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How do investors price accrual risk during crises?

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Abstract

Under rational asset pricing theory, and in efficient, frictionless market, risk should be priced contemporaneously and, thus, the market meltdown during the COVID-19 pandemic must have been a contingent valuation of newly created risk. In contrast, we find that the reduction in equity value during the pandemic was stronger for stocks with higher pre-pandemic accrued risk. This lends support to the discrete pricing proposition, which is a form of behavioural bias where investors price accrued risk during significant corporate or macroeconomic events. Furthermore, we compare the pricing of accrued risk during the pandemic with the pricing of accrued risk during non-pandemic events and during past financial crises. We report evidence that pricing of accrued risk results in a premium in normal times and a discount during financial turmoil. Finally, we report evidence that investors price accrued stocks discriminately, that is, they are more likely to price accrued risk of stocks of larger firms, smaller B/M, and weaker momentum. Several theoretical and practical implications are discussed inside the paper.

KEYWORDS

accrued risk, behavioural finance, beta, COVID-19, pandemic, earnings returns

1 | INTRODUCTION

Economic turmoil associated with the COVID-19 pandemic, hereafter the pandemic, has had severe impacts on financial markets across the world. In the United States, major equity indices dropped more than 30% in the first 2 weeks of March and about 12% in a single day (Monday 16th of March 2020). In this paper, we explore several suppositions that revolve around a central question: Did we see a spur-of-the-moment, contingent valuation of new risk? Or an inevitable pricing of accrued risk? In practical terms, did investors consider the newly created pandemic-induced risk exclusively? Or did they also price some past risk that has been accruing over time? The media, market experts, and a few academics posit that the market meltdown was an instantaneous reaction to the surging risks elicited by the pandemic (Ali et al., 2020; Baker et al., 2020; Hanke et al., 2020). In this paper, we explore the other possibility. That is, we investigate whether the drastic drop in common stock prices was fueled, at least in part, by a then-overdue corrective movement that priced past, accrued risk. We are not aware of any previous study that has investigated this possibility. We present a few a priori contentions which lead to plausible hypotheses and a few testable implications.

Both of the explanations mentioned above—pricing of accrued risk and valuation of new risk—are conceptually sound. The valuation of new risk story lends support to the market efficiency hypothesis (Fama, 1965) and the rational investor assumption that underpins most asset pricing models. It postulates that in an efficient and frictionless market, risks are priced continuously and fairly. Therefore, when the pandemic hit, all prior risks must have been priced; and the sharp decline in stock prices was a manifestation of the market's ability to process and price contingent risks presented by the pandemic.

The pricing of pre-pandemic risk story, the main premise of this study, falls under the market inefficiency and behavioural finance paradigms. In a non-efficient, fractioned market, investors price risk discretely. This is a form of behavioural bias where investors process accrued risk during significant corporate or macroeconomic events. Therefore, the observed market drop during the pandemic was attributed, in part, to the pricing of past, accrued risk (i.e., the pandemic enticed investors to price past risk that they had not priced).

Several authors have shown that stock movements are concentrated around significant corporate and macroeconomic events. Jegadeesh and Titman (1993) find that the influence of previous stock returns on subsequent stock movements becomes stronger around earning announcements. Savor and Wilson (2013) and Savor and Wilson (2016) report evidence that daily stock movements intensify, and asset prices efficiency increases during macroeconomic shocks. Jiang and Yao (2013) show that the pricing of individual stock's value and size premia is concentrated on trading days marked with stronger market movements. Sloan (1996) and Titman et al. (2013) report evidence that lagged changes in accounting accruals and capital expenditure are priced on subsequent earning announcement dates. Engelberg et al. (2018) show that anomalous stock movements around big corporate events are 150% greater than their counterparts on any other no-news day. Ben-Rephael et al. (2017) and Ben-Rephael et al. (2020) document evidence that asset prices become more efficient on days of important economic announcements and intensified information consumption by investors. Collectively, these studies suggest that risk is not always priced contemporaneously. In other words, investors price risk in a discrete fashion, that is, they let risk accrue then they process it during significant corporate or macroeconomic events. In that sense, at least a part of the stocks movement during the pandemic was inevitable.

Engelberg et al. (2018) show that the flow of material corporate and economic information naturally surges during times of economic turmoil or drastic stock markets movements. Anecdotal observation asserts that this pandemic was not an exception. In fact, it was accompanied by unprecedented surge in media coverage and flow of information (Baker et al., 2020; Hasan et al., 2021; Noman et al., 2021). Accordingly, it is plausible to suspect that the pandemic has induced investors to price past, accrued risk. A testable implication of this proposition is that pre-pandemic accrued risk explains cross-sectional variations in stock price movements during the pandemic. This is the core contribution of our work. We believe that extant COVID-19 studies have implicitly assumed that the meltdown was a pure response to pandemic risks. As such, they have ignored the possibility that what we have seen may be contaminated with pricing of accrued past risk. Formally, we test a null hypothesis that past accrued risk was not priced during the pandemic and seek to reject the null in favour of the alternative hypothesis which implies discrete pricing—a form of behavioural bias.

Empirically, we estimate accrued risk with standard CAPM beta, Fama–French multifactor model beta, adjusted market beta (Karolyi, 1992), lead and lagged excess beta (Dimson, 1979; Lewellen & Nagel, 2006) and quarterly earnings beta (Brandt et al., 2008; Kabir & Hassan, 2009; Ball & Khotari, 1991). We also take a combination-of-betas approach (Bates & Granger, 1969; Kabir et al., 2011; Hollstein et al., 2019). Each beta captures a unique type of risk. Betas of asset pricing models measure the sensitivity of stock price movements to market movements. The adjusted market betas account for prior beliefs. Excess beta with lead and lagged terms captures the impact of asynchronous trading and slow processing of information. Quarterly earnings beta measures the covariance between shocks of firm's earnings and changes in market's aggregated earnings. Many studies have shown that quarterly earnings surprises affect market's aggregated earnings through investor learning (Da & Warachka, 2009; Maroney et al., 2019; Patton & Verardo, 2012; Rubio et al., 2018; Savor & Wilson, 2016).[1] All betas are computed with pre-pandemic data. As such, a higher beta implies a higher pre-pandemic risk.

First, we apply portfolio-sorting technique which is widely used in asset pricing studies (e.g., Fama & French, 1993, 2008). For models' betas and adjusted market betas, we do not observe a meaningful association with stock movements during the pandemic. With quarterly earnings beta and lead and lagged excess beta, however, we report evidence that the drop in stock prices during the pandemic was progressively higher for stocks with higher pre-pandemic accrued risk. Next, we apply regressions analyses and control for several firm-specific characteristics and obtain qualitatively similar findings. Accordingly, we reject the null hypothesis that past accrued risk was not priced during the pandemic; and conclude that the meltdown during the pandemic was partly attributed to a behavioural bias manifested by investors' discrete pricing of risk. That is, at least a portion of the stock prices drop during the pandemic was attributed to the fact that investors were pricing past accrued risk. This finding carries a distinctive practical implication. It tells portfolio managers that when a financial turmoil hits, they should consider not only stocks' sensitivity to the new risk, but also stocks' tendency to carry past, accrued risk.

Generally, our finding supports the overarching proposition of this paper and is consistent with prior findings that pricing of accrued risk occurs concurrently with significant macroeconomic events (Savor & Wilson, 2013) and massive market movements (Jiang & Yao, 2013). In further analyses, we find that the pricing of pre-pandemic is applied discriminately. That is, past earnings volatility and excess beta exacerbate pandemic losses for large and mid-size firms, but not for small firms. Similarly, we report evidence that the relation between stock price losses and pre-pandemic risk is concentrated on small B/M stocks. That is, when investors value the company's equity higher compared to its book value, there is a greater chance that they will price past, accrued risk during crisis times. Finally, we find that the pricing of past, accrued risk is more profound for weak-momentum stocks. These findings are new to literature. We are not aware of any previous study showing that pricing of accrued risk is concentrated on certain stock subsamples.

One aspect of our finding seems to be in contrast with a prevalent belief in literature. We report a larger discount associated with larger pre-pandemic accrued risk; prior literature has reported a premium (Barth & So, 2014; Dubinsky et al., 2019; Kabir & Hassan, 2010). We suspect that pricing of accrued risk during crises may be inverted. Further analyses confirm this conjecture. We show that greater accrued risk is associated with a larger premium during non-crisis events (e.g., corporate earnings announcements) and a larger discount during two previous financial turbulences (2008 and 2015). Practitioners may find this discovery particularly interesting. It says that pricing of accrued risk exacerbates losses during financial crises and boosts profits when positive corporate news arrives.

Our study contributes to literature as follows. First, we shed some light on stocks behaviour during the 2020 pandemic in particular and during financial crises in general. We show that certain past, accrued risk has a considerable predictive power of stock behaviour during the pandemic. As such, the pandemic did not only instigate a contingent market meltdown; it also elicited investors to price pre-pandemic accrued risk. Simultaneously, we find that the pricing of accrued risk during a financial turmoil is variant with stock characteristics. Specifically, pricing of past accrued risk is concentrated on subsamples of larger, higher B/M, and weaker momentum stocks.

Second, our work contributes to a growing literature on risk accrual and discrete pricing – a form of behavioural bias. Our study refines the existing notion that pricing of accrued risk is associated with a premium (Barth & So, 2014; Dubinsky et al., 2019; Savor & Wilson, 2016). Our study provides a more nuanced view of the pricing of accrued risk. The premium reported by earlier studies is perhaps associated with positive corporate events. During crises, the pricing of accrued risk is associated with a discount.

Third, we compute several estimates of pre-pandemic betas with a wide variety of data sampling frequencies, adjustments, estimation windows, and other specifications. In that sense, our work contributes to a growing literature that attempts to refine methods to produce reliable betas (Hollstein et al., 2019; Hollstein & Prokopczuk, 2014; Katscher et al., 2020; Safa et al., 2013). We contribute to this literature by examining how various estimates of beta perform during financial turmoil. Finally, the exploration of these propositions facilitates a greater understanding of stock prices behaviour, especially during crises. As such, we believe that our work carries important insights for both academics and practitioners.

The rest of the paper is organised as follows. Section 2 explains the sample, the construction of key variables, and methodology. Section 3 is devoted for presentation and discussion of main results. Section 4 presents further analyses. Section 5 explains robustness checks and section 6 concludes the paper.

2 | SAMPLE, VARIABLES CONSTRUCTION, AND METHODOLOGY

2.1 | Sample

The sample includes U.S. companies listed on the NYSE, AMEX, or NASDAQ, and have a CRSP share code of 10 or 11 at the beginning of March 2020.[2] We obtain stock returns and market capitalization from the Center for Research in Security Prices (CRSP), asset pricing models parameters from Professor French's data library, financial accounting items from Compustat, and earnings announcement dates from Thomas Reuters Institutional Brokers' Estimate System (IBES) and Compustat. Following Patton and Verardo (2012) and Della Vigna and Pollet (2009), we use IBES for earning announcements during working hours. When IBES announcement date is reported after 4:00 pm, we use the next trading date. When no specific date is given on IBES, we revert to Compustat. We require that sufficient data is available to compute all variables used in this paper. Pandemic returns (explained next) are winsorized at 99% to remove outliers. The final sample includes 2927 companies.

2.2 | Pandemic returns

The COVID-19 crisis started in Wuhan-China in December 2019 as an endemic. Gradually, it developed into an epidemic that led to complete lockdown in China on the 23rd of January 2020. Globally, COVID-19 was rapidly developing into a pandemic.

In the U.S.A., the CDC confirmed first coronavirus case on Jan 21, 2020. On February 3rd, the United States declared public health emergency and on February 25th the CDC announced that COVID-19 is heading towards pandemic status. On Friday, March 13th President Trump declared COVID-19 a national emergency and imposed travel ban on non-U.S. citizens travelling from Europe. This was by far the most significant COVID-19 related declaration that was followed by sever market reaction on the next trading day (Black Monday, March 16th). On that day, all U.S. stock market indices dropped by almost 12%—one of the largest one-day losses in market history. Table 1 below shows pandemic-instigated stock movements within several event windows anchored on March 16th.

Panel A of Table 1 shows the daily cross-sectional average of returns for all stocks in the sample. As anticipated, the worst day is Monday March 16th where the average cross-section return was −12.32%. This is quite comparable to the reported loss in S&P500 which is −11.98% on the same date. In fact, the pattern of average daily returns in the sample is reasonably comparable to that of their S&P500 counterparts. Interestingly, standard deviations exhibit a U-shaped pattern. They start at 28.18% at the beginning of the study window and decline progressively to 18.79% on March 16th before they start to raise again. This indicates that there was progressively less disagreement by investors as the pandemic situation was heading towards its peak on March 16th. This finding supplies another justification of our choice of March 16th as an anchor date.

Panel B reports cumulative returns over several windows anchored on 16th March 2020. Panel C shows cumulative returns over several windows starting on March 16th. The numbers in Panels B and C, suggest that CR [−3, +3] is an efficient candidate for further analyses because it captures a significant portion of the losses (−17.42%) during the pandemic. The findings with the remaining windows are explained in the Robustness Check section.

2.3 | Pre-pandemic risk

Market beta, estimated with asset pricing models, is a standard measure of a stock price sensitivity to market movements. We estimate pre-pandemic market beta with asset pricing models; namely, CAPM and Fama and French's (1993) 3-factor model. These betas are denoted by $CAPM\_\beta$ and $FF3\_\beta$; respectively. For each stock i, $CAPM\_\beta_i$ is computed by running the following model:

$$R_{i,t} - R_{rf,t} = \alpha_i + CAPM\_\beta_i \times \left(R_{m,t} - R_{rf,t}\right) + \varepsilon_{i,t} \tag{1}$$

We run the model with CRSP adjusted daily returns and CRSP value-weighted index as a proxy for the market return. The estimation window is between 2 January 2019, and 31 December 2019. We require a minimum of 180 consecutive trading day returns on each stock.[3] $FF3\_\beta$ is computed in analogous manner after extending Equation (1) with *SMB* and *HML* factors and applying similar data frequency and restrictions. A higher $CAPM\_\beta$ and $FF3\_\beta$ signifies a higher sensitivity to market movement, that is, market risk. Nevertheless, many studies have raised doubts on market beta's ability to explain stock returns (Alhenawi, 2015; Fama & French, 1992; Fama & French, 1993; Frazzini & Pedersen, 2014; Lewellen & Nagel, 2006; Polk et al., 2006; Reinganum, 1981). For that reason, we use additional measures of pre-pandemic risk.

First, we apply the following shrinkage adjustment technique adopted from Karolyi (1992):

$$Adj\_CAPM\_\beta_i = W_{CAPM\_\beta_i} \times CAPM\_\beta_i + W_{Prior\_\beta_i} \times Prior\_\beta_i \tag{2}$$

were,

$Prior\_\beta_i$: cross-sectional average beta of firms in the same Global Industry Classification Standard (GICS) as firm i.

$W_{CAPM\_\beta_i}$: weight of $CAPM\_\beta_i$ computed as $\left[\sigma^2_{CAPM_{\beta_i}} / \left(\sigma^2_{CAPM_{\beta_i}} + \sigma^2_{Prior_{\beta_i}}\right)\right]$ were σ denotes standard deviation.

$W_{CAPM\_\beta_i}$: weight of $Prior\_\beta_i$ computed as $\left[\sigma^2_{Prior_{\beta_i}} / \left(\sigma^2_{CAPM_{\beta_i}} + \sigma^2_{Prior_{\beta_i}}\right)\right]$ were σ denotes standard deviation.

To generate a time series of $CAPM\_\beta$ for each stock, we run Equation (1) with five-year daily returns divided into 20 quarters. The result is a 20-data-point time series that we use to compute standard deviations for Equation (2); then we average all betas for each stock. We require a minimum of 16 consecutive quarters and 60 consecutive trading days within each quarter. $Adj\_FF3\_\beta_i$ is computed in analogous manner. $Adj\_CAPM\_\beta_i$ and $Adj\_FF3\_\beta_i$ represent posterior belief of $CAPM\_\beta_i$ and $FF3\_\beta_i$ that depends on the relative precision of prior knowledge. Karolyi (1992) shows that this adjustment improves the forecasting power of betas.[4] In the context of this study, $Adj\_CAPM\_\beta_i$ and $Adj\_FF3\_\beta_i$ connotate posterior knowledge that is not captured by $CAPM\_\beta_i$ and $FF3\_\beta_i$ and provides an improved modelling of investors' behaviour (Hollstein et al., 2019).

TABLE 1 Pandemic returns

Panel A: Daily returns around Black Monday (16 March 2020)						
Day	**Date**	**Mean (%)**	***SD* (%)**	**Min (%)**	**Max (%)**	**S&P500 ret. (%)**
−4	Tuesday, 10 March 2020	4.74	28.18	−40.26	57.24	4.94
−3	Wednesday, 11 March 2020	−5.08	24.42	−44.08	40.42	−4.89
−2	Thursday, 12 March 2020	−9.66	22.54	−45.66	32.34	−9.51
−1	Friday, 13 March 2020	8.97	20.67	−24.03	47.47	9.29
0	Monday, 16 March 2020	−12.32	18.79	−42.32	22.68	−11.98
+1	Tuesday, 17 March 2020	5.79	19.73	−25.71	42.54	6.00
+2	Wednesday, 18 March 2020	−5.84	20.67	−38.84	32.66	−5.18
+3	Thursday, 19 March 2020	1.19	20.10	−30.91	38.64	0.47
+4	Friday, 20 March 2020	−4.20	22.54	−40.20	37.80	−4.34

Panel B: Average cumulative returns							
Window	**Cum. return (%)**	**Window**	**Cum. return (%)**	**Window**	**Cum. return (%)**	**Window**	**Cum. return (%)**
CR [−4, −4]	4.74						
CR [−4, −3]	−0.59	CR [−3, −3]	−5.08				
CR [−4, −2]	−10.19	CR [−3, −2]	−14.25	CR [−2, −2]	−9.66		
CR [−4, −1]	−2.14	CR [−3, −1]	−6.56	CR [−2, −1]	−1.56	CR [−1, −1]	8.97
CR [−4, 0]	−14.19	CR [−3, 0]	−18.07	CR [−2, 0]	−13.68	CR [−1, 0]	−4.45
CR [−4, +1]	−9.22	CR [−3, +1]	−13.33	CR [−2, +1]	−8.69	CR [−1, +1]	1.08
CR [−4, +2]	−14.52	CR [−3, +2]	−18.39	CR [−2, +2]	−14.02		
CR [−4, +3]	−13.51	CR [−3, +3]	−17.42				
CR [−4, +4]	−17.14						

Panel C: Average cumulative returns	
Window	**Cum. return (%)**
CR [0, 0]	−12.32
CR [0, +1]	−7.24
CR [0, +2]	−12.66
CR [0, +3]	−11.62
CR [0, +4]	−15.33

Note: The table shows pandemic-instigated reactions of stocks within several event windows anchored on 16 March 2020. This date was chosen for a few reasons. The COVID-19 crisis started in December 2019 in China as an endemic before it rapidly developed into a global pandemic. In the United States, the CDC confirmed first coronavirus case on 21 January 2020. Public health emergency was declared on February 3rd. The CDC announced that COVID-19 is heading towards pandemic status on February 25th. On Friday, March 13th COVID-19 was declared a national emergency and a travel ban was imposed. On the next trading day, March 16th, known as Black Monday, U.S. stock market indices dropped by almost 12%—one of the largest one-day losses in market history. Panel A shows the daily cross-sectional average of returns for all stocks in the sample between Tuesday 10 March 2020 (four trading days before 16 March 2020) and Friday 20 March 2020 (four trading days after 16 March 2020). Panel B reports cross-sectional average cumulative returns over several windows anchored on 16 March 2020. Panel C shows cross-sectional average cumulative returns over several windows starting at March 16th. Subsequent discussion of results in this paper is based on CR [−3, +3]. The findings with the remaining windows are discussed in the Robustness Check section.

Second, we use Dimson (1979) and Lewellen and Nagel (2006) approach to estimate co-movements between stock returns and market returns with lag terms that accounts for asynchronous trading effects. Gilbert et al. (2014) posit that stock prices adjust gradually to new information. Accordingly, we estimate Dimson's betas with several lead and lag terms. The power of Dimson (1979) approach is that it decomposes the covariance between stock returns and market returns into several betas. To decompose beta, we run the following regression with daily returns:

$$R_{i,t} - R_{rf,t} = \alpha_i + \sum_{k=-N}^{k=M} \beta_{i,k} \times \left(R_{m,t+k} - R_{rf,t+k}\right) + \varepsilon_{i,t} \quad (3)$$

where t a day in the estimation window and k denotes a lead or lagged day. The following notation explains the model:

$R_{i,t}$: return of firm i at time t; $R_{rf,t}$: risk-free rate at time t; α_i: intercept (equivalent to Jensen's alpha); k: represents distance from day t. For instance, $k=-1$ is 1 day before and $k=+1$ is 1 day after; M: number of lead days; N: number of lagged days; $\beta_{i,k}$: market beta of firm i on $t+k$; $R_{m,t+k}$: market return at time $t+k$; $R_{rf,t+k}$: risk-free rate at time $t+k$; $\varepsilon_{i,t}$: error term.

It is worth mentioning that if we remove the summation function (i.e., if $N=M=0$), the model becomes a standard CAPM. We run the regression to obtain estimates of betas with one-year pre-pandemic window of daily returns. We require that each stock has at least 180 days of consecutive daily returns. As in Dimson (1979) and Lewellen and Nagel (2006) we aggregate betas as follows,

$$Excess\_\beta_i = \sum_{k=-N}^{k=M} \beta_{i,k} \quad (4)$$

Following Ball and Khotari (1991), we apply a 3-day window $[-1, 0, +1]$ to estimate $Excess\_\beta_i$ (i.e., $N=M=1$). Nevertheless, different lengths of estimation windows are discussed in the Robustness Checks section. Unlike previous betas, $Excess\_\beta_i$ captures stock i returns' excess co-movement with market returns due to asynchronous trading and gradual processing of new information.

Finally, we calculate quarterly earnings beta ($Earn\_\beta$). Unlike market betas explained above, this beat focuses on the covariance between the firm's realised earnings and the market's aggregated earnings. Therefore, it is less susceptible to behavioural biases such as sentiments, irrational reaction to news, and day trading vogues. Quarterly earnings present investors with additional risk because they often include a “surprise” component, that is, reported earnings are often unequal to investors' expectations (Brandt et al., 2008). We calculate quarterly earnings beta by running the following regression:

$$\Delta Earning_{i,t} = \alpha_i + Earn\_\beta_i \times \Delta Earning_{m,t} + \varepsilon_{i,t} \quad (5)$$

$\Delta Earning_{i,t}$: growth of earnings of firm i at time t computed as $\frac{NI_{i,t} - NI_{i,t-4}}{Cap_{i,t-4}}$ where $NI_{i,t}$ is net income of firm i quarterly earnings at time t and $Cap_{i,t}$ is the market capitalization of firm i at time t.[5] $\Delta Earning_{m,t}$: growth of aggregated earnings of all firms at time t computed in an analogous manner to $\Delta Earning_{i,t}$ above. α_i: intercept (equivalent to Jensen's alpha). $Earn\_\beta_i$: earnings beta of firm i. $\varepsilon_{i,t}$: error term.

We run the regression with 5-year pre-pandemic quarterly data (2015Q1 to 2019Q4), and we require a minimum of 4 years of consecutive observations (16 successive quarters). It is worth mentioning that Equation (5) resembles a CAPM equation after replacing the change of price (return) by the change in earnings (growth of earnings). Therefore, $Earn\_\beta_i$ is a measure of the volatility of firm i profitability compared to the aggregated profitability of the whole market. A higher $Earn\_\beta_i$ implies higher risk attributed to earnings volatility.

Bates and Granger (1969) suggested that a simple equal-weighted combination of different estimates might prove worthwhile, especially when the estimates exploit different information sets (Hollstein et al., 2019).[6] Following the literature, we sensor all beta estimates at 1% and 99% to remove the effect of outliers. Table 2 reports the cross-section descriptive statistics of the estimates of betas.

The average market betas, $CAPM\_\beta$ and $FF3\_\beta$ are 1.111 and 1.083; respectively. This indicates that our sample is slightly riskier than the value-weighted market return. This is quite expected because the table reports arithmetic means (i.e., equal-weighted averages) of beta estimates for all stocks in the sample. By construction, equal weighting is relatively more susceptible to the higher risk of medium and smaller companies. The same explanation applies to the means of Ajd_CAPM_β, and Adj_FF3_β (1.082 and 1.054). The average $Earn\_\beta$ is 1.000 which is quite expected given its construction. That is, we take the average of earning betas of all stocks that were used to form a proxy of aggregate market earnings. The average $Excess\_\beta$ is 1.060 while the average $Comb\_\beta$ is 1.065. Standard deviations are larger for shorter estimation windows because of higher measurement errors.

Panel B shows that $CAPM\_\beta$, and $FF3\_\beta$ are highly correlated. The same applies to Ajd_CAPM_β, and Adj_FF3_β. Interestingly, the correlations between $CAPM\_\beta$, and Ajd_CAPM_β (0.409) and between $FF3\_\beta$ and Adj_FF3_β (0.429) are positive but not impressively high. This is because the two pairs are constructed differently in terms of data frequency, horizon, and specifications. This ascertain that the two methods measure different attributes of risk. A similar finding is reported by Hollstein et al. (2019). Earning beta $Earn\_\beta$ is not

TABLE 2 Past, accrued risk (betas)

Panel A: Descriptive statistics

Beta	Data frequency	# Obs.	Max	75%	Mean	25%	Min	*SD*	Median
CAPM_Beta	Daily	2927	2.236	1.402	1.111	0.770	−0.047	0.463	1.076
FF3_Beta	Daily	2927	2.135	1.374	1.083	0.742	0.000	0.433	1.048
Adj_CAPM_Beta	Daily and Quarterly	2927	1.891	1.332	1.082	0.732	0.250	0.333	1.033
Adj_FF3_Beta	Daily and Quarterly	2927	1.858	1.304	1.054	0.704	0.227	0.331	1.015
Earn_Beta	Quarterly	2927	2.215	1.493	1.000	0.297	−0.250	0.500	1.004
Excess_Beta	Daily	2927	2.277	1.639	1.060	0.744	−0.193	0.501	1.035
Comb_Beta	-	2927	2.005	1.424	1.065	0.665	0.098	0.387	1.035

Panel B: Correlation

	CAPM_Beta	FF3_Beta	Adj_CAPM_Beta	Adj_FF3_Beta	Earn_Beta	Excess_Beta	Comb_Beta
CAPM_Beta	1	0.879***	0.409***	0.209***	−0.009	0.310***	0.257***
FF3_Beta		1	0.109***	0.429***	−0.009	0.290***	0.266***
Adj_CAPM_Beta			1	0.880***	−0.208	0.333***	0.366***
Adj_FF3_Beta				1	−0.111	0.313***	0.338***
Earn_Beta					1	0.059	0.066***
Excess_Beta						1	0.397***
Comb_Beta							1

Note: Pre-pandemic risk is gauged with several estimates of firm-market movement covariations. Panel A reports cross-sectional descriptive statistics and Panel B reports correlation. Two market betas are estimated with CAPM and Fama and French's (1993) 3-factor model. These are denoted by: *CAPM_β*, and *FF3_β*; respectively. They capture sensitivity to market movements and are computed with a minimum of 180 consecutive trading days during one pre-pandemic year (2 January 2019 to 31 December 2019). We apply shrinkage adjustment technique adopted from Karolyi (1992) to compute adjusted betas *Adj_CAPM_β* and *Adj_FF3_β*. We also apply Dimson (1979) approach to estimate co-movements between stock returns and market returns with lead and lag terms to account for asynchronous trading (Dimson, 1979; Lewellen & Nagel, 2006) and slow processing of information (Gilbert et al., 2014). To decompose beta, we run $R_{i,t} - R_{rf,t} = \alpha_i + \sum_{k=-N}^{k=M} \beta_{i,k} \times \left(R_{m,t+k} - R_{rf,t+k}\right) + \varepsilon_{i,t}$. Following Ball and Khotari (1991), we apply a three-day announcement window $[-1, 0, +1]$ (i.e., $N = M = 1$). Different lead/lag combinations are discussed in the Robustness Checks section. As in Dimson (1979) we aggregate beta as $Excess_{\beta_i} = \sum_{k=-1}^{k=1} \beta_{i,k}$. Quarterly earnings beta focuses on the covariance between the firm's realised earnings and the market's aggregated earnings. It is estimated with $\Delta Earning_{i,t} = \alpha_i + Earn_{\beta_i} \times \Delta Earning_{m,t} + \varepsilon_{i,t}$ applied to a minimum of 16 consecutive quarters during five pre-pandemic years (2015Q1-2019Q4). A higher $Earn_{\beta_i}$ implies higher risk attributed to earnings volatility. Following Bates and Granger (1969) and Hollstein et al. (2019), an equal-weighted average of all betas produces a meaningful combination $Comb\_\beta_i$. Following the literature, we sensor all beta estimates at 1% and 99% to remove the effect of outliers. The sample period varies depending on how each beta is estimated.

correlated with any other beta, which is quite expected because its constructed differently. In other words, there is no reason for quarterly earnings covariance to be correlated with daily stock price covariance (see Campbell et al., 2018). Dimson's *Excess_β* correlations reveal some interesting inferences. It is positively correlated with *CAPM_β*, *FF3_β*, *Ajd_CAPM_β*, and *Adj_FF3_β*; but the correlations coefficients are not remarkably high. This is expected given the similarity in construction and underlying construct. *Comb_β* is an equal-weighted average of all betas. As expected, it is modestly correlated with all variables.

2.4 | Methodology

If risk is priced continuously and contemporaneously, stock movements during the pandemic would be a pure revaluation of new risk and, thus, it should not be affected by past, accrued risk. In this case, we should not observe any meaningful relation between stock returns during the pandemic and betas. If risk accrues and is conveniently priced during the pandemic, we anticipate observing a meaningful relation between stock returns during the pandemic and pre-pandemic betas. In this case, stock movements during the pandemic reflect, partly, a price correction.[7]

First, we apply portfolio-sorting technique which is widely used in asset pricing studies (e.g., Fama & French, 1993; Jegadeesh & Titman, 1993).[8] We sort stocks by their past, accrued risk (i.e., betas) and allocate them to quintiles. Each quintile resembles a hypothetical investment portfolio. For each portfolio, we compute the average cumulative return during the pandemic. Then we observe the behaviour (i.e., the returns) of the portfolios during the pandemic. If past, accrued risk is priced, we should observe a monotonic trend across quintiles, which indicates an association between cross-sectional variations in stock returns during the pandemic and pre-pandemic accrued risk.[9]

The portfolio-sorting technique explained above is inherently bivariate. The literature documents evidence that stock behaviour is influenced by several factors. Therefore, we apply double sorting and multivariate regression analysis. Using Fama and MacBeth (1973) cross-section regression approach, we regress pandemic returns on past, accrued risk (i.e., betas) and a list of control variables found in literature. The composition of our regressions is inspired by prior studies (see e.g., Hou & Loh, 2016; Simlai, 2021). Specifically, we include momentum (MOM) computed as cumulative monthly returns over 2-month-lagged 12-month period (January 2019 to December 2019). We also include size (SIZE) computed as logged market capitalization at the end of January 2020 as in Fama and French (2008). We control for leverage (DEBT) which is calculated as book value of debt divided by market capitalization as of the most recent financial statement. We also control for illiquidity (ILLIQ) computed with daily returns and dollar volume over previous 3 months as in Amihud (2002) pre-multiplied by 1,000,000. Finally, we control for information uncertainty by including analyst coverage (COV) defined as the number of analysts following the firm in the last quarter of 2019 (Zhang, 2006).[10]

3 | RESULTS

3.1 | Sorted portfolio analysis

Table 3 reports average cumulative pandemic returns CR [−3, +3] for five portfolios sorted on past, accrued risk (i.e., betas). Portfolio 1 contains stocks with the lowest betas, while portfolio 5 contains stocks with the highest betas. We also report the difference between the two extreme portfolios and corresponding t-stat.

For *CAPM_β* and *FF3_β*, the average pandemic returns of different portfolios does not exhibit a progressive pattern in any direction. To illustrate, CR [−3, +3] of portfolios sorted on *CAPM_β* starts at −10.40% (portfolio 1), declines (in magnitude) to −6.01% (portfolio 2), surges sharply to −20.24% (portfolio 3), declines again to −17.45% (portfolio 4), then jumps to −23.54% (portfolio 5). Similar nonmonotonic trends are found with portfolios sorted on *FF3_β*. As such, stocks with higher pre-pandemic accrued market risk do not earn progressively higher, or lower, pandemic returns. Therefore, we cannot reject the null hypothesis that the pandemic-instigated stock reactions do not manifest pricing of accrued market risk. The same conclusion applies to *Adj_CAPM_β*, *Adj_FF3_β*, and *Comb_β*.

With earnings volatility risk (*Earn_β*) and lead/lagged excess beta risk (*Excess_β*), we observe a progressive trend. First, the average pandemic return increases progressively with betas. This indicates that stocks with higher pre-pandemic accrued risk fell more than stocks with lower pre-pandemic accrued risk. Further, the spread in average pandemic returns between the two extreme portfolios is significant both statistically and economically. With *Earn_β* we report a difference of −10.14% and with *Excess_β* we report a difference of −12.33%. Both are statistically significant at the 1% level. Between the two extreme portfolios, pandemic losses progress systematically from low-beta portfolios to high-beta portfolios. We conclude that accrued earnings volatility risk and accrued excess risk were priced during the pandemic. Consequently, stock behaviour during the pandemic was, at least in part, pricing of accrued risk. This is consistent with the view that investors price accrued risk discretely at times of momentous events.

We acknowledge that our finding of negative reaction associated with past, accrued risk is inconsistent with extant literature. Most previous studies report a premium, not a discount. That is, stocks with greater accrued risk earn higher, not lower, future returns. This issue is discussed in a subsequent section.

3.2 | Multivariate regressions

As explained in the methodology section, we run multivariate Fama and MacBeth (1973) cross-sectional regressions of pandemic returns on past, accrued risk. We control for various firm characteristics (size and leverage) and stock characteristics (momentum, liquidity, and analyst coverage). The results are reported in Table 4 below.

Consistent with our earlier finding, we observe a significantly negative relation between pandemic returns and past quarterly earning beta and excess beta. The coefficients on *Earn_β* and *Excess_β* are negative and statistically significant in all regressions and robust after controlling for firm and stock characteristics. We must keep in mind that the dependent variable is 7-day cumulative pandemic return with an average of about −17.42% (see Table 2). The coefficient of *Earn_β* in model (h) is −5.128 which means that an increase of one unit in quarterly earnings beta results in an additional stock price drop of 5.128% within 7 days during the pandemic. Similarly, an increase of one unit in lead and lagged excess beta results in an additional stock price drop of 1.139% during the pandemic. This is further illustrated by observing the intercepts. From a strict econometric perspective, the intercept is the mean value of the left-hand side variable (pandemic return) when all of the right-

TABLE 3 Pandemic returns and accrued risk—sorted portfolios

Portfolio	Obs.	%	CR [−3, +3]
Portfolios sorted on CAPM_Beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	107	3.66	−10.40%
2	438	14.96	−6.01%
3	1561	53.33	−20.24%
4	604	20.64	−17.45%
5—High	217	7.41	−23.54%
High–Low			−13.14%
t-Stat			4.77
Portfolios sorted on Adj_CAPM_Beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	155	5.30	−18.64%
2	455	15.54	−8.77%
3	1274	43.53	−19.91%
4	728	24.87	−15.07%
5—High	315	10.76	−24.68%
High–Low			−6.04%
t-Stat			1.98
Portfolios sorted on earnings beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	154	5.26%	−11.40%
2	462	15.78%	−14.01%
3	1083	37.00%	−16.83%
4	772	26.38%	−19.05%
5—High	456	15.58%	−21.54%
High–Low			−10.14%
t-Stat			3.72
Portfolios sorted on FF3_Beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	124	4.24	−8.40%
2	466	15.92	−7.01%
3	1397	47.73	−21.20%
4	625	21.35	−16.45%
5—High	315	10.76	−21.54%
High–Low			−13.14%
t-Stat			3.98
Portfolios sorted on Adj_FF3_Beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	158	5.40	−8.40%
2	487	16.64	−18.78%
3	1319	45.06	−21.20%
4	601	20.53	−16.95%
5—High	362	12.37	−6.54%
High–Low			1.86%
t-Stat			0.76
Portfolios sorted on excess beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	134	4.58	−10.41%
2	455	15.54	−13.63%
3	1339	45.75	−16.99%
4	633	21.63	−19.45%
5—High	366	12.50	−22.74%
High–Low			−12.33%
t-Stat			4.05
Portfolios sorted on Comb_Beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	112	3.83	−17.90%
2	482	16.47	−13.09%
3	1445	49.37	−17.38%
4	647	22.10	−20.97%
5—High	241	8.23	−16.54%
High–Low			1.36%
t-Stat			0.98

Note: We sort stocks by their past, accrued risk (i.e., betas) and allocate them to five brackets resembling five hypothetical investment portfolios. For each portfolio, we report the average cumulative return during the pandemic. The table shows results with CR [−3, +3] where day 0 is March 16th. Findings with other windows (see Table 2) are discussed in Robustness Check section and are available upon request from authors. If past, accrued risk is priced during the pandemic, we should observe a monotonic trend, which would be interpreted as an association between cross-sectional variations in stock returns during the pandemic and pre-pandemic accrued risk.

hand variables (risks and controls) are set to equal to zero. For instance, regression (*h*) indicates that an average stock lost 10.98% during the studied seven-day pandemic window. This loss is not attributed to accrued risk or any of the remaining factors included in the regression.

The coefficients on all market betas are statistically insignificant in the full model (h) except for $FF3\_\beta$ and Adj_FF3_β which are statistically significant with relatively small economic impact. Specifically, a one unit increase in $FF3\_\beta$ and Adj_FF3_β increases pandemic losses by 3–4 basis points. Compared to the 17.34% average stock price drop, the impact of $FF3\_\beta$ and Adj_FF3_β can be safely ignored. As such, market risk is not priced by investors during the pandemic.

TABLE 4 Pandemic returns and accrued risk: Regression analyses

		(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
1	Intercept	−17.67***	−17.58***	−17.414***	17.00***	−15.45***	−17.72***	−16.92***	−10.98***
Pre-pandemic accrued risk									
2	CAPM_Beta	−0.379*						−0.301	−0.394
3	FF3_Beta		−0.040*					−0.047*	−0.042*
4	Adj_CAPM_Beta			−0.300*				−0.288	−0.303
5	Adj_FF3_Beta				−0.032*			−0.030*	−0.029*
6	Earn_Beta					−5.883***		−5.300***	−5.128***
7	Excess_Beta						−1.130***	−1.108***	−1.139***
8	Comb_Beta							−0.078	−0.039
Control variables									
9	MOM								2.037***
10	SIZE								−3.717**
11	DEBT								−5.966**
12	ILLIQ								−0.631***
13	COV								1.177***
	# Obs.	2927	2927	2927	2927	2927	2927	2927	2927
	Adjusted R-squared	0.1332	0.1857	0.1527	0.2091	0.2527	0.2391	0.2989	0.3468

Note: This table reports the results of multiple regressions of pandemic returns (CR [−3, +3]) on past, accrued risk (betas) and a set of control variables including natural log of market capitalization (SIZE), cumulative monthly returns in 2019 (MOM), debt ratio (DEBT), Amihud (2002) illiquidity pre-multiplied by 1,000,000 (ILLIQ), and the number of analysts following the firm in the last quarter of 2019 (COV). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

The slopes of SIZE, DEBT, and ILLIQ are significantly negative while the slope of MOM and COV significantly positive. This means that the drop in stock prices was greater if the company was larger, more leveraged, and the stock is less liquid. In contrast, the losses of higher momentum stocks and stocks of companies followed by more analysts were relatively smaller. In general, these findings are quite reasonable.

Overall, the results of multivariate regressions corroborate the findings with bivariate portfolio-sorting test. To summarise, pre-pandemic, accrued risk has a considerable explanatory power for the cross-sectional variation in pandemic returns across firms. This again indicates that the meltdown was partly influenced by a behavioural bias. Particularly, investors seem to have priced past, accrued risk during the pandemic.

4 | FURTHER ANALYSES

4.1 | Effects of stock characteristics

Many studies have indicated that stocks with different fundamental characteristics behave differently, and stocks behaviour is often a function of interacting factors (Alhenawi, 2015; Campbell et al., 2010; Da & Warachka, 2009; Hollstein et al., 2019). This implies that the findings reported earlier in this paper might be attributed to, or at least more pronounced in, a subset of the sample. To explore this possibility, we apply double sorting technique. That is, we split the sample on various characteristics and repeat the analysis in Table 3. Further, we re-run the regressions in Table 4 with subsets of the sample to see if the results are concentrated on any particular subset. This technique allows us to focus on subsets of the sample and is predicated on the suspicion that the results observed in Tables 3 and 4 might not be homogenous across the sample. In other words, we suspect that the results may be concentrated on a subset of the sample and non-existent in another. The following sections show the findings with size, B/M, and momentum.[11]

4.1.1 | Size effect

We sort all stocks by the SIZE variable and allocate them to three terciles: large, mid-size, and small. Then we repeat the same procedures presented in Table 3. That is, we split each tercile into quintiles sorted on pre-pandemic betas (*Earn_β* and *Excess_β*); then we observe the

TABLE 5 Size effect

Panel A: Earnings beta					
Top tercile (large stocks)		**Portfolios sorted on earnings beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−20.44%	1—Low	59	6.05	−13.65%
		2	156	16.00	−16.01%
		3	390	40.00	−19.83%
		4	341	34.97	−23.76%
		5—High	29	2.97	−27.12%
		High–Low			−13.47%
		t-Stat			4.18
Middle tercile (mid-size stocks)		**Portfolios sorted on earnings beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−17.13%	1—Low	122	12.51	−9.40%
		2	195	20.00	−12.65%
		3	341	34.97	−17.13%
		4	195	20.00	−21.82%
		5—High	122	12.51	−24.54%
		High–Low			−15.14%
		t-Stat			3.13
Low tercile (small stocks)		**Portfolios sorted on earnings beta**			
Obs.	**977**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−14.68%	1—Low	49	5.02	−15.01%
		2	107	10.95	−9.08%
		3	288	29.48	−12.12%
		4	484	49.54	−17.81%
		5—High	49	5.02	−10.76%
		High–Low			4.25%
		t-Stat			4.27
Panel B: Excess beta					
Top tercile (large stocks)		**Portfolios sorted on excess beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−20.44%	1—Low	60	6.15	−14.98%
		2	176	18.05	−17.45%
		3	403	41.33	−20.12%
		4	293	30.05	−22.71%
		5—High	43	4.41	−27.75%
		High–Low			−12.77%
		t-Stat			5.01
Middle tercile (mid-size stocks)		**Portfolios sorted on excess beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−17.13%	1—Low	72	7.38	−5.98%
		2	196	20.10	−10.63%

(Continues)

TABLE 5 (Continued)

Middle tercile (mid-size stocks)		Portfolios sorted on excess beta			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
		3	313	32.10	−16.45%
		4	341	34.97	−22.12%
		5—High	53	5.44	−28.28%
		High–Low			−22.30%
		t-Stat			2.97
Low tercile (small stocks)		**Portfolios sorted on excess beta**			
Obs.	**977**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−14.68%	1—Low	88	9.01	−12.01%
		2	162	16.58	−19.19%
		3	287	29.38	−11.99%
		4	322	32.96	−16.88%
		5—High	117	11.98	−11.15%
		High–Low			0.86%
		t-Stat			3.45

behaviour of average pandemic return of each quintile. As before, a monotonic trend indicates pricing of pre-pandemic risk. Furthermore, having the whole sample split into size terciles, we are able to see if the relation between pandemic return and pre-pandemic risk is affected by size. The findings are reported in Table 5.

Table 5 shows that the drop in stock price during the pandemic was greater for larger firms. The average CR [−3, +3] for large, mid-size, and small terciles is −20.44%, −17.13%, and −14.68%; respectively. This generally corroborates the findings in Table 4 where the coefficient on SIZE is significantly negative. Nevertheless, the double-sorting test in Table 5 says another important thing. Looking at average CR [−3, +3] of portfolios sorted on size and bets, we observe that the pricing of pre-pandemic risk during the pandemic was limited to larger and mid-size stocks (top and middle size terciles). The monotonic trend that we observed in Table 3 seems to extend only to the larger and mid-size stocks. This is true for both quarterly earnings beta *Earn_β* (Panel A) and excess beta *Excess_β* (Panel B). To illustrate, the first two boxes in Panel A and the first two tables in Panel B show that the pandemic loss increases progressively from up (low beta quintile) to bottom (high beta quintile). This is not the case with the bottom boxes in both panels. In these boxes, average pandemic return does not exhibit any particular trend across quintiles of pre-pandemic betas. This indicates that investors did not price pre-pandemic risk when they revalued smaller stocks during the pandemic. Perhaps, this finding lends support to the mounting evidence that size effect has been fading in the U.S. market over the past three decades (Alhenawi, 2015; Alquist et al., 2018). The size effect was first documented by Banz (1981). It is perhaps the first reported anomaly to the CAPM. It implies that a small-cap stocks outperform large-cap stocks in the long-run. In accordance with this view, Fama and French (1992) augmented the CAPM with a size premium term and a B/M premium term. Nevertheless, smaller stocks no longer generate greater return than larger ones. Alhenawi (2015) argues that the size effect has been subsumed by the momentum effect. Alquist et al. (2018) list several other explanations related to the difficulty of implementing a size-based strategy in practice (e.g., higher transaction and research costs and lower appeal). Therefore, mutual fund and institutional money managers on longer organise product offerings based on the size effect.

4.1.2 | B/M effect

This test is identical to the size effect test presented above. This time, we sort all stocks by the B/M ratio and allocate them to three terciles: high, medium, and low. Then we split each tercile into quintiles sorted on pre-pandemic betas (*Earn_β* and *Excess_β*) to observe the behaviour of average pandemic return across quintiles. The findings are reported in Table 6.

Table 6 shows that the drop in stock price during the pandemic was greater for smaller B/M firms. The average CR [−3,

TABLE 6 B/M effect

Panel A: Earnings beta					
Top tercile (high B/A)		**Portfolios sorted on earnings beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−13.75%	1—Low	110	11.28	−9.65%
		2	178	18.26	−13.01%
		3	395	40.51	−16.10%
		4	196	20.10	−13.76%
		5—High	96	9.85	−10.12%
		High–Low			−0.47%
		t-Stat			1.34
Middle tercile (medium B/A)		**Portfolios sorted on earnings beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−17.15%	1—Low	81	8.31	−20.14%
		2	247	25.33	−11.65%
		3	315	32.31	−19.99%
		4	266	27.28	−16.16%
		5—High	66	6.77	−24.54%
		High–Low			−4.40%
		t-Stat			1.28
Low tercile (low B/A)		**Portfolios sorted on earnings beta**			
Obs.	**977**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−21.35%	1—Low	52	5.32	−15.64%
		2	110	11.26	−17.48%
		3	288	29.48	−20.85%
		4	484	49.54	−22.76%
		5—High	43	4.40	−25.73%
		High–Low			−10.09%
		t-Stat			3.11
Panel B: Excess beta					
Top tercile (high B/A)		**Portfolios sorted on excess beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−13.75%	1—Low	120	12.31	−18.67%
		2	177	18.15	−10.19%
		3	389	39.90	−12.65%
		4	234	24.00	−13.65%
		5—High	55	5.64	−22.75%
		High–Low			−4.08%
		t-Stat			1.01
Middle tercile (medium B/A)		**Portfolios sorted on excess beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−17.15%	1—Low	75	7.69	−20.44%
		2	202	20.72	−11.85%

(Continues)

TABLE 6 (Continued)

Middle tercile (medium B/A)		Portfolios sorted on excess beta			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
		3	319	32.72	−15.55%
		4	319	32.72	−21.30%
		5—High	60	6.15	−17.39%
		High–Low			3.05%
		t-Stat			0.97
Low tercile (low B/A)		**Portfolios sorted on excess beta**			
Obs.	**977**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−21.35%	1—Low	60	6.14	−13.29%
		2	236	24.16	−17.45%
		3	299	30.60	−21.72%
		4	239	24.46	−24.11%
		5—High	143	14.64	−25.78%
		High–Low			−12.49%
		t-Stat			5.99

Note: This table replicates Table 5 analysis with B/M ratio substituting size. That is, we explore the possibility that the results in Table 3 (full sample with all B/M terciles) are more (or less) profound in high, medium, or low B/M stocks. Panel A shows findings with portfolios sorted on B/M then on earnings beta (*Earn_β*). Panel B shows findings with portfolios sorted on B/M then on excess beta (*Excess_β*).

+3] for high, medium, and low B/M terciles is −13.75%, −17.15%, and −21.35%; respectively. Nevertheless, pricing of pre-pandemic risk during the pandemic was limited to low B/M stocks. This is true for both quarterly earnings beta *Earn_β* (Panel A) and excess beta *Excess_β* (Panel B). To illustrate, the first two boxes in Panel A and the first two boxes in Panel B show that the average pandemic return does not exhibit any particular trend across quintiles of pre-pandemic betas. This indicates that investors did not price pre-pandemic risk when they revalue high and medium B/M stocks during the pandemic. In the bottom boxes in both panels, we observe a consistent trend from low to high beta portfolios. We conclude that pricing of pre-pandemic risk was concentrated on small B/M stocks. This finding provides a supportive, nuanced view of our conjecture on discrete pricing. The B/M effect was first documented by Rosenberg et al. (1985), who found that stocks with high B/M ratios earn a premium relative to stocks with low ratios. In the light of this definition, our finding implies that investors are more likely to price accrued risk in overvalued stocks. In practical terms, when the pandemic hit, investors where more inclined to price-correct stocks that had been relatively overvalued. Such stocks naturally attract more attention. Barber and Odean (2008) show that real money managers are practically unable to follow all stocks. Instead, they pay attention to selected stocks that have gained increased attention.

4.1.3 | Momentum effect

We repeat the two tests presented above with momentum. We sort all stocks by the MOM variable and allocate them to three terciles: strong, medium, and weak. Then we split each tercile into quintiles sorted on *Earn_β* and *Excess_β* to identify possible relation between momentum and the pricing of pre-pandemic returns. The findings are reported in Table 7. Panel A shows findings with portfolios sorted on MOM then on earnings beta (*Earn_β*) and Panel B shows findings with portfolios sorted on MOM then on excess beta (*Excess_β*).

Table 7 shows that the drop in stock price during the pandemic was greater for weak momentum stocks. The average CR [−3, +3] for strong, average, and weak momentum terciles is −14.73%, −18.01%, and −19.25%, respectively. This finding corroborates the findings in Table 4 where the coefficient on variable MOM is significantly positive. Like with B/M, the pricing of pre-pandemic risk during the pandemic was limited to weak momentum stocks. This is true for both quarterly earnings beta *Earn_β* (Panel A) and excess beta *Excess_β* (Panel B). The momentum effect is the tendency of stocks that performed well in the past months to continue to do well in the following period and vice versa. The findings in Table 7 indicate that the pricing of pre-pandemic risk was concentrated on stocks that has not been doing well

TABLE 7 Momentum effect

Panel A: Earnings beta					
Top tercile (strong momentum)		**Portfolios sorted on earnings beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−14.37%	1—Low	119	12.21	−16.14%
		2	175	17.95	−12.88%
		3	388	39.79	−15.91%
		4	205	21.03	−12.71%
		5—High	87	8.92	−16.23%
		High–Low			−0.09%
		t-Stat			0.65
Middle tercile (avg. momentum)		**Portfolios sorted on earnings beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−18.01%	1—Low	87	8.92	−21.55%
		2	246	25.23	−13.16%
		3	252	25.85	−20.13%
		4	299	30.67	−17.66%
		5—High	87	8.92	−24.05%
		High–Low			−2.50%
		t-Stat			1.78
Low tercile (weak momentum)		**Portfolios sorted on earnings beta**			
Obs.	**977**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−19.52%	1—Low	98	10.03	−15.17%
		2	198	20.27	−17.31%
		3	331	33.88	−20.04%
		4	271	27.74	−21.31%
		5—High	76	7.78	−23.03%
		High–Low			−7.86%
		t-Stat			2.65
Panel B: Excess beta					
Top tercile (strong momentum)		**Portfolios sorted on excess beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−14.37%	1—Low	68	6.97	−19.19%
		2	177	18.15	−11.29%
		3	371	38.05	−13.95%
		4	274	28.10	−14.40%
		5—High	85	8.72	−22.75%
		High—Low			−3.56%
		t-Stat			0.76
Middle tercile (avg. momentum)		**Portfolios sorted on excess beta**			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−18.01%	1—Low	59	6.05	−21.77%
		2	202	20.72	−11.85%
		3	315	32.31	−17.13%

(Continues)

TABLE 7 (Continued)

Middle tercile (avg. momentum)		Portfolios sorted on excess beta			
Obs.	**975**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
		4	293	30.05	−21.70%
		5—High	107	10.97	−19.90%
		High–Low			1.87%
		t-Stat			1.67
Low tercile (weak momentum)		**Portfolios sorted on excess beta**			
Obs.	**977**	**Portfolio**	**Obs.**	**%**	**CR [−3, +3]**
Average CR [−3, +3] =	−19.52%	1—Low	131	13.41	−12.49%
		2	218	22.31	−15.39%
		3	299	30.60	−19.99%
		4	212	21.70	−23.61%
		5—High	117	11.98	−26.51%
		High–Low			−14.02%
		t-Stat			3.07

Note: This table replicates the tests in Table 5 and in Table 6 with MOM substituting size and B/M. In a manner analogous to Tables 5 and 6, we investigate the possibility that the results in Table 3 (full sample with all momentum terciles) are more (or less) profound in strong, medium, or weak momentum stocks. Panel A shows findings with portfolios sorted on MOM then on earnings beta (*Earn_β*). Panel B shows findings with portfolios sorted on MOM then on excess beta (*Excess_β*).

in the pre-pandemic era. Specifically, investors during the pandemic were more likely to price risk that has been accruing on stocks that did not do well in 2019. This finding generally validates the well-known phenomenon that underperforming stocks tend to continue to underperform subsequently. Our findings adds that this phenomenon tends to intensify during financial crises as investors price past accrued risk.

We believe that the findings in this section are new to literature. We are not aware of any previous study that documents a similar finding. This not only because we focus on stock behaviour during a crisis time, but also because we test if the pricing of pre-crisis risk is priced differently in stocks with different characteristics. Specifically, we find that pricing of accrued risk is concentrated on larger, higher B/M, and weak-momentum stocks. Regression analyses support this inference (not tabulated; see Robustness Checks section).

4.2 | Premium or discount?

Several studies explore the role of accrued risk in subsequent stock performance and report a premium (Beaver, 1968; Chari et al., 1988; Ball & Khotari, 1991; Cohen et al., 2007; Frazzini & Lamont, 2007; Barber et al., 2013; Savor & Wilson, 2016). In this study, we report a discount, not a premium. The mentioned studies analyse the pricing of accrued risk during normal market conditions, not during financial crises. As such, we suspect that the inverse relationship we report is limited to times of financial turmoil.

To investigate this possibility, we conduct two additional tests. First, we analyse the response of stocks in our sample to a major corporate event during a non-crisis time. Specifically, we look at earnings announcement during 2020 shortly before the pandemic-instigated meltdown. This choice is inspired by several studies that show that earnings announcements are significant corporate events followed closely and acted upon by investors (Chambers & Penman, 1984, p. 39; Hirshleifer et al., 2009; Ben-Rephael et al., 2020). Second, we analyse the pricing of past, accrued risk during past financial crises; namely the 2015 selloff and the 2008 global financial crisis. These were selected because they are the most recent stock market meltdowns.

These two additional tests serve two purposes. First, they allow us to test whether pricing of accrued risk extends to other events and crises. Second, they serve as a test of the direction of the relation between returns during major events and pre-event accrued risk.

TABLE 8 Non-pandemic returns and accrued risk

Panel A: Portfolios sorted on accrued risk

Portfolios sorted on earnings beta

Portfolio	Obs.	%	CR [−1, +1]
1—Low	109	5.31	0.95%
2	322	15.68	1.01%
3	752	36.61	1.30%
4	542	26.39	1.52%
5—High	329	16.02	1.67%
High–Low			0.72%
t-Stat			2.72

Portfolios sorted on excess beta

Portfolio	Obs.	%	CR [−1, +1]
1—Low	94	4.58	1.02%
2	318	15.48	1.10%
3	939	45.72	1.35%
4	444	21.62	1.49%
5—High	259	12.61	1.57%
High–Low			0.55%
t-Stat			2.95

Panel B: Regression analysis

		(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
1	Intercept	1.320***	1.364***	1.299***	1.214***	1.014***	1.311***	1.177***	0.999***
Pre-pandemic accrued risk									
2	CAPM_Beta	0.040						0.028	0.040
3	FF3_Beta		0.004					0.005*	0.005
4	Adj_CAPM_Beta			0.031				0.257	0.246
5	Adj_FF3_Beta				0.004			0.003	0.003
6	Earn_Beta					0.571***		0.546***	0.528***
7	Excess_Beta						0.123***	0.121***	0.108***
8	Comb_Beta							0.007	0.004
Control variables									
9	MOM								0.196
10	SIZE								−0.353**
11	DEBT								−0.656**
12	ILLIQ								0.065***
13	COV								−0.114
	# Obs.	2054	2054	2054	2054	2054	2054	2054	2054
	Adjusted *R*-squared	0.1412	0.1801	0.1583	0.1993	0.2502	0.2511	0.2810	0.3607

Note: The main analysis in this paper indicates a negative relationship between past, accrued risk and pandemic returns. Specifically, stocks with higher quarterly earnings beta and greater excess beta witnessed a greater price drop during the pandemic. The literature, however, reports a premium. To further explore this issue, we repeat the analyses in Tables 3 and 4 with returns around a non-pandemic event (in Table 9 will look at previous financial crises). We identify 2054 stocks in our sample that have had an earnings announcement shortly before the pandemic. Using this non-pandemic corporate event returns, Panel A repeats the tests in Table 3 (beta-sorted portfolios) and Panel B repeats the tests in Table 4 (multiple regression analyses).

TABLE 9 Financial crises returns and accrued risk

Panel A: Portfolios sorted on accrued risk			
2008 Financial crisis			
Portfolios sorted on earnings beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	89	6.03	−14.34%
2	236	15.98	−17.87%
3	539	36.49	−23.91%
4	384	26.00	−24.71%
5—High	229	15.50	−26.01%
High–Low			−11.67%
t-Stat			3.75
Portfolios sorted on excess beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	75	5.08	−13.92%
2	220	14.90	−16.97%
3	666	45.09	−23.33%
4	340	23.02	−25.76%
5—High	176	11.92	−27.01%
High–Low			−13.09%
t-Stat			3.87
2015 Financial crisis			
Portfolios sorted on earnings beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	85	5.27	−4.14%
2	253	15.69	−7.52%
3	590	36.60	−11.13%
4	426	26.43	−13.12%
5—High	258	16.00	−14.01%
High–Low			−11.67%
t-Stat			3.75
Portfolios sorted on excess beta			
Portfolio	**Obs.**	**%**	**CR [−3, +3]**
1—Low	74	4.59	−4.92%
2	250	15.51	−7.96%
3	737	45.72	−10.13%
4	348	21.59	−14.76%
5—High	203	12.59	−15.13%
High–Low			−13.09%
t-Stat			3.87

TABLE 9 (Continued)

Panel B: Regression analysis			
2008 Financial crisis			
		(g)	**(h)**
1	Intercept	−19.122***	−12.409***
2	CAPM_Beta	−0.379	−0.477
3	FF3_Beta	−0.052	−0.053
4	Adj_CAPM_Beta	−0.391	−0.401
5	Adj_FF3_Beta	−0.039	−0.419
6	Earn_Beta	−5.989***	−6.410***
7	Excess_Beta	−1.418***	−1.481***
8	Comb_Beta	−0.094**	−0.051*
9	MOM		2.322**
10	SIZE		−4.163**
11	DEBT		−7.159**
12	ILLIQ		−0.745***
13	COV		1.459*
	# Obs.	1477	1477
	Adjusted *R*-squared	0.3706	0.3954
2015 Financial crisis			
		(g)	**(h)**
1	Intercept	−10.746***	−6.753***
2	CAPM_Beta	−0.195	−0.256
3	FF3_Beta	−0.029	−0.027
4	Adj_CAPM_Beta	−0.277	−0.266
5	Adj_FF3_Beta	−0.019	−0.027
6	Earn_Beta	−3.259***	−3.256***
7	Excess_Beta	−0.642***	−0.735***
8	Comb_Beta	−0.043**	−0.022*
9	MOM		1.324**
10	SIZE		−2.416**
11	DEBT		−3.609**
12	ILLIQ		−0.410***
13	COV		0.718*
	# Obs.	1612	1612
	Adjusted *R*-squared	0.3318	0.4266

Note: The main analysis in this paper indicates a negative relation between past, accrued risk and pandemic returns. Specifically, stocks with higher quarterly earnings beta and greater excess beta report greater price drop during the pandemic. The literature, however, reports a premium. Our analysis in Table 8 also reports a premium associated with corporate earnings announcement. To further explore this issue, we repeat the analyses in Tables 3 and 4 with past financial markets meltdowns in 2008 and 2015. The first is captured with the behaviour of 1477 stocks during 8-trading-day window between 30 September and 10 October 2008, when the S&P500 lost 22.90% of its value. The second is captured with the behaviour of 1612 stocks during a 7-trading-day window between 17 August and 25 August 2015, when the S&P500 lost 11.18% of its value. Using these two market meltdowns, we repeat the tests above. All variables and method remain intact. Using these two financial crises returns, Panel A repeats the tests in Table 3 (beta-sorted portfolios). Panel B repeats the tests in Table 4 (multiple regression analyses) with past financial crises returns instead of 2020 financial crisis return. For clarity of presentation, we report regressions g and h only.

4.2.1 | Pricing of accrued risk during non-crises event

We identify 2054 stocks in the original sample (i.e., 70.17%) that had a major corporate event—earnings announcement—in January and February of 2020 (i.e., shortly before the pandemic). We calculate earnings announcement return as cumulative return in 3-day window defined as CR [−1, +1].[12] We use the same measures of past, accrued risk and we follow the same procedure to facilitate a meaningful comparison. The idea is to analyse the pricing of same accrued risk for the same stocks, during a major event that is not a financial crisis. The findings are reported in Table 8.

Consistent with literature, Panel A shows a premium associated with progressive pricing of accrued risk around earnings announcement. With earnings beta, earnings announcement returns increase monotonically from 0.95% in low-beta portfolio to 1.67% in high-beta portfolio. The difference is statistically and economically significant. The findings with Excess beta are qualitatively similar. More importantly, all returns are positive. This finding is inconsistent with our earlier finding, which indicates a deeper discount associated with pricing of accrued risk during the pandemic. The results of multiple regression analyses in Panel B corroborate the findings of Panel A. The coefficients on *Earn_β* are *Excess_β* are positive and statistically significant in all regressions and robust after controlling for firm and stock characteristics. These findings support the conjecture that pricing of accrued risk is inverted during crisis. The next section provides additional tests.

4.2.2 | Pricing of accrued risk during previous financial crises

To further explore the pricing of accrued risk in different market conditions, we turn to the most recent financial crises before the one that came with the COVID-19 pandemic. Specifically, we identify two event windows. The first is 8-trading-day window between 30 September and 10 October 2008 (see Hasan et al., 2021; Baur & McDermott, 2010; Low et al., 2016). This window captures the 2008 stock market meltdown that accompanied the 2008 global financial crisis.[13] Within this window, the S&P500 lost 22.90% of its value (dropped from 1166 to 899). The second is a 7-trading-day window between 17 August and 25 August 2015. This one captures the 2015 stock market selloff.[14] The S&P500 dropped from 2102 to 1867 and lost 11.18% of its value.

Using these two market meltdowns, we repeat the tests above to explore pricing of past accrued risk. Sample size for the 2008 global financial crises is 1477 stocks and sample size for the 2015 selloff is 1612. All variables and methods remain intact with proper shifts in estimation windows. As such, we should be able to tell whether the inversed relation between crisis return and accrued risk that was reported with 2020 pandemic extends to other financial crisis periods. The findings are shown Table 9.

The results in Table 9 support our overall proposition that investors price accrued risk during significant macroeconomic events. It also supports our conjecture that the relation between crisis returns, and pre-crisis accrued earnings-related risk is negative. That is, a greater pre-crisis risk is associated with a deeper discount, not a premium, during the pandemic.

We acknowledge that the four tests conducted in this section provide an intriguing discovery, not conclusive evidence. Our empirical findings indicate that accrued risk is priced positively during major a major corporate event during normal market conditions, and negatively during crises. We believe that more research is needed to confirm or refute this finding. Furthermore, we are not aware of an existing theory that explains this phenomenon. For that reason, we like to conclude this section with an invitation for more research in this domain.

5 | ROBUSTNESS CHECKS

5.1 | Variations in variables construction

We repeat the analyses with several variations in variables construction and model specifications. For instance, in calculating $\Delta Earning_{i,t} = \frac{IN_{i,t} - IN_{i,t-4}}{Cap_{i,t-4}}$, we replace market capitalization $Cap_{i,t-4}$ with total assets $TA_{i,t-4}$. We also replace net income *NI* with operating cash flows *OpCash*. In both cases, we did not observe a major divergence from the overall findings obtained with original specifications. The finding with operating cash flow is slightly less prominent. Perhaps, this is because operating cash flow is less visible to outside investors than net income. We also scale analyst coverage by firm size as in Hong et al. (2000) and report similar findings.

We apply several variations of estimation windows for pandemic returns. Specifically, we replace CR [−3, +3] with CR [−4, +4], CR [−2, +2], CR [−1, +1], CR [0, +1], CR [0, +2], and CR [0, +3]. With shorter estimation windows, we noticed less significant results. That is, the relation between pandemic return and pre-pandemic accrued risk remains robust with CR [−4, +4], CR [−2, +2], and CR [0, +3]. The relation virtually disappears with CR [−1, +1], CR [0, +1], and becomes considerably week with CR [0, +2]. We believe that this is attributed to the fact that shorter windows do not capture complete investors' reactions.

We test various alternative specifications of Dimson's beta. Specifically, we replace the $[-1, +1]$ window with several alternatives up to 5-day leads and lags. We notice that the larger the window in either direction, the less significant our results become. We argue that this because adding more lead and lag betas compounds measurement errors. Nevertheless, using alternative specifications for Dimson's beta does not change our core finding that investors priced pre-pandemic risk during the pandemic.

5.2 | Premium or discount: Further tests

In Tables 8 and 9, we conducted two types of tests: sorted portfolios in Panel A and cross-section Fama and MacBeth regressions in Panel B. All betas were included in the regressions (see Panel B in Tables 8 and 9). In the sorted portfolios test, however, we reported only the findings with Earnings Beta and Excess Beta (see Panel A in Tables 8 and 9). In a robustness test (not tabulated) we repeat the sorted portfolios test with all betas. We do not find any monotonic trend that indicates a strong association between these betas (CAPM, FF3, and Net Beta) and stock price movements during the studied events.

5.3 | Regression analysis on subsamples

We repeat the analysis in Table 4 with all nine subsamples described in Tables 5, 6, and 7. That is, we re-run the regressions 8 regressions in Table 4 with stocks in size tercile, then with stocks in B/M tercile, and then with stocks in momentum tercile. The result is $8 \times 9 = 72$ regressions. In the interest of clarity and concise presentation, we do not report these regressions. Observing the coefficients on *Earn_β* and *Excess_β* in those regression. We obtain qualitatively similar findings but with less statistical significance. This is because these regressions are estimated with about a third of the data used in Table 4. Full regressions results are obtainable upon request from the authors.

6 | CONCLUSIONS

The stock market meltdown that accompanied the 2020 COVID-19 pandemic was not a pure contingency. We report evidence that pre-pandemic accrued risk have substantial explanatory power of cross-sectional variations in stocks price movements during the pandemic.

Conceptually, the rational asset pricing theory predicts a continuous updating process of asset prices. That is, in an efficient and frictionless market, risk is priced contemporaneously and, thus, stock movements during the pandemic should not be affected by past, accrued risk. In an imperfect market with frictions, risk is priced discretely; that is, risk accrues on a continuous basis and is conveniently priced when investors respond to major events. Consistent with the latter view, we report a meaningful relation between stock returns during the pandemic and past accrued risk. Specifically, past earnings volatility and past excess beta were priced during the pandemic; and stocks with higher accrued risk recorded larger discounts during the pandemic. As such, stock movements during the pandemic reflect, partly, pricing of accrued risk. Further analyses indicate that this phenomenon is concentrated on large and mid-size, small B/M, and weak momentum stocks. These findings are new to literature. They provide more nuanced views of existing findings. For several practical reasons, investors pay relatively more attention to larger and more visible stocks; and the tendency of underperforming stocks to continue to underperform (momentum effect) is intensified during financial turmoil.

Our finding on the relation between accrued risk and stock price behaviour supports our overall conjecture; but raises another concern. We report a negative relation between accrued risk and price movements while the overwhelming evidence in literature leans towards a premium (Barber et al., 2013; Beaver, 1968; Frazzini & Lamont, 2007; Savor & Wilson, 2016). To investigate this matter, we study same-sample stock behaviour during non-pandemic corporate event. We also study the behaviour of stocks during past financial crises. We find that a premium is found during certain corporate events (earning announcements) and a discount is found during financial turmoil. We confess that stocks' behaviour in general, and during crises in particular, is a complex phenomenon. We contend that the behaviour of stocks is a function of a multitude of conceptual subtleties and practical considerations. This study is a humble attempt to shed some light on this complex phenomenon and to invite more future research.

ENDNOTES

[1] In practical terms, betas of asset pricing models account for the fact that a stock is considered relatively safer if its movements is less radical than those of the entire market. The adjusted market betas incorporate not only current co-movements with market, but also the cumulative knowledge that investors have obtained on the stock. Excess beta takes into account the fact the investors may not take immediate action upon the arrival news. Quarterly earnings beta captures the behaviour of certain investors who focus on corporate quarterly earnings rather than stock price movements.

[2] The selection of share codes 10 and 11 restricts the sample to ordinary common shares. It further excludes companies incorporated outsaid the United States, Trusts, ETF, U.S. in non-U.S. funds, and REITs. This selection is consistent with Professor French's selection of stocks for computation of value-weighted return on the market.

[3] Although the pandemic-instigated market movement occurred in March 2020, the pandemic news started flowing to the market in early January 2020. Following Khotari and Warner (2006), we exclude January and February of 2020 to minimize the effect of information leakage and pandemic-induced high volatility that could distort the estimation of betas.

[4] We are aware of the alternative method proposed by Cosemans et al. (2016) which uses fundamentals-based prior. We follow Hollstein et al. (2019) who compared the two methods and reported that Cosemans et al. (2016) works considerably less well.

[5] In robustness checks, we also use operating cash flows and total assets. We exclude extraordinary income and cash flows.

[6] We do not have the data needed to compute other combinations suggested by Hollstein et al. (2019). According to their analysis, the difference between the two is not material. For the propose of this study, we believe that we have a good set of betas that capture a reasonably wide spectrum of pre-pandemic risks.

[7] Practitioners and market regulators define price correction as the phenomenon wherein inflated stock price fall by a minimum of 10% from their 52-week high. This criterion has been met during the pandemic. Major U.S. stock indices lost almost a third of their values in March 2020. Further, they recorded one of their worst one-day losses on Monday 16th of March when they fell by about 12%.

[8] Portfolio-sorting is a technique that unveil possible correlation between two variables (single-sort) or three variables (double-sort). Fama and French are pioneer users of this method. One of its prominent application dates back to their seminal 1993 paper that paved the way to the introduction of multi-factor capital asset pricing models (Fama & French, 1993). Over time, sorted portfolio has found its way to other areas of finance such as M&A (Hassan & Alhenawi, 2021) and household finance (Alhenawi & Yazdanparast, 2022; Yazdanparast & Alhenawi, 2022).

[9] Some authors apply a top-minus-bottom spread approach. That is, they consider the difference between the two extreme portfolios (and discard the ones in the middle). This approach resembles a trading strategy of a hypothetical investor who shorts the stocks in one extreme portfolio and simultaneously longs the stocks in the other. This approach produces an expected return of such a thought experiment; but does not necessarily establish a relation between the studied variables. Our monotonicity test is more powerful because it requires progressive, systematic change between each two adjacent portfolios and, thus, requires several statistically significant inequalities in the same direction to reject the null hypothesis. Formally, compared to top-minus-bottom spread test, our monotonicity test entails more possible violations that will make us fail to reject the null hypothesis (no relationship) and, subsequently, it is more difficult to show evidence in favour of the alternative hypothesis (association between pre-pandemic risk and pandemic return).

[10] We also considered P/E, profitability (average profitability ratio of past four quarters), and whether the stock is trading above or below is 52-week average. These were found statistically, and economically insignificant determinants of pandemic returns in almost all regressions. For that reason, they were excluded from subsequent findings.

[11] We have considered several other variables including leverage, illiquidity, analyst coverage, P/E, profitability (average profitability ratio of past four quarters), and whether the stock is trading above or below its 52-week average. Splitting the sample on these variables reveals that pricing of pre-pandemic risk is not concentrated on any particular subsample.

[12] The event window is intentionally shortened to avoid post-earnings announcement (PEAD) effect (Bernard & Thomas, 1989). This should not affect our comparison because the focus is on the direction of pricing of past, accrued risk, not the magnitude of returns.

[13] On 16 September 2008, failures of large financial institutions in the United States, due primarily to exposure of securities of packaged subprime loans and credit default swaps, rapidly devolved into a global crisis resulting in a number of bank failures in Europe and sharp reductions in the value of equities and commodities worldwide.

[14] The Dow Jones fell 1300 points from August 18 to 21. On Monday, August 24, world stock markets were down substantially, wiping out all gains made in 2015, with interlinked drops in commodities.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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