

Two Tales of Return Expectations

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Abstract

We perform a comprehensive set of empirical analyses to understand the extent to which lower bounds for expected excess returns from option prices reflect investors' expectation of underlying equity returns. Option-implied bounds are negatively correlated with survey-based return expectations which are documented to be overextrapolative. Unlike survey-based expectations, option-implied bounds load significantly and negatively on past returns. Furthermore, we find that a large fraction of mutual and hedge fund managers trade in alignment with these option-implied bounds. These results suggest that rational investors, by explicitly betting against past returns, understand the behavioral pitfalls that naive investors fall into and trade in the option market.

Keywords: Return expectations, survey-based expectations, option-implied bounds, extrapolation, institutional investors

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1 Introduction

Understanding how investors form expectations about future asset payouts is crucial in asset pricing research. Previous studies have largely focused on retail investors in the stock market, providing convincing evidence of overextrapolation in return expectations (e.g. Amromin and Sharpe, 2014; Greenwood and Shleifer, 2014; Cassella and Gulen, 2018; Kuchler and Zafar, 2019; Da, Huang and Jin, 2021).¹ Recent studies go beyond retail investors and examine equity return expectations of public pension funds, analysts, large asset managers, and professional forecasters (e.g. Andonov, Rauh et al., 2020; Renxuan, 2020; Dahlquist and Ibert, 2024). Yet, what is surprisingly understudied—especially given its fundamental link to the stock market—is the options market and how investors in this market form their expectations of future stock returns.

In this study, we conduct a comprehensive investigation into the expectations of both market and individual stock returns implied from option prices. To this end, we proxy for such expectations by exploiting four lower bounds for equity risk premia derived from economic theory and option prices. (Martin, 2017; Martin and Wagner, 2019; Chabi-Yo and Loudis, 2020; Chabi-Yo, Dim and Vilkov, 2022). Martin (2017) (Martin Bound) shows that the risk-neutral variance of the market return scaled by the risk-free rate serves as a lower bound for the expected excess market return.² The bounds for a given time horizon can be calculated using prices of put and call options that mature at the same horizon. Chabi-Yo and Loudis (2020) (CYL Bound) improve on Martin’s work by incorporating higher-order risk-neutral moments into their bounds for the market return.³ Building on these foundations, Martin and Wagner (2019) (MW Bound) and Chabi-Yo, Dim and Vilkov (2022) (CYDV Bound) develop the bounds on the risk premia of individual stocks.

It is ex-ante unclear to what extent these bounds can represent equity return expectations of investors in the option markets. Martin (2017) shows that his bound on the S&P 500 index can positively predict the future index returns; he also documents negative correlations between the bound and various survey-based return expectations of individual investors, who have been shown to be extrapolators (Greenwood and Shleifer, 2014). Thus, if any, such lower bounds may reflect rational investors’

¹Return extrapolation is the notion that investors’ expectations about a stock’s future return are a positive function of the stock’s recent past returns. Empirical research documents evidence of overextrapolation, suggesting that future return realizations differ significantly from retail investors’ expectations.

²The result requires the negative correlation condition (NCC), where the predicted return should be negatively correlated with the product of the stochastic discount factor and the return itself. Martin shows that this is a plausible assumption for the market return.

³They do so by assuming a representative investor who performs a Taylor series expansion of the reciprocal of marginal utility and restricting the investor’s tolerances for risk, skewness, and kurtosis.

expectations, as conjectured by Martin. On the other hand, it is plausible that these bounds might not accurately reflect expectations of option investors', or could even represent the expectations of a group of behavioral investors. For the former, note that all these bounds are developed under no-arbitrage assumptions in the option market. Additionally, [Back, Crotty and Kazempour \(2022\)](#) provide mixed evidence on the forecastability of these bounds: the positive forecast power of all these bounds mainly persists in the time series, but remain insignificant in the cross section. For the latter, limits to arbitrage in the options market are well documented (e.g. [Figlewski, 1989](#); [Longstaff, 1995](#); [Figlewski, 1989](#); [Bollen and Whaley, 2004](#)), and there is ample evidence that investors' behavioral biases significantly affect option prices.⁴ Thus, determining what expectations these bounds truly represent remains an empirical question.

We conduct our empirical tests in three steps. First, we show that survey-based expectation measures and option-implied bounds exhibit a strong negative correlation, both in the time series and in the cross-section. In the time series, we find that market survey series (e.g., Gallup, AA, and II) are significantly and negatively correlated with both Martin Bound and CYL Bound. This correlation is robust across different prediction horizons, ranging from one month to one year. Furthermore, the negative correlation between these bounds and survey-based return expectations is more pronounced when past one-month returns are negative compared to when past returns are positive. These findings support [Martin \(2017\)](#), which demonstrates a negative correlation between Martin Bound and these survey-based return expectations over a fixed horizon.

In the cross-section, we utilize data from Forcerank along with MW Bound and CYDV Bound for individual stocks.⁵ We find that Forcerank scores tend to move in the opposite direction of the bounds, with the lowest (highest) points in the Forcerank scores frequently coinciding with the highest (lowest) points in the MW and CYDV Bounds. The negative correlation is robust across various prediction horizons, from one month to one year, and holds true for stocks with both negative or positive returns in the previous week, as well as across firms of different sizes. The negative correlation is more pronounced when past returns are negative and is slightly stronger for large-cap firms. These findings suggest a clash between the literature on option-implied bounds and the literature on survey-based expectation formation among individual investors.

Second, we investigate how option-implied bounds relate to past realized returns by running cross-sectional regressions, in which individual stock bounds are regressed on their past weekly (or monthly) stock returns. The coefficient estimates on the past

⁴See, for example, [Stein \(1989\)](#), [Poteshman \(2001\)](#), [Poteshman and Mahani \(2004\)](#), and [Han \(2008\)](#). [Atmaz \(2022\)](#) shows that stock market investors' biased volatility expectation can explain why past stock returns and investor sentiment affect option prices ([Bakshi and Kapadia, 2003](#); [Amin, Coval and Seyhun, 2004](#); [Goyal and Saretto, 2009](#)).

⁵We follow [Da, Huang and Jin \(2021\)](#) in defining a game and a contest, which is a particular industry group by week panel.

12 weekly returns are all significantly negative. This result contrasts with the findings on extrapolative expectations among retail investors, as documented by [Da, Huang and Jin \(2021\)](#), which we also confirm. This finding suggests that the investors whose beliefs are reflected by bounds expect high (low) future stock returns when the past returns are low (high). Moreover, the absolute values of the coefficients on recent past returns are higher, in general, than those on distant past returns.

To further illustrate how recent return appreciation affects bounds, we employ a measure of acceleration, which captures the convexity of the price path. Our results show that bounds tend to indicate lower market expectations when the market exhibits faster acceleration. This, again, starkly contrasts with the formation of survey-based return expectations, where investors typically raise their expectations when the recent market accelerates more rapidly ([Da, Huang and Jin, 2021](#)).

In our final set of analyses, we investigate whether a larger group of investors, beyond just option traders, hold expectations that align with those implied by options. Given the challenges in obtaining expectations, particularly among sophisticated investors, we adopt a revealed-preference approach ([Berk and Van Binsbergen, 2015](#); [Barberis, Greenwood, Jin and Shleifer, 2015](#)). By examining the holdings of mutual fund managers and employing the bootstrap method ([Fama and French, 2010](#)), we document the existence of a significant proportion of mutual and hedge fund managers whose trading directions strongly and positively correlate with option-implied bounds.

Taken together, our evidence supports the view that rational investors, by explicitly betting against past returns, recognize the behavioral pitfalls that naive (extrapolative) investors fall into. It is plausible that they exploit these pitfalls by trading in the option markets. For instance, during market downturns, extrapolators often exhibit excessively pessimistic expectations about future returns. However, rational traders perceive these periods as instances of market overreaction and counter past returns by buying call options and selling put options, effectively betting against past returns.

We make three contributions to the literature. First, we contribute to a nascent body of work, beginning with the seminal paper by [Martin \(2017\)](#), that uses economic theories and option prices to derive lower bounds on risk premia of the market portfolio and individual stocks ([Martin and Wagner, 2019](#); [Chabi-Yo and Loudis, 2020](#); [Kadan and Tang, 2020](#); [Chabi-Yo, Dim and Vilkov, 2022](#)). While these studies primarily focus on the derivation and validity of the bounds, our study is the first to investigate the extent to which these bounds can represent expectations of investors in the option market, as well as the nature of those expectations. Our evidence suggests that option bounds indeed represent the expectations of rational investors of stock market returns.

Second, we contribute to the literature on subjective equity return expectations. Existing work provides convincing evidence of the existence of extrapolative biases

in retail investors’ future stock return expectations (Amromin and Sharpe, 2014; Greenwood and Shleifer, 2014; Cassella and Gulen, 2018; Kuchler and Zafar, 2019; Da, Huang and Jin, 2021; Nagel and Xu, 2023). Recent studies also examine equity return expectations of public pension funds, analysts, large asset managers, and professional forecasters (Andonov, Rauh et al., 2020; Renxuan, 2020; Dahlquist and Ibert, 2024). In contrast to these studies, we focus on expectations derived from option markets.

Third, we contribute to the literature on new asset pricing models in which irrational extrapolators interact with rational investors (see, e.g., Barberis, Greenwood, Jin and Shleifer (2015); Berk and Van Binsbergen (2015); Adam, Marcet and Beutel (2017); Jin and Sui (2022); Nagel and Xu (2023)). To the best of our knowledge, we are the first to provide comprehensive evidence supporting the existence of this interaction between rational and irrational investors.

The rest of the paper is organized as follows. Section 2 presents data and summary statistics, while Section 3 describes the correlation between option bounds and survey-based expectations. Section 4 presents results on expectation formation, and Section 5 presents results on whether and how institutional Investors respond to option bounds. Section 6 concludes.

2 Data and summary statistics

2.1 Survey on individual stock markets

In this section, we describe the data from a survey on individual stock markets collected from Forcerank. Forcerank is a crowdsourcing platform that organizes weekly competitions where participants enter thematic games and rank a list of ten stocks in order of their expected performance for the upcoming week. These competitions primarily focus on individual firms or the macroeconomy.

We follow Da, Huang and Jin (2021) in defining a game and a contest. A unique game represents a distinct combination of ten stocks, typically focusing on a particular industry group within a specific market capitalization range. A game can be reintroduced over time, resulting in multiple weekly contests. A contest is defined as a ten-ticker-predicted-week panel or a game-predicted-week panel. Panel A of Table 1 lists the types of industries and their corresponding numbers of games and contests.

Regarding the competition’s goal and timeline, participants aim to correctly match their rankings with the actual results over the next week ($t + 1$) before the end of the current week (t). At the end of next week ($t + 1$), returns are realized and points are awarded within each contest based on the accuracy of a player’s rankings compared to the actual results. Specifically, the shorter the distance in positions between a

player’s ranking and a stock’s actual performance, the more points will be earned. At $t + 2$, the platform recognizes the person with the most points within the past 13 weeks.

For sample construction, we first exclude very few cases where the predicted horizon is one month. Then, consider only the final version of submissions if users edit after their initial submission. Finally, we focus on games concerning individual firms, excluding those based on macroeconomics, such as ETFs or the most heavily shorted firms. Our final sample includes 236 unique stock tickers, 1,346 contests, and 25,089 submissions by 3,660 applicants from February 2016 to December 2017. Panel B of Table 1 describes the characteristics of games, contests, and user participation in each week.

2.2 Survey on the aggregate stock market

In studying the investor expectations regarding the aggregate stock market, we follow Greenwood and Shleifer (2014) and rely on survey results from three main sources: the Gallup Investor survey (Gallup), the American Association of Individual Investors survey (AA), and the Investor Intelligence survey (II).

The Gallup survey, conducted monthly from 1996 to 2012 with intermittent gaps, collects individual investors’ beliefs about the stock market over the next twelve months. More specifically, participants were asked to categorize their outlook as being “very optimistic,” “optimistic,” “neutral,” “pessimistic,” or “very pessimistic” about stock returns in the upcoming year.

The AA survey, available from 1987 to 2011, is administered weekly to members of the American Association of Individual Investors. It measures the proportion of individual investors who feel bullish, neutral, or bearish about the stock market over the next six months. Bullish aligns with “very optimistic,” “optimistic,” and bearish aligns with “pessimistic,” or “very pessimistic” from the Gallup survey.

The II survey has been collecting forecasts of stock market performance from financial market newsletters since 1963. The editors of II categorize each newsletter’s outlook as “bullish,” “bearish,” or “neutral” regarding near-term stock market returns. Panel A of Table 2 provides an overview of the survey data and summary statistics.

Both the AA and II surveys, along with the majority of the Gallup survey, collect qualitative data. The measure of investor expectation is consistent across all these three surveys:

$$Exp = \%Bullish - \%Bearish, \tag{1}$$

which is the percentage of bullish investors minus the percentage of bearish investors. As [Greenwood and Shleifer \(2014\)](#) and [Cassella and Gulen \(2018\)](#) show, the qualitative data collected by these surveys serve as a reliable proxy for quantitative expectations. Thus, we treat the qualitative expectations data as a close substitute for quantitative data.

These market survey-based expectations are expressed in percentages. In some tests, We concentrate mainly on the two longest-running surveys (II and AA) to enhance statistical power and achieve comparability with prior studies. Moreover, in some analyses, we standardize the frequency of survey expectations to a monthly basis and, therefore, ensure the consistency of sampling frequency across the three surveys.

2.3 Option Implied Bounds

We use the bounds on the market risk premium developed by [Martin \(2017\)](#) and [Chabi-Yo and Loudis \(2020\)](#) and the bounds on the risk premia of individual stocks developed by [Martin and Wagner \(2019\)](#) and [Chabi-Yo, Dim and Vilkov \(2022\)](#).⁶ These lower bounds, annualized and in percentage points at a daily frequency, are applicable across time horizons ranging from one month to one year.

[Martin \(2017\)](#) uses index option prices to construct a lower bound on the market risk premium, termed the Martin Bound hereafter. This bound can be computed as the risk-neutral variance of the simple market return scaled by the risk-free rate as long as the negative correlation condition (NCC) holds. Martin argues that his lower bound is tight in the sense that the time-series average of the bound is about 5%, and the coefficient of regressions of realized excess returns on ex-ante bound values is around one.⁷ The Martin Bound series is available from January 1996 to January 2012 and is downloadable from Martin’s website.

[Chabi-Yo and Loudis \(2020\)](#) also derive a lower bound on the conditional expected excess market return. A key difference between their measure and Martin Bound is that their bound incorporates the effects of higher-order risk-neutral moments (i.e.,

⁶While we do not test all related premia formulas or bounds, it is worth noting the contributions of [Kadan and Tang \(2020\)](#) (Hereafter KT Bound). They extend [Martin \(2017\)](#) to individual stocks, requiring that the NCC hold on a stock-by-stock basis. Their bound, however, is applicable only to S&P 500 constituents, and the number of stocks meeting their criteria increases over time, rising from 30 stocks in 1996 to approximately 500 in 2016. The KT Bound is twice the MW Bound plus a constant term, which, as shown by [Back, Crotty and Kazempour \(2022\)](#), is consistent across stocks, resulting in a perfect cross-sectional correlation between these two bounds. Given this relationship, we use only the MW Bound in our primary analysis.

⁷[Back, Crotty and Kazempour \(2022\)](#), however, reject bound tightness for not only market bounds introduced by [Martin \(2017\)](#) and [Chabi-Yo and Loudis \(2020\)](#), but also the individual stock bound by [Martin and Wagner \(2019\)](#). [Back, Crotty and Kazempour \(2022\)](#) do not reject bound validity of these bounds.

skewness, kurtosis, and other higher moments). Also, instead of relying on NCC as proposed by [Martin \(2017\)](#), [Chabi-Yo and Loudis \(2020\)](#) requires mild assumptions about preference parameters. The paper argues that their bound estimates are tight and, hence, can serve as a viable measure of the conditional expected excess market return. [Chabi-Yo and Loudis \(2020\)](#) derive both unrestricted and restricted lower bounds. Our paper focuses on the restricted Chabi-Yo Loudis Bound (CYL Bound, hereafter) in our empirical work because it is free of preference parameters. This dataset, spanning from January 1996 to August 2015, is available on the authors' websites.

[Martin and Wagner \(2019\)](#) derive a formula for the expected return on an individual stock. This Martin and Wagner Bound (MW Bound, hereafter) incorporates the risk-neutral variance of the market and the stock's excess risk-neutral variance relative to that of the average stock. Martin and Wagner show that the null hypothesis of predictability of their model is not rejected in most tests. We obtained MW bounds data from Grigory Vilkov's website, which covers an extended period from January 1996 to December 2020, focusing on the S&P 500 stocks.

[Chabi-Yo, Dim and Vilkov \(2022\)](#) derive lower bounds on the risk premia of individual stocks, which take into account all moments of the risk-neutral distribution. They do not reject the validity of their bound, nor do they reject tightness at shorter horizons (1 and 3 months), but they do reject tightness at longer horizons (6 and 12 months). They also find that their bound generally outperforms the MW and KT Bound in predicting stock returns. We downloaded their bounds from Vilkov's website, where two versions are presented. One assumes relative risk aversion of two and a half prudence of one (GLB2, based on the second-order Taylor series expansion of the marginal utility), and the other one assumes temperance of four (GLB3, based on the third-order Taylor series expansion of the marginal utility). We use GLB2 in the period of January 1996 to December 2020 for the stocks in S&P 500 and refer to it as the CYDV Bound. ⁸

2.4 Mutual funds

We focus on US active domestic equity mutual funds spanning from 1995Q1 to 2020Q4. We construct our dataset using four data sources: CRSP's monthly stock file (stock prices and returns), Morningstar Direct (fund characteristics), CRSP's mutual fund data (fund holdings and fund characteristics), and Thomson Reuters (fund holdings). A detailed description is provided in Appendix B. We summarize the three key steps here.

We begin by merging the CRSP and Morningstar Direct mutual fund databases. We require that funds appear in the intersection of CRSP and Morningstar, allowing

⁸Using GLB3 generate similar results as GLB2 and we put the analysis using GLB3 in the appendix

us to cross-check the accuracy of all observations across both sources. We match the two files using the Ticker. Next, We rectify potential errors arising from reused Tickers or CUSIPs and correct returns and fund sizes following the methodology established by Berk and Van Binsbergen (2015) and Pástor, Stambaugh and Taylor (2015). There are discrepancies in returns across the two databases in approximately 7.99% of observations, which we reduce to 1.04% by applying Berk and Binsberger’s algorithm. All remaining return discrepancies are set to missing. Similarly, we set Net Asset Value (NAV) to missing if the discrepancies in NAV across the two databases differ by at least 100,000 dollars and 5%. Otherwise, we adopt CRSP’s values.

In the second step, we process the s12 holdings file from CRSP and Thomson Reuters separately and match the funds from the previous step with their corresponding holdings data. We rely on Thomson Reuters data from 1995 to 2008 and CRSP data from 2009 to 2020. This is due to the CRSP mutual fund holdings data commencing in 2003 and having slightly smaller coverage than Thomson Reuters until 2008. Post-2008, however, CRSP’s coverage surpasses Thomson Reuters, as noted by Schwarz and Potter (2016). We link Thomson Reuters and CRSP using the MFLINKS dataset from Wharton Research Data Services. As a precaution, we screen for actively managed US domestic equity funds from both a fund characteristics perspective and a holdings data perspective: We exclude international, balanced, sector, bond, money market, and index funds through IOC, funds’ names, and funds’ investment objectives codes from CRSP (Doshi, Elkamhi and Simutin, 2015). Since reported fund objectives may not always accurately depict a fund, we follow Kacperczyk, Sialm and Zheng (2008) and exclude funds that maintain, on average, less than 80% of net assets in equity throughout their existence. To mitigate incubator bias and small funds bias (Evans, 2010), we exclude funds with a NAV below \$5 million in 2016 dollars. Lastly, we eliminate all observations with fewer than 10 stock holdings in order to compute a meaningful measure of active weight.

In the final step, we link bounds information to stocks using permno. We exclude funds with fewer than 10 observations. Our final sample includes 1,595 distinct funds and 75,721 fund-quarter observations from 1996Q1 to 2020Q4.

2.5 Hedge funds

We utilize the 13F institutional holdings data from Thomson Reuters and identify hedge fund advisors following the approach outlined by Aragon, Chen and Shi (2022). We then screen for actively managed U.S. domestic equity funds and remove those with less than \$5 million in assets under management, adjusted for inflation in 2016 dollars. Additionally, we exclude funds with fewer than ten observations after linking with bounds information. Our final sample consists of 1,500 distinct funds and 56,761 fund-quarter observations from Q1 1996 to Q4 2020.

3 Option-implied bounds and survey-based returns

In this section, our primary focus is to explore the relation between return expectations derived from surveys and bounds on expected returns inferred from option prices. First, we study this correlation in the time-series framework, using data from market surveys and option bounds. We then extend our examination to the cross-section dimension, using Forcerank data and individual stock bounds.

3.1 Evidence from the aggregate market

Martin (2017) demonstrated a negative correlation between the Martin Bound and four survey-based return expectations—Gallup, Graham-Harvey, AA, and Shiller—as considered by Greenwood and Shleifer (2014). To further explore this finding and validate our data, we use market surveys with extended horizons and an additional measure of option-implied returns, the CYL Bound.

We start by plotting survey-based market expectations (i.e., Gallup, AA, and II) along with the Martin Bound and CYL Bound.⁹ It is clear from Figure 1 that market surveys typically move in the opposite direction from option-implied bounds. As Panel A of Table 4 shows, all three versions of the market survey series are significantly and negatively correlated with both Martin Bounds and CYL Bounds, which are robust across different prediction horizons from one month to one year. Additionally, compared with AA, Gallup and II exhibit a stronger negative correlation with the bounds in general.

Panel A of Table 4 also presents the correlations among different survey measures of investor expectations and different measures of option-implied bounds. In general, market surveys are highly and positively correlated with one another, reflecting the consistency of these surveys, as previously demonstrated in Greenwood and Shleifer (2014). Bounds across different prediction horizons also show high correlations. Specifically, the time-series correlation between Martin Bounds on one-month market future returns (Martin (1m)) and three-month market future returns (Martin(3m)) is 0.97. The correlation between Martin(1m) and Martin(12m) is slightly lower at 0.87.

Furthermore, the negative correlation between option-implied bounds and survey-based return expectations is affected by past performance. Specifically, this negative

⁹Given that these market surveys are conducted monthly but option-implied bounds are available daily, we convert each bound measure into a monthly series by taking the average within each month. To ensure comparability across different measures, we further standardize each survey and bound measure. To be consistent with the predicting horizons of each survey, we compare the Gallup to option-implied bounds at the 12-month horizon, AA to the 6-month option-implied bounds, and II to 3-month option-implied bounds.

correlation is stronger when past one-month returns are negative, compared with cases when past performance is positive, as illustrated in Panel B of Table 4.

3.2 Evidence from the cross-section

The observed negative correlation between investor expectations, as captured by surveys and those derived from option price, has primarily been explored in the time series from the perspective of the aggregate stock market. To investigate whether such a discrepancy also exists in the cross-section, we use the data from Forcerank and option-implied bounds for individual stocks.

Recall that in the Forcerank competition, each unique group of ten stocks and week t construct a distinct contest. Each week, participants are asked to rank the given ten stocks based on their perceived performance of these ten stocks for the upcoming week. We measure investors' average expectations for each stock in each contest using the average Forcerank score calculated from the submitted rankings. A stock ranked highest within a contest receives a score of ten, while the lowest-ranked stock receives a score of one. Thus, the Forcerank score for a given stock in each contest equals $(11 - \textit{Ranking})$.

To represent return expectations from option markets, we use the average contest-adjusted MW Bounds and CYDV Bounds with a one-month prediction horizon. Specifically, we compute the contest-adjusted bounds by subtracting the average MW Bounds (or CYDV Bounds) of the ten stocks in the contest from the original ones. This adjustment is made because the relative values of the bounds within a contest are more relevant than the raw bounds for comparison with investor expectations. These contest-adjusted bounds are then converted to a weekly series by averaging within weeks, and correlations are calculated for all common dates between bounds and the survey-based measure. Among the 236 unique stocks in Forcerank, 125 have bounds data, which leads to a total observations of 8068. To ensure comparability, we standardize the Forcerank score and bounds, respectively.

To illustrate the correlation between survey-based investor beliefs and option-implied bounds within the cross-section of various stocks, we start by plotting the data for several stocks, namely Amazon, eBay, and Expedia.¹⁰

Figure 3 reveals a notable trend: the Forcerank score often moves in the opposite direction from the bounds. The lowest (highest) points in the Forcerank scores often coincide with the highest (lowest) points in the MW and CYDV Bounds. As the pairwise correlation demonstrated in Table 5 shows, both MW and CYDV Bounds, across different prediction horizons from one month to one year, negatively correlate with survey-based investor expectations. This negative correlation persists regardless of

¹⁰These three stocks were chosen because the Game they belong to is conducted continuously and repetitively over the longest period of 95 weeks, from February 22, 2016, to December 18, 2017.

whether the stock has negative or positive returns in the previous week and regardless of the size of the firms.¹¹ This negative correlation appears to be stronger when past returns were negative and slightly more pronounced for larger firms. This suggests that investor expectations may respond differently to varying market conditions and firm characteristics.

We have demonstrated that survey-based investor expectations and option-implied bounds are significantly negatively correlated in both time-series and cross-section settings. This divergence suggests a clash between the survey-based and option-market return expectations. Next, we explore whether these two groups of investors exhibit the same reactions to historical returns.

4 Expectation formation

In this section, we explore the formation of return expectations using both survey data and option-implied bounds. For survey data, we start with individual stocks using the Forcerank data, followed by aggregate market return expectations. We then repeat the analysis for option market investors.

4.1 Evidence from survey on individual stocks

We first study the impact of past returns on Forcerank users' average expectations of future stock returns. Following [Da, Huang and Jin \(2021\)](#) we use a contest-level linear regression:

$$Forcerank_{i,t} = \alpha + \sum_{s=0}^{11} \beta_s \cdot R_{i,t-s} + \epsilon_{i,t}, \quad (2)$$

where we regress *Forcerank* on the past 12 weekly returns, including the current week. *Forcerank* is the consensus ranking, with the highest-ranked stock receiving a score of ten and the lowest-ranked stock receiving a score of one. [Table A1](#) shows the results. Confirming [Da, Huang and Jin \(2021\)](#), all coefficients are positive and mostly statistically significant, revealing the decaying impact of more decent past returns. This pattern suggests that investors tend to extrapolate from past returns and place greater weight on more recent performance. Forcerank demonstrates a clear extrapolation structure in retail investors' expectation formation of future individual stock returns.

¹¹The firm's size is defined as its market capitalization at the end of 2015, with larger firms being in the top 50th percentile and smaller firms in the bottom 50th percentile.

4.2 Evidence from survey on the aggregate market

Considering that Forcerank covers 236 stocks and may not be sufficiently representative to reflect the investor beliefs across the entire stock market, we supplement our analysis using market surveys of Gallup, AA, or II to attain a more comprehensive understanding of investor beliefs.

To maintain consistency with the above analysis performed on individual stocks, we use a similar linear regression model:

$$Exp_t = \alpha + \sum_{s=1}^{12} \beta_s \cdot R_{t-s} + \epsilon_t, \quad (3)$$

where Exp_t is the average expectations for the aggregate market in each month t , and R_{t-s} denotes the lagged monthly return of the market from month $t - 12$ to $t - 1$.¹²

Table 6 presents the results. Column (1) uses the raw level of past stock returns to explain the expectation measured by AA. Column (2) incorporates additional control variables, such as tones of news coverage and revisions, which are monthly weighted average tones and revisions of S&P 500 constituents. Columns (3) to (6) repeat this analysis for II and Gallup, respectively.

Overall, a consistent pattern emerges from the results: all coefficients for past monthly returns are positive, with the majority attaining statistical significance in the II and Gallup surveys. Moreover, the magnitude of the coefficients tends to decrease as the distance from past returns increases. This pattern remains consistent even after adding control variables. Notably, compared with AA survey participants, participants in the II exhibit a stronger inclination to extrapolate from past returns, placing greater emphasis on more recent performance.

AA and II also collect weekly updates on market return expectation responses from participants, allowing us to investigate how past weekly returns affect investor expectation formation. We repeat the analysis, with results shown in columns (7) to (10). The results provide a consistent message: retail investors extrapolate from past returns in forming their expectations of future market returns.

To better illustrate how the most recent return appreciation affects investor expectations, we construct *Acceleration* inspired by Greenwood, Shleifer and You (2019), which is the difference between the 1-year return and the return for the first three quarters of that 1-year period: $Acceleration = R_{t-4 \rightarrow t} - R_{t-4 \rightarrow t-1}$. It measures the convexity of the price path, indicating the extent of price appreciation that has occurred in the most recent quarter.

¹²We don't use the return of the current time t because, unlike in the Forcerank setting where participants can update their rankings until the beginning of $t + 1$ (the period being forecasted), the market survey is submitted at time t .

With *Acceleration*, Table A2 presents regression results for the following time-series specifications:

$$Exp_t = \alpha + b.Acceleration_t + \sum_{s=1}^4 \beta_s.R_{i,t-s} + c.log(P_t/D_t) + u_t. \quad (4)$$

The dependent variable, Exp_t , is the investor expectation of future stock market returns at each month t from the market survey. $\log(P_t/D_t)$ is the price-dividend ratio, which measures the price-level.

In table A2, columns (1), (4), and (7) include *Acceleration* as the only explanatory variable to explain investor expectations from the survey of Gallup, AA, and II, respectively. Other Columns add price-dividend ratio, tones and revisions as control variables. The results show that investor expectations of future market returns are positively correlated with *Acceleration*, implying that investors anticipate higher future returns when the market has experienced rapid price appreciation in the most recent quarter. Consistent with prior studies (e.g., Greenwood and Shleifer (2014)), $\log(P_t/D_t)$ loads significantly positive.

4.3 Evidence from option-implied bounds on individual stocks

While numerous studies in the expected return literature have demonstrated the predictive power of option-implied bounds (e.g., Martin, 2017), little is known about the formation of investor expectation of future stock return in option markets. In this section, we study the relation between bounds on individual stocks and historical stock returns.

We start with a linear regression model similar to Eqn.(2), but replace the dependent variable by individual stock bounds $Bound_{i,t}$, which is the average annualized (not in percentage) bounds expected returns for individual stock i at week t for the next 30 days.¹³ Recall that the explanatory variables include the lagged return of stock i from week $t - 11$ to $t - 1$.

Table 7 presents the results. We start with the MW Bounds measure as the dependent variable in columns (1) to (4). Column (1) uses the raw level of past stock returns. The coefficients on the past 12 weekly returns are all significantly negative. Contrary to the findings on extrapolative expectations for retail investors, this suggests that the investors whose beliefs are reflected by bounds expect high (low) future stock returns when the past returns are low (high). Moreover, the absolute values of the coefficients on recent past returns are generally higher than those on distant past returns.

¹³The results remain robust if we use longer predicting horizons, such as 90 days, 270 days, and 365 days.

Column (4) uses the raw level of past stock returns with control variables, including tones of news coverage and revisions.¹⁴ After adding these controls, the pattern remains similar to column (1). Since some control variables are unavailable for all time t , our sample size shrinks by 20% after adding these. Columns (5)-(8) repeat these tests for the CYDV bounds, and the results are consistent.

This finding suggests that bounds-implied investors and Forcerank participants have opposite views regarding the role of past returns in predicting future performance. While Forcerank participants tend to extrapolate from past returns, bounds-implied investors appear to be contrarian.

4.4 Evidence from option-implied bounds on the aggregate market

Next, we examine how bounds on market expected returns correlate with actual past returns to enable a comprehensive comparison with survey-based expectations. We use a similar regression as Eqn. (3), and replace the independent variable with $Bound_t$, which is the average annualized bounds expected returns at week t for the subsequent period. The predicted horizon could be 30, 91, 182, 273, or 365 days. R_{t-s} is the lagged weekly market return from week $t - 12$ to $t - 1$.

Table 8 presents the results. Column (1) uses past weekly stock returns to explain the CYL Bounds expected returns over the next 30 days. Column (2) incorporates controls such as tones of news coverage and revisions. Column (3) and onward repeat the above analysis to explain the CYL Bounds expected returns over the next 91, 182 and 365 days.

First, the analysis of market bounds reveals that investors in option markets, whose expectations are represented by bounds, exhibit a contrarian stance in relation to past returns and assign greater importance to more recent returns. Second, note that as one moves from the right to the left columns, the explanatory power of the model—the adjusted R^2 —increases. Third, for the past return in a given week (or month) t , its coefficient estimate also increases in magnitude when moving from the right to the left columns. These last two sets of results indicate that the same list of past returns plays a more critical role in forming expectations in option markets for the near future than that covering the distant future. The findings remain consistent when using past monthly returns or using Martin Bounds, as shown in table A3 and table A5.

To better illustrate the impact of the most recent return appreciation on bounds-implied expected returns, we employ a similar regression as Eqn.(4) by replacing the dependent variable with $Bound_t$. $Bound_t$ is the market bounds on expected return

¹⁴The construction details are introduced in Appendix A.1.

at each trading day t , and the predicting horizons could be 30, 91, 182, or 365 days. The explanatory variable, Acceleration, measures the convexity of the price path.

Table 9 presents regression results. Column (1) includes acceleration as an explanatory variable to explain bounds expected returns for the next 30 days. Column (2) incorporates price-dividend ratio as a control. Column (3) and onward repeat the above analysis to explain the CYL Bounds expected returns over the next 91, 182, and 365 days. In general, the investors, whose beliefs are reflected by bounds, exhibit lower expectations for the market when acceleration is greater. Furthermore, investor expectations of future market returns demonstrate a negative correlation with the log price-dividend ratio across all three survey measures.

This analysis reveals that when past market returns are high (low), option-implied market expected returns tend to be low (high). This inverse relationship is also evident for individual stock markets, as demonstrated in the previous section.

5 Institutional Investors and return expectations

What role do bounds play in the real investment world? Are investors more inclined to allocate capital to stocks with higher bounds values? In this section, we examine whether mutual funds or hedge funds adhere to bounds when making investment decisions. We introduce the empirical methodology in Sections 5.1 and 5.2, and present results for mutual funds and hedge funds in 5.3.

5.1 Measuring Bounds Beta

To investigate the propensity of fund managers to align their trading activities with bounds information, we look at the trading activities of each fund. Specifically, for each fund j , we regress the changes in the portfolio weight of stock i from the end of quarter $t - 1$ to the end of quarter t , denoted as $\Delta\omega_{j,i,t}$, on the average option implied return of stock i for next 90 days over the same quarter t , which is $\text{Bounds}_{i,t}$, along with a set of standard stock characteristics $C_{s,t}$ and time fixed effect $\theta_{j,t}$. The regression model is presented as follows:

$$\Delta\omega_{j,i,t} = \alpha_j + \beta_j \cdot \text{Bounds}_{i,t} + \gamma_j C_{s,t} + \theta_{j,t} + \epsilon_{j,i,t}, \text{ for } j = 1, \dots, J. \quad (5)$$

In this model, the coefficient β_j —termed as *bounds beta* of fund j —is of particular interest. It quantifies the extent to which fund managers' trading decisions are influenced by bounds information, i.e., the implied belief about future returns associated with the bounds. Funds with a positive beta ($\beta_j > 0$) are classified as bound followers

(believers), while those with a non-positive beta ($\beta_j \leq 0$) are considered as bound deniers.

We use a set of stock-level controls, $C_{s,t}$, to ensure that β_j accurately captures the influence of bound information on trading decisions. These controls include size, book-to-market, asset growth, and past one-month return as a proxy for short-term reversal (e.g. Fama and French, 1993; Cooper et al., 2008; Efficiency, 1993). Furthermore, we include year-by-quarter fixed effect $\theta_{j,t}$ in our regressions to account for transitory trading behaviors that could be influenced by systemic variations such as overall market sentiment, macroeconomic announcements, etc. Additionally, the time fixed effect also captures variations in fund flows and fund liquidity conditions (Lou, 2012)

To isolate the component of active managerial trading decisions on portfolio composition, we follow the method proposed by Ali, Chen, Yao and Yu (2008); Kacperczyk, Sialm and Zheng (2005) to calculate the adjusted weight changes as follows:

$$\Delta\omega_{s,j,t} = \omega_{s,j,t} - \frac{1 + r_{s,t-1 \rightarrow t}}{1 + r_{j,t-1 \rightarrow t}} \omega_{s,j,t-1}, \quad (6)$$

where $r_{j,t-1 \rightarrow t}$ is the total portfolio return for fund j in quarter $(t-1, t]$, and $r_{s,t-1 \rightarrow t}$ denotes the stock return within the fund portfolio during the same quarter. This adjustment ensures that the measured weight changes reflect active trading decisions, rather than being a result of passive market movements or external influences on the portfolio.¹⁵

5.2 Cross-sectional Distribution of Bounds Beta - Bootstrapping Simulation Setup

Our aim is to test the existence of true bound followers or deniers, with the challenge being to differentiate true followers from false ones. Considering the multitude of funds, some funds will happen to have significant positive bounds beta even if they are false followers. Moreover, an unbiased t-statistic requires an asymptotically normal distribution that is identical and independent. However, the fund sample is finite, resulting in non-normal distribution. To address these issues, we adopt the bootstrap approach that is widely-used in the literature of differentiating luck from skill in

¹⁵For the dependent variable $\Delta\omega_{j,i,t}$, using straightforward metrics such as quarter-on-quarter changes in portfolio weights or changes in the number of shares held for each stock is unsuitable for our analysis. Specifically, portfolio weights may change purely due to the relative performance of one stock against others in the fund, independent of any trades. Similarly, focusing solely on the number of shares held, without accounting for stock prices, fails to provide a precise reflection of shifts in asset allocation.

assessing the existence of outperforming mutual funds across the entire cross-section (e.g. Kosowski et al., 2006; Fama and French, 2010; Harvey and Liu, 2021).

Our goal is to draw inferences about the cross-section of true bounds beta β for actively managed US domestic equity funds, determining whether the cross-section of β estimates suggest a world where true β is zero for all funds or whether positive or negative β values exist, especially in the tails of the cross-section of β estimates. To do so, we employ the Fama and French (2010) (hereafter FF) technique to implement the bootstrap approach under the null hypothesis that no funds are true bound followers or deniers.¹⁶ Specifically, we compare the actual cross-section of bounds beta estimates with the results from 1,000 bootstrap simulations of the cross-section. The weight changes $\Delta\omega_{s,j,t}^{boot}$ in one simulation have the properties of actual weight changes $\Delta\omega_{s,j,t}$, except that we set the true bounds beta β to zero in the weight changes population from which simulation samples are drawn. Consequently, the simulations describe the distribution of β estimates when there is no tendency to execute trades following bounds information in changing portfolio weights. Comparing the distribution of β estimates from the simulations with the cross-section of β estimates for actual fund weight changes enables us to draw inferences about the existence of true bound followers or deniers.

The bootstrapping procedure is executed as follows. To obtain the actual cross-section of bounds beta estimates, we run Eqn.(5) for each fund to derive bounds beta estimate $\hat{\beta}_j$, which will be used later in the simulation. Each simulation run starts with a random sample, with replacement, of 100 quarters. t^{boot} is drawn from these 100 calendar quarters between 1996 Q1 and 2020 Q4. We then use the bootstrapped time sequence to resample regression variables, including beta estimates $\hat{\beta}_j^{boot}$, and bounds information $Bounds_{i,t}^{boot}$. Next, to perform bootstrap simulations on weight changes that maintain properties except for setting true β to zero for each fund, we subtract a fund's β part estimate from its weight changes. Consequently, the bootstrapped weight changes for each fund can be calculated as $\Delta\omega_{j,i,t}^{boot} = \Delta\omega_{j,i,t} - \hat{\beta}_j^{boot} * Bounds_{i,t}^{boot}$. We exclude funds with less than 10 observations to ensure each fund has enough performance history. We then run the baseline regression in Eqn.(5) for each fund to obtain bootstrapped beta coefficient and its corresponding bootstrapped t-statistic. Finally, we repeat the above bootstrapping steps 1,000 times to compute bootstrapped p-value¹⁷, which can be interpreted as (i) the probability that bootstrapped $t(\beta)$ estimates at the selected percentiles reaches at least as low as the $t(\beta)$ estimates

¹⁶Besides FF, other notable bootstrap approaches include Kosowski et al. (2006) (hereafter KTWW), and Harvey and Liu (2021) (hereafter HL). While KTWW separately draw factor returns and residuals for each fund, FF resample the entire cross-section across funds by simultaneously drawing factor returns and residuals. HL comprehensively review both bootstrapping approaches and generally recommend using the FF technique, despite of its undersampling issue. FF method is also more conservative than the threshold approach proposed by HL that could mitigate the limited or no power outcome of zero outperforming mutual funds.

¹⁷If the cross-sectional t-statistic is in the right tail ($\geq 50\%$ percentile), the bootstrapped p-value is computed as the total number of iterations in which the bootstrapped t-statistic is greater than the t-statistic actually observed; if the cross-sectional t-statistic is in the left tail ($< 50\%$ percentile),

from actual funds and bounds information at the same percentiles for the left tail percentiles, or (ii) the probability that bootstrapped $t(\beta)$ estimates at the selected percentiles reaches at least as high as the $t(\beta)$ estimates from actual funds and bounds information at the same percentiles for the right tail percentiles.

We perform the above procedure using MW Bounds and CYDV Bounds separately, resulting in 2 distributions of t-statistics, $t(\beta)$, for a world in which true β is zero. We focus on $t(\beta)$ and its corresponding bootstrapped p-value to infer the likelihood that the cross-section of $t(\beta)$ estimates from the actual fund and bound information points to the existence of bounds followers.

5.3 Bootstrapping Simulation Results

The simulation results are intriguing. While cross-sectional variations exist in the bounds beta, and some funds trade in accordance with bounds information while others do not, only bound followers are documented to be statistically significant and truly present across the entire cross-section.

5.3.1 Mutual funds

Table 10 presents the results of mutual funds at selected percentiles (Pct) of the distribution of $t(\beta)$ estimates. The table includes the values of β estimates, the t-statistics of β , and bootstrapped p-value associated with t-stat.

Combining t-stat and p-value offers a more robust statistical inference. For instance, in the first percentile of the MW Bounds group, a t-statistic of -3.233 indicates that approximately 1% of funds within the entire cross-section exhibit a significant tendency to be bound deniers. However, the associated bootstrapped p-value of 0.884 for the 1% percentile t-statistic suggests an 88.4% probability that the bootstrapped t-statistic at the 1% percentile reaches as low as -3.233. Under the null hypothesis that no funds are true bound deniers, this evidence demonstrates that none of the funds display a significant tendency to be bound deniers.

For the CYDV Bounds group, the presence of bound followers is strongly supported. The selected percentile values of $t(\beta)$ derived from actual funds and bounds information consistently beat the corresponding percentiles of $t(\beta)$ obtained from simulations of funds and bounds information in the most right tile from 50% percentile to 97% percentile, according to the fact that bootstrapped p-values are less than 20%¹⁸.

the bootstrapped p-value is computed as the total number of iterations in which the bootstrapped t-statistic is less than the t-statistic actually observed.

¹⁸We use 20% threshold set up by Fama and French (2010)

5.3.2 Hedge funds

Table 12 presents the results of hedges funds.

For the MW Bounds group, when t-statistics are in the left tail, all p-values are larger than 0.85, suggesting that over 85% probability that the bootstrapped t-statistics can reach as low as $t(\beta)$, and none of these left-tail funds are true bond deniers. When t-statistics are in the right tail, 50% percentile to 70% percentile are shown to be true bounds followers with less than 20% p-values. This result holds for the CYDV Bounds group.

In summary, although there are cross-sectional variations in the bounds beta, and some funds' trades follow bounds information while others do not, only bound followers are documented to be statistically significant and truly existing in the whole cross-section. This evidence holds for both the MW Bounds group and the CYDV Bounds group.

6 Conclusion

In this study, we perform the first comprehensive set of empirical analyses to show that, contrary to the findings on extrapolative expectations shown in survey data, option-implied expectation bounds load negatively on past returns. The results are highly significant, both statistically and economically. Moreover, we document the existence of a large fraction of mutual managers whose trade directions are strongly and positively correlated with option-implied bounds. Taken together, our results suggest that rational investors, by explicitly betting against past returns, understand the behavioral pitfalls that naive investors fall into and trade in the option market.

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Table 1: **Summary Statistics of Forcerank**

Panel A displays the number of games, contests, and records for each industry covered in Forcerank during the sample period from February 2016 to December 2017. Generally, each industry does not have more than one game occurring simultaneously, and each game represents a unique combination of ten tickers within the same industry. Most games are reintroduced over time, leading to multiple weekly contests. Each user submission for a contest generates one record. Additionally, a game may be updated to a new version if some original tickers are replaced, resulting in multiple games for a single industry throughout the sample period. Apart from the games focusing on industries, the data also includes games centered on the most heavily shorted stocks. In this table, industries are ordered by the number of contests in descending order. Panel B presents the descriptive statistics for users in our sample.

Panel A. Industry-level general information

Industries	Number of games	Number of contests	Number of records
Enterprise Software	3	135	2161
Biotech	4	119	1771
Social Media	3	112	2836
E-Commerce	2	106	2476
Apparel	2	101	1609
E&P	1	95	1710
Hardware	2	89	1593
Fast Food.	3	69	978
Investment Banks	2	68	1747
Airlines	2	68	1088
Media	1	68	1020
Semiconductors	2	65	1223
Restaurants	3	65	957
Chemicals	2	52	663
Pharmaceuticals	1	51	832
Oil Services.	2	42	540
Most Heavily Shorted	22	95	1885
Total	57	1400	25089

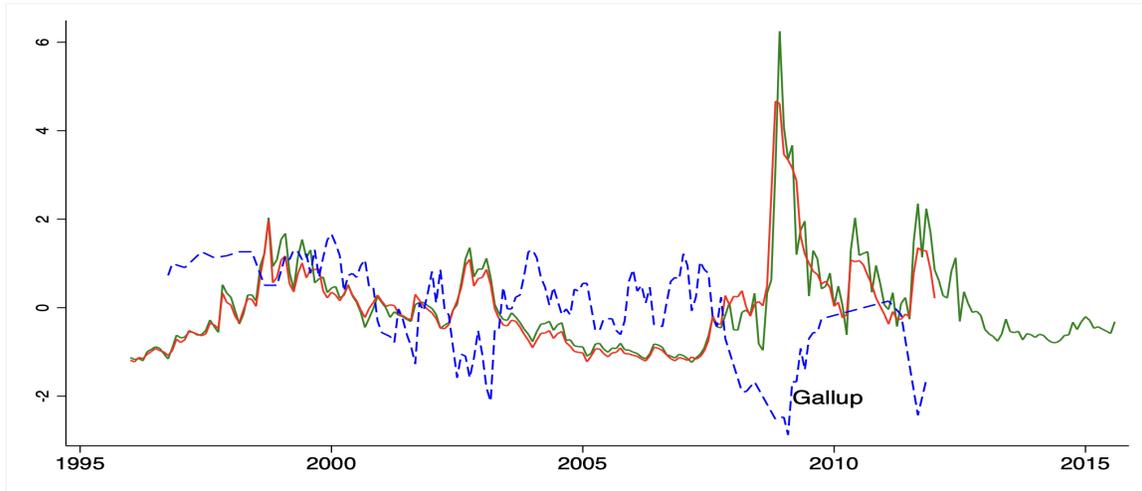
Panel B. User-level participation characteristics (Number of users = 3660)

	Mean	SD	P1	P25	P50	P75	P99
Number of games	3.12	4.33	1	1	1	3	21
Number of contests	6.85	38.46	1	1	2	4	74
Number of weeks	1.78	3.13	1	1	1	2	12

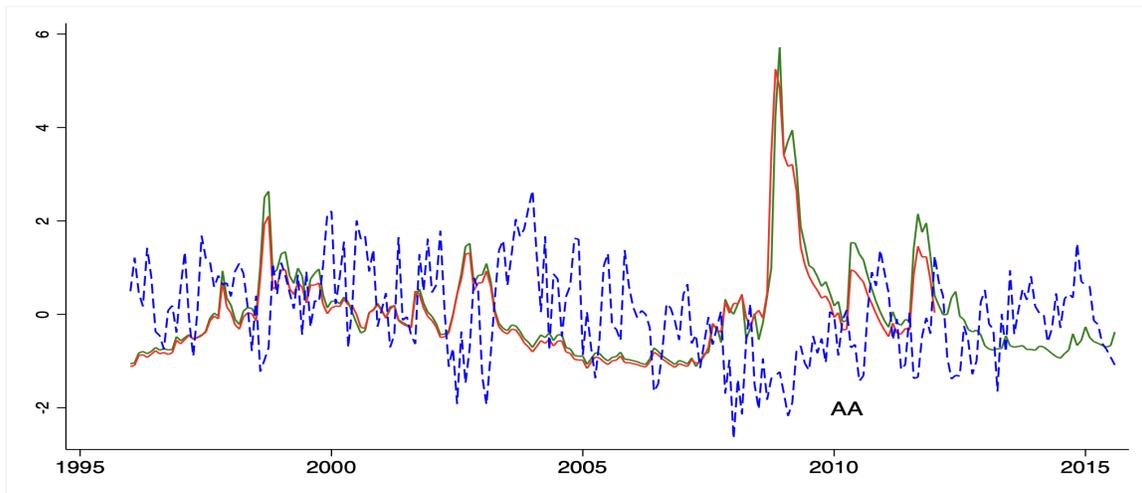
Figure 1: **Expectations of returns from market surveys and Option-Implied bounds**

In each panel, the time series are normalized to have zero mean and unit variance. The green, red, and blue lines denote CYL Bounds, Martin Bounds, and survey-based market expectations respectively. The forecasting horizon is 12 months for Panel A, 6 months for Panel B, and 3 months for Panel C.

(a) Gallup



(b) AA



(c) II

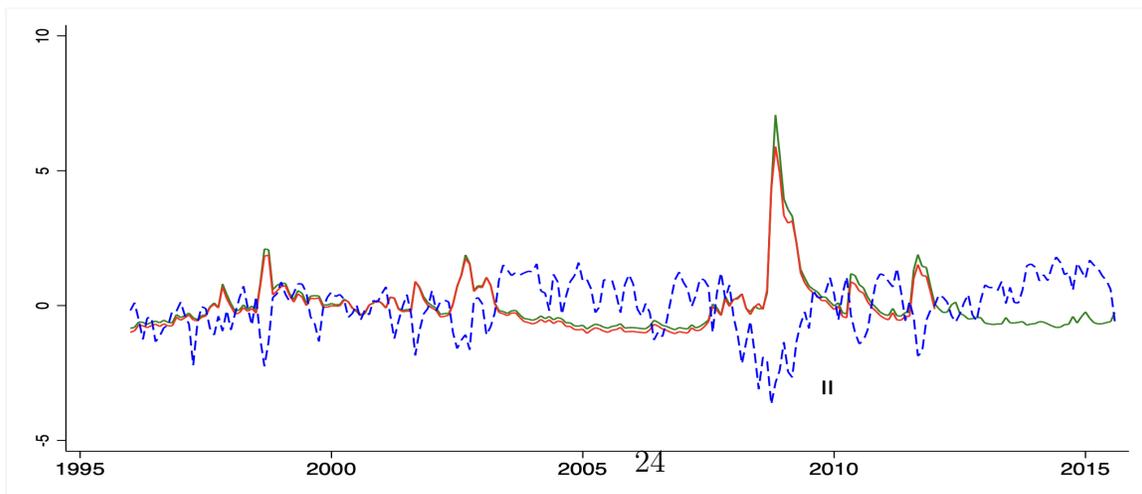
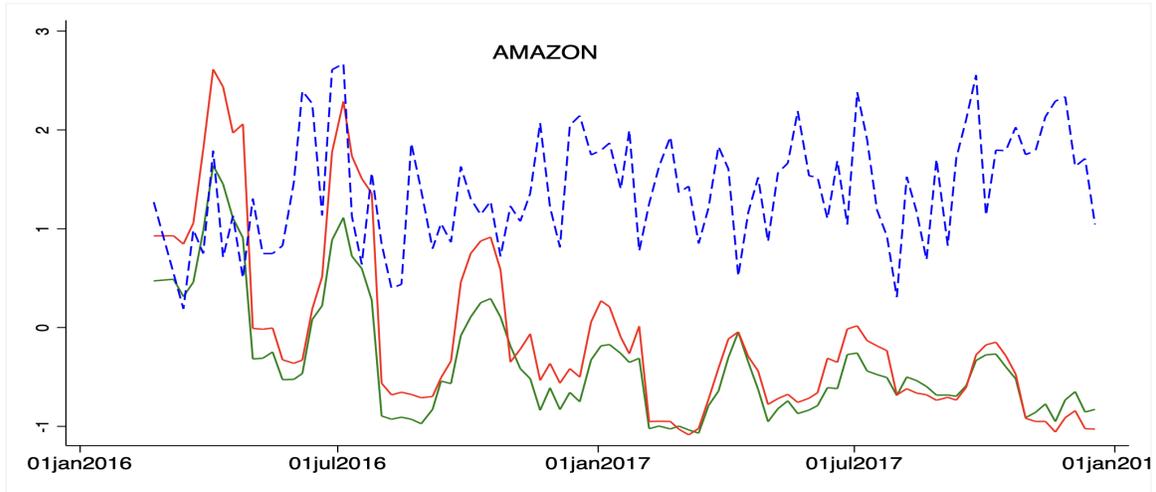


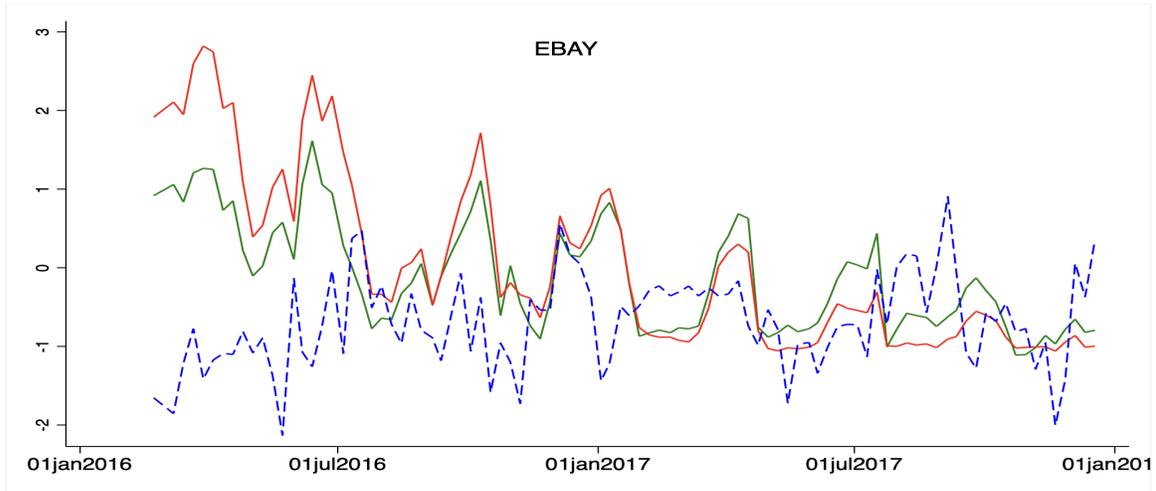
Figure 2: Expectations of returns from Forcerank and Option-Implied bounds

We pick 3 stocks from one longest Game lasting 95 weeks from February 22, 2016 to December 22, 2017. In each panel, the time series are normalized to have zero mean and unit variance. The green, red, and blue lines denote CYDV Bounds, MW Bounds, and expectations from Forcerank respectively. The forecasting horizon is 1 months for bounds and 1 week for Forcerank.

(a) AMAZON



(b) EBAY



(c) EXPE

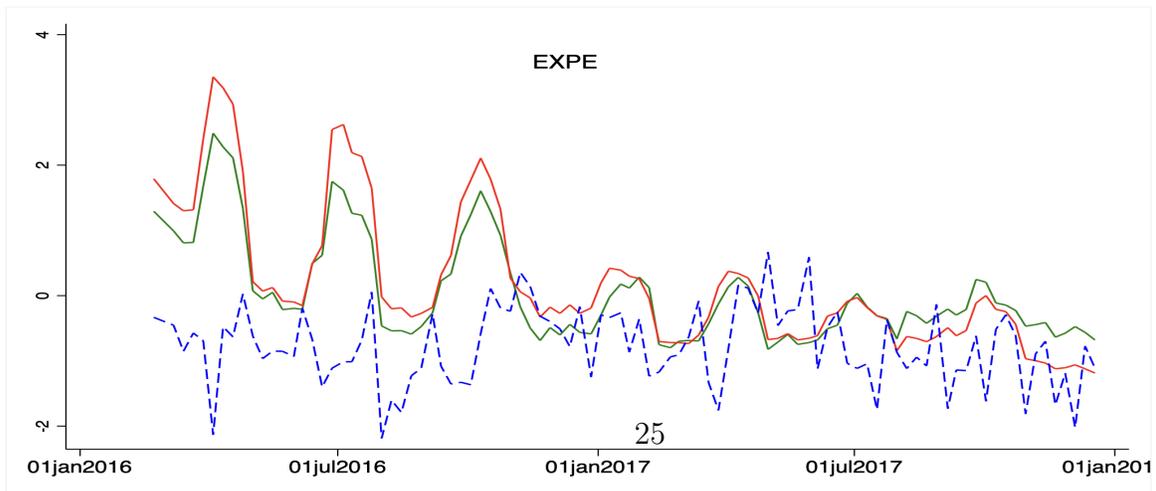


Figure 3: **Sentiment-Price Wedge Over Time NEW**

This figure plots the Sentiment-Price Wedge (SPW), defined as the difference between standardized survey expectations and standardized option-implied expected return bounds. For each survey series $s \in \{\text{Gallup, AAI, Investors Intelligence}\}$, $SPW_t^s \equiv z(\text{Survey}_t^s) - z(\text{Bound}_t)$, where $z(\cdot)$ standardizes each series to zero mean and unit standard deviation over the full sample. Bound_t is the monthly average of daily option-implied bounds on expected returns over the next 30 days (constant-maturity one-month horizon). The upper panel uses the Martin bound; the lower panel uses the CYL bound. Shaded areas indicate NBER recession dates.

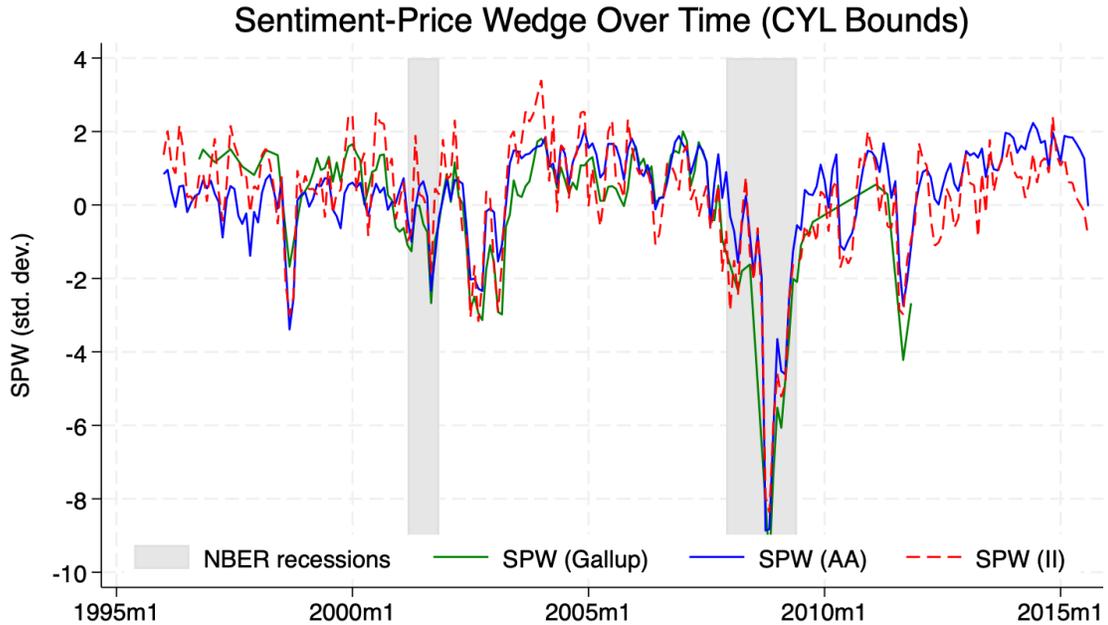
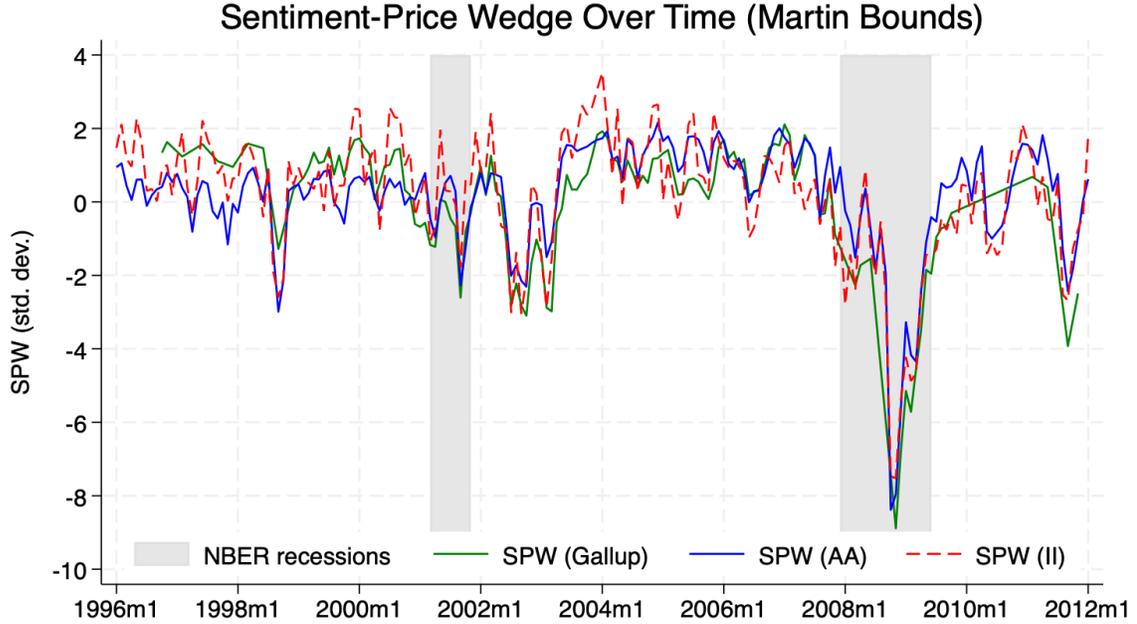


Table 2: **Summary Statistics of market survey**

This table presents a descriptive summary of three market surveys we use. (1). The AA survey has been conducted weekly since 1987. We use the period from July 1987 to December 2020. (2). The II survey began in 1963 and is available to us until October 2018. It was conducted biweekly until June 1969 and switched to a weekly frequency thereafter. (3) The Gallup survey was conducted between 1996 and 2002 with some gaps in between. All these three measures of expectations are given by AA or II or Gallup = %Bullish - %Bearish. Descriptive statistics are recorded after converting the frequency to monthly, and expressed in percentage point. The term “horizon” refers to the time period of returns expected by survey participants.

Survey	Period	Freq	Horizon	N	Mean	Med	Min	Max	σ
Gallup	1996.10-2011.11	Monthly	twelve months	135	19.68	22	-45	57	22.46
AA	1987.7-2020.12	Weekly	six months	402	7.39	7.98	-41	50.47	14.81
II	1963.1-2018.10	(Bi)Weekly	“Near term”	670	14.65	17.01	-49.2	66.64	19.84

Table 3: **Summary Statistics of bounds**

Panel A contains daily observations for two versions of bounds on the market risk premium, which are Martin Bound and CYL Bound. Martin Bound denotes the (Martin, 2017) bound, which is from January 1996 to January 2012. CYL Bound, available from January 1996 to August 2015, denotes the restricted bound from (Chabi-Yo and Loudis, 2020). Both bounds are annualized and expressed in percent. Panel B contains daily observations for two versions of bounds on the expected returns of S&P 500 constituent stocks - MW Bound and CYDV Bound. The MW Bound is derived using the methodology from (Martin and Wagner, 2019), which contains 1163 distinct stocks overall. CYDV Bound is derived from the (Chabi-Yo, Dim and Vilkov, 2022) assuming risk aversion of two and half prudence of one, which contains 1172 distinct stocks. Both MW Bound and CYDV Bound are available from January 1996 to December 2020.

Panel A. Market bounds summary statistics								
Bounds	Mean	SD	P10	P25	P50	P75	P90	N
<i>1-month horizon</i>								
Martin Bound	5	4.6	1.5	2.44	3.91	5.74	8.98	4048
CYL Bound	5.15	5.36	1.6	2.25	3.75	5.9	9.68	4688
<i>3-month horizon</i>								
Martin Bound	4.96	3.6	1.75	2.69	4.24	5.95	8.17	4048
CYL Bound	5.52	4.71	2.02	2.71	4.36	6.58	9.56	4946
<i>6-month horizon</i>								
Martin Bound	4.89	2.97	1.95	2.88	4.4	6	7.69	4048
CYL Bound	5.75	3.71	2.4	3.15	4.88	7.03	9.77	4943
<i>12-month horizon</i>								
Martin Bound	4.64	2.43	2.07	2.81	4.36	5.72	7.19	4048
CYL Bound	5.76	3.29	2.65	3.63	5.01	7.08	9.65	4778

Panel B. Stock bounds summary statistics								
Bounds	Mean	SD	P10	P25	P50	P75	P90	N
<i>1-month horizon</i>								
MW Bound	7.79	10.94	0.8	2.08	4.51	9.25	17.95	4,572,595
CYDV Bound	8.9	11.11	2.21	3.43	5.82	10.22	17.55	4,510,504
<i>3-month horizon</i>								
MW Bound	7.22	9.27	1.09	2.21	4.33	8.54	16.32	4,563,593
CYDV Bound	7.77	8.7	2.07	3.19	5.19	9.06	15.43	4,502,063
<i>6-month horizon</i>								
MW Bound	7.09	8.47	1.35	2.41	4.42	8.36	15.7	3,908,361
CYDV Bound	7.47	7.82	2.06	3.16	5.09	8.88	14.94	3,871,495
<i>12-month horizon</i>								
MW Bound	7.14	7.69	1.67	2.73	4.67	8.44	15.47	2,481,471
CYDV Bound	7.56	7.11	2.3	3.39	5.34	9.28	14.9	2,497,630

Table 4: **Correlation matrix: Market survey & Market bounds**

Panel A presents the pairwise correlation matrix between each pair of option-implied expected returns (Martin Bounds and CYL Bounds) over different horizons (1 month to 12 months) and return expectations derived from market surveys such as Gallup, AA, and II. Panel B shows the correlation between the Forcerank score and bounds under two distinct market conditions: when the market has yielded positive returns or negative returns in the last month. We compute the monthly average of the bounds predictions to be consistent with the frequency of survey data. N is the number of monthly observations in each variable during its available time period.

Panel A											
	Martin(1m) N = 193	Martin(3m) N = 193	Martin(6m) N = 193	Martin(12m) N = 193	CYL(1m) N = 236	CYL(3m) N = 236	CYL(6m) N = 236	CYL(12m) N = 232	Gallup N=135	AA N=236	II N=236
Martin(1m)	1										
Martin(3m)	0.97***	1									
Martin(6m)	0.93***	0.99***	1								
Martin(12m)	0.87***	0.95***	0.99***	1							
CYL(1m)	0.998***	0.97***	0.93***	0.87***	1						
CYL(3m)	0.97***	0.995***	0.98***	0.95***	0.97***	1					
CYL(6m)	0.83***	0.93***	0.97***	0.97***	0.84***	0.93***	1				
CYL(12m)	0.75***	0.86***	0.91***	0.94***	0.75***	0.86***	0.92***	1			
Gallup	-0.62***	-0.60***	-0.56***	-0.53***	-0.61***	-0.60***	-0.54***	-0.50***	1		
AA	-0.39***	-0.39***	-0.37***	-0.36***	-0.34***	-0.34***	-0.32***	-0.27***	0.64***	1	
II	-0.63***	-0.60***	-0.57***	-0.51***	-0.64***	-0.60***	-0.54***	-0.42***	0.60***	0.47***	1

Panel B											
	<i>past one-month return is negative</i>										
	N = 77	N = 77	N = 77	N = 77	N = 90	N = 90	N = 90	N=89	N=54	N=90	N=90
Gallup	-0.64***	-0.63***	-0.58***	-0.53***	-0.64***	-0.63***	-0.59***	-0.51***	1		
AA	-0.38***	-0.38***	-0.36***	-0.33***	-0.35***	-0.35***	-0.32***	-0.25***	0.72**	1	
II	-0.70***	-0.68***	-0.65***	-0.59***	-0.69***	-0.65***	-0.56***	-0.44***	0.75***	0.47***	1
	<i>past one-month return is positive</i>										
	N = 116	N = 116	N = 116	N = 116	N = 146	N = 146	N = 146	N=146	N=81	N=146	N=146
Gallup	-0.57***	-0.55***	-0.51***	-0.51***	-0.56***	-0.54***	-0.50***	-0.49***	1		
AA	-0.34***	-0.34***	-0.34***	-0.33***	-0.27***	-0.28***	-0.29***	-0.25***	0.54***	1	
II	-0.57***	-0.52***	-0.49***	-0.43***	-0.59***	-0.55***	-0.51***	-0.39***	0.48***	0.45***	1

Table 5: Correlation matrix: Forcerank & individual stock bounds

Panel A displays the pairwise correlations between the two option-implied expected returns, namely MW Bounds and CYDV Bounds, across varying time horizons ranging from 1 month to 12 months, and the expected returns as represented in Forcerank. Panel B shows the pairwise correlation between the Forcerank score and bounds under different conditions: when the stock experienced either positive or negative returns in the last week, or when the size of the firm falls into either the upper 50th percentile (larger firm) or the lower 50th percentile (smaller firm) of market capitalization. To align with the frequency of Forcerank, we calculate the weekly average of the contest-adjusted bounds. The sample period is the Forcerank period, which is from February 2016 to December 2017. N denotes the number of observations for each variable within this period.

Panel A

	MW(1m) N=8068	MW(3m) N=8068	MW(6m) N=7938	MW(12m) N=7627	CYDV(1m) N=8064	CYDV(3m) N=8064	CYDV(6m) N=8064	CYDV(12m) N=8064	Forcerank N=8068
MW(1m)	1								
MW(3m)	0.92 ***	1							
MW(6m)	0.90***	0.99***	1						
MW(12m)	0.87***	0.97 ***	0.98***	1					
CYDV(1m)	0.64 ***	0.45***	0.41***	0.39***	1				
CYDV(3m)	0.56 ***	0.40***	0.36***	0.35 ***	0.88***	1			
CYDV(6m)	0.55 ***	0.38 ***	0.36 ***	0.34***	0.86***	0.99***	1		
CYDV(12m)	0.53***	0.37***	0.34***	0.33***	0.83***	0.98***	0.99 ***	1	
Forcerank	-0.25***	-0.23***	-0.22***	-0.22***	-0.20***	-0.20***	-0.20***	-0.20***	1

Panel B

<i>past one-week return is negative</i>									
	N = 3597	N = 3597	N = 3543	N = 3415	N = 3596	N = 3596	N = 3596	N = 3596	N = 3597
Forcerank	-0.30***	-0.28***	-0.28***	-0.27***	-0.21***	-0.22***	-0.21***	-0.21***	1
<i>past one-week return is positive</i>									
	N = 4471	N = 4471	N = 4395	N = 4212	N = 4468	N = 4468	N = 4468	N = 4468	N = 4471
Forcerank	-0.208***	-0.183***	-0.176***	-0.173***	-0.190***	-0.188***	-0.191***	-0.198***	1
<i>smaller firms</i>									
	N = 4015	N = 4015	N = 3885	N = 3584	N = 4011	N = 4011	N = 4011	N=4011	N=4015
Forcerank	-0.059***	-0.0371**	-0.027*	-0.017	-0.128***	-0.123***	-0.120***	-0.118***	1
<i>larger firms</i>									
	N = 4053	N=4053	N=4053						
Forcerank	-0.192***	-0.177***	-0.181***	-0.178***	-0.081***	-0.094***	-0.101***	-0.108***	1

Table 6: Market survey with past returns

This table presents the result of Newey–West(6) time-series regression:

$$Exp_t = \alpha + \sum_{s=1}^{12} \beta_s \cdot R_{t-s} + \epsilon_t$$

From columns (1) to (6), Exp_t represents the monthly market forecast, calculated by averaging expectations over the weeks in each month t . The explanatory variables include the past 12 monthly returns. From columns (7) to (10), Exp_t represents the weekly market forecast in each week t , with explanatory variables including the past 12 weekly returns. The predicting horizons are different across these three market surveys - the next six months for AA, the near future for II, and the next twelve months for Gallup. The sample period is from July 1987 to December 2020 for AA, from January 1963 to October 2018 for II, and from October 1996 to November 2011 for Gallup. AA and II are expressed in raw levels.

	Dependent variable: monthly forecast						Dependent variable: weekly forecast			
	(1) AA	(2) AA	(3) II	(4) II	(5) Gallup	(6) Gallup	(7) AA	(8) AA	(9) II	(10) II
Ret(t-1)	1.170*** [6.65]	1.000*** [5.36]	1.316*** [7.85]	1.491*** [12.16]	1.282*** [7.18]	1.348*** [7.37]	2.239*** [9.09]	2.399*** [7.46]	1.832*** [11.07]	1.295*** [8.54]
Ret(t-2)	0.343* [1.87]	0.114 [0.59]	0.854*** [6.86]	0.922*** [6.54]	1.455*** [5.99]	1.390*** [5.73]	1.644*** [6.50]	1.284*** [5.07]	1.928*** [11.74]	1.510*** [11.41]
Ret(t-3)	0.256 [1.53]	0.118 [0.60]	0.519*** [3.99]	0.696*** [5.31]	1.340*** [5.53]	1.224*** [4.76]	1.145*** [5.06]	0.919*** [3.60]	1.883*** [10.89]	1.431*** [9.50]
Ret(t-4)	0.183 [1.09]	0.040 [0.23]	0.335** [2.38]	0.493*** [4.04]	0.991*** [4.85]	0.964*** [5.03]	1.039*** [4.85]	0.722*** [3.17]	1.584*** [9.96]	1.417*** [8.76]
Ret(t-5)	0.233 [1.63]	0.089 [0.57]	0.236* [1.91]	0.399*** [3.25]	0.728*** [2.78]	1.009*** [4.91]	0.908*** [3.96]	0.638** [2.31]	1.461*** [8.84]	1.347*** [7.87]
Ret(t-6)	0.174 [0.89]	0.136 [0.63]	0.155 [1.16]	0.388*** [2.77]	0.859*** [3.29]	1.058*** [3.20]	0.717*** [4.02]	0.540*** [2.75]	1.278*** [8.12]	1.032*** [6.50]
Ret(t-7)	0.198 [1.10]	0.112 [0.55]	0.130 [0.99]	0.346*** [2.98]	0.624*** [2.96]	1.113*** [5.66]	0.703*** [3.79]	0.370* [1.72]	1.011*** [6.77]	0.929*** [6.30]
Ret(t-8)	0.251 [1.35]	0.110 [0.43]	0.250 [1.62]	0.487*** [3.39]	0.962*** [3.57]	1.600*** [6.06]	0.803*** [3.91]	0.559** [2.35]	0.908*** [5.97]	1.032*** [7.20]
Ret(t-9)	0.276* [1.74]	0.194 [0.76]	0.144 [1.15]	0.360*** [2.92]	0.741*** [3.15]	1.165*** [3.86]	0.440** [2.12]	0.216 [0.90]	0.947*** [6.53]	0.976*** [6.63]
Ret(t-10)	0.367** [2.46]	0.178 [0.77]	0.043 [0.37]	0.323** [2.51]	0.627*** [4.07]	1.265*** [5.77]	0.537*** [3.03]	0.307 [1.52]	0.949*** [6.05]	0.826*** [5.76]
Ret(t-11)	0.048 [0.28]	-0.015 [-0.06]	-0.030 [-0.23]	0.173 [1.41]	0.463** [2.17]	0.805*** [3.75]	0.324* [1.67]	0.089 [0.39]	0.808*** [5.62]	0.812*** [5.61]
Ret(t-12)	0.190 [0.89]	0.063 [0.26]	0.039 [0.33]	0.164 [1.27]	0.378 [1.60]	0.415** [2.50]	0.108 [0.57]	-0.102 [-0.47]	0.785*** [5.18]	0.695*** [4.68]
Revisions		0.607 [0.14]		-4.318** [-2.03]		-21.626*** [-5.37]		2.612 [1.25]		1.572 [1.09]
Tones		0.091 [1.63]		0.147*** [2.80]		0.199*** [2.65]		0.095** [2.28]		0.219*** [6.56]
Observations	312	253	286	227	135	115	1,755	1,052	2,463	934
R-squared	0.191	0.156	0.313	0.616	0.644	0.734	0.196	0.207	0.243	0.553

Table 7: **Bounds on individual stocks with past returns**

This table presents the result of panel regression:

$$Bounds_{i,t} = \alpha + \sum_{s=1}^{12} \beta_s \cdot R_{i,t-s} + \theta_i + \theta_t + \epsilon_{i,t}$$

The dependent variable, $Bound_{i,t}$, is the annualized bounds expected returns for individual stock i at week t . The prediction horizon is the next 30 days. Column (1) to (4) use the measure of MW Bounds, and column (5) to (8) use CYDV Bounds. The explanatory variables include the lagged returns of stock i ranging from week $t - 11$ to $t - 1$. Column (1) uses the raw level of past stock returns. Columns (2) and (3) separately examine the idiosyncratic and systematic components of past stock returns using CAPM. Column (4) incorporates control variables into the analysis, including tones of news coverage and revisions. Columns (5)-(8) repeat the respective analyses for the CYDV Bounds measure. The t-statistics are reported in brackets. Standard errors are clustered by the stock and by the week. *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	MW Bounds (30d)				CYDV Bounds (30d)			
	(1) (level)	(2) (idio)	(3) (sys)	(4) (control)	(5) (level)	(6) (idio)	(7) (sys)	(8) (control)
Ret(t-1)	-0.122*** [-5.87]	-0.069*** [-3.91]	-0.554*** [-12.74]	-0.128*** [-5.61]	-0.120*** [-5.92]	-0.070*** [-4.63]	-0.534*** [-9.76]	-0.128*** [-5.84]
Ret(t-2)	-0.121*** [-6.06]	-0.067*** [-4.01]	-0.583*** [-13.38]	-0.126*** [-5.75]	-0.120*** [-6.25]	-0.068*** [-4.78]	-0.580*** [-10.98]	-0.128*** [-6.15]
Ret(t-3)	-0.119*** [-6.10]	-0.064*** [-3.99]	-0.573*** [-12.79]	-0.125*** [-5.83]	-0.119*** [-6.34]	-0.062*** [-4.70]	-0.598*** [-11.15]	-0.128*** [-6.26]
Ret(t-4)	-0.111*** [-6.22]	-0.060*** [-4.06]	-0.546*** [-13.74]	-0.116*** [-5.95]	-0.113*** [-6.59]	-0.059*** [-4.92]	-0.579*** [-11.85]	-0.121*** [-6.55]
Ret(t-5)	-0.101*** [-6.06]	-0.055*** [-3.96]	-0.531*** [-13.13]	-0.103*** [-5.67]	-0.101*** [-6.35]	-0.052*** [-4.77]	-0.558*** [-11.09]	-0.106*** [-6.17]
Ret(t-6)	-0.100*** [-5.84]	-0.051*** [-3.81]	-0.528*** [-11.04]	-0.102*** [-5.43]	-0.101*** [-6.08]	-0.049*** [-4.68]	-0.561*** [-9.41]	-0.107*** [-5.81]
Ret(t-7)	-0.089*** [-5.44]	-0.045*** [-3.41]	-0.482*** [-11.29]	-0.088*** [-4.95]	-0.094*** [-5.87]	-0.044*** [-4.28]	-0.538*** [-9.90]	-0.099*** [-5.62]
Ret(t-8)	-0.092*** [-5.77]	-0.045*** [-3.49]	-0.511*** [-11.63]	-0.091*** [-5.25]	-0.097*** [-6.26]	-0.044*** [-4.44]	-0.571*** [-10.28]	-0.103*** [-6.03]
Ret(t-9)	-0.079*** [-5.16]	-0.040*** [-3.15]	-0.415*** [-9.84]	-0.076*** [-4.60]	-0.085*** [-5.69]	-0.040*** [-4.13]	-0.468*** [-8.73]	-0.089*** [-5.46]
Ret(t-10)	-0.075*** [-5.22]	-0.040*** [-3.29]	-0.380*** [-9.41]	-0.074*** [-4.75]	-0.080*** [-5.75]	-0.040*** [-4.28]	-0.424*** [-8.33]	-0.084*** [-5.60]
Ret(t-11)	-0.067*** [-4.84]	-0.034*** [-2.88]	-0.366*** [-9.06]	-0.066*** [-4.47]	-0.071*** [-5.41]	-0.034*** [-3.86]	-0.406*** [-8.02]	-0.076*** [-5.36]
Ret(t-12)	-0.060*** [-4.31]	-0.031*** [-2.63]	-0.302*** [-7.56]	-0.062*** [-4.10]	-0.062*** [-4.67]	-0.029*** [-3.22]	-0.337*** [-6.65]	-0.067*** [-4.71]
Revisions				-0.000*** [-10.76]				-0.000*** [-23.81]
Tones				-0.009*** [-14.45]				-0.005*** [-11.44]
Observations	909,597	909,597	912,199	712,092	912,677	912,677	912,742	706,914
R-squared	0.407	0.389	0.449	0.423	0.476	0.457	0.524	0.481

Table 8: Market bounds with past lagged returns (12 weeks)

This table presents the result of Newey–West(7) time-series regression:

$$Bound_t = \alpha + \sum_{s=1}^{12} \beta_s \cdot R_{t-s} + \epsilon_t$$

$Bound_t$ is the average CYL annualized bounds expected returns for the aggregate market at week t for the next period, and this period could be 30, 91, 182, 273, 365 days. R_{t-s} is the lagged weekly market return from week $t - 12$ to $t - 1$. Column (1) use the raw level of past stock returns to explain CYL expected returns on the next 30days. Column (2) include controls such as tones of news coverage, the stock’s CAPM expected returns from the previous 12 weeks and revisions. Column (3) and onward repeat the above analysis to explain CYL expected returns on the next 91, 182, 273 and 365 days. The standard errors are in parentheses \star , $\star\star$, and $\star\star\star$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CYL(30d)	CYL(30d)	CYL(91d)	CYL(91d)	CYL(182d)	CYL(182d)	CYL(365d)	CYL(365d)
Ret(t-1)	-0.808*** [-4.44]	-0.894*** [-5.16]	-0.475*** [-4.21]	-0.522*** [-5.25]	-0.296*** [-3.86]	-0.320*** [-4.96]	-0.202*** [-3.45]	-0.217*** [-4.65]
Ret(t-2)	-0.793*** [-4.12]	-0.851*** [-4.97]	-0.471*** [-3.98]	-0.500*** [-5.20]	-0.303*** [-3.63]	-0.311*** [-4.78]	-0.212*** [-3.33]	-0.212*** [-4.42]
Ret(t-3)	-0.736*** [-3.76]	-0.785*** [-4.49]	-0.457*** [-3.75]	-0.481*** [-4.71]	-0.301*** [-3.45]	-0.305*** [-4.32]	-0.213*** [-3.24]	-0.208*** [-4.07]
Ret(t-4)	-0.688*** [-3.77]	-0.735*** [-4.64]	-0.439*** [-3.54]	-0.458*** [-4.50]	-0.291*** [-3.13]	-0.290*** [-3.85]	-0.211*** [-2.84]	-0.202*** [-3.36]
Ret(t-5)	-0.640*** [-4.09]	-0.644*** [-5.28]	-0.430*** [-3.68]	-0.421*** [-4.74]	-0.295*** [-3.26]	-0.272*** [-3.97]	-0.215*** [-2.94]	-0.189*** [-3.36]
Ret(t-6)	-0.669*** [-3.12]	-0.652*** [-3.39]	-0.456*** [-3.14]	-0.430*** [-3.47]	-0.316*** [-2.98]	-0.279*** [-3.17]	-0.235*** [-2.76]	-0.198*** [-2.78]
Ret(t-7)	-0.575*** [-3.19]	-0.566*** [-3.73]	-0.400*** [-3.09]	-0.380*** [-3.63]	-0.286*** [-2.89]	-0.254*** [-3.22]	-0.218*** [-2.69]	-0.186*** [-2.85]
Ret(t-8)	-0.625*** [-3.36]	-0.607*** [-3.80]	-0.435*** [-3.11]	-0.409*** [-3.47]	-0.312*** [-2.92]	-0.276*** [-3.10]	-0.240*** [-2.74]	-0.204*** [-2.78]
Ret(t-9)	-0.486*** [-2.71]	-0.443*** [-2.78]	-0.370** [-2.53]	-0.329** [-2.55]	-0.277** [-2.46]	-0.233** [-2.38]	-0.221** [-2.39]	-0.179** [-2.23]
Ret(t-10)	-0.436*** [-3.01]	-0.395*** [-3.26]	-0.344*** [-2.75]	-0.309*** [-2.92]	-0.260*** [-2.58]	-0.222*** [-2.61]	-0.206** [-2.49]	-0.171** [-2.43]
Ret(t-11)	-0.400*** [-2.95]	-0.364*** [-3.24]	-0.305*** [-2.64]	-0.272*** [-2.86]	-0.230** [-2.44]	-0.196** [-2.54]	-0.184** [-2.33]	-0.154** [-2.37]
Ret(t-12)	-0.293*** [-2.81]	-0.259*** [-3.34]	-0.240** [-2.54]	-0.208*** [-2.91]	-0.184** [-2.33]	-0.152** [-2.52]	-0.151** [-2.22]	-0.123** [-2.36]
Revisions		-4.657*** [-4.69]		-3.797*** [-4.53]		-2.935*** [-4.09]		-2.343*** [-3.93]
Tones		-0.064*** [-3.64]		-0.054*** [-3.61]		-0.050*** [-3.87]		-0.046*** [-4.16]
Observations	1,280	1,076	1,280	1,076	1,280	1,076	1,280	1,076
R-squared	0.342	0.516	0.268	0.478	0.208	0.437	0.166	0.413

Table 9: Relationship between market bounds expected returns and acceleration

This table presents the result of time-series regression:

$$Bounds_t = a + b.Acceleration_t + c.log(P_t/D_t) + u_t$$

This table presents the time series regression of investors' expectation for the aggregate market on the Acceleration. Acceleration is defined as the difference between the 1-year return and the return for the first 3 quarters of that 1-year period: $Acceleration = R_{t-4 \rightarrow t} - R_{t-4 \rightarrow t-1}$. This measures the convexity of the price path and how much of the price appreciation has occurred in the most recent quarter. Columns (1) include acceleration as an explanatory variable to explain bounds expected returns for the next 30 days. Column (2) incorporates price-dividend ratio as a control. Column (3) and onward repeat the above analysis to explain the CYL Bounds expected returns over the next 91, 182, and 365 days. The standard errors are in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CYL(30d)	CYL(30d)	CYL(91d)	CYL(91d)	CYL(182d)	CYL(182d)	CYL(273d)	CYL(273d)	CYL(365d)	CYL(365d)
Acceleration	-0.569*** (-52.39)	-0.547*** (-50.18)	-0.390*** (-47.28)	-0.375*** (-45.21)	-0.276*** (-41.52)	-0.266*** (-39.74)	-0.230*** (-38.51)	-0.224*** (-37.05)	-0.208*** (-36.69)	-0.204*** (-35.59)
Log(P/D)		-0.0536*** (-12.39)		-0.0358*** (-10.86)		-0.0226*** (-8.48)		-0.0147*** (-6.13)		-0.00824*** (-3.61)
<i>N</i>	6293	6293	6293	6293	6293	6293	6293	6293	6293	6293

Table 10: **Cross-Sectional Distribution of Mutual Fund Followers**

This table presents the values of β estimates at selected percentiles (Pct) of the distribution of β estimates, t statistics of $\hat{\beta}$ at selected percentiles (Pct) of the distribution of $t(\beta)$ estimates, and bootstrapped p-value associated with t-stat. Bootstrapped p-value is the percent of the 1,000 simulation runs that produce lower(higher) value of $t(\beta)$ at the selected percentiles than those observed for actual funds and bounds information for left(right) tail percentiles. The period is from 1996Q1 to 2020Q4 and results are shown for using MW Bounds and CYDV Bounds. There are 1595 funds in both samples.

Pct	MW Bounds			CYDV Bounds		
	$\hat{\beta}$	t-stat	p-value	$\hat{\beta}$	t-stat	p-value
1	-0.086	-3.233	0.884	-0.163	-3.193	0.898
2	-0.049	-2.801	0.773	-0.066	-2.722	0.809
3	-0.042	-2.397	0.796	-0.049	-2.515	0.716
4	-0.034	-2.204	0.768	-0.036	-2.195	0.765
5	-0.029	-2.054	0.735	-0.031	-2.013	0.767
10	-0.015	-1.504	0.721	-0.016	-1.379	0.833
20	-0.005	-0.939	0.672	-0.005	-0.736	0.881
30	-0.002	-0.553	0.629	-0.002	-0.348	0.890
40	-0.001	-0.191	0.692	-0.000	-0.011	0.896
50	0.000	0.145	0.269	0.001	0.374	0.063
60	0.001	0.465	0.247	0.003	0.693	0.087
70	0.003	0.828	0.243	0.005	1.063	0.102
80	0.006	1.282	0.223	0.010	1.571	0.102
90	0.013	2.038	0.202	0.021	2.299	0.119
95	0.027	2.666	0.211	0.037	2.916	0.143
96	0.032	2.941	0.192	0.045	3.012	0.185
97	0.041	3.086	0.264	0.055	3.274	0.204
98	0.056	3.381	0.324	0.072	3.583	0.246
99	0.106	3.727	0.636	0.111	4.034	0.409

Table 11: Earnings Surprise and Option-Based Measures

This table reports panel regressions relating earnings surprises to option-based measures at the stock-month level. $SUE_{i,t} = \alpha_{i,t} + \beta \text{Bound}_{i,t-1} + \gamma IV_{i,t-1} + \theta \text{Ret}_{i,t-1} + \varepsilon_{i,t}$. The dependent variable is either (i) SUE , the standardized unexpected earnings based on I/B/E/S adjusted actual EPS minus the median analyst forecast and standardized by the firm-specific standard deviation of past forecast errors, or (ii) *Price-Scaled Earnings Surprise*, defined as $(\text{Actual}^{adj} - \text{Forecast}^{adj})/P_{i,t-}$, where $P_{i,t-}$ is the CRSP closing price measured five trading days before the earnings announcement date. Option-based predictors include the MW and CYDV bounds on expected returns over the next 30 days, as well as the 30-day implied volatility (IV) from OptionMetrics. *Past 1-month return* is the lagged CRSP one-month return. “+ Ind FE” additionally include Fama–French industry fixed effects (ffind). Standard errors are two-way clustered by firm (permno) and month (yrmon). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	SUE				SUE(price)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MW Bound	-1.961*** [-5.14]	-1.856*** [-5.24]			-0.024 [-1.40]	-0.022 [-1.26]		
CYDV Bound			-1.570*** [-3.19]	-1.481*** [-3.11]			0.008 [0.49]	0.014 [0.81]
IV	0.074 [0.43]	-0.196 [-1.17]	-0.494*** [-3.95]	-0.738*** [-5.80]	-0.020* [-1.92]	-0.024** [-2.14]	-0.031*** [-3.16]	-0.035*** [-3.31]
Past 1-mon return	1.518*** [10.85]	1.505*** [11.44]	1.482*** [10.77]	1.471*** [11.29]	0.013*** [2.68]	0.013*** [2.64]	0.014*** [2.82]	0.014*** [2.80]
Time FE	Y	Y	Y	Y	Y	Y	Y	Y
Industry FE	N	Y	N	Y	N	Y	N	Y
Observations	59,677	59,677	59,429	59,429	60,617	60,617	60,020	60,020
R Square	0.047	0.061	0.046	0.060	0.025	0.029	0.025	0.029

Table 12: **Cross-Sectional Distribution of Hedge Fund Followers**

This table presents the values of β estimates at selected percentiles (Pct) of the distribution of β estimates, t statistics of $\hat{\beta}$ at selected percentiles (Pct) of the distribution of $t(\beta)$ estimates, and bootstrapped p-value associated with t-stat. Bootstrapped p-value is the percent of the 1,000 simulation runs that produce lower(higher) value of $t(\beta)$ at the selected percentiles than those observed for actual funds and bounds information for left(right) tail percentiles. The period is from 1996Q1 to 2020Q4 and results are shown for using MW Bounds and CYDV Bounds. There are 1500 funds in both samples.

Pct	MW Bounds			CYDV Bounds		
	$\hat{\beta}$	t-stat	p-value	$\hat{\beta}$	t-stat	p-value
1	-0.745	-3.298	0.949	-1.104	-3.016	0.980
2	-0.369	-2.580	0.940	-0.456	-2.446	0.964
3	-0.254	-2.238	0.939	-0.305	-2.254	0.898
4	-0.186	-2.063	0.897	-0.224	-2.107	0.830
5	-0.136	-1.920	0.872	-0.192	-1.901	0.843
10	-0.052	-1.373	0.876	-0.080	-1.348	0.861
20	-0.012	-0.835	0.881	-0.018	-0.761	0.934
30	-0.003	-0.475	0.889	-0.004	-0.412	0.949
40	-0.001	-0.152	0.969	0.000	-0.090	0.994
50	0.000	0.104	0.057	0.001	0.190	0.009
60	0.002	0.375	0.122	0.004	0.440	0.042
70	0.008	0.672	0.198	0.015	0.747	0.101
80	0.023	0.993	0.472	0.043	1.073	0.272
90	0.096	1.478	0.689	0.126	1.633	0.415
95	0.212	1.964	0.797	0.277	2.297	0.389
96	0.250	2.182	0.761	0.333	2.440	0.480
97	0.370	2.395	0.787	0.494	2.585	0.626
98	0.604	2.595	0.924	0.852	2.886	0.736
99	1.405	3.118	0.980	2.102	3.482	0.900

Appendix

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Table A1: Survey on individual stocks with past returns: linear regression model

This table presents the result of contest level linear regression:

$$\text{Forcerank}_{i,t} = \alpha + \sum_{s=0}^{11} \beta_s \cdot R_{i,t-s} + \epsilon_{i,t}$$

This represents the average Forcerank score on stock i for the week $t + 1$ over all participants in that contest before the end of week t , and $R_{i,t-s}$ is the lagged return of stock i from week $t - 11$ to t . The sample period is from Feb 2016 to Dec 2017. Column (1) uses the raw level of past stock returns. Columns (2) and onwards focus on contest-adjusted returns (i.e., the raw stock return in excess of the average return of the ten stocks in the contest). Columns (3) and (4) separately examine the idiosyncratic and systematic components of past stock return. Each stock has one Beta over the whole period and the Beta is calculated from CAPM from 1990.1 to 2020.12. Column (5) uses an ordered logit regression. Columns (6) and (7) repeat the analysis in Column (3) separately for the first half (before March 1, 2017) and the second half (after March 1, 2017) of our sample period. Column (8) includes controls such as tones of news coverage, the stock's CAPM expected returns from the previous 12 weeks and revisions. All regressions cluster the standard errors by the contest. The standard errors are in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(level)	(adj)	(idio)	(sys)	(ord.logit)	(1st half)	(2nd half)	(w controls)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Ret(t)	11.10*** (0.570)	17.63*** (0.920)	12.03*** (0.606)	-8.478*** (1.087)	7.434*** (0.381)	15.83*** (1.287)	19.63*** (1.264)	18.00*** (1.021)
Ret(t-1)	3.722*** (0.523)	5.740*** (0.802)	3.941*** (0.552)	-7.906*** (0.987)	2.406*** (0.370)	6.042*** (1.133)	5.346*** (1.117)	4.839*** (0.837)
Ret(t-2)	2.576*** (0.498)	3.637*** (0.767)	2.770*** (0.532)	-7.186*** (0.926)	1.613*** (0.366)	3.477*** (1.044)	3.788*** (1.125)	2.545** (0.827)
Ret(t-3)	2.199*** (0.493)	3.179*** (0.763)	2.362*** (0.524)	-8.126*** (0.887)	1.244*** (0.365)	3.494*** (0.996)	2.775* (1.175)	1.661* (0.837)
Ret(t-4)	2.076*** (0.516)	3.117*** (0.808)	2.321*** (0.557)	-6.177*** (0.904)	1.378*** (0.373)	2.432* (1.144)	3.821*** (1.138)	1.211 (0.869)
Ret(t-5)	2.347*** (0.514)	3.180*** (0.810)	2.577*** (0.551)	-6.706*** (0.942)	1.462*** (0.373)	2.632* (1.133)	3.615** (1.181)	2.005* (0.858)
Ret(t-6)	1.535** (0.509)	2.850*** (0.797)	1.844*** (0.556)	-4.562*** (0.922)	0.936* (0.369)	1.912 (1.040)	3.766** (1.240)	1.384 (0.852)
Ret(t-7)	1.876*** (0.484)	3.442*** (0.751)	2.423*** (0.526)	-3.634*** (0.857)	1.208*** (0.366)	2.167* (1.001)	4.814*** (1.148)	2.366** (0.794)
Ret(t-8)	1.135* (0.496)	2.138** (0.765)	1.285* (0.524)	-5.145*** (0.864)	0.696 (0.366)	0.536 (1.023)	3.920*** (1.143)	0.598 (0.798)
Ret(t-9)	1.343** (0.484)	2.238** (0.775)	1.624** (0.533)	-4.931*** (0.765)	0.789* (0.364)	0.492 (1.030)	4.429*** (1.165)	0.720 (0.832)
Ret(t-10)	1.183* (0.475)	1.410 (0.770)	0.960 (0.554)	-5.106*** (0.820)	0.511 (0.359)	-0.367 (0.966)	3.809** (1.271)	-0.000689 (0.835)
Ret(t-11)	0.490 (0.451)	0.739 (0.740)	0.659 (0.517)	-5.746*** (0.740)	0.218 (0.358)	-0.0389 (0.933)	1.826 (1.214)	-0.751 (0.790)
R-squared	0.0373	0.0598	0.0431	0.00512	0.0088	0.0567	0.0671	0.106
Observations	12960	12960	12960	12986	12960	5903	7057	11499

Table A2: **Relationship between market survey expected returns and acceleration**

This table presents the result of time-series regression:

$$Exp_t = a + b.Acceleration_t + c.log(P_t/D_t) + u_t$$

This table presents the time series regression of investors' expectations for the aggregate market on the Acceleration. Acceleration is defined as the difference between the 1-year return and the return for the first 3 quarters of that 1-year period: $Acceleration = R_{t-4 \rightarrow t} - R_{t-4 \rightarrow t-1}$. This measures the convexity of the price path and how much of the price appreciation has occurred in the most recent quarter. In the last 3 columns, we also include the log price dividend ratio. The standard errors are in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	AA			II			Gallup		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Acceleration	0.640*** [7.19]	0.563*** [6.78]	0.448*** [3.91]	1.159*** [12.64]	1.076*** [12.55]	1.121*** [11.39]	1.804*** [9.12]	1.485*** [10.21]	1.356*** [8.61]
Log(P/D)		0.184*** [8.22]	0.443*** [9.57]		0.163*** [10.17]	0.053 [1.34]		0.509*** [11.12]	0.391*** [6.90]
Revisions			1.526 [1.11]			1.316 [1.06]			1.547 [0.72]
Tones			-0.051 [-1.52]			0.173*** [4.93]			0.176*** [2.70]
Observations	402	402	253	663	663	227	135	135	115
R-squared	0.114	0.243	0.345	0.195	0.304	0.523	0.385	0.682	0.720

Table A3: Market bounds with lagged past returns (12 months)

This table presents the result of Newey–West(6) time-series regression:

$$Bound_t = \alpha + \sum_{s=1}^{12} \beta_s \cdot R_{t-s} + \epsilon_t$$

$Bound_t$ is the average CYL annualized bounds expected returns for the aggregate market at month t for the next period, and this period could be 30, 91, 182, 273, 365 days. R_{t-s} is the lagged monthly market return from month $t - 12$ to $t - 1$. CYL is daily and the sample is from Jan 1996 to Dec 2020 here. Column (1) use the raw level of past stock returns to explain CYL expected returns on the next 30days. Column (2) include controls such as tones of news coverage, the stock's CAPM expected returns from the previous 12 weeks and revisions. Column (3) and onward repeat the above analysis to explain CYL expected returns on the next 91, 182, 273 and 365 days. The standard errors are in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CYL(30d)	CYL(30d)	CYL(91d)	CYL(91d)	CYL(182d)	CYL(182d)	CYL(365d)	CYL(365d)
Ret(t-1)	-0.696*** [-3.55]	-0.788*** [-4.02]	-0.456*** [-3.47]	-0.517*** [-4.04]	-0.307*** [-3.24]	-0.338*** [-3.75]	-0.224*** [-2.98]	-0.243*** [-3.48]
Ret(t-2)	-0.466*** [-4.10]	-0.473*** [-4.82]	-0.355*** [-3.57]	-0.359*** [-4.02]	-0.267*** [-3.24]	-0.257*** [-3.40]	-0.212*** [-2.99]	-0.201*** [-3.07]
Ret(t-3)	-0.387*** [-4.02]	-0.402*** [-4.69]	-0.309*** [-3.56]	-0.323*** [-4.09]	-0.235*** [-3.15]	-0.240*** [-3.51]	-0.190*** [-2.83]	-0.196*** [-3.25]
Ret(t-4)	-0.287*** [-2.92]	-0.288*** [-3.49]	-0.229*** [-2.97]	-0.233*** [-3.49]	-0.179*** [-2.75]	-0.180*** [-3.13]	-0.145** [-2.49]	-0.150*** [-2.98]
Ret(t-5)	-0.267*** [-3.19]	-0.236*** [-2.77]	-0.223*** [-3.18]	-0.202*** [-2.93]	-0.179*** [-2.88]	-0.168*** [-2.84]	-0.145** [-2.58]	-0.145*** [-2.88]
Ret(t-6)	-0.166** [-2.26]	-0.116 [-1.30]	-0.171*** [-2.63]	-0.143** [-2.17]	-0.144** [-2.44]	-0.128** [-2.33]	-0.120** [-2.24]	-0.116** [-2.47]
Ret(t-7)	-0.179*** [-2.83]	-0.165** [-2.51]	-0.148** [-2.56]	-0.143** [-2.58]	-0.114** [-2.11]	-0.115** [-2.34]	-0.091* [-1.84]	-0.099** [-2.32]
Ret(t-8)	-0.155** [-2.52]	-0.116 [-1.55]	-0.122** [-2.31]	-0.094 [-1.50]	-0.095* [-1.93]	-0.075 [-1.45]	-0.076* [-1.67]	-0.067 [-1.60]
Ret(t-9)	-0.107 [-1.19]	-0.060 [-0.55]	-0.092 [-1.40]	-0.059 [-0.74]	-0.079 [-1.47]	-0.058 [-0.94]	-0.071 [-1.54]	-0.062 [-1.39]
Ret(t-10)	-0.208** [-2.06]	-0.221** [-2.35]	-0.139* [-1.82]	-0.145** [-2.07]	-0.104 [-1.64]	-0.107* [-1.90]	-0.081 [-1.46]	-0.088* [-1.92]
Ret(t-11)	-0.066 [-0.67]	-0.065 [-0.62]	-0.057 [-0.73]	-0.060 [-0.76]	-0.046 [-0.71]	-0.047 [-0.76]	-0.040 [-0.70]	-0.044 [-0.90]
Ret(t-12)	-0.101 [-1.46]	-0.085 [-1.17]	-0.084 [-1.30]	-0.077 [-1.19]	-0.063 [-1.06]	-0.055 [-0.97]	-0.051 [-0.94]	-0.048 [-0.98]
Revisions		-2.282 [-1.43]		-1.836 [-1.27]		-1.376 [-1.09]		-0.991 [-1.01]
Tones		-0.034 [-1.42]		-0.027 [-1.30]		-0.028 [-1.53]		-0.027* [-1.69]
Observations	300	253	300	253	300	253	300	253
R-squared	0.417	0.526	0.404	0.541	0.358	0.518	0.317	0.508

Table A4: Market bounds with past lagged returns (12 months) controlled for VIX

This table presents the result of Newey–West(6) time-series regression:

$$Bound_t = \alpha + \sum_{s=1}^{12} \beta_s \cdot R_{t-s} + VIX_t + \epsilon_t$$

$Bound_t$ is the average CYL annualized bounds expected returns for the aggregate market at month t for the next period, and this period could be 30, 91, 182, 273, 365 days. R_{t-s} is the lagged monthly market return from month $t - 12$ to $t - 1$. CYL is daily and the sample is from Jan 1996 to Dec 2020 here. Column (1) use the raw level of past stock returns to explain CYL expected returns on the next 30days. Column (2) include controls of VIX. Column (3) and onward repeat the above analysis to explain CYL expected returns on the next 91, 182, 273 and 365 days. The standard errors are in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

VIX is obtained from the Cboe VIX Index historical data (1990–present; updated daily), available at https://www.cboe.com/tradable_products/vix/vix_historical_data.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CYL(30d)	CYL(30d)	CYL(91d)	CYL(91d)	CYL(182d)	CYL(182d)	CYL(365d)	CYL(365d)
Ret(t-1)	-0.696*** [-3.55]	-0.139*** [-3.77]	-0.456*** [-3.47]	-0.023 [-0.93]	-0.307*** [-3.24]	0.039* [1.68]	-0.224*** [-2.98]	0.060** [2.46]
Ret(t-2)	-0.466*** [-4.10]	-0.096*** [-3.36]	-0.355*** [-3.57]	-0.067** [-2.03]	-0.267*** [-3.24]	-0.037 [-1.07]	-0.212*** [-2.99]	-0.024 [-0.67]
Ret(t-3)	-0.387*** [-4.02]	-0.061*** [-2.67]	-0.309*** [-3.56]	-0.055** [-2.51]	-0.235*** [-3.15]	-0.033 [-1.14]	-0.190*** [-2.83]	-0.024 [-0.71]
Ret(t-4)	-0.287*** [-2.92]	-0.060*** [-2.60]	-0.229*** [-2.97]	-0.052*** [-3.27]	-0.179*** [-2.75]	-0.039* [-1.83]	-0.145** [-2.49]	-0.030 [-1.18]
Ret(t-5)	-0.267*** [-3.19]	-0.058** [-2.51]	-0.223*** [-3.18]	-0.061*** [-3.08]	-0.179*** [-2.88]	-0.049* [-1.92]	-0.145** [-2.58]	-0.039 [-1.31]
Ret(t-6)	-0.166** [-2.26]	-0.032 [-1.26]	-0.171*** [-2.63]	-0.066*** [-3.45]	-0.144** [-2.44]	-0.060** [-2.24]	-0.120** [-2.24]	-0.052* [-1.71]
Ret(t-7)	-0.179*** [-2.83]	-0.020 [-0.83]	-0.148** [-2.56]	-0.024 [-1.60]	-0.114** [-2.11]	-0.015 [-0.80]	-0.091* [-1.84]	-0.010 [-0.44]
Ret(t-8)	-0.155** [-2.52]	-0.007 [-0.40]	-0.122** [-2.31]	-0.007 [-0.45]	-0.095* [-1.93]	-0.003 [-0.18]	-0.076* [-1.67]	-0.001 [-0.04]
Ret(t-9)	-0.107 [-1.19]	0.000 [0.01]	-0.092 [-1.40]	-0.009 [-0.72]	-0.079 [-1.47]	-0.012 [-0.65]	-0.071 [-1.54]	-0.016 [-0.65]
Ret(t-10)	-0.208** [-2.06]	-0.046* [-1.88]	-0.139* [-1.82]	-0.012 [-0.74]	-0.104 [-1.64]	-0.003 [-0.15]	-0.081 [-1.46]	0.001 [0.06]
Ret(t-11)	-0.066 [-0.67]	-0.031 [-1.17]	-0.057 [-0.73]	-0.030 [-1.54]	-0.046 [-0.71]	-0.025 [-1.11]	-0.040 [-0.70]	-0.022 [-0.90]
Ret(t-12)	-0.101 [-1.46]	-0.030* [-1.68]	-0.084 [-1.30]	-0.029 [-1.62]	-0.063 [-1.06]	-0.019 [-0.82]	-0.051 [-0.94]	-0.015 [-0.57]
VIX		0.838*** [12.95]		0.653*** [23.36]		0.520*** [21.65]		0.427*** [12.75]
Observations	300	300	300	300	300	300	300	300
R-squared	0.417	0.945	0.404	0.961	0.358	0.925	0.317	0.858

Table A5: Market Martin bounds with lagged past returns (12 weeks)

This table presents the result of Newey–West(6) time-series regression:

$$Bound_t = \alpha + \sum_{s=1}^{12} \beta_s \cdot R_{t-s} + \epsilon_t$$

$Bound_t$ is the average Martin annualized bounds expected returns for the aggregate market at week t for the next period, and this period could be 30, 91, 182, 273, 365 days. R_{t-s} is the lagged weekly market return from month $t - 12$ to $t - 1$. CYL is daily, and the sample is from January 1996 to December 2020. Column (1) uses the raw level of past stock returns to explain CYL's expected returns in the next 30 days. Column (2) includes controls such as the tone of news coverage, the stock's CAPM expected returns from the previous 12 weeks, and revisions. Column (3) and onward repeat the above analysis to explain CYL expected returns on the next 91, 182, 273, and 365 days. The standard errors are in parentheses \star , $\star\star$, and $\star\star\star$ indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Martin(30d)	Martin(30d)	Martin(90d)	Martin(90d)	Martin(180d)	Martin(180d)	Martin(360d)	Martin(360d)
Ret(t-1)	-0.399*** [-3.33]	-0.409*** [-3.90]	-0.238*** [-3.38]	-0.228*** [-4.19]	-0.158*** [-3.00]	-0.141*** [-3.53]	-0.107*** [-2.77]	-0.083*** [-2.73]
Ret(t-2)	-0.403*** [-3.35]	-0.404*** [-3.97]	-0.243*** [-3.31]	-0.230*** [-4.16]	-0.167*** [-3.03]	-0.147*** [-3.61]	-0.116*** [-2.88]	-0.087*** [-2.88]
Ret(t-3)	-0.357*** [-3.17]	-0.360*** [-3.75]	-0.234*** [-3.20]	-0.221*** [-3.76]	-0.163*** [-2.91]	-0.145*** [-3.30]	-0.115*** [-2.70]	-0.092*** [-2.75]
Ret(t-4)	-0.365*** [-3.09]	-0.368*** [-3.65]	-0.246*** [-2.90]	-0.233*** [-3.39]	-0.176*** [-2.67]	-0.154*** [-2.91]	-0.119** [-2.31]	-0.096** [-2.34]
Ret(t-5)	-0.334*** [-3.32]	-0.316*** [-4.11]	-0.239*** [-3.05]	-0.210*** [-3.61]	-0.175*** [-2.75]	-0.142*** [-3.01]	-0.119** [-2.38]	-0.086** [-2.28]
Ret(t-6)	-0.376*** [-2.62]	-0.359*** [-2.72]	-0.265** [-2.54]	-0.242*** [-2.63]	-0.193** [-2.43]	-0.162** [-2.37]	-0.135** [-2.25]	-0.103** [-2.02]
Ret(t-7)	-0.307*** [-2.69]	-0.293*** [-3.07]	-0.231** [-2.50]	-0.208*** [-2.71]	-0.172** [-2.37]	-0.144** [-2.41]	-0.124** [-2.18]	-0.098** [-2.08]
Ret(t-8)	-0.336*** [-2.87]	-0.321*** [-3.27]	-0.255*** [-2.60]	-0.234*** [-2.80]	-0.190** [-2.45]	-0.162** [-2.48]	-0.140** [-2.29]	-0.109** [-2.11]
Ret(t-9)	-0.280** [-2.51]	-0.259*** [-2.63]	-0.235** [-2.37]	-0.211** [-2.39]	-0.183** [-2.26]	-0.157** [-2.22]	-0.135** [-2.12]	-0.106* [-1.91]
Ret(t-10)	-0.256*** [-2.98]	-0.243*** [-3.68]	-0.216*** [-2.62]	-0.199*** [-2.96]	-0.171** [-2.46]	-0.151*** [-2.62]	-0.127** [-2.27]	-0.103** [-2.21]
Ret(t-11)	-0.235*** [-3.00]	-0.213*** [-3.44]	-0.192*** [-2.61]	-0.171*** [-2.94]	-0.150** [-2.34]	-0.130** [-2.56]	-0.118** [-2.21]	-0.094** [-2.23]
Ret(t-12)	-0.146** [-2.45]	-0.124*** [-2.71]	-0.138** [-2.33]	-0.119*** [-2.68]	-0.110** [-2.05]	-0.093** [-2.34]	-0.089* [-1.91]	-0.071** [-2.06]
Revisions		-1.941*** [-3.88]		-1.539*** [-3.56]		-1.182*** [-3.02]		-0.879** [-2.58]
Tones		-0.063*** [-3.90]		-0.058*** [-4.25]		-0.052*** [-4.22]		-0.046*** [-4.23]
Observations	827	622	827	622	827	622	827	622
R-squared	0.359	0.573	0.287	0.539	0.225	0.494	0.173	0.449

This table presents the result of Newey–West(7) time-series regression controlling for VIX:

$$Bound_t = \alpha + \sum_{s=1}^{12} \beta_s \cdot R_{t-s} + VIX_t + \epsilon_t$$

$Bound_t$ is the average CYL annualized bounds expected returns for the aggregate market at week t for the next period, and this period could be 30, 91, 182, 273, 365 days. R_{t-s} is the lagged weekly market return from week $t - 12$ to $t - 1$. Column (1) use the raw level of past stock returns to explain CYL expected returns on the next 30days. Column (2) include control of VIX at month t . Column (3) and onward repeat the above analysis to explain CYL expected returns on the next 91, 182, 273 and 365 days. The standard errors are in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CYL(30d)	CYL(30d)	CYL(91d)	CYL(91d)	CYL(182d)	CYL(182d)	CYL(365d)	CYL(365d)
Ret(t-1)	-0.808*** [-4.48]	-0.297*** [-5.23]	-0.475*** [-4.22]	-0.060 [-1.62]	-0.296*** [-3.86]	0.039 [1.07]	-0.202*** [-3.44]	0.074* [1.95]
Ret(t-2)	-0.793*** [-4.19]	-0.234*** [-3.81]	-0.471*** [-4.03]	-0.019 [-0.61]	-0.303*** [-3.66]	0.062** [2.28]	-0.212*** [-3.35]	0.091*** [3.04]
Ret(t-3)	-0.736*** [-3.81]	-0.205** [-2.25]	-0.457*** [-3.78]	-0.027 [-0.54]	-0.301*** [-3.47]	0.046 [1.32]	-0.213*** [-3.26]	0.074*** [2.71]
Ret(t-4)	-0.688*** [-3.88]	-0.172*** [-3.06]	-0.439*** [-3.63]	-0.021 [-0.61]	-0.291*** [-3.21]	0.046 [1.61]	-0.211*** [-2.90]	0.068** [2.45]
Ret(t-5)	-0.640*** [-4.17]	-0.096** [-2.44]	-0.430*** [-3.75]	0.011 [0.40]	-0.295*** [-3.32]	0.061** [2.33]	-0.215*** [-2.99]	0.080*** [2.98]
Ret(t-6)	-0.669*** [-3.15]	-0.190** [-2.11]	-0.456*** [-3.17]	-0.068 [-1.44]	-0.316*** [-3.00]	-0.003 [-0.10]	-0.235*** [-2.77]	0.024 [0.85]
Ret(t-7)	-0.575*** [-3.25]	-0.171*** [-2.60]	-0.400*** [-3.13]	-0.073* [-1.77]	-0.286*** [-2.92]	-0.022 [-0.69]	-0.218*** [-2.72]	0.000 [0.00]
Ret(t-8)	-0.625*** [-3.43]	-0.214*** [-2.89]	-0.435*** [-3.16]	-0.102* [-1.96]	-0.312*** [-2.96]	-0.043 [-1.10]	-0.240*** [-2.78]	-0.018 [-0.50]
Ret(t-9)	-0.486*** [-2.78]	-0.132** [-1.97]	-0.370*** [-2.59]	-0.083 [-1.54]	-0.277** [-2.51]	-0.046 [-1.13]	-0.221** [-2.44]	-0.029 [-0.80]
Ret(t-10)	-0.436*** [-3.08]	-0.106** [-2.31]	-0.344*** [-2.81]	-0.077* [-1.77]	-0.260*** [-2.64]	-0.044 [-1.21]	-0.206** [-2.54]	-0.028 [-0.85]
Ret(t-11)	-0.400*** [-3.00]	-0.071** [-1.98]	-0.305*** [-2.68]	-0.039 [-1.28]	-0.230** [-2.48]	-0.015 [-0.58]	-0.184** [-2.37]	-0.006 [-0.25]
Ret(t-12)	-0.293*** [-2.81]	0.007 [0.22]	-0.240** [-2.56]	0.003 [0.12]	-0.184** [-2.34]	0.012 [0.52]	-0.151** [-2.24]	0.011 [0.48]
VIX		0.833*** [21.22]		0.675*** [24.99]		0.544*** [21.51]		0.450*** [16.77]
Observations	1,280	1,280	1,280	1,280	1,280	1,280	1,280	1,280
R-squared	0.342	0.875	0.268	0.896	0.208	0.873	0.166	0.821

Table A6: The relationships between bounds and surveys controlled for VIX

This table presents the result of time-series regression:

$$Bound_t = \alpha + Survey_t + VIX_t + \epsilon_t$$

$Bound_t$ is the average annualized bounds expected returns for the aggregate market at month t for the next one month. The standard errors are in parentheses *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Dependent var.	Martin (1m)						CYL (1m)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Gallup	-0.121*** (-9.08)	-0.015*** (-2.80)					-0.148*** (-8.88)	-0.018** (-2.31)				
AA			-0.106*** (-5.85)	-0.006 (-1.10)					-0.113*** (-5.55)	-0.010 (-1.51)		
II					-0.212*** (-11.36)	-0.009 (-1.11)					-0.246*** (-12.73)	0.002 (0.24)
VIX		0.464*** (34.87)		0.498*** (46.56)		0.494*** (38.34)		0.568*** (29.00)		0.591*** (46.15)		0.600*** (36.49)
Observations	135	135	193	193	193	193	135	135	236	236	236	236
R-squared	0.383	0.940	0.152	0.932	0.403	0.932	0.372	0.915	0.116	0.913	0.409	0.912

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A7: Summary Statistics: Sentiment-Price Wedge

The table reports summary statistics for the Sentiment-Price Wedge (SPW) series constructed as $SPW_t^s \equiv z(\text{Survey}_t^s) - z(\text{Bound}_t)$, where $z(\cdot)$ denotes standardization to zero mean and unit standard deviation over the full sample and $s \in \{\text{Gallup}, \text{AA}, \text{II}\}$. Bound_t is the monthly average of daily option-implied bounds on expected returns over the next 30 days (constant-maturity one-month horizon). Two bound constructions are used: the Martin bound and the CYL bound. $AR(1)$ is the coefficient from an OLS regression of SPW_t on SPW_{t-1} . $\text{Corr}(SPW, \text{Past 1-month ret})$ is the Pearson correlation between SPW_t and the realized market return over month $t-1$. N denotes the number of monthly observations. Statistical significance for $AR(1)$ and correlations is indicated by ***, **, and * for the 1%, 5%, and 10% levels, respectively.

Table A8: Summary Statistics: Sentiment-Price Wedge

	N	Mean	SD	P1	P50	P99	AR(1)	Corr(SPW, Past 1-mon ret)
Sentiment-Price Wedge (Gallup - Martin)	135	0.00	1.81	-6.80	0.55	1.92	0.82***	0.44***
Sentiment-Price Wedge (AA - Martin)	193	0.22	1.73	-7.47	0.52	3.07	0.74***	0.53***
Sentiment-Price Wedge (II - Martin)	193	0.18	1.50	-7.97	0.49	2.01	0.81***	0.51***
Sentiment-Price Wedge (Gallup - CYL)	135	-0.11	1.87	-7.31	0.44	1.81	0.81***	0.44***
Sentiment-Price Wedge (AA - CYL)	236	0.19	1.66	-5.91	0.47	2.55	0.74***	0.51***
Sentiment-Price Wedge (II - CYL)	236	0.29	1.51	-6.14	0.56	2.05	0.83***	0.49***

Table A9: SPW Return Predictability

This table reports horizon- h return predictability regressions for $h = 1, \dots, 12$ months. The dependent variable in column h is the cumulative market return over the next h months, $R_{t \rightarrow t+h}$, expressed in percentage points. Panels A–B estimate $R_{t \rightarrow t+h} = \alpha_h + \beta_h SPW_t + \varepsilon_{t+h}$, while Panels C–D add standard return predictors: $R_{t \rightarrow t+h} = \alpha_h + \beta_h SPW_t + \gamma_h LGPD_t + \delta_h Slope_t + \phi_h DS_t + \varepsilon_{t+h}$, where SPW_t is the Sentiment–Price Wedge, $LGPD_t$ is the log price-dividend ratio, $Slope_t$ is the term spread, and DS_t is the default spread. Coefficients are estimated by OLS with Newey–West (HAC) standard errors using lag length h ; t -statistics are reported in brackets. The reported R^2 is from the corresponding OLS regression estimated on the same sample. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Panel A												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
SPW (AA)	-0.135 [-0.46]	-0.218 [-0.43]	-0.005 [-0.01]	-0.234 [-0.25]	-0.391 [-0.41]	-0.685 [-0.68]	-0.628 [-0.57]	-0.451 [-0.38]	-0.577 [-0.46]	-0.687 [-0.48]	-0.541 [-0.36]	-0.383 [-0.24]
Observations	193	193	193	193	193	193	193	193	193	193	193	193
R-squared	0.041	0.071	0.083	0.095	0.109	0.129	0.145	0.161	0.178	0.192	0.198	0.216
Panel B												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m	12m
SPW (II)	-0.513 [-1.43]	-0.864 [-1.38]	-0.612 [-0.60]	-0.741 [-0.57]	-1.204 [-0.95]	-1.650 [-1.31]	-1.940 [-1.43]	-2.239 [-1.60]	-2.618* [-1.89]	-2.803* [-1.88]	-2.744* [-1.77]	-3.076* [-1.89]
Observations	193	193	193	193	193	193	193	193	193	193	193	193
R-squared	0.054	0.088	0.089	0.101	0.120	0.144	0.165	0.186	0.207	0.221	0.224	0.246

Panel C											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m
SPW (AA)	-0.135 [-0.46]	-0.218 [-0.43]	-0.005 [-0.01]	-0.234 [-0.25]	-0.391 [-0.41]	-0.685 [-0.68]	-0.628 [-0.57]	-0.451 [-0.38]	-0.577 [-0.46]	-0.687 [-0.48]	-0.541 [-0.36]
LGPD	-4.773*** [-2.60]	-9.707*** [-2.92]	-14.011*** [-3.00]	-17.677*** [-2.99]	-21.378*** [-2.92]	-25.230*** [-2.91]	-29.542*** [-3.00]	-34.082*** [-3.06]	-38.258*** [-3.08]	-41.982*** [-3.06]	-45.155*** [-2.97]
Slope	-0.029 [-0.12]	-0.091 [-0.22]	-0.238 [-0.41]	-0.413 [-0.57]	-0.544 [-0.65]	-0.592 [-0.63]	-0.682 [-0.65]	-0.723 [-0.62]	-0.659 [-0.51]	-0.560 [-0.39]	-0.442 [-0.28]
DS	-2.619* [-1.78]	-4.778* [-1.82]	-5.364 [-1.47]	-6.399 [-1.42]	-7.044 [-1.40]	-8.419 [-1.48]	-9.132 [-1.45]	-9.575 [-1.44]	-10.807 [-1.57]	-11.917 [-1.61]	-12.24 [-1.53]
Obs	193	193	193	193	193	193	193	193	193	193	193
R-squared	0.041	0.071	0.083	0.095	0.109	0.129	0.145	0.161	0.178	0.192	0.198
Panel D											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	1m	2m	3m	4m	5m	6m	7m	8m	9m	10m	11m
SPW (II)	-0.513 [-1.43]	-0.864 [-1.38]	-0.612 [-0.60]	-0.741 [-0.57]	-1.204 [-0.95]	-1.650 [-1.31]	-1.940 [-1.43]	-2.239 [-1.60]	-2.618* [-1.89]	-2.803* [-1.88]	-2.744* [-1.77]
LGPD	-4.838*** [-2.74]	-9.802*** [-3.08]	-13.840*** [-3.03]	-17.833*** [-3.01]	-21.648*** [-2.97]	-25.839*** [-3.00]	-29.973*** [-3.05]	-34.144*** [-3.08]	-38.410*** [-3.10]	-42.256*** [-3.09]	-45.213*** [-2.96]
Slope	0.032 [0.14]	0.013 [0.03]	-0.143 [-0.26]	-0.329 [-0.47]	-0.410 [-0.51]	-0.429 [-0.46]	-0.465 [-0.45]	-0.435 [-0.37]	-0.330 [-0.25]	-0.217 [-0.15]	-0.089 [-0.05]
DS	-3.480** [-2.29]	-6.249** [-2.39]	-6.727* [-1.82]	-7.561 [-1.64]	-8.910* [-1.71]	-10.656* [-1.81]	-12.143* [-1.83]	-13.635* [-1.94]	-15.448** [-2.13]	-16.736** [-2.14]	-17.247* [-2.05]
Obs	193	193	193	193	193	193	193	193	193	193	193
R-squared	0.054	0.088	0.089	0.101	0.120	0.144	0.165	0.186	0.207	0.221	0.224

Table A10: Bounds on individual stocks by implied volatility and past returns (within-IV quintiles)

This table reports the mean option-implied expected return bounds (MW Bound and CYDV Bound) for stocks double-sorted into quintiles of implied volatility (rows) and past returns (columns). In each month t , we sort stocks into quintiles based on the monthly average of daily 30-day at-the-money implied volatility from OptionMetrics (Volatility Surface). Within each implied-volatility quintile, we further sort stocks into quintiles based on past-month returns (month $t-1$). We report the average bound in month t . “Spread” is the within-row difference between Losers (Q1) and Winners (Q5).

MW Bounds						
IV Quintile	Loser(Q1)	Q2	Q3	Q4	Winners(Q5)	Spread(Q1-Q5)
Q1	2.135	1.990	1.955	1.980	2.050	0.085***
Q2	3.647	3.572	3.529	3.515	3.529	0.119***
Q3	5.591	5.431	5.452	5.416	5.433	0.158***
Q4	8.898	8.617	8.616	8.549	8.599	0.298***
Q5	21.773	18.456	17.654	17.655	19.493	2.281***

CYDV Bounds						
IV Quintile	Loser(Q1)	Q2	Q3	Q4	Winners(Q5)	Spread(Q1-Q5)
Q1	6.025	5.978	5.860	5.857	5.659	0.366***
Q2	7.475	7.688	7.623	7.460	7.026	0.449***
Q3	8.669	8.818	8.765	8.586	8.075	0.593***
Q4	10.033	10.194	10.165	9.910	9.288	0.745***
Q5	13.405	13.121	12.852	12.527	11.957	1.449***