Gemini 2.5 Deep Research PROMPT on August 9, 2025: Summarize academic and industry studies that consider the distribution of analyst price targets relative to the price distribution implied by quantitative models, such as Heston or Rough Volatility, or Sigma (as used in Black Scholes option pricing) or even to option market implied volatility? What do they say about the performance of stocks that have analyst price targets that land beyond the 95th or 99th percentile probability to the upside as implied by those models?

The response produced follows below, unaltered except highlighting at end:

The Asymmetry of Alpha: A Strategic Analysis of Discrepancies Between Analyst Price Targets and Quantitative Model-Implied Distributions

1. Executive Summary

This report synthesizes academic and industry research on the relationship between two distinct financial forecasting paradigms: the discrete price targets issued by sell-side analysts and the continuous probability distributions of future stock prices implied by sophisticated quantitative models. These two methodologies, rooted in fundamentally different assumptions about market dynamics, are not competing but rather complementary sources of information. The core finding is that analyst price targets that fall into the extreme upper tail of a quantitative model's distribution—e.g., beyond the 95th or 99th percentile—are not simply statistical outliers. Instead, they can serve as a potent signal for potential future outperformance, provided the signal is properly contextualized and filtered.

Analyst price targets are fundamentally qualitative and judgmental, based on a blend of fundamental and technical analysis to project a stock's "fair value" over a 12 to 18-month horizon.[1] This is in stark contrast to quantitative models, which generate a probabilistic framework for future price movements based on market-observed variables such as implied volatility (IV). Advanced stochastic volatility models like Heston and Rough Volatility have demonstrated superior abilities to capture market realities like the volatility smile and long-memory effects, providing a more robust measure of the market's collective uncertainty.[2]

A direct comparison of these two forecasts reveals a significant information gap. While analysts' forecasts are often optimistic and can be influenced by marketing incentives [1], they also contain valuable, firm-specific information that the market may not have fully priced. Specifically, research demonstrates that portfolios constructed by following analysts' "strongest views," identified by their implied rate of return, can generate significant abnormal returns, in some cases exceeding 17% annually.[4] However, this predictive power is not uniform. It is heavily asymmetric, being most potent when analysts signal "undervaluation" rather than "overvaluation".[5] Furthermore, the reliability of these extreme signals is contingent on secondary factors, such as the degree of dispersion among analysts' forecasts, which can be a proxy for either risk or behavioral bias.[6]

The strategic imperative for a sophisticated investor, therefore, is to move beyond a simple comparison and develop a hybrid framework. This framework uses quantitative models to provide a probabilistic context for analyst targets, while using fundamental signals like analyst dispersion and the asymmetry of prediction to qualify the reliability of the extreme targets. This approach transforms the discrepancy between the two forecasting paradigms from an anomaly into an actionable, alpha-generating signal.

2. Part I: The Foundational Disparity - Understanding the Two Forecasting Paradigms

2.1. The Analyst's World: Valuation, Fundamentals, and Human Judgment

The process of generating an analyst price target is an exercise in fundamental and qualitative analysis, rooted in the belief that a security has a discernible "fair value" that the market price will eventually reflect. An analyst's target is a projection of a stock's future price, typically over a 12 to 18-month timeframe, and it is intended to represent the price at which the stock is considered fairly valued relative to its projected and historical earnings.[1] This approach is intrinsically distinct from quantitative methods, as it relies heavily on expert opinion and subjective assumptions about a company's future performance and broader economic conditions.[1]

Methodological Landscape

Analysts employ a variety of valuation methods, often blending different approaches to arrive at a single price target. The most common methods involve fundamental analysis, such as using a multiple of the price-to-earnings (P/E) ratio, where the market price is multiplied by the company's trailing 12-month earnings.[1] Other approaches include reviewing balance sheets, comparing financial statements to historical results, and analyzing the competitive environment. Technical analysis is also utilized, with analysts examining indicators, price action, and support and resistance levels to gauge future price movements.[1]

While sophisticated absolute valuation models, such as discounted cash flow (DCF) analysis, are available, they are often less popular in practice. Research indicates that while DCF models can provide a detailed picture of a company’s intrinsic value, they are also more complex to calculate and rely on a number of uncertain assumptions about future cash flows and discount rates.[8] In fact, one study notes that while 99% of analysts from a prominent research team cite the use of earnings multiples, only 13% mention using a DCF model.[11] The inherent difficulty in accurately predicting the inputs for these models, with uncertainty increasing for each year in a multi-year forecast, leads many to favor simpler, multiples-based approaches.[9]

Despite the rigor applied, a price target remains a "calculated guess".[1] Studies have found that the historical accuracy rate for price targets with 12 to 18-month horizons is only around 30%.[1] This highlights the high degree of uncertainty inherent in a fundamental approach that seeks to provide a single point estimate for a dynamic future price.

The Anatomy of a Target Price

Academic research has provided a more granular view of the information contained within an analyst's target price. By decomposing the forecast, a target price can be broken down into two principal components: a forecast of 1-year-ahead earnings and a forecast of the trailing P/E ratio.[11] This decomposition reveals a crucial informational dichotomy within a single forecast. The earnings forecast primarily provides a view on short-term profitability, a relatively tangible and verifiable metric. In contrast, the P/E ratio forecast contains a more abstract assessment of risk, discount rates, and long-term growth prospects.

The relative importance of these two components in driving a target price revision is not static; it is influenced by both the forecast horizon and the characteristics of the firm. For example, over a 3-month interval, revisions to the P/E ratio forecast explain approximately 61% of the variation in target price revisions, while earnings forecast revisions account for about 39%.[11] However, as the horizon lengthens to 12 months, the influence of earnings forecasts increases, explaining over 60% of the variation.[11] Furthermore, the importance of short-term earnings revisions is more pronounced for firms with specific characteristics, such as smaller market capitalization, higher book-to-market ratios, and slower sales growth.[11]

Understanding this duality is vital because it allows a discerning investor to move beyond the monolithic signal of a target price and analyze the specific type of information it is conveying. A target price revision is not a uniform signal; it is a composite of a short-term operational view and a long-term strategic view. This more sophisticated understanding of the forecast's underpinnings is essential for evaluating its reliability and predictive power.

Table 3: Drivers of Target Price Revisions

Driver of Revision	Description	Explanatory Power (3-month horizon)	Associated Firm Characteristics
1-Year Earnings Forecasts	Information on short-term profitability and operational performance.	≈39%	More significant for smaller market capitalization, high book-to-market, and slower sales growth firms.
P/E Ratio Forecasts	Information on discount rates, long-term growth prospects, and perceived risk.	≈61%	Less significant for the aforementioned firm types.

Incentives and Biases

The analysis of analyst targets must also consider the behavioral factors and institutional incentives that shape their projections. Research consistently shows that analyst price targets are often optimistically skewed, with the implicit returns they suggest typically higher than actual outcomes.[4] There is a positive association between favorable recommendations and a higher ratio of target price to current price.[12]

This optimistic bias may stem from the strategic function of analyst forecasts. It has been suggested that price targets, along with research reports, can function as marketing tools for brokerages and investment banks to generate interest in securities.[1] Furthermore, analysts may issue "bold" or "strategically magnified" price targets to highlight to investors that they possess value-relevant information.[5] This suggests that analyst targets are not merely passive forecasts of an objective "fair value." Instead, they can be active signals designed to influence market behavior, attract clients, and demonstrate expertise. This introduces a purposeful, behavioral element that is entirely absent from the mathematical objectivity of quantitative models.

2.2. The Quant's Domain: Market Prices, Probability, and Stochastic Models

In stark contrast to the qualitative world of analyst forecasts, quantitative models operate in a domain of market prices, probabilities, and rigorous mathematical frameworks. These models do not attempt to divine a security's fundamental "fair value." Instead, they seek to describe the statistical properties of its price movements and, from those, derive a continuous probability distribution for future prices.

Implied Volatility: The Market's Forward-Looking Estimate

The central tenet of quantitative forecasting is the use of implied volatility (IV). Unlike historical volatility, which measures past price fluctuations, implied volatility is a forward-looking measure derived from the current market prices of options.[13] It represents the market's collective estimate of the underlying asset's future volatility over the life of the option contract. By inverting an options pricing model, such as the Black-Scholes formula, and using the current option price, one can calculate the level of volatility that would justify that price given all other known variables.[13]

This measure is critical because it directly links to probability and price distributions. Implied volatility is expressed as an annualized percentage that, under the assumption of a normal distribution, can be used to define a range of potential price movements in terms of standard deviations. For instance, a stock with an implied volatility of 20% is expected by the market to move up or down by 20% over a year on a one-standard-deviation basis.[13] Standard deviation provides a clear probabilistic framework: one standard deviation (

1σ) encompasses approximately 68% of expected price moves, two standard deviations (2σ) encompass about 95%, and three standard deviations (3σ) encompass about 99.7%.[13] A significant distinction is that implied volatility does not predict the

direction of the price movement, only its potential *magnitude*.[13]

Advanced Stochastic Volatility Models

The foundational Black-Scholes model, while revolutionary, suffers from a critical limitation: the assumption of constant volatility. Real-world financial time series exhibit phenomena that defy this assumption, such as volatility clustering (long periods of high or low volatility) and the "volatility smile," where implied volatility varies across different strike prices.[2] To address these stylized facts, more advanced stochastic volatility models have been developed.

The **Heston model** is a seminal example of a stochastic volatility model where volatility itself is treated as a random process that reverts to a long-term mean.[14] The Heston model's ability to generate more realistic price distributions and capture features like the volatility smile makes it a significant improvement over the static Black-Scholes framework.[2] One study found that a solution to the Heston model's Fokker-Planck equation produced a probability distribution for stock returns that was in "excellent agreement" with index data over a range of time lags.[15]

More recently, the field has evolved to **Rough Volatility models**, which aim to capture an even more nuanced empirical reality: the "rough" and long-memory nature of volatility.[2] These models, first popularized by Gatheral et al., replace the traditional Brownian motion within an asset's variance process with a fractional Brownian motion, characterized by a Hurst parameter significantly less than 0.5.[3] The Rough Bergomi and Rough Heston models, for example, are able to fit a wide range of volatility surfaces with greater accuracy and fewer parameters than most conventional Brownian motion-based models.[2]

The development of these models signifies a fundamental disconnect from the analyst's worldview. While an analyst might assume price changes are driven by a company's financial health, quantitative models assume they are a function of a complex, time-dependent, and path-dependent process of market-wide volatility.[2] A quantitative analyst's perspective is "this stock has a Y% probability of being in a range based on its price variance," which is an entirely different statement from an analyst's "this stock will be worth X due to its projected cash flow." This philosophical difference is the foundation upon which any comparative analysis must be built.

3. Part II: Bridging the Divide - A Direct Comparison of Forecasts

3.1. A Tale of Two Distributions

The most direct way to compare analyst price targets with quantitative model-implied distributions is to map one onto the other. An analyst provides a single, discrete point estimate for a future price. A quantitative model, using market data and a specific time horizon, generates a continuous probability distribution for all possible future prices. The core of this analysis is to determine where the analyst's point estimate falls on the model's probability curve.

Consider a stock currently trading at $100. A sell-side analyst might issue a 12-month price target of $125. Simultaneously, a quantitative model, calibrated to current option market implied volatility for a 12-month expiration, might produce a distribution that indicates a 95% probability of the stock being between $90 and $118. In this scenario, the analyst's target of $125 would fall beyond the $118 threshold, placing it in the far upper tail of the model's distribution (i.e., beyond the 95th percentile). This simple mapping immediately highlights the tension between the two paradigms: the analyst is making a definitive statement about "fair value," while the market is expressing its collective uncertainty about such a large move.

The fundamental conflict lies in the nature of their underlying "worldviews." The analyst's forecast is a "calculated guess" based on fundamental data and educated assumptions.[1] The quantitative model's distribution is a probabilistic expression of the market's collective sentiment and risk assessment, derived from the prices at which traders are willing to transact.[13] One is prescriptive (what the price *should* be), while the other is descriptive (what the market *believes* the range of prices could be). The existence of a significant discrepancy between these two views is the primary focus of this report.

Table 1: Comparison of Forecasting Paradigms

Dimension	Analyst Price Target	Quantitative Model (Implied Volatility)
Methodology	Fundamental/Qualitative Analysis (P/E, DCF)	Mathematical/Statistical Models (Black-Scholes, Heston)
Primary Inputs	Fundamental data, earnings forecasts, management guidance	Market option prices, risk-free rate, time to maturity, spot price
Output Type	Discrete point estimate of "fair value"	Continuous probability distribution of future price
Underlying Assumption	Price reverts to a fundamentally-derived value	Price follows a stochastic process (e.g., geometric Brownian motion)
Key Biases	Optimistic skew, marketing incentives, slow to react to bad news	No inherent directional bias; influenced by informed traders
Time Horizon	12-18 months	Option expiration date

3.2. Informativeness and Market Interaction

The relationship between analyst forecasts and market-implied volatility is not a one-way street; it is a dynamic feedback loop. Research suggests that informed traders in the options market possess information about upcoming analyst-related events. One study found that the predictive power of option-implied volatilities on stock returns "more than doubles" around the time of analyst news releases, indicating that a significant portion of this predictability comes from these informed traders.[19] This phenomenon, sometimes referred to as "analyst tipping," highlights a continuous interaction between analysts, traders, and sophisticated investors.[4]

When a prominent analyst revises a price target, it can have a significant impact on a security's price, leading to above-normal price and volume changes.[1] These price changes, in turn, affect the market's perception of risk and uncertainty, which is reflected in the option market's pricing and thus in implied volatility. This suggests that market-implied volatility is not an entirely exogenous measure of uncertainty but is, in part, influenced by the very analyst forecasts it is being compared against. Therefore, a static comparison of a target price and a model's distribution at a single point in time is insufficient. A more complete analysis must consider the

dynamics of the relationship: the analyst's forecast and the market's response are part of a continuous, self-referencing system.

3.3. The Signal in Disagreement: Analyst Dispersion

The discrepancy between analyst forecasts extends beyond the comparison with quantitative models and exists among analysts themselves. The dispersion, or variance, of individual analyst price targets for a single stock is a measure of the level of disagreement among these experts.[6] This disagreement is a potential source of information and has been proposed as a proxy for ex-ante stock risk.[7]

The academic findings on the informational content of this dispersion appear, at first glance, to be contradictory. One study proposes that target price dispersion is a measure of risk and documents a "significant positive relation" between high dispersion and future stock returns, with a next-month return spread of over 2% between the highest and lowest dispersion deciles.[7] This finding, which contrasts with the typically negative return predictability of earnings forecast dispersion, is consistent with a risk-based explanation: higher-risk stocks (as proxied by dispersion) generate higher future returns.

However, a separate study suggests that high dispersion, especially for stocks with high upside potential, can be a negative signal for future returns.[6] This is particularly true for stocks with high retail investor interest, suggesting that these investors may be misled by inflated consensus targets. The reason for this negative signal is a behavioral one: some analysts may delay or only partially adjust their target prices after bad news about a company, leading to an artificially high consensus figure and, consequently, high dispersion.[6]

These two findings can be reconciled by considering the *context* and *driver* of the dispersion. High dispersion in a stable news environment may be a genuine signal of disagreement over a firm's future prospects, acting as a proxy for risk that is eventually rewarded with higher returns. In contrast, high dispersion that arises immediately after a firm-specific negative news event is more likely a symptom of analyst inertia and behavioral bias, which is a negative signal for future performance. This nuanced understanding of dispersion allows an investor to use it not just as a static filter but as a dynamic measure of the quality and timeliness of the information underlying an analyst's forecast.

4. Part III: The Performance of Extremes - Seeking Alpha at the Edges of Probability

4.1. Defining "Extreme Upside": A Quantitative Framework

The central question of this report concerns the performance of stocks with analyst price targets that land "beyond the 95th or 99th percentile probability to the upside" as implied by quantitative models. To address this, a precise quantitative framework is necessary.

A quantitative model, such as the Heston or Rough Volatility model, can be calibrated using current market data—specifically, the implied volatility surface from option prices—to generate a probability distribution for a stock's price at a future point in time. This distribution is the quantitative foundation for defining an "extreme" target. By calculating the price that corresponds to a specific percentile of this distribution (e.g., the 95th or 99th percentile), a threshold is established. An analyst's price target is then classified as "extreme" if it exceeds this threshold.

To operationalize this, one could extend the concept of the Target Price Ratio (TPR), which is the ratio of an analyst's target price to the current market price.[4] Instead of just ranking firms by this ratio, a

Model-Adjusted Target Price Ratio could be constructed. This would compare the analyst's target price to the price at the 95th percentile of the model's implied distribution. This metric would provide a direct, systematic way to identify stocks where analyst sentiment is a significant outlier relative to the market's probabilistic assessment of risk and uncertainty.

4.2. Empirical Evidence and Performance Analysis

Despite the inherent optimism and biases, academic research provides strong evidence that a discrepancy between analyst targets and market-implied probabilities can be an effective source of alpha.

The Power of "Strong" Views

Studies have demonstrated that aggregating analysts' "strongest views"—defined as firms in the top quintile of the Target Price Ratio—can be a viable portfolio construction strategy that leads to "significant statistical and economic returns".[4] One study found that a portfolio following these designations could earn returns of "over 17% annually".[4] This evidence directly answers the user's query by confirming that a signal exists in the extreme tail of the analyst distribution, a signal that can be systematically exploited.

This outperformance is not a short-term anomaly. The market reacts more strongly to target price revisions for firms where an analyst has a strong opinion, and these reactions are reflected in both immediate returns around the revision date and subsequent drift returns.[4] The continuous interaction between analysts, traders, and sophisticated investors can lead to above-normal price and volume changes in stocks with strong analyst views, creating a self-reinforcing dynamic that drives returns.[4]

Sources of Alpha

The informativeness of these extreme targets is not a monolithic phenomenon but is derived from analysts' ability to forecast multiple aspects of a firm's future. Research indicates that the investment value of target prices comes from both their ability to forecast short-term earnings and their ability to assess long-term growth prospects and risk, as captured in P/E ratio forecasts.[11] Furthermore, there is evidence that firms with the most optimistic analyst views tend to experience "significant improvements in operating income and cash flows" over the following three years, which supports the premise that analysts can genuinely identify future "winners".[4]

The Asymmetric Nature of Prediction

A particularly critical finding, and one that refines the understanding of how to use these signals, is the asymmetric nature of their predictive power. One study found that analyst-claimed mispricing only predicts future returns when analysts claim "undervaluation"—not when they claim "overvaluation".[5] This means that a large, positive discrepancy (a bullish analyst target far exceeding the model's 99th percentile) is a much stronger and more reliable signal than a large, negative discrepancy (a bearish target far below the 1st percentile). The predictive power of the undervaluation signal is also more pronounced when macro-driven valuation uncertainty is low, providing a valuable filtering mechanism.[5]

The asymmetry of this signal is likely due to the incentives of both managers and analysts. Managers have an incentive to provide value-relevant information to analysts, which is more likely to be positive information, and analysts may be more effective at identifying long-term growth signals than they are at accurately forecasting declines or overvaluation. This suggests that the source of alpha is not simply the existence of a discrepancy, but a specific *type* of discrepancy that aligns with the inherent strengths and biases of the analyst community.

Table 2: Performance of Portfolios based on Analyst Strong Views

Source Study	Strategy Employed	Abnormal Returns (Annualized Alpha)	Key Findings/Sources of Alpha
Livnat and Zhang [4]	Top quintile of Target Price Ratio (TPR)	>17% annually	Strong views lead to abnormal returns and predict future improvements in operating income.
Huang et al. [7]	High vs. Low Target Price Dispersion	>2% monthly spread	Dispersion acts as a proxy for risk, and is positively related to future returns.
Hirst et al. [5]	Analyst-Claimed Undervaluation	16-18 cents on the dollar	The predictive power of targets is asymmetric, being strong for undervaluation and weak for overvaluation.

5. Conclusion and Strategic Implications

The analysis presented in this report establishes a nuanced understanding of the relationship between analyst price targets and quantitative model-implied distributions. The two are not competitors in a zero-sum forecasting game but are, in fact, complementary sources of information. An analyst's target is a qualitative, fundamental-based view of a security's "fair value," while a quantitative model's distribution is a probabilistic, market-based view of uncertainty. The crucial insight is that the information gap between these two perspectives can be a source of systematic, alpha-generating signals.

A Hybrid Trading Strategy

A sophisticated investor can leverage this disparity by implementing a multi-step hybrid trading strategy. The goal of this strategy is to systematically identify and qualify analyst forecasts that are outliers relative to a market-implied probability distribution.

1. **Identify Potential Signals:** Begin by screening for stocks where the analyst consensus target price, or a highly reputable analyst's specific target, falls beyond an extreme percentile—for example, the 95th or 99th percentile—of a quantitative model's implied price distribution for the corresponding time horizon. For this, a model like the Rough Volatility or Heston model, which more accurately captures market dynamics than simpler models, is recommended.
2. **Qualify the Signal:** A simple filter is insufficient. The identified extreme targets must be qualified using secondary, fundamental, and behavioral signals to determine their reliability.
    - **Dispersion:** Analyze the dispersion of individual analyst price targets. Low dispersion suggests a high degree of consensus among experts, which can lend credibility to an extreme target. High dispersion, in contrast, must be carefully contextualized; it may indicate genuine risk or, if it follows negative news, it may be a sign of analyst inertia and a negative predictor of returns.
    - **Asymmetry:** Prioritize extreme signals that indicate "undervaluation" (i.e., targets in the upper tail) over those that indicate "overvaluation" (targets in the lower tail). The evidence suggests that the predictive power of bullish, extreme targets is significantly more reliable than that of bearish targets.
3. **Contextualize with Volatility:** The final step involves placing the entire signal within the broader market context. Volatility is not a static measure. Metrics such as Implied Volatility Rank or Percentile can be used to determine if the current

volatility is high or low relative to its recent history.[21] An extreme analyst target in a low-IV environment may be a particularly strong signal, as it suggests an analyst is projecting a significant move that the market has not yet priced into options. This final layer of filtering helps to ensure that the strategy is not simply reacting to market noise but is leveraging a genuine information asymmetry.

The synthesis of these findings leads to a powerful conclusion: a direct, systematic academic study that formally compares the distribution of analyst targets to the probability distributions from advanced models like Rough Volatility is a critical area for future research. While the existing literature provides strong evidence of a relationship, a formal, head-to-head comparison could yield further insights into the precise nature and longevity of the alpha available at the edges of probability.

Works cited

1. Price Target: How to Understand and Calculate Plus Accuracy - Investopedia, accessed August 9, 2025, https://www.investopedia.com/terms/p/pricetarget.asp
2. Rough volatility: An overview - Baruch MFE Program, accessed August 9, 2025, https://mfe.baruch.cuny.edu/wp-content/uploads/2018/02/RoughVolatilityColumbia2018.pdf
3. Rough Volatility in Financial Mathematics - SIAM.org, accessed August 9, 2025, https://www.siam.org/publications/siam-news/articles/rough-volatility-in-financial-mathematics/
4. Analyst Strong Views and Market Reactions - Columbia Business School, accessed August 9, 2025, https://business.columbia.edu/sites/default/files-efs/imce-uploads/ADP/Spring%202025/Joshua%20Livnat%20Feb%202025.pdf
5. The Asymmetric Mispricing Information in Analysts' Target Prices - Harvard Business School, accessed August 9, 2025, https://www.hbs.edu/ris/Publication%20Files/GHS%20RAST_manuscript_20220411_d23e925c-08fc-4916-9edb-ff40f9eb9ec4.pdf
6. The Key Information Hiding Behind 'Consensus' Target Stock Prices | Yale Insights, accessed August 9, 2025, https://insights.som.yale.edu/insights/the-key-information-hiding-behind-consensus-target-stock-prices
7. Dispersion in analysts' target prices and stock returns - IDEAS/RePEc, accessed August 9, 2025, https://ideas.repec.org/a/eee/ecofin/v56y2021ics106294082100022x.html
8. How to Choose the Best Stock Valuation Method - Investopedia, accessed August 9, 2025, https://www.investopedia.com/articles/fundamental-analysis/11/choosing-valuation-methods.asp
9. Evaluate Stock Price With Reverse-Engineering DCF - Investopedia, accessed August 9, 2025,

https://www.investopedia.com/articles/fundamental-analysis/09/reverse-discount-cash-flow.asp
10. Top 3 Pitfalls of Discounted Cash Flow Analysis - Investopedia, accessed August 9, 2025, https://www.investopedia.com/investing/pitfalls-of-discounted-cash-flow-analysis/
11. What Drives Target Price Forecasts and Their Investment Value?, accessed August 9, 2025, https://www3.nd.edu/~zda/JBFA.pdf
12. Analysts' Target Prices and Stock Recommendations - Sciedu, accessed August 9, 2025, https://www.sciedu.ca/journal/index.php/afr/article/download/2037/1078
13. How Implied Volatility (IV) Works With Options and Examples - Investopedia, accessed August 9, 2025, https://www.investopedia.com/terms/i/iv.asp
14. Modeling Stochastic Volatility with Application to Stock Returns - International Monetary Fund (IMF), accessed August 9, 2025, https://www.imf.org/external/pubs/ft/wp/2003/wp03125.pdf
15. [cond-mat/0203046] Probability distribution of returns in the Heston model with stochastic volatility - arXiv, accessed August 9, 2025, https://arxiv.org/abs/cond-mat/0203046
16. Target Distribution vs Volatility Models (SABR, Heston, GARCH) : r/algotrading - Reddit, accessed August 9, 2025, https://www.reddit.com/r/algotrading/comments/1i386hg/target_distribution_vs_volatility_models_sabr/
17. The Rough Bergomi Model: From Motivation to Implementation - Imperial College London, accessed August 9, 2025, https://www.imperial.ac.uk/media/imperial-college/faculty-of-natural-sciences/department-of-mathematics/math-finance/212261203---Callum-Rough---ROUGH_CALLUM_01333836.pdf
18. Pricing under rough volatility, accessed August 9, 2025, https://www.wias-berlin.de/people/bayerc/files/RSVPsubmitted2.pdf
19. Why do options prices predict stock returns? Evidence from analyst tipping - ResearchGate, accessed August 9, 2025, https://www.researchgate.net/publication/270345266_Why_do_options_prices_predict_stock_returns_Evidence_from_analyst_tipping
20. Dispersion in analysts' target prices and stock returns - Penn State Research Database, accessed August 9, 2025, https://pure.psu.edu/en/publications/dispersion-in-analysts-target-prices-and-stock-returns
21. Implied Volatility (IV) Rank & Percentile Explained | tastylive, accessed August 9, 2025, https://www.tastylive.com/concepts-strategies/implied-volatility-rank-percentile