline{BHAR} + \overline{QBHAR}$ of the one year window and the t-statistics were calculated using the standard error of the difference for each respectively, for each subsample. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels respectively.

Table 4 CE & LCE Calculations

Subsample	CAR [-2,2]	QCAR [-2,2]	CE	t-stat
Positive Recommendation	1.70%	1.00%	0.70%	4.52***
Negative Recommendation	-0.41%	-0.98%	0.57%	2.04**

Subsample	BHAR [-2,30]	BHAR [-2,250]	QBHAR [-2,30]	QBHAR [-2,250]	MCE	LCE	t-stat MCE	t-stat LCE
Positive Recommendation	0.59%	-32.48%	-0.19%	-21.62%	0.77%	-10.86%	1.95*	-4.37***
Negative Recommendation	-2.09%	-21.80%	-1.39%	-12.63%	-0.70%	-9.17%	-1.4	-3.23***

Shows the results of the short-window analysis for each subsample of small-caps. The short window analysis took place within the event window [-2, 2]. the table shows the average abnormal returns and the Cumulative average abnormal return calculated using the Fama and French three factor model with the coefficients estimated winsorized at the 5% and 95% levels, along with their corresponding cross-sectional t-statistic for each individual date of the event window along with their individual number of observations used to calculate them. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels respectively

Table 5 Aggregate Small-Cap Subsample AARs and CARs

Panel a. Positive Subsample					
Days	N. Obs.	AARs	t-stat	CARs	t-stat
t-2	1693	0.18%	1.51	0.18%	1.51*
t-1	1693	0.29%	2.06**	0.47%	2.6***
t	1694	0.83%	6.30***	1.3%	5.6***
t+1	1694	0.26%	2.26**	1.54%	6.05***
t+2	1694	0.12%	0.86	1.70%	6.02***
Panel b. Negative Subsample					
Days	N. Obs.	AARs	t-stat	CARs	t-stat
t-2	916	-0.02%	-0.21	-0.02%	-0.21
t-1	916	0.86%	1.04	0.82%	0.98
t	915	0.03%	0.08	0.60%	0.65
t+1	915	-0.68%	-4.07***	0.01%	0.01
t+2	915	-0.33%	-2.50***	-0.41%	-0.42

Shows the results of the short-window analysis for each subsample of events for mid-caps. The short window analysis took place within the event window [-2, 2], the table shows the average abnormal returns and the Cumulative average abnormal return using the Fama and French three factor model with the coefficients estimated winsorized at the 5% and 95% levels, along with their corresponding cross-sectional t-statistic for each individual date of the event window along with the number of observations used to calculate them. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels respectively.

Table 6 Aggregate Mid-cap Events AARs and CARs

Panel a. Positive Recommendation Announcements					
Days	N. Obs.	AARs	t-stat	CARs	t-stat
t-2	68483	-0.002%	-0.18	-0.002%	-0.18
t-1	68478	0.05%	3.79***	0.05%	2.60***
t	68463	0.76%	49.90***	0.81%	34.98***
t+1	68453	0.19%	17.67***	1.00%	39.55***
t+2	68450	-0.01%	-0.72	1.00%	37.00***
Panel b. Negative Recommendation Announcements					
Days	N. Obs.	AARs	t-stat	CARs	t-stat
t-2	71750	-0.01%	-1.23	-0.01%	-1.23
t-1	71742	-0.07%	-4.41***	-0.08%	-4.33***
t	71718	-0.65%	-40.49***	-0.73%	-29.01***
t+1	71713	-0.21%	-19.31***	-0.95%	-34.03***
t+2	71697	-0.04%	-4.09***	-0.98%	-33.29***

Shows the results of the Buy and Hold Abnormal Returns long-window analysis of [-2,250] calculated by comparing the returns generated with the expected returns generated using the Fama and French three factor model with the coefficients winsorized at the 5% and the 95% levels. The results presented are the end of holding period values for each of the subsamples, the number of observations used in each BHAR's calculation and the calculated cross-sectional t-statistic of the respective BHAR. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels respectively.

Table 7 Aggregate BHAR

Subsample	N. Obs.	Window	BHAR	t-stat
Small-cap Positive subsample	1669	[-2, 30]	0.59%	0.99
	1542	[-2,250]	-32.48%	-8.91***
Small-cap Negative subsample	902	[-2, 30]	-2.09%	-2.77***
	872	[-2,250]	-21.8%	-2.33**
Mid-cap Positive Events	68286	[-2, 30]	-0.186%	-2.69***
	64900	[-2,250]	-21.62%	-57.90***
Mid-cap Negative Events	70854	[-2, 30]	-1.39%	-24.54***
	68701	[-2,250]	-12.63%	-43.47***

Shows the descriptive statistics, number of observations, mean, standard deviation, min, max, median, 25th percentile and 75th percentile of the variables used for the regression analyses, firm size Ln(AT), return on assets (ROA), leverage (D/E), CEO Gender, CEO Age, Number of directors on the board, the volatility before the announcement date as the standard deviation of returns represented by S_b, the change of volatility of returns as represented by $\frac{S_b - S_a}{S_b}$, the certification effect CE, and the mid/long certification effects MCE and LCE respectively.

Table 8 Descriptive Statistics

	N	Mean	STD	Min	Max	Median	P 25	P 75
Firm Size	5480	6.24	1.43	1.30	14.33	6.15	5.18	7.20
ROA	5261	0.016	0.42	-18.28	10.97	0.076	-0.040	0.15
Leverage	5478	1.01	30.32	-713.44	1690.99	0.23	0.0062	0.85
Gender	1271	0.96	0.20	0	1	1	1	1
Age	1205	53.28	8.54	30	84.61	53	47.35	59
Board Size	1293	7.78	1.91	2	19	8	7	9
S_b	5895	0.038	0.038	0	1.41	0.029	0.018	0.046
$\frac{S_a - S_b}{S_b}_{[-30,30]}$	5895	0.1656	2.537	-0.94	172.93	-0.035	-0.26	0.27
$\frac{S_a - S_b}{S_b}_{[-30,250]}$	5895	0.32	2.75	-0.96	173	0.062	-0.18	0.40
CE	2495	-0.0031	0.13	-1.47	3.02	-0.005	-0.038	0.03
MCE	2495	-0.0032	0.24	-1.28	5.51	-0.007	-0.099	0.084
LCE	2495	-0.123	1.95	-71.95	21.25	-0.023	-0.36	0.31

Presents the multiple linear regression model for the short window certification effect CE on the derived subsamples of all firms in the sample with financial variables available, and all firms with all variables available to test H3a; t-statistics for the coefficients are presented in parentheses. The regression equations performed are as eq (11) and eq (12) respectively: $CE_i = b_0 + b_1 \, ln(AT)_i + b_2 ROA_i + b_3 \frac{D}{E} i + b_4 IND_i$ and $CE_i = b_0 + b_1 l(AT)_i + b_2 ROA_i + b_3 \frac{D}{E} i + b_4 IND_i + b_7 Gender_i + b_6 Age_i + b_7 Board\ Size_i$ represented in columns (1) and (2) respectively. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels respectively.

Table 9 Short Window Regression Results

	Coefficient (t-stat)	
	(1)	(2)
Intercept	0.005 (0.28)	0.0126 (0.13)
Firm Size	-0.0013 (-0.67)	-0.0046 (-0.54)
ROA	0.0008 (0.13)	-0.0118 (-0.33)
Leverage	0.0002*** (2.73)	0.00001 (0.02)
S_b	0.1347 (1.18)	-0.765* (-1.87)
Gender		0.0161 (0.29)
Age		0.0011 (0.98)
Board Size		-0.0041 (-0.89)
Industry FE	YES	YES
R- Squared	1.30%	3.80%
Adjusted R-Squared	0.70%	-1.70%
F-test	2.06	0.69
N. Obs.	2049	297

Presents the multiple linear regression model for the mid window certification effect MCE on the same derived samples of Table 9 to test for H3b; t-statistics for the coefficients are presented in parentheses. The regression equations performed are the eq (13) – (18). The full model is provided in column (9) and represents eq (18). $MCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_5 IND_i + b_6 CE_i + b_7 \frac{S_a - S_b}{S_b}_{i[-3\ ,30]} + b_8 Age_i + b_9 Gender_i + b_{10} Board\ Size_i + b_{11} BD_i + \overrightarrow{Interaction_{ik}}$. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels respectively.

Table 10: Mid-Window Regression Results

	Coefficient (t-stat)				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.0678** (-2.21)	-0.0649** (-2.03)	-0.0639** (-1.99)	-0.0825*** (-2.62)	-0.0744** (-1.99)
Firm Size	0.0136*** (3.85)	0.0135*** (3.77)	0.0135*** (3.77)	0.0149*** (4.24)	0.013*** (3.12)
ROA	-0.0042 (-0.37)	-0.0042 (-0.37)	-0.0039 (-0.33)	-0.0015 (-0.13)	-0.0028 (-0.21)
Leverage	-0.00005 (-0.46)	-0.00005 (-0.45)	-0.00005 (-0.45)	-0.0001 (-0.89)	0.0001 (0.92)
$\frac{S_a - S_b}{S_b}_{[-30,30]}$	0.0067 (0.7)	0.0067 (0.7)	0.0067 (0.71)	-0.000004 (0)	-0.0111 (-1.01)
CE	1.1355*** (27.41)	1.137*** (27.27)	1.135*** (27.18)	0.6679*** (10.16)	
BD		-0.0032 (-0.31)	-0.0048 (-0.46)	0.0023 (0.14)	-0.0137 (-0.69)
$BD * \frac{S_a - S_b}{S_b}_{[-30,30]}$			0.0468 (0.86)	0.0634 (1.17)	0.1526*** (2.37)
$BD * Firm\ Size$				0.00000003 (0.14)	0.0000006** (2.3)
$BD * CE$				0.761*** (9.05)	
Industry FE	YES	YES	YES	YES	YES
R- Squared	27.60%	27.56%	27.57%	30.41%	1.51%
Adjusted R-Squared	27.10%	27.02%	27.00%	29.79%	0.74%
F-test	55.39***	51.56***	48.34***	49.28***	1.95
N. Obs.	2049	2049	2049	2049	2049

	Coefficient (t-stat)				
	(6)	(7)	(8)	(9)	(10)
Intercept	0.2109 (1.37)	0.1775 (1.14)	0.3756** (2.16)	0.3671** (2.1)	0.1837 (0.86)
Firm Size	0.0102 (0.78)	0.0117 (0.9)	0.0081 (0.62)	0.0081 (0.62)	0.0126 (0.78)
ROA	-0.0709 (-1.3)	-0.0682 (-1.25)	-0.067 (-1.24)	-0.0666 (-1.23)	-0.0814 (-1.22)
Leverage	-0.0009 (-1.09)	-0.0009 (-1.08)	-0.0009 (-1.11)	-0.0009 (-1.1)	-0.0009 (-0.9)
$\frac{S_a - S_b}{S_b}_{[-30,30]}$	0.0021 (0.08)	-0.0004 (-0.01)	-0.0042 (-0.15)	-0.0046 (-0.17)	-0.0212 (-0.63)
Gender	-0.157* (-1.79)	-0.1487* (-1.69)	-0.1442 (-1.64)	-0.1444 (-1.64)	-0.1158 (-1.08)
Age	-0.0008 (-0.45)	-0.0012 (-0.68)	-0.001 (-0.55)	-0.0011 (-0.63)	0.0006 (0.29)
Board Size	-0.0086 (-1.18)	-0.0087 (-1.19)	-0.032** (-2.67)	-0.0297** (-2.44)	-0.0199 (-1.35)
CE	0.8077*** (11.71)	0.8015*** (11.63)	0.8183*** (11.92)	0.7115*** (6.2)	
Buy Dummy		0.0517 (1.58)	-0.2294** (-1.91)	-0.204 (-1.6)	-0.0584 (-0.38)
$BD * \frac{S_a - S_b}{S_b}_{[-30,30]}$			0.0339** (2.43)	0.032** (2.28)	0.0173 (1.02)
$BD * Firm\ Size$				0.0000001 (-0.23)	0.0000002 (-0.23)
$BD * CE$				0.1668 (1.16)	
Industry FE	YES	YES	YES	YES	YES
R- Squared	37.12%	37.68%	38.99%	39.30%	7.73%
Adjusted R-Squared	33.29%	33.65%	34.80%	34.66%	1.40%
F-test	9.69***	9.34***	9.32***	8.48***	1.22
N. Obs.	297	297	297	297	297

Presents the multiple linear regression model for the long window certification effect LCE on the same derived samples of Table 9 to test for H3b; t-statistics for the coefficients are presented in parentheses. The regression equations performed are the eq (19) – (22). The full model is provided in column (8) and represents eq (22). $LCE_i = b_0 + b_1 \frac{D}{E}_i + b_2 \ln(AT)_i + b_3 ROA_i + b_5 IND_i + b_6 CE_i + b_7 \frac{S_a - S_b}{S_b}_{i[-30,250]} + b_8 Age_i + b_9 Gender_i + b_{10} Board\ Size_i + b_{11} BD_i + \overrightarrow{Interaction_{ik}}$. *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels respectively.

Table 11 Long Window Regression Results

	Coefficient (t-stat)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-1.12***	-1.086***	-1.12***	-1.079***	-0.9507	-1.5408	-1.8595	-4.2129
	(-3.69)	(-3.42)	(-3.52)	(-2.45)	(-0.34)	(-0.54)	(-0.66)	(-1.21)
Firm Size	0.163***	0.1612***	0.1613***	0.1521***	0.3864	0.4101*	0.3684	0.7073*
	(4.64)	(4.55)	(4.55)	(2.66)	(1.6)	(1.7)	(1.53)	(1.86)
ROA	0.0296	0.0297	0.0233	0.0275	-0.4424	-0.391	-0.2162	-0.0167
	(0.26)	(0.26)	(0.2)	(0.24)	(-0.44)	(-0.39)	(-0.21)	(-0.02)
Leverage	-0.0002	-0.0002	-0.0002	-0.0004	-0.006	-0.006	-0.0066	-0.0067
	(-0.19)	(-0.2)	(-0.23)	(-0.34)	(-0.39)	(-0.38)	(-0.42)	(-0.43)
$\frac{S_a - S_b}{S_b}_{[-30,250]}$	0.068	0.0681	0.2878*	0.2697*	0.5203	0.4958	2.4171**	2.2909
	(0.87)	(0.87)	(1.87)	(1.75)	(1.33)	(1.27)	(2.34)	(2.2)
Gender					-0.9455	-0.7856	-0.8328	-0.8527
					(-0.59)	(-0.49)	(-0.52)	(-0.53)
Age					0.0282	0.0218	0.0232	0.0235
					(0.89)	(0.68)	(0.73)	(0.74)
Board Size					-0.2682**	-0.2695**	-0.2454*	-0.2336*
					(-1.98)	(-1.99)	(-1.82)	(-1.71)
CE	2.7778***	2.7969***	2.8145***	1.6304**	4.1774**	3.7205**	3.611**	2.9339
	(6.78)	(6.78)	(6.82)	(2.47)	(2.43)	(2.13)	(2.08)	(1.01)

	Coefficient (t-stat)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Buy Dummy		-0.0421 (-0.42)	0.0005 (0)	-0.1089 (-0.23)		0.8718 (1.42)	1.2799** (1.99)	4.4777 (1.58)
$BD * \frac{S_a - S_b}{S_b}_{[-30,250]}$			-0.2959* (-1.66)	-0.2745 (-1.53)			-2.2302** (-2)	-2.0938 (-1.86)
$BD * Firm\ Size$				0.0196 (0.29)				-0.4838 (-1.16)
$BD * CE$				1.9498** (2.31)				0.9137 (0.25)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
R- Squared	3.39%	3.40%	3.53%	3.78%	5.50%	6.19%	7.52%	7.98%
Adjusted R-Squared	2.72%	2.68%	2.77%	2.93%	-0.25%	0.11%	1.18%	0.96%
F-test	5.10	4.77	4.65	4.43	0.96	1.02	1.26	1.14
N. Obs.	2049	2049	2049	2049	297	297	297	297

Presents the analysis on the change of volatility variable ($\frac{S_b - S_a}{S_b}$) where S_b describes the volatility of the stock return within the 30 trading before the announcement date and S_a describes the volatility of the stock return within the 30 or 250 trading days after the announcement event. Panel a. shows the descriptive statistics of the variable in detail, Panel b. outlines the relationship between the change of volatility and MCE, and Panel c. outlines the relationship between the change of volatility and LCE, together they test H4 using the regression equations (24) – (31). *, **, *** indicate significance at the 0.1, 0.05, and 0.01 levels respectively.

Table 12 Change of Volatility Analysis

Panel a. t-Test Results

Sample	N	Window	Mean	STD	t - stat
Sample After Event Study	2495	[-30,30]	0.1589	3.6154	2.20**
		[-30,250]	0.2769	3.6294	3.81***
Positive Recommendation Subsample After Event Study	1622	[-30,30]	0.2008	4.45806	1.82*
		[-30,250]	0.3287	4.4772	2.96***
Negative Recommendation Subsample After Event Study	873	[-30,30]	0.0812	0.6566	3.65***
		[-30,250]	0.1805	0.6291	8.48***
Sample with COMPUSTAT Variables After Event Study	2049	[-30,30]	0.053	0.4941	4.87***
		[-30,250]	0.1477	0.5946	11.24***
Positive Recommendation Subsample with COMPUSTAT Variables After Event Study	1361	[-30,30]	0.0495	0.4689	3.90***
		[-30,250]	0.1494	0.6292	8.76***
Negative Recommendation Subsample with COMPUSTAT Variables After Event Study	688	[-30,30]	0.0603	0.5407	2.92***
		[-30,250]	0.1443	0.5199	7.28***
Sample with COMPUSTAT & BoardEx Variables After Event Study	297	[-30,30]	0.0918	0.5473	2.89***
		[-30,250]	0.2261	0.7098	5.49***
Positive Recommendation Subsample with COMPUSTAT & BoardEx Variables After Event Study	204	[-30,30]	0.1145	0.6095	2.68***
		[-30,250]	0.24697	0.7952	4.44***
Negative Recommendation Subsample with COMPUSTAT & BoardEx Variables After Event Study	93	[-30,30]	0.04200	0.3751	1.08
		[-30,250]	0.1802	0.4719	3.68***

Panel b. Relationship Analysis

	Coefficient (t-stat)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-0.0025 (-0.45)	-0.0162* (-1.7)	0.053*** (4.85)	0.0584*** (3.09)	0.0087 (0.48)	-0.04161 (-1.31)	0.0919 (2.89)	0.0545(0.96)
$\frac{S_b - S_a}{S_b}_{[-30,30]}$	-0.0114 (-1.03)	-0.01234 (-0.71)			-0.0021 (-0.06)	0.1696** (2)		
MCE			-0.0455 (-1.03)	-0.109 (-1.05)			-0.0066 (-0.06)	0.3634 (1.64)
Buy Dummy		0.0206* (1.77)		-0.0088 (-0.38)		0.0738* (1.92)		0.0635 (0.92)
$BD * \frac{S_b - S_a}{S_b}_{[-30,30]}$		0.0019 (0.09)				-1.3088** (-2.24)		
BD * MCE				0.0785 (0.69)				-0.4869* (-1.94)
R- Squared	0.05%	0.21%	0.05%	0.08%	0.001%	2.57%	0.001%	1.65%
Adjusted R-Squared	0.003%	0.06%	0.003%	-0.06%	-0.338%	1.57%	-0.338%	0.64%
F-test	1.066	1.422	1.066	0.572	0.004	2.577*	0.004	1.64
N. Obs.	2049	2049	2049	2049	297	297	297	297

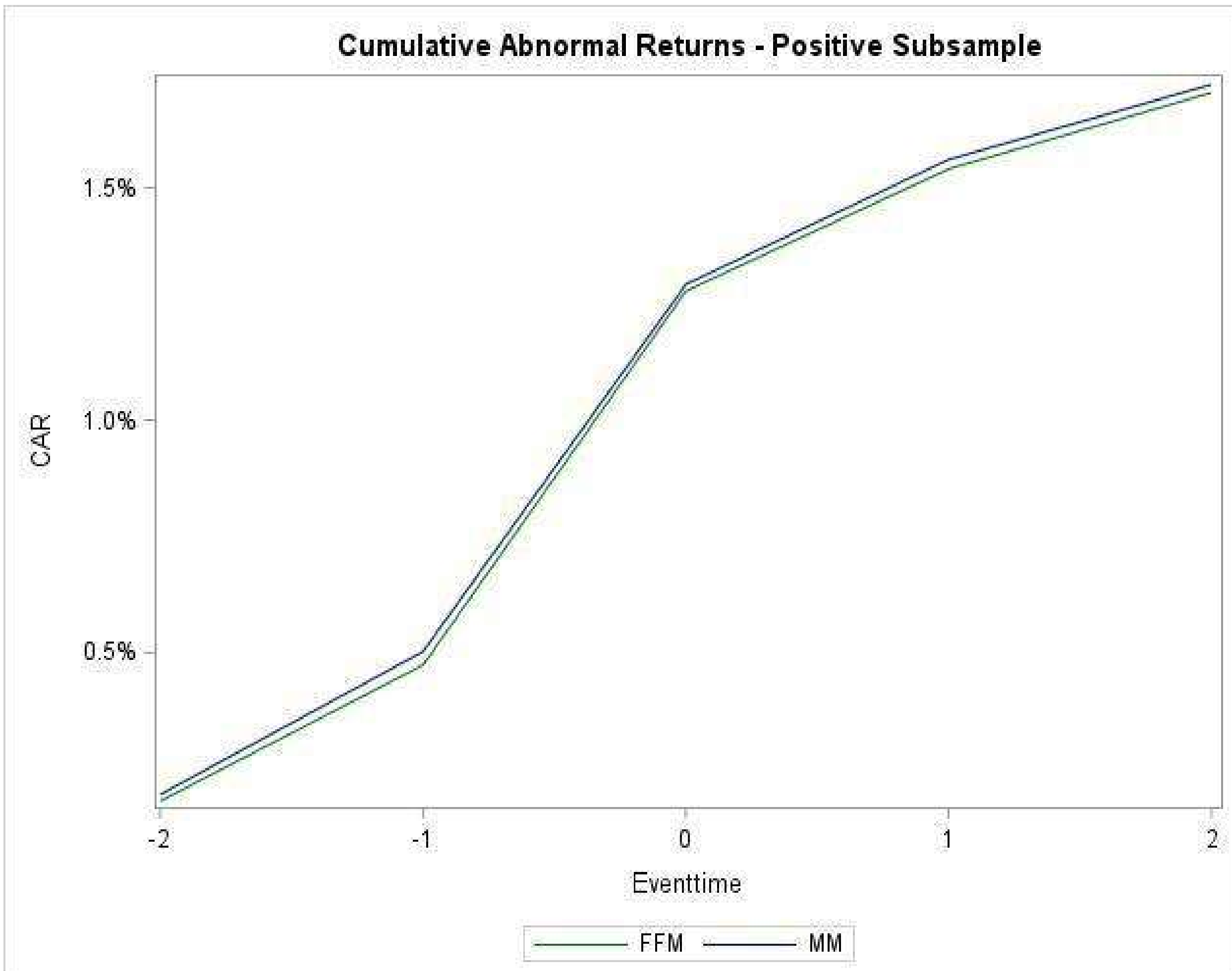
Panel c. Relationship Analysis

	Coefficient (t-stat)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	-0.18***	-0.17**	0.15***	0.15***	-0.34	-1.3**	0.23***	0.19**
Intercept	(-3.75)	(-2.08)	(11.25)	(6.4)	(-1.21)	(-2.55)	(5.54)	(2.54)
$\frac{S_b - S_a}{S_b}_{[-30,250]}$	0.04	0.25			0.41	2.64***		
	(0.51)	(1.6)			(1.08)	(2.61)		
			0.003	0.01			0.01	0.01
LCE			(0.51)	(1.03)			(1.08)	(1.05)
		-0.01		0.003		1.3**		0.06
Buy Dummy		(-0.14)		(0.11)		(2.14)		(0.65)
$BD * \frac{S_b - S_a}{S_b}_{[-30,250]}$		-0.28				-2.62**		
		(-1.56)				(-2.4)		
				-0.01				-0.01
BD * LCE				(-1.02)				(-0.3)
R- Squared	0.01%	0.15%	0.01%	0.07%	0.39%	2.96%	0.39%	0.57%
Adjusted R-Squared	-0.04%	0.00035%	-0.04%	-0.08%	0.05%	1.96%	0.05%	-0.45%
F-test	0.2576	1.002	0.2576	0.4462	1.1579	2.9742**	1.1579	0.5605
N. Obs.	2049	2049	2049	2049	297	297	297	297

Appendix B: List of Figures

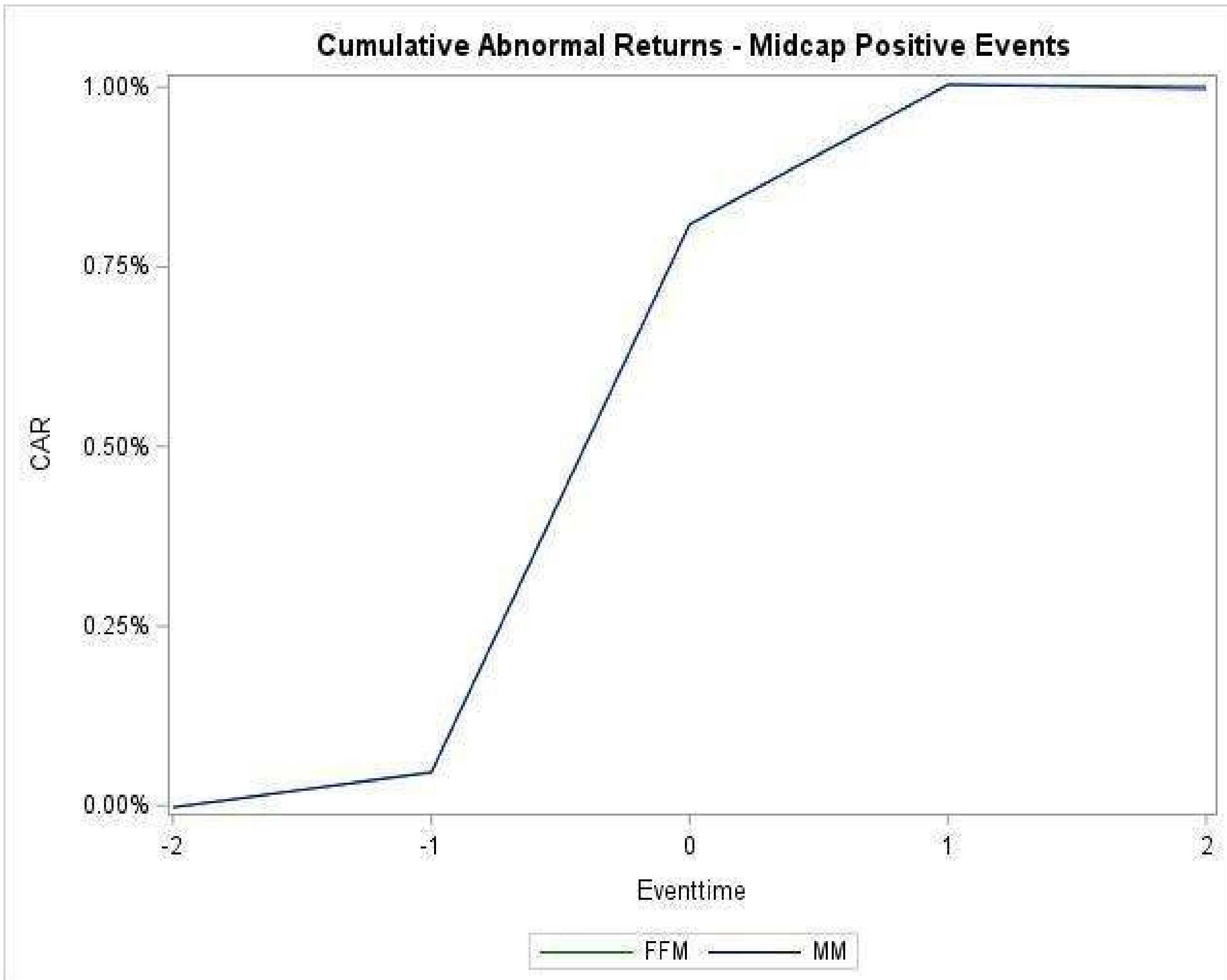
This figure indicates the cumulative abnormal return for the base positive subsample of small-cap stocks over the event window [-2,2]. The figure shows that the first recommendation being positive creates a CAR of 1.28% on the event date, under the Fama and French three factor model, that improves to 1.7% by the end of the event window.

Figure 1 Cumulative Abnormal Returns - Positive Subsample



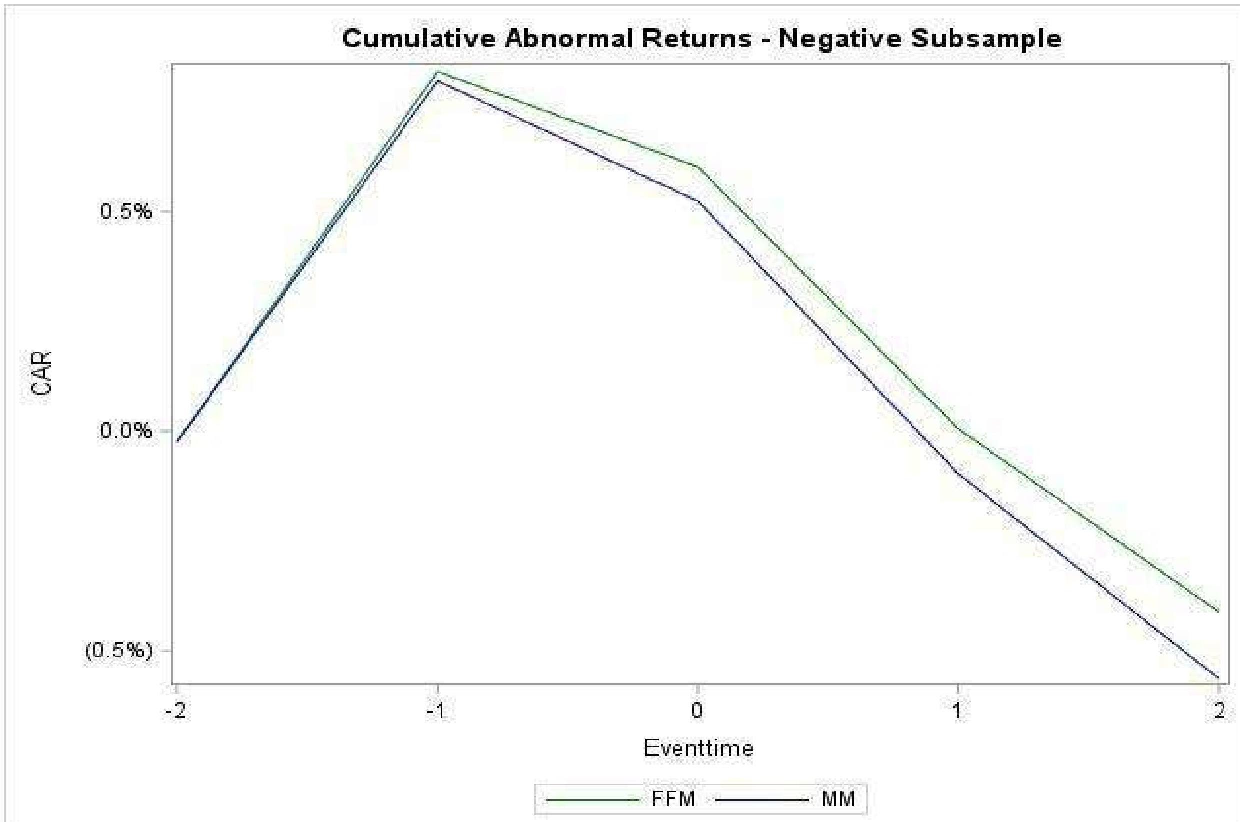
This figure indicates the cumulative abnormal return for positive recommendations on mid-cap stocks across the event window [-2,2]. This figure shows that a positive recommendation generally generates a CAR of 0.81% on the event date, under the Fama and French three factor model, the plateaus at 1% by the end of the event window.

Figure 2 Cumulative Abnormal Returns - Midcap Positive Events



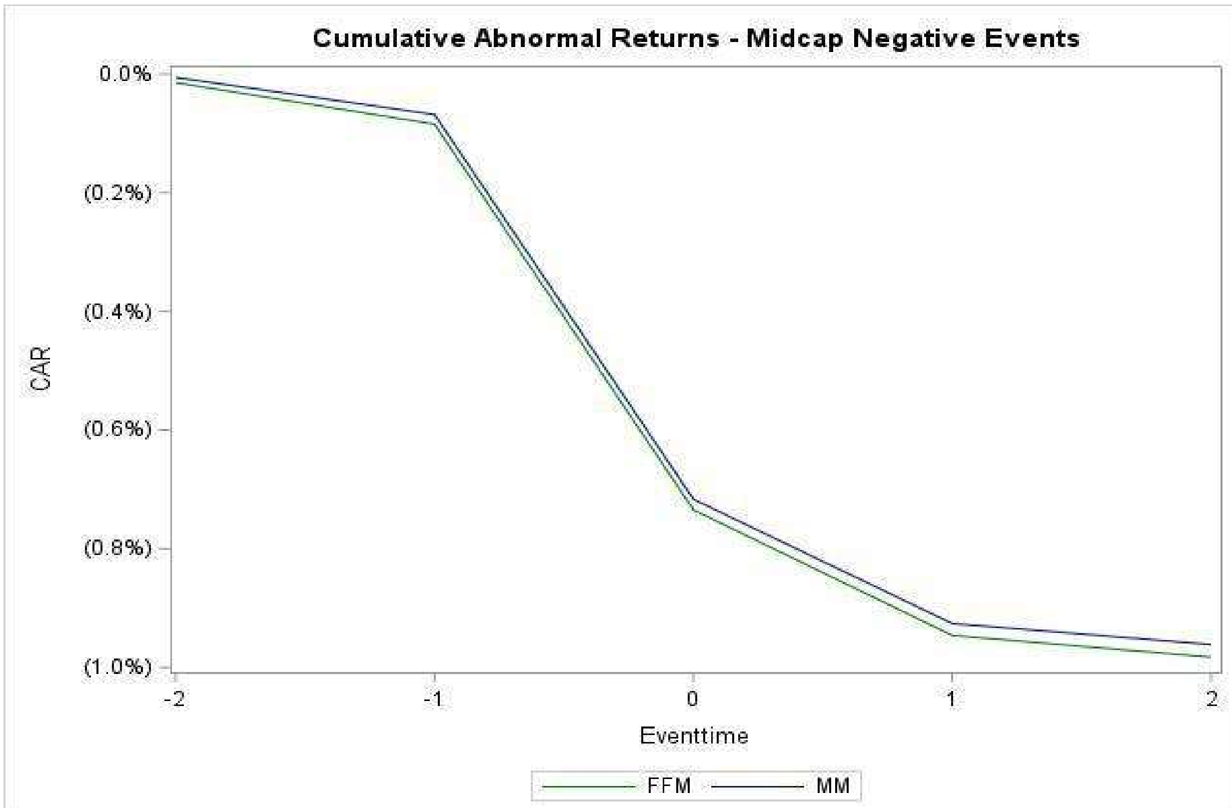
This figure indicates the cumulative abnormal return for the base negative subsample of small-cap stocks over the event window [-2,2]. The figure shows that the first recommendation being negative produces under the Fama and French three factor model an abnormal loss by the end of the event window of 0.411%.

Figure 3 Cumulative Abnormal Returns - Negative Subsample



This figure indicates the cumulative abnormal return for negative recommendations on mid-cap stocks across the event window [-2,2]. This figure shows that a negative recommendation generally generates a cumulative abnormal loss of 0.734% on the event date, under the Fama and French three factor model, that decreases further to a loss of 0.983% at the end of the event window.

Figure 4 Cumulative Abnormal Returns - Midcap Negative Events

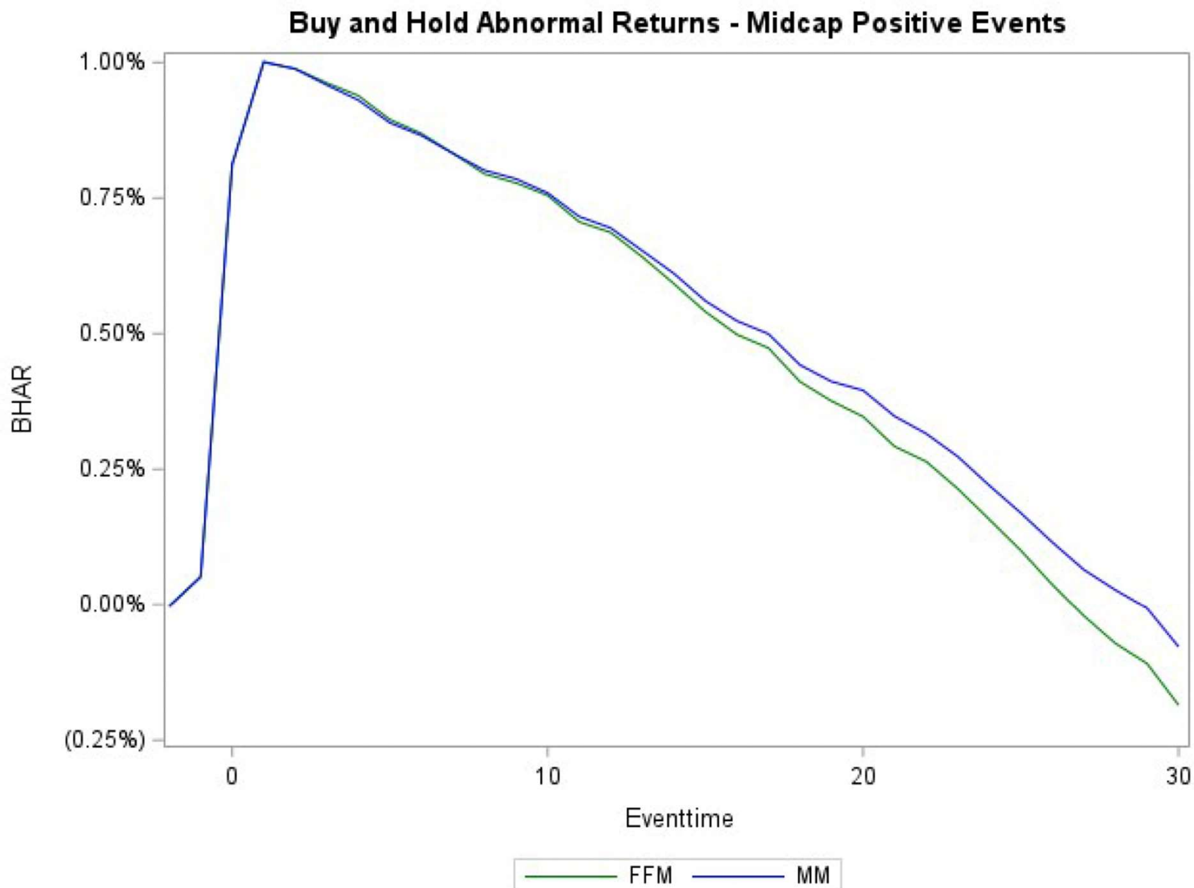


This figure indicates the Buy and Hold Abnormal Return for the base positive subsample of small-cap stocks across the event window [-2,30]. The Buy and Hold Abnormal Returns calculated on the event date is 1.29%, under the Fama and French three factor model, that decreases to a gain of 0.588% by the end of the holding period.

Figure 5 Buy and Hold Abnormal Returns - Positive Subsample

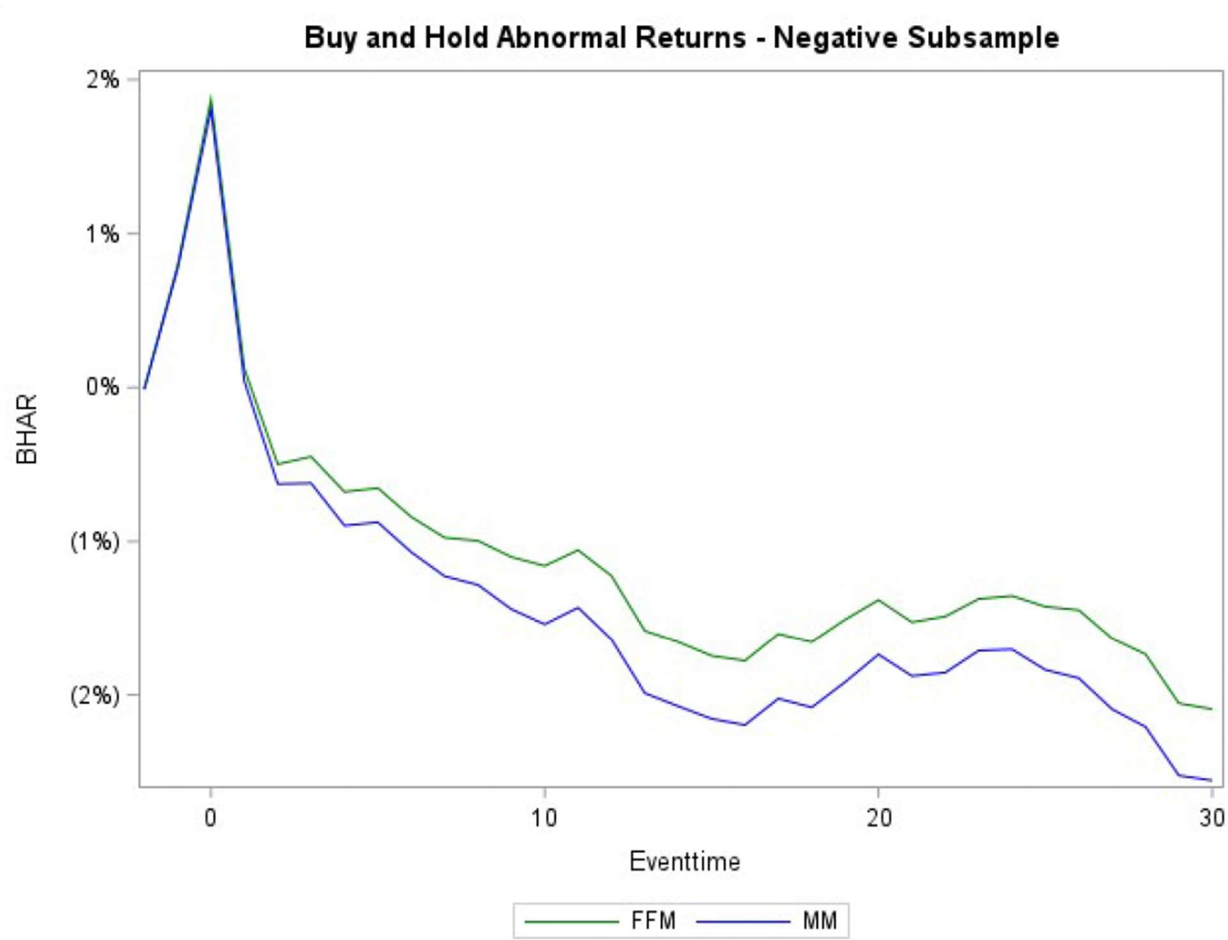
This figure indicates the Buy and Hold Abnormal Return for positive mid-cap events across the event window [-2,30]. The Buy and Hold Abnormal Return calculated on the event date is 0.812%, under the Fama and French three factor model, that decreases to a loss of 0.186 % by the end of the holding period

Figure 6 Buy and Hold Abnormal Returns - Midcap Positive Events



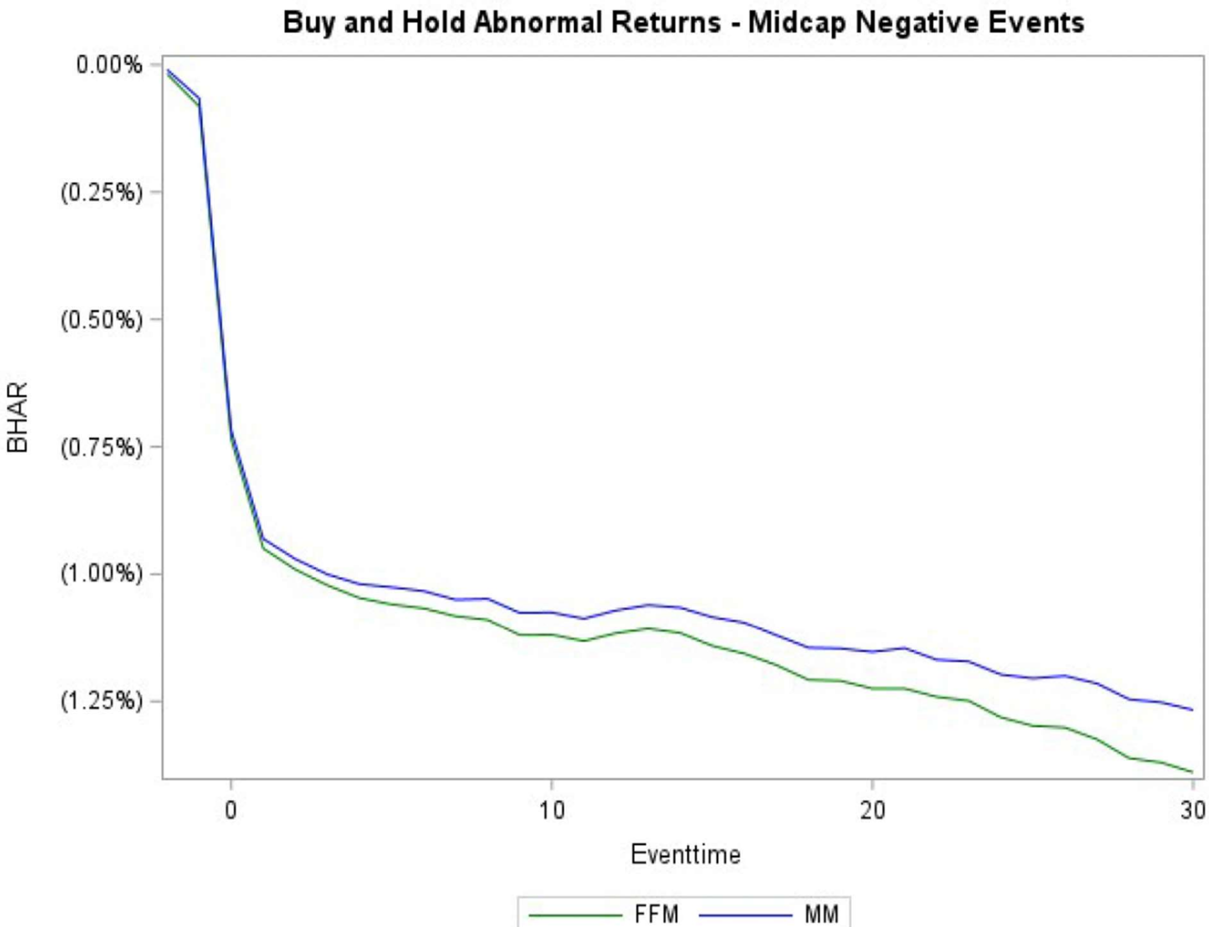
This figure indicates the Buy and Hold Abnormal Return for the base negative subsample of small-cap stocks across the event window [-2,30]. The Buy and Hold Abnormal Returns calculated on the event date is 1.87%, under the Fama and French three factor model, that decreases to a loss of 2.09% by the end of the holding period.

Figure 7 Buy and Hold Abnormal Returns - Negative Subsample



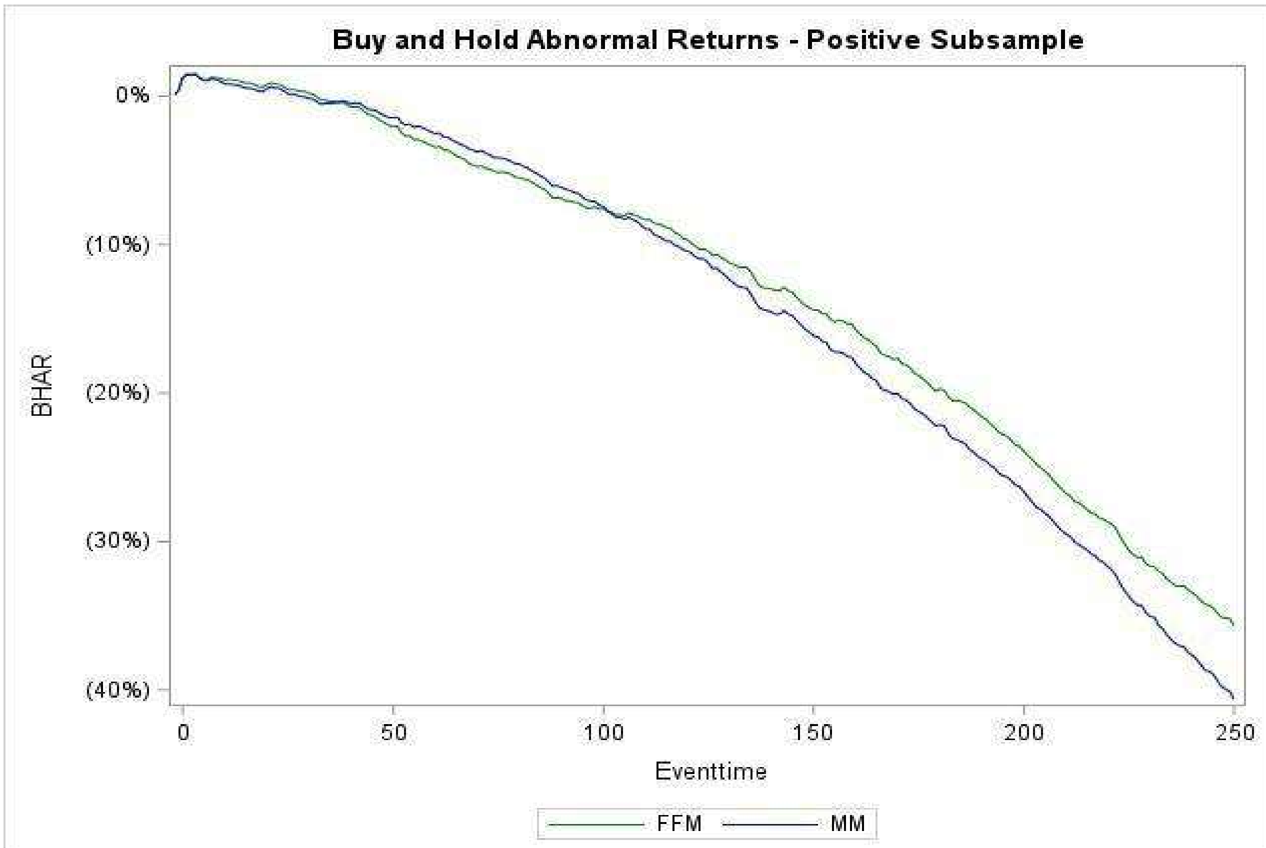
This figure indicates the Buy and Hold Abnormal Return for negative mid-cap events across the event window [-2,30]. The Buy and Hold Abnormal Loss calculated on the event date is 0.735%, under the Fama and French three factor model, that decreases to a loss of 1.39% by the end of the holding period.

Figure 8 Buy and Hold Abnormal Returns - Midcap Negative Events



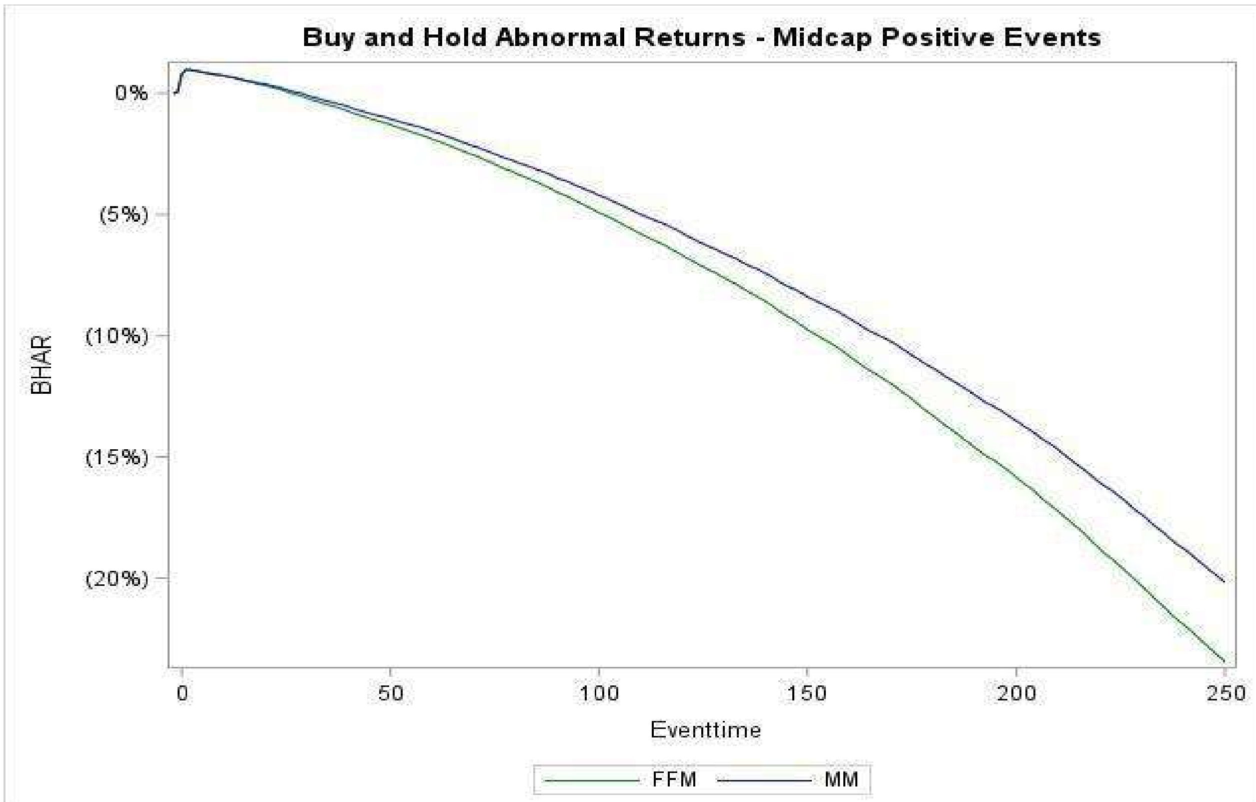
This figure indicates the Buy and Hold Abnormal Return for the base positive subsample of small-cap stocks across the event window [-2,250]. The Buy and Hold Abnormal Returns calculated on the event date is 1.29%, under the Fama and French three factor model, that decreases to a loss of 32.48% by the end of the holding period.

Figure 9 Buy and Hold Abnormal Returns - Positive Subsample



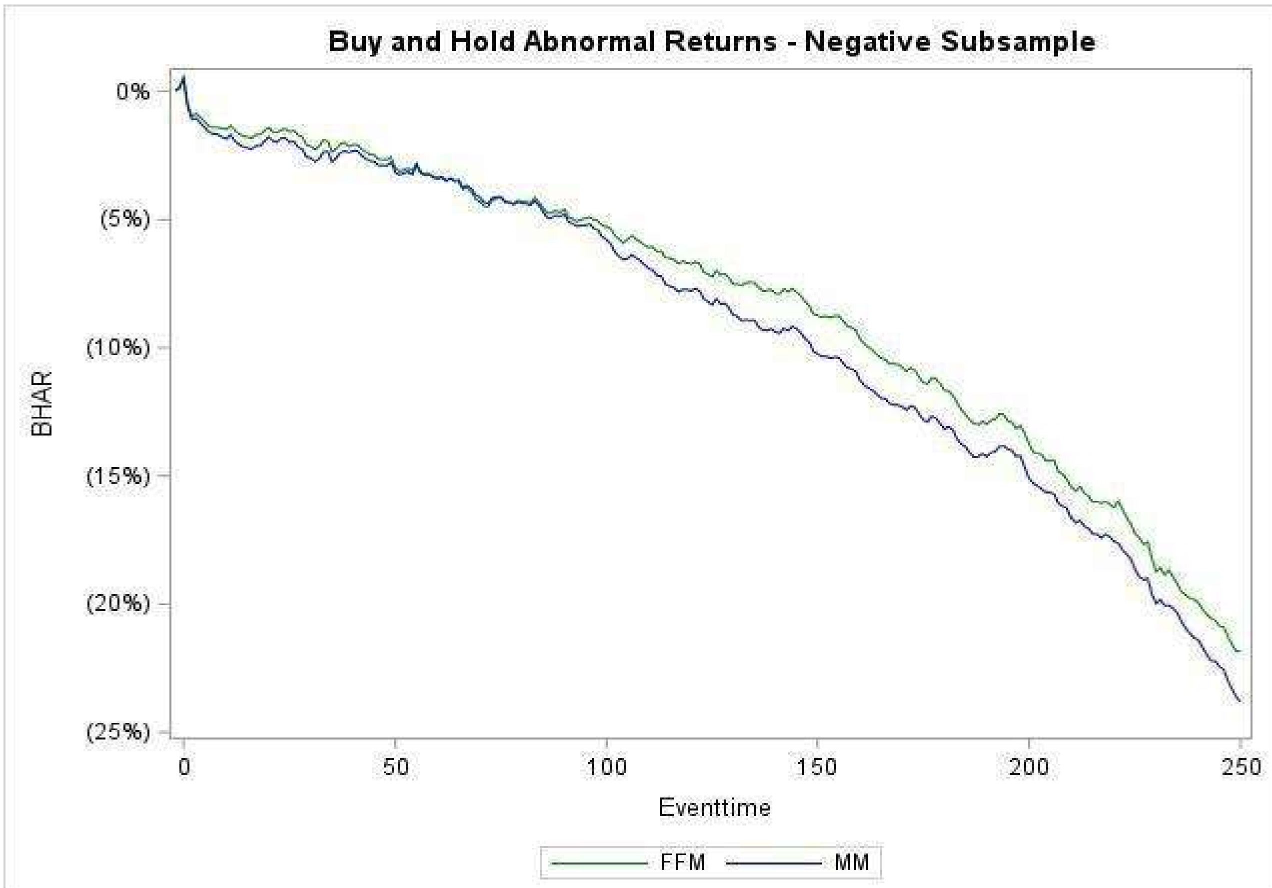
This figure indicates the Buy and Hold Abnormal Return for the mid-cap positive events across the event window [-2,250]. The Buy and Hold Abnormal Returns calculated on the event date is 0.79%, under the Fama and French three factor model, that decreases to a loss of -21.62% by the end of the holding period.

Figure 10 Buy and Hold Abnormal Returns - Midcap Positive Events



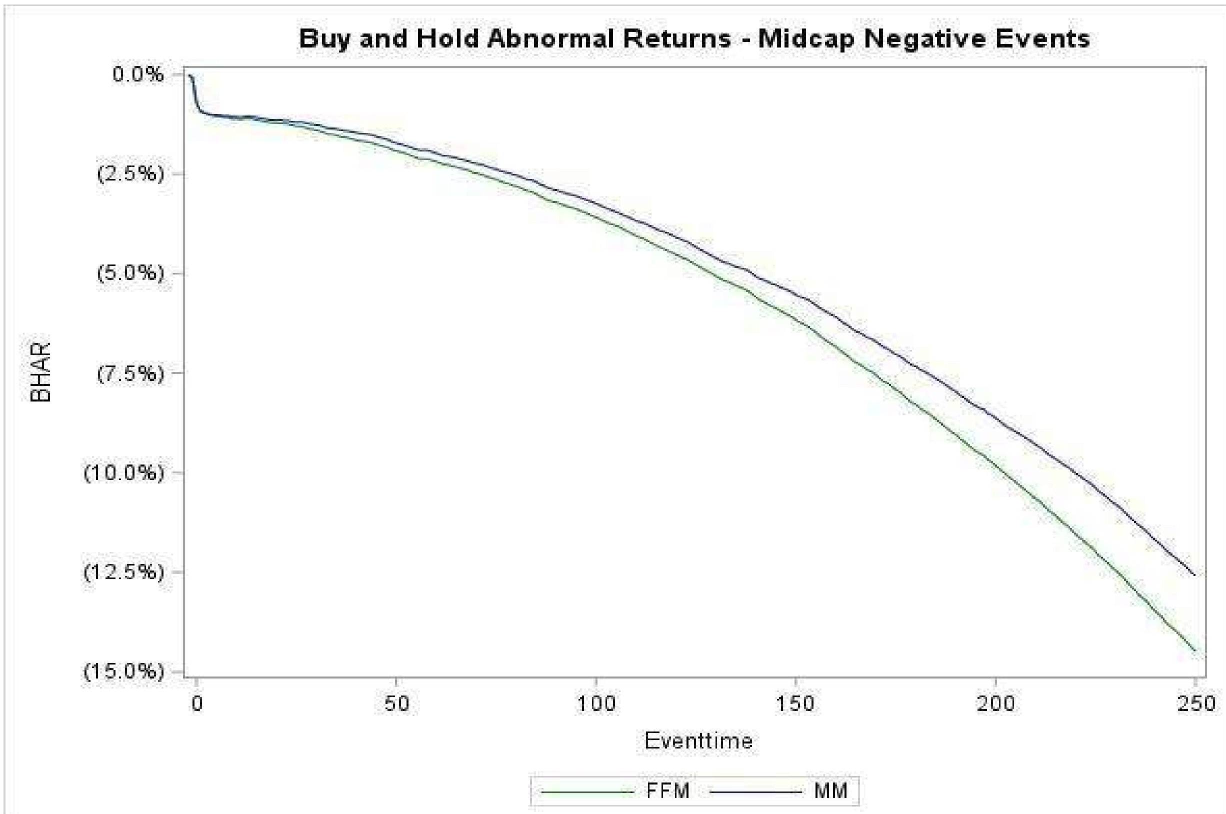
This figure indicates the Buy and Hold Abnormal Return for the base negative subsample of small-cap stocks across the event window [-2,250]. The Buy and Hold Abnormal Returns calculated on the event date is 1.87%, under the Fama and French three factor model, that decreases to a loss of 21.8% by the end of the holding period.

Figure 11 Buy and Hold Abnormal Returns - Negative Subsample



This figure indicates the Buy and Hold Abnormal Return for negative mid-cap events across the event window [-2,250]. The Buy and Hold Abnormal Loss calculated on the event date is 0.735%, under the Fama and French three factor model, that decreases to a loss of 12.63% by the end of the holding period.

Figure 12 Buy and Hold Abnormal Returns - Midcap Negative Events



Appendix C: Winsorized Results

Shows the descriptive statistics of the variables Winsorized at the 5% and 95% level

Table 13 Winsorized Descriptive Statistics

	N	Mean	STD	Min	Max	Median	P 25	P 75
Firm Size	5480	6.22	1.28	4.13	8.63	6.15	5.18	7.20
ROA	5261	0.028	0.18	-0.42	0.28	0.075	-0.040	0.15
Leverage	5478	0.68	1.02	0	3.81	0.23	0.0062	0.85
Gender	1271	0.96	0.20	0	1	1	1	1
Age	1205	53.23	7.76	39.98	67	53	47.38	59
Board Size	1293	7.71	1.64	5	11	8	7	9
S_b	5895	0.036	0.023	0.0096	0.095	0.029	0.018	0.046
$\frac{S_a - S_b}{S_b}_{[-30,30]}$	5895	0.056	0.42	-0.51	1.086	-0.034	-0.26	0.27
$\frac{S_a - S_b}{S_b}_{[-30,250]}$	5895	0.16	0.48	-0.44	1.44	0.054	-0.19	0.38
CE	2495	-0.004	0.064	-0.14	0.13	-0.005	-0.038	0.03
MCE	2495	-0.009	0.15	-0.32	0.30	-0.007	-0.099	0.084
LCE	2495	-0.058	0.61	-1.45	1.08	-0.023	-0.36	0.31

Shows the winsorized short window regression results of Table 9 when data is Winsorized at the 5% and 95% level.

Table 14 Winsorized Short Window Regression Results

	Coefficient (t-stat)	
	(1)	(2)
Intercept	0.003 (0.25)	-0.0228 (-0.42)
Firm Size	-0.0014 (-1.03)	-0.0019 (-0.38)
ROA	0.0031 (0.25)	0.001 (0.03)
Leverage	0.0019 (1.24)	0.0006 (0.13)
Sb	0.0254 (0.24)	-0.0944 (-0.31)
Gender		0.0161 (0.57)
Age		0.0009 (1.43)
Board Size		-0.0036 (-1.28)
Industry FE	YES	YES
R- Squared	0.99%	5.32%
Adjusted R-Squared	0.36%	-0.09%
F-test	1.57*	0.98
N. Obs.	2049	297

Shows the winsorized mid-window regression results of Table 10 when the data is winsorized at the 5% and 95% level.

Table 15: Winsorized Mid-Window Regression Results

	Coefficient (t-stat)				
	(1)	(2)	(3)	(4)	(5)
Intercept	-0.086*** (-4.02)	-0.0813*** (-3.64)	-0.0815*** (-3.64)	-0.0653** (-2.09)	-0.0888** (-2.48)
Firm Size	0.0131*** (4.75)	0.0128*** (4.59)	0.0128*** (4.59)	0.0104** (2.44)	0.0114** (2.35)
ROA	0.0991*** (4.18)	0.0995*** (4.2)	0.0995*** (4.2)	0.0988*** (4.16)	0.1*** (3.67)
Leverage	0.0014 (0.46)	0.0015 (0.5)	0.0015 (0.5)	0.0014 (0.46)	0.0032 (0.89)
$\frac{S_a - S_b}{S_b}_{[-30,30]}$	-0.0106 (-1.31)	-0.0106 (-1.31)	-0.0075 (-0.54)	-0.008 (-0.57)	-0.0126 (-0.79)
CE	1.1538*** (25.34)	1.1575*** (25.27)	1.1575*** (25.26)	1.1171*** (13.56)	
BD		-0.0047 (-0.73)	-0.0046 (-0.7)	-0.0294 (-0.88)	0.0053 (0.14)
$BD * \frac{S_a - S_b}{S_b}_{[-30,30]}$			-0.0047 (-0.28)	-0.0042 (-0.24)	-0.0052 (-0.26)
$BD * Firm\ Size$				0.0038 (0.78)	0.0012 (0.21)
$BD * CE$				0.595 (0.6)	
Industry FE	YES	YES	YES	YES	YES
R- Squared	25.80%	25.80%	25.80%	25.90%	2.60%
Adjusted R-Squared	25.30%	25.30%	25.30%	25.20%	1.80%
F-test	50.52***	47.13***	44.16***	39.42***	3.39***
N. Obs.	2049	2049	2049	2049	2049

	Coefficient (t-stat)				
	(6)	(7)	(8)	(9)	(10)
Intercept	0.1314 (1.25)	0.1163 (1.1)	0.115 (1.09)	0.2247* (1.72)	0.1931 (1.23)
Firm Size	0.0157 (1.58)	0.0162 (1.63)	0.0166* (1.68)	0.0012 (0.08)	0.0012 (0.07)
ROA	0.0784 (1.25)	0.0806 (1.29)	0.0918 (1.47)	0.0824 (1.31)	0.0964 (1.28)
Leverage	0.0027 (0.28)	0.0033 (0.34)	0.0029 (0.3)	0.0023 (0.24)	0.0052 (0.45)
$\frac{S_a - S_b}{S_b}_{[-30,30]}$	-0.0209 (-0.91)	-0.0215 (-0.94)	0.0563 (1.2)	0.0461 (0.97)	0.0625 (1.1)
Gender	-0.1939*** (-3.36)	-0.1883*** (-3.26)	-0.2002*** (-3.46)	-0.2007*** (-3.46)	-0.1564** (-2.26)
Age	-0.0005 (-0.38)	-0.0007 (-0.57)	-0.0007 (-0.56)	-0.0007 (-0.55)	-0.0005 (-0.34)
Board Size	0.0018 (0.32)	0.0018 (0.31)	0.0027 (0.47)	0.0019 (0.33)	-0.0033 (-0.48)
CE	1.4481*** (11.26)	1.4264*** (11)	1.4228*** (11.02)	1.4809**** (5.93)	
Buy Dummy		0.026 (1.23)	0.0309 (1.46)	-0.1155 (-1.1)	-0.0569 (-0.45)
$BD * \frac{S_a - S_b}{S_b}_{[-30,30]}$			-0.1023* (-1.9)	-0.0921* (-1.69)	-0.1035 (-1.6)
$BD * Firm\ Size$				0.0221 (1.42)	0.0181 (0.97)
$BD * CE$				-0.0735 (-0.25)	
Industry FE	YES	YES	YES	YES	YES
R- Squared	37.60%	37.90%	38.70%	39.20%	12.10%
Adjusted R-Squared	33.80%	33.90%	34.50%	34.50%	6.10%
F-test	9.89***	9.43***	9.20***	8.44***	2.01**
N. Obs.	297	297	297	297	297

Shows the winsorized mid-window regression results of Table 11 when the data is winsorized at the 5% and 95% level.

Table 16 Winsorized Long Window Regression Results

	Coefficient (t-stat)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-0.7839*** (-8.03)	-0.6965*** (-6.85)	-0.6971*** (-6.84)	-0.5284*** (-3.73)	-0.0496 (-0.11)	-0.0829 (-0.18)	-0.0923 (-0.2)	0.0966 (0.17)
Firm Size	0.1204*** (9.57)	0.1149*** (9.04)	0.1149*** (9.04)	0.0897*** (4.65)	0.1741*** (4)	0.1751*** (4.01)	0.1748*** (4)	0.1491** (2.29)
ROA	0.009 (0.08)	0.018 (0.17)	0.0177 (0.16)	0.0079 (0.07)	-0.6364** (-2.31)	-0.6319** (-2.29)	-0.6183** (-2.22)	-0.6258** (-2.23)
Leverage	-0.0322** (-2.3)	-0.0297** (-2.11)	-0.0297** (-2.11)	-0.0308** (-2.19)	-0.0933** (-2.18)	-0.0922** (-2.15)	-0.095** (-2.2)	-0.0961** (-2.21)
$\frac{S_a - S_b}{S_b}_{[-30,250]}$	-0.0404 (-1.12)	-0.0417 (-1.16)	-0.0365 (-0.58)	-0.0375 (-0.59)	0.0583 (0.64)	0.0576 (0.63)	0.1327 (0.75)	0.1369 (0.76)
Gender					-0.5175** (-2.07)	-0.5057** (-2.01)	-0.511** (-2.03)	-0.5102** (-2.02)
Age					-0.0027 (-0.49)	-0.0031 (-0.57)	-0.0031 (-0.57)	-0.0031 (-0.55)
Board Size					-0.0224 (-0.9)	-0.0226 (-0.9)	-0.022 (-0.88)	-0.023 (-0.91)
CE	1.6704*** (8.06)	1.7383*** (8.35)	1.7385*** (8.35)	1.5474*** (4.13)	2.2576*** (4.25)	2.1849*** (3.99)	2.1695*** (3.95)	2.5782** (2.55)

	Coefficient (t-stat)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Buy Dummy		-0.0881*** (-3)	-0.0872*** (-2.86)	-0.3429** (-2.27)		0.0529 (0.56)	0.0702 (0.69)	-0.1713 (-0.37)
$BD * \frac{S_a - S_b}{S_b}_{[-30,250]}$			-0.0077 (-0.1)	-0.0058 (-0.08)			-0.1022 (-0.49)	-0.1093 (-0.52)
$BD * Firm\ Size$				0.0389** (1.75)				0.0351 (0.51)
$BD * CE$				0.2878 (0.64)				-0.5678 (-0.47)
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
R- Squared	8.80%	9.20%	9.20%	9.30%	16.30%	16.40%	16.50%	16.70%
Adjusted R-Squared	8.10%	8.50%	8.40%	8.50%	11.30%	11.00%	10.80%	10.30%
F-test	14.02***	13.73***	12.87***	11.56***	3.20***	3.03***	2.88***	2.63***
N. Obs.	2049	2049	2049	2049	297	297	297	297

Shows the winsorized change of volatility analysis results of Table 12 when the data is winsorized at the 5% and 95% levels.

Table 17 Winsorized Change of Volatility Analysis

Panel a. t-Test Results

Sample	N	Window	Mean	STD	t - stat
Sample After Event Study	2495	[-30,30]	0.334	0.420	58.90***
		[-30,250]	0.374	0.483	57.35***
Positive Recommendation Subsample After Event Study	1622	[-30,30]	0.200	4.46	1.81**
		[-30,250]	0.329	4.477	2.95***
Negative Recommendation Subsample After Event Study	873	[-30,30]	0.0811	0.657	3.65***
		[-30,250]	0.180	0.629	8.48***
Sample with COMPUSTAT Variables After Event Study	2049	[-30,30]	0.030	0.368	3.64***
		[-30,250]	0.106	0.376	12.71***
Positive Recommendation Subsample with COMPUSTAT Variables After Event Study	1361	[-30,30]	0.027	0.367	3.36***
		[-30,250]	0.104	0.379	12.35***
Negative Recommendation Subsample with COMPUSTAT Variables After Event Study	688	[-30,30]	0.034	0.368	4.19***
		[-30,250]	0.11	0.371	13.43***
Sample with COMPUSTAT & BoardEx Variables After Event Study	297	[-30,30]	0.061	0.418	6.63***
		[-30,250]	0.172	0.462	16.87***
Positive Recommendation Subsample with COMPUSTAT & BoardEx Variables After Event Study	204	[-30,30]	0.07	0.443	7.20***
		[-30,250]	0.173	0.478	16.34***
Negative Recommendation Subsample with COMPUSTAT & BoardEx Variables After Event Study	93	[-30,30]	0.041	0.360	5.17***
		[-30,250]	0.171	0.426	18.19***

Panel b. Relationship Analysis

	Coefficient (t-stat)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-0.008** (-2.46)	-0.0138** (-2.31)	0.029*** (3.55)	0.033** (2.34)	-0.005 (-0.46)	-0.04* (-1.85)	0.06** (2.52)	0.051 (1.14)
$\frac{S_b - S_a}{S_b}_{[-30,30]}$	-0.015 (-1.59)	-0.011 (-0.70)			0.005 (0.18)	0.07 (1.31)		
MCE			-0.08 (-1.59)	-0.068 (-0.73)			0.02 (0.18)	0.27 (1.17)
Buy Dummy		0.007* (1.09)		-0.0.062 (-0.36)		0.048* (1.92)		0.021 (0.39)
$BD * \frac{S_b - S_a}{S_b}_{[-30,30]}$		-0.005 (-0.26)				-0.092 (-1.42)		
BD * MCE				-0.021 (-0.19)				-0.25* (-1.31)
R- Squared	0.12%	0.18%	0.12%	0.13%	0.01%	1.73%	0.01%	0.69%
Adjusted R-Squared	0.07%	0.04%	0.007%	-0.01%	-0.33%	0.73%	-0.33%	-0.32%
F-test	2.55	1.26	2.55	0.90	0.03	1.72	0.03	0.68
N. Obs.	2049	2049	2049	2049	297	297	297	297

Panel c. Relationship Analysis								
	Coefficient (t-stat)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	-0.067*** (-4.60)	-0.008 (-0.31)	0.10*** (12.46)	0.11*** (7.65)	0.026 (0.56)	-0.098 (-1.18)	0.17*** (6.37)	0.17*** (3.62)
$\frac{S_b - S_a}{S_b}_{[-30,250]}$	-0.050 (-1.47)	-0.052 (-0.79)			0.07 (0.78)	0.14 (0.78)		
LCE			-0.019 (-1.467)	-0.02 (-0.86)			0.03 (0.78)	0.05 (0.72)
Buy Dummy		-0.089*** (-2.88)		-0.008 (-0.47)		0.18* (1.80)		-0.04 (-0.07)
$BD * \frac{S_b - S_a}{S_b}_{[-30,250]}$		-0.06 (-0.08)				-0.094 (-0.44)		
BD * LCE				0.002 (0.08)				-0.03 (-0.35)
R- Squared	0.11%	0.54%	0.11%	0.12%	0.20%	1.31%	0.20%	0.25%
Adjusted R-Squared	0.05%	0.4%	0.05%	-0.03%	-0.13%	0.30%	-0.13%	-0.78%
F-test	2.15	3.76**	2.15	0.79	0.60	1.29	0.60	0.24
N. Obs.	2049	2049	2049	2049	297	297	297	297