新任教員研究紹介

RESEARCH INTRODUCTION OF NEW FACULTY

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Abstract

This paper introduces the research of Assistant Professor Vuong Bao Ngoc who started her post in April 2022. The first part describes research interest and academic background for investigating these topics. Some representative studies are presented in the next section. The final part summarizes the main findings and applications as well as introduces potential lines of future research.

Keywords: behavioral finance, investment analysis, corporate governance, CSR, sustainable development

1. Introduction

My research interests include, but are not limited to, behavioral finance, corporate governance, investment analysis, and their interaction.

Behavioral finance is the research area where psychology is applied to financial models to explain market anomalies, according to Shiller (2003). It focuses on investor behaviors and their impact on stock markets from the viewpoint of a psychologist. The foundation of behavioral finance shed light on the birth of lots of new concepts. One of them, i.e., investor sentiment, has become a trendy topic in behavioral studies recently.

Investor sentiment can be defined as investor opinion, usually influenced by emotion, about future cash flows and investment risk (Corredor et al., 2013). Until now, a great number of sentiment research have been carried out with the primary purpose being to analyze how sentiment affects stock markets (Barberis et al., 1998) and other economic activities (Cheong et al., 2017). Among related themes, scientists have enormously tried to verify the role of sentiment to explain abnormal stock returns. However, the findings are inconclusive as some studies claim a significant relationship between investor sentiment and stock returns (Bathia and Bredin, 2013; Gao et al., 2020). Conversely, others prove that sentiment has little to no return predictability, such as Lansing and Tubbs (2018) and Oprea and Brad (2014).

Besides that, in recent years, corporate social responsibility (CSR) is also a topic that has gained considerable attention, not only from firm managers but also from academic researchers. One of the popular themes is determining the driving factors behind the intention of companies' CSR practices. In general, stakeholder and legitimacy theory are often grounded as the motivations that inspire companies to commit their CSR actions. Stakeholder theory argues that a firm should create value for all stakeholders, such as customers, suppliers, employees, investors, and communities, not just its shareholders. Meanwhile, legitimacy theory advocates corporations act in a socially responsible manner so that they can legitimize their behaviors to their stakeholder groups. Based on these

two theories, prior research has investigated and revealed the stakeholders-related benefits that can drive CSR implementation.

Choi and Wang (2009) examine the effect of a firm's relations with its non-financial stakeholders, including its employees, suppliers, customers, and communities. They claim that good stakeholder relations not only enable a firm with superior financial performance to sustain its competitive advantage for a longer time but more importantly, also help poorly performing firms to recover from disadvantageous positions more quickly. Moreover, Lichtenstein et al. (2004) provide evidence that perceived CSR affects not only customer purchase behavior through customer–corporate identification but also customer donations to corporate-supported nonprofit organizations. By analyzing CSR initiatives reported by 65 US companies, Rivera et al. (2016) show a positive direct relationship between CSR and customer satisfaction. Costas and Kärreman (2013) demonstrate how CSR works as a form of control that ties employees' aspirational identities and ethical conscience to the organization, while Hur et al. (2018) suggest that employees' perceptions of CSR are positively related to employee creativity.

Nevertheless, there is one group of stakeholders, i.e., investors that has rarely been explored. Cheong et al. (2017) are the first to testify to the influence investors have in driving CSR behavior. They argue that firms are motivated to improve their CSR performance in subsequent years when investors in the previous year are in a bearish mood to rebuild investor confidence. Naughton et al. (2019) use market-level CSR premium as a sentiment proxy and suggest that investor sentiment plays a role in firms' commitment to CSR.

These research limitations above motivate me to implement comprehensive studies about the sentiment impact on firms and financial markets activities, concentrating on the Asian region. Following are some of my related works.

2. Representative research

2.1. The return predictability of investor sentiment: Insight from Asia-Pacific markets

2.1.1. Data, variables, and methodology

2.1.1.1. Data and variables

My research is carried out based on a set of monthly data from six Asia-Pacific markets, including Australia, Hong Kong, Indonesia, Japan, South Korea, and Thailand over the period between January 2004 to December 2016. Most data are obtained from Thomson Reuters Datastream. For time series available on a quarterly frequency only, I use the cubic spline interpolation method to create monthly data[1].

Stock returns at the aggregate market level are represented by the main indexes of each stock exchange which indicate the overall market performance. For each market, I collect the end-of-month price index in local currency to compute the monthly time series of stock returns: $R_t = 100*\ln(P_t/P_{t-1})$. Using local currency allows me to avoid currency and exchange rate effects.

Regarding market sentiment, in this study, I use three proxies, namely the consumer confidence index (*CCI*), advance/decline ratio (*ADR*), and volatility premium (*VP*), to construct a comprehensive sentiment index. *CCI* implies the optimism/pessimism of households about the future developments of their consumption and saving, based upon answers regarding their expected financial situation, their sentiment about the general economic situation, unemployment, and capability of savings. The second proxy is *ADR* calculated by dividing the number of advancing stocks by declining stocks during a month. Finally, to obtain *VP*, at the beginning of year *t*, I sort all stocks in each market into low volatility (the bottom 30%) and high volatility (the top 30%) stocks based on their standard de-

[1] Bathia and Bredin (2013) also use this method in their research about G7 markets.

viations of the prior year. *VP* is the log of the average market-to-book ratio of high volatility stocks over the average market-to-book ratio of low volatility stocks.

Besides that, to isolate the impact of market sentiment and prevent my results are pushed by the fluctuation in the business cycle, five macroeconomic variables are employed in my empirical analysis. These are the industrial production index (*IP*), consumer price index (*CPI*), unemployment rate (*UR*), dividend yield (*DY*), and short-term interest rate (*SR*).

2.1.1.2. Methodology

Before employing my main empirical analyses, I execute augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests for all data series to ensure that they do not have a unit root. For non-stationary series, their first differencing is used instead. Besides that, to apply principal component analysis (PCA) later, I standardize sentiment indicators described in Section 2.1.1.1 to get a mean of zero and a standard deviation of one.

Following Baker et al. (2012) and Corredor et al. (2013), I create a comprehensive sentiment index for each country from standardized sentiment proxies. The construction is as follows:

Firstly, to remove unrelated-sentiment information about expected returns in my sentiment proxies, I orthogonalize these indicators on five macroeconomic variables by running the following regression:

$$Sent_{i,t} = \alpha_i + \beta_{1,i} UR_t + \beta_{2,i} IP_t + \beta_{3,i} CPI_t + \beta_{4,i} DY_t + \beta_{5,i} SR_t + \varepsilon_{i,t} \quad (1)$$

In which $Sent_{i,t}$ is one of three sentiment indicators. The explanatory variables are the growth rate of *UR*, *IP*, *CPI*, *DY*, and *SR*. The residuals, $\varepsilon_{i,t}$, from these regressions are considered as orthogonalized sentiment indicators, $Sent^{T}_{i,t}$, with $Sent^{T}_{i,t} = \varepsilon_{i,t}$ and be employed in the next steps.

Then, through PCA, I estimate the first principal component of CCI_t, ADR_t, and VP_t and their one-year lags denoted as CCI_{t-1}, ADR_{t-1}, and VP_{t-1}. This gives the first-stage index with 6 loadings. After that, the correlations between the first-stage index and each pair of sentiment proxies, i.e., sentiment indicator and its lag, are calculated. PCA is repeated for three components having a stronger relationship with the first-stage index in each pair. The first principal component estimated from this process is stored and serves as the total sentiment index.

In addition to that, I divide total sentiment indices into one regional and six local components. The same PCA process is applied to form an aggregate index for all six markets, denoted as $Sent^{Regional}_{t}$. Finally, the total sentiment index in each market is orthogonalized to the regional index. The residuals extracted from these regressions are considered as local sentiment indexes in subsequent analyses.

The relationship between investor sentiment and future market returns is investigated by manipulating the following regression models. The regressions are run separately for each market in our sample and the Asia-Pacific region, i.e., all six markets together.

$$\frac{1}{k}\sum R_{t+k} = \alpha + \beta\, Sent^{Total}_{t} + \varepsilon_{t+k} \quad (2)$$

$$\frac{1}{k}\sum R_{t+k} = \alpha + \beta_1\, Sent^{Regional}_{t} + \beta_2\, Sent^{Local}_{t} + \varepsilon_{t+k} \quad (3)$$

In which: $\frac{1}{k}\sum R_{t+k}$ is the k-month average return of the stock market with k = 1, 3, 6, 12, and 24. $Sent_t$ is the investor sentiment at time *t*. I run regional and local sentiment together in one model to discover whether the domestic effect endures or fades when the regional effect is also considered.

To get individual market coefficients, I apply the Newey-West standard errors for OLS estimations. The estimation procedure for all markets is pooled OLS regressions with cross-section fixed effects and month-clustered standard errors.

2.1.2. Results

Table 1 reveals the results by regressing Equations (2) and (3) which indicate the relationship between investor sentiment and subsequent stock returns. Regarding the total sentiment index in each market, the outcomes

Table 1. Return predictability of investor sentiment in different horizons

	Total			Regional		Local		
	Coef.	*p-value*	R^2	*Coef.*	*p-value*	*Coef.*	*p-value*	R^2
R_{t+1}								
Australia	−0.627*	0.061	2.74%	0.390	0.238	−0.676	0.186	2.79%
Hong Kong	−0.419	0.275	0.57%	0.344	0.449	−0.326	0.394	0.66%
Indonesia	−0.357	0.428	0.34%	−0.037	0.944	−0.437	0.358	0.40%
Japan	0.522	0.107	0.98%	−0.282	0.499	0.789**	0.022	2.14%
South Korea	−0.749**	0.044	2.70%	0.160	0.675	−0.883**	0.020	3.59%
Thailand	−0.630**	0.038	1.24%	0.172	0.659	−0.766**	0.036	1.75%
All markets	**−0.382****	**0.013**	**0.81%**	**0.125**	**0.730**	**−0.379****	**0.02**	**0.75%**
R_{t+3}								
Australia	−0.049	0.873	0.04%	0.020	0.938	−0.071	0.849	0.05%
Hong Kong	−0.432	0.194	1.53%	0.029	0.921	−0.550*	0.082	1.90%
Indonesia	−0.884**	0.010	4.76%	−0.016	0.966	−1.137**	0.012	6.06%
Japan	0.395*	0.057	1.37%	−0.362	0.220	0.678***	0.005	4.53%
South Korea	−0.414*	0.051	2.36%	−0.054	0.827	−0.443*	0.056	2.56%
Thailand	−0.465**	0.022	1.68%	0.130	0.638	−0.565**	0.020	2.39%
All markets	**−0.299*****	**0.004**	**1.48%**	**−0.042**	**0.839**	**−0.344*****	**0.008**	**1.53%**
R_{t+6}								
Australia	−0.050	0.822	0.07%	0.050	0.782	−0.027	0.924	0.09%
Hong Kong	−0.278	0.243	1.17%	0.120	0.601	−0.287	0.207	1.17%
Indonesia	−0.394	0.134	1.58%	0.035	0.891	−0.535	0.134	2.27%
Japan	0.280*	0.053	1.18%	−0.300	0.130	0.503***	0.007	4.60%
South Korea	−0.285*	0.097	1.90%	−0.001	0.996	−0.296*	0.098	1.93%
Thailand	−0.188	0.446	0.45%	0.284	0.190	−0.317	0.189	2.36%
All markets	**−0.148***	**0.068**	**1.47%**	**0.031**	**0.829**	**−0.162**	**0.105**	**1.46%**
R_{t+12}								
Australia	0.052	0.717	0.15%	0.027	0.839	0.147	0.389	0.61%
Hong Kong	−0.300	0.131	3.03%	0.019	0.911	−0.382**	0.040	3.75%
Indonesia	−0.205	0.228	0.90%	0.122	0.574	−0.352	0.153	2.44%
Japan	0.155	0.149	0.74%	−0.091	0.577	0.238*	0.097	1.73%
South Korea	−0.078	0.448	0.34%	0.087	0.497	−0.108	0.349	1.02%
Thailand	0.090	0.643	0.22%	0.357**	0.038	−0.037	0.839	4.15%
All markets	**−0.050**	**0.388**	**2.65%**	**0.087**	**0.389**	**−0.090**	**0.222**	**3.05%**
R_{t+24}								
Australia	0.123	0.279	2.04%	0.004	0.965	0.258**	0.038	4.46%
Hong Kong	−0.173*	0.093	3.72%	−0.029	0.802	−0.249***	0.003	5.84%
Indonesia	−0.002	0.985	0.01%	0.036	0.817	−0.028	0.842	0.15%
Japan	0.134	0.130	1.11%	0.018	0.868	0.156	0.186	1.23%
South Korea	−0.113	0.106	2.36%	0.058	0.562	−0.137*	0.060	3.84%
Thailand	0.088	0.514	0.55%	0.267**	0.023	−0.021	0.879	6.88%
All markets	**0.001**	**0.990**	**7.59%**	**0.060**	**0.393**	**−0.029**	**0.575**	**8.00%**

The table reports the regression results obtained from Equation (2) (first column) and Equation (3) (second and third column). The dependent variable is the average market return for the next 1, 3, 6, 12, and 24 months. The independent variable is the total sentiment for Equation (2) and regional and local sentiment for Equation (3). To get individual market coefficients, I apply the Newey-West correction for OLS estimations. The estimation procedure for all markets is pooled OLS regressions with cross-section fixed effects and month-clustered standard errors. Estimated coefficients, corresponding p-values, and R^2 are presented. The data period from January 2004 to December 2016.

*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

are almost homogenous during the first 6 months. Despite the differences in magnitude, most of the markets witness negative return predictability of sentiment. The largest influence belongs to Indonesia with a coefficient of −0.884 for the 3-month horizon, followed by −0.749 and −0.630 in South Korea and Thailand for the 1-month horizon, respectively.

However, the results become diverse as the effect of total sentiment in Australia and Thailand reverses and turns positive over the next 6 to 18 months. Japan is the only market where the positive correlation between the return spread and investor sentiment is exposed all the time.

These figures, nevertheless, are statistically significant mostly in Japan, South Korea, and Thailand for short-term horizons. My results reflect those of Gao et al. (2020) who also observe in their study using the Google Search Volume Index for 38 countries around the world that all countries, except Israel and Mexico, present a negative relationship between sentiment and next week's returns and 20 of the 38 countries display a pattern that is significant at the 5% level.

The less significant forecast ability of total sentiment in some markets could be because this index cannot capture the impact of investor sentiment fully which is inclined a more global phenomenon. This viewpoint argued and proved in the studies of Baker et al. (2012), Chang et al. (2011), and Corredor et al. (2015), inspires me to decompose my total sentiment into regional and local indices and discover their influence on stock returns.

As can be seen from Table 1, the local sentiment shares the same sign and trend as those of total ones with slightly greater intensity. The regional impact, on the other hand, is more dissimilar across markets and reverses to local impact in most cases. In addition to that, in contrast to the strong effect of local sentiment, the majority of regional coefficients are statistically insignificant. Therefore, in general, I conclude that the market-level results are driven mostly by local sentiment. This outcome is in line with Corredor et al. (2013) who also create a composite sentiment index for France, Germany, Spain, and the U.K. and find that this proxy captures investor sentiment limitedly. Besides that, the opposite influences of regional and local sentiment might also explain partly the frail significance of total sentiment in my sample markets. Lastly, in tandem with the prior work, I observe the weakening effect of investor sentiment over the period when the magnitude and significance of all estimated coefficients decline through short-term to long-term horizons.

The outcomes for the panel regressions of all markets share the same picture as those of individual markets. In conclusion, for these six Asia-Pacific markets, investor sentiment can be a valid predictor of stock returns over the next 6 months.

2.2. The motivating role of investor sentiment in the environmental, social, and corporate governance (ESG) performance: Evidence from Japanese companies

2.2.1. Data, variables, and methodology

2.2.1.1. Data and variables

This study includes data from 367 non-financial Japanese firms whose financial, environmental, social, and corporate governance information is available on the Thomson Reuters' Datastream and ASSET4 database over the period between 2005 and 2019.

To determine the performance of a company relating to its corporate social activities, I use the ESG scores retrieved from the Thomson Reuters' ASSET4 database. It is a weighted-average index of the underlying ten category scores classified into three pillars, including environmental, social, and corporate governance. In detail, the environmental index (*EN*) reflects the company's strengths and weaknesses in resource use, emissions, and innovation. The social

index (*SO*) indicates the company's commitment to the workforce, human rights, community, and product responsibility. The governance index (*GO*) measures the company's efficiency in management, shareholders, and CSR strategy. Each index takes a value from 0 to 100.

For independent variables, I also employ PCA to establish a comprehensive market sentiment index, based on three fundamental proxies, namely the consumer confidence index (*CCI*), volatility index (*VIX*), and advance/decline ratio (*ADR*). Two indicators are the same as my first study while the other one, *VIX*, is a real-time market index representing the market's expectations for volatility. To begin with, I form the first stage index by estimating the first principal component of CCI_t, VIX_t, ADR_t, and their one-year lag, i.e., CCI_{t-1}, VIX_{t-1}, and ADR_{t-1}. Next, the bivariate correlations between the first stage index and each pair of sentiment indicators are calculated. In the end, I reapply PCA after selecting three components that have a higher correlation in each pair. The first principal component obtained from this process is served as raw market sentiment (*MS*).

Regarding firm-specific sentiment (*FS*), I use the cumulative monthly stock returns of the previous six months as stated in the research of Hua et al. (2020) and Polk and Sapienza (2008).

Moreover, Anusakumar et al. (2017) suggest that the common association of investor sentiment on the overall stock markets should be eliminated to guarantee the empirical results are driven purely by the sentiment effect. Therefore, I regress both firm-level and market sentiment indexes on the annual growth rates of four macroeconomic variables, including gross domestic product (*GDP*), consumer price index (*CPI*), industrial production index (*IP*), and unemployment rate (*UR*). The residuals estimated from this orthogonalization are stored and applied as sentiment indicators in my analyses later.

Besides, in harmony with other studies (Fu et al., 2021; Wu, 2006), I include several control variables that are likely to affect the relationship between investor sentiment and ESG performance. These are firm size (*SIZE*), leverage (*LEV*), return on assets (*ROA*), market-to-book ratio (*MTB*), and board structure (*IND*).

2.2.1.2. Methodology

Before executing my empirical models, I winsorize all variables at the 1% level to reduce the impact of outliers (Fosu et al., 2016). The underlying model to examine the potential impact of sentiment on the firm's ESG performance is:

$$ESG_{i,t} = \alpha_i + \beta_1 FS_{i,t-1} + \beta_2 MS_{t-1} + \sum_{k=1}^{5} \beta_3 CV_{k,i,t-1} + \varepsilon_{i,t} \qquad (4)$$

Where $ESG_{i,t}$ represents the overall ESG performance as well as its three pillars, i.e., *EN*, *SO*, and *GO*, of firm i at time t. $FS_{i,t-1}$ and MS_{t-1} are firm-specific and market sentiment at time $t-1$. $CV_{k,i,t-1}$ is a vector of control variables, k, for firm i at time $t-1$. Complying with Habib and Hasan (2017), all right-side variables in my models are lagged by one period to handle the potential reverse causality. The results from panel diagnostics, including F-test, Breusch-Pagan test, and Hausman test, suggest that the fixed-effect model is superior for my sample. I also control for the time effect by adding year dummies for all regressions. Finally, firm-cluster standard errors are employed to minimize the possibility of heteroskedasticity and autocorrelation within firms.

2.2.2. Results

Table 2 reveals the impact of sentiment on ESG performance. As shown in column (7), the coefficient of market sentiment is −3.539 and significant at the 1% level, implying a strong negative relationship between market sentiment and ESG performance. The same conclusion can be claimed for the correlation between firm-specific sentiment and ESG performance,

Table 2. Sentiment and ESG performance

	EN		SO		GO		ESG	
	(1)	(2)	(1)	(2)	(1)	(2)	(1)	(2)
FS	−0.012*	−0.016**	−0.017**	−0.025***	−0.004	−0.009	−0.012*	−0.020***
	(−1.75)	(−2.18)	(−2.21)	(−3.11)	(−0.42)	(−0.92)	(−1.74)	(−2.69)
MS	−3.533***	−3.343***	−4.161***	−4.444***	−0.510**	1.069***	−3.539***	−3.094***
	(−20.37)	(−11.40)	(−20.90)	(−12.73)	(−2.05)	(2.66)	(−19.41)	(−10.56)
SIZE		0.181**		0.105		0.032		0.107
		(2.19)		(1.11)		(0.26)		(1.26)
LEV		0.018		0.009		−0.061		−0.003
		(0.51)		(0.20)		(−1.04)		(−0.09)
ROA		−0.032**		−0.016		−0.000		−0.018
		(−2.11)		(−1.02)		(−0.00)		(−1.28)
MTB		0.038**		0.070***		0.018		0.050**
		(2.09)		(3.30)		(0.53)		(2.57)
IND		0.032		0.028		0.155***		0.081***
		(1.49)		(1.23)		(4.97)		(3.94)
CONST.	3.369***	3.178***	4.090***	4.332***	0.503**	−0.863**	3.436***	3.043***
	(20.39)	(11.68)	(21.05)	(13.29)	(2.14)	(−2.23)	(19.53)	(11.11)
Obs	4737	3675	4737	3675	4737	3675	4737	3675
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2 within	0.2967	0.2731	0.3253	0.3381	0.0038	0.0265	0.2957	0.2912
F-stat.	36.79***	19.07***	45.27***	24.92***	0.75	2.10***	37.11***	22.31***

The table reports the results for the panel fixed-effect regressions with time dummies of Equation (4). Firm-cluster t-statistics are in parentheses. The sample comprises 367 non-financial Japanese firms during the period from 2005 to 2019. *, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

although its effect is much weaker than the market one. Our findings still hold after some firm characteristics are included as control variables.

Additionally, a similar pattern can be seen in three components of ESG activities, except the corporate governance aspect. Environmental and social performance share the same vein in which the stronger sentiment impact belongs to the latter. In contrast, the correlation between firm-specific sentiment and corporate governance performance is frail and insignificant. Especially, the influence of market sentiment on governance perspective changed from negative with the coefficient being −0.510 to positive with a coefficient of 1.069 after controlling by several variables.

Overall, the estimated outcomes from my empirical models suggest that when the market and firm investors expose a negative outlook, companies tend to be more active in their CSR strategies, particularly in environmental and social commitments that might enhance their public image and gain confidence from market participants. Remarkably, the effort of enterprises in enhancing their corporate social achievements is more likely to satisfy the public than their investors. These findings support the paper of Cheong et al. (2017) and Naughton et al. (2019) about the driving role of sentiment on CSR activities. However, while Cheong et al. (2017) affirm that CSR scores are strongly affected by firm-level sentiment rather than the market one, the reverse observation is depicted in my study.

My first analysis consistently proves the adverse inference between sentiment and ESG performance. Further, I will check whether these results are robust by modifying the estimation method. As is known, one vital problem that may influence the estimators of panel data methodology is the potential endogeneity issues. Consequently, I re-estimate Equation (4) by applying the 2-step Generalized Method of Mo-

ments (GMM) to suppress any endogeneity problems. The results are presented in Table 3.

It can be seen from Table 3 that the signs of sentiment coefficients, both at the firm and market level, remain unchanged for overall ESG as well as the three pillars' scores. Besides, I observe that the magnitude of the coefficients of firm-specific sentiment is almost like what was reported in Table 2 for environmental and social performance. In contrast, those figures rise considerably in corporate governance and aggregate ESG ones. Remarkably, unlike the overall ESG score, the estimators of firm-specific sentiment for environmental and social scores are no longer statistically significant. Whereas, the relationship between firm sentiment and governance performance changes from insignificant to significant statistically.

On the contrary, the negative correlation between market sentiment and ESG achievement still holds significantly, despite the noteworthy decline in the estimated coefficients. This state can be illustrated briefly by the environmental pillar, where its coefficient drops from −3.343 (t-stat. = −11.40) in Table 2 to −0.090 (t-stat. = 2.87).

3. Conclusion

My study claims that sentiment could be a valid predictor of market returns, though its effect only lasts until the next six months. Remarkably, by decomposing each market's total sentiment index into regional and local components, I discover that sentiment impact is home-grown, i.e., driven predominantly by domestic one. These findings provide a more transparent and detailed picture of sentiment-return inference which are useful for investors interested in investing in the Asian stock markets. It is also crucial to intra-day traders and practitioners that use technical skills to measure and earn profit from the short-term price changes often inspired by investors' prevailing sentiment toward security.

Table 3. 2-step GMM

	EN	SO	GO	ESG
FS	−0.015	−0.026	−0.065**	−0.038**
	(−0.90)	(−1.48)	(−2.28)	(−2.31)
MS	−0.090***	−0.291***	0.146**	−0.202***
	(−2.87)	(−5.41)	(1.98)	(−4.26)
SIZE	0.200	0.582*	−0.183	0.455
	(0.83)	(1.80)	(−0.54)	(1.58)
LEV	−0.002	−0.014	−0.044	−0.111
	(−0.02)	(−0.11)	(−0.26)	(−1.13)
ROA	−0.047*	0.011	−0.021	−0.019
	(−1.65)	(0.34)	(−0.33)	(−0.41)
MTB	0.054	0.123**	−0.020	0.125***
	(1.41)	(2.24)	(−0.21)	(2.67)
IND	−0.119*	−0.160**	0.003	−0.100
	(−1.85)	(−2.47)	(0.04)	(−1.55)
Obs	3121	3121	3121	3121
Year FE	Yes	Yes	Yes	Yes
Wald	204.85***	392.61***	49.07***	244.38***
AR(1)	0.006	0.001	0.000	0.003
AR(2)	0.187	0.911	0.676	0.975
Hansen	0.451	0.980	0.139	0.841

The table reports the results for 2-step GMM models with time dummies of Equation (4). The instruments are the lags of independent variables, while year dummies are considered strictly exogenous variables. Firm-cluster t-statistics are in parentheses. The sample comprises 367 non-financial Japanese firms during the period from 2005 to 2019.
*, **, and *** indicate significance at 10%, 5%, and 1% confidence level, respectively.

Contrarian investors who like to trade in the opposite direction of this sentiment might get essential information from this study, too.

Additionally, I prove that investor sentiment not only affects financial markets' activities but also corporate performance as I find negative sentiment in the previous year plays a driving role in a company's actions related to its CSR strategy next year, with market sentiment holding a more powerful impact. The only exception belongs to the governance perspective, where the positive relationship between market sentiment and subsequent ESG performance is revealed. On the other hand, the influence of firm-level sentiment, although still negative, is not statistically significant. My outcomes provide a promising channel, i.e., investors' power that the government and CSR advocates can utilize to orientate companies to act responsibly.

My research, undeniably, is imperfect. For example, by using data from six Asian markets only, the regional index formed in the first study might not ideally capture the sentiment impact of the Asian area. Meanwhile, my second research's results should be used carefully in generalizing to other countries since Japanese companies may not fully represent all the characteristics of firms in different growth stages. These issues need to be addressed in future work.

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