Impact of government policy responses of COVID-19 pandemic on stock market liquidity for Australian companies

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Abstract
This study investigates the impact of government policy responses of COVID-19 pandemic on stock market liquidity for listed Australian companies and for 11 different industries separately. A quantitative deductive approach is used for a sample of 1,452 companies with a total of 292,164 firm-day observations over a period from January 25, 2020 to December 31, 2020 during the outbreak of COVID-19. Univariate and multivariate (two-way cluster-robust panel regression) analysis were conducted. Data were collected from the Oxford COVID-19 Government Response Tracker, Worldmeter, Refinitiv Workspace and Datastream. Our findings indicate that the influences of the six out of seven stringency policy responses reduced Australian equity market liquidity. However, public information campaigns enhanced market liquidity and hence trading activity. Among the 11 industries, our analysis shows that the non-pharmaceutical interventions by the Australian government have significant and positive effects on four industries: Consumer non-cyclicals, healthcare, financial and technology. However, the worse effects were depicted in the industrial (transportation) and energy industries. This study is important for investors, policymakers and regulators to understand the diverse effects of government policy responses of COVID-19 on stock market liquidity to enhance financial stability. Moreover, understanding this effect is particularly important to decision-
makers such as portfolio and fund managers to manage their portfolios and trading activities during extreme turbulence times, such as COVID-19. Unlike previous studies that focus on country analysis, this study examines on firm basis the impact of government interventions on stock market liquidity in a well developed Australian stock market.

KEYWORDS
Amihud measure, Australian government stringency policy responses, bid–ask spread, COVID-19, stock market liquidity, stringency index

1 | INTRODUCTION

Along with the emergence of financial crises, market pressures, new regulations and most importantly the COVID-19 pandemic, the need for transparency and information communication has been significantly increasing in financial markets. When liquidity is unstable, the executions of orders and prices are uncertain. This pushes investors to claim a liquidity premium for taking the risk (Khanna & Sonti, 2004). In 2020, an ongoing global pandemic of coronavirus disease 2019 (COVID-19) has caused the worst crashes across world economies since the turmoil of the 2008 global financial crisis (GFC). By the end of February 2020, the coronavirus spread globally whereby the pandemic influenced the US stock market, leading to the biggest weekly SPX collapse since the Great Recession. Then, the stock market has experienced further collapse and volatility as the cases of COVID-19 continue to surge (Baek, Mohanty & Glambosky, 2020). Hence, asymmetric information in the market surged during COVID-19 pandemic which resulted in lack of transparency attributed to the global crisis. Similar to that of 2008 financial crisis, the outbreak of COVID-19 increased the uncertainty in the world’s financial markets and reduced investors’ confidence in the stock market (Liu, Manzoor, Wang, Zhang, & Manzoor, 2020). The recession in many countries casued a debatable choice for the stringency of government policy responses between saving the economy before saving human lives or saving the people before saving the economy. Zaremba, Kizys, Aharon & Demir, (2020) argue that there were a criticism between the accommodative monetary policy that empowered economic agents and the lockdowns and stay-at-home policy that curbed economic activities. Accordingly, asset classes display extreme pricing volatility, from commodities to currencies. Smaller trading volumes activities will widen the bid–ask spreads and hence lower the market liquidity. Hameed, Kang, and Viswanathan (2010) find that companies have less market liquidity (higher bid ask spread) strictly before turbulent time and during event crisis. They conclude that event crisis has negative impact on market liquidity. Moreover, Chiu, Chung, Ho, and Wu (2018) find that negative market returns reduce stock market liquidity especially during times of tightness in the funding market.

The recent and rapidly growing literature (such as Orlik, Rush, Cousin, & Hong, 2020 and Zaremba, Aharon, Demir, Kizys & Zawadka, 2021) on the impact of COVID-19 highlights the importance of scrutinising how the pandemic has reverberated across economies and financial markets, especially after a series of unprecedented government interventions.
The need to study the dynamics of stock market liquidity and its determinants arises from two facts. The first is the importance of liquidity for hedging, risk management, asset pricing, determination of cost of capital and efficient capital allocation (Brunnermeier & Pedersen, 2009; Das & Hanouna, 2009). The second fact is associated to the potential impairment that is caused by the lack of liquidity during financial crisis and uncertain market conditions. Moreover, with all the reduced risks measures implemented by policymakers in Australia, the speed and magnitude of COVID-19 economic is still posing big risks regarding financial stability. We focus on stock market liquidity because it is a crucial financial factor for both firms’ and individuals’ investment plans. To our best knowledge, this study is the first of its kind in investigating the effect of non-pharmaceutical interventions on stock market liquidity for 1,452 Australian companies (292,164 firm-day observations) during the COVID-19 period that runs from January 25 to December 31, 2020. We examine this effect based on firm basis and for various industries.

We select the Australian settings because Australia has controlled the pandemic more effectively in comparison to other developed nations (Wyeth, 2020). It was among the first countries to implement travel bans to contain the spread of the virus and the Australian government has instigated various policies to reduce the adverse impact of the pandemic on the economy. Countries like Australia have also sophisticated financial markets. The Australian stock market is well developed by international standards, and is considered to be among the biggest stock markets in the world. According to Nyasha and Odhiambo (2013), a number of reforms have been undertaken that positively contribute to the improvement of the stock market over the previous years. To add, the Australian stock market has developed over the years, mainly through the increase of the number of listed companies, stock market capitalization, as well as the total value and turnover ratio of stocks traded. Despite the fact that Australia was not among the most affected countries of COVID-19 in terms of death and physical effect of infection, but the country’s stock market was one of the most affected by the pandemic among various international markets. This also motivate us to select the Australian market as an interesting candidate to investigate the effect of COVID-19 on stock market liquidity.

Our paper contributes in several ways to the existing literature about the effect of the pandemic on financial markets. First, we focus not only on the impact of COVID-19 in terms of changes in confirmed and death cases but also on the influence of government policy responses to this pandemic on stock market liquidity for all listed Australian firms over a wide sample period. Second, our study presents a novel analysis based on both firms’ and industries’ levels. This allows us to take into account the heterogeneity of the pandemic’s impact on each firm and industry. Third, we employ different estimation proxies and methods to analyse the impact of the COVID-19 pandemic on stock market liquidity. And finally, we extend the understanding of the effect of restrictive government measures on the stability of financial markets to enhance investors’ trading activities and risk management strategies during extremely turmoil periods, such as COVID-19.

Our findings support the fact that COVID-19 pandemic had a significant role in deteriorating Australian companies’ stock market liquidity. Among the unprecedented economic and social disruption caused by COVID-19, financial markets around the world have been severely affected. However, the pandemic has raised awareness within the general public about various measures of gauging the spread of infectious diseases, as well as policy choices for governments to curb the spread (Goodell & Huynq, 2020; Ozili & Arun, 2020; Zaremba et al., 2020). Having considered and discussed the implementations of government policy responses in Australia, our findings indicate that the influence of six out of seven stringency policy responses intensely
reduced Australian market liquidity. However, public information campaigns facilitated additional trading and thus enhanced market liquidity. Among the 11 selected industries, our analysis shows that government policy responses have significant and positive effects on 4 out of 11 industries: consumer non-cyclicals, healthcare, financials and technology. The highest positive impact was detected in the healthcare sector, as the virus enhances the demand for medical equipment. The worse effect was observed in the industrial (transportation) and energy industries. The energy sector experienced the largest negative effect due to the disorder of energy supply and demand and to the negative prices’ reaction towards the stringency measures as a result of the cancellation of large number of pre-booked flights and the decline in the use of cars on a daily basis. Global travel restrictions caused by COVID-19 could be the main cause behind the negative influence on market liquidity by most stringency measures in the industrial (transportation) industry.

Section 2 of this study reviews the influence and the elements of COVID-19 pandemic on the financial market and discusses the development of the hypotheses. Section 3 describes the adopted methodology including variables measurement and sampling procedures. Section 4 presents the empirical results of descriptive statistics, multicollinearity analysis, and a two-way cluster-robust panel regression. It also discusses the major findings and the robustness checks. Section 5 concludes the study.

2 | LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

With the global spread of COVID-19, authorities in each country have taken specific measurements in an attempt to contain this virus. Ozili and Arun (2020) state that the subprime mortgage crisis of 2008 would be relatively a minor problem affecting only the US market. However, this crisis has hit the global financial stability system. The spread of the GFC of 2008 was rapid in adversely affecting the performance of the financial markets. Through a sample of 272 German companies from 2003 to 2009, Kaserer and Rosch (2013) analyse the dynamics and the drivers of market liquidity during the financial crisis of 2008. They find that stock market liquidity suffers during market turmoil and crises and it can be a driving force for financial contagion. McTier, Tse, and Wald (2013) confirm that trading activity, volatility and bid–ask spreads are influenced by flu epidemics in the US financial market. However, these effects are not related to the mechanisms of the financial markets but rather to human activity.

The stringency government policy response followed by authorities to curb the outbreak of the pandemic and to strengthen the capacity of health systems resulted in a deterioration of the economic outlook and financial market activities. Chen, Lee, Lin, and Chen (2018) find that governments’ non-pharmaceutical interventions have sizable economic and social costs such as increase in unemployment, decline in wealth and loss of income. Ashraf (2020) finds that announcements of government restrictions have a negative impact on international stock market returns, while testing and quarantining policies, and economic support packages have positive one. Zhang, Hu, and Ji (2020) find also that global financial market risks have surged substantially in response to the pandemic and become highly volatile and unpredictable. With the hassle of some strict measures, the Australian government’s attempt is to limit the spread of the virus through lockdowns, shutting down non-essential businesses, travel restrictions and encouraging social distancing. These containment efforts have reduced the brutality of COVID-19 crisis but have caused a dramatic decline in economic activity. Ozili and Arun (2020) argue
that the increasing number of lockdown days and international travel control severely affected
the level of global economic activities as well as the closing and opening prices of major stock
market indices. There are seven main governmental interventions to mitigate the impact of the
pandemic: school closing, restrictions on internal movement, cancelled public events, interna-
tional travel control, workplace closing, closed public transport and public information cam-
paigns. Many countries like Australia, depend on international higher education as a key
factor. Thus, their economy is expected to encounter big shocks because they are imposing
harsher restrictions or bans on international arrivals. Sobieralski (2020) explains that due to
COVID-19, travel restrictions are contributing in a global incapacity in the airline sector.

Several recent papers (such as Al-Awadhi, Alsafi, Al-Awadhi, & Alhammadi, 2020; Ashraf,
2020; Goodell & Huyng, 2020; Zhang et al., 2020) argue that the influence of the
COVID-19 pandemic on financial markets is large with an unprecedented scale. Market liquid-
ity is often considered as one of the crucial features of the financial market. The economic the-
ory proposes that the existence of uncertainty and risks widen the bid–ask spread (Glosten &
Milgrom, 1985). Accordingly, liquidity is considered to attract more attention from investors
especially during the times of financial crisis due to large uncertainties in the markets.

Previous studies (such as Goyenko & Ukhov, 2009; Liu, 2015; Næs, Skjeltorp, & Ødegaard,
2011) have documented that market microstructure variables, macroeconomic vari-
ables, firm-specific characteristics, behavioural factors and investor sentiment are significant
determinants of stock market liquidity. Hameed et al. (2010) stress on the existence of a nega-
tive and significant impact of event crisis on market liquidity. Through a sample of 97,799 firm-
year observations from 46 countries during a period from 1994 to 2007, Lang, Lins, and Maffett
(2012) suggest that increased transparency could lower bid–ask spreads and enhance market
liquidity. In addition, Chiu et al. (2018) posit that negative market returns had a deteriorating
effect on stock market liquidity, especially during times of tightness in the funding market. In
this regard, Ali, Liu, and Su (2016) scrutinise the determinants of stock market liquidity in
Australia. Their results indicate that better governed firms had a higher level of market liquid-
ity. On the other hand, Debata and Mahakud (2017) examine the relationship between eco-


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nomic policy uncertainty and stock market liquidity for 510 firms listed on the National Stock
Exchange of India from January 2003 to December 2016. Their research uncovered that eco-

nomic policy uncertainty and investor sentiment are better predictors for stock market liquidity
than inflation and monetary policies during financial market crises. Similarly, Chiu et al. (2018)
find that the pessimistic sentiment of investors during the financial crisis of 2008 on propor-
tional quoted spread had deteriorated the level of market liquidity and contributed to the
increase of net-selling pressure. Moreover, they argue that stocks with high uncertainty regard-
ing intrinsic value are expected to be less liquid than those with lower uncertainty. Recently,
Rahman, Amin, and Al Mamun (2021) find that liquidity is one of the crucial factors affecting
abnormal returns of the Australian stocks towards the COVID-19 announcement.

Through a sample of 314 listed firms operating in six Middle East and North African (MENA)
countries from February to May 2020, Mdaghri, Raghibi, Thanh, and Oubdi (2020) find that
COVID-19 had a significant and negative impact on stock market liquidity on both country and sec-
tor levels. Similarly, Baig, Butt, Haroon, and Rizvi (2021) find that there is a negative impact of
COVID-19 pandemic (increases in confirmed cases and deaths) on the market liquidity of the
microstructure of US equity markets. Moreover, Chebbi, Ammer, and Hameed (2021) examine
the impact of the COVID-19 pandemic on the stock liquidity of S&P 500 firms. They also find that
the level of firm liquidity decreased as a result of an increase in the daily growth rate of the total
number of confirmed infected and death cases. Government policy interventions have also been
linked to the market liquidity. Haroon and Rizvi (2020) argue that government interventions in the form of enforcing social distancing and closing schools and businesses were associated with improved liquidity. They discover that flattening the curve of coronavirus infections improved investor confidence and helped in decreasing uncertainty. Such information enabled market players to better estimate the level of risk and the financial position of a company. Consequently, the demand on stocks with lower risk increased, which also contribute in the reduction in the bid–ask spread, and hence improves market liquidity. Through investigating the influence of government policy responses on global stock market liquidity of 49 developed and emerging countries, Zaremba, Aharon, et al. (2021) find that this impact is limited in size and scope. Their results indicate that COVID-19 information campaigns have spiked the liquidity measure around 10%. Furthermore, workplace and school closures led to a moderate decline in market liquidity within emerging markets. Similarly, Haroon and Rizvi (2020) argue that decreasing or increasing trends in the number of coronavirus cases and deaths were, respectively, linked with improving or deteriorating liquidity. During turbulent times such as a global pandemic, increased asymmetry and decreased transparency are linked to higher bid–ask spreads and lower market liquidity. Based on the above discussed studies, we develop the following hypotheses.

**Hypothesis 1.** There are negative impacts of the stringency of government policy responses on stock market liquidity of Australian companies.

The novel coronavirus pandemic has hit the global financial markets on various industries. We would expect the impact of government policy responses of COVID-19 on market liquidity to be significantly different among various industries. Prior research (such as Chen, Chen, Tang, & Huang, 2009; Ichev & Marinč, 2018) suggests that a particular industry segment may be affected in a specific way during a certain pandemic (such as SARS and Ebola outbreaks). For instance, Chen et al. (2009) found that the SARS outbreak in 2003 has a negative impact on Taiwan’s stock market in tourism, wholesale and retail industries, but it has had a positive effect on the biotechnology sector. The outbreak of the COVID-19 has substantially affected the supply and demand of the energy market resulting in changes in oil and natural gas prices. Based on daily data of the S&P GSCI Energy index over the period from January 2 to September 30, 2020, Czech and Wielechowski (2021) find that the stringency level of anti-COVID-19 government policy has a significant and negative impact on the energy commodity market on the third day after the shock. From the perspective of the impact of COVID-19 on market liquidity, Mdaghri et al. (2020) find that the daily growth in confirmed cases has negatively affected consumer goods, energy, utilities and industrials sectors in the MENA region. Recently, Chebbi et al. (2021) find that there are significant differences in stock liquidity among various sectors of S&P 500 index. In comparison to the overall market, stock liquidity in the healthcare and communications has positively affected by the COVID-19. On the other hand, sectors like consumer staples, consumer discretionary, financial, information technology, basic materials, energy and industrial have lower stock liquidity than that in the market overall. On the contrary, the real estate sector's market liquidity does not reveal any significant effect from the growing numbers of confirmed cases and deaths. Based on the above discussion, we develop the following hypothesis:

**Hypothesis 2.** The negative impact of the stringency of government policy responses on stock market liquidity of Australian companies varies among different industries.
3  |  METHODOLOGY AND DATA

Spence (2002) finds that signalling theory is primarily concerned with reducing information asymmetry between two parties. The reduction in information asymmetries improves firms’ stock liquidity and reduces firms’ cost of equity capital, leading to a lower leverage (Amihud & Mendelson, 1986). Financial markets’ reactions provide a valuable forward-looking “signal” for assessing the impact of COVID-19 outbreak. This study follows the signalling approach by considering the diverse market signals as indicators for initiating trading positions (Bird & Smith, 2005). COVID-19 related policies may influence stock market liquidity in three different channels: “infrastructure”, “Portfolio” and “behavioural and psychological” (Zaremba, Aharon, et al., 2021). Workplace closures may disrupt decision-making in financial institutions especially those with poor electronic infrastructures and policy regulations to conduct and manage trading (Ersan & Ekinci, 2016; Glantz & Kissel, 2013). Dire economic conditions may result in changes in the expectations of cash flow and in portfolio reallocations (Chen et al., 2018; Lempel, Epstein, & Hammond, 2009). When bad news are likely to come, investors become reluctant in monitoring their portfolios (Karlsson, Loewenstein, & Seppi, 2009; Sicherman, Loewenstein, Seppi, & Utkus, 2016). Recently, Haroon and Rizvi (2020) find that the declining (ascending) curve of the number of coronavirus related cases and deaths was generally associated with improving (deteriorating) liquidity in the equity markets of emerging economies.

Similar to Haldar and Sethi (2020) and Zaremba et al. (2020), we account for a government policy response index. In particular, we identify seven explanatory variables for non-pharmaceutical government Australian’s interventions denoted by “AI” that sought to curb the outbreak of the pandemic: School closing (AI1), workplace closing (AI2), cancelled public events (AI3), closed public transport (AI4), public information campaigns (AI5), restrictions on internal movement (AI6) and international travel control (AI7). The measures used in our study are either formal regulatory (“hard measures”) or government recommendations (“soft measures”). The daily observations for these variables were extracted from the Oxford COVID-19 Government Response Tracker. As a robustness check for the non-pharmaceutical government policy responses, we use an aggregate stringency index. The index has a value from 0 to 100. It includes nine indicators that examine containment policies including school and workplace closings, travel bans and stay-at-home policies (Czech & Wielechowski, 2021; Mdaghri et al., 2020). The stringency index provides an efficient and systematic measure in tracking the severity level of government responses to the COVID-19 pandemic. The higher the index score, the stricter the governments’ responses to the COVID-19 pandemic. This variable was computed as the natural logarithm of the daily stringency index and denoted as ASI.

Market liquidity is a major concern in financial markets. Bid–ask spread is widely used to measure the transaction costs associated with the trade. Heflin, Shaw, and Wild (2005) and Goyenko, Holden, and Trzcinka (2009) find that two liquidity proxies (the quoted sand the effective spreads) are perceived as being the most accurate measures for liquidity consistent with several studies (such as Chebbi et al., 2021; Dunham & Garcia, 2020; Mdaghri et al., 2020), we measure stock liquidity by utilising the quoted spread (Chung & Zhang, 2014) for every firm on a given trading day. It is computed by utilising the daily bid–ask spreads as a proportion of the mid-price for each firm on a given trading day. We denote this measure as quoted market liquidity (QML) in our study.

\[
QML_{i,t} = \frac{Ask_{i,t} - Bid_{i,t}}{\frac{Ask_{i,t} + Bid_{i,t}}{2}},
\]
where Bid\(_{i,t}\) is the bid price of firm \(i\) at day \(t\) and Ask\(_{i,t}\) is the ask price of firm \(i\) at day \(t\).

In addition to the usefulness of the Closing Percent Quoted Spread as a liquidity measure for daily frequencies, Fong, Holden, and Trzcinka (2017) find that illiquidity is considered a best cost-per-dollar volume proxy. Hence, we check the robustness of our results by employing the Amihud illiquidity measure. Lou and Shu (2017) suggest that the Amihud measure is a good alternative measure of liquidity because it considers price impact through the trading volume factor. This measure is calculated by dividing the absolute daily return of the stock by its daily dollar trading volume. Similar to the quoted spread, a higher value of the Amihud measure (higher illiquidity) implies a lower level of liquidity and vice versa. We denote the Amihud measure as AMH in our study.

\[
\text{AMH}_{i,t} = \frac{|R_{i,t}|}{\ln(\text{volume}_{i,t})},
\]

where \(R_{i,t}\) is the daily stock return of firm \(i\) at a trading day \(t\) computed as the natural logarithm of the closing price at day \(t\) divided by the closing price at day \(t - 1\), and \(\text{volume}_{i,t}\) represents the dollar volume of firm \(i\) at day \(t\).

Following the general approach established in recent studies (Al-Awadhi et al., 2020; Ashraf, 2020; Haroon & Rizvi, 2020; Zaremba, Aharon, et al., 2021), we cover seven control variables. We also account for weekday’s effect by including five weekdays’ dummies. Specifically, we control for current and lagged market returns (\(R_t, R_{t-1}\)) as measured by S&P/ASX 200 index, current volatility measured through the absolute daily firm’s stock return on day \(t\) (Abs\(R_t\)), lagged volatility proxied with the average absolute firm’s stock return through trading days \(t - 1\) to \(t - 5\) (\(\text{VOL}_{t-1}\)), and lagged market capitalization (\(\text{MC}_{t-1}\)). Following Zaremba et al. (2020), to disentangle the role of government policies from the pandemic itself, we control for the daily changes in numbers of new COVID-19 infections (\(\Delta\text{INF}\)) and in numbers of new COVID-19 deaths (\(\Delta\text{DTH}\)). Table 1 below presents the description of the variables with the source of data.

Following Thompson (2011), we use two-way cluster-robust standard errors approach in estimating the coefficients of panel regression which are robust for correlation across firms or across times. We adopt the same model in examining the impact of the COVID-19 pandemic on stock market liquidity for Australian companies among 11 industries as classified by Thomson Reuters Business Classification: Academic & Educational Services, Basic Materials, Consumer Cyclicals, Consumer Non-Cyclicals, Energy, Financials, Healthcare, Industrials, Real Estate, Technology and Utilities. We run the following panel regression:

\[
\text{QML}_{i,t} = a_i + b_t + \sum_{j=1}^{7} \beta_j \text{AI}_{j,t} + \sum_{k=1}^{K} \beta_k \text{V}_k,t + \epsilon_{i,t},
\]

where \(\text{QML}_{i,t}\) denotes quoted market liquidity for firm \(i\) at day \(t\), \(\text{AI}_{j,t}\) represents the variables of the seven different policy responses on day \(t\), \(\text{V}_k,t\) indicates a set of the control variables, \(a_i\) and \(b_t\) are firm and time-fixed effects, respectively, \(\beta_j\) and \(\beta_k\) are the regression coefficients, and \(\epsilon_{i,t}\) is the error term.

The daily data of the stringency of government policy responses to the COVID-19 pandemic was collected from the Oxford COVID-19 Government Response Tracker. The daily data of the bid/ask prices and trading volume to calculate the market liquidity measures as well as the control variables are collected from Datastream. Moreover, the daily data concerning changes in
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the number of infected and death cases by COVID-19 are extracted from Worldmeter. Information on government stringency response, number of infected and death cases are recorded and released on a daily basis regardless of the trading sessions. We exclude weekends and holidays to synchronise the trading days with the timing of the government’s announcement of the stringency responses as well as the number of cases and deaths (Zaremba, Kizys, Tzouvanas, Aharon, & Demir, 2021). We start collecting data based on the first infection case of COVID-19 at Australia on January 25, 2020.³ Refinitiv Workspace was used to obtain the list of Australian companies listed on Australian Stock Exchange (ASX). After removing the missing data and excluding the outliers,⁴ we reach a sample of 1,452 Australian companies with a total of 292,164 firm-day observations.

### 4 | EMPIRICAL RESULTS AND DISCUSSION

Table 2 shows the statistical properties of the variables. Excluding the values of COVID-19 and those for government intervention policy, the kurtosis and skewness figures for the control variables and for QML as well as AMH are within the reasonable ranges.

Table 3 presents the correlation matrix to examine any possibility of multicollinearity.⁵ The correlation coefficients of the explanatory variables with their ɑ values reveal that these figures
are relatively low. This confirms that multicollinearity does not exist across the variables especially that all correlation coefficients are less than .80 (Gujarati & Sangeetha, 2007).

Table 4 summarises the results of the panel regressions for all Australian companies in the sample. In line with our expectations, the majority of policy responses reveal a negative impact on stock market liquidity, except for public information campaigns which show a positive one. Consistent with Zaremba, Aharon, et al. (2021), we find the effect of information campaigns to be even more pronounced, with the resulting coefficient of $-0.105$ ($p = .000$). This indicates that the increase in public information campaigns leads to a lower bid–ask spread (as measured by QML) and hence higher level of firm liquidity. Spreading information about the outbreak of COVID-19 could signal to investors to reposition and rebalance their portfolios towards safer investment alternatives. This could encourage trading and hence improve stock market liquidity. On the other hand, factors such as closing workplaces may affect trading activity more severely than the other ones. Workplace closures can create challenges in investment decision-making as well as undermine proprietary trading possibilities, and hence deteriorating market liquidity (Zaremba, Aharon, et al., 2021). When considering jointly these factors with other

| Variable | Mean  | STD   | Kurtosis | Min  | First quartile | Median | Third quartile | Max  |
|----------|-------|-------|----------|------|----------------|--------|----------------|------|
| QML$_{i,t}$ | 0.053 | 0.040 | 1.890 | -0.121 | 0.018 | 0.021 | 0.073 | 0.232 |
| AMH$_{i,t}$ | 0.003 | 0.001 | 2.647 | 0.000 | 0.001 | 0.004 | 0.008 | 0.018 |
| ΔINF$_t$ | 112.830 | 212.258 | 14.201 | 0.000 | 10.000 | 25.000 | 115.000 | 1450 |
| ΔDTH$_t$ | 4.130 | 9.384 | 18.028 | -1.000 | 0.001 | 0.001 | 4.000 | 59.000 |
| R$_t$ | 0.001 | 0.013 | 0.817 | -0.036 | -0.006 | 0.001 | 0.008 | 0.044 |
| R$_{t-1}$ | 0.001 | 0.016 | 5.017 | -0.073 | -0.006 | 0.001 | 0.008 | 0.070 |
| AbsR$_{i,t}$ | 0.030 | 0.039 | 3.679 | 0.000 | 0.008 | 0.017 | 0.043 | 0.220 |
| VOL$_{i,t-1}$ | 0.032 | 0.025 | 1.369 | 0.000 | 0.014 | 0.025 | 0.044 | 0.130 |
| MC$_{i,t-1}$ | 5.104 | 0.870 | 0.534 | 1.613 | 4.483 | 4.887 | 5.601 | 8.381 |
| AI1$_t$ | 1.740 | 1.029 | -1.034 | 0.000 | 1.000 | 2.000 | 3.000 | 3.000 |
| AI2$_t$ | 1.691 | 0.947 | -0.816 | 0.000 | 1.000 | 2.000 | 2.000 | 3.000 |
| AI3$_t$ | 1.566 | 0.712 | 0.362 | 0.000 | 0.000 | 2.000 | 2.000 | 2.000 |
| AI4$_t$ | 0.744 | 0.436 | -0.715 | 0.000 | 0.000 | 1.000 | 1.000 | 1.000 |
| AI5$_t$ | 1.995 | 0.001 | 201.520 | 1.000 | 2.000 | 2.000 | 2.000 | 2.000 |
| AI6$_t$ | 1.722 | 1.029 | -1.032 | 0.000 | 1.000 | 2.000 | 3.000 | 3.000 |
| AI7$_t$ | 3.870 | 0.337 | 2.804 | 3.000 | 4.000 | 4.000 | 4.000 | 4.000 |
| ASI$_t$ | 4.051 | 0.422 | 2.461 | 2.967 | 4.135 | 4.226 | 4.267 | 4.323 |

Note: The table presents the basic statistical properties of the variables for the Australian sample of 292,164 firm-daily observations from January 25, 2020 to December 31, 2020: Quoted market liquidity (QML), Amihud measure (AMH), daily changes in numbers of new COVID-19 infections and deaths (ΔINF, ΔDTH); daily market return on days $t$ ($R_t$) and $t-1$ ($R_{t-1}$); absolute value of return on day $t$ (AbsR$_t$), volatility proxied with the trailing 5-day average absolute return (VOL), and stock market capitalization (MC). Al-variables denote dummies representing different Australian government intervention policy measures: school closing (AI1), workplace closing (AI2), cancelling of public events (AI3), closing of public transportation (AI4), public information campaigns (AI5), restrictions of internal movement (AI6), international travel controls (AI7) and Australian stringency index (ASI).
| TABLE 3 Correlation matrix |
|-----------------------------|
| **QML** | **AI1** | **AI2** | **AI3** | **AI4** | **AI5** | **AI6** | **AI7** | ΔINF | ΔDTH | R | R1 | AbsR | VOL | MC |
| QML | 1.000 | | | | | | | | | | | | | |
| **AI1** | -0.009*** (.000) | 1.000 | | | | | | | | | | | | |
| **AI2** | -0.644*** (.000) | 0.821*** (.000) | 1.000 | | | | | | | | | | | | |
| **AI3** | -0.070*** (.000) | 0.774*** (.000) | 0.810*** (.000) | 1.000 | | | | | | | | | | | |
| **AI4** | -0.131*** (.000) | 0.325*** (.000) | 0.443*** (.000) | 0.466*** (.000) | 1.000 | | | | | | | | | | |
| **AI5** | 0.012*** (.000) | 0.084*** (.000) | 0.049*** (.000) | 0.042*** (.000) | 0.041*** (.000) | 1.000 | | | | | | | | | |
| **AI6** | -0.009*** (.000) | 1.000*** (.000) | 0.821*** (.000) | 0.774*** (.000) | 0.545*** (.000) | 1.000 | | | | | | | | | |
| **AI7** | -0.067*** (.003) | 0.654*** (.000) | 0.692*** (.000) | 0.665*** (.000) | 0.599*** (.000) | 0.654*** (.000) | 1.000 | | | | | | | | |
| ΔINF | 0.011*** (.000) | 0.380*** (.000) | 0.364*** (.000) | 0.281*** (.000) | 0.166*** (.000) | -0.014*** (.000) | 0.380*** (.000) | 0.381*** (.000) | 0.181*** (.000) | 1.000 | | | | |
| ΔDTH | -0.029*** (.000) | 0.451*** (.000) | 0.495*** (.000) | 0.260*** (.000) | 0.180*** (.000) | 0.014*** (.000) | 0.451*** (.000) | 0.366*** (.000) | 0.546** (.000) | 1.000 | | | | |
| R | -0.004** (.066) | 0.051*** (.000) | 0.034*** (.000) | 0.132** (.000) | 0.035*** (.000) | 0.072*** (.000) | 0.051*** (.000) | 0.120 (.138) | 0.078*** (.001) | 0.005*** (.000) | 1.000 | | | |
| R1 | -0.035*** (.000) | 0.073*** (.000) | 0.055*** (.000) | 0.066*** (.000) | 0.118*** (.000) | 0.061*** (.000) | 0.073*** (.000) | 0.150*** (.000) | -0.034* (.077) | 0.022 (.789) | -0.194*** (.000) | 1.000 | | |
| AbsR | -0.001*** (.008) | 0.007*** (.001) | 0.009*** (.000) | 0.008*** (.000) | 0.002 (.225) | 0.007*** (.001) | 0.007*** (.001) | 0.005*** (.021) | 0.005** (.020) | 0.003* (.084) | -0.001 (.762) | 1.000 | | |
| VOL | -0.005*** (.008) | 0.008*** (.000) | 0.110*** (.000) | 0.010*** (.000) | 0.003* (.097) | 0.047*** (.000) | 0.008*** (.000) | 0.005*** (.016) | 0.010*** (.000) | 0.006*** (.002) | 0.002 (.425) | 0.001 (.697) | 0.514*** (.000) | 1.000 |
| MC | 0.006*** (.003) | 0.002 (.363) | 0.003 (.187) | 0.001 (.516) | 0.005* (.012) | 0.007*** (.000) | 0.002 (.363) | 0.002 (.380) | 0.002 (.292) | 0.002 (.339) | -0.001 (.789) | 0.000 (.829) | -0.090** (.000) | -0.198*** (.000) | 1.000 |

Note: This table shows the values of pearson correlations between the variables for the Australian sample of 292,164 firm-daily observations from January 25, 2020 to December 31, 2020: Daily changes in numbers of new COVID-19 infections and deaths (ΔINF, ΔDTH); daily market return on days t (Rt) and t - 1 (Rt-1), absolute value of return on day t (AbsRt), volatility proxied with the trailing 5-day average absolute return (VOL), and stock market capitalization (MC). AI-variables denote dummies representing different Australian government intervention policy measures: school closing (AI1), workplace closing (AI2), closing of public events (AI3), closing of public transportation (AI4), public information campaigns (AI5), restrictions of internal movement (AI6) and international travel controls (AI7). p Values are given in parenthesis and significant results are marked in bold. ***, ** and * denote two-tailed significance at 1%, 5% and 10% level, respectively.
| Dependent variable (QML<sub>i,t</sub>) | Independent variables (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|-------------------------------------|---------------------------|-----|-----|-----|-----|-----|-----|-----|
| A1<sub>1</sub>                      | 0.005** (.020)            |     |     |     |     |     | 0.043** (.023) |
| A1<sub>2</sub>                      | 0.068*** (.000)           |     |     |     |     | 0.141*** (.000) |
| A1<sub>3</sub>                      | 0.031*** (.000)           |     |     |     |     | 0.052*** (.000) |
| A1<sub>4</sub>                      |                           | 0.130*** (.000) |     |     |     | 0.115*** (.000) |
| A1<sub>5</sub>                      |                           |     | -0.105*** (.000) |     |     | -0.135*** (.000) |
| A1<sub>6</sub>                      |                           |     |     | 0.005** (.020) |     |     | 0.052* (.061) |
| A1<sub>7</sub>                      |                           |     |     |     | 0.063*** (.000) |     | 0.018*** (.061) |
| ΔINF<sub>t</sub>                   | 0.019*** (.000)           | 0.029*** (.000) | 0.026*** (.000) | 0.033*** (.000) | 0.020*** (.000) | 0.019*** (.000) | 0.028*** (.000) | 0.022*** (.000) |
| ΔDTH<sub>t</sub>                   | -0.041*** (.000)          | -0.011*** (.000) | -0.035*** (.000) | -0.023*** (.000) | -0.039*** (.000) | -0.041*** (.000) | -0.033*** (.000) | -0.006** (.026) |
| R<sub>t</sub>                      | -0.012*** (.000)          | -0.011*** (.000) | -0.008*** (.000) | -0.005** (.012) | -0.012*** (.000) | -0.012*** (.000) | -0.003 (.172) | -0.018*** (.000) |
| R<sub>t-1</sub>                    | -0.036*** (.000)          | -0.032*** (.000) | -0.032*** (.000) | -0.018*** (.000) | -0.035*** (.000) | -0.036*** (.000) | -0.024*** (.000) | -0.026*** (.000) |
| AbsR<sub>i,t</sub>                 | 0.003 (.209)              | 0.003 (.165) | 0.003 (.189) | 0.003 (.185) | 0.003 (.206) | 0.003 (.209) | 0.003 (.180) | 0.003 (.181) |
| VOL<sub>i,t-1</sub>                | -0.006** (.016)           | -0.005** (.025) | -0.005** (.020) | -0.005** (.020) | -0.006** (.026) | -0.006** (.016) | -0.006** (.018) | -0.005** (.028) |
| MC<sub>i,t-1</sub>                 | 0.005** (.011)            | 0.005** (.008) | 0.005** (.012) | 0.006*** (.004) | 0.005** (.011) | 0.005** (.011) | 0.005** (.009) | 0.006*** (.003) |
| Weekday dummies                    | Yes                       | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R<sup>2</sup>                  | 0.152                     | 0.166 | 0.153 | 0.224 | 0.152 | 0.152 | 0.156 | 0.194 |
| F stat                             | (.000)                    | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) |

Note: This table shows the results of two-way cluster-robust panel regression coefficients (Thompson, 2011) for the dependent variable quoted market liquidity (QML) of the Australian companies for the period January 25, 2020 to December 31, 2020 (292,164 firm-daily observations in each of the specifications). The independent variables are different Australian government intervention policy responses on day t—school closing (A1i), workplace closing (A12), cancelling of public events (A13), closing of public transportation (A14), public information campaigns (A15), restrictions of internal movement (A16) and international travel controls (A17)—with the control variables of: Daily changes in numbers of new COVID-19 infections and deaths (ΔINF, ΔDTH); daily market return on days t (R<sub>t</sub>) and t-1 (R<sub>t-1</sub>), absolute value of return for firm i on day t (AbsR<sub>t</sub>), volatility for firm i proxied with the trailing 5-day average absolute return (VOL), and stock market capitalization (MC) for firm i on day t. The numbers in parenthesis are p values. All the regression specifications include fixed effects and weekday dummies. Adj. R<sup>2</sup> is the adjusted coefficient of determination and F stat denotes the p values associated with the regression F statistic. The asterisks ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.
measures (Specification 8 of Table 4), as opposed to information campaigns, they also display a negative impact on stock market liquidity (high bid–ask spread). To add, the adverse effect of school closures, closed public transport, cancelled public events and restrictions on internal movement could indirectly lead to similar consequences. This can be specifically caused by the increased level of work absenteeism (Viner et al., 2020), or by the possible signals of forthcoming stricter measures (Lindzon, 2020). Furthermore, another reason that may explain the negative impact of workplace and school closures on market liquidity is attributed to the tendency of ignoring bad news, or the “information overload” effect (Agnew & Szykman, 2005). This overload refers to the reluctance of investors to realise losses and to hold losing stocks for long terms. When the above mentioned behaviours coupled with signals of a new upcoming restriction, an initial government response can be perceived by financial investors as a negative sign, and hence can be interpreted as a precursor for economic and financial instabilities. To sum up, our results reveal that COVID-19 containment measures (Specifications 2–8 except for Specification 5) have negative influence on stock market liquidity. This is consistent with several studies (Baig et al., 2021; Ozili & Arun, 2020; Scherf, Matschke, & Rieger, 2022; Yang & Deng, 2021) who find that lockdown policy and government interventions have negative influence on the stock market. Specifically, our findings show the existence of negative spillover effects, as an increase in the government response intensity in Australia leads to a decrease in the stock market liquidity.

We further examine the impact of stringency of government policy responses on stock market liquidity of Australian companies among 11 industries (similar to Gunay & Kurtulms, 2020 in industry classifications). Table 5 reveals different reactions of the stringency measures on stock market liquidity for various industries. Three policy response measures (workplace closing, closed public transport and restrictions on internal movement) for the academic and educational services industry (denoted by A) have significantly negative impact on market liquidity. Consistent with Zaremba, Aharon, et al. (2021), the introduction of stricter measures such as community isolation, stay-at-home and online studying along with the closing public transport have significant effects in reducing market liquidity.

Our findings concerning the basic materials industry (denoted by B) show a significant negative effect on stock market liquidity by all policy responses measures (except for school closing and public information campaigns). As expected, mineral resources like gold (subcategorized under the basic materials industry) are significantly affected by the pandemic. This is consistent with Ji, Zhang, and Zhao (2020) and Akhtaruzzaman, Boubaker, and Sensoy (2021) who show that the role of safe haven becomes less effective for most assets, except for gold and soybean commodity futures which remain robust as safe-haven assets during this pandemic. Unlike the consumer cycicals industry (denoted by C), most of the stringency responses have significantly positive influence on stock market liquidity for firms operating in the non-cycicals industry (denoted by D). Consistent with Nicola et al. (2020) and Huynh, Nguyen, and Dao (2021), the food industry experienced high demand during the pandemic due to panic buying and hoarding of food. According to Alam, Wei, and Wahid (2021), supermarkets and grocery stores earned promising revenue and profits due to panic buying habits.

Furthermore, the policy responses measures, in the energy industry (denoted by E) show a significant negative impact on market liquidity. However, school closing and public information campaigns have insignificant effect. This could be attributed to the negative impact caused by low global demand for oil in 2020 due to government restrictions. Moreover, the decline in demand for petrol was also the result of home quarantine policy that obliges the residents to use their cars less and other mode of transportation vehicles and to cancel their planned flights.
Impact of government policy responses of COVID-19 pandemic on quoted stock market liquidity for Australian companies for each of the 11 industries

| Independent variables | (A) | (B) | (C) | (D) | (E) | (F) | (G) | (H) | (I) | (J) | (K) |
|-----------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| AI1                   | 0.011 (.624) | −0.037*** (.000) | 0.029*** (.000) | 0.025*** (.001) | 0.009 (.131) | 0.024*** (.000) | 0.033 (.708) | 0.018*** (.001) | 0.064*** (.000) | −0.035*** (.000) | 0.021 (.179) |
| AI2                   | 0.219*** (.000) | 0.162*** (.000) | −0.128*** (.000) | −0.134*** (.000) | 0.097*** (.000) | −0.163*** (.000) | −0.188*** (.000) | 0.167*** (.000) | −0.185*** (.000) | −0.198*** (.000) | −0.063 (.155) |
| AI3                   | 0.095 (.152) | 0.050*** (.000) | 0.059*** (.001) | −0.065*** (.001) | 0.057*** (.001) | 0.081*** (.000) | −0.042*** (.006) | 0.056*** (.000) | 0.145*** (.000) | 0.065*** (.000) | −0.031 (.512) |
| AI4                   | 0.119*** (.003) | 0.157*** (.000) | 0.167*** (.000) | −0.176*** (.000) | 0.047*** (.000) | −0.130*** (.000) | −0.154*** (.000) | −0.173*** (.000) | −0.187*** (.000) | −0.180*** (.000) | −0.058 (.042) |
| ΔINFt                 | −0.028 (.202) | −0.014*** (.000) | −0.005 (.450) | −0.002 (.321) | −0.004 (.491) | −0.004*** (.000) | −0.104*** (.000) | 0.115*** (.000) | 0.076*** (.000) | −0.014*** (.000) | 0.09*** (.001) |
| ΔDTHt                 | 0.122*** (.025) | 0.101*** (.000) | 0.084*** (.000) | −0.104*** (.000) | 0.079*** (.000) | −0.087*** (.000) | −0.032*** (.029) | 0.120*** (.000) | 0.076*** (.000) | −0.152*** (.000) | 0.041 (.292) |
| R1t                   | −0.061 (.334) | −0.003 (.678) | 0.045*** (.008) | 0.056*** (.003) | 0.051*** (.002) | 0.062*** (.000) | 0.002 (.229) | 0.056*** (.000) | 0.108*** (.000) | 0.026*** (.025) | 0.033 (.468) |
| Rt_{i-1}              | −0.011 (.703) | −0.023*** (.000) | −0.040*** (.000) | −0.028*** (.002) | 0.001 (.983) | −0.038*** (.000) | −0.039*** (.000) | −0.048*** (.000) | −0.045*** (.000) | −0.036*** (.000) | −0.032 (.124) |
| AbsRt_{i-1}           | −0.007 (.830) | 0.003 (.412) | −0.002 (.837) | 0.003 (.751) | −0.001 (.904) | 0.005 (.404) | 0.002 (.749) | −0.004 (.594) | 0.024** (.028) | 0.004 (.599) | 0.019 (.418) |
| VOLt_{i-1}            | 0.028 (.410) | 0.010*** (.013) | 0.004 (.648) | −0.006 (.576) | −0.032*** (.000) | 0.022*** (.001) | 0.007 (.367) | −0.019*** (.014) | −0.015 (.160) | −0.028*** (.000) | 0.106*** (.000) |
| MCt_{i-1}             | −0.102*** (.001) | 0.003 (.306) | 0.036*** (.000) | 0.102*** (.000) | 0.010 (.197) | −0.099*** (.000) | 0.033*** (.000) | 0.020*** (.002) | −0.108*** (.000) | −0.023*** (.000) | −0.025 (.208) |

| Weekday dummies       | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| No. of Obs            | 1664 | 99130 | 19304 | 19082 | 21866 | 36292 | 25140 | 25752 | 12220 | 32843 | 2871 |

Note: This table shows the results of two-way cluster-robust panel regression coefficients (Thompson, 2011) for the dependent variable quoted market liquidity (QML) of the Australian companies for the period January 25, 2020 to December 31, 2020 in each of the 11 main industries. The independent variables are different Australian government intervention policy responses on day $t$—school closing (AI1), workplace closing (AI2), cancelling of public events (AI3), closing of public transportation (AI4), public information campaigns (AI5), restrictions of internal movement (AI6) and international travel controls (AI7)—with the control variables of: Daily changes in numbers of new COVID-19 infections and deaths ($ΔINF_t$, $ΔDTH_t$); daily market return on days $t$ ($R_t$) and $t-1$ ($R_{t-1}$), absolute value of return for firm $i$ on day $t$ ($AbsR_{t,i}$), volatility for firm $i$ proxied with the trailing 5-day average absolute return (VOL), and stock market capitalization (MC) for firm $i$ on day $t$. The numbers in parenthesis are p values. All the regression specifications include fixed effects and weekday dummies. Adj. $R^2$ is the adjusted coefficient of determination and $F$ stat denotes the p values associated with the regression $F$ statistic. The asterisks ***, ** and * denote significance at 1%, 5% and 10% levels, respectively. Each of the 11 industries denote for: A = Academic & Educational Services; B = Basic Materials; C = Consumer Cyclicals; D = Consumer Non-Cyclicals; E = Energy; F = Financials; G = Healthcare; H = Industrials; I = Real Estate; J = Technology and K = Utilities industries.
The COVID-19 epidemic has severely affected the energy markets due to the disorder of energy supply and demand especially in the first quarter of 2020 (Wang, Yang, & Li, 2022). Our findings are also consistent with Czech and Wielechowski (2021) who observe a significantly negative energy commodity prices’ reaction to the stringency level of the anti-COVID-19 government policy. Various policy responses measures have positive impact on stock market liquidity in the financial industry (denoted by F). This is in line with Mdaghri et al. (2020) who find that the market liquidity in the financial sector has been positively impacted by the stringency measures. It is worth mentioning that many fin-tech companies has performed well during the COVID-19. In this regard, Fu and Mishra (2022) find a significant increases in adoption of finance-related mobile applications as a result of the COVID-19’s spread and government restrictive measures. They suggest that “Bigtech” and fin-tech startups were able to accelerate the acceptance of their digital services over-and-above traditional incumbents who did well in the early stages of the pandemic. Hence, niche and unbundled products (such as pure-play payment and investment apps) appear to have higher relative uptake over time compared to general banking apps (Fu & Mishra, 2022).

Moreover, five out of seven policy responses have significant positive impact on stock liquidity in the healthcare industry (denoted by G). It is obvious that this pandemic yields a positive influence on the performance of this industry. This is associated to the fact of increasing demand for medical equipment and medicine (Alam et al., 2021; Al-Awadhi et al., 2020). According to Huynh et al. (2021), the increased expenditures on medical equipment and research coupled with an expected future spending could raise confidence to invest more in this sector, which in turn enhances its stock market liquidity.

Concerning the industrial industry (denoted by H) which also covers transportation sector, our results shows significantly negative influence on the level of market liquidity by most stringency policy measures. The negative impacts are attributed to the fact that transportation companies lost main profit sources due to the great decline in passenger flow. According to Al-Awadhi et al. (2020), the stock returns of beverages, air transportation, water transportation, and highway transportation sectors performed significantly worse than the market throughout the pandemic. Our results are also consistent with Chebbi et al. (2021) and Alam et al. (2021) who find poor performance of the transportation industry in the stock market due to global travel restrictions caused by COVID-19.

The Real Estate industry (denoted by I) reveals diverse results. Some policy response measures have positive impact on stock market liquidity, while others have negative ones. According to Alam et al. (2021), as new equity investment slows, property companies will struggle to get funding. Therefore, the impact of coronavirus on the real estate industry should not be underestimated. Gunay, Bakry, and Somar (2021) recommend that the regulatory authorities should take actions to support specific sectors, such as real estate.

Regarding the technology industry (denoted by J) that also covers the telecommunication sector, five out of seven policy responses (except cancelled public events and international travel control) have significantly positive influence on stock market liquidity. This positive performance is associated to the increasing demand for distance learning and online working. The consequences of travel restrictions and social distancing have helped in accelerating the development of online connection services which in turn encourage investors to have good prospects for this industry (Huynh et al., 2021). On the other hand, international travel control could affect the performance of the technology industry because of delay to shipments of electronic goods. Finally, most of the government stringency measures have no significant impact on stock market liquidity for firms operating in the utilities industry (denoted by K). The pandemic pushed this industry to extend resilience to the entire value chain.
Overall, the government policy responses of COVID-19 adversely affected stock market liquidity in several Australian industries. Lockdowns, travel restrictions, quarantines and extreme forms of physical distancing across the country have affected different sectors of the Australian economy. However, the magnitudes of the impact vary in different industries. Our findings indicate that government interventions are associated with lower stock market liquidity. The only exception is public information campaigns, which have a positive and significant effect on market liquidity. Consistent with the findings of Zaremba et al. (2020), COVID-19-related information campaigns may motivate investors to restructure their portfolio positions to enhance trading in the market. To add, investors may also rebalance their portfolios to target safer assets in uncertain times. All these activities may result in additional trading, which enhances stock market liquidity. Our results support the Hypothesis 1 that there is a negative impact of the stringency of government policy responses on stock market liquidity of Australian companies. In line to the existing literature (such as Mdaghri et al., 2020; Alam et al., 2021; Gunay et al., 2021; Huynh et al., 2021), our findings reveal that consumer non-cyclicals, healthcare, financials and technology industries perform better than other industries in terms of the impact of government response policies on market liquidity. According to Gunay et al. (2021), the positive impact of the government policy responses in the consumer non-cyclicals was attributed to the panic-buying behaviour. This caused an immense increase in household spendings on non-discretionary products that usually have a low-income elasticity of demand (Funck & Gutierrez, 2018). As people are required to quarantine themselves, information technology is less likely to be affected because it provides services that support remote studying and working. Ramelli and Wagner (2020) argue that travel restrictions and working from home accelerate the development of the telecommunications industry. Therefore, investors may perceive the possible implementation of further policies as good prospects for the telecommunications industry.

The government intervention measures adversely affected market liquidity in the remaining industries (academic and educational services, basic materials, energy and transportation). The negative effect of the pandemic on the transportation industry was mainly caused by the decrease in the number of passengers. As for the energy industry, energy commodity prices react negatively to the stringency level of the anti-COVID-19 government policy. This is attributed to the fact of supply and demand disorder especially after the cancellation of large number of pre-booked flights and the decline in the use of transportation vehicles. In conformity with Corbet, Larkin, and Lucey (2020), Xiong et al. (2020) and Huynh et al. (2021), the response to the COVID-19 outbreak was stronger in industries that are directly vulnerable to the pandemic’s effects. This led investors to have pessimistic views about the market, and caused a decline in trading as well as in share prices. To secure their current financial positions, many investors are trying to liquidate their assets including stocks, which simultaneously distress the stock market performance (Okorie & Lin, 2021). The above results support our Hypothesis 2 that the negative impact of the stringency of government policy responses on stock market liquidity of Australian companies varies among different industries.

To confirm the reliability of our findings, we perform a battery of robustness tests. We change the estimation method by employing the generalised linear model (GLM). We also use the Amihud measure (dependent variable) as an alternative familiar measure to the quoted spread (Amihud, 2002) and replace the seven government stringency responses by the Australian stringency index (ASI). Similar to the QML as a spread measure, a lower value of the Amihud measure implies lower illiquidity (higher liquidity). Table 6 presents the findings for the whole sample and for each industry. The Amihud measure (AMIH) was significantly and
### Table 6 Robustness check

| Dependent variable (AMH<sub>i</sub>, t) | Independent variables | ALL | (A) | (B) | (C) | (D) | (E) | (F) | (G) | (H) | (I) | (J) | (K) |
|--------------------------------------|-----------------------|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|-----|
| ASI<sub>t-1</sub>                    | 0.058*** (.000)       | 0.129*** (.000) | 0.111** (.021) | 0.037** (.035) | -0.017*** (.000) | 0.049*** (.000) | -0.001 (.207) | -0.044*** (.000) | 0.040** (.000) | 0.040*** (.000) | 0.040*** (.000) | 0.040*** (.000) |
| ΔINF<sub>t-1</sub>                   | 0.029*** (.000)       | 0.079** (.023) | 0.022*** (.000) | 0.027*** (.004) | 0.043*** (.000) | 0.035*** (.000) | 0.039*** (.000) | 0.027*** (.001) | 0.043*** (.000) | 0.046*** (.000) | 0.047*** (.000) | 0.057** (.018) |
| ΔDTH<sub>t-1</sub>                   | 0.019** (.026)        | -0.035 (.365) | 0.026*** (.000) | 0.032*** (.001) | -0.052*** (.000) | -0.020** (.028) | 0.044*** (.000) | -0.024*** (.002) | -0.051*** (.000) | 0.019*** (.001) | -0.032*** (.000) | -0.028 (.244)  |
| R<sub>t</sub>                        | -0.004* (.052)        | -0.034 (.243) | -0.005 (.123) | -0.004 (.649) | -0.014 (.124) | -0.004 (.538) | 0.005 (.419) | -0.001 (.916) | -0.005 (.983) | -0.001 (.920) | -0.001 (.860) | 0.010 (.622)  |
| R<sub>t-1</sub>                      | -0.026*** (.000)      | -0.011 (.702) | -0.020*** (.000) | -0.043*** (.000) | -0.013*** (.000) | 0.000 (.986) | -0.038*** (.000) | -0.040*** (.000) | -0.048*** (.000) | -0.045*** (.000) | -0.034*** (.000) | -0.031 (.135) |
| AbsR<sub>t</sub>                     | 0.003 (.179)          | -0.005 (.875) | 0.004 (.337) | -0.003 (.717) | 0.003 (.767) | -0.001 (.934) | 0.005 (.421) | 0.002 (.749) | -0.004 (.576) | 0.020** (.067) | 0.004 (.571) | 0.021 (.356)  |
| VOL<sub>i</sub>, t                   | -0.005** (.019)       | 0.040 (.237) | 0.010** (.012) | 0.006 (.535) | -0.006 (.550) | -0.029*** (.001) | 0.022*** (.001) | 0.001 (.908) | -0.024*** (.002) | -0.022** (.052) | -0.027*** (.000) | 0.106*** (.000) |
| MC<sub>i</sub>, t                     | 0.005*** (.009)       | -0.080*** (.010) | 0.003 (.376) | 0.030*** (.000) | 0.104*** (.000) | 0.011 (.153) | -0.099*** (.000) | 0.033*** (.000) | 0.020** (.019) | -0.115*** (.000) | -0.024*** (.000) | -0.024 (.236) |
| Weekday dummies                      | Yes                   | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Adj R<sup>2</sup>                    | 0.229                 | 0.212 | 0.190 | 0.209 | 0.221 | 0.191 | 0.217 | 0.207 | 0.202 | 0.225 | 0.199 | 0.228 |
| F stat                               | (.000)                | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) | (.000) |
| No. of Obs                           | 292164                | 1664 | 99130 | 19304 | 15082 | 21866 | 36292 | 25140 | 25752 | 12220 | 32843 | 2871 |

**Note:** This table shows the results of the generalised linear model (GLM) estimation for an alternative measure of the dependent variable (AMH) of the Australian companies for the period January 25, 2020 to December 31, 2020 for the whole sample and for each of the 11 main industries. The independent variable was Australian stringency index (ASI) that aggregate different Australian government intervention policy responses—with the control variables of: Daily changes in numbers of new COVID-19 infections and deaths (ΔINF, ΔDTH); daily market return on days t (R<sub>t</sub>) and t − 1 (R<sub>t-1</sub>), absolute value of return for firm i on day t (AbsR<sub>i</sub>), volatility for firm i proxied with the trailing 5-day average absolute return (VOL), and stock market capitalization (MC) for firm i on day t. The numbers in parenthesis are p values. All the regression specifications include fixed effects and weekday dummies. Adj. R<sup>2</sup> is the adjusted coefficient of determination and F stat denotes the p values associated with the regression F statistic. The asterisks ***, ** and * denote significance at 1%, 5% and 10% levels, respectively.
positively associated with the stringency index (ASI) for the whole sample. This suggests that an increase in the stringency measures has adversely affected the stock market liquidity. The industry findings confirm our main model’s results in Table 5. The stringency index measure has a positive impact on stock market liquidity in consumer non-cyclicals, healthcare and technology industries but a negative one in academic and educational services, basic materials, energy, real estate and industrial (transportation) industries. These results are also consistent with Mdaghri et al. (2020) and Alam et al. (2021).

In addition to the above robustness check, we modified the selection and construction of the control variables. For instance, we discarded the weekday dummies and the numbers of COVID-19 infections or deaths, and use raw market capitalization instead of its natural logarithm. Similar to the quoted method in measuring stock market liquidity, we use the effective one (Fong et al., 2017). We also replicated our analysis by running the regression on the dependent variable at day $t+1$ to account for endogeneity issues. For brevity reasons, we did not present the results of the remaining checks. Ultimately, these robustness tests do not qualitatively change our findings about the impact of government policy responses of COVID-19 pandemic on stock market liquidity for listed Australian companies and for their relevant industries.

5 | CONCLUSION

This study assesses the impact of non-pharmaceutical interventions of COVID-19 pandemic on stock market liquidity for all listed Australian companies and among 11 different industries.

Similar to Zaremba, Aharon, et al. (2021), this study considers seven different policy responses in examining the impact of COVID-19 pandemic on stock market liquidity. Our findings indicate that the influences of the six out of seven stringency policy responses intensely deteriorated stock market liquidity of Australian companies (as depicted through higher bid-ask spreads). However, public information campaigns facilitate additional trading and thus enhance market liquidity which is consistent with Zaremba et al. (2020).

In investigating the impact of the seven stringency policy response on market liquidity among 11 industries, our findings show that government responses to the pandemic have significant positive effects on 4 out of 11 industries: consumer non-cyclicals, healthcare, financials and technology. The highest positive impact was detected in the healthcare sector, as the virus enhances the demand for medical equipment. Moreover, the positive impact observed in consumer non-cyclicals industry could be attributed to the general panic-buying and stockpiling behaviour of households during the pandemic. The worse effect was in the industrial (transportation) and energy industries. The negative effect in the energy sector could be attributed to the disorder of energy supply and demand and to the negative prices’ reaction to the stringency measures especially after the cancellation of large number of pre-booked flights and the decline in the use of residents’ cars on a daily basis. Global travel restrictions caused by COVID-19 could be the main cause behind the negative influence on the level of market liquidity by most stringency measures in the industrial (transportation) industry. Our baseline results show how investor confidence changes during the announcement of stringent government responses. Hence, governments should engage in public information campaigns, which are instrumental for incenting greater trading activity in positively impacted sectors such as healthcare and consumer non-cyclicals. The robustness tests especially in using alternative measures (Amihud and stringency index) and estimation method (GLM) confirm our findings about the impact of
government policy responses of COVID-19 on stock market liquidity for Australian companies and their relevant industries.

Our findings hold several practical implications. They confirm the importance of the availability of valuable information to investors to better assess stock market liquidity and shape properly their investment decisions. Therefore, the findings are meaningful for equity investors, companies and governments. Investors and business managers will have a better idea about which sector is riskier amid the spread of the COVID-19 pandemic. Moreover, shareholders and investors will benefit from our findings to appropriately manage the liquidity risk of the stock markets in the short run during comparable conditions (similar to COVID-19 pandemic) to make the best financial decisions. The Australian government may offer assistance and extend policy support, such as tax deductions, or free interest loans to the vulnerable sectors which are suffering the most from the pandemic. In addition, our findings have some implications for policy makers and regulatory authorities. Effective and proactive coordination among governments, central banks and securities regulators may reduce market instabilities and increase investors' confidence during severe events such as COVID-19. The main limitations in this study range from missing data for some dependent and control variables, to the availability of outliers, which reduce the sample size. Our research paves the way for future studies that could focus on examining different waves or separate periods that can affect market liquidity, such as the “Delta” and “Omicron” mutations. Furthermore, when the pandemic ends, researchers can examine the impact of COVID-19 on stock market liquidity and volatility before, during and after the pandemic. Another extension of this research would be to investigate the influence of monetary policies on reducing the impact of COVID-19 on stock market liquidity.

CONFLICT OF INTEREST
The authors declare no conflict of interest.

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

ENDNOTES
1. HTTPS://WWW.BSG.OX.AC.UK/RESEARCH/RESEARCH-PROJECTS/COVID-19-GOVERNMENT-RESPONSE-TRACKER. This database gathers information on numerous and different common policy responses, such as government interventions and stringency of such measures, as well as provides aggregates scores that form a common stringency index. Scores are assigned to each item based on the occurrence and frequency of each one. The index yields a final score between −1 and 0 or 0 and 1 for certain items.
2. The daily data for this index was obtained from the Ourworldindata website.
3. According to Worldometer, the first COVID-19 case in Australia was confirmed on January 25, 2020. Since January 25 and 26, 2020 are weekends and January 27 is a public holiday, we effectively started collecting our data from January 28, 2020.
4. Based on Park (2011), we remove outliers by excluding any value for every variable that is not between the minimum value (Q1 − 3IQR) and maximum value (Q3 + 3IQR).
5. To further test for any possible issue of multicollinearity, we use variance inflation factor (VIF) and tolerance test. All VIF values fall under 5 (Hair, Page, & Brunsveld, 2019) and tolerance levels are more than 0.2 (Field, 2013) The acceptable values of VIF and tolerance confirm that our model does not suffer from multicollinearity problem.
6. Effective spread = \frac{1}{2} \frac{[\text{Bid}_{i,t} - \text{Ask}_{i,t}]}{\text{Ask}_{i,t} + \text{Bid}_{i,t}}.
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