FROM WALLSTREETBETS TO C-SUITE: ESSAYS ON ATTENTION, EMOTION, AND INCENTIVES IN MODERN FINANCIAL MARKETS

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Abstract

This dissertation consists of three empirical finance essays on two key group of actors in the stock market – retail investors and CEOs. The information explosion era that we live in creates a deluge of data spanning the textual, audio and visual space beyond structured panel data's cold, hard numbers. With the help from concurrent technological advancements and ever-growing computing powers to analyze this sea of data, this dissertation documents my attempt to dig further into questions posed by the forerunners in the finance research field. In the three essays, I parse through and analyze unstructured textual, audio, and visual data to gain insight into the age-old debates on attention, emotion, and incentives: If retail investors are losers in the stock market, what situations turn the table around and make them winners? If financial television and interviews are only regurgitated stale news, why would audience still tune in? Why do executives appear in the TV recording studios to chat with interviewers instead of spending this time at work? If managers hedge less of their firms' risk when they are provided with stock options, why do most firms still offer them? These are some of the questions that my essays try to address.

The first essay examines the discussion and attention in online stock forum r/WallStreetBets, and documents outperformance of the consensus bullish portfolio. I provide evidence that positive online discussion leads to retail net buying. Despite being usually wrong, when retail attention herds, the abnormal returns from attention herding events do not reverse in the short term (20-day, 40-day and 60-day windows). "Apes", as the forum users call themselves, are "together strong".

The second essay examines the impact of TV interviews of CEOs and documents that CEOs' positive emotions have positive market impact when the company misses earnings; when

news is good, the interview generates only short term alpha on the company stock for a brief period. I also show that CEOs appear on TV interviews with disproportionate amount of good news. Most CEOs who appear in Mad Money interviews come after their company report earnings above market expectations.

The third essay uses agency theory to show that managers are motivated to maintain the same level of hedge intensity even if they are provided with stock option incentives. However, stock options do induce managers to add speculative positions on the downside to supplement their hedging operations.

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Chapter 1 : Dumb Money? Social Network Attention Herding, Sentiment, and Markets[1]

1. Introduction

In January 2021, Wallstreetbets (WSB), an online investor forum on the Reddit platform, caught the attention of mainstream media when its users joined forces and orchestrated a short squeeze on GameStock (GME) and a few other "meme" stocks.[2] While not the first short squeeze in history, this event and the forum shot to global fame because it was the first time retail investors successfully took on Wall Street veterans, acting like a crowdsourced hedge fund. The forum membership grew from less than 2 million in early January 2021 to over 13.36 million by the end of Dec 2022.[3]

The concept of "dumb money" - that uninformed retail investors consistently make poor buy and sell decisions - has prevailed in literature for more than two decades (e.g., Barber and Odean (2000), Frazzini and Lamont (2008), Barber, Lin, and Odean (2024)). The 2021 episode, however, highlights the possibility that when there is extreme attention herding facilitated by the echo chamber effect of social networks (Pedersen, 2022), retail investors could overcome their dumb money fate. This hypothesis is the focus of our paper. We show that both outcomes - retail investors underperforming or outperforming - can be observed, and it depends on the scale of the attention.

[1] Chapter 1, in full, is a reprint of the material as it appears in Huang, C. C., & Nolan, P. S. (2025). Dumb money? Social network attention herding, sentiment, and markets. *The Journal of Finance and Data Science*, *11*, 100169. The dissertation author was the co-author of this paper working alongside Dr. Pauline Shum Nolan and handled the following responsibilities: Conceptualization, Data Curation, Formal Analysis, Visualization, and Review & Editing.
[2] At the peak, GME traded at 30 times its January 1, 2021 market capitalization of the $1.5 billion. This led to large losses for the short sellers of the stock.

[3] https://subredditstats.com/r/wallstreetbets, accessed at different dates.

We select WSB for our study for several reasons. First, since WSB is the largest online forum for retail investors, it is ripe for testing the effects of social networks on the stock market. Second, the forum provides a new way for us to measure investor attention. Google Trends captures Google users' attention, but the indices are rescaled frequently, and it is difficult to obtain consistent results when empirical tests are updated. Further, Google's user base is not exclusively retail. Third, Barber et al. (2022) uses an ex-post measure: the observed changes in user holdings on the trading app, Robinhood. Unfortunately, Robinhood only provided this data for a short period of time, from May 2018 to August 2020, and so their attention measure can no longer be constructed. Through WSB, we can measure retail investor attention directly rather than infer it from user holding changes. In fact, since WSB and Robinhood likely share a significant portion of their respective clienteles,[4] we can test the lead-lag relationship between our WSB attention measures and Robinhood user holding changes.

We collected 2.2 million WSB posts from January 2016 to December 2022. Since these posts appear in user feeds and are unstructured, we must first devise several rules to identify posts that contain a valid stock name or ticker symbol and then use machine learning to extract investor sentiment for each relevant post. We use Google's Bidirectional Encoder Representations from Transformers (BERT) model (Devlin, Chang, Tan and Toutanova (2018)) for natural language processing (NLP), trained on a proprietary dataset of online investor comments.[5] Note that the

[4] We manually go through 100 user posts between August 2021 and September 2021 that have screenshots of their trading accounts. Ninety-six of them were screenshots from the Robinhood trading app.

[5] We also tested FinBERT as an alternative, but since this model was trained on corporate communication documents, the classification of retail sentiment is not as accurate for our purpose.

BERT model is capable of interpreting context,[6] and is therefore a considerable improvement upon prior classification systems using a dictionary approach (Loughran and McDonald (2011), Long, Lucey, Yarovaya, and Xie (2023)), or computational linguistics methods that assume the occurrence of words are independent of each other (Antweiler & Frank (2004)).

Unlike Antweiler and Frank (2004) who pre-selected 45 stocks for their study, we create a time series of stocks that receive varying amounts of attention on WSB. From that list, we also form a subset of stocks that are the most talked about on the forum, which we refer to as attention herding. Herding is based on user engagement in the discussion, measured by the number of comments each post receives about a stock.[7] We should note that we do not differentiate between posts by genuine users and by "bots". We only concern ourselves with the salient information – fundamental or otherwise – in front of users in their feeds when they log into the forum. Using our fine-tuned BERT model, for each stock i on day t, we measure the daily aggregate user sentiment. And based on the sentiment of all stocks mentioned on day t, we construct a forum-wide sentiment measure.

To preview our results, first, we find that our monthly rebalanced WSB Attention Herding Portfolio, constructed with the *three most popular* positive sentiment stocks from the previous month, generates a Fama-French-Carhart (FFC) four-factor alpha of 108.25 percent (annualized), for the sample period January 1, 2016 to December 31, 2022. The alpha is bigger but not by much (at 120.75 percent annualized) when we exclude the tumultuous year of 2022 in which FED started

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[6] For example, the BERT model can distinguish between the use of the word *bank* in "I am going to the river *bank* for a walk" versus "I am going to the *bank* to take some money out" because it considers the context provided by the adjacent words in a sentence.

[7] In an earlier draft of the paper, we used the number of upvotes as the measure of engagement. We switched to the number comments, because it has since come to our attention that comments are more reliably captured in the dataset (Pushshift API) than upvotes. Also, comments represent a better measure of engagement.

hiking interest rates. Therefore, it might be surprising that even after significant global attention on WSB in 2021, there is some persistence in the alpha.

Second, we study whether investor attention generally leads to actual retail trading and its impact on subsequent stock returns. We begin by looking at the *full* sample of stocks discussed in relevant WSB posts. We find significantly more Robinhood users holding a particular stock the more it is discussed. Sentiment – whether positive or negative – both lead to more user holdings. In terms of next-month risk-adjusted returns (four-factor alpha), we find significant evidence of poor prediction at the *aggregate* level: positive sentiment stocks on the WSB forum are associated with a negative next-month alpha, and negative sentiment stocks are associated with the opposite. The finding that monthly attention and sentiment are contrarian indicators of stock performance lends support to Barber et al. (2022)'s main conclusion about dumb money.

Interestingly, in our event study where we narrow our focus to stocks that receive the top attention each day on the forum, i.e., when there is attention *herding*, the results differ. We find a buy-and-hold abnormal return ($BHAR$) for positive sentiment stocks of 1.03 percent over the next month, and -0.25 percent for the negative sentiment sample. We observe no reversal in returns. Further, matching the Robinhood data to our event window, we show a clear relationship between WSB attention herding events and net changes in Robinhood user holdings. These daily attention herding results are closer to Welch (2022), in which he sheds a more positive light on the wisdom of the retail crowd. He finds that not only did Robinhood users not panic through the 2020 Covid market downturn, collectively their portfolios generated some positive alphas.

We acknowledge that WSB online discussions and Robinhood user activities could be driven by an exogenous common factor, leading to a shared information effect. To investigate, we conduct intraday tests with the two examples to confirm that there is indeed a lead-lag relationship.

Specifically, we find that WSB forum discussion peaks before Robinhood user holding change peaks.

To ensure that our findings are not specific to investors on the Robinhood trading platform, we also leverage data from the Nasdaq Retail Trading Activity Tracker (RTAT) to investigate the impact of WSB attention and sentiment on the broader retail market. We confirm that WSB forum posts and sentiment significantly influence aggregate retail investors' trading activities at the monthly level as well.

The contributions of our paper can be summarized as follows. Using the WSB forum over a span of seven years, we create a new and direct measure of investor attention and attention herding, rather than relying on an inferred measure of attention. Another advantage of our measure is that it can be continually constructed going forward.[8] As well, we fine-tune a large language model (BERT) that understands the *context* of retail investors' comments and therefore can classify their sentiment with good accuracy, which previous methods lack.[9] Using WSB posts and comments, we document the effects of an echo chamber on Robinhood users and the broader retail market. Our empirical tests address several important questions. While most studies have focuses on firm-specific attention, our study differentiates between the impact of individual stock (micro) attention and forum-wide (macro) attention, where the latter refers to attention *herding*. We take a more nuanced approach to address whether retail investors are "smart" or "dumb" (and when) and contribute new insights to the conflicting findings in the existing literature.[10]

[8] Some of the measures in the literature are discontinued. For example, the Robintrack data used in Barber et al. (2022) is no longer provided by Robinhood.

[9] We also experimented with ChatGPT 4, which came out in March 2023. The accuracy improves only slightly.

[10] Examples of papers that find a positive conclusion for retail investors include: Farrell, Green, Jame, and Markov (2022), Gu and Kurov (2020), Tan and Tas (2020), and Welch (2022). Examples of papers that

The remainder of the paper is organized as follows: Section 2 provides a literature review of papers that our study builds upon; Section 3 describes our data and methodologies. Section 4 presents our empirical findings. The last section summarizes the paper and concludes.

2. Literature Review

In this section, we expand on the literature mentioned in the introduction and review other closely related literature. Specifically, we review the literature on retail trading success, community-based investing, and other papers that also examine the WSB forum.

2.1 Retail Trading Success

Academic research has long shown interest in retail investors. Research focus include the behaviour and investment outcomes of individual investors (e.g., Barber and Odean (2000), Kaniel et al. (2008), Kumar (2009), Bryzgalova, Pavlova, and Sikorskaya (2023), Barber, Lin, and Odean (2024)), retail traders' impact on stock returns and market quality (Kelley and Tetlock (2013) and Eaton, Green, Roseman and Wu (2022)), as well as investor attention on stock returns, investor risk taking and herding (Da et al. (2011), Hsieh, Chan, Wang (2020), Barber, Huang, Odean, and Schwarz (2022), Arnold, Pelster, Subrahmanyam (2022), Warkulat and Pelster (2024)). The general findings from these literature usually point towards counterproductive trading decisions that result in the underperformance of the retail portfolio: Barber and Odean (2000) finds that those who actively trade underperform the market by six percent each year, based on a study of over 66,000 household stock accounts. Kelley and Tetlock (2013) attribute the negative performance to passive orders of retail investors who act contrarian to market direction and provide liquidity to the market.

2.2 Community-based Investing

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find a negative conclusion include: Barber, Huang, Odean and Schwarz (2022), Barber, Lin and Odean (2024). Cookson, Lu, Mullins and Miessner (2024) find mixed evidence.

There is also literature on community-based investing, such as messaging boards for individual stocks (Antweiler and Frank (2004)), and crowdsourced investment research platforms such as Seeking Alpha (Farrell, Green, Jame, and Markov (2022)). Both papers document short-term movement of stock prices that are in line with retail sentiment. Cookson, Engelberg and Mullins (2023) use StockTwits that has about 400,000 users as an example of an echo chamber and find that beliefs formed on the platform are associated with lower ex-post returns. Cookson and Niessner (2020) use the same platform to study the sources of investor disagreement. Together, these two papers document retail underperformance when attention is high. Gu and Kurov (2020) examine stock return predictability of firm-specific sentiment on Twitter and find that tweets provide information not already reflected in stock prices. Tan and Tas (2021) obtain similar results for international stocks using Twitter and Stockwits. Cookson, Lu and Niessner (2024) provide an interesting comparison of user attention and sentiment on Twitter, Stockwits and Seeking Alpha.

2.3 Echo Chamber Effect and Wallstreetbets

A literature specific to the echo chamber setting of WSB gained academic interest recently. Bradley, Hanousek, Jame and Xiao (2024) study the due diligence (DD) recommendations in the forum and document a decline in informativeness in DD reports after the GME short squeeze saga. Long, Lucey, Yarovaya, and Xie (2023) study user sentiment and intraday GME returns in the first two months of 2021 and have directly shown that forum activity during the herding period significantly impact the market. Fernandez-Perez, Indriawan and Khomyn (2025) classify WSB discussions into emotions, we also expand beyond their sample period to verify the effects of emotions and number of posts affect intraday returns. Warkulat and Pelster (2024) examine the relationship between WSB posts and investor risk taking and welfare using a proprietary dataset from a trading platform from January 2020 to February 2021. Münster, Reichenbach, and Walther

(2024) study the impact of three different sub-Reddits versus traditional news articles on retail trading from May 2018 to August 2020.

In terms of theoretical work, Pedersen (2022) has developed several hypotheses about the effects of social networks on stock prices and trading volumes. This paper provides the foundation for our empirical work. Pedersen's model proposes six stages to explain the observed social network effect, bubbles, price momentum, and reversal. As we will show, the initial displacement stage, the speculation stage, and the mania and emulation stage are consistent with our empirical observations for attention herding events, and they are distinctly different from run-of-the mill retail underperformance. While the last and inevitable stage of the model is the burst of the bubble, it is only observed ex-post when uncertainty on how long it will last is revealed. We test for reversal with our window of 20 trading days (as well as 40 days in the Appendix).

3. Data and Methodology

In this section, we describe the WSB posts, explain how we identify posts relevant to individual stocks, and outline the sentiment classification procedure.

Our WSB data consists of 2.2 million posts parsed from the Reddit online platform, for the period January 1, 2016 to December 31, 2022. In order to construct meaningful measures and proxies for user attention and aggregate sentiment of stocks, we first screen out posts that do not mention a specific stock by its ticker symbol. We also clean the data to exclude ambiguous cases that likely are not referring to a ticker symbol. For the remaining posts, we classify whether they are relevant for investing or trading. After that, our task is to classify whether a relevant post contains "positive" (bullish) or "negative" (bearish) sentiment. Screenshots of sample forum posts is provided in the Appendix, Figure A1. Details of these procedures are described below.

3.1 Ticker Identification

Most users will put a dollar sign in front of a capitalized ticker symbol in their posts, which is the standard format for discussing a stock in the forum. The dollar sign is the easiest way to identify a stock. However, some users may not conform to this forum convention. To catch these cases, we find words in post titles that match a valid ticker symbol, either in lower- or upper-case, as long as the ticker symbol is separated from other text by two spaces. Then, to reduce the noise caused by false identification where a ticker symbol could also be a frequently used word, such as ON (On semiconductor), LOVE (Lovesac Co) and HAS (Hasbro), we tabulate the frequency of the identification channels for each ticker symbol (percentages identified by $, all-CAP, or lowercase, respectively). We remove those ticker symbols that have more than 50 percent identifications from lowercase. For example, posts that contain 'HAS' and 'LOVE' are excluded because more than 50 percent of the identifications are from lowercase. If a dollar sign is present, however, we do not remove the post from the sample.

3.2 Relevance, Sentiment Classification, and the VIX Index

To classify the relevance and the sentiment of each post where there is a reference to a specific stock, we use the BERT model re-trained on a proprietary dataset of 12,000 unique, hand-labelled user comments from *Investing.com*. The relevance indicator classifies whether a text contains belief on a stock's direction, whether negative or positive. The sentiment indicator classifies whether a text is bullish or bearish on the outlook of a stock, given that such sentiment exists for the stock. We take a similar approach to FinBERT (Araci (2019)), but our model outperforms FinBERT out-of-sample, likely because the latter was trained on financial text such as 10k reports, instead of retail investors' online language. Specifically, our model achieves 80 percent accuracy on the classification of "relevance", and 85 percent on the classification of "sentiment" out-of-sample. In Figure 1, we provide a diagram of the classification flow chart.

Figure 1.1 about here

The main reason we employ a two-stage classification instead of one stage with three outcomes (positive/neutral/negative) is that the overall result is more precise with a two-stage classification. We believe higher precision (True Positive Rate of correcting classifying bullish and bearish posts) is more important than recall (rate of all sample that contains sentiments being identified) in this context, i.e., throwing out some observations that may be "relevant" is more acceptable for our purpose than having a wrongly classified sentiment (e.g., labelling a neutral sentiment to either positive or negative.) We provide examples of relevant and irrelevant posts in Appendix Table A1.2.

To give the reader a preview of our data, we present the following visual of the forum-wide sentiment measure against the VIX index in Figure 1.2.

Figure 1.2 about here

We see an overall negative relationship between sentiment and the VIX; that is, a more positive sentiment across the WBS forum is generally associated with a lower than VIX index, on a rolling monthly (20-day) basis. In a regression framework (not shown), a one standard deviation increase in sentiment is associated with a 0.1 standard deviation drop in the VIX index.

3.3 Robintrack, Nasdaq Retail Trading Activity Tracker and Other Market Data

We believe that many users on WSB are also customers of the trading app, Robinhood. We manually go through 100 user posts between August 2021 and September 2021 with screenshots of their trading accounts and find that 96 of them are screenshots of the Robinhood trading app. Robinhood made available their customer holdings data to the public for a short window of time, from May 2018 to August 2020. The Robintrack data is intraday with timestamps that are one hour apart. It documents the number of holders of all tradable stocks on the platform, identified by their ticker symbols.

We also explore broader retail flows for the full sample period, January 1, 2016 to December 31, 2022. For this purpose, we use the Nasdaq Retail Trading Activity Tracker (RTAT). It is a proprietary dataset constructed from consolidated quotes and trades data across U.S. equity markets. It is designed to capture the intensity and the direction of retail investor activities at a daily frequency. RTAT provides two primary dimensions of information: “activity” and “sentiment”. The “activity” variable reflects the share of trades attributable to retail investors. Specifically, it is a percentage measure that captures a given stock’s daily retail trading volume relative to the total retail trading volume across the U.S. equity universe covered by RTAT (~ 9,500 traded securities). A higher percentage indicates that a stock represents a larger fraction of aggregate retail trading on that day. This variable serves as our baseline measure of retail trading intensity. The “sentiment” variable ranges from -100 to +100. It is not a survey-based measure of retail investor sentiment, but instead a flow-based net measure derived from the directional imbalance of retail trades (buy vs. sell). Values closer to +100 represent heavily buyer-initiated net flows from retail investors, while values closer to -100 correspond to mostly seller-initiated net flows. Because the “sentiment” variable only measures direction and not magnitude, we construct our key proxy for retail flows as the interaction of “activity” and “sentiment”. This product, which we refer to as net retail trading volume, expresses the net retail order imbalance in percentage points, scaled by the relative size of the stock relative to the total retail volume.

Our stock market return data comes from CRSP. The Fama-French factors are downloaded from Kenneth R. French Data Library.

Table A1.1 contains the definitions of all of the variables used in our empirical tests.

Table A1.1 about here

3.4 Posts and Comments

In our empirical tests, each WSB post has the following two attributes: i) number of comments – this is our proxy for a post's user engagement, gauging the amount of attention it receives by how much discussion it generates in the forum; ii) post sentiment (conditioned on being "relevant") – it takes on the value of zero if it is negative, and one if it is positive. By aggregating post sentiment for each ticker symbol every day, we construct a daily *ticker sentiment* measure. It weighs the number of positive and negative posts for each ticker symbol, and it is equal to the fraction of positive posts. This measure takes on values between zero and one. In addition, we construct a daily forum-wide sentiment measure, taking all posts that have a sentiment classification into account. This measure also takes on values between zero and one. Posts that mention more than one ticker symbol are removed from the sample. Each relevant post may also receive user comments. We construct an alternative sentiment measure using comment-weighted post sentiment, using the number of comments each relevant post has as the weight.

4. Empirical Results

In this section, we perform our empirical analysis of the effects of WSB attention. We first construct monthly attention herding portfolios of the top three attention stocks with positive sentiment and estimate their alphas. Then we examine the impact of daily and monthly attention and sentiment on retail trading using the full sample of stocks from WSB. We end with an event study that focuses on daily attention herding on the most discussed stock and provide evidence of the lead-lag effects between WSB posts and Robintrack user holding changes.

4.1 Monthly Attention Herding Portfolios

We examine the performance of a trading strategy based on WSB user attention and find highly positive alphas throughout the sample period. Monthly attention herding portfolios are constructed by taking the top three stocks with the highest *positive* attention in month t.[11] The ranking is first done based on the number of times a post is made about a ticker symbol. If a ticker symbol is mentioned more than once in the same post, only one mention is counted. After the monthly ranking is established, we include only stocks that have more than 50 percent positive mentions.

A monthly attention herding portfolio would purchase the month-t top three posted about stocks at the end of the last trading day of month t and hold for exactly one month until the last trading day of month $t+1$, at which time the positions would be rebalanced. We chose the monthly frequency instead of daily or weekly to minimize noise and reduce transaction costs.

The Fama-French-Carhart 4-factor results based on daily returns of the Monthly Attention Portfolio are shown in Table 1.1. We use daily returns in the regressions to have a larger number of observations in the time series.

Table 1.1 about here

[11] We show the results for the monthly negative attention portfolio in Appendix Table A6. The alpha is negative as expected, but they are not statistically significant. This observation supports Avila, Martineau, and Mondria (2023) that retail investors in social networks have an optimism bias. Also, it is more difficult for retail investors to short stocks. For example, the Robinhood platform does not allow shorting in our sample period.

There are three columns in Table 1.1, Panel A. In column 1, the regression is for the full sample from January 2016 to December 2022. The FFC 4-factor alpha is very large and statistically significant at one percent, at 108.25 percent (annualized). One might argue that GME and AMC were anomaly stocks in 2021, and that they could have inflated the returns. For this reason, we exclude GME in the regression in the second column and we exclude GME and AMC in the third. The alphas are muted, but they are nonetheless still statistically significant at one percent, ranging from 67.50 percent (annualized) when GME is excluded, and 61.75 percent (annualized) when both GME and AMC are excluded. In terms of risk factors, there is a strong positive loading on the market, a significant growth tilt across all three regressions. The full sample result (column 1) also shows a small size tilt.

The alphas in Table 1.1 are robust. We re-run the regressions to *exclude* the year 2022, a negative year for the market as a whole due to the war in Ukraine and multiple interest rate hikes. We want to see if after the 2021 frenzy and global attention on WSB, whether more users joining the forum would arbitrage away some of the profits from the monthly attention herding portfolio. It is interesting that the alphas are larger, but not by much, when we end the sample at the end of 2021. These results are presented in Panel B. The annualized alphas range from 71 percent (column 3) to 120.75 percent (column 1). Given that this monthly attention herding portfolio can be continuously constructed, its performance is worth monitoring.

We find positive but statistically insignificant alphas for comment-based attention, where the top stocks with the highest number of comments in the month do not outperform or underperform.

For readers interested in the full list of top attention stocks, we show their ticker symbols in Table A1.5 in the Appendix.

4.2 Daily Effects of WSB Attention

The regression analysis in this subsection includes the full sample of stocks identified in the WSB forum posts. For these daily regressions, we use retail investor data from Robintrack as well as from the Nasdaq Retail Trading Activity Tracker. In Table 1.2, we provide the summary statistics for the data.

Table 1.2 about here

Robinhood made public its Robintrack data for the short period from May 2018 to August 2020. It tracks how many of its users hold a particular stock over time. We take advantage of this data to test if WSB attention and individual stock sentiment have any actual impact on retail investors that use the Robinhood trading app.

In Table 1.3, we present the daily regression results. Panels A and B use data from Robintrack and Panels C and D use data from RTAT.

Table 1.3 about here

The dependent variable in Panel A is the next-day percentage change in Robinhood user holdings, and in Panel B, it is the next-day (raw) change in user holdings. The regressions control for day fixed effect. Not surprisingly, the previous day's stock return is the most significant determinant of user holding change, as retail investors chase returns. However, attention on WSB, regardless of sentiment towards the stock, also significantly increases user holdings on the following day. The economic magnitude of the attention effect is in fact greater. Take regression (2) in Panel B, for example. A one percent stock return is associated with a 0.06 percent increase in user holdings (or 15 users), while a one standard deviation (0.54) increase in log(Posts) is associated with 0.27 percent increase in user holdings (or 269 users). To put the effect into perspective, at the average post of 2.5 per day for the entire sample of stocks on WSB, an increase of 4.3 posts has the same effect in increasing user holdings as 17.7% in stock returns.

Understanding that the Robintrack data is limited in scope, we make use of data from the Nasdaq Retail Trading Activity Tracker (RTAT) to test whether WSB attention has any impact on the broader retail market. The results are presented in Panel C (Retail Trading Volume) and in Panel D (Net Retail Trading Volume). Both sets of results strongly support the hypothesis that the number of posts for each stock, whether positive or negative in sentiment, leads to more retail trading. The main difference between the Robintrack sample and the broader RTAT sample is the directional effect of stock return, with the broader retail investors acting as contrarians.

4.3 Monthly Effects of WSB Attention

We now turn to monthly regressions of next-month (four-factor) alphas on WSB attention and sentiment for all stocks mentioned in the forum during the full sample period. We can see from the results in Table 1.4 that posting about a stock does not predict next-month alphas, but stock sentiment does, and it is a contrarian indicator for stock performance. That means, on average, the redditors are incorrect at the monthly level. The more positive posts there are about a stock, the more likely the stock will underperform in the following month; the more negative posts there are about a stock, the more likely the stock will outperform. This finding supports the existing literature on dumb money as it relates to retail investors and echo chambers. We believe that opposite conclusions between Table 1.4 (dumb money) and Table 1.1 (smart money) highlight the difference between retail sentiment in general versus herding amongst the top attention stocks.

Table 1.4 about here

4.4 Event Study: Effect of Herding Events

To select WSB attention *herding* events for the study, we use a more stringent definition. For each day t, we pick the stock that is the most discussed on the forum. We select the stock that is most posted about and the most commented about. Typically, they are the same stock. On days when that is not the case, we include both stocks in the sample. We note that WSB posts are time-stamped and tend to cluster around lunch time. In total, there are 723 daily herding events during the Robintrack sample period, representing 168 unique ticker symbols. We further classify each stock into positive or negative sentiment, based on its post-weighted average sentiment. That is, if the majority of the posts are classified as positive (negative), then its sentiment of the day is positive (negative). We have also conducted tests with comment-weighted sentiment (using the number of comments as weight for post sentiment) and abnormal attention (the number of posts and comments above 20 day average number), the results are similar to that of the daily post sentiment, and they are reported in the Appendix Table A1.3.

The first set of results are shown in Figure 3. The graph has two y-axes. On the left is the average change in Robinhood user holdings for the stocks in the daily attention herding event sample. The dark purple bars represent the subsample of stocks associated with a positive sentiment, and the light purple bars represent those with a negative sentiment.[12] On the right is the buy-and-hold abnormal returns ($BHARs$) over the next 20 trading days. To mitigate the bad model problem (Fama (1998)), we follow Barber et al. (2022) and define daily abnormal return as the return of the stock minus the market return. The green time series shows the $BHARs$ for the

[12] Note that user change, the change in the number of Robinhood users holding a particular stock, is always positive for the stocks in the daily attention herding sample. For it to be negative, we need more Robinhood users to completely close out their positions in the stock than the number of new stockholders. Since the sample period was a period of tremendous growth for Robinhood, we do not observe negative user changes very often.

positive sentiment high attention stocks and the red time series shows that for the negative sentiment high attention stocks.

Figure 1.3 about here

Focusing first on user holdings change, we see that there is a distinct difference between positive and negative attention stocks. For positive attention stocks, there is a clear upward trend in the number Robinhood users that hold the stocks, spiking on day $t = 0$, the attention herding event date. Thereafter, there is no continued momentum, suggesting that users might have switched their attention to other stocks. For negative attention stocks, the pattern is a lot weaker. It is not a surprise that positive attention stocks receive more action on Robinhood, since short-selling is not allowed on the trading platform. In terms of $BHARs$, there is a big difference between positive attention versus negative attention stocks. For positive attention stocks, the sharp rise in abnormal returns started a few days before user change peaked, and there is a moderate continued rise without a reversal, over the next month. The corresponding pattern between the rise in $BHARs$ and Robinhood user holdings change prior to day $t = 0$ closely resembles a social network spillover effect. This result, however, is in sharp contrast to the negative attention herding stocks. In the sample, there is a lot more daily attention herding to positive sentiment stocks (456) than negative sentiment stocks (267). In Table 1.5, we show the statistical significance of the results for positive sentiment stocks. They confirm the key observation in Figure 3 discussed above, in that there is no evidence of statistically significant reversal in returns. We further test for robustness with alternative comment-based sentiment measure (using number of comments as a weight for user engagement sentiment) and abnormal attention (using 20-day moving average of number of posts and comments as baseline number and calculating abnormal number of posts and comments as the difference). The results are reported in Appendix Table A1.3.

Table 1.5 about here

In Table 1.6, we replicated the results in Table 1.5 but with an equally weighted portfolio of the top three attention herding stocks instead of one.[13] The results in terms of the patterns are very similar, but as expected, the average abnormal returns and average user holdings change are smaller because of diversification. We further incorporate a threshold of at least 18 posts to ensure meaningful separation of attention events and find stronger results. The results are reported in Appendix Table A1.4.

Table 1.6 about here

To confirm that there is no meaningful reversal in returns, we extended the $BHARs$ to 40 days. (Of course, the trade-off is that a longer window increases the chance of confounding events.) The chart is shown in Figure A1.2 Panel A in the Appendix. There is no sign of a reversal of earlier gains. In fact, the trend tends to continue.

Figure A1.2 about here

The previous analysis assumes that the daily attention herding events are independent of one another. However, a stock can build momentum in attention and receive top rankings more than once within a few days. In this case, it might be more appropriate to explore combining two

[13] The daily total number of posts for the top three most posted stocks represents 80 percent of the top 10 most posted stocks. We use top 3 as a cut off for attention herding. The median number of posts for the third most posted stock is 18.

attention episodes into one event. We define an alternative classification of two top rankings within the five days: if today ($t = 0$), stock i is ranked first and it has ranked first once in the past four days ($t = -1$ to $t = -4$), then today is an attention herding event for stock i. However, that any top rankings for stock i in the past four days that have already been included in a previous attention herding event will not be counted again, i.e., the count is reset. To illustrate, a stock's daily attention [1,1,0,0,0] will now be classified as [0,1,0,0,0], [1,1,1,0,0] as [0,1,0,0,0], [1,1,1,1,0] as [0,1,0,1,0], and [1,1,1,1,1] as [0,1,0,1,0]), where one is an attention herding event, and zero otherwise. The sample consists of 259 positive sentiment stocks and 153 negative sentiment stocks. The results are presented in Figure 4. Compared to Figure 3, there is an earlier run-up in user holdings returns prior to day $t = 0$, and the BHAR at the end of 20 days from $t = -10$ is higher by almost two hundred basis points, and user holdings change is higher on the event day, jumping to 2410, which is expected since now attention is more concentrated. t

Figure 1.4 about here

Again, a longer 40-day window shows that there is no reversal in earlier gains, and the trend continues more decisively for each sentiment. The graph is shown in Figure A2 Panel B in the Appendix.

What we have accomplished using our proprietary sentiment classification with the Robintrack user data is that we are able to divide attention herding into two distinct samples, obtaining different results for positive versus negative sentiments. Also, by using user interactions from the WSB forum, we are measuring attention at the source, or at least one direct source. These are likely the reasons why our event study results stand in sharp contrast to Barber et al. (2022)'s. The authors find a post-event negative 20-day $BHAR$ when Robinhood users herd on the same stocks, where a herding event is defined as the top 0.5 percent of the *user change ratio* on a given day t:

$$User\ Change\ Ratio_{i,t} = UserCount_{i,t}\ /UserCount_{i,t-1}$$

This (ex-post) definition, based solely on Robintrack user holdings, also leads to a very different sample of stocks in their study, as smaller, less popular stocks tend to have bigger change ratios: the firm size in Barber et al.'s sample has an average market capitalization of $2.23 billion. To put this figure into perspective, the median market capitalization of the Vanguard Small Cap ETF stands at $5.6 billion as of November 30, 2022. Our sample, in contrast, has an average market capitalization of $175 billion. In Table 1.8, we provide the sector and style characteristics of our sample of complete attention stocks. Some sector diversification is evident in Panel A, and in Panel B, we see that over 60 percent of the stocks are in the large-cap category.

Table 1.8 about here

In addition, Barber et al.'s sample has an average change (in the number of Robinhood users holding a particular stock over one day) of 900 users, compared to 2154 for our positive sentiment sample and 1085 for our negative sentiment sample when we consider independent daily attention herding events. In Figure 5, Panel A, we provide a visual contrast between our post-event $BHARs$ versus Barber et al. (2022)'s.

Figure 1.5 about here

Our positive sentiment attention sample shows a $BHAR$ of 1.03 percent (albeit statistically insignificant per Table 1.4)[14] over the 20 trading days post event (i.e., after the attention herding spiked), and -0.25 for the negative sentiment sample. In other words, we find that once attention has peaked, no further abnormal returns can be earned, but there is no reversal for the initial run-up 10 days prior either. Barber et al.'s finding in contrast, was -4.7 percent and statistically significant (they did not differentiate investor sentiment). Therefore, our results here side with Welch (2022) that not all retail money is "dumb".

Since our sentiment and attention herding analysis is not dependent on the availability of Robinhood user holdings data, we repeat the event study for the post Robintrack period, from September 2020 to the end of 2022. There are 134 observations in 2020 (after August), 239 observations in 2021, and 295 observations in 2022. The difference suggests that attention is most concentrated in 2021 and less concentrated in 2022, since there are more stocks that were both the most posted about and the most commented about in 2021.

Again, due to the frenzy surrounding GME in 2021, we exclude this stock in the sample. The results are shown in Figure 5, Panel B. We find that positive sentiment attention herding leads to a $BHAR$ of 1.39 percent over 20 trading days, peaking on day 13 at 4.42 percent. Negative sentiment attention herding yields a $BHAR$ of -1.91 percent, with day 17 being the lowest, at -3.07 percent.

4.4 Lead-Lag Test of Forum Attention Peaks and Robintrack User Change Peaks

In this subsection, we test and show that forum attention peaks lead user change peaks during our attention herding events.

[14] In Table 4, the variables have been winsorized at 95 percent. In the winsorized sample, the $BHAR$ is lower, at 0.78 percent.

A natural question that arises from our event study is the causality issue. Could a shared information shock on the event day create the coincidence of forum attention peak (highest forum-wide number of posts and comments) and Robintrack peak (high net user change)? It is possible that a common shock impacts both the forum and the Robinhood investors, leading to a positive feedback loop of attention. We think that testing for which measure peaks first during the day can shed light on whether the forum has a causal impact on Robinhood user holdings. In this test, we investigate more granular data and compute posts and user changes at the hourly level.

Robintrack data is available at the hourly frequency and Wallstreetbets posts contain timestamps accurate to the second and are normalized to the UTC time zone. We tabulate the number of posts belonging to each Robintrack user change hourly bracket for each daily attention herding stock on the day of the attention herding event. We focus on the regular trading hours, 9:30 a.m. to 4:00 p.m. Eastern Time (daylight savings adjusted). For the sample of attention herding events, the average number of posts as a percentage of posts and the average user change as percentage of the daily net change in user holdings are charted in Panel A. In Panel B, we graph the distribution of post arrivals and user change as percentage of the day's user change for stocks that have at least one mention for the day. In Panel B, we show the 24-hour post arrival distribution for the benefit of readers who are interested in the forum's attentions profile. WSB post number is highest from 10 a.m. to 11 a.m. Eastern Time and the number of posts bottoms out between 3 a.m. and 4 a.m. This shows that user activities align closely with North American time zones. To alleviate the potential concern that forum posts naturally peak before actual trading, we normalize the attention peak measure with the observed typical daily attention profile. We discount the activity profile in Panel A using that in Panel B to generate a normalized activity profile, as shown in Panel C. The result shows that on average, the peaks in post attention leads the peaks in user holding change by 13.6 minutes.

Figure 1.6 about here

As a robustness test with the normalized attention profile, we weigh the number of posts and user change based on the unconditional sample distribution of WSB post arrivals and user change percentage as shown in Panel B of Figure 1.6. As shown in Table 1.7, the resulted lead time is reduced to 5.82 minutes, but still statistically significant.

Table 1.7 about here

5. Conclusion

In this paper, our goal is to shed light on the influence of investor attention and sentiment on retail trading behaviour and the stock market. We contribute to the literature by proposing a new, direct measure of investor attention, classifying their sentiment using unstructured data from the WSB forum on the Reddit platform, and correlating them to user positions on the Robinhood app as well as the broader retail market trading activities. While previous research focuses mostly on firm-specific attention, we differentiate between the impact of individual stock (micro) attention and forum-wide (macro) attention, where the latter refers to attention *herding*. We take a more nuanced approach to address whether retail investors are "smart" or "dumb" by providing new insights to the conflicting findings in the existing literature.

Using a machine learning model fine-tuned on 12,000 hand-labelled comments written by retail investors, we start by determining which of the 2.2 million WSB user posts over a span of seven years from January 2016 to December 2022 we collected are relevant for sentiment classification. Then we construct a novel measure of retail investor sentiment using posts that discuss a stock, both at the individual stock level and aggregated (all stock posts) at the forum level. We find that forum-wide sentiment generally moves inversely to the VIX. We then construct a monthly attention herding portfolio using the top three most discussed stocks that receive an aggregate positive sentiment, disregarding those that garner negative attention (due to short sale constraints). For the full sample period, we show that whether the two meme stocks, GME and AMC, are excluded or not, the abnormal returns are outsized and statistically significant. They suggest that our attention herding measure captures hot stocks that outperform the Fama-French-Carhart four-factor model. When the turbulent year of 2022 is removed from the sample, the abnormal returns are higher as expected, but not by much, therefore suggesting some persistence into 2022.

Continuing to look at returns, we venture to see if attention and sentiment have material impact on retail trades and returns in general, for all of the stocks discussed on WSB. For retail trades, we focus on the Robintrack sample period, May 2018 to August 2020, when Robinhood made public their user holdings data. We document that attention on WSB, regardless of sentiment towards a stock, significantly increases user holdings on the following day. The economic magnitude of the attention effect is significant: On average, an increase of 4.3 posts, regardless of sentiment, is associated with 269 more Robinhood users holding the stock, after controlling for stock return. In terms of the impact of returns, we extend the analysis to the full sample period. We show that for all stocks that are discussed, investor sentiment is a contrarian indicator of next-month risk-adjusted returns. This means that on average, the redditors are incorrect. The more positive sentiment posts there were about a stock this month, the more likely the stock will underperform next month and vice versa. This finding supports the existing literature on dumb money as it relates to retail investors and echo chambers.

Interestingly, the results on returns differ and tell a different story when we narrow our focus on the most discussed stocks with the highest user engagement each day. In our daily attention herding event study, we find a positive sentiment stock's buy-and-hold abnormal return experiences a significant upward trend prior to its peak attention from WSB users in the forum, indicating momentum. At the same time, over at Robinhood we observe a corresponding, steady increase in the number of investors holding the stock. At the intraday level, posts numbers peak before Robinhood platform buying activity peaks. We interpret this pattern as the social network spillover effect, large enough to impact stock prices, as predicted by the theoretical model in Pedersen (2022). Even after attention has peaked, there was no statistically significant price reversal over the next month or two, thereby refuting the general label of dumb money in favour of wisdom of the crowd. Note that this pattern is only true for positive sentiment stocks. For negative sentiment stocks, we do not see any particular abnormal return pattern, before or after the event. Therefore, positive sentiment seems to have a stronger effect in a social network. That said, it can also be partly explained by the fact that short selling is not allowed on Robinhood, and smaller retail investors do not qualify for leverage with traditional brokers. There is also a general sentiment amongst WSB users that short sellers are bad actors, as evidenced by their choice of meme stocks to "defend" against hedge funds.

Finally, our attention herding events can be constructed past the Robintrack sample period. We show that after the end of Robintrack and until the end of 2022, WSB attention herding events, separately analyzed for positive and negative sentiment stocks, have more pronounced impact on stock prices (even when GME is excluded). For these attention events, we show that forum posts number peak arrive before user buying peak, suggesting retail investors taking forum information into account when making stock purchase decisions. Perhaps this is not surprising as the forum gain global notoriety in 2021 with the rise of meme stocks.

Table 1.1 Monthly Positive Attention Portfolios

Daily Return Regressions

Panels A shows the results from Fama-French-Carhart 4-factor regressions on equally-weighted portfolios of the top three stocks with the highest attention and positive aggregate sentiment on the WSB forum in the previous month. Portfolios are rebalanced monthly. In parentheses are t statistics, where one asterisk represents $p < 0.05$, two asterisks represent $p < 0.01$, and three asterisks represent $p < 0.001$.

Panel A: Portfolio of Top three positive attention stocks, January 1, 2016 – December 31, 2022

	(1) Full Sample	(2) GME Excluded	(3) GME and AMC Excluded
MKT	1.283***	1.320***	1.322***
	(17.76)	(18.00)	(18.42)
SMB	1.072***	0.151	-0.0389
	(5.47)	(0.92)	(-0.26)
HML	-0.259**	-0.463***	-0.564***
	(-2.27)	(-3.00)	(-3.78)
MOM	0.0815	-0.0742	-0.185
	(0.86)	(-0.58)	(-1.53)
Constant	0.433***	0.270***	0.247***
	(4.43)	(2.97)	(2.79)
Number of Obs.	1743	1240	1197
R^2	0.177	0.202	0.220

Panel B: Portfolio of Top three positive attention stocks, January 1, 2016 – December 31, 2021

	(1)	(2)	(3)
	Full Sample	GME Excluded	GME and AMC Excluded
MKT	1.223***	1.332***	1.332***
	(14.13)	(17.63)	(18.17)
SMB	1.022***	0.150	-0.0386
	(5.02)	(0.90)	(-0.25)
HML	-0.00696	-0.477***	-0.590***
	(-0.04)	(-2.88)	(-3.67)
MOM	0.277**	-0.0802	-0.200
	(2.01)	(-0.58)	(-1.55)
Constant	0.483***	0.284***	0.257***
	(4.52)	(3.07)	(2.86)
Number of Obs.	1492	1219	1176
R^2	0.145	0.201	0.219

Table 1.2 Summary Statistics for Daily Regressions

This table reports the summary statistics for the variables used in the daily user change regressions (Table 1.3) for the Robintrack sample period and in the monthly regressions for the full WSB sample period (Table 1.4). User Change refers to the number of users holding a specific stock on the Robinhood platform closest to but before 4pm. Retail Trading Volume is the percentage value of a stock's daily trading volume divided by market retail trading volume reported by Retail Trader Activity Tracker (RTAT). The Net Retail Trading Volume is a percentage computed as the daily retail volume times the RTAT flow-based sentiment that ranges from -100 to 100, divided by 100. Log(Posts) is the natural log of the number of WSB posts that mention the ticker before 3:30pm. Log(Positive) and Log(Negative) are the natural log of one plus the number of posts that mention the ticker with a positive / negative sentiment before 3:30pm, excluding the cases where the post is classified as irrelevant. Percent Positive is the ratio of positive posts from all relevant posts about the ticker.

	N	Mean	SD	Median	P10	P90
Panel A: Daily Regression (May 03, 2018 to Aug 13, 2020)						
Percentage User Change	30980	0.92	6.29	0.00	-0.63	2.26
User Change	30980	312.88	1863.09	1.00	-130.00	740.00
Retail Trading Volume	30496	0.44	0.91	0.10	0.01	1.36
Net Retail Trading Volume	30496	0.01	0.03	0.00	-0.01	0.02
Same-day Return	31086	1.07	13.56	0.19	-5.16	6.63
Posts	31098	2.50	5.73	1.00	1.00	4.00
Log(Posts)	31098	1.01	0.54	0.69	0.69	1.61
Log(Positive)	31098	0.30	0.47	0.00	0.00	0.69
Log(Negative)	31098	0.20	0.41	0.00	0.00	0.69
Percent Positive Posts	31098	0.22	0.37	0.00	0.00	1.00
Panel B: Monthly Regression (Full WSB Sample Period)						
Next Month Alpha	68913	0.50	23.10	-0.11	-18.92	17.46
Log(Posts)	69567	1.42	0.96	1.10	0.69	2.71
Log($Positive_{posts}$)	69567	0.53	0.79	0.00	0.00	1.61
Log($Negative_{posts}$)	69567	0.32	0.63	0.00	0.00	1.10
Percent $Positive_{posts}$	69567	0.22	0.32	0.00	0.00	1.00
Log(Comments)	69567	2.38	1.90	2.08	0.00	5.00
Log($Positive_{comments}$)	69567	0.90	1.54	0.00	0.00	3.33
Log($Negative_{comments}$)	69567	0.59	1.32	0.00	0.00	2.56
Percent $Positive_{comments}$	58207	0.22	0.35	0.00	0.00	1.00

Table 1.3 Daily Retail Trading and Investor Attention

May 03, 2018 to Aug 13, 2020

The sample of stocks include all stocks discussed in WSB posts. Panels A and B use Robinhood user data Panels A shows the regresson results for the percentage change in user holdings for stock i. Change is defined as the number of Robinhood users holding stock i between two trading days at 4:00 p.m. Panel B shows the raw change in the number of users. Panels C and D use retail trades data from the Nasdaq Retail Trading Activity Tracker (RTAT). Panel C shows the regression results for the next-day retail volume for stock i. The volume is expressed as a percentage of all retail trading volume reported by RTAT. It is the percentage value of a stock's daily trading volume divided by market retail trading volume. Panel D shows the regression results for the next-day net retail volume for stock i. The net volume is a percentage computed as the daily retail volume times the RTAT flow-based sentiment that ranges from -100 to 100. All of the explanatory variables are lagged. In parentheses are the t statistics, where one asterisk represents $p < 0.10$, two asterisks represent $p < 0.05$, three asterisks represent $p < 0.01$.

Panel A: Percentage Change in Robinhood User Holdings

	Next Day Percentage Change in User Holdings			
	(1)	(2)	(3)	(4)
Stock Return	0.0625***	0.0617***	0.0622***	0.0619***
	(23.21)	(22.91)	(23.08)	(22.96)
Log(Posts)		0.498***		0.632***
		(7.49)		(6.57)
Log(Positive)			0.177**	
			(2.26)	
Log(Negative)			0.267***	
			(2.94)	
Percent Positive				0.445*
				(1.66)
Log(Posts) × Percent Positive				-0.578*
				(-1.92)
Constant	0.859***	0.359***	0.752***	0.256***
	(24.34)	(4.75)	(17.37)	(2.63)
Day FE	Yes	Yes	Yes	Yes
Number of Obs.	30969	30969	30969	30969
R^2	0.0488	0.0505	0.0494	0.0506

Panel B: Raw Change in Robinhood User Holdings

	Next Day Raw Change in User Holdings			
	(1)	(2)	(3)	(4)
Stock Return	15.94***	15.14***	15.53***	15.18***
	(20.13)	(19.30)	(19.72)	(19.35)
Log(Posts)		497.9***		544.9***
		(25.71)		(19.44)
Log(Positive)			265.7***	
			(11.61)	
Log(Negative)			334.6***	
			(12.60)	
Percent Positive				182.7**
				(2.34)
Log(Posts) × Percent Positive				-203.3**
				(-2.32)
Constant	296.7***	-203.3***	150.6***	-245.2***
	(28.60)	(-9.25)	(11.89)	(-8.65)
Day FE	Yes	Yes	Yes	Yes
Number of Obs.	30969	30969	30969	30969
R^2	0.0611	0.0811	0.0735	0.0813

Panel C: Retail Trading Volume

	Next Day Retail Trading Volume as Percentage of Market Aggregate Volume			
	(1)	(2)	(3)	(4)
Stock Return	-0.0022***	-0.0038***	-0.0033***	-0.0040***
	(-4.66)	(-8.83)	(-7.75)	(-9.31)
Log(Posts)		0.717***		0.637***
		(81.33)		(49.94)
Log(Positive)			0.492***	
			(46.63)	
Log(Negative)			0.526***	
			(43.02)	
Percentage Positive				-0.189***
				(-5.28)
Log(Posts) × Percent Positive				0.342***
				(8.56)
Constant	0.442***	-0.280***	0.190***	-0.235***
	(85.28)	(-27.84)	(32.41)	(-18.18)
Day FE	Yes	Yes	Yes	Yes
Number of Obs.	30492	30492	30492	30492
R^2	0.029	0.204	0.182	0.208

Panel D: Net Retail Trading Volume

	Next Day Net Retail Trading Volume as Percentage of Market Aggregate Volume			
	(1)	(2)	(3)	(4)
Stock Return	-0.0000	-0.0000**	-0.0000*	-0.0000***
	(-0.54)	(-2.38)	(-1.92)	(-2.67)
Log(Posts)		0.014***		0.011***
		(40.21)		(22.41)
Log(Positive)			0.010***	
			(23.76)	
Log(Negative)			0.010***	
			(20.11)	
Percentage Positive				-0.009***
				(-6.13)
Log(Posts) × Percent Positive				0.012***
				(7.35)
Constant	0.006***	-0.008***	0.001***	-0.006***
	(30.05)	(-21.12)	(3.75)	(-12.47)
Day FE	Yes	Yes	Yes	Yes
Number of Obs.	30492	30492	30492	30492
R^2	0.032	0.082	0.074	0.083

Table 1.4 Stock Return and WSB Investor Attention

Monthly Return Regressions
January 2016 – December 2022

The following regressions show each stock's next month return regressed on the WSB attention measures in the previous month, for the full sample of stocks discussed in WSB posts. Alpha is estimated using the Fama-French-Carhart four-factor model. In parentheses are *t* statistics, where two asterisks represent $p < 0.05$ and three asterisks represent $p < 0.01$.

Panel A: Attention Measured with Post and Post-based Sentiments

	Next Month Alpha			
	(1)	(2)	(3)	(4)
Log(Posts)	-0.135		-0.133	0.206
	(-1.53)		(-1.50)	(1.43)
Log($Positive_{posts}$)		-0.471***		
		(-3.37)		
Log($Negative_{posts}$)		0.472***		
		(2.71)		
Percent $Positive_{posts}$			-0.288	1.147**
			(-1.11)	(2.10)
Log(Posts) × Percent $Positive_{posts}$				-1.472***
				(-2.98)
Constant	-0.500***	-0.577***	-0.437**	-0.759***
	(-2.93)	(-4.58)	(-2.44)	(-3.63)
Number of Obs.	68913	68913	68913	68913
R^2	0.0937	0.0938	0.0937	0.0938

Panel B: Attention Measured with Comments and Comment-based Sentiments

	Next Month Alpha			
	(1)	(2)	(3)	(4)
Log(Comments)	-0.018		0.160***	0.155**
	(-0.41)		(3.17)	(2.49)
Log($Positive_{comments}$)		-0.095		
		(-1.53)		
Log($Negative_{comments}$)		0.150**		
		(2.08)		
Percent $Positive_{comments}$			-0.250	-0.303
			(-1.01)	(-0.65)
Log(Comments) × Percent $Positive_{comments}$				0.022
				(0.13)
Constant	-0.658***	-0.695***	-1.342**	-1.331***
	(-4.41)	(-5.76)	(-7.11)	(-6.40)
Number of Obs.	68913	68913	57654	57654
R^2	0.0937	0.0937	0.0970	0.0970

Table 1.1.5: Event Time Abnormal Returns and User Changes

Top Attention Herding Positive Sentiment Stock

Robintrack Period: May 2018 to August 2020

This table reports abnormal returns (ARs), buy-and-hold abnormal returns (BHARs) from $t = -10$ to $t = 0$ and from $t = 0$ to $t = 20$, user holding changes around WSB attention herding events during the Robintrack data coverage period. ARs are computed as the difference between the raw return and the CRSP value-weighted average return. BHARs are computed as the product of one plus AR though event day t less the product of one plus the market return for the same period. Returns are winsorized at five percent. An attention herding stock has the highest number of posts and comments, as well as more positive than negative sentiment on a given trading day before 3:30pm.

Event Day	BHAR	Std. Error	User Change	Std. Error	AR	Std. Error
-10	0.0000	0.0000	238.26**	119.948	0.1522	0.3902
-9	0.4097	0.6089	375.91**	147.783	0.7240	0.4813
-8	1.3122	0.9233	666.58**	275.082	0.5514	0.4621
-7	1.5768	1.3141	463.67**	175.555	0.7104*	0.4210
-6	2.5532*	1.4573	617.72**	215.019	0.4208	0.4698
-5	3.2643*	1.8833	571.06**	208.932	1.1510**	0.4980
-4	4.4866**	2.2908	483.59**	182.454	0.9258*	0.490
-3	5.8812**	2.6695	451.61**	171.656	1.4349**	0.6280
-2	7.1944**	2.890	700.47**	253.625	1.2365**	0.5970
-1	8.6218**	3.3009	1421.63**	507.247	0.7471	0.8077
0	9.6474**	3.910	2334.17**	756.874	1.4974	1.3328
1	0.0910	0.6692	763.52**	314.797	0.0910	0.6692
2	-0.0905	0.9512	184.85	160.940	-0.1641	0.5936
3	0.1493	1.1944	429.39*	242.576	0.3225	0.4855
4	0.2200	1.3160	585.44**	288.060	0.0006	0.4404
5	0.2848	1.4208	689.34**	331.422	0.2406	0.4902
6	0.3239	1.3333	472.58**	237.447	0.3709	0.4874
7	0.7047	1.4630	645.69**	292.119	0.2934	0.5173
8	0.4012	1.5983	709.96**	303.528	0.0113	0.4556
9	0.6802	1.7544	385.98**	182.425	-0.0139	0.5329
10	0.5836	1.8328	501.62*	263.401	0.0829	0.4224
11	1.2567	1.9889	900.61**	435.457	0.2340	0.5782
12	1.6019	2.0808	1145.44*	615.584	0.0887	0.4768
13	1.6360	2.1833	1158.56*	603.857	-0.1747	0.4453
14	2.1385	2.2628	1179.78**	592.886	0.0164	0.4770
15	1.4296	2.2786	631.30	449.760	-0.5034	0.4816
16	1.3599	2.3455	399.27	357.653	-0.0133	0.4618
17	0.9616	2.4175	377.57*	218.715	-0.4049	0.4420
18	1.0509	2.5055	384.55*	215.356	-0.0491	0.4773
19	0.8835	2.4764	310.26*	184.658	0.1742	0.4904
20	1.4268	2.7713	467.29	371.766	0.0952	0.4393

Table 1.6: Event Time Abnormal Returns and User Changes

Top Three Attention Herding Positive Sentiment Stocks (Equal Weight)

Robintrack Period: May 2018 to August 2020

This table reports abnormal returns (ARs), buy-and-hold abnormal returns (BHARs) from $t = -10$ to $t = 0$ and from $t = 0$ to $t = 20$, and user holding changes around WSB attention herding events during the Robintrack data coverage period. ARs are computed as the difference between the raw return and the CRSP value-weighted average return. BHARs are computed as the product of one plus AR though event day t less the product of one plus the market return for the same period. Returns are winsorized at five percent. A top three attention herding stock has the top three highest number of posts, as well as more positive than negative sentiment on a given trading day before 3:30pm.

Event Day	BHAR	Std. Error	User Change	Std. Error	AR	Std. Error
-10	0.000	0.000	375.82**	192.624	0.3097	0.4449
-9	0.517	0.621	422.48**	209.474	0.4908	0.4751
-8	0.853	0.944	620.53**	285.198	0.4286	0.5021
-7	1.414	1.291	743.06**	311.175	0.5215	0.4934
-6	2.096	1.487	685.89**	301.848	0.6295	0.5236
-5	2.362	1.625	455.81**	214.319	0.4749	0.4988
-4	2.824	1.796	410.24**	199.493	0.8873	0.5770
-3	3.910*	2.120	429.97**	188.363	0.8587	0.5646
-2	4.961**	2.399	494.74**	208.096	0.6087	0.5709
-1	5.546**	2.638	908.12**	323.467	0.8175	0.7146
0	6.363**	2.897	1386.15**	470.416	1.4594	1.0386
1	-0.023	0.673	611.71**	275.016	-0.0233	0.6727
2	-0.199	0.909	235.10	144.188	-0.2187	0.5876
3	-0.278	1.056	312.32*	174.401	0.0129	0.5304
4	-0.184	1.186	395.04*	211.205	0.1316	0.5119
5	-0.144	1.272	379.41*	204.250	0.0946	0.4960
6	-0.036	1.357	397.45*	211.249	0.2113	0.4607
7	0.015	1.448	576.89**	282.130	0.1492	0.4642
8	-0.014	1.552	404.51**	205.690	-0.0396	0.4263
9	-0.168	1.620	238.35	147.369	-0.0899	0.4542
10	0.020	1.691	312.14*	165.584	0.1050	0.4855
11	0.235	1.774	387.28*	201.267	0.0199	0.4800
12	0.416	1.883	485.72**	236.222	-0.0098	0.4422
13	0.267	1.950	510.52**	254.861	-0.1353	0.4614
14	0.212	1.975	618.56**	310.848	0.0172	0.4620
15	0.287	2.089	476.03*	268.093	0.0174	0.4553
16	0.039	2.182	377.52	240.299	-0.1678	0.4448
17	-0.036	2.279	515.06*	293.361	-0.0715	0.4537
18	-0.130	2.335	642.66*	344.766	0.0524	0.4737
19	0.030	2.411	603.35*	314.999	0.1297	0.4349
20	-0.045	2.478	695.36*	386.215	0.0386	0.4777

Table 1.7: Attention Peak Time Between Attention Proxies

This table reports the t-test result of the difference in attention peak time between two attention proxies – WSB activity-based and Robintrack activity-based attention peak, for stocks on attention herding days. Top attention time is measured as the Robintrack user change observations' hours bracket's close. Number of posts is counted for the exact same bracket. The difference between groups' attention peak time is reported as number of minutes.

Group 1	Group 2	Difference 2 – 1 (Minutes)	T-statistics	P-value
Posts Peak	User Change Peak	13.62***	5.235	0.000
Normalized Posts Peak	Normalized User Change Peak	5.82**	2.137	0.033

Table 1.8: Sector and Style Characteristics of Top Attention Herding Stocks

Robintrack Period: May 2018 to August 2020

This table reports the style characteristics of the stocks in the WSB attention sample. In Panel A, the industry classifications are SIC(2) codes, and in Panel B, the market capitalization classifications follow conventional definitions, where large cap is $10 billion plus, mid cap is $2 to $10 billion, small cap is $300 million to $2 billion, micro cap is less than $300 million.

Panel A: Industry Concentration of WSB attention stocks

	All Observations		Unique Observations	
Industry	**N**	**Percentage**	**N**	**Percentage**
Electronic & Other Electric Equipment	458	19.77	23	6.25
Holding & Other Investment Offices	443	19.12	61	16.58
Transportation Equipment	254	10.96	16	4.35
Business Services	250	10.79	50	13.59
Furniture & Homefurnishings Stores	214	9.24	2	0.54
Chemical & Allied Products	102	4.40	42	11.41
Miscellaneous Retail	92	3.97	12	3.26
Motion Pictures	70	3.02	2	0.54
Security & Commodity Brokers	40	1.73	9	2.45
Metal, Mining	38	1.64	3	0.82
Others	356	15.36	148	40.22
Total	2317	100.00	368	100.00

Panel B: Market Capitalization of WSB Attention Stocks

	All Observations		Unique Observations	
Style	**N**	**Percentage**	**N**	**Percentage**
Large Cap	1398	60.57	129	35.44
Mid Cap	516	22.36	97	26.65
Small Cap	247	10.70	76	20.88
Micro Cap	147	6.37	62	17.03
Total	2308	100.00	364	100.00

Figure 1.1: Classification System for Investor Sentiment

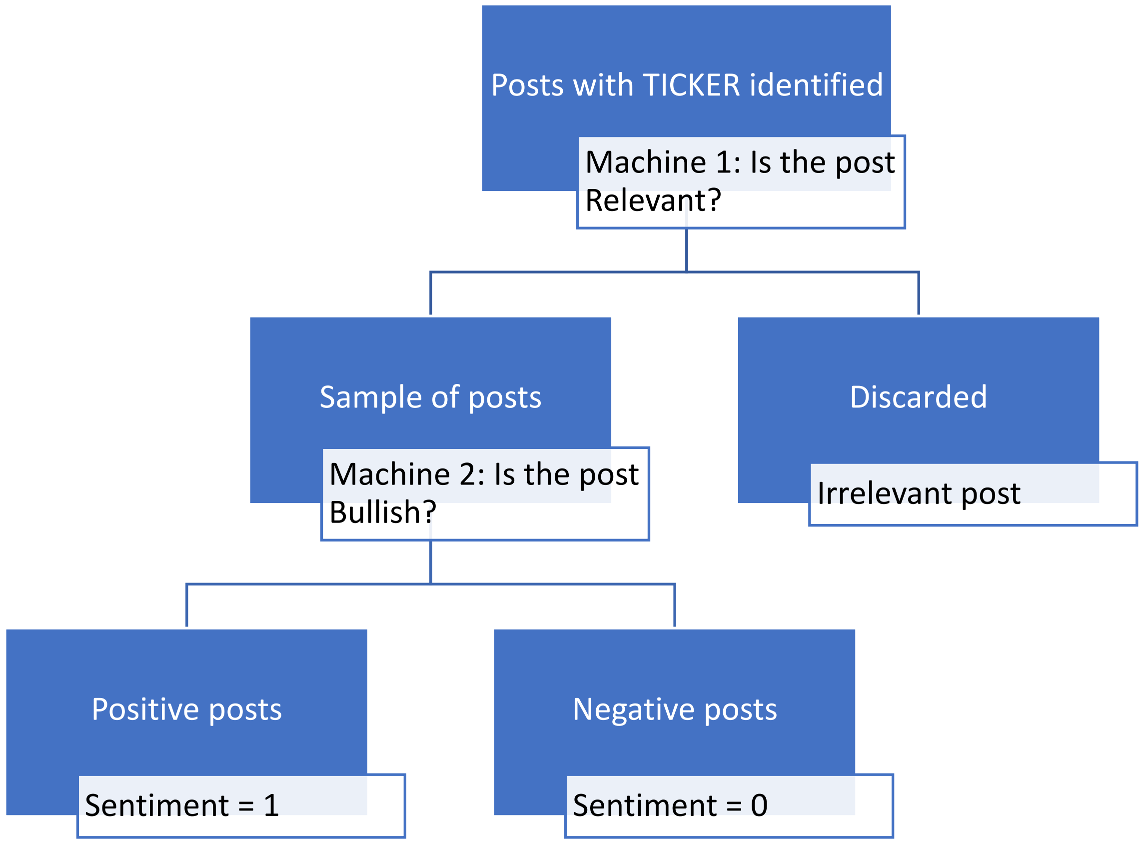


Figure 1.2: Forum-wide Sentiment and the VIX

Twenty-day Smoothed Averages, January 2016 – December 2021

The Sentiment Index level on the left axis is the average ratio of posts classified as positive among all posts classified as relevant. The VIX index level is shown on the right axis. Both time series shown are 20-day smoothed averages.

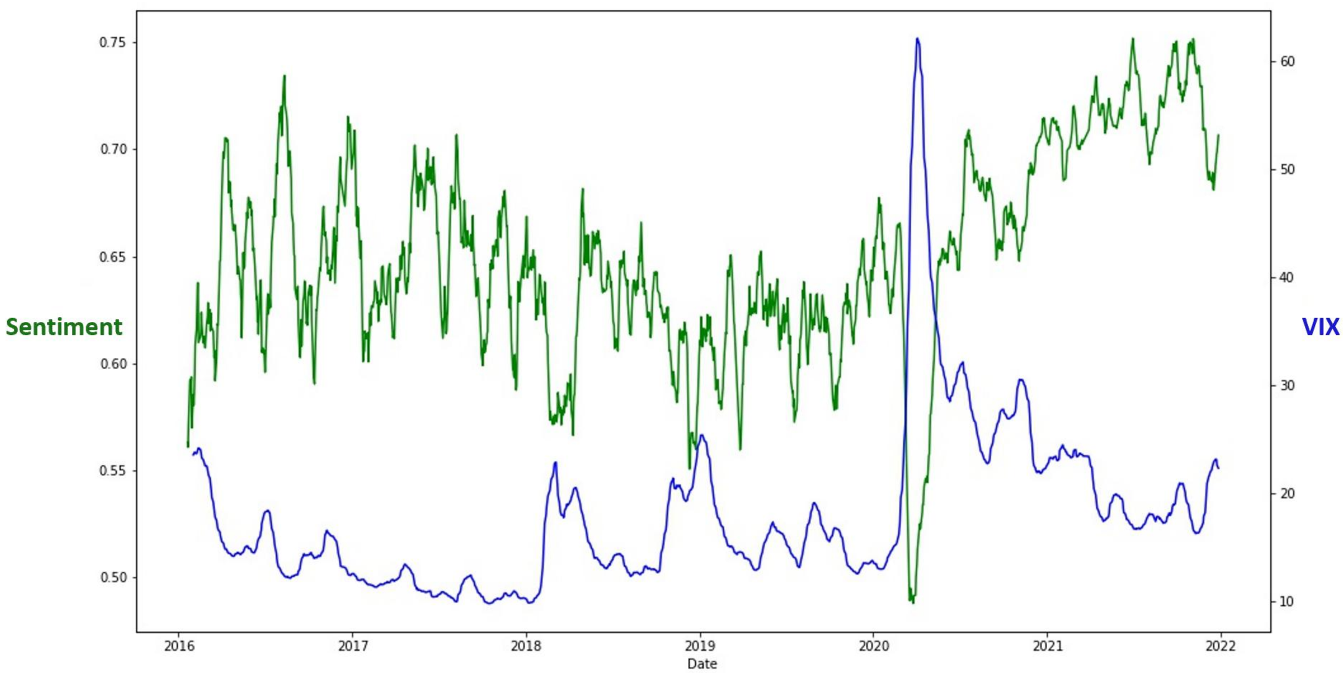


Figure 1.3: Event Study: Daily Attention Herding Events

Robintrack Period: May 2018 – August 2020

The sample consists of stocks that are ranked first in posts and comments (or both stocks if they are different) on a given day during the period when Robintrack data is available. Each stock is further classified as positive or negative sentiment. The buy-and-hold abnormal return ($BHAR$) for positive (green) and negative (red) sentiment surrounding the event day are plotted. The bar chart shows the average net increase in Robinhood users holding the top ranked stock on a given day, again separated into positive (dark blue) versus negative (light blue) sentiment. Sentiment scores lie between zero and one.

Positive (Negative) Sentiment = Average Sentiment Score > 0.50 (< 0.50)

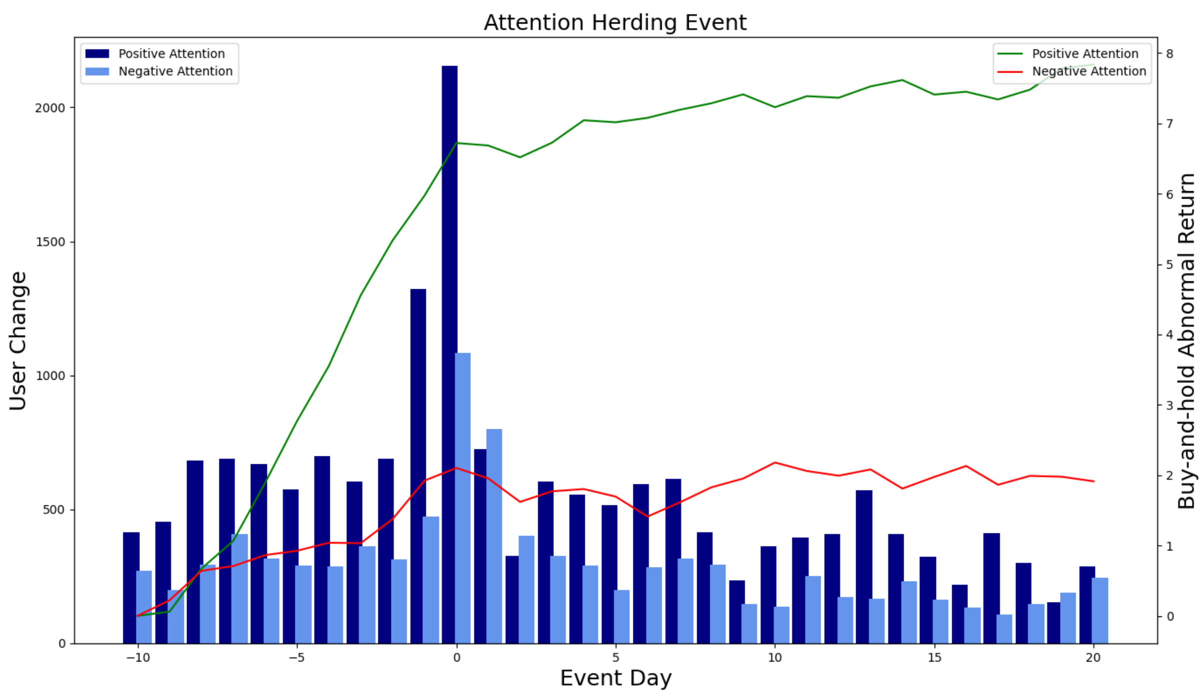


Figure 1.4: Event Study: Forum-wide Attention Herding Events

Change in Number of Robinhood Users Holding the Stock and $BHAR$ around Event Day
Robintrack Period: May 2018 – August 2020

Two Attention Herding Events Within Five Days

An attention herding event is defined more strictly compared to the baseline result in Figure 3. It occurs when a stock is top ranked in both posts and comments for two out of the previous five days. Each stock in the sample is further classified as positive or negative sentiment. The buy-and-hold abnormal returns ($BHAR$) for positive (green) and negative (red) sentiment surrounding the event day are plotted. The bar chart shows the average net increase in Robinhood users holding the top ranked stock on a given day, again separated into positive (dark blue) versus negative (light blue) sentiment. Sentiment scores lie between zero and one.

Positive (Negative) Sentiment = Average Sentiment Score > 0.50 (< 0.50)

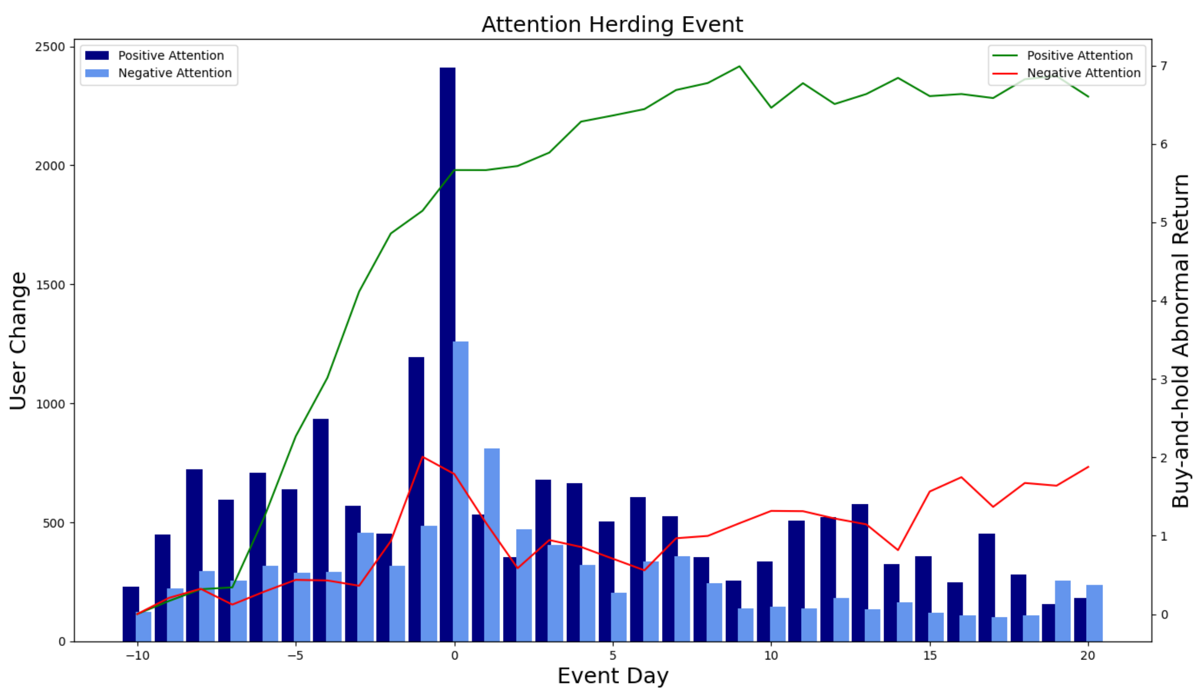
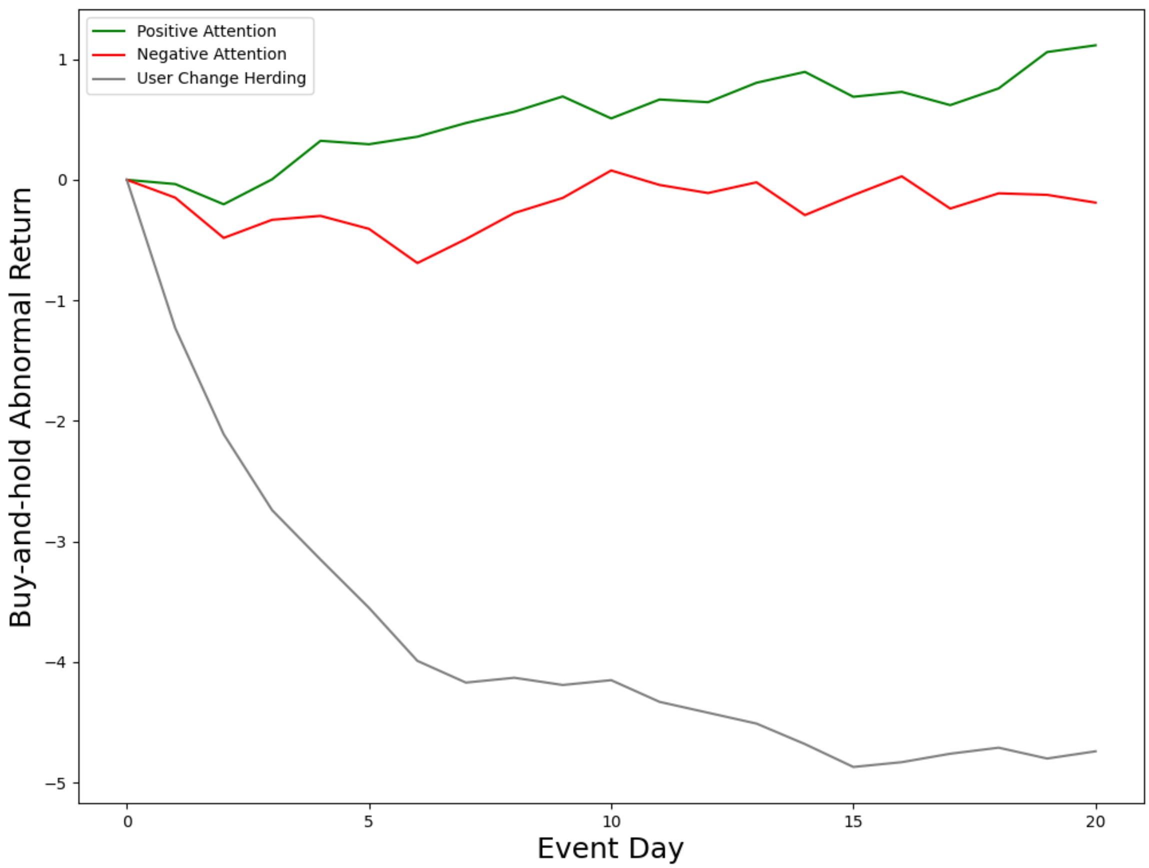


Figure 1.5: Post Event Drift: BHARs After Event Day

Panel A depicts the post-event buy-and-hold abnormal returns ($BHAR$s) for forum-wide attention events during the Robintrack sample period, separately for postive attention (green) and negative attention (red) events. As a contrast, we also show the $BHAR$s using Barber et al. (2022)'s definition, where retail attention is defined as the top percentage change in the number of Robinhood users holding a particular stock during the Robintrack sample period (grey). Panel B depicts the same, but for *after* the discontinuation of Robintrack data and hence not in Barber et al.'s sample.

Panel A: Robintrack Sample Period (May 2018 to August 2020)



Panel B: Post Robintrack Sample Period (September 2020 to December 2022), excluding GME

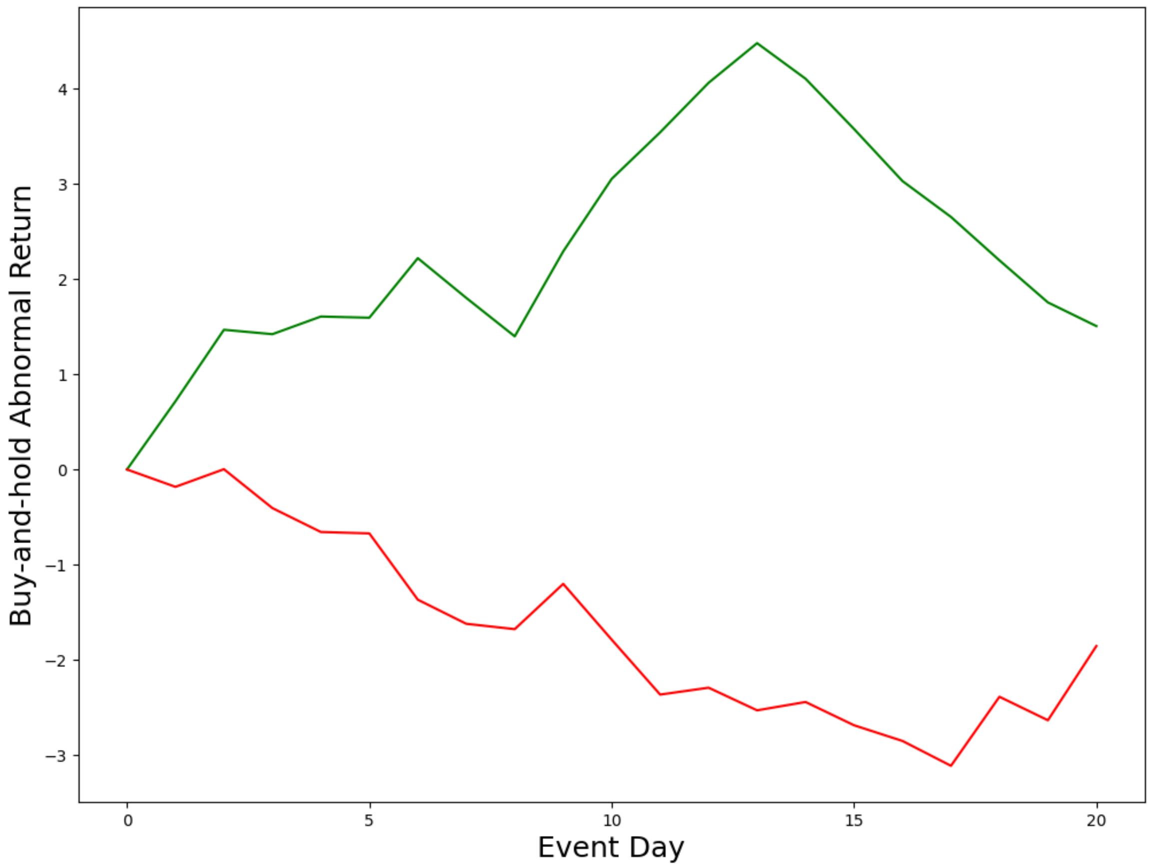
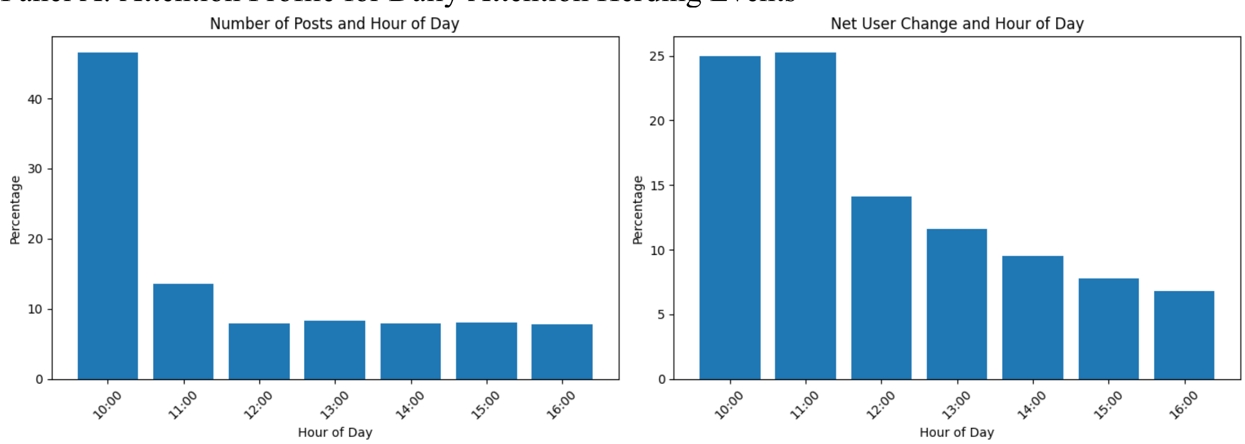


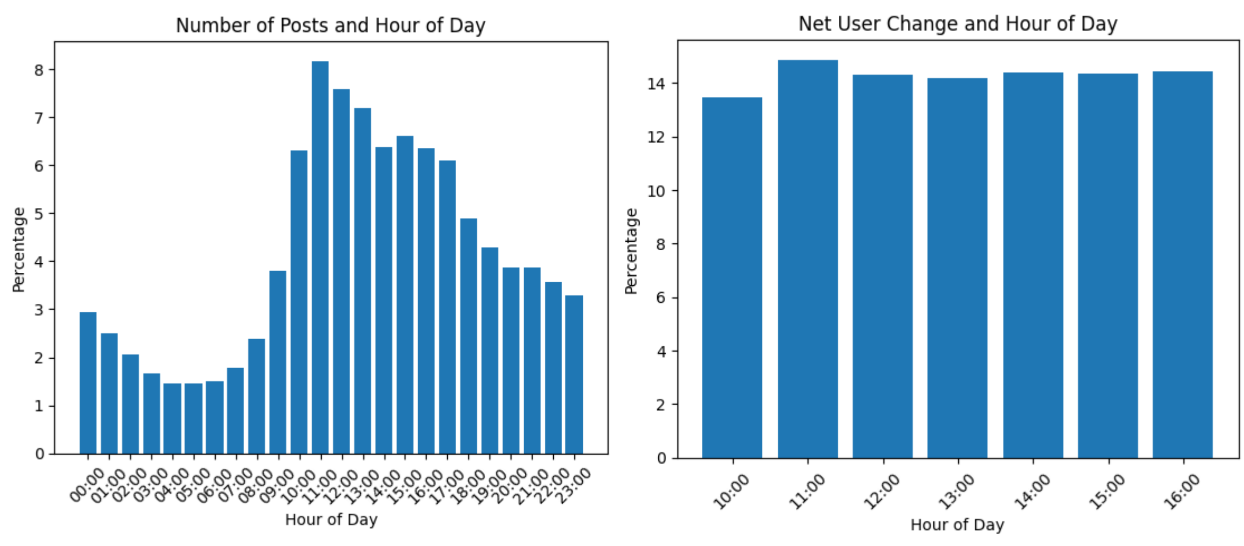
Figure 1.6: Intraday Attention Profile for Forum Posts and Robintrack User Changes

This panel of graphs show the intraday attention profile for forum posts and Robintrack user changes. An attention profile for WSB posts show the aggregate number of posts of a stock until a given hour of day excluding previous hour. A cutoff at 10:00 a.m. includes all posts made after 9:00 a.m. until 10:00 a.m. Time cutoff is each hour close in eastern standard time. Panel A shows the market hour attention profile for attention herding days where a positive sentiment stock has both the highest number of posts and number of comments. Panel B shows the average attention profile for the entire sample for days a stock is at least mentioned once in the forum. Panel C shows the normalized attention profile computed by weighting attention profile in Panel A with the attention profile of Panel B used as discount factor. Note that test conducted on use precise observation of Robintrack user holding observation cutoffs.

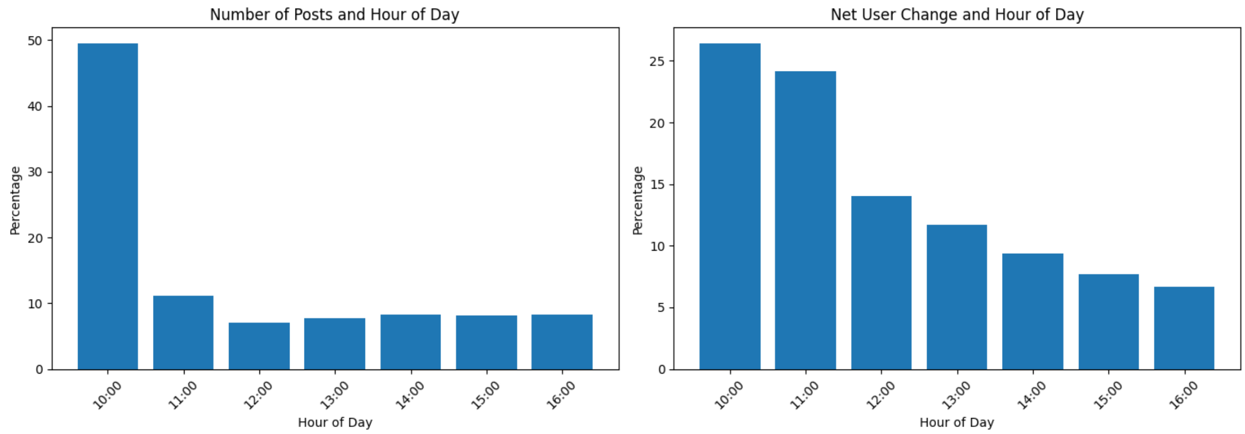
Panel A: Attention Profile for Daily Attention Herding Events



Panel B: Attention Profile for Typical Daily Activity



Panel C: Normalized Attention Profile on Attention Herding Days



APPENDIX

Table A 1.1: Variable Definitions

This table summarizes the definition of variables that are used in the empirical tests.

Variable Name	Used in	Definition
User Change	Daily Regression, Intraday Test	The Change in number of users holding a particular stock. For daily user change, it is the difference between last observed user holding number of day t and day t-1, before 4pm. For intraday test, it is the difference between hour h and hour $h-1$.
Percent User Change	Daily Regression	The percentage (in %) of the change in user holding number.
Retail Trading Volume	Daily Regression	The percentage (in %) of all retail trading volume reported by Nasdaq Retail Trading Activity Tracker. It is the percentage value of a stock's daily trading volume divided by market (9,500 US traded stocks) 's retail trading volume
Net Retail Volume	Daily Regression	Constructed as the product of Retail Trading Volume and RTAT "Sentiment" (as fraction).
Same-day Return	Daily Regression	The raw return of a stock on a given day.
Log(Posts)	Daily Regression	The natural log value of one plus the number of WSB posts that mention the stock before 3:30 p.m. on a given day.
Log(Positive)	Daily Regression	The natural log value of one plus the number of WSB posts that mention the stock before 3:30 p.m. on a given day that is relevant and positive.
Log (Negative)	Daily Regression	The natural log value of one plus the number of WSB comments to posts that mention the stock before 3:30 p.m. on a given day that is relevant and negative.
Percent Positive Posts	Daily Regression	The number of posts that mention the stock before 3:30 p.m. that is relevant and positive, divided by number of all posts that mention the same stock.
Next Month Alpha	Monthly Regression	The alpha of the stock's next month return, estimated using Fama-French-Carhart four-factor model.
Log(Posts)	Monthly Regression	The natural log value of one plus the number of WSB posts that mention the stock within the given month.
Log($Positive_{posts}$)	Monthly Regression	The natural log value of one plus the number of WSB posts that mention the stock and is relevant and positive, within the given month.

Log($Negative_{posts}$)	Monthly Regression	The natural log value of one plus the number of WSB posts that mention the stock and is relevant and negative, within the given month.
Percent $Positive_{posts}$	Monthly Regression	The number of posts that mention the stock within the month that is relevant and positive, divided by number of all posts that mention the same stock.
Log(Comments)	Monthly Regression	The natural log value of one plus the number of WSB comments to posts that mention the stock on a given month that is relevant.
Log($Positive_{comments}$)	Monthly Regression	The natural log value of one plus the number of WSB comments to posts that mention the stock on a given month that is relevant and positive.
Log($Negative_{comments}$)	Monthly Regression	The natural log value of one plus the number of WSB comments to posts that mention the stock on a given month that is relevant and negative.
Percent $Positive_{comments}$	Monthly Regression	The number of comments to WSB posts that mention the stock within the month that is relevant and positive, divided by number of all comments to posts that mention the same stock.

Figure A 1.1: Reddit Wallstreetbets Forum User Interface

We show Wallstreetbets user interface in desktop and mobile format for readers. The main difference between Wallstreetbets and other forums is that there do not exist a dedicated forum space for each ticker that. Instead, all posts appear on the same main webpage / mobile application interface: Web Application compact view is shown on the left and mobile application compact view is shown on the right.

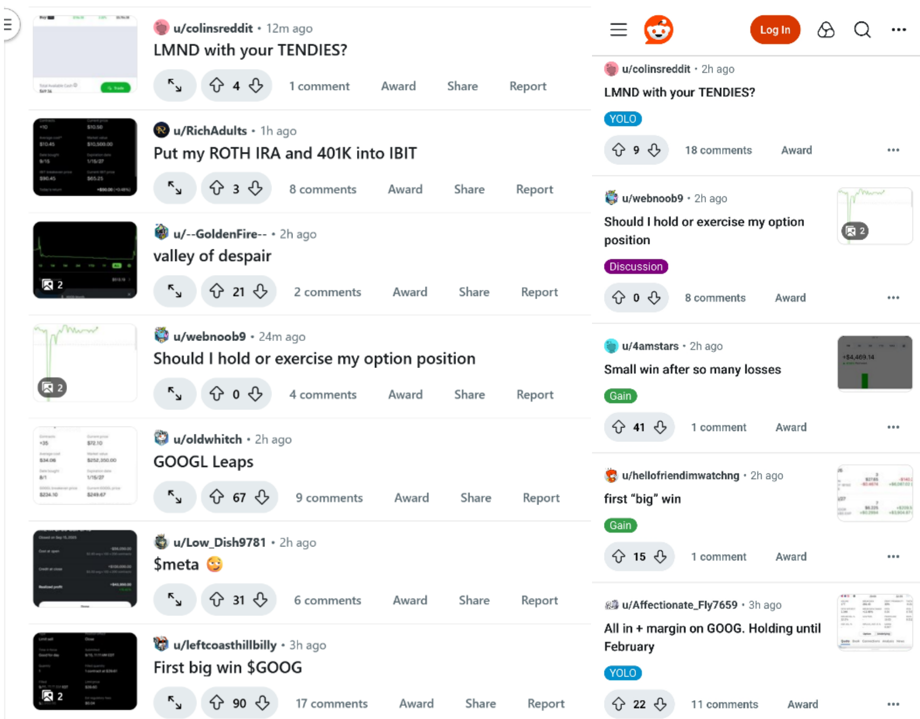
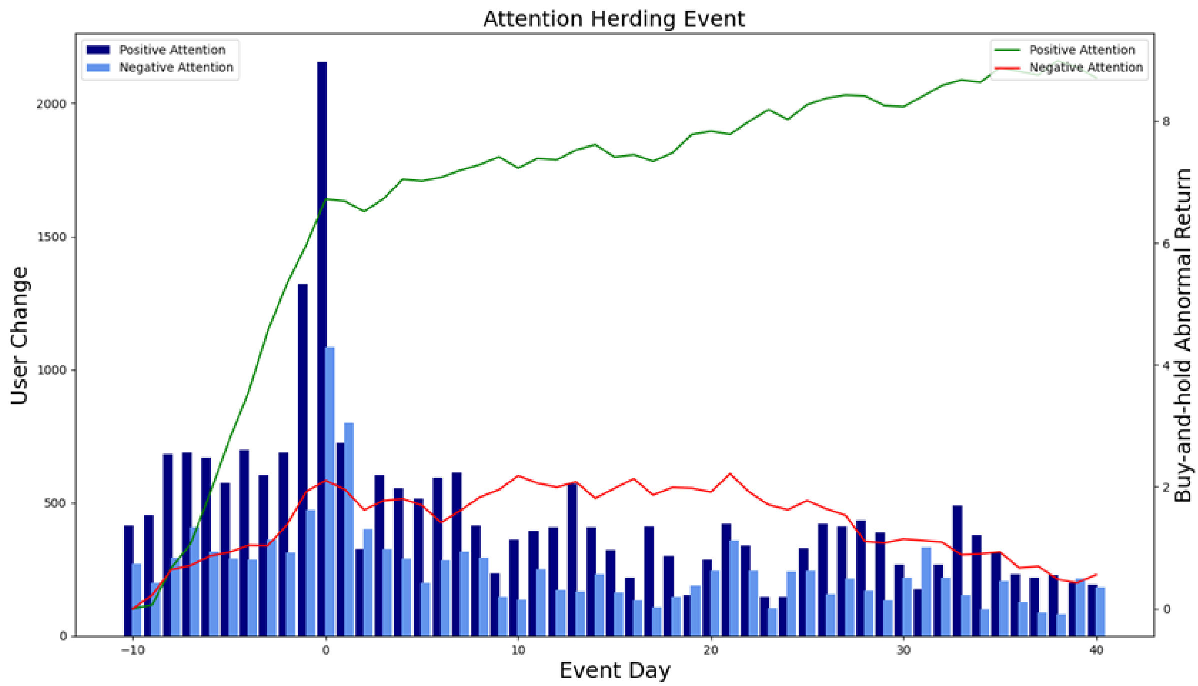


Figure A 1.2 Event Study: Forum-wide Attention Herding Events

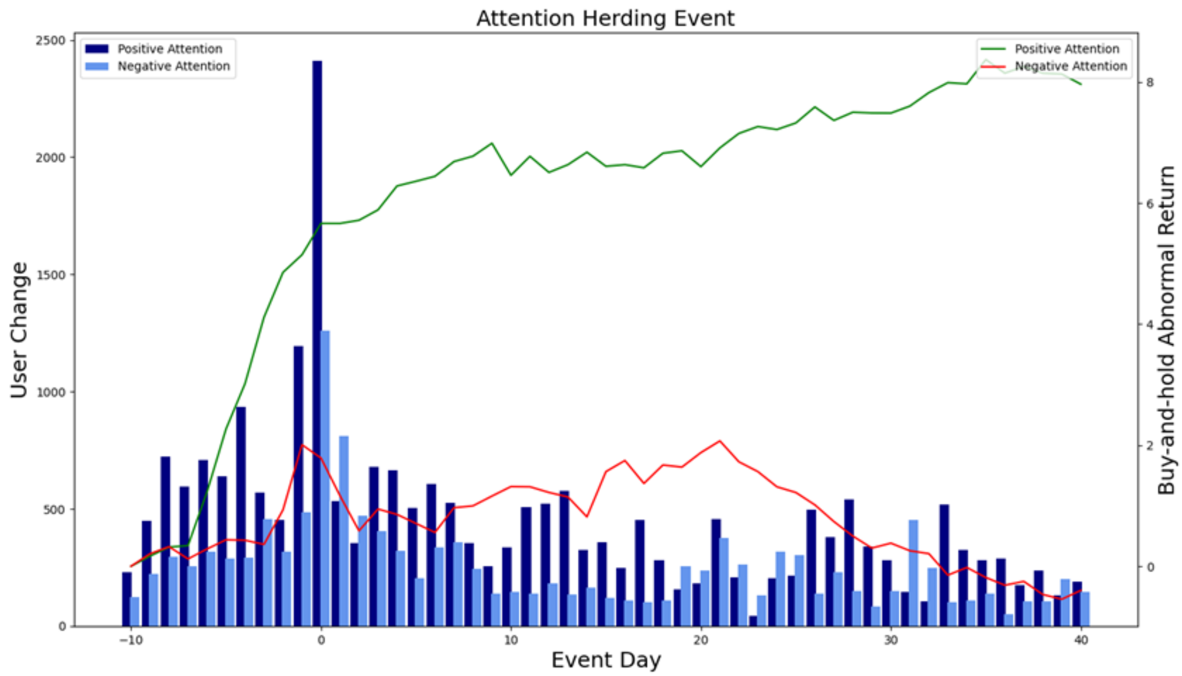
Change in Number of Users on Robinhood and $BHAR$ over 40 Days

The graphs below are extensions of those in Figures 2.3 and 2.4. The only difference is that the post-event period is extended to 40 days. The sample consists of stocks that are ranked first in both posts and comments on a given day during the period when Robintrack data is available. Each stock is further classified as positive or negative sentiment. The buy-and-hold abnormal returns ($BHAR$) for positive (green) and negative (red) sentiment surrounding the event day are plotted. The bar chart shows the average net increase in Robinhood user holdings on a given day, again separated into positive (dark blue) versus negative (light blue) sentiment. In Panel B, an attention event occurs when a stock is top ranked in both posts and comments for two out of the previous five days. Sentiment scores lie between zero and one.

Panel A: Daily Events; Positive (Negative) Sentiment = Average Sentiment Score > 0.50 (< 0.50)



Panel B: Two Forum-wide Attention Herding Events within Five Days; Positive (Negative) Sentiment = Average Sentiment Score > 0.50 (< 0.50)



Chapter 2 : Poker Face? Information Content from CEO Interviews[15]

1 Introduction

The Chief Executive Officer (CEO) serves as both the face and strategic leader of a company, making their public appearance an interesting setting to study its impact on their companies' market valuation. Few individuals possess more comprehensive knowledge about a company's current situation and future trajectory than the CEO. Therefore, investors may scrutinize not only a company's public releases and analyst forecasts, but also its CEO behaviour and communication cues. These types of soft information may contain predictive power beyond just the numbers and estimates, as shown in pioneering studies on 10-K reporting and CEO conference call. ((Tetlock et al., 2008), (Mayew and Venkatachalam, 2012)).

Technologies to analyze such soft information have become more accessible with the rise of artificial intelligence and specifically, open source and publicly accessible computer vision and large language models. These innovations enable us to study CEO characteristics beyond textual and voice analysis of earnings calls, and to see how the visual context of CEO media appearances impacts the market.

Naturally, the opportunity cost for managers' media appearance is huge. Media appearance takes time away from managers' daily management job, and there are inherent risks of appearing in the spotlight. Therefore, for managers' media appearance to be rational, the expected benefits of being in the spotlight should outweigh the apparent costs. Managers' decisions to engage

[15] Chapter 2 is currently being prepared for submission for publication of the material. The dissertation author was the co-author of this paper working alongside Dr. Pauline Shum Nolan and handled the following responsibilities: Conceptualization, Data Curation, Formal Analysis, Visualization, Original Draft and Review & Editing.

with the media should therefore serve strategic purposes, whether they are to highlight business developments or manage public relations challenges.

Despite the extensive literature on CEO characteristics and market outcomes, several important areas remain underexplored. First, while studies have examined CEO communication in formal settings like earnings calls, less attention has been paid to more dynamic, interactive contexts such as media interviews to give these interviews context (rather than treating these interviews as only one type of event). While Mayew and Venkatachalam (2012) innovates the literature by examining the challenging questions from analysts during earnings calls, we build on their idea and go from textual and tonal to visual analysis. While earnings calls are already closely monitored by a great number of market participants, the reach of Mad Money is perhaps more extensive. In Engelberg, Sasseville and Williams (2012), the average daily viewership of Mad Money is 196,000. CNBC claims its content is consumed by more than 355 million people per month.[16]

Our study innovates by confirming that CEOs do display human emotions, in line with our hypothesis, influenced not only by the recent performance of their company but also by the interview's topic. Secondly, the relationship between CEO emotional displays and market response in different topic contexts has not been fully explored in the same way as Curti and Kazinnik (2023). The potential challenges other research faces are either they classify CEO emotion without context or the events' potential impact on the market is limited.[17]

While previous studies have documented the market impact of media coverage (Engelberg et

[16] "CNBC is the recognized world leader in business news and provides real-time financial market coverage and business content consumed by more than 355 million people per month across all platforms." source: https://www.cnbc.com/about/

[17] For example, Akansu et al. (2017) focuses on CEO emotions but does not explore the market response in the context of recent firm financial performance.

al., 2012) and CEO communication style (Mayew and Venkatachalam, 2012) separately, few have attempted to disentangle these effects or examine their potential interactions. We mitigate this issue by looking at both the earnings performance prior to the interview as well as the CEO communication during the interview. Thirdly, we show that emotional dispositions of CEOs, as inferred from their emotion during interviews, correlate with the types of companies they lead. This adds another piece of evidence to the literature that CEO dispositions correlate with company fundamentals. Finally, we show a unique relationship between market response and CEO interview. Conditional on companies' recent earnings reports, CEO emotion impacts the next day returns. Our paper is also innovative in our empirical setting – using CNBC Mad Money interview which airs after market close, which gives the audience time to digest the information, rather than reacting immediately. Specific interviews also isolate the specific company being discussed, making identification issues easier.

Our research reveals that managers' promotional efforts are indeed successful when supported by strong underlying business performance regardless of how they deliver the information. Optimism improves stock price following missed expectations, yet the positive effects of CEO optimism are usually overshadowed by the inherently negative effect of appearing in the spotlight with bad news.

The paper is structured in the following way: We first conduct a literature review on the topics which our research lies in the intersection of, as well as how our research relates to the current discussions on the topic. Then we outline our hypothesis development.

In Section III, we describe the data and present summary statistics. In Section IV, we elaborate on our methodologies. In Section V, we review our empirical findings. In Section VI, we conclude the paper.

2 Literature Review and Hypothesis Development

We begin the literature review with the Upper Echelon Theory and discuss the relevant literature on the impact of CEO characteristics on firm outcomes. Then we examine and address the recent findings on the impact of nonverbal communication in financial market disclosure and discuss prominent papers that motivate our research. Since our research is set in the specific context of mass media and financial markets, we briefly review the main literature on market reaction to general news media. We then focus our literature review on papers that study the same data source, namely CNBC CEO Interviews, and stylize the findings relevant to our research. Finally, we discuss how our research relates to the strands of literature and the similarities and differences in our approach.

2.1 Upper Echelon Theory and the Impact of CEO Characteristics

Since Hambrick and Mason (1984) formulated the "upper echelon perspective" – the theory that managers' background characteristics partially predict firm outcomes significant research interest has been placed on the effect of CEOs characteristics on firm outcomes. The theory posits that since top management are responsible for choosing strategic options in areas such as product innovation, acquisition and financial leverage.

Managers' characteristics, which shape these decisions, will consequently shape company performance such as profitability, volatility, growth and even survival. Since then, an ever-growing empirical literature focusing on the managerial behavioral side shows us how their experiences, values and personalities influence their decision making in varying situations. For example, CEO narcissism likely leads to riskier strategic decisions, and increase of R&D activity and M&A activities (Chatterjee and Hambrick (2011), Cragun et al. (2020)); CEO overconfidence leads to more value-destroying mergers yet increases innovation intensity (Malmendier and Tate

(2008), Galasso and Simcoe(2011)); CEO early-life experiences also make lasting impact on their risk preferences, reflecting in their corporate risk-taking decisions (Bernile et al. (2017)).

There are also cross-disciplinary efforts to bring together Psychology and Finance. Harrison et al. (2020) provides theoretical framework for how CEO's observable personality traits influence market perceptions of firm risk and shareholder returns. The authors devise and empirically employ a personality trait linguistic tool to extract CEO personalities through transcripts during their earnings call presentations. The literature has also moved beyond the internal characteristics which impact the firms' strategic decisions and operations. Recently, external characteristics of managers have also been a subject of interest. Studies also show CEO compensation is related to physical attributes such voice frequency (Mayew, Parsons and Venkatachalam, 2013) [20], and even appearance (Halford and Hsu (2020), Cook and Mobbs (2023)). In our research, we use the emotion feature extracted from videos as both proxy for the instantaneous response to the interview, as well as proxy for personality and characteristics.

2.2 Soft Information

Studies on soft information reveal that there is information about a company's outlook beyond just the reported hard numbers and projections. Tetlock et al. (2008) find that negative words in 10-K documents predict lower earnings as well as negative future returns. Loughran and McDonald (2011) improve on the traditional dictionary approaches of analyzing 10-K and also find that improving accuracy in financial textual classifications of 10-K documents reduces the noise in predicting market reaction.

Recent research has also explored beyond the textual element of corporate disclosure – namely, the influence of nonverbal communication on market outcomes. Mayew and Venkatachalam (2012) found that financial analysts tend to provide more favorable forecasts for CEOs who maintain positive tones during earnings calls when analysts ask tough questions. Their research indicates that vocal cues can serve as important signals of firm performance and management confidence, influencing professional market participants' judgments. Gorodnichenko et al. (2023) show that the tone of Federal Reserve Chair communications can influence markets in real time during the press conference.

These findings suggest that how information is delivered can be as important as the information itself in shaping market responses.

The role of visual cues in financial communication has emerged as another important area of study. Curti and Kazinnik (2023) provided compelling evidence that facial expressions of Federal Reserve Chairs during press conferences can also significantly influence market sentiment. Their research employed computer vision technology to analyze expressions and show that market reacts to the Fed Chairs' positive and negative emotions. Hsieh et al. (2020) find negative association between perceived trustworthiness of CFO faces and audit fees. Akansu et al. (2017) classify CEO emotion through their proprietary emotion detection software and find that negative expressions predict favorable company performance in the near future while positive expression predicts deterioration in company performance. Blankespoor, Hendricks and Miller (2017) conduct an experiment and find that experiment participants' overall perceptions of managers from a 30 second roadshow clip positively associate with the actual IPO pricing outcome.

While our study is not the first to utilize CEO videos or to classify emotions and make inference from the managers' visual affective states, we add to the literature of the information content of CEO emotion expressions, and we use open-source software instead of proprietary software for better replicability of our study.

2.3 Media and the Mad Money Effect

The interaction between financial media and market behavior represents another crucial dimension of this research area. Engelberg and Parsons (2011) document direct causal impact of local media on local trading through examining news in regional newspapers.

Financial media platforms, particularly CNBC's Mad Money program, have also been shown to have significant effects on market behavior. Engelberg et al. (2012) document that stocks recommended on the Mad Money program typically experience substantial overnight returns, followed by subsequent reversals. This pattern suggests that Mad Money coverage can create temporary price pressure through increased investor attention.

These research also highlight the role of viewer attention and market sentiment in determining the magnitude of price responses. Neumann and Kenny (2007) identified potentially profitable trading strategies based on both buy and sell recommendations from the program. Their research suggests that while market reactions to media coverage may be predictable, the underlying mechanisms driving these reactions remain complex and multifaceted, which leaves opportunities for us to explore Mad Money effect beyond just the stock recommendations during the program. While these study of media exposure treats the exposure as "events", our research adds context to these events by classifying their topics and tones. Finally, Kang and Kim (2017) find that following CEO media appearance, the next year compensation of CEOs increases. Our study sheds light on this phenomenon by providing empirical explanation on the economic benefits of appearing in media interviews.

2.4 Hypothesis Development

Facial expressions provide valuable insights into an individual's emotional state, and aggregating observations of these expressions offers a better understanding of their character.

An intriguing question emerges: Do CEOs exhibit emotional responses just the way an average person does, or are they exceptional in this regard?

Our hypothesis development aligns with that in Mayew and Venkatachalam (2012) and Akansu et al. (2017). Both papers laid out the psychological foundations of how human emotions can convey information about perspectives and beliefs. We build upon their premises that CEO emotions are responses to interview/earnings call contexts and that these emotions evoke reactions in their audience. While the previous two studies consider CEO emotions as entirely "temporal" (rather than innate), others such as Halford and Hsu (2020) and Cook and Mobbs (2023) treat facial features as innate fixed characteristics. We adopt a hybrid approach. We recognize that both temporary and innate components can contribute to the emotions observed during television interviews. Our research extends beyond examining the outcomes of CEO emotions we also investigate the underlying causes of these expressed emotions.

Hypothesis 1: CEO's emotions are influenced by external stimuli.

Although human emotions can stem from internal processes, substantial research indicates that emotional displays primarily represent reactions to external events. For CEOs who navigate demanding and typically stressful environments, these external stimuli are abundant. We hypothesize that CEO's wealth and the interviewer's questions can both have effect on CEO's displayed emotions.

Our hypothesis that emotions correlate with wealth changes is supported by psychology and neuroscience research. For instance, Knutson et al. (2001) discovered that anticipation of monetary gain activates reward pathways and correlates with self-reported happiness, while Zhou et al. (2009) demonstrated that handling money reduces distress and even diminishes physical pain.

To test our first hypothesis, we focus on two clearly defined stimuli that plausibly affect CEO mood: recent corporate performance and interview topic. If CEO's emotions are indeed influenced by these stimuli, we should see explanatory power of these variables.

Hypothesis 2: CEO's displayed emotions contain innate components.

While external stimuli significantly influence emotional displays, innate aspects can also contribute to CEOs' exhibited emotions. Research in personality psychology suggests that individuals possess measurable innate dispositions. Davidson (1992) found that genetic factors influence emotional response intensity, while Matsumoto (1990) identified cultural differences in emotional communication across social contexts. Gender represents another significant factor influencing personality traits, with studies revealing higher levels of agreeableness and anxiety in certain demographics.

We test our second hypothesis by examining differences in average emotion measures across individual CEOs, gender categories, and firms. If no innate differences exist in emotional display tendencies, measured emotions should demonstrate consistent averages across samples. Our preliminary data analysis contradicts this expectation, suggesting innate components in emotional displays.

Hypothesis 3: Market reacts to the soft information conveyed through CEO facial emotions.

Our third hypothesis integrates two research streams. Numerous studies document various soft information effects on markets ((Tetlock, 2007); (Gorodnichenko et al., 2023); (Curti and Kazinnik, 2023)), while another research stream demonstrates that attention influences stock performance. Since Engelberg et al. (2012) documented that retail investors respond to television stock recommendations, we hypothesize that CEO facial expressions also influence audience impressions, potentially affecting stock returns independently of the CEO's appearance or interview topic.

This effect may be driven by sophisticated investors, as suggested by Mayew and Venkatachalam (2012). However, unsophisticated investors—the primary audience for programs like CNBC's Mad Money—may react similarly. CEOs who appear charismatic and convey optimism may reassure retail investors about company performance, functioning similarly to advertisements.

We test this hypothesis by conducting event study around the interview and examining the stock performance of the CEO's company conditional on the CEO's emotional display during the interview. We focus on the happy emotion conveyed by CEOs since it is the most consistent with optimism, and the least likely to be incorrectly measured (compared to other emotions such as anger or sadness).

3 Data

Our study draws from multiple data sources to analyze CEO interviews on CNBC's Mad Money program, and their relationship with market reaction. We begin by describing our primary data source – the Mad Money show itself – followed by supplementary data sources that enable our analysis of the information content from CEO interviews, such as company fundamentals, market performance and other executive characteristics.

3.1 CNBC Mad Money Program Overview

Mad Money is a prominent financial television program that has been a cornerstone of CNBC's programming since 2005. Hosted by former hedge fund manager Jim Cramer, the show airs weekdays from 6:00 P.M. to 7:00 P.M. Eastern Time. While the program features various segments, including "The Lightning Round" for rapid-fire stock recommendations and "Cramer's Game Plan" for weekly market outlooks. Our study specifically examines the "Executive

Decision" segment, featuring Cramer's in-depth interviews with corporate executives. These discussions cover economic fundamentals, industry innovations, company developments, and earnings reports. The segment functions primarily as a platform for CEOs to address the viewing audience directly. Interviews occur both in-person and via video conferencing. Typically, executives highlight positive company developments or address negative issues and outline recovery strategies. Prominent CEO appearances include Tim Cook (CEO of Apple) and Jensen Huang (CEO of Nvidia). While CFOs and other executives occasionally appear on the segment, we exclude these instances from our analysis. Table 2.1 provides summary statistics on interview topics, days since last earnings report, and year of interview.

We collect our interview data from CNBC's YouTube channel, specifically from their "CEO Interviews" and "Mad Money" playlists. Our sample spans from 2013 through 2023, consisting of interviews where CEOs engage in direct conversation with Cramer.

We selected this format because the conversational setting tends to elicit more natural emotional responses compared to more structured corporate communications. To ensure accuracy of information such as the interview day, we verify each video's original upload day through Youtube API, since the some of the interviews are posted on YouTube at a later date. It is worth noting that our sample size shows some abnormal number of observations during and after 2020. There are less interviews than previous years, likely due to the COVID-19 pandemic's impact on in-person broadcasting. Additionally, CNBC's shift toward a premium subscription model for some CEO interviews in recent years has affected our sample composition, as we include only publicly available interviews from YouTube.

3.2 Supplementary Data Sources

To conduct our analysis, we integrate several additional datasets. We utilize the I/B/E/S summary database to obtain earnings announcement dates, analyst forecasts, and earnings surprises. To maintain data quality, we exclude companies whose most recent earnings report precedes the interview date by more than 100 days, ensuring our sample focuses on companies with regular earnings reporting patterns. We source company fundamental information from Compustat's annual updates, to construct control variables for our sample firms such as size, capital expenditure, leverage, return on assets and Tobin's Q. Stock return data comes from CRSP's Daily Stock File, while we obtain market factor data from Kenneth R. French's Database to control for broader market movements. We collect CEO demographic information, including name, gender, and age, from the Execucomp database. For retail investor proxy, we use Robintrack data. Robinhood made available their customer holdings data to the public for a short window of time, from May 2018 to August 2020. The Robintrack data is intraday with timestamps that are one hour apart.

It documents the number of holders of all tradable stocks on the platform, identified by their ticker symbols. We use the Robintrack data to compute daily user number change for stocks traded in this period.

3.3 Interview Topic and Corporate Events

To show the context of the interviews on CNBC Mad Money program, we classify them into positive, neutral and negative topics (see Table 2.1).

Table 2.1 about here

Our analysis reveals a notable positive bias in the interview topics, with more than two-thirds of interviews falling into the positive category (detailed methodology for the classification is provided in the Methodology section). We are most interested in the interview environment since positive topic and negative topic can have different effects on audiences' perception of the company and expectations of the interview.

The timing of interviews relative to earnings announcements presents an interesting pattern. Our analysis shows that more than half of the interviews (53.07%) occur within three weeks of the company's previous earnings announcement. Figure 2.1 in the Appendix shows more detail on the distribution of days since last earnings report at the time of the interview's aired date. This clustering is particularly noteworthy given that companies typically report earnings quarterly (approximately every 91 days). The distribution of interview timing exhibits several key characteristics: Firstly, the most common timing (mode) is one day after earnings announcements, suggesting CEOs often use the platform to elaborate on recent financial results. Secondly, interviews become increasingly rare beyond 80 days post-earnings (which is around the time for the next earnings call), indicating that executives tend to avoid media appearances as their next earnings announcement approaches. Finally, the concentration of interviews immediately following earnings reports raises important questions about executives' strategic use of media appearances to amplify positive earnings news.

This interview timing pattern provides valuable context for understanding the strategic timing of CEO media appearances and their potential relationship with corporate disclosure practices.

4 Methodologies

4.1 Video Emotion Classification

Our emotional classification methodology employs a multi-stage process using OpenCV and DeepFace frameworks to analyze CEO emotions during interviews. We begin by extracting video frames at 10 frames per second for maintaining computational efficiency (the videos are usually 60 frames per second). This sampling rate gives us enough data points to ensure accurate average emotion scores are statistically close to the theoretical sample mean. Our interviews are unlike Gorodnichenko et. al (2023), or Curti and Kazinnik (2023), where the FOMC press conference has only the Fed Chair as the speaker. In our sample, both Jim Cramer and the interviewed CEO are present in the video. In order to isolate CEO faces for analysis, we implement a two-stage comparison process using facial recognition. First, we use OpenCV to crop out the faces in each of the video frames, then we use OpenCV to compare each detected face against two reference images of Jim Cramer: a professional stock portrait and a screen shot from a Mad Money interview. This dual-reference approach accounts for the variations in Cramer's appearance under different lighting conditions and camera angles typical in the show's setting. We remove any face captures identified as Jim Cramer, ensuring that our dataset contains only CEO faces for subsequent emotional analysis.

The emotion detection stage analyzes the filtered frames using DeepFace's pre-trained emotion recognition model. For each frame that contains the CEO's facial expression, the algorithm estimates the probability of each of the 7 emotions: (happy, neutral, surprise, angry, fear, disgust, sad). The sum of the probabilities (all 7 emotions) equals to 100% in each frame.

We then aggregate these frame-level probabilities over the entire interview duration to create emotional scores that we use for the analysis. The sum of emotional scores variables for each interview is also 100%. To simplify the analysis and maintain rigor, we use the raw average emotion score where possible. We compute positive emotion score as the sum of happy and surprise scores; We compute negative emotion score as the sum of sad, fear, disgust and angry scores. Subsequently, we categorized these emotions into two broader groups: positive (comprising happy and surprise) and negative (comprising of sad, fear, disgust, and angry). For CEOs who appeared in multiple interviews, we calculated a historical mean for the positive and negative sentiment values. This historical mean served as a benchmark, enabling us to generate two indicators: pos_{roll} and neg_{roll}. These indicators represented the rolling measure of positive and negative sentiments' deviation from their previously observed mean, respectively, computed by taking the ratio of current positive (negative) emotion score and historical positive (negative) emotion score and subtracting 1. By comparing the sentiment scores from a specific interview to the CEO's historical benchmarks, we are able to calculate the departure from the usual sentiment for each CEO. When the CEO is interviewed for the first time, we use the sample mean of all other CEOs instead. This departure provides insights into any deviations from the CEO's emotional expression profile over time.

4.2 Interview Transcription

We use OpenAI's Whisper software to perform speech transcription based on the audio portion of the video interview. Since Whisper does not have speaker diarization capabilities (the ability to distinguish speech attributable to different speakers), we use ChatGPT 4o to analyze the transcript again, using contextual patterns to label the interview transcript with speakers (either the interviewer or the CEO), before feeding the transcript for the Interview Topic Classification.

4.3 Interview Topic Sentiment Classification

We use OpenAI's ChatGPT 4o to classify interviews by their topic sentiment into "positive", "neutral" and "negative" events. Positive sentiment events are interviews that center on favorable company developments including but not limited to strong financial performance, product launches, strategic partnerships, or positive operational metrics; negative sentiment events are those that the CEO addresses company challenges such as missed targets, operational setbacks, competitive and macroeconomic pressures; neutral events are interviews that either focus on broader macroeconomic conditions or industry conditions, without particular good or bad news from the company. To validate the reliability of our classification system, we benchmark the interview topic identified by GPT 4o model against human classifications of 100 interview topics. The GPT 4o model has an accuracy rate of 83% for the three-class classification.

5 Empirical Results

This section presents the empirical analysis of the three main hypotheses concerning CEO emotional expression, its determinants, and market consequences. First, we document cross-sectional variation in emotion measures across gender, firm size, and CEO identity, establishing face validity for the emotion classification procedure. Second, we study situational determinants of CEO affect, focusing on firm performance and interview context.

Third, we examine selection into interviews and show evidence consistent with media appearance timing. Finally, we evaluate the market response to televised appearances and its interaction with CEO emotional displays.

5.1 Variation in CEO Emotions

The average observed levels of emotions are shown in the summary statistics in Table 2.2. The sample classified interview emotions show CEO aggregate average emotion to be 10.5% happy, 23.1% neutral, 4.0% surprise, 23.2% angry, 17.1% fear, 1.7% disgust and 20.3% fear.

Table 2.2 about here

Table 2.3 presents the Pearson correlation coefficients for the CEO interview emotions, CEO observed characteristics and firm fundamentals. Notably, the seven emotions have a negative correlation against each other, mainly due to the fact that in each interview, the sum of seven emotion measures sum up to 100%. The exception to this observation is that fear and disgust are not negatively correlated; neither are happy and surprise.

This lends support to our positive and negative emotion classification as sum of negative emotions (fear, disgust, sadness, angry) and positive emotions (happy, surprised).

Table 2.3 about here

Our investigation reveals notable differences in emotional expression between male and female CEOs during interviews. In Table 2.4, we show that female CEOs demonstrate distinctly different emotion patterns, exhibiting 27% higher frequencies of happy emotions and 19% higher frequencies of fear compared to their male counterparts. Conversely, they display 27% lower frequencies of angry emotions and 61% lower expressions of disgust. These findings are statistically significant with robust standard error clustered on CEO names. These observed differences (unconditional on interview topic) align with established research on gender-based personality traits, particularly regarding agreeableness. The consistent nature of these differences across the sample suggests that these emotional patterns represent stable personality characteristics rather than situational responses. This provides validation for our emotion detection methodology, and shows that we should expect a fixed individual element to the emotions that are similar to a fixed effect in a regression, and that we should not expect each individual to have the same baseline emotions for our analysis.

Table 2.4 about here

In Table 2.5, we compare the interview emotions against firm size terciles to investigate whether firm size observed personality differences between CEOs across firms with different sizes. We find that on average, the smallest firms that appear on the interview have CEOs that are less expressive. Expressiveness is defined as the sum of all of the emotion classifications other than "neutral". We find CEOs of larger companies show more disgust (32% more), fear (9.5 % more), compared to CEOs of the smallest companies, who show 19% more surprised emotions. These systematic differences suggest that company size may influence either the selection of CEOs with certain emotional characteristics (such as expressiveness as well as a less agreeable disposition) or that the development of this specific emotion expression pattern is a response to organizational complexity.

Table 2.5 about here

As a robustness check, we further compare the difference between CEOs who appear multiple times and those who only appeared once in our sample to test whether there is learning or CEO manipulation of their expressed emotions. If the CEOs learn to have better control of their emotions to appear more agreeable, there will be differences in our measured emotions. Throughout firm fundamentals, age or gender variables, we find that there are no significant differences between those who have only appeared once versus those who appear more than once, except the "disgust" emotion. However, since "disgust" is a rare emotion, the difference between 1.94% and 1.23% is statistically significant but not economically large.

Table 2.6 about here

5.2 CEO Emotion as Response to External Stimuli

Having established that there is a fixed part of observed CEO emotions, we look at the variation in emotions – specifically, how situational factors influence CEO emotions, and whether CEO express emotions in the same way as regular people do. We conduct regression analysis on the happiness expression during interviews to test our hypothesis 1 that CEO emotions are indeed affected by recent company performance and the interviewer's topic choice. We define the earnings surprise as the consensus error (CE) of analyst estimates from I/B/E/S for the company's latest earnings report a positive earnings surprise suggests the company's EPS is higher than analyst estimates. To ensure a clean measurement, we excluded interviews conducted on the earnings report dates. Then we add interview context and market performance prior to the CEO appearance to test the factors that affect the temporal emotion expressed by the CEOs. We find that earnings surprise as well as interview topic sentiment, have significant impact on CEO's happiness emotion percentage during the interview. We also tested in the same specification that the return on the day of interview's airing does not impact the executive's emotion, likely due to the fact that the interview is done before the day's stock return is revealed. We also tested and found no impact of next quarter earnings report on happiness during the interview. This is quite intuitive, since it would be improbable for the CEOs to know whether their company will beat analyst estimation in the next earnings report months later in the future.

Table 2.7 about here

5.3 Interview Timing and Earnings Performance

Having established that CEOs' displayed emotions are influenced by external factors, we shift our analysis to the interview timing and show that CEOs' appearance on Mad Money is not random to the scheduling of CEO's company earnings report. More than 53% of interviews are conducted within 21 calendar days from the company's latest earnings report and 37% of interviews are conducted within 7 calendar days from the company's latest earnings report. Given that each company's quarterly earnings reports are around 92 days apart, this shows that CEOs interviews tend to follow the company earnings reports.

Upon closer inspection of the earning reports that CEO interviews follow, 75% of them have beaten analyst estimates in the previous earnings report, significantly higher than the unconditional probability of 54% for all I/B/E/S sample. This number is close to our positive sentiment interview topic classification of 68%. Furthermore, the CEOs who appear on the Mad Money interview within 3 days of their earnings report have an even higher chance of having beaten the analyst estimates at around 81%. Interviews are likely scheduled and arranged days or even weeks ahead of the company's earnings release and CEOs likely know the company's earnings numbers. Therefore, we interpret the result as indication that CEOs are more likely to agree to an interview request if the company earnings numbers are greater than analyst estimates. As for financial market implication of this finding, we speculate that there is an arbitrage opportunity with the interview appearance information. This is confirmed when we conduct event study on the CNBC interview in the next section. Our finding signals that CEO's willingness to appear on interview contains strong private information that a company will beat analyst earnings forecasts in the upcoming earnings call. Unfortunately, even though we find that in some episodes of Mad Money Cramer announces the next guest appearing on the show, the guest is usually not announced before the interview has aired.

Table 2.8 about here

5.4 Market Response to Mad Money CEO Interviews

The unique finding that CEOs who appear on Mad Money interviews likely have good company earnings leads us to examine the market impact of the interviews. We examine the cumulative abnormal returns following interview air dates to understand market reactions to CEO emotional displays. Our analysis considers both raw happy emotions and relative positive sentiment, Positive_{roll}, defined as deviations from the rolling average positive emotion for a CEO who has been previously observed. If the CEO is new, the deviation is computed from the population mean for CEOs of the same gender. We find that CEO's optimism (happy), beating earnings (as an indicator variable) have positive effects on company stock return while their interaction term is negative. Our findings suggest that the interaction between being optimistic during an interview and the information of an earnings beat negates the effect of optimism. In other words, having beaten earnings, CEOs do not have to appear happy (even though they empirically still appear more happy) in order for the promotion of earnings to be effective, and CEO's happiness even slightly offsets the appearance's alpha. On the other hand, when the CEO's company did not beat earnings prior to the interview appearance, CEO optimism plays a significant role in shaping the post-interview return. Another interesting observation is that the significance of "happy" is higher than "Positive_{roll}", in the CAR[1,3] regression specification. This result can be interpreted that the effect of the raw emotion is more significant than the "inferred" emotion. This could mean that audiences may have limited knowledge of the CEO being interviewed and rely only on what they see. Even if a CEO is innately more happy than average CEO population, this information might not be obvious to the audience.

Table 2.9 about here

We also test for heterogeneous effects on CEOs who appear for the first time on Mad Money Interview in our sample versus CEOs who appear in the interview multiple times.

We find similar findings to Table 2.9. However, the response time of the market differs. Market reacts positively to CEO optimism on the first day the interview airs for CEOs who appear for the first time, as shown in column 1, Panel B in Table 2.10, but market takes longer to digest the optimism for repeat-interviewed CEOs. Furthermore, the magnitude of reaction is also smaller for repeat-interview CEOs. The effect of company's earnings beat generates 3.15% alpha for the company in the next trading day (column 1, Panel B) for first-interview CEOs compared to 1.28% over next trading days for repeat CEOs (column 1, Panel A). This result is intuitive from an information point of view and further refines our finding of market's reaction to CEO interviews. CEOs who are fresh faces to the audience have higher effect on the market response to the interview.

Table 2.10 about here

We test for retail investor response to CEO interviews through user change percentage in Robintrack from May 2018 to August 2020, with results shown in Table 2.11. The finding on the effect of CEO optimism as well as earnings beats on user change is contrarian to the market return response to the interviews. Robinhood retail investors holding increase by around 3% on the day after the CEO interview if the previous earnings result is above expectation; in situation that a company misses earnings expectation, the increase in retail positions is around 1%. The interaction effect also works in reverse. If a company beats earnings, retail investors position changes are not affected by CEO optimism; If a company misses earnings expectations, retail investors' net purchase of the stock decrease more with more CEO optimism. The result reverts by around half for the next two days.

This finding could imply that retail investors are acting as contrarians to the information expressed through CEO emotions. Nonetheless, retail investors are net buyers after the CEO interview. Our findings show that CEO optimism does not affect retail buying following above-expectation earnings and negatively affect retail buying following earnings expectation misses.

Table 2.11 about here

5.5 Interview as Stale Information

Interviews discussing company operations could also be treated as a form stale information. In Table 2.12, we conduct a test similar to Tetlock (2011) for the stale information effect that the interview could be repeating old news such as the earnings report which had already released days before the interview. We use the same specification of regressing CAR[2,5] on CAR[1,1] to test the return reversal following stale news. Unsurprisingly, if we only consider the return on the day after interview, 12% of the return reverts. CEO optimism does not affect the reversal effect, while the interaction effect of CAR[1,1] and CEO Happy (%) as well as interaction of CAR[1,1] and "Earn Week" exacerbate the reversal. One notable effect on post interview return is from "Earn Week" if the interview takes place within 7 days of the company's earning, there is a persistent alpha for the post interview cumulative return from day 2 to day 5. The result together shows that the CEO interview can be viewed as a form of stale information, with CEO's optimism exacerbating the reversal. In this analysis, the CEO optimism helps company stock performance in the short term, but the market readjusts to the optimism. Nevertheless, there does not seem to be a full reversal of the effect in, and the overall average positive performance from day 2 to day 5 is around 0% from our estimation in column, with around 20% of the first day return being reversed.

Table 2.12 about here

6 Conclusion

Our study provides novel insights into the information content of CEO facial expressions during media appearances and their impact on market dynamics. By applying computer vision analysis to CNBC "Mad Money" interviews, we demonstrate that CEO emotional displays serve as meaningful signals that contain both fixed personality components and responses to situational factors.

Several key findings emerge from our research. First, we confirm that CEO emotions during interviews are authentic reactions to external stimuli, correlating significantly with their companies' recent performance and the context of the interview. CEOs display more happiness when discussing positive topics and following earnings beats, suggesting that their emotional expressions are usually congruent with the company's past performance.

Second, we document systematic differences in baseline emotional profiles across CEOs. These differences correlate with company characteristics, with CEOs of larger firms exhibiting more negative emotions such as disgust and fear, while CEOs of smaller firms display more surprise. Gender differences are also evident, with female CEOs showing higher frequencies of happiness and fear but lower expressions of anger and disgust compared to their male counterparts. These findings suggest that there are fixed parts of the CEO disposition that we observe from CEO interviews.

Third, we identify a strategic pattern in CEO media appearances, with 75% of CEOs in our sample having beaten analyst estimates in their previous earnings reports. This percentage increases further for appearances within three days of earnings announcements, suggesting that CEOs strategically leverage media platforms to amplify positive news and manage investor perceptions.

Finally, we show that markets process and respond to the soft information conveyed through CEO emotional displays. The effect of CEO optimism on post-interview returns depends on recent financial performance. When companies have recently beaten earnings expectations, CEO optimism has limited incremental impact on stock prices.

However, following missed expectations, CEO optimism can significantly improve stock performance, although this positive effect rarely fully offsets the negative impact of earnings disappointment.

In conclusion, our findings show that CEO facial expressions during televised interviews constitute an important channel of communication in financial markets. These non-verbal cues complement traditional disclosure mechanisms and provide investors with additional soft information that influences market valuations beyond the quantitative metrics typically emphasized in financial analysis.

Table 2.1: Interview Topic Sentiment, Days Since Last Earnings Report and Interview Year

Interview Topic Sentiment	N	Percentage of Obs
Positive	1254	67.86%
Neutral	357	19.32%
Negative	237	12.82%
Total	1848	100%
Days Since Last ER	N	Percentage of Obs
0 Days	36	2.26%
1-7 Days	558	34.96%
8-21 Days	253	15.85%
22 Days+	749	46.93%
Total	1596	100%
Year of Interview	N	Percentage of Obs
2013	19	1.03%
2014	155	8.39%
2015	268	14.50%
2016	258	13.96%
2017	311	16.83%
2018	256	13.85%
2019	181	9.79%
2020	24	1.30%
2021	89	4.82%
2022	146	7.90%
2023	52	2.81%
Total	1848	100%

This table reports the summary statistics for the samples of CEO interviews we study. The interview topics are classified by ChatGPT 4o model, days since last ER summarizes the calendar day distance between the interview date and the previous earnings release of the company.

Table 2.2: Summary Statistics

	N	Mean	SD	Median	P10	P90
happy	1596	10.511	6.605	8.920	4.176	18.366
neutral	1596	23.118	10.141	21.931	10.785	36.820
surprise	1596	3.977	3.359	3.056	1.205	7.557
angry	1596	23.221	10.714	20.862	11.973	38.135
fear	1596	17.129	6.589	16.110	10.292	25.810
disgust	1596	1.718	3.295	0.719	0.196	3.608
sad	1596	20.326	8.354	18.923	11.416	31.448
posroll	1596	0.023	0.436	-0.054	-0.415	0.527
negroll	1596	-0.033	0.199	-0.047	-0.272	0.264
female	1331	0.068	0.251	0.000	0.000	0.000
age	1331	57.339	6.781	57.000	50.000	65.000
mv assets	1444	70677	220547	17022	2444	145625
capex	1452	0.040	0.043	0.027	0.004	0.088
size	1444	9.807	1.586	9.742	7.801	11.889
leverage	1441	0.430	17.040	0.559	0.000	2.478
ROA	1453	0.017	0.151	0.041	-0.129	0.140
tobinq	1444	-2.292	3.150	-1.271	-5.916	0.212
last surprise	1596	0.105	1.350	0.036	-0.050	0.220
days since	1596	26.316	25.509	18.500	1.000	66.000

This table reports the summary statistics for the CEO Reaction (Table 2.7) and Market Reaction (Table 2.9) regressions. The seven reported emotions are the average percentage of emotion classification for the CEO during the interview. posroll and negroll are defined as the deviation from the CEO's rolling emotion observation, replaced by the population mean for CEOs who appear for the first time. Company fundamental variables are calculated from Compustat Fundamentals. Last surprise is the difference between the company's last earnings per share and the latest analyst consensus before the earnings release. Days since is the trading days difference from the interview date to the earnings date.

Table 2.3: Correlation Table

	angry	disgust	fear	happy	neutral	sad	surprise	female	age
angry	1.000								
disgust	-0.067	1.000							
fear	-0.274	0.020	1.000						
happy	-0.240	-0.018	-0.136	1.000					
neutral	-0.438	-0.257	-0.280	-0.102	1.000				
sad	-0.283	-0.040	-0.053	-0.255	-0.202	1.000			
surprise	-0.101	0.046	0.112	0.028	-0.098	-0.289	1.000		
female	-0.061	-0.090	-0.018	-0.043	0.090	0.041	0.039	1.000	
age	0.193	-0.009	-0.035	-0.025	-0.179	0.021	-0.024	0.005	1.000

	mv_assets	leverage	ROA	liquidity	pay_div	firm_cash	payout_ratio	tobin_q
mv_assets	1.000							
leverage	-0.009	1.000						
ROA	0.140	0.051	1.000					
liquidity	-0.171	-0.010	-0.490	1.000				
pay_div	0.293	0.035	0.401	-0.468	1.000			
firm_cash	0.718	0.001	0.088	0.057	0.189	1.000		
Payout_ratio	0.036	0.003	0.009	-0.041	0.098	0.084	1.000	
tobin_q	0.127	0.008	0.246	-0.531	0.318	0.099	0.039	1.000
angry	0.015	0.023	-0.018	-0.037	-0.039	0.022	-0.006	0.007
disgust	-0.029	0.042	0.076	-0.033	0.129	0.007	-0.002	-0.006
fear	0.041	-0.091	0.017	-0.009	0.049	0.057	0.037	0.021
happy	0.006	-0.002	0.082	-0.038	0.053	-0.024	-0.008	-0.035
neutral	-0.033	0.051	-0.086	0.070	-0.050	-0.045	0.003	-0.020
sad	0.026	-0.049	0.000	-0.017	-0.034	0.013	-0.018	0.033
surprise	-0.073	0.031	0.050	0.073	0.021	-0.041	-0.001	-0.012

This table shows correlations between the emotions extracted from CEO interview videos with the firm fundamentals as well as CEO characteristics.

Table 2.4: Gender and Interview Emotion

Interview Emotion	Female CEO	Male CEO	T-stat	P-value
happy	13.613	10.743	2.864	0.004**
neutral	24.103	22.433	0.769	0.442
angry	17.306	23.847	-3.656	0.000***
disgust	0.734	1.875	-4.176	0.000***
fear	20.261	17.023	2.377	0.018**
sad	19.642	20.188	-0.377	0.707
surprise	4.342	3.891	0.912	0.362
N	94	1237		

This table tests the difference between observed emotion averages between female and male CEO. The emotion values are emotion occurrence averages for the CEO during the interview. T-statistics is computed based on robust standard error clustered on CEO names.

Table 2.5: Firm Fundamentals and CEO Dispositions

Market Capitalization	Happy	Disgust	Fear	Sad	Surprise
Lowest Tercile	10.337	1.419	16.368	19.985	4.378
Middle Tercile	10.512	1.857	17.111	20.279	3.878
Highest Tercile	10.684	1.877	17.910	20.716	3.675
Difference (High-Low)	0.347	0.458	1.543	0.731	-0.702
T-stat	0.589	1.977	2.803	0.941	-2.268
P-value	0.556	0.049**	0.005***	0.347	0.024**

This table compares the firm size and CEO dispositions by splitting the company-CEO observations into terciles for each year. During interviews, the CEOs who work for higher market capitalization companies display more negative emotions such as disgust and fear and less surprise. The t-statistics is computed based on robust standard error clustered on CEO names.

Table 2.6: T-test between CEOs who appear more than once vs. only once

Variable	Only Once	Multiple Appearance	Difference	t-statistic	p-value
mv assets	55208.052	58891.719	-3683.668	-0.512	0.609
firm_cash	2765.291	2947.265	-181.974	-0.335	0.738
leverage	-0.923	1.142	-2.065	-1.369	0.172
neutral	24.121	23.120	1.001	1.638	0.102
disgust	1.230	1.938	-0.708	-4.407	0.000***
sad	20.578	20.008	0.570	1.199	0.231
payout_ratio	0.298	0.836	-0.537	-1.699	0.090*
age	56.547	56.974	-0.427	-0.861	0.390
happy	10.268	10.597	-0.329	-0.852	0.394
surprise	3.634	3.945	-0.311	-1.651	0.099*
angry	23.084	23.293	-0.209	-0.328	0.743
tobin_q	-2.337	-2.543	0.206	0.921	0.358
frequent	0.000	0.151	-0.151	-13.104	0.000***
ROA	-0.010	0.026	-0.036	-3.039	0.003
liquidity	0.247	0.221	0.025	1.604	0.109
fear	17.085	17.099	-0.014	-0.035	0.972
female	0.047	0.037	0.010	0.810	0.418
pay_div	0.495	0.504	-0.010	-0.315	0.753
capex	0.047	0.042	0.005	1.860	0.063***

This t-test compares the difference between CEOs who appear more than once on the CNBC Mad Money interview and those who appear only once. The first appearance of CEOs are included in the sample of those who only appear once for, and subsequent appearances are included in the sample of those who appear multiple times.

Table 2.7: CEO Reaction to Previous Earnings Surprise and Interview Topic

		Happy %	
Earnings Surprise	2.615**	2.831***	2.577**
	(3.02)	(3.31)	(2.98)
Positive Interviewer Attitude	-0.071	-0.127	-0.184
	(-0.18)	(-0.32)	(-0.46)
Positive Topic Sentiment	0.758**		0.642**
	(2.36)		(1.96)
Negative Topic Sentiment		-1.198**	-0.998*
		(-2.28)	(-1.87)
Constant	9.777***	10.620***	10.040***
	(29.43)	(50.30)	(27.82)
CEO Fixed Effect	Yes	Yes	Yes
N	1380	1380	1380
Adj. R^2	0.355	0.355	0.357

This table shows the regression result for CEO's displayed happiness level during interview. Earnings Surprise is the difference between company's actual earning and latest available analyst consensus. Positive Topic Sentiment and Negative Topic Sentiment are dummy variables equal to 1 if the interview topic is classified as positive/negative (the base case being the topic is neutral) through transcript. CEO fixed effect is applied to consider different baseline levels of emotional displays.

Table 2.8: Future Earnings Beat and Interview Time Frame

Group	N	Earnings Beat Percentage
Total IBES	642507	53.85
All Interview	1596	75.44
Within 3 Days	428	81.07
Difference (3-1)		27.23
T-test		14.36***
Difference (3-2)		21.59
T-test		20.00***
Difference (2-1)		5.64
T-test		2.58***

This table compares the probability of a company having beat earnings before the CEO appears on Cramer's interview. For all of the interviews in sample, three quarters of observations have beaten earnings; for companies who reported earnings within 3 days (inclusive) of the interview, the ratio is 81%.

Table 2.9: Market Reaction to CEO Emotions During Interview

	(1)	(2)	(3)	(4)
	CAR[1,1]	CAR[1,3]	CAR[1,1]	CAR[1,3]
Happy (%)	0.0203**	0.0338**		
	(2.13)	(2.01)		
Positive_{roll}			0.158**	0.0733
			(2.37)	(0.62)
Beats Earnings	1.325**	1.200	1.328**	1.138
	(3.09)	(1.58)	(3.21)	(1.55)
Positive Interviewer Attitude	-0.188	-0.327	-0.167	-0.308
	(-1.43)	(-1.41)	(-1.27)	(-1.32)
Interaction Term	-0.0482**	-0.0446	-0.829**	-0.724
	(-3.13)	(-1.63)	(-3.24)	(-1.59)
Size	0.0433	0.119	0.0327	0.107
	(0.98)	(1.52)	(0.74)	(1.37)
ROA	-0.486	-2.403**	-0.432	-2.238**
	(-0.76)	(-2.13)	(-0.68)	(-1.98)
Investment Growth	0.0327	0.182	0.0207	0.163
	(0.25)	(0.78)	(0.16)	(0.70)
Leverage	-0.00117	-0.000523	-0.000674	-0.000276
	(-0.41)	(-0.10)	(-0.23)	(-0.05)
Liquidity	-0.418	-0.0430	-0.368	0.0379
	(-1.03)	(-0.06)	(-0.91)	(0.05)
Payout Ratio	-0.00962	-0.0101	-0.0114	-0.0136
	(-0.50)	(-0.30)	(-0.59)	(-0.40)
Pay Dividend	-0.186	-0.324	-0.178	-0.318
	(-1.36)	(-1.34)	(-1.30)	(-1.31)
Capex	-0.138	-0.668	-0.173	-0.769
	(-0.09)	(-0.26)	(-0.12)	(-0.30)
Female	-0.162	0.0951	-0.145	0.152
	(-0.63)	(0.21)	(-0.56)	(0.33)
Age	-0.0125	-0.0435**	-0.0119	-0.0431**
	(-1.29)	(-2.54)	(-1.23)	(-2.51)
Constant	0.386	1.449	0.554	1.847
	(0.52)	(1.11)	(0.76)	(1.43)
N	1315	1315	1315	1315
Adj. R^2	0.007	0.012	0.007	0.009

This table shows the regression result of market reaction to the CEO emotions during interview. Happy (%) is the average percentage of happiness emotion for the CEO during the interview. Positive roll is the average percentage of above-average positive emotion. Beats Earnings is a dummy variable equaling to 1 if the CEO's company has beat earnings estimate before the interview. Interaction term is the product of Happy(%) and Beats Earnings.

Table 2.10: Market Reaction to CEO Interview, Sub-Sample Test

Panel A: Sample where CEO have previously been interviewed on CNBC				
	CAR[1,1]	CAR[1,3]	CAR[1,1]	CAR[1,3]
Happy (%)	0.0156	0.0440**		
	(1.38)	(2.51)		
Positive_{roll}			0.0616	0.180
			(0.69)	(1.30)
Beats Earnings	1.275**	1.802**	1.016**	1.522**
	(2.46)	(2.25)	(2.10)	(2.03)
Positive Interviewer Attitude	-0.247	-0.399	-0.237	-0.364
	(-1.55)	(-1.61)	(-1.49)	(-1.47)
Interaction Term	-0.0727*	-0.121*	-0.436	-0.905
	(-1.68)	(-1.81)	(-1.22)	(-1.63)
Constant	0.771	0.995	0.883	1.363
	(0.85)	(0.71)	(0.99)	(0.98)
Firm Controls	Full	Full	Full	Full
N	895	895	895	895
Adj. R^2	-0.001	0.009	-0.004	0.003

Panel B: Sample where CEO appears for the first time on CNBC				
	CAR[1,1]	CAR[1,3]	CAR[1,1]	CAR[1,3]
Happy (%)	0.0420**	0.0169		
	(2.08)	(0.38)		
Positive_{roll}			0.504**	0.300
			(2.73)	(0.74)
Positive Interviewer Attitude	-0.0487	-0.269	-0.0174	-0.251
	(-0.21)	(-0.52)	(-0.07)	(-0.49)
Beats Earnings	3.152**	1.369	2.227**	1.063
	(2.29)	(0.46)	(2.58)	(0.56)
Interaction Term	-0.114**	-0.0510	-1.394**	-0.694
	(-2.31)	(-0.48)	(-2.62)	(-0.59)
Constant	-0.0886	1.952	0.275	2.066
	(-0.07)	(0.66)	(0.21)	(0.71)
Firm Controls	Full	Full	Full	Full
N	420	420	420	420
Adj. R^2	0.008	0.012	0.021	0.013

This table shows the same regression as table 2.6 with sub-samples of CEOs who have appeared more than once and CEOs who are appearing for the first time. The first appearance of CEOs who have appeared more than once is treated as the first time.

Table 2.11: Retail Investors' Reaction to CEO Emotions During Interview

Regressant: % Change in Retail Positions on Robinhood				
	(1)	(2)	(3)	(4)
	Change [1,1]	Change[2,3]	Change[1,1]	Change[2,3]
Happy(%)	-0.178**	0.0808**		
	(-2.16)	(2.06)		
$Positive_{roll}$			-2.509***	1.124***
			(-4.92)	(4.60)
Positive Interviewer Attitude	0.0839	0.190	0.135	0.157
	(0.31)	(1.50)	(0.76)	(1.29)
Beats Earnings	-1.957**	0.839**	-2.432***	1.006**
	(-2.46)	(2.21)	(-4.75)	(4.10)
Interaction Term	0.167*	-0.0743*	2.537***	-1.102***
	(1.94)	(-1.87)	(4.71)	(-4.27)
Constant	5.175***	-1.545**	5.379***	-1.720**
	(4.11)	(-2.56)	(4.93)	(-3.29)
Firm Controls	Full	Full	Full	Full
N	217	218	217	218
Adj. R^2	0.003	0.003	0.001	0.002

This table shows the regression result of retail investors' reaction to the CEO emotions during interview. Happy(%) is the average percentage of happiness emotion for the CEO during the interview. $Positive_{roll}$ is the average percentage of above-average positive emotion. Beats Earnings is a dummy variable equaling to 1 if the CEO's company has beat earnings estimate before the interview. Interaction term is the product of Happy and Beats Earnings. We use the same set of controls as in table 2.6. We use percentage change in number of Robinhood users holding the stock as proxy for retail trades. Change[1,1] measures the change in user holding on the day after the interview is aired; Change [2,3] measures subsequent change in user holding on the second and third day.

Table 2.12: CEO Interview as Stale Information

	Regressand: CAR[2,5]					
	(1)	(2)	(3)	(4)	(5)	(6)
CAR[1,1]	−0.121**	−0.122**	0.406***	−0.0401	−0.0406	0.459***
	(-2.43)	(-2.44)	(4.21)	(-0.65)	(-0.66)	(4.57)
Happy(%)	0.0231			0.0247	0.0316*	
	(1.32)			(1.36)	(1.75)	
$Positive_{roll}$		0.0118				
		(0.12)				
CAR[1,1] * Happy(%)			−0.0500***			−0.0495***
			(-6.35)			(-6.27)
CAR[1,1] * Earn Week				−0.243**	−0.245**	−0.183*
				(-2.34)	(-2.36)	(-1.78)
Earn Week				0.701**	0.695**	0.685**
				(2.75)	(2.72)	(2.72)
Beats Earnings				0.303	0.515	0.627
				(0.54)	(0.88)	(1.09)
Happy(%) * Beats Earnings				−0.131	−0.269	−0.346
				(-0.37)	(-0.74)	(-0.96)
Constant	−0.317	−0.0839	−0.0818	−0.288**	−0.551**	−0.631**
	(-1.46)	(-0.59)	(-0.72)	(-2.09)	(-2.32)	(-2.68)
N	1595	1595	1595	1595	1595	1595
Adj. R^2	0.004	0.002	0.027	0.009	0.009	0.033

This table tests the stale information effect of CEO interviews. We regress CAR[2,5] on CAR[1,1] and interview variables. CAR[1,1] * Happy(%) and CAR[1,1] * Earn Week are interaction terms of CAR[1,1] and Happy(%) , Earn Week. Earn week is indicator of whether the CEO's company has earnings announcement during the same week as the interview.

Appendix

Table A 2.1: Variable Definitions

Variable Name	Emotion Variables Definition
Emotions: Happy Neutral Surprise Angry Fear Disgust Sad	For each interview we collected, each emotion variable represents the average of the sum of probabilities of the frames that include the CEO's facial expressions. The sum of all emotions (happy, neutral, surprise, angry, fear, disgust, sad) equal to 100 in each frame, and we average each emotion throughout the eligible frames to get the average emotional variable. The sum of these variables for each interview observation is also 100.
Pos_{roll}	The ratio of deviation from the CEO's rolling average emotion observation (reference replaced by the population mean for CEOs who appear for the first time). Positive emotion includes happy and surprise. For example, if a CEO has been interviewed once and has a positive emotion history of 25, then the next observation of 30 would imply a Pos_{roll} value of 0.2
Neg_{roll}	The ratio of deviation from the CEO's rolling average emotion observation (reference replaced by the population mean for CEOs who appear for the first time). Positive emotion includes happy and surprise. For example, if a CEO has been interviewed once and has a negative emotion history of 50, then the next observation of 60 would imply a Neg_{roll} value of 0.2

Chapter 3 : Stock Option Incentives and Corporate Hedging Decisions: Theory and Empirical Evidence[18]

1. Introduction

Do managerial equity incentives, especially high-powered ones like stock options,[19] impact corporate hedging decisions? Stulz (1984) and Smith and Stulz (1985) argue that risk-averse managers have incentives to hedge if their utility is concave in firm value. Such incentives are reversed if their utility function is convex, suggesting that managers who are incentivized with more stock options may hedge less than other managers do. Indeed, there is empirical evidence supporting a negative relationship between a firm's hedge ratio and its CEO's option portfolio vega (e.g., Tufano, 1996; Rajgopal and Shevlin, 2002; Knopf, Nam, & Thorton, 2002; Rogers, 2002; Ertugrul, Sezer, & Sirmans, 2008; Kumar and Rabinovich, 2013; Bakke et al., 2016).

In this study, we question the notion that managers hedge less of their firms' risk if they are provided with more powerful equity incentives. By nesting the corporate hedging model of Brown and Toft (2002) within a principal-agent framework, we show that managers are motivated to maintain the same level of hedge intensity even if they are provided with more equity (either restricted stock or option) incentives. The optimal hedging strategy does depend on the types of equity incentives provided to the managers, however. If managers were only provided with restricted stock as incentive pay, they would make hedging decisions exactly like owner-managers would have (i.e., in the absence of principal-agent conflict). In other words, restricted stock incentives do not influence the way managers hedge at all. In comparison, stock option incentives

[18] Chapter 3 has been submitted for publication of the material. The dissertation author was the co-author of this paper working alongside Dr. Yisong Tian and handled the following responsibilities: Data Curation, Regression Analysis, and Review & Editing.

[19] By stock options, we mean call options on the firm's common stock, typically granted to top executives, and sometimes rank-and-file employees, with a ten-year maturity, vesting restrictions and American exercise style.

do motivate managers to add speculative positions on the downside using concave derivatives (e.g., sold put options). Specifically, the optimal hedging strategy has two distinct components in this case: a hedging component that is identical to the hedge positions that would have been chosen by an owner-manager and a speculative component on the downside. This speculative behavior is induced by the convex payoff of their stock options, making managers more willing to accept downside losses in exchange for more upside gains. This type of hybrid hedging strategy is consistent with surveys of CEOs and CFOs that they often alter the size and timing of their firms' hedge positions, depending on their own market assessments or in reaction to changing market conditions (e.g., Bodnar, Hayt, & Marston, 1998; Geczy, Minton, & Schrand, 2007; Bodnar et al., 2011; Lins, Servaes, & Tamayo, 2011). While these managers do not explicitly state how exactly they actively manage their firm's hedge positions, our theoretical analysis suggests that selling put options (or equivalent) is the most likely choice.

Guided by the predictions of our theoretical model, we implement a unique identification strategy to examine the relationship between managerial equity incentives and corporate hedging strategy in our empirical analysis. We distinguish between derivative contracts that are used purely for hedging purposes (mostly linear contracts such as forwards and swaps) and those for speculative purposes (mostly concave contracts such as sold put options) and construct two non-overlapping coverage ratios, the *pure hedge ratio* and the *pure speculative ratio*. By analyzing both coverage ratios, we separate the impact of managerial equity incentives on the use of derivatives for hedging purposes from that for speculative purposes. In comparison, previous studies (e.g., Bakke et al., 2016) use a single hedge ratio covering all derivative positions regardless of their orientation for hedging or speculation, effectively netting out the pure speculative ratio from the pure hedge ratio. In other words, such a *net hedge ratio* is equivalent to the difference between our pure hedge ratio and pure speculative ratio and is thus smaller than the pure hedge ratio whenever the firm has speculative positions. It underestimates the true extent of a firm's hedge intensity, especially for firms that provide their managers with more stock option incentives, leading to a bias towards finding a negative relationship between stock option incentives and the net hedge ratio. For comparison with previous studies, we use all three coverage ratios in our empirical analysis. We find that stock option incentives have little impact on either the pure hedge ratio or net hedge ratio but a positive impact on the firm's pure speculative ratio. This means that stock option incentives do not motivate managers to hedge less as previous studies claim.[20] Rather, they motivate managers to add speculative positions with concave downside payoffs as a supplement to the firm's usual hedge positions.

In our empirical analysis, we follow prior research (e.g., Jin and Jorion, 2006) and investigate the choice of hedging instruments and hedge positions of oil and gas companies in relation to their CEOs' equity incentives. Oil and gas companies are an ideal choice for studying corporate hedging decisions because, unlike multinationals or conglomerates with business operations internationally or across multiple sectors of the economy, oil and gas companies have a common source of risk across all firms in the industry – the fluctuations of energy prices. With such uniformity in the risk source and similarity in business operations, it is an ideal setting for investigating the relationship between managerial equity incentives and corporate hedging decisions. More importantly, oil and gas companies disclose detailed information on their oil and gas reserves, annual production figures and hedging decisions. These companies disclose in their annual reports exactly what types of derivative contracts they use (e.g., swaps, collars or spreads),

[20] Consistent with previous studies, we do find that stock option incentives have a negative impact on the net hedge ratio. It is never statistically significant, however.

long or short positions, and contract volumes and prices involved. All these unique features of the oil and gas industry allow us to test the predictions of our theoretical model.

Our sample of U.S. oil and gas companies has 173 unique firms in the period 1998-2015, with 1,200 firm-year observations. Details of these companies' hedging decisions are hand collected from their 10-K reports filed with the Securities and Exchange Commission (SEC), accessed through SEC's Edgar database. In addition to the usual linear contracts such as forwards, futures and swaps, these companies also use call options, put options, call spreads, put spreads, collars, three-way collars and other derivatives contracts as hedging instruments during our sample period. Overall, the top two types of derivative contracts are swaps and collars, accounting for 41.9% and 28.5% of all derivative contracts used, respectively. None of the other contract types accounts for more than 7.3% of all contracts used. While most derivative contracts are indeed used for hedging purposes, some are used for speculative purposes. For example, there are a total of 175 sold put option positions used by firms in our sample, in the form of either a standalone contract or part of a three-way collar.

To see how option incentives impact corporate hedging decisions, we first divide firms into terciles of the CEO's equity portfolio vega and compare the differences in hedging strategies between firms in different terciles. In each year, the top tercile has firms that provide their CEOs the strongest risk-taking incentives while the bottom tercile the weakest. As predicted by our theoretical model, firms in the top vega tercile indeed speculate more than the corresponding firms in the bottom vega tercile do. The average speculative coverage ratios are 5.5% and 3.2%, respectively, for firms in the top and bottom terciles. The difference is statistically significant at the 5% level and clearly economically significant as well because the former is nearly 72% higher than the latter. The opposite is true for the pure hedge ratio, which is lower for firms in the top vega tercile (37.2%) than for firms in the bottom vega tercile (43.2%). The difference is relatively small (in percentage terms) and not statistically significant. These results provide preliminary support for the prediction that option incentives may induce speculative behavior in hedging operations but have little impact on pure hedge intensity.

Of course, the previous analysis is far from conclusive as we have yet to take into account other factors such as firm and CEO characteristics that may have also influenced corporate hedging decisions. To perform a more rigorous analysis, we run multivariate regressions of the three coverage ratios to see how managerial equity incentives, both delta and vega of the CEO's equity portfolio, impact corporate hedging decisions while controlling firm and CEO characteristics, and firm and year fixed effects. Consistent with our theoretical predictions, multivariate regression analysis confirms that the CEO's equity portfolio vega has a positive impact on the firm's pure speculative ratio (statistically significant at the 5% level) but little impact on either hedge ratio (statistically insignificant). More importantly, the impact of the CEO's risk incentives is economically meaningful. Given the average pure speculative coverage ratio of 2.7%, a typical firm in our sample has speculative derivative contracts covering roughly $1,045,710 of its annual production of $38.7 million. A one standard deviation increase in the CEO's portfolio vega would lead to additional speculative positions covering $120,506 of the firm's annual production.[21] The size of these additional speculative positions is roughly 11.5% of the firm's total speculative positions in financial derivatives. The impact of the CEO's vega on the firm's speculative position is therefore quite large economically. In comparison, the same increase in the CEO's vega would

[21] The increase in speculative position is calculated as ($38.73 million)×0.0342×0.257×0.354 = $120,506 where 35.4% and 25.7% are the average hedge coverage ratio and the standard deviation of the CEO's portfolio scaled vega, respectively, for firms in our sample.

lead to a \$383,214 decrease in the size of the firm's pure hedge position in financial derivatives.[22] This is a fairly small decline in its pure hedge position because the average pure hedge coverage ratio of 35.4% implies that the typical firm in our sample uses derivatives to hedge \$13.710 million of its annual production. The decline is only 2.8% of the firm's hedge position. The impact of the CEO's vega on the firm's pure hedge position is thus quite small economically.

In comparison, the CEO's equity portfolio delta, also known as pay-performance sensitivity, has little impact on any of the three coverage ratios. Not only is the effect statistically insignificant but also economically negligible. In magnitude, the estimated coefficient is only a fraction of the corresponding coefficient for CEO's equity portfolio vega. This is consistent with the prediction of our theoretical model that stock-based equity incentives do not change the way managers hedge. These managers maintain their firms' hedge positions as if they were owner-managers without any principal-agent conflict. Only stock option incentives motivate managers to alter the firms' hedging operations by adding speculative positions in financial derivatives.

In addition, there is also evidence that the effect of stock option compensation on hedging decisions is more elevated for managers who are more risk tolerant. While the degree of risk aversion is not directly observable, we use several commonly used proxies for the CEO's degree of risk aversion including age, tenure and cash pay as a fraction of total compensation (*cashfrac* for short).[23] CEOs are likely to be more tolerant of risk if they are younger, have been on the job longer or have less cash compensation. Compared to other CEOs, they are more likely to make riskier investments with their own wealth (e.g., Tufano, 1996; Bloom and Milkovich, 1998; Croci,

[22] Similarly, the decrease in the hedge position is calculated as (\$38.73 million)×(–0.0385)×0.257 = –\$383,214 where –0.385% is the percentage change in the firm's hedge position if the CEO's scaled vega is increased by 10%.
[23] While inside debt is the most commonly used proxy for risk preference, so few firms in our sample report such figures, rendering it ineffective in our case.

del Giudice, & Jankensgard, 2017; Albuquerque et al., 2024). In corporate hedging operations, more risk-tolerant CEOs might speculate more with financial derivatives than less risk-tolerant CEOs do even if they are provided with the same level of risk-taking incentives (as measured by their equity portfolio vega). Our empirical evidence is consistent with this prediction.

Interestingly, stock option incentives do not appear to induce reckless risk-taking behavior when CEOs do speculate using financial derivatives. In fact, the speculative coverage ratio has little impact on either the firm's cash flow volatility or its valuation (e.g., Tobin's Q).[24] Neither effect is statistically or economically significant, suggesting that the speculative behavior has little impact on shareholders' welfare. This is not entirely unexpected as the use of speculative positions in financial derivatives is quite modest for firms in our sample, with an average speculative coverage ratio of only 2.7% of annual production in comparison with an average hedge coverage ratio of 35.4%. Financial derivatives are thus mostly used for hedging purposes instead of speculation. Even for firms that are more "prolific" in their use of speculative positions in financial derivatives (e.g., Anadarko Petroleum), there is no evidence that their speculative positions would ever lead to overall hedging losses on the downside. Instead, these firms appear to be more willing to give up a small fraction of downside hedging gains in order to have a lower level of upside hedging losses (as shown in Figure 3 subsequently). While this trade-off is clearly beneficial for CEOs who are compensated with stock options, they do not pursue it to the extent that is noticeably harmful to shareholders. Perhaps, these CEOs are mindful of the financial distress cost if they were to take excessive amount of risk in their firms' speculative positions in financial derivatives. Even though such risk-taking activities may lead to short-term gains via enhanced payoffs from their

[24] In our theoretical model, we make the implicit assumption that managerial equity incentives are endogenized in an equilibrium framework such that the use of derivatives has no impact on firm value. Our empirical findings are consistent with this assumption.

stock options, they might be weary of the long-term repercussions to their reputation and future career prospects if shareholders blame them for any losses from such speculative positions.

For robustness, we investigate endogeneity concerns and the impact of CFO stock option portfolio on the relationship between managerial risk-taking incentives and corporate hedging decisions. The board of directors may have a particular view of how the firm should hedge and recruit top executives to implement that vision and devise compensation plans to incentivize these executives. This may lead to an endogenous relationship between managerial equity incentives and corporate hedging decisions. It is also possible that our empirical analysis does not include all the relevant control variables that are determinants of hedging policies. To alleviate such endogeneity concerns, we follow Bakke et al. (2016) and take advantage of the exogenous shock on executive compensation due to the implementation of Financial Accounting Standard (FAS) 123R in 2005. In response to this exogenous shock, companies reduced their stock option grants and simultaneously increased their restricted stock grants. The shock is arguably exogenous to hedging policies, allowing us to identify the causal effect of risk-taking incentives corporate hedging decisions. The results of this analysis confirm the positive impact of stock option grants on the speculative use of derivatives in corporate hedging operations. In addition, it is also possible that it is the CFO who is behind corporate hedging decisions (e.g., Barbi, Febo, & Massimiliani, 2024). To verify this possibility, we include both the CEO and CFO equity incentives in the regression analysis. We find that the CEO's stock option grants remain the key driver behind the positive relationship between risk-taking incentives and the speculative use of derivatives while the CFO's stock option grants have little impact on the relationship. This is different from Barbi, Febo & Massimiliani (2024) who find that CFO's stock option grants have a negative impact on the net hedge ratio and dominate the impact of the CEO's stock option grants. One possible explanation is that the two studies differ in sample period and the impact of the CFO's stock option grants may vary over time.

Our study makes several unique contributions to the corporate hedging literature. Firstly, we provide both theoretical and empirical support for a positive linkage between stock option incentives and speculative behavior in corporate hedging operations. In comparison, previous studies provide either theoretical arguments for a negative relationship between stock option incentives and hedge intensity (e.g., Stulz, 1984; Smith and Stulz, 1985; Knopf, Nam, & Thornton, 2002), surveys of corporate managers who admit that they sometimes take active positions in their firms' hedging operations (e.g., Bodnar, Hayt, & Marston, 1998) or evidence of time series variations in hedge ratios that appear to be consistent with speculative behavior in hedging operations (e.g., Faulkender, 2005; Chernenko and Faulkender, 2011).

Secondly, we distinguish between hedging and speculative uses of financial derivatives in our empirical analysis and investigate their unique roles in corporate risk management, especially when managers are provided with stock option incentives.[25] By doing so, we confirm the positive relationship between the CEO's stock option incentives and the firm's speculative usage of financial derivatives. In comparison, previous studies rely on a single hedge ratio that encompasses derivative contracts for both hedging and speculative purposes. With this net hedge ratio, these studies find a negative relationship between stock option incentives and hedge intensity (e.g., Tufano, 1996; Rajgopal and Shevlin, 2002; Knopf, Nam, & Thornton, 2002; Rogers, 2002; Ertugrul, Sezer, & Sirmans, 2008; Bakke et al., 2016) and interpret it as evidence that managers hedge less if they are provided with stock option incentives. We question this interpretation

[25] Ahmed et al. (2020) also study both hedging and speculative uses of financial derivatives. The difference is that there is no distinction between stock ownership and stock options in their empirical analysis and the manager owns a fraction of the firm but has no stock option grants in their theoretical model.

because the use of the net hedge ratio is biased towards finding such a negative relationship. As stock options motivate managers to take speculative positions while maintaining the same hedge positions, the net hedge ratio is smaller for managers who have more stock option incentives. Such downward bias may have played a role in their finding of a negative relationship between stock option incentives and the net hedge ratio.

In addition, our theoretical model has a clear-cut prediction on how firms speculate in their hedging operations if their managers are provided with stock option incentives: they speculate by selling put options. This prediction is verified empirically as firms in the oil and gas industry indeed speculate mostly by selling put options, either directly or as part of three-way collars. More importantly, these managers treat the speculative activities as a supplement to the firms' pure hedge positions which are not materially impacted by managerial equity incentives. In other words, they first implement the same hedge positions as owner-managers do in the same circumstances and but then supplement them with speculative positions, consistent with surveys of CEOs and CFOs on corporate hedging practices (e.g., Bodnar, Hayt, & Marston, 1998; Geczy, Minton, & Schrand, 2007; Bodnar et al., 2011; Lins, Servaes, & Tamayo, 2011).

Finally, our empirical work has some similarities with Croci, del Giudice, and Jankensgard (2017) who also examine how managerial risk preferences and stock option grants influence corporate hedging decisions in the oil and gas industry. They find no evidence that stock option grants incentivize CEOs to preserve more upside payoff by using more financial derivatives with convex payoffs. Our study differs from theirs by focusing on the whole payoff structure of the hedging instruments instead of just the upside. In fact, our theoretical model predicts that the optimal hedge has linear payoffs on the upside even if managers are compensated with stock options. The main difference is on the downside, with highly concave payoffs (e.g., sold put options) if managers are compensated with stock options. By focusing only on the upside, Croci, del Giudice and Jankensgard (2017) reach the conclusion that managerial stock options have no effect on corporate hedging strategies. Both our theoretical model and empirical evidence suggest otherwise.

The rest of the paper proceeds as follows. Section 2 describes a principal-agent model for corporate hedging decisions where the manager is compensated with either restricted stock or stock options. In Section 3, we discuss the empirical implications of the optimal hedging strategy. In Section 4, we describe the sample of oil and gas firms and the usage of financial derivatives in their hedging operations. In Section 5, we perform empirical analysis of the impact of managerial equity incentives on corporate hedging decisions and shareholders' welfare. The final section concludes.

2. A Model of Corporate Hedging Decisions

Consider an all equity-financed firm that has a single product for sale. Its operating profit in a given period is a function of the quantity of the product sold (q_0), the product's market price per unit (p), variable cost per unit (v) and the fixed cost of production (F_0):

$$\pi_{NOI} \equiv q_0(p - v) - F_0 \quad (1)$$

While the quantity sold (q_0) and total fixed cost (F_0) in one period are fixed, both price and variable cost are uncertain and subject to random variations. To make the hedging problem relevant and yet mathematically tractable, we assume that the price risk can be hedged, via derivative contracts (e.g., forward and option contracts), while the uncertainty associated with the variable cost is not. This is roughly the hedging problem faced by a traditional manufacturer whose production is capped by its plant capacity, its product is sold in a competitive market and its variable cost is subject to idiosyncratic uncertainties (due to, for example, labor relations or other firm-specific factors). If the firm chooses to hedge the price risk using a derivative contract, its net profit is then given by:

$$\pi \equiv q_0(p - v) - F_0 + \theta(p) \tag{2}$$

where $\theta(p)$ is the payoff of the derivative contract, net of its cost which is paid at maturity instead of upfront, such that its expected payoff is zero:

$$\int_0^T \theta(p)\phi(p)dp = 0$$

and $\phi(p)$ is the state price density function.

The choice of the derivative contract is made by a manager who is compensated with both fixed and variable pay:

$$P = s + b \cdot g(\pi) \tag{3}$$

where $s \geq 0$ is the manager's fixed cash pay, $b \geq 0$ is their share of the firm's net profit, and $g(\pi)$ is the payoff structure of the equity-based pay. To focus on the impact of equity-based pay on hedging decisions, we do not explicitly model how the firm chooses the optimal compensation contract of the manager and simply assume that the optimal pay has both a fixed component and a variable component such as the one described in Eq. (3). The variable component is in the form of either restricted stock, $g(\pi) = \pi$, or a call option on the firm's net profit:[26]

$$g(\pi) = \begin{cases} \pi, & \text{if } \pi_{NOI} > \pi_0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

where π_0 is the strike price of the call option. The manager is risk averse and chooses the payoff structure of the hedge contract to maximize their expected utility:

[26] Technically, this is a digital call option (known as an asset-or-nothing call) instead of a standard call option where the payoff is net of the strike price. We choose this particular form of the call option for technical simplicity.

$$\max_{\theta(p)} \mathrm{E}\{u(P)\} \quad s.t.: \int_{0}^{T} \theta(p)\phi(p)dp = 0 \tag{5}$$

where $u(\bullet)$ is the manager's utility of wealth. For simplicity, the manager's outside wealth is normalized to be zero or absorbed in the fixed pay component (s).

2.1. Hedging under restricted stock-based incentives

As stock and options provide different risk-taking incentives to managers (e.g., Johnson and Tian, 2000), they may also have differential effects on corporate hedging decisions. To study these effects, we evaluate two separate cases of managerial equity incentives: restricted stock-based equity incentives and option-based equity incentives. We first examine the case of a manager who is provided with fractional ownership of the firm's stock that mimics the payoff of restricted stock grants ($b \cdot \pi$). Such a compensation contract between the firm and the manager leads to a simple relationship (i.e., perfect correlation) between the firm's profit and the manager's pay.

To keep the hedging problem tractable, we make some simplifying assumptions that are similar to those in previous studies (e.g., Brown and Toft, 2002). First, the price (p) and variable cost (v) of the firm's product are joint normally distributed with mean μ_p and μ_v, variance σ_p^2 and σ_v^2, respectively, and correlation coefficient ρ. The joint, marginal and conditional density functions are, respectively, given by:

$$\phi(p,v) = \frac{1}{2\pi\sigma_p\sigma_v\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left[\left(\frac{p-\mu_p}{\sigma_p}\right)^2 + \left(\frac{v-\mu_v}{\sigma_v}\right)^2 - 2\rho\left(\frac{p-\mu_p}{\sigma_p}\right)\left(\frac{v-\mu_v}{\sigma_v}\right)\right]}$$

$$\phi(p) = \frac{1}{\sqrt{2\pi}\sigma_p} e^{-\frac{1}{2}\left(\frac{p-\mu_p}{\sigma_p}\right)^2}$$

$$\phi(v|p) \equiv \phi(p,v)/\phi(p) = \frac{1}{\sqrt{2\pi}\sigma_v\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left[\frac{v-\mu_v}{\sigma_v}-\rho\left(\frac{p-\mu_p}{\sigma_p}\right)\right]^2}$$

In addition, the manager has negative exponential utility:

$$u(w) = -\frac{1}{\lambda} e^{-\lambda w} \tag{6}$$

and pursues an optimal hedging strategy in order to maximize the expected utility of their terminal wealth (w) at the end of the period where $\lambda \geq 0$ is the manager's degree of risk aversion.

With this setup, the manager's expected utility of terminal wealth is given by:

$$EU = \int_{-\infty}^{+\infty}\int_{-\infty}^{+\infty} u(P)\phi(p,v)dpdv = \int_{-\infty}^{+\infty} \phi(p)dp \int_{-\infty}^{+\infty} u(P)\phi(v|p)dv \tag{7}$$

Solving the inner integral, we have a simplified expression for the manager's expected utility:

$$EU = \int_{-\infty}^{+\infty} u\left(P_0 + b\left[\theta(p) + q_0\left(1-\rho\frac{\sigma_v}{\sigma_p}\right)(p-\mu_p)\right]\right)\cdot\phi(p)dp \tag{7a}$$

where

$$P_0 = s + b\left[q_0(\mu_p - \mu_v) - F_0 - \frac{1}{2}\lambda b q_0^2(1-\rho^2)\sigma_v^2\right]$$

Solving the manager's utility maximization problem in Eq. (5), together with Eq. (7a), we have the following first-order condition:

$$b \cdot e^{-\lambda\left\{P_0 + b\left[\theta(p) + q_0\left(1-\rho\frac{\sigma_v}{\sigma_p}\right)(p-\mu_p)\right]\right\}} + \gamma = 0, \quad \text{for all } p \tag{8}$$

where γ is the Lagrange multiplier. For Eq. (8) to hold for all p, in conjunction with the constraint that the expected hedge payoff is zero, the optimal hedge must have the following payoff structure:

$$\theta^*(p) = q_0\left(1-\rho\frac{\sigma_v}{\sigma_p}\right)(\mu_p - p) \tag{9}$$

The optimal hedge above has a linear payoff structure that resembles the payoff of a short position in a forward contract. Interestingly, the manager's factional ownership (b) has no impact at all on the optimal hedge as it is absent in Eq. (9). More importantly, the optimal hedge here is identical to the one in the original model of Brown and Toft (2002) where the manager is also the owner of the firm without any principal-agent conflict. In other words, managers incentivized with restricted stock adopt the same hedging strategy as owner-managers do in similar circumstances. Consequently, restricted stock-based incentives have no impact at all on corporate hedging decisions.

In addition, the optimal hedge ratio does not vary with the market price of the product (p):

$$HR^* \equiv \frac{\partial \theta^*(p)}{\partial p} \Big/ q_0 = -\left(1 - \rho \frac{\sigma_v}{\sigma_p}\right) \tag{10}$$

Since the correlation between price and variable cost is typically positive, the optimal hedge ratio should be less than the full (or naïve) hedge ratio of –1 (in magnitude).

2.2. Hedging under option-based incentives

We next consider the case of a manager who is provided with option-based equity incentives with a payoff structure specified by Eq. (4). Unlike owners of the firm whose fortune is perfectly correlated with the firm's profit on both the upside and the downside, the option payoff is asymmetric. It provides the same payoff as the restricted stock does (π) if the operating profit (π_{NOI}) is above a specified level (π_0) but pays nothing otherwise. The parameter b specifies the fraction of the firm's net profit that is paid to the manager if the option is in the money. Because of the asymmetry in option payoff, it is commonly believed that option-based equity incentives motivate managers to hedge less or take on more risky investments (e.g., Haugen and Senbet, 1981; Smith and Stulz, 1985; Tufano, 1996; Guay, 1999; Rajgopal and Shevlin, 2002; Coles, Daniel, & Naveen, 2006; Armstrong and Vashishtham, 2012).

To keep the hedging problem tractable, we maintain the same technical assumptions as in the previous section. The manager's expected utility of terminal wealth is then:

$$EU = \int_{-\infty}^{+\infty} \phi(p)dp \int_{-\infty}^{+\infty} u(P)\phi(v|p)dv = \int_{-\infty}^{+\infty} [I_1(p) + I_2(p)]\phi(p)dp \tag{11}$$

where

$$I_1(p) = \int_{-\infty}^{v_0(p)} u(\mathrm{s} + b \cdot \pi) \cdot \phi(v|p)dv \tag{11a}$$

$$I_2(p) = \int_{v_0(p)}^{+\infty} u(\mathrm{s}) \cdot \phi(v|p)dv \tag{11b}$$

and

$$v_0(p) = p - \frac{F_0 + \pi_0}{q_0} \tag{11c}$$

Solving the integrals in Eqs. (11a) and (11b), we have:

$$I_1(p) = u\left(P_0 + b\left[\theta(p) + q_0\left(1 - \rho\frac{\sigma_v}{\sigma_p}\right)(p - \mu_p)\right]\right) \cdot N[-d_1(p)] \tag{11d}$$

$$I_2(p) = u(s) \cdot N[d_2(p)] \tag{11e}$$

where

$$d_1(p) = \frac{m_0 - \left[\mu_p - \mu_v + \left(1 - \rho\frac{\sigma_v}{\sigma_p}\right)(p - \mu_p) - \frac{1}{2}\lambda b q_0^2 (1 - \rho^2)\sigma_v^2\right]}{\sigma_v\sqrt{1 - \rho^2}}$$

$$d_2(p) = \frac{m_0 - \left[\mu_p - \mu_v + \left(1 - \rho\frac{\sigma_v}{\sigma_p}\right)(p - \mu_p)\right]}{\sigma_v\sqrt{1 - \rho^2}}$$

$$m_0 = \frac{F_0 + \pi_0}{q_0}$$

Solving the manager's utility maximization problem in Eq. (5), together with the expected utility in Eqs. (11)-(11e), we have the following first-order condition:

$$b \cdot e^{-\lambda\left\{P_0 + b\left[\theta(p) + q_0\left(1 - \rho\frac{\sigma_v}{\sigma_p}\right)(p - \mu_p)\right]\right\}} \cdot N[-d_1(p)] + \gamma = 0, \quad \text{for all } p \tag{12}$$

where γ is the Lagrange multiplier. For Eq. (12) to hold for all p, in conjunction with the constraint that the expected hedge payoff is zero, the optimal hedge must be:

$$\theta^*(p) = q_0\left(1 - \rho\frac{\sigma_v}{\sigma_p}\right)\left(\mu_p - p\right) + \frac{1}{\lambda b}\ln\{N[-d_1(p)]\} - \theta_0 \tag{13}$$

where

$$\theta_0 = \frac{1}{\lambda b}\int_{-\infty}^{+\infty} \ln\{N[-d_1(p)]\} \cdot \phi(p)dp \tag{13a}$$

The optimal hedge in Eq. (13) has two distinct components: 1) a linear component:

$$q_0\left(1 - \rho\frac{\sigma_v}{\sigma_p}\right)\left(\mu_p - p\right)$$

that is identical to the optimal hedge in Eq. (9) when the manager is compensated with restricted stock as equity incentives and 2) a nonlinear component:

$$\frac{1}{\lambda b}\ln\{N[-d_1(p)]\} - \theta_0$$

The nonlinear component appears quite complex and varies with the manager's level of risk aversion (λ), the level of equity compensation (b) and the price of the product (p). In comparison, the linear component is invariant to all these variations.

Due to its complexity, it is not straightforward to know the exact shape of the payoff structure exhibited by the optimal hedge in Eq. (13). We may however get a sense of its features from the hedge ratio:

$$HR^{*}(p) = -\left(1 - \rho\frac{\sigma_v}{\sigma_p}\right)\left\{1 - \frac{1}{\lambda b q_0 \sigma_v \sqrt{1-\rho^2}} \cdot \frac{N'[-d_1(p)]}{N[-d_1(p)]}\right\} \tag{14}$$

where

$$N'(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2}$$

The optimal hedge ratio is clearly different from the corresponding optimal hedge ratio under restricted stock-based equity incentives shown in Eq. (10). It is no longer constant and depends on the level of price and the manager's level of risk aversion and equity compensation. Numerical analysis is needed to understand the optimal hedge and the implied hedge ratios in this case.

3. The Impact of Managerial Equity Incentives on Corporate Hedging Decisions

The theoretical model in the previous section suggests that corporate hedging decisions are influenced by the types of equity incentives firms provide to their managers. Managers compensated with restricted stock-based equity incentives are motivated to use linear derivative contracts (e.g., forwards) to hedge and while those compensated with option-based equity incentives use nonlinear derivative contracts (e.g., options) to hedge. In this section, we perform numerical analysis to evaluate and compare these different hedging strategies.

3.1. Understanding the optimal hedging strategy

To analyze the impact of managerial equity incentives on optimal hedge strategies, we select a set of base-case parameters that characterize the firm's production and the manager's degree of risk aversion and equity compensation. Following previous studies (e.g., Brown and Toft, 2002), we choose these parameters to mimic the business operations of a typical manufacturer in a competitive industry. Starting with the firm's production, both the expected price of the firm's product (μ_p) and its quantity manufactured (q_0) during the period are normalized at 1; The fixed cost is 0.4; The mean of the variable cost per unit (μ_v) is 0.25; The correlation coefficient between price and variable cost is 0.25; The volatility (standard deviation) of both the price and variable cost are 20%. The manager's degree of risk aversion (λ) is 5; The manager's equity compensation (either stock or option) represents a 5% ownership of the firm (b); For option compensation, the strike price (or target net operating profit π_0) is zero. In other words, the manager's options provide a positive payoff as long as the firm's production is profitable.

To evaluate the variations in optimal hedging strategies, we compare three types of hedge positions: the full (or naïve) hedge using forward contracts with a hedge ratio of -1, the optimal hedge under restricted stock-based equity incentives (as described in Eq. (9)), and the optimal hedge under option-based equity incentives (as described in Eq. (13)). The payoffs of these hedge positions are compared and illustrated in Figure 1. The optimal hedge under option-based incentives clearly stands out from the other two hedge positions. While the payoffs of both the full hedge and the optimal hedge under restricted stock-based incentives are linear, the payoff of the optimal hedge under option-based incentives is not, especially at prices below the mean. At higher prices (e.g., above 1.2), the payoff of the optimal hedge under option-based incentives appears to be linear and parallel to the optimal hedge under restricted stock-based incentives, albeit at a higher level. At lower prices (e.g., below 1), the payoff drops off sharply with the slope of the curve becoming positive just above the mean price of 1. The positive slope of the curve at low price levels suggests that the manager is no longer hedging. They are in fact speculating on low prices, leading to hedging losses if the market price drops that low. Such a speculative position magnifies the risk of low prices instead of reducing it. This type of speculative behavior is rational for the manager because their stock options have convex payoffs. The payoff of their stock options benefits 100% from the upside of the stock price movement but does not suffer at all from the downside of the stock price movement. The manager is thus motivated to take on more downside risk in order to benefit more from the upside of the stock price swings, leading to a highly concave payoff structure for the optimal hedge.

Figure 3.1 about here

To further understand the optimal hedging strategy under option-based incentives, we search for a combination of forward and put option contracts that have a payoff structure matching closely to that of the optimal hedge. Such as replicating portfolio would not only show how the optimal hedging strategy can be implemented in practice but also provide more insight on the nature of the optimal hedging strategy. After some experimentation, we find that the combination of a short forward contract plus a short position of six at-the-money put options comes quite close to matching the optimal hedging strategy under option-based incentives.[27] The payoff of this forward-put portfolio is also shown in Figure 1, together with the other three hedging strategies we have already evaluated. The match between the forward-put portfolio and the optimal hedge under option-based incentives is not perfect but reasonably close for all practical purposes. This suggests that the optimal hedging strategy under option-based incentives has two components: a hedging component that is identical to the optimal short forward hedge under restricted stock-based incentives and a speculative component of sold put options. This replication strategy highlights the difference between the manager's optimal hedging strategies under the two incentive schemes, especially on the downside. How managers are compensated is thus critically important

[27] A better replicating portfolio can be created if we use both at-the-money and out-of-the-money put options, with strike prices spread out over a wider range below the mean price of 1. We only use at-the-money put options in Figure 1 in order to keep the replicating portfolio as simple as possible.

for the type of hedging strategies they are likely to pursue. This unique feature of the optimal hedging strategy leads to the following testable hypothesis:

H1: Managers are more likely to add a speculative position using concave derivative contracts (e.g., sold put options) to the firms' short forward hedge position if they are provided with option-based equity incentives.

Another way to compare the optimal hedging strategies under the two incentive schemes is by measuring the concavity of the hedge payoff function. Concavity, as measured by the second-order derivative, captures the extent that a nonlinear curve deviates from a straight line. The payoff of optimal hedge under restricted stock-based incentives is linear and thus has zero concavity. In comparison, the payoff of the optimal hedge under option-based incentives is concave and has negative concavity:

$$Concv^*(p) \equiv \frac{\partial^2\theta^*(p)}{\partial p^2} = \frac{\left(1-\rho\frac{\sigma_v}{\sigma_p}\right)^2}{\lambda b\sigma_v^2(1-\rho^2)} \cdot \frac{N'[-d_1(p)]}{N[-d_1(p)]} \cdot \left\{d_1(p) - \frac{N'[-d_1(p)]}{N[-d_1(p)]}\right\} \qquad (15)$$

Although there is no standard benchmark for the magnitude of concavity, the base-case scenario depicted in Figure 1 provides a reference point. Visually, the payoff of the optimal hedge under option-based incentives is quite curvy and clearly deviates substantially from the linear hedge under both naïve and the optimal hedging strategy under restricted stock-based incentives. In this case, the concavity measure for the payoff of the optimal hedge under option-based incentives is –9.8 when it is calculated at the mean price (μ_p = 1) (see Panel A of Table 3.1). To further understand what this level of concavity means, we calculate hedge ratios at three different price points: a low price of p = 0.75 (25% below the mean), a medium price of p = 1 (the mean), and a high price of p = 1.25 (25% above the mean). As shown in Panel A of Table 3.1, these hedge ratios are 5.01, 0.62 and –0.60, respectively, for the case under option-based incentives. The manager is clearly pursuing a very "dynamic" hedging strategy, with the hedge ratio varying drastically across these three price points in both magnitude and direction, in comparison with the static hedging strategy under restricted stock-based incentives.

These differences have important implications for empirical studies of corporate hedging strategies. Previous studies (e.g., Tufano, 1996; Rajgopal and Shevlin, 2002; Rogers, 2002; Bakke et al., 2016) typically use a point estimate of the hedge ratio to examine corporate hedging strategies. Such an approach is valid if firms only use linear derivative contracts in their hedging operations. If derivative contracts with concave payoffs are used, as is the case with the optimal hedge for firms using option-based equity incentives, the single hedge ratio approach may lead to inconsistent empirical findings. Depending on market conditions, the point estimate of the hedge ratio may vary substantially if the derivative contract has a highly concave payoff structure. This is potentially problematic as the hedge ratio may change drastically as market prices vary while the firm's hedging strategy remains the same. In our empirical analysis, we utilize two distinct hedge coverage ratios to deal with this problem, one for derivative contracts designated for hedging purposes (mostly linear contracts) and another for derivative contracts designated for speculative purposes (mostly nonlinear contracts).

Table 3.1 about here

3.2. Manager's risk aversion

We next explore how a manager's degree of risk aversion may influence the way they hedge. Do more risk-tolerant managers hedge less or speculate more (everything else being equal)? To find out, we compare three types of managers with low, medium and high levels of risk aversion. The degrees of risk aversion (λ) of these managers are 2, 5 and 8, respectively. The medium level of risk aversion (λ = 5) is identical to the value used in the base-case analysis as depicted in Figure 1. All other model parameters are identical to those used in the base case.

For each type of managers, we examine the optimal hedging strategy under both restricted stock-based and option-based equity incentives. The effect of risk aversion on hedging strategies is illustrated in Figure 2. Two distinct features of the optimal hedging strategies are clearly observed. One is that the manager's degree of risk aversion has no impact at all on the optimal hedging strategy if the manager is provided with restricted stock-based incentives. All three types of managers with varying degrees of risk aversion adopt the same linear contract for their optimal hedge. This is also clear from Eq. (9) which shows that the degree of risk aversion does not play any part in the optimal hedge under restricted stock-based equity incentives. These observations lead to the following testable hypothesis:

H2: Risk preference has no impact at all on the optimal hedging strategy if managers have no option-based equity incentives.

In comparison, the manager's degree of risk aversion can have a substantial impact on the optimal hedging strategy if the manager has option-based incentives. At a low level of risk aversion (e.g., λ = 2), the manager is more risk tolerant and willing to take on a more speculative position on the downside in order to gain a better payoff on the upside. The concavity of the optimal hedge payoff is –63.5 in this case (Panel B of Table 3.1), nearly two and a half times the magnitude of the corresponding measure in the base case (–25.9). At a high level of risk aversion (e.g., λ = 8), the manager is still willing to take a speculative position on the downside but to a lesser degree. Indeed, more risk-tolerant managers speculate more and are more willing to give up downside hedging gains in order to reduce upside hedging losses. These observations lead to the next testable hypothesis:

H3: For managers who are compensated with option-based equity incentives, their tendency to speculate on the downside is elevated for those who are more risk tolerant.

Figure 3.2 about here

Notice, however, that the slope or hedge ratio on the upside of the optimal hedging instrument is invariant to the manager's degree of risk aversion. While this is visually obvious in Figure 2, it is further confirmed by the optimal hedge described in Eq. (13) which has both linear and nonlinear components. The linear component

$$q_0\left(1-\rho\frac{\sigma_v}{\sigma_p}\right)(\mu_p-p)$$

is invariant to the manager's degree of risk aversion and identical to the optimal hedge for managers incentivized with restricted stock (as shown in Eq. (9)). This is the reason that the slope or hedge ratio on the upside is invariant to the manager's degree of risk aversion.

These results suggest that all managers, irrespective of their risk tolerance or type of equity incentives, pursue the same hedge position as specified by the linear component of the optimal hedge. Where they differ is their willingness to supplement this linear hedge with a speculative component on the downside. When managers have no option-based equity incentives, they are not willing to engage in any speculative activities at all. In comparison, managers are willing to take on speculative positions (e.g., sold put options) if they have option-based equity incentives. Their willingness is also stronger, the more risk tolerant they are. It is thus important to separate pure hedge positions from pure speculative positions in empirical analysis of corporate hedging decisions. To the best of our knowledge, we are the first to recognize this important distinction and incorporate it into our empirical investigation.

3.3. Other factors

Of course, the manager's risk aversion is not the only factor influencing the optimal hedging strategy. Other factors such as managerial equity ownership (*b*), stock option's strike price (π_0), the product price risk (σ_p), variable cost uncertainty (σ_v) and correlation between product price and variable cost (ρ) can also have material impact on the optimal hedging strategy. We briefly analyze these factors below.

For managerial equity ownership (*b*), its impact on optimal hedging strategy depends critically on whether the managers are compensated with stock options. In fact, the manager's equity ownership level has no impact at all on the optimal hedging strategy if they are not provided with any option-based incentives. In comparison, the manager's equity ownership has a strong influence on the optimal hedging strategy if they are provided with option-based incentives. At a higher ownership level (e.g., $b = 8\%$), the manager behaves more like someone who has a higher level of risk aversion and is less willing to take on a highly speculative position (as illustrated by the hedge ratio and concavity measures in the bottom row of Panel C). At a lower ownership level (e.g., $b = 2\%$), the reverse is true (as shown in the top row of Panel C). In these cases, the manager's cash pay as a fraction of total pay ($1–b$) becomes a reasonable proxy for the manager's risk tolerance. This theoretical result lends support to the common practice of using cash pay as a proxy for risk tolerance (e.g., Tufano, 1996; Bloom and Milkovich, 1998; Croci, del Giudice, & Jankensgard, 2017; Albuquerque et al., 2024), especially when managers have stock option incentives.

Similarly, the option's strike price (π_0), the price risk (σ_p), the uncertainty in variable cost (σ_v) and correlation between price and variable cost (ρ) can also have material impact on the optimal hedging strategy. As shown in Panels D-G in Table 3.1, all four factors have a strong impact on the optimal hedge payoff if the manager has option-based equity incentives. Both the hedge ratio and concavity can vary substantially in these cases. Take the impact of strike price on the optimal hedge payoff for example. In the base case (Panel A), the strike price is set equal to zero meaning that the manager shares the firm's profit as long as the net operating profit ($\hat{\pi}$) is positive. In this case, the concavity of the optimal hedge payoff is –9.8 suggesting that the hedge payoff is quite nonlinear (as illustrated in Figure 1). The same concavity measure rises (in magnitude) to –31.3 if the strike price increases to 0.25 and drops (in magnitude) to –0.7 if the strike price declines to –0.25. The strike price thus has a huge impact on the concavity of the optimal hedging strategy.

The other three parameters (σ_p, σ_v, and ρ) also have a large impact on the optimal hedge ratio under option-based equity incentives. While the price risk has a positive impact on the hedge ratio (in magnitude), both the uncertainty in variable cost and the correlation between price risk and uncertainty in variable cost have a negative impact. In comparison, these parameters have a much smaller impact on the optimal hedge ratio if the manager is provided with stock-based equity incentives. This is not surprising as the optimal hedging strategy calls for the use of linear derivative contracts in this case.

4. Sample Selection and Descriptive Statistics

To test the predictions of our model, we empirically investigate how managerial equity incentives impact corporate hedging decisions for U.S. firms in the oil and gas industry. Our sample includes 173 unique firms in the 18-year period from 1998 to 2015, with 1,200 firm-year observations. In order to have access to accounting and other firm related information, we restrict our sample to those covered by the Standard and Poors' Compustat database. We also exclude a handful of firms whose CEOs own 20% or more of the common shares outstanding as these firms are essentially run by owners without principal-agent conflict.[28] As summarized in Panel A of Table 3.2, firms in our sample have, on average, \$4.93 billion in total assets, \$3.95 billion in market value of equity and \$1.54 billion of proven oil and gas reserves. Most firms in our sample are profitable as indicated by the average (median) ROA of 0.18% (3.3%).

Table 3.2 about here

To find the information on the derivative contracts used in their hedging operations, we hand collect details of these contracts from their 10-K reports filed with the SEC, accessed through its Edgar database. Collectively, we have records of 3,321 individual derivative contracts used by these companies during our sample period, approximately split evenly between oil and gas contracts. There are also a small number of derivative contracts on liquified natural gas, which we classify as oil contracts because liquified natural gas is stored and priced similarly to oil. Our results are not materially affected if we exclude these contracts from the sample.

Consistent with previous studies (e.g., Croci, del Giudice, & Jankensgard, 2017), firms in our sample use both linear and nonlinear derivative contracts in their hedging operations (as shown in Table 3.3). In addition to the usual linear contracts such as forwards, futures and swaps, there are also various nonlinear contracts such as call options, put options, call spreads, put spreads, collars and three-way collars. Of course, not all contracts are employed to the same extent, with two types of contracts, swaps and collars, being used the most often, accounting for 41.9% and 28.5% of all derivative contracts used, respectively. None of the other types accounts for more than 7.3% of the contracts used. The hedging activities are also quite similar between oil and gas

[28] We also use other ownership cutoffs such as 15% or 25% to define owner managed firms and the results are not materially different.

operations, with very little difference in either the total number of derivative contracts or distribution among different types of contracts used. Overall, derivative contracts used in their hedging operations are roughly evenly split between linear and nonlinear contracts.

Table 3.3 about here

While the majority of the derivative contracts are indeed used for hedging purposes, some contracts are used for speculative purposes. As shown in Table 3.4, we identify 243 derivative contracts that are used for speculative purposes, with three-way collars, call options and put options accounting for most of these contracts. The most common type of derivative contracts used for speculative purposes is the sold put contract. There are 175 sold put option contracts employed by firms in our sample, either as a standalone sale of put options (23) or part of a three-way collar (152). These sold put contracts are roughly 72% of all contracts used for speculative purposes. This is consistent with the predictions of our theoretical model on how managers are likely to speculate if they are compensated with stock options.

Table 3.4 about here

Of course, each derivative contract alone does not capture the overall hedging strategy deployed by the firm. We need to combine all derivative positions in order to piece together the firm's overall hedging strategy. The hedging operations of Anadarko Petroleum Corp. in 2002, illustrated in Figure 3, are a good example. In that year, Anadarko used four different types of derivative contracts including collars, three-way collars, swaps and call options. For oil hedging operations, it used a *swap* at a price of \$25.56 per barrel, covering 0.4 million barrels, and a *three-way collar* with threshold prices set at \$19.11, \$23.33 and \$30.51 per barrel, covering 3.3 million barrels. The payoff of the oil hedges, ignoring the cost of the derivative contracts, is illustrated in Panel A of Figure 3. For natural gas hedging operations, it used a *collar* with a ceiling price of $5 and a floor price of $3 per MMBTU,[29] covering 2.3 million MMBTUs, a *three-way collar* with threshold prices at $2.2, $3 and $4.83 per MMBTU, covering 6.8 million MMBTUs, a *sold call option* at strike price $3.66 per MMBTU, covering 10.1 million MMBTUs, and a *purchased call option* at strike price $3.50 per MMBTU, covering 4.9 million MMBTUs. The payoff of the gas hedges is illustrated in Panel B of Figure 3. In both cases, it is clear that the upside (i.e., at higher oil or gas prices) of the payoff resembles a short forward position while the downside of the payoff is "rotated" downwards substantially by the deployment of the three-way collar position, especially below the strike price of the embedded put option ($19.11 per barrel for oil and $2.2 per MMBTU for gas). Without the sold put position embedded in the three-way collars, both oil and gas hedge payoffs would have been much closer to the straight line of the short forward contracts.

Figure 3.3 about here

While the example in Figure 3 is informative, it may not be representative of the hedging operations at other oil and gas firms. Hedging activities of most firms in our sample tend to vary from year to year and larger companies such as Anadarko tend to have more sophisticated hedging operations. To characterize the hedging strategy for each firm-year, we first identify every derivative contract used by the firm for both oil and gas operations. In the example shown in Figure 3, this would encompass two and four contracts for oil and gas hedging operations, respectively. For each contract, we classify whether it is used for hedging or speculative purposes or a combination of both. If a derivative contract is solely used for hedging purposes (e.g., a short

[29] MMBTU stands for Metric Million British Thermal Unit, a widely used volume measure for natural gas in global trades.

forward contract or a bought put option), we calculate a *pure hedge ratio* (or just *hedge ratio* when its meaning is clear from context) for such a contract:

$$Pure\ hedge\ ratio = \frac{Volume\ covered\ by\ the\ hedge}{Annual\ production\ volume}$$

where the *Annual production volume* is the total production of the commodity by the firm in the fiscal year and the *Volume covered by the hedge* is simply the annualized volume covered by the derivative contract if it is a linear contract (e.g., a short forward contract) or the annualized volume covered by the contract multiplied by the delta[30] of the derivative contract if it is a nonlinear contract (e.g., a bought put option). On the other hand, if a derivative contract is solely used for speculative purposes (e.g., a sold put option), we calculate a *pure speculative ratio* (or just *speculative ratio* when its meaning is clear from context) for such a contract:

$$Pure\ speculative\ ratio = \frac{Volume\ covered\ by\ the\ speculation}{Annual\ production\ volume}$$

where the *Volume covered by the speculation* is simply the annualized volume covered by the contract if it is a linear contract (e.g., a long forward contract) or the annualized volume covered by the contract multiplied by the delta of the derivative contract if it is a nonlinear contract (e.g., a sold put option).

In cases where a derivative contract has both hedging and speculative components, we separate the two components and calculate both a hedge ratio (for the hedge component) and a speculative ratio (for the speculative component). For example, a three-way collar is essentially a regular collar (the hedging component) plus a sold put option (the speculative component). We thus calculate a hedge ratio using the collar component and a speculative ratio using the sold put

[30] Delta is a sensitivity measure of the derivative contract, defined as the change in the value of the derivative contract with respective to a $1 change in the price of the underlying commodity (oil or gas).

option component for the three-way collar. Other derivative contracts (e.g., call or put spreads) with both components are treated similarly.[31] In addition, a derivative contract may cover only a fraction of a year or multiple years. In the former case, we annualize the coverage by multiplying the volume covered by the fraction of the year. In the latter case, we separate the volume covered in different years and include the volume in each year it covers.

Once the hedge or speculative ratio is calculated for each derivative contract, we then add up the hedge ratios across all derivative contracts for each firm-year, first for oil contracts and then for gas contracts. The speculative ratios are aggregated similarly for each firm-year separately for oil and gas contracts, respectively. Summary statistics of these firm-year hedge and speculative ratios are shown in Table 3.5. The average hedge ratio is quite similar for both oil and gas contracts, covering 36.4% and 34.5% of the annual production, suggesting that firms hedge roughly 35% of their annual production. There are also substantial variations in the hedge ratio across firm-years as the 95th and 5th percentiles of the hedge ratio are 90% and 0.1%, respectively, for both oil and gas contracts. In comparison, the average speculative ratios are 3.6% and 1.9% for oil and gas contracts, respectively, suggesting that speculative positions are much smaller in size relative to hedge positions but firms do speculate more with oil than gas contracts. There are also substantial variations in the speculative ratio across firm-years as the 95th percentile is 25.9% and 12.7% for oil and gas contracts, respectively, and the 5th percentile is 0.0% for both oil and gas contracts. We also report another version of the speculative ratio in Table 3.5, called the *normalized speculative ratio*, defined as the speculative ratio divided by the hedge ratio for the same firm-year. This is a unique speculative measure that captures the strength of the speculative component relative to the hedge component. For example, a 50% normalized speculative ratio means that roughly half of the

[31] For both hedge and speculative ratios, we define them as positive numbers, ignoring the direction of the derivative position (long or short).

hedge positions are supplemented with speculative positions in the same firm-year, typically on the downside of the payoffs. While the two speculative ratios capture different aspects of the hedging operations, the normalized version is less dependent on the scale of the hedging operations and thus more meaningful for cross sectional comparisons between firms. As such, we use normalized speculative ratio as our main speculative measure in subsequent empirical analysis.

Table 3.5 about here

Finally, we require CEO compensation data for firms in our sample, including annual total compensation (salary and bonus, restricted stock, stock options and other compensation), the portfolio of restricted stock and common stock held, and the portfolio of all outstanding stock option grants. Some firms in our sample are covered by the Execucomp database and we extract the compensation data from that database. For other firms, we search their proxy statements (schedule 14A) filed with the SEC to collect the compensation data manually. Table 3.6 provides a summary of the compensation data for firms in our sample. On average, the CEO is provided with annual total compensation of \$4.9 million, consisting of \$1.3 million in cash, \$2.7 million in restricted stock and \$1.2 million in stock options. Of course, annual compensation is not sufficient for gauging the equity incentives provided to the CEOs. In addition to the stock and options received in the annual compensation, they also have portfolios of previously granted stock and options which tend to be the dominant portion of their equity incentives. The CEOs in our sample hold a portfolio of restricted and unrestricted shares of the firm's common stock worth an average of \$45 million in market value (Panel B of Table 3.6); in comparison, their average annual stock compensation of \$2.7 million (Panel A of Table 3.6) represents only 6.0% of the total holdings.

Similarly, these CEOs hold a portfolio of stock options worth an average of $10.1 million, with the newly granted options accounting for only 11.8% of that total.

Table 3.6 about here

Following previous studies (e.g., Core and Guay, 2002; Cole, Daniel & Naveen, 2006), we calculate two measures for managerial equity incentives, delta_CEO and vega_CEO, from the portfolio of stock and options held by the CEO at the end of the fiscal year. Delta_CEO is the commonly used pay-performance sensitivity measure defined as the change in the value of the CEO equity portfolio (both stock and options) for a 1% change in the stock price. While this is sufficient to capture how the CEO's wealth is linked to shareholders' wealth, it does not reflect the risk incentives provided by the CEO's stock options. Risk-taking incentives are provided by the vega of the CEO's option portfolio, which is defined as the change in the value of the option portfolio for a 1-percentage point change in stock return volatility. Based on the median of the sample, the typical CEO's equity portfolio has a delta_CEO of $1.176 million and a normalized vega, defined as vega_CEO/delta_CEO, of 16.1%. This means that a 1% increase in the firm's stock price would lead to an increase of $1.176 million increase in the value of their equity portfolio. Likewise, a 1-percentage point increase in stock return volatility would lead to a $189,336 (i.e., 0.161×$1.176 million) increase in the value of their option portfolio. These are non-trivial levels of equity incentives for aligning the interests of the CEO with that of shareholders and for risk-taking. In the following section, we empirically investigate how these managerial equity incentives impact corporate hedging decisions.

5. Empirical Analysis

Our principal-agent model has several predictions for corporate hedging decisions as summarized by the testable hypotheses in Section 3. We empirically examine these hypotheses in this section.

5.1. Do stock options encourage speculation?

We first divide firms in our sample into terciles of their CEOs' risk incentives provided by their equity portfolios. In each year, we rank firms based on their CEOs' risk incentives as measured by their equity portfolio's normalized vega. This scaled vega measure is shown to be a good proxy for managerial risk-taking incentives (e.g., Bakke et al., 2016). While the top tercile (Tercile 3) consists of firms whose CEOs have the highest level of risk-taking incentives, the bottom tercile (Tercile 1) is exactly the opposite. Our theoretical model predicts that while all firms would have similar hedge positions by shorting forward-based derivative contracts, firms in the top tercile would be more likely to supplement these hedging positions by adding speculative positions on the downside than firms in the bottom tercile would. The results in Table 3.7 provide preliminary support for this prediction.

We report two sets of hedge and speculative coverage ratios in Table 3.7. The first set consists of the *pure* hedge ratio and *pure* speculative ratio, constructed using only derivative contracts deemed to be used for hedging and speculative purposes, respectively. The second set consists of the net hedge ratio and normalized speculative ratio. The net hedge ratio is defined as the pure hedge ratio minus the pure speculative ratio. This alternative hedge ratio is included in our analysis for robustness because it is comparable to the hedge coverage ratio used in previous studies. The normalized speculative ratio is defined as the pure speculative ratio scaled by the pure hedge ratio. It measures the size of the firm's speculative position relative to the size of its hedge position. For example, consider two firms (A and B) with the same pure speculative ratio of 3% but different pure hedge ratios of 100% and 10%, respectively. For firm A, speculation is a negligible component of its hedging operations because the size of the speculative position is merely 3% (3/100) of the size of the hedge position. In contrast, the corresponding fraction is 30% (3/10) for firm B, suggesting that speculation is sizable component of its hedging operations. The normalized speculative ratio is thus more informative of the firm's speculative activities and our primary measure of speculation in subsequent empirical analysis.

A comparison of the pure and net hedge ratios across vega terciles shows that there is little difference in how firms manage their hedge positions regardless of the level of risk incentives provided to their CEOs. While firms in the top tercile do have a slightly lower hedge ratio, the difference is quite small and statistically insignificant. This is true for both hedge ratios. For example, the average pure hedge ratio is 40.0% for firms in the top tercile while the same average is 45.4% for firms in the bottom tercile. There is thus a negative relationship between the level of the CEO's risk incentives and the firm's hedge ratio. However, the negative relationship is quite weak and statistically insignificant. These results are consistent with the prediction of our model that managerial risk-taking incentives have no impact on the firm's hedge positions.

In contrast, managerial risk incentives have a much stronger impact on how firms manage their speculative positions in financial derivatives. For firms in the top tercile of managerial risk incentives, the normalized speculative coverage ratio is on average 5.5%, suggesting that these firms use speculative financial derivatives (e.g., sold puts) to counteract 5.5% of their hedge positions. Motivated by stock option incentives, these speculative positions are likely undertaken to reduce hedging gains on the downside in order to have lower hedging losses on the upside side. The corresponding number for firms in the bottom tercile is 3.2%, suggesting that the speculative use of financial derivatives by firms in the top tercile is 72% (i.e., 5.5/3.2–1) larger than firms in the bottom tercile. Such a large difference is clearly economically substantial. The difference is also statistically significant at the 5% level. We thus have preliminary evidence that managerial risk-taking incentives indeed have a positive impact on the speculative use of financial derivatives in their hedging operations.

Table 3.7 about here

Of course, such univariate comparisons are not sufficient to confirm the predictions of our theoretical model. There are other factors that might have influenced corporate hedging decisions. To provide a more rigorous analysis of the relationship between managerial risk-taking incentives and hedging decisions, we run regressions of the hedge and speculative coverage ratios on pay-performance sensitivity (i.e., delta_CEO) and risk-taking incentives (i.e., vega_CEO/delta_CEO), controls for firm characteristics such as firm size, ROA, investment growth rate, leverage, financial distress (Altman's Z-score), cash and dividend, and firm and year fixed effects:[32]

$$
\begin{aligned}
&Coverage\ ratio_{i,t} \\
&\qquad = \alpha + \beta_1 \times ln\left(1 + delta\_CEO_{i,t-1}\right) \qquad (16) \\
&\qquad + \beta_2 \times \left(vega\_CEO_{i,t-1}/delta\_CEO_{i,t-1}\right) + \ controls \ + \varepsilon_{i,t}
\end{aligned}
$$

where *Coverage ratio*$_{i,t}$ is either the pure hedge ratio, net hedge ratio or pure speculative ratio for firm *i* in year *t* and *controls* are for the control variables included in the regression. Results of the

[32] Controls for CEO characteristics such as age, tenure and cash pay are not included here as they are also used as proxies for risk aversion. They are included subsequently when the impact of the CEO's attitude toward risk is investigated.

regression analysis are summarized in Table 3.8, with columns (1) – (4) reporting the results for the hedge ratio regressions and columns (5) and (6) for the speculative ratio regressions.

Starting with the hedge ratio regressions, neither of the CEO's equity incentive measures (delta_CEO or vega_CEO/delta_CEO) has any impact on how firms manage their hedge positions. The estimated coefficient is never statistically significant in any of the regressions for either incentive measure. This is true for both pure and net hedge ratios, suggesting that firms use similar hedge coverage ratios to manage their hedge positions regardless of the level or type of managerial equity incentives provided to their CEOs. When it comes to the use of financial derivatives in hedge positions, all firms appear to adopt similar policies.

In contrast, managerial risk incentives do influence the level of speculative activities managers engage in to supplement their firms' hedge positions. As shown in columns (5) and (6) of Table 3.8, the level of the CEO's risk incentives is positively related to the firm's speculative ratio. The coefficient of the CEO's risk incentives is positive and statistically significant in both regressions. To understand the economic significance of this positive relationship, we focus on the regression results in column (6) as it includes the full set of control variables. In that regression, the coefficient of vega_CEO/delta_CEO is 0.0342 and statistically significant at the 5% level. The size of the coefficient suggests that a one standard deviation increase in risk incentives would lead to 21% increase in the normalized speculative ratio based on the summary statistics reported in Tables 3.5 and 3.6.[33] The impact of the CEO's risk incentives on the firm's speculative activities is thus quite large economically.

[33] As reported in Tables 5 and 6, the standard deviation of the CEO's scaled risk incentives (vega_CEO/delta_CEO) is 25.7% and the mean normalized speculative ratio is 4.1%. A one standard deviation increase in the CEO's risk incentives would thus lead to an increase in the normalized speculative ratio of 25.7%×0.0342 = 0.88%. Compared to the mean normalized speculative ratio, the increase is 21.4% (0.88/4.1).

It is also interesting to note that the commonly used pay-performance sensitivity (i.e., delta_CEO) has little impact on either the hedge or speculative ratio. This is consistent with our theoretical prediction that managers implement similar hedge positions using linear derivatives (e.g., swaps) if they are only incentivized with restricted stock-based incentives. Without stock options, these managers have little incentives for speculation and are motivated to pursue hedging strategies that are comparable to those preferred by owner-managers in the absence of principal-agent conflict.

Table 3.8 about here

5.2. The impact of managerial risk aversion

Our principal-agent model also predicts that the impact of managerial risk incentives on corporate hedging decisions is further amplified for those managers who are more risk tolerant. To verify this prediction empirically, we need a proxy for the manager's degree of risk aversion. While the CEO's inside debt is the commonly used proxy in previous studies, very few CEOs in our sample have any inside debt disclosed in the firm's annual report, rendering this proxy ineffective in our setting. In addition to inside debt, previous studies (e.g., Berger, Ofek, & Yermack, 1997; Guay, 1999; Armstrong and Vashishtha, 2012) also use three other proxies for the CEO's degree of risk aversion – age, tenure and *cashfrac* (or fraction of cash pay in total compensation). We add these proxies to our main multivariate regressions:

$$
\begin{aligned}
&Coverage\ ratio_{i,t} \\
&\qquad = \alpha + \beta_1 \times ln\big(1 + delta\_CEO_{i,t-1}\big) \\
&\qquad + \beta_2 \times \big(vega\_CEO_{i,t-1}/delta\_CEO_{i,t-1}\big) \\
&\qquad + \ \gamma \times \big(Risk\ aversion_{i,t}\big) \\
&\qquad + \ \delta \times \big(Risk\ aversion_{i,t}^{High}\big) \times (vega\_CEO_{i,t-1} \\
&\qquad /delta\_CEO_{i,t-1}) + controls \ + \varepsilon_{i,t}
\end{aligned}
\tag{17}
$$

where "*Risk aversion*" is a proxy for the CEO's degree of risk aversion and "*Risk aversion*^{High}" is a dummy variable that takes the value of 1 if the risk aversion proxy is above its median and 0 otherwise. If the CEO's risk aversion has no impact at all on hedging decisions, we expect both coefficient γ and δ to be zero. If it has impact on hedging decisions, the coefficient of the interaction term δ picks up the differential impact between CEOs with high vs. low levels of risk aversion. Results of these regressions are reported in Table 3.9, separately for the pure hedge ratio, the net hedge ratio and normalized speculative ratio in Panels A-C, respectively.

Analyzing the regression results for the pure and net hedge ratios (Panels A and B, respectively), we see that the manager's degree of risk aversion has little impact on how firms use financial derivatives to hedge. The estimated coefficient for the risk aversion term (γ) is quite small and never statistically significant. The same is essentially true for the interaction term (δ) as well except that the coefficient is weakly significant at the 10% level in two of the six cases. This is not surprising as we already have confirmation that managerial equity incentives have little impact on hedge ratios (Table 3.8). Regardless of their age, tenure or level of cash compensation, there is little difference in how these managers choose the hedge ratios in their risk management program.

It is a different story when it comes to how managers supplement the firms' hedge positions with speculative positions, as shown in Panel C of Table 3.9. While neither age nor cashfrac appears to have any influence on these decisions, the CEO's tenure has a positive impact on the speculative ratio and the estimated coefficient is statistically significant at the 5% level. Entrenched CEOs are thus more likely to take on speculative positions using financial derivatives than newly appointed CEOs do, suggesting that more risk averse CEOs are less likely to speculate. This interpretation is based on the premise that risk aversion is inversely related to tenure and entrenched CEOs have more discretion over their firms' corporate policies (e.g., Tufano, 1996; Bloom and Milkovich, 1998; Albuquerque et al., 2024).

In addition, the estimated coefficient of the interaction term between the cashfrac dummy and the CEO's risk incentives is negative and statistically significant at the 1% level. It suggests that CEOs with above median level of cash compensation are less likely to take on speculative positions in financial derivatives than CEOs with below median level of cash compensation. Since cash compensation is believed to be positively related to the CEO's degree of risk aversion (e.g., Guay, 1999; Grant, Markarian, & Parbonetti, 2009; Graham, Harvey, & Puri, 2013), the negative coefficient (δ) provides further support for the positive relationship between the CEO's degree of risk tolerance and the level of the firm's speculative activities.

Table 3.9 about here

5.3. Stock options and cash flow volatility

We have already confirmed that firms speculate more with financial derivatives if their CEOs are provided with stronger risk-taking incentives. This positive association suggests that stronger managerial option incentives do indeed lead to more risk-taking behavior in corporate hedging operations. However, these speculative positions in financial derivatives are also much smaller in scale and comparable to only 4.1% of the firm's hedge positions in size. At such a small scale, do these speculative activities have any negative impact on shareholders' welfare even if managers undertake these activities for their own benefit?

In this section, we investigate whether the positive relationship between managerial option incentives and speculative behavior in hedging operations has any impact on the firm's investment risk. This is important as an excessive level of investment risk may be harmful to shareholders' welfare. Following prior research (e.g., Bakke et at., 2016), we use cash flow volatility to measure a firm's investment risk. While there are other measures of volatility such as the standard deviation of stock returns, cash flow volatility is more appropriate in our setting since it directly captures the impact of hedging decisions on cash flows from operations. In comparison, stock return volatility is impacted by overall stock market activities and industry trends as well as corporate hedging decisions. Similar to Bakke et al. (2016), we calculate cash flow volatility as the standard deviation of quarterly net cash flow from operations as a fraction of total assets, using the eight quarters in the concurrent year and the previous fiscal year. We then run regressions of the cash flow volatility on pay-performance sensitivity (delta_CEO), managerial risk incentives (vega_CEO/delta_CEO), hedge and speculative ratios, and control variables. Results of these regressions are summarized in Panel A of Table 3.10.

Neither hedge nor speculative ratio has much impact on cash flow volatility. In particular, the estimated coefficient is quite small and statistically insignificant for both coverage ratios in the full regression with all control variables included, as reported in column (3) of Panel A in Table 3.10. Similarly, neither the CEO's pay-performance sensitivity nor risk-taking incentives have any visible impact on cash flow volatility. These results suggest that the firm's investment risk is not influenced by the CEO's risk-taking incentives or speculative behavior in hedging operations. It is interesting, however, that both coefficients of the hedge and speculative coverage ratios are negative, suggesting that both types of activities tend to reduce cash flow volatility. As expected, the negative relationship is slightly stronger between hedge ratio and cash flow volatility. Nevertheless, the magnitude of such impact is quite small, both statistically and economically.

Table 3.10 about here

5.4. Stock options and firm valuation

Although managerial option incentives have little impact on cash flow volatility, do they have any impact on firm valuation? Ultimately, it is valuation that shareholders pay the most attention to. To answer this question, we calculate each firm's Tobin's Q and use it as a proxy for firm valuation. We then run regressions of Tobin's Q on pay-performance sensitivity (delta_CEO), risk incentives (vega_CEO/delta_CEO), hedge and speculative ratios, and control variables. Results of these regressions are summarized in Panel B of Table 3.10.

Consistent with previous studies (e.g., Allayannis and Weston, 2001; Carter, Rogers, & Simkins, 2006; Campello et al., 2011), we find a positive relationship between hedging and firm valuation. The estimated coefficient of the pure hedge ratio is positive and statistically significant at the 1% level. The economic significance is also substantial, with a one standard deviation increase in the hedge ratio leading to a 4.1% increase in the firm's Tobin's Q.[34] The impact on firm value is slightly less than, but in line with, what is reported in previous studies (e.g., Allayannis and Weston, 2001; Carter, Rogers, & Simkins, 2006). Such positive value effect could

[34] As reported in Table 3.5, the standard deviation of (pure) hedge ratio is 33.4% (combining both oil and gas contracts). Given the estimated coefficient of the (pure) hedge ratio of 0.1230 in column (3) of Panel B Table 3.10, a one-standard deviation increase in the hedge ratio would thus lead to a 4.11% (= 0.334×0.123) increase in the Tobin's Q.

be due to a reduction in expected costs of financial distress, lower borrowing cost or increase in investments (e.g., Campello et al., 2011).

In comparison, speculative activities in the hedging operations have no impact at all on firm valuation. As reported in column (3) of Panel B in Table 3.10, the estimated coefficient of the normalized speculative ratio is virtually zero, with a zero Student *t*-statistic. The lack of any statistical and economic significance provides further confirmation that managers are not reckless in pursuing their own interests at the cost of shareholders' welfare. While these speculative positions in financial derivatives (mostly sold put positions) may be potentially costly during a downturn, there is no evidence that shareholders' welfare is compromised. The small size of these speculative positions, relative to the size of the firm's hedge positions, may be a contributing factor.

5.5. Endogeneity

While there are different approaches to dealing with endogeneity in prior literature such as comparison of treatment and control firms based on propensity score matching or two-stage least squares regressions (e.g., Bartram et al., 2011; Chen, 2011; Chen and King, 2014; Ahmed et al., 2020), we follow Bakke et al. (2016) and use a quasi-natural experiment approach. The idea is to take advantage of an exogenous shock due to the implementation of FAS 123R in 2005 that requires companies to expense their stock option grants in their reported earnings. In reaction to the requirement, companies have reduced their use of stock option grants as incentive pay in favor of more restricted stock grants. As the requirement does not have any obvious impact on how firms should hedge (other than through the reduction in stock option grants), it is an ideal experiment to deal with endogeneity concerns.

As in Bakke et al. (2016), we use the four-year window (2003-2006) surrounding the implementation of FAS 123R to implement the tests. The choice of the relatively short period is to ensure that the impact of the shock remains strong during the window. In the pre-event period (2003 and 2004), we class firms into two non-overlapping groups: treated firms and control firms. Control firms are those that either did not grant any stock options in the two years before the event or did grant stock options but pre-emptively adopted FAS 123R before 2003.[35] The rest of the firms are regarded as treated firms that are impacted more heavily by the adoption of FAS 123R. We expect that the adoption to have little impact on how control firms hedge but reduce the tendency for treated firms to speculate (due to the reduction in their use of stock option grants).

We first use the following difference-in-differences (DID) regressions to confirm that the implementation of FAS 123R leads to a reduction in stock option grants and a corresponding increase in restricted stock grants:

$$
\begin{aligned}
ln\left(1 + delta\_CEO_{i,t}\right) \\
&= \alpha_{delta} + \beta_{delta} \times \mathrm{FAS}_t + \gamma_{delta} \times \mathrm{Treat}_i + \delta_{delta} \times (\mathrm{FAS}_t \times \mathrm{Treat}_i) \\
&+ \ controls \ + \varepsilon_{i,t}
\end{aligned}
$$

$$
\begin{aligned}
ln\left(1 + vega\_CEO_{i,t}\right) \\
&= \alpha_{vega} + \beta_{vega} \times \mathrm{FAS}_t + \gamma_{vega} \times \mathrm{Treat}_i + \delta_{vega} \times (\mathrm{FAS}_t \times \mathrm{Treat}_i) \\
&+ \ controls \ + \varepsilon_{i,t}
\end{aligned}
$$

where FAS_t is a dummy variable that is 1 after the adoption and zero before the adoption and Treat_i is an indicator variable that is 1 for treated firms and zero for control firms. We expect to find $\delta_{vega} < 0$ and $\delta_{delta} = 0$ because treated firms reduce their stock option grants and simultaneously increase

[35] There is only one firm in our sample that preemptively adopted the measure, Remington oil & gas.

their restricted stock grants after the adoption of FAS 123R. Untabulated results confirm that this is indeed the case.

We then use the following DID regression to investigate the impact of the FAS 123R adoption on the speculative use of derivatives:

$$\begin{aligned} &Normalized\ Speculative\ ratio_{i,t} \\ &\quad = \alpha + \gamma \times \mathrm{FAS}_t + \delta \times \mathrm{Treat}_i + \theta \times (\mathrm{FAS}_t \times \mathrm{Treat}_i) \\ &\quad + \beta_1 \times ln\left(1 + delta\_CEO_{i,t-1}\right) + \beta_2 \times \left(vega\_CEO_{i,t-1}/delta\_CEO_{i,t-1}\right) \\ &\quad + \ controls \ + \varepsilon_{i,t} \end{aligned}$$

We expect that $\theta < 0$ because treated firms reduce their stock option grants after the adoption of FAS 123R. Results of these regressions are summarized in Table 3.11, together with the corresponding regressions for the pure hedge ratio and net hedge ratio for comparison purposes.

Table 3.11 about here

As shown in Table 11, the coefficient of *FAS*×*Treat* (θ) is indeed negative and statistically significant in the normalized speculative ratio regression (column 6), confirming that treated firms reduce their speculative use of derivatives relative to control firms after the adoption of FAS 123R. The corresponding coefficients for the pure hedge ratio regression (column 2) and net hedge ratio regression (column 4), respectively, are positive but statistically insignificant. The adoption of FAS 123R has a positive impact on the use of derivatives for hedging purposes for treated firms in comparison with control firms, consistent with the findings of Bakke et al. (2016). The effect is relatively small in comparison with the corresponding impact on the use of derivatives for speculative purposes, however. These findings further confirm that stock option grants have a positive impact on the speculative use of derivatives and little impact on the hedging use of derivatives, even after accounting for endogeneity concerns such as omitted variables, selection bias or reverse causality.

5.6. CFO risk-taking incentives

Barbi, Febo & Massimiliani (2024) document a negative relationship between CFO compensation convexity and corporate hedging intensity and, more interestingly, the CFO's risk-taking incentives have a stronger impact on corporate hedging intensity than the CEO's. To verify if this is also true in our sample, we replicate the regression results reported in Table 8 by including the CFO's pay-performance sensitivity (*delta_CFO*) and risk incentives (*vega_CFO/delta_CFO*) together with the corresponding CEO measures. While we use three hedge coverage ratios (the pure hedge ratio, net hedge ratio and normalized speculative ratio), Barbi, Febo & Massimiliani (2024) use only one hedge coverage ratio (which is similar to our net hedge ratio). The new results are reported in Table 3.12.

Table 3.12 about here

As shown in Table 3.12, the positive relationship between the CEO's risk-taking incentives (vega) and the speculative use of derivatives (normalized speculative ratio) continues to hold but the CFO's risk-taking incentives have little impact on any of the three coverage ratios. This is also true if we drop the CEO's incentive measures (both delta and vega) and replace them with the CFO's incentive measures in the regression analysis (not reported here for brevity). We do not have a good explanation for the diverging findings between the two studies except that they use a different hedging measure and a different sample period. We argue that our results are more reasonable because the CEO is ultimately responsible for the firm's performance and the board is more likely to blame the CEO instead of the CFO if the firm's hedging operations do not work out as expected. Even though the CFO is responsible for designing and executing the hedging strategy, the buck stops here with the CEO. It would reflect very poorly on the CEO's leadership if they failed to understand or keep an eye on the firm's hedging strategy.

6. Conclusion

In this paper, we study how managerial equity incentives impact corporate hedging decisions in the presence of principal-agent conflict. We show, both theoretically and empirically, that the optimal hedging strategy depends critically on the types of equity incentives managers have. If managers have linear equity incentives (e.g., restricted stock), they are motivated to pursue a simple hedging strategy by shorting forward-like derivative contracts, just like what owner-managers would do in the absence of principal-agent conflict. In comparison, managers are motivated to pursue a hybrid hedging strategy with a hedging component identical to the one used by owner-managers and a speculative position in concave derivative contracts (e.g., sold put options) if they are compensated with stock option grants. The willingness to speculate is more pronounced for managers who are more risk tolerant.

One caveat of our analysis is that our empirical methodology may not directly apply outside of the oil and gas industry because other industries do not disclose detailed information on financial derivatives they use in their hedging operations. The precise measures of the pure hedge and pure speculative ratios may not be possible outside of the oil and gas industry. It is possible that the positive relationship between risk-taking incentives and the speculative use of derivatives does extend beyond the oil and gas industry. It requires a different approach to investigate it, however, and is left for future research.

Table 3.1: Optimal hedge ratio and payoff concavity

Parameter value	Hedge ratio					Concavity
	Naive	Stock pay	Option pay			Option pay
			Low price (p = 0.75)	Medium price (p = 1)	High price (p = 1.25)	
Panel A: Base case – all parameters assume the base-case values						
	–1	–0.75	5.01	0.62	–0.60	–25.9
Panel B: The impact of managerial risk aversion						
$\lambda = 2$	–1	–0.75	13.16	2.49	–0.40	–63.5
$\lambda = 8$	–1	–0.75	2.97	0.15	–0.65	–16.5
Panel C: The impact of managerial ownership						
b = 2%	–1	–0.75	13.16	2.49	–0.40	–63.5
b = 8%	–1	–0.75	2.97	0.15	–0.65	–16.5
Panel D: The impact of option strike price						
$\pi_0 = -0.25$	–1	–0.75	–0.03	–0.69	–0.75	–5.9
$\pi_0 = 0.25$	–1	–0.75	16.93	7.39	1.63	–43.9
Panel E: The impact of price volatility						
σ_p = 10%	–1	–0.50	2.06	0.41	–0.27	–9.0
σ_p = 30%	–1	–0.83	6.39	0.69	–0.71	–34.3
Panel F: The impact of cost volatility						
σ_v = 10%	–1	–0.88	5.67	–0.85	–0.87	–89.4
σ_v = 30%	–1	–0.63	3.35	1.45	0.27	–9.0
Panel G: The impact of correlation between price and cost						
$\rho = 0$	–1	–1.00	9.70	0.97	–0.90	–52.7
$\rho = 0.5$	–1	–0.50	1.84	0.17	–0.38	–9.8

Optimal hedging strategies are compared on hedge ratio and payoff concavity. For the case of option-based equity incentives, hedge ratio is reported at different price levels. While Panel A presents the base-case results, other panels show results if one model parameter deviates from the base-case value. The following set of parameter values are taken as the base case values: Both the expected price of the firm's product (μ_p) and its quantity manufactured (q_0) during the period are normalized at 1; The fixed cost is 0.4; The mean of the variable cost per unit (μ_v) is 0.25; The correlation coefficient between price and variable cost is +0.25; The volatility (standard deviation) of both the price and variable cost are 20%. The manager's degree of risk aversion (λ) is 5; The manager's equity compensation (either restricted stock or option) represents 5% ownership (or potential ownership) of the firm (b). The strike price (i.e., target net operating profit π_0) of the manager's stock options is zero.

Table 3.2: Summary statistics of firm characteristics

	N	Mean	SD	Median	Min	Max
Total assets ($b)	1193	4.926	11.578	1.123	0.031	52.081
Market value of equity ($b)	1166	3.951	9.310	0.822	0.006	4.312
Value of reserves ($b)	1164	1.542	5.142	0.007	0.000	29.120
Value of production ($m)	1182	38.50	128.83	0.06	0.00	722.02
ROA (%)	1200	0.18	15.16	3.29	-15.52	28.03
Leverage (%)	1193	35.98	22.81	33.28	0.00	114.34
Inv_growth (%)	1200	63.46	1500.06	1.85	-87.14	403.30
Fin_distress	1200	12.73	125.74	2.26	-3.27	10.21
Dividend	1200	0.370	0.483	0.000	0.000	1.000
Payout ratio	1186	0.472	11.812	0.000	0.000	3.892
Cash flow volatility	1160	0.057	0.029	0.051	0.013	0.168
Tobin's Q	1163	1.483	0.703	1.338	0.600	3.901

This table reports the summary statistics of firm characteristics such as firm size (total assets), the value of reserves, profitability (ROA), leverage and valuation (Tobin's Q). Definitions of all variables are in the appendix. To remove extreme outliers, all continuous variables are winsorized at the 1% and 99% cutoffs.

Table 3.3: Types and frequency of derivative contracts used in hedging operations

	Oil		Gas		Total	
Contract type	Number	%	Number	%	Number	%
Forward	35	2.22	66	3.78	101	3.04
Futures	50	3.17	77	4.41	127	3.82
Swap	691	43.85	701	40.17	1,392	41.92
Call	54	3.43	41	2.35	95	2.86
Put	115	7.30	127	7.28	242	7.29
Call spread	4	0.25	5	0.29	9	0.27
Put spread	3	0.19	7	0.40	10	0.30
Collar	455	28.87	490	28.08	945	28.46
Three-way collar	89	5.65	65	3.72	154	4.64
Other	80	5.08	166	9.51	246	7.41
Total	1,576	100.0	1,745	100.0	3,321	100.0

For the 173 unique oil and gas firms in our 1998-2015 sample period, a total of 3,321 derivative contracts are identified in their hedging operations. These contracts are used to hedge either oil or gas productions. There are also a small number of observations for Liquified Natural Gas (LNG) which are included in the oil category as LNG is stored and priced much closer to oil than natural gas.

Table 3.4: Derivative contracts used for hedging vs. speculative purposes

	Hedging		Speculative		Total	
Contract type	Number	%	Number	%	Number	%
Forward	89	3.16	3	1.23	92	3.16
Futures	97	3.44	7	2.88	104	3.58
Swap	1,328	47.14	6	2.47	1,334	45.87
Call	44	1.56	49	20.16	93	3.20
Put	206	7.31	23	9.47	229	7.87
Call spread	5	0.18	3	1.23	8	0.28
Put spread	2	0.07	0	0	2	0.07
Collar	894	31.74	0	0	894	30.74
Three-way collar	152	5.40	152	62.55	152	5.23
Total	2,817	100.0	243	100.0	2,908	100.0

This table shows the different types of derivative contracts used for pure hedging purposes and pure speculative purposes. These contracts are about evenly split between linear (e.g., forward, futures and swap) and nonlinear (e.g., call, put and collar) contracts. If a derivative contract is used for both hedging and speculative purposes, it is included in both categories.

Table 3.5: Hedge and speculative coverage ratios for oil and gas productions

Statistic	Oil coverage ratio			Gas coverage ratio			Total coverage ratio		
	Hedge	Speculative		Hedge	Speculative		Hedge	Speculative	
	Pure	Pure	Normalized	Pure	Pure	Normalized	Pure	Pure	Normalized
Mean	0.364	0.036	0.051	0.345	0.019	0.032	0.354	0.027	0.041
St. dev	0.347	0.131	0.151	0.320	0.081	0.111	0.334	0.110	0.133
95th percentile	0.900	0.259	0.440	0.900	0.127	0.287	0.900	0.211	0.390
90th percentile	0.856	0.077	0.219	0.759	0.000	0.017	0.802	0.026	0.130
Q3	0.577	0.000	0.000	0.534	0.000	0.000	0.550	0.000	0.000
Median	0.314	0.000	0.000	0.277	0.000	0.000	0.291	0.000	0.000
Q1	0.092	0.000	0.000	0.082	0.000	0.000	0.085	0.000	0.000
10th percentile	0.007	0.000	0.000	0.007	0.000	0.000	0.007	0.000	0.000
5th percentile	0.001	0.000	0.000	0.001	0.000	0.000	0.001	0.000	0.000

This table provides summary statistics for hedge and speculative coverage ratios for the 1,757 firm-year observations of oil and gas firms in the period 1998-2015. For each commodity (oil or gas) in each firm-year, we calculate the pure hedge coverage ratio for all derivative contracts that are used for hedging purposes (i.e., whose payoffs are negatively correlated with the price of the underlying commodity). Similarly, we calculate a corresponding pure speculative coverage ratio for all derivative contracts that are used for speculative purposes (i.e., whose payoffs are positively correlated with the price of the underlying commodity). We also calculate the normalized speculative coverage ratio which is defined as the pure speculative coverage ratio divided by the hedge coverage ratio. We also aggregate coverage ratios, combining both oil and gas contracts, and calculate a total coverage ratio for both commodities. This total coverage ratio is an average of the two coverage ratios, weighted by the dollar values covered by oil and gas contracts, respectively.

Table 3.6: CEO annual compensation, equity portfolio incentives and risk aversion

Panel A: Annual compensation ($m)				
Statistic	Cash	Stock	Options	Total
Mean	1.330	2.710	1.192	4.879
St. Dev	3.437	4.457	2.948	8.158
99th percentile	4.400	23.925	9.263	35.712
90th percentile	2.472	7.192	3.285	10.748
Q3	1.350	3.405	1.355	5.357
Median	0.845	1.128	0.250	2.610
Q1	0.522	0.000	0.000	0.981
10th percentile	0.338	0.000	0.000	0.476
1st percentile	0.152	0.000	0.000	0.160
Panel B: Equity portfolio incentives ($m)				
Statistic	Stock	Options	Delta_CEO	Vega_CEO/Delta_CEO
Mean	45.433	10.090	1.176	0.161
St. Dev	197.931	22.909	2.834	0.257
99th percentile	755.691	104.902	16.682	1.123
90th percentile	72.092	24.651	2.681	0.545
Q3	24.290	10.697	1.000	0.216
Median	8.374	2.738	0.350	0.031
Q1	1.878	0.276	0.119	0.000
10th percentile	0.365	0.000	0.004	0.000
1st percentile	0.000	0.000	0.002	0.000
Panel C: Proxies for risk aversion				
Statistic	Age	Tenure	Cashfrac	
Mean	55.35	6.75	0.41	
St. Dev	7.23	5.79	0.29	
99th percentile	74.00	26.69	1.00	
90th percentile	64.00	14.22	0.91	
Q3	60.00	9.09	0.59	
Median	55.00	5.00	0.35	
Q1	51.00	2.48	0.17	
10th percentile	47.00	1.00	0.10	
1st percentile	36.00	0.60	0.03	

This table reports summary statistics of the CEO's annual compensation including cash pay (salary and bonus), stock awards, option awards, and total compensation (Panel A), the incentives provided by their equity portfolios (Panel B), and proxies for risk aversion (Panel C). Definitions of all variables are in the Appendix.

Table 3.7: The Impact of stock option incentives on corporate hedging decisions: tercile comparison

		Mean coverage ratio			
		Hedge		Speculative	
Group	N	Pure	Net	Pure	Normalized
3. Top vega tercile	257	0.400	0.372	0.024	0.055
2. Middle vega tercile	249	0.418	0.401	0.012	0.023
1. Bottom vega tercile	257	0.454	0.432	0.018	0.032
Difference (3 – 1)		-0.054	-0.063	0.006	0.024
t-test		-1.330	-1.556	0.933	2.125**

This table compares the use of derivative contracts in hedging and speculative activities when the CEO is provided with different levels of stock option incentives, as measured by the pure hedge ration, net hedge ratio and pure speculative ratio. The normalized speculative ratio is a scaled ratio, defined as the pure speculative ratio divided by the pure hedge ratio. Each of the four coverage ratios is compared between firms that provide their CEOs with different levels of stock option incentives from the top tercile to the bottom tercile of Vega_CEO/Delta_CEO (i.e., the normalized vega of the CEO's option portfolio). Definitions of all variables are in the Appendix. Statistical significance is provided for the difference in mean coverage ratios between the top and bottom terciles of vega incentives, with 1%, 5% and 10% significance denoted by ***, ** and *, respectively.

Table 3.8: Regressions of hedge and speculative ratios on managerial equity incentives

	Hedge ratio				Speculative ratio	
	Pure		Net		Normalized	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1 + delta_CEO)	-0.0057	0.0046	-0.0104	-0.0008	0.0062***	0.0033
	(-0.68)	(0.37)	(-1.25)	(-0.06)	(3.24)	(1.10)
vega_CEO/ delta_CEO	0.0536	-0.0097	0.0244	-0.0385	0.0354***	0.0342**
	(0.94)	(-0.14)	(0.44)	(-0.55)	(2.79)	(2.06)
Ln (Total assets)		0.0187		0.0168		0.0030
		(0.72)		(0.64)		(0.48)
ROA		0.2150*		0.2170*		-0.0254
		(1.82)		(1.84)		(-0.89)
Inv_growth		0.0058		0.0117		-0.0025
		(0.27)		(0.54)		(-0.49)
Leverage		0.1250*		0.1160*		0.0060
		(1.80)		(1.67)		(0.36)
Fin_distress		-0.0025		-0.0039		0.0009
		(-0.75)		(-1.20)		(1.19)
Payout ratio		-0.1250		-0.1200		-0.0178
		(-1.67)		(-1.59)		(-0.98)
Dividend		-0.0334		-0.0541		0.0359**
		(-0.42)		(-0.68)		(1.92)
Constant	0.4110***	0.2020	0.4210***	0.2450	-0.0093	-0.0339
	(7.55)	(1.05)	(7.84)	(1.27)	(-0.75)	(-0.73)
Year fixed effect	No	Yes	No	Yes	No	Yes
Firm fixed effect	No	Yes	No	Yes	No	Yes
# of observations	990	945	990	945	932	893
Adjusted R^2	0.000	0.398	0.001	0.378	0.011	0.308

This table reports the results of regressions of the pure hedge ratio, net hedge ratio and normalized speculative ratio on managerial equity incentives and control variables. The level of the CEO's equity incentives is proxied by their equity portfolio's delta_CEO and vega_CEO. Control variables for firm characteristics include firm size, ROA, investment growth rate, leverage, financial distress (Altman's Z-score), payout ratio and dividends. Control variables for CEO characteristics include age, tenure and cash pay as a fraction of total compensation. Definitions of all variables are in the Appendix. The table reports *t*-values in parentheses, with standard errors are clustered at the firm level. 1%, 5% and 10% significance are denoted ***, ** and *, respectively.

Table 3.9: The influence of the CEO's risk aversion on hedging decisions

Panel A: Pure hedge ratio				
Variable	(1)	(2)	(3)	(4)
LN (1 + delta_CEO)	0.0056	0.0036	0.0042	0.0055
	(0.44)	(0.28)	(0.33)	(0.41)
Vega_CEO/delta_CEO	-0.0648	0.0143	0.0387	0.0096
	(-0.80)	(0.19)	(0.50)	(0.11)
Age	-0.0021			-0.0045
	(-0.54)			(-1.06)
Tenure		0.0037		0.0043
		(0.90)		(0.95)
Cashfrac			0.0178	0.0207
			(0.26)	(0.30)
Age_high×(Vega_CEO/delta_CEO)	0.1470			0.1580
	(1.36)			(1.46)
Tenure_high×(Vega_CEO/delta_CEO)		-0.1070		-0.1380
		(-0.82)		(-1.05)
Cashfrac_high×(Vega_CEO/delta_CEO)			-0.1860*	-0.1970*
			(-1.81)	(-1.92)
Ln (Total assets)	0.0195	0.0185	0.0225	0.0218
	(0.74)	(0.71)	(0.86)	(0.83)
ROA	0.2170*	0.2120*	0.1890	0.1840
	(1.84)	(1.80)	(1.60)	(1.55)
Inv_growth	0.0059	0.0070	0.0016	0.0024
	(0.27)	(0.33)	(0.07)	(0.11)
Leverage	0.1230*	0.1260*	0.1210*	0.1200*
	(1.78)	(1.81)	(1.74)	(1.72)
Fin_distress	-0.0023	-0.0024	-0.0021	-0.0021
	(-0.70)	(-0.74)	(-0.65)	(-0.63)
Cash	-0.1250*	-0.1240	-0.1120	-0.1080
	(-1.66)	(-1.65)	(-1.44)	(-1.38)
Dividend	-0.0337	-0.0399	-0.0394	-0.0437
	(-0.42)	(-0.50)	(-0.49)	(-0.54)
Constant	0.3040	0.1880	0.1720	0.3930
	(1.05)	(0.98)	(0.87)	(1.29)
Number of observations	945	945	936	936
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.397	0.397	0.401	0.401

Panel B: Net hedge ratio				
Variable	(1)	(2)	(3)	(4)
LN (1 + delta_CEO)	0.0010	0.0005	-0.0004	0.0034
	(0.08)	(0.04)	(-0.03)	(0.26)
Vega_CEO/delta_CEO	-0.110	-0.0254	-0.0087	-0.0633
	(-1.37)	(-0.35)	(-0.11)	(-0.70)
Age	-0.0037			-0.0049
	(-0.95)			(-1.16)
Tenure		0.0007		0.0012
		(0.17)		(0.26)
Cashfrac			0.0012	0.0067
			(0.02)	(0.10)
Age_high×(Vega_CEO/delta_CEO)	0.1880*			0.1970*
	(1.73)			(1.81)
Tenure_high×(Vega_CEO/delta_CEO)		-0.0848		-0.1150
		(-0.65)		(-0.88)
Cashfrac_high×(Vega_CEO/delta_CEO)			-0.1300	-0.1430
			(-1.26)	(-1.38)
Ln (Total assets)	0.0171	0.0162	0.0183	0.0177
	(0.65)	(0.62)	(0.70)	(0.67)
ROA	0.2190*	0.2140*	0.1980*	0.1930
	(1.85)	(1.81)	(1.67)	(1.63)
Inv_growth	0.0115	0.0123	0.0064	0.0065
	(0.53)	(0.57)	(0.29)	(0.30)
Leverage	0.1140	0.1180*	0.1130	0.1120
	(1.64)	(1.69)	(1.62)	(1.61)
Fin_distress	-0.0038	-0.0039	-0.0037	-0.0036
	(-1.15)	(-1.19)	(-1.13)	(-1.09)
Cash	-0.1180	-0.1190	-0.0917	-0.0875
	(-1.57)	(-1.58)	(-1.18)	(-1.12)
Dividend	-0.0529	-0.0543	-0.0609	-0.0590
	(-0.66)	(-0.67)	(-0.76)	(-0.73)
Constant	0.4340	0.2400	0.2340	0.4810
	(1.50)	(1.24)	(1.18)	(1.58)
Number of observations	945	945	936	936
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.379	0.377	0.380	0.380

Panel C: Normalized speculative ratio				
Variable	(1)	(2)	(3)	(4)
LN (1 + delta_CEO)	0.0031	0.0018	0.0024	0.0011
	(1.02)	(0.57)	(0.79)	(0.35)
Vega_CEO/delta_CEO	0.0321*	0.0436**	0.0577***	0.0653***
	(1.66)	(2.48)	(3.10)	(3.02)
Age	0.0003			(3.02)
	(0.34)			-0.0007
Tenure		0.0023**		0.0026**
		(2.32)		(2.42)
Cashfrac			0.0238	0.0235
			(1.44)	(1.42)
Age_high×(Vega_CEO/delta_CEO)	0.0074			0.0109
	(0.28)			(0.42)
Tenure_high×(Vega_CEO/delta_CEO)		-0.0260		-0.0367
		(-0.84)		(-1.18)
Cashfrac_high×(Vega_CEO/delta_CEO)			-0.0721***	-0.0739***
			(-2.87)	(-2.94)
Ln (Total assets)	0.0033	0.0031	0.0057	0.0055
	(0.53)	(0.49)	(0.91)	(0.88)
ROA	-0.0248	-0.0264	-0.0335	-0.0353
	(-0.87)	(-0.92)	(-1.17)	(-1.23)
Inv_growth	-0.0024	-0.0021	-0.0017	-0.0012
	(-0.47)	(-0.41)	(-0.32)	(-0.23)
Leverage	0.0058	0.0049	0.0053	0.0043
	(0.34)	(0.29)	(0.32)	(0.25)
Fin_distress	0.0010	0.0009	0.0011	0.0010
	(1.23)	(1.18)	(1.36)	(1.33)
Cash	-0.0184	-0.0181	-0.0307	-0.0302
	(-1.01)	(-1.00)	(-1.64)	(-1.61)
Dividend	0.0352*	0.0314*	0.0356*	0.0315*
	(1.87)	(1.67)	(1.90)	(1.67)
Constant	-0.0525	-0.0387	-0.0591	-0.0270
	(-0.75)	(-0.83)	(-1.23)	(-0.37)
Number of observations	893	893	884	884
Year fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Adjusted R^2	0.306	0.311	0.311	0.313

This table reports the results of regressions of the pure hedge ratio, net hedge ratio and normalized speculative ratio on managerial equity incentives, a proxy for the CEO's risk aversion, an interaction term between the CEO's risk aversion and normalized vega, and control variables. The level of the CEO's equity incentives is proxied by their equity portfolio's delta_CEO and vega_CEO. Control variables for firm characteristics include firm size, ROA, investment growth rate, leverage, financial distress (Altman's Z-score), cash and dividend. Control variables for CEO characteristics include age, tenure and cash pay as a fraction of total compensation. Definitions of all variables are in the Appendix. The table reports *t*-values in parentheses, with standard errors are clustered at the firm level. 1%, 5% and 10% significance are denoted ***, ** and *, respectively.

Table 3.10: The impact of managerial equity incentives on cash flow volatility and firm valuation

Panel A: Cash flow volatility			
Variable	(1)	(2)	(3)
Ln (1 + delta_CEO)	0.0011*		0.0007
	(1.92)		(1.11)
Vega_CEO/delta_CEO	0.0003		-0.0012
	(0.10)		(-0.36)
Pure hedge ratio		-0.0033*	-0.0030
		(-1.89)	(-1.63)
Speculative ratio		-0.0090	-0.0071
		(-1.24)	(-0.95)
Ln (Total assets)	-0.0088***	-0.0087***	-0.0091***
	(-7.29)	(-7.59)	(-7.37)
ROA	0.0000	-0.0048	-0.0025
	(0.00)	(-0.87)	(-0.45)
Inv_growth	0.0008	-0.0002	0.0004
	(0.85)	(-0.22)	(0.36)
Leverage	-0.0006	-0.0010	-0.0008
	(-0.21)	(-0.32)	(-0.24)
Fin_distress	0.0007***	0.0008***	0.0008***
	(4.75)	(5.05)	(4.84)
Cash	0.0010	0.0008	0.0008
	(0.27)	(0.25)	(0.22)
Dividend	-0.0026	-0.0024	-0.0023
	(-0.68)	(-0.63)	(-0.59)
CEO age	0.0001	0.0003*	0.0002
	(0.62)	(1.77)	(1.24)
CEO tenure	0.0002	0.0002	0.0002
	(0.95)	(1.22)	(0.95)
CEO cashfrac	-0.0026	-0.0031	-0.0028
	(-0.94)	(-1.10)	(-0.97)
Constant	0.1090***	0.1060***	0.1100***
	(8.17)	(8.01)	(8.01)
Year and industry fixed effect	Yes	Yes	Yes
Number of observations	940	894	851
Adjusted R^2	0.535	0.558	0.542

Panel B: Tobin's Q			
Variable	(1)	(2)	(3)
Ln (1 + delta_CEO)	-0.0673***		-0.0621***
	(-4.99)		(-4.48)
Vega_CEO/delta_CEO	-0.0148		0.0464
	(-0.20)		(0.62)
Pure hedge ratio		0.1240***	0.1230***
		(3.11)	(3.06)
Speculative ratio		0.0437	0.0000
		(0.26)	(0.00)
Ln (Total assets)	-0.0676**	-0.1000***	-0.0735***
	(-2.48)	(-3.82)	(-2.68)
ROA	-0.2180*	-0.3060**	-0.3390***
	(-1.79)	(-2.45)	(-2.69)
Inv_growth	-0.0621***	-0.0708***	-0.0625***
	(-2.77)	(-3.19)	(-2.72)
Leverage	0.6780***	0.6490***	0.6220***
	(9.50)	(8.97)	(8.38)
Fin_distress	-0.0422***	-0.0448***	-0.0451***
	(-12.24)	(-12.80)	(-12.83)
Cash	-0.0111	0.0564	-0.0306
	(-0.14)	(0.79)	(-0.37)
Dividend	-0.0684	-0.1020	-0.0735
	(-0.83)	(-1.20)	(-0.88)
CEO age	0.0041	0.0022	0.0036
	(1.02)	(0.53)	(0.87)
CEO tenure	-0.0096**	-0.0142***	-0.0085**
	(-2.23)	(-3.41)	(-1.98)
CEO cashfrac	0.0720	0.1020	0.0984
	(1.15)	(1.57)	(1.49)
Constant	0.3120	0.2940	0.3170
	(1.03)	(0.97)	(1.03)
Year and industry fixed effect	Yes	Yes	Yes
Number of observations	974	925	880
Adjusted R^2	0.730	0.729	0.745

This table reports the results of regressions of cash flow volatility (Panel A) and firm valuation as proxied by Tobin's Q ratio (Panel B), respectively, on managerial equity incentives, the use of derivatives and control variables. The level of the CEO's equity incentives is proxied by their equity portfolio's delta and vega. The use of derivatives is proxied by the firm's pure hedge ratio and normalized speculative ratio. Control variables for firm characteristics include firm size, ROA, investment growth rate, leverage, financial distress (Altman's Z-score), cash and dividend. Control variables for CEO characteristics include age, tenure and annual cash pay as a fraction of annual total pay (cashfrac). Definitions of all variables are in the Appendix. The table reports *t*-values in parentheses, with standard errors are clustered at the firm level. 1%, 5% and 10% significance are denoted ***, ** and *, respectively.

Table 3.11: Difference-in-differences regressions: endogeneity tests utilizing FAS 123R

	Hedge ratio				Speculative ratio	
	Pure		Net		Normalized	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
FAS	-0.0110	-0.0123	-0.0205	-0.0215	0.0220**	0.0235**
	(-0.17)	(-0.18)	(-0.31)	(-0.32)	(2.33)	(2.45)
Treat	-0.1130*	-0.0916	-0.1080*	-0.0851	-0.0044	-0.0049
	(-1.75)	(-1.33)	(-1.68)	(-1.25)	(-0.48)	(-0.50)
Treat×FAS	0.0002	0.0243	0.0084	0.0335	-0.0223	-0.0257*
	(0.00)	(0.25)	(0.09)	(0.35)	(-1.62)	(-1.88)
Ln (1 + delta_CEO)	0.0326**	0.0339**	0.0320**	0.0340**	0.0016	0.0007
	(2.23)	(2.23)	(2.21)	(2.26)	(0.76)	(0.30)
Vega_CEO/delta_CEO	0.1760	0.1540	0.1660	0.1490	0.0124	0.0026
	(1.26)	(1.04)	(1.19)	(1.02)	(0.63)	(0.13)
Ln (Total assets)		-0.0012		-0.0051		0.0051*
		(-0.06)		(-0.25)		(1.74)
ROA		-0.0092**		-0.0092**		0.0004
		(-2.29)		(-2.30)		(0.65)
Inv_growth		0.0002		0.0003		-0.0001
		(0.46)		(0.52)		(-1.00)
Leverage		0.0030**		0.0032**		-0.0003
		(2.21)		(2.34)		(-1.53)
Fin_distress		0.0063		0.0067*		-0.0013**
		(1.54)		(1.67)		(-2.21)
Payout ratio		0.1600		0.1670		-0.0015
		(0.36)		(0.38)		(-0.02)
Dividend		0.0094		0.0203		-0.0196*
		(0.12)		(0.26)		(-1.73)
Constant	0.2050**	0.1040	0.2040**	0.1130	-0.0031	-0.0095
	(2.20)	(0.62)	(2.21)	(0.68)	(-0.23)	(-0.40)
Year fixed effect	No	Yes	No	Yes	No	Yes
Firm fixed effect	No	Yes	No	Yes	No	Yes
# of observations	133	133	133	133	133	133
Adjusted R^2	0.029	0.070	0.024	0.073	0.028	0.069

This table reports the results of difference-in-differences (DID) regressions to analyze the impact of Financial Accounting Standard (FAS) 123R on corporate hedging. *FAS* is an indicator variable that equals one if the observation is after the adoption of FAS 123R. *Treat* is an indicator variable that is one if the observation is part of the treated group, i.e. firms that included options in chief executive officer pay prior to the adoption of FAS 123R and those that did not adopt the fair value method for expensing options prior to the adoption of FAS 123R. *Treat* is equal to zero if the firm is in the control group, i.e., firms that preemptively adopted the fair value method prior to FAS 123R or did not pay options prior to FAS 123R.

Treat×FAS is the DID estimate. All other variables are identical to those used in Table 8 and their definitions are in the Appendix. The table reports *t*-values in parentheses, with standard errors are clustered at the firm level. 1%, 5% and 10% significance are denoted ***, ** and *, respectively.

Table 3.12: Comparison of CEO and CFO equity incentives

	Hedge ratio				Speculative ratio	
	Pure		Net		Normalized	
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Ln (1 + delta_CEO)	-0.0037	0.0054	-0.0083	-0.0003	0.0053***	0.0033
	(-0.43)	(0.39)	(-0.98)	(-0.02)	(2.72)	(1.15)
vega_CEO/ delta_CEO	0.0603	-0.0013	0.0298	-0.0314	0.0320*	0.0328**
	(1.04)	(-0.02)	(0.52)	(-0.39)	(1.94)	(2.04)
Ln (1 + delta_CFO)	-0.0156	-0.0093	-0.0185*	-0.0130	0.0082***	0.0040
	(-1.62)	(-0.60)	(-1.94)	(-0.80)	(3.87)	(0.86)
vega_CFO/ delta_CFO	0.0034	0.0030	0.0028	0.0023	-0.0019	-0.0005
	(0.56)	(0.59)	(0.47)	(0.38)	(-1.42)	(-0.36)
Ln (Total assets)		0.0218		0.0215		0.0014
		(0.79)		(0.79)		(0.30)
ROA		0.2200		0.2260		-0.0285
		(1.55)		(1.62)		(-1.01)
Inv_growth		0.0057		0.0120		-0.0027
		(0.25)		(0.53)		(-0.69)
Leverage		0.1230*		0.1120		0.0075
		(1.72)		(1.58)		(0.51)
Fin_distress		-0.0023		-0.0036		0.0008
		(-0.76)		(-1.21)		(1.46)
Payout ratio		-0.126***		-0.1220**		-0.0170
		(-2.91)		(-2.58)		(-1.02)
Dividend		-0.0358		-0.0555		0.0361
		(-0.52)		(-0.87)		(1.03)
Constant	0.414***	0.182	0.428***	0.220	-0.0116	-0.0265
	(7.38)	(0.88)	(7.74)	(1.07)	(-0.92)	(-0.62)
Year fixed effect	No	Yes	No	Yes	No	Yes
Firm fixed effect	No	Yes	No	Yes	No	Yes
# of observations	990	945	990	945	932	893
Adjusted R^2	0.002	0.396	0.004	0.376	0.027	0.306

This table reports the results of regressions of both hedge and speculative coverage ratios on CEO and CFO equity incentives and control variables. Hedge and speculative coverage ratios measure the firm's extent of hedging and speculative usage of derivatives in their hedging operations, respectively. By including both CEO and CFO equity incentives, we evaluate their relative impact on hedging decisions. Definitions of all variables are in the Appendix. The table reports *t*-values in parentheses, with standard errors are clustered at the firm level. 1%, 5% and 10% significance are denoted ***, ** and *, respectively.

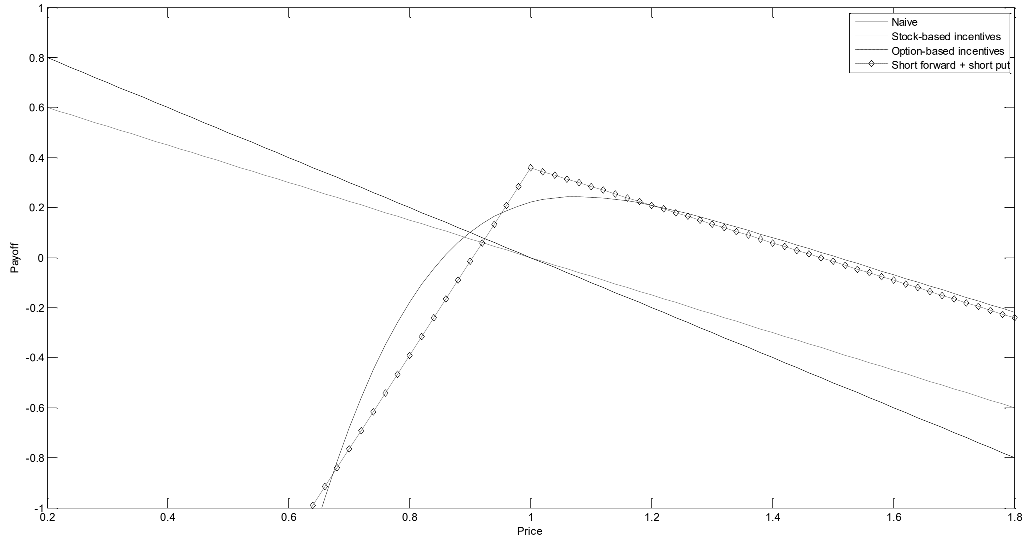
Appendix

Table A 3.1: Variable Definitions

Variable	Definition
Total Assets	Book value of the firm's total assets ($ billion).
Market Value of Equity	Stock price times the number of common shares outstanding ($ billion).
Value of Reserves	The firm's reported value of proved oil and gas reverses ($ billion).
Value of Production	The firm's reported value of annual oil and gas production ($ million).
ROA	Net income divided by total assets (%).
Leverage	Total debt divided by total assets (%).
Investment Growth	The change in capital expenditure from the previous fiscal year (%).
Financial Distress	Altman's Z-score.
Dividend	Indicator variable which is equal to 1 if the firm pays a cash dividend during the year and 0 otherwise.
Payout Ratio	Total cash dividend divided by net income.
Cash Flow Volatility	Standard deviation of quarterly net cash flow from operations scaled by total assets, computed over the current and previous fiscal years.
Tobin's Q	The sum of market value of equity, total debt and preferred stock, divided by the sum of book value of equity, total debt and preferred stock.
Age	The CEO's age (years).
Tenure	The CEO's tenure (years).
CEO Annual Compensation	Total annual CEO compensation including salary, bonus, stock awards, option awards and other compensation ($ million).
Cashfrac	Cash compensation (salary and bonus) as a fraction of total annual CEO compensation.
Delta	The change in the value of the manager's equity portfolio for a 1 percent increase in the firm's stock price ($ thousand), for either the CEO or CFO.
Vega	The change in value of manager's option portfolio for a 1 percentage point increase in stock return volatility ($ thousand), for either the CEO or CFO.
Vega / Delta	Normalized risk-taking incentive, as scaled by Delta, for either the CEO or CFO.
Pure Hedge Ratio	Annualized volume covered by derivative contracts used for hedging purposes only, divided by the firm's total exposure.
Pure Speculative Ratio	Annualized volume covered by derivative contracts used for speculative purposes only, divided by the firm's total exposure.
Net Hedge Ratio	Pure Hedge Ratio – Pure Speculative Ratio
Normalized Speculative Ratio	Pure speculative ratio dividend by Pure Hedge Ratio.

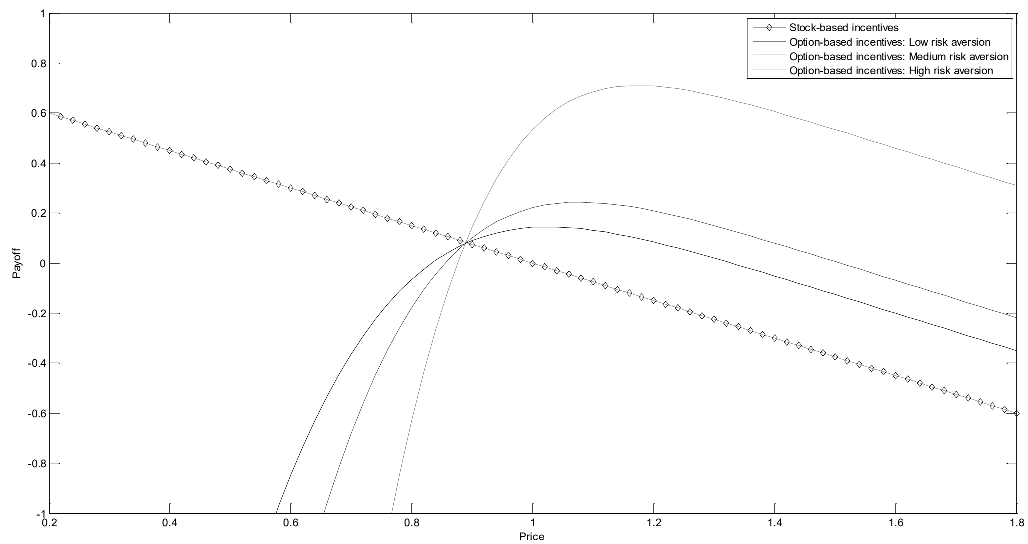
This appendix provides a summary of all variables used in the analysis and their definitions.

Figure 3.1: Comparison of optimal hedge payoffs under restricted stock-based vs. option-based incentives



The hedging strategy is illustrated by plotting its net payoff against the price of the firm's product. Net payoff is the payoff of the derivative contract minus its cost, both of which are realized at maturity. Four hedging strategies are compared: the optimal hedge under restricted stock-based incentives, the optimal hedge under option-based incentives, the full hedge with a short forward contract (and a hedge ratio of -1), and the portfolio of a short forward contract and six sold at-the-money put options. The following set of base-case model parameters are used: Both the expected price of the firm's product (μ_p) and its quantity manufactured (q_0) during the period are normalized at 1; The fixed cost is 0.4; The mean of the variable cost per unit (μ_v) is 0.25; The correlation coefficient between price and variable cost is +0.25; The volatility (standard deviation) of both the price and variable cost are 20%. The manager's degree of risk aversion (λ) is 5; The manager's equity compensation (either restricted stock or option) represents 5% ownership (or potential ownership) of the firm (b). The strike price (i.e., target net operating profit π_0) of the manager's stock options is zero.

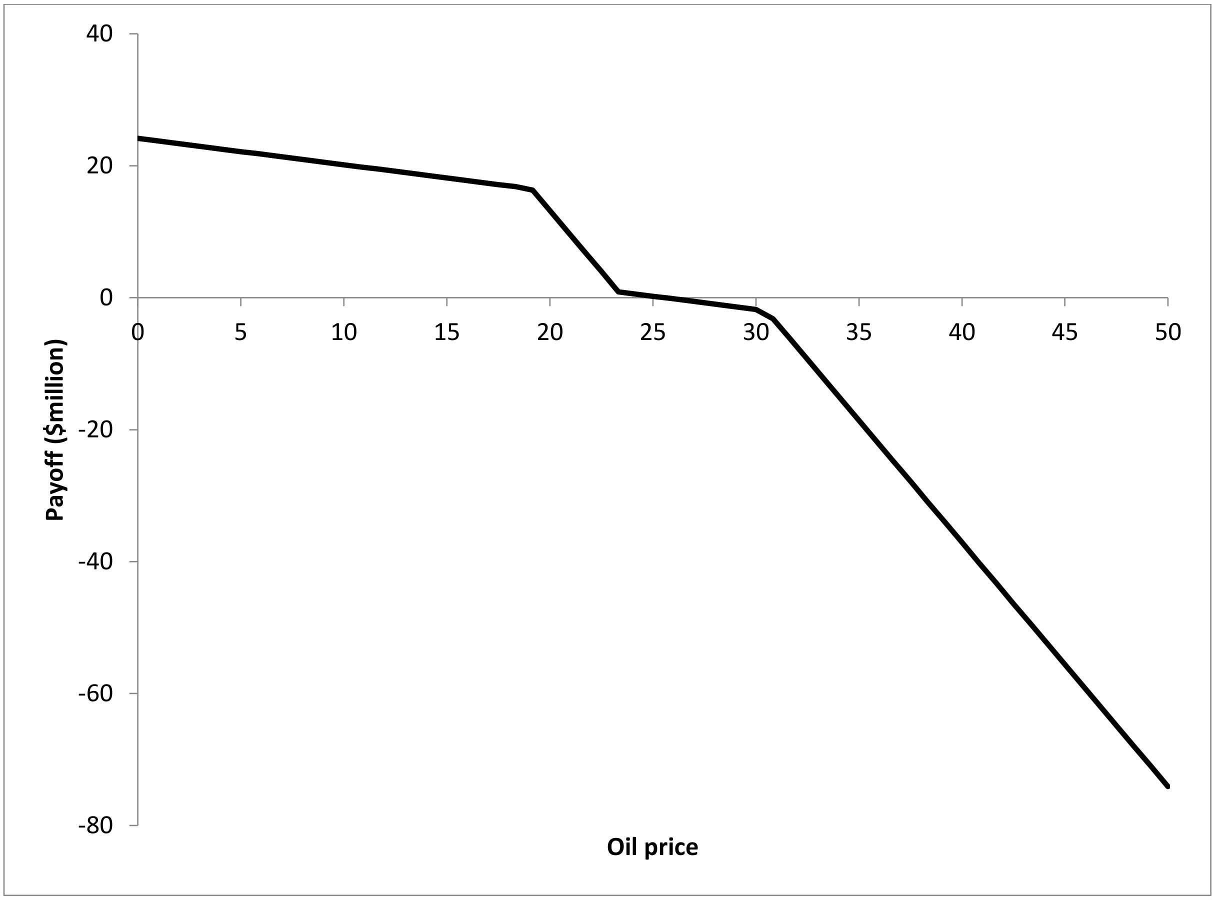
Figure 3.2: The impact of managerial risk aversion on the optimal hedging strategy



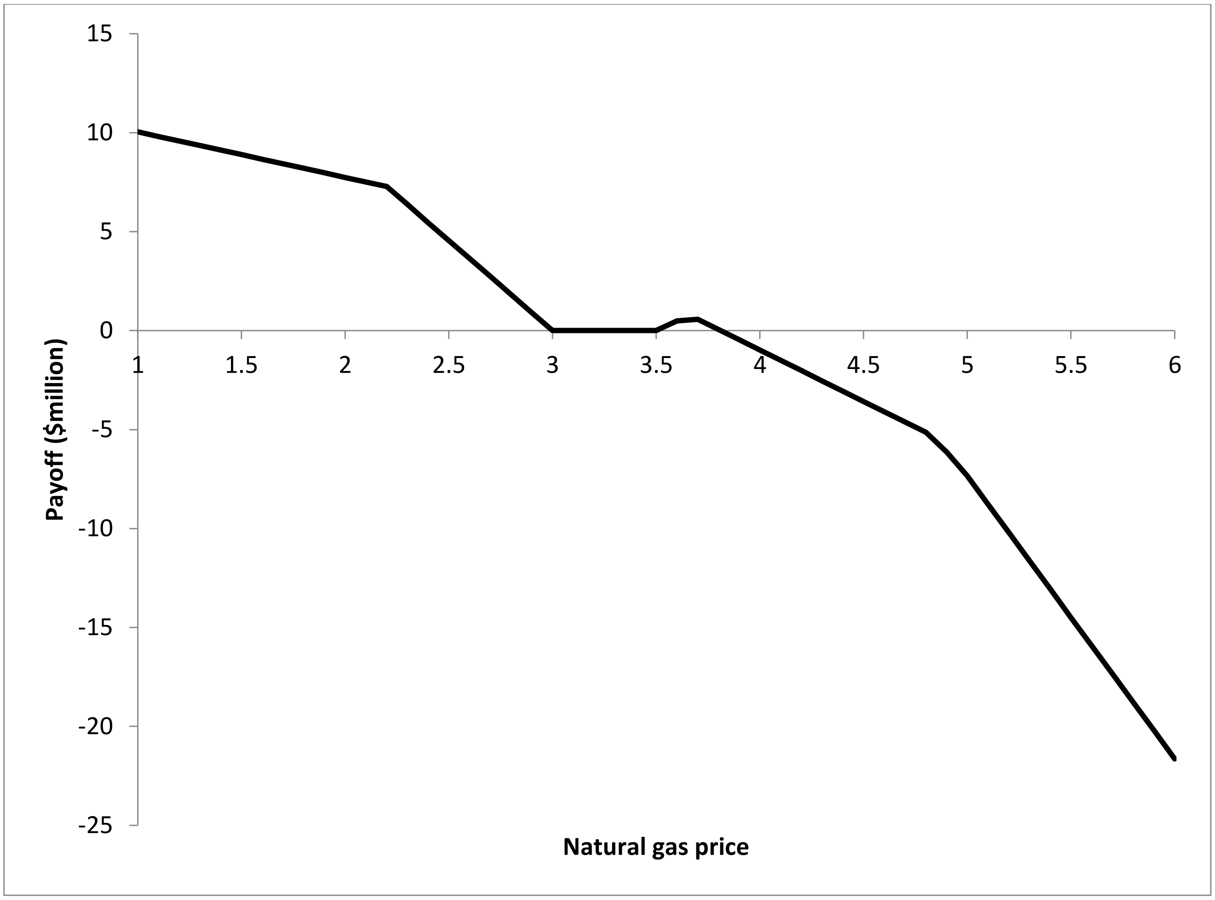
Hedging strategy payoffs are illustrated for different levels of managerial risk aversion: a low degree of risk aversion ($\lambda = 2$), a medium degree of risk aversion ($\lambda = 5$), and a high degree of risk aversion ($\lambda = 8$). Other parameters are the same as in the base case: Both the expected price of the firm's product (μ_p) and its quantity manufactured (q_0) during the period are normalized at 1; The fixed cost is 0.4; The mean of the variable cost per unit (μ_v) is 0.25; The correlation coefficient between price and variable cost is +0.25; The volatility (standard deviation) of both the price and variable cost are 20%. The manager's equity compensation (either restricted stock or option) represents 5% ownership (or potential ownership) of the firm (b). The strike price (i.e., target net operating profit π_0) of the manager's stock options is zero.

Figure 3.3: An example of oil and gas hedging operations

Panel A: Payoff of oil derivatives



Panel B: Payoff of gas derivatives



This figure illustrates the hedging operations of Anadarko Petroleum Corp. in 2002, involving several derivative contracts including collars, three-way collars, swaps and call options. While a swap (at the $25.56 price per barrel and the volume of 0.4 million barrels) and a three-way collar (at threshold prices of $19.11, $23.33 and $30.51 per barrel and the volume of 3.3 million barrels) are used for oil hedging operations, a collar (at prices of $3 and $5 per MMBTU and a volume of 2.3 million MMBTUs), a three-way collar (at the threshold prices of $2.2, $3 and $4.83 per MMBTU and a volume of 6.8 million MMBTUs), a sold call option (at strike price $3.66 per MMBTU and a volume of 10.1 million MMBTUs), and a purchased call option (at strike price $3.50 per MMBTU and a volume of 4.9 million MMBTUs) for natural gas hedging operations. The aggregate payoffs of the oil and gas contracts are illustrated in Panels A and B, respectively.

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