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The Effect of COVID-19 on the Relationship between Idiosyncratic Volatility and Expected Stock Returns

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Abstract: This study examines the effect of the COVID-19 pandemic on the relationship between idiosyncratic volatility and expected stock returns. Using daily stock return data in the US market from the Center for Research in Security Prices (CRSP), we estimate monthly idiosyncratic volatility and investigate the effect of the COVID-19 pandemic at the portfolio and firm level. The results of portfolio analysis and cross-sectional regression show that the relationship between idiosyncratic volatility and subsequent stock returns switches from negative to positive during the pandemic period. Furthermore, we find that the relationship is robust to skewness for the "before the pandemic" and "after pandemic" periods. On the contrary, when we control for the one-month return reversal, the effect of idiosyncratic volatility on the subsequent stock returns becomes insignificant in both periods. Therefore, the short-term return reversal effect is the underlying reason for the relationship switching from negative to positive in the pandemic period. Our results are beneficial for investors and researchers.

Keywords: COVID-19; idiosyncratic volatility; stock returns; return reversal

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1. Introduction

The COVID-19 pandemic, reported for the first time in December 2019, has influenced human life and the economy all around the world. The World Health Organization (WHO) announced COVID-19 as a global phenomenon on 11 March 2020 (WHO 2020). Among over 170 affected countries, the number of confirmed cases is the highest in the US. By the end of January 2020, it was declared an 'emergency of international concern', which sounded an alarm across the globe, and it was officially declared a pandemic mid-March, 2020. Europe was declared as the epicenter of the pandemic and it quickly spread to the USA, eventually leading them to become a country with the highest number of affected people. A pandemic of this size and speed directly affects the economy and stock market.

At first, the uncertainty of the COVID-19 and the market downfall seemed relentless, but then governments across the globe provided unprecedented monetary support for its citizens. This allowed for losses to be regained in some industries but other industries were still significantly affected. In the summer of 2020, most sectors were able to regain losses and over half were able to fully bounce back. "While the average returns rose in each successive act, the spread between the best- and worst-performing sectors also grew, from 27 percentage points in mid-March to 80 percentage points today–the widest in recent history" (Bradley and Stumpner 2021). Looking forward, the trend is showing great acceleration in all areas.

The pandemic severely affected stock markets in the US, Europe, and Asia. During the first three months of the year 2020, the Dow Jones Industrial Average index and FTSE index,

the UK's main index, dropped by 23% and 25%, respectively; this plunge was the biggest quarterly drop since 1987.[1] During the same quarter, the S&P 500 also saw its biggest drop by 20% since 2008. The Japanese stock market has dropped by more than 20% since its peak in December 2019.[2]

Several studies examined the effect of the COVID-19 pandemic on stock market volatility. Baker et al. (2020) stated that the COVID-19 outbreak has caused far greater volatility in the US market than any previous events, such as global influenza in 1918, SARS in 2003, or Ebola in 2015. They reported that 18 market jumps existed in a period of 22 trading days from 24 February and 24 March 2020 in the US stock market; this number of jumps was bigger than any other period with the same number of trading days. Additionally, the VIX, also known as the "fear index", surged to levels far above those seen during the financial crisis of 2007–2008 (Ciner 2021). Zhang et al. (2020) showed that as a result of the pandemic, global financial market risks have risen significantly. They also argued that the magnitude of the outbreak in each country determines how the stock market reacts.

While several studies have investigated the impact of the COVID-19 pandemic on stock returns and market volatility, none have examined the relationship between idiosyncratic risk and stock returns during the pandemic. Idiosyncratic volatility of stock return is the nonsystematic component of risk that is firm-specific and not driven by uncertainty in systematic changes. Change in the idiosyncratic component of risk is generally not explained by traditional systematic model factors such as market, size and book-to-market ratio by Fama and French (1993). Theoretically, idiosyncratic volatility is uncorrelated with systematic risk and therefore should have no relationship with stock returns. According to Modern Portfolio Theory (MPT), idiosyncratic risk is not priced in the risk-returns equilibrium (Markowitz 1952), therefore, there is no relation between idiosyncratic risk and stock returns. However, empirical evidence has been presented that there is a relation between idiosyncratic volatility and stock returns. Some studies find different directions in the relation between idiosyncratic risk and expected stock returns. Merton (1987) and Xu and Malkiel (2004) suggest that idiosyncratic volatility is positively related to expected stock returns. According to Xu and Malkiel (2004), investors expect a premium for bearing idiosyncratic risk, because they are unable to fully diversify their portfolio holdings. On the contrary, another group of studies such as Ang et al. (2006, 2009) and Hou and Loh (2016) find a negative relation between idiosyncratic risk and future stock returns. Given all this studies in the literature, it is still interesting to explore the relation between idiosyncratic volatility and returns. However, little research has been conducted under the recent financial environment with COVID-19 pandemic. In a recent study, Baek et al. (2020) examine the idiosyncratic risk changes across 30 industries and show that idiosyncratic risk increased for all industries during the COVID-19 pandemic. However, they do not investigate the relationship between idiosyncratic volatility and stock returns during the pandemic.

During the COVID-19, the market volatility was very high. The VIX index dramatically increased to an extent more than what has been seen during the financial crisis of 2007–2008, and idiosyncratic volatility increased in 30 industries (Baek et al. 2020). These changes motivate us to examine the relationship between idiosyncratic volatility and expected returns during the COVID-19 pandemic and compare the direction and magnitude of this relationship before and during the COVID-19 pandemic. Ang et al. (2006) examine the robustness of the negative relationship between idiosyncratic volatility and subsequent stock returns during different periods and subsamples. They found that the negative relation is robust to stable and volatile periods of the market; however, in the volatile periods, the magnitude of the negative relationship was lower than the stable periods.

In terms of uncertainty, COVID-19 caused the largest shift in employment for American citizens in the last 100 years. Because of restrictions put in place by the WHO, many people lost their jobs and were put in a position where they had to file for unemployment benefits. There were also fear-based decisions that were made by American citizens, where many people were afraid to go to work, thinking they would contract COVID-19, which would

lead to their death. This caused a spike of over 10 million Americans lining up and applying for unemployment benefits over a two-week period in March of 2020. There were also many other American citizens who lost their jobs or refused to attend work, but did not file for benefits. All of these situations have a direct effect on the US economy and market. The shift in employment was not predicted; therefore, "backward looking statistical analyses and historic data were unlikely to yield suitable measures of forward-looking uncertainty" (Baker et al. 2020). The Spanish flu pandemic, and the market crashes in 1987 and 2008 could not provide suitable data given the modern times in America. COVID-19 spread faster than any other virus because of increased mobility of people around the world. Never has there been a time where so many people in America have visited other countries, or so many people from other countries have visited America (Baek et al. 2020).

The main goal of this study is to examine the relationship between subsequent stock returns and idiosyncratic volatility before and during the COVID-19 pandemic at the portfolio and firm level. To date, no study has examined this relationship during the recent pandemic. In this way, this research contributes to the idiosyncratic volatility literature. This study will also benefit investors who are interested in investing in stocks with high idiosyncratic risk as a part of their portfolio and will help them in investing decision making. This study is structured as follows. Section 2 reviews literature related to idiosyncratic volatility and COVID-19 pandemic. Section 3 describes data and methodology. Section 4 presents empirical results and Section 5 concludes.

2. Literature Review

"Higher risk is associated with a greater probability of higher return" widely used phrase. Will that apply to the idiosyncratic risk? The relationship between idiosyncratic risk and return is a popular topic. Many researchers have conducted much work in this area. Among them are Ang et al. (2009), Malkiel and Xu (2002). Ang et al. (2009) showed something interesting. The authors use the Fama and French (1993) three-factor model, to examine international data and close the U.S. stock market data. The data were divided into local, regional, and global, testing the relationship between past idiosyncratic volatility and future returns. The results show the negative relationship between past idiosyncratic risk and stocks return. The authors also stated that the higher the past idiosyncratic risks, the lower the future stock returns. This relation appears in both U.S. and international markets. How powerful can idiosyncratic volatility explains the return? Chowdhury et al. (2021) find that foreign stocks have lower idiosyncratic volatility than comparable U.S. stocks. Fu (2021) demonstrate that the relation between idiosyncratic volatility and return changes over time. Malkiel and Xu (2002) argue that idiosyncratic volatility can help explain expected return for constrained investors while the traditional approach considers free investors. The authors categorized stocks into five groups by size, combined time series, and cross-section test and found the relationship between idiosyncratic risk and expected return. The paper also concluded the idiosyncratic volatility has a high explanatory value in the sample period.

There are studies on the impact on the market from the COVID-19 from different viewpoints. Zhang et al. (2020) provide analysis to measure the risk impact on markets in different countries and global financial markets. The study showed that both the global market and the individual stocks are positively related to the severity and worldwide spread, and in a specific country. Zaremba et al. (2020) focus more on government intervention. The article uses data from 67 countries during the pandemic period and examines the relationship between market risk and government interventions. The study provides evidence that market volatility reacted strongly to government policy change, or in other words, the government interventions are highly influential. The authors suggest that the government should be cautious about the policy-making corresponding to COVID-19. Haroon and Rizvi (2020) extend the stream of research that delves into mood variables by exploring the COVID-19 media news influence on the market return. The world and

U.S. indices were used for analysis. The paper found that the risk is heightened with the negative pandemic news.

Moreover, other studies focus on the risk of financial markets under the influence of COVID-19. Baek et al. (2020) extended the past recent research, such as Zaremba et al. (2020), Baker et al. (2020), Zhang et al. (2020), and Haroon and Rizvi (2020). The extension includes the first dill in the risk detail and identifies the regime change, COVID-19 news, and data pattern during the COVID-19 period. The researchers found the total risk and the idiosyncratic volatility for the U.S. stock market. The study also stated that defensive industries had increased systematic volatility, and on the contrary aggressive industries have decreased systematic volatility during the period.

The effects of COVID-19 on the financial markets have been further studied in most recent studies. Ciner (2021) examines the 4-month stock indexes data from the beginning of 2020 and determines if the returns can be predicted in such an event. Supported by corporate bonds and their ETFs purchasing decision made by the Federal Reserve, the finding shows that the corporate bond ETFs and most industries returns are predictable during the time of COVID-19. Contessi and De Pace (2021) test the data in 18 different markets worldwide to try to identify the periods of mild explosiveness of the markets. The study found the instability and crash transition from China to other countries. Market reactor with a slow diffusion and followed by a rapid collapse. Bollain-Parra et al. (2021) demonstrate the effects of COVID-19 pandemic on the US VIX index. De la Torre-Torres (2021) present the link between COVID-19 news and high volatility spillover across markets. De la Torre-Torres et al. (2021) propose a new trading algorithm that beats the market during high volatility periods. Xu (2022) shows the effects of COVID-19 on the volatility of Canadian stock market.

The risk return trade-off has also been investigated by a few studies. For example, Kusumahadi and Permana (2021) conducted the study using the fundamental equation and the threshold generalized autoregressive conditional heteroskedasticity model. The study showed that the stock return is positively correlated with volatility during the pandemic. Moreover, the level of volatility is positively related to the magnitude of the pandemic. Furthermore, the exchange rate is negatively impacting the market return. In sum, all existing studies in the literature ignores the idiosyncratic volatility and the effects of COVID-19 pandemic on the relation between stock return and idiosyncratic volatility. To date, no study has examined this relationship during the recent pandemic. To the best of our knowledge, this study is the first to contribute to the idiosyncratic volatility literature under COVID-19. It contributes by examining the relationship between stock returns and idiosyncratic volatility before and during the COVID-19 pandemic at the portfolio and firm levels.

3. Data and Methodology

To examine the effect of the COVID-19 pandemic on the relation between idiosyncratic volatility and stock returns, we adopt two sub-samples: Before the Pandemic (January 2018 to December 2019) and During the Pandemic (January 2020 to December 2020) sub-samples. Data on stock returns and other equity market information is collected from the Center for Research in Security Prices (CRSP) database. Stocks with prices less than USD 1 are excluded and only stocks with at least 15 daily returns in a month are included in the sample.

Idiosyncratic volatility (IVOL) is measured by the standard deviation of the residuals from the following regression based on the three-factor model of Fama and French (1993) (hereafter, FF-3) model:

$$R_{i,t} = \alpha_i + \beta_{i,MKT}MKT_t + \beta_{i,SMB}SMB_t + \beta_{i,HML}HML_t + \epsilon_{i,t} \tag{1}$$

where $R_{i,t}$ is the return of portfolio or asset i at the time t, MKT_t is the excess return on the market portfolio at the time t. SMB_t and HML_t are Small Minus Big and High Minus Low factors at the time t, respectively.

A trading strategy was adopted to examine the relationship between idiosyncratic volatility and subsequent stock returns at the portfolio level. Two sets of portfolios were created based on equal-weighted and value-weighted schemes. At the month t, stocks are sorted into quintile portfolios based on their level of idiosyncratic volatility estimated at the time $t-1$. These portfolios are held for one month and then are rebalanced monthly. Next, the difference in average returns of stocks with the highest level and lowest level of idiosyncratic volatility is calculated as the yield of the trading strategy.

In this research, Fama and MacBeth (1973) cross-sectional approach is adopted to investigate the relationship between idiosyncratic volatility and future stock returns at the firm level. The regression is developed with additional controlling variables as shown in the following equation.

$$R_{i,t} = c + \gamma\sigma_{i,t-1} + \acute{\gamma}_1 Ret(-2,-7)_{i,t-1} + \acute{\gamma}_2 Ln(ME)_{i,t-1} + \acute{\gamma}_3 Ln(Illiquidity)_{i,t-1} + \acute{\gamma}_4 Skewness_{i,t-1} \\ + \acute{\gamma}_5 Lagreturn_{i,t-1} + \epsilon_{i,t} \tag{2}$$

where $R_{i,t}$ is the excess return of stock i at the month t, $\sigma_{i,t-1}$ is the idiosyncratic volatility estimated at the previous month using Equation (1), and controlling variables inclue Size, Momentum, Amihud's Illiquidity measure, Skewness, Maximum daily return, and One-month return reversal. To control for the momentum effect, we add Ret(−2,−7) as proxy of the momentum, which is measured as compound gross return from the month $(t-7)$ to $(t-2)$. The size effect is controlled by including Ln(ME), the size of a firm, which is measured by the log market capitalization of the firm at the end of the previous month. It is uncertain about whether stock liquidity affect the relation between idiosyncratic risk and stock return. Liquidity is controlled by adding Ln(Illiquidity), the Amihud's (2002) illiquidity measure calculated by dividing the average of daily absolute return by daily dollar trading volume in the month $t-1$. Following (Barberis and Huang 2008), we control skewness of stock return calculated as the skewness of daily returns during the previous month. Finally, we want to see the one-month return reversal effect (Fu 2009; Huang et al. 2009) and add Lagreturn as the return of the month $t-1$, which is a proxy for the return reversal. We estimate the Newey-West adjusted t-statistics to overcome autocorrelation and heteroskedasticity in the error terms in the model.

The following tests will be conducted in the subperiod of before pandemic and during pandemic. By using this subperiod analysis, it will be clear about the effects of COVID-19 pandemic on the relation between idiosyncratic risk and stock return. To test whether the effects of COVID-19 pandemic is driven by the discovered factors that affect the idiosyncratic volatility–return relation, we control for those factors in the following tests. In the literature, some researchers suggest explanations for the relationship between idiosyncratic volatility and expected stock returns. Among those explanations are Return reversal (Fu 2009; Huang et al. 2009) and Skewness (Hou and Loh 2016). Following these studies in the literature, we control for one-month return reversal and Skewness to see whether these variables can influence the effects of COVID-19 pandemic on the relationship between idiosyncratic volatility and subsequent stock returns. Barberis and Huang (2008) suggest that skewness of stock returns can explain the stock returns. Investors are more biased towards positively skewed securities. Besides, Fu (2009) and Huang et al. (2009) argue that the one-month return reversal effect plays a role in the relationship between idiosyncratic volatility and stock returns. Therefore, in the portfolio sorting process, we sort stocks into 5×5 portfolios independently based on their level of idiosyncratic volatility and skewness (or return reversal). The average return of five portfolios within the same idiosyncratic volatility ranking will be reported in a row. Then, the difference in average returns of portfolios with the highest level and lowest level of idiosyncratic volatility is calculated as the yield of the trading strategy.

The use of both portfolio analysis and cross-sectional regression will provide more information about the relation between idiosyncratic risk and stock return under the effects of COVID-19 pandemic. Portfolio sorting process will eliminate the noise within individual stock returns. Moreover, cross-sectional regression allows us to control for

more independent variables. It will present a clear picture about the relation between idiosyncratic risk and stock return when several other potential factors are controlled. Overall, this methodology fits the research questions in this study and the empirical test results are presented in the next section.

4. Results

4.1. Portfolio Analysis

Table 1 shows the average returns of equal-weighted sorted on idiosyncratic volatility. We perform portfolio analysis for two samples, Before the Pandemic (January 2018 to December 2019) and During the Pandemic (January 2020 to December 2020), and compare the IVOL–returns relationship found in Before the Pandemic sample with that of During the Pandemic sample. For each sample, stocks are sorted into quintile portfolios based on idiosyncratic volatility.

Table 1. Portfolio analysis for equal-weighted portfolios.

| | Ranking on Idiosyncratic Volatility | | | | | 5−1 | Sample Period |
	1 Low	2	3	4	5 High		
Equal−Weighted Portfolios Returns							
No Control	0.05	0.21	−1.02	−1.12	−6.14	−6.19 ***	Before Pandemic
	(0.06)	(0.28)	(−1.58)	(−1.14)	(−2.35)	(−3.00)	18 January–19 December
No Control	1.01	1.76	2.87	2.27	3.61	2.59 ***	During Pandemic
	(0.39)	(0.65)	(0.90)	(0.70)	(1.10)	(3.30)	20 January–20 December
Skewness Controlled	0.98	1.78	2.89	1.94	3.94	2.96 **	During Pandemic
	(0.36)	(0.63)	(0.88)	(0.56)	(1.08)	(2.65)	20 January–20 December
Return Reversal Controlled	1.48	1.9	2.75	2.23	3.15	1.67	During Pandemic
	(0.53)	(0.65)	(0.86)	(0.68)	(0.87)	(1.52)	20 January–20 December

This table presents the average returns of equal-weighted portfolios with or without controlling for Skewness and Return reversal. Skewness is the skewness of daily returns during the previous month. The return of month $t − 1$ is used as a proxy for the one-month return reversal effect. At month t, stocks are sorted into quintile portfolios based on their ranking of idiosyncratic volatility estimated at the time $t − 1$. These portfolios are held for one month and then are rebalanced monthly. Next, the difference in average returns of stocks with the highest level and lowest level of idiosyncratic volatility is calculated as the yield of the trading strategy. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

The first row of Table 1 shows the average returns of five equal-weighted portfolios of Before the Pandemic sample. The average return decreases monotonically when we go from quintile 1 to quintile 5. The difference in average returns between portfolios with the highest level and the lowest level of idiosyncratic volatility is −6.19% per month, with a robust *t*-statistic of −3.00. This result is aligned with Ang et al.'s (2006) findings indicating a negative relation between idiosyncratic volatility and expected stock returns. The second row of Table 1 shows that the 5−1 difference in average returns is significantly positive with the magnitude of 2.59% per month for the During the Pandemic sample. This finding is consistent with studies that find a positive relationship between idiosyncratic volatility and expected stock returns (e.g., Fu 2009; Spiegel and Wang 2005; Xu and Malkiel 2004)

Why does the relationship between idiosyncratic risk and stock returns switch from negative to positive during the pandemic? Some researchers suggest explanations for the relationship between idiosyncratic volatility and expected stock returns. Among those explanations are Return reversal (Fu 2009; Huang et al. 2009) and Skewness (Hou and Loh 2016). To find a possible answer to the question above, we control for One-month return reversal and Skewness to see whether these variables can explain the positive relationship between idiosyncratic volatility and subsequent stock returns.

Barberis and Huang (2008) suggest that skewness of stock returns can explain the stock returns. Investors are more biased towards positively skewed securities. As a result, these stocks become overpriced and have negative subsequent excess returns. Similarly, negatively skewed stocks tend to earn higher future returns (Conrad et al. 2013). In this

regard, if stocks with high idiosyncratic volatility have negative skewness, Skewness would explain the positive relationship between idiosyncratic volatility and subsequent stock returns found in the During the Pandemic period. The third row of Table 1 shows that the relationship remains positive after controlling for Skewness. Therefore, Skewness cannot explain the positive relationship.

We also control for the one-month return reversal to see whether this anomaly explains the positive relationship between idiosyncratic volatility and expected stock returns. De Bondt and Thaler (1985) find that stock prices tend to reverse after periods of dramatic price swings. This phenomenon is known as the Short-term reversal, in which stocks with low (high) returns over a past short time (i.e., a month or a week) earn positive (negative) abnormal returns in the following period. Fu (2009) and Huang et al. (2009) argue that when they control for the one-month return reversal effect, the negative relationship between idiosyncratic volatility and stock returns becomes insignificant. Fu (2009) argues that high idiosyncratic stocks with high contemporaneous returns, which tend to reverse in the following month, mainly drive the negative relation documented by Ang et al. (2006). Accordingly, if the return reversal is an explanation of the positive idiosyncratic volatility effect on subsequent stock returns in the During the Pandemic sample, the high idiosyncratic volatility portfolios are mainly stocks with contemporaneous low abnormal returns, which tend to be reversed in the next month. The fourth row of Table 1 shows that the 5−1 difference in average returns becomes insignificant after controlling for the one-month return reversal. This finding implies that return reversal explains the positive relationship between idiosyncratic volatility and expected stock returns found during the pandemic.

Furthermore, we repeat the portfolio analysis for value-weighted portfolios. Table 2 reports the average returns of quintile value-weighted portfolios. The 5−1 differences between the portfolios with the highest and lowest idiosyncratic volatilities are similar two those of Table 1 in terms of significance, which shows that the relationship between idiosyncratic volatility and subsequent stock return is not significantly different among equal-weighted and value-weighted portfolios.

Table 2. Portfolio analysis for value-weighted portfolios.

	Ranking on Idiosyncratic Volatility					5−1	Sample Period
	1 Low	2	3	4	5 High		
Value−Weighted Portfolios Returns							
No Control	0.92	0.71	0.49	0.46	−2.58	−3.50 **	Before Pandemic
	(1.73)	(1.38)	(0.72)	(0.62)	(−1.76)	(−2.78)	18 January−19 December
No Control	1.69	1.89	2.74	4.54	5.01	3.32 **	During Pandemic
	(1.09)	(1.09)	(1.11)	(2.07)	(1.89)	(2.70)	20 January−20 December
Skewness Controlled	1.86	1.67	2.95	3.44	5.47	3.61 **	During Pandemic
	(1.00)	(0.84)	(1.12)	(1.44)	(1.64)	(2.31)	20 January−20 December
Return Reversal Controlled	1.94	1.74	2.14	3.8	3.25	1.31	During Pandemic
	(1.00)	(0.87)	(1.02)	(1.40)	(1.15)	(1.29)	20 January−20 December

This table presents the average returns value-weighted portfolios with or without controlling for Skewness and Return reversal. Skewness is the skewness of daily returns during the previous month. The return of month $t-1$ is used as a proxy for the one-month return reversal effect. At month t, stocks are sorted into quintile portfolios based on their ranking of idiosyncratic volatility estimated at the time $t-1$. These portfolios are held for one month and then are rebalanced monthly. Next, the difference in average returns of stocks with the highest level and lowest level of idiosyncratic volatility is calculated as the yield of the trading strategy. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

4.2. Cross-Sectional Analysis

In order to test the relationship between idiosyncratic volatility and expected stock returns before and during the pandemic, we adopt the cross-sectional Fama-MacBeth model. We run the regression for the Before the Pandemic and During the Pandemic samples separately. Table 3 reports the outputs of Fama-MacBeth regression through 4 sets

of tests. This table shows the results of the firm-level Fama and MacBeth (1973) regressions of monthly stock returns on idiosyncratic volatility, and other firm characteristics for the Before the Pandemic sample. Model 1 shows that the coefficient of IVOL is significantly negative. Model 2 shows that when Skewness is controlled, the negative IVOL–returns relationship is still significant at the significance level of 5%. However, when we control for the One-month return reversal in model 3, the IVOL coefficient becomes marginally significant and its magnitude decreases. This implies that return reversal can explain the negative IVOL–returns relationship. The results of model 4 indicate that after controlling for all the control variables, the coefficient significance of IVOL is still marginally significant similar to that of model 3.

Table 3. Cross-sectional analysis before the pandemic.

	Model 1	Model 2	Model 3	Model 4
Intercept	−0.0838 *	−0.0812 *	−0.0381	−0.0410
	(−1.87)	(−1.95)	(−1.13)	(−1.27)
IVOL	−2.1041 **	−2.1701 **	−0.5897 *	−0.5694 *
	(−2.59)	(−2.59)	(−1.97)	(−1.99)
Ret(−2, −7)	0.0260	0.0256	0.0242	0.0232
	(1.00)	(0.99)	(0.85)	(0.81)
Ln(ME)	−0.0139 *	−0.0128 *	0.0072	0.0077
	(−1.75)	(−1.76)	(1.11)	(1.15)
Ln(Illiquidity)	−0.0125 **	−0.0119 **	0.0009	0.0009
	(−2.12)	(−2.19)	(0.21)	(0.22)
Skewness		0.0123 **		−0.0018
		(2.13)		(−0.41)
Lagreturn			−0.0278	−0.0409
			(−0.30)	(−0.40)
R^2	0.0083 ***	0.0091 ***	0.1155 ***	0.1165 ***
	(3.40)	(3.54)	(3.00)	(3.02)
Adjusted R^2	0.0072 ***	0.0076 ***	0.1142 ***	0.1149 ***
	(2.92)	(2.97)	(2.96)	(2.97)
Average Number of Observations	76,900	76,900	76,900	76,900
Sample Period	18 January−19 December	18 January−19 December	18 January−19 December	18 January−19 December

This table reports the result of Fama-MacBeth regression estimated over the period before the pandemic. IVOL is the stock idiosyncratic volatility measured by the standard deviation of the residuals from regressions using equation (1). Ln(ME) is the size of a firm, which is measured by the log market capitalization of the firm at the end of the previous month. Ret(−2,−7) is the momentum, which is measured as compound gross return from the month ($t − 7$) to ($t − 2$). Amihud's (2002) illiquidity measure is calculated by dividing the average of daily absolute return by daily dollar trading volume in the month $t − 1$. Ln(Illiquidity) is the log of Amihud's (2002) illiquidity measure. Skewness is the skewness of daily returns during the previous month. The return of month t-1 is used as a proxy for the one-month return reversal effect. Newey-West adjusted t-statistics are reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Furthermore, we repeat the Fama and MacBeth (1973) regression for the "During the Pandemic" sample in Table 4. Model 5 shows that the coefficient of IVOL is 0.2073, which is significantly positive. This finding implies that IVOL is positively related to subsequent stock returns in the During the Pandemic sample. Controlling for Skewness in model 6, we find that the IVOL–returns relationship does not change in terms of significance. Therefore, Skewness cannot explain the positive relationship in the During the Pandemic period. However, when Lagreturn is controlled in model 7, the coefficient of IVOL becomes insignificant and its magnitude reduces to 0.0471; it implies that this relationship is derived by the One-month return reversal. Therefore, return reversal can explain the positive IVOL–returns during the pandemic. The results of model 8 indicate that no relationship exists between idiosyncratic volatility and expected stock returns in the "During the pandemic" period after controlling for all the variables.

Table 4. Cross-sectional analysis during the pandemic.

	Model 5	Model 6	Model 7	Model 8
Intercept	0.0180	0.0153	−0.0041	−0.0053
	(0.52)	(0.45)	(−0.10)	(−0.13)
IVOL	0.2073 **	0.2418 ***	0.0471	0.0606
	(2.84)	(3.29)	(0.54)	(0.72)
Ret(−2, −7)	0.0009 *	0.0009 *	0.0008 *	0.0008 *
	(1.99)	(1.99)	(1.99)	(1.99)
Ln(ME)	−0.0025	−0.0027	−0.0050	−0.0053
	(−0.53)	(−0.57)	(−1.40)	(−1.53)
Ln(Illiquidity)	−0.0011	−0.0012	−0.0033 **	−0.0035 **
	(−0.53)	(−0.62)	(−2.75)	(−3.01)
Skewness		−0.0027 **		−0.0003
		(−2.62)		(−0.33)
Lagreturn			−0.0468 *	−0.0445 *
			(−2.16)	(−2.07)
R^2	0.0120 **	0.0122 **	0.0172 ***	0.0179 ***
	(2.93)	(2.92)	(6.10)	(6.62)
Adjusted R^2	0.0108 **	0.0107 **	0.0157 ***	0.0161 ***
	(2.62)	(2.54)	(5.54)	(5.92)
Average Number of Observations	39,061	39,061	39,061	39,061
Sample Period	20 January−20 December	20 January−20 December	20 January−20 December	20 January−20 December

This table reports the result of Fama-MacBeth regression estimated over the period during the pandemic. IVOL is the stock idiosyncratic volatility measured by the standard deviation of the residuals from regressions using equation (1). Ln(ME) is the size of a firm, which is measured by the log market capitalization of the firm at the end of the previous month. Ret(−2,−7) is the momentum, which is measured as compound gross return from the month ($t − 7$) to ($t − 2$). Amihud's (2002) illiquidity measure is calculated by dividing the average of daily absolute return by daily dollar trading volume in the month $t − 1$. Ln(Illiquidity) is the log of Amihud's (2002) illiquidity measure. Skewness is the skewness of daily returns during the previous month. The return of month t-1 is used as a proxy for the one-month return reversal effect. Newey-West adjusted t-statistics are reported in the parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

Overall, the results from cross-sectional analysis confirms that the relationship between idiosyncratic volatility and stock returns changes from negative to positive after the breakout to COVID-19. The return reversal could be a potential driving factor of this change. This is consistent with results from portfolio analysis. Finally, the effect of skewness seems to be marginal.

5. Conclusions

The mutation of the COVID-19 virus also makes it difficult to study uncertainties on the American stock market. In late 2020, the Delta variant rushed across America, and now the Omicron variant is causing a similar disruption to working Americans and its economic stability in 2021. These variants, as well as the possibility of other variants emerging, makes the forecasting of the future of financial markets difficult. When statistical forecasting is difficult it creates uncertainty, but not uncertainty that can be statistically forecasted. "The strong propensity for the volatility of many economic time series to rise in recessions—but their backward-looking character makes them less useful in the wake of abrupt shifts and once-in-a-century shocks" (Baker et al. 2020). It is impossible to reflect on recently collected data when the current situation is already dramatically changing (Baek et al. 2020). Understanding the market volatility is therefore crucial for investors.

This paper examines the effect of the COVID-19 pandemic on the relationship between idiosyncratic volatility and expected stock returns at the portfolio and firm level. The results of portfolio analysis and cross-sectional regression show that the relationship between idiosyncratic volatility and subsequent stock returns switches from negative to positive during the pandemic period. To find a possible explanation for this direction change, Skewness and One-month return reversal are controlled. When the One-month return

reversal is controlled, the positive IVOL–returns relationship disappears at both portfolio and firm level. The reason might be related to the negative effect of the COVID-19 pandemic on the stock returns, especially during the first phases of this global phenomenon, leading to abnormal negative stock returns on 20 March 2020. Then, the negative abnormal returns started to be reversed in the following months. It implies that short-term return reversal derives the positive relationship between idiosyncratic volatility and subsequent stock returns in the During the Pandemic period. In contrast to return reversal, Skewness can explain nor the negative IVOL–returns relationship before the pandemic neither the positive relationship during the pandemic period. Another finding is that portfolio analysis presents similar results for value-weighted portfolios compared to equal-weighted portfolio analysis.

The results in this study will benefit investors who are interested in investing in stocks with high idiosyncratic risk, will assist them in their portfolio construction, and will help them in investing decision making. Researchers will also benefit from this study as it fills the gap in the literature about the effects of COVID-19 pandemic on the relation between idiosyncratic risk and stock return. This study lays the foundation for two streams of future research that (i) examine the effects of COVID-19 pandemic on financial markets and (ii) investigate the puzzling relation between idiosyncratic risk and stock return. This study has its limitations in the relatively short time period in the tests. This is mainly due to the lack of stock return data after the breakout of COVID-19. Future research could be conducted on the long-run effects of COVID-19 pandemic on the idiosyncratic volatility–return relation once there is enough data for tests.

Notes

1   https://www.bbc.com/news/business-52113841 (accessed on 12 November 2021).

2   https://www.bloomberg.com/news/articles/2020-03-09/perfect-storm-is-plunging-asia-stocks-to-bear-markets-one-by-one (accessed on 12 November 2021).

References

Amihud, Yakov. 2002. Illiquidity and stock returns: Cross-section and time-series effects. *Journal of Financial Markets* 5: 31–56. [CrossRef]

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. 2006. The Cross-Section of Volatility and Expected Returns. *The Journal of Finance* 61: 259–99. [CrossRef]

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang. 2009. High idiosyncratic volatility and low returns: International and further U.S. evidence. *Journal of Financial Economics* 91: 1–23. [CrossRef]

Baek, Seungho, Sunil K. Mohanty, and Mina Glambosky. 2020. COVID-19 and stock market volatility: An industry level analysis. *Finance Research Letters* 37: 101748. [CrossRef] [PubMed]

Baker, Scott R., Nicholas Bloom, Steven J. Davis, and Stephen J. Terry. 2020. *COVID-Induced Economic Uncertainty*. National Bureau of Economic Research Working Paper Series, No. 26983; Cambridge: National Bureau of Economic Research. [CrossRef]

Barberis, Nicholas, and Ming Huang. 2008. Stocks as Lotteries: The Implications of Probability Weighting for Security Prices. *American Economic Review* 98: 2066–100. [CrossRef]

Bollain-Parra, Leticia, Oscar V. De la Torre-Torres, Dora Aguilasocho-Montoya, María de la Cruz del Río-Rama, and Pandemics and Travel. 2021. Pandemic (COVID-19) News Sentiment, Economic Policy Uncertainty and Volatility Spillover in Global Leisure and Recreation Stocks. In *Pandemics and Travel (Tourism Security-Safety and Post Conflict Destinations)*. Edited by Cláudia Seabra, Odete Paiva, Carla Silva and José Luís Abrantes. Bingley: Emerald Publishing Limited, pp. 141–56. [CrossRef]

Bradley, Chris, and Peter Stumpner. 2021. The Impact of COVID-19 on Capital Markets, one Year in. McKinsey&Company. Available online: https://www.mckinsey.com/business-functions/strategy-and-corporate-finance/our-insights/the-impact-of-covid-19-on-capital-markets-one-year-in#:~{}:text=While%20the%20average%20returns%20rose,the%20widest%20in%20recent%20history (accessed on 12 November 2021).

Chowdhury, Reza H., Chengbo Fu, Qiping Huang, and Nanying Lin. 2021. CSR disclosure of foreign versus U.S. firms: Evidence from ADRs. *Journal of International Financial Markets, Institutions and Money* 70: 101275. [CrossRef]

Ciner, Cetin. 2021. Stock return predictability in the time of COVID-19. *Finance Research Letters* 38: 101705. [CrossRef]

Conrad, Jennifer, Robert F. Dittmar, and Eric Ghysels. 2013. Ex Ante Skewness and Expected Stock Returns. *The Journal of Finance* 68: 85–124. [CrossRef]

Contessi, Silvio, and Pierangelo De Pace. 2021. The international spread of the COVID-19 stock market collapses. *Finance Research Letters* 42: 101894. [CrossRef]

De Bondt, Werner F. M., and Richard Thaler. 1985. Does the Stock Market Overreact? *The Journal of Finance* 40: 793–805. [CrossRef]

De la Torre-Torres, Óscar V. 2021. COVID-19 news and high volatility episodes in the Mexican stock exchange. *Contaduria y Administracion* 65. Available online: http://www.cya.unam.mx/index.php/cya/article/view/3088 (accessed on 18 February 2022).

De la Torre-Torres, Oscar V., Francisco Venegas-Martínez, and Mª Isabel Martínez-Torre-Enciso. 2021. Enhancing Portfolio Performance and VIX Futures Trading Timing with Markov-Switching GARCH Models. *Mathematics* 9: 185. [CrossRef]

Fama, Eugene F., and James D. MacBeth. 1973. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy* 81: 607–36. [CrossRef]

Fama, Eugene F., and Kenneth R. French. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics* 33: 3–56. [CrossRef]

Fu, Chengbo. 2021. Time-Varying Risk and the Relation between Idiosyncratic Risk and Stock Return. *Journal of Risk and Financial Management* 14: 432. [CrossRef]

Fu, Fangjian. 2009. Idiosyncratic risk and the cross-section of expected stock returns. *Journal of Financial Economics* 91: 24–37. [CrossRef]

Haroon, Omair, and Syed Aun R. Rizvi. 2020. COVID-19: Media coverage and financial markets behavior—A sectoral inquiry. *Journal of Behavioral and Experimental Finance* 27: 100343. [CrossRef]

Hou, Kewei, and Roger K. Loh. 2016. Have we solved the idiosyncratic volatility puzzle? *Journal of Financial Economics* 121: 167–94. [CrossRef]

Huang, Wei, Qianqiu Liu, S. Ghon Rhee, and Liang Zhang. 2009. Return Reversals, Idiosyncratic Risk, and Expected Returns. *The Review of Financial Studies* 23: 147–68. [CrossRef]

Kusumahadi, Teresia Angelia, and Fikri C. Permana. 2021. Impact of COVID-19 on Global Stock Market Volatility. *Journal of Economic Integration* 36: 20–45. [CrossRef]

Malkiel, Burton G., and Yexiao Xu. 2002. *Idiosyncratic Risk and Security Returns*. Working Paper. Richardson: University of Texas at Dallas, Available online: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.8.8510&rep=rep1&type=pdf (accessed on 12 November 2021).

Markowitz, Harry. 1952. Portfolio Selection. *The Journal of Finance* 7: 77–91. [CrossRef]

Merton, Robert C. 1987. A Simple Model of Capital Market Equilibrium with Incomplete Information. *The Journal of Finance* 42: 483–510. [CrossRef]

Spiegel, Matthew I., and Xiaotong Wang. 2005. Cross-Sectional Variation in Stock Returns: Liquidity and Idiosyncratic Risk. Yale ICF Working Paper, No. 05-13, EFA 2005 Moscow Meetings Paper. Available online: https://ssrn.com/abstract=709781 (accessed on 12 November 2021).

WHO. 2020. Coronavirus Disease 2019 Situation Report-67. Available online: https://www.who.int/emergencies/diseases/novel-coronavirus-2019/situation-reports (accessed on 12 November 2021).

Xu, Dinghai. 2022. Canadian stock market volatility under COVID-19. *International Review of Economics and Finance* 77: 159–69. [CrossRef]

Xu, Yexiao, and Burton G. Malkiel. 2004. Idiosyncratic Risk and Security Returns. Available online: https://ssrn.com/abstract=255303 (accessed on 12 November 2021). [CrossRef]

Zaremba, Adam, Renatas Kizys, David Y. Aharon, and Ender Demir. 2020. Infected Markets: Novel Coronavirus, Government Interventions, and Stock Return Volatility around the Globe. *Finance Research Letters* 35: 101597. [CrossRef] [PubMed]

Zhang, Dayong, Min Hu, and Qiang Ji. 2020. Financial markets under the global pandemic of COVID-19. *Finance Research Letters* 36: 101528. [CrossRef]