Mark-to-market or Mark-to-sentiment – The Sensitivity of Fair Value Measurement to Investor Sentiment

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We thank Szu-Fan Chen, Chia-Chi Lu, Su-Ming Lin, Hsin-Tsai Liu, Ju-Chun Yen, Martin Bugeja, Samir Ghannam, Matthew Grosse, Le Ma, Helen Spiropoulos, Stephen Taylor, Sue Wright and the participants at seminars at National Taiwan University, National Central University, University of Technology Sydney, 2023 Annual Congress of the European Accounting Association, and 2023 Annual Meeting of Accounting and Finance Association of Australia and New Zealand (AFAANZ) for their valuable comments.

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ABSTRACT

This paper studies how bias in fair value measurement potentially impacts the financial market. We propose an approach to decompose FV asset value into two parts: one reflects the fundamental value, and the other covaries with investment sentiment. Using these measures and a sample of U.S. financial firms, we document a set of original findings. First, we validate our measures by showing that only the fundamental-related FV assets predict the future cash flow while the sentiment-related FV assets do not. Second, sentiment-related FV is priced by investors but is negatively associated with long-term stock returns, consistent with the notion that investors do not fully understand the short-lived nature of this component of FV measurement. Third, we show that the sentiment-related FV also leads to higher future crash risk. Fourth, we explore firms' reasons for holding sentiment-sensitive FV assets and find the asset FV sensitivity to investor sentiment is higher for firms with higher managerial risk-taking incentives, higher CEO overconfidence, lower auditor quality, lower auditor effort, and lower auditor independence. Taken together, using a new empirical approach, we provide direct evidence of how the bias in FV measurement distorts firm valuation and investor perception

***JEL*:** G15, G30, M41.

***Keywords*:** Fair value measurement; Decision usefulness, Investor sentiment; Long-run performance; Crash risk.

1. Introduction

Over the past few decades, fair value measurement (FVM hereafter) has been the subject of academic scrutiny, with an emphasis on its ability to provide useful information for economic decision-making. Proponents, such as standard setters, argue that fair value (FV hereafter) information is useful as it reflects firms' underlying risks and economic performance, providing insights into future inflows and outflows of economic benefits (Evans et al. 2014). In contrast, skeptics, such as bank regulators and executives, allege that FV provides noisy information, raising earnings volatility and obscuring a firm's actual performance (McDonough et al. 2020). This viewpoint is echoed in a Financial Times article that highlights the dispute among company directors regarding the extent to which FVM offers "a more meaningful insight into a company's economic performance than other measures" (Hargreaves 2005).

Despite the prevalence of FVM in financial reporting, extant research has yet to reach a consensus regarding FVM's decision usefulness. Ideally, FV is an exit-value-based measurement that contains no measurement error and reflects only the underlying economic value of assets and liabilities. However, in practice, the effectiveness of this measure is undermined by the presence of "investor sentiment," which describes irrational investor psychology resulting in the misevaluation of an asset's long-term value. Prior studies show that during periods of high or low sentiment, the market price of an asset can deviate from its efficient level for an extended period of time (Baker and Wurgler 2006; Stambaugh et al. 2012). With mark-to-market accounting, the construct of FVM might not only capture the underlying economic fundamentals but also contain the "noise" ascribed to investor sentiment.

However, to the best of our knowledge, no study in the literature has explicitly separated the two components of FVM and investigated their respective impacts on the decision usefulness of FVM. The empirical approach of our study is based on a simple concept – if FVM captures only asset fundamentals, it should have zero covariance with a quality empirical proxy of investor sentiment. Conversely, any association between FVM and sentiment would represent a potential bias in the FV estimate.

There are at least three reasons why FVM might vary with investor sentiment. First, the asset FV may reflect the inefficient market price. According to the Financial Accounting Standards Board (FASB) and the International Accounting Standards Board (IASB)'s standards, both Levels 1 and 2 of FV assets consider observable inputs consisting of quoted prices in active markets. To the extent that the market prices of the Level 1 and 2 assets might deviate from the efficient level during times of strong sentiments, the asset FV actually reflects the biased market price rather than just the economic value of these assets. Second, for Level 2 and 3 assets, managers' subjective inputs in the reported FV can also be biased by market sentiment. Prior studies show that both management and analysts' forecasts of future earnings are not immune to the influence of market sentiment (Hribar and McInnis 2012; Hurwitz 2018; Clarkson et al. 2020). Therefore, given that Level 2 and 3 assets both require managers' unobservable inputs, a bias in FV recording associated with sentiment might arise, resulting from managers' overly optimistic or pessimistic estimates. Third, managers might even opportunistically report FV during high-sentiment times. Hanley, Jagolinzer, and Nikolova (2018) find that managers are tempted to strategically inflate asset FV when there is relatively weak external scrutiny. Hence, managers may take advantage of the high market sentiment and manipulate FV reporting when investors and analysts are likely to agree with such optimistic estimates. As such, we hypothesize and empirically show that asset FV is significantly correlated with market sentiment.

To this end, we empirically decompose the FVM into two components: (1) the efficient component that integrates prevailing market conditions and timely information to indicate the fundamental value of assets and liabilities (the efficient component hereafter); and (2) the transitory deviation from economic fundamentals resulting from the influence of investor sentiment on market prices, which represents a bias in the estimated value of assets and liabilities (the sentiment-related component hereafter). Utilizing our sentiment-related FV measure, we empirically investigate and answer the following questions: (1) What are the magnitudes of the efficient and sentiment-related FV components? (2) Does potential bias in FVM adversely affect the overall decision usefulness of FVM to financial market participants? Specifically, does it result in unfavorable outcomes, such as share mispricing and higher crash risk? (3) Which firm characteristics are associated with larger holdings of sentiment-sensitive fair value assets? The answers to these questions would be direct evidence of the consequences of inefficient FVM and also a valuable reference to regulators as to which firms are more susceptible to the risk of holding sentiment-sensitive FV assets.

For our empirical investigations, we proxy market sentiment with the investor sentiment index of Baker and Wurgler (2006), which is widely used in literature and advocated by many researchers (e.g., Zhou 2018). Next, we construct a sample of quarterly observations during 2008 – 2018 of U.S. financial firms because they typically hold a large number of financial instruments that are mainly measured at FV (McDonough et al. 2020). With such an empirical setting, we document a positive relation between asset FV and the sentiment index, supporting our prediction. As the next step, we decompose the asset FV into the parts related to a firm's fundamental value and to market sentiment. To this end, we estimate the firm-level sensitivity between asset FV and the sentiment index, where a high sensitivity indicates that a firm holds a portfolio of assets of which the value fluctuates significantly with market sentiment. Using this sensitivity, combined with the level of sentiment index, we can estimate the part of asset FV that correlates with market sentiment. We term this component of FV as the "sentiment-related FV" and posit that it represents the deviation of asset FV from its efficient level. A high value of sentiment-related FV indicates that unsustainably inflated asset value is reported in financial statements.

We first validate our measure by examining cash flow predictability. We aim to show that given an inefficient part of FV would not be realized; the sentiment-related FV should not predict future operating cash flows. By decomposing the asset FV into the efficient component (*FVAEFFI*) and the sentiment-related component (*FVASENT*), we expect that only *FVAEFFI* can predict future cash flows and *FVASENT* cannot because the value recorded as *FVASENT* represents a transient noise in the asset value and cannot realize in the future. Our empirical analysis yields evidence consistent with this notion supporting the validity of our measure.

We further examine how investors receive sentiment-related FV in the stock market. We start by estimating an Ohlson model as in Song, Thomas, and Yi (2010), where we regress share price on *FVAEFFI* and *FVASENT* scaled by the share price. A significant coefficient of any of these two variables would indicate that investors price in the value recorded in the respective FV components. Curiously, we find both coefficients of *FVAEFFI* and *FVASENT* are significantly positive. Such a finding seems to suggest that financial market investors do not understand the transitory nature of sentiment-related FV and place the same weight on it as they do on the efficient FV component in the equity valuation process. To provide further insights, we further examine how these two FV components affect future stock returns. If investors are misled by *FVASENT*, we expect to find a long-term correction in price, resulting in a negative relation between *FVASENT* and future stock returns. Our empirical finding is consistent with this prediction, whereby *FVASENT* negatively predicts future stock returns over a horizon of up to 3 years. Such a finding is robust to several model specifications, including alternative measures of long-term returns, rolling-window estimation of our FV measures, and controlling for the effect of the sentiment index itself. Combined, our evidence indicates that investors do not fully understand the inefficiency in FVM, which results in temporary inflation in stock price and long-term price correction associated with the sentiment-related FV.

To shed further light on the impact of sentiment-related FV in the capital market, we next examine whether it is related to subsequent crash risk. Prior studies discussed the possibility that FV accounting exacerbated the financial crisis in 2008 because the mark-to-market practice results in a downward spiral between asset sales and loss recognition (Laux and Leuz 2009; 2010). We are thus motivated to examine whether the inefficient FV component indeed contributes to the large share price fall. There are at least two reasons why one expects a positive association between the level of *FVASENT* and crash risk. First, to the extent that the trend of market sentiment shifts faster than that of economic fundamentals (e.g., Pontiff 1997; Brown 1999), a firm with a large amount of sentiment-sensitive assets is more likely to experience a substantial change in firm value within a short period of time, resulting in high crash risk. Second, facing a market downturn, managers who are influenced by market sentiment might be reluctant to admit they applied overly optimistic inputs on FV estimates. They, therefore, might "stockpile" such negative information until the revision of asset FV is sufficient to trigger a price crash. Consistent with such a notion, our empirical investigation reveals a positive relation between *FVASENT* and subsequent crash risk. Hence, we identify another negative influence of sentiment-related FV in the capital market as it increases the likelihood of subsequent crash risk.

Lastly, given the likely share value distortion resulting from such holdings, the question arises of whether companies should choose to hold the "sentiment-sensitive assets," namely, the assets whose value varies significantly with market sentiment. Specifically, we explore the determinants of the sensitivities of asset FV to investor sentiment. We identify the following determinants and provide empirical support. First, to the extent that the fluctuation of market sentiment is greater than that of economic fundamentals (e.g., Pontiff 1997; Brown 1999), managers with high risk-taking incentives might hold sentiment-sensitive assets in order to increase firm risk. Supporting such a hypothesis, we document a positive association between CEO compensation Vega and asset FV's sentiment sensitivity.[1] Second, we examine the role of auditor quality. Auditors who hold high standards are likely conservative on value recognition and hence

[1] Compensation Vega measures the sensitivity of a manager's equity holding portfolio to changes in the volatility of the company's stock, calculated as the change in equity portfolio value in relation to a 1% change in the stock volatility. Prior studies showed that granting managers high-Vega equity portfolios has the effect of incentivizing them to undertake more aggressive corporate policies (e.g. Coles, Daniel, and Naveen, 2006).

discourage managers from holding sentiment-sensitive assets. Third, we consider the auditor's effort and incentive because diligent and independent auditors should understand the risky nature of sentiment-sensitive assets and refrain managers from making excessively risky investments. Consistent with these notions, we show sentiment sensitivity is negatively related to auditor quality (proxied by if an auditor is from one of the Big 4 accounting firms) and auditor effort (proxied by auditor fee) and positively related to auditor independence (inversely proxied by non-audit fee). Fourth, we show that overconfident managers might hold more sentiment-sensitive assets because they believe they can "time the market" and capture the profit generated from the short-lived FV overpricing. In sum, these findings help explain firms' incentives for holding sentiment-sensitive assets.

Our study makes threefold contributions to the literature. First, our study quantifies the bias in FVM. Numerous prior studies show that FVM is value relevant in the sense that stock investors indeed update the share price as a response to FV reporting (e.g., Song et al. 2010; Goh et al. 2015; Cedergren et al. 2019). Other studies, however, contend that FVM contains noise by showing a shock transmitted across sectors through mark-to-market accounting (Allen and Carletti 2008), misleading investors about the economic substance of an item. Our study breaks new ground by proposing that the two aspects are not necessarily contradictory. By empirically decomposing asset FV into its efficient and sentiment-related components, our findings uncover inherent disparities between the two components, with the efficient part offering useful information and the sentiment-related part containing undesirable noise. More importantly, our study provides compelling evidence that investors fail to grasp the distinct nature of the two components, resulting in equal pricing and subsequent long-term corrections in share price. As such, our study broadens the current understanding of FVM, offering insights into its indirect, unintended consequences in financial markets.

Second, our study explores the heterogeneity in firms' incentives of using FVM. Although the usefulness of FVM arguably hinges upon factors such as managerial incentives and audit quality, only a relatively small set of studies investigate the factors associated with aggressive FV reporting. Song et al. (2010) find that the value relevance of FVM is higher for firms with stronger corporate governance. Dechow et al. (2010) show that managers tend to use FVM more objectively when they have relatively well-structured boards of directors. However, as stated by McDonough et al. (2020), the reasons adopting FV reporting remains relatively unexplored, representing a 'black box' despite being critical for understanding the decision usefulness of FVM. Our study adds to this literature by documenting the factors associated with the holding of sentiment-sensitive assets. Specifically, firms managed by aggressive and overconfident CEOs are prone to hold more sentiment-sensitive assets, whereas firms that are audited by Big 4 auditors and diligent auditors are less likely to hold such assets. Our findings suggest that the extent of FVM's decision usefulness is heterogeneous, exhibiting variations across firms based on their distinct characteristics.

Third, our study also contributes to investor sentiment research. Specifically, we identify FV accounting as a channel through which investor sentiment affects the capital market. Prior studies show that market sentiment affects financial reporting and how investors perceive financial information. Bergman and Roychowdhury (2008) show that managers issue forecasts to reduce the bias in investors' expectations induced by market sentiment. Ge, Seybert, and Zhang (2019) find that firms report earnings more conservatively in response to higher investor sentiment. Mian and Sankaraguruswamy (2012) document that the stock price sensitivity to earnings news is different during high and low sentiment periods, consistent with the notion of potential mispricing. We add to this line of studies and identify FVM as another channel through which investor sentiment impacts financial markets and results in mispricing.

This paper is organized as follows. Section 2 discusses the theoretical framework. Section 3 discusses the sample and variable construction. Section 4 describes how we decompose FVM. Section 5 presents empirical findings. Section 6 discusses the effect of FVM on crash risk. Section 7 concludes.

2. Background and theoretical discussion

2.1 Theoretical discussion

The FASB defines fair value in ASC 820, *Fair Value Measurements and Disclosures*, as "the price that would be received to sell an asset or paid to transfer a liability in an orderly transaction between market participants at the measurement date" (ASC 820-10-20).[2] Given the pervasive reliance on the FVM in financial reporting, it is perhaps surprising that the current state of research does not present a unanimous agreement concerning the usefulness of FVM for decision-making.

[2] ASC 820 was formerly SFAS157, *Fair Value Measurement* (FASB, 2006).

One stream of research argues that FVM provides useful information. In tests of the value relevance of FV information, this body of studies generally finds that FV information relates to the firm share price. For instance, Song et al. (2010) find that value relevance applies to all levels of FVM. Koonce et al. (2011) show that investors consider FVM to be more relevant for financial assets than for financial liabilities.

Another stream of research presents a contrasting perspective. Their argument posits that FVM includes “noise” that stems from market sentiment rather than economic fundamentals. Consequently, FVM introduces unwarranted and artificial earning volatility posing challenges for investors wishing to effectively interpret FV information (Hitz 2007; Byard et al. 2011). In line with the argument, Barth et al. (1995) show that FV measures of net income are more volatile than historical cost-based measures. Using a sample of commercial banks, Hodder et al. (2006) find that the full FV income exhibits significant volatility. McInnis et al. (2018) also find that FVM is not as value-relevant as expected due to the inclusion of transitory change in FV. The noise and volatility concerns are especially acute in the wake of the global financial crisis of 2008. Critics argue that the required markdown of asset values under FV reporting contributed to economic distortion in the financial system, causing the credit crunch and subsequent economic downturn (Allen and Carletti 2008; Plantin et al. 2008).[3]

Fair value, under its ideal condition, represents the underlying economic reality of an asset so that there should be no difference between the exit value of an asset and its fundamental value. Thus, the reported FV should be able to indicate the future cash flows that can be realized from the asset. In practice, however, fair value deviates from the ideal form because market prices are impacted by “investor sentiment,” which is a market-wide erroneous belief about the fundamental value of an asset (Baker and Wurgler 2006; Stambaugh et al. 2012). Such erroneous belief occurs when investors update their expectations about asset returns using signals that are unrelated to fundamentals. Consequently, the reported FV may depart from the asset returns that align with underlying fundamentals, leading to either overvaluation or undervaluation. Consistent with this view, the early literature on investor sentiment reveals that financial markets cannot be explained by investors acting based purely on fundamental values (Shleifer and Summers 1990; Bodurtha et al. 1995). Linking investor sentiment to accounting issues, Amin et al. (2020) find that the

[3] Some have argued that FVM was a convenient scapegoat to blame for exacerbating the financial crisis (i.e., Laux and Leuz, 2009; Laux and Leuz, 2010; Cantrell and Yust, 2019).

likelihood of misstatement in financial reporting is associated with investor sentiment. Drawing parallels from this research evidence, we posit that the reported FV includes two elements: the efficient component and the sentiment-related component. In particular, the efficient component integrates prevailing market conditions and timely information to indicate the fundamental value of assets and liabilities; the sentiment-related component represents a transitory deviation from economic fundamentals. Such deviation captures the bias derived from investors' erroneous expectation of the underlying value of the asset.

The distinct nature of the two components implies that they deliver different levels of usefulness for decision-making. To be more specific, we predict that the efficient component enhances the overall decision usefulness of FVM while the sentiment-related component undermines FVM's decision usefulness. Building upon this prediction, this study aims to address a set of research questions. First, we are curious whether users of financial statements can effectively differentiate between the two components and thus respond to them differently in the stock market. If financial statement users do not understand their distinct nature and price them equally, a long-term correction in firm value is expected due to investors' disappointment caused by the misleading sentiment-related FV. Second, to better understand the implications of sentiment-related FV, we investigate whether the sentiment-related FV is associated with an increased likelihood of subsequent crash risk. Lastly, given the potential distortion in firm value arising from holding sentiment-sensitive assets, we will investigate the underlying determinants that drive companies' decisions to retain such assets. Detailed discussion about each of these research questions is provided in the relevant section of the paper.

2.2 The use of FVM in financial firms

Under US GAAP, FVM is used to measure a wide range of financial instruments. Specifically, trading assets held by financial firms, including securities held primarily with the intention of selling them in the near term, are measured at FV with changes in FV recognized directly in the income of financial instruments. Available-for-sale securities are also measured at FV with unrealized gains and losses recognized in other comprehensive income. In contrast, hold-to-maturity securities are measured at historical cost.

Based on the data from U.S. bank holding companies, McDonough et al. (2020) provide insights into the extent to which FVM is employed by financial firms. Their findings reveal that, as of 2017, financial firms had approximately 28% of their assets measured using FV, which is substantially higher than the figure found in non-financial firms. While loans are financial firms' largest assets (70% of total assets),[4] available-for-sale securities and trading securities also represent a substantial portion of financial firms' total assets (>16%). The widespread adoption of FVM in financial instruments makes financial firms one of the most powerful settings in which to investigate the decision usefulness of FVM. If FVM does not demonstrate decision usefulness even within financial firms, it raises significant doubts about the ability of FVM to improve the decision usefulness of financial statements on a broader scale.

3. Sample and Variable

We construct a sample of quarterly observations of financial firms by focusing on firms in GICS Industry Groups 4010 or 4020 in Compustat Quarterly during 2008 – 2018 (Goh et al. 2015). The sample period starts in 2008 because Statement of Financial Accounting Standards (SFAS) 157, *Fair Value Measurements* (now known as ASC 820) became effective in 2008 (Badia et al. 2021). We then search for these financial firms in CRSP and retain only the observations with common shares traded in the U.S. market. Such a process yields our initial sample consisting of 18,386 firm-quarter observations, with which we estimate the Ohlson model and discover similar results to Song et al. (2010). Furthermore, to prepare a sample for estimating the firm-specific sensitivity of FV assets to investor sentiment, we include only the firms that have existed for at least 20 quarters (i.e., 5 years) during 2008-2018, resulting in a sample of 14,800 firm-quarter observations from 415 distinctive firms. Detailed descriptions of our sample construction process are provided in Table 1.

We describe the sample composition with the information presented in Table 2. Panel A of Table 2 presents the yearly distribution of our sample. The number of observations is mostly stable across years, with a peak in 2013. Panel B presents the number of observations of the stocks traded in different major stock exchanges in the U.S., where we observe roughly 80% of our sample firms are traded in NASDAQ. In Panel C, we present the breakdown of our sample by finer industry classification in the financial sector. The traditional bank is the industry with the largest presentation in our sample (12,362 observations, accounting for roughly 83.5% of our sample). The rest of our sample firms (2,438 observations) operate in other financial industries, including

[4] Under US GAAP, loans are recognized on the balance sheet at historical cost.

diversified financial services, consumer finance, and capital markets. However, we observe firms in consumer finance and capital markets industries have particularly large market capitalization, reflecting the fact that some of them manage a significant amount of capital.

To capture investor sentiment, we use the index developed by Baker and Wurgler (2006).[5] This index is a market-wide measure capturing the common variation of six financial market variables: the closed-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. Intuitively, this index reflects investors' enthusiasm for participating in financial markets. Baker and Wurgler (2006) present strong evidence that their sentiment index is correlated with the mispricing of stock prices. Since its creation, a large number of accounting and finance studies have used this index to capture the irrational sentiment prevalent in the financial market (e.g., Hribar and McInnis 2012; Mian and Sankaraguruswamy 2012; Stambaugh et al. 2012; Yu and Yuan 2011).[6] Zhou (2018) provides a discussion: "As it turns out, this (Baker and Wurgler) index captures sentiment much better than any single components in explaining the cross-section of stock returns, and it has become the most widely used measure of investor sentiment in various applications." Therefore, we rely on this index (denoted as *SENT*) as our main measure to investigate how the value of FV assets varies with investor sentiment.

4. Sentiment-sensitive Fair Value Assets

In this section, we explain our process of decomposing FV assets into a component reflecting efficient asset price and a component induced by investor sentiment.[7] We use a sample of 14,800 firm-quarter observations (denoted as the final sample) in which every firm existed for at least 20 quarters during 2008-2018. Such a requirement on the minimum number of observations for each firm is necessary for us to carry out quality firm-level regression estimation.

We begin by examining the association between the value of FV assets held by financial firms and investor sentiment. Firstly, we regress the ratio of FV assets relative to total assets

[5] We thank Jeffrey Wurgler for sharing the investor sentiment data on https://pages.stern.nyu.edu/~jwurgler/
[6] As of July of 2022, this paper has received 2,839 citations.
[7] We focus on FV assets only because the use of FV to measure liabilities for financial firms is limited. As reported by McDonough et al. (2020), only 3% of the liabilities were measured at FV for financial firms in 2017.

(*FVA_TA*) on the investor sentiment (*SENT*) using this sample as a panel dataset. As reported in column (I) of Panel A, Table 3, we find a significantly positive relation between *FVA_TA* and investor sentiment. To investigate such an effect on the within-firm variation of *FVA_TA*, in column (II), we further include firm fixed effects and continue to obtain a positive and significant coefficient of *SENT*. The estimation result indicates that, on average, a one-standard deviation increase of *SENT* is associated with a roughly 2.7% increase in *FVA_TA* relative to the sample mean.[8] Hence, we find that, in general, a positive association between the value of FV assets and investor sentiment exists, consistent with the notion that the market value of assets is affected by the behavioral enthusiasm of market investors.

Next, we focus on the firm-level sensitivity of FV assets to investor sentiment. This sensitivity is expected to reflect each firm's asset allocation strategy in terms of the extent to which their asset value correlates with optimism (or pessimism) in the financial market. To this end, we estimate the same regression as in column 1 of Panel A for each firm, whereby we regress *FVA_TA* on *SENT* across quarterly observations for every given firm and obtain a coefficient of *SENT*, denoted as *b_SENT*, for each firm in our sample. The coefficient *b_SENT* thereby captures the firm-level sensitivity of FVA to investor sentiment.

Lastly, we derive the fitted value of this firm-level regression (i.e., the multiplication product between *b_SENT* and *SENT* in each quarter, denoted as *FVASENT_TA*) as the part of asset FV induced by sentiment. Conceptually, *FVASENT_TA* represents the deviation of asset FV from its efficient level. For instance, if a firm invests only in assets that are completely free of the influence of market sentiment, then the value of *b_SENT* would be zero, which in turn results in zero *FVASENT_TA* as well. Hence, we interpret the difference between *FVASENT_TA* and the total FV asset ratio *FVA_TA* as the FV asset value that reflects the fundamental value of these assets (denoted as *FVAEFFI_TA*).

We present the summary statistics of *b_SENT, FVASENT_TA, FVAEFFI_TA,* and *FVA_TA* in Panel B of Table 3. We make several observations. First, although the mean of *b_SENT* is similar in magnitude to the coefficient we derive in column (II) of Panel A, the value of *b_SENT* is markedly large for some firms. The 90th percentile of *b_SENT* is as high as 0.156, indicating a one-

[8] A single standard deviation increase of *SENT* (0.275) results in a 0.0058 (=0.275*0.021) increase in *FVA_TA*, which translates to roughly 2.7% increase relative to its sample mean of 0.217.

standard-deviation increase of *SENT* results in an almost 20% increase in *FVA_TA* relative to the sample mean. This indicates some financial firms hold FV assets that are highly sensitive to non-fundamental price fluctuation. Second, for 43% of observations, the value of *b_SENT* is negative, indicating a significant number of firms' FV assets effectively work as a hedge against the fluctuation of investor sentiment, highlighting the heterogeneous FV assets portfolios held by financial firms. Third, given the mean of *FVASENT_TA* and *FVA_TA* are 0.016 and 0.217, respectively, we can infer, on average, the sentiment-induced part of FV assets value constitutes 7.4% of the entire value, which is an economically significant magnitude.

5. Cash Flow Predictability and FVM Usefulness in Capital Market

5.1 Sample Description

In this section, we conduct analyses to investigate the property of our sentiment-related FV component. To do so, firstly, we supplement our quarterly and annual samples with financial statement firm characteristics from the Compustat database and stock price information from the CRSP database. We present the summary statistics in Table 4. To conserve the maximum number of observations in each analysis, we use the initial sample (18,386 observations) for estimating the Ohlson model and the final sample (14,800 observations) for examining the effect of our *FVASENT_TA* measure on future cash flows and stock returns. Hence, we present the descriptive statistics of the variables in Table 4 based on the sample used in each of these tests. In Panel A of Table 4, we present the statistics of our initial sample. We learn that our sample consists of a group of financial firms with average total assets of \$11.5 billion and average total liabilities of \$10.3 billion. Following the Ohlson model estimated by Song et al. (2010), we construct FV assets per share, *FVA_S*, as FV assets divided by shares outstanding. Also following Song et al. (2010), we divide the total FV assets into different categories, Level 1, 2, and 3, and construct *FVA1_S*, *FVA2_S*, and *FVA3_S* as each category of FV assets scaled by shares outstanding, respectively. Using the sample mean of these variables, we calculate the Level 1 and Level 2 FV assets combined account for roughly 93% of the total FV assets in our sample. This indicates the main part of the FV assets of our sample firms is highly sensitive to both market price fluctuation and managerial subjective assumption.

Next, in Panel B, using the final sample, we present the statistics of the variables used for the examination of cash flow predictability and future stock performance. Besides the FV variables scaled by total assets (*FVASENT_TA* and *FVAEFFI_TA*), we also follow the variable construct in the Ohlson model and scaled FV assets variables by total shares outstanding. Specifically, we first derive the implied FV assets dollar amount of each firm by multiplying *FVASENT_TA* with *TA*; then dividing by total shares outstanding as the sentiment-related FV assets per share, *FVASENT_S*. The efficient part of FV assets per share, *FVAEFFI_TA*, is similarly derived. Stock performance measures include cumulative abnormal returns (*CAR*) and buy-and-hold returns (*BHAR*) over 2, 4, 8, and 12 quarters after a quarter end. The cash flow measures include operating cash flows scaled by shares outstanding (*OCF_S*) and operating cash flows scaled by total assets (*OCF_TA*). A slight sample attrition results from the unavailability of operating cash flow information for some firms.

5.2 Cash flow predictability

Financial information is decision-useful when it can accurately predict future cash flows. Hence, we start our analysis by examining whether sentiment-related FV would realize and convert into cash flows in the future. If sentiment-related FV indeed captures the short-lived deviation of asset value from the efficient level, we expect to find it has no, or weak, predictive power on future cash flows. In contrast, to the extent that *FVAEFFI* reflects the fundamental value of FV assets, it should positively predict future cash flows. Referring to Barth et al. (2012) and Huffman (2018), we estimate the following regression:

$$\textit{Future OCF} = \alpha + \beta_1{*}\textit{FVASENT} + \beta_2{*}\textit{FVAEFFI} + \beta_3{*}\textit{OCF} + \textit{quarter and industry fixed effect effects,}$$

where *Future OCF* is the operating cash flow realized in 4, 8, and 12 quarters ahead, respectively; *FVASENT* and *FVAEFFI* are the sentiment- and fundamental-related parts of asset FV in the current quarter, and *OCF* is the operating cash flow in the current quarter. To examine the robustness of the estimation results, we scale all variables by total assets as the original variable construction and also by total shares outstanding (as in the Ohlson model), respectively, and report the results in Table 5.

In the first three columns, we report results when all variables are scaled by total assets. We observe significant and positive coefficients of operating cash flow (*OCF_TA*) and efficient value of FV (*FVAEFFI_TA*), indicating that both two variables have predictive power on cash flows up to 12 quarters in the future. This finding shows that there is a degree of persistence in terms of cash flow. The finding also confirms that useful information is conveyed by the fundamental-related FV assets. However, interestingly, we find an insignificant coefficient of the sentiment-related FV assets (*FVASENT_TA*), consistent with the notion that sentiment-related FV provides little, if any, information on future firm value. To examine the robustness of these findings, we re-estimate these regressions in which all variables are scaled by the number of shares outstanding and find similar results, as reported in the next three columns of Table 5. As such, we view these results as evidence supporting the notion that our *FVASENT* variable indeed captures the non-informational mispricing of FV assets resulting from market sentiment, adversely impacting the decision usefulness of FVM.

5.3 Price Relevance

We have shown that sentiment-related FV conveys little information about future profitability. This raises the question of whether capital market investors understand this and how they perceive short-lived turbulence in the value of FV assets. We begin our investigation by examining whether stock market investors price in sentiment-related FV. Specifically, we refer to Song et al. (2010) and estimate an Ohlson model as follows:

$$PRICE = \alpha + \beta_1 * FVA\_S + \beta_2 * NFVA\_S + \beta_3 * LIAB\_S + \beta_4 * NI\_S + \textit{quarter and industry fixed effect effects},$$

where *PRICE* is the stock price at the end of a quarter, *FVA_S* is fair value per share, *NFVA_S* is non-fair value assets per share, *LIAB_S* is total liabilities per share, and *NI_S* is net income before extraordinary items per share.

A significant coefficient of *FVA_S* indicates that FV provides value-relevant information to the capital market. The estimation results, as reported in column (I) of Table 6, are all consistent with the results of prior studies, whereby the coefficients of *NFVA_S* and *NI_S* are positive, and the coefficient of *LIAB_S* is negative. The magnitude of these coefficients also aligns with the estimates reported by Song et al. (2010). Importantly, the coefficient of *FVA_S* is significantly positive and close to the theoretically predicted value of 1. Furthermore, following Song et al. (2010), we decompose fair value assets into Levels 1, 2, and 3 and construct FV assets per share variables with different levels of FV assets (*FVA1_S1*, *FVA1_S2*, and *FVA1_S3*). We then re-estimate the Ohlson model by including these three variables and report the results in column (II).

We find that the magnitude of the coefficient of *FVA1_S1* is larger than that of *FVA1_S2*, and the coefficient of *FVA1_S2* is larger than that of *FVA1_S3*. This is also largely consistent with the finding of Song et al. (2010), indicating that investors place low weight on fair value reporting when credible asset price information is unavailable. With these results, we gain confidence that our Ohlson model is well-specified.

Next, we re-estimate the Ohlson model by including *FVASENT_S* and *FVAEFFI_S* instead of *FVA_S*. If capital market investors understand the lack of cash flow predictability associated with *FVASENT_S*, they should place little weight on it in the pricing process. Conversely, if investors do not understand the nature of sentiment-related FV and incorrectly perceive it as useful information, we might observe mispricing as a result. We report the estimation results in column (III). Interestingly, we find significantly positive coefficients for both *FVASENT_S* and *FVAEFFI_S*. Although the magnitude of *FVASENT_S* (0.902) is slightly lower than that of *FVAEFFI_S* (0.924), the result indicates that investors still consider *FVASENT_S* to be an important input in the evaluation process. Therefore, our findings suggest that investors still price in the sentiment-related FV, even though this part of FV assets is unlikely to be realized in the future.

5.4 Long-term Stock Performance

Our finding from the Ohlson model estimation is notable because it appears to suggest that investors do not fully understand the short-lived nature of sentiment-related FV and continue to view it as useful information. We, therefore, question if such misinterpretation is responsible for unfavorable outcomes in the financial market. To do so, we examine the association between sentiment- and fundamental-related FV and future stock returns. If these two components of FV assets are both fairly priced, we should observe no relation between them and future stock price movement, as all relevant information has been incorporated into the stock price. However, if investors indeed are misled by sentiment-related FV, we expect investors to be surprised by the subsequent firm performance and correct their belief in the future, resulting in a negative relation between sentiment-related FV assets and future stock returns.

We start the analysis by examining whether there is any relation between the sentiment-related FV and the cumulative abnormal returns (CAR) over different spans after the earnings announcements. We construct the CAR after the earnings announcement with the following procedure. Firstly, for each firm *I*, we define the period [-210, -31] as the estimation period, where day 0 denotes the earnings announcement day. Then we estimate the coefficient α_i and β_i over the estimation period in the following regression: $R_{i,t}=\alpha_i+\beta_i R_{m,t}+\varepsilon_i$, where R_i is the raw return for each firm *I* on day *t*, R_m is the market return as proxied by CRSP value-weighted market portfolio daily return including all distributions. The daily abnormal returns (*AR*) after the announcement day are calculated as $AR_{i,t}=R_{i,t} - \alpha_i - \beta_i R_{m,t}$. As such, the CAR over the next 2 quarters (*CAR_Q2*) is computed as the sum of daily abnormal returns over the 126-day after the quarterly earnings announcement date. Cumulative abnormal returns over the next 4, 8, and 12 quarters (*CAR_Q4, Q8, Q12*) are similarly computed over the 252-day, 504-day, and 756-day period starting from the quarterly earnings announcement date.

We regress CAR over different spans (CAR_Q 4, 8, 12) on FV variables and numerous control variables. To be consistent with the variable constructs in the Ohlson model, we regress CAR on the same set of variables as in Table 6 – *FVASENT_S, FVAEFFI_S, NFVA_S, LIAB_S, NI_S*. Moreover, referring to Cremers and Pareek (2015), we also include numerous additional control variables. Specifically, we estimate the following regression:

$$CAR=\alpha+\beta_1*FVASENT\_S+\beta_2*FVAEFFI\_S+\beta_3*NFVA\_S+\beta_4*LIAB\_S+\beta_5*NI\_S$$

$$+\beta_6*BM+\beta_7*MCAP+\beta_8*PRICE+\beta_9*TURNOVER+\beta_{10}*INSTOWN$$

$$+\beta_{11}*IDIORISK+\beta_3*ANALYSTS + \textit{quarter and industry fixed effects},$$

where *BM* is the quarter-end book-to-market ratio; *MCAP* is the quarter-end market capitalization; *PRICE* is the quarter-end share price; *TURNOVER* is the average ratio of monthly trading volume relative to total shares issued over the quarter; *INSTOWN* is the most recent institutional ownership reported before the quarter end; *IDIORISK* is the annualized idiosyncratic risk for each quarter; *ANALYST* is the number of analysts following the firm in the year in which a quarter locates.

We report the results in Table 7 and find insignificant coefficients on *FVAEFFI_S* and *NFVA_S*, indicating that investors correctly price the useful fundamental-FV and non-FV assets. Interestingly, we find significantly negative coefficients on *FVASENT_S* in all regressions of *CAR_Q2, CAR_Q4, CAR_Q8, and CAR_Q12*, consistent with the notion that investors misprice sentiment-related FV due to their misinterpretation of its decision usefulness. Such misinterpretation results in a subsequent correction in asset valuation. Next, we repeat the estimation with our FV variable constructs, whereby we scale FV, liabilities, and net income variables by total assets (*FVASENT_TA, FVAEFFI_TA, NFVA_TA, LIAB_TA, NI_TA*). The results, as reported in Panel B of Table 7, are qualitatively similar – we find a significantly negative coefficient on *FVASENT_TA* but not for other variables. The effect is also economically significant. Using the coefficient of *FVASENT_TA* in *CAR_Q12* regression in column (VIII), we estimate one standard deviation increase of *FVASENT_TA* is associated with almost 3% negative abnormal stock return over the future 12 quarters. Therefore, firms that report higher sentiment-related FV experience a larger magnitude of price correction in the future, revealing the unfavorable implications of sentiment-related FV in the financial market.

5.5 Robustness Tests

We conduct several tests to show our results are robust to alternative measures of long-term stock performance, estimation approach, and controlling for the effect of market sentiment itself. First, we employ buy-and-hold return (BHAR) as an alternative stock performance. Specifically, the BHAR of firm *I* over the two quarters after the quarterly earnings announcement is computed as:

$$BHAR_{i,Q2} = \prod_{t=1}^{126}(1 + R_{i,t}) - \prod_{t=1}^{126}(1 + R_{m,t}),$$

where subscript *t* refers to the day and day 0 denotes earnings announcement day; market return R_m is proxied by the return of CRSP value-weighted market portfolio (including all distributions). Buy-and-hold returns over the next 4, 8, and 12 quarters (*BHAR_Q4, Q8, Q12*) are similarly computed over the 252-day, 504-day, and 756-day periods starting from the quarterly earnings announcement date. We then repeat the analyses and report the results in Panel A of Table 8. The results are qualitatively similar.

Second, we construct the sentiment-related FV measure with the rolling window approach to address the concern that a firm's holding of FV assets should vary over time. Therefore, instead of a constant sentiment sensitivity (*b_SENT*) for each firm, we estimate a set of firm-specific sensitivities that varies across quarters for a given firm by regressing the ratio of FV assets to total assets (*FVA_TA*) on sentiment index (*SENT*) across the prior 8 quarters. We then construct the sentiment- and fundamental-related FV using the rolling *b_SENT* and repeat the analyses of its effect on future long-term stock returns. The results, as reported in Panel B of Table 8, are qualitatively similar, where sentiment-related FV negatively predicts subsequent stock returns.

Third, we include several potential proxies of the market sentiment index as control variables in the regression. A cause of concern is that the negative predicting power of sentiment-related FV on future stock returns captures the effect of market sentiment itself rather than the effect of it taking place through FV as a channel. To mitigate this concern, we augment the long-term stock return regression by including several independent variables that arguably capture market sentiment to an extent, including the Baker-Wurgler index (*SENT*), consumer confidence index (*CCI*) (e.g., Lemmon and Portniaguina 2006), and GDP growth rate (*GDP_GROW*). The results are reported in Panel C of Table 8. Some of the coefficients of these variables indeed are significantly negative, indicating a price correction following a high-sentiment period. Nevertheless, the negative significance of the coefficients of sentiment-related FV variables remains intact, supporting the notion that the value recognition of FV assets is a channel through which market sentiment results in stock overpricing.

5.6 Crash Risk

To gain further insight into the impact generated by the sentiment-related FV, we explore whether it results in heightened crash risk. Literature offers a debate on whether fair value accounting injects excessive volatility into financial markets and results in greater crash risk. On the one hand, one group of researchers suggests that FVM results in artificial volatility generated from managers' subjective inputs (Allen and Carletti 2008; Plantin et al. 2008). On the other hand, Badertscher et al. (2012) find that fair value provisions have minimal effect on the regulatory capital of U.S. banks, unsupportive to the hypothesis that fair value accounting contributes to downside risk.

In the hope of reconciling this debate, we examine the respective effects of sentiment- and fundamental-related FV on the probability of a sudden price fall. Using the logic of Allen and Carletti (2008) and Plantin et al. (2008), there are at least two reasons why we expect a positive association between sentiment-related FV and crash risk. First, prior studies show that the trend of market sentiment shifts at a speed significantly faster than that of economic fundamentals (e.g., Pontiff 1997; Brown 1999). The value of sentiment-sensitive assets, thereby, may experience a sizable change within a short period of time, resulting in high crash risk. Second, to the extent that managers' subjective inputs to FV estimates are influenced by market sentiment, they may be reluctant to acknowledge faulty prediction when an asset price moves in the opposite direction. They, therefore, might "stockpile" such negative information until the accumulated revision becomes a shock to the investors, triggering a price crash. By contrast, fundamental-related FV should be updated in a timely and objective manner and have little effect on crash risk.

To empirically test such a prediction, we follow Chen et al. (2001) and Kim et al. (2011) and measure firm-specific crash risk with two methods. First, we estimate the negative coefficient of skewness of firm-specific weekly returns (*NCSKEW*), which is the negative of the third moment of firm-specific weekly return divided by the standard deviation of firm-specific weekly returns to the third power. Second, we compute the "down-to-up volatility" (*DUVOL*), which intuitively is the ratio of the standard deviation of "down" days (days with returns below period mean) to the standard deviation of "up" days (days with returns above the period mean). These two measures essentially capture the extent to which a stock is likely to experience a large downward price change.

We estimate a regression in which the dependent variable is either of these two crash risk measures calculated over the 12-month period starting from the quarterly report announcement, and the key independent variables are our decomposed FV measures, *FVASENT* and *FVAEFFI*, scaled by either total assets or total shares outstanding variables. For the control variables, we refer to Kim et al. (2011) and include a market-to-book ratio (*MB*), return-on-assets (*ROA*), firm size (*SIZE*), financial leverage (*LEV*), discretionary accruals (*DA*), mean of weekly return in percent (*RET*), standard deviation of weekly return (*SIGMA*), detrended monthly share turnover (*DTURN*). The details of variable constructs are provided in the appendix.

The estimation results, as reported in Table 9, show that sentiment-related FV significantly and positively predicts future crash risk, as the coefficients of *FVASENT_S FVASENT_TA* are significantly positive in regressions of both crash risk measures. In contrast, the coefficients of *FVAEFFI* variables are all insignificant across these regressions, indicating that reporting fundamental-related asset FV does not lead to greater crash risk. Taken together, these results suggest that, given the biased information contained in the sentiment-related FV, this component indeed introduces greater crash risk to the financial market while the fundamental-related part is innocent for such an effect. Hence, we identify another negative impact engendered from the holding of sentiment-sensitive FV assets in the capital market.

6. The determinants of holding sentiment-sensitive FV assets

Thus far, we have established that the sentiment-related FV does not predict future cash flows but appears to mislead investors when they assess the firm value. Given holding such assets should be a disservice to shareholders, it is intriguing why firms choose to hold them in the first place. In this section, we explore a few factors that induce firms to undertake these risky investments. Specifically, we aim to investigate the determinants of the *b_SENT* coefficient derived from our estimation. To the extent that *b_SENT* captures the directional correlation between FV assets and market sentiment, our investigation would answer the question of which kinds of firms hold more sentiment-sensitive FV assets. Since the firm characteristics variables in this investigation are constructed on a yearly basis, we convert our sample of quarterly observations to a sample with 3,676 yearly observations and present the descriptive statistics of this sample in Panel A of Table 10.

Using this sample, we conduct investigations on several determinant factors. First, managers who have high risk-taking incentives might see the high correlation between the value of sentiment-sensitive FV assets and market psychology as a preferable trait. They thereby invest in such assets in order to increase the riskiness of assets even though the expected returns of these assets are not high enough to justify the risk. To empirically test such a possibility, we use the incentives offered by a manager's compensation arrangement to capture a manager's risk preference. Specifically, using the data from Execucomp, we compute *DELTA* and *VEGA* associated with a CEO's equity compensation portfolio, where *DELTA* and *VEGA* estimate the change in compensation portfolio value for a 1% change in stock price and in annualized stock volatility, respectively. Conceptually, *DELTA* captures a CEO's incentive to increase shareholder wealth, and *VEGA* captures a CEO's incentive to increase firm risk. We include both variables in our investigation to consider the effects of both incentives.

As such, we regress *b_SENT* on *DELTA* and *VEGA*, and report the results in column (I) in Panel B of Table 10. The key variable we focus on are the coefficients of *VEGA* and *DELTA*, representing a CEO's risk-taking incentive. Since Execucomp covers only S&P1500 firms, the number of observations in this regression reduces to 1,232 observations. Interestingly, we find a significant coefficient on *VEGA* but an insignificant coefficient on *DELTA*, indicating that CEOs with high-risk preferences hold more sentiment-sensitive FV assets. We are aware that the value of our sentiment sensitivity measure *b_SENT* is a constant number for a given firm. Hence, we further collapse our annual sample to a cross-sectional firm-level sample, where each observation represents a firm. In this sample, for each given firm, we construct the independent variables by taking the average values of each of the independent variables across years. We then re-estimate the *b_SENT* regression using this firm-level sample in column (V). The results are qualitatively similar.

Second, we examine the role of auditors. We start by considering the auditor quality. Given the high "noisiness" associated with the value of sentiment-sensitive FV assets, auditors who hold high standards are likely to be conservative on value recognition (Gaynor et al. 2016; Lennox and Kausar 2017). Hence, facing the relatively low value of these assets, managers should be discouraged from undertaking such investments. To seek evidence for this prediction, we first regress *b_SENT* on an indicator variable *BIG4*, which equals 1 if a firm hires one of the four largest accounting firms as their auditor and 0 otherwise. The negative coefficients of *BIG4*, as reported in columns (II) and (VI), indeed indicate that firms audited by big four accounting firms invest less in sentiment-sensitive FV assets.

Next, we further consider the auditor's effort and incentive. Intuitively, diligent auditors are more likely to analyze the invested assets and gain insights into the risky nature of the sentiment-sensitive FV assets. We follow prior studies and proxy the auditor effort with the audit fees an auditor charges its client (Eshleman and Guo 2014; Bronson et al. 2017; Beck et al. 2022). Moreover, numerous studies show that undertaking non-audit services might impair auditor independence by creating bonding incentives and compromise audit quality as a result (Frankel et al. 2002; Larcker and Richardson 2004; Gul et al. 2007; Krishnan et al. 2011). Hence, to maintain a good relationship with client firms, auditors who earn substantial non-audit income might show leniency when recognizing sentiment-sensitive FV assets. To empirically test these predictions, we regress *b_SENT* on the fees an auditor receives for providing audit service, *AUDIT FEES*, and non-audit services, *NONAUDIT FEES*. The results are reported in columns (III) and (VII). Interestingly, we find a significantly negative coefficient on *AUDIT FEES* but a significantly positive coefficient on *NONAUDIT FEES*. Such findings are consistent with the notion that diligent and independent auditors are less likely to approve the investment in sentiment-sensitive FV assets.

Last, we investigate the possibility that overconfident managers might be tempted to profit from the short-lived FV overpricing. Malmendier and Tate (2005) show that overconfident CEOs systematically underestimate the risk of an investment project and hence tend to over-invest. In a similar vein, CEOs who are confident in their skills of timing the market are likely to aggressively hold sentiment-sensitive FV assets. They might believe that they can seize the benefit of the overly high price of FV assets and unwind the position before the price trend reverses. We follow Banerjee et al. (2015) and identify overconfident CEOs as CEOs who hold deep-in-the-money options. The intuition behind this measure is that CEOs who do not exercise vested in-the-money options must be confident about their own ability to deliver firm performance. Specifically, we define an indicator variable *OVERCONFIDENCE* that takes the value of 1 when the extent to which a CEO retains in-the-money options is ranked in the highest quartiles across all firms in the same year and 0 otherwise. The details of the variable construct are provided in the appendix. The estimation results, as reported in columns (IV) and (VIII), show a positive relation between *OVERCONFIDENCE* and *b_SENT*, supporting the notion that confident CEOs are more likely to undertake risky investment strategies by holding sentiment-sensitive FV assets.

6. Conclusion

The decision usefulness of FVM has received much attention in accounting literature. Evidence is presented from both sides to advocate and question the use of FV (e.g., Barth and Clinch 1998; Hodder et al. 2006; Song et al. 2010; Koonce et al. 2011; Goh et al. 2015; McInnis et al. 2018). Based on the evidence in the literature, it is reasonable to say that FV is decision-useful to some extent but still contains certain biases. However, no studies have provided a quantified measure estimating the magnitude of such bias. We aim to fill this gap by distilling the component of FVM that correlates with Baker and Wurgler's (2006) investor sentiment index. To the extent that this index captures the irrational market sentiment, the value of FVM should not vary with the sentiment index if FVM only reflects the fundamental asset. We thereby extract the part of FVM that correlates and posit that it represents a bias.

By partitioning the asset FV into the efficient part and the sentiment-related part, we document three sets of evidence. First, we find that only the efficient part of FV has the predictive power of future cash flows. The sentiment-related FV does not have this ability which is consistent with the view that FV contains transient noise in the asset value that cannot be realized in the future. Second, users of financial statements are misled by the sentiment-related FV and thus price it in the equity valuation process, causing a subsequent long-term price correction. Third, we find that the sentiment-related FV is associated with subsequent crash risk. This finding contributes to the discourse on the potential amplifying impact of FVM on the severity of the financial crisis. Lastly, we document a set of firm characteristics that are associated with larger holdings of sentiment-sensitive FV assets.

The findings of this study have significant implications for various stakeholders. For regulators, we document the consequences of practicing FVM. These include the correlation between FVM and the inefficiency in the market value of assets, as proxied by investor sentiment, as well as how such bias in FVM further results in mispricing in the financial markets. In this sense, FVM becomes a channel through which the financial market inefficiency amplifies. Therefore, as accounting standard setters and bank regulator continue to grapple with the extent to which FVM should be used in financial reporting, our findings call for a thorough consideration and sophisticated strategy for the implementation of FVM. For investors, our findings are supportive of further education and communication with investors to enhance their understanding of the limitations of FVM. The later price correction associated with sentiment-related FV underscores the importance for investors to understand and exercise skepticism when they interpret financial statement information. For company managers and accountants, our study illuminates the potential bias embedded in the information they provide to financial statement users, even though they impeccably follow the guidelines of FV reporting. They thereby should be aware of this issue and engage with financial statement users to further communicate about this. Taken together, this study provides important information to various stakeholders regarding the informational value and limitations of FVM.

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Appendix: Variable definitions

Variable	Definition	Source
Sentiment variables		
SENT	One plus investor sentiment averaged over the quarter, where investor sentiment data are provided by Baker and Wurgler.	Access available at: https://pages.stern.nyu.edu/~jwurgler/
b_SENT	Estimated firm-level sentiment coefficient	
FV variables		
FVA_S	Fair value assets per share.	Compustat Quarterly
FVA_S1, 2, 3	Fair value assets per share from Levels 1, 2, and 3 inputs, respectively.	Compustat Quarterly
FVASENT_S	Investor sentiment-sensitive fair value assets per share	
FVAEFFI_S	Estimated efficient fair value assets per share, calculated as deducting *FVSENT* from *FVA.*	
NFVA_S	Non-fair value assets per share.	Compustat Quarterly
FVA_TA	Fair value assets scaled by the total assets at the beginning of the quarter.	Compustat Quarterly
FVASENT_TA	Estimated investor sentiment-sensitive fair value assets scaled by the total assets at the beginning of the quarter.	
FVAEFFI_TA	Estimated efficient fair value assets scaled by the total assets at the beginning of the quarter, calculated as deducting *FVSENT_TA* from *FVA_TA.*	
Stock performance		
CAR_Q2 (Q4, Q8, Q12)	The cumulative abnormal return is computed with the market model. Specifically, for each firm *i*, using the daily observations over the period [-210, -31] with day 0 denoting the earnings announcement day, we estimate the coefficient α_i and β_i in the following regression: $R_{i,t}=\alpha_i+\beta_i R_{m,t}+\varepsilon_i$, where R_i is the raw return for each firm *i* on day *t*, R_m is the market return as proxied by CRSP value-weighted market portfolio daily return including all distributions. The daily abnormal returns (*AR*) after the announcement day are calculated as $AR_{i,t}=R_{i,t} - \alpha_i - \beta_i R_{m,t}$. Cumulative abnormal return over the next 2 quarters (*CAR_Q2*) then is computed as the sum of daily abnormal returns over the 126-day period starting from the date after the quarterly earnings announcement date: $$CAR_{i,t} = \sum_{t=1}^{126} AR_{i,t}.$$ Cumulative abnormal returns over the next 4, 8, 12 quarters (*CAR_Q4, Q8, Q12*) are similarly computed over the 252-day, 504-day, 756-day period starting from the quarterly earnings announcement date.	CRSP

BHAR_Q2 (Q4, Q8, Q12)	The buy-and-hold abnormal return of firm *i* over the two quarters after the quarterly earnings announcement is computed as: $$BHAR_{i,Q2} = \prod_{t=1}^{126}(1 + R_{i,t}) - \prod_{t=1}^{126}(1 + R_{m,t}),$$ where subscript *t* refers to the day and day 0 denotes earnings announcement day; market return R_m is proxied by the return of CRSP value-weighted market portfolio (including all distributions). Buy-and-hold returns over the next 4, 8, 12 quarters (*BHAR_Q4, Q8, Q12*) are similarly computed over the 252-day, 504-day, 756-day period starting from the quarterly earnings announcement date.	CRSP
NCSKEW	The crash risk measure is constructed as follows. We first estimate the expanded market index model regression for each firm and quarter: $$R_{i,t} = \alpha_{0,i} + \alpha_{1,i} \cdot R_{m,t-2} + \alpha_{2,i} \cdot R_{m,t-1} + \alpha_{3,i} \cdot R_{m,t} + \alpha_{4,i} \cdot R_{m,t+1} + \alpha_{5,i} \cdot R_{m,t+2} + \varepsilon_{i,t},$$ where $R_{i,t}$ is the return on stock *i* in week *t* and $R_{m,t}$ is the return on the CRSP value-weighted market index in week *t*. We include the lead and lag terms for the market index return to allow for nonsynchronous trading. The firm-specific weekly return for firm *i* in week *t*, $W_{i,t}$, is measured by the natural log of one plus the residual return, that is, $W_{i,t} = ln(1 + \varepsilon_{i,t})$. *NCSKEW* for a given firm *i* and quarter τ in the next 12-month period (beginning the first week of quarter τ) is then calculated as: $$-\frac{n(n-1)^{\frac{3}{2}}\sum W_{i,t}^3}{(\text{n-1})(\text{n-2})(\sum W_{i,t}^2)^{\frac{3}{2}}}$$ where *n* is the number of observations of firm-specific weekly returns during the 12-month period beginning the first week of quarter *τ*.	CRSP
DUVOL	$$\text{DUVOL}_{i,\tau} = \log\left[\frac{(n_u - 1)\sum_{\text{DOWN}} W_{i,t}^2}{(n_d - 1)\sum_{\text{UP}} W_{i,t}^2}\right]$$ where n_u and n_d are the numbers of up and down weeks over the 12-month period beginning the first week of quarter τ, respectively. For any stock $_i$ over the 12-month period, we separate all the weeks with firm-specific weekly returns above (below) the mean of the period and call this the ''up'' (''down'') sample. We further calculate the standard deviation for the ''up'' and ''down'' samples separately. We then compute the log ratio of the standard deviation of the ''down'' sample to the standard deviation of the ''up'' sample.	CRSP
RET	The mean of firm-specific weekly returns over the fiscal year period, times 100.	CRSP

SIGMA	The standard deviation of firm-specific weekly returns over the fiscal year period.	CRSP
DTURN	The average monthly share turnover over the current fiscal year period minus the average monthly share turnover over the previous fiscal year period, where monthly share turnover is calculated as the monthly trading volume divided by the total number of shares outstanding during the month.	CRSP
Firm characteristics		
LIAB_S	Total liabilities per share.	Compustat Quarterly
NI_S	Net income before extraordinary items per share.	Compustat Quarterly
NI_MCAP	Net income before extraordinary items scaled by market capitalization.	Compustat Quarterly, CRSP
BM	Book-to Market ratio, calculated as the book value of the bank divided by the market capitalization of the bank.	Compustat Quarterly
MCAP	Market capitalization of the bank.	Compustat Quarterly
OCF	Operating cash flows per share.	Compustat Quarterly
OCF_MCAP	Operating cash flows scaled by market capitalization.	Compustat Quarterly
OCF_TA	Operating cash flows scaled by total assets.	Compustat Quarterly
TA	Total assets at the beginning of the quarter.	Compustat Quarterly
MB	Market-to-Book ratio, calculated as the market capitalization of the bank divided by the book value of the bank.	Compustat Quarterly
SIZE	The log of the market value of equity.	Compustat Quarterly
LEV	The total long-term debt divided by total assets.	Compustat Quarterly
DA	We follow Hutton, Marcus, and Tehranian (2009) to construct a three-month moving sum of absolute discretionary accruals.	Compustat Quarterly
ROA	Ratio of operating income to total assets	Compustat Quarterly
TURNOVER	Average monthly trading volume divided by total shares outstanding in the beginning of the year.	CRSP
PRICE	The stock price at the end of a quarter or a year.	CRSP
INSTOWN	Institutional ownership percentage, measured as the sum of shares held by institutional investors, divided by total number of shares outstanding.	Factset

IDIORISK	Annualized idiosyncratic risk as the standard deviation of the residual ε extracted from the CAPM estimation regression: $R_i-R_f=\alpha+\beta*(R_m-R_f)+\varepsilon$, where R_i is the weekly returns of a firm i, R_f is one-month U.S. Treasury Bill Rate, R_m is weekly return of CRSP value-weighted market portfolio (including all distributions).	CRSP
ANALYSTS	The number of analysts following a company within a year.	I/B/E/S
VEGA	The change in a CEO's compensation portfolio value for a 1% change in annualized stock volatility	Execucomp
DELTA	The change in a CEO's compensation portfolio value for a 1% change in stock price	Execucomp
BIG4	An indicator variable equal to 1 for firms with a Big4 auditor.	Audit Analytics
SPECIALIST	An indicator variable equal to 1 if an audit firm is specialised in the banking industry (i.e., KPMG).	Audit Analytics
AUDIT FEES	The audit fees paid to the incumbent auditor.	Audit Analytics
NON-AUDIT FEES	The sum of all non-audit fees paid to the incumbent auditor.	Audit Analytics
OVERCONFIDENCE	We follow Banerjee, Humphery-Jenner and Nanda (2015) to construct the overconfidence measure as follows. We first obtain the total value per option for the in-the-money options by dividing the value of all unexcercised options by the number of options. Next, we scaled this variable per option by the price at the year-end. This overconfidence measure captures the extent to which the CEOs retain in-the-money options. Lastly, the indicator variable *OVERCONFIDENCE* equals to 1 if the value of this overconfidence measure for a firm is in the top quartile of all firms in a year, and 0 otherwise.	Execucomp
Macroeconomic variables		
CCI	The University of Michigan consumer sentiment for the U.S.	Federal Reserve Bank of St. Louis
GDP_GROW	U.S. growth rate of gross domestic product.	Bureau of Economic Analysis

TABLE 1
Sample construction

Sample construction process	**Number of firm-quarter observations**
All reporting entities in the U.S. available in Compustat Quarterly with a fiscal quarter ending in 2008 –2018 that operate in financial industries (GICS Industry Groups 4010 or 4020).	40,480
Less: Entities that do not have common shares traded in the U.S. market as reported in CRSP (e.g. closed-end funds or foreign firms with ADR issues)	(15,617)
Less: Firms with missing or negative total assets or with no fair value information	(5,621)
Initial sample	19,242
Less: Observations with studentized residuals greater than 2 in the estimation of the Ohlson model, following the process in Song *et al.* (2010).	(856)
Sample for the Ohlson model	18,386
Less: Firms that exist for less than 20 quarters during 2008-2018	(3,586)
Sample for the sentiment-related FV estimation	14,800

TABLE 2
Sample composition

Panel A. The number of unique banks

Year	Number of unique banks	Year	Number of unique banks
2008	305	2014	376
2009	346	2015	358
2010	351	2016	335
2011	364	2017	311
2012	392	2018	296
2013	399		

Panel B. Sample composition by exchange listing

NYSE	2,644
AMEX	270
NASDAQ	11,886
Total	14,800

Panel C. Sample composition by industry classification

GICS code	Description	Number of obs.	Mean market capitalization ($b)	Median market capitalization ($b)
401010	Commercial banks	10,035	3.23	0.26
401020	Thrifts & Mortgage finance	2,327	0.57	0.10
4010	**Traditional banks**	12,362	2.73	0.22
402010	Diversified financial services	135	1.43	0.25
402020	Consumer finance	498	7.09	0.72
402030	Capital markets	1,805	6.49	1.05
4020	**Diversified financials**	2,438	6.33	0.84
	Total	14,800		

Notes: This table provides details of our sample composition. Panel A shows the number of unique banks in each sample year. Panel B shows the distribution of observations by exchange listing. Panel C shows the distribution of observations by industry classification based on the Standard & Poor's Global Industry Classification standard (GICS) Industry Grouping.

TABLE 3

Estimates of sentiment-sensitive fair value assets

Panel A. Regression analysis

	FVA_TA	
Variables	(I)	(II)
Intercept	0.191***	0.199***
	(21.36)	(39.59)
SENT	0.031***	0.021***
	(3.91)	(3.57)
Firm FEs	No	Yes
Cluster by firms	Yes	Yes
N	14,800	14,800
Adj. R^2 (%)	0.19	79.68

Panel B: Estimated variables

Variable	N	Mean	Std Dev	P10	P25	P50	P75	P90
SENT	14,800	0.859	0.275	0.397	0.803	0.923	1.050	1.11
b_SENT	415	0.031	0.147	-0.067	-0.029	0.013	0.070	0.156
FVASENT_TA	14,800	0.016	0.110	-0.063	-0.022	0.008	0.046	0.110
FVAEFFI_TA	14,800	0.201	0.201	0.017	0.086	0.155	0.248	0.401
FVA_TA	14,800	0.217	0.196	0.044	0.103	0.170	0.262	0.415

Notes: This table presents an analysis of the relation between investor sentiment and fair value assets using 2008-2018 fair value quarterly data. Panel A reports the estimated coefficient of investor sentiment on fair value assets. Panel B reports the descriptive statistics of estimated sentiment-sensitive fair value assets and estimated efficient fair value assets. The numbers in parentheses are *t*-statistics based on robust standard errors clustered by firm. All variables are defined in the Appendix. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

TABLE 4

Descriptive statistics

Panel A. Initial sample

Variable	N	Mean	Std Dev	P25	P50	P75
FVA_S ($)	18,386	29.426	36.872	8.886	19.697	36.423
FVA1_S ($)	18,386	1.905	6.470	0.000	0.044	0.687
FVA2_S ($)	18,386	25.599	31.160	5.934	17.284	33.613
FVA3_S ($)	18,386	1.400	5.283	0.000	0.000	0.340
NFVA_S ($)	18,386	122.275	93.334	60.959	108.003	158.759
LIAB_S ($)	18,386	0.135	0.107	0.066	0.118	0.174
NI_S ($)	18,386	0.260	0.601	0.097	0.251	0.476
PRICE ($)	18,386	19.445	17.774	8.490	15.080	26.370
TA($b)	18,386	11.536	40.447	0.737	1.523	5.035
LIAB ($b)	18,386	10.273	36.291	0.613	1.333	4.342

Panel B. Final sample

Variable	N	Mean	Std Dev	P25	P50	P75
<u>FV variables</u>						
FVASENT_S ($)	14,800	2.208	13.166	-2.535	0.613	5.370
FVAEFFI_S ($)	14,800	28.219	31.640	7.474	19.303	35.282
FVASENT_TA	14,800	0.016	0.110	-0.022	0.008	0.046
FVAEFFI_TA	14,800	0.201	0.201	0.086	0.155	0.248
NFVA_TA	14,800	0.806	0.228	0.599	0.749	0.843
<u>Stock performance</u>						
CAR_Q2	14,800	0.006	0.274	-0.135	0.001	0.137
CAR_Q4	14,800	0.005	0.450	-0.218	0.013	0.224
CAR_Q8	14,800	-0.013	0.812	-0.405	0.009	0.393
CAR_Q12	14,800	-0.019	1.139	-0.550	0.013	0.537
BHAR_Q2	14,800	-0.040	0.310	-0.172	-0.023	0.116
BHAR_Q4	14,800	-0.138	0.698	-0.312	-0.034	0.184
BHAR_Q8	14,800	-0.670	3.296	-0.691	-0.097	0.331
BHAR_Q12	14,800	-2.381	16.392	-1.201	-0.141	0.461
NCSKEW	14,457	-0.096	0.693	-0.457	-0.082	0.290
DUVOL	14,457	-0.038	0.206	-0.165	-0.035	-0.096
RET	14,457	0.002	0.006	-0.000	0.003	0.005
SIGMA	14,457	0.044	0.020	0.029	0.038	0.055
DTURN	14,457	-0.004	0.316	-0.088	-0.004	0.077
<u>Firm characteristics</u>						
OCF_S ($)	14,505	1.423	2.620	0.362	1.026	2.105
OCF_TA	14,505	0.013	0.036	0.003	0.008	0.014
LIAB_TA	14,800	0.854	0.171	0.862	0.897	0.926
NI_TA	14,800	0.003	0.008	0.001	0.002	0.003

MCAP($b)	14,800	2.478	1.152	0.083	0.259	1.102
BM	14,800	0.970	0.664	0.613	0.830	1.114
PRICE ($)	14,800	20.578	18.203	9.240	15.800	27.540
TURNOVER	14,800	0.086	0.099	0.020	0.052	0.118
INSTOWN	14,800	0.440	0.276	0.190	0.432	0.668
IDIORISK	14,800	0.020	0.015	0.011	0.015	0.024
ANALYSTS	14,800	4.558	5.852	0.000	2.000	6.000
MB	14,457	1.317	0.839	0.871	1.140	1.496
ROA	14,457	0.003	0.008	0.001	0.002	0.003
SIZE	14,457	5.816	1.792	4.416	5.556	6.999
DA	14,457	0.027	0.082	0.002	0.004	0.013
LEV	14,457	0.096	0.131	0.021	0.054	0.115

Notes: This table reports the descriptive statistics of the sample. All variables are defined in the Appendix.

TABLE 5

The cash flow predictability of sentiment-related FV

Variables	Future OCF_TA			Future OCF per share		
	4-quarter ahead	8-quarter ahead	12-quarter ahead	4-quarter ahead	8-quarter ahead	12-quarter ahead
FVASENT_TA	-0.027 (-1.38)	-0.042 (-1.42)	0.002 (0.10)			
FVAEFFI_ TA	0.022** (2.29)	0.018** (2.09)	0.033** (2.40)			
OCF_ TA	0.303*** (4.21)	0.355*** (6.49)	0.348*** (5.17)			
FVASENT_S				0.003 (0.42)	0.003 (0.36)	0.015 (1.34)
FVAEFFI_S				0.014*** (5.76)	0.017*** (7.35)	0.017*** (5.25)
OCF_S				0.262*** (4.87)	0.335*** (7.50)	0.314*** (5.70)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firms	Yes	Yes	Yes	Yes	Yes	Yes
N	14,505	13,985	13,410	14,505	13, 985	13,410
Adj. R^2 (%)	51.45	47.91	49.31	26.27	25.89	24.49

Notes: This table presents an analysis examining the ability of sentiment-sensitive fair value assets and efficient fair value assets to predict future operating cash flows for up to 12-quarter (i.e., 3 years) ahead using 2008-2018 fair value quarterly data. The numbers in parentheses are *t*-statistics based on robust standard errors clustered by firm. All variables are defined in the Appendix. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

TABLE 6

Value relevance of assets marked at fair value

		PRICE	
Variables	(I)	(II)	(III)
FVA_S	0.999***		
	(16.89)		
FVA1_S		1.032***	
		(18.69)	
FVA2_S		0.971***	
		(17.56)	
FVA3_S		0.846***	
		(11.03)	
FVASENT_S			0.902***
			(12.58)
FVAEFFI_S			0.924***
			(13.24)
NFVA_S	1.005***	0.983***	0.944***
	(17.23)	(17.63)	(13.71)
LIAB_S	-1.005***	-0.982***	-0.935***
	(-15.97)	(-16.41)	(-12.42)
NI_S	4.663***	4.606***	6.623***
	(12.96)	(12.63)	(11.43)
Quarter FEs	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes
Cluster by firms	Yes	Yes	Yes
N	18,386	18,386	14,800
Adj. R^2 (%)	77.08	77.43	78.31
F-test (F-stat)			
FVA1_S = FVA2_S		7.02***	
FVA1_S = FVA3_S		14.11***	
FVA2_S = FVA3_S		6.49**	
FVASENT_S = FVAEFFIC_S			1.90

Notes: This table presents an analysis of the relation between the stock price and the fair value assets per share using 2008-2018 fair value quarterly data. The numbers in parentheses are *t*-statistics based on robust standard errors clustered by firm. All variables are defined in the Appendix. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

TABLE 7

The effect of sentiment-sensitive FV assets on long-run performance

Variables	CAR_Q4		CAR_Q8		CAR_Q12	
	(I)	(II)	(III)	(IV)	(V)	(VI)
FVASENT_S	-0.001**		-0.002**		-0.002**	
	(-2.43)		(-2.43)		(-1.99)	
FVAEFFI_S	-0.000		-0.000		-0.000	
	(-0.10)		(-1.22)		(-1.43)	
NFVA_S	0.000		-0.000		-0.000	
	(1.02)		(-0.48)		(-0.51)	
LIAB_S	0.000		0.000		0.001	
	(1.59)		(1.42)		(1.62)	
NI_S	-0.007		-0.041		-0.109	
	(-0.39)		(-1.32)		(-1.41)	
FVASENT_TA		-0.131**		-0.240**		-0.267*
		(-2.09)		(-2.32)		(-1.71)
FVAEFFI_TA		0.026		-0.005		0.044
		(0.62)		(-0.08)		(0.52)
NFVA_TA		-0.015		-0.046		-0.052
		(-0.54)		(-1.22)		(-0.89)
LIAB_TA		-0.053		-0.007		0.029
		(-1.14)		(-0.09)		(0.26)
NI_TA		-1.465		-0.965		-1.110
		(-1.41)		(-1.21)		(-0.86)
BM	0.196***	0.217***	0.360***	0.362***	0.511***	0.525***
	(10.62)	(11.57)	(10.76)	(11.38)	(10.06)	(11.72)
MCAP	-0.000**	-0.000**	-0.000***	-0.000	-0.000***	-0.000
	(-2.60)	(-2.51)	(-3.39)	(-3.20)	(-4.27)	(-3.87)
PRICE	-0.002***	-0.001***	-0.003***	-0.003***	-0.004**	-0.004***
	(-3.86)	(-4.09)	(-3.72)	(-4.68)	(-2.50)	(-4.72)
TURNOVER	-0.399***	-0.406***	-0.927***	-0.959***	-1.695***	-1.542***
	(-5.64)	(-5.40)	(-6.38)	(-6.52)	(-7.70)	(-7.20)
INSTOWN	0.074***	0.080***	0.088**	0.086**	0.114*	0.085

	(3.15)	(3.31)	(2.00)	(2.01)	(1.76)	(1.38)
IDIORISK	0.140	0.043	-1.774	-2.162*	-5.856***	-4.410***
	(0.22)	(0.06)	(-1.49)	(-1.88)	(-3.49)	(-2.75)
ANALYSTS	0.005***	0.005***	0.011***	0.012***	0.020***	0.019***
	(3.97)	(3.79)	(5.06)	(5.17)	(6.11)	(6.04)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firms	Yes	Yes	Yes	Yes	Yes	Yes
N	14,798	14,798	14,798	14,798	14,798	14,798
Adj. R^2 (%)	20.38	19.57	21.46	21.49	19.68	20.69

Notes: This table presents an analysis examining the effect of sentiment-sensitive fair value assets and efficient fair value assets on long-run stock performance (cumulative abnormal returns) using 2008-2018 fair value quarterly data. The numbers in parentheses are *t*-statistics based on robust standard errors clustered by firm. All variables are defined in the Appendix. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

TABLE 8

Robustness Tests

Panel A. Buy-and-hold abnormal returns

Variables	BHAR _Q4		BHAR _Q8		BHAR _Q12	
	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
FVASENT_S	-0.001**		-0.003**		-0.005*	
	(-2.13)		(-2.04)		(-1.91)	
FVAEFFI_S	0.000		-0.007		-0.002	
	(0.28)		(-0.32)		(-0.57)	
NFVA_S	0.000		0.000		0.000	
	(0.82)		(0.78)		(1.01)	
LIAB_S	0.000		0.000		0.001	
	(0.83)		(0.35)		(0.73)	
NI_S	0.025		0.147		-0.172	
	(0.63)		(0.63)		(-0.63)	
FVASENT_TA		-0.150**		-0.612**		-0.735**
		(-2.06)		(-2.00)		(-2.13)
FVAEFFI_TA		0.030		-0.039		-0.021
		(0.55)		(-0.20)		(-0.09)
NFVA_TA		-0.033		-0.186		-0.225
		(-0.73)		(-1.01)		(-1.15)
LIAB_TA		-0.045		-0.040		0.007
		(-0.75)		(0.15)		(0.03)
NI_TA		-1.043		-2.924		-7.384
		(-0.77)		(-0.49)		(-1.38)
Controls variables	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firms	Yes	Yes	Yes	Yes	Yes	Yes
N	14,798	14,798	14,798	14,798	14,798	14,798
Adj. R^2 (%)	19.71	20.02	17.32	19.52	22.02	20.91

Panel B. Rolling Window Estimation

Variables	CAR_Q4		CAR_Q8		CAR_Q12	
	(I)	(II)	(III)	(IV)	(V)	(VI)
FVASENT_S	-0.001**		-0.001*		-0.002**	
	(-2.07)		(-1.82)		(-2.02)	
FVAEFFI_S	0.000		-0.000		-0.000	
	(0.54)		(-0.38)		(-1.13)	
NFVA_S	-0.000		-0.000		-0.001	
	(-0.53)		(-0.54)		(-1.16)	
LIAB_S	0.001		0.000		0.001	
	(1.10)		(0.69)		(1.38)	
NI_S	-0.014		-0.067		-0.115	
	(-0.70)		(-0.69)		(-1.37)	
FVASENT_TA		-0.180**		-0.359***		-0.470***
		(-2.31)		(-3.13)		(-2.84)
FVAEFFI_TA		-0.022		-0.088		-0.116
		(-0.50)		(-1.54)		(-1.28)
NFVA_TA		-0.067		-0.146**		-0.269***
		(-1.30)		(-2.24)		(-2.75)
LIAB_TA		-0.026		0.018		0.033
		(-0.57)		(0.20)		(0.22)
NI_TA		-1.576		-1.223		-2.136
		(-1.18)		(-1.60)		(-1.41)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firms	Yes	Yes	Yes	Yes	Yes	Yes
N	11,857	11,857	11,857	11,857	11,857	11,857
Adj. R^2 (%)	22.30	20.02	24.35	24.83	22.25	23.71

Panel C. Controlling for sentiment proxies

Variables	CAR_Q4		CAR_Q8		CAR_Q12	
	(I)	(II)	(III)	(IV)	(V)	(VI)
FVASENT_S	-0.001**		-0.001**		-0.002**	
	(-2.29)		(-2.04)		(-2.19)	
FVAEFFI_S	-0.000		-0.000		-0.000	
	(-0.14)		(-0.37)		(-1.20)	
NFVA_S	0.000		0.000		-0.000	
	(0.92)		(0.29)		(-0.44)	
LIAB_S	0.000		0.000		0.001	
	(1.64)		(0.93)		(1.60)	
NI_S	-0.015		-0.033		-0.047	
	(-0.86)		(-1.47)		(-1.13)	
SENT	-0.163		-1.175		-0.312	
	(-0.30)		(-1.28)		(-0.10)	
CCI	-0.137		-0.212		-0.409*	
	(-1.60)		(-1.53)		(-1.71)	
GDP_GROW	0.058		0.067		0.043	
	(1.64)		(1.18)		(0.67)	
FVASENT_TA		-0.119**		-0.122*		-0.462**
		(-2.02)		(-1.77)		(-2.14)
FVAEFFI_TA		0.026		0.013		0.022
		(0.70)		(0.30)		(0.24)
NFVA_TA		-0.015		-0.026		-0.074
		(-0.54)		(-0.82)		(-1.27)
LIAB_TA		-0.052		-0.031		-0.021
		(-1.18)		(-0.59)		(-0.16)
NI_TA		-1.264		-0.803		-1.768
		(-1.39)		(-1.64)		(-1.35)
SENT		-0.267		-1.265*		-2.223
		(-0.43)		(-1.73)		(-0.91)
CCI		-0.121		-0.176		-0.301
		(-1.40)		(-1.16)		(-1.45)
GDP		0.056		0.042		0.035
		(1.55)		(1.00)		(0.62)

Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firms	Yes	Yes	Yes	Yes	Yes	Yes
N	14,798	14,798	14,798	14,798	14,798	14,798
Adj. R^2 (%)	21.45	20.84	23.35	22.59	21.58	22.01

Notes: This table presents results from the robustness tests. Panel A presents the results of the long-term stock performance using buy-and-hold return as an alternative stock performance. Panel B shows the results when the rolling window approach is in use to estimate *b_sent*. Panel C reports results after including additional measures for the market sentiment index. The numbers in parentheses are *t*-statistics based on robust standard errors clustered by firm. All variables are defined in the Appendix. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

TABLE 9

The impact of sentiment-related FV on stock price crash risk

	NCSKEW		DUVOL	
Variables	(I)	(II)	(III)	(IV)
FVASENT_S	0.002**		0.001*	
	(1.97)		(1.91)	
FVAEFFI_S	0.001		0.000	
	(1.05)		(1.30)	
NFVA_S	0.001		0.000*	
	(1.23)		(1.92)	
LIAB_S	-0.001		-0.000**	
	(-1.38)		(-2.17)	
NI_S	-0.032		-0.005	
	(-1.35)		(-0.76)	
FVASENT_TA		0.456**		0.102*
		(2.07)		(1.95)
FVAEFFI_TA		0.233		0.044
		(1.17)		(1.07)
NFVA_TA		0.288		0.073
		(1.63)		(1.58)
LIAB_TA		-0.114		-0.014
		(-0.96)		(-0.39)
NI_TA		0.057		-0.337
		(0.05)		(-0.82)
MB	0.080***	0.067***	0.021***	0.022***
	(3.89)	(4.09)	(3.81)	(3.89)
ROA	4.988***	4.325***	1.247***	1.483***
	(4.34)	(4.50)	(3.88)	(3.82)
SIZE	0.050***	0.045***	0.017***	0.017***
	(6.25)	(6.41)	(7.81)	(7.80)
LEV	0.020	0.023	0.027	0.016
	(0.18)	(0.22)	(0.90)	(0.50)
DA	0.048	0.014	0.020	-0.004
	(0.38)	(0.13)	(0.48)	(-0.07)
RET	3.605	3.451*	1.379**	1.422***
	(1.50)	(1.76)	(2.19)	(2.16)
SIGMA	-1.106	-1.170	-0.527	-0.516
	(-1.57)	(-1.57)	(-1.56)	(-1.51)
DTURN	-0.051	-0.043	-0.015	-0.008
	(-1.55)	(-1.43)	(-1.70)	(-0.82)
Quarter FEs	Yes	Yes	Yes	Yes

Industry FEs	Yes	Yes	Yes	Yes
Cluster by firms	Yes	Yes	Yes	Yes
N	14,457	14,457	14,457	14,457
Adj. R^2 (%)	9.50	9.05	13.68	13.65

Notes: This table presents an analysis examining the association sentiment-related FV with subsequent crash crisis using 2008-2018 fair value annual data. The numbers in parentheses are *t*-statistics based on robust standard errors clustered by firm. All variables are defined in the Appendix. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.

TABLE 10

The determinants of holding sentiment-sensitive FV assets

Panel A. Annual sample

Variable	N	Mean	Std Dev	P25	P50	P75
ROA	3,676	0.003	0.011	0.001	0.002	0.003
TA($b)	3,676	13.195	45.925	0.834	1.744	6.003
BIG4	3,676	0.417	0.493	0.000	0.000	1.000
SPECIALIST	3,676	0.187	0.390	0.000	0.000	0.000
VEGA	1,232	0.060	0.114	0.000	0.011	0.053
DELTA	1,232	0.405	0.712	0.049	0.121	0.414
OVERCONFIDENCE	1,232	0.160	0.367	0.000	0.000	0.000
AUDIT FEES ($m)	3,622	1.273	3.577	0.192	0.386	0.966
NON_AUDIT FEES ($m)	3,622	0.424	1.703	0.028	0.067	0.192

Panel B. Determinant of FV assets' sensitivity to investor sentiment

	b_SENT							
	Firm-year level				Firm level			
	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
VEGA	0.166**				0.283**			
	(2.33)				(2.28)			
DELTA	-0.004				-0.023			
	(-0.18)				(-1.14)			
BIG4		-0.026**				-0.030*		
		(-2.00)				(-1.71)		
SPECIALIST		0.013				0.012		
		(0.93)				(0.66)		
AUDIT FEES			-0.002***				-0.003***	
			(-3.24)				(-3.41)	

NONAUDIT FEES			0.007**				0.008*	
			(2.27)				(1.95)	
OVERCONFIDENCE				0.043*				0.175**
				(1.91)				(2.01)
ROA	-0.249	-0.105	-0.128**	-0.375	-3.391	-0.178	0.270	-7.511**
	(-0.38)	(-0.24)	(-0.98)	(-0.46)	(-1.40)	(-0.10)	(0.16)	(-2.32)
CF	0.350**	-0.041	-0.078	0.473**	1.859***	-0.162	-0.229	2.436***
	(2.17)	(-0.37)	(-1.27)	(2.23)	(3.46)	(-0.44)	(-0.62)	(3.26)
BM	0.026**	0.015***	0.013***	0.022*	0.022	0.027***	0.033***	-0.019
	(2.35)	(3.64)	(3.04)	(1.87)	(0.66)	(2.29)	(2.93)	(-0.43)
Ln(TA)	-0.031***	-0.001	-0.009*	-0.021	-0.055	0.071	0.038	0.021
	(-2.89)	(-0.13)	(-1.67)	(-1.25)	(-0.43)	(1.44)	(0.84)	(0.13)
ANALYSTS	0.002	0.000	0.001	0.001	-0.000	-0.001	-0.001	0.001
	(1.44)	(0.41)	(0.97)	(0.80)	(-0.19)	(-0.90)	(-0.85)	(0.20)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster by firms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,232	3,676	3,622	1,232	128	407	403	128
Adj. R^2 (%)	24.65	18.18	10.46	22.19	36.80	7.92	6.15	44.93

Notes: This table presents an analysis examining the factors that would affect a bank's decision on pursuing sentiment-sensitive fair value assets using 2008-2018 fair value annual data. Panel A presents the descriptive statistics for variables used in this analysis while Panel B shows the regression results. The numbers in parentheses are *t*-statistics based on robust standard errors clustered by firm. All variables are defined in the Appendix. ***, **, and * indicate statistical significance based on two-sided tests at the 1%, 5%, and 10% levels, respectively.