“The impact of ambiguity on the value-relevance of earnings volatility: Evidence from the COVID-19 pandemic”

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THE IMPACT OF AMBIGUITY ON THE VALUE-RELEVANCE OF EARNINGS VOLATILITY: EVIDENCE FROM THE COVID-19 PANDEMIC

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Abstract

Prior research states that during extreme uncertainties stock prices deviate from their fundamentals. This study examines the cross-section of share price returns during the COVID-19 and pre-COVID periods to determine how investors' reaction to prior earnings volatility is affected by the COVID-19-induced ambiguity. The sample consists of 840 firms listed on the New York Stock Exchange (NYSE) from January 1, 2020 to May 31, 2021. Consistent with the notion that ambiguity-aversion is not a universal phenomenon, COVID-period stock returns exhibit a positive ($\beta = 0.23$) and statistically significant relationship with prior earnings volatility. In contrast, the stable period returns show a very weak, if any, correlation with prior earnings volatility. The positive relationship is more pronounced for firms that experience greater information asymmetry. When comparing the results with previous research, it appears that different crises evoke varied levels of ambiguity-aversion possibly because of the ways in which each crisis's features and anticipated outcomes influence how the market reacts. Thus, before crafting responses to a crisis, policymakers and firms should thoroughly examine the crisis and identify the underlying causes, dynamics, and possible effects on decision-makers' ambiguity-aversion behavior.

Keywords uncertainty, information asymmetry, stock returns, asset pricing, investment behavior, stock markets, behavioral finance, financial crisis

JEL Classification M41, G12, G40, C31

INTRODUCTION

In the aftermath of the 2008 financial crisis, there has been a renewed interest in knowing about investor behavior during times of increased economic uncertainty. This is owing to findings that during times of increased uncertainty, stock prices tend to disconnect from fundamentals, acting in a way not explained by traditional asset pricing models (Epstein & Schneider, 2008). As a result, accounting researchers have started looking at how investors process and respond to earnings news in the face of a macroeconomic crisis. This study contributes to this literature by investigating how COVID-19-induced ambiguity affects investors' reactions to prior earnings volatility.

According to conventional asset pricing models, systematic risk alone determines the relationship between risk and return under stable economic conditions; therefore, the idiosyncratic volatilities of fundamentals are irrelevant. However, ambiguity-based models (e.g., Epstein & Schneider, 2008) propose that during a crisis situation, both idiosyncratic and systematic risks are value-relevant. Thus, investors

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are expected to demand a premium for the pre-crisis uncertainty caused by high earnings volatility, in addition to the COVID-19-caused ambiguity premium. The additional premium should result in a more pronounced inverse relationship between the COVID-19-period share price returns and earnings volatility.

1. LITERATURE REVIEW

Prior accounting-related valuation research has mainly focused on the information content of accounting numbers and their association with firm value (Ball & Brown, 1968; Choi et al., 2016; Collins & Kothari, 1989). Recently, however, several studies have reported that earnings volatility (*EVOL*) also helps predict firms' future performance. For example, Graham et al. (2005) argue that corporate executives believe that forecasting the future performance of a firm that has experienced high *EVOL* is more challenging. Similarly, Jiang et al. (2005) corroborate Graham et al. (2005) and propose that higher *EVOL* negatively affects firm value by impairing investor capacity to predict future earnings. Consistent with these findings, Dichev and Tang (2009) note that prior earnings with low volatility have substantially higher predictive power than those with high volatility and that their predictive power can extend up to five years. Several other studies (Frankel & Litov, 2009; Khodadadi et al., 2012; Cao & Narayanamoorthy, 2012; Dichev & Tang, 2009) have tested the validity of this notion. However, more recently, Barberis et al. (2005), Epstein and Schneider (2008), and Williams (2015) discovered an interesting phenomenon wherein share prices deviate from their fundamentals during periods of heightened uncertainty or ambiguity. Although the informativeness of accounting numbers has been widely investigated during stable times, very few studies have examined it during times of crisis and ambiguity.

Ambiguity-based theories (Knight, 1921; Gilboa & Schmeidler, 1989; Bewley, 2002) that explain how individuals make their decisions under ambiguity serve as the foundation for our hypotheses. Knight was the first to distinguish risk from ambiguity by saying that risk is characterized by situations in which the likelihood of possible outcomes is known, whereas the likelihood of outcomes in ambiguity is unknown. Ellsberg (1961) found that human behavior changes when a situation shifts from risky to ambiguous. Ellsberg was the first to put forth the theory that people have a strong dislike for ambiguity. His observations laid the groundwork for understanding investor behavior in times of extreme uncertainty or ambiguity. Epstein and Schneider (2008) examine how ambiguity affects investors' behavior and find that investors who do not like ambiguity may demand an additional premium and thus push stock prices downward. In line with these results, Chen and Epstein (2002) demonstrate that the excess stock returns of a security in the presence of ambiguity are equal to the total risk premium plus the ambiguity premium. Hence, ambiguity-based models have one thing in common: investors who are ambiguity-averse look for a premium for pre-crisis risk, as well as an additional ambiguity premium.

Drawing upon ambiguity-based notions, it is expected that during times of ambiguity, firms exhibiting higher *EVOL* will exhibit larger drops in their share prices than firms with low *EVOL*. This is because investors would seek a premium for the perceived firm-level uncertainty caused by increased *EVOL* in addition to the ambiguity premium. The COVID-19 pandemic, with its enormous and far-reaching effects on global economies, the financial sector, and individuals, offers an opportunity to evaluate the value-relevance of *EVOL* during ambiguity. Thus, the general ambiguity surrounding the pandemic offers an ideal context for examining how ambiguity influences the correlation between *EVOL* and share price returns. The purpose of this study is to examine how COVID-19-induced ambiguity affects investors' reactions to prior earnings volatility.

2. METHODOLOGY

As this study aims to examine the cross-section of share price returns during the COVID-19 and pre-COVID periods, the buy-and-hold abnormal returns (*BHAR*) are calculated for each sample. The *BHAR* is calculated as:

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$$BHAR_i = \prod_{t = September\ 2018}^{December\ 2019} \left(1+R_{it}\right) - \prod_{t = January\ 2020}^{May\ 2021} \left(1+VWR_{mt}\right), \qquad (1)$$

where R_{it} measures the stock price return (monthly) of firm *i* at time *t*, and VWRmt represents market return (value-weighted) at time *t*. According to Fahlenbrach and Stulz (2011), using holding-period returns allows us to incorporate several variables into a multivariate regression model to explain cross-sectional variations in performance.

Several studies, examining the factors influencing crisis-period returns, use holding-period returns (*BHAR*). For example, Beltratti and Stulz (2009) use *BHAR* to study the effects of bank attributes on crisis period returns, while Francis et al. (2013) use them to evaluate the correlation between crisis-period returns and accounting conservatism.

An alternative to firm-level *BHAR* could be to study the time series of a stock portfolio built based on firms' attributes and events. Abnormal stock returns can then be assessed as the intercept of the portfolio returns regression on the identified dependent variable. Mitchell and Stafford (2000) state that the time-series technique may not be able to capture significant abnormal stock returns in cases where abnormal returns are concentrated in some months of high event activity and are relatively weaker during other months. This limitation is particularly relevant to our research methodology, as prior research states that COVID-19 has not affected all firms uniformly on a monthly basis. Thus, a firm-level buy-and-hold period return (*BHAR*) is a better metric for assessing returns over the sample period, providing a more realistic estimation of investors' returns than monthly portfolio rebalancing.

The *EVOL* is computed as the standard deviation of firms' accounting earnings within the five-year period preceding the sample period. Earnings refer to accounting earnings before extraordinary items, scaled by total assets. Computing firms' *EVOL* during the pre-COVID period removes the likelihood of simultaneity in the tests. This issue would cause concern if management used its discretionary powers to adjust earnings volatility in reaction to share price returns. This study employs the natural logarithm of *EVOL*, as the transformation helps decrease the impact of skew.

2.1. Control variables

The primary variable of interest is *EVOL*. In addition to *EVOL*, cash flow volatility (*CFV*) is included as an independent variable to acknowledge the potential supplementary effect of *CFV* on stock returns. The *CFV* is quantified in a way comparable to how *EVOL* is measured. Moreover, several other control variables, that may affect stock prices, are added[1]. These factors include leverage, cash, firms' tangibility, sales growth, profitability, and risk measures such as market beta, firm size, and market-to-book ratio.

Leverage is the ratio of a firm's total debt to assets. Prior research shows an inverse relationship between firms' leverage ratios and stock prices (Adami et al., 2010). Similarly, the control variable 'cash' refers to the ratio of a firm's total cash and cash equivalents to its total assets. Firms that possess substantial financial reserves are better positioned to maintain their worth during times of turmoil. The variable 'sales growth' reflects how a firm's sales revenue has evolved over time. Firms with a history of sturdy sales growth are expected to face and tolerate the challenges of a crisis more effectively because their increased revenue provides them with a cushion. Tangibility is the total value of a firm's equipment, plant, and property, scaled by the value of the firm's assets. Firms possessing a greater quantity of tangible assets can leverage such assets to secure loans and other financial support during difficult times. Similarly, return on assets (*ROA*) is a control variable that assesses a firm's profitability. The '*ROA*' ratio of a firm is equal to the firm's earnings before extraordinary items scaled by the firm's total assets. A firm's strong '*ROA*' indicates that the firm is generating significant earnings in relation to its assets, which helps position the firm to weather the storm of a crisis. Furthermore, an industry dummy variable is added by employing the 2-digit Standard Industrial Classification codes to categorize firms into various groups of industries.

1 See, e.g., Ali (2022), Kumar Mishra et al., (2021), Ali et al., (2017), and Francis et al. (2013).

2.2. The role of information asymmetry

Jensen and Meckling (1976) posit that information asymmetry arises when agents (managers) possess more information about firms' prospects than principals (shareholders). As managers have access to firms' internal information, the opportunistic use of information at the expense of investors may reduce the relevance of available information (Ataullah et al., 2014; Chowdhury et al., 2018). Thus, information asymmetry amplifies ambiguity and uncertainty. Therefore, it is expected that investors will demand an additional premium for the increased uncertainty caused by information asymmetry. Thus, it is expected that a firm with higher information asymmetry will exhibit a more pronounced inverse relationship between its *EVOL* and COVID-period share price returns. In line with prior literature, size (total assets), analyst following, and institutional investors are employed as measures of information asymmetry[2].

This study uses firm-level data from publicly listed US firms. The US stock market's size, global importance, powerful and efficient regulatory bodies, and rigorous rules make it excellent for assessing investor behavior, market movements, asset pricing, and financial performance. The sample period is divided into two sub-periods: i) the pre-COVID-19 period (August 2018 to December 2019) and ii) the COVID-19 period (January 2020 to May 2021). To ascertain if the degree of uncertainty influences investors' responses to *EVOL*, the responses from investors to *EVOL* over the two sub-periods are compared. Data was collected from the Bloomberg database. Observations with a negative share price, equity, assets, or outstanding shares were excluded. In addition, financial institutions (SIC: 6000-6499), utility firms (SIC: 4400-4999), and delisted firms were also excluded from the sample. The data is winsorized for each variable at 1 percent and 99 percent levels. The final sample for this study includes 840 firms listed on the New York Stock Exchange (NYSE).

3. RESULTS

Table 1 summarizes the key statistics for the two sample periods. This shows that during the crisis period, the mean and median values of *BHAR* were 12 percent and –23 percent, respectively. These skewed results are in line with prior research (e.g., Ali, 2023), showing that COVID-19 had a predominantly negative effect on the share prices of a large number of firms. It is noteworthy that a few sectors not only weathered the crisis well but also managed to successfully reshape the overall outlook of the stock market. The results show that the majority of the sample firms (66 percent) experienced negative returns during the COVID-19 crisis. Therefore, it is apparent that COVID-19 has shocked the economy, causing stock prices to be re-priced.

Additionally, Table 1's positive values for earnings volatility and negative values for cash flow volatility imply that accounting earnings have greater volatility than cash flow[3]. This implication is inconsistent with previous research (see, e.g., Jayaraman,

Table 1. Descriptive statistics for COVID-19 and pre-COVID-19 periods

Variables	Pre-COVID (August 2018 – December 2019)					COVID (January 2020 – May 2021)				
	Mean	St. Dev	Q1	Median	Q3	Mean	St. Dev	Q1	Median	Q3
BHAR	–0.11	0.63	–0.50	–0.18	0.14	0.12	1.22	–0.39	–0.23	0.20
Earnings Vol.	1.91	1.34	0.87	1.65	2.77	1.81	1.31	0.84	1.67	2.65
Cash flow vol.	–1.29	0.57	–1.68	–1.36	–0.96	–2.82	1.30	–3.72	–3.00	–2.01
Cash	0.17	0.25	0.04	0.12	0.27	0.16	0.24	0.04	0.11	0.27
Leverage ratio	0.57	0.32	0.36	0.55	0.72	0.51	0.30	0.30	0.50	0.67
Tangible Assets	0.74	0.23	0.62	0.87	0.99	0.68	0.30	0.50	0.73	0.92
Size	7.88	2.43	4.56	6.32	7.95	8.10	2.41	4.69	6.41	7.99
Market–to–book	5.67	8.18	1.81	3.08	5.61	5.43	8.05	1.46	2.73	5.15
Sales_growth	2.74	1.59	1.67	2.59	3.55	2.65	1.61	1.71	2.60	3.60
Market Beta	1.21	2.43	0.09	1.09	2.16	1.17	2.10	2.31	.06	2.03
ROA	–0.02	11.95	–0.08	0.00	.01	–0.02	8.91	–0.10	0.00	.01

2 See Ali et al. (2017) and Ali (2023) for a review of relevant literature.

3 Due to log transformation, we get a negative average value for the CFV.

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2008; Ahmed et al., 2020). The remaining descriptive data are mostly consistent over the two sample periods, indicating an analogous cohort of firms in the sample periods.

3.1. Univariate tests

This subsection presents the results of some univariate tests that show the relationship between *EVOL* and share price returns. Table 2 lists the results of these tests. To compute the values in Panel A of Table 2, first, the pre-crisis subsample is divided into quintiles based on the *EVOL*, and then the average (column 1) and median (column 2) stock returns for each quintile are calculated. The process is repeated for the crisis period subsample and the mean (column 3) and median (column 4) stock returns for each *EVOL* quintile are computed. For the pre-crisis sample, stock returns declined monotonically across the *EVOL* quintiles, exhibiting an inverse relationship between share price returns and *EVOL* during the pre-COVID period. In contrast, the COVID-period mean and median returns exhibit a positive relationship with the *EVOL* quintiles, suggesting that firms exhibiting *EVOL* experience larger increases in their stock prices during the COVID period.

A number of factors can affect stock returns in an identical manner to *EVOL*. Therefore, additional univariate tests using conditionally sorted portfolios were performed. The samples are sorted based on information asymmetry metrics, including firm size, analyst following, and institutional investors. The sole purpose of using these conditional factors was to determine whether information asymmetry affected the results. The results of these tests are listed in Table 2 (Panels B–D). Panel B1 of Table 2 shows that smaller firms with higher *EVOL* experience excessive positive returns compared with larger firms with low *EVOL*. Similarly, the results for analyst coverage (Panel C1) and institutional investors (Panel D1) are also consistent with these findings. Irrespective of the information asymmetry proxy employed, one consistent result emerges: COVID-19-period returns exhibit a positive relationship with *EVOL*, with the correlation stronger for firms that experience high information asymmetry. By contrast, the association is less clear for firms during pre-crisis (stable) times. These results imply that trying to influence investors' behavior during crises by providing them with firm-level information is unlikely to be useful.

Table 2. Univariate results: Prior earnings volatility (EVOL) quintiles and stock returns

Panel A: Avg. Returns

Earnings Volatility Quintiles	Pre-Crisis Period		Crisis Period	
	Mean	Median	Mean	Median
Lowest EVOL	–0.05	–0.07	0.01	–0.14
2	–0.08	–0.12	0.08	–0.09
3	–0.12	–0.22	0.13	–0.07
4	–0.07	–0.26	0.44	–0.10
Highest EVOL	–0.13	–0.37	0.53	–0.12
Diff. (Low–High)	0.08 (0.00)	0.3 (0.00)	–0.52 (0.00)	–0.02 (0.00)
P-value	(0.00)		90	

Panel B: Avg. Returns

	Firm Size. Quintile (Pre-Crisis)						
	Small	2	3	4	Large	Diff.	P-Value
Lowest EVOL	–0.16	–0.06	–0.04	–0.02	–0.00	–0.16	(0.00)
2	–0.11	–0.06	–0.07	–0.05	–0.10	–0.01	(0.00)
3	–0.11	–0.16	–0.11	–0.14	–0.10	–0.01	(0.01)
4	–0.01	–0.03	0.03	–0.09	–0.25	0.24	(0.01)
Highest EVOL	–0.02	–0.25	–0.10	0.06	–0.33	0.31	(0.00)
Diff. (Low–High) *P*-value	–0.14 (0.00)	0.19 (0.00)	0.6 (0.00)	–0.08 (0.00)	–0.33 (0.00)		

Table 2 (cont.). Univariate results: Prior earnings volatility (EVOL) quintiles and stock returns

Panel B1: Avg. Returns							
Firm Size. Quintile (Crisis Period)							
	Small	**2**	**3**	**4**	**Large**	**Diff.**	***P*-Value**
Lowest EVOL	0.29	0.20	0.04	0.04	–0.07	0.36	(0.00)
2	0.26	0.15	0.06	–0.06	0.03	0.23	(0.00)
3	0.26	0.07	0.16	0.12	0.11	0.15	(0.01)
4	1.18	0.69	0.12	0.21	0.26	0.92	(0.01)
Highest EVOL	0.97	0.88	0.39	0.34	0.25	0.72	(0.00)
Diff. (Low–High) *P*-value	–0.68 (0.00)	–0.68 (0.00)	–0.35 (0.00)	–0.3 (0.00)	–0.32 (0.00)		
Panel C: Avg. Returns							
Analyst Following Quintile (Pre-Crisis)							
	Low	**2**	**3**	**4**	**High**	**Diff.**	***P*-Value**
Lowest EVOL	–0.25	–0.34	–0.12	0.00	–0.03	–0.22	(0.00)
2	–0.02	–0.19	–0.08	–0.04	–0.05	0.03	(0.00)
3	–0.14	–0.20	–0.16	–0.04	–0.08	–0.06	(0.01)
4	–0.04	–0.07	–0.08	–0.13	–0.10	0.06	(0.00)
Highest EVOL	–0.10	–0.12	–0.09	–0.19	–0.22	0.12	(0.01)
Diff. (Low–High) *P*-value	–0.15 (0.00)	–0.22 (0.00)	–0.03 (0.00)	0.19 (0.00)	0.19 (0.00)		
Panel C1: Avg. Returns							
Analyst Following Quintile (Crisis)							
	Low	**2**	**3**	**4**	**High**	**Diff.**	***P*-Value**
Lowest EVOL	–0.52	1.13	0.01	0.02	–0.03	–0.49	(0.00)
2	0.28	–0.05	0.11	0.09	–0.00	0.28	(0.00)
3	0.35	0.03	0.05	0.19	–0.01	0.36	(0.00)
4	0.68	0.82	0.35	0.21	0.25	0.43	(0.01)
Highest EVOL	0.46	1.20	0.49	0.38	0.13	0.33	(0.00)
Diff. (Low–High) *P*-value	–0.98 (0.01)	–0.07 (0.00)	–0.48 (0.01)	–0.36 (0.00)	–0.16 (0.00)		
Panel D: Avg. Returns							
Institutional Ownership Quintile (Pre-Crisis)							
	low	**2**	**3**	**4**	**high**	**Diff.**	***P*-Value**
Lowest EVOL	–0.20	–0.05	–0.01	–0.11	–0.01	–0.19	(0.00)
2	–0.18	–0.08	–0.09	–0.10	–0.08	–0.1	(0.00)
3	–0.26	–0.10	–0.11	–0.10	–0.18	–0.08	(0.00)
4	–0.12	0.06	–0.23	–0.03	–0.15	0.03	(0.01)
Highest EVOL	–0.18	–0.24	–0.02	–0.08	–0.39	0.21	(0.00)
Diff. (Low–High) *P*-value	–0.02 (0.00)	0.19 (0.01)	0.01 (0.01)	–0.03 (0.01)	0.38 (0.00)		
Panel D 1: Avg. Returns							
Institutional Ownership Quintile (Crisis Period)							
	low	**2**	**3**	**4**	**high**	**Diff.**	***P*-Value**
Lowest EVOL	0.55	0.08	–0.04	–0.07	–0.01	0.56	(0.00)
2	0.31	0.03	0.07	–0.03	0.14	0.17	(0.00)
3	0.56	0.19	–0.06	0.17	–0.05	0.61	(0.01)
4	1.19	0.69	0.22	0.11	0.24	0.95	(0.00)
Highest EVOL	0.79	1.05	0.26	0.60	0.12	0.67	(0.00)
Diff. (Low–High) *P*-value	–0.24 (0.00)	–0.97 (0.01)	–0.3 (0.00)	–0.67 (0.01)	–0.13 (0.00)		

Note: This table lists the univariate results. The sample firms are categorized into quintiles based on their prior earnings volatility (EVOL), and the quintiles are sorted from the lowest to the highest. The average and median stock returns for each EVOL quintile are reported. The 'p values' in brackets show the variance in average and median stock returns between the lowest and highest quintiles. In panels (B–D1), the sample firms are sorted based on EVOL and information asymmetry measures (size, analyst following, and institutional investors)

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3.2. Multivariate regression analysis

The following multivariate regression model is employed to study the correlation between prior earnings volatility and share price returns.

$$\begin{aligned} BHAR_{it} &= \beta_0 + \beta_1 earnvol_{i,t-1} \\ &+ \beta_1 cfvol_{i,t-1} + \beta_2 cash_{i,t-1} + \beta_3 tangib_{i,t-1} \\ &+ \beta_4 MTB_{i,t-1} + \beta_5 size_{i,t-1} + \beta_6 ROA_{i,t-1} \\ &+ \beta_7 sgrowth_{i,t-1} + \beta_8 lev_{i,t-1} + \beta_9 beta_{i,t-1} \\ &+ \beta_* indummy_{i,t-1}, \end{aligned} \tag{2}$$

where $BHAR_{it}$ denotes the buy-and-hold returns for firm *i* in year *t*. *Earnvol*, *cfvol*, and *cash* are measures of prior earnings volatility, cash flow volatility, and cash holdings, respectively. The variable '*size*' is equal to the natural logarithm of total assets. Additionally, *ROA*, *sgrowth*, *lev*, and *indummy* denote return on assets, sales growth, leverage ratio, and industry dummies, respectively. The values of the control variables are computed at the beginning of the sample period. Using this model, a cross-sectional view of the firms during each sample period is captured[4]. The beta 'β_1' is the primary coefficient of interest in equation 2, which reflects the impact of *EVOL* on share price returns. Following prior similar research, a dummy variable "*indummy*" is included to control for industry-fixed effects.

Table 3 lists the regression coefficients for equation (2), for each sample period. During the COVID period, the coefficient on *EVOL* (β_1) is positive (0.23) and statistically significant, implying that firms with higher *EVOL* exhibit a larger increase in their stock prices during COVID-19. By contrast, the coefficient remains positive but statistically insignificant during the pre-COVID period, indicating that the impact of *EVOL* on share price returns is less clear or potentially weaker in the stable period. These findings support prior research (e.g., Kocher et al., 2018; Gassmann et al., 2022; Kishishita et al. 2022, among others), which shows a reduction in ambiguity aversion or ambiguity-seeking behavior during crises.

Table 3. The relation between BHAR and prior earnings volatility (EVOL)

Variables	Pre-COVID period	COVID period
Prior earnings vol. (EVOL)	0.01 (0.79)	0.23 (0.00)***
Cash flow vol. (CFV)	0.00 (0.95)	0.01 (0.81)
Cash	0.25 (0.11)	–0.40 (0.17)
Leverage ratio	0.33 (0.00)***	–0.08 (0.67)
Tangible assets	–0.06 (0.95)	0.08 (0.59)
Size	–0.04 (0.01)***	–0.10 (0.00)***
Market-to-Book	0.00 (0.59)	–0.00 (0.47)
Sales growth	0.04 (0.01)***	0.00 (0.91)
Market Beta	–0.00 (0.76)	0.02 (0.22)
Returns on Assets (ROA)	0.01 (0.61)	–0.72 (0.00)***
Industry_dummy	–Yes–	–Yes–
Number of Observations	801	840

Note: This table shows the regression coefficients calculated from regressing BHAR on EVOL and other control factors for the pre-COVID-19 and COVID-19 samples. Control variables were computed at the beginning of each sample period. P-values are reported in the parentheses. *, **, and *** show the significance levels at 0.10, 0.05, and 0.01, respectively.

Furthermore, in line with the findings of Fama and French (1995) and Brounen et al. (2004), the study shows a positive relationship between leverage and stock price returns in the pre-COVID period, suggesting that companies with higher leverage ratios tend to have higher returns in normal business conditions. However, the relationship is negative and statistically insignificant during the crisis period, suggesting that high leverage ratios increase the risk of firms' bankruptcy during crises and thus negatively affect their stock values. The lack of statistical significance of the CFV coefficient implies that this variable does not contribute to increasing ambiguity concerns. The coefficient for the size variable is negative and statistically significant, which is consistent with our univariate results. This shows that smaller firms have a larger positive correlation between stock returns and EVOL. This finding supports the notion that business size plays an important role in determining how stock returns respond to changes in

4 Beltratti and Stulz (2009) and Francis et al. (2013) also use similar models in their studies.

EVOL, with smaller companies potentially being more responsive to market signals during a crisis situation. The p-values for the industry dummy variables show that the differences between industries are statistically significant. This shows that the impact of COVID-19 varied greatly among industries, with some facing more severe consequences than others. As a result, our findings are consistent with previous studies, which found that the pandemic's economic effects were not uniform across industries.

3.3. Tests of the effects of firms' Information Asymmetry

Following similar literature, firm size, analyst following, and the number of institutional investors are employed as proxies for information asymmetry.

Prior research has proposed an inverse relationship between firm size and information asymmetry. According to Diamond and Verrecchia (1991), larger firms might experience less information asymmetry because they receive greater scrutiny and attention from regulatory bodies and the market. Yohn (1998) argues that firm size indicates the quantity of available information, while Mohammed and Yadav (2002) suggest that a firm's size informs us about the quality of the firm's reported earnings. Therefore, firm size is employed as a metric to measure information asymmetry. It is hypothesized that during the COVID-19 crisis, smaller firms, which are inherently more uncertain, should exhibit a more significant impact of ambiguity. To test the hypothesis, each of the COVID-19 and pre-COVID-19 samples is further split into two subgroups: small and large firms. Table 4 shows that the EVOL coefficients are weak and statistically insignificant for both large and small firms during the pre-COVID period. In contrast, during the COVID-19 period, the coefficients for both types of firms were positive and statistically significant, with smaller firms exhibiting a stronger positive relationship (0.62) than larger firms (0.09). These findings suggest that investors seek a relatively high negative premium for companies that exhibit more uncertainty during ambiguity.

Table 4. Firm size and the relationship between stock returns and prior earnings volatility (EVOL)

Variables	Pre-COVID		COVID	
	Small	Large	Small	Large
Earnings Vol. (EVOL)	0.05 (0.55)	–0.02 (0.43)	0.62 (0.00)***	0.09 (0.00)***
Cash flow vol. (CFV)	–0.34 (0.34)	–0.04 (0.94)	–0.12 (0.95)	–0.04 (0.25)
Cash	0.12 (0.70)	0.21 (0.29)	–1.18 (0.11)	–0.25 (0.35)
Leverage ratio	0.89 (0.00)***	0.10 (0.36)	0.34 (0.67)	0.00 (0.25)
Tangible assets	0.16 (0.61)	0.06 (0.51)	–0.58 (0.33)	0.16 (0.13)
Market–to–Book	–0.02 (0.02)**	0.01 (0.00)***	–0.04 (0.01)**	0.00 (0.36)
Sales_growth	0.13 (0.00)***	0.00 (0.82)	–0.17 (0.17)	0.09 (0.00)***
Market Beta	–0.00 (0.94)	0.01 (0.30)	0.05 (0.24)	0.02 (0.07)*
Returns on Assets (ROA)	0.05 (0.23)	2.93 (0.15)	–0.37 (0.02)	10.88 (0.00)***
Industry_dummy	–Yes–	–Yes–	–Yes–	–Yes–
Number of Observations	175	626	153	663

Note: Table 4 shows the regression coefficients calculated by regressing BHAR on EVOL and other control factors for the pre-COVID-19 and COVID-19 samples. The pre-COVID-19 and COVID-19 samples were further subdivided into two distinct categories based on the median size. Control variables were computed at the beginning of each sample period. P-values are reported in the parentheses. *, **, and *** show the significance levels at 0.10, 0.05, and 0.01, respectively.

In addition to firm size, we use analyst following as a proxy for the level of information asymmetry. The analyst following indicates the total number of financial analysts tracking a specific firm or security and offering investors' research reports, earnings projections, and investment advice. Prior research reports an inverse relationship between analyst following and information asymmetry (e.g., Isniawati et al., 2018; Roulstone, 2003). Therefore, analyst following is used as a measure of information asymmetry. Firms with fewer analysts following are expected to exhibit a relatively stronger ambiguity impact on the correlation between *EVOL* and COIVD-period share price returns. The COVID and pre-COVID period samples are divided into two subgroups based on the number of analysts and apply the regression model from equation (2). Table 5 shows that, during COVID-19, firms with fewer analysts have a stronger *EVOL* coefficient than those with high analyst following. By contrast, during the pre-COVID period, analyst following does not affect the relation-

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ship between *EVOL* and share price returns. These results are in line with the main findings, showing that firms with heightened uncertainty exhibit a more pronounced positive relationship between *EVOL* and crisis-period stock price returns.

Table 5. Analyst following and the association between share price returns and prior earnings volatility (EVOL)

Varialbles	Pre-COVID		COVID	
	Low analysts	High analysts	Low analysts	High analysts
Prior earnings vol. (EVOL)	0.10 (0.11)	–0.04 (0.09)*	0.38 (0.00)***	0.10 (0.00)***
Cash flow vol. (CFV)	0.05 (0.90)	–0.31 (0.23)	0.22 (0.22)	–0.04 (0.44)
Cash	0.05 (0.91)	0.33 (0.06)*	–1.42 (0.10)	–0.12 (0.61)
Leverage ratio	0.93 (0.00)***	0.16 (0.18)	0.57 (0.36)	–0.09 (0.54)
Tangible assets	–0.10 (0.70)	0.00 (0.98)	0.25 (0.59)	0.01 (0.93)
Size	–0.10 (0.09)*	–0.02 (0.59)	–0.43 (0.00)***	–0.02 (0.33)
Market–to–Book	–0.02 (0.06)*	0.01 (0.03)**	–0.03 (0.08)*	0.00 (0.41)
Sales_growth	0.11 (0.01)***	0.02 (0.33)	0.14 (0.16)	0.03 (0.23)
Market Beta	–0.01 (0.75)	–0.01 (0.42)	0.01 (0.86)	0.01 (0.45)
Returns on Assets (ROA)	0.04 (0.25)	–0.06 (0.79)	–0.40 (0.00)***	–0.59 (0.12)
Industry_dummy	–Yes–	–Yes–	–Yes–	–Yes–
Number of Observations	203	593	220	620

Note: Table 5 shows the regression coefficients calculated by regressing BHAR on EVOL and other control factors for the pre-COVID-19 and COVID-19 samples. Each of the pre-COVID-19 and COVID-19 samples was further subdivided into two distinct categories based on analyst followings (median). Control variables were computed at the beginning of each sample period. P-values are reported in the parentheses. *, **, and *** show the significance levels at 0.10, 0.05, and 0.01, respectively.

The final proxy used for information asymmetry is the number of institutional investors. Institutional investors often possess more resources and expertise to gather relevant information. They usually can: i) use a variety of research tools and conduct in-depth analyses; ii) have access to company management to learn about company plans and strategies; and iii) use their networks and relationships. Thus, institutional investors are better equipped to accumulate firms' public and private information, incorporate it into stock prices, and enable stock prices to be a better reflection of available information. As a result, other stakeholders in the market benefit from obtaining a clearer view of firm value and can make more informed decisions. Previous empirical research has supported this premise. Several studies show that institutional monitoring is a useful tool for reducing information asymmetry (e.g., O'Neill & Swisher, 2003; Velury & Jenkins, 2006; Brous & Kini, 1994).

Firms with fewer institutional investors are expected to exhibit a more pronounced ambiguity impact on the correlation between *EVOL* and share price returns in the crisis period. The COVID and pre-COVID samples are classified into two subgroups based on the median number of institutional investors and apply the regression model from Equation (2).

Table 6. Institutional investors and the relationship between stock returns and prior earnings volatility

Variables	Pre COVID		COVID	
	Small inst. Investors	Large inst. Investors	Small inst. Investors	Large inst. Investors
Prior earnings vol. (EVOL)	0.01 (0.86)	–0.02 (0.47)	0.74 (0.00)***	0.08 (0.02)**
Cash flow vol. (CFV)	0.38 (0.37)	–0.31 (0.25)	0.01 (0.96)	–0.02 (0.74)
Cash	0.53 (0.11)	–0.05 (0.79)	–1.02 (0.24)	–0.37 (0.14)
Leverage ratio	0.89 (0.00)	0.02 (0.89)	0.09 (0.90)	–0.09 (0.54)
Tangible Assets	–0.24 (0.37)	0.01 (0.94)	–0.93 (0.12)	0.16 (0.21)
Size	–0.04 (0.34)	–0.02 (0.21)	–0.25 (0.00)***	–0.02 (0.44)
Market–to–Book	0.00 (0.63)	0.01 (0.01)**	–0.02 (0.24)	0.00 (0.94)
Sales growth	0.12 (0.00)	0.01 (0.94)	–0.16 (0.17)	0.02 (0.36)
Market Beta	0.01 (0.70)	–0.01 (0.34)	0.07 (0.09)*	–0.02 (0.18)
Returns on Assets (ROA)	0.05 (0.15)	–0.71 (0.06)*	–0.56 (0.00)***	–3.10 (0.00)***
Industry_ dummy	–Yes–	–Yes–	–Yes–	–Yes–
Number of Observations	195	605	159	663

Note: Table 6 shows the regression coefficients calculated by regressing BHAR on EVOL and other control factors for the pre-COVID-19 and COVID-19 samples. The pre-COVID-19 and COVID-19 samples were further subdivided into two distinct categories based on institutional investors (median). Control variables were computed at the beginning of each sample period. P-values are reported in the parentheses. *, **, and *** show the significance levels at 0.10, 0.05, and 0.01, respectively.

Table 6 shows that during the pre-COVID period, the *EVOL* coefficients were weak and statistically insignificant for each of the subgroups. These results imply that the level of information asymmetry does not influence the correlation between EVOL and share price returns during stable times. In contrast, during the COVID period, the EVOL coefficients are positive and statistically significant for both groups. Furthermore, the positive relationship is more pronounced in firms with low institutional investors (β_1=0.74) than in firms with a large number of institutional investors (β_1=0.08). These findings are in line with the main findings, implying that investors tend to seek a relatively higher negative premium for firms that exhibit more uncertainty during ambiguity.

4. DISCUSSION

This study examines the impact of ambiguity on the correlation between prior accounting earnings volatility (*EVOL*) and share price returns. In other words, how ambiguity affects investors' responses to EVOL is analyzed. Building on ambiguity-based models, an inverse relationship between *EVOL* and COVID-period share price returns is anticipated.

The results of this study do not show a correlation between *EVOL* and share price returns in the pre-COVID-19 era. This tendency still exists in firms with high information asymmetry and substantial EVOL, implying that investors do not penalize firms because of their elevated levels of uncertainty under stable conditions. These findings are consistent with those of conventional asset-pricing models (Durnev et al., 2003; Morck et al., 2000). These models posit that in periods of economic stability, investors possess superior-quality information regarding the likelihood of future events, rendering the idiosyncratic volatility of fundamentals irrelevant.

In contrast to the pre-crisis period results, the COVID-period results exhibit a strong positive relationship between *EVOL* and share price returns. Surprisingly, this positive correlation is stronger for firms with higher information asymmetry, suggesting that investors do not punish companies with higher uncertainty levels, but reward them by raising their share prices. These results contradict Ellsberg's (1961) universal ambiguity-aversion hypothesis and support Kocher et al.'s (2018) findings that ambiguity aversion is not a universal phenomenon. The results of this study also support the proposition that share prices deviate from their fundamentals in times of heightened uncertainty and ambiguity.

Unlike the results of this study, Ahmed et al. (2020) show an inverse relationship between *EVOL* and share price returns during the global financial crisis of 2008 (GFC). If these results are analyzed in combination with those of prior studies, it appears that investors' ambiguity-aversion attitudes depend on the nature and origins of the crises. For example, a health crisis may affect individuals' ambiguity-aversion behavior differently than a financial or political crisis. Different types of crises pose different sets of challenges and may lead to different potential consequences, affecting how people perceive the resulting ambiguity and shape their responses.

Because crises, based on their nature and origin, have varying impacts on investors' ambiguity aversion behavior, adopting a one-size-fits-all response approach for different types of crises will be ineffective. Policymakers and firms should thoroughly examine the crisis to identify its causes, dynamics, and possible effects on decision-makers' behavior. In this way, they can develop policies and plans to minimize the negative impact of the crisis.

Since this study only looks at the US market, future studies could investigate whether the findings apply to other regions or different demographic groups. Understanding these variations will help in designing and adapting effective communication and financial education strategies for diverse markets and demographic groups.

CONCLUSION

This study examines the impact of COVID-19-induced ambiguity on investors' reaction to prior earnings volatility. Building on ambiguity-based models, an inverse relationship between earnings volatility and COVID-period share price returns was anticipated.

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The study's findings show that there is no clear correlation between prior earnings volatility and share price returns during pre-COVID-19 conditions; however, the variables exhibit a positive relationship during the COVID-19 crisis. More simply, during the crisis period, market forces reward firms with higher earnings uncertainty, even when these forces do not believe these firms would be worth more under normal conditions. Additionally, a positive relationship is more evident for firms that exhibit greater information asymmetry. These results support the findings of previous studies that report a decrease in ambiguity aversion or ambiguity-seeking behavior during crises.

AUTHOR CONTRIBUTIONS

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Formal analysis: Ijaz Ali.
Investigation: Ijaz Ali.
Methodology: Ijaz Ali.
Project administration: Ijaz Ali.
Resources: Ijaz Ali.
Software: Ijaz Ali.
Supervision: Ijaz Ali.
Validation: Ijaz Ali.
Visualization: Ijaz Ali.
Writing – original draft: Ijaz Ali.
Writing – review & editing: Ijaz Ali.

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