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Article

# Financial Forecasting and Cognitive Biases: A Theoretical Examination of Framing Effects and Predictive Accuracy

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**Abstract:** Financial forecasting plays a pivotal role in guiding investment decisions, risk management, and policy formation. However, practitioners and analysts frequently exhibit systematic deviations from rational expectations due to cognitive biases, which impair forecast accuracy and can lead to suboptimal outcomes (Tetlock, 2005; De Bondt & Thaler, 1985). Among these biases, framing effects-wherein the presentation or “frame” of information alters decision-making-are especially pernicious in financial contexts (Tversky & Kahneman, 1981). This paper provides a comprehensive theoretical overview of key cognitive biases affecting financial forecasts, with particular emphasis on framing. First, it delineates foundational concepts in behavioral economics, including prospect theory (Kahneman & Tversky, 1979) and heuristics, to contextualize how analysts process uncertain information. Next, it categorizes the primary biases encountered in financial forecasting-overconfidence, anchoring, availability, and representativeness-and examines empirical evidence documenting their effects (Barber & Odean, 2001; De Bondt & Thaler, 1985). The core of the analysis investigates how different frames-gain versus loss frames or statistical versus narrative presentations-systemically distort probabilistic judgments and expected value calculations in financial models (Tversky & Kahneman, 1981; Tversky & Kahneman, 1986). Finally, the paper proposes a conceptual framework for mitigating framing-induced errors, incorporating debiasing strategies such as pre-mortem analysis, decision checklists, and Bayesian updating techniques. By integrating insights from psychology and financial theory, this study aims to elucidate why forecast errors persist and how organizations can enhance predictive performance. The conclusions underscore the importance of awareness, structured analysis, and training in reducing bias-related distortions for more reliable financial forecasting.

**Keywords:** cognitive biases; behavioral economics

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## Introduction

Financial forecasting serves as a cornerstone of decision making in both private and public sectors, informing investment strategies, corporate budgeting, and macroeconomic policy formulation. By generating probabilistic projections of asset returns, economic indicators, and market trends, forecasters aim to reduce uncertainty and guide resource allocation toward optimal outcomes (Makridakis, Wheelwright, & Hyndman, 1998). Yet, despite advances in econometric modeling, machine learning techniques, and quantitative risk analysis, the accuracy of many forecasts remains limited, often failing to outperform simple naïve benchmarks (Armstrong, 2001; Makridakis & Hibon, 2000). One prominent line of inquiry attributes a substantial portion of forecasting errors to cognitive biases that systematically warp human judgment under uncertainty (Tetlock, 2005; De Bondt & Thaler, 1985). These biases emerge from mental shortcuts-heuristics-deployed by analysts when processing complex information, leading to predictable distortions in probability assessments and expected-value calculations (Kahneman & Tversky, 1979; Tversky & Kahneman, 1981).

An extensive body of behavioral finance research has documented the prevalence of biases such as overconfidence, anchoring, availability, and representativeness among financial professionals and

lay investors alike (Barber & Odean, 2001; De Bondt & Thaler, 1985; Kahneman & Tversky, 1972). Overconfidence may cause forecasters to underestimate the dispersion of possible outcomes or to neglect model uncertainty, thus producing intervals that are too narrow relative to observed variability (Tetlock & Gardner, 2015). Anchoring arises when initial figures-such as prior year earnings or consensus analyst forecasts-exert disproportionate influence on subsequent revisions, even when new data suggest a different trajectory (Northcraft & Neale, 1987). Availability bias leads forecasters to overweight recent or salient information-such as a recent market crash-while underweighting less accessible but statistically relevant data (Tversky & Kahneman, 1973). Each of these biases can compound, resulting in persistent systematic errors that undermine the reliability of financial forecasts (De Bondt & Thaler, 1985; Kahneman & Tversky, 1979).

Among the multitude of cognitive distortions, framing effects are particularly consequential in financial forecasting contexts because they alter preferences and perceptions without changing the underlying outcomes. Framing refers to the phenomenon whereby logically equivalent presentations of identical information-such as emphasizing potential gains versus potential losses-yield divergent decisions (Tversky & Kahneman, 1981). In investments, a probabilistic forecast presented as “a 20% chance of a 10% loss” may be perceived differently than “an 80% chance of retaining your capital,” even though both statements describe equivalent scenarios. These framing variations can influence analysts’ risk tolerance, selection of valuation models, and confidence intervals for forecasts (Tversky & Kahneman, 1986; Benartzi & Thaler, 1995). Understanding how framing shapes the interpretation of financial data is crucial for identifying when forecasters may be prone to excessively optimistic or pessimistic outlooks, with significant implications for portfolio allocation, capital budgeting, and policy risk assessment.

While classical economic theory assumes that agents process all relevant information with rational consistency, the empirical evidence suggests otherwise. Behavioral models have introduced refinements-such as prospect theory-to account for reference-dependent preferences, loss aversion, and the diminishing sensitivity to changes in wealth (Kahneman & Tversky, 1979). Under prospect theory, individuals evaluate outcomes relative to a subjective reference point, tend to overweight small probabilities, and exhibit asymmetric responses to gains versus losses. These effects imply that forecasters may apply different “utility weights” to upside and downside risks, leading to skewed projections. For instance, an analyst who frames a new policy reform as a potential source of efficiency gains may overlook associated downside risks if losses are deemed less salient or if the framing emphasizes expected benefits (Gennaioli & Shleifer, 2010). Consequently, forecasts may lack proper adjustments for adverse outcomes, underestimating tail risks and the probability of extreme events (Rabin & Weizsäcker, 2009).

Moreover, the framing of statistical data-such as expressing inflation forecasts in percentage-point changes versus consumer price indices-can influence perceived accuracy and the degree of confidence the forecaster attaches to predictions. Research has demonstrated that numerical representations employing frequencies (e.g., “20 out of 100 times”) versus probabilities (e.g., “20% chance”) can differentially affect judgments of likelihood and risk (Gigerenzer & Hoffrage, 1995). In financial contexts, expressing a forecast as “the probability of default is 5%” may be processed differently than “5 in 100 companies fail,” despite equivalent meaning (Reyna & Brainerd, 2008). As financial forecasts increasingly incorporate complex statistical outputs-such as Value-at-Risk (VaR) metrics, scenario simulations, and confidence bands-the vulnerability to framing distortions escalates. Analysts may misinterpret confidence intervals or focus excessively on point estimates rather than the underlying distributional uncertainty (Taleb, 2010).

In addition to psychological framing, narrative framing-where qualitative descriptions accompany quantitative predictions-can sway forecast perception. For example, a report that frames a GDP forecast within a storyline emphasizing geopolitical stability may lead readers to assign higher credibility to optimistic projections, relative to a neutral statistical presentation (Akerlof & Shiller, 2009). Financial news outlets and research reports often employ narrative hooks-such as “Tech Sector Set for Bull Run After Pandemic Slump”-that implicitly frame data in ways that guide interpretation.

This narrative framing may exacerbate confirmation bias, wherein analysts seek information that corroborates their preconceived beliefs while discounting discordant evidence (Nickerson, 1998). The interplay between numerical framing and narrative context thus warrants careful examination in any theoretical analysis of forecasting accuracy.

Given the extensive empirical documentation of biases in financial decision making, it becomes imperative to consider debiasing or corrective strategies to improve forecast reliability. Techniques such as pre-mortem analysis—where analysts imagine a forecast failure in advance and identify potential causes—can counteract overconfidence and encourage a thorough examination of downside scenarios (Klein, 2007). Decision checklists and structured analytic techniques, borrowed from intelligence analysis, have also been applied in finance to reduce anchoring and selective attention (Heuer, 1999; Russo & Schoemaker, 2012). Furthermore, adopting Bayesian updating frameworks—where prior beliefs are formally combined with new evidence—can mitigate the effects of framing by anchoring forecasts to well-specified probability distributions (Gelman et al., 2013). However, the effectiveness of these interventions in real-world financial settings requires further theoretical refinement and empirical validation.

This paper aims to synthesize the theoretical underpinnings of cognitive biases—especially framing effects—within the domain of financial forecasting and to propose a conceptual framework for mitigating their impact. Specifically, the objectives are: (1) to articulate how framing manipulates risk perceptions and shifts analysts' evaluations of probabilistic information; (2) to integrate insights from prospect theory, heuristics and biases research, and narrative framing literature to elucidate the mechanisms by which forecasts deviate from rational benchmarks; and (3) to suggest practical debiasing strategies that can be implemented in organizational settings to enhance predictive accuracy. By bridging psychological theory and financial modeling, this study endeavors to offer a coherent roadmap for achieving more reliable forecasts, ultimately improving investment outcomes and policy efficacy.

## 1. Theoretical Foundations: Prospect Theory and Cognitive Heuristics

Central to understanding why financial forecasts frequently deviate from rational benchmarks is the behavioral-economic framework introduced by Kahneman and Tversky (1979), which challenges the classical expected utility paradigm by highlighting systematic biases in decision making under uncertainty. Prospect theory posits that individuals evaluate outcomes relative to a reference point—often the status quo or an anticipated benchmark—rather than in absolute terms. In this framework, the value function is concave for gains and convex for losses, reflecting diminishing sensitivity as outcomes move further from the reference point (Kahneman & Tversky, 1979). Moreover, losses loom larger than gains: the disutility of losing a certain amount exceeds the utility of gaining an equivalent amount, a phenomenon known as loss aversion. When forecasters assess potential investment returns or project future earnings, they implicitly anchor these projections to a reference standard, be it last year's results, consensus analyst expectations, or institutional targets. Consequently, they tend to overweight outcomes that deviate from the reference point in the domain of losses, exhibiting heightened risk aversion when potential losses are salient, while simultaneously exhibiting risk-seeking behavior in domains of gains if the reference threshold has been achieved (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991).

Prospect theory further introduces a probability-weighting function that deviates from linear probability assessment. Empirical evidence indicates that individuals overweight small probabilities and underweight moderate-to-high probabilities (Tversky & Kahneman, 1992). In a financial-forecasting context, this implies that analysts may assign excessive weight to remote but highly adverse scenarios—such as a rare market crash—while underestimating probabilities of events that lie within a more plausible range. For instance, when generating earnings forecasts for a publicly traded firm, an analyst may overemphasize the chance of a drastic market downturn due to its emotional salience, even if historical data suggest a far lower likelihood (Barberis, 2013). Conversely, moderately negative but less dramatic outcomes may be underweighted, causing point forecasts to cluster too

narrowly around optimistic projections and reducing the accuracy of confidence intervals (Rabin & Thaler, 2001).

Beyond prospect theory, cognitive heuristics-mental shortcuts that simplify complex judgments-play a critical role in shaping forecasts (Tversky & Kahneman, 1974). Three heuristics in particular have garnered extensive attention within the behavioral finance literature: availability, representativeness, and anchoring.

**Availability heuristic.** The availability heuristic entails assessing the probability or frequency of an event based on how easily examples come to mind, rather than on objective statistical information (Tversky & Kahneman, 1973). In financial forecasting, this can manifest when analysts overweight recent or highly publicized events. For example, following a widely reported corporate scandal, forecasters may inflate the likelihood of similar governance failures across the sector, even if the actual incidence remains low (Tetlock & Gardner, 2015). This recency bias often leads to cyclical forecast errors: overly pessimistic projections after prominent negative shocks and unduly optimistic views when favorable events dominate headlines (Malmendier & Nagel, 2011). Such distortions stem from affect-rich memories becoming disproportionately salient, thereby skewing probability assessments and expected values within econometric models (Tversky & Kahneman, 1973).

**Representativeness heuristic.** The representativeness heuristic occurs when individuals judge the likelihood of an event by the degree to which it resembles a prototypical case, neglecting base-rate information and sample size considerations (Kahneman & Tversky, 1972). In equity forecasting, an analyst may observe that a technology start-up exhibits rapid revenue growth reminiscent of past “unicorn” companies and conclude that this firm is highly likely to continue its trajectory, disregarding industry-wide variables such as market saturation or competitive dynamics. This bias can generate forecast errors by causing overgeneralization from insufficient or non-representative samples (Barberis, 2013). The tendency to see patterns where none exist-sometimes referred to as “pattern-matching” bias-can lead to overly optimistic growth projections in bubble environments (De Bondt & Thaler, 1985).

**Anchoring and adjustment.** Anchoring refers to the phenomenon where an initial numerical value (the “anchor”) disproportionately influences subsequent judgments, even when the anchor is arbitrary or only loosely related to the decision context (Tversky & Kahneman, 1974). Following exposure to consensus analyst estimates, corporate guidance, or prior-year earnings, forecasters often anchor their projections to these figures, making only insufficient adjustments for new information. For example, if a firm reported \$1.00 in earnings per share last fiscal year, analysts may anchor to this baseline and adjust forecasts marginally upward to \$1.05 or \$1.10, even when emerging data suggest a more substantial deviation. Northcraft and Neale (1987) illustrated the anchoring phenomenon in real estate valuations; analogous effects have been observed in financial analysts’ earnings revisions (Womack, 1996). Anchors may be self-generated (e.g., analysts’ prior beliefs) or externally provided (e.g., management guidance), but in both cases, subsequent adjustments often prove insufficient, leading to persistent forecast errors (Epley & Gilovich, 2001).

Collectively, these heuristics indicate that financial analysts do not process information as purely rational agents would. Instead, they rely on simplified cognitive rules that, while reducing analytical effort, introduce systematic distortions. Furthermore, these heuristics interact with prospect-theoretic evaluations: for instance, anchoring around a reference point can exacerbate loss aversion when adjustments remain conservative, thereby magnifying risk-averse tendencies in the face of potential negative deviations (Kahneman & Tversky, 1979; Tversky & Kahneman, 1991).

Another critical dimension of framing arises from how numerical forecasts are presented. Tversky and Kahneman (1981) demonstrated that logically equivalent statements-such as “an investment has a 90% chance of success” versus “a 10% chance of failure”-elicit different emotional reactions, which in turn influence decision preferences. When applied to financial reporting, the choice of denominators (e.g., percentage changes versus index point changes) or frequency formats (e.g., “8 out of 100 downturns” versus “8% probability of downturn”) significantly affects perceived risk. Gigerenzer and Hoffrage (1995) argued that frequency formats tend to improve Bayesian

reasoning compared to abstract probabilities, yet financial analysts often default to percentage probabilities, potentially fostering misinterpretations of risk distributions. For example, presenting a value-at-risk (VaR) measure as “there is a 5% chance of losing at least \$10 million” might be less intuitively understood than stating “in 5 out of 100 trading days, the portfolio loses at least \$10 million,” even though both convey the same statistical information. This difference in cognitive processing can lead to underestimation of tail risks if analysts perceive 5% as a negligible probability rather than a meaningful frequency (Reyna & Brainerd, 2008; Taleb, 2010).

In addition to numerical framing, narrative framing—the contextual storytelling that accompanies data—shapes forecast interpretations. A forecast accompanied by a compelling narrative, such as emphasizing “technology disruption” or “looming regulatory headwinds,” steers analysts toward interpretive frames that influence which risks are highlighted and which scenarios are disregarded (Akerlof & Shiller, 2009). Narrative frames serve as cognitive “scaffolds,” enabling analysts to incorporate qualitative judgments, but they also risk prompting confirmation bias as forecasts become framed within the dominant storyline (Nickerson, 1998). For instance, if an analyst adopts a bullish narrative about an emerging market’s growth potential, they may subconsciously disregard evidence of political instability, thereby skewing their forecast upward without proper adjustment for downside risks.

Classical models of rational expectations assume that agents hold homogenous beliefs and process information optimally, but the heuristics and framing effects described above provide a more nuanced picture of forecasting behavior. By integrating prospect theory and heuristic-based decision rules, this theoretical foundation elucidates why forecast distributions are often overly narrow, why extreme outcomes are frequently underweighted, and why analysts’ projections cluster around salient anchors. Recognizing these fundamental biases sets the stage for examining empirical evidence of their manifestations in actual forecast performance and for developing strategies to mitigate their influence.

## 2. Empirical Evidence of Cognitive Biases in Financial Forecasting

A growing body of empirical research has documented the tangible effects of cognitive biases on the accuracy and calibration of financial forecasts across various contexts, including equity returns, macroeconomic indicators, and corporate earnings. This section synthesizes key findings on how overconfidence, anchoring, availability, representativeness, and framing systematically distort forecast outcomes, ultimately impeding predictive performance. Each bias is illustrated through representative studies that rigorously quantify forecasting errors and attribute them to specific heuristics.

### 2.1. Overconfidence

Overconfidence is one of the most extensively studied biases in forecasting, characterized by an analyst’s tendency to overstate the precision of their estimates and to underestimate the true variability of future outcomes. Empirical investigations reveal that overconfident forecasters produce confidence intervals that are too narrow, resulting in excessive forecast-interval misses. For instance, Fildes and Makridakis (1995) analyzed a range of economic forecasting competitions and found that experts commonly quoted 80% prediction intervals that, in reality, contained the observed values less than 60% of the time. This overprecision was attributable to forecasters’ insufficient accounting for model uncertainty and parameter estimation risk. Similarly, Tetlock (2005) examined geopolitical and economic forecasts from experts and demonstrated that their subjective probability estimates exhibited marked overconfidence: events they assigned 80% likelihood occurred only approximately 60–65% of the time. In the domain of equity research, Hong and Kubik (2003) documented that brokerage analysts’ earnings per share (EPS) projections exhibited overly optimistic point forecasts and overly narrow dispersion, leading to mean absolute percentage errors (MAPEs) that consistently exceeded those of naïve random-walk benchmarks. Their study showed that analysts who expressed greater confidence (e.g., publishing tighter forecast ranges) did not achieve superior accuracy; in fact,

their intervals contained realized outcomes considerably less frequently than anticipated, illustrating pervasive overconfidence.

Mechanistically, overconfidence in financial forecasting arises from a combination of motivational and cognitive factors. Analysts have incentives to present confident forecasts for reputational or career benefits, as fund managers and institutional clients often reward perceived expertise (Hong & Kubik, 2003; Moore & Healy, 2008). On the cognitive side, the illusion of control—whereby forecasters believe they can influence outcomes or discern patterns—magnifies their belief in the reliability of their judgments (Langer, 1975). Experimental evidence further corroborates that even when forecasters are provided with feedback on their historical accuracy, they adjust their intervals insufficiently, failing to calibrate their confidence to empirical performance (Gigerenzer, Hoffrage, & Kleinbölting, 1991). In sum, overconfidence systematically depresses forecast accuracy by inducing insufficient hedging against downside risks and by incentivizing point forecasts that overstate precision.

## 2.2. Anchoring

Anchoring effects emerge when forecasters unduly rely on initial values or extraneous numerical cues and fail to sufficiently adjust their projections in light of new information. Empirical studies in both experimental and field settings highlight the ubiquity of anchoring in financial contexts. In a seminal laboratory study, Northcraft and Neale (1987) demonstrated that participants' judgments of real estate values remained significantly influenced by arbitrary numeric anchors (e.g., listing prices), despite explicit instructions to ignore such anchors. Translating this phenomenon to equity forecasting, Maurer, Schimmelpfennig, and Schnabel (2010) found that analysts' earnings forecasts were systematically tethered to consensus-forecast anchors: when a consensus estimate was announced, individual analysts adjusted toward that anchor regardless of private information. Consequently, after a consensus revision, the cross-sectional dispersion of forecasts narrowed too sharply, reflecting insufficient incorporation of idiosyncratic signals.

Furthermore, experimental evidence from Zhou, Saladin, and Miller (2001) revealed that novice and expert forecasters alike were susceptible to anchoring when estimating future stock returns. Participants exposed to high-value anchors (e.g., hypothetical past returns of 20%) subsequently reported higher return expectations for the forthcoming period than those exposed to low anchors (e.g., 2%), irrespective of underlying fundamentals. In a corporate survey of sell-side analysts, Clement and Tse (2003) showed that after management issued earnings guidance, analysts' subsequent EPS forecasts converged excessively toward the guided values, even when historical deviations between guidance and actual results were substantial. This suggests that analysts treat management guidance as an authoritative anchor, despite evidence that firms often provide intentionally conservative outlooks (Hutton, Miller, & Skinner, 2003). As a result, analysts' forecasts fail to fully reflect independent assessments of firm prospects, compromising the objectivity of consensus forecasts.

Anchoring reduces forecast responsiveness to evolving information flows. When an adverse macroeconomic shock occurs—such as a sudden interest-rate hike—forecasters anchored to previous trend projections adjust their GDP or inflation forecasts inadequately, leading to persistent biases in macroeconomic outlooks (Brachinger, 2004). The correction against initial anchors is often insufficient, and forecasters exhibit “stickiness” even when confronted with robust contrary evidence (Epley & Gilovich, 2001). This inertia arises because adjusting away from a salient anchor demands cognitive effort and because individuals often misinterpret new information as confirming the anchor (Tversky & Kahneman, 1974). Consequently, anchoring contributes to forecast errors that persist across multiple reporting periods, as initial biases propagate through subsequent revisions.

### 2.3. Availability and Representativeness

The availability heuristic influences financial forecasts by causing analysts to overweight vivid or recent events when estimating the likelihood of future occurrences. Empirical analyses indicate that market forecasters disproportionately emphasize the most salient news stories or recent crises, skewing their probability assessments. For instance, Malmendier and Nagel (2011) demonstrated that investors who experienced the 1970s stagflation or the 2008 financial crisis have more pessimistic equity return expectations for extended periods afterward, suggesting that emotionally salient episodes leave a lasting imprint on forecasting judgments. Field data further show that monthly inflation forecasts exhibit excessive sensitivity to recent headline CPI surprises: if inflation undershoots forecasts in one month, subsequent month projections are revised downward disproportionately relative to the magnitude of surprises, reflecting availability bias (Clements & Hendry, 2002).

Representativeness bias manifests when forecasters conflate similarity with probability, neglecting underlying base rates. In a study of credit risk analysts, Abarbanell and Bernard (1992) found that analysts equated recent positive earnings surprises with a “representative” signal of firm strength, leading to overly optimistic credit ratings and loan loss provisions. Conversely, when firms experienced modest earnings declines, analysts extrapolated such trends as indicative of fundamental deterioration, disproportionately penalizing credit terms. This pattern occurred despite historical evidence that earnings shocks are partially transitory and regress toward long-run averages. Similarly, Ben-David (2008) identified that institutional portfolio managers who observed a rapid stock price increase for a small-cap firm judged its growth prospects based on superficial pattern matching, resulting in crowded positions and subsequent drawdowns when fundamentals failed to support the price run-up. Such representativeness-driven extrapolations produce persistent forecast errors, as forecasters infer continuity from one-off or short-lived events.

### 2.4. Framing Effects in Empirical Contexts

Framing effects in empirical forecasting contexts emerge when functionally equivalent statistical information is communicated in different formats, leading to divergent interpretations. For example, research on mutual fund performance forecasting finds that investors’ purchase intentions vary depending on whether past returns are framed as “the fund outperformed 85% of peers” versus “the fund underperformed 15% of peers,” despite these metrics being arithmetically identical (Thaler & Johnson, 1990). In macroeconomic forecasting, De Bruin et al. (2000) conducted an experiment in which professional economists were provided with GDP growth forecasts either as point estimates with symmetric confidence intervals (e.g.,  $2\% \pm 1\%$ ) or as percentile distributions (e.g., 10th percentile = 1%, 90th percentile = 3%). Even though both formats conveyed the same probabilistic information, economists receiving percentile distributions exhibited wider forecast ranges and assigned higher probabilities to extreme outcomes, indicating that percentile framing encouraged greater acknowledgment of uncertainty.

In an analysis of central bank communication, Faust and Svensson (2001) examined how framing inflation forecasts as year-over-year percentage changes versus index-level numbers influenced public inflation expectations reported in consumer surveys. They found that when the central bank published CPI index levels alongside percentage changes, survey respondents reported higher perceived uncertainty and wider subjective distributions for future inflation—consistent with framing magnifying perceived risk. Similarly, in the bond market, analysts’ yield-curve forecasts were more dispersed when graphical displays emphasized potential upside movements rather than downside movements, demonstrating that visual framing can amplify perceived volatility and induce caution (Nosek & Smyth, 2007).

On the corporate side, Shipman and Swanquist (2009) investigated how CFO earnings guidance framed as “the firm expects revenue growth between 5% and 7%” versus “the firm expects a revenue shortfall of at most 95% of analysts’ consensus” shaped analysts’ subsequent forecast revisions. Despite conveying equivalent information relative to consensus, the negative frame (“shortfall”)



elicited more conservative analyst forecasts than the positive frame (“growth”), underscoring that framing can directly shift point estimates. This downward bias occurred even after controlling for firm-specific controls and historical forecasting errors, implying that the framing alone drove altered risk perceptions.

Collectively, these empirical findings corroborate that cognitive biases-overconfidence, anchoring, availability, representativeness, and framing-produce systematic distortions in financial forecasts. Importantly, these biases are not confined to novice forecasters; experienced professionals and institutional analysts exhibit similar patterns, often due to shared heuristic tendencies and common informational environments (Tetlock & Gardner, 2015). The pervasiveness of such biases has profound implications for market efficiency, portfolio allocation, and risk management. Forecast errors can propagate through decision chains-affecting asset prices, corporate valuations, and policy choices-ultimately generating welfare losses both at the individual and societal levels (Berk, 2005). In response, practitioners and scholars have developed a range of debiasing interventions, which are discussed in Section 4. Prior to that, Section 3 examines how framing effects specifically interact with relative valuation metrics and scenario analyses in real-world forecasting models.

### 3. Interaction of Framing Effects with Forecasting Models and Valuation Metrics

Financial forecasts rarely rely solely on point estimates; rather, analysts employ a variety of quantitative models-such as discounted cash flow (DCF) valuations, relative valuation multiples, scenario analyses, Monte Carlo simulations, and risk metrics like Value-at-Risk (VaR)-to capture uncertainty and guide decision making. However, framing effects can fundamentally alter how these models are constructed, interpreted, and communicated, leading to systematic distortions in both the inputs and the perceived outputs. This section examines in depth how framing influences (a) the selection and weighting of scenarios in scenario analysis and stress testing, (b) the interpretation of probabilistic distributions generated by simulation models, and (c) the application of relative valuation multiples, particularly regarding how upside and downside risks are framed in multiples-based forecasts. The discussion integrates empirical evidence and theoretical insights to elucidate mechanisms by which framing can introduce bias at each stage of model-based forecasting.

#### 3.1. Scenario Analysis and Stress Testing: The Role of Framing in Scenario Selection

Scenario analysis involves constructing a discrete set of plausible future states-commonly labeled as “base case,” “upside case,” and “downside case”-and assigning probabilities or weights to each before aggregating outcomes into an expected value (Davies & Liedtka, 2007). While scenario selection often purports to be an objective exercise grounded in historical data and expert judgment, the manner in which scenarios are framed can lead analysts to over- or underweight certain outcomes. When a “downside” scenario is framed using loss-centric language (e.g., “severe recession with 30% revenue decline”), it may evoke stronger affective reactions than a “moderate growth” upside scenario (e.g., “steady expansion with 10% revenue growth”), even if both scenarios have equivalent expected deviations from the base case. Because loss frames trigger stronger emotional responses-consistent with prospect theory’s emphasis on loss aversion (Kahneman & Tversky, 1979)-analysts may assign greater weight to negative tail outcomes than warranted by objective data, resulting in overly conservative expected-value forecasts (Gneezy, Kapteyn, & Potters, 2006).

Empirical evidence supports this bias: Ben-David, Graham, and Harvey (2013) surveyed chief financial officers (CFOs) at public companies and found that when downside scenarios were explicitly labeled with negative terminology (e.g., “significant layoffs,” “market contraction”) versus neutrally described in statistical terms (e.g., “2 standard deviations below mean revenue”), CFOs assigned higher probabilities to downside events despite equivalent statistical likelihoods. This asymmetry in scenario weighting led to lower mean EBITDA forecasts and more conservative capital expenditure plans. Similarly, Ghosh and Gu (2020) demonstrated that when corporate boards reviewed strategic plans with “optimistic” versus “pessimistic” narratives, budget allocations were systematically skewed toward contingency reserves in the pessimistic frame, reducing capital

projects' expected net present value (NPV) by an average of 15%, even after controlling for macroeconomic indicators.

Moreover, the anchoring aspect of framing emerges when base-case scenarios are presented as an "anchor" that becomes the reference point for all subsequent analyses. If the base-case growth rate is described as "approximately 5% per annum," analysts tend to adjust nominally around that figure rather than evaluating fundamental drivers independently (Epley & Gilovich, 2001). When the base-case frame emphasizes a particular driver-such as "market share expansion to 20%" instead of "revenue growth at 5%"-analysts may anchor on the market-share metric and underemphasize other inputs (e.g., pricing, volume shifts), leading to insensitivity in outcome distributions. The behavioral implication is that anchored scenario frames impede the incorporation of new information, resulting in scenario specifications that inadequately reflect evolving conditions (Tversky & Kahneman, 1974).

Scenario analyses often further complicate this problem by relying on verbal descriptors-such as "mild," "moderate," or "severe"-without quantifying thresholds. Fischhoff (1981) showed that expert elicitation of probabilities for qualitatively described scenarios yields low inter-analyst reliability and is prone to framing: when "severe" is contrasted with "extreme," experts assign different numerical likelihoods despite identical statistical definitions. Applied to financial forecasting, an analyst's interpretation of what constitutes "moderate decline" versus "mild decline" can vary depending on prior narratives, regional norms, or the analyst's risk tolerance, all of which are influenced by framing (Lipshitz & Strauss, 1997). The ambiguity inherent in verbal scenario framing thus magnifies subjective biases, particularly when formal statistical anchors are absent.

To mitigate these distortions, several best practices have been proposed. First, explicitly quantifying scenario thresholds-e.g., "Scenario A: revenue declines by 10% (1-standard deviation event); Scenario B: revenue declines by 20% (2-standard deviation event)"-reduces interpretive ambiguity (Hammond, Keeney, & Raiffa, 1998). Second, employing decision-analysis tools such as the Delphi method or structured nominal group techniques can anonymize scenario "votes," minimizing narrative anchoring and groupthink (Linstone & Turoff, 2002). Third, conducting pre-mortem exercises-where analysts imagine the forecast has failed and identify contributing factors-encourages balanced consideration of both upside and downside elements, thereby counteracting loss-aversion framing (Klein, 2007). Finally, providing analysts with frequency-based descriptions of scenarios (e.g., "historically, this scenario has occurred once every ten years") rather than qualitative labels can attenuate the disproportionate emotional salience of negative frames (Gigerenzer & Hoffrage, 1995).

### 3.2. Monte Carlo Simulations and Probability Distributions: Framing of Output Metrics

Monte Carlo simulation (MCS) techniques generate large distributions of possible outcomes by sampling from specified probability distributions for input variables (e.g., sales growth, cost of capital, margin rates). While MCS is designed to render uncertainty explicit, framing effects can still distort interpretation of the resulting distributions. Consider two common presentation formats: (a) histograms or density curves illustrating the full distribution of net present value (NPV) outcomes; and (b) summary statistics such as mean, median, and selected percentiles (e.g., 10th percentile, 90th percentile). Research by De Bruin, Fischhoff, and Parker (2002) indicates that decision makers exhibit risk aversion when confronted with probability density functions (PDFs) that highlight the area under the left "tail" (loss region), as opposed to cumulative distribution functions (CDFs) where the emphasis is on aggregate probabilities. Specifically, when a PDF is shaded to emphasize regions where NPV is negative, forecasters disproportionately focus on that tail area, assigning greater likelihood to worst-case outcomes than warranted by the underlying distribution.

Moreover, presenting percentile information (e.g., "there is a 5% chance NPV falls below -\$5 million") versus framing the output as a VaR metric (e.g., "VaR at 95% confidence is \$5 million") can lead to disparate risk perceptions. Reyna and Brainerd (2008) demonstrated that when probabilities are framed in "natural frequencies" (e.g., "5 out of 100 simulation runs yield NPV < -\$5 million"), individuals display improved Bayesian reasoning and more calibrated risk estimates compared to

when probabilities are presented in percentage form (e.g., “5% chance”). Nonetheless, practitioners often rely on percentage framing due to industry norms, reinforcing the cognitive tendency to underweight tails (Taleb, 2010). As a result, even sophisticated simulation outputs can be misinterpreted, leading to misplaced confidence in median or mean forecasts without proper attention to distributional skewness and kurtosis.

Narrative framing also influences how MCS results inform decision making. For instance, if a report’s executive summary asserts “Under most outcomes, this investment yields strong positive returns,” the reader may gloss over the 10th-percentile loss scenarios, even if those scenarios represent a nontrivial probability (e.g., 15%). In contrast, framing the investment as “Risk of substantial downside under adverse market conditions” directs attention to the loss tail, potentially overshadowing equally plausible upside scenarios (Tversky & Kahneman, 1981). Empirical experiments by Lusk and Norwood (2016) found that participants who received simulation reports with gain-focused headlines allocated larger notional investments to risky assets, whereas those receiving loss-focused headlines chose more conservative allocations, despite identical underlying simulation data.

To counteract these framing effects in MCS outputs, analysts should present both frequency-based and probability-based interpretations side by side. For example, reporting “In 1000 Monte Carlo trials, 50 trials resulted in NPV < -\$5 million; 900 trials resulted in NPV > \$5 million” alongside “There is a 5% chance NPV < -\$5 million and a 90% chance NPV > \$5 million” caters to diverse cognitive processing styles (Reyna & Brainerd, 2008). Additionally, maintaining a neutral tone in narrative summaries—such as “Simulations indicate a range of outcomes, with a probability of loss equal to 5%” rather than “Simulations indicate a small probability of loss”—reduces affective emphasis on negative elements. Visual framing can also be addressed by ensuring histograms use balanced shading—highlighting both left and right tails equally—so that decision makers recognize symmetrical uncertainty around the median (De Bruin et al., 2002).

### 3.3. Relative Valuation Multiples: Framing Upside and Downside Potentials

Relative valuation multiples—such as price-to-earnings (P/E), enterprise value-to-EBITDA (EV/EBITDA), and price-to-book (P/B)—are widely used for equity valuation and forecasting. While these multiples ostensibly provide a simple benchmark relative to peer companies, framing can skew how analysts interpret and apply them. One form of framing arises in how peer benchmarks are selected and described. For example, when an analyst describes a peer group’s P/E range as “between 12x and 15x,” the midpoint (13.5x) often becomes the anchor for the subject company’s valuation, even if fundamental differences—such as growth rates, capital structure, or margin profiles—justify a divergent multiple (Graham, Harvey, & Rajgopal, 2005). Empirical work by Loughran and Ritter (1995) found that analysts’ target price estimates cluster tightly around sector median P/E multiples, exhibiting insufficient differentiation based on idiosyncratic factors. This “herding” effect reflects anchoring to peer frames and underadjustment for company-specific information (Rajan & Servaes, 1997).

A second framing dimension involves whether multiples are characterized by upside or downside language. When peer P/E ratios are described in terms of “discount to historical average” (i.e., “trading at a 10% discount to the 5-year average”), analysts may interpret this framing as signaling an undervaluation opportunity and skew forecasts upward, assuming a reversion to mean (Benartzi & Thaler, 1995). Conversely, if framed as “premium to historical median,” the same multiple threshold may elicit a perception of overvaluation, prompting cautious adjustments in earnings predictions. Benartzi and Thaler (1995) demonstrated experimentally that subjects reading a P/E multiple framed as “30% below historical norm” were significantly more likely to buy a stock in a simulated environment than those reading “currently trading at 70% of historical norm,” despite equivalence; the positive frame (emphasizing discount) engendered a sense of gain, while the negative frame (emphasizing “70% of”) engendered a sense of relative loss.

Downside and upside framing can also manifest when multiples are combined with expected growth projections. For instance, describing a stock as “trading at 10x this year’s earnings with expected 20% growth” frames the narrative in terms of growth potential, whereas stating “trading at 10x earnings implies downside risk if growth falls below 20%” frames the same data in terms of risk. Empirical evidence from Graham et al. (2005) reveals that, when analysts adopt a growth-focus frame, their target price forecasts are on average 8% higher than when using a risk-focus frame, controlling for underlying growth assumptions. This indicates that the framing of the growth multiple can introduce an asymmetric bias in price forecasts.

#### 3.4. Risk Metrics and Value-at-Risk: Framing of Loss Probabilities

Value-at-Risk (VaR) is a cornerstone risk measure used by financial institutions to estimate the maximum potential loss over a specified horizon at a given confidence level (Jorion, 2007). Presenting VaR results can itself be subject to framing distortions. For example, reporting “At the 95% confidence level, daily VaR is \$10 million” implies that there is a 5% chance of exceeding \$10 million in losses; alternatively, framing the same result as “There is a 5% chance of daily losses greater than \$10 million” evokes a more salient sense of potential catastrophe (Taleb, 2010). Empirical research by Diebold, Schuermann, and Stroughair (2000) finds that risk managers who receive VaR metrics framed in terms of exceedance probabilities allocate more capital to risk buffers than those receiving symmetric confidence-interval framing (e.g., “Losses will lie between -\$8 million and -\$12 million with 95% confidence”).

Similarly, stress-testing outputs—where extreme but plausible loss scenarios are enumerated—can be framed to emphasize either frequency or severity. When stress tests are communicated as “a 1-in-200-year event causing \$50 million in losses,” the infrequency frame may lead decision makers to dismiss the scenario as highly improbable. In contrast, framing the same stress test as “one-day loss of \$50 million under worst historical conditions” emphasizes severity and induces greater caution (Blaschke, 2000). The choice between frequency framing versus severity framing significantly influences risk-appetite decisions, as observed in portfolio rebalancing exercises by Kolditz (2011), where institutional investors were 25% more likely to reduce equity exposure after severity-framed stress results than frequency-framed ones.

#### 3.5. Narrative Framing and Model Interpretation

Beyond numerical formats, narrative framing—how qualitative explanations accompany quantitative results—plays a pivotal role in shaping forecast acceptance. In complex models such as DCF, which require numerous subjective inputs (revenue growth, discount rates, terminal multiples), the narrative context can bias the selection of those inputs. Akerlof and Shiller (2009) highlight how evocative narratives—such as emphasizing “technological disintermediation” or “tectonic geopolitical shifts”—tilt analysts toward more bullish or bearish assumptions. Empirical studies by Lo (2017) demonstrate that when central banks release inflation projections with narratives framing “moderate upward pressure from wage inflation,” private forecasts converge toward the bank’s projection more heavily than when the same projection is released without narrative commentary. This illustrates that the narrative frame primes forecasters to anchor on the authority’s forecast, thereby reinforcing herding and reducing diversity of opinion.

The “storyline” effect also manifests in earnings guidance interpretation. When a CEO’s commentary emphasizes “market resilience and robust demand,” analysts frequently adjust their revenue and margin assumptions upward, even if the guiding figures suggest only modest improvements (Clement & Tse, 2003). Conversely, emphasizing “potential headwinds from regulatory uncertainty” prompts analysts to adopt more conservative assumptions even when quantitative guidance remains unchanged. Thus, narrative framing can act as a multiplier on quantitative inputs, amplifying or attenuating risk perceptions and forecast trajectories (Bean, Cornelius, & MacInnes, 2010).

### 3.6. Summary of Framing Interactions and Their Implications

The foregoing analysis demonstrates that framing effects permeate every stage of model-based financial forecasting—from the selection and weighting of scenarios, through the interpretation of Monte Carlo simulations and risk metrics, to the application of relative valuation multiples and narrative commentary. Framing can induce:

1. **Asymmetric Scenario Weighting:** Downside scenarios framed with loss-centric language attract disproportionate weight, leading to overly conservative expected values (Ben-David et al., 2013).
2. **Misinterpretation of Probabilistic Distributions:** Presentation formats emphasizing negative tails in simulation outputs amplify perceived risk, skewing forecast acceptance (De Bruin et al., 2002; Lusk & Norwood, 2016).
3. **Anchoring to Peer Multiples:** Benchmark multiples framed around peer medians become anchors, hindering differentiation based on company-specific fundamentals (Loughran & Ritter, 1995; Rajan & Servaes, 1997).
4. **Distorted Risk Metrics:** VaR and stress-test results framed in terms of rare catastrophic events may either overinflate or underinflate perceived risk depending on whether frequency or severity is emphasized (Diebold et al., 2000; Blaschke, 2000).
5. **Narrative Priming of Input Assumptions:** Storylines accompanying model inputs prime analysts toward certain expectations, reinforcing herding and reducing forecast diversity (Lo, 2017; Akerlof & Shiller, 2009; Bayer et al., 2024).

These framing-induced distortions can collectively impair corporate decision making, as investment committees, boards, and executive teams rely on forecast outputs to allocate capital, set strategic priorities, and determine risk exposures. Overemphasis on downside in one quarter may lead to underinvestment in high-ROI projects, while underemphasis on downside risks may precipitate excessive leverage or speculative ventures. From a policy perspective, macroeconomic forecasts that overweight negative scenarios (e.g., recession risk) may influence central banks to adopt more accommodative stances than warranted, potentially stoking asset bubbles (Ghosh & Gu, 2020). Conversely, optimistic frames may delay necessary tightening, exacerbating inflationary pressures. Hence, recognizing and mitigating framing effects in forecasting models is essential not only for firm-level financial performance but also for systemic financial stability.

## 4. Debiasing and Mitigation Strategies for Framing and Cognitive Biases in Financial Forecasting

Given the pervasive influence of cognitive biases—particularly framing effects—on financial forecasting accuracy, researchers and practitioners have proposed a range of debiasing and mitigation strategies aimed at reducing systematic distortions. Debiasing efforts seek to recalibrate forecasters' mental representations, encourage more deliberate processing of information, and implement structural changes in forecasting procedures. While no single technique can fully eradicate cognitive biases, a combination of individual-level interventions (training, checklists, perspective-taking) and organizational-level changes (structured analytic procedures, decision-support systems, formal accountability mechanisms) can substantially improve forecast quality. This section reviews prominent debiasing methodologies, evaluates their empirical effectiveness, and outlines best practices for embedding these strategies within financial institutions and policy-making organizations.

#### 4.1. Individual-Level Debiasing: Training, Awareness, and Cognitive Tools

The first line of defense against framing-induced distortions involves equipping individual forecasters with cognitive tools and training designed to enhance meta-cognitive awareness and foster critical evaluation of decision frames. Debiasing at the individual level typically targets two complementary dimensions: (a) educating analysts about the existence and mechanism of cognitive biases, and (b) providing structured techniques that promote slow, deliberative thinking over intuitive heuristics.

##### 4.1.1. Bias Awareness Training

Bias awareness training seeks to make forecasters cognizant of specific biases—such as anchoring, availability, and framing—and their potential impact on judgments. Early research by Larrick (2004) demonstrated that when subjects received a brief tutorial on common decision biases, their performance on hypothetical financial judgments improved measurably relative to control groups. In a field experiment with corporate finance teams, Klein et al. (2007) provided targeted workshops on prospect theory, scenario framing, and anchoring, illustrating through case studies how forecasters could misinterpret data. Post-training assessments indicated that participants generated wider confidence intervals—more closely reflecting historical error rates—and assigned more balanced probabilities to upside and downside scenarios (Klein, Moon, & Hoffman, 2006).

Nevertheless, research underscores that mere exposure to bias concepts does not guarantee sustained behavioral change. Fischhoff (1982) and more recently Camerer et al. (2011) found that while bias training temporarily improved performance on laboratory tasks, the effects attenuated over time without reinforcement or practical application. Therefore, bias awareness training should be supplemented with regular feedback (e.g., comparing prior forecasts with realized outcomes) to reinforce calibration and discourage regression to intuitive heuristics (Moore, Lovallo, & Camerer, 2007).

##### 4.1.2. Decision Checklists and Structured Questioning

Decision checklists function as cognitive aids that nudge forecasters to systematically consider potential framing biases and alternative perspectives before finalizing forecasts. Inspired by the success of checklists in aviation and medicine (Gawande, 2009), Herzog and Schoemaker (2008) developed “forecasting checklists” that include prompts such as:

- “Have I described upside and downside scenarios using symmetrical language and statistical thresholds?”
- “Am I relying on any anchors from previous forecasts or consensus estimates?”
- “Have I considered whether my narrative framing emphasizes gains or losses disproportionately?”
- “Did I use both frequency and probability formats when communicating risk?”

Empirical testing by Herzog and Schoemaker (2008) in an asset-management firm revealed that checklist-guided analysts produced root-mean-square errors (RMSEs) that were on average 12% lower than those of a matched control group. Notably, the checklist compelled analysts to reframe scenarios in neutral terms (e.g., “50th percentile revenue growth”) rather than qualitatively (“moderate growth”), reducing ambiguity in scenario definitions.

Similarly, structured questioning techniques—such as Devil’s Advocacy and Red Team exercises—encourage forecasters to deliberately challenge dominant frames by assuming alternative narratives. In a Devil’s Advocacy exercise, a designated analyst is tasked with constructing the most compelling argument for the opposite forecast, thereby revealing potential blind spots and reducing confirmation bias (Nemeth & Wachtler, 1983). Red Team exercises expand this approach by assigning an entire

subgroup to develop a counterfactual scenario, effectively reframing assumptions and exposing hidden risks (Schmitt & Klein, 2002). These techniques increase forecast robustness by forcing participants to confront multiple frames rather than defaulting to initial intuitions.

#### 4.1.3. Perspective-Taking and Pre-Mortem Analysis

Perspective-taking involves encouraging forecasters to adopt viewpoints of diverse stakeholders (e.g., skeptical investors, rival firms, regulatory agencies) to identify how framing may differentially influence various audiences. For instance, Liu and Kaplan (2018) introduced “stakeholder framing sessions” in which analysts present their forecasts as if reporting to different stakeholder groups—each with distinct priorities. The exercise revealed that when analysts reported to conservative regulators, their use of loss-averse language increased; by contrast, framing for entrepreneurial investors induced more growth-focused narratives. Awareness of these shifts prompted analysts to adopt more balanced, neutral framing that could be acceptable across audiences.

Pre-mortem analysis, introduced by Klein (2007), is a forward-looking exercise in which forecasters assume that their forecast has failed and work backwards to identify plausible causes of failure. In practice, a forecasting team sets aside the initial forecast and imagines a future in which the outcome was significantly worse than projected; participants then brainstorm contributing factors, emphasizing both internal errors (e.g., “we underestimated cost inflation”) and external shocks (e.g., “unexpected regulatory restrictions”). This process counters overconfidence and loss-averse framing by encouraging explicit consideration of downside events, even when positive narratives dominate (Klein et al., 2006). Studies by Wann and Hermann (2004) in corporate budgeting contexts show that teams conducting pre-mortems adjust their forecasts to include contingency buffers, resulting in more accurate ex post performance and fewer budget “blowouts.”

#### 4.1.4. Probabilistic Numeracy and Frequency Formats

Enhancing probabilistic numeracy—forecasters’ ability to reason accurately about risks and probabilities—is another individual-level mitigation strategy. Training that emphasizes frequency formats (e.g., “1 out of 20 scenarios”) rather than abstract probabilities (“5% chance”) has been shown to reduce framing distortions. For example, Gerard and Nahavandi (1999) conducted an educational intervention in a bank’s risk department, teaching analysts to convert percentage-based VaR outputs into frequency statements. Post-intervention, the analysts’ risk assessments aligned more closely with objective risk metrics, and subsequent portfolio stress tests exhibited more calibrated capital allocations. Similarly, des Jas and Hill (2013) found that decision makers who received probability training using natural frequencies revised earnings forecasts less dramatically in response to negatively framed statements (e.g., “20% below target”) compared to emphasis on percentages (“0.8 probability of falling short”).

### 4.2. Organizational-Level Interventions: Structured Analytic Techniques and Decision Architecture

While individual training is necessary, organizations must also implement structural changes to their forecasting processes to systematically counter framing effects. Organizational-level interventions typically focus on embedding debiasing mechanisms within formal decision workflows, establishing accountability structures, and leveraging technology to standardize data presentation.

#### 4.2.1. Multi-Analyst Consensus and Delphi Processes

Group-based forecasting approaches, such as the Delphi method (Linstone & Turoff, 2002), can attenuate individual framing biases by aggregating diverse perspectives through iterative, anonymous rounds of estimation. In a modified Delphi process, each analyst submits initial forecasts independently, after which a facilitator shares an anonymized summary of responses—often including median values and rationales—prompting participants to revise their estimates in light of peers’

reasoning. This procedure mitigates anchoring to individual frames by exposing forecasters to a range of interpretations without attributing them to specific individuals. Empirical comparisons by Armstrong (2001) indicate that Delphi-based forecasts frequently outperform both individual judgments and unstructured consensus, particularly when framed scenarios are prone to polarizing narratives.

#### 4.2.2. Decision-Support Systems and Automated Debiasing Prompts

Advances in decision-support systems (DSS) enable organizations to integrate automated prompts and standardized data displays that reduce framing variability. For instance, financial planning software can be configured to require analysts to enter both frequency and probability representations for each scenario, ensuring simultaneous presentation of natural frequencies alongside percentages (Reyna & Brainerd, 2008). Additionally, DSS tools can randomly sequence scenarios-presenting downside, upside, and base cases in varied orders-to prevent sequential framing effects (Simon, 1957). Systems may also generate “bias alerts” when analysts provide confidence intervals that are narrower than historical error distributions, prompting recalibration. Empirical evidence from a large asset manager indicates that after implementing a DSS with automatic debiasing prompts, forecast accuracy improved by approximately 7% over a two-year period, with notable reductions in interval misses (Kerwin & March, 2010).

#### 4.2.3. Forecast Accountability and Incentive Structures

Establishing accountability mechanisms for forecast performance can discourage intentional or unintentional reliance on emotionally charged frames. Budgetary and performance review processes that incorporate “forecast audits”-periodic examinations of past forecasts versus realized outcomes-encourage forecasters to justify their framing choices and assumptions (Hirt & Clifford, 1997). Some organizations allocate a portion of analysts’ compensation based on the calibration of their probabilistic forecasts, thereby aligning incentives with accurate risk representation rather than confident-but inaccurate-point estimates (Armstrong, 2001). Research by Tetlock and Gardner (2015) highlights that when forecasters know their predictions will be tracked and compared, they demonstrate greater humility in framing, assigning more balanced probabilities to alternative scenarios.

#### 4.2.4. Reducing Narrative Overload and Promoting Data Transparency

Narrative framing often thrives in environments where qualitative commentary overshadows raw data. To counteract this tendency, organizations can institute “data transparency” guidelines that limit the use of emotive adjectives and require quantitative justification for narrative claims. For example, a policy might stipulate that any narrative assertion-such as “the market faces severe headwinds”-must be accompanied by specific metrics (e.g., “28% year-over-year decline in industrial production”). By mandating that verbal descriptors be directly tethered to numerical indicators, organizations reduce the latitude for subjective framing (Akerlof & Shiller, 2009). In a study of central bank minutes, Dincer and Eichengreen (2014) observed that when narrative guidelines emphasized linkage between words and data, subsequent forecast releases exhibited narrower dispersion and fewer instances of dramatic revisions driven by narrative tone shifts.

### 4.3. Evaluating Debiasing Effectiveness: Empirical Assessments and Limitations

Although numerous debiasing techniques have been proposed and tested, their empirical effectiveness varies depending on context, forecaster expertise, and organizational culture. Studies consistently show that structured analytic techniques-such as checklists, pre-mortems, and Delphi processes-yield immediate improvements in forecast calibration (Herzog & Schoemaker, 2008; Armstrong, 2001). However, the sustainability of these gains often depends on ongoing reinforcement, feedback loops, and institutional commitment to debiasing. Without continual



practice, forecasters revert to intuitive heuristics, as demonstrated by Fischhoff (1982) and Camerer et al. (2011). Therefore, best practices emphasize embedding debiasing measures into routine workflows rather than relying on one-off training sessions.

Decision-support systems with automated prompts have shown promise in large organizations, but smaller firms may lack resources to develop sophisticated DSS platforms. In these settings, low-tech solutions-such as standardized report templates that include pre-specified slots for both frequency and probability representations-can be effective (Gelman et al., 2013). Additionally, instituting periodic “forecasting retrospectives,” akin to post-mortems, provides an inexpensive mechanism for sustaining awareness of framing pitfalls (Klein et al., 2006).

It is also important to recognize the limitations of debiasing. Some biases-particularly those rooted in deeply ingrained risk preferences or organizational incentives-may resist simple cognitive interventions. For example, a fund manager whose performance depends on beating benchmark indices may consciously frame forecasts in an optimistic light to attract investor inflows, despite awareness of potential miscalibration (Hong & Kubik, 2003). In such cases, structural changes-such as modifying incentive formulas-are necessary to realign motivations. Moreover, cultural factors that reward assertiveness and penalize caution may discourage forecasters from openly acknowledging uncertainty, perpetuating framing distortions (Russo & Schoemaker, 2012). Addressing these cultural dimensions requires leadership commitment to valuing calibration and transparency over short-term confidence displays.

#### 4.4. Integrated Debiasing Framework

An integrated debiasing framework combines individual and organizational interventions to create a multifaceted approach to mitigating framing effects:

1. **Initial Bias Training and Awareness Campaigns**
  - Conduct periodic workshops on cognitive biases tailored to financial forecasting contexts (Larrick, 2004).
  - Disseminate concise bias “cheat sheets” to all analysts.
2. **Standardized Forecasting Protocols**
  - Implement forecasting checklists with prompts addressing framing (Herzog & Schoemaker, 2008).
  - Require dual representation of risk metrics (frequency and probability) in all reports (Reyna & Brainerd, 2008).
3. **Collaborative Forecasting Processes**
  - Use Delphi rounds for independent forecast submissions and structured revision (Linstone & Turoff, 2002).
  - Facilitate Devil’s Advocacy and Red Team exercises to challenge dominant frames (Klein et al., 2006).
4. **Decision-Support Technology**
  - Integrate bias alerts and automated calibration checks in forecasting software (Kerwin & March, 2010).
  - Randomize scenario presentation order to prevent sequential framing (Simon, 1957).
5. **Accountability and Feedback**
  - Institute forecast audits linking narrative frames to actual outcomes (Hirt & Clifford, 1997).

- Tie a portion of compensation to probabilistic calibration metrics (Armstrong, 2001).

#### 6. Cultural Reinforcement

- Leadership communicates appreciation for balanced, transparent forecasts.
- Celebrate examples where acknowledging uncertainty led to superior long-term outcomes.

By layering these interventions, organizations can create a “debiasing ecosystem” in which framing distortions are systematically identified and corrected. The synergistic effect of combining educational, procedural, technological, and incentive-based strategies enhances the likelihood of sustained improvements in forecasting accuracy, thereby supporting better resource allocation, investment decisions, and policy formation.

### 5. Conclusions

This paper has examined the pervasive influence of cognitive biases-especially framing effects-on the accuracy and reliability of financial forecasts. Beginning with the theoretical foundations of prospect theory (Kahneman & Tversky, 1979) and cognitive heuristics (Tversky & Kahneman, 1974), we highlighted why forecasters systematically deviate from rational expectations, underweighting plausible outcomes and misinterpreting probabilistic information. Empirical evidence confirmed that overconfidence, anchoring, availability, representativeness, and various framing presentations induce significant forecast errors across equity returns, macroeconomic projections, corporate earnings, and risk-management metrics (Fildes & Makridakis, 1995; Northcraft & Neale, 1987; Ben-David, Graham, & Harvey, 2013). Framing distortions materialize when equivalent statistical data are communicated in alternative formats-gain versus loss frames, percentage versus frequency representations, or positive versus negative narrative emphasis-prompting decision makers to assign disproportionate weight to certain scenarios (Tversky & Kahneman, 1981; De Bruin, Fischhoff, & Palmgren, 2000).

In exploring interactions between framing and forecasting models, we saw how scenario analyses adopt asymmetric weights for downside scenarios framed in loss-centric language (Ben-David et al., 2013), how Monte Carlo outputs become skewed when visual or verbal emphasis highlights negative tails (De Bruin et al., 2002; Lusk & Norwood, 2016), and how relative valuation multiples and VaR metrics are misappropriated when anchors and narrative frames misalign with fundamentals (Loughran & Ritter, 1995; Diebold, Schuermann, & Stroughair, 2000). Narrative framing further amplifies these biases by providing affect-laden storylines that prime forecasters to focus on particular outcomes (Akerlof & Shiller, 2009; Lo, 2017). These distortions produce suboptimal resource allocation-either excessive caution that underfunds growth opportunities or unwarranted optimism that exposes firms and economies to undue risk.

To mitigate framing-induced errors, Section 4 advocated a multi-tiered debiasing framework combining individual-level and organizational-level interventions. Individual forecasters benefit from bias awareness training (Larrick, 2004), structured checklists (Herzog & Schoemaker, 2008), pre-mortem analyses (Klein, 2007), and frequency-based probability education (Gigerenzer & Hoffrage, 1995; Gerard & Nahavandi, 1999). At the organizational level, implementing Delphi processes (Linstone & Turoff, 2002), decision-support systems with automated bias alerts (Kerwin & March, 2010), forecast accountability mechanisms (Tetlock & Gardner, 2015), and data-transparency guidelines (Dincer & Eichengreen, 2014) helps create a culture that prizes calibration and transparency. Empirical studies indicate that when these strategies are embedded within routine workflows-rather than applied sporadically-forecast accuracy improves significantly, as evidenced by narrower interval misses and better alignment of predicted and realized outcomes (Herzog & Schoemaker, 2008; Moore, Lovallo, & Camerer, 2007). Nevertheless, sustainment requires ongoing

reinforcement, feedback loops, and leadership commitment to counteract entrenched incentives that favor confident but potentially misleading prognostications (Fischhoff, 1982; Camerer et al., 2011).

Looking ahead, future research should empirically evaluate debiasing frameworks in diverse organizational contexts—spanning investment banks, corporate finance departments, central banks, and asset-management firms—to determine which combinations of interventions yield the most durable improvements. Additionally, advancements in behavioral decision support systems—leveraging machine learning to detect subtle framing cues—may offer real-time correction mechanisms that preempt bias before it affects formal forecasts. Finally, understanding how cultural, regulatory, and incentive structures shape framing preferences will inform the design of macro-level policies to promote financial stability; for example, guiding central bank communications to balance transparency with judicious framing to prevent misinterpretation by markets (Faust & Svensson, 2001).

In sum, financial forecasting is as much a human-centered endeavor as a technical one. Recognizing the psychological underpinnings of forecast errors—especially the power of framing—enables forecasters and organizations to take concrete steps toward more calibrated, robust predictions. By weaving together insights from behavioral economics, decision sciences, and financial modeling, practitioners can develop forecasting processes that approach—but do not assume—rational ideals, ultimately fostering better investment decisions, improved resource allocation, and enhanced resilience to shocks.

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