From random walk to silly walk hypothesis: Do earnings per share surprises affect stock prices?

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Abstract

According to the efficient market hypothesis, share prices reflect all available information in the market, including earnings per share estimates provided by equity analysts covering the stocks. Therefore, any deviation between the reported earnings per share and the earnings per share consensus estimates is expected to influence the stock price after the earnings per share announcement. The purpose of the study is to empirically investigate whether earnings per share surprises affect stock prices in the presence of industry and market conditions. Using a unique panel dataset of public maritime shipping companies and employing the Generalized Method of Moments to address endogeneity, our study suggests that earnings per share surprises are not a significant factor in stock returns when considered alongside industry and stock market performance. The presence of industry conditions leads to the decoupling of the effect of earnings per share surprises on stock prices, causing them to follow what we call a 'silly walk' pattern. These empirical findings yield important implications for principal financial officers, as discussed herein.

Keywords: Street expectations, equity analyst estimates, EPS surprises, stock returns, maritime shipping

1. Introduction

Earnings announcement is like a quarterly ritual for many in the stock market. Equity analysts spend considerable amounts of time and energy on forecasting firms' next earnings results, and investors anticipate earnings results with excitement and anxiety (Tsafack et al., 2023). According to the efficient market hypothesis, share prices reflect all relevant information about the fortunes of a stock, including earnings per share (EPS) estimates provided by equity analysts covering the stocks. Therefore, any unexpected deviation between the actual (reported) EPS and EPS forecast estimates provided via analysts' consensus will influence stock prices after the announcement of earnings. For instance, a positive deviation, i.e. reported EPS being higher than consensus EPS, is expected to lead to an increase in share price and vice-versa.

There is well documented evidence on the prevalence of earnings announcement premia, which is the tendency for firms to earn abnormally high returns during their earnings announcements. Starting from the seminal study of Ball and Brown (1968), the leading proposition in literature is that stock prices respond positively to announcements of earnings greater than expected and negatively to announcements of earnings less than expected for the firms. Similarly, there are large, rapid stock price reactions to earnings announcements, which suggest that equity volatility increases in response to earnings news.

Despite the extensive evidence on the existence of earnings announcement premia, there is little evidence on how premia vary relative to industry factors. In particular, do EPS surprises mostly affect the response of stock prices to earnings announcements, or do industry characteristics, such as industry's anticipated profitability also play a role? Examination of this question is motivated by anecdotal evidence for specific stocks and sectors that, contrary to expectations, negative EPS surprises are associated with increases in stock prices and positive EPS surprises are associated with decreases in stock prices (silly walk pattern), or that the stock reaction may be random without any clear pattern (random walk pattern). Therefore, are company-specify EPS surprises driving the stock reactions, or do external-environment factors influence most the stock prices, downplaying EPS surprises and making them follow a random-walk, or even a silly-walk, pattern?

In this paper we examine the behavior of stocks of publicly listed maritime shipping companies around their earnings announcements. Focusing on the maritime shipping industry allows us to control industry-related market conditions. In addition to being able to monitor stock performance of maritime shipping companies, one can also observe the revenue-generating capacity of the assets (vessels) that maritime shipping companies operate and own. This enables us to examine whether industry performance factors, or ESP surprises, affect most the predictability and performance of stocks around their earnings announcements. It should be highlighted that freight markets of shipping are efficient (Alizadeh and Nomikos 2011) and are made available to market participants via respective daily or weekly indices. To the best of our knowledge, there is no other industry where monitoring of industry market conditions is possible, making maritime shipping a unique industry to test our research question.

The structure of this paper is as follows. The next section presents the literature review. Section 3 discusses the data and the methodology. Section 4 presents the empirical results. Finally, section 5 concludes the paper.

2. Literature review

Analysts spend a lot of time and energy on forecasting firms' next earnings results, and investors anticipate the earnings results with excitement and anxiety (Tsafack et al., 2023). There is well documented evidence on the prevalence of earnings announcement premia, which is the tendency for firms to earn abnormally high returns during their earnings announcements (e.g., Barber et al. 2013; Hartzmark and Solomon 2018). This is often justified on the basis that earnings announcement periods are unique periods in the life of each stock. Stocks are under more scrutiny, investors and traders react more actively to all news related to them, and they respond to this activity with higher prices around the dates of the earnings announcements.

Starting from the seminal study of Ball and Brown (1968), the leading proposition in literature is that stock prices respond positively to announcements of earnings greater than expected and negatively to announcements of earnings less than expected for the firms. Similarly, there are large, rapid stock price reactions to earnings announcements which suggest that equity volatility increases in response to earnings news. Diether et al. (2002) find that firms with more uncertain earnings (as measured by the dispersion of analysts' forecasts) do worse. Equally, it seems that stocks with higher dispersion in analysts' earnings forecasts earn lower future returns than otherwise similar stocks. This effect is most pronounced in small stocks and stocks that have performed poorly over the past year (Johnson, 2005). More recent studies find that the earnings announcement premium still exists, but that its magnitude decreased following the 2008 financial crisis (Tsafack et al., 2023).

Given the impact of earnings announcements on share prices, it is not surprising that firms take active steps in engaging in expectations management. For instance, companies regularly walk-down pre-announcement earnings expectations in hopes of conveying upbeat news during earnings announcements. Johnson et al. (2020) establish expectations management as a contributing factor to the prevalence of earnings announcement premia. Firms that are more likely to manage expectations toward beatable levels earn lower returns before, and higher returns during their earnings announcements. This pattern repeats across firms' fiscal quarters, suggesting firms manufacture positive “surprises” by negatively biasing investors’ expectations ahead of announcing earnings.

Similarly, managers smooth the volatility of reported EPS by using accruals to offset cash flow shocks. Smoother EPS is easier to forecast, resulting in smaller forecast errors. Managers also differentially guide forecasts to improve accuracy. Cheong and Thomas (2017) find that whereas unmanaged forecast errors are much larger for high-price firms, they are compressed to the point their magnitudes resemble those for low-price firms. Managers also guide analyst forecasts to generate patterns of forecast walkdowns that vary with share price. That is, the level of compression increases with share price to completely offset natural scale variation in forecast error magnitudes. Equally, there is also evidence of managerial smoothing of EPS to reduce across-firm variation in EPS volatility (Cheong and Thomas, 2011).

Finally, there is growing empirical evidence that managers are willing to sacrifice economic value, including delaying or reducing investments, to meet short-run earnings objectives. For example, Graham et al. (2005) using survey data report that most managers surveyed would forgo a project with positive Net Present Value (NPV) if the project would cause them to fall short of the current quarter consensus forecast. When asked what actions they might take to meet an earnings target, approximately 80 percent suggest they would decrease discretionary spending, including research and development and advertising expenses. Markarian and Michenaud (2019) find that firm-level investment is negatively related to the likelihood of meeting or beating analysts’ short-term EPS forecasts. Firms that invest less than usual meet or exceed analysts’ consensus EPS forecasts more often. The reduction in investment related to earnings surprises affects primarily firms with good investment opportunities. It seems therefore that there is a tension managers face in deciding whether to manage earnings to exceed analyst forecasts. Beating forecasts increases contemporaneous returns, and a consecutive string of such positive surprises can increase the valuation premium that a firm receives (Bartov et al., 2002). In addition, missing analyst forecasts by even a small margin can lead to a dramatic reduction in stock price (Skinner and Sloan, 2002). However, cutting discretionary expenditures or managing accruals to beat a forecast induces a transitory component to earnings, increasing the likelihood that future earnings will reverse, and future performance will suffer (Markarian and Michenaud, 2019).

3. Data and Methodology

3.1. Research setting

The maritime shipping industry has been selected as the setting of the empirical research to test our hypothesis for several reasons. First, the shipping industry provides a very interesting market to tests the response of stocks to EPS earnings announcements since one can delineate between the performance of the company and the performance of the sector on which the company operates. Second, the different segments of the shipping industry play an important role in global international trade since over 80% of the world trade in volume terms is carried by sea, according to UNCTAD (2023). In 2023, tanker and dry bulk vessels carried more than 60% of the world's seaborne trade. Similarly, the contribution of container trade to global economic activity is well documented (Kilian et al, 2023). Today, 60% of the value of seaborne trade and nearly 90% of non-bulk dry cargo is transported as containerized cargo, including most trade in manufactured goods and high-value-added goods. Containerized trade has greatly reduced transport times and shipping costs (Hummels, 2007) and has been a key driver of the globalization of the world economy and the growth in global trade in recent decades (Bernhofen and Kneller, 2016; Cosar and Demir, 2018).

3.2. Dataset

Our sample includes the public maritime shipping companies listed in Stock Watch section of TradeWinds. TradeWinds, the world's biggest shipping-related news publisher, has been used as a source of sampling frame in previous financial empirical studies (see Andrikopoulos et al., 2022; Mantzari et al., 2023; Sigalas and Gerakoudi, 2024). Our sample consists of active and publicly traded maritime shipping companies. Financial-related data, such as daily stock prices, daily stock market indices, daily volatility index, quarterly reported EPS, quarterly equity analysts' consensus EPS estimate were collected from Bloomberg. Shipping-related data, i.e., the weekly maritime shipping segments indices were collected from Clarksons' Shipping Intelligence Network, the world-leading maritime research firm (Campello at al., 2024). Based on the sample of active publicly-listed maritime shipping companies, we compiled an unbalanced unique quarterly panel dataset with 98 companies for the period between the first quarter of 2010 to the third quarter of 2023.

3.3. Variables

The dependent variable of our study is the two-day stock price change, calculated from one day prior the EPS announcement. For robustness purposes, we also employ the three-day, days -1 to 1, which is commonly used to measure medium-term stock price impact. Lastly, we also used the 11-day, days -5 to 5 for measuring the long-term stock price impact.

Our main independent variable is the deviation of earnings per share, calculated by the ratio of the actual, or as reported, EPS over equity analysts' consensus estimate. A ratio value higher than 1, represents an EPS positive surprise, or that the company beat analysts' consensus expectations for EPS. A ratio value lower than 1, signifies an EPS negative surprise, or that the company missed analysts' consensus expectations for EPS. Lastly, ratio value equal to 1, denotes no EPS surprise, or that the company's EPS is in line with analysts' consensus expectations for EPS.

Apart from EPS surprise, either positive or negative, the stock price is expected to be affected by other non-company specific factors, pertaining to external-environment factors, such as market conditions of the industry. There are several indices that monitor the freight rates, and thus the profitability, of the maritime shipping industry. Our sample includes maritime companies operating in all seven shipping sectors depending on the type of cargo transportation capacity, i.e., dry bulk, crude oil, product oil, liquefied petroleum gas (LPG), liquefied natural gas (LNG), containers, and diversified. Each of these seven shipping sectors have different indices to monitor their weekly freight rates. We use Baltic Exchange Dry Index, Baltic Dirty Tanker Index, Baltic Clean Tanker Index, Clarksons Average LPG Carrier Earnings, LNG 145K CBM Spot Rate, Clarksons Average Containership Earnings, and ClarkSea Index, as profitability proxies for dry bulk, crude oil, product oil, LPG, LNG, containers, and diversified shipping sectors, respectively. From these individual indices, we compiled the second independent variable measuring "Industry Market Conditions", depending on the shipping segment that each company in our sample operates in.

Stock market conditions are also expected to affect stock prices. Therefore, we supplemented our analysis with a third independent variable. The companies in our sample are publicly traded in 21 stock exchanges (in alphabetic order: Bangkok, Borsa Italiana, BSE India, Bursa Malays, Copenhagen, EN Brussels, Hong Kong, Johannesburg, Korea SE, London, MICEX Main, NASDAQ, Natl India, New York, Oslo, Qatar, Shanghai, Singapore, Taiwan, Tokyo, and Xetra). For each of these stock exchanges we used its primary index, i.e., SET Index, FTSEMIB Index, SENSEX Index, FBMKLCI Index, KFX Index, BEL20 Index, HSI Index, JSEVAL Index, KOSPI Index, UKX Index, INDEXCF Index, CCMP Index, BXTRNIFT Index, NYA Index, OSEBX Index, DSM Index, SHCOMP Index, STI Index, TWSE Index, NKY Index, and DAX Index, respectively. The price of each index is reported on a daily basis. From these individual indices, we compiled the third independent variable measuring "Stock Market Conditions", depending on the stock exchange that each company in our sample is publicly traded.

Lastly, we included a fourth independent variable, measuring the "Market Volatility". The daily VIX index was employed as a proxy for market volatility due to its status as one of the most widely recognized and reported measures of volatility, closely monitored by various market participants and financial media (Cboe, 2025). The definition, naming, and calculation of our variables is provided in Table 1.

Table 1. Variables

Variable	Coding	Calculation
Stock Price Change, 1st measure	**SPX1**	Stock Price at announcement date divided by Stock Price at 1-day prior announcement date (SPX1)
Stock Price Change, 2nd measure	**SPX2**	Stock Price at 1-day post announcement date divided by Stock Price at 1-day prior announcement date
Stock Price Change, 3rd measure	**SPX3**	Average Stock Price of 5-days post announcement date divided by Average Stock Price of 5-days prior announcement date
Deviation of earnings per share	**DEPS**	Reported EPS divided by Analyst Consensus EPS
Industry Market Conditions, 1st measure	**IMARK1**	Industry Market Index at announcement date divided by Industry Market Index at 1-week prior announcement date
Industry Market Conditions, 2nd measure	**IMARK2**	Industry Market Index at 1-week post announcement date divided by Industry Market Index at announcement date
Industry Market Conditions, 3rd measure	**IMARK3**	Industry Market Index at 1-week post announcement date divided by Industry Market Index at 1-week prior announcement date
Stock Market Conditions, 1st measure	**SMARK1**	Stock Market Index at announcement date divided by Stock Market Index at 1-day prior announcement date
Stock Market Conditions, 2nd measure	**SMARK2**	Stock Market Index at 1-day post announcement date divided by Stock Market Index at 1-day prior announcement date
Stock Market Conditions, 3rd measure	**SMARK3**	Average Stock Market Index of 5-days post announcement date divided by Average Stock Market Index of 5-days prior announcement date
Market Volatility, 1st measure	**VOL1**	VIX Index at announcement date divided by VIX Index at 1-day prior announcement date
Market Volatility, 2nd measure	**VOL2**	VIX Index at 1-day post announcement date divided by VIX Index at 1-day prior announcement date
Market Volatility, 3rd measure	**VOL3**	Average VIX Index of 5-days post announcement date divided by Average VIX Index of 5-days prior announcement date

4. Analysis

We employ panel data analysis to empirically test our research hypothesis. Panel data allow to test the cross-sectional and time series association of stock price change with changes in industry market, stock market, as well as U.S. volatility. This allows us to investigate companies' heterogeneity regarding their stock price change and its determinants. We specify our model with the *SPX1* as dependent variable and the *DEPS, IMARK1, SMARK1, VOL1* as independent variables; we dub this Model 1 as shown in equation 1. For robustness purposes we specify a second model with the *SPX2* as dependent variable and the *DEPS, IMARK2, SMARK2, VOL2* as independent variables, as well as a third model with the *SPX3* as dependent variable and the *DEPS, IMARK3, SMARK3, VOL3* as independent variables; we dub these models, Model 2 and model 3, respectively.

Model 1:

$$SPX1_{it} = f(DEPS_{it},\ IMARK1_{it}, SMARK1_{it}, VOL1_{it}) \tag{1}$$

i = number of companies, i.e., 98 companies, and

t = number of quarters, i.e., 55 quarters

Model 2:

$$SPX2_{it} = f(DEPS_{it},\ IMARK2_{it}, SMARK2_{it}, VOL2_{it}) \tag{2}$$

i = number of companies, i.e., 98 companies, and

t = number of quarters, i.e., 55 quarters

Model 3:

$$SPX3_{it} = f(DEPS_{it},\ IMARK3_{it}, SMARK3_{it}, VOL3_{it}) \tag{3}$$

i = number of companies, i.e., 98 companies, and

t = number of quarters, i.e., 55 quarters

Table 2 presents the descriptive statistics for the variables used in our models. We observe that the variable DEPS has outlier values. We windsorized our models across the relevant observations without any significant influence on the results. Therefore, we kept the outlier values to utilize all information available and all company-quarters in our dataset.

Table 2. Descriptive statistics

	Mean	Median	Maximum	Minimum	Std. Dev.	N
DEPS	2.179	1.009	1,589.712	-146.364	32.765	2,875
SPX1	0.999	1.000	3.000	0.315	0.060	3,618
SPX2	0.996	0.996	1.625	0.375	0.071	2,836
SPX3	0.999	0.996	2.182	0.318	0.082	4,291
FMARK1	0.999	1.000	1.935	0.544	0.075	4,513
FMARK2	1.004	1.000	1.722	0.600	0.078	4,515
FMARK3	1.005	1.000	2.272	0.443	0.132	4,513
VOL1	1.001	0.991	1.480	0.730	0.082	3,706
VOL2	1.000	0.987	1.644	0.682	0.110	2,876
VOL3	1.010	0.991	2.333	0.656	0.133	4,521

In our panel data analysis, first, we run the Hausman test to assess whether we should use random effects or fixed effects specification (Wooldridge, 2010). The results of Hausman test indicates that random effects should be used (see Table 3)

Table 3. Hausman Test

	Effects Specification	Chi-Sq Statistic	P-value
Model 1	Random Effects	0.863	0.930
Model 2	Random Effects	1.779	0.776
Model 3	Random Effects	0.826	0.935

Preliminary tests indicate that the DEPS regressor in all three models is statistically insignificant when estimated with panel least squares (LS) using random effects (see column 1, in Tables 4, 5, and 6). Re-estimating the models with panel two-stage least squares (2SLS) using random effects and instrumenting for endogeneity by employing the lagged values of the regressors as internal instruments also results in F-statistics that are statistically insignificant see column 2, in Tables 4, 5, and 6).

As such, we re-estimate our models with Arelano-Bond (A-B) dynamic generalized method of moments (GMM) (see column 3, in Tables 4, 5, and 6). The A-B GMM panel estimator accounts for autocorrelation by including lagged dependent variable as a control variable, and thus, controlling for the influence of prior stock price changes on subsequent stock price changes. It also addresses heteroscedasticity by weighting the generalized methods of sample moments and autoregression associated with stock price changes over the company-quarters (Ahn and Schmidt, 1999). Lastly, by using internal instruments it also addresses endogeneity concerns (Arellano and Bond, 1991). This is an important advantage of the A-B GMM panel estimator because it is quite difficult to find external instruments that are highly correlated with the endogenous variables, which are present on the right-hand side of a regression model, and uncorrelated with the error term or the part of the dependent variables that are not explained by the included regressors in exploratory empirical studies (Drobetz et al., 2021). Lastly, the Arellano-Bond dynamic panel estimator is commonly used in both finance (see Pindado et al., 2020; Mantzari et al., 2023; Sigalas and Gerakoudi) and transportation (see Drobetz et al., 2019; Drobetz et al., 2021) research studies.

Table 4. Empirical results for model 1

	Panel LS (1)		**Panel 2SLS (2)**	**A-B GMM (3)**	
C	0.271	**	-3.280		
	(0.112)		(4.053)		
SPX1(-1)				-0.088	***
				(0.000)	
DEPS	0.000		-0.001	0.000	***
	(0.000)		(0.001)	(0.000)	
IMARK1	0.011		0.249	0.022	***
	(0.015)		(0.203)	(0.000)	
SMARK1	0.724	***	4.073	0.707	***
	(0.104)		(3.913)	(0.001)	
VOL1	-0.009		-0.040	-0.002	***
	(0.015)		(0.309)	(0.000)	
Prob(F-statistic)	*0.000*		*0.392*		
Prob(J-statistic)				*0.896*	

Note: *Figures in ( ) are standard errors. **, and ***, indicate significance at the 5%, and 1% levels, respectively. The selected method of estimation is the A-B GMM.*

Table 5. Empirical results for model 2

	Panel LS (1)		Panel 2SLS (2)	
C	0.009		(13.191)	
	(0.139)		0.004	
DEPS	0.000		(0.004)	***
	(0.000)		0.549	
IMARK2	0.048	**	(0.176)	
	(0.021)		-8.211	
SMARK2	0.934	***	(12.213)	
	(0.126)		-1.299	
VOL2	0.006		(1.117)	
	(0.018)		0.000	
Prob(F-statistic)	*0.000*		*0.572*	

Note: *Figures in ( ) are standard errors. **, and ***, indicate significance at the 5%, and 1% levels, respectively. The selected method of estimation is the panel LS.*

Table 6. Empirical results for model 3

	Panel LS (1)		Panel 2SLS (2)		A-B GMM (3)	
C	-0.079		0.548			
	(0.104)		(7.164)			
SPX3(-1)					-0.080	***
					(0.002)	
DEPS	0.000		-0.003	*	0.000	***
	(0.000)		(0.002)		(0.000)	
IMARK3	0.050	***	0.301	*	0.064	***
	(0.011)		(0.173)		(0.001)	
SMARK3	1.042	***	0.596		1.109	***
	(0.094)		(7.119)		(0.019)	
VOL3	-0.013		-0.435		0.009	***
	(0.014)		(0.405)		(0.003)	
Prob(F-statistic)	*0.000*		*0.516*			
Prob(J-statistic)					*0.544*	

Note: *Figures in ( ) are standard errors. *, and ***, indicate significance at the 10%, and 1% levels, respectively. The selected method of estimation is the A-B GMM.*

For model 1, the A-B GMM indicates that the regressors for all the determinants of SPX1 are statically significant at the 1% level. In addition, the p-value of the J-statistics suggests satisfactory instruments specification. Moreover, the Chi-square of the Wald test (p-value = 0.000) suggests that the explanatory variables in model 1 are jointly significant. Lastly, Arellano-Bond serial correlation test (p-value of AR(2) = 0.986) indicates the absence of second order serial correlation in the first-differenced residuals of model 1. For that reason, the A-B GMM is the selected method of estimation for model 1. For model 2, the A-B GMM could not be estimated because the number of instruments is greater than the number of panel observations. Therefore, since the 2SLS is an insignificant model (p-value of F-statistics = 0.516), the panel LS is the selected method of estimation for model 2. For model 3, the A-B GMM indicates that the regressors for all the determinants of SPX3 are statically significant at the 1% level. In addition, the p-value of the J-statistics suggests satisfactory instruments specification. Moreover, the Chi-square of the Wald test (p-value = 0.000) suggests that the explanatory variables in model 3 are jointly significant. Lastly, Arellano-Bond serial correlation test (p-value of AR(2) = 0.999) indicates the absence of second order serial correlation in the first-differenced residuals of model 3. For that reason, the A-B GMM is the selected method of estimation for model 3.

The results of our analysis indicate that the control variables, i.e., IMARK1, IMARK2, IMARK3, and SMARK1, SMARK2, SMARK3, are positive and significant determinants of SPX1, SPX2, SPX3, respectively. This finding suggests, as expected, that both industry market conditions and stock market conditions have a positive effect on stock price changes. For the regressors coefficients, we can argue that stock market conditions have higher impact compared to industry market conditions on stock price changes.

Turning to our main explanatory variable, our results imply that DEPS is a significant determinant of SPX1, and SPX3, but its effect is zero. Therefore, deviation of the as reported EPS versus analyst consensus EPS does not have any material positive impact on stock price changes. On the contrary, model 2 suggests that the impact of DEPS on SPX2 is not even statistically significant. Thus, our empirical findings confirm our silly walk hypothesis.

5. Concluding remarks

The purpose of this study is to conduct an empirical study to test which factors matter most on stock returns: EPS surprises or the industry performance indicators? The results of the study indicate that contrary to mainstream literature, ESP surprises are not an important factor of stock returns, if they are investigated in conjunction with industry performance. Industry market conditions, stock market conditions, as well as market volatility, are significant and positive factors of stock returns. The positive impact of industry market conditions, stock market conditions and market volatility dilute the effect of EPS surprises on stock prices. In particular, we provide empirical evidence that the impact of deviations between the actual (reported) EPS and EPS consensus estimates on stock prices is zero. Our results contradict prior studies, which report that missed EPS estimates have negative effects on stock prices (Almeida et al., 2016;

Bartov at al., 2002). Furthermore, our findings explain the anecdotal real-life evidence that in some cases negative EPS surprises are associated with increases in stock prices and positive EPS surprises are associated with decreases in stock prices. A phenomenon that we call "silly walk" hypothesis. In addition, stock reactions in real-life to EPS surprises may be random without any clear pattern, well acknowledged by literature as "random walk" hypothesis.

The results of the study also have some important managerial implications. Our findings underscore the irrelevance of the "walk-down to beatable analyst forecasts" management practice (Richardson et al., 2004). Since industry and market conditions drive stock prices, and positive EPS surprises do not have any material impact on stock returns, financial managers and chief finance officers should stop engaging in the practice of providing earnings guidance, where analysts initially set overly optimistic EPS forecasts and then lower their estimates to a level that companies can beat when the official earnings are announced. Additionally, our results corroborate prior managerial implications, which suggest that the link between EPS targets and short-termism should be broken (Almeida, 2019). Specifically, since beating consensus estimates is not driving superior stock returns, chief executive officers should drop the practice of focusing on short-term profits at the expense of long-term investments. Prioritizing immediate EPS without considering investments that will yield long-term results and improved EPS in the future is not beneficial for either the short-term or the long-term.

Due to the lack of empirical studies of the impact of EPS surprise on stock returns under the influence of external market and industry factors, the results presented herein beckon replication. Even though the findings of this study offer empirical evidence of several external-environment factors that mostly affect stock returns, future researchers are encouraged to further investigate empirically these factors by using similar datasets in other industries. Along the same vein, future studies should also employ samples in diverse and broader industries in repetitive attempts to falsify our results. Lastly, future scholars may want to supplement the external-environment factors, with some company-specific factors that there is indication that also affect stock returns, such as firm size, number of equity analysts, institutional ownership, book-to-market ratio, and leverage ratio (Michaely et al., 2016). Responding to our call for future research, literature will have more rigorous evidence not only about the external-environment factors, but also on how firm-idiosyncratic factors affect stock returns.

References

Ahn, S.C., Schmidt, P. (1999). *Estimation of linear panel data models using GMM. In L. Matyas* (Ed.), Generalized Method of Moments Estimation (pp. 211–247). Cambridge University Press.

Alizadeh, A. H., Nomikos, N.K. (2011). Dynamics of the Term Structure and Volatility of Shipping Freight Rates. *Journal of Transport Economics and Policy 45*(1), 105–128.

Almeida, H. (2019). Is It Time to Get Rid of Earnings-per-Share (EPS)? *The Review of Corporate Finance Studies, 8*(1), 174–206.

Almeida, H., Fos, V., Kronlund, M. (2016). The real effects of share repurchases. *Journal of Financial Economics 119*, 168–85.

Andrikopoulos, A., Merika, A., Sigalas., C. (2022). Net Asset Value Discounts and Premiums in the Maritime Shipping Industry. *European Financial Management 28*(2), 510–544.

Arellano, M., Bond, S. (1991). Tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Review of Economic Studies*, *58*, 277–297.

Ball, R., Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting research, 6*, 159–177.

Barber, B.M., Lehavy, R., McNichols, M., Trueman, B. (2006). Buys, holds, and sells: The distribution of investment banks' stock ratings and the implications for the profitability of analysts' recommendations. *Journal of Accounting and Economics 41,*87–117.

Bartov, E., Givoly, D., Hayn, C. (2002). The Rewards to Meeting or Beating Earnings Expectations. *Journal of Accounting and Economics 33*(2), 173–204.

Bernhofen, D.M., El-Sahli, Z., and R. Kneller (2016), "Estimating the Effects of the Container Revolution on World Trade," *Journal of International Economics*, 98, 36-50

Campello, M., Kankanhalli, G., Kim, H. (2024). Delayed creative destruction: How uncertainty shapes corporate assets. Journal of Financial Economics, 153, https://doi.org/10.1016/j.jfineco.2024.103786.

Cboe. (2025). VIX Index Overview. Website. Accessed on January 13, 2025. https://www.cboe.com/tradable_products/vix/.

Cheong, F.S., Thomas, J. (2011). Why Do EPS Forecast Error and Dispersion Not Vary with Scale? Implications for Analyst and Managerial Behavior. *Journal of Accounting Research, 49*(2), 359-401.

Cheong, F.S., Thomas, J. (2017). Management of Reported and Forecast EPS, Investor Responses, and Research Implications. *Management Science, 64*(9), 4277–4301.

Cosar A K, Demir B. (2018). Shipping Inside the Box: Containerization and Trade. *Journal of International Economics, 114*, 331-345

Diether, K.B., Malloy, C.J., Scherbina, A. (2002). Differences of opinion and the cross-section of stock returns. *Journal of Finance 57*, 2113–2141.

Drobetz, W., Ehlert, S., Schröder, H. (2021). Institutional ownership and firm performance in the global shipping industry. *Transportation Research Part E: Logistics and Transportation Review, 146*, https://doi.org/10.1016/j.tre.2020.102152.

Drobetz, W., Janzen, M., Requejo, I. (2019). Capital allocation and ownership concentration in the shipping industry. *Transportation Research Part E: Logistics and Transportation Review, 122*, 78-99.

Graham, J.R., Campbell R.H., Rajgopalc, S. (2005). The economic implications of corporate financial reporting. *Journal of Accounting and Economics 40*, 3–73.

Hartzmark, S.M., Solomon, D.H. (2018). Recurring firm events and predictable returns: The within-firm time series. *Annual Review of Financial Economics, 10*, 499–517.

Hummels D. (2007). Transportation Costs and International Trade in the Second Era of Globalization. *Journal of Economic Perspectives, 21*, 131-154.

Johnson, T.L., Kim, J., So, E.C. (2020). Expectations Management and Stock Returns. *The Review of Financial Studies, 33*(10), 4580-4626.

Johnson., T.C. (2005). Forecast Dispersion and the Cross Section of Expected Returns. *Journal of Finance, 59*(5), 1957-1978.

Kilian, L., Nomikos, N.K., Zhou, X. (2023). Container Trade and the US Recovery. *International Journal of Central Banking, 19*(1), 417-450.

Mantzari, E., Merika, A., Sigalas, C. (2023). Determinants and effects of trade credit financing: Evidence from the maritime shipping industry. *European Financial Management, 30*(3), 1385-1421.

Markarian, G., Michenaud, S. (2019). Corporate investment and earnings surprises. *The European Journal of Finance, 25*(16), 1485-1509.

Michaely, R., Rubin, A., Vedrashko, A. (2016). Are Friday announcements special? Overcoming selection bias. Journal of Financial Economics, 122 (1), 65-85.

Pindado, J., Requejo, I., Rivera J.C. (2020). Does money supply shape corporate capital structure? International evidence from a panel data analysis. *The European Journal of Finance, 26*(6), 554-584.

Richardson, S., Teoh, S.H., Wysocki, P.D. (2004). The Walk-down to Beatable Analyst Forecasts: The Role of Equity Issuance and Insider Trading Incentives. *Contemporary Accounting Research, 21*, 885-924.

Sigalas C., Gerakoudi, K. (2024). Idiosyncratic factors that shape shareholder reward policies in capital intensive companies, *The European Journal of Finance*, https://doi.org/10.1080/1351847X.2024.2424804.

Skinner, D., Sloan., R. (2002). Earnings Surprises, Growth Expectations, and Stock Returns or Don't Let an Earnings Torpedo Sink Your Portfolio. *Review of Accounting Studies, 7*, 289–312.

Tsafack, G., Becker, Y., Han, K. (2023). Earnings announcement premium and return volatility: Is it consistent with risk-return trade-off? *Pacific basin Finance Journal, 79*, https://doi.org/10.1016/j.pacfin.2023.102029.

Wooldridge, J. (2010). *Econometric Analysis of Cross Section and Panel Data*. MIT Press.