

## **Impact of Coronavirus on liquidity in financial markets**

### **Abstract**

We examine the liquidity impact of the COVID-19 Pandemic upon equity markets in the USA, UK, Brazil, China, Germany and Spain. We establish that the pandemic causes a short-term loss in liquidity, confirmed by the significant increases in bid-ask spreads. Further, analysing long-term financial stability using price impact ratios, shows that for China alone, there is an impact of COVID-19. Also, examination of spread decomposition reveals the role of information asymmetry in the widening of spreads, rather than changes in cost of trading around the news of the pandemic. This finding holds for all of the observed capital markets with the exception of China.

Keywords: COVID-19 Pandemic; Liquidity; Amihud Ratio; Bid-Ask Spread.

JEL Codes: G10.

## **1. Introduction**

One of the most interesting research issues in financial markets concerns market liquidity. How liquidity should be defined, what it connotes and how it should be measured have long been an area of inquiry. Although traders have always adjusted the bid-ask spread to compensate for the risks of taking a position, famously it was Demsetz (1968), using New York Share Exchange data, who was one of the first economists to analyse how the behaviour of traders affects the formation of prices. He argued that while a trader willing to wait might trade at the single price envisioned in the Walrasian framework, a trader not wanting to wait could pay a price for immediacy, i.e., liquidity. More recently, refining the definition of liquidity, according to Liu (2006) a security is *liquid* if large volumes may be traded with little or no price impact. While according to further research, including Amihud and Mendelson (1986a), Amihud (2002), Hasbrouck (2009) and Le and Gregoriou (2020) liquidity is measured across four different dimensions: trading quantity (how much a security can be traded at a given cost), trading speed (how quickly can a share be traded at a certain cost with given quantity), trading costs (all expenses related to the trade of a given quantity of an asset) and price impact (how easy it is to trade a security of a given quantity with minimum impact on price). But how these four dimensions may interact and be incorporated into a comprehensive general equilibrium model, awaits specification. With inevitably limited data to test theories, how shocks and system perturbations impact liquidity is also not well understood. It is for this reason that the global pandemic of 2020-21 presents a particularly interesting opportunity to expand our knowledge of how liquidity responds to secular events.

Reports of virus spreading across the globe began in early 2020. According to Aljazeera (2020), on December 31, 2019, the World Health Organization (WHO) was alerted by China that a virus with pneumonia like symptoms was spreading in the city of Wuhan. Chinese health officials suspected it to be the return of the severe acute respiratory syndrome (SARS) virus-

an illness that originated in China and killed more than 770 people worldwide in 2002-2003. On January 07, 2020, the WHO identified the virus as a member of the coronavirus family which includes SARS and the one causing the common cold, naming it 2019-nCoV. Not surprisingly, given the challenges of quarantining cities, regions and even countries, global trade and travel has led to the COVID virus spreading to nearly every country with great consequences.

As reported by Salo (2020), the WHO declared COVID-19 to be a pandemic during March 2020. Governments across the globe responded by imposing various quarantine measures including the closing of borders, restricting various forms of economic activity such as closing restaurants, limiting density levels in public places like shops and requiring the wearing of personal protection surgical masks. Nor surprisingly, these drastic actions had large impacts upon economic activity particularly in sectors involving travel and social interaction, notably tourism. The combination of economic restrictions and general fears resulted in a 4.7 percent economic contraction across the OECD in 2020. The financial markets were affected as investors/savers become more risk averse, yield curve steepened and businesses facing reduced profitability, cut-back on capital expenditure. As described by Klebnikov (2020), fears grow and savers seek to reduce exposures to particular markets and sectors, liquidating their investments, leading ultimately to falling valuations across capital markets. Falling share volumes signify reduced liquidity and the risk that securities *may* be sold only at significantly lower prices. Without buyers, sellers cannot close positions.

The pandemic and its economic fall-out provides unique opportunity to investigate the impact upon market liquidity in both developed and emerging capital markets. Our study makes the following contributions to the existing literature. First, it is the only paper to examine the impact of the COVID-19 pandemic on liquidity in the USA, Europe and Emerging capital markets. Previous studies on liquidity and COVID-19 have focused on the United States alone

(Just and Echaust, 2020) or the Middle East, Africa and Asian (MENA) nations (Mdaghri et al. 2020). As mentioned above, as liquidity may be defined in different manners, we provide a comprehensive analysis of liquidity during COVID-19 using bid-ask spread measures (see among others, Fong et al. (2017)) as well as the price impact illiquidity ratios of Amihud (2002) and Florackis et al. (2011). Previous studies have either looked at short term liquidity (Mdaghri et al. 2020) or long-term financial stability (Just and Echaust, 2020). Finally, following Zhang and Gregoriou (2020), we investigate the impact on liquidity of COVID by decomposing the spread into adverse selection, inventory holding and order processing cost components using the Huang and Stoll (1997) model. Critically, our research presents an objective means of predicting the financial consequences of the pandemic which may assist investors in achieving a well-allocated portfolio in light of liquidity risk. While from a regulatory perspective, our research has implications for how bank portfolios are stressed and the adequacy of risk capital.

Our empirical results show that upon the financial performance of capital markets in the EU and Latin America the pandemic has had the largest impact. In the short run, the bid-ask spread and the illiquidity ratios have increased for all of the indices except China but in the long run the Hong Kong and Shanghai exchanges face severe liquidity issues. Interestingly, when we decompose the bid-ask spread, we observe that the increases in bid-ask spreads are due to the adverse selection component for all of the indices, except for China. Notwithstanding the above concerns, our research shows the strength of global capital markets in coping with this unique secular stressful event.

The remainder of the paper is organized in the following way. The next Section reviews the previous literature. Section 3 discusses the data and methods employed. Our empirical results are reported in Section 4. We conclude, in Section 5 by reviewing our major findings while drawing attention to policy implications.

## **2. Literature Review**

Already many empirical studies have been conducted investigating the influence of Coronavirus pandemic outbreaks on capital markets and the greater economy. The literature to date, roughly falls into three categories:

- Research examining the micro-effects of the pandemic shock employing various liquidity related metrics;
- Research analysing how the pandemic shocks precipitated changes between markets and asset classes; and
- Researchers appraising the overall effect of the pandemic upon financial institutions.

Investigating the micro-effects of the pandemic in a study involving 320 listed firms operating in six MENA countries from February to May 2020, Mdaghri, et al. (2020) found that bid-ask spreads widened while the liquidity of shares declined as measured by the depth and tightness of markets fell. Building upon the classic work of Demsetz (1968) in which the bid-ask spread is framed as a form of transaction costs, Wang et al. (2020), examining the effects of the pandemic, used relative rather than absolute spreads on several indices. In the research of Gormsen and Kojien (2020) dividend futures on the aggregate share market were used to directly compute a lower bound on growth expectations across maturities. Using dividend futures, the expected return in excess of risk-free bonds increased because of the pandemic, as markets responded quickly to negative expectations of growth. Zhang et al. (2020) state that the pandemic led to an increase in the volatility of share markets though ironically, some domestic policies may have amplified such phenomena. Looking at earlier events, researchers Huang and Heian (2010) and Douch, et al., (2018) have examined the effect of secular shocks upon trading volume. In this vein, Baker, et al. (2020) comparing the 2019

pandemic with previous pandemics, discover that impact upon share markets was much smaller than that under COVID-19, as would be expected given that the ownership of securities per capita was historically lower. According to Baker et al., policy actions and regulations play a greater role in explaining the fall in share prices rather than the virus itself although such policies would not have been enacted without the pandemic. Barro et al. (2020) compared the effects of Coronavirus and Spanish Flu and found as mortality climbs, real returns on securities, especially on short-term government bills fell. Looking at the role of expectations, Papadamou et al. (2020) using panel data analysis, report that internet searching for topics related to COVID-19 was associated with panic behaviour increasing risk-aversion and volatility in the share market. As we can see from this sampling of research, according to various liquidity related metrics, bid-ask spread, market depth, returns and volatility, the shock of the 2019 pandemic affected global capital markets in diverse manners.

The pandemic also led to changes between markets and asset classes as well as changes between securities within an asset class. Like the 2008 financial crisis when we saw previously low correlated asset classes now moving in tandem under stress conditions, reducing the scope for diversification, similar phenomena were observed in response to the pandemic (Gao and Mei, 2019). As was observed in response to the 2008 shocks, asset classes which may have had low linear correlation proved to have high degrees of non-linear correlation, reducing scope for diversification and risk mitigation. Similarly, during the pandemic, it was found that secular shocks like Covid precipitated changes to the correlation structure between asset classes (Kinatader, Campbell and Choudhury 2021). According to research by Bouri, et al., (2021) during the COVID pandemic returns across different securities becoming more “connected”. Similarly, in research by Ali et al. (2022) using the wavelet-based Granger causality approach, it was established that that the oil and share indices have less co-movement on a smaller scale but greater movement on a larger scale across all periods. In addition, the same researchers

found significant bidirectional causality from oil to stock markets. In addition to correlation structures, “volatility spill-over effects” were also observed in security markets, where greater risk in one market leads to greater risks in other markets (Shahzad, et al., 2021). Naturally, adjusted for non-diversifiable risk all securities should earn the same returns and thus it is intuitive that a pandemic induced change in one asset class should lead to changes for others. So called, volatility “spill-over” is a form of transmission of risk across sectors and prevalent during crisis, the after-math of shocks. According to Laborda and Olmo (2021) the effects of the pandemic were first felt in the banking and insurance, energy, technology and biotechnology sectors before rippling-out causing secondary shocks across the rest of the economy. For purposes of contrast, during the 2007-2009 financial crisis, matters began with disturbances to the banking sector while the energy sector was first to be affected by the COVID pandemic, as consumption of petroleum particularly in the transport sector decreased. Health Care and Pharmaceuticals sectors, as is well known, benefited from the pandemic seeing upward adjustments to the quantity and quality of returns. Firms selling personal protection equipment and disinfectants saw sales climb sharply in 2020-21. Most notably, the world’s largest retailer, Amazon, gained handsomely from the pandemic for well-known reason (John Harris, 2020). Though no general inferences or “theory” of how shocks are transmitted between markets or sectors or asset classes has been formalised, clearly in a modern economy, the combination of specialisation and network effects, means no sector or market is isolated.

Looking lastly at sectoral and macro effects of the pandemic has also been a fruitful area of research. Given the aforementioned shocks within and between asset classes, it is not surprising that the pandemic negatively affected the performance of financial institutions. For instance, in Boot et al. (2020) the impact of the pandemic upon the banking industry was investigated. Greater correlation between securities and even asset classes, reduces scope for risk mitigation. Faced with greater risk exposure and reduced liquidity, banks pursue a de-

risking strategy. Such pro-cyclic effects were also seen during the 2008 financial crisis and led to the Basel III counter-cyclic capital buffer (<https://www.bankofengland.co.uk/financial-stability>). In this vein, Fernandes (2020) examined how COVID-19 impacts the industries and the economic potential across 30 countries providing insights into how long it would take for the effects of the pandemic shock to dissipate in terms of GDP and sectoral effects. Comparing traded markets, in a study by Chatjuthamard, et al. (2021) it was shown that an increase in the growth rate of the number of confirmed cases increases market volatility and jumps while reducing return. The intuition here is that while traders generally welcome market volatility as it may present opportunities (Haar and Gregoriou, 2021), systematically profiting from purely non-predictable chaotic events, is not possible. Interestingly, the same authors (op cit., 2021) found that the impact of COVID-19 on market volatility was weaker in emerging markets and countries with greater sovereign risk. In such markets, the impact of the pandemic is amplified presumably because there is less scope for fiscal measures (“automatic stabilisers”) and macro policy intervention. This finding mirrors the work of Zaremba et al. (2021) in research on the impact of lock-downs on financial markets and economic activity according to which it was shown that COVID-19-related restrictions may adversely influence the trading environment of financial markets with the largest effects in emerging markets. In general, it has been shown, as studied by Elnahass, Trinh and Li (2021) the performance of the financial sector fell sharply, reducing stability through enhanced default risk while the liquidity of banking assets fell. Altogether, from the above literature exploring the relationship between market conditions, notably liquidity and secular events like the latest pandemic, it appears that impacts upon financial markets can be anticipated although how this perturbation is manifested, its magnitude and persistence remains to be explored. Recognising this “gap” in the present research, focus upon the micro-effects and in particular, the extent to which the concurrence of



the COVID pandemic reduced liquidity, according various metrics in the financial markets of USA, UK, China, Brazil, Germany and Spain.

### **3. Data and Methods**

#### *3.1. Data*

Our sample consists of the benchmark indices of the USA, UK, China, Brazil, Germany and Spain, namely the S&P 500, FTSE100, SHCOMP, IBOVESPA, DAX and IBEX 35. As indicators of conditions in equity markets, all of these indices have merit. Incorporating the 500 largest companies listed on various US exchanges, the S&P 500 is followed globally and is widely viewed as a key indicator of market conditions. Representing approximately 80% of the total trading volume of the London Share Exchange, the FTSE100 is another important index and may provide insights into how pandemic affected the liquidity of financial markets. The Shanghai Composite Index (SHCOMP) is constructed upon the daily price performance of the A-shares and B-shares of, the largest of the three mainstream indices representing Chinese share markets. Following around 50 shares traded on the Sao Paulo Share, Mercantile & Futures Exchange, the IBOVESPA Index denotes the benchmark of a key emerging markets- Brazil. The Brazilian index incorporates around 80% of the total trading volume during the last 12 months and captures the movement of shares being traded on at least 80% of the trading days.

The German index, DAX, representing the performance of the 30 blue-chip companies traded on the Frankfurt Share Exchange, is the most widely used measure of shares traded in Europe's largest economy. Lastly, the IBEX 35 index consists of the 35 most liquid shares of the Madrid Share Exchange. In addition to examining the performance of the above indices, to further investigate the abnormal returns and volume impact, we collect MSCI World Index data, as it comprises the performance of the global large and mid-cap companies and often

considered as an indicator for the world share market. For each index, for a period of [-60, +60] days around March 11, 2020, we collected the daily closing price for each index. We used March 11, 2020 as the event date, as that is when the WHO declared COVID-19 as a pandemic (Salo, 2020). From this data, to calculate our liquidity metrics, we computed value-weighted daily bid and ask prices, trading volume, number of shares traded and number of shares outstanding for each index. All the data was obtained from Thomson Reuters DataStream.

### 3.2. Methods

#### 3.2.1. Event Study

Turning on how liquidity may be measured, to investigate the effects of the pandemic, we have calculated the daily abnormal returns (ARs) for each of the six indices for event periods from [-5 to +5] in the short run and up to [-60, +60] in the long run around the pandemic announcement date, March 11, 2020 by the WHO. There are alternative models for computing abnormal returns such as the Capital Asset Pricing Model (CAPM) of Treynor (1961, 1962,) Sharpe (1964) and Lintner (1965). Given its well-known assumptions, there are several limitations to the CAPM model including, inter alia, that it does not account for the compensation of value premium for risk as articulated by Fama and French (1993, 2004). Thus, following Zhang and Gregoriou (2020), we use the econometric market-adjusted model in order to calculate the abnormal returns:

$$AR_{i,t} = R_{i,t} - R_{m,t} \quad (1)$$

Where,  $AR_{i,t}$  represents the abnormal return of the index  $i$  at time  $t$ .  $R_{i,t}$  represents the return on index  $i$  at time  $t$  and  $R_{m,t}$  represents the value-weighted market return (MSCI World Index) at time  $t$ .

### 3.2.2. Trading Volume Effects

In addition to returns, we also examined trading volume effects as a means of measuring liquidity. Events such as Brexit or the global pandemic provide unique opportunities to see how markets in terms of trading volume respond to secular shocks. Like Huang and Heian (2010) or Douch, et al., (2018) who looked at trading volume effects for earlier events, we sought to see the response to the pandemic. Looking at the effects of the COVID pandemic and in particular the response to WTO announcement of March 11<sup>th</sup>, 2020, we use the approach of Gregoriou (2015) and compute the impact on trading volume for each of the six indices namely S&P 500, FTSE 100, SHCOMP, IBOVESPA, DAX and the IBEX 35 using the following regression model with a ten-day window [-5, +5], which proved to have the most statistically significant results.

$$Volume_{jt} = \alpha_j + \sum_{-5}^{+5} D_i \beta_i + \varepsilon_{jt} \quad \text{for } j = 1,6 \quad (2)$$

and  $t = -5, +5$

Where, the dependent variable,  $Volume_{jt}$ , represents the logarithm of the trading volume for index  $j$  at time  $t$ . The constant,  $\alpha_j$ , shows the variation in trading volume.  $D_i$  represents the dummy variables for each trading day in the event window [-5, +5]. The coefficient of the eleven dummy variables,  $\beta_i$ , represents the impact on the abnormal trading volume of the pandemic over the event period and is the main concern of the regression model.  $\varepsilon_{jt}$  is a random disturbance term with a mean of zero and a variance of  $\sigma^2$ .

### 3.2.3. Liquidity measures

#### Relative Spread

In addition to trading volume, many researchers have focused upon direct measures of market liquidity. In our research we have used three such metrics:

- Relative Spread
- Spread Decomposition; and
- Price Impact Ratios

We begin by explaining how we looked at Relative Spreads. Although market returns and trading volumes are regarded as manifestations of changes to market liquidity, bid-ask spreads, essentially the transaction cost of a trade, as first proposed by Demsetz (1968), are widely seen as key indicators of liquidity. Following Chordia et al. (2001), bid-ask spread represents the difference between the highest price a buyer is willing to pay for the asset and the lowest price the seller is willing to accept for it. Although tautological, as bid-ask widens, the transaction cost of executing a trade will mean that the frequency of trading will be lower and as a result asset liquidity will decrease. Arguably, the wider bid-ask spread is the risk adjusted compensation for taking a position. The less liquid market, the wider the spread and thus should be related to the aforementioned “abnormal returns”. According to Madhavan et al. (1997) the price impact of a trade is critical to understanding pre-trade and post-trade analysis and introduces a framework to assess the market price of liquidity risk. Accordingly, while the absolute bid-ask spread may not be useful in measuring an investor’s trading costs, the relative spread overcomes this disadvantage, hence following Wang et al. (2020), we compute the relative spread of the six indices around the 60 days pre- and post- the pandemic announcement date, March 11, 2020 by the WHO using the following equation:

$$RS_{i,t} = \frac{A_{i,t} - B_{i,t}}{(A_{i,t} + B_{i,t})/2} \quad (3)$$

Where  $RS_{i,t}$  represents the relative spread of index  $i$  at time period  $t$  and  $A_{i,t}$  is the ask price of index  $i$  at time  $t$ .  $B_{i,t}$  denotes the bid price of index  $i$  at time period  $t$ .

As a further means of measuring liquidity, we have implemented and estimated the Huang and Stoll (1997) model to decompose the *effective spread*, (Effective spread = 2

(transaction price - mid price) According to the model, we define the trader indicator as Q, Q=1 if a transaction is buyer (low) initiated, Q= - 1 if it is seller initiated (high) and Q=0 if the transaction occurs at the midpoint. Therefore, the three-way decomposition model is:

$$E(Q_{t-1}|Q_{t-2})=(1-2\pi)Q_{t-2} \quad (4)$$

$$\Delta \text{Mid-Point} = (\alpha+\beta)\frac{S_{t-1}}{2}Q_{t-1}\alpha\frac{S_{t-2}}{2}Q_{t-2}(1-2\pi)+\varepsilon_t \quad (5)$$

Where the spread of index i at time t is indicated by S.  $\pi$  is the probability of a trade flow reversal. The midpoint of the bid-ask spread of share i at time t is indicated by Mid. The adverse selection and inventory holding cost attributes are captured by the coefficients  $\alpha$  and  $\beta$ . Since  $\alpha$  and  $\beta$  are stated as proportions, the order processing component equal to  $1-(\alpha+\beta)$ .  $\frac{S_{t-1}}{2}$  is the half-spread at time t-1. The public information component is captured by  $\varepsilon_t$ .

Lastly, to understand the impact of secular shocks upon liquidity, we use Price Impact Ratios. By definition, shocks are highly infrequent, secular perturbations from outside the economic system (e.g., natural catastrophes) making analysis of their persistence very challenging. According to Le and Gregoriou (2020) analysing the impact upon liquidity in terms of bid-ask spread is best applied to short-term effects while for longer terms effects of shocks, metrics based on daily returns and volume are viewed as appropriate. In light of the above, and as our data set incorporates time series analysis, we have applied the Amihud (2002) illiquidity ratio, RtoV, to the six indices:

$$RtoV = \frac{1}{D_i} \sum_{d=1}^{D_i} \frac{|R_{i,d}|}{V_{i,d}} \quad (6)$$

Where,  $|R_{i,d}|$  and  $V_{i,d}$  represent the absolute return and monetary volume of index i on day d respectively and  $D_i$  is the number of trading days for index i. The limitations of the illiquidity ratio RtoV should be noted: According to extensive research the Amihud illiquidity ratio involves size biasedness, since the monetary volume being used is directly correlated with

market capitalisation. To overcome this, Florackis et al. (2011) introduced a new liquidity measure RtoTR which controls for size biasedness:

$$RtoTR = \frac{1}{D_i} \sum_{d=1}^{D_i} \frac{|R_{i,d}|}{TR_{i,d}} \quad (7)$$

Where,  $TR_{i,d}$  represents the turnover ratio of index  $i$  at day  $d$ ,  $D_i$  and  $R_{i,d}$  are the same as the Amihud ratio shown in equation (6).  $RtoTR_i$  does not involve any size biasedness as monetary volume is replaced by the turnover ratio. This is because there is no significant association between turnover and market capitalization.

### Multivariate Regression Analysis

In order to investigate how other exogenous factors besides the pandemic announcement, per se, affected market liquidity, we used the following multivariate time-pooled regression model as employed by Gregoriou (2015),

$$Liquidity_{jt} = \alpha_j + \beta_1 D_t + \beta_2 Volume_{jt} + \beta_3 (Volume_{jt} * D_t) + \beta_4 Close_{jt} + \beta_5 StdDev_{jt} + \varepsilon_{jt} \quad (8)$$

for  $j = 1$  to  $6$  and  $t = -60, +5$

Where, the dependent variable,  $Liquidity_{jt}$ , represents Relative Spread, RtoV and RtoTR respectively for index  $j$  at time  $t$ . The constant,  $\alpha_j$ , shows the variation in the liquidity ratios of the index.  $D_t$  represents the dummy variable which is equal to 1 in the post pandemic announcement period, and zero otherwise. Volume, Close and StdDev (Standard Deviation) represent the traded volume, closing price and return volatility for index  $j$  at time period  $t$  for each trading day in the event window  $[-60, +5]$ .

## **4. Empirical Results**

### *4.1. Descriptive Statistics*

In Table 1, we display the average of the descriptive statistics of the six world indices namely S&P 500, FTSE 100, SHCOMP, IBOVESPA, DAX and IBEX 3 over the period [-60, +60] surrounding the pandemic announcement date, March 11, 2020 by the WHO. We report that over the 121-day period, among the six countries, the USA has the strongest index with an average market capitalisation of £20.40 trillion. When compared, however, with the other five countries over the period, the USA had the second largest fall in the average closing index (2,366,03). On the other hand, among the six countries, China has the second largest share market value with an average market capitalisation of £3.77 trillion. However, China has experienced the lowest average closing price (327.30) among the six indices. Notably, the average volume (25,057.36 trillion) of the Chinese capital markets is the largest with the lowest average relative spread (0.013).

Our findings show that despite a fall in the closing price index, the liquidity of the Chinese capital market is superior to the other indices justified by the trading volume and spread. The most volatile index over the period is Brazil with a 1.41% average standard deviation and the largest average relative spread (0.037). US equity markets experience the smallest risk (0.32%) and the second lowest spread (0.0204). A reason for this can be that the capital market of the USA is considered the world leader, suggesting the best financial stability. During our sample, the pharmaceutical companies of the S&P 500 started to develop the vaccine, which has caused the share prices of them to increase leading to an overall index gauge from the pandemic.

**[INSERT TABLE 1 HERE]**

*4.2. Abnormal Returns*

Table 2 reports the abnormal returns of the six indices, S&P 500, FTSE 100, SHCOMP, IBOVESPA, DAX and IBEX 35, for a period of [-60, +60] around the pandemic announcement date, March 11, 2020 by the WHO. The table shows significant negative returns for the USA (-1.00 %) and Brazil (-4.97 %) on the event day with a t statistic of -4.44 and -3.44, respectively, significant at the 1% level. The largest positive return (3.30%) on the event day has been experienced by Spain with a 5.31 t statistic, significant at all conventional levels. As markets moved forward from the pandemic, the negative returns being experienced by the USA tend to improve. For instance, the average abnormal return over the [-60, +60] period for the USA capital market is 0.04%. A major cause for this can be that the S&P 500 includes the pharmaceutical companies, which are heavily invested in producing the vaccine for the virus causing the share price of these companies to increase and hence pulling the index up. However, China has experienced a decrease in returns over the pandemic period. For instance, over the [-1, +1] day period, the average abnormal returns of SHCOMP are 3.09% with a t statistic of 2.56. As China is the epicentre of the virus, panic sales have led to a fall in the share price of the index.

The table also shows that over the period, the European and Latin American financial markets have experienced consecutive negative returns. For instance, during the [-1, +1] period, the average abnormal returns (t statistics) for the FTSE 100, IBOVESPA, DAX and IBEX 35 are -1.72% (-3.00), -1.63% (-1.13), -1.82% (-2.77) and -3.03% (-4.86) respectively. The negative returns of the FTSE 100, DAX and IBEX 35 are significant at the 1% level. During the [-60, +60] period, the average abnormal returns (t statistics) for the FTSE 100, IBOVESPA, DAX and IBEX 35 are -0.13% (-0.22), -0.16% (-0.11), -0.0003% (-0.005) and -0.13% (-0.20) respectively. This shows that the magnitude as well as the significance of the



negative returns for the European and Latin American countries tend to improve in the long run. As these countries are more invested in tourism and the locked down measures has banned international travel, hence the markets of these regions plummeted in the short run. As the long run period started to approach, the countries slowly started to open up while maintaining the health and safety measures causing the public to gain market confidence and share prices of the companies to improve. The table also reflects that the returns of all nations, except China tend to improve in the long run.

**[INSERT TABLE 2 HERE]**

#### *4.3. Trading Volume Effects*

Table 3 observes the impact on trading volume of the six indices namely, S&P500, FTSE100, SHCOMP, IBOVESPA, DAX and IBEX35 for a period of [-60, +60] surrounding the COVID-19 pandemic announcement date, March 11, 2020 by the WHO. The coefficients show that in the short run, the impact on trading volume has the greatest influence on Germany (t test on day +1 is 2.89, significant at the 1% level). The effect on volume of Germany tends to persist following the pandemic announcement. The table also reports that in the long run, there is no significant impact on trading volume after the pandemic announcement for any country in our sample.

**[INSERT TABLE 3 HERE]**

#### *4.4. Liquidity Measures*

Table 4 shows the average of the liquidity measures of the six world indices, namely the S&P500, FTSE100, SHCOMP, IBOVESPA, DAX and IBEX35 for a period of [-60, +60] surrounding the COVID-19 pandemic announcement date, March 11, 2020 by the WHO. From Panel A, we observe that the relative bid-ask spread is positive and significant in most cases. This provides evidence that the pandemic has decreased the liquidity in equity markets,

resulting in less market efficiency. In China, however, equity markets conditions more or less recovered from the impact of COVID-19, sixty days after the event. This suggests that the share market in China recovered more quickly from the impact of COVID. This could be because the pandemic entered China before the rest of the world, and also due to the fact that they had fewer deaths from the virus.

Panel B displays the results of the RtoV price impact ratio. We observe that all equity markets have significant RtoV ratios as a result of COVID-19. The results suggest that the pandemic did not have significant price impact in the UK, Germany, Brazil and Spain. Arguably, this result is because even though they were significantly different from zero, the magnitude of the ratios was relatively small. However, in the USA and China the price impact ratios were greater than 1. Given that RtoV is an illiquidity ratio, this implies that equity markets in the USA and China possess significant price impacts as a result of COVID-19. In both the USA and China, the share price movement continued for up to 60 days post the pandemic.

Panel C shows the findings of the RtoTR price impact ratio. We observe that once we account for the firm size bias in RtoV, the USA equity market does not provide evidence of significant price movement due to the pandemic. In China, the price impact persists for up to 60 days after the event news.

The fall in liquidity as a result of the pandemic for the USA, UK, China, Brazil, Germany and Spain could be linked to volatility spillovers. Laborda and Olmo (2021) report that the effects of the pandemic spills over from the banking industry to the rest of the economy. Our results provide evidence of volatility spillovers across nations, as the escalation in volatility as a result of the pandemic in one country, leads to an increase in uncertainty across the global economy (Shahzad, et al., 2021). This is because Chatjuthamard, et al. (2021)

provide evidence that a rise in the number of confirmed COVID-19 cases enhances market volatility and jumps. Also, Zaremba et al. (2021) report that COVID-19-related restrictions including lockdowns may adversely affect the trading volume in financial markets.

**[INSERT TABLE 4 HERE]**

#### *4.5. Spread Decomposition*

We next examine results for Spread Decomposition and see in Table 5 the effective spread decomposition findings for the six indices, namely, the S&P500, FTSE100, SHCOMP, IBOVESPA, DAX and the IBEX35 for a period of [+1, +60]. According to the results with the exception of China, adverse selection components of all the indices show significance. On the other hand, the inventory holding component shows significance except for Germany. We observe that the inventory holding cost is more responsible for increases in spread for the USA, UK, China and Brazil whereas adverse selection is more important for Spain. Moreover, it shows that China has performed well with respect to the other indices, indicating again that China is able to overcome the pandemic crisis better than the other nations in our sample although to put matters in context, US share markets are ten-times the size of those of China and therefore it is not surprising that smaller markets can respond and correct themselves more quickly.

**[INSERT TABLE 5 HERE]**

#### *4.6. Multivariate Regression*

We estimate equation (8) in order to determine if the liquidity of share markets in the respective countries has decreased when we incorporate the volume, closing index and risk of the indices. Panel A of Table 6 shows that the coefficients of the dummy variable  $\beta_1$  is negative for all of the indices except for China (0.01) and Brazil (0.17). This shows that the spread has increased over the event period. The increase in spread does not have a significant impact on the USA (t statistic: -1.64) and China (t statistic: 0.64). The largest index being affected by the

pandemic is the UK, with the highest significance level (t statistic of 5.43, significant at the 1% level). The coefficient of the dummy variable,  $\beta_3$ , shows negative values for China and Brazil indicating that trading volume is less affected for these indices. This again validates that the trading volume of the other indices are more widely affected, resulting a fall in liquidity. When price impact has been taken into account in Panel B and Panel C, the coefficient of the dummy variable  $\beta_1$  is positive for Brazil. As the RtoV and RtoTR are illiquidity ratios, a positive coefficient indicates a decrease in liquidity. The coefficients of the dummy variable  $\beta_3$ , is negative for China and Brazil for both cases.

**[INSERT TABLE 6 HERE]**

## **5. Conclusion**

Though one cannot anticipate when the next secular shock to global markets will transpire, in light of our findings, it is helpful to understand the long-term impact of the COVID pandemic upon financial markets? We have examined the impact of the COVID-19 pandemic on the liquidity of the major financial markets using a sample of a period of 121 days using the indices of USA, UK, China, Brazil, Germany and Spain. Our analysis shows that during the pandemic the impact upon returns and trading volume was the greatest for European and Latin America, as measured by respective indices when we estimate relative spreads, we observe that in all equity markets a decrease in liquidity was observed following the pandemic. The exception is China, where the liquidity effect disappears from 10 to 60 days, post the announcement of the pandemic but as noted above, in relation to the scale of its economy and absolute size, its share capitalisation is less than Japan and one-tenth that of the United States.<sup>1</sup>

---

<sup>1</sup> The fact that between the American Exchange, Nasdaq and the New York Stock Exchange, just before the pandemic began, there were 156 Chinese companies listed on these U.S. exchanges with a total market capitalization of \$1.2 trillion, should also be noted in how we interpret these results.

Using price impact ratios, however, to capture long run financial stability and eliminate size bias, we have also discovered that China alone exhibits long run liquidity issues. According to our results, the pandemic caused a short-term loss in liquidity, observed by a significant impact upon bid-ask spreads. When we look at long run financial stability, however, through price impact ratios, only China is affected by the impact of COVID-19. Moreover, when we decomposed the spread, it shows that the adverse selection component was more important for all indices except China. Our findings should be qualified by the extent to which different exchanges have different trading limits as set by local regulators and central banks as well as the scope for hedging index exposures. Examining the relationship between the depth of the futures markets and the Index liquidity might be an interesting area for future research.

Finally, our results enhance our understanding of the cost/liquidity hypothesis. But apart from learning the reaction of markets to this unique event, COVID-19, can we draw any general inferences which may inform policy making on how to handle future shocks?

From a policy perspective, the key issue is, the impact upon financial institutions, insurance companies, pension funds, private equity groups all of which trade equities and whether they are affected by the changes in market liquidity. We should ask if firms exposed to equity market shocks, have sufficient capital to withstand such events. As is well known, through the various Bank for International Settlement Accords (“Basel”), the quantity and quality of capital required of financial institutions has been sharply increased. In addition to having sufficient risk capital, under Basel III, to tackle the issue of liquidity, two new ratios linking the assets of a bank to its liabilities were introduced: The Liquidity Coverage Ratio (LCR) and the Net Stable Funding Ratio (NSFR). These are not requirements to hold capital against tail-risk in liquid form. Rather, the two ratios specify the relationship between the assets

and the liabilities of a bank to ensure a ratio of liquid assets to expected cash flow as well as having more liquid assets and more stable funding. Under NSFR, banks must weight their assets according to the ability to liquidate them in a stressed market and on the liability side weighting funding according to its likelihood of being withdrawn.

From a policy viewpoint, it is useful to consider if these two initiatives that emerged from the 2008 financial crisis and designed to redress market illiquidity, proved helpful during the COVID pandemic? During the 2008 crisis, the inability to close a position without great costs because of reduced liquidity, led to great losses. The Value at Risk assumptions of five-day without cost liquidation window, proved erroneous. In our research findings we have seen in detail how liquidity by various measures has changed across global equity markets but were any institutions trading in these markets threatened with insolvency? Were there systemic risks from the observed changes to liquidity? Critically, were these two new liquidity ratios useful during the COVID pandemic? Or more generally, were financial institutions better able to bear the impact of reduced liquidity in equity markets. From a policy standpoint, having analysed the nature and extent of liquidity shocks arising from the pandemic, exploring in future research how financial institutions themselves were affected, might be useful and informative.

## References

- Ali, S.R.M., Mensi, W., Anik, K.I., Rahman, M. and Kang, S.H., 2022. The impacts of COVID-19 crisis on spillovers between the oil and stock markets: Evidence from the largest oil importers and exporters. *Economic Analysis and Policy*, 73, pp.345-372
- Aljazeera. 2020. Timeline: How the new coronavirus spread. *Aljazeera*.
- Amihud, Y. and Mendelson, H., 1986. Asset pricing and the bid-ask spread. *Journal of financial Economics*, 17(2), pp.223-249.
- Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, 5(1), pp.31-56.
- Baker, S.R., Bloom, N., Davis, S.J., Kost, K.J., Sammon, M.C. and Viratyosin, T., 2020. *The unprecedented stock market impact of COVID-19* (No. w26945). national Bureau of economic research.
- Bank of England. 2021. Financial Stability. *Bank of England*
- Barro, R.J., Ursúa, J.F. and Weng, J., 2020. *The coronavirus and the great influenza pandemic: Lessons from the “spanish flu” for the coronavirus’s potential effects on mortality and economic activity* (No. w26866). National Bureau of Economic Research.
- Boot, A.W., Carletti, E., Haselmann, R., Kotz, H.H., Krahnert, J.P., Pelizzon, L., Schaefer, S.M. and Subrahmanyam, M.G., 2020. *The coronavirus and financial stability* (No. 78). SAFE Policy Letter.
- Bouri, E., Cepni, O., Gabauer, D. and Gupta, R., 2021. Return connectedness across asset classes around the COVID-19 outbreak. *International Review of Financial Analysis*, 73, p.101646.

Chatjuthamard, P., Jindahra, P., Sarajoti, P. and Treepongkaruna, S., 2021. The effect of COVID-19 on the global stock market. *Accounting & Finance*, 61(3), pp.4923-4953.

Chordia, T., Subrahmanyam, A. and Anshuman, V.R., 2001. Trading activity and expected stock returns. *Journal of financial Economics*, 59(1), pp.3-32.

Demsetz, H., 1968. The cost of transacting. *The quarterly journal of economics*, 82(1), pp.33-53.

Douch, M., Edwards, T.H. and Soegaard, C., 2018. The trade effects of the Brexit announcement shock. *Warwick Economics Research Papers*, 1176.

Douch, M., Edwards, T.H. and Soegaard, C., 2018. The trade effects of the Brexit announcement shock. *Warwick Economics Research Papers*, 1176.

Elnahass, M., Trinh, V.Q. and Li, T., 2021. Global banking stability in the shadow of Covid-19 outbreak. *Journal of International Financial Markets, Institutions and Money*, 72, p.101322.

Fama, E.F. and French, K.R., 2004. The capital asset pricing model: Theory and evidence. *Journal of economic perspectives*, 18(3), pp.25-46.

Fernandes, N., 2020. Economic effects of coronavirus outbreak (COVID-19) on the world economy.

Florackis, C., Gregoriou, A. and Kostakis, A., 2011. Trading frequency and asset pricing on the London Stock Exchange: Evidence from a new price impact ratio. *Journal of Banking & Finance*, 35(12), pp.3335-3350.

Fong, K.Y., Holden, C.W. and Trzcinka, C.A., 2017. What are the best liquidity proxies for global research? *Review of Finance*, 21(4), pp.1355-1401.



- Gao, H.L. and Mei, D.C., 2019. The correlation structure in the international stock markets during global financial crisis. *Physica A: Statistical Mechanics and its Applications*, 534, p.122056.
- Gormsen, N.J. and Kojien, R.S., 2020. Coronavirus: Impact on stock prices and growth expectations. *The Review of Asset Pricing Studies*, 10(4), pp.574-597
- Gregoriou, A., 2015. Market quality of dealer versus hybrid markets for illiquid securities: new evidence from the FTSE AIM Index. *The European Journal of Finance*, 21(6), pp.466-485.
- Haar, L. and Gregoriou, A., 2021. Risk management and market conditions. *International Review of Financial Analysis*, 78, p.101959.
- Harris, J., 2021. Combatting Covid-19. Or, “All Persons Are Equal but Some Persons Are More Equal than Others?”. *Cambridge Quarterly of Healthcare Ethics*, 30(3), pp.406-414
- Hasbrouck, J., 2009. Trading costs and returns for US equities: Estimating effective costs from daily data. *The Journal of Finance*, 64(3), pp.1445-1477.
- Huang, R.D. and Stoll, H.R., 1997. The components of the bid-ask spread: A general approach. *The Review of Financial Studies*, 10(4), pp.995-1034.
- Huang, Z. and Heian, J.B., 2010. Trading-volume shocks and stock returns: An empirical analysis. *Journal of Financial Research*, 33(2), pp.153-177.
- Just, M. and Echaust, K., 2020. Stock market returns, volatility, correlation and liquidity during the COVID-19 crisis: Evidence from the Markov switching approach. *Finance Research Letters*, 37, p.101775.
- Kinateder, H., Campbell, R. and Choudhury, T., 2021. Safe haven in GFC versus COVID-19: 100 turbulent days in the financial markets. *Finance Research Letters*, 43, p.101951.

Klebnikov, S. 2020 The Share Market Is In Free Fall On Coronavirus Fears. How Much Worse Will It Get? Forbes

Laborda, R. and Olmo, J., 2021. Volatility spillover between economic sectors in financial crisis prediction: Evidence spanning the great financial crisis and Covid-19 pandemic. *Research in International Business and Finance*, 57, p.101402.

Le, H. and Gregoriou, A., 2020. How do you capture liquidity? A review of the literature on low-frequency stock liquidity. *Journal of Economic Surveys*, 34(5), pp.1170-1186.

Lintner, J., 1965. Security prices, risk, and maximal gains from diversification. *The journal of finance*, 20(4), pp.587-615.

Liu, W., 2006. A liquidity-augmented capital asset pricing model. *Journal of financial Economics*, 82(3), pp.631-671.

Madhavan, A., Richardson, M. and Roomans, M., 1997. Why do security prices change? A transaction-level analysis of NYSE stocks. *The Review of Financial Studies*, 10(4), pp.1035-1064.

Mdaghri, A.A., Raghbi, A., Thanh, C.N. and Oubdi, L., 2020. Stock market liquidity, the great lockdown and the COVID-19 global pandemic nexus in MENA countries. *Review of Behavioral Finance*.

Papadamou, S., Fassas, A., Kenourgios, D. and Dimitriou, D., 2020. Direct and indirect effects of COVID-19 pandemic on implied stock market volatility: Evidence from panel data analysis.

Salo, J. 2020. World Health Organization declares coronavirus a pandemic. *NEW YORK POST*

Shahzad, S.J.H., Naeem, M.A., Peng, Z. and Bouri, E., 2021. Asymmetric volatility spillover among Chinese sectors during COVID-19. *International Review of Financial Analysis*, 75, p.101754.

Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, 19(3), pp.425-442.

Treynor, Jack L.1962. Toward a Theory of Market Value of Risky Assets. Unpublished manuscript. Subsequently, published as Chapter 2 of Korajczyk (1999).

Wang, A., Hudson, R., Rhodes, M., Zhang, S. and Gregoriou, A., 2021. Stock liquidity and return distribution: Evidence from the London Stock Exchange. *Finance Research Letters*, 39, p.101539.

Zaremba, A., Aharon, D.Y., Demir, E., Kizys, R. and Zawadka, D., 2021. COVID-19, government policy responses, and stock market liquidity around the world: A note. *Research in International Business and Finance*, 56, p.101359.

Zhang, D., Hu, M. and Ji, Q., 2020. Financial markets under the global pandemic of COVID-19. *Finance research letters*, 36, p.101528.

Zhang, S. and Gregoriou, A., 2020. Post earnings announcement drift, liquidity and zero leverage firms: Evidence from the UK stock market. *Journal of Business Research*, 116, pp.13-26.

**Table 1. Descriptive Statistics**

The following table represents the mean of the mentioned descriptive statistics of the 7 world indices namely S&P 500, FTSE 100, SHCOMP, IBOVESPA, DAX and IBEX 35 for the period of [-60, +60] surrounding the COVID-19 pandemic announcement date, March 11, 2020 by the World Health Organization (WHO).

	<b>S&amp;P 500</b>	<b>FTSE 100</b>	<b>SHCOMP</b>	<b>IBOVESPA</b>	<b>DAX</b>	<b>IBEX 35</b>
<b>Market Capitalisation (£trillion)</b>	20.3962	1.7527	3.7741	0.5135	0.9468	0.4443
<b>Closing Index</b>	2,366.0344	6,563.2334	327.3049	1,6270.2204	1,0239.0147	70,46.9640
<b>Volume(trillion)</b>	768.4063	1024.9768	25057.3568	903.4534	126.5470	320.8106
<b>Daily Standard Deviation of</b>						
<b>Return(%)</b>	0.0032	0.0074	0.0105	0.0141	0.0078	0.0074
<b>Bid-Ask Spread</b>	0.0204	0.0247	0.0131	0.0374	0.0221	0.0232

**Table 2. Abnormal Returns around the COVID-19 pandemic announcement date, March 11, 2020**

The following table represents the Average Abnormal Returns (AAR) of the 7 world indices, namely, S&P500, FTSE100, SHCOMP, IBOVESPA, DAX and IBEX35 for a period of [-60, +60] surrounding the COVID-19 pandemic announcement date, March 11, 2020 by the World Health Organization (WHO). The AAR has been calculated using the market model. The t test represents the t-statistic which has been computed following the standard event study methodology. The null hypothesis is that AAR is equal to unity. (\*\*significance at 1%, \*\*significance at 5% and \*significance at 10%.)

	<b>S&amp;P 500</b>	<b>FTSE 100</b>	<b>SHCOMP</b>	<b>IBOVESPA</b>	<b>DAX</b>	<b>IBEX 35</b>
<b>0</b>	-0.998%	1.922%	2.929%	-4.972%	3.289%	3.304%
<b>T test</b>	-4.4420***	3.3516***	2.4227**	-3.4373***	5.0019***	5.3069***
<b>[-1,+1]</b>	0.513%	-1.720%	3.093%	-1.629%	-1.820%	-3.028%
<b>T test</b>	2.2846**	-3.0003***	2.5579**	-1.1259	-2.7669***	-4.8631***
<b>[-2,+2]</b>	0.912%	-2.130%	1.243%	-0.618%	-2.235%	-2.364%
<b>T test</b>	4.0578***	-3.7143***	1.0279	-0.4269	-3.3988***	-3.7973***
<b>[-5,+5]</b>	0.080%	-1.108%	1.255%	-2.547%	-1.144%	-0.982%
<b>T test</b>	1.7476	-1.9327	1.0376	-1.7604	-1.7395	-1.5779
<b>[-10,+10]</b>	0.080%	-0.338%	0.601%	-0.878%	-0.125%	-0.238%
<b>T test</b>	0.3578	-0.5888	0.4967	-0.6069	-0.1907	-0.3820
<b>[-30,+30]</b>	0.071%	-0.232%	0.109%	-0.824%	-0.165%	-0.334%
<b>T test</b>	0.3173	-0.4042	0.0906	-0.5698	-0.2505	-0.5368
<b>[-60,+60]</b>	0.037%	-0.125%	-0.001%	-0.159%	-0.003%	-0.125%
<b>T test</b>	0.1641	-0.2183	-0.0011	-0.1100	-0.0046	-0.2014

**Table 3. Trading Volume around the COVID-19 pandemic announcement date, March 11, 2020**

The sample consists of the 7 world indices, namely, S&P500, FTSE100, SHCOMP, IBOVESPA, DAX and IBEX35 for a period of [-60, +60] surrounding the COVID-19 pandemic announcement date, March 11, 2020 by the World Health Organization (WHO). The effect on the trading volume has been examined using the following regression model for a period of [-60, +60] surrounding the event day, March 11, 2020 to investigate the short term and long-term impact on the trading volume. The period of [-5, +5] has been reported for the most significant results.

$$\text{Volume}_{jt} = \alpha_j + \sum_{i=-5}^{+5} D_i \beta_i + \mathcal{E}_j \quad \text{for } j = 1,7 \text{ (representing 7 indices in the order respectively) and } t = -60, +5$$

Where, the dependent variable,  $\text{Volume}_{jt}$ , represents the logarithm of the trading volume for index  $j$  at time  $t$ . The constant,  $\alpha_j$ , shows the variation in trading volume.  $D_i$  represents the dummy variables for each trading day in the event window [-5, +5]. The coefficient of the eleven dummy variables,  $\beta_i$ , represents the impact on the abnormal trading volume of the pandemic over the event period and is the main concern of the regression model.  $\mathcal{E}_j$  is a random disturbance term with a mean of zero and a variance of  $\sigma^2$ . (\*\*significance at 1%, \*\*significance at 5% and \* significance at 10%.)

	<b>S&amp;P 500</b>	<b>FTSE 100</b>	<b>SHCOMP</b>	<b>IBOVESPA</b>	<b>DAX</b>	<b>IBEX 35</b>
<b><math>\alpha_j</math></b>	20.3861	20.6378	23.9118	20.5515	18.5562	19.4684
<b><i>T test</i></b>	583.7979***	464.7821***	1045.6100***	588.1463***	464.1505***	427.6031***
<b><math>\beta_{-5}</math></b>	0.1795	0.1834	0.3685	-0.0013	0.2576	0.2632
<b><i>T test</i></b>	0.4639	0.3726	1.4656	-0.0034	0.5817	0.5218
<b><math>\beta_{-4}</math></b>	0.2456	0.1728	0.6031	0.0210	0.2592	0.4552
<b><i>T test</i></b>	0.6352	0.3511	2.4363**	0.0541	0.5854	0.9044
<b><math>\beta_{-3}</math></b>	0.4079	0.3751	0.3948	0.3456	0.5369	0.3699
<b><i>T test</i></b>	1.0580	0.7634	1.5727	0.8946	1.2183	0.7341
<b><math>\beta_{-2}</math></b>	0.6128	0.8196	0.5310	0.5579	0.9888	0.8202
<b><i>T test</i></b>	1.5991	1.6838	2.1328**	1.4522	2.2779**	1.6423
<b><math>\beta_{-1}</math></b>	0.4891	0.6180	0.4764	0.4782	0.8551	0.6452
<b><i>T test</i></b>	1.2712	1.2632	1.9064	1.2417	1.9591	1.2864
<b><math>\beta_0</math></b>	0.4563	0.4720	0.3640	0.3390	0.6431	0.5457
<b><i>T test</i></b>	1.1849	0.9621	1.4477	0.8774	1.4633	1.0860
<b><math>\beta_{+1}</math></b>	0.7023	0.8646	0.2305	0.3578	1.2369	1.0527
<b><i>T test</i></b>	1.8386	1.7773	0.9119	0.9264	2.8851**	2.1235**
<b><math>\beta_{+2}</math></b>	0.6631	0.7514	0.4065	0.6323	1.0546	0.5730
<b><i>T test</i></b>	1.7334	1.5409	1.6201	1.6499	2.4368**	1.1407
<b><math>\beta_{+3}</math></b>	0.6357	0.8087	0.3661	0.4259	0.9785	0.8923
<b><i>T test</i></b>	1.6602	1.6689	1.4561	1.1044	2.2530**	1.7906
<b><math>\beta_{+4}</math></b>	0.6304	0.7326	0.2250	0.5784	0.6588	0.5527
<b><i>T test</i></b>	1.6460	1.5015	0.8901	1.5065	1.4995	1.0999
<b><math>\beta_{+5}</math></b>	0.6148	0.6797	0.1738	0.6934	0.5996	0.4152
<b><i>T test</i></b>	1.6044	1.3913	0.6866	1.8136	1.3627	0.8246

**Table 4. Liquidity Ratios around the COVID-19 pandemic announcement date, March 11, 2020**

Table 4 represents the average of the liquidity measures of the 7 world indices, namely S&P500, FTSE100, SHCOMP, IBOVESPA, DAX and IBEX35 for a period of [-60, +60] surrounding the COVID-19 pandemic announcement date, March 11, 2020 by the World Health Organization (WHO). The liquidity measures are the Relative Spread, RtoV and RtoTR price impact ratios. Relative Spread is calculated as ask minus bid divided by the midpoint of the bid-ask spread. RtoV is calculated the absolute daily stock return divided by the monetary volume. RtoTR is computed as the absolute daily stock return divided by the turnover ratio. The ratios are tested using a standard t-test with a null hypothesis stating that the mean of the reported ratio is equal to unity. Two tailed tests of significance are reported as( \*\*\*significance at 1%, \*\*significance at 5% and \*significance at 10% level.)

$$RS_{i,t} = \frac{A_{i,t} - B_{i,t}}{(A_{i,t} + B_{i,t})/2} \quad RtoV = \frac{1}{D_i} \sum_{d=1}^{D_i} \frac{|R_{i,d}|}{V_{i,d}} \quad RtoTR = \frac{1}{D_i} \sum_{d=1}^{D_i} \frac{|R_{i,d}|}{TR_{i,d}}$$

*Panel A: Relative Spread*

	<i>S&amp;P 500</i>	<i>FTSE 100</i>	<i>SHCOMP</i>	<i>IBOVESPA</i>	<i>DAX</i>	<i>IBEX 35</i>
<i>0</i>	0.0428	0.0381	0.0139	0.1319	0.0351	0.0467
<i>T test</i>	55.3433***	67.2122***	1.7786	191.2465***	48.9011***	84.6590***
<i>[-1,+1]</i>	0.0555	0.0677	0.0198	0.1391	0.0583	0.0763
<i>T test</i>	76.4922***	138.6499***	11.6240***	203.1808***	95.7477***	154.3813***
<i>[-2,+2]</i>	0.0594	0.0759	0.0229	0.1383	0.0625	0.0758
<i>T test</i>	82.9285***	158.5104***	16.8770***	201.8157***	104.1023***	153.1729***
<i>[-5,+5]</i>	0.0552	0.0619	0.0239	0.1123	0.0536	0.0626
<i>T test</i>	75.9359***	124.6945***	18.5885***	158.9376***	86.1649***	121.8962***
<i>[-10,+10]</i>	0.0520	0.0558	0.0219	0.0944	0.0497	0.0535
<i>T test</i>	70.6626***	109.9389***	15.2666***	129.3723***	78.3160***	100.5826***
<i>[-30,+30]</i>	0.0300	0.0336	0.0167	0.0539	0.0293	0.0305
<i>T test</i>	34.0626***	56.1672***	6.4852***	62.6524***	37.2856***	46.4375***
<i>[-60,+60]</i>	0.0204	0.0247	0.0131	0.0374	0.0221	0.0232
<i>T test</i>	18.0550***	34.7633***	0.3850***	35.4432***	22.7244***	29.0805***

*Panel B: RtoV*

	<i>S&amp;P 500</i>	<i>FTSE 100</i>	<i>SHCOMP</i>	<i>IBOVESPA</i>	<i>DAX</i>	<i>IBEX 35</i>
<i>0</i>	0.6837	2.1451	0.0986	19.9196	0.0529	0.0831
<i>T test</i>	27.2442***	5.1881***	-9.4915***	40.7237***	-14.3505***	-12.3547***
<i>[-1,+1]</i>	0.8567	5.2731	0.3380	28.7330	3.8213	16.9930
<i>T test</i>	37.2438***	32.1469***	-2.3805***	64.9817***	10.6848***	32.8046***
<i>[-2,+2]</i>	1.0286	5.4663	0.4374	29.7571	4.2008	19.6534
<i>T test</i>	47.1868***	33.8125***	0.5725	67.8005***	13.2059***	39.9096***
<i>[-5,+5]</i>	0.8561	4.8929	0.3750	23.1422	3.8344	16.9086
<i>T test</i>	37.2111***	28.8706***	-1.2816	49.5935***	10.7717***	32.5792***
<i>[-10,+10]</i>	0.6325	4.6225	0.3737	17.6222	3.5931	14.4127
<i>T test</i>	24.2829***	26.5399***	-1.3181	34.4002***	9.1686***	25.9138***
<i>[-30,+30]</i>	0.4539	3.7596	0.3998	10.8355	3.7632	12.0754
<i>T test</i>	13.9574***	19.1028***	-0.5437	15.7206***	10.2982***	19.6719***
<i>[-60,+60]</i>	0.3493	3.3049	0.3116	8.6873	3.6214	11.2214
<i>T test</i>	7.9089***	15.1836***	-3.1636***	9.8078	9.3564***	17.3911***

Panel C: *RtoTR*

	S&P 500	FTSE 100	SHCOMP	IBOVESPA	DAX	IBEX 35
<b>0</b>	12.8426	3.3848	0.3801	9.2684	0.0450	0.0340
<i>T test</i>	27.1607***	1.8452	-9.4518***	29.7820***	-14.6238***	-12.5144***
<b>[-1,+1]</b>	15.6854	7.8859	1.2881	12.5576	3.0879	6.6374
<i>T test</i>	36.0032***	22.2327***	-1.6780	45.4406***	6.2509***	23.1398***
<b>[-2,+2]</b>	18.8438	8.4063	1.6700	13.0701	3.5043	7.8058
<i>T test</i>	45.8270***	24.5899***	1.5913	47.8809***	9.1079***	29.4483***
<b>[-5,+5]</b>	15.8739	7.5840	1.4403	10.1283	3.1994	6.7431
<i>T test</i>	36.5894***	20.8653***	-0.3750	33.8754***	7.0159***	23.7105***
<b>[-10,+10]</b>	11.7441	7.1174	1.4303	7.6802	3.0039	5.8132
<i>T test</i>	23.7441***	18.7518***	-0.4605	22.2209***	5.6753***	18.6892***
<b>[-30,+30]</b>	8.6872	6.0476	1.4931	4.8486	3.3398	5.0643
<i>T test</i>	14.2358***	13.9060***	0.0764	8.7404***	7.9795	14.6458***
<b>[-60,+60]</b>	6.8832	5.5049	1.1698	3.9658	3.3327	4.7314
<i>T test</i>	8.6245***	11.4480***	-2.6912***	4.5380***	7.9304***	12.8485***

**Table 5. Spread Decomposition around the COVID-19 pandemic announcement date, March 11, 2020**

Table 5 represents the value-weighted components of the bid-ask spread for the S&P500, FTSE100, SHCOMP, IBOVESPA, DAX and IBEX35 indices, estimated 60 days after the pandemic announcement period (March 11, 2020). We use the Huang and Stoll (1997) three-way decomposition model to represent the adverse selection ( $\alpha$ ) and inventory costs components ( $\beta$ ). Two tailed tests of significance are reported as \*\*\*significance at 1%, \*\*significance at 5% and \*significance at 10%.

	S&P 500	FTSE 100	SHCOMP	IBOVESPA	DAX	IBEX 35
<b><math>\alpha</math>(%)</b>	0.0511%	-0.0397%	0.0697%	0.0241%	-0.0596%	-0.0738%
<i>T test</i>	2.3254***	-2.2526**	1.2980	0.7899	-4.6372***	-4.3784***
<b><math>\beta</math>(%)</b>	-0.0161%	-0.0144%	-0.4268%	-0.0064%	-0.0090%	-0.0066%
<i>T test</i>	-3.7649***	-2.5320***	-6.7749***	-3.4557***	1.3739	2.7927***

**Table 6. Multivariate Regression around the COVID-19 pandemic announcement date, March 11, 2020**

Table 6 represents the average of the multivariate regression model of the 7 world indices, namely S&P500, FTSE100, SHCOMP, IBOVESPA, DAX and IBEX35 for a period of [-60, +60] surrounding the COVID-19 pandemic announcement date, March 11, 2020 by the World Health Organization (WHO). The following regression model has been used for a period of [-60, +5] surrounding the event day to determine whether the average market liquidity of the stocks deteriorates following the COVID-19 pandemic announcement date by the WHO. In addition, the model tests if the slope coefficient on trading volume has changed following the pandemic announcement. The model states as:

$$Liquidity_{jt} = \alpha_j + \beta_1 D_t + \beta_2 Volume_{jt} + \beta_3 (Volume_{jt} * D_t) + \beta_4 Close_{jt} + \beta_5 StdDev_{jt} + \epsilon_{jt} \quad \text{for } j = 1,7 \text{ (representing 7 indices in the order respectively) and } t = -60, +5$$

Where, the dependent variable,  $Liquidity_{jt}$ , represents Relative Spread, RtoV and RtoTR respectively for the stock  $j$  at time  $t$ . The constant,  $\alpha_j$ , shows the variation in the liquidity ratios as per the index.  $D_t$  represents the dummy variable which is equal to 1 in the post pandemic announcement period, otherwise 0. Volume, Close and StdDev (Standard Deviation) represent the traded volume in shares, closing price and return volatility for the index  $j$  at time period  $t$  for each trading day in the event window [-60, +5]. The coefficient,  $\beta_1$  and  $\beta_3$  captures the impact of the pandemic on the liquidity as well as on the volume and is of main concern. (\*\*significance at 1%, \*significance at 5% and .significance at 10%.)

*Panel A: Relative Spread*

Var	S&P 500	FTSE 100	SHCOMP	IBOVESPA	DAX	IBEX 35
C	0.1141	0.1711	0.0614	0.1280	0.1284	0.2284
<i>T test</i>	3.8816***	5.2518***	2.1755***	3.0075***	3.3357***	8.7153***
$\beta_1$	-0.0649	-0.1433	0.0128	0.1681	-0.0418	-0.0322
<i>T test</i>	-1.6395	-5.4311***	0.4020	4.2255***	-2.7138***	-2.4982***
$\beta_2$	0.1480	0.1790	0.0051	0.0663	0.4130	0.0673
<i>T test</i>	3.6974***	4.2409***	4.4623***	0.5062	1.4029	0.9377
$\beta_3$	0.6060	0.7570	-0.0348	-0.9160	1.6300	0.5570
<i>T test</i>	2.0147***	5.4108***	-0.0355	-3.3511***	3.4489***	2.7489***
$\beta_4$	-0.4620	-0.2270	-0.0190	-0.0580	-0.1090	-0.2710
<i>T test</i>	-4.1134***	-5.5609***	-2.2122***	-3.3890***	-3.4022***	-8.7633***
$\beta_5$	1.5205	-0.3516	0.0669	0.9900	0.5901	0.4363
<i>T test</i>	5.7982***	-1.8582	0.6966	6.1655***	3.7382***	3.3834***

*Panel B: RtoV*

Var	S&P 500	FTSE 100	SHCOMP	IBOVESPA	DAX	IBEX 35
C	3.2798	22.9389	3.4336	38.0523	32.8288	135.0518
<i>T test</i>	4.6311***	3.0660***	2.3934***	3.0655***	3.5055***	4.8510***
$\beta_1$	-1.0747	-22.1532	-0.0599	36.9785	-13.3906	-56.7649
<i>T test</i>	-1.1271	-3.6552***	-0.0370	3.1877***	-3.5758***	-4.1455***
$\beta_2$	-0.0180	0.0572	-0.0115	-0.0838	-0.0626	-0.0203
<i>T test</i>	-1.8677	0.5902	-1.9682	-2.1943***	-0.8744	-2.6658***
$\beta_3$	0.0744	0.1190	-0.2560	-0.2440	0.0411	0.8000
<i>T test</i>	1.0254	3.7036***	-0.5135	-3.0558***	3.5857***	3.7170***
$\beta_4$	-0.1202	-0.0278	-0.9104	-0.1501	-0.2584	-0.1505
<i>T test</i>	-	-2.9603***	-2.0875***	-3.0060***	-3.3009***	-4.5776***
	4.4456***					
$\beta_5$	42.0783	-164.0278	30.4638	413.6703	-137.8712	-215.2889
<i>T test</i>	6.6590***	-3.7752***	6.2387***	8.8339***	-3.5903***	-1.5718



Panel C : *RtoTR*

<b>Var</b>	<b>S&amp;P 500</b>	<b>FTSE 100</b>	<b>SHCOMP</b>	<b>IBOVESPA</b>	<b>DAX</b>	<b>IBEX 35</b>
<b>C</b>	61.8809	38.7225	11.1510	18.3161	27.4809	60.0198
<b>T test</b>	4.2717***	2.7440***	2.1240***	2.6148***	2.8537***	4.4172***
<b><math>\beta_1</math></b>	-16.2163	-33.8771	-0.2135	15.7259	-11.8732	-25.0745
<b>T test</b>	-0.8314	-2.9635***	-0.0360	2.4024***	-3.0834***	-3.7520***
<b><math>\beta_2</math></b>	-0.0345	0.0525	-0.4070	-0.0436	-0.6030	-0.0102
<b>T test</b>	-1.7539	0.2873	-1.9050	-2.0252***	-0.8192	-2.7389***
<b><math>\beta_3</math></b>	0.1000	0.1740	-0.0931	-0.1170	0.3500	0.3280
<b>T test</b>	0.6746	2.8682***	-0.5101	-2.6056***	2.9640***	3.1263***
<b><math>\beta_4</math></b>	-0.0224	-0.0458	-0.0290	-0.0677	-0.2108	-0.6599
<b>T test</b>	-4.0547***	-2.5904***	-1.8195	-2.4027***	-2.6192***	-4.1120***
<b><math>\beta_5</math></b>	783.8610	-256.3534	110.9412	196.5922	-114.7856	-93.9113
<b>T test</b>	6.0645***	-3.1281***	6.2082***	7.4397***	-2.9069***	-1.4049