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The COVID-19 outbreak and stock market reactions: Evidence from Australia

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ABSTRACT

We examine how the Australian stock market responded to the uncertainties created by the COVID-19 pandemic and whether the stimulus package offered by the Government helped restore confidence in the market. This study finds a negative stock market reaction to the pandemic announcement, however, among two stimulus packages related announcements, the market reacted positively only to "JobKeeper" package. The cross-sectional results suggest that the smallest, least profitable and value portfolios suffered more during the pandemic. Finally, size and liquidity are found to be the significant drivers of abnormal returns. These results generally hold for a battery of robustness checks.

1. Introduction

The novel coronavirus (COVID-19) outbreaks in China in December 2019. As of 5 May 2020, the virus has affected more than 3.5 million people with 243,401 global deaths (WHO, 2020). The COVID-19 has also resulted in an unprecedented negative impact not only on human lives but also on the global economy mostly due to loss of economic activity arising from lockdowns, strict quarantine policies, and social distancing practices. While the economic impact is still to be quantified, global financial markets have exhibited an unparalleled albeit heterogeneous reaction to the pandemic.[1] To restore confidence in the financial markets, governments and central banks have immediately come forward with their stimulus packages and policy instruments to combat the adversaries.[2] Although in general, stock markets have responded negatively to the COVID-19 and somewhat rebounded after the announcement of bailout programs, the exact direction and magnitude of stock markets' responses to these events (announcements of COVID-19 outbreak and stimulus packages) are yet to be explored.

The main objective of this paper is to examine the effect of COVID-19 and subsequent government stimulus packages on the Australian stock returns. The choice of Australia is driven by several factors. First, although Australia was not among the most affected

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[1] For example, on 3 February 2020, the Shanghai stock market plunged 8%; on 28 February 2020, the S&P 500 declined by 4.4%; and on 12 March 2020, FTSE, the UK's main index dropped more than 10%.

[2] For example, on 15 March 2020, the US Federal Reserve announced a US$700 billion quantitative easing program while on 22 March 2020, the Australian Prime Minister announced a US$43 billion coronavirus stimulus package.

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countries in terms of human costs (for example, death, the physical effect of infection, mental trauma) of the pandemic,[3] the country's stock market was one of the most affected in the world making it an interesting candidate to study the market reaction. The S&P ASX 200, the benchmark Australian stock price index declined more than 25% from 31 January 2020 to 31 March 2020 which surpasses the decline in S&P 500 for the same period (See Table 1 for details). Second, the Australian stock market was largely de-coupled from the global financial crisis in 2008 which originated in the USA. However, the eventual reaction of the Australian stock market to the recent global pandemic originated in China is still unclear. Third, Australia is among the first countries to implement travel restrictions to contain the spread of the virus and the Australian government has introduced several policy instruments to combat the economic consequences. However, potentially the strong mutual trade dependence between Australia and China has led to heightened economic uncertainties, which could have dampened the expectation among stock market investors. Therefore, it would be interesting to see how the Australian stock market responded to specific events surrounding the COVID-19 and subsequent government policy responses.

The efficient market hypothesis (EMH) states that, in general, stock prices quickly impound all available information. However, proponents of behavioral finance posit that as investors are not always rational, they may over- or under-react to information due to their psychological biases. Therefore, ex-ante, it is difficult to predict whether market reactions to the COVID-19 related announcements are consistent with the EMH, making it an empirical question. We use an event-study methodology to explore the effects of two negative (the declaration of the pandemic) and two positive (government's policy responses) events on the Australian stock returns. The analysis is done for the whole market and at the portfolio level. Finally, idiosyncratic firm-characteristics are used to identify the drivers of abnormal returns associated with the event dates. We find a cumulative abnormal return of −4.39% and 2.73% for [−5,5] event window resulting respectively from the declaration of COVID-19 as global pandemic and the government announcement of the JobKeeper package. The smallest, least profitable and value portfolios suffered more during the pandemic. Finally, size and liquidity are found to be the significant drivers of abnormal returns. These findings have important policy implications.

There is a very limited prior literature on how epidemics affect financial markets. We, therefore, make an important contribution to this literature. Chen et al. (2009) and Loh (2006) find that the Severe Acute Respiratory Syndrome outbreak negatively affected sectors like aviation, tourism, wholesale, and retail. About the COVID-19 outbreak, Zhang et al. (2020) show that the pandemic has resulted in a significant increase in global financial market risks. Yan et al. (2020) offer a trading strategy to profit from the outbreak. Baker et al. (2020) report that the COVID-19 has affected the stock market most powerfully among all infectious disease outbreaks since 1900. None of these studies, however, examine the effect of specific events surrounding the pandemic on stock returns. This paper fills up the gap. The rest of the paper proceeds as follows. Section 2 describes the sample and methodological aspects; results are explained in Section 3; a conclusion is drawn in Section 4.

2. Sample and methodology

The sample consists of the top two hundred companies listed in the Australian Stock Exchange (ASX) in terms of their market capitalization. The S&P ASX 200, a float-adjusted market capitalization-based index of the 200 largest stocks, is considered as a benchmark.[4] We focus on two negative events and two positive events. The negative event dates are 30 January 2020 (the COVID-19 is declared as a public health emergency) and 11 March 2020 (the COVID-19 is declared as a pandemic). Since these declarations were made by the World Health Organization (WHO) in Geneva, Switzerland, we consider the immediate next trading day as the event date due to time zone difference. The positive event dates are 22 March 2020 (the Australian Prime Minister announced AUD66.4 billion stimulus package) and 8 April 2020 (the Australian government passed AUD130 billion JobKeeper package). Since 22 March 2020 was a holiday, the next trading day is considered as the event date.

Following the event study literature (Krüger, 2015; Loipersberger, 2018), abnormal returns are calculated as follows:

$$AR_{i,t} = R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i R_{M,t} \tag{1}$$

where $AR_{i,t}$ is the abnormal return of an individual stock, $R_{i,t}$, and $R_{M,t}$ are respectively actual realized return of individual stock and aggregate market index. $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ are estimated parameters from a market model where realized return of an individual stock is regressed on the returns of the market index in the pre-event period, the so-called estimation period. In line with Krüger (2015), we consider an estimation period of 250 days (approximately one full trading year) ending 50 days before the first event date. The estimation period spans from 21 November 2018 to 15 November 2019. Since there is a potential of information overflow before the event dates or investors' underreaction in the post-event period, we calculate cumulative abnormal returns (CAR). If an event date is defined as $t = 0$, CAR for a 5-day window is the sum of abnormal returns from $t = -5,\ldots..,0,\ldots.,5$. Although the literature often calculates CAR up to 30 trading days (Krüger, 2015; Lanfear et al., 2019), we restrict the estimation up to 7 trading days before and after an event date to reduce confounding effect of the other events. The statistical significance of CAR is primarily tested using the cross-sectional t-test. However, the robustness of results is checked using the tests developed by Patell (1976), Boehmer et al. (1991), Wilcoxon (1992), and Kolari and Pynnonen (2010).[5]

We estimate the following regression model to identify drivers of the realized CARs.

[3] As of 5May 2020, the nation reported 6,825 confirmed cases with 95 deaths (WHO, 2020).

[4] We also consider the ASX All Ordinaries index, an index of the 500 largest companies in the Australian equity market, as a benchmark to check the robustness of results.v

[5] The results derived from these tests are presented in the Internet Appendix.

Table 1.
The changes in the benchmark stock price indices during the COVID-19 outbreak.

Index	Index values		Decline (%)
	31 January 2020	31 March 2020	
NASDAQ Composite Index	9150.94	7700.10	15.85
S&P 500	3225.52	2584.59	19.87
FTSE 100	7286.01	5563.74	23.64
EURO STOXX 50	3640.91	2765.62	24.04
Nikkei 225	23,205.18	18,917.01	22.67
S&P ASX 200	7017.22	5181.38	26.16

Notes: Source: FACTSET. Since 31 March 2020 value of Nikkei 225 was not available, 27 March 2020 value was considered.

$$CAR_{i,[\tau_1;\tau_1]} = \gamma_0 + \gamma_1 SIZE + \gamma_2\ LEVERAGE + \gamma_3\ LIQUIDITY + \gamma_4 PROFITABILITY + \varepsilon_i \tag{2}$$

where $CAR_{i,[\tau_1;\tau_1]}$ is the cumulative abnormal returns for different window periods. The independent variables are idiosyncratic firm characteristics that are chosen from the literature (Kolaric and Schiereck, 2016; Krüger, 2015). See notes to Table 4 for further details.

3. Results

Table 2 reports several key findings concerning average CAR (%) for different events and window periods. First, as we pool all the events together, it is found (Panel A) that the average CAR is negative and statistically significant for all the window periods (except the [−3,3] event window) indicating that the stock prices of Australian companies declined significantly due to the pandemic despite government interventions in the form of various stimulus packages.

Second, we find statistically significant negative CARs for both the negative events particularly from the event window [−5,5] to [−7,7] (Panel B). The declaration of COVID-19 as a pandemic (the second negative event) appears to have a greater impact on the stock returns compared to that of the news reflecting the declaration of COVID-19 as a public health emergency (the first negative impact). For instance, the average CAR for the event window [−5,5] is respectively −0.77% and −4.39% for the first and second events. While these results are statistically significant, they are also economically meaningful. Since the average market capitalization of the sample firms is AUD8,011 million, the average cost associated with the second event over the window [−5,5] is about AUD352 million (0.0439 x AUD8,011 million).

Third, interestingly, in Panel C, we find a negative and statistically significant average CAR for the first positive event. This result may arise as the AUD66.4 billion stimulus package fails to reduce the uncertainty associated with the pandemic and build investors' confidence. Nonetheless, the declaration of JobKeeper package (the second positive event) exerts a significant positive impact on the stock returns. For example, the average CARs are 2.73% and 5.13% for the [−5,5] and [−6,6] event windows, respectively. This result may be attributed to a more objective and target-oriented stimulus package which have helped investors to boost up their confidence.

Fourth, while the EMH argues that the CAR should no longer change significantly after an event date due to rapid incorporation of information into stock prices, we observe that the magnitude of the average CAR is typically higher in the longer event windows compared to that in [−3,3] event window. The average CARs of [−3,3] event window are also mostly statistically insignificant. This result may be attributed to investors' under-reaction. Due to sluggish response to the events potentially arising from investors' limited cognitive abilities, the market appears to take more than three days to adjust the information. Overall, while our finding may be inconsistent with informational efficiency, it may support the behavioral argument of gradual information diffusion in stock prices.

The literature reports that firms with different size, profitability, and price-to-book value (P/B) ratio exhibit anomalous return behavior toward extreme events. For example, small firms, due to operating inefficiencies and poor performance, are less likely to survive an adverse event than large firms (Lanfear et al. (2019). In line with this argument, Kaplanski and Levy (2010) and Lanfear et al. (2019) show that event effect is greater on small and riskier stocks. Further, value (low P/B) and growth (high P/B) firms exhibit asymmetric adjustment cost to a disastrous event and value firms are argued to be burdened with more unproductive capital and they find it more difficult to adjust their capital than growth firms (Bai et al., 2019). Bai et al. (2019) and Tsai and Wachter (2016) report that value stocks are more exposed to disaster risk.

Based on the above arguments, we extend the analysis to average CARs for different characteristics-sorted portfolios to explore three well-known anomalies in the literature, size (market value of equity), P/B ratio, and return on equity (ROE). All the stocks are sorted into quartile portfolios and average CARs are calculated at the portfolio level. Although four portfolios are generated for each factor, to conserve space, we report average CARs for the largest and smallest, most profitable and least profitable, and value and growth portfolios in Table 3. Each portfolio comprises 50 stocks and 25% of the aggregate market.

We report two important findings from this analysis. First, for size- and ROE-sorted portfolios, particularly for the [−5,5] and [−7,7] event windows, it is found that the average CAR is statistically significant for the smallest and least profitable portfolios while that for the largest and most profitable portfolios are mostly statistically insignificant. This result holds for all the events (except for the first negative event). The signs of the average CARs are consistent with the results presented in Table 2. This result implies that small and less profitable portfolios are more vulnerable to a global pandemic situation. Overall, these findings are consistent with Lanfear et al. (2019). Second, about the P/B-sorted portfolio, it is found that the value portfolio responds negatively when all the events are pooled together (Panel A). The average CARs represent that the abnormal returns declined by 5.12% and 5.10% respectively for the

Table 2.
Average cumulative abnormal returns (%).

Window	[−3,3]	[−4,4]	[−5,5]	[−6,6]	[−7,7]
Panel A: All events					
All events	−0.640	−1.267	−2.065	−1.862	−1.875
	(1.604)	(2.492**)	(3.180***)	(2.452***)	(2.362**)
Panel B: Negative events					
All negative events	−0.872	−2.001	−2.580	−3.941	−2.809
	(−1.162)	(−2.583**)	(−2.833***)	(−3.473***)	(−2.586**)
1st negative event	−0.022	−0.345	−0.774	−0.989	−1.387
	(−0.054)	(−0.808)	(−1.666*)	(−1.973**)	(−2.479**)
2nd negative event	−1.723	−3.656	−4.386	−6.894	−4.232
	(−1.284	(−2.625***)	(−2.585**)	(−3.228***)	(−2.073**)
Panel C: Positive events					
All positive events	−0.407	−0.534	−1.550	0.218	−0.941
	(−0.836)	(−0.885)	(−2.415**)	(0.349)	(−1.306)
1st positive event	−3.422	−3.325	−5.830	−4.693	−3.887
	(−3.286***)	(−2.677***)	(−4.006***)	(−3.301***)	(−2.634***)
2nd positive event	2.608	2.257	2.730	5.129	2.006
	(3.889***)	(3.728***)	(3.807***)	(6.393***)	(2.670***)

Notes: This table shows the average cumulative abnormal returns (CAR) (test statistics within parenthesis) for different event windows. The daily abnormal returns are calculated by estimating a standard market model of this form: $AR_{i,t} = R_{i,t} - \widehat{\alpha}_i - \widehat{\beta}_i R_{M,t}$ where $AR_{i,t}$ is the abnormal return of an individual stock, $R_{i,t}$, and $R_{M,t}$ are respectively actual realized return of individual stock and aggregate market index. $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ are estimated parameters from a market model where realized return of an individual stock is regressed on the returns of the market index in the estimation period. The estimation period consists of 250 days ending 50 days prior to the first event date. The negative event dates are 30 January 2020 (the COVID-19 is declared as a public health emergency) and 11 March 2020 (the COVID-19 is declared as a pandemic) while the positive event dates are 22 March 2020 (the Australian Prime Minister announced AUD66.4 billion stimulus package) and 8 April 2020 (the Australian government passed AUD130 billion JobKeeper package). The statistical significance of CAR is tested using the cross-sectional *t*-test. *, **, *** denote statistical significance at the 10%, 5% and 1% level, respectively.

[−5,5] and [−7,7] event windows which are highly statistically significant. However, interestingly, the growth portfolio exhibits a 2.20% and 2.93% increase in abnormal returns respectively for the [−5,5] and [−7,7] event windows over the pandemic period considered in this paper. Regarding the positive events (Panel C), we find that the average CARs are statistically significant only for the value portfolio. Overall, this result may imply that value stocks potentially due to less obvious growth opportunities suffered more than the growth stocks in response to the COVID-19 outbreak. This finding is also in line with Bai et al. (2019) and Tsai and Wachter (2016).

From Table 4, we find that SIZE has a statistically significant negative impact on the cross-sectional CARs indicating that investors holding stocks of small companies react more strongly towards an event (either positive or negative) in the pandemic situation. The negative coefficient representing the inverse relationship between firms' SIZE and CAR is consistent with our previous finding of a larger (smaller) average CAR for the smallest (largest) portfolio. This result also appears economically significant. For instance, since the standard deviation of the CARs of [−7,7] event window (all events) is 11.23%, a one standard deviation increase in SIZE is expected to result in a 14.60% (11.23%) decline in the average CAR in the univariate (multivariate) case. The result is also consistent with Kolaric and Schiereck (2016) and Krüger (2015).

Further, the cross-sectional CARs respond positively to liquidity indicating that firms with higher liquidity show higher abnormal returns during the pandemic situation. This result contradicts the idea that investors should regard the companies with high liquidity in a better position to encounter any potential negative cash flow implications associated with the adverse event. The result however may indicate that investors take high liquidity as a signal of management anticipation of potential cash flow or liquidity crisis. Therefore, investors of high liquidity firms appear to overreact to both the negative and positive events. Finally, the cross-sectional CARs are found to be invariant to LEVERAGE and PROFITABILITY. Overall, these results are consistent with Krüger (2015).

We conduct a battery of robustness checks and present the results in Internet Appendix. First, while we calculate abnormal returns using a single-factor market model (Eq. (1)) in our baseline estimation, we also check the sensitivity of our results by computing abnormal returns using Fama and French (1993) and Carhart (1997) multifactor models.[6] The results are presented respectively in Tables A.1 and A.2. Second, we explore if the listing of the Australian companies in overseas exchanges affect our results. We observe that thirty-eight out of two hundred companies included in our sample are cross-listed both in the Australian and overseas exchanges. To check if the cross-listing has driven our results, we exclude the cross-listed stocks from our sample and re-estimate average CARs. The results are presented in Table A.3. Third, we also check if potential thin trading has an influence on how the Australian stock returns responded to the events surrounding the COVID-19. In this regard, we estimate CARs based on abnormal returns calculated from expanded market model of Dimson (1979) that includes two lead and two lag terms of the market returns. The results are in Table A.4. Fourth, while we consider S&P ASX 200 index as benchmark for our analysis, we also check if our results are robust to the use of alternative benchmark such as ASX All Ordinaries. The results are displayed in Table A.5. Fifth, we also check robustness of our

[6] The daily observations for size, value and momentum factors for the Australian stock market is obtained from the AQR datasets (https://www.aqr.com/Insights/Datasets).

Table 3.
Average cumulative abnormal returns (%) of characteristic-sorted portfolios.

	Size				ROE				Price-to-book value		
Window	[−3,3]	[−5,5]	[−7,7]		[−3,3]	[−5,5]	[−7,7]		[−3,3]	[−5,5]	[−7,7]
Panel A: All events											
All events											
Largest	−0.152	−0.944	−0.964	Most profitable	−0.183	−0.650	−0.258	Growth	2.137**	2.196**	2.932**
Smallest	−1.150	−3.166**	−2.383	Least profitable	−1.278*	−4.059***	−4.439***	Value	−1.580**	−5.120***	−5.100***
Panel B: Negative events											
All negative events											
Largest	−1.275	−1.633	−1.404	Most profitable	0.935	−0.647	−1.838	Growth	4.237***	3.383**	3.605*
Smallest	−0.749	−3.436**	−4.092**	Least profitable	−2.973**	−5.677***	−5.844***	Value	−1.528	−5.114***	−5.380***
1st negative event											
Largest	−0.042	−0.124	−0.898	Most profitable	0.653	−0.237	−0.717	Growth	1.560	0.762	0.727
Smallest	−0.176	−1.446	−2.542**	Least profitable	−0.071	−0.747	−1.888	Value	0.975	−0.062	−0.648
2nd negative event											
Largest	−2.507	−3.143	−2.800	Most profitable	1.216	−1.057	−2.960	Growth	6.913***	6.004**	6.483*
Smallest	−1.321	−5.426**	−5.643**	Least profitable	−5.700**	−9.982***	−9.839***	Value	−4.032**	−10.165***	−10.112***
Panel C: Positive events											
All positive events											
Largest	0.970	−0.255	−0.525	Most profitable	−1.301	−0.654	1.321	Growth	0.037	1.009	2.259*
Smallest	−1.552	−2.896	−0.675	Least profitable	0.418	−2.441**	−3.035***	Value	−1.632**	−5.127***	−4.820***
1st positive event											
Largest	0.674	−2.435	−2.425	Most profitable	−4.986**	−3.464	−0.684	Growth	−0.521	2.012	4.311*
Smallest	−8.369***	−10.394***	−5.479**	Least profitable	−5.750**	−9.783**	−5.213**	Value	−7.251***	−14.208***	−11.895***
2nd positive event											
Largest	1.266	1.925	1.376	Most profitable	2.384	2.156	3.327**	Growth	0.596	0.007	0.207
Smallest	5.265***	4.602**	4.130**	Least profitable	5.362***	5.296***	3.665**	Value	3.987***	3.954***	2.255

Notes: This table shows the average cumulative abnormal returns (CAR) (test statistics within parenthesis) for different event windows and for different characteristics-sorted portfolios. Firms characteristics considered are size (market value of equity), price-to-book value ratio, and return on equity (ROE). All the stocks are sorted into quartile portfolios, average CARs are calculated and they are reported for the largest and smallest, most profitable and least profitable, and value and growth portfolios. *, **, *** denote statistical significance at the 10%, 5% and 1% level, respectively. See notes to Table 2 for further details.

Table 4.
Determinants of cumulative abnormal returns.

	Model 1	Model 2	Model 3	Model 4	Model 5
Panel A: All events					
Constant	0.097	0.008	−0.027	−0.010	0.075
	(2.547**)	(0.597)	(−3.015***)	(−1.277)	(1.847*)
Size	−0.013				−0.010
	(−2.838***)				(−2.297**)
Leverage		−0.001			0.000
		(−1.793*)			(−0.696)
Liquidity			0.138		0.110
			(2.960***)		(2.265**)
Profitability				−0.007	−0.060
				(−0.107)	(−0.912)
R squared	3.430	12.422	3.782	0.003	6.478
Panel B: Negative events					
Constant	0.089	0.000	−0.035	−0.013	0.068
	(1.667*)	(−0.014)	(−2.744***)	(−1.218)	(1.181)
Size	−0.012				−0.010*
	(−1.975**)				(−1.724)
Leverage		−0.001			0.000
		(−1.119)			(−0.405)
Liquidity			0.153		0.131**
			(2.334**)		(1.923)
Profitability				−0.064	−0.110
				(−0.707)	(−1.193)
R squared	1.717)	0.472	2.383	0.135	4.028
Panel C: Positive events					
Constant	0.098	0.018	−0.018	−0.006	0.071
	(3.095***)	(1.687*)	(−2.441**)	(−0.874)	(2.110**)
Size	−0.011				−0.009
	(−3.226***)				(−2.440**)
Leverage		−0.001			0.000
		(−2.459**)			(−0.988)
Liquidity			0.128		0.095
			(3.298***)		(2.380**)
Profitability				0.061	0.015
				(1.117)	(0.278)
R squared	4.206	2.312	4.494	0.389	7.758

Notes: This table shows result of a regression model of this form: $CAR_{i,[\tau_1;\tau_1]} = \gamma_0 + \gamma_1 SIZE + \gamma_2\ LEVERAGE + \gamma_3\ LIQUIDITY + \gamma_4 PROFITABILITY + \varepsilon_i$ where $CAR_{i,[\tau_1;\tau_1]}$ is the cumulative abnormal returns for [−7, +7] event window. *SIZE* is the log of total assets, *LEVERAGE* is total debt as a percentage of total asset, *LIQUDITY* is cash and short-term investment scaled by total assets, and *PROFITABILITY* is net income as a percentage of total asset. All income statement and balance sheet information are collected for the last completed financial year. The regression model is estimated using the robust least squares method (Yohai, 1987) due to the presence of some extreme values. Statistical inference is derived based on heteroscedasticity consistent robust standard error of Huber (1981). *, **, *** denote statistical significance at the 10%, 5% and 1% level, respectively.

results using alternative approaches to measure statistical significance of average CAR. The results are in Table A.6. Finally, while Table 4 presents determinants of cross-sectional CARs considering [−7,7] window period and pooling all, negative and positive events together, Tables A.7 and A.8 respectively present regression results of individual events and findings derived from different event windows. Overall, the results derived from the robustness checks are mostly qualitatively similar to the baseline results presented in Tables 2 and 4.

4. Conclusion

This paper is the first to explore the effect of COVID-19 outbreak and subsequent government policy instruments on stock returns. The average CAR associated with the declaration of COVID-19 as a global pandemic was −4.39% which is equivalent to an average loss of market capitalization of AUD352 million per firm. The market however regained by 2.73% in response to the announcement of JobKeeper package by the government. The magnitude of average CAR in the longer event windows is relatively higher compared to that in the shorter windows supporting investors' underreaction phenomena. Finally, the smallest, least profitable, and value portfolios are found to be more vulnerable to the pandemic while size and liquidity are the main drivers of the cross-sectional abnormal returns. These results are found to be robust to the use of alternative models to estimate abnormal returns and alternative measures of statistical significance of average CAR.

Overall, our results indicate that governments and regulatory authorities need to devise more objective and target-oriented bailout programs to boost investors' confidence following an extreme adverse event. Our results, however, should be interpreted cautiously as the Australian stock return dynamics during the COVID-19 crisis may also have been affected by other regional and global financial markets. Akhtaruzzaman et al. (2020) and Corbet et al. (2020), in general, indicate a significant increase in correlation between returns across stocks, sectors and markets during the pandemic period. While we recognize this issue, we leave this for future research.

Authors statement

The project has been initiated by the first author. Upon completion of the empirical analysis, the second author joined and assisted in writing the manuscript. The third author completed all the revision requests. All the authors participated in finalizing the revised manuscript and writing the response letters.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.frl.2020.101832.

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