Price path convexity and analyst recommendations

Joshy Jacob [*] Huzaifa Shamsi [†] Ellapulli V. Vasudevan [‡]

Abstract

We find that analysts' stock recommendations are influenced by the shape of recent price paths. Analysts are more likely to issue downgrades following convex price trajectories. This pattern of downgrades is especially pronounced for stocks exhibiting strong past return momentum. The relationship weakens for firms with low information asymmetry and during periods of macroeconomic uncertainty and elevated investor sentiment. Moreover, stocks downgraded following convex price paths exhibit lower subsequent returns, suggesting that convexity is an informative price signal and that analysts respond rationally.

Keywords: Price Path Convexity; Analyst Recommendations; Contrarian Behavior; Extrapolation bias

JEL Classification: G14, G24, G41

[*]Professor, Finance and Accounting Area, Indian Institute of Management Ahmedabad
[†]Doctoral candidate, Finance and Accounting Area, Indian Institute of Management Ahmedabad
[‡]Assistant Professor, Finance and Accounting Area, Indian Institute of Management Ahmedabad

1 Introduction

Investors tend to extrapolate future stock returns from past performance, and place excessive weight on more recent observations relative to distant ones (Cassella and Gulen, 2018; Greenwood and Shleifer, 2014). This extrapolative bias has been shown to contribute to price distortion, misvaluation, and the formation of asset price bubbles in financial markets (Barberis et al., 2018). Liu et al. (2021) employs a market-level measure of extrapolation and shows that the relationship between expected returns and expected variance becomes negative during elevated extrapolative beliefs, further suggesting that extrapolation distorts prices. Da et al. (2021) find that investor expectations are positively associated with recent returns but negatively associated with future returns, highlighting the role of extrapolation in driving mispricing and investor irrationality.

Although most studies examine extrapolative behavior primarily from the perspective of investors, research on other key market participants, such as sell-side analysts, remains relatively limited and fragmented. Financial analysts play a critical role as information intermediaries in capital markets and are instrumental in shaping the information environment of market participants (Chen et al., 2015; Merkley et al., 2017). However, they are not immune to cognitive biases and constraints such as limited attention, herding, and optimism (Hirshleifer et al., 2019; Li et al., 2021).

Several studies have investigated whether sell-side analysts also exhibit extrapolative behavior. The evidence on this front is mixed. Some studies find analyst behavior to be consistent with extrapolative tendencies observed in retail investors, while others suggest a more contrarian stance. For example, Jegadeesh et al. (2004) documents that an analyst recommends stocks that have a stronger price momentum, a higher trading volume, and elevated past and projected growth patterns consistent with extrapolation. In contrast, the parallel literature on target prices, such as Brav et al. (2005) and Renxuan (2020), reports a negative relationship between past returns and analyst-implied returns in the cross-section, suggesting that analysts may counteract investor-driven mispricing and serve as a stabilizing force in financial markets.

The literature on extrapolation has predominantly used recent returns as proxies for extrapolative expectations and subsequent mispricing. However, investors may also extrapolate from other dimensions of past price behavior. One such dimension is the trajectory of recent price paths. Emerging evidence suggests that the shape of a stock's price path—specifically, whether it is convex or concave, may influence investor expectations and lead to mispricing. Experimental studies show that individuals tend to prefer stocks with convex price paths, perceiving recent upward momentum as indicative of continued positive performance, while staying out of stocks with concave price paths, perceiving recent downward momentum as a signal of lower future returns (Borsboom and Zeisberger, 2020; Nolte and Schneider, 2018). Bansal and Jacob (2022) find that investors are less likely to sell stocks that have recently transitioned from a decline to an uptrend, interpreting such patterns as signals of favorable future returns. This behavioral tendency to infer future gains from a specific price pattern may lead to mispricing. In support of this, Gulen and Woeppel (2025) documents that, at both the firm and the aggregate level, stocks with convex price trajectories subsequently experience lower future returns, consistent with mispricing driven by extrapolative beliefs. This shows that different price paths with identical returns can lead to substantially different perceptions by investors.

This motivates an investigation into whether sell-side analysts exhibit extrapolative behavior based on the recent price path trajectory of a stock when issuing upgrade or downgrade recommendations. Mixed evidence on analyst rationality versus behavioral bias provides a foundation for a two-sided hypothesis. On the one hand, analysts can contribute to investor-driven mispricing if they extrapolate from convex price paths, characterized by a transition from a declining to a rising trend, leading them to issue upgrades following convex patterns and downgrades after concave ones. On the other hand, if analysts act contrarian and anticipate overextrapolation by investors, they may serve as a corrective force, issuing downgrades after convex trajectories in anticipation of mean reversion.

Accordingly, our objective is to examine the association between price path convexity and analyst recommendation changes. Actual recommendations are less informative, which prompts us to look into changes in analyst recommendations (Jegadeesh et al., 2004). We analyze the changes in recommendations as a signal of the analyst's position on the stock. If the current recommendation is more pessimistic than the last one, it is labelled as a downgrade. If it is optimistic than the last one, it is labelled as an upgrade. If it stays the same, it is labelled as a reiteration.

We are specifically analyzing the downgrade recommendations for this study, as upgrades and downgrades are almost symmetric to each other. I follow the convexity measure proposed by (Gulen and Woeppel, 2025), which captures the shape of the price path over a given time horizon. This measure is estimated as the scaled difference between the midpoint of the initial and final prices and the average of daily prices over the period. If the midpoint, calculated as the average of the starting and ending prices, is higher than the average of daily prices over the period, the measure takes a positive value, indicating convexity. This suggests a price path that initially declined and then rose. Conversely, if the midpoint is lower than the average prices, the measure is negative, indicating concavity. This suggests that initially it rises and then declines. Our key findings and implications are as follows.

First, we find that stocks exhibiting more convex price trajectories are significantly more likely to be downgraded by analysts. The results are robust across specifications, economically and statistically. Our findings suggest that analysts exhibit a form of contrarian behavior relative to investors, who tend to extrapolate by loading up on stocks having a convex path while staying out of the stocks having a concave path. By counteracting such extrapolative expectations, analysts may play a role in correcting or attenuating mispricing in the market that arises from extrapolation on convexity by investors. We also find that the association between price path convexity and downgrades is stronger when past returns are high, absolutely and cross-sectionally, suggesting that analysts interpret high returns aligned with convex trajectories as being driven by mispricing, thereby prompting more downgrades.

We also find that the association of convexity and downgrades is particularly pronounced among more experienced analysts, suggesting that seasoned professionals are more attuned to the risks of extrapolation and better equipped to detect extrapolative patterns. The responsiveness of analysts to recent price trajectories is also increased when they are more focused and less fatigued. The effect is further amplified for firms with lower levels of information asymmetry, where convexity is a clear signal of extrapolation as prices are fundamentally efficient and mispricing is more likely to get corrected. Moreover, the influence of convexity on analyst behavior weakens during periods of heightened macroeconomic uncertainty, as broad market concerns tend to overshadow firm-specific signals—consistent with prior findings that macro shocks can crowd out micro-level information. Similarly, we observe that higher levels of market sentiment are associated with fewer downgrades, indicating that optimistic environments may dampen analysts' willingness to issue negative revisions.

Lastly, we examine the informativeness of downgrades that occur during periods of high convexity by analyzing subsequent stock returns. We find that such downgrades are followed by significantly lower future returns compared to firms with similarly high convexity that were not downgraded. This result underscores the rationality of analyst behavior and supports the idea that their recommendations, when informed by price path patterns, are predictive of mispricing corrections.

Our results also hold under a wide range of robustness checks, including the use of comprehensive fixed effects, propensity score matching, alternative variable specifications, varying definitions and durations of convexity, and a crude control for potential analyst self-selection in issuing recommendations.

These findings indicate that analysts act as a corrective force against mispricing that may arise from investors' tendency to extrapolate recent price trends. Although investors often rely on convexity and exhibit optimism based on upward momentum, analysts appear to adopt a more tempered and contrarian approach. By systematically downgrading stocks that exhibit convex price paths, analysts help mitigate the market distortions driven by extrapolative investor behavior. This suggests a potential stabilizing role for analysts in maintaining market efficiency, especially when prices deviate from fundamentals due to behavioral biases.

Our study contributes to the literature in two important ways. First, we identify price path convexity as a novel and informative stock price characteristic that influences analyst recommendations. Unlike traditional price levels or short-term momentum indicators, convexity captures the shape and structure of the price trajectory, providing a signal for analysts to interpret underlying firm performance and investor overreaction. Second, our analysis tries to contribute to the debate in the literature on whether analysts behave in an extrapolative or contrarian manner. Our evidence supports the view that analysts generally act contrarian, challenging investor extrapolation.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature and develops the key hypotheses. Section 3 describes the data and outlines the empirical methodology. Section 4 presents the main results. Section 5 reports a series of robustness checks. Section 6 concludes.

2 Literature review and hypothesis development

A growing body of research on extroplation documents that investors often project future returns based on past price trends, and place disproportionately higher weight on more recent outcomes (Barberis et al., 2018; Cassella and Gulen, 2018; Greenwood and Shleifer, 2014). When analysts observe significantly high past returns, they are more likely to assign a higher probability to continued positive performance relative to a potential reversal. Conversely, when past returns have been significantly poor, they tend to expect continued underperformance. This behavioral tendency leads analysts to form overly optimistic expectations following recent gains and overly pessimistic forecasts after declines, resulting in systematic deviations from rational benchmark models.

In Figure 1, we illustrate how investors can form expectations based on recent price trends. The two historical price paths shown, one trending upward and one trending downward, represent stocks with strong recent gains and losses, respectively. From the point of observation (day 0), we extend these paths into the future using two different assumptions about investor behavior. First, the rational expectation lines (shown flat for simplicity) reflect the view that future returns are driven by fundamentals and are not influenced by past return trends. Although these lines are depicted as flat, they could slope in any direction based on a firm's intrinsic value. The key idea is that they do not mechanically extend past trends. In contrast, the extrapolative expectations lines slope upward or downward, projecting recent price momentum into the future. Investors following this behavior assume that stocks that have gone up have a higher chance of continuing to rise, and those that have fallen have a higher chance of continuing to fall. This bias leads to excessive optimism or pessimism, especially after strong price movements. When extrapolative beliefs dominate, they can result in overreaction, for instance, overbuying a stock that recently surged or overselling one that recently declined. These behaviors create deviations from fundamental values, potentially contributing to mispricing, bubbles, and crashes, as emphasized in prior work (Barberis et al., 2018; Liu et al., 2021).

In addition to returns, the investor can extrapolate based on other characteristics of the price path as well. Identical cumulative returns can evoke different investor reactions depending on the underlying price path. Experimental evidence shows that salient features of a stock price trajectory, such as peaks, troughs, and crashes, strongly influence perceived risk, beyond what is explained by returns or volatility alone (Borsboom and Zeisberger, 2020). Investors tend to prefer price paths where values initially decline and then recover, and are least satisfied with the reverse pattern, regardless of final outcomes (Grosshans and Zeisberger, 2018). Such patterns have been shown to systematically affect risk perception, return expectations, and trading behavior. Nolte and Schneider (2018) further demonstrates that investors place greater weight on recent outcomes, implicitly anchor on focal prices, and assess risk based on path amplitude rather than return variance. Bansal and Jacob (2022) shows investors see convexity as a signal of continued upward momentum and reduce the selling propensity of such stocks. Research also analyzed the positive association between the convexity of net asset value and the fund flows into the mutual fund. This shows us that investors prefer to load up on stocks that have a down-to-up (convex) price path rather than an up-to-down (concave) price path. This tendency to extrapolate based on the convexity of the price path may contribute to mispricing, as evidenced by Gulen and Woeppel (2025), who show that price path convexity is associated with negative future returns, indicating that convexity reflects mispricing.

In Figure 2, we illustrate how investors can form expectations not only based on return magnitudes but also on the trajectory of price movements, specifically, whether the path is convex (decline followed by rise) or concave (rise followed by decline). The figure presents two stocks that began and ended at the same price level over the past 100 days, implying identical cumulative returns. However, the paths they take differ markedly. One stock follows a convex, ”U-shaped” path characterized by an initial decline and subsequent recovery, reflecting upward momentum near the end of the period. The other stock follows a concave, ”inverted U-shaped” path, rising initially before declining, indicating downward momentum approaching the present.

Although both price series converge at the same endpoint, the curvature shapes investor beliefs differently. The extrapolated future paths (dashed lines) depict how investors project recent momentum forward. For the convex path, the upward momentum observed at the end leads to expectations of continued gains; for the concave path, the recent decline prompts expectations of further losses. These patterns contrast with the rational expectation, shown as a flat dashed line, which assumes that future prices are independent of past price movements.

The figure highlights a key insight: even when cumulative returns are identical, investors may extrapolate differently based on the curvature of the price path. Convexity may serve as an additional signal that drives extrapolation beyond what is explained by past returns alone. Investors may exhibit greater net buying (selling) of stocks with convex (concave) price paths, potentially resulting in overvaluation (undervaluation), after controlling for past returns and relative valuation. This underscores the role of price path curvature as an implicit characteristic influencing investor extrapolation and contributing to mispricing. This tendency to extrapolate based on convexity may also be reflected in the behavior of other market participants, particularly intermediaries between firms and investors, such as financial analysts.

Analysts are sophisticated market participants who play a central role in the dissemination of information and the interpretation of firm fundamentals, thereby shaping investor beliefs and influencing capital markets (Lang et al., 2024; Merkley et al., 2017). Despite their expertise and informational advantages, analysts are not immune to behavioral biases. They may exhibit limited attention and rely on heuristics, such as herding with the consensus, repeating prior forecasts (self-herding), and issuing rounded estimates—reflecting cognitive shortcuts (Hirshleifer et al., 2019). Like investors, analysts may also anchor on salient but uninformative benchmarks, such as the 52-week high. Although this price merely reflects historical performance and lacks predictive value, analysts are more likely to issue downgrades as prices approach this perceived peak, treating it implicitly as a ceiling despite the absence of fundamental justification (Li et al., 2021). Collectively, this evidence indicates that analysts, notwithstanding their sophistication, are susceptible to systematic behavioral biases.

The mixed evidence on analyst rationality versus bias extends into the extrapolation literature as well. A growing body of research examines how past returns shape analyst recommendations, controlling for fundamentals and other firm-specific factors. On one hand, several studies find that analysts' forecasts and recommendations exhibit extrapolative tendencies, mirroring behavioral biases documented among broader investor populations (Cannon and Lynch, 2025; Jegadeesh et al., 2004). These findings suggest that analysts may overproject recent trends in firm performance, thereby contributing to market mispricing. On the other hand, a contrasting literature on target prices emphasizes the disciplining role of analysts, who can identify and correct mispricings arising from investor overreaction or return-chasing behavior. From this perspective, analysts function as a stabilizing force, guiding prices back toward fundamentals (Brav et al., 2005; Renxuan, 2020). This interplay, where analysts extrapolate and act contrarian as well based on past returns, makes them a compelling group for studying how they take into account price path convexity to make their recommendations.

Our analysis focuses on the relationship between convex price trajectories and analysts' recommendation decisions. If analysts are extrapolative and align with investor-driven mispricing, they may issue favorable (unfavorable) recommendations when the recent price path is convex (concave). Conversely, if analysts act as contrarian forces countering investor bias, they may issue unfavorable (favorable) recommendations in response to convex (concave) price paths.. The variable we construct to capture curvature is higher when the price path is more convex and lower when it is concave. For ease of interpretation, we refer to this as high versus low convexity.

We examine changes in analyst recommendations as a signal of their stance on the stock, since prior research suggests that recommendation levels themselves are biased, particularly toward growth stocks, and thus less informative (Jegadeesh et al., 2004). A recommendation is classified as a downgrade if it is more pessimistic relative to the prior recommendation, an upgrade if it is more optimistic, and a reiteration if it remains unchanged. Our analysis focuses specifically on downgrades, as they often reflect perceived overvaluation, just as upgrades typically follow perceived undervaluation. Our first hypothesis is as follows:-

Hypothesis 1: Higher convexity is associated with a higher downgrade

Identifying the relevant duration over which analysts perceive convexity is inherently complex, as analysts may focus on different time horizons when assessing price trajectories. To address this, we measure the convexity of a stock's price path over the past 3, 6, and 12-month intervals that correspond to typical analyst recommendation horizons, which are usually updated on a quarterly, semi-annual, or annual basis. While analysts may operate on longer horizons, investors tend to focus on shorter-term price movements when making trading decisions (Borsboom et al., 2022). Consequently, analysts may also anchor on more recent trends when interpreting convexity as a signal. To account for this, we place greater weight on recent observations when estimating convexity, allowing us to capture potential analyst overextrapolation of short-term price dynamics.

We then examine the relationship between convexity and recommendation downgrades across deciles (or quantiles) of the convexity distribution to test whether the association is monotonic or nonlinear, providing deeper insight into the nature and consistency of the relationship.

Building on the baseline relationship between convexity and analyst behavior, it is essential to consider how this association interacts with recent stock performance, both in absolute terms and cross-sectionally. Analysts do not evaluate price trajectories in isolation; instead, they interpret convexity in the context of broader return dynamics. In this framework, convexity may function as an incremental signal, layered atop return-based evaluations. Consequently, the association between convexity and downgrades may vary depending on the analyst's interpretation of both convexity and recent return performance.

Figure 3 presents an illustrative price path of a stock having positive returns. It demonstrates how investors may extrapolate based on both recent returns and the shape of the trajectory (i.e., convexity). As shown, extrapolating solely from past returns can already drive prices beyond levels justified by fundamentals. If convexity is further interpreted as a signal of continued strong performance, suggesting future returns even greater than those already realized, buying pressure may increase further, amplifying mispricing. The resulting price path, therefore, may reflect the compounded effect of extrapolation on both returns and convexity. In such settings, part of the mispricing stems from return-based expectations, and part from extrapolative interpretations of price path curvature. Analysts, accordingly, may account for both elements in forming their recommendations, seeking to disentangle the distinct contribution of convexity to mispricing.

Prior research suggests that analysts often extrapolate from recent return trends when issuing recommendations. Jegadeesh et al. (2004) show that analysts are more likely to issue favorable recommendations for momentum stocks by adopting an extrapolative outlook. This finding is echoed in Lockwood et al. (2023) and Cannon and Lynch (2025), who also document analysts' tendency to chase past returns.

We examine how the association between price path convexity and analyst downgrades is moderated by recent return performance. This analysis helps uncover whether analysts exhibit extrapolative behavior responding to recent trends by projecting them forward or act as contrarians who seek to correct perceived mispricing. If analysts are extrapolative, they may interpret high convexity combined with strong recent returns as a signal of sustained momentum, thereby reducing the likelihood of a downgrade. In contrast, if analysts behave as contrarians, they may view high past returns in the presence of high convexity as a byproduct of extrapolation, increasing the probability of a downgrade to correct mispricing. This dichotomy motivates our second hypothesis:

Hypothesis 2: The association of convexity on downgrades is stronger following higher past returns.

We will also examine past returns absolutely and cross-sectionally, by distinguishing between winner and loser stocks. We take past returns of the same duration as we have taken of convexity i.e., past 3 months, 6 months, and 12 months.

2.1 Cross-sectional heterogeneity tests

We will be examining some cross-sectional heterogeneities based on analyst characteristics, firm characteristics, and macroeconomic environment.

We examine how analyst experience and attention moderate the relationship between convexity and recommendations. The prior literature shows that experienced, reputable, and focused analysts are less susceptible to heuristics and cognitive biases (Hirshleifer et al., 2019; Li et al., 2021; Loh and Stulz, 2011). If convexity acts as a non-reflective anchor, analysts with less experience or limited attention may be more prone to extrapolate and issue upgrades. Conversely, If convexity reflects mispricing, experienced and attentive analysts may be more likely to issue downgrades in response.

We next examine whether firm-level characteristics moderate the association between price path convexity and analyst downgrades. Prior research suggests that analysts may exhibit behavioral biases when covering firms with high information asymmetry—typically those that are smaller in size, exhibit high idiosyncratic volatility, or have low institutional ownership (Li et al., 2021). However, we argue that the association between convexity and analyst downgrades should be more pronounced in firms with low information asymmetry. In such firms, stock prices are more likely to reflect fundamental information rather than noise or investor sentiment (Hong and Stein, 1999), making price path convexity a cleaner and more credible signal of extrapolative investor behavior. Additionally, mispricing in low information asymmetry firms is more likely to be corrected promptly, making them safer targets for downgrades when convexity is high. In contrast, where information asymmetry is high, persistent noise and delayed correction of mispricing may reduce the informativeness and actionability of the convexity signal.

In addition, we explore how periods of heightened macroeconomic uncertainty influence the role of convexity. Consistent with Xu et al. (2023), we expect that during such periods, macro-level factors dominate market dynamics and crowd out firm-specific signals, thereby diminishing the influence of convexity on analyst recommendations. Finally, we investigate the interaction between market sentiment and convexity. As shown by Wu et al. (2018), elevated investor sentiment is typically associated with fewer downgrades, which may attenuate the effect of convexity on analyst behavior. We also examine the relationship between convexity, downgrades, and future returns, aiming to assess the informativeness of analyst recommendations based on subsequent stock performance.

Next, we look into the sample used and the methodology required to execute the study.

3 Data and methodology

3.1 Sample

The data for this study is sourced from the I/B/E/S recommendation file, covering the period from 1994 to 2022. We adjusted the recommendation after 16:00:00 hrs to the next trading day, as well as adjusted the holiday and weekend recommendations to the next trading day.

I/B/E/S encodes analyst recommendations on a five-point scale ranging from 1 (strong buy) to 5 (sell) with buy, hold, and underperform coming in between. Consistent with prior research, we focus on individual analyst recommendation changes, as recommendation levels alone have been shown to be less informative (Jegadeesh et al., 2004; Li et al., 2021). Following prior literature, we define a downgrade as a binary variable equal to 1 if an analyst's current recommendation is more pessimistic than their previous one. Recommendation changes range from -4 to 4, where values from -4 to -1 are classified as upgrades, 0 indicates no change, and 1 to 4 are classified as downgrades. Following Jegadeesh et al. (2004), we apply a 12-month window to exclude stale recommendations. If the recommendation is not revised within 12 months, it will be considered stale, and the next recommendations will be considered as re-initiation. First time recommendations and re-initiations are excluded, as they lack a previous reference point and offer limited information about directional change. Finally, we merge the recommendation data with CRSP stock price data, through which we have estimated the price path convexity. CRSP stock prices are adjusted for dividends and splits. We also filter out the illiquid stocks and restrict the sample to stocks that traded on all days in the preceding 250 trading days. We also winsorized all the independent variables at the 1% and the 99% level.

3.2 Methodology

We employ the price path convexity measure from Gulen and Woeppel (2025), which quantifies the curvature of a time-series price path by computing the scaled difference between the midpoint price and the average price over the period. A positive value indicates that the midpoint lies above the average, consistent with a convex price path—one that initially declines and then rises.

Conversely, a negative value suggests a concave trajectory, where prices first rise and subsequently fall. Values near zero reflect linear or relatively unshaped price paths. Thus, higher (more positive) values indicate stronger convexity, while lower (more negative) values indicate stronger concavity.

$$\text{Convexity} = \frac{\left(\frac{P_1+P_N}{2} - \bar{P}\right)}{\frac{P_1+P_N}{2}}$$

where P_{mid} is the midpoint price (typically the price halfway through the observation window), and $\bar{P}$ is the average price over the same period.

To account for sensitivity to more recent price movements, we also compute a weighted version of the convexity measure using exponentially increasing weights. In this specification, greater emphasis is placed on more recent observations, with the most recent price receiving twice the weight of the earliest one, and intermediate prices weighted accordingly in an exponentially decreasing manner. We calculate this weighted convexity measure over three distinct time windows: the past 3 months, 6 months, and 12 months.

$$\text{Convexity} = \frac{N}{P_1 + P_N}\left(\frac{\sum_{t=1}^{N-1} w_t \cdot \Delta P_t}{\sum_{t=1}^{N-1} w_t} - \frac{P_N - P_1}{N}\right)$$

We use a downgrade dummy equal to 1 if the analyst's current recommendation is more pessimistic than their previous one as the dependent variable in our regression. Since the outcome is binary, we employ a linear probability model (LPM) to estimate the association of price path convexity with the likelihood of a recommendation downgrade. The convexity variable is lagged by two days relative to the dependent variable to account for the information leakage and analyst report preparation time. Table 1 shows the description of the variables used in the study. Table 2 shows the summary statistics for the basic variables.The stock price variables shown here correspond to the 6-month window, as the baseline analysis focuses on 6-month convexity; results using other durations are presented in the appendix. Convexity appears largely symmetric, with a median around zero. To aid interpretation, the convexity variable is standardized to have a mean of 0 and a standard deviation of 1. Specifically, we run the following LPM regression:

$$\begin{aligned} \text{Downgrade}_{ijt} = \beta_0 + \beta_1 \,\text{Convexity}_{i(t-2)} + \beta_x \,\text{Controls}_{x(t-2)} \\ + \gamma_i + \delta_j + \alpha_s t + \lambda_u + \varepsilon_{ijt} \end{aligned} \tag{1}$$

We estimate the association of price path convexity with probability of a downgrade using the following fixed-effects specification, where i indexes firms, j indexes analysts, t denotes time (year), u refers to the year quarter, and s refers to industry classifications (defined by 2-digit SIC codes).

β_1 captures the association of convexity and the probability of a downgrade. The model includes controls for stock-level characteristics such as return skewness, volatility, turnover, size, and market beta; firm-level fundamentals including size, earnings, and capital expenditures; and analyst-level attributes such as experience, coverage breadth, and attention. We include fixed effects of firm, fixed effects of analyst, fixed effects of year-quarter, and industry × year fixed effects to account for unobserved heterogeneity. Standard errors are clustered at the analyst ID and year-quarter for baseline specification.

4 Findings and discussion

This section presents the core findings and robustness checks from the analysis. To facilitate interpretation, the convexity measure is standardized to have a mean of 0 and a standard deviation of 1. The main results are based on variables estimated over the past 6 months, while results from alternative horizons (3 months and 12 months) are reported in the Appendix. I use an exponential measure of convexity where recent prices have higher weights relative to the distant ones. Results for the simple measure of convexity are reported in the appendix.

Table 3 presents the association between price path convexity and analyst downgrades. The results reveal a positive and statistically significant association, consistent with the notion that analysts are contrarian and take convexity as an informative anchor to counter the mispricing by investor extrapolation on it. Specifically, a one standard deviation increase in convexity is associated with approximately a 3% increase in the probability of a downgrade. This suggests that analysts view convex price paths as indicative of potential mispricing due to investor extrapolation and respond with more pessimistic recommendations, acting as a stabilizing force in the market.

Similar patterns are observed for other return horizons. The results remain statistically significant when convexity is measured over the past 3 months (Table A1) and the past 12 months (Table A2). These findings highlight that analysts respond to convexity signals across varying durations, indicating the robustness of the effect, however the higher coefficient is for more recent observations as larger duration attenuates the essence of convexity.

To ensure that these results are not driven by confounding factors such as past returns, volatility, or firm and analyst characteristics, we control for a comprehensive set of variables. Additionally, we employ a fixed effects specification that accounts for unobserved heterogeneity at multiple levels, reinforcing the validity of our inference.

We also examine whether the relationship between convexity and downgrades is linear or exhibits more complex patterns. It is plausible that analysts respond differently to extreme convexity and concavity—possibly issuing similar recommendations at both ends due to perceived noise or overreaction—while responding more distinctly to linear price paths. To test this, we divide convexity into yearly deciles and estimate the predicted probability of downgrades for each decile. Figure 4 shows the predicted probability of downgrades by each convexity decile. The results are mostly consistent and show the linear relationship between convexity and downgrades.

Analysts typically issue recommendations on a five-point scale, ranging from strong buy to sell. Changes in these recommendations are categorized as upgrades, downgrades, or reiterations. To further explore whether the tendency to downgrade in response to convex price paths is consistent across all prior recommendation levels, we analyze the interaction between convexity and the analyst's last issued recommendation. Specifically, for each observation, we identify the most recent recommendation issued by the analyst and stratify the convexity measure into five quantiles within each recommendation category. We then examine whether the probability of a downgrade differs across these convexity quantiles for each initial recommendation level. Table 4 presents the results, showing the difference in downgrade probabilities between the highest and lowest convexity quantiles within each prior recommendation category. The results indicate that the positive association between convexity and downgrades holds across all previous recommendation levels, suggesting that analysts consistently factor in price path convexity when revising their recommendations, regardless of the starting position.

One potential concern is that the observed association between convexity and downgrades may simply reflect the influence of past returns—either overshadowing the role of convexity or being inadvertently captured by it. To disentangle these effects, we classify both convexity and past returns into five quantiles, constructed annually, and examine how the relationship between convexity and downgrades varies across different levels of past returns.

Table 5 presents the results, showing the difference in downgrade probabilities between the highest and lowest convexity quantiles within each return quantile. We find that the effect of convexity persists even after conditioning on return levels, particularly when returns are moderate to high. The association weakens only in the lowest return quintile, possibly due to other overriding signals of poor performance. Overall, the results suggest that convexity offers incremental explanatory power beyond past returns, with its impact on downgrade likelihood strengthening as prior returns increase. We also examine how convexity is associated with other analyst decisions, namely upgrades and reiterations. Figure 5 presents the summary statistics of downgrades, upgrades, and reiterations across convexity deciles. The statistics indicate that the effect of convexity is concentrated in the highest deciles, as the distribution of upgrades and downgrades appears similar across the lower deciles. Notably, reiteration patterns offer additional insight: analysts are more likely to take active positions (i.e., issue upgrades or downgrades) when convexity is more pronounced. However, when convexity is at an intermediate level and does not provide a clear signal, analysts are more inclined to issue passive recommendations (i.e., reiterations). This suggests that analysts act decisively—through upgrades or downgrades—when convexity is both evident and interpretable, whereas in more ambiguous cases, they adopt a "wait and watch" approach by reiterating previous recommendations.

As an illustrative example, Figure 6 shows Tesla's stock price movements in 2012 alongside recommendations made by an analyst named O'NEILL. This example is based on the convexity of the preceding three months, chosen for visual clarity within a shorter time frame. The analyst's first recommendation of the year is a BUY, which represents an upgrade from the previous HOLD (issued more than three months prior, and therefore not shown). This decision follows a clearly concave price path. The subsequent recommendation is a HOLD, representing a downgrade, with visible convexity in the prior three months. The final recommendation is a SELL, another downgrade following a convex price path. This example illustrates how analysts may incorporate price path curvature into their recommendation decisions, aligning with our broader findings on convexity and downgrades.

As an alternative specification, I employ a logit regression to examine the relationship between convexity and the likelihood of downgrades. Table A3 presents the results, controlling for analyst, firm, industry-by-year, and year-quarter fixed effects. The estimates are stronger, indicating that a one standard deviation increase in convexity is associated with approximately a 10% increase in the probability of a downgrade, based on the interpretation of the log-odds ratio. Additionally, I run a regression using the actual recommendation level as the dependent variable, rather than just focusing on downgrades or upgrades. Table A4 shows that higher convexity is associated with a greater likelihood of unfavorable recommendations (i.e., movement towards Strong Sell (5) or away from Strong Buy (1)). This reinforces the interpretation that convexity is linked to more pessimistic analyst views. Finally, I also test a simpler version of the convexity measure—without applying exponentially higher weights to more recent price movements. As shown in Table A5, the main results continue to hold, confirming the robustness of the association.

4.1 Association of convexity with stock prices and return characteristics

In this section, we explore how the relationship between price path convexity and analyst downgrades is moderated by past stock returns, both in absolute terms and in the context of momentum versus contrarian stock classifications. The Table 5 shows the average probability of downgrade in each return and convexity quantile, showing the propensity of downgrade increasing with increase in return quantiles.

To facilitate interpretation in the regression, we standardize past returns to have a mean of 0 and a standard deviation of 1. While previous regressions employed an extensive set of fixed effects, including high-dimensional interactions, we scale this back in the current and subsequent sections to preserve degrees of freedom and maintain statistical power. Specifically, we include fixed effects for analyst, firm, industry-by-year, and year-month, and also control for a full set of firm and analyst-level covariates.

We focus on convexity and return measures computed over the past six months and present results for three key interactions: convexity with absolute past returns, convexity with momentum stocks, and convexity with contrarian stocks. Momentum and contrarian stocks are defined based on the quintiles of past six-month returns, where stocks in the top quintile are classified as momentum and those in the bottom quintile as contrarian.

Column (1) of Table 6 shows the results for the interaction between convexity and absolute past returns. The positive interaction term suggests that the association between convexity and downgrades becomes stronger when past returns are higher. This supports the interpretation that analysts adopt a contrarian stance—viewing high returns achieved alongside a convex price path as indicative of potential mispricing, and thus responding with a higher likelihood of issuing downgrades.

Columns (2) and (3) present results for momentum and contrarian stocks, respectively. The findings indicate that convexity has a stronger association with downgrades for momentum stocks, consistent with the view that analysts expect reversals in stocks that have recently experienced strong performance and exhibit convex price patterns—further signaling overvaluation. In contrast, for contrarian stocks with low past returns, the interaction with convexity is weaker, suggesting that convexity alone may not be interpreted as mispricing in such cases, possibly because the recent underperformance does not reinforce the extrapolative signal based on convexity, and the association gets weaker but persists nonetheless.

The negative coefficient on past returns suggests that analysts are less likely to issue downgrades following periods of strong stock performance, consistent with extrapolative behavior of analysts (Cannon and Lynch, 2025; Lockwood et al., 2023)

4.2 Association of convexity with analyst characteristics

Hirshleifer et al. (2019); Li et al. (2021) suggest that inexperienced analysts are more prone to relying on irrelevant anchors when forming recommendations. In contrast, our earlier findings point to convexity as a potentially relevant anchor, with analysts demonstrating contrarian behavior in response to convex price patterns. Building on this, we expect that the informativeness of convexity is more likely to be recognized by analysts who are more experienced, attentive, and less subject to cognitive fatigue.

Table 7 reports the interaction effects between price path convexity and various analyst characteristics. Column (1) incorporates the logarithm of an analyst's total experience (in years) since their first appearance in the I/B/E/S database. Column (2) measures firm-specific experience, capturing the analyst's tenure covering a given firm. Column (3) considers the analyst's experience relative to peers covering the same firm in a given year. Mostly, the interaction terms are positive and significant, indicating that more experienced analysts are more likely to issue downgrades in response to convex price paths. This supports the view that convexity-related downgrades reflect informed decision-making rather than anchoring bias.

Columns (4) and (5) examine the moderating effects of fatigue and workload. Following Hirshleifer et al. (2019), fatigue is proxied by the number of forecasts an analyst issues earlier on the same day, while analyst busyness is measured by the total number of forecasts made by the analyst over the year. The results suggest that both fatigue and high workload reduce the analyst's responsiveness to convex price patterns, weakening the association between convexity and downgrades. Taken together, these findings reinforce the notion that convexity is a salient and informative signal, one that is more likely to be acted upon by analysts who are more experienced, focused, and cognitively available. For this and all subsequent heterogeneity tests, standard errors are clustered at the analyst level.

4.3 Association of convexity with firm characteristics

We also investigate how the relationship between price path convexity and analyst downgrades varies with the level of firm specific information asymmetry. Prior research suggests that both convex price paths and associated mispricing are more prevalent among firms with high information asymmetry (Gulen and Woeppel, 2025). However, the correction of such mispricing may be more prompt in firms with low information asymmetry, due to lower arbitrage costs and more efficient information dissemination in the market. As a result, downgrading based on convexity may be perceived as less risky and more effective in these firms. Analysts, therefore, may exhibit greater proactiveness in issuing downgrades when the firm is more transparent and information is more readily available.

To examine this, we classify firms annually into high versus low information asymmetry groups based on whether their characteristics fall above or below the yearly cross-sectional median. The proxies used for information asymmetry include market capitalization (size), idiosyncratic volatility, firm age since IPO, recent earnings forecast errors, institutional ownership, and the number of analysts covering the firm.

Table 8 reports the results. Consistent with our expectations, the association between convexity and the probability of a downgrade is significantly weaker for firms typically characterized by higher information asymmetry—namely, those with smaller size, higher idiosyncratic volatility, larger forecast errors, lower institutional ownership, and higher estimated probability of informed trading (PIN).

Interestingly, analyst coverage shows a contrasting effect. Firms with high analyst coverage exhibit a diminished sensitivity to convexity in downgrade decisions. One possible explanation is that increased analyst attention facilitates faster correction of mispricing, thereby reducing the marginal informativeness of convexity as a signal for such firms. Overall, the results suggest that analysts are more likely to act on convexity signals in firms with lower information asymmetry. This may reflect a more conservative approach—where analysts prefer to act when the mispricing signaled by convexity is more likely to be corrected. Alternatively, in firms with high information asymmetry, convex price paths may reflect private information or uncertainty rather than pure mispricing, weakening the predictive power of convexity for analysts' decisions.

4.4 Association of convexity with downgrades during high uncertainty and sentiment

We further examine how macroeconomic uncertainty and market sentiment affect the relationship between price path convexity and analyst downgrades. We hypothesize that high macroeconomic uncertainty may attenuate the effect of convexity, as macro-level shocks tend to crowd out firm-specific information (Xu et al., 2023). Similarly, high investor sentiment is generally associated with a lower frequency of analyst downgrades (Wu et al., 2018), potentially weakening the informativeness of convexity signals.

To capture macroeconomic uncertainty, we use three measures: the Economic Policy Uncertainty (EPU) index (Baker et al., 2016), the Volatility Index (VIX) (Adrian et al., 2019), and NBER-defined recession periods (Romer and Romer, 2020). EPU and VIX are converted into binary indicators based on whether they exceed the 75th percentile in their respective time series, while NBER recession months are inherently represented as a binary dummy. The first three columns of Table 9 report the results. Across all three uncertainty proxies, we find that macro uncertainty significantly dampens the positive association between convexity and the likelihood of a downgrade. This finding is consistent with the view that during uncertain times, analysts shift their attention away from firm-level signals (such as price path convexity) and toward broader macroeconomic risks, leading to a reduced responsiveness to convexity-based mispricing cues.

We next examine market sentiment using two widely cited indices: the AAII investor sentiment survey (Cassella and Gulen, 2018) and the Baker–Wurgler sentiment index (Baker and Wurgler, 2006). As with the uncertainty measures, we define high sentiment periods as those exceeding the 75th percentile. The last two columns of Table 9 show that the interaction between sentiment and convexity is also significantly negative.

One plausible explanation is that elevated market sentiment leads to a general optimism bias among investors and analysts alike, making downgrades less likely overall. Alternatively, high sentiment may distort price signals, causing convex price paths to reflect investor over-exuberance rather than true mispricing, thereby weakening the signal's reliability for downgrade decisions. Overall, our results suggest that the informativeness of convexity in driving downgrades is statedependent—being significantly attenuated during periods of high macroeconomic uncertainty and investor optimism.

4.5 Association of convexity and downgrades with future returns

Analysts issue downgrades when they expect a firm's future performance to deteriorate, often anticipating lower expected returns. In this section, we investigate whether analyst downgrades associated with price path convexity are indeed informative, in the sense that they predict lower future returns. Li et al. (2021) examines the informativeness of analyst downgrades issued near a stock's 52-week high. They find that such downgrades do not lead to significantly lower future returns compared to firms that were not downgraded, suggesting that the 52-week high serves as a salient but irrelevant anchor, leading to biased recommendations.

We extend this idea by exploring whether convexity serves as a relevant anchor by examining the interaction between convexity and analyst downgrades in predicting future returns. Specifically, we assess whether firms with high convexity that receive a downgrade experience lower subsequent returns compared to firms with similar convexity that are not downgraded. If analysts are rational and convexity is an informative signal, we should observe significantly worse future returns for the downgraded group.

To test this, we estimate regressions where the dependent variable is future stock returns measured over various horizons—1 month, 3 months, 6 months, and 12 months—and the key independent variables are convexity, a downgrade indicator, and their interaction. The results are presented in Table 10. We find that convexity alone is associated with negative future returns, consistent with the idea that convex price paths capture mispricing. Downgrades are also associated with subsequent negative returns, indicating that analysts are generally informative. Crucially, the interaction term between convexity and downgrades is significantly negative, suggesting that the returns are lower when a downgrade follows a convex price pattern.

These findings indicate that downgrades informed by convexity are not merely mechanical or biased responses to salient patterns but are rational and informative; analysts appear to correctly identify mispricing and act on it, and the market subsequently adjusts in the expected direction.

5 Robustness

To substantiate our results, we conduct a series of robustness checks to address concerns related to self-selection and omitted variable bias.

First, we implement propensity score matching (PSM), where control variables are matched using propensity scores, and convexity is defined as the treatment group based on the 75th percentile threshold. While this is not a fully robust PSM—since covariates may also vary with the independent variable, raising concerns of exogeneity—we attempt to mitigate this by exactly matching treatment and control observations within defined bounds. Table 11 presents the results. Column 1 shows results from simple matching based on control variables. Column 2 matches treatment and control within a year. Column 3 performs matching within firm and year. Column 4 does so within the analyst and year. Column 5 further restricts matching to within analyst, firm, and year. These layered bounds aim to improve robustness, especially in the absence of an exogenous shock that would allow a cleaner PSM. The results remain consistent across all specifications, underscoring the strength of the association between convexity and downgrades.

Second, we control for analyst recommendation timing. Analysts are not required to make recommendations at fixed intervals—they may intervene proactively in response to potential mispricing, react ex post after mispricing materializes, or even contribute to mispricing by issuing upgrades before later downgrading. To account for such variation, we restrict the sample to analysts who appear regularly—either for at least three consecutive quarters, or in the same quarter across at least three years. While this is not a definitive control for self-selection, given the absence of a clearly defined recommendation schedule, it provides a reasonable proxy. Table 12 presents the results. Columns 1 and 2 report estimates for analysts who appear in the same quarter for at least three and four years, respectively. Columns 3 and 4 show results for analysts who appear in at least three and four consecutive quarters, respectively. The findings remain robust under all specifications. The coefficient also improves, which signals that the dominant effect is the analyst recommending downgrades when analyzing convexity, and a lower chance of joining in by providing upgrades first and then providing downgrades, when the extrapolation is at its peak.

Third, we address potential confounding variables that could mimic the effect of convexity.

Table 13 summarizes the results. In Column 1, we control for extrapolated past returns. While the main analysis controls for raw past returns, investors are often more sensitive to recent returns. Thus, we construct an extrapolated return measure by applying exponentially declining weights to past returns, assigning more importance to recent performance. In Column 2, we address the correlation between returns and the convexity measure by conducting yearly cross-sectional regressions of convexity on extrapolated returns. We then use the residuals from these regressions as our new convexity measure to isolate the effect from returns. The results hold. In Column 3, we test whether the convexity effect is driven by very recent returns by decomposing six-month past returns into monthly components and including them as separate control variables. The results remain consistent. In Column 4, we rule out the possibility that proximity to a 52-week high—often associated with analyst downgrades and potentially correlated with convexity—is driving the effect. We remove observations where current prices are near the 52-week high and re-run the regression on the remaining sample. The results persist. In Column 5, we control for additional variables that may confound the relationship, such as return skewness, recent turnover, and the number of times prices cross the midpoint between the start and end values—factors that may distort convexity. Again, the results remain robust.

Overall, our findings consistently hold across all these robustness checks, reinforcing the conclusion that the convexity-downgrade association is strong, meaningful, and robust.

6 Discussion and conclusion

Analysts issue upgrades when they find a stock undervalued relative to its fundamentals and projected growth, expecting it to perform well in the future. Conversely, they issue downgrades when they perceive a stock to be overvalued and anticipate a correction. However, analysts have also been found to rely on stock price characteristics such as the 52-week high and recent returns in forming their recommendations. We examine an additional price-based characteristic—namely, the curvature of the stock's price path—and whether it influences analyst behavior. Our results indicate that the curvature of stock prices reflects investor extrapolation and is incorporated by analysts in their recommendations.

The literature on analysts' use of price characteristics offers mixed evidence. One strand suggests that analysts, like other investors, engage in extrapolation and issue favorable recommendations for stocks already being extrapolated by the market. Another perspective views analysts as contrarians who act as a corrective force against mispricing induced by investor extrapolation.

Our findings support the contrarian view: analysts are more likely to issue downgrades for stocks exhibiting convex price paths, which are associated with investor extrapolation and mispricing. This behavior is more pronounced among experienced, focused, and less fatigued analysts, suggesting that higher-quality analysts are better able to detect mispricing through curvature and act as a stabilizing force in the market. We also find that downgrades associated with convexity predict lower future returns, indicating that these recommendations are informed and that mispricing is ultimately corrected. Our results remain robust across a series of empirical checks.

Analysts have a responsibility to provide better information to market participants, and their buy and sell recommendations should ideally correlate with higher and lower future returns, respectively. However, they may not always be concerned with correcting mispricing; they can choose to ride momentum when they anticipate further extrapolation, and issue downgrades only when overextrapolation becomes unsustainable. Distinguishing between these motivations is complex and beyond the scope of our study. Our focus is on identifying the dominant effect of convexity, which tends to drive mispricing and is generally associated with more downgrades. Future research can further disentangle the specific firm characteristics under which analysts are more likely to issue upgrades versus downgrades.

References

Adrian, T., Crump, R. K., and Vogt, E. (2019). Nonlinearity and flight-to-safety in the risk-return trade-off for stocks and bonds. *The Journal of Finance*, 74(4):1931–1973.

Baker, M. and Wurgler, J. (2006). Investor sentiment and the cross-section of stock returns. *The journal of Finance*, 61(4):1645–1680.

Baker, S. R., Bloom, N., and Davis, S. J. (2016). Measuring economic policy uncertainty. *The quarterly journal of economics*, 131(4):1593–1636.

Bansal, A. and Jacob, J. (2022). Impact of price path on disposition bias. *Journal of Banking & Finance*, 143:106616.

Barberis, N., Greenwood, R., Jin, L., and Shleifer, A. (2018). Extrapolation and bubbles. *Journal of Financial Economics*, 129(2):203–227.

Borsboom, C., Janssen, D.-J., Strucks, M., and Zeisberger, S. (2022). History matters: How short-term price charts hurt investment performance. *Journal of Banking & Finance*, 134:106351.

Borsboom, C. and Zeisberger, S. (2020). What makes an investment risky? an analysis of price path characteristics. *Journal of Economic Behavior & Organization*, 169:92–125.

Brav, A., Lehavy, R., and Michaely, R. (2005). Using expectations to test asset pricing models. *Financial management*, 34(3):31–64.

Cannon, B. and Lynch, J. (2025). Return extrapolation and dividends. *Review of Finance*, page rfaf018.

Cassella, S. and Gulen, H. (2018). Extrapolation bias and the predictability of stock returns by price-scaled variables. *The Review of Financial Studies*, 31(11):4345–4397.

Chen, T., Harford, J., and Lin, C. (2015). Do analysts matter for governance? evidence from natural experiments. *Journal of financial Economics*, 115(2):383–410.

Da, Z., Huang, X., and Jin, L. J. (2021). Extrapolative beliefs in the cross-section: What can we learn from the crowds? *Journal of Financial Economics*, 140(1):175–196.

Greenwood, R. and Shleifer, A. (2014). Expectations of returns and expected returns. *The Review of Financial Studies*, 27(3):714–746.

Grosshans, D. and Zeisberger, S. (2018). All's well that ends well? on the importance of how returns are achieved. *Journal of Banking & Finance*, 87:397–410.

Gulen, H. and Woeppel, M. (2025). Price-path convexity and short-horizon return predictability. *Kelley School of Business Research Paper*, (2021-09).

Hirshleifer, D., Levi, Y., Lourie, B., and Teoh, S. H. (2019). Decision fatigue and heuristic analyst forecasts. *Journal of Financial Economics*, 133(1):83–98.

Hong, H. and Stein, J. C. (1999). A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of finance*, 54(6):2143–2184.

Jegadeesh, N., Kim, J., Krische, S. D., and Lee, C. M. (2004). Analyzing the analysts: When do recommendations add value? *The journal of finance*, 59(3):1083–1124.

Lang, M., Pinto, J., and Sul, E. (2024). Mifid ii unbundling and sell-side analyst research. *Journal of Accounting and Economics*, 77(1):101617.

Li, F., Lin, C., and Lin, T.-C. (2021). Salient anchor and analyst recommendation downgrade. *Journal of Corporate Finance*, 69:102033.

Liu, Q., Su, Z., Wang, H., and Yu, J. (2021). Extrapolation and risk-return trade-offs. *PBCSF-NIFR Research Paper Forthcoming*.

Lockwood, J., Lockwood, L., Miao, H., Uddin, M. R., and Li, K. (2023). Does analyst optimism fuel stock price momentum? *Journal of Behavioral Finance*, 24(4):411–427.

Loh, R. K. and Stulz, R. M. (2011). When are analyst recommendation changes influential? *The review of financial studies*, 24(2):593–627.

Merkley, K., Michaely, R., and Pacelli, J. (2017). Does the scope of the sell-side analyst industry matter? an examination of bias, accuracy, and information content of analyst reports. *The Journal of Finance*, 72(3):1285–1334.

Nolte, S. and Schneider, J. C. (2018). How price path characteristics shape investment behavior. *Journal of Economic Behavior & Organization*, 154:33–59.

Renxuan, W. (2020). Subjective return expectations. *Available at SSRN 3740792*.

Romer, C. D. and Romer, D. H. (2020). Nber recession dates: Strengths, weaknesses, and a modern upgrade. *Mimeo*.

Wu, Y., Liu, T., Han, L., and Yin, L. (2018). Optimistic bias of analysts' earnings forecasts: Does investor sentiment matter in china? *Pacific-Basin Finance Journal*, 49:147–163.

Xu, L., Zhang, X., and Zhao, J. (2023). Limited investor attention and biased reactions to information: Evidence from the covid-19 pandemic. *Journal of Financial Markets*, 62:100757.

Figure 1: Extrapolation with past returns

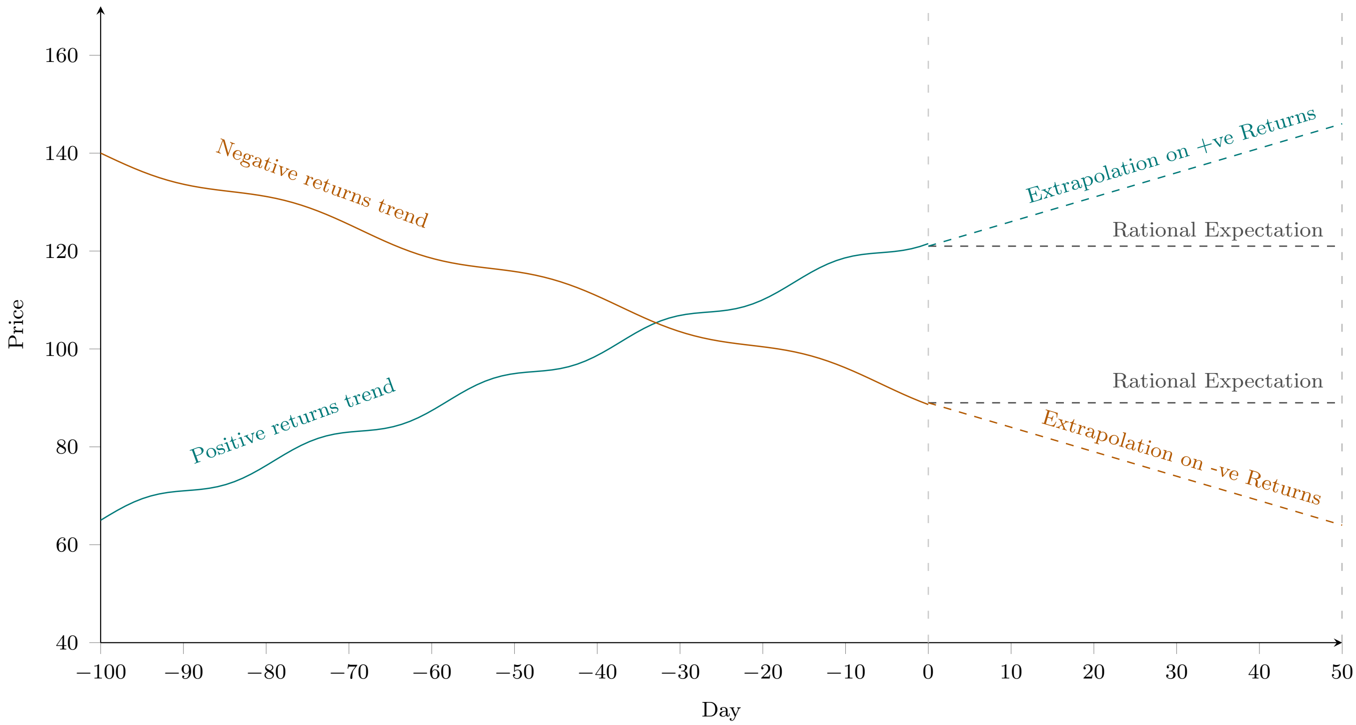

Figure 2: Extrapolation with price path convexity

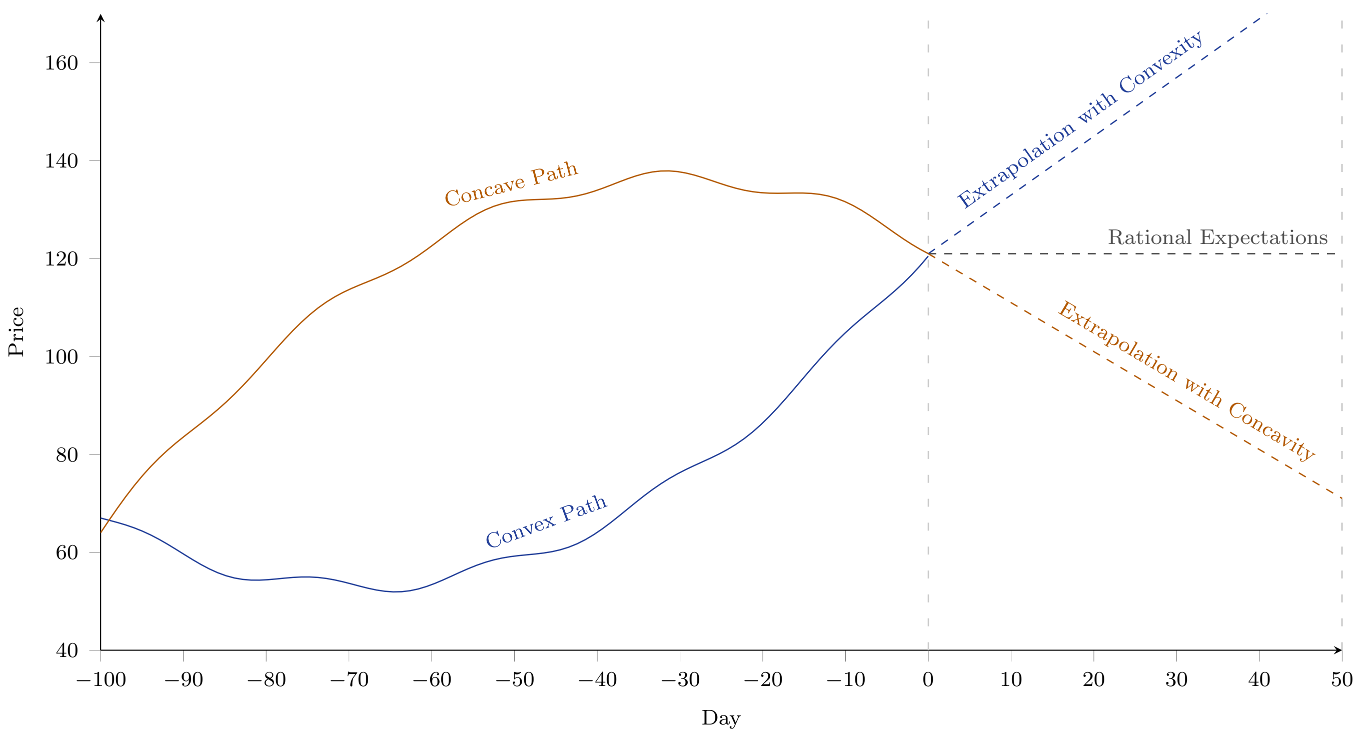

Figure 3: Extrapolation with price path convexity and past returns

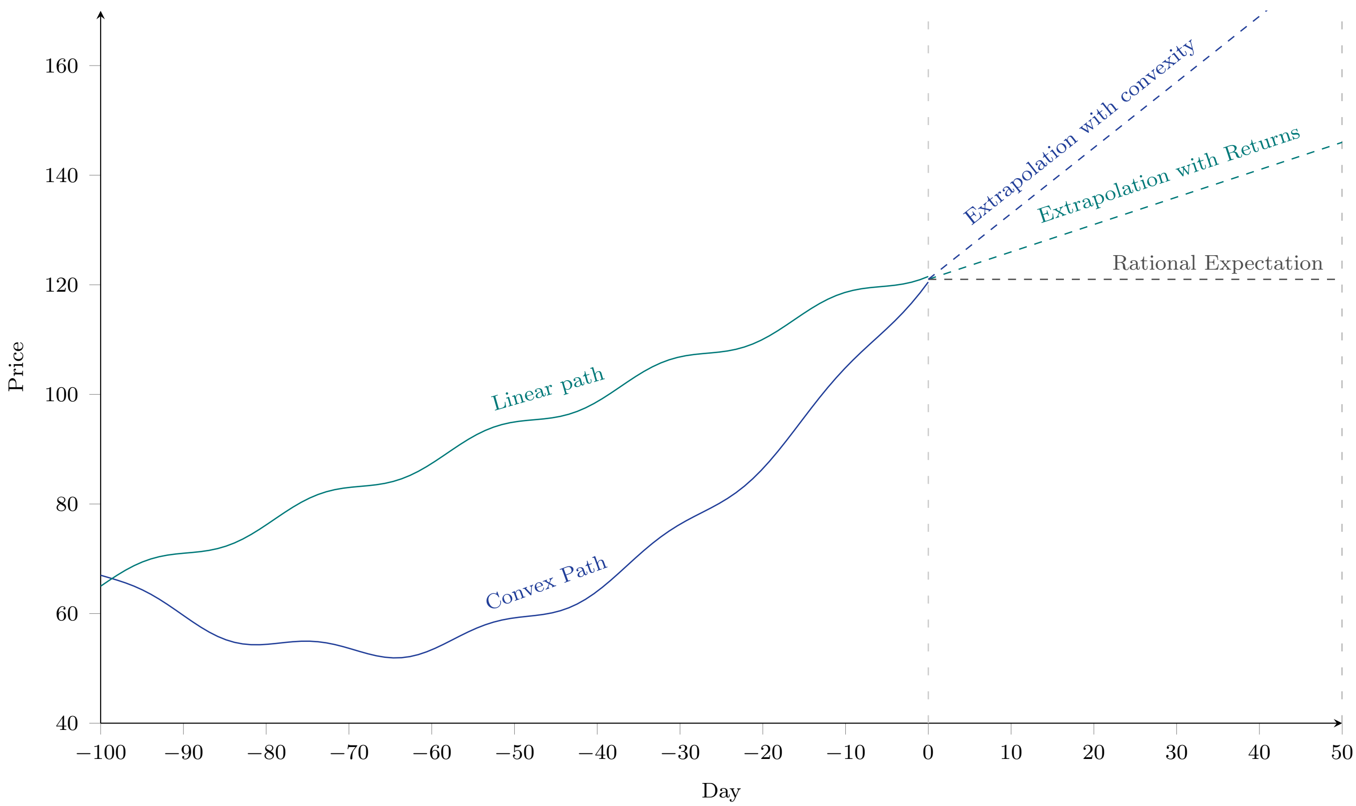

Figure 4: Predicted probability of downgrade by convexity decile

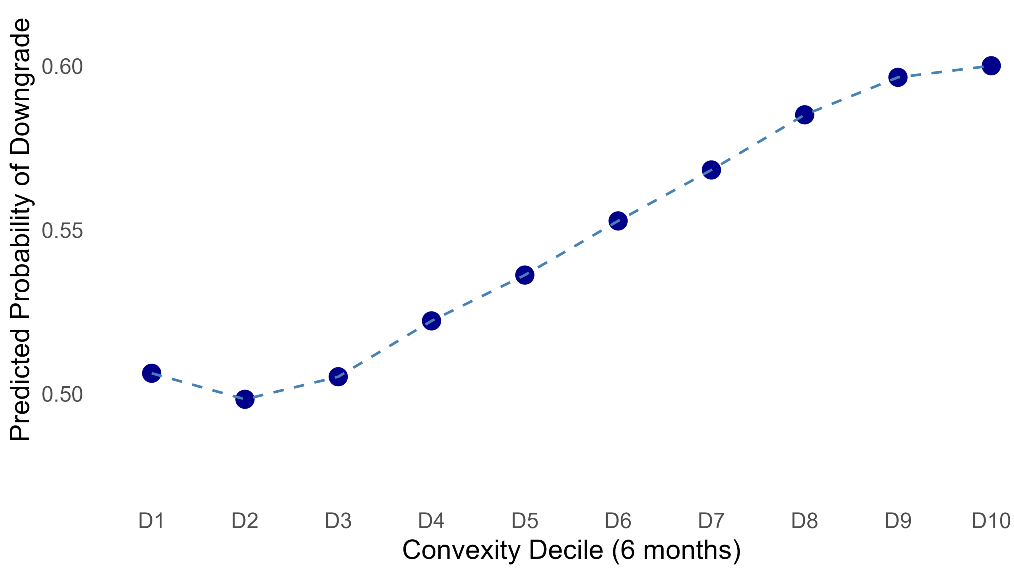

Figure 5: Probability of Downgrade, upgrade, and reiterations

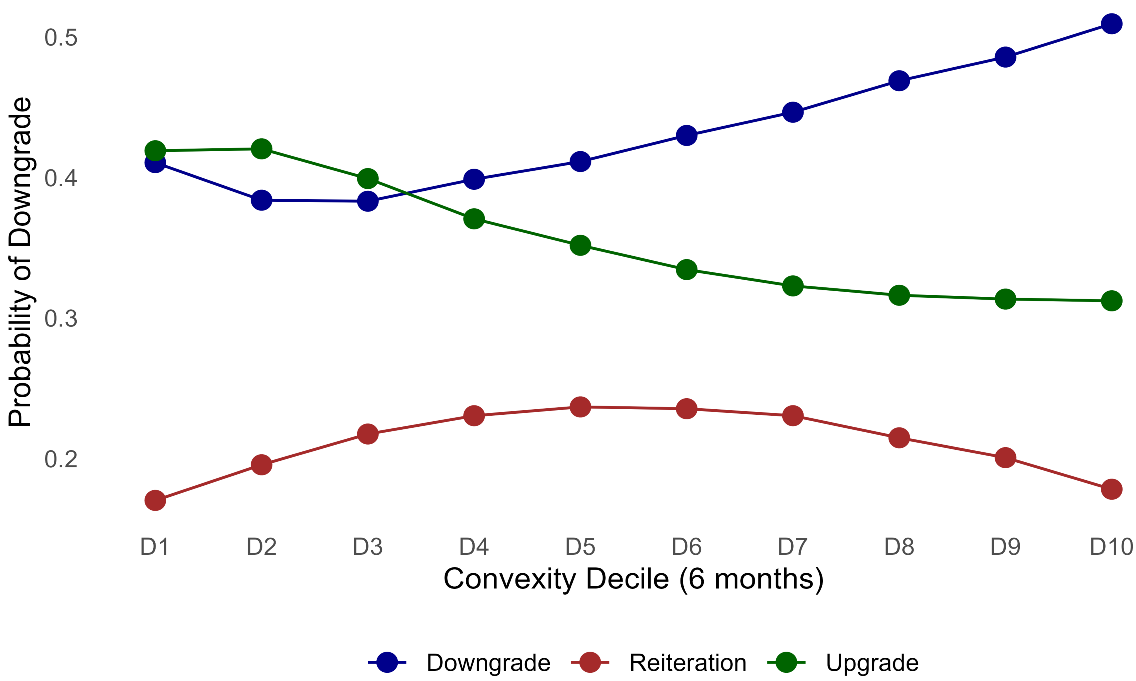

Figure 6: Tesla example, Convexity (3 months)

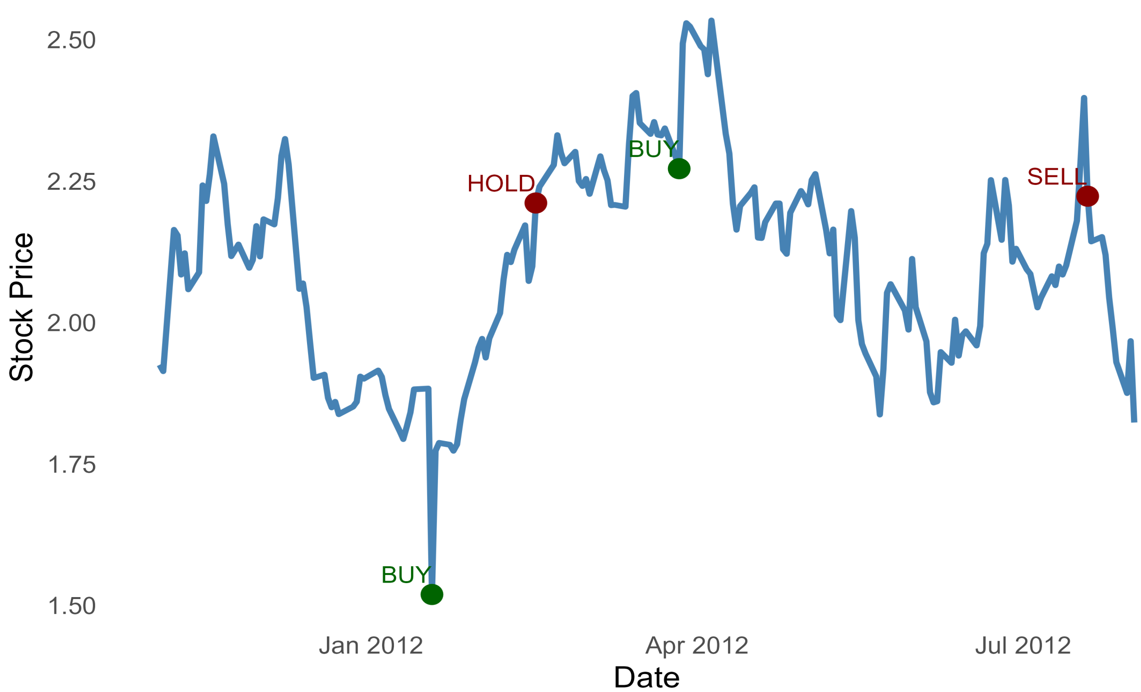

Table 1: Description of variables

Variable	Description
Downgrade	A dummy variable indicating a downgrade recommendation relative to the analyst's previous rating.
Price Path Convexity (Exponential, X-months lag)	A convexity measure that applies exponentially higher weights to more recent observations. It is estimated for X months ending at t–2.
Return over the past (X-Month Lag)	Stock return over the last X months ending at t–2.
Skewness (X-Month Lag)	The return skewness with exponentially higher weights for more recent observations. It is estimated for X months ending at t–2.
Turnover (X-Month Lag)	Average daily volume divided by number of shares over the last 3, 6, and 12 months with exponentially higher weights to recent observations, ending at t–2.
Approaching_52_wk_high	A dummy equal to 1 if the stock price at day t–1 is within 5% below the 52-week high.
Market beta	The CAPM beta estimated over the last 252 days ending at t–2.
Log market cap	The log of market capitalization of the firm on day t–2.
Log fatigue	Log of the number of previous forecasts given on a day by an analyst.
Analyst experience	Analyst's experience, measured as the log of the number of years between their first and current rating.
Idiosyncratic volatility	Residual volatility estimated using the residual returns over the past 252 days.
Institutional ownership	The portion of institutional ownership of a firm in a given quarter.
Capital gain overhang	The proportion of investors at a gain over the purchase price of an asset (as per Grinblatt and Han).
EPU, VIX, recession	Economic policy uncertainty, volatility index, and NBER recession months, sorted based on the 75th percentile and above.
AA, BW sentiment	AA investor survey and Baker-Wurgler sentiment index, sorted based on the 75th percentile.
Winner stocks (X months)	Stocks in the top quantile in a cross-section based on the last X months' returns.
Loser stock (X months)	Stocks in the bottom quantile in a cross-section based on the last X months' returns.
High PIN	Sorted cross-sectionally based on the probability of informed trading in the last quarter.

Table 2: Summary Statistics

Variable	Mean	SD	P25	Median	P75	N
Pricepath convexity 6 months	-0.0003	0.03	-0.02	0.00	0.02	348486
Return 6 months	0.0465	0.35	-0.15	0.03	0.20	348407
Skewness 6 months	0.1252	1.17	-0.29	0.13	0.55	348486
Volatility 6 months	0.0282	0.02	0.02	0.02	0.03	348486
Turnover 6 months	0.0103	0.01	0.00	0.01	0.01	348486
Approaching 52wh dummy	0.0964	0.30	0.00	0.00	0.00	333772
Approaching hist.high dummy	0.0576	0.23	0.00	0.00	0.00	356684
Beta	1.0902	0.46	0.78	1.05	1.35	350357
Log Analyst exp.	1.8077	0.76	1.39	1.79	2.40	359165
BM	0.5162	0.40	0.24	0.42	0.68	279934
ROA	0.1233	0.14	0.06	0.13	0.20	285942
Log mcap	21.6079	1.73	20.36	21.54	22.80	359165
Institution Ownership	0.6561	0.28	0.49	0.71	0.87	345372
Log analyst firm exp	1.1540	0.72	0.69	1.10	1.61	359165
Log fatigue	0.4303	0.77	0.00	0.00	0.69	359165
CGO	-0.0238	0.27	-0.10	0.03	0.13	336957

Table 3: Association of price path convexity (6 months) with downgrade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Convexity	**0.028*****	**0.031*****	**0.028*****	**0.033*****	**0.036*****	**0.033*****	**0.037*****
	(6.47)	**(7.67)**	**(7.60)**	**(8.14)**	**(8.33)**	**(7.09)**	**(7.26)**
Returns_6m		−0.037***	−0.017*	−0.002	0.031***	0.062***	0.076***
		(−3.76)	(−1.96)	(−0.20)	(2.71)	(3.92)	(4.37)
Volatility_6m		0.820***	0.795***	0.509**	0.122	−0.031	−0.055
		(3.11)	(4.30)	(2.33)	(0.50)	(−0.08)	(−0.13)
52-wk-high		−0.014**	−0.005	−0.004	−0.002	0.004	0.005
		(−2.60)	(−1.26)	(−0.67)	(−0.25)	(0.56)	(0.63)
Historical-high		0.028***	0.017***	0.020***	0.023***	0.015*	0.023**
		(4.57)	(3.05)	(3.02)	(3.05)	(1.94)	(2.39)
Mcap		−0.012***	0.039***	0.066***	0.082***	0.173***	0.189***
		(−8.09)	(10.75)	(13.09)	(12.36)	(9.25)	(8.73)
Analyst_firm_exp		−0.002	0.005***	0.021***	0.016**	0.013*	0.030***
		(−0.60)	(2.80)	(4.42)	(2.12)	(1.86)	(2.66)
Num. obs.	348,486	333,772	333,730	333,730	333,730	333,772	333,772
R^2 (full model)	0.003	0.008	0.113	0.272	0.430	0.427	0.548
Analyst FE			Y				
Firm FE			Y				
Ind-Year FE			Y	Y	Y		
Year Month FE			Y	Y	Y	Y	Y
Analyst-Firm FE				Y	Y	Y	Y
Analyst-Year FE					Y		Y
Firm-Year FE						Y	Y

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Probability to downgrade and last recommendation by an analyst

Last Reco. ↓ / Convexity →	CON1	CON2	CON3	CON4	CON5	CON5 - CON1
Strong buy	0.837	0.816	0.821	0.834	0.875	0.038
Buy	0.567	0.548	0.580	0.619	0.659	0.092
Hold	0.136	0.139	0.160	0.180	0.206	0.070
Underperform	0.0234	0.0301	0.0317	0.0415	0.0411	0.0177

Table 5: Probability of downgrade by Returns and Convexity quantiles

Returns ↓ / Convexity →	CON1	CON2	CON3	CON4	CON5	CON5 - CON1
RET1	0.498	0.477	0.477	0.487	0.485	-0.013
RET2	0.390	0.392	0.413	0.424	0.451	0.061
RET3	0.354	0.358	0.387	0.427	0.468	0.114
RET4	0.326	0.365	0.409	0.466	0.508	0.182
RET5	0.323	0.378	0.442	0.487	0.543	0.220

Table 6: Association of convexity with downgrade moderated by past returns

	Returns	Momentum	Contrarian
Convexity	0.030^{***}	0.021^{***}	0.039^{***}
	(8.64)	(5.61)	(9.85)
Returns_std	-0.011^{***}	-0.011^{***}	-0.009^{***}
	(-3.81)	(-3.41)	(-2.77)
Convexity:Returns_std	$\mathbf{0.023}^{***}$		
	(13.19)		
Momentum_stock		0.030^{***}	
		(5.85)	
Convexity:Momentum_stock		$\mathbf{0.028}^{***}$	
		(7.18)	
Contrarian_stock			-0.020^{***}
			(-3.78)
Convexity:Contrarian_stock			$\mathbf{-0.039}^{***}$
			$(\mathbf{-10.34})$
Num. obs.	333,730	333,287	333,287
R^2 (full model)	0.116	0.114	0.114

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Price Path Convexity with analyst characteristics

	Analyst Exp	Ana. firm Exp	Normalized Exp.	Fatigue	Busyness
Convexity	0.011*	0.022***	0.028***	0.036***	0.054***
	(1.73)	(4.91)	(6.85)	(8.74)	(5.41)
Analyst_exp.	0.009				
	(1.64)				
Convexity:Analyst_exp.	**0.009***				
	(3.04)				
Analyst_firm_exp		0.005**			
		(2.50)			
Convexity:Ana._firm_exp		**0.006**			
		(2.36)			
Analyst_exp_2			−0.003		
			(−1.03)		
Convexity:Ana._exp_2			**−0.002**		
			(−0.48)		
Fatigue				−0.077***	
				(−12.89)	
Convexity:Fatigue				**−0.022***	
				(−5.34)	
Busyness					−0.085***
					(−7.83)
Convexity:Busyness					**−0.011***
					(−2.81)
Num. obs.	333,730	333,730	333,730	333,730	333,730
R^2 (full model)	0.113	0.113	0.113	0.123	0.117

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: Price Path Convexity with firm characteristics

	Size	Ivol	PIN	Age	Forecast Error	Inst_own.	Coverage
Convexity	0.0394***	0.0688***	0.0293***	0.0312***	0.0383***	0.0348***	0.0236***
	(14.1824)	(19.0563)	(11.0656)	(11.2757)	(15.6580)	(15.6853)	(9.9498)
Small	−0.0175***						
	(−4.3461)						
Convexity:Small	**−0.0093*****						
	(−3.2545)						
High		−0.0087***					
		(−2.6250)					
Convexity:High		**−0.0481*****					
		(−13.8648)					
High			0.0201***				
			(5.5751)				
Convexity:High			**−0.0136*****				
			(−4.5891)				
New				−0.0123**			
				(−2.0573)			
Convexity:New				**0.0007**			
				(0.2361)			
High					−0.0078***		
					(−3.0240)		
Convexity:High					**−0.0081*****		
					(−3.1953)		
Low						−0.0240***	
						(−8.5372)	
Convexity:Low						**−0.0059****	
						(−2.5629)	
Low							−0.0221***
							(−7.0840)
Convexity:Low							**0.0189*****
							(6.4525)
Num. obs.	248203	248203	156860	121645	231284	248203	248203
R^2 (full model)	0.0978	0.0995	0.1045	0.1239	0.0997	0.0980	0.0984

Robust standard errors clustered at the analyst levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Convexity and downgrades in uncertainty and sentiment

	EPU	VIX	Recession	AA Sentiment	BW Sentiment
Convexity	0.0337^{***}	0.0476^{***}	0.0367^{***}	0.0407^{***}	0.0415^{***}
	(15.7122)	(19.4816)	(17.3606)	(18.1701)	(18.7575)
High	0.0052				
	(1.3313)				
Convexity:High	$\mathbf{-0.0050}^{*}$				
	$(\mathbf{-1.6678})$				
High		-0.0257^{***}			
		(-3.4755)			
Convexity:High		$\mathbf{-0.0330}^{***}$			
		$(\mathbf{-11.8848})$			
Recession			0.0359^{***}		
			(3.9458)		
Convexity:Recession			$\mathbf{-0.0138}^{***}$		
			$(\mathbf{-3.7739})$		
High				-0.0169^{***}	
				(-4.2579)	
Convexity:High				$\mathbf{-0.0283}^{***}$	
				$(\mathbf{-9.5233})$	
High					-0.0396^{***}
					(-6.8990)
Convexity:High					$\mathbf{-0.0352}^{***}$
					$(\mathbf{-10.7609})$
Num. obs.	248203	248203	248203	248203	248203
R^2 (full model)	0.0980	0.0989	0.0979	0.0986	0.0991

Robust standard errors clustered at the analyst levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Convexity, downgrade, and future returns

	1 month	3 months	6 months	12 months
Convexity	$\mathbf{-0.005}^{***}$	$\mathbf{-0.007}^{***}$	$\mathbf{-0.008}^{***}$	$\mathbf{-0.012}^{***}$
	$(\mathbf{-10.17})$	$(\mathbf{-9.63})$	$(\mathbf{-8.69})$	$(\mathbf{-8.64})$
downgrade	-0.0104^{***}	-0.0089^{***}	-0.0056^{***}	0.0073^{***}
	(-21.3237)	(-11.5800)	(-5.6449)	(5.2216)
Returns_6m	-0.0125^{***}	-0.0211^{***}	-0.0343^{***}	-0.0741^{***}
	(-11.3689)	(-10.5160)	(-11.5762)	(-16.6409)
Volatility_6m	0.1565^{***}	0.5132^{***}	1.0744^{***}	2.7210^{***}
	(3.5843)	(6.4250)	(9.0853)	(14.7885)
52-wk-high	-0.0001	-0.0008	-0.0005	0.0025
	(-0.0997)	(-0.6340)	(-0.3190)	(1.0433)
Historical-high	0.0005	0.0065^{***}	0.0129^{***}	0.0275^{***}
	(0.5375)	(4.2640)	(6.0382)	(8.8563)
Mcap	-0.0249^{***}	-0.0743^{***}	-0.1435^{***}	-0.2820^{***}
	(-38.6706)	(-59.2258)	(-66.8400)	(-80.4622)
Analyst_exp.	0.0009	-0.0012	-0.0036	-0.0029
	(0.7508)	(-0.6263)	(-1.2009)	(-0.6195)
Convexity:downgrade	$\mathbf{-0.0012}^{*}$	$\mathbf{-0.0047}^{***}$	$\mathbf{-0.0032}^{**}$	$\mathbf{-0.0046}^{**}$
	$(\mathbf{-1.8239})$	$(\mathbf{-4.7940})$	$(\mathbf{-2.4551})$	$(\mathbf{-2.3304})$
Num. obs.	332117	325774	316793	301429
R^2 (full model)	0.2874	0.3760	0.4371	0.5310

Robust standard errors clustered at the analyst levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 11: Propensity score matching

	(1)	(2)	(3)	(4)	(5)
Treatment	**0.066*****	**0.066*****	**0.069*****	**0.080*****	**0.125*****
	(**11.40**)	(**11.49**)	(**10.58**)	(**12.49**)	(**8.32**)
Num. obs.	158,204	155,908	63,184	58,886	15,520
R^2 (full model)	0.181	0.181	0.269	0.271	0.331

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Controlling for self-selection

	Years (3)	Years (4)	Quarters (3)	Quarters (4)
Convexity	**0.045*****	**0.068*****	**0.043*****	**0.058*****
	(**7.07**)	(**5.26**)	(**8.74**)	(**8.38**)
Num. obs.	24,495	5,827	69,145	27,180
R^2 (full model)	0.235	0.373	0.111	0.133

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 13: Alternative tests

	(1)	(2)	(3)	(4)	(5)
Convexity	**0.031*****	**0.031*****	**0.033*****	**0.033*****	**0.027*****
	(**9.84**)	(**10.38**)	(**6.55**)	(**6.49**)	(**7.66**)
Num. obs.	333,730	333,730	333,730	301,564	333,730
R^2 (full model)	0.115	0.115	0.116	0.121	0.115

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix

Table A1: Association of price path convexity (3 months) with downgrade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Convexity	**0.029*****	**0.029*****	**0.022*****	**0.026*****	**0.029*****	**0.026*****	**0.030*****
	(**7.63**)	(**8.14**)	(**6.94**)	(**7.35**)	(**7.73**)	(**6.05**)	(**6.43**)
return_3m_lag		0.013	0.034**	0.058***	0.095***	0.107***	0.126***
		(0.74)	(2.26)	(3.41)	(5.19)	(5.19)	(5.41)
ewma_vol_3m		1.188***	1.297***	1.222***	0.907***	1.000***	1.003***
		(4.86)	(7.67)	(6.22)	(4.54)	(3.80)	(3.33)
52-wk-high		−0.014**	−0.006	−0.004	−0.000	0.006	0.007
		(−2.57)	(−1.34)	(−0.65)	(−0.03)	(0.87)	(0.91)
Historical-high		0.027***	0.016***	0.020***	0.023***	0.015**	0.023**
		(4.37)	(2.98)	(3.03)	(3.06)	(1.98)	(2.44)
Mcap		−0.012***	0.037***	0.063***	0.082***	0.186***	0.203***
		(−7.69)	(9.81)	(12.03)	(12.00)	(10.28)	(9.88)
Analyst_firm_exp		−0.001	0.005***	0.022***	0.017**	0.013*	0.031***
		(−0.28)	(2.87)	(4.62)	(2.27)	(1.93)	(2.75)
Num. obs.	354,061	333,772	333,730	333,730	333,730	333,772	333,772
R^2 (full model)	0.003	0.008	0.113	0.272	0.430	0.427	0.548
Analyst FE			Y				
Firm FE			Y				
Ind-Year FE			Y	Y	Y		
Year Month FE			Y	Y	Y	Y	Y
Analyst-Firm FE				Y	Y	Y	Y
Analyst-Year FE					Y		Y
Firm-Year FE						Y	Y

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A2: Association of price path convexity (12 months) with downgrade

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Convexity	**0.007**	**0.010****	**0.014*****	**0.019*****	**0.026*****	**0.023*****	**0.028*****
	(1.54)	**(2.17)**	**(3.74)**	**(4.44)**	**(5.73)**	**(4.60)**	**(5.11)**
return_1y_lag		−0.025***	−0.023***	−0.016***	0.008	0.049***	0.062***
		(−4.07)	(−4.81)	(−2.78)	(1.19)	(4.07)	(4.61)
ewma_vol_1y		0.467	0.133	−0.266	−0.487	−0.916	−0.890
		(1.48)	(0.68)	(−1.08)	(−1.58)	(−1.33)	(−1.21)
52-wk-high		−0.016***	−0.006	−0.004	−0.002	0.003	0.005
		(−2.99)	(−1.32)	(−0.71)	(−0.29)	(0.47)	(0.56)
Historical-high		0.029***	0.018***	0.021***	0.023***	0.015*	0.023**
		(4.71)	(3.21)	(3.12)	(3.06)	(1.96)	(2.37)
Mcap		−0.013***	0.041***	0.069***	0.085***	0.171***	0.183***
		(−8.31)	(11.44)	(13.82)	(12.44)	(8.45)	(7.81)
Analyst_firm_exp		−0.003	0.005**	0.020***	0.016**	0.012*	0.030***
		(−0.87)	(2.59)	(4.17)	(2.03)	(1.84)	(2.68)
Num. obs.	337,080	333,772	333,730	333,730	333,730	333,772	333,772
R^2 (full model)	0.000	0.004	0.111	0.270	0.429	0.426	0.547
Analyst FE			Y				
Firm FE			Y				
Ind-Year FE			Y	Y	Y		
Year Month FE			Y	Y	Y	Y	Y
Analyst-Firm FE				Y	Y	Y	Y
Analyst-Year FE					Y		Y
Firm-Year FE						Y	Y

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Association of price path convexity with downgrade (Logit model)

	3 months	6 months	12 months
Convexity	**0.105*****	**0.131*****	**0.069*****
	(**7.33**)	(**7.83**)	(**3.99**)
Returns	0.164**	−0.072*	−0.096***
	(2.44)	(−1.79)	(−4.46)
Volatility	6.044***	3.674***	0.546
	(7.89)	(4.38)	(0.62)
52-wk-high	−0.025	−0.023	−0.026
	(−1.29)	(−1.22)	(−1.31)
Historical-high	0.070***	0.073***	0.079***
	(2.93)	(3.03)	(3.27)
Mcap	0.182***	0.187***	0.181***
	(10.28)	(10.83)	(11.10)
Analyst_exp.	0.033	0.031	0.027
	(1.47)	(1.39)	(1.23)
Num. obs.	327,156	327,156	327,156
Pseudo R^2	−0.012	−0.012	−0.013

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Association of price path convexity with actual recommendations

	3 months	6 months	12 months
Convexity	**0.033*****	**0.050*****	**0.037*****
	(**8.20**)	(**10.35**)	(**6.68**)
Returns	0.046**	−0.052***	−0.080***
	(2.15)	(−3.66)	(−9.49)
Volatility	3.728***	3.609***	3.156***
	(10.58)	(7.91)	(6.70)
52-wk-high	−0.003	−0.000	−0.000
	(−0.32)	(−0.04)	(−0.04)
Historical-high	0.007	0.007	0.010
	(0.76)	(0.82)	(1.12)
Mcap	−0.086***	−0.079***	−0.072***
	(−10.40)	(−9.56)	(−8.94)
Analyst_exp.	0.037***	0.036***	0.034***
	(3.34)	(3.30)	(3.09)
Num. obs.	333,730	333,730	333,730
R^2 (full model)	0.205	0.205	0.205

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A5: Alternative measure of price path convexity

	3 months	6 months	12 months
Convexity	**0.023*****	**0.027*****	**0.013*****
	(**7.60**)	(**7.73**)	(**3.55**)
Returns	0.043***	−0.012	−0.020***
	(2.81)	(−1.29)	(−4.17)
Volatility	1.307***	0.812***	0.126
	(7.70)	(4.39)	(0.65)
52-wk-high	−0.006	−0.005	−0.005
	(−1.35)	(−1.29)	(−1.28)
Historical-high	0.016***	0.016***	0.018***
	(2.95)	(3.07)	(3.31)
Mcap	0.040***	0.041***	0.040***
	(10.26)	(10.83)	(11.12)
Analyst_exp.	0.007	0.007	0.006
	(1.47)	(1.37)	(1.20)
Num. obs.	333,730	333,730	333,730
R^2 (full model)	0.115	0.115	0.113

Robust standard errors clustered at the analyst and year_quarter levels. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.