

Raithel, Sascha

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The temporal volatility of nonfinancial performance and stock return

Sascha Raithel¹ 

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Abstract

Uncertainty about input factors and potential outcomes characterize almost any business-relevant decision. By using signals about uncertainty such as historical performance volatility (temporal volatility) as inputs, investors adjust their expectation about future firm value. This decision calculus has found broad empirical support concerning the temporal volatility of financial performance. However, concerning the temporal volatility of nonfinancial performance, research offers only limited insights. This study addresses this research gap. Two observational studies ($N_1 = 513$ and $N_2 = 348$) provide empirical evidence that investors downweigh changes in nonfinancial performance—measured as brand perception in one study and customer satisfaction in the other—when updating their beliefs about future firm value (as reflected by stock returns) if the volatility of historical nonfinancial performance is high.

Keywords Nonfinancial performance · Firm value · Stock return · Volatility · Uncertainty

JEL Classification G11 · G41

Introduction

Uncertainty is an important element of decision making and has played a central role in numerous studies for decades (e.g., Ruefli et al. 1999; Tversky and Kahneman 1974). The reason is that agents (must) make decisions and act upon them before they (can) have complete and certain knowledge about the outcome of their decisions. Faced with uncertain decision outcomes, intelligent decision makers such as investors would like to counteract post decision disappointment (Smith and

✉ Sascha Raithel
sascha.raithel@fu-berlin.de

¹ School of Business & Economics, Freie Universität Berlin, Arnimallee 11, 14195 Berlin, Germany



Winkler 2006): they react less (more) to a performance signal if the *temporal* volatility (i.e., variance *over time*) of this signal is high (low). A very large strand of literature shows empirically how noisy and thus less reliable financial performance signals affect financial market actors (e.g., Imhoff and Lobo 1992; Posen et al. 2018; Savor 2012). However, this research provides only very limited insights into the effects of the *temporal* volatility of *nonfinancial* performance signals.¹ This research gap is important because other research shows that nonfinancial performance (e.g., corporate reputation, brand performance) has an impact on firm value and investor response (e.g., Edeling and Fischer 2016; Raithel and Schwaiger 2015).

To address this research gap, this study performs two empirical tests for the hypothesis that investors act as Bayesian optimizers who also weigh nonfinancial performance signals by these signals' historical volatilities. Two studies ($N_1=513$ and $N_2=348$) provide empirical evidence that investors downweigh changes in nonfinancial performance—measured as brand perception in one study and customer satisfaction in the other—when updating their beliefs about future returns (as reflected by stock returns) if the temporal volatility of historical nonfinancial performance is high. Findings further suggest that this attenuation effect of the volatility of nonfinancial performance is not only complementary to but also similar in magnitude to the effects of the temporal volatilities of common financial variables such as cashflow, profitability, and analyst recommendation.

Theoretical background and hypothesis development

The optimizer's curse: disappointment bias

Decision-makers only have access to limited resources (e.g., time, money, power, experience, computing capability), which makes it impossible to conduct a complete analysis and ex ante estimate of the actual value V_i (e.g., return, utility) of an alternative i . Their resulting analysis, given this limitation, uses an imprecise value to estimate X_i as a substitute for the currently unobservable future value of the alternative (Brown 1974; Harrison and March 1984; Smith and Winkler 2006). The rational decision-maker then ranks all alternatives $i=1, \dots, n$ by their internal estimates X_i and selects the alternative i^* with the highest estimate $X_{i^*} = \max[X_1, \dots, X_n]$. The difference between the ex post realized value V_{i^*} and the ex ante estimated value X_{i^*} is considered the post-decision surprise, which can either be positive (satisfaction and euphoria) or negative (dissatisfaction and disappointment). The intuitive expectation is that $E[V_{i^*} - X_{i^*}] = 0$, i.e., the decision process, sometimes produces satisfaction and sometimes disappointment but on average produces a “surprise-neutral” outcome. Strikingly, the expected post-decision surprise $E[V_{i^*} - X_{i^*}]$ is *negative* and

¹ The volatility of a nonfinancial performance signal should not be confused with disagreement among raters about a nonfinancial performance signal. For instance, prior research has investigated the impact of such disagreements in evaluations of nonfinancial performance, such as ESG ratings (Serafeim and Yoon 2023) or brand perceptions (Luo et al. 2013). In contrast, this study focuses on variations in the mean of nonfinancial performance ratings *over time* (*temporal volatility*), rather than on the dispersion of ratings at a single point in time.



therefore results in disappointment (Brown 1974; Harrison and March 1984; Smith and Winkler 2006). What explains this counterintuitive decision outcome?

The answer is that a rational decision-maker will always select the alternative with the maximum estimated value X_{i*} . The decision process is, however, based on an analysis with limited resources and incomplete information, which exposes decision-makers to the risk of large positive errors in X_{i*} . In particular, decision-makers are more likely to select the alternatives for which they have overestimated the actual value V_{i*} (Brown 1974). Strikingly, this overestimation bias exists even if the decision-maker's estimation errors are random and unbiased (Harrison and March 1984). How can investors deal with this disappointment bias?

Counteracting disappointment: discounting for the volatility of the information signal

Rational decision-makers learn from positive and negative post-decision outcomes: estimates about future returns are noisy and biased. If the disappointment bias results from the fact that selecting the alternative with the maximum estimated value X_{i*} bears the risk of large positive errors in X_{i*} , the following adapted selection mechanism would discount for these errors (Smith and Winkler 2006):

$$\hat{V}_i = \alpha_i X_i \text{ with } \alpha_i = \left(1 + \sigma_{X_i}^2\right)^{-1} \quad (1)$$

The (ex post observed) realized value \hat{V}_i is a function of the value estimate X_i . To avoid disappointment bias, an intelligent investor would weight the value estimate X_i by the inverse of the volatility of the value estimate $\sigma_{X_i}^2$. If $\sigma_{X_i}^2 = 0$, then weight $\alpha_i = 1$ (with a discounting factor of zero), and if $\sigma_{X_i}^2 > 0$, weight $\alpha_i < 1$ (with a discounting factor larger than zero). It is therefore possible that an alternative i^* with the highest estimate $X_{i*} = \max[X_1, \dots, X_n]$ is not the optimal alternative when accounting for $\sigma_{X_i}^2$ because the α_i -weighted rank order $\alpha_1 X_1, \dots, \alpha_n X_n$ might suggest another alternative j^* to have the highest estimate $\alpha_{j*} X_{j*} = \max[\alpha_1 X_1, \dots, \alpha_n X_n]$.

This study suggests that investors incorporate this (or a similar) principle into their stock selection process. To mitigate potential disappointment bias, informed investors seek signals that provide insights into potential variability in a firm's future performance.

One such signal could be disagreement in evaluations of nonfinancial performance, such as ESG ratings (Serafeim and Yoon 2023) or brand perceptions (Luo et al. 2013), at one point in time. Another valuable signal could be the variation in nonfinancial performance *over time*, herein referred to as *temporal volatility*. Unlike the dispersion of ESG or brand ratings at a single point in time, temporal volatility reflects fluctuations in performance across past periods and may serve as another boundary condition for how investors respond to changes in signals about firm performance.



This study posits that investors respond more (less) strongly to updates about a firm's nonfinancial performance when temporal volatility of the nonfinancial performance suggests lower (higher) uncertainty.²

The moderating effect of the temporal volatility of nonfinancial performance

Many performance signals are easily available to investors. For instance, a firm reports in its annual report a year-over-year increase in return on sales from 12% to 13%. Investors may ask themselves whether this improved profitability is short-lived or not. The (expected) temporal variation of profitability carries the answer to this question. Only if improved profitability is temporally stable (low temporal variation) does its improvement indicate a sustainable effect on future profits. If investors were to assume that profitability changes are volatile over time and not representative of the average profitability of future periods (high temporal variation), then they would discount for this expected temporal variation and give the profitability growth less weight in future periods. Do investors apply this decision calculus also to nonfinancial performance signals?

"Good" reputations, brand perceptions, or customer satisfaction can influence stakeholders' decision-making processes and facilitate closer relationships between firms and their stakeholders (e.g., Frooman 1999; Keller 1993; Raithel et al. 2012). These intangible assets are scarce resources that are difficult to imitate. A large body of research documents that investors' expectations about future returns are also affected by nonfinancial performance, such as corporate reputation, brand perception, and customer satisfaction (e.g., Edeling and Fischer 2016; Raithel and Schwaiger 2015).

From the above discussion, it follows that investors should also discount for the temporal volatility of nonfinancial performance signals:

Hypothesis: The positive relationship between nonfinancial performance signals and stock return is negatively moderated by the volatility of nonfinancial performance signals.

To test this hypothesis, two empirical studies are presented. Study 1 examines the effects of the temporal volatility of brand perception. Study 2 aims to replicate the findings of the first, with a specific focus on the temporal volatility of customer satisfaction. Additionally, Study 2 seeks to provide insights into the temporal relationships between the volatility of nonfinancial performance and investor reactions.

² This predicted interaction effect is also warranted by the efficient market hypothesis (EMH), which assumes that the stock market always incorporates all available information about a stock efficiently (Fama 1970). Disappointment bias implies a *systematic mispricing* of stocks and, thus, would represent a (rather strong) violation of the EMH. The adapted decision rule assumes that the stock market is efficient and anticipates disappointment bias caused by historical volatility of financial and nonfinancial performance signals.



Study 1: the temporal volatility of brand perception

Measures and sample

The empirical study combines several data sources covering stocks listed at U.S. stock exchanges. After introducing the measures and their data sources, this section concludes with the data matching procedure and sample details.

Buy-and-Hold Abnormal Stock Return (BHAR). To estimate investors' response to information signals, this study uses stock returns. To adjust the raw stock return (including dividends) for general risk factors, this study applies the Four-Factor Model of Fama and French (Carhart 1997; Fama and French 1993):

$$R_{im} - R_{RFm} = a_i + b_i \cdot RMRF_m + s_i \cdot SMB_m + h_i \cdot HML_m + u_i \cdot UMD_m + e_{im} \quad (2)$$

where R_{it} is the stock return i in month m ; R_{RFm} is the risk-free rate of return in month m ; $RMRF_m$ is the risk-free adjusted market return in month m ; SMB_t is the stock return difference between small and large firms; HML_m is the return difference between high and low book-to-market stocks; UMD_m is the return difference between stocks with upward and downward momentum; a_i is the intercept; the slope estimates b_i , s_i , h_i , and u_i measure the sensitivity of stock i 's return for the four risk factors; and e_{im} is the model error term. For each calendar year, the 60 monthly returns of the preceding five years serve as input for model calibration. The monthly abnormal return AR would be the ex post difference between the raw and expected returns, i.e., $AR_{im} = R_{im} - E(R_{im})$. However, the annual level analysis requires aggregation of monthly returns. The following formula for calculating the buy-and-hold abnormal returns ($BHAR_{it}$) applies:

$$BHAR_{it} = R_{it} - E(R_{it}) \text{ with } R_{it} = \prod_{m=1}^{12} (1 + R_{im}) \text{ and } E(R_{it}) = \prod_{m=1}^{12} (1 + E(R_{im})) \quad (3)$$

The data sources for the stock return, dividends, and the four stock return risk factors are *Thomson Reuters Datastream (Refinitiv)* and *Kenneth French's website*, respectively.

ΔBrand Perception and Volatility of ΔBrand Perception. The data source for the nonfinancial performance measure is a customer-based brand equity index (*BrandIndex*) provided by *YouGov Group*. Prior studies have used these data to estimate the effects of non-financial performance on investor response (e.g., Colicev et al. 2018; Luo et al. 2013; Malshe et al. 2020). *YouGov* specializes in online panels and monitors brands in several major markets worldwide. In the U.S., *YouGov* monitors consumer perceptions of more than 1,000 brands in more than 40 sectors by surveying a representative sample of 5,000 people each day (from a panel size of 1,500,000 consumers). To ensure that the brand responses represent the general population, *YouGov* weights respondents by age, race, gender, education, income, and geography (region) using census data. Their *BrandIndex* consists of six nonfinancial indicators that overlap with other nonfinancial performance measures used by prior research (e.g., Fornell et al. 2006; Mizik and Jacobson 2008; Raitchel and Schwaiger 2015; Roberts and Dowling 2002):



- *Quality*: “Which of the brands in the sector do you associate with good/poor quality?”
- *Value*: “Which of the brands do you associate with good/poor value-for-money?”
- *Satisfaction*: “Would you identify yourself as a recent satisfied/unsatisfied customer of any of these brands?” [only answered by current or former customers]
- *Recommendation*: “Which brands would you recommend to a friend/suggest avoiding?”
- *Affect*: “For which brands do you have a generally positive/negative feeling?”
- *Reputation*: “Which of the brands would you be proud/embarrassed to work for?”

YouGov collects the data in the following manner. First, for a given sector, respondents select all brands that they are aware of. For this brand subset, they select the brands for which they agree to the positive question (e.g., good brand quality). Then, they select the brands for which they agree to the negative question (e.g., poor brand quality). Unselected brands obtain a “neutral” rating. Hence, three responses are possible: positive, negative, and neutral. Only those respondents who have consumer experience with a brand answer the satisfaction questions. For each of the six indicators, the raw rating scores equal the differences between the number of respondents who agree with the positive judgments and the number of respondents who agree with the negative judgments divided by the total number of respondents (= number of positive + negative + neutral respondents). The average of these six brand-rating scores represents the measure of the overall brand perception. This measure can theoretically range between -1 and $+1$. These data are available on a daily level, but the total number of daily ratings is frequently less than 100 per brand. After aggregation on a monthly level, a brand receives approximately 1,500 ratings per month, which represents a reasonable sample size. The natural logarithm of the standard deviation of $\Delta \text{Brand Perception}$ of the sixty months in years $t-4$ to t measures the historical volatility of brand perception (*Volatility of $\Delta \text{Brand Perception}$*).

To compare the expected effects of nonfinancial performance with financial performance signals, this study analyzes the following three common financial variables:

$\Delta \text{Cashflows}$ and Volatility of $\Delta \text{Cashflows}$. The data source is *Thomson Reuters Datastream (Refinitiv)*. The annual changes in the firm’s free cashflow deflated by total assets ($\Delta \text{Cashflows}$) serve as the first proxy for an internal, financial performance signal. The natural logarithm of the standard deviation of $\Delta \text{Cashflows}$ of years $t-4$ to t measures the historical volatility of cashflows (*Volatility of $\Delta \text{Cashflows}$*).

$\Delta \text{Profitability}$ and Volatility of $\Delta \text{Profitability}$. The data source is *Thomson Reuters Datastream (Refinitiv)*. The annual changes in the firm’s operating income deflated by sales ($\Delta \text{Profitability}$) serve as a second proxy for an internal, financial performance signal. The natural logarithm of the standard deviation of $\Delta \text{Profitability}$ of years $t-4$ to t measures the historical volatility of profitability (*Volatility of $\Delta \text{Profitability}$*).

$\Delta \text{Analyst Recommendations}$ and Volatility of $\Delta \text{Analyst Recommendations}$. The data source is the *Institutional Brokers Estimate System I/B/E/S (Refinitiv)*. The



annual changes in the mean analyst recommendations ($\Delta Analyst\ Recommendations$), defined as 1 (strong buy), 2 (buy), 3 (hold), 4 (sell) and 5 (strong sell), serve as proxies for an external, financial performance signal. By multiplying this variable by -1 , the interpretation of its direction aligns with the other performance signals. The natural logarithm of the standard deviation of $\Delta Analyst\ Recommendations$ of the years $t-4$ to t measures the historical volatility of analyst recommendation (*Volatility of $\Delta Analyst\ Recommendations$*).

Control variables. Several financial (all data retrieved from *Refinitiv*) and non-financial (all data retrieved from *YouGov BrandIndex*) variables serve as additional controls in the model. The annual changes in the natural logarithm of sales ($\Delta Firm\ Size$) control for size effects; the annual changes in total debt deflated by total assets ($\Delta Debt$) control for financial leverage effect; the annual changes in research and development expenses deflated by total assets measure effects attributable to innovation-related expenses ($\Delta R\&D$). If these data are missing, $R\&D$ is imputed with zero (O'Brien 2003). The annual changes in the percentage of strategic investors ($\Delta Strategic\ Holdings$) control for effects related to concentrated ownership. Several variables control for effects attributable to information availability, awareness, knowledge, familiarity, visibility, and attention. The annual changes in brand awareness ($\Delta Awareness$) are measured by changes in the percentage of consumers who know a brand according to the *BrandIndex* question “Which of the following brands have you ever heard of?”. The natural logarithm of the standard deviation of $\Delta Awareness$ of years $t-4$ to t measures the historical volatility of brand awareness (*Volatility of $\Delta Awareness$*). The annual changes in advertising awareness ($\Delta Ad\ Awareness$) are measured by changes in the percentage of consumers who know a brand from advertising according to the *BrandIndex* question “Which of the following brands have you seen an advertisement for in the past two weeks?”. The annual changes in word-of-mouth chatter about a brand (ΔWOM) are measured by changes in the percentage of consumers who have talked about a brand according to the *BrandIndex* question “Which of the following brands have you talked about with friends and family in the past two weeks (whether in person, online, or through social media)?”. The annual changes in the percentage of customers who are familiar with the firm’s services or products ($\Delta Experience$) are measured with the *BrandIndex* question “Have you ever purchased [product or service] from any of the following brands?”. Finally, prior research reports on spillovers of nonfinancial indicators between firms (Borah and Tellis 2016; Janakiraman et al. 2009). Hence, variation of the variable *Volatility of $\Delta Brand\ Perception$* could be partially explained by externally driven spillover effects rather than firm-specific idiosyncrasies. To control this effect, the variable *Vol. $\Delta Competitor\ Perception$* is defined as the volatility of the past changes of the average brand perceptions of all competitors in the same industry as the focal firm. The calculation of this variable follows the same procedure already outlined above for *Volatility of $\Delta Brand\ Perception$* .

Data matching and final sample. The brand perception database is available for the period from Dec 2012 to Dec 2019. This database includes publicly listed “brand name stocks” for which the brand and stock names are identical (Frieder and Subrahmanyam 2005). For average investors, it is therefore easy



to connect the nonfinancial performance signal with the stock. The nonfinancial data of these brand name stocks are matched with the financial data. The analysis requires five years of data to calculate the volatility measures. Furthermore, the model includes variables in first differences. Therefore, the usable sampling period covers from 2017 to 2019. After excluding observations with missing data (for several firms, the brand and analyst data are not complete), the unbalanced sample includes 513 observations of 179 firms from 27 industries.

Modeling

The following equation models the relationship between *BHAR* and the covariates:

$$BHAR_{it} = \alpha + \beta^T \cdot \Delta Performance_{it} + \gamma^T \cdot Vol \cdot \Delta Performance_{it} + \delta^T \cdot \Delta Performance * Vol \cdot \Delta Performance_{it} + \theta^T \cdot Controls_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

The dependent variable is abnormal stock return *BHAR* for firm *i* in year *t*. The vector $\Delta Performance_{it}$ includes the focal nonfinancial ($\Delta Brand Perception$) as well as the three financial performances ($\Delta Cashflow$, $\Delta Profitability$, $\Delta Analyst Recommendation$). The expectation is that each regression coefficient β_1 , β_2 , β_3 , β_4 in vector β has a positive sign because positive changes in any performance measure are a “buy” signal for investors. The vector $Vol \cdot \Delta Performance_{it}$ includes the volatility measures for the four performance signals: *Vol. $\Delta Brand Perception$* as well as *Vol. $\Delta Cashflow$* , *Vol. $\Delta Profitability$* , *Vol. $\Delta Analyst Recommendation$* . The expectation about the signs of the regression coefficients γ_1 , γ_2 , γ_3 , γ_4 in vector γ is ambiguous because of contradictory arguments and empirical findings (Bartram et al. 2012; Minton et al. 2002; Pástor and Pietro 2003; Rountree et al. 2008).

The relevant covariates are in vector $\Delta Performance * Vol \cdot \Delta Performance_{it}$, which includes the interaction terms of the focal nonfinancial ($\Delta Brand Perception * Vol \cdot \Delta Brand Perception$) and the financial ($\Delta Cashflow * Vol \cdot \Delta Cashflow$, $\Delta Profitability * Vol \cdot \Delta Profitability$, $\Delta Analyst Recommendation * Vol \cdot \Delta Analyst Recommendation$) performance signals with their volatilities. The hypothesis predicts that the higher the volatility of the nonfinancial performance signal, the weaker the effect of the mean financial performance signal on investors. The expectation is therefore that the sign of the focal regression coefficient δ_1 in vector δ is negative. In line with prior research, the expectation is that δ_2 , δ_3 , and δ_4 are negative as well.

The vector $\Delta Controls_{it}$ includes the control variables (see above); the vector θ includes the corresponding regression coefficients. The model uses the parameters μ_i and λ_t to account for unobserved firm- and period-specific fixed effects. The parameters α and ε_{it} represent the intercept and error term, respectively. This panel regression model is estimated with robust standard errors clustered at the firm level.



Findings

Descriptive analysis. Table 1 shows pairwise correlations and descriptive statistics for all model variables. To facilitate interpretation and comparison of effects, all model variables are z-standardized for any subsequent analyses. The six pairwise correlations between the four volatility measures range between -0.024 and 0.185 (Table 1). Only two correlations are significantly different from zero but still rather low in magnitude: $r(\text{Vol. } \Delta\text{Cashflow}, \text{Vol. } \Delta\text{Analyst Recom.}) = 0.105$ ($p < 0.05$) and $r(\text{Vol. } \Delta\text{Profitability}, \text{Vol. } \Delta\text{Brand Perception}) = 0.185$ ($p < 0.05$). These descriptive results suggest that the overlap between nonfinancial and financial volatility measures is relatively small. The nonfinancial volatility measure is therefore not considered a substitute for the financial performance volatility information.

Model-free evidence. The estimation results could be biased by modeling assumptions or selection of control variables. To rule out such biases, the abnormal stock return is simply expressed as a linear function of $\Delta\text{Performance}$, $\text{Vol. } \Delta\text{Performance}$, $\Delta\text{Performance} * \text{Vol. } \Delta\text{Performance}$ that uses the full variation in the data while excluding control variables. The results suggest that each performance metric is positively related to stock return: $\beta_{\Delta\text{Brand Perception}} = 0.173$ ($\text{SE} = 0.046$, $p = 0.000$), $\beta_{\Delta\text{Cashflow}} = 0.372$ ($\text{SE} = 0.098$, $p = 0.000$), $\beta_{\Delta\text{Profitability}} = 0.433$ ($\text{SE} = 0.079$, $p = 0.000$), $\beta_{\Delta\text{Analyst. Recom.}} = 0.397$ ($\text{SE} = 0.067$, $p = 0.000$). As predicted by the hypothesis, the positive effect of the nonfinancial performance signal is moderated negatively by the historical volatility of this performance metric: $\delta_{\Delta\text{Brand Perception} * \text{Vol. } \Delta\text{Brand Perception}} = -0.075$ ($\text{SE} = 0.034$, $p = 0.027$). The same finding holds for the three financial performance signals: $\delta_{\Delta\text{Cashflow} * \text{Vol. } \Delta\text{Cashflow}} = -0.154$ ($\text{SE} = 0.039$, $p = 0.000$), $\delta_{\Delta\text{Profitability} * \text{Vol. } \Delta\text{Profitability}} = -0.147$ ($\text{SE} = 0.044$, $p = 0.001$), $\beta_{\Delta\text{Analyst. Recom.} * \text{Vol. } \Delta\text{Analyst. Recom.}} = -0.108$ ($\text{SE} = 0.027$, $p = 0.000$).

Model results. Table 2 displays the results and shows that stock returns are positively associated with nonfinancial performance ($\beta_{\Delta\text{Brand Perception}} = 0.135$, $\text{SE} = 0.060$, $p = 0.026$) as well as financial performance ($\beta_{\Delta\text{Cashflow}} = 0.225$, $\text{SE} = 0.102$, $p = 0.029$; $\beta_{\Delta\text{Profitability}} = 0.293$, $\text{SE} = 0.097$, $p = 0.003$; $\beta_{\Delta\text{Analyst. Recom.}} = 0.320$, $\text{SE} = 0.091$, $p = 0.001$). The hypothesized negative interaction effect (highlighted in bold in Table 2) captured by $\Delta\text{Brand Perception} * \text{Vol. } \Delta\text{Brand Perception}$ is negative: $\delta_{\Delta\text{Brand Perception} * \text{Vol. } \Delta\text{Brand Perception}} = -0.086$ ($\text{SE} = 0.041$, $p = 0.036$). The same finding holds for the three financial performance measures: $\delta_{\Delta\text{Cashflow} * \text{Vol. } \Delta\text{Cashflow}} = -0.083$ ($\text{SE} = 0.037$, $p = 0.027$), $\delta_{\Delta\text{Profitability} * \text{Vol. } \Delta\text{Profitability}} = -0.096$ ($\text{SE} = 0.056$, $p = 0.088$), $\beta_{\Delta\text{Analyst. Recom.} * \text{Vol. } \Delta\text{Analyst. Recom.}} = -0.081$ ($\text{SE} = 0.035$, $p = 0.022$). Notably, the magnitudes of the four interaction effects are very similar: the discounting effect of volatility in either signal is almost identical. The only difference is that the main effect of $\Delta\text{Brand Perception}$ is approximately 50% smaller than that of the three financial performance metrics, whereby the positive effect of $\Delta\text{Brand Perception}$ on stock return becomes insignificant already at mean levels of $\text{Vol. } \Delta\text{Brand Perception}$ (cp. Panel A to Panels B/C/D in Fig. 1). In sum, these findings provide support for the hypothesis.



Table 1 Descriptive statistics and correlations for model variables (study 1)

#	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	BHAR	1.000																		
2	Δ Cashflow	0.143*	1.000																	
3	Vol. Δ Cashflow	0.083	-0.121*	1.000																
4	Δ Profitability	0.220*	0.200*	-0.023	1.000															
5	Vol. Δ Profitability	0.028	0.138	0.026	0.214*	1.000														
6	Δ Analyst Recom	0.188*	0.035	0.001	0.082	0.065	1.000													
7	Vol. Δ Analyst Recom	0.008	0.003	0.105*	0.000	0.019	0.094*	1.000												
8	Δ Brand Perception	0.112*	0.042	-0.062	0.122*	0.017	0.061	0.107*	1.000											
9	Vol. Δ Brand Perception	0.062	-0.010	-0.024	-0.027	0.185*	0.030	0.094*	0.096*	1.000										
10	Δ Firm Size	0.233*	0.144*	0.050	0.096*	0.137*	0.116*	-0.089*	0.001	0.071	1.000									
11	Δ Debt	0.005	0.113*	0.060	0.028	0.008	0.051	0.036	-0.005	0.048	-0.023	1.000								
12	Δ R&D	-0.028	0.120*	-0.044	-0.007	-0.024	-0.054	-0.080	0.045	0.024	-0.016	-0.070	1.000							
13	Δ Strategic Holdings	0.015	-0.066	-0.027	-0.088*	0.009	-0.077	-0.009	-0.053	-0.074	-0.085	-0.051	-0.032	1.000						
14	Δ Awareness	0.033	0.001	0.147*	0.011	-0.035	0.115*	0.064	-0.040	0.271*	0.091*	0.102*	-0.145*	-0.027	1.000					
15	Vol. Δ Awareness	0.055	-0.011	0.166*	0.013	0.131*	-0.049	0.087*	0.060	-0.046	0.027	-0.017	-0.048	-0.033	0.039	1.000				
16	Δ Ad Awareness	0.059	0.083	0.120*	0.028	0.042	0.068	0.067	0.041	0.172*	0.162*	0.046	-0.009	0.006	0.441*	0.250*	1.000			
17	Δ WOM	-0.020	0.019	0.025	0.014	-0.087*	0.009	0.074	-0.113*	0.013	0.015	0.150*	-0.040	0.039	0.361*	0.024	0.540*	1.000		
18	Δ Experience	0.007	0.000	0.073	0.001	0.060	0.044	0.139*	0.224*	0.170*	-0.013	0.060	-0.066	0.021	0.423*	0.281*	0.249*	0.082	1.000	
19	Vol. Δ Competitor Perception	0.041	0.119*	-0.131*	0.101*	0.202*	-0.033	0.080	0.101*	0.279*	0.149*	0.034	0.013	-0.015	-0.027	0.259*	0.152*	0.036	0.038	1.000
	Mean	0.051	-0.006	-7.342	0.002	-7.651	-0.007	-2.756	0.004	-3.846	0.053	0.003	0.000	0.275	-0.008	-4.302	-0.003	0.001	-0.003	-4.757
	Std. Dev	29.570	0.053	1.844	0.037	1.898	0.428	1.237	0.023	0.354	0.110	0.084	0.006	6.541	0.017	0.264	0.014	0.008	0.009	0.287
	Min	-85.956	-0.472	-13.710	-0.118	-13.289	-2.000	-5.776	-0.177	-4.467	-0.580	-0.917	-0.105	-29.000	-0.053	-5.072	-0.098	-0.047	-0.070	-5.349
	Max	185.891	0.400	-0.751	0.293	-1.316	3.000	1.504	0.079	-2.568	0.548	0.534	0.044	75.000	0.088	-3.740	0.068	0.073	0.035	-4.025

* $p < 0.05$, $N = 513$

Table 2 Model results (study 1)

Covariates	Hyp. (exp. sign)	Dependent Variable: Buy-and-Hold Abnormal Stock Return		
		Coefficient	Robust Std.Err. ^a	p-value
<i>Nonfinancial Performance Signal</i>				
ΔBrand Perception	(+)	0.135	0.060	0.026
Vol. ΔBrand Perception	(+/-)	0.222	0.151	0.144
ΔBrand Perception*Vol. ΔBrand Perception	Hyp. (-)	-0.086	0.041	0.036
<i>Financial Performance Signals</i>				
ΔCashflow	(+)	0.225	0.102	0.029
Vol. ΔCashflow	(+/-)	0.196	0.277	0.480
ΔCashflow*Vol. ΔCashflow	(-)	-0.083	0.037	0.027
ΔProfitability	(+)	0.293	0.097	0.003
Vol. ΔProfitability	(+/-)	0.043	0.151	0.775
ΔProfitability*Vol. ΔProfitability	(-)	-0.096	0.056	0.088
ΔAnalyst Recom	(+)	0.320	0.091	0.001
Vol. ΔAnalyst Recom	(+/-)	0.100	0.128	0.437
ΔAnalyst Recom.*Vol. ΔAnalyst Recom	(-)	-0.081	0.035	0.022
<i>Controls</i>				
ΔFirm Size		0.079	0.072	0.273
ΔDebt		0.032	0.065	0.623
ΔR&D		-0.053	0.067	0.428
ΔStrategic Holdings		0.169	0.066	0.012
ΔAwareness		0.014	0.094	0.885
Vol. ΔAwareness		0.267	0.177	0.133
ΔAd Awareness		-0.029	0.067	0.662
ΔWOM		-0.091	0.063	0.149
ΔExperience		-0.088	0.068	0.193
Vol. ΔCompetitor Perception		-0.430	0.216	0.048
Firm Fixed Effects		YES		
Year Fixed Effects		YES		
<i>Model Fit</i>				
F-value		3.090		0.000
R ² (within)		0.166		
R ² (overall)		0.094		
N		513		

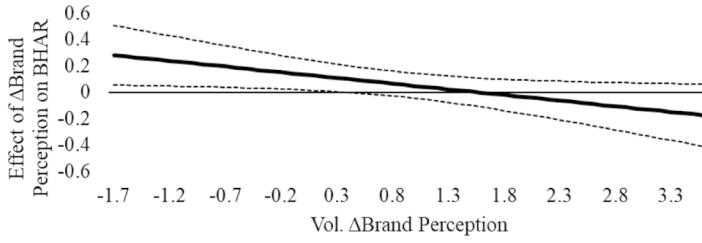
^aRobust standard errors clustered at the firm level

Discussion of study 1

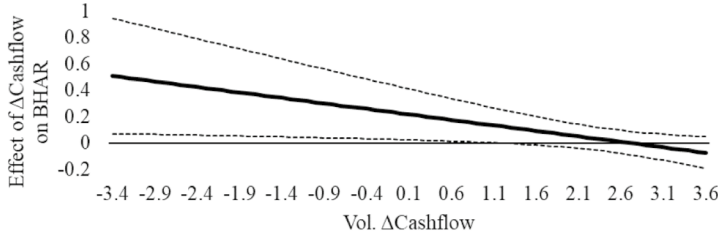
The findings from Study 1 reveal that temporal volatility in past changes of brand perception negatively interacts with current changes in brand perception, thereby reducing the potential future benefits of improvements in brand perception among



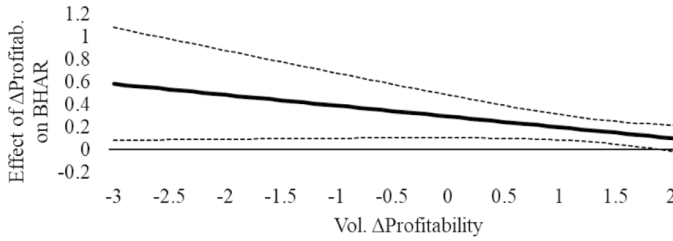
Panel A: Brand Perception



Panel B: Cashflow



Panel C: Profitability



Panel D: Analyst Recommendation

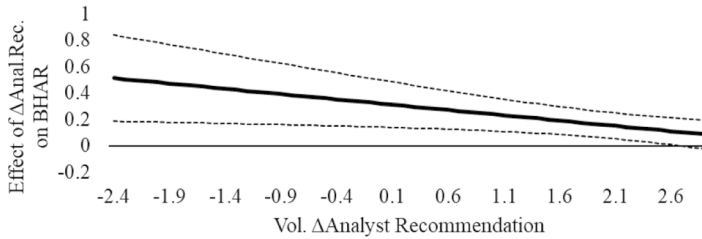


Fig. 1 Conditional effect of firm performance on abnormal stock returns at different volatility values of firm performance (Study 1). Note: The black solid line represents the conditional effect, while the dashed lines represent the 95% confidence bands of this conditional effect

customers. As a result, investors downweigh changes in brand perception when updating their beliefs about future firm value if the temporal volatility of brand perception is high. Additionally, the study highlights that this interaction effect is analogous to the negative interaction effect observed between financial performance signals and their respective temporal volatilities.



A potential limitation of Study 1 is that it does not account for potential temporal dynamics and feedback loops among the model variables. To address this, the subsequent study not only seeks to replicate the findings of Study 1 but also employs a different methodology to incorporate temporal dynamics. This approach aims to determine whether the volatility of nonfinancial performance can serve as a predictor of future investor responses.

Study 2: the temporal volatility of customer satisfaction

Measures and sample

The second study combines data from two sources, focusing on U.S. stock exchange listed stocks in the automotive industry. After introducing the measures and their data sources, this section concludes with details on the data matching procedure and sample characteristics.

Buy-and-Hold Abnormal Stock Return (BHAR): Investors' responses are modeled using the same approach as in Study 1 (see formula (2) above). However, since the analysis is conducted at a quarterly level, the buy-and-hold abnormal returns ($BHAR_{it}$) are calculated as the sum of the three monthly abnormal stock returns for each quarter (similar to formula (3) above). Stock return, dividends, and the four risk factors for stock returns are sourced from *Thomson Reuters Datastream (Refinitiv)* and *Kenneth French's website*, respectively.

ΔCustomer Satisfaction and Volatility of ΔChange in Customer Satisfaction. The nonfinancial performance measure is derived from *YouGov Group's BrandIndex*, which provides quarterly customer satisfaction metrics. This measure is based on responses to the question: "Would you identify yourself as a recent satisfied or unsatisfied customer of any of these brands?" Only current or former customers answer this question. Prior studies (e.g., Mafael et al. 2022) have used this metric. For more details on the online panel and data collection process, please refer to Study 1 above. The customer satisfaction indicator is calculated as the difference between the number of satisfied and dissatisfied respondents, divided by the total number of respondents (positive, negative, and neutral). This metric theoretically ranges from -1 to $+1$. On average, a brand receives approximately 4,500 ratings per quarter, providing a robust sample size. The temporal volatility of customer satisfaction (*Volatility of ΔCustomer Satisfaction_{it}*) of firm i in quarter t is measured as the standard deviation of changes in satisfaction $\Delta Customer Satisfaction_{it}$ over the five quarters from $t-4$ to t .

Data matching and final sample: The database covers brands from 12 automotive firms listed on U.S. stock exchanges between Q1 2013 and Q4 2021 (36 quarters). For firms with multiple brands, brand-level customer satisfaction data are aggregated to the firm level using annual brand-level sales data from *goodcarbadcar.net* as weights for the brand-level satisfaction scores. A panel vector autoregression (PVAR) model is employed to capture the temporal dynamics between customer satisfaction variables and abnormal stock returns (explained in the following section).



Due to the model's requirements, the first seven quarters cannot be used for model estimation.³ This results in a usable sample size of 29 quarters across 12 firms ($N=348$).

Modeling

Panel vector-autoregressive system of equations. Study 2 employs a dynamic, multi-equation autoregressive distributed lag modeling framework, specifically the panel vector autoregressive (PVAR) methodology (Holtz-Eakin et al. 1988; Love and Zicchino 2006). The PVAR approach helps address endogeneity bias by treating all endogenous variables as mutually interdependent within a fully interactive modeling system. This system accounts for direct effects, feedback loops, autocorrelation, and cross-variable interactions (Abrigo and Love 2016). The relationships between the variables are modeled using the following PVAR framework, which includes four equations:

$$\begin{bmatrix} Abn.StockReturn_{it} \\ \Delta Cust.Satisfaction_{it} \\ Vol.(\Delta Cust.Satisfaction)_{it} \\ \Delta Cust.Satisfaction * Vol.(\Delta Cust.Satisfaction)_{it} \end{bmatrix} = \quad (5)$$

$$\sum_{l=1}^L \Gamma_{1l} \begin{bmatrix} Abn.StockReturn_{i,t-l} \\ \Delta Cust.Satisfaction_{i,t-l} \\ Vol.(\Delta Cust.Satisfaction)_{i,t-l} \\ \Delta Cust.Satisfaction * Vol.(\Delta Cust.Satisfaction)_{i,t-l} \end{bmatrix} + M_i + \Lambda_t + E_{it}$$

The vector Γ_{1l} contains the regressors for the four lagged endogenous variables. Panel unit root tests with cross-section-demeaned time series (Levin et al. 2002) confirm that all variables are stationary ($p < 0.001$). This PVAR model uses a lag order of $L=1$ to capture the longer-term effects of changes in any endogenous variable on subsequent values of other endogenous variables. Based on the criteria proposed by Andrews and Lu (2001)—the modified Akaike Information Criterion (MAIC), the modified Bayesian Information Criterion (MBIC), and the modified Quasi-Information Criterion (MQIC)— $L=1$ minimizes all three measures.

The PVAR model is estimated using the Generalized Method of Moments (GMM). Firm-fixed effects M_i are controlled using the Helmert procedure (Arellano and Bover 1995), while Λ_t includes several period controls (year dummies and time trend). A minimum of two (up to 12) prior lags of the endogenous variables are used as GMM style instruments for the one-period lagged endogenous variables, following the procedure proposed by Holtz-Eakin et al. (1988). Hansen (1982)'s J -statistic

³ Specifically: The model uses first differences of the customer satisfaction data, excluding one quarter. It calculates the volatility measure based on four lagged quarters, excluding four more quarters. One-period lagged variables are used to predict future stock returns, excluding another quarter. Finally, a minimum of two-period lagged variables is applied to instrument the one-period lagged variables, excluding one additional quarter.



confirms that the overidentifying restrictions are satisfied ($p > 0.10$). The model is stable, as all moduli of the companion matrix are strictly less than one (Lütkepohl 2005).

Based on the estimation results and Cholesky decomposition (Hamilton 1994), cumulative Impulse Response Functions (IRFs) enable a Granger-causal interpretation of parameters—for example, the cumulative effect of changes in customer satisfaction on subsequent abnormal stock returns. Monte Carlo simulations (5,000 replications) generate 95% confidence intervals for the cumulative IRF effects up to four quarters after the change in the impulse variable (effects stabilize after four quarters).

Findings

Granger-causality test results. Table 3 shows the results for the Granger causality tests. The findings confirm that each of the four model variables affects at least one other variable and is affected by at least one other variable ($p < 0.001$), thereby justifying the PVAR model set-up. The results also show for the abnormal stock return equation that $\Delta Customer Satisfaction$, *Volatility of $\Delta Customer Satisfaction$* , and, as hypothesized, the interaction $\Delta Customer Satisfaction * Volatility of \Delta Customer Satisfaction$ Granger-cause abnormal stock return.

PVAR regression results. Table 4 shows the estimation results for the system of equations. Although lagged $\Delta Customer Satisfaction * Vol. of \Delta Customer Satisfaction$ has a significantly negative coefficient ($\beta = -0.065$, $SE = 0.017$, $p = 0.000$), this is not sufficient evidence for the hypothesized negative interactive effect on abnormal stock return. The reason lies in the dynamic nature of the PVAR model, where each variable depends not only on its own lag but also on the lags of other variables in the system. Cumulative Impulse Response Functions account for these interdependencies, offering a clear and intuitive interpretation of the effects over time.

Cumulative Impulse Response Function results. Table 5 shows the cumulative IRFs for up to four quarters after a one standard deviation shock in the impulse variable on the response variable (effects do not change in subsequent quarters). Results show that $\Delta Customer Satisfaction$ has a significantly positive effect on subsequent abnormal stock return at a 95% confidence level (effect is 0.042 in the fourth quarter). Initially, *Volatility of $\Delta Customer Satisfaction$* has a negative effect on subsequent stock return (effect is -0.065 in the second quarter after the shock, the 95% confidence interval does not include the zero). However, this effect is not stable because in the following quarters this effect is not significantly different from zero anymore (95% confidence interval includes zero). Finally, the interaction $\Delta Customer Satisfaction * Volatility of \Delta Customer Satisfaction$ has a significantly negative effect on subsequent abnormal stock return in all quarters following the shock (the effect is -0.051 in the fourth quarter, the 95% confidence interval does not include the zero). This finding provides support for the hypothesis.



Table 3 Granger causality test results (study 2)

Abnormal Stock Return equation	Chi ²	p-value
Δ Satisfaction	10.586	0.001
Vol.(Δ Satisfaction)	6.228	0.013
Δ Satisfaction*Vol.(Δ Satisfaction)	13.992	0.000
All	18.565	0.000
<i>ΔSatisfaction equation</i>		
Abnormal Stock Return	5.616	0.018
Vol.(Δ Satisfaction)	22.444	0.000
Δ Satisfaction*Vol.(Δ Satisfaction)	3.833	0.050
All	25.167	0.000
<i>Vol.(ΔSatisfaction) equation</i>		
Abnormal Stock Return	20.600	0.000
Δ Satisfaction	4.309	0.038
Δ Satisfaction*Vol.(Δ Satisfaction)	0.465	0.495
All	36.409	0.000
<i>ΔSatisfaction*Vol. (ΔSatisfaction) equation</i>		
Abnormal Stock Return	0.014	0.907
Δ Satisfaction	12.503	0.000
Vol.(Δ Satisfaction)	44.277	0.000
All	51.672	0.000

N = 348

H₀: Excluded variable does not Granger cause equation variable

Table 4 PVAR regression results (study 2)

Abnormal Stock Return equation	Coef	SE	p-value
Lagged Abnormal Stock Return	0.041	0.017	0.564
Lagged Δ Cust. Satisfaction	0.050	0.015	0.001
Lagged Vol.(Δ Cust. Satisfaction)	−0.044	0.017	0.013
Lagged Δ Cust. Satisfaction*Vol.(Δ Cust. Satisfaction)	−0.065	0.017	0.000
<i>ΔCust. Satisfaction equation</i>			
Lagged Abnormal Stock Return	−0.968	0.121	0.018
Lagged Δ Cust. Satisfaction	0.062	0.104	0.551
Lagged Vol.(Δ Cust. Satisfaction)	−0.641	0.135	0.000
Lagged Δ Cust. Satisfaction*Vol.(Δ Cust. Satisfaction)	−0.238	0.121	0.050
<i>Vol.(ΔCust. Satisfaction) equation</i>			
Lagged Abnormal Stock Return	0.365	0.022	0.000
Lagged Δ Cust. Satisfaction	−0.041	0.020	0.038
Lagged Vol.(Δ Cust. Satisfaction)	0.753	0.033	0.000
Lagged Δ Cust. Satisfaction*Vol.(Δ Cust. Satisfaction)	−0.015	0.022	0.495
<i>ΔCust. Satisfaction*Vol.(ΔCust. Satisfaction) equation</i>			
Lagged Abnormal Stock Return	−0.029	0.095	0.907
Lagged Δ Cust. Satisfaction	0.265	0.075	0.000
Lagged Vol.(Δ Cust. Satisfaction)	−0.701	0.105	0.000
Lagged Δ Cust. Satisfaction*Vol.(Δ Cust. Satisfaction)	−0.419	0.095	0.000
<i>Model statistics</i>			
Final GMM Criterion Q(b)	0.504		
N	348		
Stability (criterion: max. Eigenvalue < 1)	0.775		
Hansen's J Chi2 (criterion: p > 0.1)	175.360	df = 160	0.192

Lags t-2 up to t-12 of endogenous variables used as instrumental variables (GMM style)

Each equation includes period controls



Table 5 Cumulative impulse response functions (study 2)

Post-Impulse Quarter	Cumulative IRF	95% CI low	95% CI high
<i>ΔCust. Satisfaction \rightarrow Abn. Stock Return [exp. sign: +]</i>			
1	0.050	0.020	0.080
2	0.040	0.013	0.066
3	0.041	0.016	0.065
4	0.042	0.017	0.066
<i>Vol.(ΔCust. Satisfaction) \rightarrow Abn. Stock Return [exp. sign: +/–]</i>			
1	– 0.044	– 0.078	– 0.010
2	– 0.065	– 0.128	– 0.002
3	– 0.081	– 0.166	0.003
4	– 0.095	– 0.196	0.007
<i>ΔCust. Satisfaction*Vol.(ΔCust. Satisfaction) \rightarrow Abn. Stock Return [Hyp., exp. sign: –]</i>			
1	– 0.065	– 0.098	– 0.031
2	– 0.051	– 0.079	– 0.024
3	– 0.050	– 0.075	– 0.025
4	– 0.051	– 0.076	– 0.025

Cum. IRFs based on PVAR results shown in Table 4

95% confidence intervals based on 5000 Monte Carlo simulations

Discussion of study 2

The findings of Study 2 replicate those of Study 1, reinforcing the conclusion that the volatility of nonfinancial performance negatively moderates the relationship between changes in nonfinancial performance and stock returns. Specifically, Study 2 confirms this effect using customer satisfaction as the nonfinancial performance indicator.

Additionally, the study shows that the interaction of the changes of customer satisfaction and the temporal volatility in past changes of customer satisfaction *precede* stock market performance. This suggests that the temporal volatility of nonfinancial performance can be a valuable predictive tool and may serve as an early indicator of a company's future stock market performance.

General discussion

Research has long acknowledged the ability to anticipate and manage uncertainty as a prerequisite for economic development (Bernstein 1996). Uncertainty about input factors and potential outcomes characterize almost any business-relevant decision (e.g., Abdellaoui et al. 2011; Ruefli et al. 1999; Tversky and Kahneman 1974). Smith and Winkler (2006) theorize how intelligent decision makers can counteract post-decision disappointment borne out of pre-decision uncertainty. Intelligent actors such as investors (should) use signals about uncertainty such as historical



performance volatility as inputs prior to adjusting their expectation about future firm value. This decision calculus found already broad support for the temporal volatility of financial performance. However, concerning temporal volatility of nonfinancial performance, research offers only limited insights. This study addresses this research gap and provides empirical support that investors do also discount for the temporal volatility of nonfinancial performance.

Beyond managing financial volatility over time, managing nonfinancial performance volatility over time is also “a must have”. Managing temporal volatility of nonfinancial performance is, however, not a straightforward path. Many decisions involve trade-offs such as enhancing the mean response at the expense of enhancing the volatility of the response (Fischer et al. 2015), which could then reduce the future returns of this response, thus enhancing the decision importance more than expected. The following recommendations may assist firms in successfully managing nonfinancial performance volatility.

Managers and researchers claim to already have a good understanding of how nonfinancial performance emerges, how managerial actions or events alter nonfinancial performance, and how important nonfinancial performance improvement is for future returns. This research shows that managers can improve future returns in response to improvements of nonfinancial performance only by also developing an understanding of how their actions affect temporal volatility of nonfinancial performance. Since temporal volatility of nonfinancial performance diminishes the returns from investments into nonfinancial performance-enhancing activities, firms should closely watch the relationship between the rate of nonfinancial performance enhancement and temporal volatility of nonfinancial performance (“signal-to-noise ratio”).

To help internal and external stakeholders make more informed decisions, to avoid sentiment of mistrust, and to build confidence in decisions, firms should disclose information about temporal volatility of nonfinancial performance. Transparency empowers internal stakeholders to apply the Bayesian decision principle and may further reveal a competitive advantage if temporal volatility of nonfinancial performance is low, therefore enabling external stakeholders to make decisions that benefit the firm with greater confidence. Transparency (not only about temporal volatility of nonfinancial performance) is a tool to manage temporal volatility.

The findings presented in this study offer research opportunities in several areas. First, the empirical findings of this study reveal that temporal volatility of nonfinancial performance is an important boundary condition for the relationship between current nonfinancial performance and future firm value. This raises the question of whether firms have the power to manage temporal volatility of nonfinancial performance and what internal and external factors can cause temporal volatility of nonfinancial performance. Second, successful management of temporal volatility of nonfinancial performance also requires a profound understanding of the dynamic nature of nonfinancial performance volatility. Studies in finance show that financial performance volatility is not stable over time (Bartram et al. 2012). Future research should therefore further examine the temporal dynamics of nonfinancial performance volatility. Third, prior research shows that individuals (including experts and well-educated managers) find it difficult to comprehend the concepts of volatility.



One remedy is to make volatility visible and transparent to decision-makers. However, an optimal visual representation of volatility and risk in dashboards is not straightforward (Weber et al. 2005). Future research is therefore needed to identify techniques that provide decision makers intuitive access to the concept of nonfinancial performance volatility. This study hopefully stimulates more work in these areas.

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Declarations

Conflict of interests On behalf of all authors, the corresponding author states that there is no conflict of interest.

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