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LIQUIDITY OF FUTURES MARKETS OVER THE LAST QUARTER OF A CENTURY: TECHNOLOGY & MARKET STRUCTURE VERSUS ECONOMIC INFLUENCES

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Abstract

This study examines the major technological and market forces that have acted on the liquidity of futures markets over almost the last quarter of a century – equivalent to Professor Robert Webb's tenor as Editor-in-Chief at the *Journal of Futures Markets*. We examine the impact of electronic trading replacing open outcry, the impact of high frequency trading and co-located trading, compare the liquidity impacts of these developments with the impact of major economic events, including the Global Financial Crisis and Covid-19 Pandemic. Using a stock index futures contract traded on Australian futures exchanges as an example, we find that technological advances have had a statistically significant but almost imperceptible influence on measures of liquidity of Australian futures contracts. In contrast, economic crises, and crashes such as the Global Financial Crash and the Covid-19 crash have had a massive and sustained impact on the liquidity of futures markets. Our results suggest that liquidity effects from technological innovations, while important, remain dwarfed by those from extreme outlier events.

JEL Classification: G12, G13, G15

Keywords: Futures markets, Liquidity, Market microstructure, Economic crises, Technology improvements.

1. Introduction

The last quarter century has seen remarkable growth in the trading of options and futures contracts. In 1998, around 2 billion contracts[1] were traded on exchanges. In contrast, in 2021, the total number of options and futures contracts traded on exchanges reached nearly 62.58 billion contracts[2] – representing a massive 3,000 percent increase or more than 100 percent per year. The stock index futures contract traded on the Sydney futures exchange, which we examine as a case study in this paper, has also had a very large increase in notional volume. In 1998, notional turnover of the contract

[1] We compute this from data and percentage increase in 1999 retrieved from https://www.fia.org/articles/2005-volume-survey-shows-futures-and-options-surge.

[2] https://www.fia.org/articles/2005-volume-survey-shows-futures-and-options-surge.

was $134 billion Australian dollars while last year it was $1,251 billion Australian dollars – an 833 percent increase or roughly 35 percent per year[3].

This huge growth in the significance of futures markets has been accompanied by enormous technological change – including the introduction of electronic trading by futures exchanges. In turn, this innovation itself has spawned the introduction of high frequency and algorithmic trading, and co-located trading to facilitate such activity. Furthermore, the last 24 years has witnessed two events that can truly be called black swans – the Global Financial Crisis and the Covid-19 Pandemic. In this paper, we will assess the impact of all these factors on the liquidity of markets. The analysis demonstrates that despite the 'revolutionary' changes in technology that have impacted markets, the effect of these factors on the *raison d'etre* of markets – liquidity – has been minuscule. In contrast, the extreme outlier events with enormous economic impact have had massive impacts on liquidity.

The remainder of this paper is structured as follows. The next section will discuss the evidence surrounding the introduction of major technological changes and their impact on markets. This is followed by a section which examines the impact that the outlier events with economic impact have had. The following section examines the liquidity of futures markets over the last 24 years and compares the impact of technology versus the market outlier events. A final part concludes.

2. Technology & Liquidity of Futures Markets

One of the most profound changes to futures markets over the last 24 years has been the scrapping of open outcry trading on floors around the world, and their replacement with screen trading. Gone are the loud trading floors with traders wearing coloured jackets aggressively gesticulating to each other in the hopes of getting a trade. In their place we now have people sitting neatly in rows on trading floors of the major broking houses silently entering trades.

2.1. The Beginning of the End

Here we describe marketwide liquidity measures and data required. We use the aggregate market liquidity measures in three markets including stock market, corporate bond market and Treasury market.

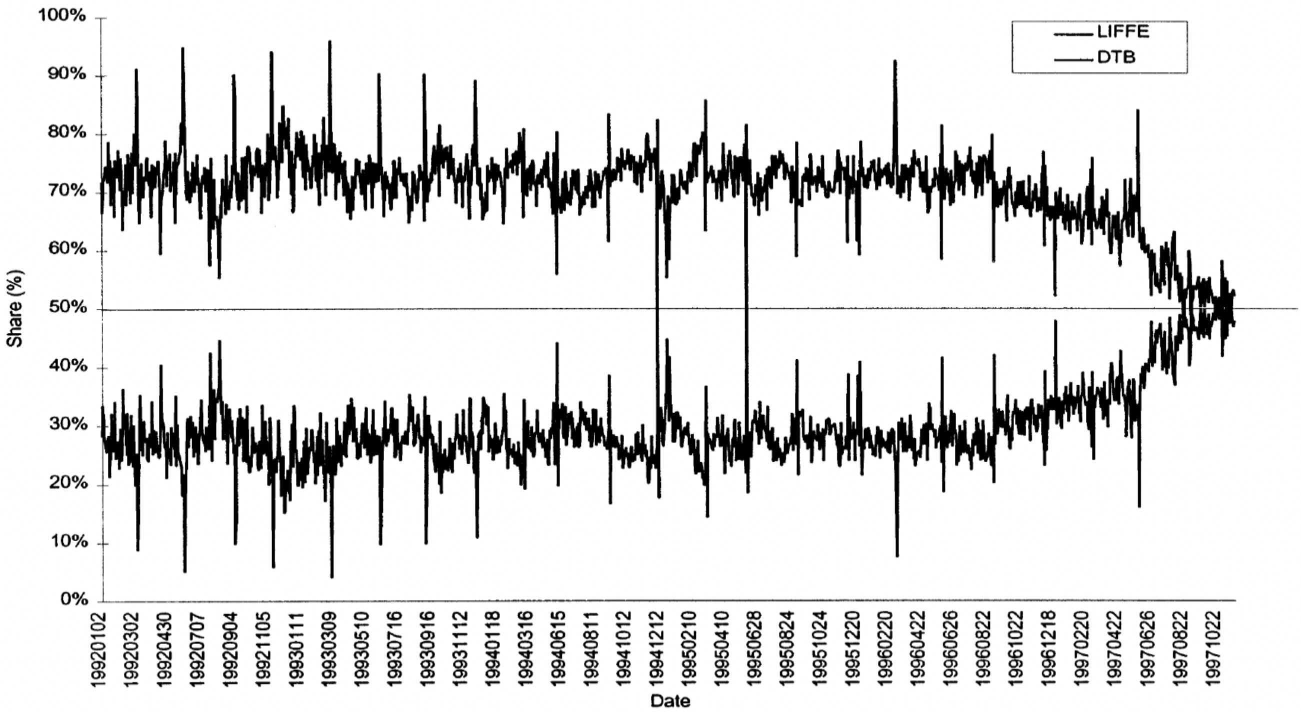
One of the first futures exchanges in the world to go fully electronic was the German futures exchange known at the time as the Deutsche Terminbörse (DTB). The DTB listed German Bund futures, which at the time were also listed on the London International Financial Futures Exchange (LIFFE). For many years, LIFFE enjoyed the majority of the market share in bund, however, late in 2007 something breath-taking started to happen. With a little persuasion from German regulatory authorities at the time, volume started shifting from LIFFE to the DTB. This development, which is illustrated in Extract 1 below, not only made the world stand up and take notice of electronic trading. Although commonplace today, it was widely criticised at the time as being unable to provide the "colour" required for efficient market clearing processes to work. Importantly, this change provided the first like for like comparison between traditional and electronic trading. In October 1997, when the volumes traded on LIFFE and the DTB were roughly the same, we had a natural experiment which could be used to fairly compare liquidity in the two market mechanisms.

This was a challenge taken up by Frino, McInish and Toner (1998) who examined the bid-ask spreads of Bunds traded on LIFFE and the DTB for 30 days in October and November 1997 when volume traded

[3] Computed as $\sum_{i=1}^{n}$ *Mid-Price* * *Volumes* * $25 from Refinitiv data, in each minute interval throughout all the observations within the year.

on each market was approximately the same and found that bid-ask spreads on the German electronically traded market were approximately 5 to 10 percent less than those traded on LIFFE. Sounds large – but according to statistics published in the paper the average bid-ask spread of the product was roughly 1 basis point or 25 marks at the time. Thus, the improvement in pricing of the contracts was approximately 5 to 10 percent of 1 basis point. While this sounds small, given the billions of dollars traded daily in bunds on the markets at the time, it represented transactions cost savings to liquidity demanders who would have otherwise traded on the LIFFE to the tone of 30 to 60 million deutsche mark per year.

Extract 1: Market Shares of Side-by-Side Traded Bond Futures on the Floor Traded LIFFE and the Electronically Traded DTB

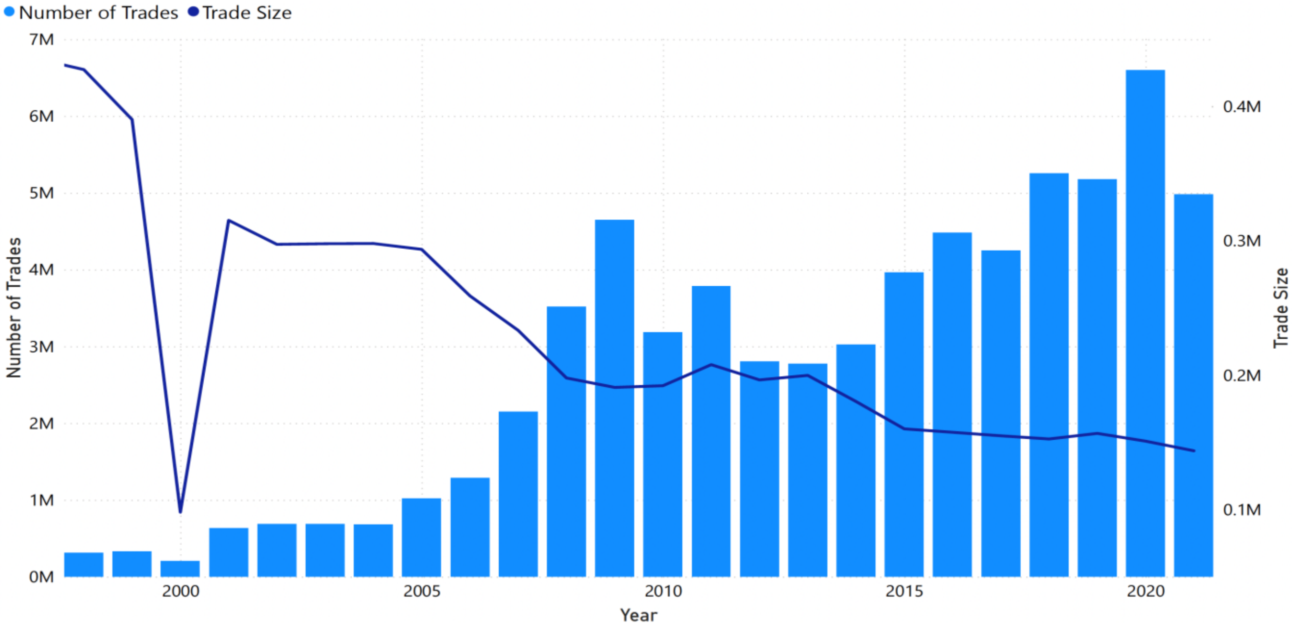


Source: Frino et al. (1998)

This paper uses the SPI (Share Price Index Futures Contract) traded previously on the Sydney Futures Exchange and currently on the Australian Securities Exchange (ASX) as a case study. The findings by researchers for the SPI are similar to those documented for other markets. Aitken, Frino, Hill and Jarnecic (2004) in a paper published in the Journal of Futures Markets demonstrated that bid-ask spreads of stock index futures traded in London, Hong Kong and Australia declined following the introduction of electronic trading on those exchanges in 1999 and 2000. Specifically, for the SPI contract traded on the Sydney Futures Exchange at the time, they demonstrated that the bid-ask spread which averaged 1.4 points on the trading floor fell systematically by approximately 0.202 points or 15 percent. Given the volumes traded in the SPI at the time the savings to liquidity demanders trading the stock index futures contract at the time was worth 10's of millions of dollars per year.

2.2. Enter of Algorithmic Trading

Figure 1: Trade Sizes and Number of Trades for SPI Futures Contracts



Electronic trading radically changed how people worked in the markets, but it also enabled a far bigger change – the rise of algorithmic trading, which generally eschews human involvement at all. Thus, while human traders used to synthesize and react to market information, algorithms now do that at lightning speed. This resulted in the introduction of massive firms that specialised in algorithmic trading like CITADEL and GETCO that were accused of trying to "guess" when large traders were present in the market, and then trade ahead of them and then provide liquidity back to the large traders in small chunks. This type of stealth trading activity resulted in the chopping-up of trades in the market and are very clear in figure 1 above, which sets out the average trade size of SPI futures contracts. From the late 1990's until about 2007, the average size of trades halved as algorithmic traders took hold – at the same time the number of trades doubled, of course. While this hinted at the increasing presence of algorithmic traders, it wasn't until the introduction of colocation that a neat experiment was provided to academics to enable them to estimate the impact that algorithmic traders were having on the market and whether they enhanced or detracted from liquidity – and by how much.

2.3. Co-Location Facilities

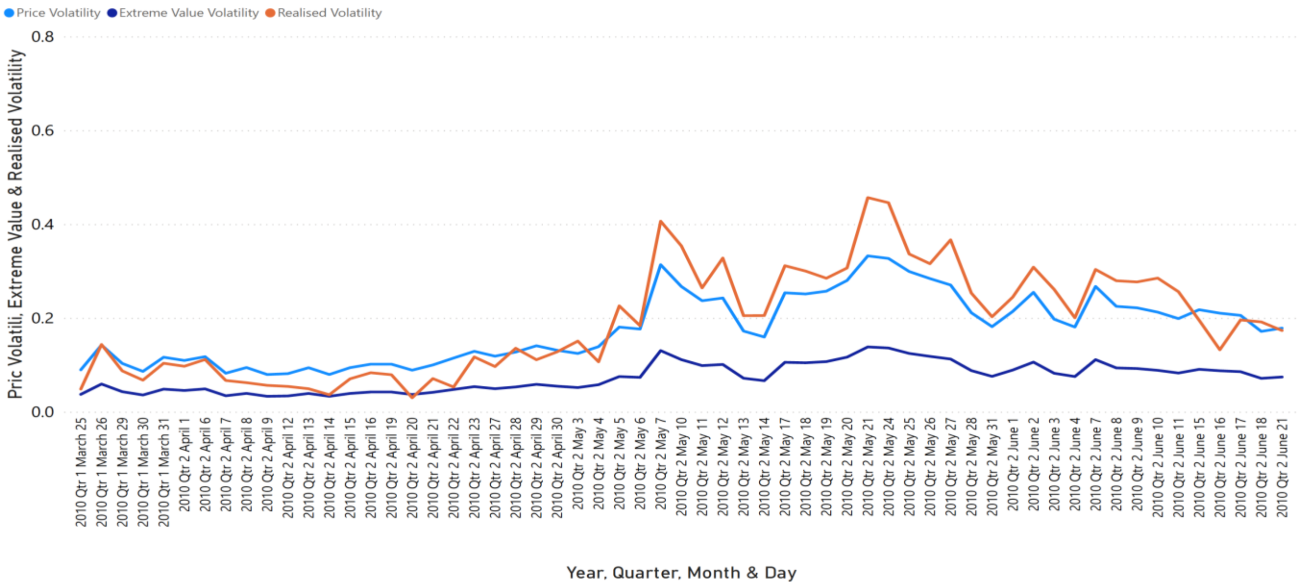
In February 2012, the ASX introduced a new colocation facility which enabled researchers to study the impact of the introduction of colocation, and whether the increase in algorithmic trading facilitated by collocated ICT facilities would positively impact liquidity. Frino, Mollica & Webb (2014) analysed the impact of this introduction of co-located trading and the impact that this facility had on the liquidity of the major futures contract traded on the ASX. In a statistically controlled analysis, the authors produced two important findings. First, the volume of message traffic (number of orders) following the introduction of collocated facilities increased significantly – consistent with the notion that algorithmic trading had increased. Second, the bid-ask spread of the SPI decreased by approximately 2.5 percent after the introduction of collocated trading. These findings suggest that the impact of co-location on liquidity is positive.

2.4. Flash Crashes and Massive Markets Adjustments

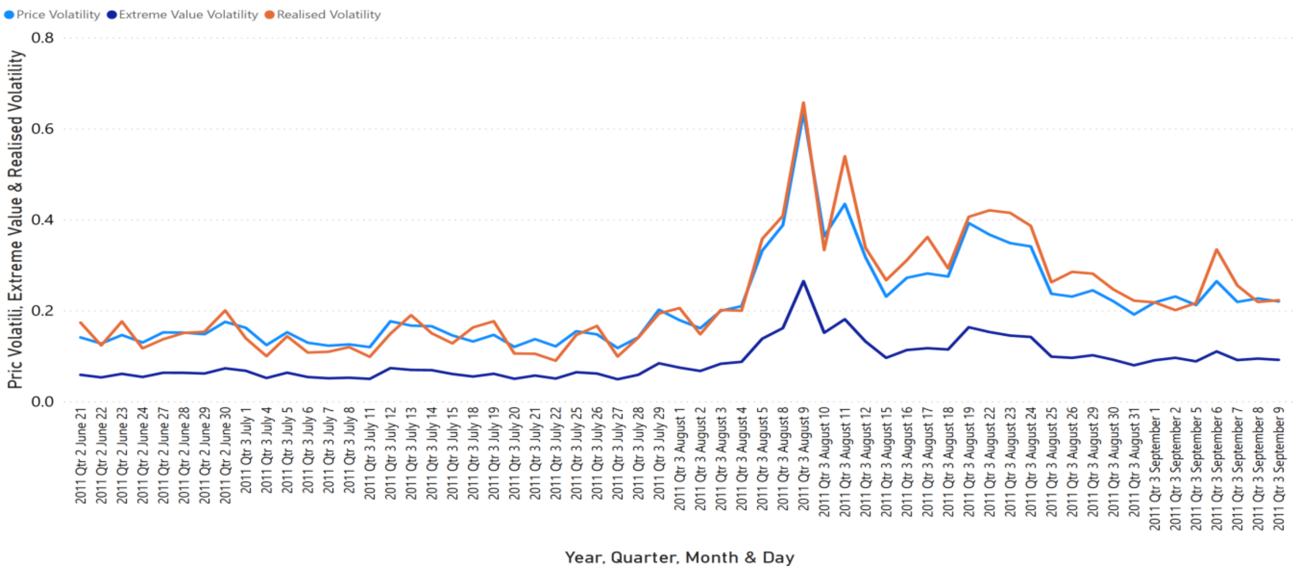
While the speed with which trading can be executed has the potential to increase the efficiency of trading and enhance the liquidity of the market, they also have the potential to exacerbate volatility as markets are able to move faster in an unchecked manner over small periods of time. The Flash Crash of 2010 is a case in point. Kirilenko, Kyle, Samadi & Tuzun (2017) and Easley, Lopez, de Prado & O'Hara (2011) document that a massive sell order in the E-mini S&P 500 Stock index futures entered around 2:45 pm on May 6, 2010 caused the Dow Jones to lose 1,000 points equivalent to wiping out approximately 1 trillion in market capitalisation at the time – before recovering 600 points a mere 30 minutes later. This volatility reverberated around the world – including for stock index futures – as illustrated in panel A of figure 2 below. However, its impact was very short-lived and had little impact on liquidity over the longer term.

Figure 2: Daily Volatility, Extreme Value & Realised Volatility for SPI Futures Contracts

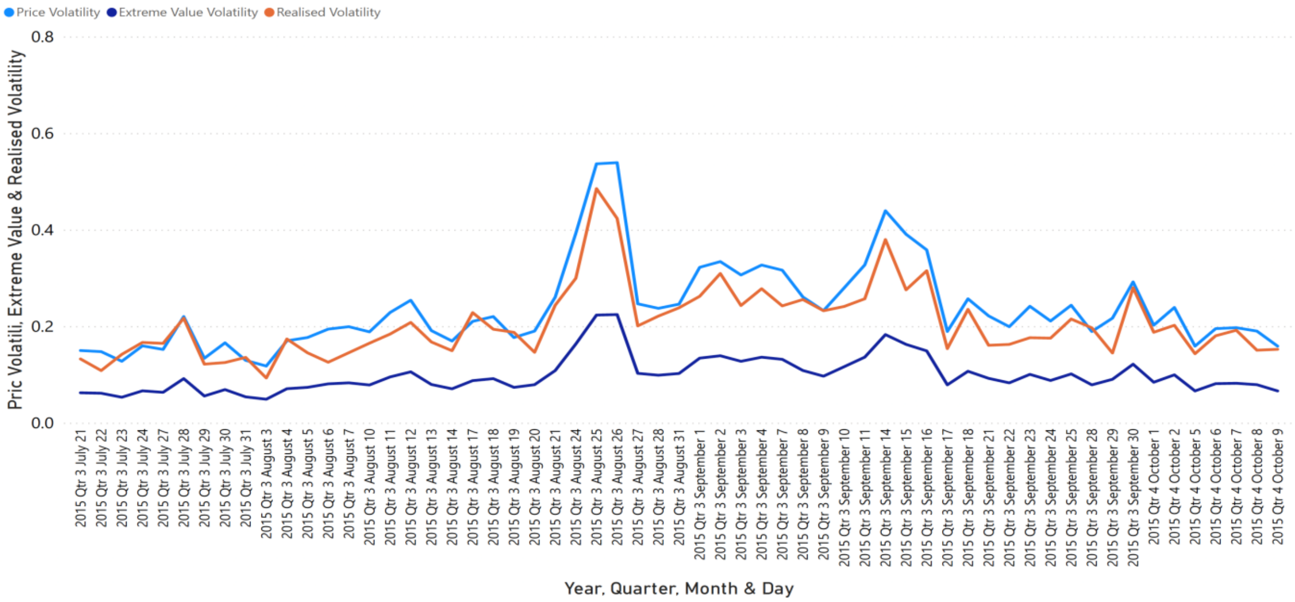
Panel A: from March 2010 to June 2010



Panel B: from June 2011 to September 2011



Panel C: from July 2015 to October 2015



While the Flash crash of 2010 is the most studied, other market "adjustments", (1) whose size and speed and (2) transfer to other markets, can only have been facilitated by electronic and algorithmic trading, include the "Black Monday" on 8 August 2011 Ferreira et al. (2021) and the flash crash of August 24, 2015, all of which are evident in panels B and C of figure 2 below. In the last section of this paper, we will examine the impact of those volatility episodes on liquidity.

2.5. Summary of Impact of Technology of Futures Markets Liquidity

Technology has provided important mechanisms in futures markets including screen trading, algorithmic trading and collocated trading which has improved liquidity by small but highly significant amounts. However, the same innovations have provided the speed which has brought on very large intraday price movements and the transfer of volatility across markets. In the next section, we explore the impact of broad economic events on markets.

3. Economic Events & the Liquidity of Futures Markets

Within the sample period analysed there were two major macroeconomic events with significant macroeconomic force that had an impact on stock market volatility: the Global Financial Crisis (GFC) and the Covid-19 Pandemic Crisis (CPC). While the GFC and CPC occurred just over a decade apart, they share some major similarities from a financial perspective. The S&P 500 saw a fall of 48% during the GFC period,[4] while the index fell 34% during the Covid-19 pandemic.[5] Both led to major falls in real asset prices. Both crises led to a crisis of confidence in financial markets, with major institutions like the Federal Reserve in USA and the European Central Bank forced to step in to prop up the markets.[6] In both crises, stock price falls were ameliorated or reversed by the announcement of quantitative easing (Chen & Yeh, 2021).

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[4] https://www.atlantafed.org/cenfis/publications/notesfromthevault/0909

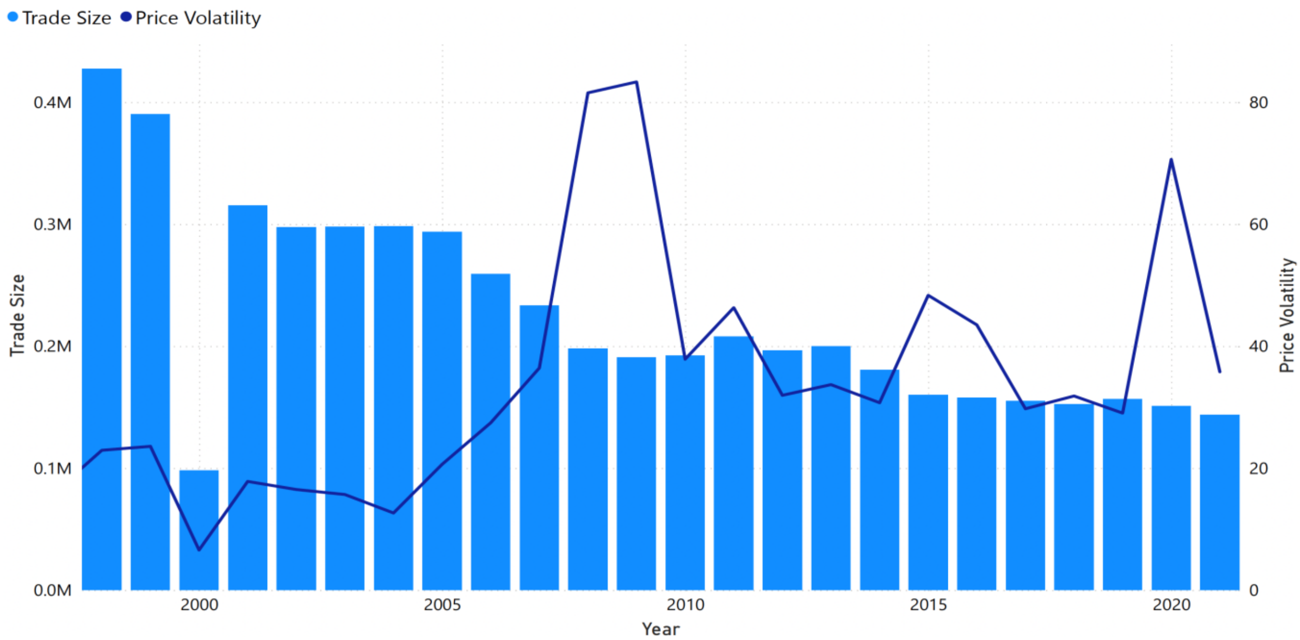
[5] https://www.cnbc.com/2021/03/16/one-year-ago-stocks-dropped-12percent-in-a-single-day-what-investors-have-learned-since-then.html

[6] One major difference between the two crises is the duration of their stock market falls. The CPC stock crash lasted less than 40 days, while the GFC stock crash lasted over a year.

The GFC saw the balance sheet of the Federal Reserve quadruple from around 2008's figure of $1 trillion to 2014's $4.5 trillion.[7] While it fell to $3.7 trillion after action taken in 2018 and 2019, it exploded by $2 trillion in a mere two months in 2020.[8] The speed and confidence at which Fed action was taken is likely due to the experience and success of policies undertaken during the GFC period, which correlate with reduced unemployment from 2009-2015 (Bhar & Malliaris, 2020). The quick turnaround in asset prices seen during the COVID-19 pandemic – with the S&P 500 recovering from the 34% drop in less than six months – suggests the effectiveness of government-led financial support. While Fed support achieved the desired effect, the vast sums on the Fed balance sheet show the massive cost of such intervention. It is possible these costs are here to stay. In his presentation "Risk Capital and Risk Appetite" Robert Webb argues that the crash of 1987 was turned around by locals on derivatives exchanges like the Chicago Board of Trade who played an outsized role in financial markets by their willingness to bear risk during turbulent times despite their relatively smaller amounts of risk capital.[9] Now that most trading pits are a relic of trading history, the replacement of locals by HFT sources may increase the sensitivity of markets to sudden changes in risk appetite or risk capital.

The Covid-19 pandemic was responsible for not only an equity selloff due to concerns about its economic impact, but also a liquidity crash. The Covid-19 crisis and resulting plunge in equities around the world had a significant impact on derivatives markets, which saw a significant increase in open interest and volumes (Emm et al., 2022), and a dramatic drop in liquidity in corporate bonds, with average transaction costs nearly tripling to 90 basis points (O'Hara & Zhou, 2021). Treasuries, generally seen as a safe haven asset, dropped too.[10] As markets fell, margin requirements increased, which put traders at risk of a downward liquidity spiral (Foley et al., 2021). These alarming events prompted the Fed to backstop fixed-income markets to the tune of trillions of dollars.

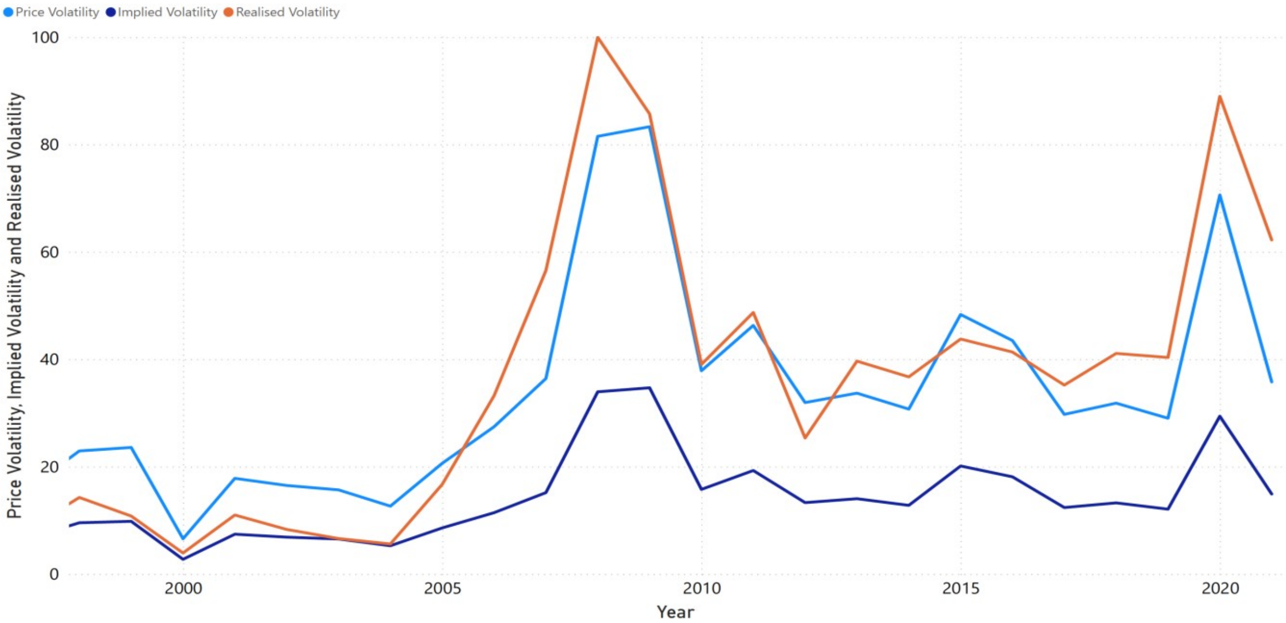
Figure 3: Price Volatility and Trade Sizes for SPI Futures Contracts



[7] https://theconversation.com/stock-markets-have-been-a-one-way-bet-for-many-years-thanks-to-the-fed-put-but-those-days-are-over-177506.
[8] https://www.federalreserve.gov/monetarypolicy/bst_recenttrends.htm.
[9] "Risk Capital and Risk Appetite" Robert Webb, Presented at SKKU on 15, July 2021. PowerPoint accessed 10 February 2022.
[10] https://www.brookings.edu/wp-content/uploads/2020/10/wp69-liang_1.pdf

In figure 3, the light blue bars indicate the number of trades, and the dark blue line shows the price volatility. Overall, except for the year 2000 in which there was a change in the underlying from the All-Ordinaries Stock Index to the SPI200 Stock Index in the Australian futures contracts, the trade size has consistently declined throughout the sample period. Price volatility, on the other hand, has seen a couple of surges around, again, 2008 and 2020, and has appreciated slightly in 2010/2011 and 2015 when there were three major flash crashes of the Dow Jones, S&P 500, and the Nasdaq Composite. These results, *prima facie*, indicates that technological and market structure incidents are far less impactful on price volatility than economic crisis episodes.

Figure 4: Price Volatility, Extreme Value & Realised Volatility for SPI Futures Contracts



To sum up, as figure 4 of the 24-year time series chart above shows, the two largest macroeconomic events that impacted the derivatives markets were the 2007-2009 Global Financial Crisis and the 2020-2021 Covid-19 Pandemic. Although major technology and market structure events provoked some movements in SPI futures liquidity (e.g., the "Black Monday" in 2011), economic forces have a distinctly greater impact on markets. The data from Australian futures markets clearly shows dramatic increases in price volatility, implied volatility, and realized volatility during both the GFC and the CPC periods.

4. A 24 Year View of the Liquidity of Futures Markets: Technology vs Major Economic Events

Figure 5 illustrates the two major market liquidity measures for SPI futures contracts. The market depth, seen in the bar chart, shows a remarkable decrease in both 2008 and 2020. meanwhile, the bid-ask spread reached its peak from 2007 to 2009 and had a big spike also in 2020, with an overall increasing (and therefore widening) trend throughout the years. It is likely no coincidence that these are the two moments in which futures liquidity suffered the most, as they directly coincide with the two deep economic crises. The same pattern can be clearly seen in figure 6 for PBAS and the value of the market depth.

Figure 5: **Bid-Ask Spread and Market Depth for SPI Futures Contracts**

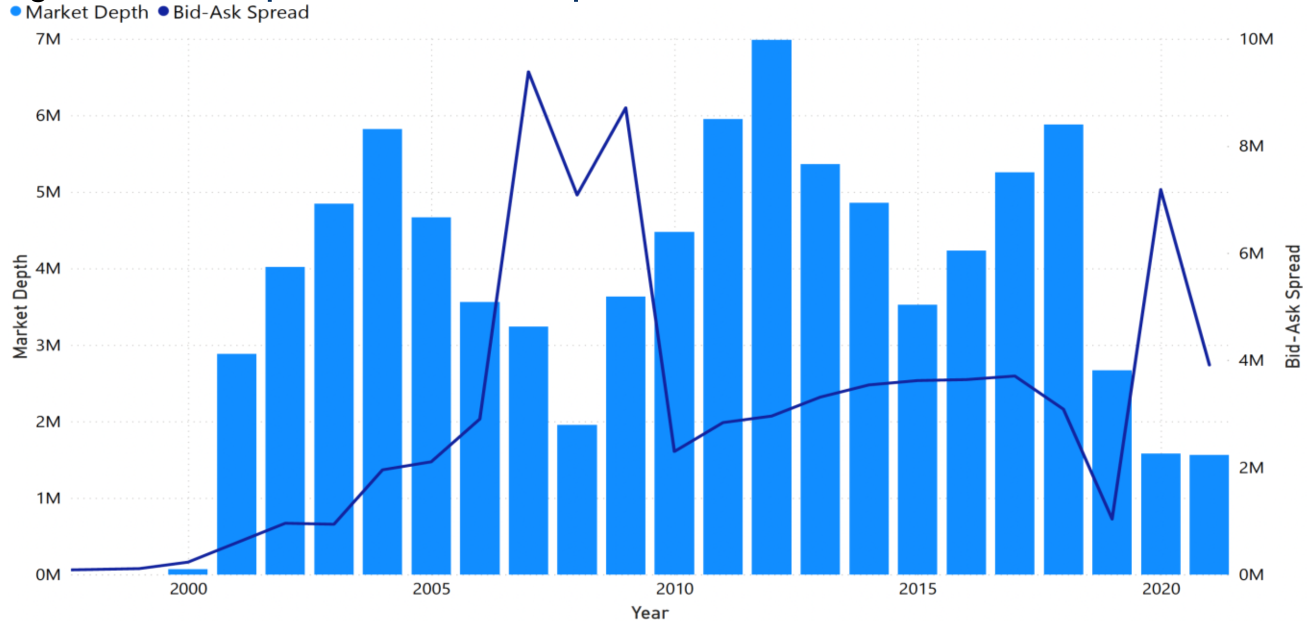
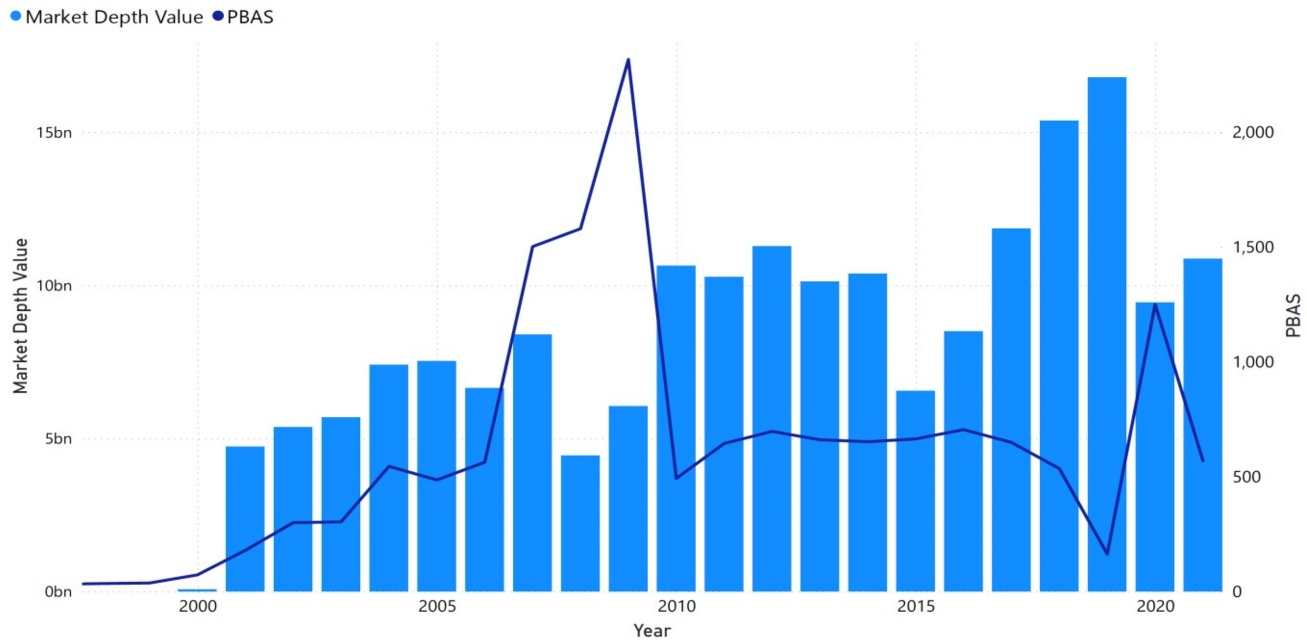


Figure 6: **PBAS and Value of Market Depth for SPI Futures Contracts**



4.1. Liquidity: The Impact of Technology vs Major Economic Events

To provide an indication of the impact of technology compared to major economic events on the liquidity of markets, we run a simple OLS regression as follows:

$$BAS_I = \alpha_0 + \beta_1 ET + \beta_2 HFT + \beta_3 CLF + \beta_4 GFC + \beta_5 CPC + I \qquad (1)$$

where, a_0 is the intercept, *ET* is a dummy variable which takes the value 1 for the years following the introduction of the Electronic Trading in 1999 and 0 otherwise, *HFT* is a dummy taking on a value of 1 after 2010 following the introduction of High Frequency Trading, *CLF* is a dummy taking on a value of 1 in the years following the introduction of Co-Located Trading Facilities in Australian futures markets in 2012, *GFC* is a dummy variable taking the value 1 in the years 2007, 2008, and 2009 surrounding the Global Financial Crisis and 0 otherwise, *CPC* is a dummy variable which takes on the value 1 for the years surrounding the Covid-19 Pandemic Crisis in 2020 and 2021, and *I* is the error term.

Table 1 presents estimates of the parameters of the regression model for bid-ask spreads. All the coefficients in the regression are statistically significant at the 0.001 level. The coefficient β_4 representing the Global Financial Crisis is four times the size of the coefficients on the variables indicating the introduction of the electronic trading in 1999, the introduction of HFT in 2010 and Co-located services in 2012. The coefficient on the Covid-19 pandemic dummy variable is the largest, which has liquidity effects 20 times larger than the two technology related variables.

Table 1: OLS Regressions Results

	Coefficient	Standard Error	T-Value
Constant	1.523	0.141	10.81***
Electronic Trading	2.424	0.143	17.00***
High Frequency Trading	2.344	0.044	52.77***
Co-Location Facilities	2.253	0.043	52.46***
Global Financial Crisis	9.946	0.034	292.40***
Covid Pandemic Crisis	51.114	0.103	500.69***
N	8,661,139		
Residual Standard Error	34.77		
R-Squared	0.039		
F-Statistic	70,230***		

Note: The table presents the estimates of the OLS regression for the bid-ask spread model, carried out as follow:

$$BAS_I = a_0 + \beta_1 ET + \beta_2 HFT + \beta_3 CLF + \beta_4 GFC + \beta_5 CPC + I$$

where, a_0 is the intercept, *ET* is a dummy variable which takes the value 1 for the years following the introduction of the Electronic Trading in 1999 and 0 otherwise, *HFT* is a dummy taking 1 after 2010 following the proliferation of High Frequency Trading, *CLF* is a dummy being 1 in the years following the introduction of Co-Located Trading Facilities in Australian futures markets in 2012, *GFC* indicates the dummy variable taking the value 1 for the years 2007, 2008, and 2009 surrounding the Global Financial Crisis and 0 otherwise, *CPC* is a dummy variable which takes the value 0 for all the years preceding the Covid-19 Pandemic Crisis in 2020 and 2021, and *I* is the error term. *p<0.05, *p<0.01, ***p<0.001.

5. Summary and Conclusion

In this paper we discussed several major influences on liquidity in futures markets during the past quarter century, including the introduction of screen-based trading, the rise of high frequency algorithmic trading, the impact of co-location, and several dramatic episodes with enormous economic impact including the GFC, the "Flash Crash" and the CPC. Using data from the SPI futures contract in the Australian market as a case study, we find that technological effects on liquidity, while important, are dwarfed by the major events with economic impact. We conclude that despite the ingenuity of exchanges and market participants in building markets which are more liquid, the impact of these innovations on liquidity is limited. The liquidity of futures markets is captive to outlier events.

The data document that the deterioration in liquidity from macroeconomic events swamps the impact of any technological market structure improvements. Stated differently, economic forces cause huge episodic impacts on liquidity that dwarf any market structure changes. This is consistent with the hypothesis that economic uncertainty is the factor influencing, by far, market liquidity.

Future research may extend these tests to other futures contracts and markets, expand the time period examined, or pursue other tests to look at liquidity effects of HFT or algorithmic trading during crises. As regulatory support of markets during crises seems likely to continue, further examinations of the effects of sovereign action on liquidity may also be warranted.

Declarations

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Availability of data
Research Data is not shared. The data that support the findings of this study are available from Refinitiv Limited, an LSEG business, and Rozetta Institute (formerly CMCRC-SIRCA). Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of Refinitiv and Rozetta.

Competing Interest
The authors declare that they have no competing interests.

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Appendix A: Data and Method of Underlying Charts, Tables and Regression Analysis Reported in the Paper

1. Data and Sample

The analysis uses 1-minute intraday trades and quotes data for the All-Ordinaries Stock Index futures contract and SPI200 Stock Index futures contract over a 26-year sample period extending from January 8, 1996, to December 31, 2021, sourced from the Thomson Reuters Tick History (TRTH) database. It samples data between 9.50 a.m. and 4.30 p.m. (AEDT Sydney Time) during which time both instruments are traded in the normal daytime trading sessions only. The unique microstructure dataset consists of 9,170,193 observations of trades prices and volumes (with the number of contracts executed) at the high and low for each minute, bid and ask prices and sizes of the quotes that triggered the trade at the close of each 1-minute interval, the date and time stamp to the nearest second, and the Reuters Identification Code (RIC) of the instrument. Since the underline contract changed in May 2000 as a consequence of Standard & Poor's taking over the production of ASX indices, the dataset shows the first two years and half of the future contract based on the All-Ordinaries Stock Index (also generally called the SPI) and continues with the new futures contracts based on the SPI200 Stock Index. We finally eliminated the delivery contract in 2016, consistent with Frino & McKenzie (2002), as we noted few anomalies in the data.

2. Number of Trades and Trade Size

We calculate, for the Australian futures contracts, the average trade size. This is done by dividing the volume, which is the lot size of a transaction or simply the number of contracts traded, by the number of trades executed in each 1-minute interval.

3. Volatility, Extreme Value Volatility and Realised Volatility

Furthermore, following Frino et al. (2014), we compute the volatility as the log difference between the highest and the lowest price during each 1-minute interval:

$$Volatility_t = \text{Log}\left(\frac{\text{High}^i_{d,t}}{\text{Low}^i_{d,t}}\right) \qquad (2)$$

where $\text{High}^i_{d,t}$ is the i^{th} highest trade price in the interval t of day d, $\text{Low}^i_{d,t}$ is the lowest trade price during the interval t of day d. Consistent with Parkinson (1980), and following Frino et al. (2021b), we also calculate the so-called high-low volatility in a different way:

$$Extreme\ Value\ Volatility_t = \sqrt{\frac{(\log(\text{High}^{\text{i}}_{\text{d,t}}) - \log(\text{Low}^{\text{i}}_{\text{d,t}}))^2}{4\log(2)}} \qquad (3)$$

Used also in Frino et al. (2021b), we finally measured the *realised volatility* as the squared percentage log-returns based on open and close prices for each day.

4. Market Liquidity Measures

We measure market liquidity in two ways. First, consistent with McInish & Wood (1992), we calculate the bid-ask spread in points for each 1-minute interval:

$$BAS_{d,t} = \frac{\sum_{i=1}^{n} (Ask_{d,t}^{i} - Bid_{d,t}^{i})}{n_{d,t}} \tag{4}$$

where $Ask_{d,t}^{i}$ is the i^{th} ask price in the interval t of day d, $Bid_{d,t}^{i}$ is the i^{th} bid price in the interval t of day d, and $n_{d,t}$ is the total number of quotes in the interval t of day d. From here, consistent with Frino et al. (2021a), we also compute the *relative spread*, also known as the *percentage quoted spread*, as the difference between the bid-ask spread and the prevailing quoted mid-point preceding the trade: $PBAS_{d,t} = BAS_{d,t}^{i} / MidPoint_{d,t}^{i}$. Second, consistent with Lee, Mucklow & Ready (1993), we calculate the market depth for each 1-minute interval using available quote sizes at the first level:

$$Market\ Depth_{d,t} = \frac{\sum_{i=1}^{n} [(Bid\ Size_{d,t}^{i} - Ask\ Size_{d,t}^{i}) / 2]}{n_{d,t}} \tag{5}$$

where, $Bid\ Size_{d,t}^{i}$ is the i^{th} bid size in the interval t of day d, $Ask\ Size_{d,t}^{i}$ is the i^{th} ask size in the interval t of day d, and $n_{d,t}$ is the total number of quotes in the interval t of day d. Lastly, consistent with Frino et al. (2021a), we define the actual *value of market depth* by multiplying the latter by the correspondent trade price: $Value\ Depth_{d,t} = MDepth_{d,t}^{i} * P_{d,t}^{i}$.