Subjective Expectations for Variance and Skewness: Evidence from Analyst Forecasts *

Shuaiyu Chen† Shuaiqi Li‡ Yucheng Yang§

April 2025

Abstract

We propose novel firm-level measures for subjective expectations on variance and skewness derived from analysts' price forecast ranges in their research reports. We find that analyst expectations *positively* predict future variance and skewness of stock return, even after controlling for corresponding option-implied moments and past realized moments. Moreover, analyst variance (skewness) expectation *positively* predicts returns on straddle (skewness asset) and generates a profitable option strategy with an annualized Sharpe ratio of 0.93 (1.27). Using the same analyst's expectations for return, variance, and skewness, we uncover a *positive* subjective risk-return trade-off and a *negative* skewness-return trade-off that are consistent with classical finance theories. To examine the formation of analyst expectations, we employ large language models to identify key topics from analysts' discussions and apply machine learning techniques to quantify their impacts. Bankruptcy, government debt, and commodities play a crucial role in shaping analysts' variance expectations, while earnings losses, bank loans, and business cycles are the dominant drivers of their skewness expectations. We find strong interaction effects between narratives and option-implied and realized moments in shaping analysts' risk perceptions.

Keywords: Subjective expectations, Variance, Skewness, Analysts, Option returns, Large language model, Machine learning

*We are grateful for the comments from Kewei Hou. All errors are our own.

†Mitch Daniels School of Business, Purdue University, chen4144@purdue.edu
‡Department of Economics and Finance, City University of Hong Kong, shuaiqli@cityu.edu.hk
§School of Accountancy, The Chinese University of Hong Kong, yuchengyang@cuhk.edu.hk

I. Introduction

Investors allocate capital based on their subjective expectations of an asset's return, variance, and skewness, which determine its equilibrium price. The finance literature commonly infers subjective expectations from surveys and analyst forecasts. At the aggregate market level, Ben-David, Graham, and Harvey (2013) and Nagel and Xu (2022) construct subjective return expectations using surveys of executives and individual investors. At the firm level, Brav and Lehavy (2003) among many others estimate subjective return expectations from returns implied by analyst price targets.

While the literature has predominantly explored subjective return expectations, subjective expectations of higher-order moments, such as return variance and skewness, have received considerably less attention. Prior studies infer market-level variance expectations from survey-based return forecast ranges, such as the 10th and 90th percentile market return forecasts in the Graham and Harvey CFO survey (e.g., Ben-David, Graham, and Harvey, 2013; Lochstoer and Muir, 2022). As to firm-level variance and skewness expectations, researchers commonly use option-implied moments as proxies for their subjective expectations. However, these market-based measures are under risk-neutral measure and incorporate the variance and skewness risk premium.[1] Despite their importance in asset pricing, firm-level subjective expectations on variance and skewness remain unexplored due to the lack of direct survey data. To our knowledge, no existing measure directly captures these subjective expectations at the firm level.

Our paper fills this gap by proposing novel firm-level measures of subjective expectations on variance and skewness derived from analysts' price forecast ranges in Morgan Stanley equity research reports. We further assess the informativeness

[1]For literature on variance risk premium, see Bollerslev, Tauchen, and Zhou (2009) and Carr and Wu (2009). For literature on skewness risk premium, see Bakshi, Kapadia, and Madan (2003), Kozhan, Neuberger, and Schneider (2013), and Orlowski, Schneider, and Trojani (2023).

of these subjective expectations in predicting future realized return moments and option returns, evaluate the mean-variance-skewness trade-off from an analyst's perspective, and analyze the formation of these expectations by applying large language models and machine learning to the textual data in analyst reports.

Since 2007, Morgan Stanley has required its analysts to include scenario-based valuations under the risk-reward framework in their research reports. These valuations include "bull-case" and "bear-case" price targets, representing upside and downside scenarios for the following year, respectively, alongside discussions of key value drivers. We extract analyst price forecasts and textual data from these discussions in Morgan Stanley analyst reports spanning 2007 to 2016.[2] We then merge firms covered by Morgan Stanley with the CRSP/Compustat database. Our final sample consists of 1,537 unique firms.

Using a binomial tree model, we infer analysts' subjective expectations on variance (IV^{Analyst} henceforth) and skewness ($Skew^{\text{Analyst}}$ henceforth) for the next 12-month stock return. In our sample, IV^{Analyst} has a mean of 17.8%, closely aligning with the mean of realized variance (RV henceforth) of 18.6%, suggesting that our measure of subjective variance expectations has a reasonable economic magnitude. The option-implied variance (IV^{Option} hereafter), constructed following Bakshi, Kapadia, and Madan (2003), has a sample mean of 21.2%, exceeding that of RV. The difference between IV^{Option} and RV is consistent with the well-documented variance risk premium in the option literature. In contrast, IV^{Analyst} is derived under the physical measure and is therefore unaffected by the variance risk premium.

As to skewness, realized skewness ($RSkew$ hereafter) has an average of -0.092, less negative than that of option-implied skewness ($Skew^{\text{Option}}$ hereafter), which is -0.608. The relative magnitude is consistent with Bakshi, Kapadia, and Madan

[2]Morgan Stanley was the first brokerage to mandate scenario-based analysis. The uniform implementation of this policy across all Morgan Stanley analysts mitigates selection bias that could arise from individual analysts selectively incorporating such information for only a subset of stocks. Our sample ends in 2016 because ThomsonOne, our source of analyst reports, discontinued coverage of Morgan Stanley that year.

(2003), who show that $Skew^{\text{Option}}$ is more negative than the physical skewness within a power-utility economy in which returns are leptokurtic. $Skew^{\text{Analyst}}$ has a mean of -0.164, much closer to realized skewness than the option-implied skewness. This further confirms that our subjective expectations measures are not influenced by the risk premia under the risk-neutral measure.

Equity research analysts are generally regarded as informed agents, suggesting that their expectations may provide valuable insights into future outcomes. However, prior studies document that analyst forecasts and recommendations often exhibit low predictive accuracy for stock returns, potentially due to biased beliefs or distorted incentives.[3] Whether IV^{Analyst} and $Skew^{\text{Analyst}}$ are informative about second- and third-moments remains an empirical question.

To test the informativeness of IV^{Analyst} and $Skew^{\text{Analyst}}$, we run pooled regressions to predict next-year RV and $RSkew$, respectively. We find that they significantly and *positively* predict corresponding moments even after controlling for option-implied moments and past realized moments computed from rolling-one-year stock returns, suggesting that analysts' subjective expectations provide incremental information on variance and skewness beyond option markets.

Consistent with this, we find that IV^{Analyst} positively predicts cross-sectional straddle returns and that $Skew^{\text{Analyst}}$ positively predicts returns on skewness assets constructed following the method in Bali and Murray (2013). Their predictive power remains strong after controlling for a range of well-documented predictors in the option return predictability literature. A long-short option strategy that goes long on the straddles (skewness assets) of firms with high IV^{Analyst} ($Skew^{\text{Analyst}}$) and short on those with low IV^{Analyst} ($Skew^{\text{Analyst}}$) generates a monthly return of 4.58% (0.8%) with an annualized Sharpe ratio of 0.93 (1.27). Their profitabilities remain highly significant after adjusting for risk factors in options markets.

Our subjective expectations measures provide new insights into the mean-variance-

[3]See, e.g., Lim (2001), Chan, Karceski, and Lakonishok (2007), Ke and Yu (2006).

skewness trade-off faced by investors, particularly those who hold and closely monitor a limited set of stocks, such as equity research analysts.

Firm-level variances are largely idiosyncratic. Finance theories, such as Merton (1987), suggest that firm-level variance should be positively related to expected stock returns due to investors' underdiversified portfolios. However, Ang, Hodrick, Xing, and Zhang (2006) document a negative relation between past realized idiosyncratic volatility and future stock returns. Since realized stock return is a noisy realization of objective risk premia, which could be different from subjective expectation (see, e.g., Nagel and Xu, 2023; Jensen, 2023), the cleanest test of the perceived risk-return trade-off is to use the same investor's expectations for both return and variance. Our novel measure, IV^{Analyst}, in conjunction with analysts' return expectations, constructed from analysts' price targets and current stock prices, allows us to test this trade-off using the same analyst's expectations. We find a significantly positive risk-return relation, indicating that the risk-return trade-off is evident from the analyst's perspective.

The skewness risk literature develops models in which investors favor assets with high total skewness and optimally choose to hold under-diversified portfolios (Brunnermeier, Gollier, and Parker (2007), Barberis and Huang (2008), and Mitton and Vorkink (2007)), implying a negative skewness-return trade-off. Using the same analyst's expectation on return and skewness, we document a strong negative skewness-return relationship consistent with the theory.

We also construct analysts' subjective expectation on individual stock crashes ($Crash^{Analyst}$) where stock prices decline by more than 20%. $Crash^{Analyst}$ positively and significantly predicts crashes even after controlling for option-implied crash probability in Martin (2017) and firm characteristics related to crashes proposed in Chen, Hong, and Stein (2001). The evidence suggests that analysts' scenario-based analysis provides incremental information to downside risk.

Next, we investigate firm characteristics that are related to IV^{Analyst} and $Skew^{\text{Analyst}}$.

We find strong positive relationships between IV^{Analyst} and the two dominant volatility predictors in the literature, IV^{Option} and past RV, confirming that analysts incorporate both historical and option-implied volatility when forming variance expectations. The coefficient on market beta is positive, indicating that analysts expect firms with higher systematic risk to have greater variance. Other firm characteristics, such as size, book-to-market ratio, profitability, and investment, exhibit weak or insignificant relations with IV^{Analyst}. $Skew^{\text{Analyst}}$ has a positive relationship with option-implied skewness, while being negatively associated with historical skewness and firm size.

Analysts not only provide explicit price forecast ranges but also discuss key economic, industry-specific, and firm-level factors when forming their expectations (see Figure 1 for examples). To better understand the drivers of analysts' expectations for variance and skewness, we identify and quantify these topic-specific discussions. Specifically, we focus on the 35 business topics extracted from Wall Street Journal articles by Bybee, Kelly, Manela, and Xiu (2024) and then use large language models (ChatGPT-4o) to numerically measure the intensity of each topic mentioned in a report's risk-reward section.[4] Our analysis highlights a range of key topics, including macroeconomic factors (e.g., economic growth, government debt, commodity markets, and recessions), industry-specific trends (e.g., competition, M&A activity, and IPOs), and firm fundamentals (e.g., earnings forecasts, product prices, and credit risk).

Next, we apply Boosted Regression Trees and Shapley values to evaluate the relative importance of these topics and examine their interactions in shaping analysts' variance and skewness expectations. Our findings indicate that discussions related to bankruptcy risks, earnings, government debt, commodity markets, and

[4]Although large language models (e.g., ChatGPT, Gemini, BERT, among others) have been developed only recently, they have already seen widespread applications in finance and accounting research (see, e.g., Lopez-Lira and Tang, 2023; Jiang, Kelly, and Xiu, 2024; Li, Mai, Shen, Yang, and Zhang, 2023; Eisfeldt, Schubert, and Zhang, 2023; Jha, Qian, Weber, and Yang, 2024; Chen, Peng, and Zhou, 2024).

recessions are among the most significant narratives driving IV^{Analyst}, suggesting that analysts incorporate both macroeconomic conditions and firm-specific factors into their risk assessments. For $Skew^{\text{Analyst}}$, we find that key topics revolve around firms' ability to generate profits and secure financing, including earnings losses, profitability, bank loans, market sentiment (bear/bull market), and oil market conditions.

Interestingly, although our interpretable machine-learning techniques suggest that market-based predictors, IV^{Option} and RV, are the two most important factors that analysts rely on when forming their variance expectations, $Skew^{\text{Option}}$ and past realized skewness play a comparatively smaller role in shaping analyst skewness expectations. Specifically, $Skew^{\text{Option}}$ ranks third in importance, while past realized skewness ranks 11th, below topics such as earnings losses and profits. These findings underscore the importance of incorporating textual data and focusing on narratives to better infer analysts' information sets and understand their expectation formation processes.

Finally, we document strong interaction effects between market-based predictors and selected topics influencing analyst variance and skewness expectations. For instance, the interaction between IV^{Option} and bankruptcy suggests that analysts assign greater weight to bankruptcy risks when option-implied variance is high, indicating heightened uncertainty for distressed firms in analysts' expectations. We also identify macroeconomic factors as critical conditioning variables. For example, analysts adjust their variance expectations more substantially when oil market uncertainty coincides with high IV^{Option}, reflecting their sensitivity to commodity-driven macroeconomic risks.

The formation of analyst skewness expectations appears even more intricate, as evidenced by the non-monotonic relationships between $Skew^{\text{Analyst}}$ and market-predictors ($Skew^{\text{Option}}$ and $RSkew$), along with significant interactions with firm fundamentals (e.g., earnings and debts) and macroeconomic conditions, particularly in bear and bull market environments. These interaction effects suggest that analysts do not assess future risks in isolation but rather integrate multiple sources of information, highlighting the complexity and multidimensional nature of analysts' perceptions of variance and higher-moment risk.

Our paper makes several contributions. First, we develop novel firm-level measures of subjective expectations on variance and skewness using analysts' price forecast ranges. Unlike prior studies that rely on aggregate market-level surveys or risk-neutral moments, our measures capture analysts' forward-looking assessments of individual stock's variance and skewness under the physical measure. Using these subjective measures, we provide a new perspective on how analysts form and communicate risk expectations, contributing to the growing body of research on market participants' subjective beliefs.

Second, we demonstrate that analyst subjective expectations about the second- and third-moments of stock returns contain valuable information by documenting their predictability for future realized moments and the returns of option portfolios designed to track these moments. This finding is striking because prior research primarily highlights biases in analysts' expectations of first-moment returns, with expected returns negatively associated with future realized returns. Our study extends this literature by examining analyst expectations of higher-order moments. Moreover, the predictive power of analyst expectations regarding variance and skewness has important implications for sophisticated investors, such as hedge fund managers, whose option positions likely affect the pricing of variance and higher-order moments in both individual stocks and broader index options (see, e.g., Aragon, Chen, and Shi, 2022; Chen and Li, 2024).

Third, our study contributes to the rapidly growing literature that leverages large language models (LLMs) to address economics and finance questions.[5] We in-

[5] For example, Jiang, Kelly, and Xiu (2024) and Lopez-Lira and Tang (2023) use LLMs to predict future returns. Li, Mai, Shen, Yang, and Zhang (2023) extract corporate culture from analyst reports. Jha, Qian, Weber, and Yang (2024) analyze corporate investment-related information, while

tegrate LLMs and machine learning techniques to systematically analyze textual discussions in analyst reports, identifying key macroeconomic, industry-specific, and firm-level factors likely in analysts' information sets regarding variance and skewness expectations. Related to our work, Cao, Han, Li, Yang, and Zhan (2024) examine the information content of financial news articles and derive text-based signals that can predict cross-sectional delta-hedged option returns. However, their study does not examine subjective risk expectations. Moreover, our findings reveal novel and significant interaction effects between market-based metrics and qualitative narratives. This methodological contribution extends beyond our specific setting, providing a framework for incorporating textual analysis into empirical asset pricing research.

The rest of this paper is organized as follows. Section II describes the data. Section III examines the predictive power of analysts' subjective expectations for future return moments and option returns. Section IV explores the formation of analysts' subjective expectations by analyzing analysts' topic-specific narratives. Section V concludes.

II. Data and Variables

A. *Stock and Option Data*

We obtain option price data from the OptionMetrics Ivy DB database, which provides daily closing bid and ask quotes for U.S. equity options. Stock price data are sourced from CRSP, while firm accounting information is retrieved from Compustat. Analyst reports are obtained from the ThomsonOne database in 2016.

Eisfeldt, Schubert, and Zhang (2023) investigate the susceptibility of jobs to replacement with the advent of GPTs. Huang, Qiao, and Zhou (2024) examine investor narratives on social media, and Chen, Peng, and Zhou (2024) use LLMs to analyze trading strategies of individual investors based on discussions from a leading investor social media platform.

B. Morgan Stanley's Scenario-Based Framework

As detailed in Joos, Piotroski, and Srinivasan (2016), Morgan Stanley developed its Risk-Reward Framework in response to heightened market uncertainty following the dot-com bubble collapse in 2000 and the September 11th terrorist attacks in 2001, as well as increasing regulatory scrutiny of Wall Street research practices.[6]

The primary objective of this framework was to differentiate Morgan Stanley's equity research in a highly competitive environment of brokerage houses. It introduced scenario-based analysis, which moves beyond single-point price targets by incorporating bull-case and bear-case price estimates to quantify a stock's upside and downside potential. A key component of this approach is the identification and discussion of critical value drivers and their impact across different scenarios. By explicitly considering multiple potential investment outcomes, the framework seeks to mitigate the "false precision" inherent in single-point forecasts and encourage analysts to provide a more comprehensive valuation assessment Weyns, Perez, Hurewitz, and Jenkins (2011). This approach also fosters deeper engagement with institutional investors, who pay for equity research through trading commissions.

The scenario-based analysis provides valuable textual insights into how analysts assess firm-specific and macro-level risks and opportunities when forming their price target ranges. Figure 1 presents three examples from Visa, Enterprise Products Partners, and Apple. In addition to providing numerical bull, base, and bear price targets, analysts elaborate on key value drivers, potential catalysts, and macroeconomic factors influencing stock performance. These qualitative discussions contextualize the underlying factors shaping analysts' perceptions of risk at both the firm-specific and macroeconomic levels. By systematically analyzing these

[6]The Risk-Reward Framework was initially introduced in 2003 within Morgan Stanley's European research division under then-head of research Juan-Luis Perez. Following Perez's promotion to global research director in 2006, the framework—having gained acceptance in Europe—was implemented firmwide in January 2007. Weyns, Perez, Hurewitz, and Jenkins (2011) describe the procedures Morgan Stanley used to ensure consistency in the framework's application, including linking its adoption to analysts' performance evaluations and compensation.

textual components, we can extract additional insights into how analysts perceive uncertainty and risk. This not only enhances our understanding of the determinants of analyst variance expectations but also complements the implied variance derived from price targets.

C. *Analyst Subjective Expectation on Variance and Skewness*

From each Morgan Stanley analyst research report, we collect scenario-based valuations, stock ratings, industry views, and the number of contributing analysts for the period 2007–2016.[7] The sample begins in 2007, the year Morgan Stanley mandated scenario-based valuations. The sample period ends in 2016 due to ThomsonOne's discontinuation of Morgan Stanley analyst report coverage.[8]

Using the extracted price target, bull, and bear price forecasts, we infer analysts' subjective expectations on variance and skewness by assuming that stock prices follow a binomial tree model. Specifically, we assume that with probability p $(1-p)$, the stock price will move to the bull (bear) price over the next 12 months. Notably, this probability is under physical measure. We derive p from the following equation:

$$p \cdot Bull + (1-p) \cdot Bear = Target, \tag{1}$$

where $Bull$ and $Bear$ represent the highest and lowest prices mentioned in the report, and $Target$ is the analyst's price target. Then we can use the inferred probability to compute the variance and skewness of $\log R_{i,t\to t+12}$, where $R_{i,t\to t+12}$ is firm i's

[7]To ensure our sample is representative, we replicate the results of Joos, Piotroski, and Srinivasan (2016), finding that both the descriptive statistics and regression estimates from our sample closely align with their findings. We process each Morgan Stanley analyst report using a Python algorithm to extract key parameters, including the official ticker, announcement date, industry view, and valuations for the bull, base, and bear cases. Additionally, we extract the names of the analysts contributing to the report. To ensure data accuracy, we manually compare a subset of extracted values against the original reports.

[8]After 2017, ThomsonOne tops providing Morgan Stanley analyst reports as its parent company, Thomson Reuters, transitions into Refinitiv following the 2018 spin-off of its Financial & Risk division. Currently, Refinitiv has resumed offering Morgan Stanley analyst reports on its own platform, but they are priced per page and do not support bulk data downloads, making them economically infeasible for purchasing across a large sample of firms.

gross return over the next 12 months, defined as bull or bear prices scaled by firm i's current stock price.

To validate our subjective measures, we compare them with realized variance ($RV_{i,t\to t+12}$), calculated as sum of daily squared log returns over the following twelve months, and realized skewness ($RSkew_{i,t\to t+12}$) computed from daily log returns in the next twelve months. Additionally, we construct option-implied variance (IV^{Option}) and skewness ($Skew^{\text{Option}}$) using the 365-day implied volatilities from the Option-Metrics Volatility Surface database, following the methodology of Bakshi, Kapadia, and Madan (2003).

Table I presents the summary statistics for our sample. Between 2007 and 2016, our dataset includes 1,537 unique firms covered by Morgan Stanley analysts, with a total of 22,162 reports issued. The mean of IV^{Analyst} is 0.178, closely matching the average realized variance (0.186), with similar percentiles across both measures. This suggests that IV^{Analyst} is economically meaningful. The average of IV^{Option} is 0.212, exceeding that of realized variance, consistent with the well-documented variance risk premium in the option literature.

Realized skewness has an average of -0.092, less negative than that of $Skew^{\text{Option}}$, which equals -0.608. The mean of $Skew^{\text{Analyst}}$ is -0.164, much closer to realized skewness than the option-implied skewness. $Skew^{\text{Analyst}}$ can be positive at the 75th and 90th percentile, the same as realized skewness. In contrast, $Skew^{\text{Option}}$ stays negative for all percentiles in the table. The average market capitalization of firms in our sample is \$24.34 billion. To assess the frequency of forecast updates, we compute the median number of days between consecutive reports on the same firm, which is 76 days.

D. *Option-Related Variables*

We compute returns on straddle and skewness asset using options written on common equities. Option portfolios are formed on the third Friday of each month and held to expiration, typically the third Friday of the following month, resulting in returns at a monthly frequency. The sample period spans January 2007 to December 2017.

Straddle consists of one call and one put with the same strike price, selected as the strike closest to the current stock price. Following Bali and Murray (2013), the skewness asset comprises a long position in out-of-the-money (OTM) call, a short position in OTM put, and a static position in the underlying stock. The OTM put (call) is the contract with a delta closest to -0.1 (0.1). To isolate the third movement from the first and second moments, this asset is constructed to be both delta- and vega-neutral. Let Δ_P (Δ_C) denote the delta of put (call), and ν_P (ν_C) represent the vega of put (call). The asset consists of one contract in the OTM call, $-\nu_C/\nu_P$ contracts in the OTM put, and $-(\Delta_C - \nu_C/\nu_P \cdot \Delta_P)$ shares in the underlying stock.[9] The skewness asset return is measured at monthly frequency as follows:

$$r^{\text{Skew}} = \frac{Payoff - Price}{|Price|}.$$

Bali and Murray (2013) use the absolute value of the skewness asset price because the price is not guaranteed to be positive. We construct the price using bid-ask midpoints of options. The skewness asset is designed to increase in value if the realized skewness rises, representing a long skewness position. When held to expiration, the asset realizes a high (low) payoff in the event of high (low) stock return, but it is insensitive to small stock price movements.

To ensure the tradability of straddles, we apply a series of selection filters on the formation day. First, we exclude options with zero open interest or a bid price

[9]Deltas and vegas are obtained from the OptionMetrics.

of zero. Second, we remove options whose ask prices are lower than bid prices, as well as those violating standard arbitrage bounds. Third, we discard options with missing implied volatilities or deltas. Lastly, we exclude options with underlying stock prices below $5 at the formation date and those subject to stock splits during the holding period. These filters ensure that the selected option contracts are actively traded and yield reliable return estimates.

To predict cross-sectional option returns, we use firms' most recent available $IV^{\text{Analyst}}_{i,t\to t+12}$ and $Skew^{\text{Analyst}}_{i,t\to t+12}$. To mitigate concerns over stale forecasts, we require that the analyst report release date falls within the 12 months preceding the option portfolio formation date. Additionally, we exclude months with fewer than 100 firms in the cross-section, eliminating 4 out of 132 months.

Our set of control variables largely follows Heston, Jones, Khorram, Li, and Mo (2023). Market capitalization is measured as the logarithm of a firm's market value on the third Friday of each month. Idiosyncratic volatility is computed following Cao and Han (2013) as the standard deviation of residuals from a 22-day rolling regression using the Fama-French three-factor model. Volatility deviation, as defined in Goyal and Saretto (2009), is the log difference between historical volatility, computed from rolling one-year daily stock returns, and at-the-money implied volatility. The implied volatility (IV) term spread, which captures the slope of the implied volatility term structure, follows the methodology in Vasquez (2017). The IV smirk slope is measured as the difference between the implied volatility of a 30-day call with a delta of 0.3 and that of a 30-day put with a delta of -0.3. It is related to the risk-neutral skewness variable that can predict r^{Skew} as documented by Bali and Murray (2013). In addition, we control for the volatility of volatility, defined as the standard deviation of the daily percentage change in at-the-money 30-day implied volatilities. Following Horenstein, Vasquez, and Xiao (2023), we incorporate this measure, as it has been shown to be an important factor in explaining option returns.

III. How Informative Is Analyst Subjective Expectation?

This section examines whether analyst subjective expectations contain valuable information for forecasting future return moments. Section III.A evaluates the predictive power of IV^{Analyst} and $Skew^{\text{Analyst}}$ for realized variance and skewness, respectively. Section III.B examines option return predictability. Section III.C explores whether analysts' expectations exhibit a mean-variance-skewness trade-off consistent with the literature. Section III.D investigates the firm-level characteristics that influence analysts' subjective expectations. Section III.E studies whether analysts' crash beliefs can forecast stock crashes.

A. *Predicting Realized Variance and Skewness*

If analysts are capable of collecting and processing valuable information about future firm-specific risks, their subjective expectations should be informative about future return variance and skewness. To test this conjecture, we estimate the following panel regression using firm-days when analysts issue reports:

$$RV_{i,t\to t+12} = \alpha + q_t + \beta IV^{\text{Analyst}}_{i,t\to t+12} + \gamma \text{Controls}_{i,t} + \epsilon_{i,t};$$

$$RSkew_{i,t\to t+12} = \alpha + q_t + \beta Skew^{\text{Analyst}}_{i,t\to t+12} + \gamma \text{Controls}_{i,t} + \epsilon_{i,t}.$$

To assess whether IV^{Analyst} and $Skew^{\text{Analyst}}$ provide incremental information, we control for corresponding option-implied moments (IV^{Option} and $Skew^{\text{Option}}$) and past realized moments ($RV_{i,t-12\to t}$ and $RSkew_{i,t-12\to t}$). All regressions include month-fixed effects q_t, and standard errors are clustered at the firm-month level. To mitigate the influence of extreme outliers, we winsorize independent variables at the 1% level.

Table II reports the regression results. In Panel A, we predict future-12-month variance. In column (1), when used as the sole predictor, IV^{Analyst} positively predicts future RV with a coefficient of 0.45 and a t-statistic of 14.56. Column (2) shows that IV^{Option} also strongly predicts future variance, with a coefficient of 0.717 and a t-statistic of 15.00, consistent with prior findings that option-implied variance is a strong predictor of future volatility. Realized variance is known to be persistent, suggesting that past RV should also predict future RV. Column (3) confirms this, showing that past-12-month RV has a positive coefficient of 0.747 with a t-statistic of 11.47. To evaluate the incremental information in IV^{Analyst}, column (4) includes all three predictors. We find that even though the coefficient of IV^{Analyst} drops to 0.085, it remains statistically significant with a t-statistic of 3.22.

In Panel B, we predict future-12-month skewness. In column (1), $Skew^{\text{Analyst}}$ positively predicts future skewness with a coefficient of 0.106 and a t-statistic of 2.5, suggesting that analyst forecasts contain valuable information about higher-order moment. In contrast, option-implied and historical skewness are not statistically significant in columns (2) and (3), highlighting the importance of our subjective measure in forecasting higher-order moments. When we include all three predictors in column (4), the coefficient and significance of $Skew^{\text{Analyst}}$ barely changes.

Overall, these results indicate that analysts' subjective expectations contain unique and non-redundant information. Analysts do not merely form expectations based on information from option markets or past realized moments, but contribute additional insights that help forecast variance and skewness.

B. *Predicting Option Returns*

A straddle is a volatility-sensitive asset that delivers a payoff resembling the realized volatility of the underlying stock return. Its price is closely linked to option-implied volatility. If IV^{Analyst} contains volatility information beyond what is already incorporated into option-implied variance, it should positively predict straddle returns. The exact same logic applies to skewness asset: If $Skew^{\text{Analyst}}$ truly contains skewness information that cannot be subsumed by option markets, it should positively predict skewness asset returns.

To test this hypothesis, we estimate the following monthly Fama and MacBeth (1973) regression:

$$r_{i,t+1}^{\text{Straddle}} = \alpha_t + \beta_t IV_{i,t\rightarrow t+12}^{\text{Analyst}} + \gamma_t \text{Controls}_{i,t} + \epsilon_{i,t+1};$$

$$r_{i,t+1}^{\text{Skew}} = \alpha_t + \beta_t Skew_{i,t\rightarrow t+12}^{\text{Analyst}} + \gamma_t \text{Controls}_{i,t} + \epsilon_{i,t+1},$$

where $IV_{i,t\rightarrow t+12}^{\text{Analyst}}$ ($Skew_{i,t\rightarrow t+12}^{\text{Analyst}}$) is firm i's latest available analyst subjective variance (skewness) forecast. We require that the analyst report is released within 12 months prior to the asset formation date. Since our analyst data end in 2016, the sample for straddle returns extends one additional year to 2017. Control variables include those discussed in Section II. Independent variables are winsorized at the 1% level. Standard errors are Newey-West adjusted with 12 lags.

Table III presents the regression results. We predict straddle returns in Panel A. In column (1), IV^{Analyst} positively predicts cross-sectional straddle returns with a t-statistic of 3.2, confirming that it contains incremental volatility information beyond option-implied variance. After controlling for additional option return predictors in column (3), the t-statistic of IV^{Analyst} increases slightly to 3.90.

In column (1) of Panel B, $Skew^{\text{Analyst}}$ positively predicts cross-sectional skewness asset returns with a t-statistic of 4.49, echoing the earlier result that it can predict future skewness after controlling for option-implied skewness. Its return predictability remains strong with other controls included in column (3).

To assess the economic significance of IV^{Analyst} and $Skew^{\text{Analyst}}$ as trading signals, we implement long-short portfolio strategies. We sort straddles (skewness assets) into quintiles based on IV^{Analyst} ($Skew^{\text{Analyst}}$), and form an equally weighted portfolio that takes a long position in the highest quintile and a short position in the lowest.

Table IV reports the results. In Panel A, the mean straddle return monotonically increases with IV^{Analyst}. The lowest quintile yields a monthly average return of -5.91%, while the highest quintile has a mean return of -1.33%. The long-short portfolio generates a highly significant monthly return of 4.58% with a t-statistic of 3.03, corresponding to an annualized Sharpe ratio of 0.93. To account for risk exposures in options markets, we adjust returns using the option risk factor model proposed by Horenstein, Vasquez, and Xiao (2023), whose factors include equally weighted straddle returns across firms, and straddle returns sorted by volatility deviation and volatility of volatility. The strategy's alpha remains significant, averaging 3.90% per month with a t-statistic of 2.44. Furthermore, the strategy does not exhibit strong exposure to crash risk, as its skewness is 0.01 and its worst monthly return is -44.52%.

Panel B presents results associated with skewness asset returns. The mean r^{Skew} monotonically increases with $Skew^{\text{Analyst}}$: The lowest quintile yields a monthly average return of -0.47%, while the highest quintile has a mean return of 0.33%. The long-short portfolio generates a highly significant monthly return of 0.8% with a t-statistic of 4.15, corresponding to an annualized Sharpe ratio of 1.27. Since no established factor model exists for skewness assets, we compute risk-adjusted returns using equally weighted skewness asset returns across firms and skewness asset returns sorted by IV smirk slope, and volatility of volatility.[10] The strategy's alpha remains significant with a monthly average of 0.56% and a t-statistic of 2.4. In addition, the strategy does not suffer from crash risk: Its skewness is 0.59 with a minimum monthly return of -4.81%.

To track the performance of option strategies over time, Figure 2 and Figure 3

[10]We use IV smirk slope and volatility of volatility because they are the only two control variables that are significant in predicting r^{Skew} in Panel B of Table III.

plot the rolling three-year returns for the straddle and skewness long-short portfolios, respectively. The two strategies have positive performance in almost all subsamples.

In sum, results in this section support the notion that analysts' subjective expectations cannot be subsumed by option-implied measures and they serve as valuable trading signals in option markets.

C. Risk-Return Trade-Off and Skewness-Return Trade-Off

With analysts' expectations available for return, variance, and skewness, a natural question arises: does a positive (negative) risk (skewness) -return trade-off exist, as suggested by classical finance theories? To investigate this, we estimate the following regressions using firm-days when analysts issue reports:

$$r^{\text{Stock}}_{i,t\rightarrow t+12} = \alpha + q_t + \beta IV^{\text{Analyst}}_{i,t\rightarrow t+12} + \gamma \text{Controls}_{i,t} + \epsilon_{i,t},$$

$$r^{\text{Stock}}_{i,t\rightarrow t+12} = \alpha + q_t + \beta Skew^{\text{Analyst}}_{i,t\rightarrow t+12} + \gamma \text{Controls}_{i,t} + \epsilon_{i,t},$$

where $r^{\text{Stock}}_{i,t\rightarrow t+12}$ represents the return expectation of the analyst on firm i. Following the literature, we define it as the log of the analyst's price target divided by the stock price on the report date t. $IV^{\text{Analyst}}_{i,t\rightarrow t+12}$ ($Skew^{\text{Analyst}}_{i,t\rightarrow t+12}$) is the same analyst's expectation of variance (skewness).

For robustness, we control for firm characteristics as in Fama and French (2015). Specifically, we include market beta (β), estimated from a rolling one-year CAPM regression using daily stock returns; firm size, measured as the logarithm of market capitalization on the report date; valuation, proxied by log book-to-market ratio; and the profitability and investment factors. All regressions include month-fixed effects q_t, and standard errors are clustered at the firm-month level. Independent variables are winsorized at the 1% level.

Table V presents the results. Panel A studies the risk-return trade-off. Column (1) shows that IV^{Analyst} is positively associated with analyst's return expectation, with a t-statistic of 4.69, indicating a positive risk-return trade-off from analyst's perspective. A one-standard deviation increase in IV^{Analyst} translates into a 4.43% increase in the analyst's return expectation (0.270 $\times$ 0.164). The positive relationship remains highly significant after including additional controls in column (2), where the coefficient of IV^{Analyst} decreases slightly to 0.156 with a t-statistic of 3.64.

Panel B examines skewness-return trade-off. Column (1) shows that $Skew^{\text{Analyst}}$ is negatively related to analyst's return expectation, with a t-statistic of -16.00, indicating a negative skewness-return trade-off from analyst's perspective. A one-standard deviation increase in $Skew^{\text{Analyst}}$ translates into a 12.75% decrease in the analyst's return expectation (-0.129×0.988). The negative relationship remains highly significant after including additional controls in column (2).

To summarize, using the same analyst's expectations on return, variance, and skewness, we uncover a positive risk-return trade-off and a negative skewness-return trade-off that are consistent with theories in the literature.

D. Determinants of Analyst Subjective Expectations on Variance and Skewness

This section examines firm characteristics that influence IV^{Analyst} and $Skew^{\text{Analyst}}$.

Panel A in Table VI presents the relationships between IV^{Analyst} and two primary volatility predictors in the literature—option-implied variance (IV^{Option}) and past-year realized variance ($RV_{t-12\to t}$). Across specifications in columns (1)–(3), both variables exhibit strong positive relationships with IV^{Analyst}, confirming that analysts incorporate both historical and option-implied volatility when forming expectations of future risk. Notably, IV^{Option} consistently carries a larger coefficient than RV, underscoring the dominant role of forward-looking option-implied variance in shaping analysts' variance expectations.

As additional firm characteristics are introduced in column (4), the explanatory power of IV^{Option} and $RV_{t-12\to t}$ diminishes, suggesting that analysts also account for fundamental firm attributes in their volatility assessments. The coefficient on market beta is positive and significant, indicating that firms with higher systematic risk tend to have greater IV^{Analyst}. Firm size exhibits a weakly negative association with IV^{Analyst}. Other firm characteristics, including the book-to-market ratio, profitability, and investment, do not have statistically significant relationships with IV^{Analyst}, suggesting that these fundamentals play a secondary role in shaping analysts' variance expectations.

Panel B investigates the determinants of $Skew^{\text{Analyst}}$. Option-implied skewness ($Skew^{\text{Option}}$) exhibits a strong positive association with $Skew^{\text{Analyst}}$, while past-year realized skewness ($RSkew_{t-12\to t}$) displays a negative relationship. This suggests that analysts are contrarian when forming expectations on skewness: If the stock return already experienced a high skewness in the past year, analysts would expect a reversal in the following year. After we include other firm characteristics in column (4), the coefficients of $Skew^{\text{Option}}$ and $RSkew_{t-12\to t}$ are almost halved but remain highly significant. Among other characteristics, only firm size is significantly associated with $Skew^{\text{Analyst}}$. Specifically, analysts expect smaller firms to have higher future skewness.

E. Analysts' Crash Beliefs

This section investigates whether analysts' scenario-based analysis can provide downside information that can help forecast stock crashes.

We construct analysts' crash beliefs for stock i at time t, $Crash^{Analyst}_{i,t\to t+12}$, based on bear price: if bear price divided by current stock price at t is larger than 0.8, it means that analysts do not think it is possible for stock price to decline by more than 20% in the next year even in the worst scenario, and $Crash^{Analyst}_{i,t\to t+12}$ equals 0; if the ratio is smaller than 0.8, $Crash^{Analyst}_{i,t\to t+12}$ equals the probability of bear price.

We run the panel regression below using firm-days when analysts issue reports:

$$I(R_{i,t\to t+12} \leq 0.8) = \alpha + q_t + \beta Crash^{\text{Analyst}}_{i,t\to t+12} + \gamma \text{Controls}_{i,t} + \epsilon_{i,t},$$

where $R_{i,t\to t+12}$ is firm i's gross return, and $I(R_{i,t\to t+12} \leq 0.8)$ is a dummy equal to 1 if stock price declines by more than 20% over the next 12 months. To evaluate the incremental information from analysts, we control for crash predictors in the existing literature: we use the 365-day implied volatilities from the OptionMetrics Volatility Surface database to construct option-implied crash probability, $Crash^{Option}_{i,t\to t+12}$, following the method in Martin (2017); we control firm characteristics used in Chen, Hong, and Stein (2001) such as past stock returns and turnover; we further include short interests. We include month-fixed effects q_t and cluster standard errors at the firm and month levels. To facilitate the interpretation of economic magnitudes, all independent variables are standardized.

Table VII reports the regression results. Used alone as a predictor in column (2), $Crash^{Analyst}_{i,t\to t+12}$ positively predicts crashes: a one standard deviation increase raises the predicted crash probability by 4.4%. $Crash^{Option}_{i,t\to t+12}$ also strongly forecasts crashes in column (3) with a coefficient of 6.6%. When we include all predictors in column (4), the coefficient of $Crash^{Analyst}_{i,t\to t+12}$ decreases to 1.2% but remains highly significant. The evidence suggests that analysts' scenario-based analysis indeed provide incremental downside information that can help forecast stock crashes.

IV. What's in Analysts' Information Sets?

A. Extracting Topic-Related Information Using ChatGPT

Analysts not only provide explicit price forecast ranges but also discuss key economic, industry-specific, and firm-level factors that shape their expectations (see Figure 1 for examples). To understand the information embedded in their assessments of future stock price movements, we identify and quantify these discussions, providing deeper insights into the drivers of analysts' expectations for both *variance* and *skewness*.

We begin with the 35 topics identified by Bybee, Kelly, Manela, and Xiu (2024) from financial articles, as these topics are highly relevant to market participants and capture key sources of uncertainty affecting stock return moments. Focusing on this predefined list allows us to bypass the high-level topic identification process within Morgan Stanley's analyst reports and directly quantify the relevance and intensity of topic-specific discussions related to stock variance and skewness using large language models (LLMs).

Specifically, we employ ChatGPT-4o to measure the intensity of each topic mentioned in the risk-reward section of analyst reports. To extract structured topic information, we use the following prompt:

You are an experienced **equity analyst** with a deep understanding of **individual stock variances and skewness** in financial markets.

Please evaluate the intensity of specific topics discussed in an analyst's report. Below is a list of 35 topics:

Federal Reserve, Economic growth, Recession, Macroeconomic data, Financial crisis, Treasury bonds, Bond yields, Earnings forecasts, Earnings losses, Earnings, Profits, M&A, Corporate governance, Competition, Revenue growth, SEC, Short sales, IPOs, Bank loans, Credit ratings, Mortgages, Real estate, Bear/bull market, Share payouts, Commodities, Oil market, Currencies/metals, European sovereign debt, Convertible/preferred, Options/VIX, Bankruptcy, Takeovers, Savings & loans, Trading activity, Product prices.

Assign each topic an **intensity score** from 1 (least intensive) to 10 (most intensive) based on the prominence or frequency of its narrative in the report. Use integer values only. Provide an **explanation** for how and why the topic narratives indicate the analyst's expectations about future stock variance and skewness. Format your output in JSON using the following structure:

```
{ "Topic": "<topic_name>",
  "Intensity": <integer_score>,
  "Explanation": "<text>" }
```

As depicted in Figure 4, discussions surrounding *earnings forecasts*, *revenue growth*, and *economic growth* dominate analyst reports, reaffirming their central role in valuation models. Meanwhile, topics exhibiting greater dispersion, such as *financial crises* and *commodity markets*, indicate that analysts allocate varying levels of attention to these areas depending on broader market uncertainty, potentially influencing their expectations for both variance and skewness.

B. Important Topics in Variance and Skewness Expectation

To assess the role of topic-specific discussions in shaping analyst expectations, we model the relationship between IV^{Analyst} and $Skew^{\text{Analyst}}$ and a vector of explanatory variables X, which includes IV^{Option}, RV, $Skew^{\text{Option}}$, $RSkew$, and various topic intensity measures extracted from analyst reports. The general regression framework is specified as follows:

$$\begin{aligned} IV^{\text{Analyst}}_{j,t} &= \Phi\left(\mathbf{X}_{j,t};\theta\right) + \epsilon_{j,t}, \\ Skew^{\text{Analyst}}_{j,t} &= \Psi\left(\mathbf{X}_{j,t};\theta\right) + \epsilon_{j,t}. \end{aligned} \tag{2}$$

where $\Phi(\mathbf{X}_{j,t}|\theta)$ and $\Psi(\mathbf{X}_{j,t}|\theta)$ represent an analyst's expectations for variance and skewness, respectively, driven by reliance on market-based predictors as well as the analyst's interpretation of firm-specific and macroeconomic information. The function Φ (Ψ) is flexible and accommodates nonlinearity and high dimensionality due to the large number of topic intensity measures.

Given these complexities, we employ Boosted Regression Trees (BRT), a machine-learning approach well-suited for handling high-dimensional datasets, capturing feature interactions, and modeling nonlinear relationships (Gu, Kelly, and Xiu, 2020; Lundberg and Lee, 2017). We quantify feature importance using SHapley Additive exPlanations (SHAP), a widely adopted technique to quantify the marginal impact of individual predictors. SHAP values decompose model predictions, showing how each feature increases or decreases the predicted outcome relative to a baseline expectation.

Figure 5 presents the results from the BRT model for variance and skewness expectations. The findings indicate that IV^{Option} and RV are the dominant predictors of IV^{Analyst}, while $Skew^{\text{Option}}$ and $RSkew$ exhibit strong explanatory power for $Skew^{\text{Analyst}}$. Beyond market-based measures, topic-specific factors such as *bankruptcy risk*, *oil market*, and *economic growth* play a crucial role in explaining variance expectations, whereas *earnings losses*, *corporate profits*, and *bank loans* emerge as key determinants of skewness expectations.

The summary of distributions of SHAP values in Figure 7 further illustrates that textual information provides incremental predictive power for both variance and skewness expectations. While option-implied and realized moments remain fundamental, analysts adjust their forecasts based on qualitative factors, which vary significantly across reports.

C. *Interaction Effects between Market-Based Predictors and Topics*

Figure 9 examines the interaction effects between traditional variance and skewness predictors and selected topic-specific factors in shaping analyst expectations. The scatter plots illustrate the joint impact of these variables using SHAP interaction values. Interestingly, the interaction between IV^{Option} and *bankruptcy* suggests that analysts assign heightened importance to bankruptcy risks when option-implied volatility is high, indicating that distressed firms exhibit greater uncertainty amplification in analysts' expectations.

Moreover, the interaction between IV^{Option} and oil market discussions highlights the role of macroeconomic conditions in shaping variance forecasts. Analysts tend to adjust their expectations more substantially when oil market uncertainty coincides with high option-implied volatility, reflecting sensitivity to commodity-driven macroeconomic risks. The relationship between IV^{Option} and treasury bond discussions further supports this interpretation, as variance expectations appear to be influenced by perceived shifts in interest rates and bond market stability.

The rich and strong interaction effects are also evident for skewness. For example, the interaction between $Skew^{\text{Option}}$ and *earnings losses* highlights the role of downside risk considerations in shaping skewness expectations. Analysts tend to adjust their skewness expectations more substantially when negative earnings discussions coincide with high option-implied skewness, suggesting that expectations of left-tail risk are heightened under conditions of financial distress.

Overall, these interaction effects demonstrate that analysts do not assess variance and skewness expectations in isolation but rather synthesize multiple sources of information. By integrating traditional market-based predictors and narratives, our findings highlight the complexity of subjective return expectations and the nuanced decision-making processes underlying analysts' risk assessments.

V. Conclusion

This paper constructs the first firm-level measures of subjective expectations on variance and skewness. Unlike option-implied moments, which are derived under the risk-neutral measure and incorporate variance and skewness risk premium, our measures capture analysts' subjective expectations under the physical measure.

We find that analyst variance and skewness expectations significantly and positively predict future realized variance and skewness, and contain incremental volatility and skewness information that is not fully reflected in option markets. Consistent with this, analyst expectations positively predict cross-sectional returns of option portfolios designed to track variance and skewness.

Using the same analyst's subjective expectations for return, variance, and skewness, we uncover a positive risk-return trade-off and a negative skewness-return trade-off, consistent with classical asset pricing theories.

Beyond quantitative forecasts, analysts provide qualitative discussions underlying their variance and skewness expectations. Using large language models and machine learning, we analyze the textual content of analyst reports to identify key macroeconomic, industry-specific, and firm-level topics influencing variance and skewness expectations. Our results reveal that analysts place particular emphasis on bankruptcy risks, government debt, and commodity markets when forming expectations of future uncertainty, whereas *earnings losses*, *corporate profits*, and *bank loans* emerge as key determinants of skewness expectations. Moreover, we find strong interaction effects between market-based predictors and qualitative narratives, demonstrating that analysts synthesize multiple sources of information rather than relying solely on quantitative measures of dispersion and asymmetry in return distributions.

Overall, this paper introduces a novel subjective measure of variance and skewness, establishes its empirical relevance in forecasting future variance, skewness, and option returns, and provides evidence that analysts' expectations exhibit a positive risk-return relation and a negative skewness-return relation. We also offer new insights into how qualitative information contributes to the formation of subjective variance and skewness expectations, highlighting the importance of integrating structured financial data with unstructured narratives to better understand investors' risk perceptions and higher-order moment expectations in financial markets (see, e.g., Barth, Monin, Siriwardane, and Sunderam, 2024).

REFERENCES

Ang, A., R. J. Hodrick, Y. Xing, and X. Zhang, 2006, "The cross-section of volatility and expected returns," *The journal of finance*, 61(1), 259–299.

Aragon, G. O., S. Chen, and Z. Shi, 2022, "Volatility Timing Using ETF Options: Evidence from Hedge Funds," *Available at SSRN 4246146*.

Bakshi, G., N. Kapadia, and D. Madan, 2003, "Stock return characteristics, skew laws, and the differential pricing of individual equity options," *The Review of Financial Studies*, 16(1), 101–143.

Bali, T. G., and S. Murray, 2013, "Does risk-neutral skewness predict the cross-section of equity option portfolio returns?," *Journal of Financial and Quantitative Analysis*, 48(4), 1145–1171.

Barberis, N., and M. Huang, 2008, "Stocks as lotteries: The implications of probability weighting for security prices," *American Economic Review*, 98(5), 2066–2100.

Barth, D., P. Monin, E. Siriwardane, and A. Sunderam, 2024, "Hidden Risk," .

Ben-David, I., J. R. Graham, and C. R. Harvey, 2013, "Managerial miscalibration," *The Quarterly journal of economics*, 128(4), 1547–1584.

Bollerslev, T., G. Tauchen, and H. Zhou, 2009, "Expected stock returns and variance risk premia," *The Review of Financial Studies*, 22(11), 4463–4492.

Brav, A., and R. Lehavy, 2003, "An empirical analysis of analysts' target prices: Short-term informativeness and long-term dynamics," *The Journal of Finance*, 58(5), 1933–1967.

Brunnermeier, M. K., C. Gollier, and J. A. Parker, 2007, "Optimal beliefs, asset prices, and the preference for skewed returns," *American Economic Review*, 97(2), 159–165.

Bybee, L., B. Kelly, A. Manela, and D. Xiu, 2024, "Business news and business cycles," *The Journal of Finance*, 79(5), 3105–3147.

Cao, J., and B. Han, 2013, "Cross section of option returns and idiosyncratic stock volatility," *Journal of Financial Economics*, 108(1), 231–249.

Cao, J., B. Han, G. Li, R. Yang, and X. Zhan, 2024, "Forecasting option returns with news," *Available at SSRN*.

Carr, P., and L. Wu, 2009, "Variance risk premiums," *The Review of Financial Studies*, 22(3), 1311–1341.

Chan, L. K., J. Karceski, and J. Lakonishok, 2007, "Analysts' conflicts of interest and biases in earnings forecasts," *Journal of Financial and Quantitative Analysis*, 42(4), 893–913.

Chen, J., H. Hong, and J. C. Stein, 2001, "Forecasting crashes: Trading volume, past returns, and conditional skewness in stock prices," *Journal of financial Economics*, 61(3), 345–381.

Chen, S., and S. Li, 2024, "Hedge Fund Option Usage and Skewness Risk Premium," *Available at SSRN 4592419*.

Chen, S., L. Peng, and D. Zhou, 2024, "Wisdom or Whims? Decoding Investor Trading Strategies with Large Language Models," *Available at SSRN 4867401*.

Eisfeldt, A. L., G. Schubert, and M. B. Zhang, 2023, "Generative AI and Firm Values," working paper, National Bureau of Economic Research.

Fama, E. F., and K. R. French, 2015, "A five-factor asset pricing model," *Journal of financial economics*, 116(1), 1–22.

Fama, E. F., and J. D. MacBeth, 1973, "Risk, return, and equilibrium: Empirical tests," *Journal of political economy*, 81(3), 607–636.

Goyal, A., and A. Saretto, 2009, "Cross-section of option returns and volatility," *Journal of Financial Economics*, 94(2), 310–326.

Gu, S., B. Kelly, and D. Xiu, 2020, "Empirical Asset Pricing via Machine Learning," *Review of Financial Studies*, 33(5), 2223–2273.

Heston, S. L., C. S. Jones, M. Khorram, S. Li, and H. Mo, 2023, "Option momentum," *The Journal of Finance*, 78(6), 3141–3192.

Horenstein, A. R., A. Vasquez, and X. Xiao, 2023, "Common factors in equity option returns," *Available at SSRN 3290363*.

Huang, L., B. Qiao, and D. Zhou, 2024, "Are Memes a Sideshow: Evidence from WallStreetBets," *Available at SSRN 4785481*.

Jensen, T. I., 2023, "Subjective risk and return," *Available at SSRN 4276760*.

Jha, M., J. Qian, M. Weber, and B. Yang, 2024, “ChatGPT and Corporate Policies,” working paper, National Bureau of Economic Research.

Jiang, J., B. T. Kelly, and D. Xiu, 2024, “Expected Returns and Large Language Models,” *Available at SSRN*.

Joos, P., J. D. Piotroski, and S. Srinivasan, 2016, “Can analysts assess fundamental risk and valuation uncertainty? An empirical analysis of scenario-based value estimates,” *Journal of Financial Economics*, 121(3), 645–663.

Ke, B., and Y. Yu, 2006, “The effect of issuing biased earnings forecasts on analysts’ access to management and survival,” *Journal of Accounting Research*, 44(5), 965–999.

Kozhan, R., A. Neuberger, and P. Schneider, 2013, “The skew risk premium in the equity index market,” *The Review of Financial Studies*, 26(9), 2174–2203.

Li, K., F. Mai, R. Shen, C. Yang, and T. Zhang, 2023, “Dissecting Corporate Culture Using Generative AI–Insights from Analyst Reports,” *Available at SSRN 4558295*.

Lim, T., 2001, “Rationality and analysts’ forecast bias,” *The journal of Finance*, 56(1), 369–385.

Lochstoer, L. A., and T. Muir, 2022, “Volatility expectations and returns,” *The Journal of Finance*, 77(2), 1055–1096.

Lopez-Lira, A., and Y. Tang, 2023, “Can ChatGPT Forecast Stock Price Movements? Return Predictability and Large Language Models,” *arXiv preprint arXiv:2304.07619*.

Lundberg, S. M., and S.-I. Lee, 2017, “A unified approach to interpreting model predictions,” *Advances in neural information processing systems*, 30.

Martin, I., 2017, “What is the Expected Return on the Market?,” *The Quarterly Journal of Economics*, 132(1), 367–433.

Merton, R. C., 1987, “A simple model of capital market equilibrium with incomplete information,” .

Mitton, T., and K. Vorkink, 2007, “Equilibrium underdiversification and the preference for skewness,” *The Review of Financial Studies*, 20(4), 1255–1288.

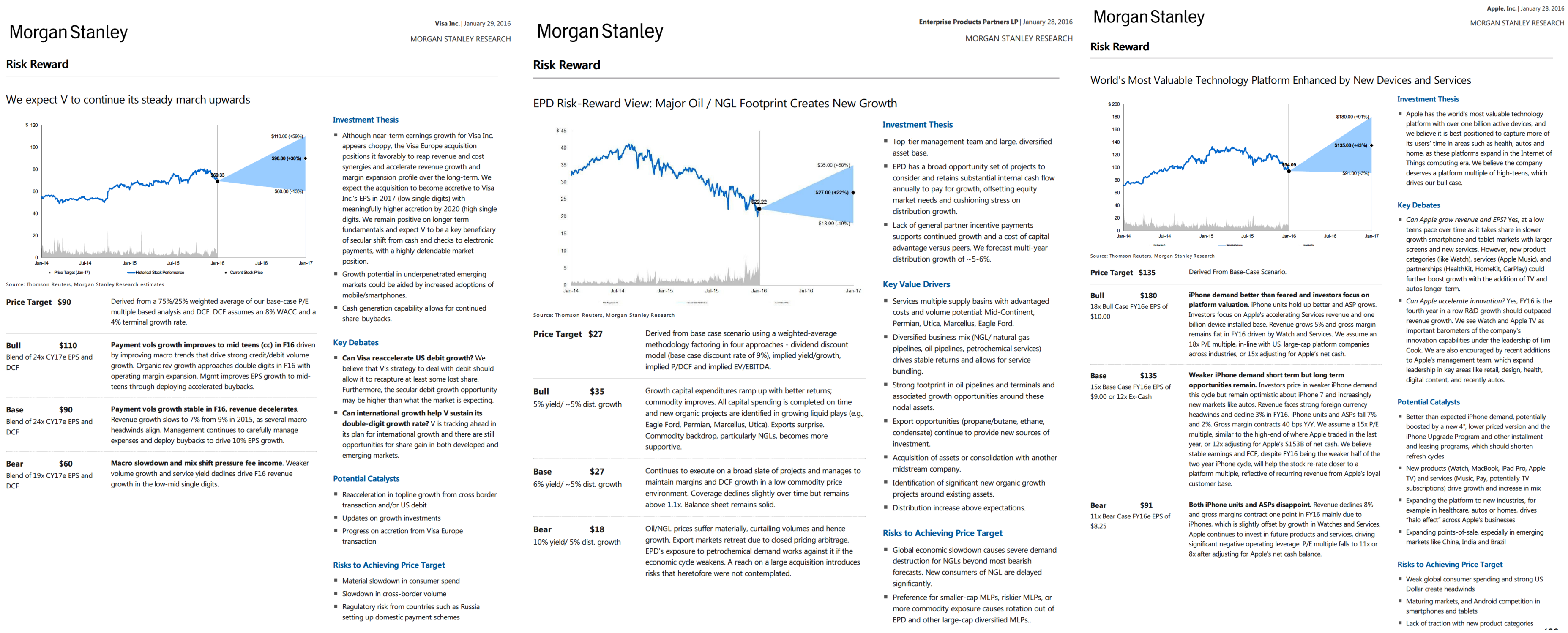
Nagel, S., and Z. Xu, 2022, “Asset pricing with fading memory,” *The Review of Financial Studies*, 35(5), 2190–2245.

———, 2023, "Dynamics of subjective risk premia," *Journal of Financial Economics*, 150(2), 103713.

Orlowski, P., P. Schneider, and F. Trojani, 2023, "On the nature of (jump) skewness risk premia," *Management Science*.

Vasquez, A., 2017, "Equity volatility term structures and the cross section of option returns," *Journal of Financial and Quantitative Analysis*, 52(6), 2727–2754.

Weyns, G., J.-L. Perez, B. Hurewitz, and V. Jenkins, 2011, "Morgan Stanley's Risk-Reward Views: Unlocking the Full Potential of Fundamental Analysis," *Journal of Applied Corporate Finance*, 23(2), 59–68.



Morgan Stanley

Visa Inc. | January 29, 2016
MORGAN STANLEY RESEARCH

Risk Reward

We expect V to continue its steady march upwards

Source: Thomson Reuters, Morgan Stanley Research estimates

Price Target	**$90**	Derived from a 75%/25% weighted average of our base-case P/E multiple based analysis and DCF. DCF assumes an 8% WACC and a 4% terminal growth rate.
Bull Blend of 24x CY17e EPS and DCF	**$110**	**Payment vols growth improves to mid teens (cc) in F16** driven by improving macro trends that drive strong credit/debit volume growth. Organic rev growth approaches double digits in F16 with operating margin expansion. Mgmt improves EPS growth to mid-teens through deploying accelerated buybacks.
Base Blend of 24x CY17e EPS and DCF	**$90**	**Payment vols growth stable in F16, revenue decelerates.** Revenue growth slows to 7% from 9% in 2015, as several macro headwinds align. Management continues to carefully manage expenses and deploy buybacks to drive 10% EPS growth.
Bear Blend of 19x CY17e EPS and DCF	**$60**	**Macro slowdown and mix shift pressure fee income.** Weaker volume growth and service yield declines drive F16 revenue growth in the low-mid single digits.

Investment Thesis

- Although near-term earnings growth for Visa Inc. appears choppy, the Visa Europe acquisition positions it favorably to reap revenue and cost synergies and accelerate revenue growth and margin expansion profile over the long-term. We expect the acquisition to become accretive to Visa Inc.'s EPS in 2017 (low single digits) with meaningfully higher accretion by 2020 (high single digits. We remain positive on longer term fundamentals and expect V to be a key beneficiary of secular shift from cash and checks to electronic payments, with a highly defendable market position.
- Growth potential in underpenetrated emerging markets could be aided by increased adoptions of mobile/smartphones.
- Cash generation capability allows for continued share-buybacks.

Key Debates

- **Can Visa reaccelerate US debit growth?** We believe that V's strategy to deal with debit should allow it to recapture at least some lost share. Furthermore, the secular debit growth opportunity may be higher than what the market is expecting.
- **Can international growth help V sustain its double-digit growth rate?** V is tracking ahead in its plan for international growth and there are still opportunities for share gain in both developed and emerging markets.

Potential Catalysts

- Reacceleration in topline growth from cross border transaction and/or US debit
- Updates on growth investments
- Progress on accretion from Visa Europe transaction

Risks to Achieving Price Target

- Material slowdown in consumer spend
- Slowdown in cross-border volume
- Regulatory risk from countries such as Russia setting up domestic payment schemes

Morgan Stanley

Enterprise Products Partners LP | January 28, 2016
MORGAN STANLEY RESEARCH

Risk Reward

EPD Risk-Reward View: Major Oil / NGL Footprint Creates New Growth

Source: Thomson Reuters, Morgan Stanley Research

Price Target	**$27**	Derived from base case scenario using a weighted-average methodology factoring in four approaches - dividend discount model (base case discount rate of 9%), implied yield/growth, implied P/DCF and implied EV/EBITDA.
Bull 5% yield/ ~5% dist. growth	**$35**	Growth capital expenditures ramp up with better returns; commodity improves. All capital spending is completed on time and new organic projects are identified in growing liquid plays (e.g., Eagle Ford, Permian, Marcellus, Utica). Exports surprise. Commodity backdrop, particularly NGLs, becomes more supportive.
Base 6% yield/ ~5% dist. growth	**$27**	Continues to execute on a broad slate of projects and manages to maintain margins and DCF growth in a low commodity price environment. Coverage declines slightly over time but remains above 1.1x. Balance sheet remains solid.
Bear 10% yield/ 5% dist. growth	**$18**	Oil/NGL prices suffer materially, curtailing volumes and hence growth. Export markets retreat due to closed pricing arbitrage. EPD's exposure to petrochemical demand works against it if the economic cycle weakens. A reach on a large acquisition introduces risks that heretofore were not contemplated.

Investment Thesis

- Top-tier management team and large, diversified asset base.
- EPD has a broad opportunity set of projects to consider and retains substantial internal cash flow annually to pay for growth, offsetting equity market needs and cushioning stress on distribution growth.
- Lack of general partner incentive payments supports continued growth and a cost of capital advantage versus peers. We forecast multi-year distribution growth of ~5-6%.

Key Value Drivers

- Services multiple supply basins with advantaged costs and volume potential: Mid-Continent, Permian, Utica, Marcellus, Eagle Ford.
- Diversified business mix (NGL/ natural gas pipelines, oil pipelines, petrochemical services) drives stable returns and allows for service bundling.
- Strong footprint in oil pipelines and terminals and associated growth opportunities around these nodal assets.
- Export opportunities (propane/butane, ethane, condensate) continue to provide new sources of investment.
- Acquisition of assets or consolidation with another midstream company.
- Identification of significant new organic growth projects around existing assets.
- Distribution increase above expectations.

Risks to Achieving Price Target

- Global economic slowdown causes severe demand destruction for NGLs beyond most bearish forecasts. New consumers of NGL are delayed significantly.
- Preference for smaller-cap MLPs, riskier MLPs, or more commodity exposure causes rotation out of EPD and other large-cap diversified MLPs..

Morgan Stanley

Apple, Inc. | January 28, 2016
MORGAN STANLEY RESEARCH

Risk Reward

World's Most Valuable Technology Platform Enhanced by New Devices and Services

Source: Thomson Reuters, Morgan Stanley Research

Price Target	**$135**	Derived From Base-Case Scenario.
Bull 18x Bull Case FY16e EPS of $10.00	**$180**	**iPhone demand better than feared and investors focus on platform valuation.** iPhone units hold up better and ASP grows. Investors focus on Apple's accelerating Services revenue and one billion device installed base. Revenue grows 5% and gross margin remains flat in FY16 driven by Watch and Services. We assume an 18x P/E multiple, in-line with US, large-cap platform companies across industries, or 15x adjusting for Apple's net cash.
Base 15x Base Case FY16e EPS of $9.00 or 12x Ex-Cash	**$135**	**Weaker iPhone demand short term but long term opportunities remain.** Investors price in weaker iPhone demand this cycle but remain optimistic about iPhone 7 and increasingly new markets like autos. Revenue faces strong foreign currency headwinds and decline 3% in FY16. iPhone units and ASPs fall 7% and 2%. Gross margin contracts 40 bps Y/Y. We assume a 15x P/E multiple, similar to the high-end of where Apple traded in the last year, or 12x adjusting for Apple's $153B of net cash. We believe stable earnings and FCF, despite FY16 being the weaker half of the two year iPhone cycle, will help the stock re-rate closer to a platform multiple, reflective of recurring revenue from Apple's loyal customer base.
Bear 11x Bear Case FY16e EPS of $8.25	**$91**	**Both iPhone units and ASPs disappoint.** Revenue declines 8% and gross margins contract one point in FY16 mainly due to iPhones, which is slightly offset by growth in Watches and Services. Apple continues to invest in future products and services, driving significant negative operating leverage. P/E multiple falls to 11x or 8x after adjusting for Apple's net cash balance.

Investment Thesis

- Apple has the world's most valuable technology platform with over one billion active devices, and we believe it is best positioned to capture more of its users' time in areas such as health, autos and home, as these platforms expand in the Internet of Things computing era. We believe the company deserves a platform multiple of high-teens, which drives our bull case.

Key Debates

- *Can Apple grow revenue and EPS?* Yes, at a low teens pace over time as it takes share in slower growth smartphone and tablet markets with larger screens and new services. However, new product categories (like Watch), services (Apple Music), and partnerships (HealthKit, HomeKit, CarPlay) could further boost growth with the addition of TV and autos longer-term.
- *Can Apple accelerate innovation?* Yes, FY16 is the fourth year in a row R&D growth should outpaced revenue growth. We see Watch and Apple TV as important barometers of the company's innovation capabilities under the leadership of Tim Cook. We are also encouraged by recent additions to Apple's management team, which expand leadership in key areas like retail, design, health, digital content, and recently autos.

Potential Catalysts

- Better than expected iPhone demand, potentially boosted by a new 4", lower priced version and the iPhone Upgrade Program and other installment and leasing programs, which should shorten refresh cycles
- New products (Watch, MacBook, iPad Pro, Apple TV) and services (Music, Pay, potentially TV subscriptions) drive growth and increase in mix
- Expanding the platform to new industries, for example in healthcare, autos or homes, drives "halo effect" across Apple's businesses
- Expanding points-of-sale, especially in emerging markets like China, India and Brazil

Risks to Achieving Price Target

- Weak global consumer spending and strong US Dollar create headwinds
- Maturing markets, and Android competition in smartphones and tablets
- Lack of traction with new product categories

Figure 1: **Examples of Scenario-based Risk-Reward Framework in Morgan Stanley Analyst Report**

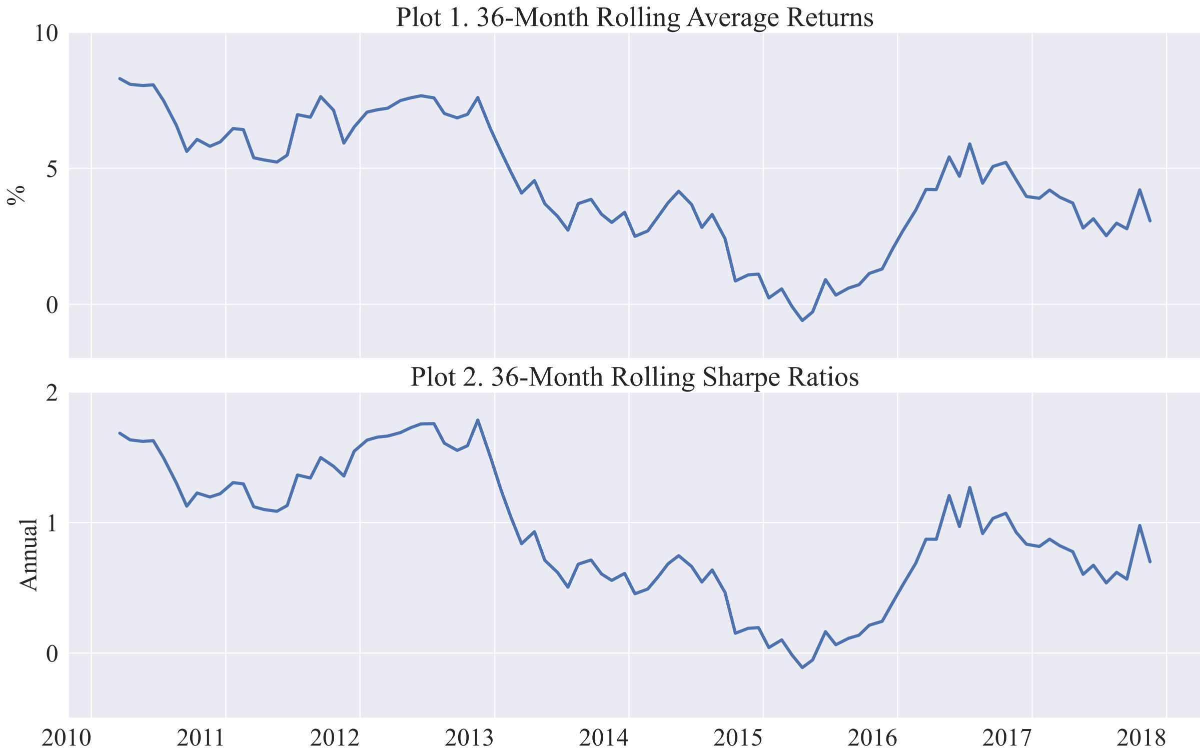


Figure 2: **Performance of the Long-Short Straddle Strategy by *Analyst Variance Expectation***
The figure plots the rolling three-year performance of the long-short portfolio of straddles sorted by analyst variance expectation. The upper panel illustrates the rolling average monthly return (in percentage) of the portfolio. The lower panel plots the rolling annualized Sharpe ratio.

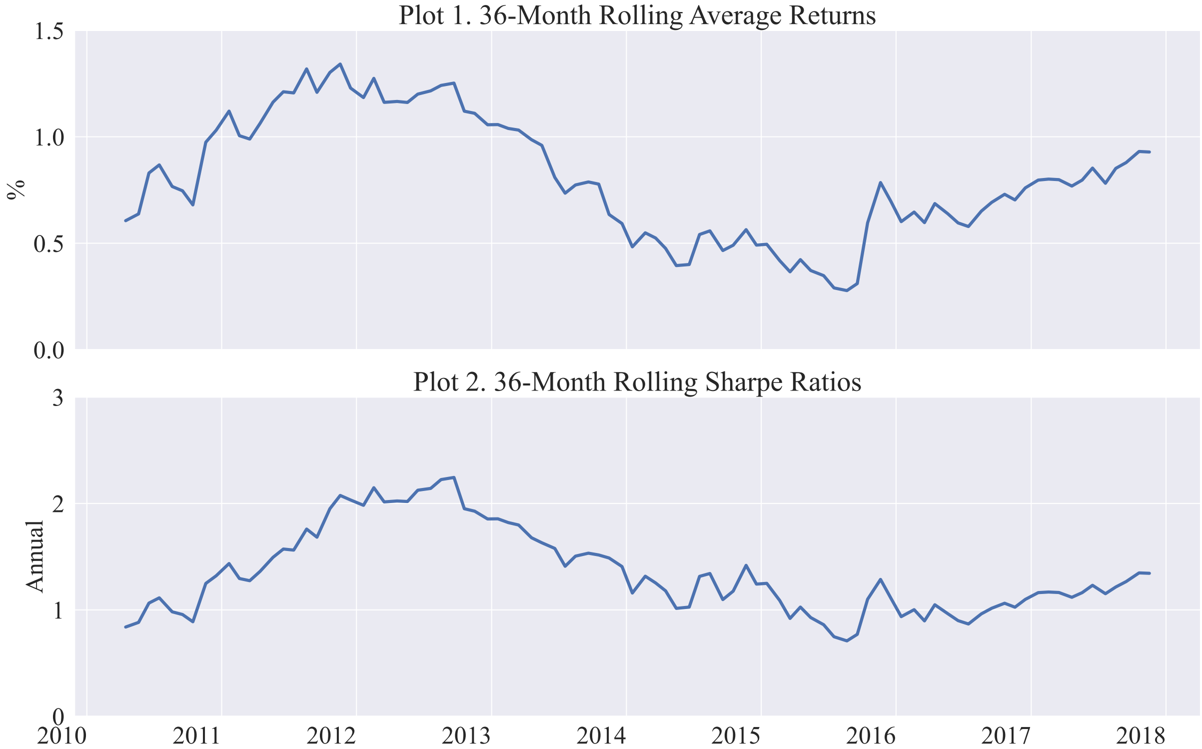


Figure 3: **Performance of the Long-Short Skewness Asset Strategy by *Analyst Skewness Expectation***
The figure plots the rolling three-year performance of the long-short portfolio of skewness assets sorted by analyst skewness expectation. The upper panel illustrates the rolling average monthly return (in percentage) of the portfolio. The lower panel plots the rolling annualized Sharpe ratio.

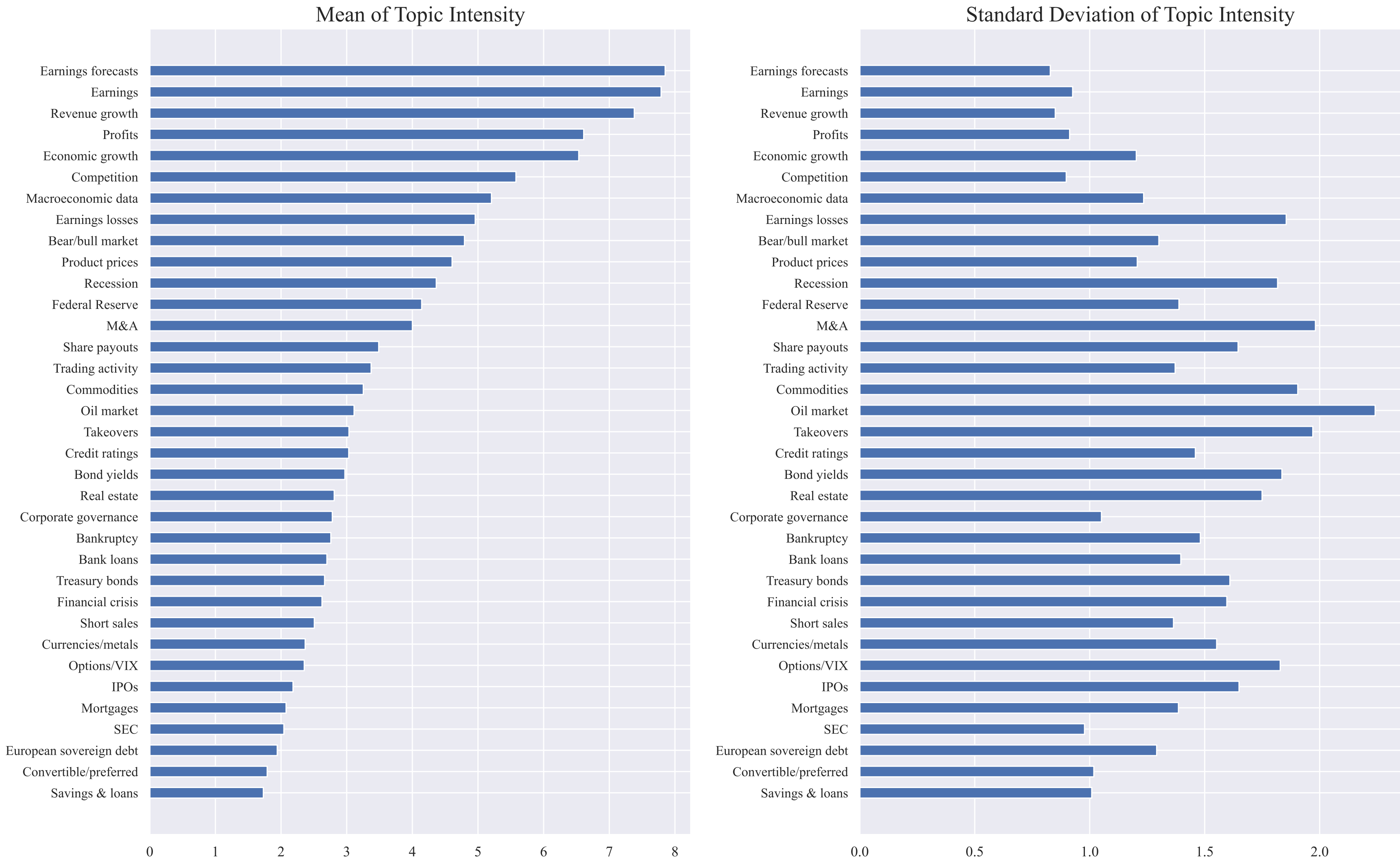


Figure 4: **Topic-specific information Intensity in analyst reports**

The left panel displays the mean intensity of various topics across analyst reports, while the right panel shows the standard deviation of topic intensity. Analysts frequently discuss macroeconomic, industry-specific, and firm-level topics, highlighting the broad scope of their assessments. Topics such as recession and commodity markets (e.g., oil) exhibit high dispersion, indicating substantial variation in analysts' attention to these factors. These findings underscore the diverse range of information incorporated into analysts' evaluations.

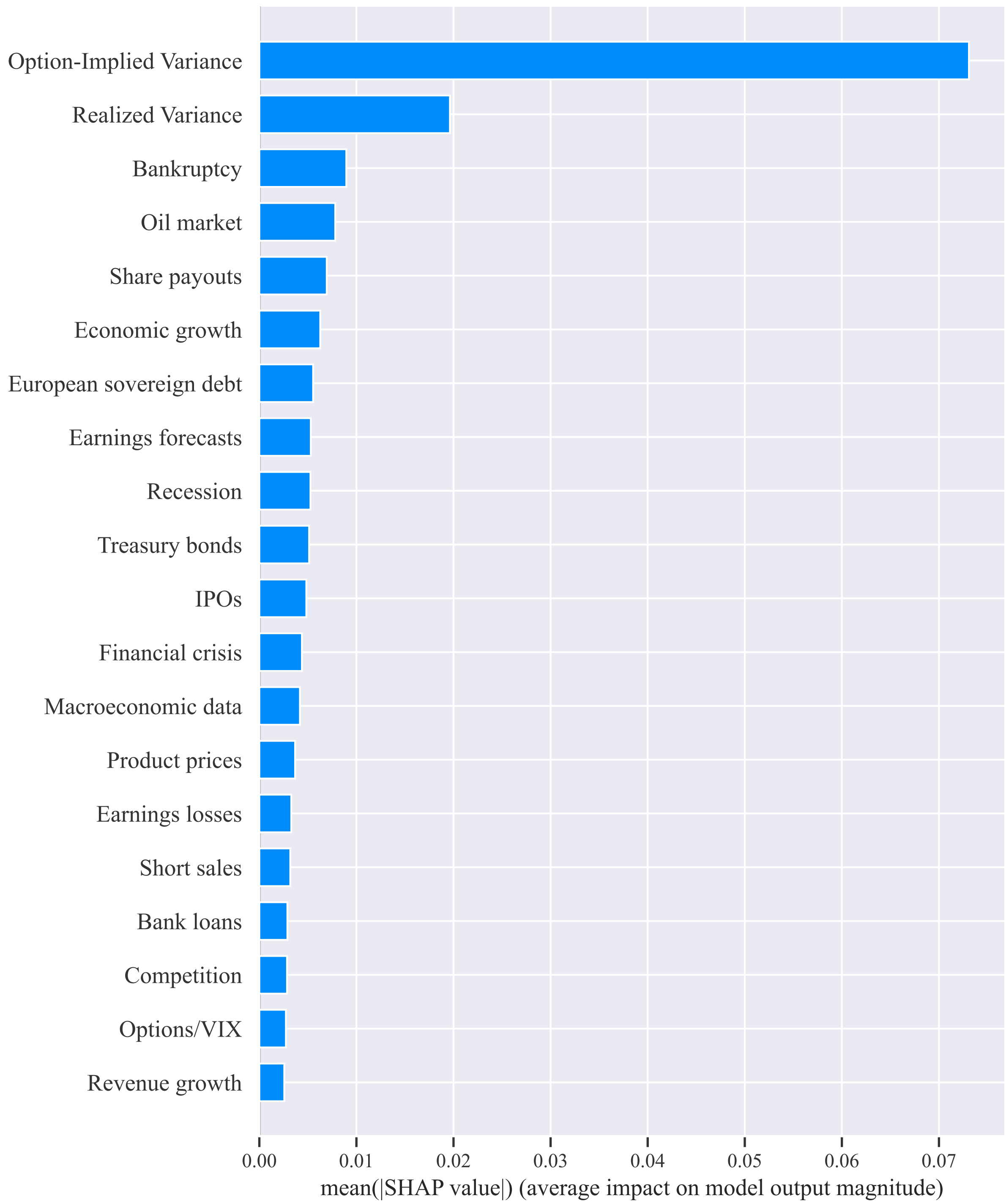


Figure 5: **Important Topics in Explaining Analyst Variance Expectation**

This figure presents the importance of different predictors in explaining analyst variance expectations, measured by the mean absolute SHAP values from an XGBoost model. Option-implied variance, realized variance, and bankruptcy emerge as the most influential factors, while topic-specific intensities such as oil market, economic growth, and share payouts also contribute to the model's explanatory power.

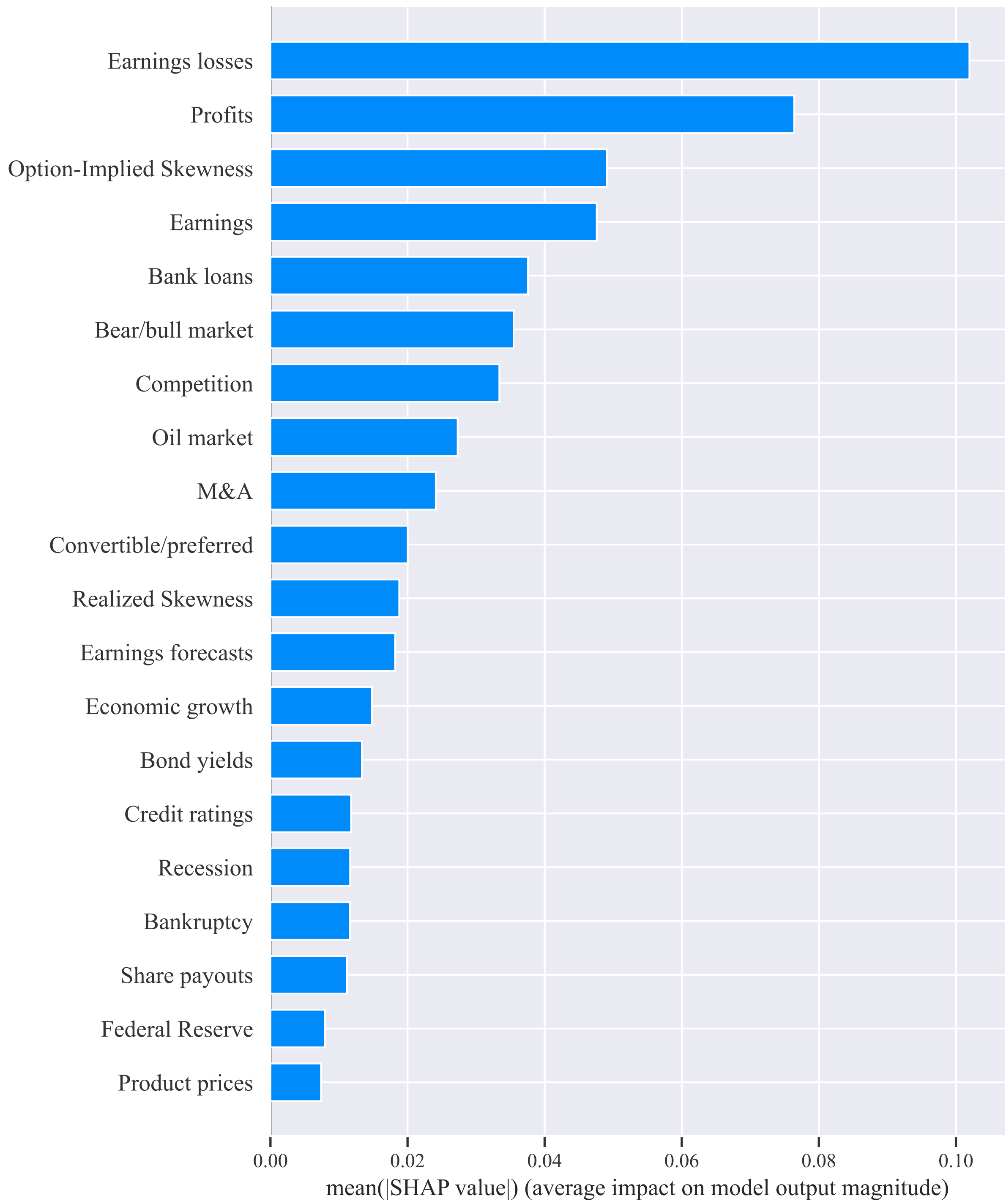


Figure 6: **Important Topics in Explaining Analyst Skewness Expectation**

This figure presents the importance of different predictors in explaining analyst skewness expectations, measured by the mean absolute SHAP values from an XGBoost model. Earnings losses, corporate profits, and option-implied skewness emerge as the most influential factors, while topic-specific intensities such as bank loans, bear/bull market, competition, and oil market also contribute to the model's explanatory power.

Figure 7: **SHAP Summary Plot for Topics in Analyst Variance Expectation.**

This figure presents the distribution of SHAP values for each feature in the XGBoost model, indicating the impact of individual predictors on the model's output. Option-implied variance, realized variance, and bankruptcy are the most significant contributors to analysts' assessments of variance expectations.

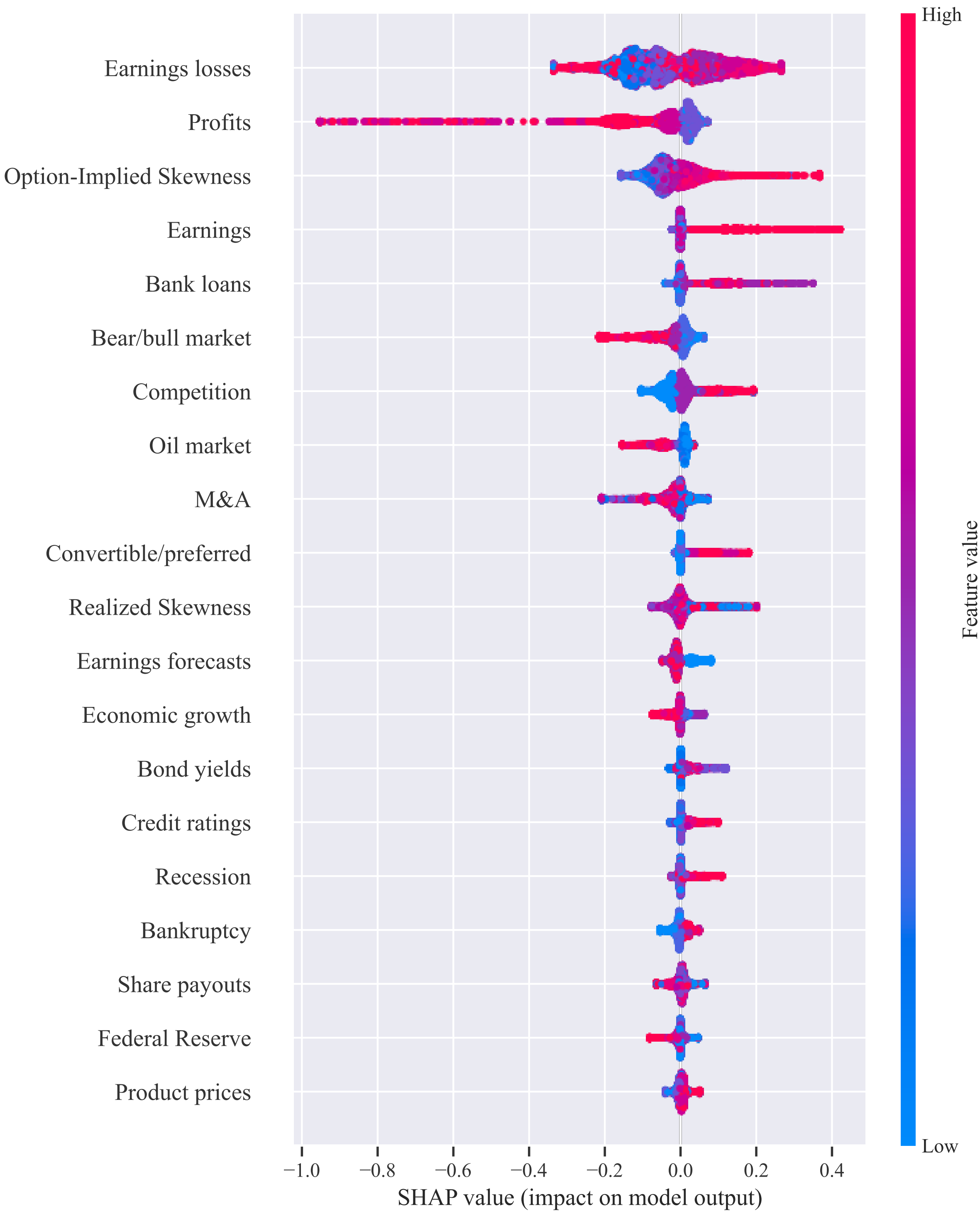


Figure 8: **SHAP Summary Plot for Topics in Analyst Skewness Expectation.**

This figure presents the distribution of SHAP values for each feature in the XGBoost model, indicating the impact of individual predictors on the model's output. Earnings losses, corporate profits, and option-implied skewness are the most significant contributors to analysts' assessments of variance expectations.

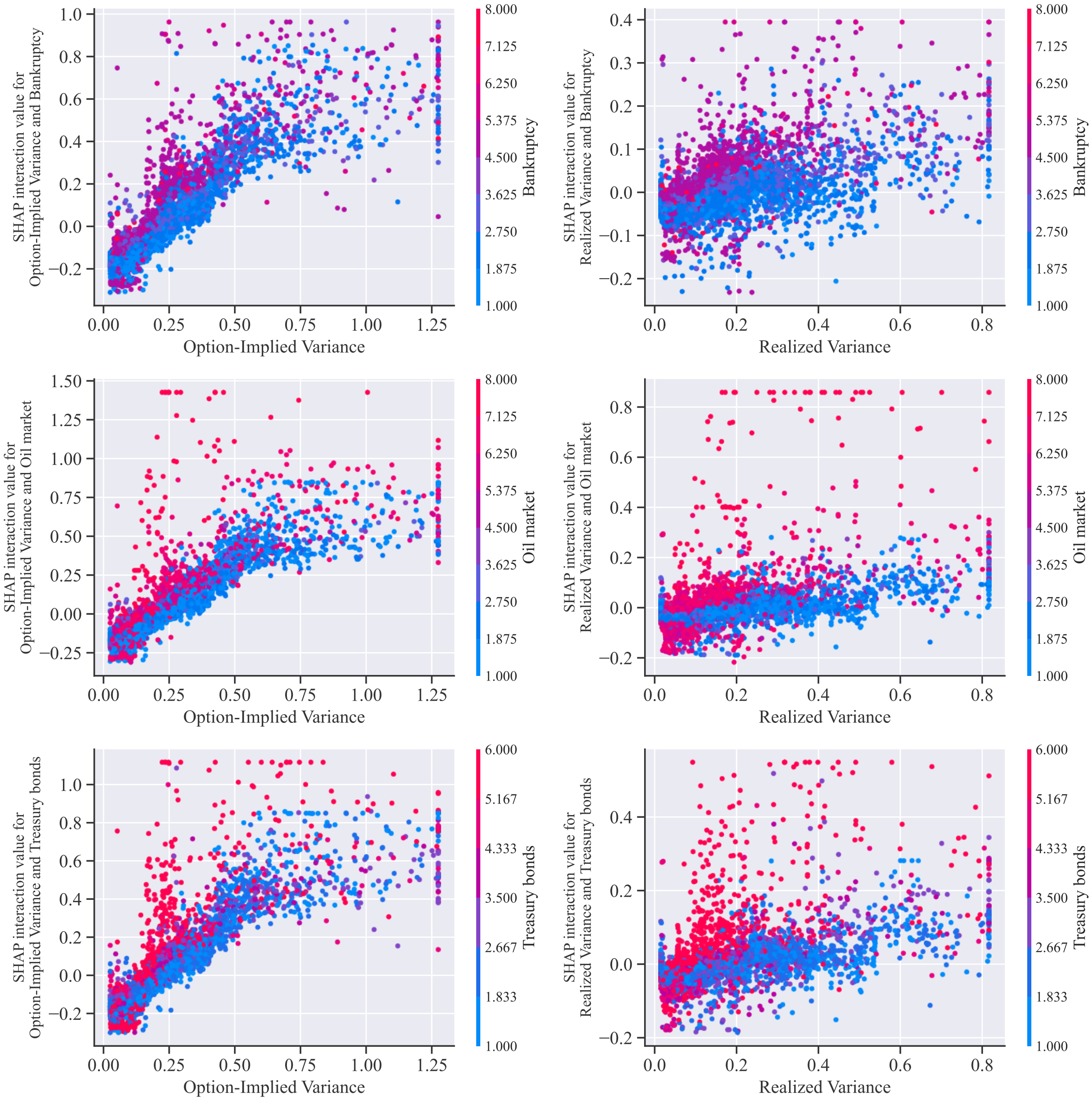


Figure 9: **Interaction Effects of Various Topics in Shaping Analyst Variance Expectations**

This figure visualizes the interaction effects between option-implied variance and realized variance on the x-axis and selected topic-specific factors such as bankruptcy, oil market, and treasury bonds. The scatter plots display SHAP interaction values, illustrating how different predictors jointly influence analyst subjective variance expectations.

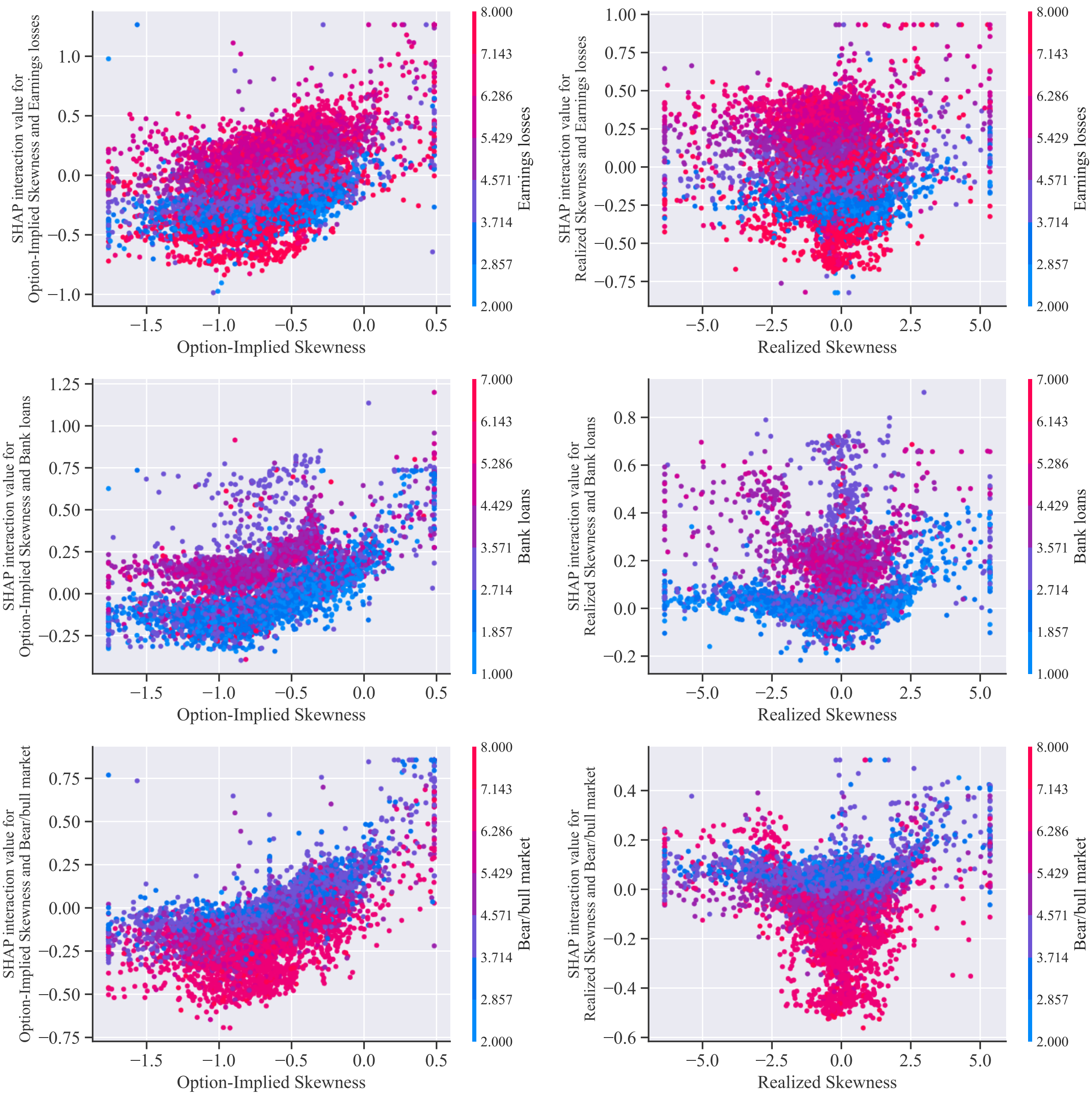


Figure 10: **Interaction Effects of Various Topics in Shaping Analyst Skewness Expectations**

This figure visualizes the interaction effects between option-implied skewness and realized skewness on the x-axis and selected topic-specific factors such as earnings losses, bank loans, and bear/bull market. The scatter plots display SHAP interaction values, illustrating how different predictors jointly influence analyst subjective skewness expectations.

Table I: **Summary Statistics**

The sample in Panel A includes firm-days with analyst reports release from January 2007 to December 2016. $IV_{i,t\to t+12}^{Analyst}$ ($Skew_{i,t\to t+12}^{Analyst}$) is analyst's subjective expectation on variance (skewness) of log stock return in the next 12 months. $RV_{i,t\to t+12}$ ($RSkew_{i,t\to t+12}$) is firm i's realized variance (skewness) 12 months after the report release day. $IV_{i,t\to t+12}^{Option}$ ($Skew_{i,t\to t+12}^{Option}$) is the option-implied variance (skewness) constructed with 365-day implied volatilities in Volatility Surface database following the method in Bakshi, Kapadia, and Madan (2003). Report interval is the number of days between adjacent reports written on the same firm. Panel B presents summary statistics for monthly returns of straddles ($r^{Straddle}$) and skewness assets (r^{Skew}). The sample includes firm-months with at least one analyst report release within 12 months before the option portfolio formation date.

	N	Mean	StdDev	P10	P25	Median	P75	P90
Panel A: Summary Statistics of Key Variables								
$IV_{i,t\to t+12}^{\text{Analyst}}$	22,162	0.178	0.270	0.033	0.056	0.101	0.195	0.369
$RV_{i,t\to t+12}$	22,162	0.186	0.319	0.033	0.052	0.097	0.203	0.393
$IV_{i,t\to t+12}^{\text{Option}}$	21,547	0.212	0.238	0.056	0.082	0.138	0.247	0.445
$Skew_{i,t\to t+12}^{\text{Analyst}}$	22,104	-0.164	0.988	-0.850	-0.532	-0.212	0.118	0.476
$RSkew_{i,t\to t+12}$	22,104	-0.092	1.673	-1.374	-0.543	-0.099	0.319	1.047
$Skew_{i,t\to t+12}^{\text{Option}}$	21,490	-0.608	0.363	-1.021	-0.801	-0.610	-0.415	-0.221
Market Cap ($\$10^6$)	22,156	24.34	53.87	0.91	2.28	7.00	20.24	56.89
Report Interval (days)	20,627	105	182	9	31	76	94	186
Panel B: Summary Statistics of Returns								
$r_{i,t\to t+12}^{\text{Straddle}}$	60,819	-0.036	0.797	-0.858	-0.623	-0.204	0.360	0.970
$r_{i,t\to t+12}^{\text{Skew}}$	56,336	-0.002	0.129	-0.090	-0.044	-0.003	0.044	0.094

Table II: **Predicting Future Realized Variance and Skewness**

This table presents the results of panel regressions. The dependent variable is the future-12-month realized variance ($RV_{i,t\to t+12}$) or skewness ($RSkew_{i,t\to t+12}$). $RV_{i,t-12\to t}$ ($RSkew_{i,t-12\to t}$) represents firm i's realized variance (skewness) over the past year. Independent variables are winsorized at the 1% level. The sample includes days with analyst report releases. Regressions include month fixed effects. Standard errors are clustered at the firm and month levels. t-statistics are reported in parentheses. The sample spans from 2007 to 2016.

Panel A: Predicting Future Variance ($RV_{i,t\to t+12}$)

	(1)	(2)	(3)	(4)
$IV^{Analyst}_{i,t\to t+12}$	0.450			0.085
	(14.56)			(3.22)
$IV^{Option}_{i,t\to t+12}$		0.717		0.553
		(15.00)		(9.79)
$RV_{i,t-12\to t}$			0.747	0.169
			(11.47)	(3.33)
Intercept	0.109	0.032	0.063	0.024
	(19.66)	(3.38)	(5.85)	(2.43)
Month FE	Yes	Yes	Yes	Yes
Observations	22,162	21,547	22,152	21,542
Adj. R^2	0.308	0.397	0.350	0.403

Panel B: Predicting Future Skewness ($RSkew_{i,t\to t+12}$)

	(1)	(2)	(3)	(4)
$Skew^{Analyst}_{i,t\to t+12}$	0.106			0.103
	(2.50)			(2.46)
$Skew^{Option}_{i,t\to t+12}$		0.133		0.116
		(1.73)		(1.54)
$RSkew_{i,t-12\to t}$			0.020	0.027
			(0.82)	(1.04)
Intercept	-0.072	-0.007	-0.087	0.006
	(-3.13)	(-0.13)	(-4.04)	(0.11)
Month FE	Yes	Yes	Yes	Yes
Observations	22,104	21,547	22,150	21,483
Adj. R^2	0.005	0.004	0.004	0.005

Table III: **Predicting Future Straddle Return and Skewness Asset Return**

This table presents results of Fama-MacBeth regressions. The dependent variable is firm i's next-month straddle return or skewness asset return. $IV^{Analyst}_{i,t\to t+12}$ ($Skew^{Analyst}_{i,t\to t+12}$) is the latest available analyst-implied variance (skewness). We require that the release day of the analyst report is within 12 months before the option portfolio formation day. Control variables include the logarithm of market capitalization, idiosyncratic volatility of Fama-French 3 factors in the past month, the log difference between the historical and at-the-money implied volatilities (Volatility Deviation), the difference between the long- and short-term implied volatilities (IV Term Spread), the difference between the implied volatilities of the 30-day call with a delta of 0.3 and the 30-day put with a delta of -0.3 (IV Smirk Slope), and the standard deviation of daily percentage change of at-the-money 30-day implied volatility (Volatility of Volatility). Independent variables are winsorized at the 1% level in the cross-section. t-statistics (in parentheses) are Newey-West adjusted with 12 lags. The sample spans from 2007 to 2017, focusing on months with more than 100 firms.

Panel A: Predicting Straddle Return

	(1)	(2)	(3)
$IV^{Analyst}_{i,t\to t+12}$	0.098		0.136
	(3.20)		(3.90)
log(Market Cap)		-0.008	-0.005
		(-1.26)	(-0.71)
Idiosyncratic Volatility		-0.698	-1.770
		(-0.91)	(-2.30)
Volatility Deviation		0.052	0.050
		(1.83)	(1.67)
IV Term Spread		0.257	0.272
		(2.42)	(2.48)
IV Smirk Slope		0.174	0.170
		(1.43)	(1.37)
Volatility of Volatility		-0.213	-0.159
		(-1.17)	(-0.85)
Intercept	-0.050	0.180	0.095
	(-2.53)	(1.24)	(0.61)
Observations	60,819	60,787	60,787
Adj. R^2	0.004	0.019	0.021

Panel B: Predicting Skewness Asset Return

	(1)	(2)	(3)
$Skew^{Analyst}_{i,t\to t+12}$	0.004		0.004
	(4.49)		(4.08)
log(Market Cap)		-0.001	-0.000
		(-1.22)	(-0.36)
Idiosyncratic Volatility		-0.026	-0.046
		(-0.18)	(-0.32)
Volatility Deviation		0.004	0.004
		(0.87)	(0.84)
IV Term Spread		0.004	0.005
		(0.33)	(0.38)
IV Smirk Slope		-0.193	-0.194
		(-6.05)	(-6.18)
Volatility of Volatility		0.071	0.070
		(2.02)	(2.01)
Intercept	-0.001	0.003	-0.006
	(-0.54)	(0.25)	(-0.49)
Observations	56,336	55,877	55,784
Adj. R^2	0.004	0.039	0.043

Table IV: **Portfolio Sorts**

We sort straddles (skewness assets) into quintiles by analyst-implied variance (skewness). Portfolios are equally weighted. The mean represents the monthly average portfolio return. The Sharpe ratio is annualized. For straddle return, alpha is adjusted for equally weighted straddle returns across firms, volatility deviation, and volatility of volatility, following the factor model in Horenstein, Vasquez, and Xiao (2023). For skewness asset return, alpha is adjusted for equally weighted skewness asset returns across firms, IV smirk slope, and volatility of volatility. (%) indicates that a variable is reported in percentage points. The sample spans from 2007 to 2017. We focus on months with more than 100 firms in the cross-section.

Panel A: Straddle

	Low	2	3	4	High	H - L
Mean (%)	-5.91	-3.78	-3.45	-3.04	-1.33	4.58
(t-statistic)	(-2.64)	(-1.44)	(-1.38)	(-1.19)	(-0.55)	(3.03)
Standard Deviation (%)	25.30	29.75	28.20	28.90	27.27	17.07
Skewness	2.61	3.04	2.47	2.70	2.54	0.01
Minimum (%)	-43.72	-43.00	-42.53	-42.06	-47.79	-44.52
Alpha (%)	-2.32	0.24	-0.06	0.54	1.58	3.90
(t-statistic)	(-2.56)	(0.29)	(-0.08)	(0.79)	(1.59)	(2.44)
Sharpe Ratio (annualized)	-0.81	-0.44	-0.42	-0.36	-0.17	0.93

Panel B: Skewness Asset

	Low	2	3	4	High	H - L
Mean (%)	-0.47	-0.23	-0.23	-0.31	0.33	0.80
(t-statistic)	(-1.55)	(-0.82)	(-0.72)	(-1.13)	(1.06)	(4.15)
Standard Deviation (%)	3.43	3.17	3.55	3.06	3.52	2.18
Skewness	-2.91	-2.74	-3.65	-2.53	-1.83	0.59
Minimum (%)	-24.54	-21.62	-26.46	-19.85	-18.85	-4.81
Alpha (%)	-0.35	0.06	0.06	-0.01	0.21	0.56
(t-statistic)	(-2.80)	(0.54)	(0.52)	(-0.09)	(1.26)	(2.40)
Sharpe Ratio (annualized)	-0.47	-0.25	-0.22	-0.35	0.32	1.27

Table V: **Risk-Return Trade-Off and Skewness-Return Trade-Off**

This table reports the results of panel regressions. The dependent variable in both panels is the analyst's expectation for future stock returns, defined as the log ratio of the analyst price target to the current stock price. Independent variables are winsorized at the 1% level. The sample includes days with analyst report releases. Regressions include month fixed effects. Standard errors are clustered at the firm and month levels. t-statistics are in parentheses. The sample spans from 2007 to 2016.

Panel A: Risk-Return Trade-Off

	(1)	(2)
$IV^{Analyst}_{i,t\rightarrow t+12}$	0.164	0.156
	(4.69)	(3.64)
Market Beta		0.055
		(4.72)
log(Market Cap)		0.014
		(4.90)
log(B/M)		0.011
		(1.91)
Profitability		0.006
		(0.72)
Investment		0.034
		(3.64)
Intercept	0.076	-0.298
	(13.35)	(-4.37)
Month FE	Yes	Yes
Observations	22,162	18,518
Adj. R^2	0.086	0.115

Panel B: Skewness-Return Trade-Off

	(1)	(2)
$Skew^{Analyst}_{i,t\rightarrow t+12}$	-0.129	-0.150
	(-16.00)	(-17.33)
Market Beta		0.083
		(9.14)
log(Market Cap)		-0.006
		(-2.09)
log(B/M)		0.007
		(1.46)
Profitability		-0.002
		(-0.22)
Investment		0.043
		(4.91)
Intercept	0.080	0.127
	(20.79)	(1.86)
Month FE	Yes	Yes
Observations	22,104	18,472
Adj. R^2	0.175	0.249

Table VI: **Determinants of Analyst Subjective Variance and Skewness**

This table presents the results of panel regressions explaining firm *i*'s analyst subjective variance and skewness. Panel A examines analyst subjective variance as a function of option-implied variance ($IV^{Option}_{i,t\to t+12}$), realized variance ($RV_{i,t-12\to t}$), and firm characteristics. Panel B examines analyst subjective skewness using option-implied skewness ($Skew^{Option}_{i,t\to t+12}$), realized skewness ($RSkew_{i,t-12\to t}$), and similar firm characteristics. Independent variables are winsorized at the 1% level. All regressions include month fixed effects. Standard errors are clustered at the firm and month levels. t-statistics are reported in parentheses. The sample period spans from 2007 to 2016.

Panel A: Explaining Analyst Subjective Variance

	(1)	(2)	(3)	(4)
$IV^{Option}_{i,t\to t+12}$	0.652		0.480	0.422
	(19.05)		(11.93)	(8.79)
$RV_{i,t-12\to t}$		0.704	0.270	0.211
		(16.96)	(6.73)	(4.35)
Market Beta				0.044
				(3.23)
log(Market Cap)				-0.005
				(-1.87)
log(B/M)				-0.003
				(-0.44)
Profitability				-0.012
				(-1.39)
Investment				0.013
				(1.24)
Intercept	0.033	0.055	0.024	0.111
	(5.16)	(8.46)	(3.59)	(1.65)
Month FE	Yes	Yes	Yes	Yes
Observations	21,547	22,152	21,542	18,324
Adj. R^2	0.360	0.299	0.376	0.388

Panel B: Explaining Analyst Subjective Skewness

	(1)	(2)	(3)	(4)
$Skew^{Option}_{i,t\to t+12}$	0.349		0.340	0.176
	(11.40)		(11.02)	(5.47)
$RSkew_{i,t-12\to t}$		-0.039	-0.032	-0.021
		(-6.17)	(-5.00)	(-3.27)
Market Beta				-0.002
				(-0.08)
log(Market Cap)				-0.085
				(-12.11)
log(B/M)				-0.011
				(-0.77)
Profitability				-0.008
				(-0.42)
Investment				-0.009
				(-0.52)
Intercept	0.021	-0.197	0.008	1.861
	(0.94)	(-19.14)	(0.36)	(11.21)
Month FE	Yes	Yes	Yes	Yes
Observations	21,490	22,092	21,483	18,279
Adj. R^2	0.050	0.019	0.054	0.097

Table VII: **Predict Stock Crashes**

This table reports the results of panel regressions. The dependent variable is a dummy for future-12-month stock crashes, which equals 1 if stock simple return is less than -20% and 0 otherwise. $Crash^{Analyst}_{i,t\to t+12}$ is analyst's subjective expectation on crashes. It equals the probability of bear price if bear price divided by current stock price is smaller than 0.8, and 0 otherwise. $Crash^{Option}_{i,t\to t+12}$ is option-implied crash probability computed following the method in Martin (2017). $Ret_{i,t-1\to t}$ is past-one-month log return. $Ret_{i,t-12\to t-1}$ is stock momentum. Turnover is the average monthly turnover (volume scaled by stock shares outstanding) during the past year. Short Interest is the number of shares shorted scaled by the number of shares outstanding. Independent variables are standardized and winsorized at the 1% level. The sample includes days with analyst reports release. Regressions include month fixed effects. Standard errors are clustered at the firm and month levels. T statistics are in parentheses. The sample is from 2007 to 2016.

	(1)	(2)	(3)	(4)
$Crash^{Analyst}_{i,t\to t+12}$		0.044		0.012
		(9.69)		(3.13)
$Crash^{Option}_{i,t\to t+12}$			0.066	0.028
			(12.45)	(5.97)
Market Beta	0.012			0.005
	(1.60)			(0.63)
log(Market Cap)	-0.019			-0.004
	(-3.14)			(-0.63)
log(B/M)	-0.002			0.001
	(-0.45)			(0.21)
Profitability	-0.009			-0.006
	(-1.57)			(-0.96)
Investment	0.012			0.011
	(2.25)			(2.05)
$Ret_{i,t-1\to t}$	-0.012			-0.011
	(-2.91)			(-2.70)
$Ret_{i,t-12\to t-1}$	-0.005			-0.004
	(-0.79)			(-0.58)
$RV_{i,t-12\to t}$	0.031			0.029
	(3.24)			(3.05)
Turnover	0.024			0.021
	(3.05)			(2.62)
Short Interest	0.024			0.024
	(2.98)			(3.02)
Intercept	0.168	0.175	0.172	0.167
	(46.41)	(42.17)	(45.66)	(46.18)
Month FE	Yes	Yes	Yes	Yes
Observations	18517	22162	21537	18317
Adj. R^2	0.273	0.233	0.248	0.277