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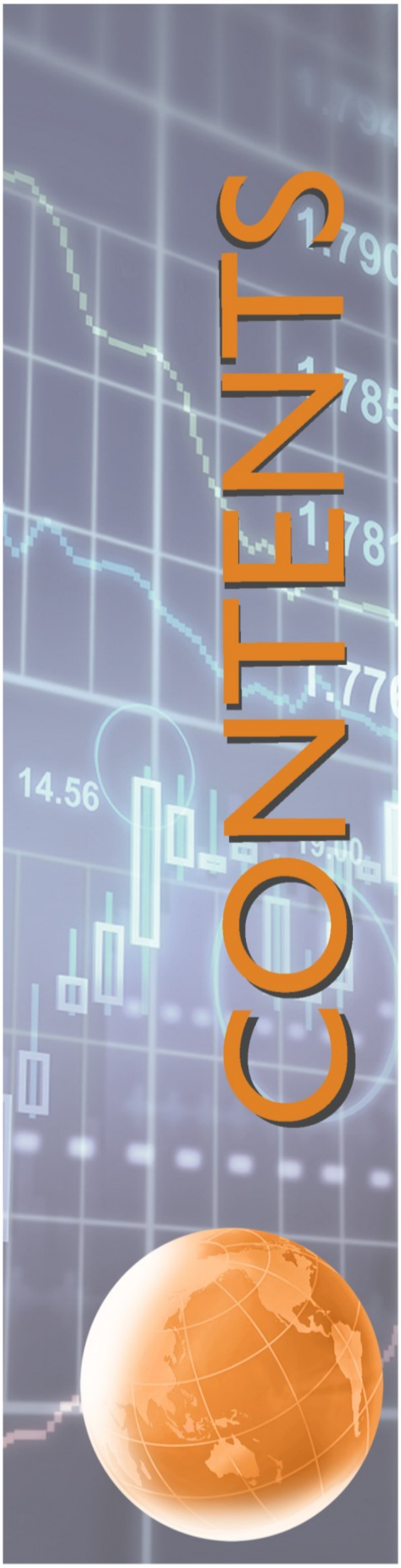

# PROFESSOR ROBERT I. WEBB'S CONTRIBUTIONS TO THE FIELD OF DERIVATIVES

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It is a great pleasure to publish this special issue dedicated to Professor Robert I. Webb for his outstanding contributions to academia. Professor Web, the Paul Tudor Jones II Research Professor at the McIntire School of Commerce at the University of Virginia in Charlottesville, was the Editor-in-Chief of the Journal of Futures Markets for 24 years, from 1997 to 2021. Through his efforts as an Editor, he has shaped and influenced derivatives research around the globe, lifting standards, indicating research directions, and engaging with derivative communities worldwide. To recognize the contributions of Prof. Webb, we have solicited papers from various editorial board members of the Journal of Futures Markets that make up this special issue.

Professor Webb has long been affiliated with the Auckland Centre for Financial Research (ACFR) and is an Honorary Fellow of that Centre. Since the inception of the ACFR, Prof. Webb has attended many of the conferences organized by the ACFR and has delivered keynote speeches, was involved as a member of the organizing committee, and acted as session chair. Most noteworthy are the contributions to the New Zealand Derivative Markets Conference that, over the years, grew to be a leading derivatives conference within the Asia-Pacific region. The Auckland Centre for Financial Research is very grateful for the many contributions of prof. Webb over more than a decade, and so we felt it was very appropriate to dedicate a special issue of Applied Finance Letters, the Journal of the ACFR, to Prof. Webb.

Our special issue is organized by the first publication of a specific editorial board member in the Journal of Futures Markets, where our first paper in this special issue is, of course, the paper by Prof. Webb.

Professor Robert Webb published his first paper in the Journal of Futures Markets in 1987, entitled "*A note on volatility and pricing of futures options during choppy markets*" (Webb, 1987). That paper started with the enticing sentence: "*Eskimos have a different word to describe each of the several types of snow they perceive*" (Webb, 1987, p. 333). This analogy was used in reference to the different types of volatility traders perceive in financial markets. The commonly accepted definition of standard deviation was just one of the "volatilities" experienced by traders. Nowadays, we indeed have different measures that indicate different "types of volatility": jumps, price discreteness-induced volatility, liquidity-induced volatility, etc.

In the current article published in this special issue, Professor Webb first reflects on the editorial process and the role of an editor. Second, he reflects on 24 years of derivatives research and how this research has evolved. In particular, he highlights a few fundamental changes that occurred to derivatives and derivative markets and how these changes have led to new avenues of research. The advent of electronic markets was, of course, one of these big changes that led to not only changes in market structure but also data availability. Over the years, many more changes have substantially altered the way research is conducted and the research questions that are asked.

The second article of this special issue is by Professor Gerald Gay. Professor Gay's first publication in the Journal of Futures Markets was in 1982, entitled "*Managing foreign interest rate risk*" (Kolb et al., 1982), which dealt with a strategy in how to deal with foreign exchange rate risk for foreign investors in US interest rate futures markets. In the article published in this special issue, Professor Gay and co-authors look at the global market for exchange-traded derivatives. Specifically, they look at trade activity and contract innovation in exchange-traded options and futures. They note that trading volume in exchange-traded derivatives has grown considerably over the last 20 years, where product innovation mostly appeared in North America.

The third article of this special issue is by Professor Yiuman Tse. Professor Tse's first publication in the Journal of Futures Markets was in 1995, entitled "*Long memory in interest rate futures markets: A fractional cointegration analysis*" (Booth & Tse, 1995). That paper provided new insights into the long-run relationship between US Treasury Bill and Eurodollar futures by making use of a fractional cointegration approach. The article for this special issue focuses on the impact of oil price uncertainty on US stock returns. The paper documents a negative relationship between oil price uncertainty and stock returns for the period since 2002, but not prior to this period, which suggests that the financialization of commodities may be a contributor to this negative relationship in the more recent time period.

The fourth paper is by Professor John Angus. Professor Angus published his first paper in the Journal of Futures Markets in 1999, the title of the paper was "*A note on pricing Asian derivatives with continuous geometric averaging*" (Angus, 1999). Professor Angus presented a pricing model for European-style Asian Contingent claims with certain properties in that paper. The contribution of Prof. Angus and co-authors to this special issue introduces a new regularization technique that increases prediction accuracy in linear regression models. An application of this technique demonstrates how a limited set of stock can track the S&P500 index and offers improved tracking errors.

The fifth paper of this special issue is by Professor Alex Frino. Professor Frino published his first paper in the Journal of Futures Markets in 2000 entitled "*The lead-lag relationship between equities and stock index futures markets around information releases*" (Frino et al., 2000). That paper demonstrates that the price leadership of stock index futures over stock index returns increases around macroeconomic news releases. The strengthening price leadership of index futures over index returns suggests that informed traders prefer to trade in futures contracts. The current contribution of Prof. Frino and co-authors to this special issue looks at the major technological and market forces that have acted on the liquidity of futures markets over almost the last quarter of a century. More specifically, using a stock index futures contract traded on Australian futures exchanges, they examine the impact of electronic trading replacing open outcry, the impact of high-frequency trading and co-located trading, and compare the liquidity impacts of these developments with the impact of major economic events, including the Global Financial Crisis and Covid-19 Pandemic. They observe that liquidity effects from extreme events are far more pronounced than technological innovations.

The sixth paper of this special issue is by Professor Jin Zhang. Professor Zhang's first publication in the Journal of Futures Markets was in 2003, entitled "*Pricing continuously sampled Asian options with perturbation method*" (Zhang, 2003). In that paper, Professor Zhang provided an analytical solution to the pricing of continuously sampled Asian options. In the current special issue, Prof. Zhang and his co-author study the relationship between market-wide liquidity and the options market. They document that higher market-wide liquidity reduces the price of options and causes market participants to lower their expectations of crash risk.

The seventh and final paper of this special issue is by Professor Isabel Figuerola-Ferretti. Professor Figuerola-Ferretti had her first publication in the Journal of Futures Markets in 2005, with a paper entitled "*Price discovery in the aluminum market*" (Figuerola-Ferretti & Gilbert, 2005). In that paper, Prof. Figuerola-Ferretti focuses on price leadership of various aluminum contracts and documents a shift in price leadership towards the prices set on the London Metals Exchange. In the current paper, Prof. Figuerola-Ferretti and co-authors focus on mispricing in global energy markets. Specifically, they implement a pairs-trading strategy for various energy stocks within the US, European, and Asian markets and document positive risk-adjusted returns to such a strategy.

We hope you will enjoy reading this special issue in honor of Professor Robert I. Webb.

## References

Angus, J.E. (1999), A note on pricing Asian derivatives with continuous geometric averaging. Journal of Futures Markets, 19: 845-858. https://doi.org/10.1002/(SICI)1096-9934(199910)19:7<845::AID-FUT6>3.0.CO;2-D

Booth, G.G. and Tse, Y. (1995), Long memory in interest rate futures markets: A fractional cointegration analysis. Journal of Futures Markets, 15: 573-584. https://doi.org/10.1002/fut.3990150505

Figuerola-Ferretti, I. and Gilbert, C.L. (2005), Price discovery in the aluminium market. Journal of Futures Markets, 25: 967-988. https://doi.org/10.1002/fut.20173

Frino, A., Walter, T. and West, A. (2000), The lead-lag relationship between equities and stock index futures markets around information releases. Journal of Futures Markets, 20: 467-487. https://doi.org/10.1002/(SICI)1096-9934(200005)20:5<467::AID-FUT4>3.0.CO;2-L

Kolb, R.W., Gay, G.D. and Jordan, J.V. (1982), Managing foreign interest rate risk. Journal of Futures Markets, 2: 151-158. https://doi.org/10.1002/fut.3990020206

Webb, R.I. (1987), A note on volatility and pricing of futures options during choppy markets. Journal of Futures Markets, 7: 333-337. https://doi.org/10.1002/fut.3990070309

Zhang, J.E. (2003), pricing continuously sampled Asian options with perturbation method. Journal of Futures Markets, 23: 535-560. https://doi.org/10.1002/fut.10073

APPLIED FINANCE LETTERS

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# REFLECTIONS ON EDITING THE JOURNAL OF FUTURES MARKETS AND FACTORS INFLUENCING DERIVATIVES MARKETS RESEARCH

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## Introduction

The ***Journal of Futures Markets*** is the leading academic journal specializing in publishing scholarly research on derivative securities and markets. I had the privilege of serving as Editor of the Journal of Futures Markets for 24 years. That position provided me with a catbird seat with which to view the evolution of the financial-economic literature on derivative securities and markets. It also provided me with an opportunity to reflect on how changes in derivative securities and markets, have influenced research. These include the influence of technological advances; changes in market microstructure; financial crises; the growth of derivatives markets in emerging economies; the introduction of credit default swaps, VIX derivatives, cryptocurrency derivatives; and other new products; among others. Although my reflections on the impact of market events on derivatives research is the principal focus of this article, I want to preface that discussion with some comments on the editing process and the influence of my education, research, and experience on my role as an Editor.

## 1. Editors and the Nature of the Editing Process

Although Editors act as arbiters on what should be published and what should not be published in journals, they are essentially stewards for the finance profession. The focus and flow of research publications is determined by the topics researchers in finance are working on rather than by journal Editors alone. Indeed, published research on a given topic often sparks additional research on that topic which leads, in turn, to a natural temporal clustering of research on various topics.

The selection of which papers to publish and which not to publish is a process measured with error as the high-profile failure of various Editors at leading journals in finance and economics to publish the path-breaking Black-Scholes option pricing article illustrates. Editors are not omniscient. They rely on the assistance of others with specialized expertise in certain areas. Timely, constructive, and insightful peer reviews are integral to the publication process for academic journals. The growth of highly specialized research within increasingly narrow areas has increased both the importance of the review process and the weight accorded reviewers' comments in the editorial decision-making process. It has also increased the difficulty of finding qualified and impartial reviewers who are also subject matter experts, and who will return their comments in a timely fashion. Indeed, the scarcest resource of any academic journal is the time that qualified reviewers are willing to devote to commenting on papers. The success of the *Journal of Futures Markets* during my tenure as Editor was truly a group achievement. It reflects the many excellent contributions of numerous researchers, the constructive criticism of reviewers and Editorial Board members, as well as my Editorial decisions.

## 2. The Impact of My Education, Research, and Experience on My Role as Editor

None of us exist in a vacuum and the lens through which I evaluated research and the perspectives I brought to the position of Editor of the *Journal of Futures Markets* were shaped by my education, research, and professional experience. These factors need to be acknowledged. I am also obliged to pay homage to those who influenced me.

### 2.1 Education

I have been very fortunate. I studied at the University of Chicago in the mid-1970s during the height of the influence of the Efficient Capital Markets Hypothesis. Indeed, Chicago was the "home" of the efficient markets school of thought. Fischer Black, Merton Miller, Myron Scholes, and Eugene Fama were all Professors at the Graduate School of Business (GSB) when I entered as a doctoral student in finance in 1974. Arnold Zellner, who was also at the GSB, led the research charge on Bayesian statistics and econometrics—another important area of study that was changing how much empirical research was done. (Arnold also chaired my dissertation committee and had the most impact on how I think about research.) These were only two areas of the torrent of research activity occurring at the University of Chicago at the time.[1]

My education at Chicago instilled in me an appreciation of the power of economic incentives, the likelihood of rational decision-making by individuals, and the belief that free markets usually work very well. These ideas shaped my priors. However, the principal lesson at Chicago was the focus on empiricism (i.e., positive economics in the words of Milton Friedman) in explaining "what is" or the actual relationships observed in markets preferably using *sophisticatedly simple* models and appropriate data. Finance or Economics are not religions with immutable truths that are to be believed based on faith alone. Rather, concepts such as 'market efficiency" or "rational expectations" are hypotheses to be tested. Indeed, the fact that The University of Chicago is home to arguably both the leading proponent of market efficiency (Eugene Fama) and the leading proponent of behavioral finance (Richard Thaler) is testament to that philosophy in action.

It was an auspicious and exciting time to study at Chicago both for the academic advances occurring at The University of Chicago and the financial innovations introduced by, and traded on, the derivatives exchanges in Chicago. I entered Chicago only a year after the Black-Scholes option pricing article was published in the *Journal of Political Economy* in 1973 and slightly more than a year after exchange traded equity call options started to trade on the Chicago Board Options Exchange on 26 April 1973, and over two years after foreign currency futures –the first successful financial futures--started to trade on the International Monetary Market (IMM) division of the Chicago Mercantile Exchange.[2]

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[1] This torrent of intellectual activity included: a focus on rational expectations (Robert Lucas); applications of economics to explain various kinds of human behaviour (Gary Becker); and the monetary approach to the balance of payments (Harry Johnson) among others in the Department of Economics. While I did not work with any of these three Economics professors, I was influenced by the ideas they developed and their impact on the economics literature. A debt of gratitude is also owed to George Stigler in the GSB, and Milton Friedman in the Department of Economics who were both at Chicago when I entered and helped create the strong research environment that existed at Chicago at the time.

[2] Black, F., and M. Scholes, "The Pricing of Options and Corporate Liabilities," The *Journal of Political Economy* May-June 1973, Vol. 81, Issue 3, pages 637-654. There is also a direct link between The University of Chicago and financial market innovations as Milton Friedman played an important role in assisting the Chicago Mercantile Exchange in securing regulatory approval of its International Monetary Market foreign currency futures contracts.

### 2.2 Research

My dissertation would be classified as "macrofinance" today as it examined the impact of Federal Reserve security transactions (i.e., *open market operations*) on Treasury bill yields. It was also a "high frequency" study as daily data (considered high frequency data at the time) were examined. My early derivatives market research post-graduation, focused on market microstructure issues, namely, the use of batch auctions on the Tokyo Grain Exchange and an examination of the behaviour of provisional prices in the determinization of batch auction transaction prices. I also conducted research on the impact of taxation on economic incentives. My research topics have changed as time has passed. However, my research tends to be empirical in nature, frequently exploits natural experiments, and oftentimes focuses on policy issues.

### 2.3 Experience in Business, Government, and Academia

Although my training at the University of Chicago and experience conducting research on my own prepared me well to be an Editor of an academic finance journal, my experience in business, government, and supranational organizations prior to becoming Editor also proved invaluable in evaluating research. That experience includes: trading fixed income securities for the Investment Department of the World Bank; trading financial futures and options as a member in the open outcry pits on the floor of the Chicago Mercantile Exchange; designing new financial futures and option contracts for the Chicago Mercantile Exchange; analysing the effects of deregulating the financial services industry, among others, at the Executive Office of the President, Office of Management and Budget; examining issues related to international futures markets at the U.S. Commodity Futures Trading Commission. This experience helped give me a better understanding of real-world financial markets, the critical role of derivative markets within financial markets, the needs of users of derivative contracts, and the proper role of regulation. I believe that my background also made me a better Editor especially on issues involving trading; market microstructure; contract design; regulation. It also gave me an appreciation for the importance of institutional details and a better understanding of financial history.

## 3. The Impact of Market Events on Derivatives Research

I have also been very fortunate that my tenure as Editor occurred during a period of very rapid growth in the exchange traded derivatives market, sharp changes in market microstructure with a shift from pit trading to electronic trading, the growth in algorithmic and high frequency trading, and periodic turmoil and crises in financial markets. Indeed, I think that it is important to understand some of the changes that were impacting financial markets or the overall economy to understand some of the research thrusts that occurred during my tenure as Editor of the *Journal of Futures Markets*.

What follows is a necessarily abbreviated and incomplete list of factors and events that impacted financial markets. It is not in strict chronological order as some of the events overlap. I have also included some representative articles on many of the topics.

### 3.1 The Rise of Electronic Trading and Exchange Consolidation

Although the demise of pit trading and the transition to electronic trading seems inevitable in retrospect it was not the case at the time. The futures markets in Chicago, New York, London, Paris, Singapore, Hong Kong, and Sydney were dominated by open outcry or pit trading. The move to electronic trading was not led by the derivative exchanges in Chicago or New York. Rather, it occurred overseas first. The Tokyo Grain Exchange (later acquired by TOCOM and now part of the Japan Exchange Group or JPX) was trading entirely electronically in the late 1980s albeit via periodic batch auctions.[3] The Deutsche Termin Boerse or DTB (a predecessor of Eurex) was all electronic when it opened for trading in January 1990. Nevertheless, the pit-traded London International Financial Futures Exchange (LIFFE) dominated trading in German interest rate futures and continued to do so for several years. Order flow usually goes to the market where liquidity is, or is perceived to be, greatest. Nor was the introduction of the electronic trading venue Globex by the CME in 1992 immediately embraced by market participants. To be sure, it was not intended to compete with open outcry markets during the regular trading day. (Globex was intended to facilitate night trading for a number of exchanges around the world while leaving pit trading for the regular business day.) Initially, the largest fraction of trading volume on the Globex was from "curb" or after-hours trading on the Marché à Terme International de France (MATIF) in Paris.

The threat to pit trading suddenly became real in 1997 when there was a concerted effort by the DTB to attract order flow from German financial institutions for German interest rate futures contracts that had been going to LIFFE. The subsequent loss of significant order flow proved devastating to the pit-traded London International Financial Futures Exchange (LIFFE) as it quickly lost trading volume in its German interest rate futures to the electronically traded Deutsche Termin Boerse (DTB). The speed with which trading in German interest rate futures contracts on the LIFFE declined also illustrates how a large fraction of trading volume in open outcry auction markets comes from floor traders "scalping" or making a market. Much of this activity dries up in the absence of public order flow (because floor traders are simply "picking each other's pockets" as futures trading is a zero-sum game ignoring transaction costs) This, in turn, discourages pit traders from making a market –thus reducing trading volume further which reduces liquidity and discourages outside order flow. Liquidity in German interest rate futures shifted from London to Frankfurt. The imminent demise of pit trading became more apparent in April 1998 when the MATIF introduced electronic trading alongside of pit trading. Pit trading "died" within a month. The sudden collapse of pit trading on the MATIF when side-by-side electronic and pit trading was introduced seemingly sounded an imminent death knell for pit trading everywhere. The termination of pit trading on the Sydney Futures Exchange (now part of the ASX) happened in December 1999. Pit trading ended on LIFFE in November 2000. Not surprisingly, the transition from pit trading to electronic trading sparked much research as did evening trading.[4]

Meanwhile, pit trading continued to dominate the derivatives markets in Chicago. However, a threat to continued pit trading on the key interest rate futures markets in Chicago appeared on the horizon. Eurex which was formed from the merger of DTB and the Swiss Options and Financial Futures Exchange in mid-1998 promised to introduce a US subsidiary and take on the key Chicago exchanges by offering electronically traded futures contracts on U.S. Treasury securities and other markets. There was a period where it appeared to many observers that the pit-traded exchanges in Chicago would be wiped away by their fully electronically traded rival Eurex US which listed similar futures contracts. That did not happen. Part of the explanation was the slow approval process. Eurex US did not start to trade until 8 February 2004. Although depicted in the financial press at the time as a fight between pit-trading and electronic trading, a significant part of the total trading volume on the Chicago futures exchanges was already electronically traded when the battle with Eurex US began. The late start of Eurex US coupled with some temporary fee cuts and the existing deep liquid markets for the various futures contracts (which attracted outside order flow), meant that the exchanges in Chicago ultimately prevailed. Eurex US (later the US Futures Exchange) closed in 2008.

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[3] The International Futures Exchange (INTEX) based in Bermuda opened on October 25, 1984 as a venue that offered electronic trading of several financial futures contracts similar to those traded on U.S. futures markets.

[4] Examples include: Tse, Y. and Zabotina, T.V. (2001), Transaction Costs and Market Quality: Open Outcry Versus Electronic Trading. *Journal of Futures Markets*., 21: 713-735 . https://doi.org/10.1002/fut.1802
Ates, A. and Wang, G.H.K. (2005), Information transmission in electronic versus open-outcry trading systems: An analysis of U.S. equity index futures markets. *Journal of Futures Markets*., 25: 679-715. https://doi.org/10.1002/fut.20160
Frino, A., Harris, F.H.d., McInish, T.H. and Tomas III, M.J. (2004), Price Discovery in the Pits: The Role of Market Makers on the CBOT and the Sydney Futures Exchange. *Journal of Futures Markets*., 24: 785-804. https://doi.org/10.1002/fut.20105

The rationale for physical trading floors largely disappeared with the dominance of electronic trading as did the need for numerous exchanges. This prompted exchanges to demutualize and become publicly traded firms (which lessened the power of the former trader members). The Chicago Mercantile Exchange went public in 2002. The Chicago Board of Trade went public in 2005. The dominance of electronic trading in both stock and futures markets as well as demutualized and listed exchanges sparked a wave of mergers and attempted mergers among exchanges worldwide. Although the consolidation among derivatives exchanges received less attention than the consolidation of equity markets, the high market capitalizations attached to derivatives exchanges reflected their greater growth potential and pricing power. Moreover, the important role that clearinghouses played in the valuation of derivatives exchanges was largely overlooked in the academic literature.

### 3.2 High Frequency Trading, Algorithmic Trading, and Co-location

Having information before other market participants or being able to process or trade on publicly available information faster than other market participants is a tremendous advantage. The race for a speed advantage is as old as financial markets. The dominance of electronic trading fundamentally changed the race for speed in financial markets as participants tried to gain a temporal advantage over other market participants.[5] Algorithmic trading as well as technological advances in communications and information processing made it possible to trade at ever-lower latencies. It also created a demand for co-location services from high frequency trading (HFT) firms desiring to be as close as possible to exchange servers to minimize latency.[6] The rise of algorithmic and high frequency trading stimulated much research. Most of the literature has found that HFT has increased liquidity without increasing volatility.[7] Much HFT consists of market making. This latter point is not surprising as the founders of many prominent HFT firms are former floor traders who made markets on exchange trading floors. Recall that in the heyday of open outcry or pit trading it was commonly believed that 30% to 40% of total trading volume came from "locals" making a market on the trading floor. This is part of the reason why trading volume in German interest rate futures on LIFFE fell so much so quickly when public order flow started to fall in late 1997. Studies of the profitability of HFT firms in the e-mini S&P 500 stock index futures market showed huge pre-tax Sharpe ratios and that most of profits were earned by a few HFT firms. The immense profits of a handful of HFT firms given the limited risks taken helped stimulate research on whether the investment in technology required to be a successful HFT trader is socially beneficial from a societal perspective.

### 3.3 Flash Crashes and Rallies

The Flash Crash (and sudden rebound) of U.S. stock prices on 6 May 2010 captured the attention of market participants, regulators, academics, and the general public alike. A subsequent joint study of the Flash crash by the U.S. Securities and Exchange Commission and the U.S. Commodity Futures Trading Commission argued that an algorithmic order to sell 75,000 e-mini stock index futures contracts on a volatile day where the equity market was already down 4% likely precipitated a liquidity crisis in

[5] An example of the literature in this regard is: Zhang, SS. Need for speed: Hard information processing in a high-frequency world. *Journal of Futures Markets*. 2018; 38: 3– 21. https://doi.org/10.1002/fut.21861

[6] See for example: Frino, A., Mollica, V. and Webb, R.I. (2014), The Impact of Co-Location of Securities Exchanges' and Traders' Computer Servers on Market Liquidity. *Journal of Futures Markets*, 34: 20-33. https://doi.org/10.1002/fut.21631

[7] See for example: Bollen, N.P. and Whaley, R.E. (2015), Futures Market Volatility: What Has Changed?. *Journal of Futures Markets,* 35: 426-454. https://doi.org/10.1002/fut.21666
An exception is: Lee, E.J. (2015), High Frequency Trading in the Korean Index Futures Market. *Journal of Futures Markets*, 35: 31-51. https://doi.org/10.1002/fut.21640

the stock index futures market and later in the cash stock market.[8] A high frequency trader from the United Kingdom was later charged with "contributing to the Flash Crash" on 6 May 2010 by engaging in price manipulation and "spoofing."[9] A flash crash in yields or flash rally in Treasury securities on 15 October 2014 precipitated an investigation by the U.S. Treasury Department.[10] However, no cause was discovered.

The 6 May 2010 flash crash in equities received widespread attention and stimulated substantial research on high frequency trading. The flash rally in Treasury prices on 15 October 2014 has received less attention in the academic literature despite the central role that the U.S. Treasury market plays in U.S. dollar denominated fixed income markets. Flash crashes in commodity markets have also occurred but not received the attention they deserve in the financial economic literature nor has spoofing. Observations of flash crashes have stimulated research on their causes and how to manage "flow toxicity."[11] The success of market making by HFT firms makes market making by humans riskier. Although HFT dominates market making and makes markets more liquid during most times, it seemingly also increases the odds of flash crashes. The various flash crashes highlight the fragility of financial markets and illustrate how liquidity can suddenly vanish.[12]

### 3.4 New Securities and New Markets

The establishment of the Chicago Board of Trade in 1848 and the subsequent introduction of standardized futures contracts in 1865 is usually considered the beginning of exchange traded futures markets. However, exchange traded futures owe their origin to the Dojima Rice Exchange which was established in Osaka, Japan in the late 1600s and became legal by 1730. Although commodity futures markets were established in a number of cities around the world after the creation of the Chicago Board of Trade, Chicago continued to play an outsized role. The creation of financial futures on the International Monetary Market division of the Chicago Mercantile Exchange in 1972 changed futures markets as financial futures markets were later established around the world to emulate its success. What changed during my tenure as Editor of the *Journal of Futures Markets* was the strong growth in trading volume outside North America in both commodity and financial futures and options.

Measured in terms of the number of derivative contracts traded, there was a sharp shift towards Asia. Indeed, he Korea Exchange (KRX) held the title as the largest derivatives exchange in the world for almost 8 years due to the popularity of the KOSPI 200 option contracts among retail investors. (Nor was the title due to small notional size option contracts.) There has been tremendous growth in both South America and Russia. The National Stock Exchange (NSE) of India was the largest derivatives exchange in the world in terms of number of contracts traded in 2021 followed by the B3 exchange in Brazil. The NSE traded 17.26 billion contracts in 2021 followed by 8.76 billion contracts on the B3 and the CME

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[8] U.S. Securities and Exchange Commission; Commodity Futures Trading Commission "Findings Regarding the Market Events of May 6, 2010," September 30, 2010, https://www.sec.gov/files/marketevents-report.pdf

[9] https://www.justice.gov/criminal-vns/file/1175901/download The trader pled guilty to one count of wire fraud and one count of spoofing in a plea agreement. https://www.justice.gov/criminal-vns/file/1175911/download

[10] U.S. Department of the Treasury, Joint Staff Report: "The U.S. Treasury Market on October 15, 2014," July 13, 2015. https://www.treasury.gov/press-center/press-releases/Documents/Joint_Staff_Report_Treasury_10-15-2015.pdf

[11] Kang, J, Kwon, KY, Kim, W. Flow toxicity of high-frequency trading and its impact on price volatility: Evidence from the KOSPI 200 futures market. *Journal of Futures Markets,* 2020; 40: 164– 191. https://doi.org/10.1002/fut.22062

[12] The notion that electronic trading might provide tighter bid-ask spreads during normal tranquil periods but deteriorate "during periods of information arrival" (i.e., turbulent periods) was noted by Aitken et al [2004]. Aitken, M.J., Frino, A., Hill, A.M. and Jarnecic, E. (2004), The impact of electronic trading on bid-ask spreads: Evidence from futures markets in Hong Kong, London, and Sydney. *Journal of Futures Markets*, 24: 675-696. https://doi.org/10.1002/fut.20106

Group in the USA with 4.94 billion derivative contracts according to the Futures Industry Association.[13] The rise of Mainland Chinese futures markets has been phenomenal with the Shanghai Futures Exchange (SFE), Dalian Commodity Exchange, (DCE) and Zhengzhou Commodity Exchange (ZCE) dominating trading in various commodities and trading a number of commodities that are not traded elsewhere. Not surprisingly, there has been a substantial amount of academic research on Mainland Chinese commodity futures markets. However, there are still unexploited opportunities to examine some of the unique commodities traded on the DCE and ZCE especially. Moreover, some of the research from emerging markets sometimes reports substantially different results from those reported from studies examining similar questions using data from developed markets.[14]

The introduction of VIX and other volatility-based derivatives precipitated much research as did the introduction of credit default swaps.[15] Another new product that attracted significant attention was the introduction of derivatives on bitcoin and other cryptocurrencies. One difference between the cryptocurrency derivatives and other new products is the volume traded on lightly regulated or unregulated exchanges. Indeed, if the reported trading volumes are correct, the trading volume of cryptocurrency derivatives on lightly or unregulated exchanges exceeds that on conventionally regulated derivative exchanges.[16]

## 4. Interventions

Direct or indirect interventions in financial markets by governments or central banks during this time period have also impacted academic research on derivative markets. Several examples come immediately to mind. The 1998 attack on the Hong Kong dollar by hedge funds (after a failed attempt in 1997 in the wake of the start of the Asian Financial Crisis) prompted the Hong Kong Monetary Authority (HKMA) to buy stocks in the cash market and Hang Seng stock index futures. The HKMA did so to punish the hedge funds who had gone short 80,000 Hang Seng stock index futures contracts from which they hoped to make substantial gains as they also sold Hong Kong dollars to force interest rates up. The intervention distorted the basis between cash and futures.[17] Another example of an intervention was the decision of the Taiwanese authorities to reduce the tax on futures transactions by half on 1 May 2000. This led to a substantial increase in trading volume and narrower bid-ask spreads with no apparent impact on volatility.[18] One lesson from the Global Financial Crisis of 2007-2009 is that exchange traded derivatives markets worked well. However, the bankruptcy of Lehman Brothers

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[13] https://www.fia.org/resources/global-futures-and-options-trading-hits-another-record-2021

[14] See for example the following two studies: Guo, Han, and Ryu of the Korean market. Guo, B., Han, Q. and Ryu, D. (2013), Is the KOSPI 200 Options Market Efficient? Parametric and Nonparametric Tests of the Martingale Restriction. *Journal of Futures Markets*, 33: 629-652.
Yang, J., Yang, Z. and Zhou, Y. (2012), Intraday price discovery and volatility transmission in stock index and stock index futures markets: Evidence from China. *Journal of Futures Markets*, 32: 99-121. https://doi.org/10.1002/fut.20514

[15] Zhang, J.E. and Zhu, Y. (2006), VIX futures. J. Fut. Mark., 26: 521-531. https://doi.org/10.1002/fut.20209
Frijns, B., Tourani-Rad, A. and Webb, R.I. (2016), On the Intraday Relation Between the VIX and its Futures. Journal of Futures Markets, 36: 870-886. https://doi.org/10.1002/fut.21762
Luo, X. and Zhang, J.E. (2012), The Term Structure of VIX. J. Fut. Mark., 32: 1092-1123. https://doi.org/10.1002/fut.21572

[16] See for example: Alexander, C, Choi, J, Park, H, Sohn, S. BitMEX bitcoin derivatives: Price discovery, informational efficiency, and hedging effectiveness. *Journal of Futures Markets*. 2020; 40: 23– 43. https://doi.org/10.1002/fut.22050

[17] Draper, P., and J.K.W. Fung, "Discretionary Government Intervention and the Mispricing of Index Futures," *Journal of Futures Markets*, Vol. 23, December 2003, pp. 1159-1189.
Yam, J., "Coping with Financial Turmoil," Inside Asia Lecture 1998, 23 November 1998, Sydney, Australia
https://www.hkma.gov.hk/eng/news-and-media/speeches/1998/11/speech_231198b/

[18] Chou, R.K., and G.H.K. Wang, "Transaction Tax and Market Quality of the Taiwan Stock Index Futures," *Journal of Futures Markets*, Vol. 26, December 2006, pp. 1195-1216.

highlighted some potential problems in the over the counter (OTC) derivatives market for credit default swaps. This led to a demand by G-20 leaders at the 2009 Pittsburgh Summit to require trade repositories and central clearing mechanisms for OTC credit default swap transactions[19].

As the above examples demonstrate, there are many types of interventions. Sometimes the intervention is a required change in the notional size of the derivatives contract to achieve some regulatory objective. Such was the case in the decision by the Korean authorities to increase the notional size of the KOSPI 200 options contract almost five-fold on 9 March 2012 to discourage speculative trading by individuals. This action (which was later partially reversed) cost the Korea Exchange its position as the largest derivatives exchange in the world in terms of trading volume—a title it had held for several years as noted above. Yet another example of government intervention in derivatives markets was the decision by the Chinese authorities to limit trading in CSI 300 and CSI 500 stock index futures in the wake of the sharp decline in Chinese equity prices in 2015. The decision resulted in Chinese stock index futures trading volume falling by 99%.[20] These decisions illustrate the power of regulatory actions on derivative markets. Not surprisingly, each of these incidents sparked academic research on the impact of the actions.

## 5. Behavioral Finance, New Techniques, and New Data

The growth of interest in behavioral finance has also impacted research on derivative securities and markets.[21] Interest in issues such as investor attention and investor sentiment have also sparked research on the behavior of derivative securities and markets. Other developments in finance as well as new econometric techniques have also sparked the examination of new issues or the re-examination of old issues in the literature.

This changed as access to tick data (which reflects only price changes), trade, and quote data became more readily available to researchers. One consequence of electronic trading venues is the greater availability of high frequency data. This has allowed studies of phenomena such as latency arbitrage. Having access to a unique data set is sometimes key to getting the research published. For instance, trader identification data are often difficult to obtain. Trader identification data can provide greater insights into trader decision-making, reveal the profitability of various trading strategies, as well as whether the trader falls prey to various cognition illusions noted in the behavioral finance literature, among other things.[22]

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[19] https://www.treasury.gov/resource-center/international/g7g20/Documents/pittsburgh_summit_leaders_statement_250909.pdf

[20] Han, Q., and J. Liang, "Index Futures Trading Restrictions and Spot Market Quality: Evidence from the Recent Chinese Stock Market Crash," *Journal of Futures Markets,* Vol. 37, April 2017, pp. 411-428.

[21] See for instance: Liu, Y.-J., Wang, M.-C. and Zhao, L. (2010), "Narrow framing: Professions, sophistication, and experience." *Journal of Futures Markets,* 30: 203-229. https://doi.org/10.1002/fut.20407

[22] Three examples that use account level data from the Taiwan Futures Exchange are:
Chou, R.K. and Wang, Y.-Y. (2009), Strategic order splitting, order choice, and aggressiveness: Evidence from the Taiwan futures exchange. J. Fut. Mark., 29: 1102-1129. https://doi.org/10.1002/fut.20416
Chou, R.K., Wang, G.H.K. and Wang, Y.-Y. (2015), The Effects of Margin Changes on the Composition of Traders and Market Liquidity: Evidence from the Taiwan Futures Exchange. *Journal of Futures Markets,* 35: 894-915. https://doi.org/10.1002/fut.21718
Chang, MC, Tsai, C-L, Wu, RC-F, Zhu, N. Market uncertainty and market orders in futures markets. *Journal of Futures Markets*. 2018; 38: 865– 880. https://doi.org/10.1002/fut.21918

## 6. Conclusions

Most readers have always lived in a world where exchange traded financial futures have existed. Most readers have always lived in a world where exchange traded equity options existed. Most readers have always lived in a world where interest rate swaps existed. Most readers have always lived in a world where exchange traded derivatives on energy, in general, and crude oil, in particular, existed and were important markets. Many readers have lived in a world where credit default swaps have always existed. I have not. 2022 marks the 50th year since the successful introduction of financial futures on the International Monetary Market. 2023 will mark the 50th anniversary of exchange traded equity options and the publication of the seminal paper by Fischer Black and Myron Scholes on option pricing. Interest rate swaps were introduced in 1981. Crude oil futures were introduced on the New York Mercantile Exchange in 1983. Credit default swaps were introduced in the early 1990s. And more changes are likely in financial markets given the success of cryptocurrencies and cryptocurrency derivatives,

I have had the opportunity to live through these changes and see how the innovations and changes have impacted both financial markets and financial market research. For the past 41 years, the *Journal of Futures Markets* has chronicled many the changes in derivative securities and markets. I expect it to continue to do so. It was my pleasure to serve as Editor of the *Journal of Futures Markets* for 24 years.

APPLIED FINANCE LETTERS

SPECIAL ISSUE, 2022

# THE GLOBAL MARKET FOR EXCHANGE-TRADED DERIVATIVES: 21ST CENTURY TRENDS, INNOVATION AND FAILURE

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**Abstract**

Utilizing a comprehensive database spanning 110 exchanges in five geographic regions, we examine trends in trade activity and contract innovation of exchange-traded futures and options over the period 2002–2021. We find that global volume has experienced a ten-fold increase driven by significant increases at Asian and North American exchanges, and primarily in the equity, interest rate and currency asset classes. New contract innovation has been greatest in North America and in the energy and equity asset classes. Further, volume and open interest attributable to new contract innovation have now surpassed those of legacy contracts. Turnover showed a significant increase driven largely by trade activity in Asian markets. Finally, new contract failure rates have been highest at North American exchanges as well as in the interest rate and energy asset classes.

**JEL Classification:** G12; G13; G15; G23; L11

**Keywords:** Futures, options, derivatives, volume, open interest

## 1. Introduction

This study contributes to the special issue honouring Professor Robert I. Webb who has served as editor of the *Journal of Futures Markets* (JFM) for more than two decades. Under his leadership, the *JFM* has broadened its reputation as a leading field journal in financial economics while expanding interest in derivatives research. Over this same period the global market for derivatives has continued to grow and innovate. To illustrate, coinciding with the time of Professor Webb's assumption of editor duties in June 1998, the notional value of the open interest of exchange-listed futures and options on interest rate, currency and equity instruments stood at $14.5 trillion, and by June 2021 had grown to over $87 trillion. The larger OTC derivatives market also grew tremendously from $72 trillion to $610 trillion.[1] These parallel developments are not coincidental. Derivatives research has expanded in line with the growth of the market and the generation of data, and at the same time has played a significant role in educating market participants and furthering the acceptance of derivatives among both end users and policy makers as indispensable vehicles for risk transference and price discovery.

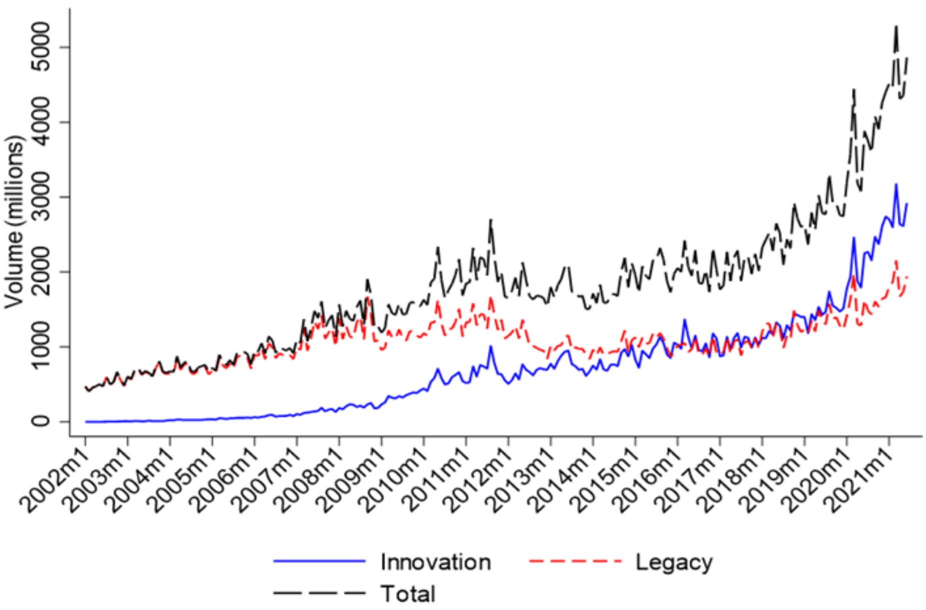
Our purpose in this paper is to provide a largely descriptive examination of how the global market for exchange-traded derivatives has evolved over the past two decades. Our study complements the

[1] See Bank of International Settlements (1999) and https://www.bis.org/publ/otc_hy2111.htm.

work of Emm and Gay (2005) who analyze the global market for OTC derivatives and Gorham and Kundu (2012) who study innovations in U.S. exchanged-traded futures. Our analysis is facilitated by a database containing trade volume and open interest information for nearly all futures and option contracts listed on derivatives exchanges across the globe over the period 2002–2021. To help motivate our research questions we present two related illustrations depicting the growth in exchange-traded derivatives. Figure 1a presents the monthly time series of combined futures and option global volume that shows a nearly ten-fold increase from 472 million contracts in January 2002 to 4,866 million contracts in June 2021. The figure further provides volume breakdowns for "legacy" and "innovation" contracts. We deem legacy contracts as those already trading as of January 2002 and innovation contracts as those subsequently introduced.[2] We see that legacy volume grew to 1,943 million contracts in June 2021, representing 40% of total volume. Interestingly, innovation volume has now surpassed legacy volume, growing from 0 to 2,923 million contracts, or 60% of total volume.

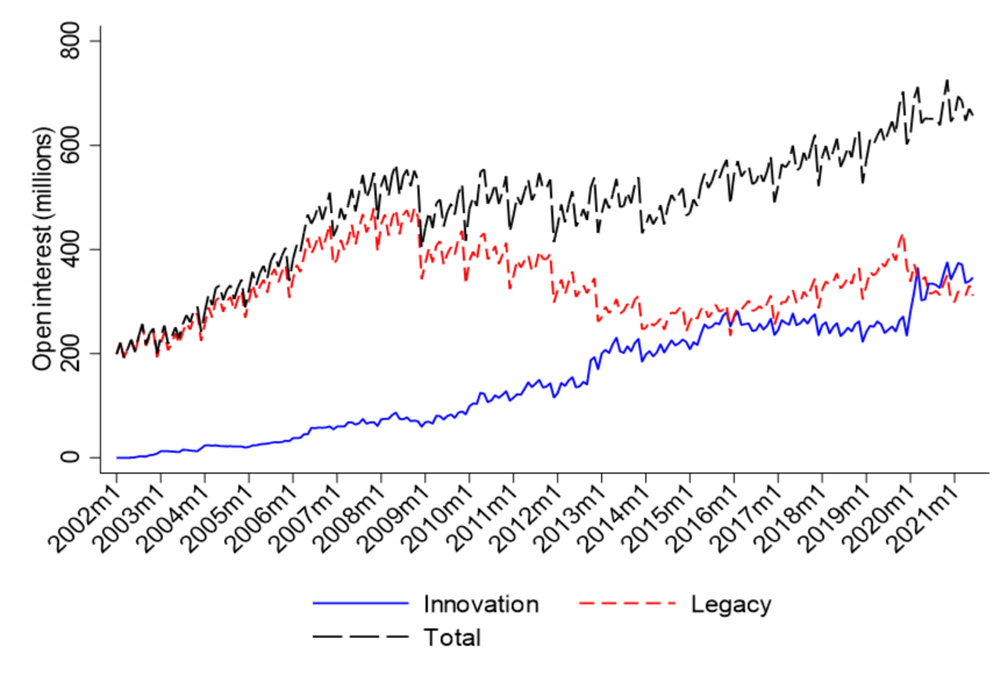
Figure 1b shows that combined futures and options global open interest also grew substantially, but at a much lower rate of about 230%, from 200 million to 657 million contracts. Legacy open interest grew from 200 to 311 million contracts, while innovation open interest grew from 0 to 346 million contracts, also surpassing that of legacy. Comparing total global volume to open interest (i.e., a coarse approximation of scaled turnover), the global ratio in January 2002 was about 236%, but increased by over a factor of three to 740% as of June 2021.

**Figure 1A & B: Growth in global monthly volume and open interest: 2002–2021**




*Note: Figure 1a – Total, legacy and innovation contract volume*

[2] As discussed in Gorham and Kundu (2012), a new contract innovation can fall within a broad spectrum ranging from being a true innovation, an extension of a similar contract at the same exchange, or an imitation of a contract at a competitor exchange.




*Note: Figure 1b: Total, legacy and innovation contract open interest*

To better understand these observations and other related developments, we explore the following research questions that focus on four primary areas of inquiry:

(1) To what extent have the major geographic trading regions contributed to market growth and how have their respective market shares evolved over time?
(2) What has been the attribution to market growth of the various instrument types (futures versus options) and asset classes (agriculture, currency, energy, equity, interest rates and metals)?
(3) How do the observed increases in global scaled turnover, suggestive of an increase in speculative activity, relate to changes in market composition at the geographic region and asset class levels?
(4) What has been the extent of new contract innovation, its breakdown by geographic region and asset class, and the associated failure rates of new contracts?

## 2. Data and Empirical Analysis

We utilize a database created for us by the Futures Industry Association (FIA), which is the leading global trade organization for futures, options, and other centrally cleared derivatives. Our data cover the period January 2002–June 2021 (henceforth "2002-2021" or "study period") and include information on monthly futures and option trade activity on 110 exchanges in 40 countries spanning multiple (a) geographic regions, including North America, Europe, Asia, Latin America and Other (Greece, Israel, Turkey, and South Africa), and (b) commodity (agriculture, energy, and metals) and financial (currency, equity, and interest rates) asset classes.

### 2.1 Region Analysis

As noted above, over our study period the global market for exchange-traded derivatives increased approximately ten-fold based on trading volume and about 2.3 times based on open interest. To investigate how the various geographic regions contributed to this growth, we provide in Table 1 regional breakdowns of monthly volume and month-end open interest for the beginning and ending months, January 2002, and June 2021, of our study period. Panel A reports on trade activity of futures, while panel B reports that for options. In panel A we see that in January 2002 global futures volume was 179 million contracts (representing about 38% of total combined futures and options volume).

Europe and North America dominated futures trading with market shares of 41% and 34%, respectively. Asia was a distant third at 17%, while Latin America had a minor 8% market share. By June 2021, total futures monthly volume grew remarkably to 2,258 million contracts (now representing 46% of total combined volume) with all regions experiencing dramatic increases. Still, there were significant changes in market shares. Asia by far has the largest market share at 35%, or a 19% increase. Both Europe and North America declined notably to 17%, while Latin America tripled its market share to about 24%.

**Table 1: Regional volume and open interest: January 2002 and June 2021**

| | January 2002 | | | | June 2021 | | | | Percentage change in market share | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Volume | Percent | Open Interest | Percent | Volume | Percent | Open Interest | Percent | Volume | Open Interest |
| **Panel A: Futures** | | | | | | | | | | |
| **Asia** | 30.1 | 16.8% | 6.7 | 14.6% | 798.2 | 35.4% | 47.7 | 18.2% | 18.5% | 3.6% |
| ***Europe*** | 72.6 | 40.6% | 13.4 | 29.2% | 375.0 | 16.6% | 71.7 | 27.4% | -24.0% | -1.8% |
| ***Latin America*** | 14.2 | 7.9% | 13.7 | 29.7% | 538.7 | 23.9% | 42.0 | 16.1% | 15.9% | -13.6% |
| ***North America*** | 60.9 | 34.1% | 11.9 | 25.9% | 374.3 | 16.6% | 79.6 | 30.4% | -17.5% | 4.5% |
| **Other** | 0.8 | 0.5% | 0.3 | 0.6% | 171.4 | 7.6% | 20.5 | 7.8% | 7.1% | 7.2% |
| **Totals** | **178.7** | **100.0%** | **46.0** | **100.0%** | **2257.6** | **100.0%** | **261.5** | **100.0%** | | |
| **Panel B: Options** | | | | | | | | | | |
| **Asia** | 122.2 | 41.6% | 4.3 | 2.8% | 1353.4 | 51.9% | 34.4 | 8.7% | 10.2% | 5.9% |
| ***Europe*** | 65.3 | 22.2% | 117.0 | 76.5% | 74.9 | 2.9% | 176.4 | 44.6% | -19.4% | -31.9 |
| ***Latin America*** | 6.8 | 2.3% | 2.6 | 1.7% | 221.9 | 8.5% | 109.0 | 27.5% | 6.2% | 25.8% |
| ***North America*** | 92.4 | 31.5% | 26.3 | 17.2% | 948.2 | 36.3% | 69.4 | 17.5% | 4.9% | 0.4% |
| **Other** | 6.9 | 2.3% | 2.8 | 1.8% | 10.5 | 0.4% | 6.4 | 1.6% | -1.9% | -0.2% |
| **Totals** | **293.6** | **100.0%** | **153.0** | **100.0%** | **2608.9** | **100.0%** | **395.5** | **100.0%** | | |

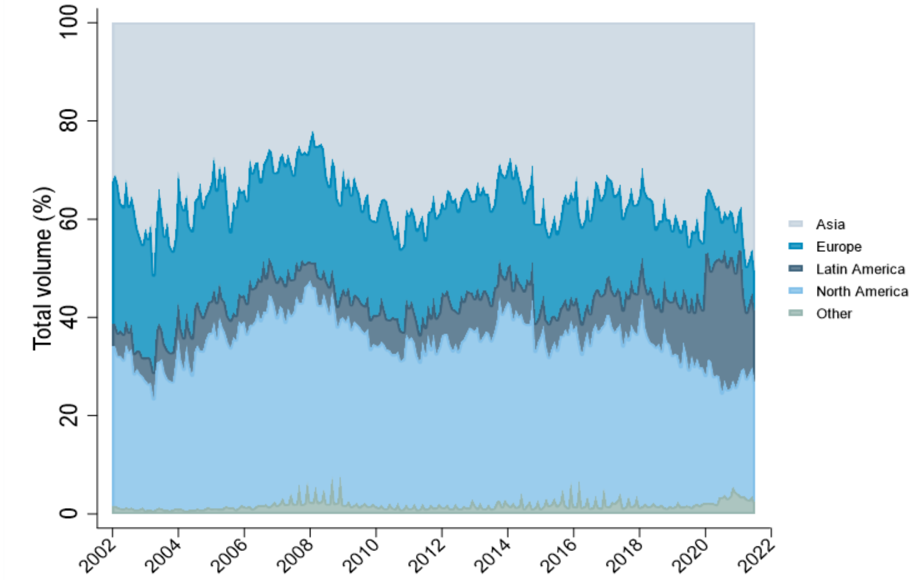
*Note: This table reports monthly volume and month-end open interest in millions of contracts by geographic region along with percent market shares for June 2002 and June 2021.*

Based on futures open interest, in January 2002, Europe, Latin America and North America had similar levels of market share (26-30%) followed by Asia (15%). In June 2021, North America and Europe remained dominant at 30% and 27%, respectively, while Latin America was at 16%. In contrast to Asia's dominant market share of 35% based on volume, its market share based on open interest was only 18%, suggesting a large increase in turnover.

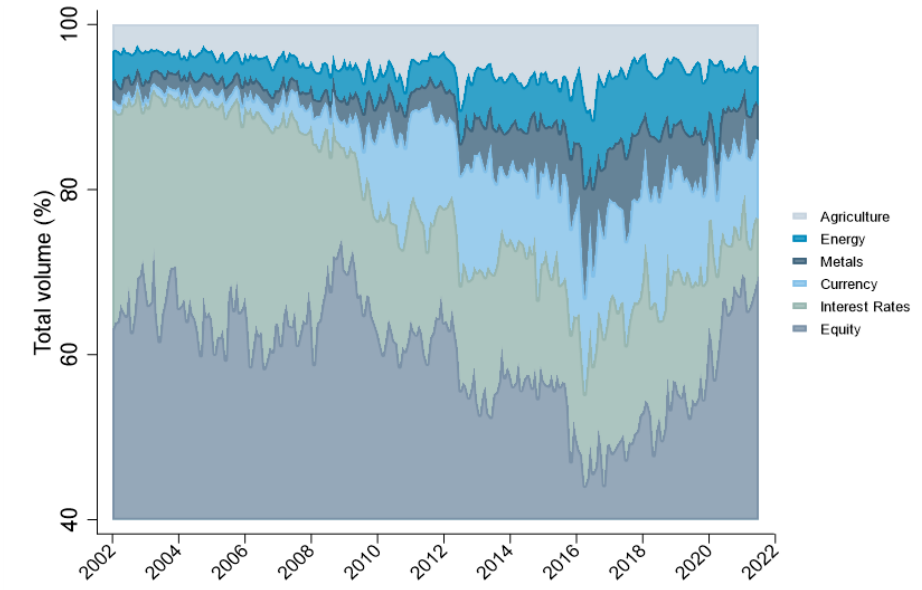
In panel B, in January 2002 global option volume was about 294 million contracts or 62% of total combined volume. Of this total, Asia had the largest market share (42%) followed by North America (32%) and Europe (22%). Based on option open interest, Europe was largest at 77% followed by North America at 17%. Option volume also grew significantly over time and by June 2021 reached 2,609 million contracts, of which Asia's market share further increased to 52%. North America and Latin American also grew notably to 36% and 9%, respectively, while Europe shrank to a distant fourth at 3%. Based on option open interest, Europe was largest at 45% followed by Latin America 28% and North America at 18%. Similarly, to the trade activity of futures, despite Asia having the largest option volume in June 2021, its market share of option open interest was the lowest of the four main regions at 9%.

To provide additional context, we present in Figure 2a the time series graph of the regional market shares of combined futures and option global volume. For Asia in the upper portion of the figure, we observe a reduction in market share from the beginning of the time period up to shortly before the commencement of the financial crisis in late 2007 to early 2008. In contrast, North America shows an increase over the same period. Subsequently, Asia exhibited a general increase to the end of the study period, while North America declined. Europe's market share is somewhat stable throughout the study period but declined notably in early 2020 upon the outbreak of the Covid-19 pandemic. In contrast, Latin America showed a large increase in market share coinciding with the pandemic.

**Figure 2 A & B: Monthly market shares of combined futures and option volume: 2002–2021**




*Note: Figure 2a: Market shares by geographic region*




*Note: Figure 2b: Market shares by asset class*

## 2.2 Asset Class Analysis

Table 2 (organized similarly to Table 1) compares the breakdowns of both volume and open interest by each asset class. In panel A, in January 2002 interest rate futures volume comprised more than one-half (58%) of all futures volume followed by futures on equity (18%), energy (9%) and agriculture (8%). Currency futures volume comprised a somewhat low 2% market share. By June 2021, we observe several notable changes. While interest rate futures volume more than tripled, its market share dropped dramatically to just 15%. In contrast, equity futures volume increased significantly to 44%. Currency futures volume also increased notably to a 13% market share. Based on open interest, the market share of interest rate futures at the beginning of the study period was largest at 61% followed by equity (18%) and agriculture (9%). At the end of the study period, interest rate futures again had the largest market share (33%) followed by equity (28%) and energy (19%).

**Table 2: Volume and open interest by asset class: January 2002 and June 2021**

| | January 2002 | | | | June 2021 | | | | Percentage change in market share | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Volume | Percent | Open Interest | Percent | Volume | Percent | Open Interest | Percent | Volume | Open Interest |
| **Panel A: Futures** | | | | | | | | | | |
| **Commodity** | | | | | | | | | | |
| *Agriculture* | 13.7 | 7.7% | 4.2 | 9.1% | 229.5 | 10.2% | 16.5 | 6.3% | 2.5% | -2.8% |
| *Energy* | 15.3 | 8.6% | 2.5 | 5.5% | 193.5 | 8.6% | 50.6 | 19.4% | 0.0% | 13.8% |
| *Metals* | 10.6 | 6.0% | 1.8 | 4.0% | 216.5 | 9.6% | 12.6 | 4.8% | 3.6% | 09.% |
| **Financial** | | | | | | | | | | |
| *Currency* | 3.2 | 1.8% | 1.2 | 2.7% | 296.1 | 13.1% | 22.0 | 8.4% | 11.3% | 5.7% |
| *Equity* | 31.9 | 17.9% | 8.2 | 17.7% | 992.5 | 44.0% | 73.4 | 28.1% | 26.1% | 10.3% |
| *Interest rates* | 103.9 | 58.1% | 28.0 | 61.0% | 329.5 | 16.4% | 86.3 | 33.0% | -43.5% | -28.0% |
| **Totals** | **178.7** | **100.0%** | **46.0** | **100.0%** | **2257.6** | **100.0%** | **261.5** | **100.0%** | | |
| **Panel B: Options** | | | | | | | | | | |
| **Commodity** | | | | | | | | | | |
| *Agriculture* | 1.4 | 05% | 1.7 | 1.1% | 15.8 | 0.6% | 7.0 | 1.8% | 0.1% | 0.7% |
| *Energy* | 2.0 | 0.7% | 2.0 | 1.3% | 14.8 | 0.6% | 18.1 | 4.6% | -0.1% | 3.3% |
| *Metals* | 0.6 | 0.2% | 0.7 | 0.5% | 5.4 | 0.2% | 2.6 | 0.7% | 0.0% | 0.2% |
| **Financial** | | | | | | | | | | |
| *Currency* | 1.6 | 0.5% | 1.2 | 0.8% | 165.1 | 6.3% | 8.6 | 2.2% | 5.8% | 1.4% |
| *Equity* | 265.6 | 90.5% | 128.4 | 83.9% | 2336.0 | 89.5% | 255.3 | 64.5% | -0.9% | -19.4% |
| *Interest rates* | 22.4 | 7.6% | 19.1 | 12.5% | 71.8 | 2.8% | 103.9 | 26.3% | -4.9% | 13.8% |
| **Totals** | **293.6** | **100.0%** | **153.0** | **100.0%** | **2608.9** | **100%** | **395.5** | **100.0%** | | |

*Note: This table reports monthly volume and month-end open interest in millions of contracts by geographic region along with percent market shares for June 2002 and June 2021.*

In panel B of Table 2 for options, in January 2002 the market was dominated by equities with a 91% market share based on volume followed by interest rates at a distant 8%. These market shares changed modestly in June 2021 with equities remaining at 90% and interest rates declining to 3%. Currency options did experience a noticeable increase from 1% to 6%. Based on open interest, options on equities remained dominant throughout the period, followed by interest rates.

We next observe in Figure 2b the time-series graph of the combined futures and option volume for the various asset classes. We noted earlier that North America lost a significant portion of global market share over the study period commencing with the outset of the financial crisis. We observe in the figure a large decline in the market share of interest rate derivatives, which make up a large portion of North America volume. This trend is consistent with the start of a long-term decline in global interest rate volume. We also observe around the time of the financial crisis a large increase in the market share of currency futures.

## 2.3 League Tables and Discussion

We report in Table 3 the ten leading derivatives exchanges (by overall volume) at the beginning and ending of the study period. In 2002 the two largest derivatives exchanges were the Korea Exchange and Eurex (Germany).[3] Further, six of the top exchanges were based in the U.S. In total, the ten exchanges comprised 83% of global volume. In 2021, the two leading derivatives exchanges were the National Stock Exchange of India and the B3 of Brazil. Further, five out of the ten exchanges were carryovers from 2001. Interestingly, the concentration of trading on these ten leading exchanges fell to 68% of global volume.

**Table 3: Exchange league tables: January 2002 and June 2021**

| | Exchange | Country | Volume | Percent |
|---|---|---|---|---|
| | | January 2002 | | |
| 1 | Korea Exchange | South Korea | 125.9 | 26.7 % |
| 2 | Eurex | Germany | 65.3 | 13.8 % |
| 3 | ICE Futures Europe | France | 55.6 | 11.8 % |
| 4 | Chicago Mercantile Exchange | US | 44.2 | 9.4 % |
| 5 | Chicago Board Options Exchange | US | 26.2 | 5.5 % |
| 6 | Chicago Board of Trade | US | 22.8 | 4.8 % |
| 7 | NYSE Amex | US | 17.7 | 3.7 % |
| 8 | B3 | Brazil | 15.1 | 3.2 % |
| 9 | International Securities Exchange | US | 11.3 | 2.4 % |
| 10 | New York Mercantile Exchange | US | 9.2 | 1.9 % |
| | Other | | 78.8 | 16.7 % |
| | **Total** | | **472.2** | **100.0 %** |
| | | June 2021 | | |
| 1 | National Stock Exchange of India | India | 1,229 | 25.3 % |
| 2 | B3 | Brazil | 751 | 15.4 % |
| 3 | Chicago Mercantile Exchange | US | 205 | 4.2 % |
| 4 | Korea Exchange | South Korea | 193 | 4.0 % |
| 5 | Shanghai Futures Exchange | China | 185 | 3.8 % |
| 6 | Eurex | Germany | 168 | 3.4 % |
| 7 | Borsa Istanbul | Turkey | 149 | 3.1 % |
| 8 | Moscow Exchange | Russia | 147 | 3.0 % |
| 9 | Chicago Board of Trade | US | 141 | 2.9 % |
| 10 | Dalian Commodity Exchange | China | 140 | 2.9 % |
| | Other | | 1,558 | 32.0 % |
| | **Total** | | **4,867** | **100.0 %** |

*Note: This table reports the top ten futures and options exchanges by trading volume in millions of contracts for January 2002 and June 2021.*

In Table 4 we similarly report the ten leading futures and option contracts.[4] In panel A, in 2002, the Chicago Mercantile Exchange's (CME) Eurodollar futures contract was the most actively traded futures followed closely by the Euro-Bund futures traded on Eurex. Of note, nine of the ten leading futures were from the interest rate asset class. The one exception was the CME's E-mini S&P 500 stock

[3] For profiles of the leading exchanges around the start of our study period, see Battley (2000).

[4] We focus on individual contracts and do not include broad groupings such as "all futures [or options] on individual equities [or ETFs]."

index. In 2021, the leading futures by far was the Mini Ibovespa stock index futures traded on Brazil's B3, which as a result became the second largest exchange by volume as seen earlier in Table 3. Also, the leading contracts represented a significant mix of asset classes. Further, only four futures from 2002 remained in the top ten.

**Table 4: Contract league tables: January 2002 and June 2021**

| | Name | Exchange | Country | Asset class | Volume | Percent |
|---|---|---|---|---|---|---|
| **Panel A: Futures** | | | | | | |
| **January 2002** | | | | | | |
| 1 | Eurodollar | Chicago Mercantile Exchange | US | Interest Rates | 19.5 | 10.9% |
| 2 | Euro-Bund | Eurex | Germany | Interest Rates | 17.9 | 10.0% |
| 3 | Euro-Bobl | Eurex | Germany | Interest Rates | 9.6 | 5.4% |
| 4 | Euro-Schatz | Eurex | Germany | Interest Rates | 9.6 | 5.4% |
| 5 | 3-Month Euribor | ICE Futures Europe | UK | Interest Rates | 8.6 | 4.8% |
| 6 | 10-Year Treasury Note | Chicago Board of Trade | US | Interest Rates | 5.5 | 3.1% |
| 7 | TIIE 28 | Mexican Derivatives Exchange | Mexico | Interest Rates | 5.5 | 3.1% |
| 8 | E-mini S&P 500 | Chicago Mercantile Exchange | US | Equity Index | 4.9 | 2.8% |
| 9 | 20-Year Treasury Bond | Chicago Board of Trade | US | Interest Rates | 4.1 | 2.3% |
| 10 | One-Day Interbank Deposit | B3 | Brazil | Interest Rates | 4.0 | 2.2% |
| | Other | | | | 89.4 | 50.0% |
| | **Total** | | | | **178.7** | **100.0** |
| **June 2021** | | | | | | |
| 1 | Mini IBovespa Index | B3 | Brazil | Equity Index | 387.2 | 17.2% |
| 2 | Mini US Dollar Spot | B3 | Brazil | Currency | 71.3 | 3.2% |
| 3 | Eurodollar | Chicago Mercantile Exchange | US | Interest Rates | 60.6 | 2.7% |
| 4 | One-Day Interbank Deposit | B3 | Brazil | Interest Rates | 58.5 | 2.6% |
| 5 | US Dollar/Russian Ruble | Moscow Exchange | Russia | Currency | 57.2 | 2.5% |
| 6 | US Dollar/Indian Rupee | National Stock Exchange of India | India | Currency | 54.3 | 2.4% |
| 7 | Steel Rebar | Shanghai Futures Exchange | China | Non-Precious Metals | 50.6 | 2.2% |
| 8 | Brent Oil | Moscow Exchange | Russia | Energy | 35.0 | 1.5% |
| 9 | 10-Year Treasury Note | Chicago Board of Trade | US | Interest Rates | 33.5 | 1.5% |
| 10 | E-mini S&P 500 | Chicago Mercantile Exchange | US | Equity Index | 32.5 | 1.4% |
| | Other | | | | 1,416.9 | 62.8% |
| | **Total** | | | | **2,257.6** | **100.0%** |
| **Panel B: Options** | | | | | | |
| **January 2002** | | | | | | |
| 1 | KOSPI 200 | Korea Exchange | South Korea | Equity Index | 120.9 | 41.2% |
| 2 | 3-Month Eurodollar | Chicago Mercantile Exchange | US | Interest Rates | 11.3 | 3.9% |
| 3 | DAX | Eurex | Germany | Equity Index | 3.6 | 1.2% |
| 4 | TA-35 Index | Tel-Aviv Stock Exchange | Israel | Equity Index | 3.4 | 1.1% |
| 5 | 3-Month Euribor | ICE Futures Europe | UK | Interest Rates | 3.3 | 1.1% |
| 6 | 10-Year Treasury Note | Chicago Board of Trade | US | Interest Rates | 2.5 | 0.9% |
| 7 | Euro STOXX 50 Index | Eurex | Germany | Equity Index | 2.2 | 0.7% |
| 8 | S&P 500 Index (SPX) | Chicago Board Options Exchange | US | Equity Index | 2.2 | 0.7% |
| 9 | All Share Index | JSE Securities Exchange | South Africa | Equity Index | 1.7 | 0.6% |
| 10 | Euro-Bund | Eurex | Germany | Interest Rates | 1.6 | 0.5% |
| | Other | | | | 140.9 | 48.0% |
| | **Total** | | | | **293.6** | **100.0%** |
| **June 2021** | | | | | | |
| 1 | Bank Nifty Index | National Stock Exchange of India | India | Equity Index | 632.0 | 24.2% |
| 2 | CNX Nifty Index | National Stock Exchange of India | India | Equity Index | 332.3 | 12.7% |
| 3 | US Dollar/Indian Rupee | National Stock Exchange of India | India | Currency | 115.6 | 4.4% |
| 4 | US Dollar/Indian Rupee | BSE | India | Currency | 41.0 | 1.6% |
| 5 | KOSPI 200 | Korea Exchange | South Korea | Equity Index | 34.2 | 1.3% |
| 6 | S&P 500 Index (SPX) | Chicago Board Options Exchange | US | Equity Index | 28.1 | 1.1% |
| 7 | Eurodollar Mid-Curve | Chicago Mercantile Exchange | US | Interest Rates | 19.5 | 0.7% |
| 8 | Avg. One-Day Interbank DRI | B3 | Brazil | Interest Rates | 19.2 | 0.7% |
| 9 | Euro STOXX 50 Index | Eurex | Germany | Equity Index | 17.5 | 0.7% |
| 10 | India 50 Index | India International Exchange | India | Equity Index | 17.2 | 0.7% |
| | Other | | | | 1,352.4 | 51.8% |
| | **Total** | | | | **2,608.9** | **100.0%** |

*Note: This table reports the top ten futures and options contracts by trading volume in millions of contracts for January 2002 and June 2021.*

In panel B, the most actively traded option in 2002 was the KOSPI 200 equity index option. Six of the ten leading contracts were based on equity indices, while the other four were based on interest rates. In 2021, the three leading options all traded on the National Stock Exchange of India with the leading two options based on equity indices. Again, six of the leading options were based on equity indices with two on interest rates and two on currencies.

### 2.4 Turnover

The above analyses suggest that turnover, at least at the global level, increased notably over our study period. Such change in trade activity could be attributed to several factors. In particular, changes in macro conditions can affect both hedging and speculative demand and, accordingly, the mix of commercial (hedgers) and non-commercial (speculators) participants in a specific contract market, who may each have differing trade horizons.[5] The change in turnover could also be an artifact of changes in market composition at the region or asset class levels. We focus on this latter dimension to understand whether such fixed effects related to turnover are present.

**Table 5: Monthly turnover by geographic region and asset class**

| Asset class | Asia | Europe | Latin America | North America | Total |
|---|---|---|---|---|---|
| **Panel A: January 2002** | | | | | |
| *Commodity* | | | | | |
| Agriculture | 3.9 | 0.9 | 0.8 | 2.2 | 2.6 |
| Energy | 6.7 | 5.2 | 0.7 | 2.9 | 3.9 |
| Metals | 5.0 | 5.2 | 0.3 | 2.7 | 4.4 |
| *Financial* | | | | | |
| Currency | 5.6 | 0.5 | 1.5 | 2.5 | 1.8 |
| Equity | 25.3 | 0.6 | 3.5 | 1.7 | 1.7 |
| Interest rates | 2.6 | 4.8 | 0.8 | 2.5 | 2.6 |
| **Total** | **13.8** | **1.1** | **1.2** | **2.3** | **2.0** |
| **Panel B: June 2021** | | | | | |
| *Commodity* | | | | | |
| Agriculture | 19.2 | 1.7 | 1.7 | 4.1 | 10.5 |
| Energy | 26.7 | 3.6 | 9.3 | 1.4 | 3.1 |
| Metals | 21.0 | 6.6 | 3.6 | 6.2 | 15.2 |
| *Financial* | | | | | |
| Currency | 26.9 | 12.1 | 13.3 | 6.8 | 17.5 |
| Equity | 30.2 | 1.0 | 9.2 | 6.9 | 7.5 |
| Interest rates | 6.1 | 2.9 | 1.0 | 2.7 | 2.1 |
| **Total** | **26.2** | **1.8** | **5.0** | **3.1** | **6.1** |
| **Panel C: Monthly average** | | | | | |
| *Commodity* | | | | | |
| Agriculture | 16.8 | 1.6 | 1.6 | 3.6 | 8.9 |
| Energy | 21.8 | 3.6 | 1.1 | 1.5 | 3.1 |
| Metals | 19.6 | 6.3 | 0.3 | 5.4 | 13.6 |
| *Financial* | | | | | |
| Currency | 26.8 | 11.7 | 11.7 | 6.0 | 16.4 |
| Equity | 29.7 | 0.8 | 9.0 | 4.9 | 5.7 |
| Interest rates | 4.8 | 3.4 | 1.0 | 2.7 | 2.2 |
| **Total** | **24.8** | **1.6** | **4.7** | **2.9** | **5.1** |

*Note: This table reports monthly turnover statistics for January 2002, June 2021, and monthly averages over the period January 2002–June 2021. Turnover is computed as the ratio of monthly volume to month-end open interest.*

[5] Wiley and Daigler (1998) and Ederington and Lee (2002) show that hedgers hold positions longer than speculators in financial and commodity futures, respectively.

For each month in our study period, we compute the scaled turnover for each contract as the ratio of its monthly volume to its month-end open interest.[6] We require that each contract have a minimum month-end open interest of 100 contracts. We then compute weighted average turnovers at the asset class and region levels, where the weighting is based on the open interest of each contract. We present in panels A, B and C of Table 5 turnover statistics for the beginning and ending months as well as the monthly average over the study period, respectively. In the last row of Panel A for January 2002, we see that Asia had the highest turnover (13.8) of the four major regions, North America (2.3) was a distant second, and Europe (1.1) had the lowest turnover. Further, Asia had the highest turnover in four of the six asset classes. In panel B for June 2021, we observe increases in turnover across all regions and asset classes (with the exception of energy and interest rates) with the increases most pronounced in Asia and to a lesser extent in Latin America. Moreover, Asia had the highest turnover in all asset classes.

To see whether these observations are unique to these two months, we report in panel C the average turnovers across all months and observe consistent findings. To test the hypotheses that all regions and asset classes have equal turnover, we compute *F*-tests on the total row and column values. For regions, the *F*-statistic was a highly significant 10.62 suggesting a strong region fixed effect. On the other hand, the *F*-statistic based on asset classes was an insignificant 1.50.

## 2.5 New Contract Innovation

**Table 6: Total number of contracts: January 2002 and June 2021**

| Region | Futures | Options | Commodity | | | Financial | | | Total |
|---|---|---|---|---|---|---|---|---|---|
| | | | Agriculture | Energy | Metals | Currency | Equity | Interest rates | |
| **Panel A: January 2002** | | | | | | | | | |
| Asia | 105 | 28 | 48 | 6 | 8 | 3 | 39 | 29 | 133 |
| Europe | 109 | 77 | 23 | 7 | 18 | 11 | 97 | 30 | 186 |
| Latin America | 29 | 11 | 11 | 1 | 2 | 6 | 7 | 13 | 40 |
| North America | 137 | 122 | 64 | 13 | 14 | 53 | 83 | 32 | 259 |
| Other | 12 | 12 | 8 | 0 | 0 | 2 | 11 | 3 | 24 |
| **Total** | **392** | **250** | **154** | **27** | **42** | **75** | **237** | **107** | **642** |
| **Panel B: June 2021** | | | | | | | | | |
| Asia | 475 | 85 | 82 | 79 | 104 | 123 | 151 | 21 | 560 |
| Europe | 556 | 172 | 20 | 194 | 33 | 44 | 369 | 68 | 728 |
| Latin America | 72 | 24 | 22 | 1 | 1 | 39 | 22 | 11 | 96 |
| North America | 455 | 237 | 74 | 223 | 54 | 128 | 168 | 45 | 692 |
| Other | 75 | 30 | 24 | 8 | 13 | 26 | 34 | 0 | 105 |
| **Total** | **1,633** | **548** | **222** | **505** | **205** | **360** | **744** | **145** | **2,181** |
| **Panel C: Percent legacy contracts, June 2021** | | | | | | | | | |
| Asia | 7.2 % | 15.3 % | 3.7 % | 3.8 % | 1.9 % | 0.8 % | 19.2 % | 42.9 % | 8.4 % |
| Europe | 8.3 % | 22.1 % | 25.0 % | 1.5 % | 42.4 % | 4.5 % | 11.1 % | 27.9 % | 11.5 % |
| Latin America | 13.9 % | 16.7 % | 18.2 % | 0.0 % | 0.0 % | 10.3 % | 18.2 % | 18.2 % | 14.6 % |
| North America | 14.5 % | 21.5 % | 48.6 % | 2.7 % | 16.7 % | 20.3 % | 15.5 % | 31.1 % | 16.9 % |
| Other | 8.0 % | 33.3 % | 33.3 % | 0.0 % | 0.0 % | 7.7 % | 17.6 % | n/a % | 15.2 % |
| **Total** | **9.9 %** | **21.2 %** | **25.2 %** | **2.4 %** | **12.2 %** | **9.7 %** | **14.2 %** | **30.3 %** | **12.7 %** |

*Note: This table reports in Panels A and B, respectively, the total number of contracts in January 2002 and June 2021 with breakdowns by geographic region, product group and asset class. Panel C reports the percent of legacy contracts still traded as of June 2021.*

[6] Measuring volume on a daily basis, Garcia, Leuthold and Zapata (1986), Etienne, Irwin and Garcia (2015) and Bohl and Stefan (2020) refer to this ratio as the speculation ratio.

Market growth is a function of three inter-related factors: the volume growth of legacy contracts, the degree of new contract innovation and their growth, and the failure rate of both legacy and innovation contracts. We first inspect the number of legacy contracts at the outset of our study period with these statistics reported in Panel A of Table 6. In January 2002 there were 642 actively traded contracts, including 392 futures contracts and 250 option contracts. As shown in panel B, by June 2021 these totals had grown to 2,181 contracts, with futures (1,633) largely outnumbering options (548). Inspecting the distribution across the geographical regions, in January 2002, North America had the largest number of contracts at 259 (40%), followed by Europe with 186 contracts (29%) and Asia with 133 contracts (21%). As of June 2021, while North American still had the largest number of contracts at 692, Asia had the largest increase in the number of contracts at 321%. Further, the global market became less concentrated as Europe, North America, and Asia became more evenly distributed with 728 contracts (33%), 692 contracts (32%), and 560 contracts (26%), respectively.

Panel C of Table 6 reports on the percent of contracts in June 2021 that were originally legacy contracts. We see that only 13% of all legacy contracts were still trading nearly two decades later. Of the four major regions, North America (17%) and Latin America (15%) had the highest percentages of remaining legacy contracts, while Asia had the lowest at 8%. The option survival rate (21%) exceeded that of futures (10%). Among the various asset classes, interest rates had the highest survival rate at 30% and energy had the lowest at 2%.

We report in Table 7 statistics on the extent and sources of new contract innovation. As shown in the last row of panel A, there were 5,715 new contracts, of which North America accounted for 2,482 (43%), followed by Europe (28%) and Asia (20%). North America also had the largest share of both new futures (39%) and options (57%). With respect to innovation in the specific asset classes shown in panel B, Asia was the leader in agriculture (45%) and metals (55%), whereas Europe was the leader in equity (43%) and interest rates (43%). North America was the predominant region for innovation in energy (70%) and to a lesser extent in currency (32%).

**Table 7: New contract innovation: February 2002–June 2021**

| | Number of new contracts | | | | | | Percent of row totals | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Asia | Europe | Latin America | North America | Other | Total | Asia | Europe | Latin America | North America | Other | Total |
| **Panel A: Product group** | | | | | | | | | | | | |
| Future | 1,029 | 1,261 | 175 | 1,669 | 159 | 4,293 | 24% | 29% | 4% | 39% | 4% | 100% |
| Option | 137 | 361 | 54 | 813 | 57 | 1,422 | 10% | 25% | 4% | 57% | 4% | 100% |
| **Total** | **1,166** | **1,622** | **229** | **2,482** | **216** | **5,715** | **20%** | **28%** | **4%** | **43%** | **4%** | **100%** |
| **Panel B: Asset class** | | | | | | | | | | | | |
| *Commodity* | | | | | | | | | | | | |
| Agriculture | 268 | 90 | 52 | 132 | 53 | 595 | 45% | 15% | 9% | 22% | 9% | 100% |
| Energy | 159 | 416 | 7 | 1,379 | 12 | 1,973 | 8% | 21% | 0% | 70% | 1% | 100% |
| Metals | 230 | 55 | 7 | 107 | 20 | 419 | 55% | 13% | 2% | 26% | 5% | 100% |
| **Total** | **657** | **561** | **66** | **1,618** | **85** | **2,987** | **22%** | **19%** | **2%** | **54%** | **3%** | **100%** |
| *Financial* | | | | | | | | | | | | |
| Currency | 195 | 213 | 56 | 243 | 47 | 754 | 26% | 28% | 7% | 32% | 6% | 100% |
| Equity | 259 | 646 | 39 | 497 | 64 | 1,505 | 17% | 43% | 3% | 33% | 4% | 100% |
| Interest rates | 55 | 202 | 68 | 124 | 20 | 469 | 12% | 43% | 14% | 26% | 4% | 100% |
| **Total** | **509** | **1,061** | **163** | **864** | **131** | **2,728** | **19%** | **39%** | **6%** | **32%** | **5%** | **100%** |

*Note: This table presents the number of new contract innovations by geographic region, product group and asset class.*

## 2.6 New Contract Failure

Next we examine the failure rates of contract innovations for the different regions and asset classes. We deem a contract to have failed upon the determination of its last month of having positive trading volume.[7] For each contract innovation we determine if it failed and, if so, the time to failure. We present in Table 8 the failure rates for futures and options combined.[8] In the last row of the table we see that the overall failure rate was 68% or about two-thirds of all new contracts. Approximately 21% of contracts failed within their first year of trading, 48% within 5 years, and 62% within 10 years.

**Table 8: New contract failure rates: February 2002-June 2021**

| Failure within | Number of contracts | Failure rate | Cumulative failure rate |
|---|---|---|---|
| 1 year | 1,221 | 21% | 21% |
| 2 years | 518 | 9% | 30% |
| 3 years | 434 | 8% | 38% |
| 4 years | 318 | 6% | 44% |
| 5 years | 244 | 4% | 48% |
| 6 years | 228 | 4% | 52% |
| 7 years | 140 | 2% | 54% |
| 8 years | 161 | 3% | 57% |
| 9 years | 128 | 2% | 59% |
| 10 years | 133 | 2% | 62% |
| 11 years | 88 | 2% | 63% |
| 12 years | 68 | 1% | 64% |
| 13 years | 43 | 1% | 65% |
| 14 years | 39 | 1% | 66% |
| 15 years | 25 | 0% | 66% |
| 16 years | 32 | 1% | 67% |
| 17 years | 24 | 0% | 67% |
| 18 years | 15 | 0% | 68% |
| 19 years | 9 | 0% | 68% |
| **Total failures** | **3,868** | **68%** | |
| **Total new contracts** | **5,715** | | |

*Note: This table reports failure rates by years of trading for all new contract innovations from February 2002 to June 2021.*

We illustrate in Figure 3a the failure rates by region. While North America had the largest number of contract innovations (2,482), it also had the highest failure rate at all times to failure. To illustrate, its one- and ten-year failure rates were 24% and 68%, respectively, and its overall failure rate was about 77%. Latin America had the lowest one-year failure rate (17%), while Asia had the lowest long-term failure rate at 56%.

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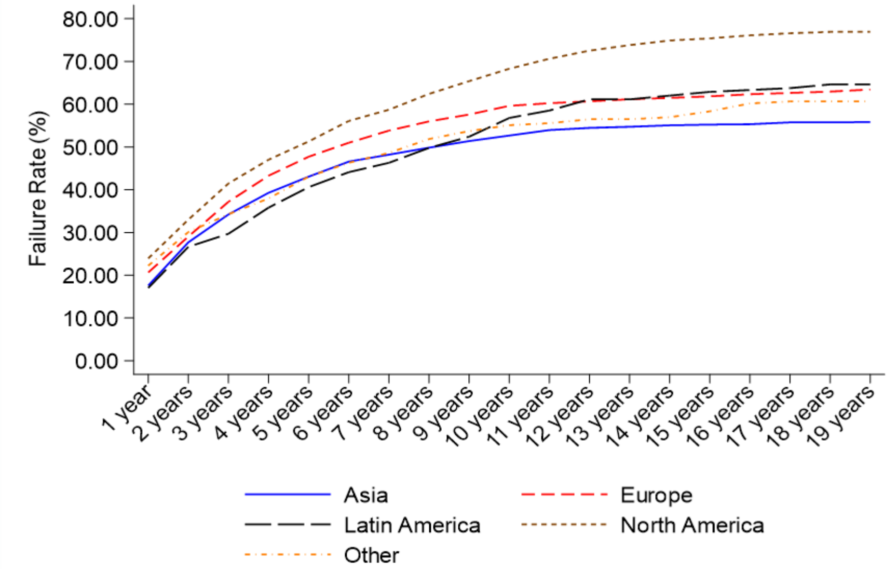
[7] Our defining of contract failure does not necessarily imply a contract was otherwise a "success." There is a literature proposing alternative measures as to what constitutes a successful contract at an exchange. For a summary of this literature, see Gorham and Kundu (2012).

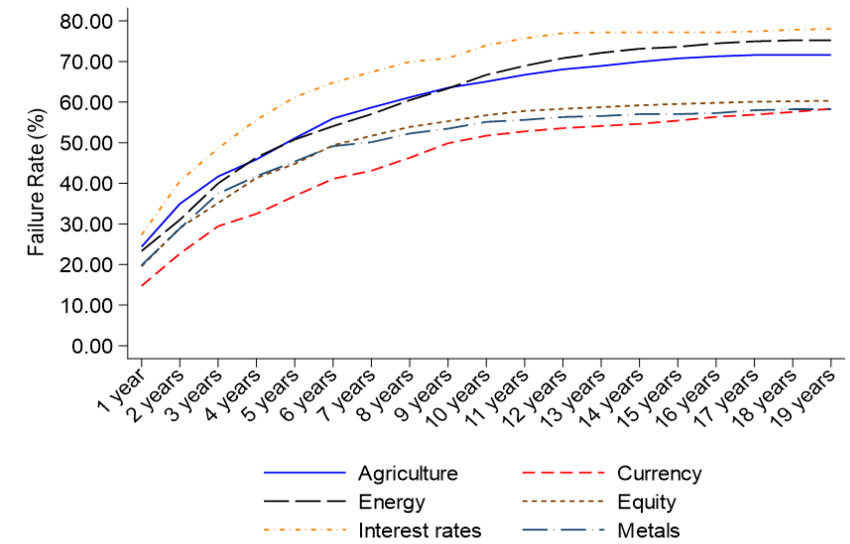
[8] In results not reported, we find little overall differences in the failure rates of futures and options separately and, hence, report results for futures and option failures combined.

For failures by asset class, we show in Figure 3b that interest rates had the highest failure rate at all times to failure with a 78% long-term failure rate and that 27% of these contracts failed within one year. Energy and agriculture contracts also had relatively high failure rates at most of the times to failure. Interesting, metals had relatively high short-term failure rates, but its long-term failure rate was among the lowest.

**Figure 3 A & B: New contract failure rates by years to failure**




*Note: Figure 3a: Failure rates by region*




*Note: Figure 3b: Failure rates by asset class*

## 5. Conclusion

We document a dramatic growth in global trade activity of exchange-traded derivatives over the 2002–2021 period. For futures, volume and open interest grew by factors of 12.6 and 5.7, respectively, while for options the growth factors were 8.9 and 2.6, respectively. While all major trading regions experienced significant growth in volume, Asia and Latin America were the largest contributors followed by North America. Similarly, there was significant growth in all asset classes with equity and currency derivatives showing the largest increase and with interest rate derivatives the lowest, perhaps due to a generally declining and low interest rate environment over a significant portion of the study period.

Noting the disparity in growth between volume and open interest over the study period, we find that scaled turnover at the global level increased by a factor of three. While we do not assert that this was necessarily driven by a general increase in speculative trading, we do find that this increase in turnover was prevalent across all regions and asset classes. Of note, Asia was the largest contributing region, while currency and metals had the largest turnover among asset classes.

We also document the importance to market growth of new contract innovation. We find that North American exchanges accounted for 43% of all new contracts, followed by exchanges in Europe (28%) and Asia (20%). With respect to specific asset classes, Asia led in the growth of agriculture and metal derivatives, Europe led in equity and interest rates, and North America led in the innovation of energy and currencies. Finally, we find an overall long-term failure rate of 68% in new contract innovations. Failure rates were highest in the North American region (77%) and in the interest rates (78%) and energy (75%) asset classes.

## References


Bank of International Settlements, 1999. Central bank survey of foreign exchange and derivatives market activity: 1998. Monetary and Economic Department, Basle.

Battley, N., 2000. *The world's futures and options markets*. 2nd edition. John Wiley & Sons, Inc., West Sussex, England.

Bohl, M.T., and Stefan, M., (2020). Return dynamics during periods of high speculation in a thinly traded commodity market. *Journal of Futures Markets*. Vol. 40, No. 1, 145-159.

Ederington, L., and Lee, J.H., 2002. Who trades futures and how: Evidence from the heating oil futures market. *Journal of Business*. Vol. 75, No. 2, 353–373.

Emm, E.E., and Gay, G.D., 2005. The global market for OTC derivatives: An analysis of dealer holdings. *Journal of Futures Markets*. Vol. 25, No. 1, 39-77.

Etienne, X.L., Irwin, S.H., and Garcia, P., 2015. Price explosiveness, speculation, and grain futures prices. *American Journal of Agricultural Economics*. Vol. 97. No. 1, 65-87.

Garcia, P., Leuthold, R.M., and Zapata, H., 1986. Lead-lag relationships between trading volume and price variability. *Journal of Futures Markets*. Vol. 6, No. 1, 1-10.

Gorham, M., and Kundu, P., 2012. A half-century of product innovation and competition at U.S. futures exchanges. *Review of Futures Markets*. Vol. 20 Special Edition, 105-140.

Wiley, M.K., and Daigler, R.T., 1998. Volume relationships among types of traders in the financial futures markets. *Journal of Futures Markets*. Vol. 18, No. 1, 91–113.



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APPLIED FINANCE LETTERS

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# THE IMPACT OF OIL PRICE UNCERTAINTY ON THE US STOCK RETURNS

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## Abstract

Oil price uncertainty has a negative and significant impact on stock returns during the period of 2003-2020, but not the earlier period of 1984-2002. The impact of stock price uncertainty on oil returns for both periods is not significant. Oil price uncertainty is important in examining stock price movement, particularly during years of financial crises. The cross-market causalities in returns and volatilities are not significant in both directions.

**JEL classification:** G14, G15

**Keywords:** Oil price uncertainty, futures markets, return causality, volatility spillovers

## 1. Introduction

Many papers have studied the relationship between oil and stock prices over the past four decades. The results, nevertheless, are not conclusive. Kling (1985) and Jones and Kaul (1986) report that oil price shocks negatively affect the stock market because higher oil prices increase the cost of production for firms. In contrast, Chen et al. (1986) and Huang et al. (1996) find no significant relationship between oil and stock returns. Hamilton (2009) and Kollias et al. (2013) document that the relationship is positive because rising oil prices suggest a thriving economy and high business confidence.

Kilian (2009) and Kilian and Park (2009) point out that previous empirical studies on the relationship between oil and stock returns restrict the oil price to be exogenous with respect to the US economy. However, the oil price since 1970s has responded to economic forces that drive stock prices. Oil and stock returns, therefore, should be considered endogenous in a dynamic model. Killian (2009) and Kilian and Park (2009) also show that how the stock price responds to oil price shocks depends on where the shocks come from.[1]

Instead of examining the relationship between oil and stock returns, several recent papers have provided theories and empirical results to show the negative effects of oil price uncertainty on economic activities. Elder and Serletis (2010) show that uncertainty about oil prices depresses investment, consumption, and total productivity in the US. Rahman and Serletis (2012) find similar results in the Canadian economy. According to Gao et al. (2022), firms accumulate inventories and postpone investments in order to mitigate the negative consequences of oil shocks, resulting in lower

[1] Killian (2009) states that the sharp oil price increase did not cause a recession because it was driven by sustained strong demand for oil fueled by a booming world economy, not by supply shocks or unanticipated increases in the precautionary demand for oil. See, e.g., Bauseister and Kilian, 2016, and Kilian et al., 2020, for recent evidence.

economic growth and negative stock returns. Christofferson and Pan (2018) show that oil price volatility is significantly related to various measures of funding constraints of financial intermediaries.

Elder and Serletis (2010) and Rahman and Serletis (2012) use a vector autoregressive (VAR) model that is modified to accommodate GARCH-in-mean shocks. As a measure of oil price uncertainty, the authors use the conditional standard deviation of the forecast error for the change in the oil returns. They only examine the oil price uncertainty on the economy, assuming that the oil price is exogenous. In this paper, I follow their models but consider oil and stock returns endogenous, examining both the impact of the oil price uncertainty on stock returns and that of the stock price uncertainty on oil returns.

I use daily returns of the crude oil futures and S&P 500 futures for the period of January 1984 through December 2020. I separate all the results into two subperiods: 1984-2002 and 2003-2020. For the earlier subperiod, the impact of the oil price uncertainty on stock returns is insignificant, but the impact is negative and significant for the more recent subperiod. The second subperiod overlaps the financialization of commodities and the 2008 global financial crisis. The impact of the stock price uncertainty on oil returns is negative, but not significant in both subperiods.

I also examine the return causality in a VAR model (without oil and stock price uncertainties) and find no cross-market causality in both subperiods. To investigate the volatility spillovers or connectedness between the oil and stock returns, I use the variance decomposition of the intraday range-based volatility proposed by Booth et al. (1997) and Diebold and Yilmaz (2009, 2012). The volatility connectedness between these two markets is small for both subperiods, with a total volatility connectedness index of less than 10%. Overall, the oil price uncertainty negatively affects the stock returns for recent years, but not the reverse. There is no cross-market return and volatility causality in both directions for both subperiods.

## 2. Data and Methodology

I obtain futures prices, open ($P_t^{open}$), high ($P_t^{high}$), low ($P_t^{low}$), and close ($P_t^{close}$), from Commodity Systems Inc. for NYMEX West Texas Intermediate (WTI) crude oil futures (ticker symbol, *CL*), the world's most liquid oil contract, and S&P 500 index futures (*SP*). Both futures contracts are traded on CME Group. I use the most liquid contracts (usually the nearby contracts) from January 3, 1984 through December 30, 2020, sample of 9283 days. 1984 is the first full year after crude futures started trading in March 1983. I separate this 37-year period into two subperiods: 1984-2002 (4761 days) and 2003-2020 (4522 days).[2]

The daily returns, $\Delta CL_t$ and $\Delta SP_t$, are calculated as the log price changes in $P_t^{close}$. The bivariate VAR-GARCH-m model is as follows:

$$\Delta CL_t = a_1 + \sum_{j=1}^{q} b_{1j}\Delta CL_{t-j} + \sum_{j=1}^{q} c_{1j}\Delta SP_{t-j} + k_{11}\sigma_{1,t-1} + k_{12}\sigma_{2,t-1} + \varepsilon_{1t} \quad (1)$$

$$\Delta SP_t = a_2 + \sum_{j=1}^{q} b_{2j}\Delta CL_{t-j} + \sum_{j=1}^{q} c_{2j}\Delta SP_{t-j} + k_{21}\sigma_{1,t-1} + k_{22}\sigma_{2,t-1} + \varepsilon_{2t} \quad (2)$$

$$\varepsilon_{it}|\Omega_t \sim N(0, \sigma_{it}^2) \quad (3)$$

$$\sigma_{it}^2 = \omega_i + \alpha\varepsilon_{i,t-1}^2 + \beta\sigma_{i,t-1}^2, \; i = 1 \; or \; 2 \quad (4)$$

[2] I discard the week of April 20, 2020 because oil prices plummeted to negative for the first time as stockpiles overwhelmed storage facilities.

The parameters of interest are $k_{12}$ in Eq. (1) and $k_{21}$ in Eq. (2). $k_{12}$ captures the stock price uncertainty (measured by $\sigma_{1,t-1}$) on oil return and $k_{21}$ captures the oil price uncertainty ($\sigma_{2,t-1}$) on stock returns. Elder and Serletis (2010) assume $k_{12} = 0$.[3] A negative coefficient indicates negative impact of cross-market uncertainty.

$k_{11}$ in Eq. (1) and $k_{22}$ in Eq. (2) describe the own-market risk premium of the oil and stock markets, respectively. A positive coefficient of $k_{11}$ ($k_{22}$) shows that the oil (stock) return is positively related to its volatility. I include $q = 10$ lags of returns in the VAR of Eqs. (1) and (2). The results are virtually the same using 5 lags. Eqs (1)-(4) are jointly estimated using maximum likelihood with heteroscedasticity adjusted standard errors.

The usual return causality is examined in a VAR with the two null hypotheses of all cross-markets coefficients being zero and the sum of cross-market coefficients being zero. The GARCH-*m* model uses the conditional standard deviation of shocks as uncertainty or volatility. In the following VAR (denoted by GK-VAR) and the forecast error variance decomposition, intraday volatility is measured by the Glass-Klass volatility estimator, $\sigma_i^{GK}$ :

$$\sigma_{CL,t}^{GK} = f_1 + \sum_{j=1}^{q} g_{1j}\sigma_{CL,t-j}^{GK} + \sum_{j=1}^{q} h_{1j}\sigma_{SP,t}^{GK} + \epsilon_{1t} \tag{5}$$

$$\sigma_{SP,t}^{GK} = f_2 + \sum_{j=1}^{q} g_{2j}\sigma_{CL,t-j}^{GK} + \sum_{j=1}^{q} h_{2j}\sigma_{SP,t}^{GK} + \epsilon_{2t} \tag{6}$$

$\sigma_i^{GK}$ is the square root of

$$(\sigma_i^{GK})^2 = 0.5\left(\log(P_{i,t}^{high}) - \log(P_{i,t}^{low})\right)^2 - 0.386\left(\log(P_{i,t}^{close}) - \log(P_{i,t}^{open})\right)^2 \tag{7}$$

as in the volatility spillovers across international index futures by Booth et al. (1997). [4]

I use the variance decomposition of the GK-VAR (5) and (6) in a 20-day forecast interval to examine volatility connectedness named by Diebold and Yilmaz (2009, 2012). Booth et al. (1997) and Diebold (2009) use Cholesky factorization to identify orthogonal innovations. In their examination of volatility spillovers across US stock, bond, foreign exchange, and commodities markets, Diebold and Yilmaz (2012) use the generalized VAR of Koop et al. (1996) and Pesaran and Shin (1998) that eliminates the dependence of results of ordering.

In addition to calculate the contributions from and to each market's volatility, Diebold and Yilmaz (2009, 2012) summarize the volatility connectedness across all the markets in a single index, the total spillover index. Higher the value of the index, higher the volatility spillovers across all the markets.

## 3. Empirical Results

I present all the results in three panels of each table, the first subperiod (1984-2002), the second subperiod (2003-2020), and the whole period (1984-2020). Table 1 reports the summarized statistics of

[3] They consider oil price uncertainty exogenous in a structural VAR and use $\sigma_{1,t}$, instead of $\sigma_{1,t-1}$, in the VAR.

[4] As Garman and Klass (1980, p.74) point out, Eq. (7) is more "practical" than the longer GK estimator that includes the cross-product terms. The results using the longer GK estimator as in Diebold et al. (2017) are qualitatively the same.

daily futures returns. CL offered moderately higher returns than SP during the first subperiod, but much lower return during the second subperiod, resulting in a lower return for the whole period (0.0036% vs 0.027%). CL is about twice as volatile as SP in both subperiods, measured by the standard deviation of returns (2.33% vs 1.23% for the whole period).

### Table 1: Summary Statistics of Daily Returns

| | N | Mean | Median | Std | t-stat | Min | Max | Corr. |
|---|---|---|---|---|---|---|---|---|
| **Panel A: January 1984 – December 2002** | | | | | | | | |
| | **N** | **Mean** | **Median** | **Std** | **t-stat** | **Min** | **Max** | **Corr.** |
| ΔCL | 4761 | 0.0339 | 0.055 | 2.212 | 1.06 | -38.41 | 13.57 | N/A |
| ΔSP | 4761 | 0.0209 | 0.043 | 1.243 | 1.16 | -33.7 | 17.75 | -0.048 |
| **Panel B: January 2003 – December 2020** | | | | | | | | |
| | **N** | **Mean** | **Median** | **Std** | **t-stat** | **Min** | **Max** | **Corr.** |
| ΔCL | 4522 | -0.0283 | 0.069 | 2.444 | -0.78 | -28.22 | 22.05 | N/A |
| ΔSP | 4522 | 0.0335 | 0.074 | 1.209 | 1.86 | -10.95 | 13.2 | 0.288 |
| **Panel C: January 1984 – December 2020** | | | | | | | | |
| | **N** | **Mean** | **Median** | **Std** | **t-stat** | **Min** | **Max** | **Corr.** |
| ΔCL | 9283 | 0.0036 | 0.058 | 2.328 | 0.15 | -38.41 | 22.05 | N/A |
| ΔSP | 9283 | 0.027 | 0.059 | 1.227 | 2.21 | -33.7 | 17.75 | 0.121 |

*Note: The daily returns, $\Delta CL_t$ and $\Delta SP_t$, are calculated as the log changes in closing prices.*

The correlation between the oil and stock returns is close to zero, -0.048, during the first subperiod, but it increases to 0.288 during the second subperiod. Figure 1 plots the normalized futures prices (starting at 100). It shows that the higher correlation in the later subperiod is the result of the comovement during the financialization of commodities from 2004 to 2012 (Tang and Xiong, 2012, Cheng and Xiong, 2014). The price collapses during the 2008 global financial crisis and the Covid-19 pandemic in the first half of 2020 for both markets are also noticeable in the figure.

### Table 1: Bivariate GARCH-m Models

$$\Delta CL_t = a_1 + \sum_{j=1}^{10} b_{1j}\Delta CL_{t-j} + \sum_{j=1}^{10} c_{1j}\Delta SP_{t-j} + k_{11}\sigma_{1,t-1} + k_{12}\sigma_{2,t-1} + \varepsilon_{1t}$$

$$\Delta SP_t = a_2 + \sum_{j=1}^{10} b_{2j}\Delta CL_{t-j} + \sum_{j=1}^{10} c_{2j}\Delta SP_{t-j} + k_{21}\sigma_{1,t-1} + k_{22}\sigma_{2,t-1} + \varepsilon_{2t}$$

$$\varepsilon_{it}|\Omega_t \sim N(0, \sigma_{it}^2), \qquad \sigma_{it}^2 = \omega_i + \alpha\varepsilon_{i,t-1}^2 + \beta\sigma_{i,t-1}^2, \ \ i = 1 \ or \ 2$$

| | ΔCL | | ΔSP | |
|---|---|---|---|---|
| | **Coef.** | **t-stat** | **Coef.** | **t-stat** |
| **Panel A: January 1984 – December 2002** | | | | |
| $k_{i1}$ | 0.051 | 2.585 | 0.019 | 1.374 |
| $k_{i2}$ | -0.057 | -1.909 | 0.063 | 4.397 |
| $\omega_i$ | 0.023 | 2.905 | 0.034 | 2.164 |
| $\alpha_i$ | 0.087 | 6.338 | 0.125 | 2.287 |
| $\beta_i$ | 0.908 | 65.284 | 0.858 | 15.286 |
| **Panel B: January 2003 – December 2020** | | | | |
| $k_{i1}$ | 0.07 | 1.884 | -0.031 | -5.65 |
| $k_{i2}$ | -0.043 | -0.517 | 0.125 | 6.317 |
| $\omega_i$ | 0.078 | 2.773 | 0.028 | 5.848 |
| $\alpha_i$ | 0.087 | 5.185 | 0.15 | 9.988 |
| $\beta_i$ | 0.899 | 47.57 | 0.829 | 57.141 |
| **Panel C: January 1984 – December 2020** | | | | |
| $k_{i1}$ | 0.056 | 5.642 | 0.003 | 1.163 |
| $k_{i2}$ | -0.045 | -1.757 | 0.083 | 11.694 |
| $\omega_i$ | 0.035 | 5.349 | 0.029 | 3.557 |
| $\alpha_i$ | 0.087 | 9.858 | 0.133 | 4.587 |
| $\beta_i$ | 0.908 | 102.23 | 0.851 | 35.923 |

*Note: t-statistics are calculated with heteroscedasticity adjusted standard errors.*

Table 2 presents the results of the GARCH-*m* model. For the first subperiod, although both own-market risk premia are significant, 0.051 ($t$ = 2.59) and 0.063 ($t$ = 4.40), the cross-market impact of uncertainties are not significant at the 5% level. For the second subperiod, while the impact of stock price uncertainty on oil returns is not significant, the impact of oil price uncertainty on stock returns is negative and significant, -0.031 ($t$ = -5.65). The cross-market impact of uncertainty is not significant for both markets using the whole period. In sum, the GARCH-m model shows significant own-market risk premium, but it only shows significant oil price uncertainty on stock returns during the second subperiod. This subperiod contains the period of financialization of commodities and the 2008 global finance crisis.

I examine the usual return causality in the VAR and present the results in Table 3. The cross-market return causality is not significant in both subperiods and the whole period. Table 4 further shows that volatility spillovers between the two markets are weak for all periods, although the second period has greater spillovers. The total spillover indexes of Diebold and Yilmaz (2009, 2012) are 1.7%, 8.2%, and 4.7% for the first, second, and the whole periods, respectively, indicating that over 90% of a market's volatility is contributed by its own volatility. For example, for the whole period, 94% of oil volatility is contributed by the oil market itself and 96% of stock volatility by itself. These results are consistent with Diebold and Yilmaz (2012) who find that cross-market volatility spillovers across US stocks, bonds, foreign exchange, and commodities markets are quite limited. In short, both the cross-market causality in returns and volatilities are not significant in both directions for all periods.

## Table 3: Return Causality

| | ΔCL ($i$ = 1) value | statistic | p-value | ΔSP ($i$ = 2) value | statistic | p-value |
|---|---|---|---|---|---|---|
| **Panel A: January 1984 – December 2002** | | | | | | |
| $b_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$ | N/A | 20.04 | 0.0289 | N/A | 5.8 | 0.8315 |
| $c_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$ | N/A | 7.21 | 0.7053 | N/A | 6.37 | 0.7837 |
| $\sum\{j$=1 to 10$\}$ $b_{ij} = 0$, t-stat. | -0.144 | -1.87 | 0.061 | -0.019 | -0.77 | 0.4425 |
| $\sum\{j$=1 to 10$\}$ $c_{ij} = 0$, t-stat. | 0.026 | 0.26 | 0.7964 | -0.219 | -1.27 | 0.2044 |
| **Panel B: January 2003 – December 2020** | | | | | | |
| $b_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$ | N/A | 12.12 | 0.2771 | N/A | 14.18 | 0.1651 |
| $c_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$ | N/A | 11.31 | 0.334 | N/A | 12.34 | 0.2623 |
| $\sum\{j$=1 to 10$\}$ $b_{ij} = 0$, t-stat. | -0.031 | -0.28 | 0.7776 | 0.03 | 0.73 | 0.4674 |
| $\sum\{j$=1 to 10$\}$ $c_{ij} = 0$, t-stat. | 0.31 | 1.42 | 0.1559 | -0.166 | -1.16 | 0.2443 |
| **Panel C: January 1984 – December 2020** | | | | | | |
| $b_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$ | N/A | 9.55 | 0.4811 | N/A | 13.94 | 0.1756 |
| $c_{ij} = 0, \forall j$=1 to 10, $\chi^2(10)$ | N/A | 7.13 | 0.7129 | N/A | 13.63 | 0.1905 |
| $\sum\{j$=1 to 10$\}$ $b_{ij} = 0$, t-stat. | -0.033 | -0.47 | 0.6383 | 0.016 | 0.54 | 0.596 |
| $\sum\{j$=1 to 10$\}$ $c_{ij} = 0$, t-stat. | 0.162 | 1.33 | 0.1831 | -0.207 | -1.75 | 0.0799 |

*Note: The usual return causality is examined in a VAR (without oil and stock price uncertainties) with the two null hypotheses of all cross-markets coefficients ($c_{1j}$ for ΔSP and $b_{2j}$ for ΔCL) being zero and the sum of cross-market coefficients being zero. Statistics are calculated with heteroscedasticity adjusted standard errors.*

## Table 4: Volatility connectedness in return volatilities

| | Oil | | Stock |
|---|---|---|---|
| **Panel A: January 1984 – December 2002** | | | |
| | **Oil** | | **Stock** |
| **Oil** | 97.97 | | 2.03 |
| **Stock** | 1.40 | | 98.60 |
| **Contribution including own** | 99.40 | | 100.60 |
| **Total spillover index** | | 1.70 | |
| **Panel B: January 2003 – December 2020** | | | |
| | **Oil** | | **Stock** |
| **Oil** | 90.12 | | 9.88 |
| **Stock** | 6.50 | | 93.50 |
| **Contribution including own** | 96.60 | | 103.40 |
| **Total spillover index** | | 8.20 | |
| **Panel B: January 1984 – December 2020** | | | |
| | **Oil** | | **Stock** |
| **Oil** | 94.45 | | 5.55 |
| **Stock** | 3.92 | | 96.08 |
| **Contribution including own** | 98.40 | | 101.60 |
| **Total spillover index** | | 4.70 | |

*Note: The total spillover index (%) proposed by Diebold and Yilmaz (2009, 2012) estimates the overall cross-market volatility spillovers.*

## 4. Conclusions

Previous studies have shown that oil price uncertainty has a negative impact on economy activities. Using daily crude oil and US stock index futures for the period of 1984 through 2020, I examine the impact of a market's price uncertainty on the other. I find oil price uncertainty decreased stock returns during the subperiod of 2003-2020, but not the earlier subperiod. The impact of stock price uncertainty on oil returns (albeit, negative) is not significant. Neither are cross-market causalities in returns and volatilities are significant in both directions. These results suggest that oil price uncertainty should be included in examining stock price movement, particularly during crisis periods.

## References

Baumeister, C., Kilian, L., 2016. Lower oil prices and the US economy: Is this time different? Brookings Papers on Economic Activity, 287-336.

Booth, G.G., Chowdhury, M., Martikainen, T., Tse, Y., 1997. Intraday volatility in international stock index futures markets: meteor showers or heat waves? *Management Science* 43, 1564-1576.

Chen, N.-F., Roll, R., Ross, S.A., 1986. Economic forces and the stock market. *Journal of Business* 59, 383-403.

Cheng, I.-H., Xiong, W., 2014. Financialization of Commodity Markets. *Annual Review of Financial Economics* 6, 419-441.

Christoffersen, P., Pan, X., 2018. Oil volatility risk and expected stock returns. *Journal of Banking and Finance* 95, 5–26.

Diebold, F.X, Yilmaz, K., 2009. Measuring financial asset returns and volatility spillovers, with application to global equity markets. *Economic Journal* 119, 158-171.

Diebold, F.X, Yilmaz, K., 2012. Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28, 57-66.

Diebold, F.X., Liu, L, Yilmaz, K., 2017. Commodity connectedness. NBER Working Paper 23685.

Elder, J., Serletis, A., 2010. Oil price uncertainty. *Journal of Money, Credit and Banking* 42, 1137-1159.

Gao, L., Hitzemann, S., Shaliastovich, I., Xu, L., 2022. Oil volatility risk. Journal of Financial Economics, forthcoming.

Garman, M., Glass, M., 1980. On the estimation of security price volatilities from historical data. *Journal of Business* 53, 67-78.

Hamilton, J.D., 2009. Causes and consequences of the oil shock of 2007-08. NBER Working Paper, 15002.

Huang, R.D., Masulis, R.W., Stoll, H.R., 1996. Energy shocks and financial markets. *Journal of Futures Markets* 16, 1-27.

Jones, C.M., Kaul, G., 1996. Oil and stock markets. *Journal of Finance* 51, 463-491

Kilian, L., 2009. Not all oil price shocks are alike: Disentangling demand and supply shocks in the crude oil market. *American Economic Review* 3, 1053-1069.

Kilian, P., Park, C., 2009. The impact of oil price shocks on the US stock market. *International Economic Review* 50, 1267-1287.

Kilian, L., Plante, M.D., Zhou, X. 2020. How falling oil prices in early 2020 weakened the US economy. Working Paper, Federal Reserve Bank of Dallas.

Kling, J.L., 1985. Oil price shocks and the stock market behavior. Journal of Portfolio Management 12, 34-39.

Kollias, C., Kyrtsou, C., Papadamou, S. 2013. The effects of terrorism on the oil price stock index relationship. Energy Economics 40, 743-752.

Koop, G., Pesaran, M.H., and Potter, S.M., 1996. Impulse response analysis in non-linear multivariate models. *Journal of Econometrics* 74, 119-147.

Pesaran, M.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. *Economics Letters* 58, 17-29.

Rahman, S., Serletis, A., 2012. Oil price uncertainty and the Canadian economy: Evidence from a VARMA, GARCH-in-mean, asymmetric BEKK model. *Energy Economics* 34, 603-310.

Tang, K., Xiong, W., 2012. Index investment and financialization of commodities. *Financial Analysts Journal* 68, 54-74.

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# BOAREN: IMPROVING REGULARIZATION IN LINEAR REGRESSION WITH AN APPLICATION TO INDEX TRACKING

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## Abstract

In this paper we introduce the Arbitrary Rectangle-range Elastic Net (AREN): an elastic net with coefficients restricted to some rectangle in $\mathbb{R}^{p}$, $p \geq 1$. The AREN method is one of many regularization techniques intended to increase prediction accuracy in linear regression models by shrinking the magnitude (and possibly eliminating some) of the regression coefficients in an effort to control over-fitting and under-fitting. In this work we describe the AREN features and discuss its statistical consistency properties in estimation and in selecting the correct set of predictors. We also introduce bootstrapping as a way to improve the "small-sample" performance of AREN in selecting predictors. We then apply the AREN (with and without bootstrapping) to tracking the value of the S&P 500 index using a reduced set of stocks.

**MSC2020 subject classifications:** Primary 62P05, 62J07; secondary 62F12.

**Keywords:** Arbitrary rectangle-range elastic net, variable selection, asymptotic consistency, bootstrap.

## 1. Introduction

Variable selection and regularization are essential tools in high-dimensional data analysis. They aim at deriving the most valuable information from the data by finding the right balance of bias (under-fitting) and variance (over-fitting) to optimize the model's prediction capability. Perhaps the earliest example of this type of regularization is the so-called "Ridge Regression" which enforces a penalty proportional to the squared $l_2$-norm of the regression coefficients in the least squares estimation problem. The "lasso" (Least Absolute Shrinkage and Selection Operator) (Tibshirani, 1996) replaces the squared $l_2$-norm penalty in Ridge Regression with an $l_1$-norm penalty, which adds the benefit of actually assigning $0$ to certain regression coefficients. Due to its computational efficiency (Efron et al., 2004), variable selection consistency (Zhao and Yu, 2006), and estimation consistency (Negahban et al., 2012), lasso has overtaken the popularity of Ridge Regression. Refer to (Bickel et al., 2009; Efron et al., 2007; Lounici, 2008; Wang et al., 2007; Yuan and Lin, 2006; Zhao et al., 2009; Zou, 2006) for more in-depth discussions of lasso. Recently, the elastic net was introduced to extend the lasso (Zou and Hastie, 2005). This method involves linearly combining the lasso and ridge regression-like penalties.

Recall that in the classical regression each regression coefficient can assume any value in the real numbers; they are not constrained in any way. However, there can be practical constraints on the regression coefficients; some may be bounded, some may be restricted to be positive or negative. For example, it is known that body height is positively correlated to age; allocations (as a fraction of the total) of assets in a fund should be in $[0,1]$. Based on the above concerns in practice, it is natural to consider regressions with coefficients restricted to some specific range. For instance, Wu et al. (2014) and Wu and Yang (2014) introduced the non-negative lasso and non-negative elastic net to solve the index tracking problem without short sales (with non-negative constraints on weights). More flexible methods are needed to address problems that require arbitrary constraints. To this end, in this paper we examine a recently developed method that assumes the regression coefficients to be in some rectangular range. This model, the arbitrary rectangle-range elastic net method (abbreviated throughout AREN), is a regularization method that deals with high-dimensional problems, and most importantly, generalizes and outperforms the lasso, ridge, and non-negative elastic net. Compared with the non-negative elastic net, AREN allows adding arbitrary lower and upper constraints on the coefficients. This feature makes AREN more adaptable to practical problems. We summarize the contribution of our paper as follows:

1. We introduce AREN to increase the adaptability of the elastic net method when dealing with regressions with constrained-range coefficients.
2. Sufficient conditions for estimation consistency and variable selection consistency of the AREN are discussed.
3. We apply AREN to the problem of tracking the S&P 500 index and following show that AREN (and likely other similar regularization approaches) can be improved through the use of bootstrapping.

The paper is organized as follows. In Section 2, we introduce the mathematical model of AREN and survey its estimation consistency (Theorem 2.1) and variable selection consistency properties (Theorem 2.4). Section 3 is devoted to an application of two-step AREN and bootstrapped two-step AREN to the practical problem of S&P 500 index-tracking. The interested reader may refer to Ding et al. (2021) for simulations that compare the performance of a variety of similar methods of this type.

## 2. The AREN

### 2.1 Definition and Basic Setup

Throughout the paper, the transpose of a matrix $A$ is denoted by $A'$. The $i$-th column of $A$ is denoted by $A_i$, and the entry in the $i$-th row and $j$-th column of $A$ is expressed as $A_{ij}$. The notation $\max(v)$ (resp. $\min(v)$) signifies the maximum (resp. minimum) element of the vector or the matrix $v$. When necessary to identify the elements of an $n \times n$ matrix $X$ we write $X = \left(X_{ij}\right)_{1\le i,j\le n}$. The element-wise absolute value of the matrix $X = \left(X_{ij}\right)_{1\le i,j\le n}$ is $|X| = \left(\left|X_{ij}\right|\right)_{1\le i,j\le n}$ with obvious modification if $X$ is a vector. From two vectors $\mathbf{x} = \left(x_1, \dots, x_p\right)$, $\mathbf{y} = \left(y_1, \dots, y_p\right)$, we define the corresponding rectangle in $\mathbb{R}^p$ as the cartesian product $[\mathbf{x}, \mathbf{y}] = [x_1, y_1] \times \cdots \times \left[x_p, y_p\right]$.

Let us consider the linear regression model

$$Y = X\beta^* + \epsilon, \qquad \textit{(Error! No text of specified style in document..1)}$$

where $X$ is a deterministic $n \times p$ design matrix, $Y = (y_1 \ \dots \ y_n)'$ is an $n \times 1$ response vector and $\epsilon = (\epsilon_1 \ \dots \ \epsilon_n)'$ is a zero-mean Gaussian noise vector with $\mathbb{V}\mathrm{ar}(\epsilon_1) = \sigma^2$. Without loss of generality, we assume all the predictors are centered, so the intercept is not included. $\beta^* \in \mathbb{R}^p$ denotes the vector of regression coefficients.

When $p$ is large, it is natural to assume that the linear model, Equation (Error! ***No text of specified style in document..1)***, is $q$-sparse; i.e., $\beta^*$ has at most $q$ ($q \ll p$) nonzero elements. For the AREN regularization, we assume there is a rectangular region $\mathcal{I} = [\mathbf{s}, \mathbf{t}]$ in $\mathbb{R}^p$ that contains $\beta^*$, with $\mathbf{s} = (s_1, \dots, s_p)$, $\mathbf{t} = (t_1, \dots, t_p)$, $s_i \in \mathbb{R} \cup \{-\infty\}$, $t_i \in \mathbb{R} \cup \{+\infty\}$, $s_i < t_i$ for all $i = 1, \dots, p$. For the linear model Equation (Error! ***No text of specified style in document.**.1)*, the AREN estimator of $\beta^*$ is given by

$$\hat{\beta}\left(\lambda_n^{(1)}, \lambda_n^{(2)}\right) = \arg\min_{\beta \in \mathcal{I}} \left(\frac{1}{2n}\|Y - X\beta\|_2^2 + \lambda_n^{(1)}\|\beta\|_1 + \lambda_n^{(2)}\|\beta\|_2^2\right).$$

*(**Error! No text of specified style in document.**.2)*

Here $\lambda_n^{(1)}, \lambda_n^{(2)} \geq 0$ are tuning parameters which control the importance of the $l_1$ and $l_2$ regularization terms, respectively. These are typically tuned to minimize the prediction mean-squared error by repeatedly performing AREN on training data for each pair in a lattice of values of $\lambda_n^{(1)}, \lambda_n^{(2)} \geq 0$, using the resulting model to predict the responses for an out-of-sample testing set and computing the observed mean-squared error in those predictions. A search over that lattice can then select the pair with the smallest mean-squared error.

The AREN, Equation (Error! ***No text of specified style in document.**.2)* method extends the elastic net method when $\mathcal{I} = \mathbb{R}^p$. It extends the non-negative elastic net when $\mathcal{I} = [0, +\infty)^p$.

Observe that, taking $\dot{X} = X/\sqrt{2n}$ and $\dot{Y} = Y/\sqrt{2n}$, the mean-squared error loss function in Equation (Error! ***No text of specified style in document.**.2)* can be transformed to the residual sum of squares loss function, i.e., Equation (Error! ***No text of specified style in document.**.2)* becomes

$$\hat{\beta}\left(\lambda_n^{(1)}, \lambda_n^{(2)}\right) = \arg\min_{\beta \in \mathcal{I}} \left(\left\|\dot{Y} - \dot{X}\beta\right\|_2^2 + \lambda_n^{(1)}\|\beta\|_1 + \lambda_n^{(2)}\|\beta\|_2^2\right),$$

*(**Error! No text of specified style in document.**.3)*

which is a particular case of the Arbitrary Rectangle-range Generalized Elastic Net (ARGEN) studied in Ding et al. (2021). As a result, the AREN problem, Equation (Error! ***No text of specified style in document.**.2)*, can be solved numerically using the so-called "multiplicative updates for solving quadratic programming with rectangle-range $l_1$ regularization" algorithm. We refer the reader to Ding et al. (2021, Algorithm 1) for more detail on this algorithm.

Also observe that the AREN problem can be transformed to a rectangle-range lasso problem. If we take

$$\tilde{X} = \frac{1}{\sqrt{1 + \lambda_n^{(2)}}} \begin{pmatrix} X \\ \sqrt{\lambda_n^{(2)}} 1_{p \times p} \end{pmatrix}_{(n+p) \times p}, \quad \tilde{Y} = \begin{pmatrix} Y \\ 0 \end{pmatrix}_{(n+p) \times 1}, \quad \lambda_n = \frac{\lambda_n^{(1)}}{\sqrt{1 + \lambda_n^{(2)}}},$$

$$\tilde{\beta}^* = \sqrt{1 + \lambda_n^{(2)}} \beta^*, \quad \tilde{\mathcal{I}} = \prod_{i=1}^{p} \left[\sqrt{1 + \lambda_n^{(2)}} s_i, \sqrt{1 + \lambda_n^{(2)}} t_i\right],$$

then the problem, Equation (Error! ***No text of specified style in document.**.2)*, is equivalent to

$$\hat{\tilde{\beta}}(\lambda_n) = \arg\min_{\beta\in\tilde{\mathcal{J}}} \left( \frac{1}{2n} \|\tilde{Y} - \tilde{X}\beta\|_2^2 + \lambda_n \|\beta\|_1 \right), \quad \text{(Error! No text of specified style in document..4)}$$

where $1_{p\times p}$ denotes the $p \times p$ identity matrix and $\hat{\tilde{\beta}}(\lambda_n)$ is the estimator of $\tilde{\beta}^*$. Both estimation and model consistencies of the lasso have been studied in the literature, and this work is easily adapted to apply to the estimation and model consistencies of the rectangle-range lasso, as well as the AREN. We therefore simply state these results for the AREN without proof in the next two sections.

## 2.2 Upper Bounds of Tail Probability and Estimation Consistency

We say the AREN has estimation consistency if the AREN estimator $\hat{\beta}$ satisfies

$$\|\hat{\beta} - \beta^*\|_1 \xrightarrow[n\to\infty]{\mathbb{P}} 0 \quad \text{or} \quad \|\hat{\beta} - \beta^*\|_2 \xrightarrow[n\to\infty]{\mathbb{P}} 0,$$

where $\xrightarrow[n\to\infty]{\mathbb{P}}$ denotes the convergence in probability. As pointed out earlier, our AREN model is in fact equivalent to the rectangle-range lasso studied further in Ding et al. (2021, Corollary 2.5). The main difference between AREN and the model in Ding et al. (2021, Corollary 2.5) lies in whether there is the multiplier $1/(2n)$ in the loss function (see Equation (Error! ***No text of specified style in document.**.2)*). This difference makes the conditions (ii) and (iii) below slightly different from those in Ding et al. (2021, Corollary 2.5). Nevertheless, those results prove the estimation consistency of the AREN, subject to the following conditions, adapted and modified from Ding et al. (2021):

(i) $\boldsymbol{\beta}^* \in \boldsymbol{\mathcal{J}}$.

(ii) The designed matrix $\mathbf{X}$ satisfies

$$\frac{X_j{}'X_j + \lambda_n^{(2)}}{\left(1 + \lambda_n^{(2)}\right)n} \leq 1, \text{ for all } j = 1, \dots, p.$$

(iii) There exists a constant $\boldsymbol{\kappa} > \mathbf{0}$, such that

$$\frac{\|X\beta\|_2^2 + \lambda_n^{(2)}\|\beta\|_2^2}{\left(1 + \lambda_n^{(2)}\right)n} \geq \kappa\|\beta\|_2^2$$

for all $\beta \geq 0$ satisfying

$$\sum_{j\in\{1,\dots,p\}:\, \beta_j^*=0} |\beta_j| \leq 3 \sum_{j\in\{1,\dots,p\}:\, \beta_j^*\neq 0} |\beta_j|.$$

(iv) $\boldsymbol{\lambda_n^{(1)}}$ and $\boldsymbol{\lambda_n^{(2)}}$ satisfy

$$\frac{\lambda_n^{(1)}}{1 + \lambda_n^{(2)}} \underset{n\to\infty}{\longrightarrow} 0 \quad \text{and} \quad \exp\left( -\frac{n}{8\sigma^2} \frac{(\lambda_n^{(1)})^2}{1 + \lambda_n^{(2)}} \right) \underset{n\to\infty}{\longrightarrow} 0,$$

where $\sigma > 0$ is the residual standard deviation of each component of the error term in the linear model, Equation (Error! ***No text of specified style in document.**.1)*.

The estimation consistency of the AREN is provided by this theorem:

**Theorem 2.1:** Consider a $q$-sparse instance of the AREN, Equation (Error! ***No text of specified style in document.**.2)*. Let $X$ satisfy the conditions (i) - (iii) and let the regularization parameters satisfy $\lambda_n^{(1)} > 0, \lambda_n^{(2)} \geq 0$. Then the AREN solution $\hat{\beta} = \hat{\beta}(\lambda_n^{(1)}, \lambda_n^{(2)})$ satisfies:

$$\mathbb{P}\left(\|\hat{\beta} - \beta^*\|_2^2 > \frac{9q(\lambda_n^{(1)})^2}{\kappa^2(1+\lambda_n^{(2)})^2}\right) \leq 2p \exp\left(-\frac{n(\lambda_n^{(1)})^2}{8\sigma^2(1+\lambda_n^{(2)})}\right),$$

$$\mathbb{P}\left(\|\hat{\beta} - \beta^*\|_1 > \frac{12q\lambda_n^{(1)}}{\kappa(1+\lambda_n^{(2)})}\right) \leq 2p \exp\left(-\frac{n(\lambda_n^{(1)})^2}{8\sigma^2(1+\lambda_n^{(2)})}\right).$$

In addition, if $(\mathrm{iv})$ holds, the AREN, Equation (Error! ***No text of specified style in document.**.2)*, has the property of estimation consistency: $\|\hat{\beta} - \beta^*\|_2 \xrightarrow[n\to\infty]{\mathbb{P}} 0$.

Theorem 2.1 provides fine upper bounds of the tail probabilities of the estimation errors in $l_1$ and $l_2$-norms. It then makes clear that the estimation consistency holds whenever $\lambda_n$ goes to zero slower than $n^{-1/2}$. If we take $\mathcal{J} = [0, +\infty)^p$, $\lambda_n^{(2)} = 0$ and $\lambda_n^{(1)} = 4\sigma\sqrt{\log(p)/n}$ in Theorem 2.1, the tail probability bounds for the non-negative lasso follow as in Wu etal. (2014, Proposition 1). If we further assume $\mathcal{J} = \mathbb{R}^p$ in Theorem 2.1, the tail bounds for the unconstrained lasso follow (Negahban et al., 2012, Corollary 2). In the above two cases, if we assume $p = p_n$, $q = q_n$ with $p_n \longrightarrow +\infty$ and $p_n \log(q_n)/n \longrightarrow 0$, as $n \to \infty$, the estimation consistency holds. However, if $\lambda_n = \lambda_0 n^{-1/2}$ for some $\lambda_0 > 0$, whether the estimation consistency holds is an open problem. In this situation what can be derived is the sign pattern consistency: there is positive probability that all signs of $\hat{\beta}$ are consistent with those of $\beta^*$, i.e., Propositions 1 and 2 in Bach (2008) can be obtained for AREN. Such sign pattern consistency can be viewed as a weak form of variable selection model consistency. When $\lambda_n$ goes to infinity, it is possible to establish the strong version of variable selection consistency for AREN. In the next section we present the variable selection consistency of AREN subject to the assumption that $\lambda_n^{(1)}$ goes to infinity faster than $\sqrt{n}$ and some other conditions.

## 2.3 Variable Selection Consistency

Recall that our AREN problem is equivalent to the problem, Equation (Error! ***No text of specified style in document.**.3)*, whose variable selection consistency can be derived as a special case of the generalized version in Ding et al. (2021, Theorem 2.3). In the interests of completeness, we state the variable selection consistency conditions for our AREN, which have been modified and adapted from those in Ding et al. (2021, Theorem 2.3). Denote by

$$G = \{i \in \{1, \dots, p\}: \beta_i^* = 0\} \text{ and } \hat{G} = \{i \in \{1, \dots, p\}: \hat{\beta}_i = 0\},$$

and let $\#G$ be the cardinality of the group of indexes $G$. The variable selection consistency for the AREN is defined as follows.

**Definition 2.2:** We say that the AREN, Equation (Error! ***No text of specified style in document.**.2)*, satisfies variable selection consistency if there exist $\lambda_n^{(1)}$ and $\lambda_n^{(2)}$ such that $\mathbb{P}(\hat{G} = G) \xrightarrow[n\to\infty]{} 1$.

The above variable selection consistency is a stronger property than the sign pattern consistency discussed in Bach (2008). It says that, if $\beta_i^* = 0$, then with probability approaching $1$, the $i$-th predictor will not be selected, as $n$ becomes large. Note that the variable selection consistency of the non-negative elastic net and elastic net (Wu and Yang, 2014; Wu et al, 2014; Zhao and Yu, 2006) are implied by variable consistency of the AREN.

Let $X_{(1)} = (X_i)_{i\notin G}$ be the observed predictor values corresponding to the group of indexes $G^c$, the complementary of $G$. Let $\beta^*_{(1)} = (\beta^*_i)_{i\notin G}$, $s_{(1)} = (s_i)_{i\notin G}$ and $t_{(1)} = (t_i)_{i\notin G}$. Similarly let $X_{(2)} = (X_i)_{i\in G}$, $\beta^*_{(2)} = (\beta^*_i)_{i\in G}$, $s_{(2)} = (s_i)_{i\in G}$ and $t_{(2)} = (t_i)_{i\in G}$. Moreover, denote by

$$C_{ij} = \frac{X'_{(i)}X_{(j)}}{2n^2}, \text{ for } i,\ j = 1,2;$$
$$\rho_n^{(1)} = \max\left\{\left(C_{11} + \frac{\lambda_n^{(2)}}{n}1_{(p-\#G)\times(p-\#G)}\right)^{-1} C_{11}\beta^*_{(1)} - t_{(1)}\right\};$$
$$\rho_n^{(2)} = \min\left\{\left(C_{11} + \frac{\lambda_n^{(2)}}{n}1_{(p-\#G)\times(p-\#G)}\right)^{-1} C_{11}\beta^*_{(1)} - s_{(1)}\right\};$$
$$C_n = \left(C_{11} + \frac{\lambda_n^{(2)}}{n}1_{(p-\#G)\times(p-\#G)}\right)^{-1}\left(\frac{\lambda_n^{(1)}}{2}\operatorname{sign}\left(\beta^*_{(1)}\right)\right);$$
$$C_n^{max} = \max C_n,\quad C_n^{min} = \min C_n,$$

(Error! No text of specified style in document..5)

where for a vector $v = (v_1, \ldots, v_n)$, $\operatorname{sign}(v) = \left(\operatorname{sign}(v_1)\ \ldots\ \operatorname{sign}(v_n)\right)'$ denotes the vector of signs of the elements in $v$. The sign equals $1$ for positive entry, $-1$ for negative entry and $0$ for zero entry. To show the AREN, Equation (Error! ***No text of specified style in document.**.2)*, admits the variable selection consistency, we assume that the following conditions hold:

$$q > 1,\ p - q > 1,\ \frac{\lambda_n^{(1)}}{\sqrt{n}} \underset{n\to\infty}{\longrightarrow} +\infty,\ \frac{\max_{1\le i\le p} X_i'X_i}{n^2} \underset{n\to\infty}{\longrightarrow} 0,$$

***(Error! No text of specified style in document..6)***

and

$$\frac{1}{\rho_n^{(1)}}\left(\frac{8\sigma\sqrt{\#G_{(1)}\operatorname{trace}(C_{11})\log\left(\#G_{(1)}\right)}}{n\Lambda_{min}\left(C_{11} + \lambda_n^{(2)}1_{(p-\#G)\times(p-\#G)}/n\right)} + \frac{\left|C_n^{min}\right|}{n}\right) \underset{n\to\infty}{\longrightarrow} 0,$$

***(Error! No text of specified style in document..7)***

$$\frac{1}{\rho_n^{(2)}}\left(\frac{8\sigma\sqrt{\#G_{(1)}\operatorname{trace}(C_{11})\log\left(\#G_{(1)}\right)}}{n\Lambda_{min}\left(C_{11} + \lambda_n^{(2)}1_{(p-\#G)\times(p-\#G)}/n\right)} + \frac{\left|C_n^{max}\right|}{n}\right) \underset{n\to\infty}{\longrightarrow} 0,$$

***(Error! No text of specified style in document..8)***

where $\operatorname{trace}(C_{11})$ denotes the trace of the matrix $C_{11}$ and $\Lambda_{min}(M)$ denotes the minimal eigenvalue of the matrix $M$. In addition, we assume that the arbitrary rectangle-range elastic irrepresentable condition (AREIC), defined below, is satisfied.

**Definition 2.3:** If there exists a positive constant vector $\eta$, such that

$$C_{21}\left(C_{11}+\frac{\lambda_n^{(2)}}{n}1_{(p-\#G)\times(p-\#G)}\right)^{-1}\left(\mathrm{sign}\left(\beta^*_{(1)}\right)+\frac{2\lambda_n^{(2)}}{\lambda_n^{(1)}}\beta^*_{(1)}\right)-\frac{2\lambda_n^{(2)}}{\lambda_n^{(1)}}s_{(2)}\leq \mathbf{1}-\eta,$$

where $\mathbf{1}=(1\dots 1)'$, we say that AREIC holds.

When $\mathcal{I}=[0,+\infty)^p$, the AREIC becomes the non-negative elastic irrepresentable condition (NEIC) as follows:

$$C_{21}\left(C_{11}+\frac{\lambda_n^{(2)}}{n}1_{(p-\#G)\times(p-\#G)}\right)^{-1}\left(\mathbf{1}+\frac{2\lambda_n^{(2)}}{\lambda_n^{(1)}}\beta^*_{(1)}\right)\leq \mathbf{1}-\eta.$$

***(Error! No text of specified style in document..9)***

The NEIC was crucial to get the variable selection consistency of the non-negative elastic net (Zhao et al., 2014). If further $\lambda_n^{(2)}=0$ in Equation (Error! ***No text of specified style in document.****.9)*, the NEIC then becomes the non-negative irrepresentable condition (NIC): $C_{21}C_{11}^{-1}\mathbf{1}\leq\mathbf{1}-\eta$, which was needed to obtain the variable selection consistency of the non-negative lasso in Wu et al. (2014). Note that, NIC is a non-negative version of the following irrepresentable condition (IC): $\left|C_{21}C_{11}^{-1}\mathrm{sign}\left(\beta^*_{(1)}\right)\right|\leq\mathbf{1}-\eta$, for the variable selection consistency of the lasso (Zhao and Yu, 2006). It was proved in Zhao and Yu (2006) that IC is a sufficient and necessary condition for the variable selection consistency of the lasso, while NIC is only a sufficient condition. However, since NIC is less restrictive than IC (it does not depend on the unknown parameters $\beta^*$), so easier verified than IC in practice. Nevertheless, AREIC is a natural extension of the previous conditions NEIC and NIC for the variable selection consistency. We state below the variable selection consistency theorem for the AREN.

**Theorem 2.4:** Assume that the conditions, Equations (Error! ***No text of specified style in document.****.6)* - (Error! ***No text of specified style in document.****.8)*, and the AREIC hold. Then the AREN, Equation (Error! ***No text of specified style in document.****.2)*, possesses the variable selection consistency property given in Definition 2.2.

Estimation consistency and variable selection consistency are important statistical properties because they guarantee that as the sample size $n$ increases (which is tantamount to a proportional increase in information), so does the accuracy of estimation and variable selection. Although the somewhat esoteric sufficient conditions outlined in this section are difficult to verify in practice, it is almost certain that less restrictive, more general conditions for these types of consistency hold and apply broadly. Still, this is no guaranty of accuracy in any specific moderate or large sample. Accordingly, it is possible that AREN could under-perform in practice if conditions are sufficiently extreme. To help mitigate this, we introduce BoAREN, or "Bootstrapped AREN", following Bach (2008). As long as $n$ is not critically small, the estimation consistency and variable selection consistency would guarantee a high likelihood that most of the variables are correctly chosen and estimated accurately. By performing bootstrap replications of the data, each bootstrap replicate should also produce a result with most of the variables correctly chosen and estimated accurately. By definition of bootstrap replication, each bootstrap replicate of fitting the AREN is likely to be slightly different (i.e. contain a slightly different set of variables selected). By estimation consistency, each of these sets should be "close" to the correct set, though some may be lacking some important variables, while others may contain slightly too many. Intersecting (or alternatively, "soft" intersecting - see the next section) these sets can therefore improve the accuracy of variable selection. The two models, AREN and BoAREN, are applied to the index tracking problem in the next section.

## 3. BoAREN and S&P 500 Index Tracking[1]

An index fund is a passively managed mutual fund that is designed to track a given component of the market, for example, the S&P 500. Index tracking is a generic term for the various methods/algorithms used by portfolio managers to guarantee that the index fund remains in close agreement with the target market component. Here, the main objective for the index tracking problem is minimizing the tracking error, which we define as the standard deviation of the difference between the returns of the selected portfolio ($\mathrm{R}^{\mathrm{P}}$) and the benchmark ($\mathrm{R}^{\mathrm{B}}$). Assuming the total number of periods is $\mathrm{n}$, the tracking error ($\mathrm{TE}$) per perod is computed by

$$\mathrm{TE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\left(R_i^P - R_i^B\right) - \frac{1}{n}\sum_{l=1}^{n}\left(R_l^P - R_l^B\right)\right)^2}.$$

***(Error! No text of specified style in document.**.10)*

**Algorithm 1:** BoAREN[2]

Input: $X \in \mathbb{R}^{n \times p}$
$Y \in \mathbb{R}^n$
Number of bootstrap replicates $m$
Soft index S
$l_1$ regularization parameter $\lambda_n^{(1)}$
$l_2$ regularization parameter $\lambda_n^{(2)}$
AREN coefficient lower constraints $\mathbf{s} \in (\mathbb{R} \cup \{-\infty\})^p$
AREN coefficient upper constraints $\mathbf{t} \in (\mathbb{R} \cup \{+\infty\})^p$

For $i \leftarrow 1$ to $m$ do
    Generate bootstrapped $X^{(i)} \in \mathbb{R}^{n \times p}$ and $Y^{(i)} \in \mathbb{R}^n$
    Compute AREN estimate $\hat{\beta}^{(i)}$ from $X^{(i)}$ and $Y^{(i)}$ with $\lambda_n^{(1)}, \lambda_n^{(2)}$, $\mathcal{I} = [0, \infty)^p$
    Compute support $J^{(i)} = \{j,\ \hat{\beta}_j^{(i)} \neq 0\}$
Compute $J = (\cap_S)_{i=1}^{m} J^{(i)}$
Compute AREN estimate $\hat{\beta}_J$ from $X_J$ and $Y$ with $\lambda_n^{(1)} = \lambda_n^{(2)} = 0$, $\mathcal{I} = [\mathbf{s}, \mathbf{t}]$

**Algorithm 2:** Two-step AREN

Input: $X \in \mathbb{R}^{n \times p}$
$Y \in \mathbb{R}^n$
$l_1$ regularization parameter $\lambda_n^{(1)}$

[1] Code for the AREN/BoAREN computations in this section can be found in https://github.com/yujiading/bootstrapped-aren.

[2] "BoAREN" refers to the AREN algorithm enhanced by bootstrapping.

$l_2$ regularization parameter $\lambda_n^{(2)}$
AREN coefficient lower constraints $\mathbf{s} \in (\mathbb{R} \cup \{-\infty\})^p$
AREN coefficient upper constraints $\mathbf{t} \in (\mathbb{R} \cup \{+\infty\})^p$

1 Compute AREN estimate $\hat{\beta}$ from $X$ and $Y$ with $\lambda_n^{(1)}$, $\lambda_n^{(2)}$, $\mathcal{I} = [0, \infty)^p$
2 Compute support $J = \{j,\ \hat{\beta}_j \neq 0\}$
3 Compute AREN estimate $\hat{\beta}_J$ from $X_J$ and $Y$ with $\lambda_n^{(1)} = \lambda_n^{(2)} = 0$, $\mathcal{I} = [\mathbf{s}, \mathbf{t}]$

We apply the two-step AREN (Algorithm 2) and BoAREN (Algorithm 1) to creating an index fund to track the performance of S&P 500 index. The main idea is to follow a two-step method that applies a (bootstrapped) non-negative elastic net to select a subset of stocks, then apply constrained least squares on the selected stocks to estimate the unknown coefficients. In this section the two-step BoAREN is simply called BoAREN. The index tracking procedure is summarized in Algorithm 3. Wu and Yang (2014) find that the index tracking results can be greatly improved through this two-step method. For bootstrap approach, it has been observed in Bach (2008) that intersecting the supports for each bootstrap replication might be too strict and a so-called "soft" version improves the performance. We include a soft index $S$ (e.g. 90%, 80%, 70%) in the BoAREN algorithm so that $\cap_S$ (Algorithm 1, Line 5) selects the supports which are present in at least the percentage $S$ of the bootstrap replications. The non-negative setting, i.e. $\mathcal{I} = [0, \infty)^p$ in Line 3 of Algorithm 1 and Line 1 of Algorithm 2, ensures that we focus on "long-only" strategies.

**Algorithm 3:** Index Tracking using Two-step AREN or BoAREN

Input: $X \in \mathbb{R}^{n \times p}$
$Y \in \mathbb{R}^n$
Number of bootstrap replicates $m$, if using BoAREN
Soft index $S$, if using BoAREN
$\lambda_n^{(1)}$ tuning grid $\Lambda^{(1)}$
$\lambda_n^{(2)}$ tuning grid $\Lambda^{(2)}$
AREN coefficient lower constraints $\mathbf{s} \in (\mathbb{R} \cup \{-\infty\})^p$
AREN coefficient upper constraints $\mathbf{t} \in (\mathbb{R} \cup \{+\infty\})^p$

$X_{train}, Y_{train}, X_{val}, Y_{val}, X_{test}, Y_{test} \leftarrow X, Y$
For each $\lambda_n^{(1)} \in \Lambda^{(1)}$ and $\lambda_n^{(2)} \in \Lambda^{(2)}$ do
  If using BoAREN
    Compute $\hat{\beta}_J$ from $X_{train}$, $Y_{train}$, $m$, $S$, $\lambda_n^{(1)}$, $\lambda_n^{(2)}$, $\mathbf{s}$, $\mathbf{t}$, using Algorithm 1
  Else if using two-step AREN
    Compute $\hat{\beta}_J$ from $X_{train}$, $Y_{train}$, $\lambda_n^{(1)}$, $\lambda_n^{(2)}$, $\mathbf{s}$, $\mathbf{t}$, using Algorithm 2
  $R^B \leftarrow Y_{val}$
  $R^P \leftarrow X_{val}\hat{\beta}_J$
  Compute tracking error from $R^B$, $R^P$, using Equation
  (Error*! No text of specified style in document..10)*
Find the corresponding $\hat{\beta}_J$ with the smallest tracking error
$R^B \leftarrow Y_{test}$
$R^P \leftarrow X_{test}\hat{\beta}_J$
Compute tracking error from $R^B, R^P$, using Equation
(Error*! No text of specified style in document..10)*

We use one year (from 2020-9-1 to 2021-9-1) of daily adjusted closing prices (253 observations) of the S&P 500 and 302[3] S&P 500 component stocks. In Algorithm 3, the input $Y$ represents the daily percentage return of S&P 500, each column of the input $X$ represents the daily percentage return of one of the 302 stocks. The total number of columns of $X$ is $p = 302$. We use the first 70% of the 252 data points for training, the next 20% for validation, and the last 10% for testing. We use the mean value of the training set to center the whole data set so that the regression can be fit without intercept (Hastie et al., 2009, p. 64). To simplify the tuning process, we use the strategy in Friedman et al. (2010, Section 2.5) to rewrite the regularization as $\lambda(\alpha\|\beta\|_1 + 0.5(1-\alpha)\|\beta\|_2^2)$, where all coefficients will shrink to zero if $\lambda > \lambda_{\max} = 2\max_l\{X_l Y\}/\alpha$. We use a grid of 10 equally spaced points on $[0,1]$ for $\alpha$. We set $\lambda_{\min} = 0.001\lambda_{\max}$ and use a grid of 100 equally spaced points on $[\lambda_{\min}, \lambda_{\max}]$ for $\lambda$.

The possibility of adding constraints to coefficients in AREN allows us to select the values of $\mathbf{s}$ and $\mathbf{t}$ in Algorithm 3 to avoid concentrated stock positions, that is to avoid over investing in any single stock which can expose the investor to significant risk based on the fortunes of a few companies. To elaborate, suppose we invest money in $\#J$ (cardinality of $J$) stocks with returns $R_j^l = (P_j^l - P_j^{l-1})/P_j^{l-1}, j = 1, \dots, \#J$ to track S&P 500 with return $\widehat{R}_{SP}^l = (\widehat{P}_{SP}^l - P_{SP}^{l-1})/P_{SP}^{l-1}$ using $l$ as indexes of date. Let $\overline{R}_{SP}^{\text{Train}}, \overline{R}_j^{\text{Train}}, j = 1, \dots, \#J$ represent the mean returns on the training set for the S&P 500 and the selected stocks. The regression gives:

$$\widehat{R}_{SP}^l - \overline{R}_{SP}^{\text{Train}} = \sum_{j=1}^{\#J} (\hat{\beta}_J)_j (R_j^l - \overline{R}_j^{\text{Train}});$$

$$\widehat{P}_{SP}^l = \sum_{j=1}^{\#J} \frac{(\hat{\beta}_J)_j P_{SP}^{l-1} P_j^l}{P_j^{l-1}} + \left(1 + \overline{R}_{SP}^{\text{Train}} - \sum_{j=1}^{\#J} (1 + \overline{R}_l^{\text{Train}})(\hat{\beta}_J)_j\right) P_{SP}^{l-1},$$

which means to track $P_{SP}^l$ dollar amount of S&P 500, we invest $(\hat{\beta}_J)_j P_{SP}^{l-1} P_j^l / P_j^{l-1}$ dollar amount on stock j for $j = 1, \dots, \#J$ and hold or borrow

$$\left(1 + \overline{R}_{SP}^{\text{Train}} - \sum_{j=1}^{\#J} (1 + \overline{R}_l^{\text{Train}})(\hat{\beta}_J)_j\right) P_{SP}^{l-1}$$

dollar amount. So, the percentage of money spent on each stock is

$$\frac{(\hat{\beta}_J)_i}{(\hat{\beta}_J)_i + \frac{P_i^{l-1}}{P_i^l} \sum_{j=1, j\neq i}^{\#J} \frac{(\hat{\beta}_J)_j P_j^l}{P_j^{l-1}}} = \frac{(\hat{\beta}_J)_i}{(\hat{\beta}_J)_i + \sum_{j=1, j\neq i}^{\#J} \frac{(\hat{\beta}_J)_j (1 + R_j^l)}{1 + R_i^l}}$$

for $i = 1, \dots, \#J$. To avoid concentrated stock positions, we want each percentage less than an amount $M$ (e.g. 10%, 20%, 30%), i.e., for $i = 1, \dots, \#J$,

$$\frac{(\hat{\beta}_J)_i}{(\hat{\beta}_J)_i + \sum_{j=1, j\neq i}^{\#J} \frac{(\hat{\beta}_J)_j (1 + R_j^l)}{1 + R_i^l}} \leq \frac{t_i}{t_i + \frac{1 + R^{\min}}{1 + R^{\max}} \sum_{j=1, j\neq i}^{\#J} s_j} \leq M \leq 1,$$

[3] We only consider the daily prices from 302 stocks that have not been changed during the period of interest.

where $R^{min}$ and $R^{max}$ are the smallest and largest prices for all stocks, respectively. Assume $s_i = s_0, t_i = t_0$ for all $i$, we guarantee that the percentage of money spent on a single stock is less that $M$ through selecting $s_0, t_0$ such that

$$s_0 \leq t_0 \leq \frac{M}{1-M}\frac{1+R^{min}}{1+R^{max}}(\#J-1)s_0.$$

A variety of approaches could be used to tune $s_0, t_0$ to improve performance, but here we use the following simple steps to select $s_0, t_0$. First, we find the maximum and minimum coefficients, $(\hat{\beta}_J)_{max}, (\hat{\beta}_J)_{min}$, when $M = 100\%$ (i.e., $[\mathbf{s}, \mathbf{t}] = [0, \infty)^p$). Then given $M$, we set $s_0 = (\hat{\beta}_J)_{min}$ and calculate the biggest $t_0$, and set $t_0 = (\hat{\beta}_J)_{max}$ and calculate the smallest $s_0$. The final $s_0, t_0$ are taken to be the case that has the largest distance between them. Note that the scale needs to be

$$\frac{M}{1-M}\frac{1+R^{min}}{1+R^{max}}(\#J-1) \geq 1 \Leftrightarrow M \geq \frac{1}{1+\frac{1+R^{min}}{1+R^{max}}(\#J-1)}$$

to make this process work. Hence for this method there will be a bound below which $M$ cannot be set, depending on the data.

**Table 1:** **Tracking errors (TE in units of 10^(-3)), root mean-squared errors (RMSE in units of 10^(-3)), and number of selected stocks for two-step AREN and BoAREN with varying soft index S and number of bootstrap replicates m using Algorithm 3. M is the largest percentage of money spent on a single stock**

| M | Measure | Two-step AREN | BoAREN S=1 m=32 | m=64 | m=128 | m=256 | BoAREN S=0.95 m=32 | m=64 | m=128 | m=256 |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | TE | 1.11 | 1.25 | 1.41 | 1.50 | 1.40 | 1.13 | **1.01*** | 1.13 | 1.24 |
| | RMSE | 1.14 | 1.30 | 1.47 | 1.57 | 1.46 | 1.16 | 1.04 | 1.18 | 1.30 |
| | Stocks | 259 | 182 | 161 | 145 | 155 | 238 | 243 | 234 | 204 |
| 0.3 | TE | 1.02 | 1.27 | 1.23 | 1.43 | 1.43 | 1.19 | **1.01** | 1.09 | 1.11 |
| | RMSE | 1.11 | 1.36 | 1.31 | 1.52 | 1.52 | 1.27 | 1.08 | 1.18 | 1.19 |
| | Stocks | 259 | 184 | 192 | 154 | 155 | 216 | 243 | 234 | 236 |
| 0.2 | TE | 1.13 | 1.24 | 1.29 | 1.40 | 1.98 | 1.25 | 1.13 | 1.19 | 1.19 |
| | RMSE | 1.24 | 1.34 | 1.38 | 1.47 | 2.06 | 1.35 | 1.23 | 1.28 | 1.28 |
| | Stocks | 259 | 204 | 192 | 171 | 80 | 216 | 243 | 234 | 236 |
| 0.1 | TE | 3.66 | 3.92 | 4.00 | 4.29 | **3.59** | 3.80 | **3.53** | **3.24** | **3.34** |
| | RMSE | 3.82 | 3.98 | 4.01 | 4.30 | 3.72 | 3.90 | 3.66 | 3.34 | 3.47 |
| | Stocks | 190 | 67 | 31 | 26 | 33 | 95 | 152 | 121 | 121 |
| **M** | **Measure** | **Two-step AREN** | **BoAREN S=0.9 m=32** | **m=64** | **m=128** | **m=256** | **BoAREN S=0.85 m=32** | **m=64** | **m=128** | **m=256** |
| 1 | TE | 1.11 | 1.15 | 1.15 | **1.03** | **1.05** | 1.20 | 1.11 | 1.23 | 1.13 |
| | RMSE | 1.14 | 1.20 | 1.19 | 1.08 | 1.10 | 1.25 | 1.15 | 1.28 | 1.16 |
| | Stocks | 259 | 247 | 259 | 258 | 259 | 262 | 254 | 248 | 252 |
| 0.3 | TE | 1.02 | 1.09 | 1.07 | 1.02 | **1.01** | 1.13 | 1.05 | 1.12 | 1.06 |
| | RMSE | 1.11 | 1.17 | 1.15 | 1.10 | 1.09 | 1.22 | 1.12 | 1.20 | 1.13 |
| | Stocks | 259 | 247 | 259 | 258 | 259 | 251 | 254 | 248 | 248 |
| 0.2 | TE | 1.13 | 1.24 | 1.24 | 1.24 | 1.24 | 1.20 | 1.17 | 1.22 | 1.19 |
| | RMSE | 1.24 | 1.35 | 1.34 | 1.34 | 1.34 | 1.32 | 1.27 | 1.33 | 1.29 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Stocks | 259 | 242 | 242 | 242 | 243 | 254 | 254 | 253 | 248 |
| | TE | 3.66 | **2.97*** | **3.23** | **3.11** | **3.31** | **3.41** | **3.34** | **3.13** | **3.57** |
| 0.1 | RMSE | 3.82 | 3.10 | 3.34 | 3.21 | 3.44 | 3.53 | 3.47 | 3.24 | 3.68 |
| | Stocks | 190 | 133 | 153 | 150 | 147 | 144 | 121 | 118 | 154 |

| M | Measure | Two-step AREN | BoAREN $S$=0.8 | | | | BoAREN $S$=0.75 | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | m=32 | m=64 | m=128 | m=256 | m=32 | m=64 | m=128 | m=256 |
| | TE | 1.11 | 1.35 | 1.14 | 1.13 | 1.12 | 1.34 | 1.38 | 1.39 | 1.42 |
| 1 | RMSE | 1.14 | 1.41 | 1.17 | 1.16 | 1.15 | 1.40 | 1.45 | 1.46 | 1.48 |
| | Stocks | 259 | 179 | 258 | 261 | 259 | 198 | 187 | 200 | 201 |
| | TE | 1.02 | **0.95** | 1.06 | 1.03 | 1.06 | **0.94*** | **0.95** | **0.95** | **0.95** |
| 0.3 | RMSE | 1.11 | 1.08 | 1.14 | 1.11 | 1.13 | 1.07 | 1.07 | 1.07 | 1.08 |
| | Stocks | 259 | 295 | 258 | 261 | 259 | 299 | 297 | 295 | 295 |
| | TE | 1.13 | **1.12** | 1.18 | 1.14 | 1.17 | **1.09** | **1.07*** | 1.13 | 1.11 |
| 0.2 | RMSE | 1.24 | 1.22 | 1.29 | 1.24 | 1.28 | 1.19 | 1.17 | 1.22 | 1.20 |
| | Stocks | 259 | 262 | 258 | 261 | 259 | 245 | 266 | 233 | 233 |
| 0.1 | TE | 3.66 | **3.42** | 3.94 | **3.33** | **3.44** | **3.44** | **3.53** | **3.47** | **3.59** |
| | RMSE | 3.82 | 3.54 | 4.06 | 3.45 | 3.56 | 3.57 | 3.65 | 3.59 | 3.70 |
| | Stocks | 190 | 114 | 116 | 145 | 147 | 166 | 154 | 154 | 156 |

Table 1 shows tracking errors ($\mathrm{TE}$), root mean-squared errors (RMSE), and the number of selected stocks over two-step AREN and BoAREN using different bootstrap replicates $m$, different limits on the amount spent on each stock $M$, different BoAREN soft indexes $S$, and not limit on the number of stocks that can be selected. For all $M = 1,0.3,0.2,0.1$, two-step AREN performs well, and BoAREN performs even better. It appears that a soft index of $S = 1$ seems too strict, selecting only a few stocks, and as bootstrap replications increase, the tracking error does not converge and becomes increasingly large. In the case of no limit on the amount spent on a single stock (i.e., $M = 1$), BoAREN with a soft index of $S = 1$ also seems too strict, $S = 0.8,0.75$ seems too soft, and $S$ in between works better with the lowest tracking error $1.01$ obtained when $m = 64, S = 0.95$. By limiting the amount spent on each stock to $M = 0.3$ and $M = 0.2$, a softer index of $S = 0.75$ performs better, giving tracking errors of $0.94$ and $1.07$, respectively. In the case of no more than $10\%$ of the total amount spent on each stock, BoAREN with $S = 1$ shows decreasing tracking errors as bootstrap replications increase and outperforms two-step AREN when $m = 256$. Moreover, most cases of BoAREN with $S = 0.95,0.9,0.85,0.8,0.75$ show improvement over the two-step AREN case in terms of tracking errors.

**Table 1: Tracking errors ($\mathrm{TE}$ in units of $10^{-3}$), root mean-squared errors (RMSE, in units of $10^{-3}$), and number of selected stocks for two-step AREN and best BoAREN model using Algorithm 3. $M$ is the largest percentage of money spent on a single stock. $m$ is the number of bootstrap replicates. $S$ is the soft index.**

| Stocks | M | Two-step AREN | | | Best BoAREN | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | $TE$ | RMSE | Stocks | $TE$ | RMSE | Stocks | m | S |
| No limit | 1.0 | 1.11 | 1.14 | 259 | 1.01 | 1.04 | 243 | 64 | 0.95 |
| | 0.3 | 1.02 | 1.11 | 259 | 0.94 | 1.07 | 299 | 32 | 0.75 |
| | 0.2 | 1.13 | 1.24 | 259 | 1.07 | 1.17 | 266 | 64 | 0.75 |
| | 0.1 | 3.66 | 3.82 | 190 | 2.97 | 3.10 | 133 | 32 | 0.90 |
| ≤200 | 1.0 | 1.44 | 1.52 | 196 | 1.25 | 1.30 | 186 | 128 | 0.90 |
| | 0.3 | 1.33 | 1.42 | 196 | 1.20 | 1.29 | 192 | 32 | 0.95 |
| | 0.2 | 1.33 | 1.43 | 196 | 1.21 | 1.32 | 192 | 32 | 0.95 |
| | 0.1 | 3.66 | 3.82 | 190 | 2.97 | 3.10 | 133 | 32 | 0.9 |
| ≤150 | 1.0 | 1.47 | 1.55 | 146 | 1.37 | 1.43 | 147 | 64 | 1.00 |
| | 0.3 | 1.46 | 1.57 | 146 | 1.36 | 1.45 | 147 | 64 | 1.00 |
| | 0.2 | 1.49 | 1.58 | 149 | 1.39 | 1.47 | 144 | 32 | 0.85 |
| | 0.1 | 4.46 | 4.58 | 139 | 2.97 | 3.10 | 133 | 32 | 0.90 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| ≤100 | 1.0 | 2.14 | 2.20 | 84 | 1.53 | 1.60 | 97 | 64 | 0.80 |
| | 0.3 | 2.24 | 2.32 | 84 | 1.61 | 1.70 | 97 | 64 | 0.80 |
| | 0.2 | 2.43 | 2.49 | 88 | 1.71 | 1.83 | 95 | 32 | 0.95 |
| | 0.1 | 6.40 | 6.52 | 88 | 3.59 | 3.72 | 33 | 256 | 1.00 |

Note that in the majority of cases in Table 1, a large number of stocks were selected. Due to transaction fees and management effort for retail or individual fund managers, it is of interest to examine cases with the limit on stocks to be no greater than $50,100,150,200$ during the tuning process (Lines 2-10) of Algorithm 3. We examine models with $S = 1,0.95,0.9,0.85,0.8,0.75$, $m = 32,64,128,256$ and summarize the best model for each $M$ and limit on stocks in Table 2. As compared with two-step AREN which generally performs well, BoAREN performs better in terms of tracking errors, mean-squared errors, and picking about the same number or even fewer stocks. To see the sensitivity of the BoAREN parameters, in Figure 1, we plot the predicted S&P 500 index using the best BoAREN models for each stocks number constraint and each $M$ (see Table 2) and compare them with the actual S&P 500 index values. We use predicted returns for next time step $R_{\text{pred}}^{\text{next}}$ and the actual price from last time step $P_{\text{real}}^{\text{last}}$ to calculate each fitted or predicted S&P 500 index $\left(R_{\text{pred}}^{\text{next}} + 1\right)P_{\text{real}}^{\text{last}}$. To make the difference between the actual and predicted values more visible, in Figure 2, we plot the ratio of actual to predicted S&P 500 index using the best BoAREN models in Table 2. From Figure 1 and Figure 2 we see that BoAREN tends to show better performance as the limits on stocks and $M$ get larger. However, this difference is not significant among the cases $M = 1,\ 0.3,\ 0.2$ and among the various conditions imposed on stock count, i.e. no limit, $\leq 200$, $\leq 150$. Since there is a trade-off between the model accuracy and the expense in applying the model, these results imply that portfolio managers may consider using a relatively small number of stocks and a suitable constraint on the amount spent on each stock to track the S&P 500 index while retaining high tracking accuracy.

**Figure 1:** Predicted S&P 500 index (from 2021-2-24 to 2021-9-1) using the best BoAREN models in Table 2. Green dot lines correspond to actual values of S&P 500 index; red solid lines correspond to predicted values by BoAREN; blue dash lines correspond to predicted values by two-step AREN.

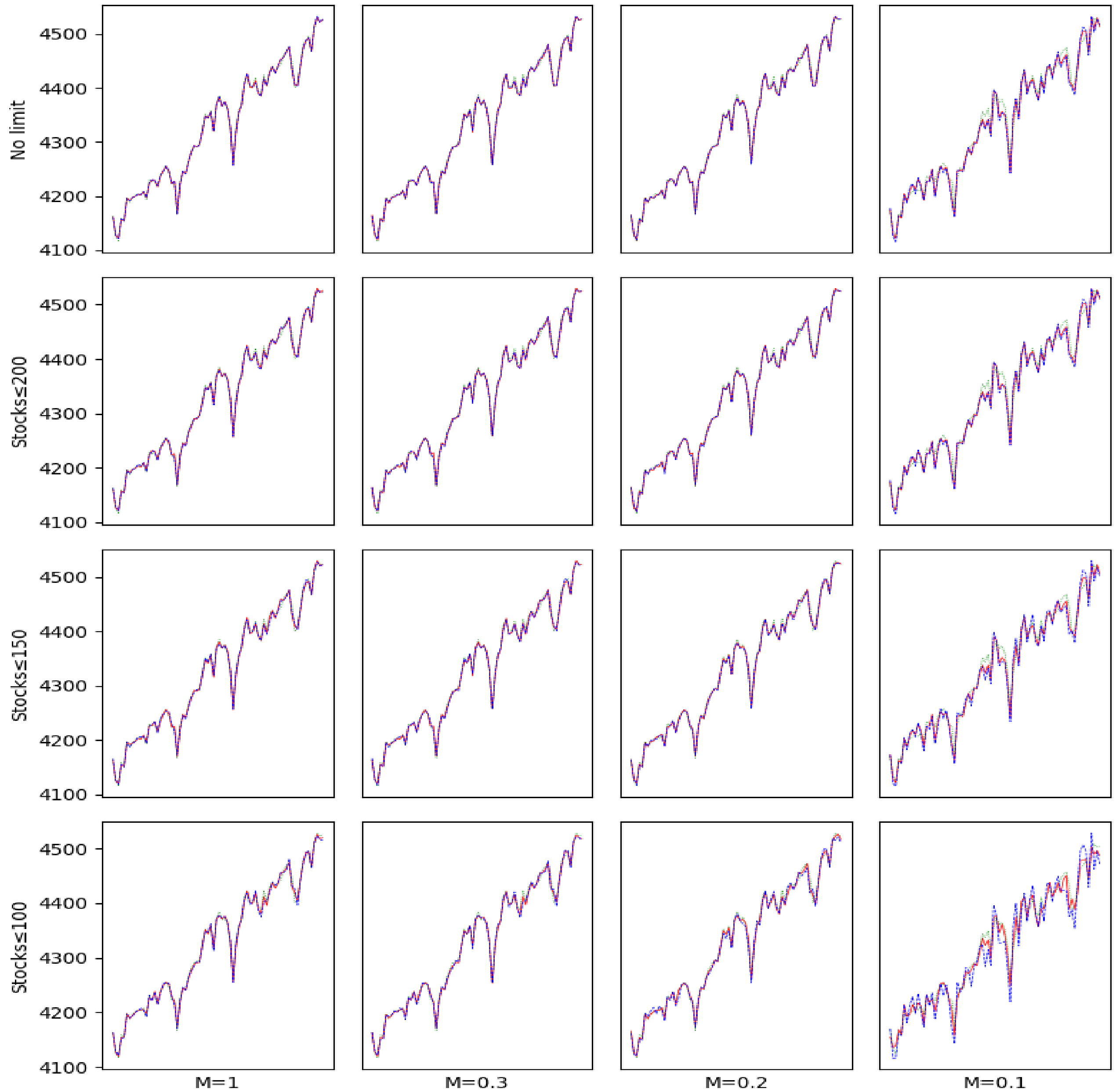
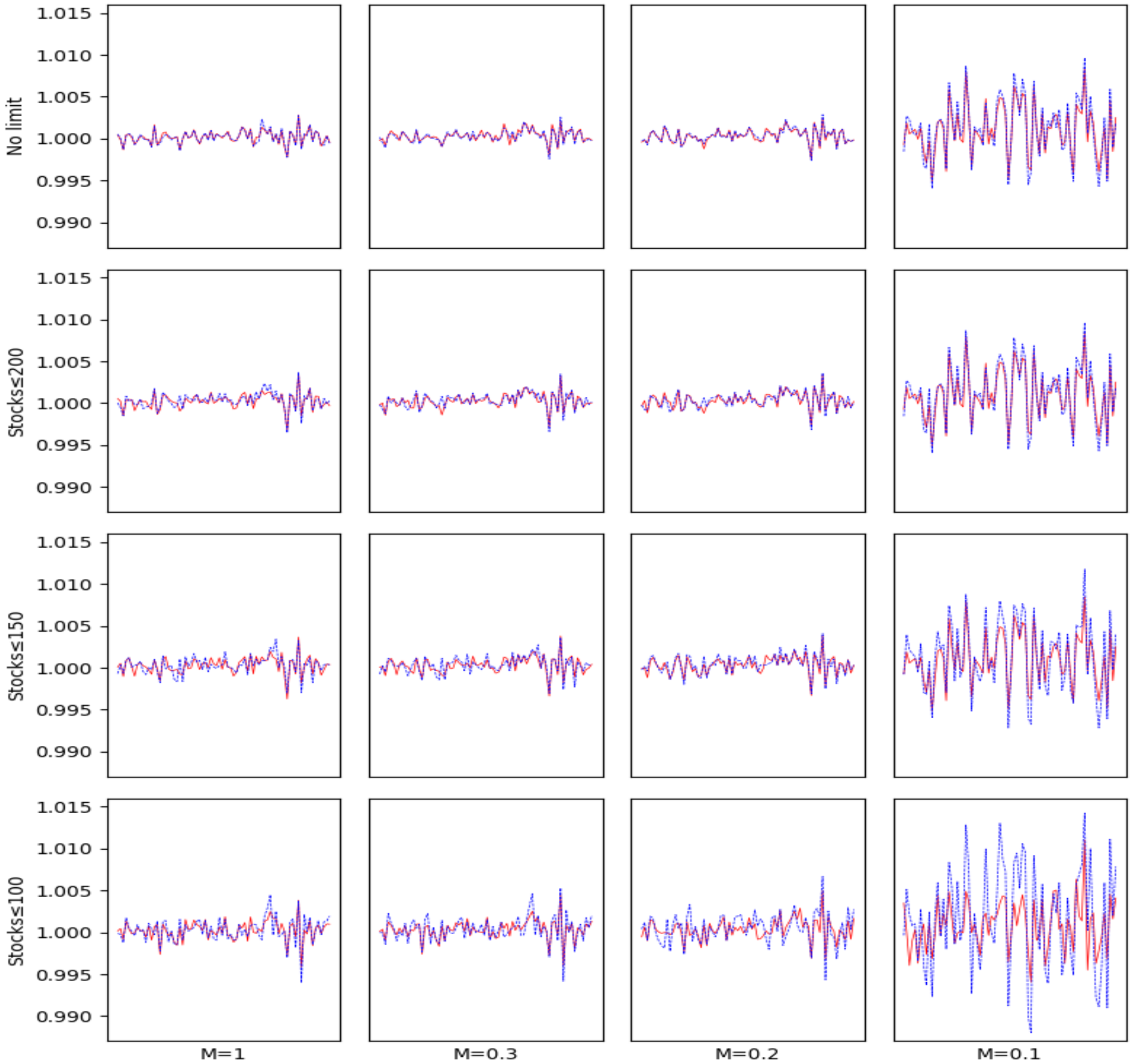



**Figure 2:** Actual over predicted S&P 500 index (from 2021-2-24 to 2021-9-1) using the best BoAREN models in Table 2. Red solid lines correspond to actual over predicted values by BoAREN; blue dash lines correspond to actual over predicted values by two-step AREN.




## 4. Summary and Conclusions

The objective of this study has been to illuminate a growing body of research that aims at improving the generality and prediction capability of linear statistical models applied to large quantities of data. The prototypical example we have chosen here is that of index tracking in financial modeling, but the potential applications to large-scale data analysis in finance extend well beyond this. To accomplish this, we have chosen to present an exposition of the Arbitrary Rectangle-range Elastic Net (AREN), one of many algorithmic approaches to regularization of linear statistical models having a large number of unknown parameters. The challenge for these models is to find the most influential predictors and to estimate their coefficients in a way that minimizes the model prediction error. The AREN is a special case of the more general ARGEN model studied in Ding et al. (2021) and is ideal in this context because it is broadly applicable, and its important properties (tractability, estimation consistency, and variable selection consistency) follow from the more general ARGEN, allowing these results to be described without lengthy proofs. Progress in this field of research has been accelerating along with the influence of data science and the availability of extensive and inexpensive computing resources. Accordingly, following the work of Bach (2008) our main contribution here has been to demonstrate that the prediction capability of the AREN method can be further improved through the use of bootstrapping. This has been shown here to be the case for the index-tracking problem applied to the S&P 500. The literature in mathematical finance has been for some time mostly dominated by stochastic calculus and derivations of derivative-pricing formulae. Less well represented are methods for carefully analyzing financial data to design portfolios or reliably estimate the many unknown parameters that the aforementioned pricing formulae require. It is our hope that this work has reinforced the importance of methods essential to the empirical side of finance.

## References

Bach, F. R. (2008). Bolasso: model consistent Lasso estimation through the bootstrap. In Proceedings of the 25th international conference on Machine learning (ICML '08) (pp. 33–40). New York, NY, USA: Association for Computing Machinery. DOI:10.1145/1390156.1390161.

Bickel, P. J., Ritov, Y., & Tsybakov, A. B. (2009). Simultaneous analysis of lasso and Dantzig selector. Ann. Statist., 37(4), 1705-1732. MR2533469. DOI: 10.1214/08-AOS620.

Ding, Y., Peng, Q., Song, Z., & Chen, H. (2021). Variable selection and regularization via arbitrary rectangle-range generalized elastic net. arXiv:2112.07785.

Efron, B., Hastie, T., & Tibshirani, R. (2007). Discussion: "The Dantzig selector: statistical estimation when p is much larger than n". Ann. Statist., 35(6), 2358-2364. MR2382646. DOI: 10.1214/009053607000000433.

Efron, B., Hastie, T., Johnstone, I., & Tibshirani, R. (2004). Least angle regression. Ann. Statist., 32(2), 407-499. MR2060166. DOI: 10.1214/009053604000000067.

Friedman, J. H., Hastie, T., & Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. J. Stat. Softw., 33(1), 1-22. DOI:10.18637/jss.v033.i01.

Hastie, T., Tibshirani, R., & Friedman, J. (2009). The Elements of Statistical Learning. Data mining, Inference, and Prediction. Springer, New York: Springer Series in Statistics. MR2722294. DOI:10.1007/978-0-387-84858-7.

Lounici, K. (2008). Sup-norm convergence rate and sign concentration property of Lasso and Dantzig estimators. Electron. J. Stat., 2, 90-102. MR2386087. DOI: 10.1214/08-EJS177.

Negahban, S. N., Ravikumar, P., Wainwright, M. J., & Yu, B. (2012). A unified framework for high-dimensional analysis of M-estimators with decomposable regularizers. Statist. Sci., 27(4), 538-557. MR3025133. DOI: 10.1214/12-STS400.

Tibshirani, R. (1996). Regression shrinkage and selection via the lasso. J. Roy. Statist. Soc. Ser. B, 58(1), 267-288. MR1379242. DOI:10.1111/j.2517-6161.1996.tb02080.x.

Wang, H., Li, G., & Tsai, C.-L. (2007). Regression coefficient and autoregressive order shrinkage and selection via the lasso. J. R. Stat. Soc. Ser. B Stat. Methodol., 69(1), 63-78. MR2301500. DOI:10.1111/j.1467-9868.2007.00577.x.

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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.

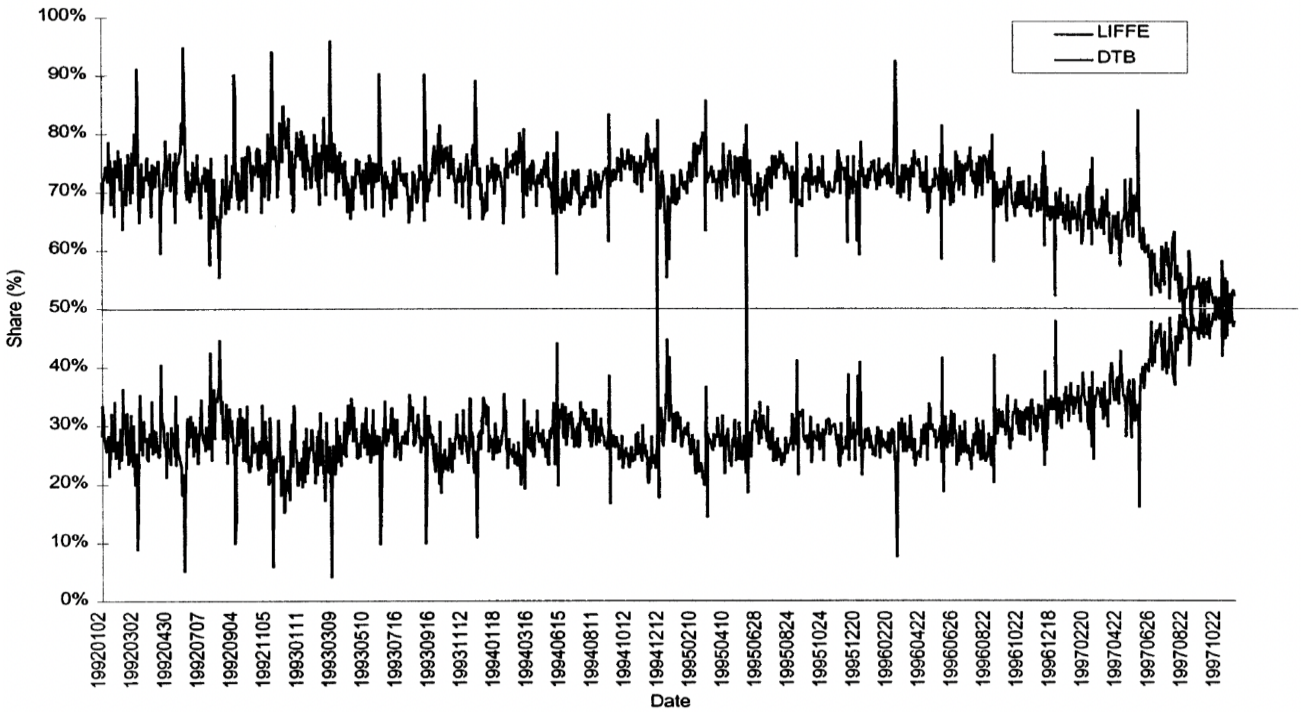
One of the first futures exchanges in the world to go fully electronic was the German futures exchange known at the time as the Deutsche Terminbörse (DTB). The DTB listed German Bund futures, which at the time were also listed on the London International Financial Futures Exchange (LIFFE). For many years, 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**

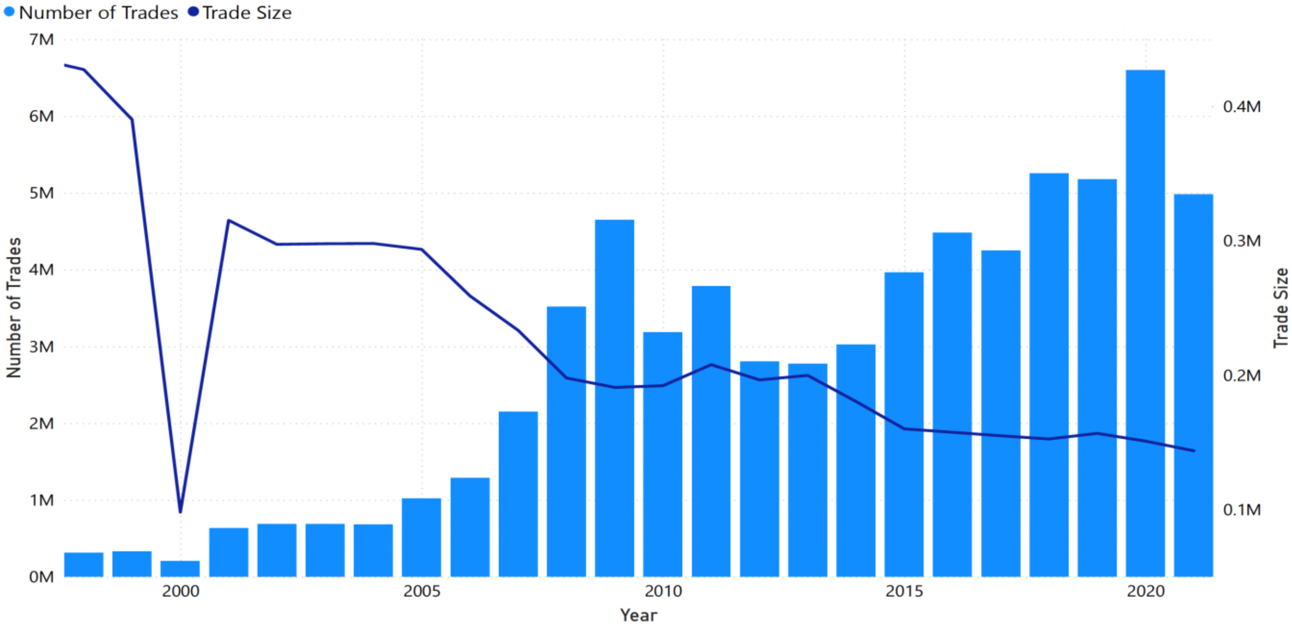



*Source:* Frino et al. (1998)

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

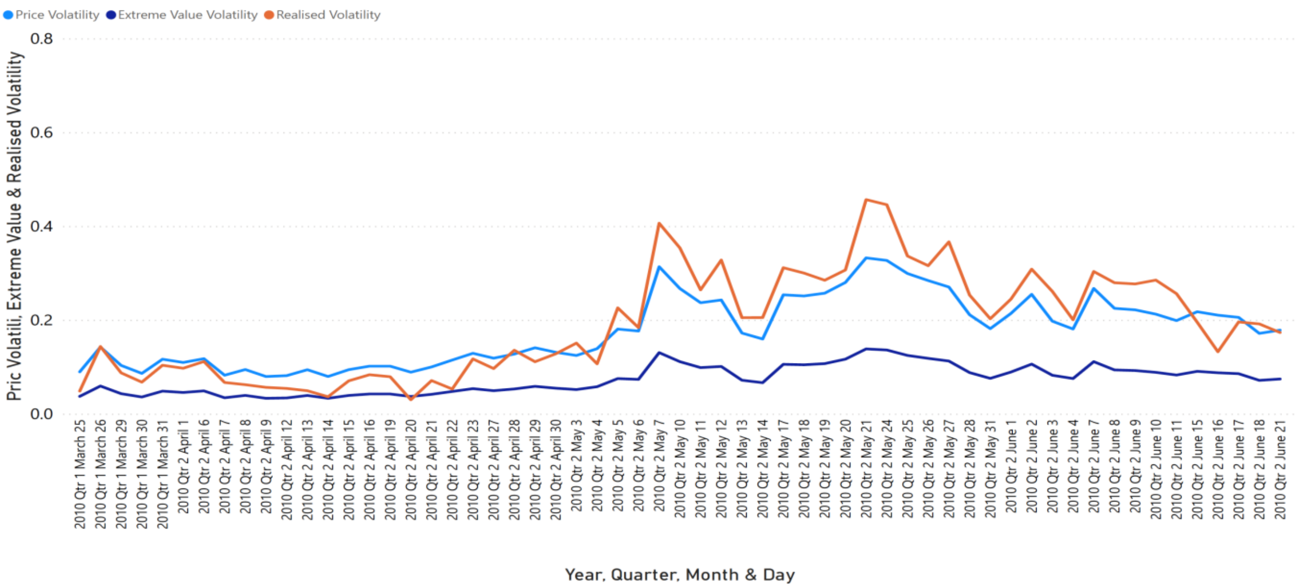
In February 2012, the ASX introduced a new colocation facility which enabled researchers to study the impact of the introduction of colocation, and whether the increase in algorithmic trading facilitated by collocated ICT facilities would positively impact liquidity. Frino, Mollica & Webb (2014) analysed 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

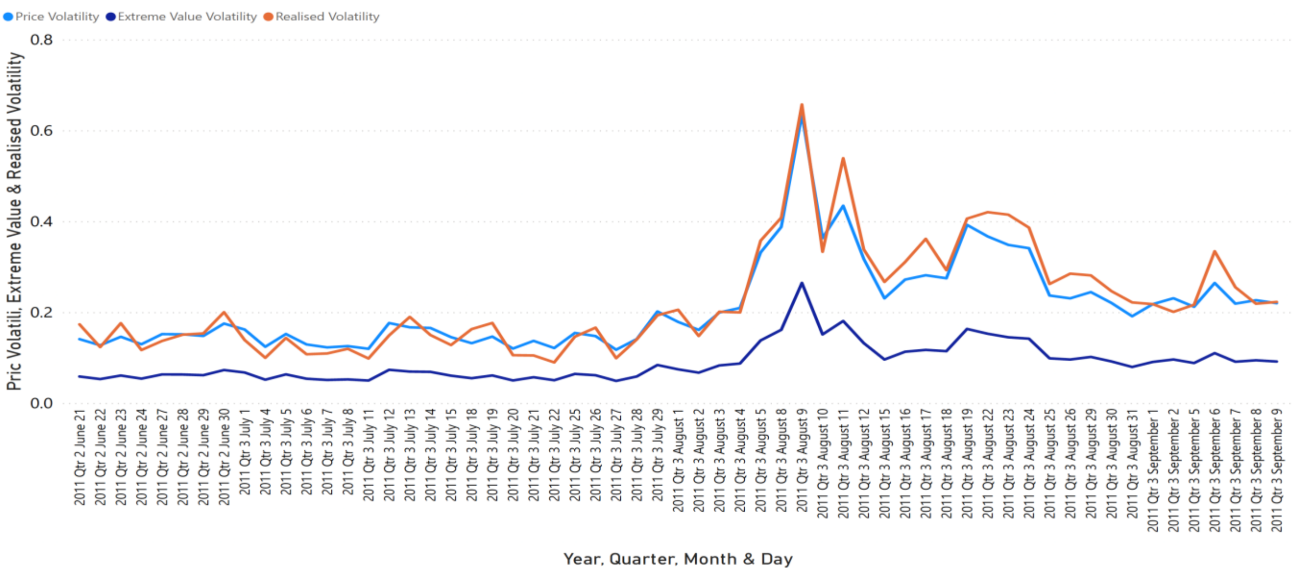
While the speed with which trading can be executed has the potential to increase the efficiency of trading and enhance the liquidity of the market, they also have the potential to exacerbate volatility as markets are able to move faster in an unchecked manner over small periods of time. The Flash Crash 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**

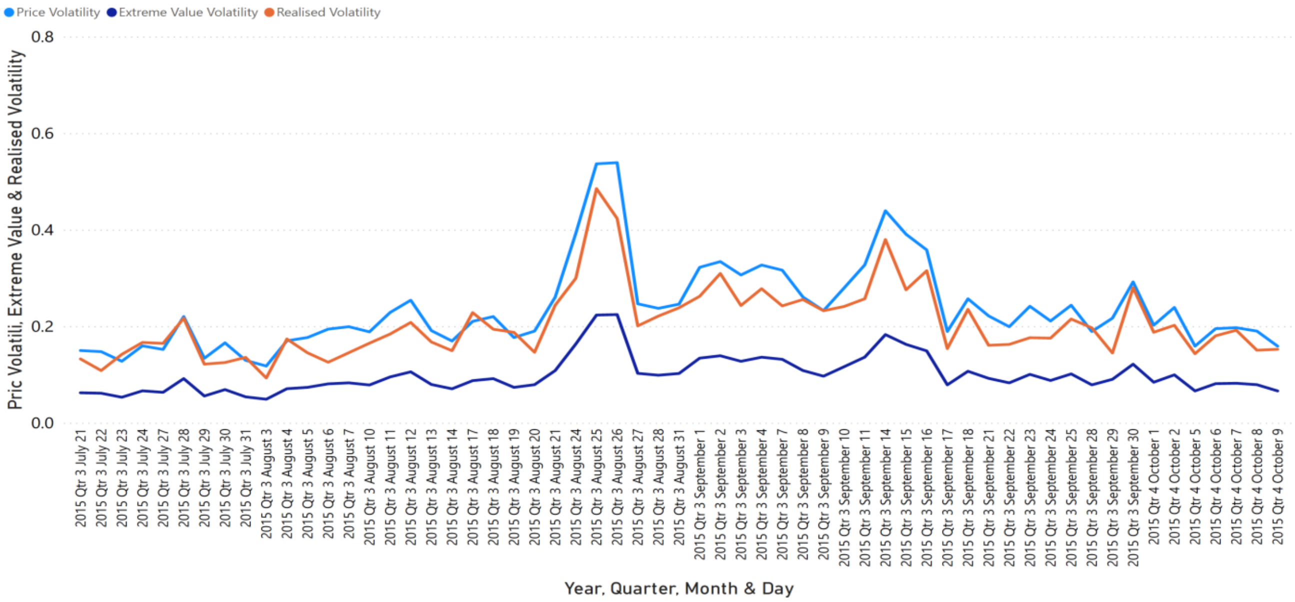
*Panel A: from March 2010 to June 2010*




*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

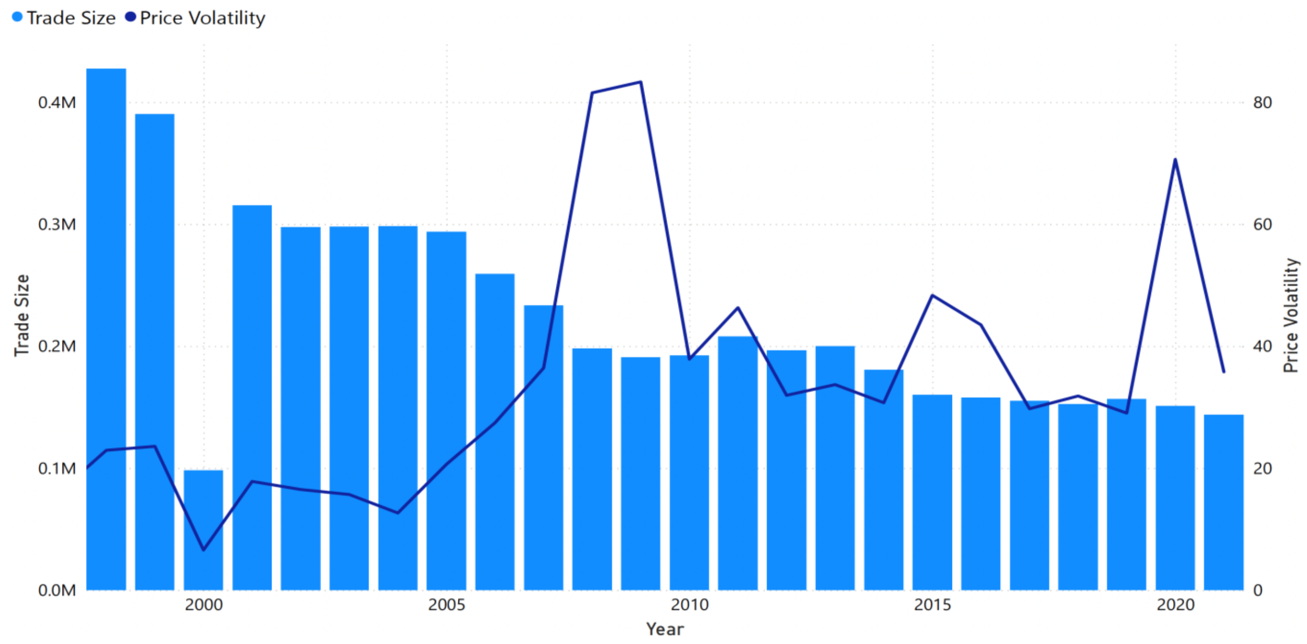
[5] https://www.cnbc.com/2021/03/16/one-year-ago-stocks-dropped-12percent-in-a-single-day-what-investors-have-learned-since-then.html

[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.

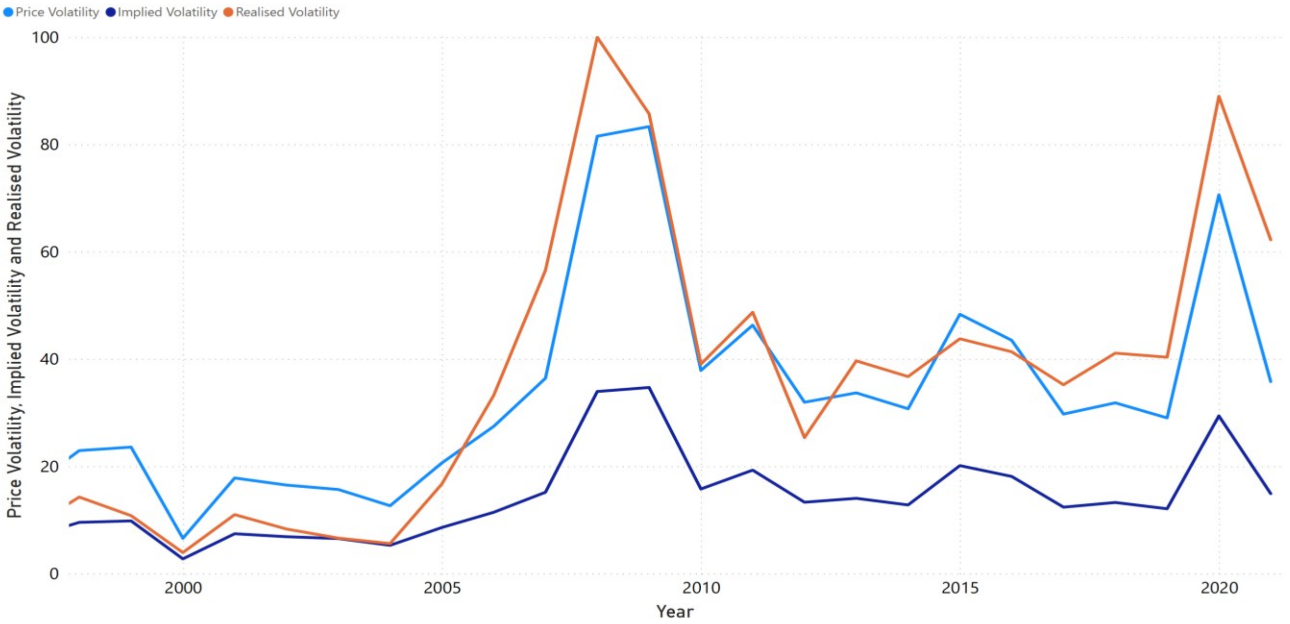
**Figure 3: Price Volatility and Trade Sizes for SPI Futures Contracts**




[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**

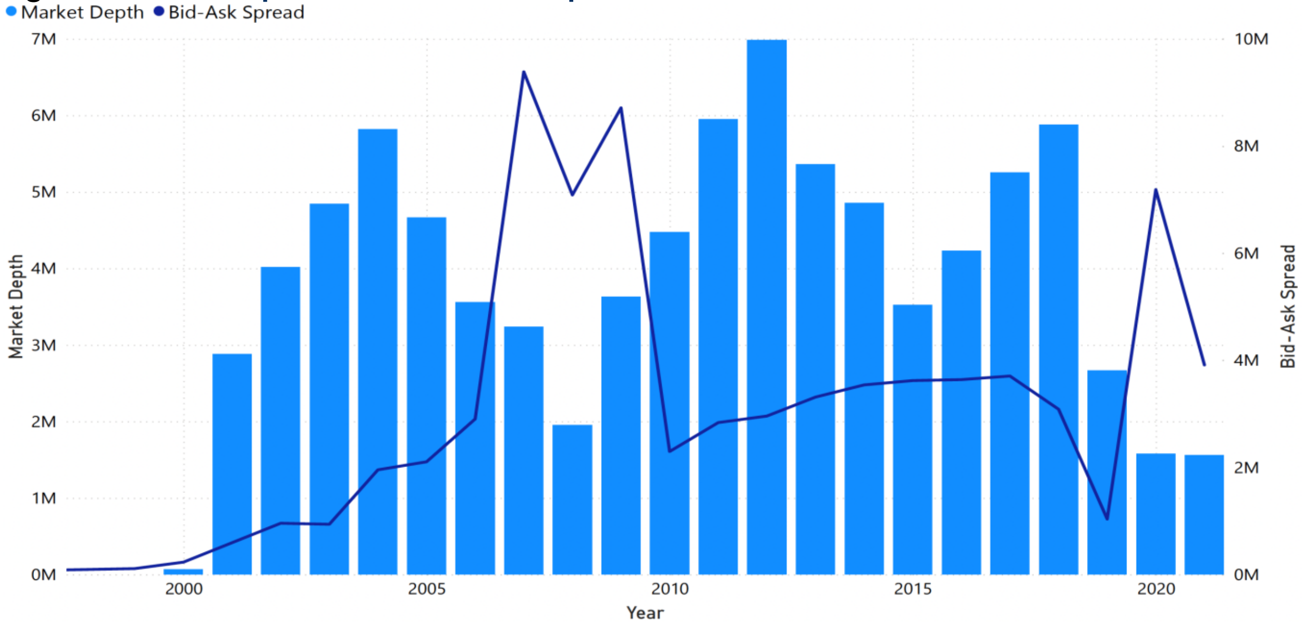
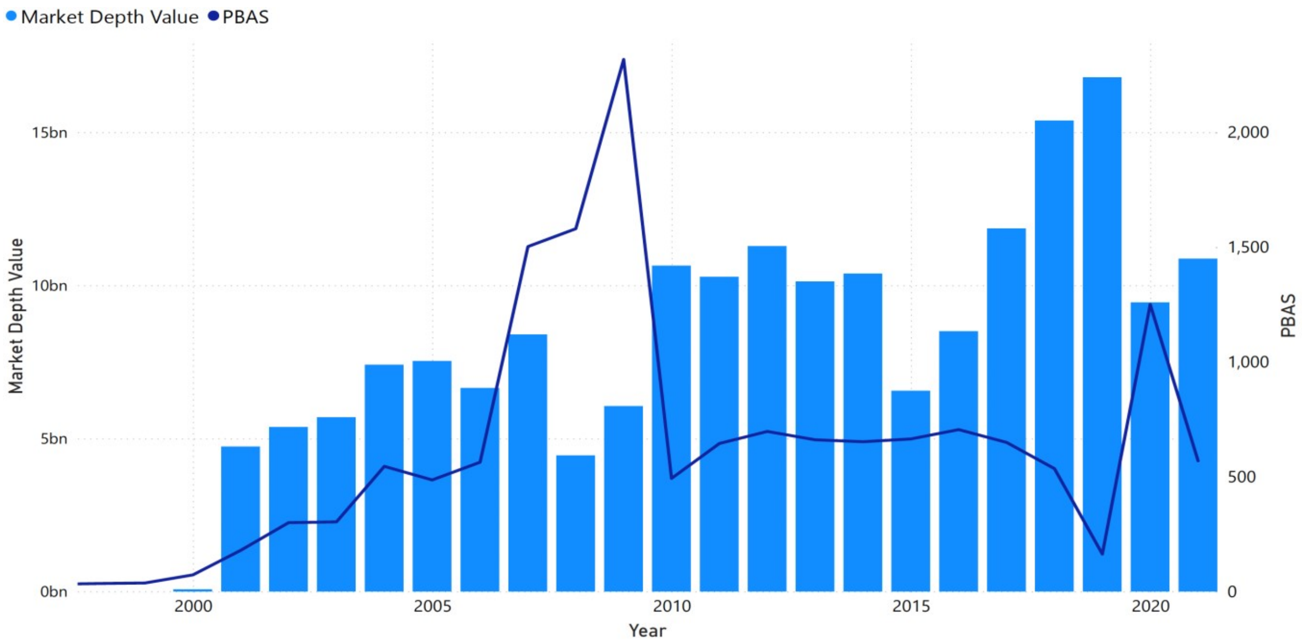



**Figure 6:** **PBAS and Value of Market Depth for SPI Futures Contracts**




## 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 *l* 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 $\beta_4$ 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:

$$BAS_l = a_0 + \beta_1 ET + \beta_2 HFT + \beta_3 CLF + \beta_4 GFC + \beta_5 CPC + l$$

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 *l* 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.

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## 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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## References

Bhar, R., & Malliaris, A. G. (2021). Modeling US monetary policy during the global financial crisis and lessons for Covid-19. *Journal of Policy Modeling, 43*(1), 15–33.

Chen, H. C., & Yeh, C. W. (2021). Global financial crisis and COVID-19: Industrial reactions. *Finance Research Letters, 42,* 101940.

Easley, D., De Prado, M. M. L., & O'Hara, M. (2011). The microstructure of the "flash crash": Flow toxicity, liquidity crashes, and the probability of informed trading. *Journal of Portfolio Management, 37*(2), 118–128.

Emm, E. E., Gay, G. D., Ma, H., & Ren, H. (2022). Effects of the Covid-19 pandemic on derivatives markets: Evidence from global futures and options exchanges. *Journal of Futures Markets*.

Ferreira, E., Orbe, S., Ascorbebeitia, J., Álvarez Pereira, B. & Estrada, E. (2021). Loss of structural balance in stock markets. *Nature, Scientific Reports,11*(1), 12230–12230.

Foley, S., Kwan, A., Philip, R., & Ødegaard, B. A. (2021). Contagious margin calls: How COVID-19 threatened global stock market liquidity. *Journal of Financial Markets*, 100689.

Frino, A., Gerace, D., & Behnia, M. (2021a). The impact of algorithmic trading on liquidity in futures markets: New insights into the resiliency of spreads and depth. *Journal of Futures Markets, 41*(8), 1301–1314.

Frino, A, McInish, TH & Toner, M 1998, The liquidity of automated exchanges: new evidence from German Bund futures. *Journal of International Financial Markets, Institutions & Money, 8*(3), 225–241.

Frino, A., & McKenzie, M. D. (2002). The pricing of stock index futures spreads at contract expiration. *Journal of Futures Markets, 22*(5), 451–469.

Frino, A., Mollica, V., & Webb, R. I. (2014). The impact of co-location of securities exchanges' and traders' computer servers on market liquidity. *Journal of Futures Markets, 34*(1), 20–33.

Frino, A., Xu, C., & Zhou, Z. I. (2021b). Are option traders more informed than Twitter users? A PVAR analysis. *Journal of Futures Markets*, 1–29.

Kirilenko, A. A., Kyle, A. P. S., Samadi, M., & Tuzun, T. (January 6, 2017). The Flash Crash: High-Frequency Trading in an Electronic Market. *Journal of Finance*, Forthcoming, Available at SSRN: http://dx.doi.org/10.2139/ssrn.1686004

Lee, C. M., Mucklow, B., & Ready, M. J. (1993). Spreads, depths, and the impact of earnings information: An intraday analysis. *The Review of Financial Studies, 6*(2), 345–374.

McInish, T. H., & Wood, R. A. (1992). An analysis of intraday patterns in bid/ask spreads for NYSE stocks. *The Journal of Finance, 47*(2), 753–764.

O'Hara, M., & Zhou, X. A. (2021). Anatomy of a liquidity crisis: Corporate bonds in the COVID-19 crisis. *Journal of Financial Economics, 142*(1), 46–68.

Parkinson, M. (1980). The extreme value method for estimating the variance of the rate of return. *Journal of Business, 53*(1), 61–65.

## 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:

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

where $\mathrm{High}^i_{d,t}$ is the $i^{th}$ highest trade price in the interval $t$ of day $d$, $\mathrm{Low}^i_{d,t}$ 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:

$$Extreme\ Value\ Volatility_t = \sqrt{\frac{(\log(\mathrm{High}^i_{d,t}) - \log(\mathrm{Low}^i_{d,t}))^2}{4\log(2)}} \tag{3}$$

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: $Value\ Depth_{d,t} = MDepth_{d,t}^{i} * P_{d,t}^{i}$.

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# MARKETWIDE LIQUIDITY AND OPTIONS MARKET

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## Abstract

In this paper, we study the relationship between marketwide liquidity and options market. Using the Chicago Board Options Exchange (CBOE) Volatility Index, VIX as a measure of overall value of the S&P 500 (SPX) options, and the CBOE SKEW Index as a measure of market crash risk premium in the options market, we study the relation among marketwide liquidity, VIX and SKEW. Empirical results show that higher the marketwide liquidity, less expensive the options and the less likely options traders anticipate a market crash.

**JEL classification:** G12; G13

**Keywords:** Marketwide liquidity; VIX; SKEW

## 1. Introduction

Poor liquidity in the credit derivatives market, caused by the US subprime mortgage collapse, helped to trigger the 2009 financial crisis. Liquidity is the ability of an asset to be sold with a minimum loss of value. As a result of the liquidity crisis, many financial firms wrote down large portfolios of credit derivatives known as Collateralized Debt Obligations (CDOs). Because of the large size of the derivatives market, understanding the impact of liquidity on derivatives is crucial to understanding why financial markets crash. In this paper, we study the impact of marketwide liquidity as a state variable on the pricing of derivatives, in particular index options, a popular kind of derivative.

Existing literature mainly focuses on the impact of liquidity on stock and bond markets. Pastor and Stambaugh (2003) documented that marketwide liquidity is a state variable important for pricing stocks cross-sectionally. Acharya and Pedersen (2005) develop a liquidity-adjusted capital asset pricing model under time varying liquidity, and empirically show that liquidity risk is important in the stock market. Lin, Wang and Wu's (2011) empirical results suggest that liquidity risk is an important determinant of expected corporate bond returns.

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The liquidity risk in derivatives comes from three sources: the level of underlying stock liquidity, derivative liquidity and the marketwide liquidity. Research on the impact of liquidity on derivatives markets is scarce. Brenner, Eldor and Hauser (2001) investigate the effect of nontradability on currency derivatives. Cetin et al. (2006) include liquidity into the standard Black-Scholes framework. Bongaerts, De Jong and Driessen (2011) study liquidity risk premium in Credit Default Swap market. To the best of our knowledge, the impact of marketwide liquidity on derivatives markets has never been studied in the literature. That is the focus of this paper.

## 2. Marketwide Liquidity and Option Expensiveness Measures

### 2.1 Marketwide liquidity measure

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.

#### 2.1.1. Stock market liquidity index

We use Pastor-Stambaugh stock market liquidity measure (PS_stock) and Sadka liquidity measures (Sadka_TF and Sadka_PV). Pastor and Stambaugh (2003) investigate whether marketwide liquidity is a state variable of stock pricing. Their study focuses on a particular dimension of liquidity associated with temporary price fluctuations induced by order flow and finds that expected stock returns are positively related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity. Sadka (2006) decomposes equity-based liquidity into variable and fixed components and finds that the permanent variable component is priced in stock returns. These two data sets are available in the database of WRDS. The data period of PS stock market liquidity measure is from January 1990 to December 2010. The data period of Sadka liquidity measures is from January 1990 to December 2008.

#### 2.1.2. Corporate bond market liquidity index

The corporate bond market liquidity indexes used in the empirical analysis include Amihud corporate bond liquidity measure and PS corporate bond liquidity measure. These two measures are constructed by Lin, Wang and Wu (2010) using transaction based corporate bond data. They find that liquidity risk is priced in the cross section of expected corporate bond returns. The data period covers from March 1994 to September 2009.

#### 2.1.3. Treasury market liquidity index

We use on-off-the-run spread (On/off spread) to measure the liquidity of Treasury market. The on-the-run yield is represented by the constant maturity five-year Treasury rate by Federal Reserve, while the off-the-run yield is the five-year generic Treasury rate reported by the Bloomberg system, which is based on the yields of non-benchmark Treasury notes. On-off-the-run spread has been used extensively in the literature as a measure of aggregate market liquidity (Longstaff, Mithal and Neis, 2005; Lin, Liu and Wu, 2011).

#### 2.1.4 Aggregate market liquidity index

Asness, Moskowitz and Pedersen (2009) find that various liquidity measures are not very correlated to each other and construct an illiquidity index of all measures using the first principal component of all liquidity measures. Following Asness, Moskowitz and Pedersen (2009), we also construct the aggregate liquidity index, which is the first principal component of individual liquidity index, including Pastor-Stambaugh stock market liquidity measure, Sadka Transitory Fixed and Permanent Variable liquidity measure, Amihud corporate bond liquidity measure, Pastor-Stambaugh Corporate bond liquidity measure and On-off-the-run spread.

### 2.2. Option overall value measure

It is difficult to measure the overall value of options because options prices depend on underlying stock price, strike price and time to maturity. To eliminate the dependency along the direction of underlying stock, it is very natural to use the Black-Scholes implied volatility, which is still a function of strike price and time to maturity. In order to come up with a unique measure of options overall value, certain operation is required to aggregate the information of implied volatility surface.

In 2003, the Chicago Board Options Exchange (CBOE) adopted a new methodology to calculate a Volatility Index, VIX by using all the out-of-the-money (OTM) S&P 500 (SPX) index options.[2] It is a proxy of 30-day variance swap rate, can be used as a measure of overall value of SPX options.

In 2011, the CBOE started to publish values for the CBOE S&P 500 Skew Index (ticker symbol: SKEW), a benchmark measure of the perceived risk of extreme negative moves[3]. It is calculated as 100 minus 10 times 30-day risk-neutral skewness of SPX options. The SKEW can be used as a measure of the value of deep OTM options relative to the ATM ones. Since the deep OTM options are often used as a hedging instrument against a large market fall, the SKEW can be regarded as a measure of market crash risk premium embedded in the options market.

## 3. Empirical Methodology

The research is empirical. Our methodology is mainly based on single- or multiple-variable linear regressions.

### 3.1. The impact of liquidity on VIX and SKEW

First, we examine the relationship between marketwide liquidity and VIX by running the regression

$$VIX_t = a + b\, LIQ_t + \varepsilon_t. \tag{1}$$

We then examine the relationship between marketwide liquidity and SKEW

$$SKEW_t = a + b\, LIQ_t + \varepsilon_t. \tag{2}$$

Zhang, Zhao and Chang (2012) show that the third central moment (TCM) is more appropriate than skewness to measure of market crash risk premium. Therefore, we further examine the relationship between marketwide liquidity and TCM

$$TCM_t = a + b\, LIQ_t + \varepsilon_t, \tag{3}$$

where

$$TCM_t = SKEW_t \times VIX_t^3. \tag{4}$$

[2] See the CBOE white paper available at: http://www.cboe.com/micro/VIX/vixwhite.pdf

[3] See the CBOE white paper available at: http://www.cboe.com/micro/skew/documents/SKEWwhitepaperjan2011.pdf

### 3.2. The decomposition of variance

In a jump-diffusion setting, Zhang, Zhao and Chang (2012) show that the variance and TCM of stock return over the period from $t$ to $t+\tau$, can be written as

$$\begin{aligned} Var &= \sigma^2\tau + \lambda x^2\tau, \\ TCM &= \lambda x^3\tau, \end{aligned} \tag{5}$$

where $\sigma$ is volatility coming from Brownian motion, $\lambda$ is jump intensity and $x$ is jump size. The result is derived under the assumption that $\sigma$, $\lambda$ and $x$ are constant, but we can extend the result to case that both $\sigma$ and $\lambda$ are stochastic with an understanding that these two formulas work for average $\sigma$ and $\lambda$ over the period. From this analysis, we may conclude that the variance can be decomposed into two parts. One of them comes from the risk of small change, i.e., Brownian motion, the other one comes from the risk of big change, i.e., jumps. By running the regression

$$Var_t = a + b\,TCM_t + \varepsilon_t, \tag{6}$$

The residual obtained will capture the change of variance form Brownian motion. In order to detect which of the two factors, liquidity and TCM dominates the change in variance, we can also run a regression of variance on liquidity by using TCM as a control variable

$$Var_t = a + b\,TCM_t + \ c\,LIQ_t + \varepsilon_t. \tag{7}$$

### 3.3. The impact of liquidity on Brownian motion variance

We run following regression

$$\varepsilon_t = \alpha + \beta\,LIQ_t + \eta_t, \tag{8}$$

where Brownian motion variance, $\varepsilon_t$, is the residual from the regression of variance on TCM

$$\varepsilon_t = Var_t - a - b\,TCM_t. \tag{9}$$

## 4. Empirical Results

Table 1 reports the summary statistics of variables used in the empirical analysis. For VIX, SKEW and Pastor-Stambaugh stock liquidity, we have 21 years of data. Using monthly sample, we have 252 observations[4]. For Amihud and Pastor-Stambaugh corporate liquidity, we have 187 observations, slightly shorter.

[4] Monthly VIX and SKEW are calculated by the mean of all daily value within this month.

## Table 1: Summary Statistics

| Variable | Sample period | Obs. | Mean | Std | Max | Min |
|---|---|---|---|---|---|---|
| **VIX** | 1/1990-12/2010 | 252 | 20.42 | 8.00 | 62.64 | 10.82 |
| **SKEW** | 1/1990-12/2010 | 252 | 116.50 | 4.43 | 128.97 | 106.88 |
| **TCM** | 1/1990-12/2010 | 252 | 1.56 | 3.00 | 29.19 | 0.15 |
| **PS_stock** | 1/1990-12/2010 | 252 | 0.00 | 0.06 | 0.29 | -0.27 |
| **Sadka_TF** | 1/1990-12/2008 | 228 | 0.00 | 0.00 | 0.01 | -0.01 |
| **Sadka_PV** | 1/1990-12/2008 | 228 | 0.00 | 0.01 | 0.02 | -0.03 |
| **Amihud_Corporate** | 3/1994-09/2009 | 187 | 0.00 | 1.00 | 2.21 | -4.73 |
| **PS_Corporate** | 3/1994-09/2009 | 187 | 0.00 | 0.18 | 0.36 | -1.33 |
| **On/off spreads (bps)** | 1/1990-12/2010 | 252 | 3.49 | 16.05 | 47.30 | -35.10 |
| **ALIQ** | 1/1990-12/2010 | 252 | -0.02 | 1.30 | 2.31 | -9.49 |

*Note: This table reports the summary statistics of variables used in the empirical analysis. These variables are Volatility Index (VIX), Skew Index (SKEW), the third central moment (TCM) which equals $SKEW \times VIX^3$, Pastor-Stambaugh stock market liquidity measure (PS_Stock), Sadka Transitory Fixed (Sadka_TF) and Permanent Variable (Sadka_PV) liquidity measure, Amihud corporate bond liquidity measure (Amihud_Corporate), Pastor-Stambaugh Corporate bond liquidity measure (PS_Corporate), On-off-the-run spread (On/off spreads) and aggregate liquidity measure (ALIQ). The aggregate liquidity index is the first principal component of individual liquidity index.*

Table 2 reports correlation matrix of the variables. VIX and SKEW are almost independent, with a correlation coefficient -0.02. VIX is negatively correlated with all the liquidity measures. We notice that the on/off spread measures negative liquidity. Smaller the on/off spread, higher the liquidity is. SKEW is independent of liquidity, but TCM is negatively correlated with liquidity. The liquidity measures of different markets are positively correlated each other with reasonable coefficients.

## Table 2: Correlation Matrix

| | VIX | SKEW | TCM | PS_ stock | Sadka_TF | Sadka_PV | Amihud_ Corporate | PS_ Corporate | On/off spread | ALIQ |
|---|---|---|---|---|---|---|---|---|---|---|
| **VIX** | 1.00 | | | | | | | | | |
| **SKEW** | -0.02 | 1.00 | | | | | | | | |
| **TCM** | 0.86 | 0.04 | 1.00 | | | | | | | |
| **PS_stock** | -0.23 | 0.09 | -0.15 | 1.00 | | | | | | |
| **Sadka_TF** | -0.14 | -0.17 | -0.13 | 0.03 | 1.00 | | | | | |
| **Sadka_PV** | -0.27 | 0.09 | -0.23 | 0.14 | 0.17 | 1.00 | | | | |
| **Amihud_ Corporate** | -0.23 | -0.04 | -0.33 | 0.26 | 0.17 | 0.26 | 1.00 | | | |
| **PS_ Corporate** | -0.30 | 0.04 | -0.35 | 0.11 | 0.06 | 0.24 | 0.33 | 1.00 | | |
| **On/off spread** | 0.14 | -0.08 | 0.10 | -0.05 | 0.10 | -0.12 | -0.11 | -0.02 | 1.00 | |
| **ALIQ** | -0.40 | 0.04 | -0.42 | 0.51 | 0.30 | 0.64 | 0.77 | 0.63 | -0.21 | 1.00 |

*Note: This table reports correlation matrix of variables used in the empirical analysis. These variables are Volatility Index (VIX), Skew Index (SKEW), the third central moment (TCM) which equals $SKEW \times VIX^3$, Pastor-Stambaugh stock market liquidity measure (PS_Stoock), Sadka Transitory Fixed (Sadka_TF) and Permanent Variable (Sadka_PV) liquidity measure, Amihud corporate bond liquidity measure (Amihud_Corporate), Pastor-Stambaugh Corporate bond liquidity measure (PS_Corporate), On-off-the-run spread (On/off spread) and aggregate liquidity measure (ALIQ). The aggregate liquidity index is the first principal component of individual liquidity index.*

Table 3 reports the results of time series regressions of VIX, SKEW and TCM on different liquidity measures. The results of Panel A show that VIX is linearly related to all liquidity measures except Sadka_TF with statistical significance at 1% level. The fact that VIX is not related to Sadka_TF is consistent with Sadka's (2006) result that Transitory Fixed component is not priced in stock. The results of Panel B show that SKEW is not related to any liquidity measures except Sadka_TF. It is interesting to see that Sadka's Transitory Fixed component is picked up by SKEW. The results of Panel C show that TCM is in general linearly related to all liquidity measures, but less significant than VIX for stock and Treasury markets and more significant for corporate bond market. These regressions results are consistent with the correlation coefficients presented in Table 2.

## Table 3: Time Series Regressions

**Panel A.** $VIX_t = a + b\, LIQ_t + \varepsilon_t$

| | Liquidity index | | | | | | |
|---|---|---|---|---|---|---|---|
| | Stock Market | | | Corporate Bond Market | | Treasury Market | Aggregate |
| | PS_Stock | Sadka_TF | Sadka_PV | Amihud _Corporate | PS _Corporate | On/off spread | ALIQ |
| *Intercept* | 20.39 | 20.48 | 20.48 | 20.32 | 20.50 | 19.98 | 20.35 |
| | (34.36) | (33.72) | (35.13) | (34.96) | (34.98) | (32.73) | (37.30) |
| *$LIQ_t$* | -26.69 | -672.56 | -447.44 | -2.55 | -14.45 | 0.11 | -2.53 |
| | (-3.18) | (-1.57) | (-4.08) | (-4.36) | (-3.88) | (3.12) | (-2.65) |
| *Adj.$R^2$* | 4.90% | 0.82% | 8.13% | 8.83% | 7.37% | 4.70% | 19.62% |

**Panel B.** $SKEW_t = a + b\, LIQ_t + \varepsilon_t$

| | Liquidity index | | | | | | |
|---|---|---|---|---|---|---|---|
| | Stock Market | | | Corporate Bond Market | | Treasury Market | Aggregate |
| | PS_Stock | Sadka_TF | Sadka_PV | Amihud _Corporate | PS _Corporate | On/off spread | ALIQ |
| *Intercept* | 116.35 | 116.41 | 116.34 | 116.34 | 116.34 | 116.42 | 116.35 |
| | (345.13) | (385.03) | (353.51) | (351.99) | (351.75) | (343.24) | (351.97) |
| *$LIQ_t$* | 7.36 | -616.69 | 88.98 | -0.27 | 1.20 | -0.02 | 0.14 |
| | (1.58) | (-2.69) | (1.44) | (-0.79) | (0.57) | (-0.93) | (0.61) |
| *Adj.$R^2$* | 0.85% | 3.40% | 0.60% | -0.21% | -0.38% | -0.01% | -0.36% |

**Panel C.** $TCM_t = a + b\, LIQ_t + \varepsilon_t$, **where** $TCM_t = SKEW_t \times VIX_t^3$

| | Liquidity index | | | | | | |
|---|---|---|---|---|---|---|---|
| | Stock Market | | | Corporate Bond Market | | Treasury Market | Aggregate |
| | PS_Stock | Sadka_TF | Sadka_PV | Amihud _Corporate | PS _Corporate | On/off spread | ALIQ |
| *Intercept* | 1.57 | 1.62 | 1.60 | 1.53 | 1.62 | 1.45 | 1.55 |
| | (6.43) | (6.62) | (6.71) | (6.72) | (7.00) | (5.82) | (7.05) |
| *$LIQ_t$* | -5.56 | -355.65 | -151.01 | -1.28 | -7.19 | 0.03 | -1.02 |
| | (-1.61) | (-2.07) | (-3.37) | (-5.48) | (-4.90) | (2.18) | (-6.68) |
| *Adj.$R^2$* | 0.89% | 1.82% | 5.51% | 14.08% | 11.49% | 2.08% | 19.75% |

*Note: This table reports the time series regression results of VIX, SKEW and TCM on different liquidity measures. The liquidity measures used in the regressions include Pastor-Stambaugh stock market liquidity measure (PS_Stoock), Sadka Transitory Fixed (Sadka_TF) and Permanent Variable (Sadka_PV) liquidity measure, Amihud corporate bond liquidity measure (Amihud_Corporate), Pastor-Stambaugh Corporate bond liquidity measure (PS_Corporate) and On-off-the-run spread (On/off spread). Panel A, B and C report the regression results of VIX, SKEW and TCM respectively.*

Table 4 reports the result of times series regressions of Variance (Var) on TCM, liquidity and jointly. As we can see from Panel C, the impact of liquidity on variance mainly comes from its impact on TCM. In other word, liquidity shocks affect variance via jump risk.

## Table 4: Result of Times Series Regressions of Variance

**Panel A.** $Var_t = a + b\, TCM_t(LIQ_t) + \varepsilon_t$, **where** $Var_t = VIX_t^2$

| | Liquidity index | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Stock Market | | | | Corporate Bond Market | | Treasury Market | Aggregate |
| | TCM | PS_Stock | Sadka_TF | Sadka_PV | Amihud _Corporate | PS _Corporate | On/off spread | ALIQ |
| *Intercept* | 2.47 | 4.81 | 4.87 | 4.86 | 4.76 | 4.88 | 4.59 | 4.78 |
| | (29.25) | (13.37) | (13.42) | (13.82) | (13.94) | (14.12) | (12.46) | (14.82) |
| *$TCM_t(LIQ_t)$* | 1.52 | -12.89 | -502.93 | -254.53 | -1.83 | -10.27 | 0.06 | -1.60 |
| | (60.09) | (-2.53) | (-1.96) | (-3.85) | (-5.21) | (-4.68) | (2.78) | (-7.14) |
| *Adj.$R^2$* | 93.23% | 2.96% | 1.59% | 7.24% | 12.88% | 10.56% | 3.67% | 22.00% |

**Panel B.** $Var_t = a + b\, TCM_t + c\, LIQ_t + \varepsilon_t$, **where** $Var_t = VIX_t^2$

| | Liquidity index | | | | | | |
|---|---|---|---|---|---|---|---|
| | Stock Market | | | Corporate Bond Market | | Treasury Market | Aggregate |
| | PS_Stock | Sadka_TF | Sadka_PV | Amihud _Corporate | PS _Corporate | On/off spread | ALIQ |
| *Intercept* | 2.56 | 2.55 | 2.59 | 2.55 | 2.55 | 2.52 | 2.60 |
| | (25.44) | (24.08) | (24.72) | (24.05) | (23.85) | (32.73) | (24.65) |
| *$TCM_t$* | 1.42 | 1.44 | 1.42 | 1.44 | 1.44 | 1.43 | 1.41 |
| | (50.83) | (49.05) | (48.22) | (45.94) | (46.59) | (3.12) | (43.96) |
| *$LIQ_t$* | -4.97 | 8.54 | -39.85 | 0.02 | 0.07 | 0.02 | -0.17 |
| | (-3.84) | (0.13) | (-2.20) | (0.17) | (0.11) | (2.56) | (-2.30) |
| *Adj.$R^2$* | 93.81% | 93.29% | 93.47% | 93.29% | 93.29% | 93.53% | 93.49% |

*Note: This table reports the time series regression results of Variance (Var) on TCM and different liquidity measures, where the Variance is defined as the square of VIX. The liquidity measures used in the regressions include Pastor-Stambaugh stock market liquidity measure (PS_Stock), Sadka Transitory Fixed (Sadka_TF) and Permanent Variable (Sadka_PV) liquidity measure, Amihud corporate bond liquidity measure (Amihud_Corporate), Pastor-Stambaugh Corporate bond liquidity measure (PS_Corporate), On-off-the-run spread (On/off spread) and aggregate liquidity measure (ALIQ). The aggregate liquidity index is the first principal component of individual liquidity index. Panel A reports the results of univariate regressions while Panel B reports the results of bivariate regressions.*

Table 5 reports the result of time series regressions of Brownian motion variance on liquidity. As we can see most of them are not significant except PS-Stock and on/off spread. This confirms our previous finding that liquidity shocks affect variance mainly through jump risk.

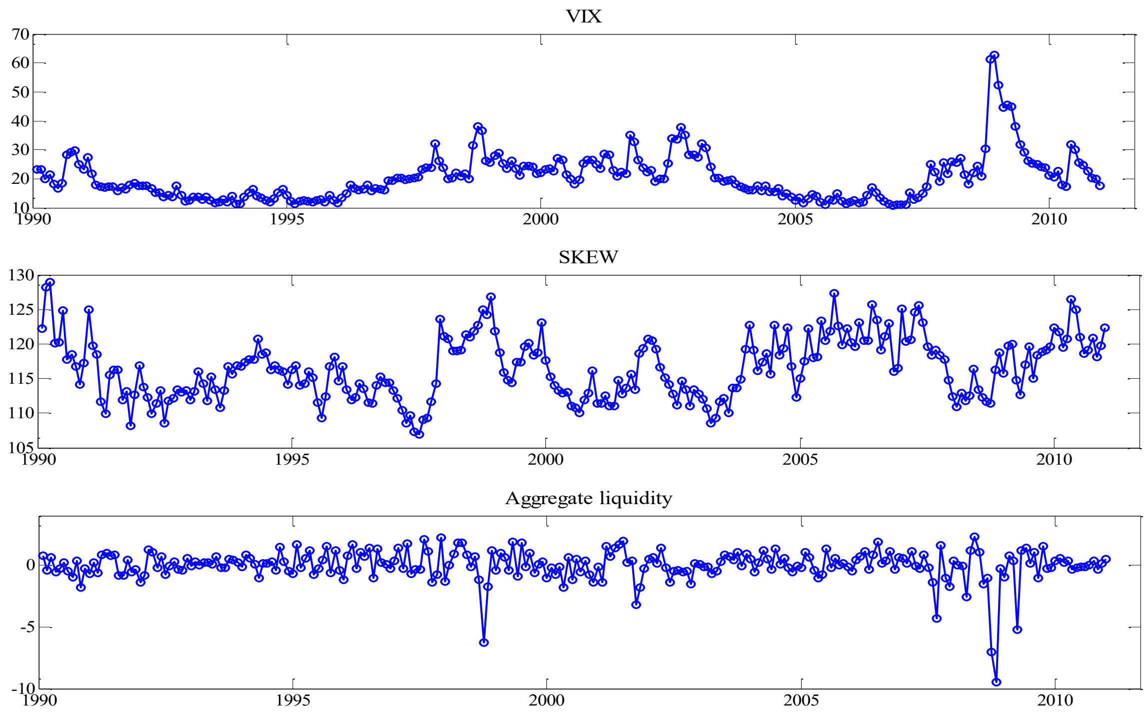
## Table 5: Brownian Motion Variance on Liquidity

| | Stock Market Liquidity Index | | | Corporate Bond Market Liquidity Index | | Treasury Market Liquidity Index | Aggregate Market Liquidity Index |
|---|---|---|---|---|---|---|---|
| | PS_Stock | Sadka_TF | Sadka_PV | Amihud _Corporate | PS _Corporate | On/off spread | *ALIQ* |
| *Intercept* | -0.04 | -0.04 | -0.03 | -0.03 | -0.04 | -0.08 | -0.04 |
| | (-0.41) | (-0.38) | (-0.30) | (-0.30) | (-0.38) | (-0.81) | (-0.26) |
| *$LIQ_t(ALIQ_t)$* | -0.49 | 34.70 | -26.24 | 0.11 | 0.59 | 0.02 | -0.06 |
| | (-3.41) | (0.51) | (-1.46) | (1.12) | (0.97) | (2.06) | (-0.86) |
| *Adj.$R^2$* | 5.65% | -0.42% | 0.64% | 0.15% | -0.03% | 1.80% | -0.14% |

Note: This table reports the time series regression results of Variance residuals ($\varepsilon$) on the different liquidity measures. The Variance residuals is from the regression of Variance on TCM. The liquidity measures used in the regressions include Pastor-Stambaugh stock market liquidity measure (PS_Stock), Sadka Transitory Fixed (Sadka_TF) and Permanent Variable (Sadka_PV) liquidity measure, Amihud corporate bond liquidity measure (Amihud_Corporate), Pastor-Stambaugh Corporate bond liquidity measure (PS_Corporate) , On-off-the-run spread (On/off spread) and aggregate liquidity measures (*ALIQ*). The aggregate liquidity index is the first principal component of individual liquidity index.

$\varepsilon_t = \alpha + \beta LIQ_t\left(ALIQ_t\right) + \eta_t$, where $\varepsilon_t = Var_t - \hat{a} - \hat{b}TCM_t$

## Figure 1:




VIX, SKEW and aggregate liquidity index. This table plots the VIX, SKEW and aggregate liquidity index from 1990 to 2010. The aggregate liquidity index is the first principal component of individual liquidity index, including Pastor-Stambaugh stock market liquidity measure (PS_Stoock), Sadka Transitory Fixed (Sadka_TF) and Permanent Variable (Sadka_PV) liquidity measure, Amihud corporate bond liquidity measure (Amihud_Corporate), Pastor-Stambaugh Corporate bond liquidity measure (PS_Corporate) and On-off-the-run spread (On/off spread).

## 5. Conclusions

In this paper, we study the relationship between marketwide liquidity and options market. Through empirical analysis, we observe that the liquidity does have an impact on the options overall value and market crash risk premium observed in options market. Higher the marketwide liquidity, less expensive the options and the less likely options traders anticipate a market crash. The impact of liquidity on total variance is mainly through jump risk. The variance that comes from Brownian motion is almost insensitive to the change of liquidity.

## References


Asness, Clifford S., Tobias J. Moskowitz and Lasse H. Pedersen, 2009, Value and momentum everywhere, Working paper, University of Chicago.

Acharya, Viral V. and Lasse Heje Pedersen, 2005, Asset pricing with liquidity risk, *Journal of Financial Economics*, 77, 375–410.

Bongaerts, Dion, Frank De Jong and Joost Driessen, 2011, Derivative pricing with liquidity risk: Theory and evidence from the credit default swap market, *Journal of Finance*, 66(1), 203-240.

Brenner, Menachem, Rafi Eldor and Shmuel Hauser, 2001, The price of options illiquidity, *Journal of Finance*, 46(2), 789-805.

Cetin, U., R. Jarrow, P. Protter and M. Warachka, 2006, Pricing options in an extended Black-Scholes economy with illiquidity: Theory and empirical evidence, *Review of Financial Studies*, 19(2), 493-529.

Lin, Hai, Sheen Liu and Chunchi Wu, 2011, Dissecting corporate bond and CDS spreads, *Journal of Fixed Income*, 20, 7-40.

Lin, Hai, Junbo Wang and Chunchi Wu, 2011, Liquidity risk and expected corporate bond returns, *Journal of Financial Economics*, 99, 628-650.

Longstaff, Francis A., Sanjay Mithal and Eric Neis, 2005, Corporate yield spreads: Default risk or liquidity? New evidence from the credit default swap market, *Journal of Finance*, 60, 2213-2253.

Pastor, Lubos and Robert F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy*, 111(3), 642–685.

Zhang, Jin E., Huimin Zhao and Eric C. Chang, 2012, Equilibrium asset and option pricing under jump diffusion, *Mathematical Finance*, 22(3), 538-568.

# MISPRICINGS IN GLOBAL ENERGY MARKETS

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**Abstract**

Financial market participants can benefit from understanding how shocks affect equity mispricings. Energy corporates have been exposed to multiple structural changes over the past decades. This paper applies the pairs trading algorithm of (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018) (Journal of Futures Markets, 2018) to analyse mean reversion of cointegrated stocks in global energy equity markets. Using daily data covering the US, Europe and Asia we report positive risk adjusted returns that supersede their corresponding equity index counterparts. Pairs trading profitability is enhanced when filtering stocks with the measure of capital expenditure (CAPEX).

**Keywords:** Mispricings, Energy markets, Energy transition, Pairs trading

## 1. Introduction

Revenues in the oil and gas industry have been hit hard over the past two decades. The 2014-2016 crude oil price plunge and the pandemic driven turmoil in energy markets have caused a huge rise of stock price volatility in energy corporates. Energy equities are in consequence trading at less than half of the levels prior to the 2014 oil price shock. The sector has severely undercut business growth and investment in new capacity at a time in which green investing and the global commitment to achieve climate neutrality reaches its momentum.[1] In this paper we illustrate the process by which recent periods of instability in the energy sector led to stock pricing inefficiencies in long term related assets. Our paper relates to a significant part of Robert Webb´s work as it uses the cointegration approach to examine asset pricing inefficiencies. There are a number of important contributions of Robert in the area including (Low, Muthuswamy, and Webb 1999), (Frijns, Tourani-Rad, and Webb 2016). (Webb 1985) among others. Here we exploit temporary mispricings via the use of arbitrage-based pairs trading strategies across cointegrated assets that share a common underlying factor. We apply the framework introduced in (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018) (FFPT thereafter) to which Robert Webb contributed extensively as an editor. Pairs trading is an arbitrage-based strategy that it is activated when the underlying spread value reaches a threshold or strike level. It is therefore equivalent to a derivative in that it represents a contingent claim.

Pairs trading relies on a well-known trading rule for cointegrated price series based on simultaneous long–short positions that are closed when prices revert to a long-run relationship. When an investor

[1] Indicatively, BP´s share prices fell by 44% over 2014-2015 period and by 55% in the first three quarters of 2020. Over the same period the US company Exxon Mobil Corp´s market value has fallen from more than $400 billion in 2014 to around $260 billion in October 2021 (source Bloomberg October 2021 available athttps://www.bloomberg.com/news/articles/2021-10-13/trillion-dollar-esg-boom-is-punishing-old-school-energy-stocks

opens a position, he shorts the overpriced asset and longs the underpriced one, until the mispricing is eliminated (see (Gatev, Goetzmann, and Rouwenhorst 2006)).

In this paper we use the framework introduced by (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018) to identify how deviations from underlying fundamentals can be used to earn pairs trading profitability with a persistence linked trading trigger. We analyze for this purpose a sample of daily prices of European, US and Asian energy corporations covering the 2002-2021 period. Results from pairs trading strategies show that there is positive profitability in the three geographical areas that supersede profitability obtained by benchmark indexes. Reported risk adjusted returns of the proposed strategies capture the multiple price shocks seen in the energy market and are also higher than those estimated in the pairs trading literature. The novelty of the approach applied here is that it considers the capital expenditure (CAPEX) ratio as a key metric for reflecting the response of energy corporates to time changing (financial, regulatory, and economic) conditions. By measuring the evolution of new capacity investment, the CAPEX measure signals the degree of commitment with the energy transition. Our results demonstrate improved performance under the CAPEX restriction for the three geographical areas considered.

While crude oil has been an integral component for economic development it is currently at the center of the climate change debate due to the contribution of fossil fuel energy sources to global greenhouse emissions. (Atanasova and Schwartz 2019) have recently analyzed the extent to which capital markets reflect the possibility that fossil fuel reserves may become "stranded assets" in the transition to a low carbon economy. They underline that mispricing of stranded assets can bring potential systemic risk to an economy that is transforming to fulfil the objectives under the Paris Agreement (COP26). In this paper we shed light to this recent literature by analyzing price inefficiencies in global energy markets.

The rest of the paper is organized as follows. Section 2 presents the empirical cointegration framework. Cointegration results are presented in Section 3. Section 4 describes pairs trading profitability. Conclusions are presented in section 5.

## 2. The Empirical Model

In this section we summarize the account of the empirical framework in FFPT. Let´s assume that $y_t$ and $x_t$ are two $I(1)$ cointegrated stocks. If there are no limitations on borrowing no cost other than arbitrage transaction cost and no limitations in short sale, we can write the long-term relationship as

$$y_t = \gamma_0 + \gamma_1 x_t + z_t \qquad (1)$$

where $z_t$ is the cointegrating error. The resulting dynamics between $y_t$ and $x_t$ are represented by the following VECM:

$$\Delta P = \begin{pmatrix} \Delta y_t \\ \Delta x_t \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \end{pmatrix} z_{t-1} + u_t \qquad (2)$$

where: $\alpha_1$ and $\alpha_2$ refer to the speed of mean reversion; $u_t$ is a vector white noise with i.i.d shocks.

Note that the lags of $\Delta P$ are chosen in order to obtain white noise errors.

## 3. Price Discovery and Pairs Trading

We collect the daily closing prices for the January 2002- November 2021 period from the following energy index components: S&P 500 Energy traded in dollar, Europe Energy and minerals index, and Asia Energy and Minerals. Prices are all in dollars. Column 1 in Table **1** reports the number of corporates included in each of the indexes analyzed, while the column 2 in the same table reports the number of companies for which we have data available from 2002. The number of companies considered for each geographical area are therefore 40, 68 and 138 for the US, Europe, and Asia. The data source is Factset [2] from which we also collect quarterly data on capital expenditure (CAPEX) for the corresponding companies. By analyzing pairs trading from 2002 our analysis covers a number of regime changes in the crude oil price seen over the past two decades which include: a) the period prior to the GFC, characterized by the industrialization of the Asian countries and boom and bust cycles in commodity markets (see (Figuerola-Ferretti, Gilbert, and McCrorie 2015); b) the GFC episode and the corresponding crude oil price swing in July 2008 ((Figuerola-Ferretti, McCrorie, and Paraskevopoulos 2020)); c) the 2010-2012 European sovereign debt crisis (see (Lane 2012) for a full account of this episode); d) the 2014-2016 commodity price shock, and the signature of the Paris agreement in 2015; e) the 2020 pandemic driven energy shock and the 2021 post COVID recovery energy market´s turmoil. We are therefore able to analyze pairs trading profitability under different market states. We follow the method in (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018) and perform a cointegration analysis to identify paired corporates traded (and whose headquarters are located) within three different geographical areas: US, Europe, and Asia. The underlying presumption is that cointegrated pairs are linked via the long-term relationship represented by the linear process specified in Equation 1). Long term commonalities are driven by related demand and supply fundamentals across paired assets. These arise because assets are restricted to trade in the same geographical area and to belong to the same (or highly related) sector. Once these filters have been imposed, we proceed to test for cointegration. Firms that are restricted to be in the same sector and geographical area will have common monetary policy exposures, similar patterns of R&D intensities as well as common regulation schemes.

### Table 1: Number of Firms

| Sector | Total | Total since 2002 |
|---|---|---|
| US Energy | 64 | 40 |
| EU Energy | 70 | 68 |
| Asia Energy | 144 | 138 |

*Note: This table presents the number of firms included in the sample for the period between January 2002 and November 2021.*

Two I(1) series will be cointegrated if there is a linear combination between them that is stationary or I(0). In order to identify the paired stocks that belong to the same geographical area we first apply the Augmented Dickey Fuller method to test for unit roots which are a necessary condition for cointegration. We fail to reject the unit root hypothesis all individual stocks traded in the samples of US, European and Asian companies (results can be provided upon request). In what follows we find cointegrated pairs of stocks with the restriction that they belong to the same geographical area as well as to the same sector (the energy sector in the case of US, and the energy and mineral sector for the case of Europe and Asia.) In order to calculate out of sample profitability the VECM model specified in Equation (2) is estimated for the cointegrated pairs using a rolling window approach. Estimation details for this framework are specified in (Johansen 1995) and (Juselius 2006). We follow the procedure in FFPT implying that we use a three-year window from t to t+3 (estimation period) to identify paired stocks and then estimate the cointegrated vector for each of the identified pairs. Estimated coefficients of the selected pairs are then used to perform the trading strategy for the next 6-month window covering the t+3 to t+3.5. This process is repeated trough the remaining sample period. Cointegration is also exploited to determine price leadership between paired assets. The

[2] The data codes corresponding to US, Europe, and Asia in Factset are SPN03, FS2100R3, and FS2100A2 respectively. SPN03 represents 63 US Energy companies and FS2100R3 includes 72 European Energy and Mineral companies. FS2100A2 covers 147 Energy and Refinery companies traded in Asia Pacific.

leader asset is thus used to replicate the follower. Following FFPT price discovery is determined as a function of the speed of mean reversion to temporary deviations from long term equilibrium as specified in Equation (2). Table 2 reports descriptive statistics for the number of cointegrated pairs. As it is expected from Table 1, the highest number of cointegrated pairs arises in the Asian area.

VECM estimates across the three geographical areas considered are reported in Table 3. Given the time rage exploited in this exercise (from January 2002 to November 2021) our moving window approach imply that we have 35 rolling samples. We therefore report average values of estimated parameters for the different percentile levels. We find that the coefficient $\alpha_1$ is significantly negative for all percentiles in the three geographical areas suggesting that the price follower restores temporary mispricings in the cointegrating error by decreasing $\alpha_1$ units in response to one unit increase in the error correction term. The corresponding $\alpha_2$ parameter is positive in all percentiles for all geographical areas. However, it is not significant in 80% of the cases as VECM estimates are obtained in a context in which the follower is the dependent variable set to be explained by the leader, which acts as an independent variable.

**Table 2: Descriptive Statistics for the Number of Cointegrated Pairs**

| Sector | Mean | Standard Deviation | Maximum | Minimum |
|---|---|---|---|---|
| US Energy | 28 | 34 | 167 | 10 |
| EU Energy | 151 | 129 | 540 | 14 |
| Asia Energy | 373 | 266 | 1288 | 33 |

*Note: This table presents descriptive statistics of the number of pairs. Pairs are identified over a 3-year period according to the Johansen cointegration test at the 5% significant level. The Johansen test is conducted on a rolling-window basis. The sample period is January 2002 to November 2021.*

**Table 3: VECM Coefficient Estimation Results**

| | | Percentiles | | | | |
|---|---|---|---|---|---|---|
| Sector | Parameter | $5^{th}$ | $25^{th}$ | Median | $75^{th}$ | $95^{th}$ |
| US Energy | $\alpha_1$ | -0.069 | -0.101 | -0.207 | -0.494 | -0.211 |
| | $\alpha_2$ | 0.009 | 0.022 | 0.042 | 0.060 | 0.077 |
| EU Energy | $\alpha_1$ | -0.004 | -0.015 | -0.042 | -0.407 | -0.510 |
| | $\alpha_2$ | 0.000 | 0.001 | 0.004 | 0.011 | 0.036 |
| Asia Energy | $\alpha_1$ | -0.001 | -0.002 | -0.0052 | -0.015 | -0.098 |
| | $\alpha_2$ | 0.000 | 0.000 | 0.001 | 0.002 | 0.005 |

*Note: This table presents the values of a_1 and a_2 obtained using the Johansen cointegration methodology. The percentiles for $\alpha_2$ is computed using the absolute values. As the Johansen test is conducted on a rolling-window basis, these reported values are an average value computed from a series of estimates of each percentile. The sample period is January 2002 to November 2021. VECM, vector error correction model.*

Table 4 reports average estimated $\gamma_1$ coefficients by percentiles and geographical areas. This coefficient measures the units of the leader asset that are required to replicate the follower and therefore represents the hedge ratio under pairs trading strategies. Reported average estimates are varied, and the differences across percentiles are larger if the number of energy corporates in each of the geographical areas considered is higher.

### Table 4: Slope Coefficient Estimation Results for Cointegration Error

| | | Percentiles | | | | |
|---|---|---|---|---|---|---|
| **Sector** | **Parameter** | $5^{th}$ | $25^{th}$ | **Median** | $75^{th}$ | $95^{th}$ |
| US Energy | $\gamma_1$ | 0.27 | 0.52 | 0.97 | 3.41 | 16.57 |
| EU Energy | $\gamma_1$ | 0.07 | 0.53 | 3.61 | 8.69 | 16.29 |
| Asia Energy | $\gamma_1$ | 0.06 | 0.38 | 1.25 | 5.91 | 33.49 |

*Note: The summary statistics of the estimated values of $\gamma_1$ are reported. As the Johansen test is conducted on a rolling-window basis, these reported values are an average value computed from a series of estimates of each percentile. The sample period is January 2002 to November 2021.*

## 4. Profitability of Pairs Trading

The identification of price leadership and cointegration allows design of the pairs trading algorithm. The trading mechanism is described as follows: An arbitrager will open a long-short position when temporary mispricings measured by the cointegration spread reaches the persistence dependent trigger defined as $\rho = (1 + \alpha_1 - \gamma_1\alpha_2)$ units of the standard deviation of historical cointegration spreads. Note that ρ is the first order autoregressive coefficient of the cointegration error (see FFPT). The pair's trading position is closed the day after reversion occurs. If there is no convergence the position is closed at the end of the 6-month trading period. Given that the data starts in January 2002 the first trading date starts in the first business day of January 2005. We follow the framework of FFPT, which implies mean reverting pairs are identified to deliver stationary profits. Slow adjustment to the long-term equilibrium implies that mispricings can be exploited to earn pairs trading long-term profitability.

### 4.1 The baseline case

In what follows, pairs trading performance is analysed for the three geographical areas of interest: US, EU, and Asia. The underlying presumption is that high volatility in the energy markets complicates the stock valuation process leading to temporary mispricings. Applying the "persistence calibrated" standard deviation trigger introduced in FFTP, the risk and return characteristics are examined at the portfolio level.

### Table 5: Persistency Linked Trading Trigger (ρ)

| | | Percentiles | | | | |
|---|---|---|---|---|---|---|
| **Sector** | **Parameter** | $5^{th}$ | $25^{th}$ | **Median** | $75^{th}$ | $95^{th}$ |
| US Energy | ρ | 0.69 | 0.77 | 0.84 | 0.91 | 0.98 |
| EU Energy | ρ | 0.67 | 0.91 | 0.97 | 0.98 | 0.99 |
| Asia Energy | ρ | 0.90 | 0.96 | 0.97 | 0.97 | 0.97 |

*Note: This table presents the values of persistency-linked trading trigger $\rho = 1 + \alpha_1 - \alpha_1\gamma_2$, which is computed using vector error correction model estimates obtained from the Johansen cointegration methodology. As the trading strategy is conducted on a rolling-window basis, these reported values are an average value computed from a series of threshold numbers of each percentile. The sample period is January 2002 to November 2021.*

Estimates reported in Table 5 show that there is error persistence delivering average value comparable to that reported by FFPT for the oil and energy sectors. A comparison of estimated coefficients across the different geographical areas shows that pairs within the Asian market exhibit the highest degree of persistence in the 5th percentile with a value of 0.90. The highest coefficient reported for the 75th and 95th percentiles are 0.98 and 0.99 respectively.

Because strategy profitability is induced from two positions, payoffs generated from pairs trading strategies are interpreted as excess returns from one dollar investment in simultaneous long-short positions.

### Table 6: Pairs Trading Profitability

| | | | | | Percentiles | | | |
|---|---|---|---|---|---|---|---|---|
| **Sector** | **Mean** | **Median** | **Stdev** | **Skewness** | **Kurtosis** | **Max** | **Min** | **Sharpe Ratio** |
| US Energy | 0.0979<br>(2.01)** | 0.0000 | 0.1638 | 0.62 | 11.37 | 0.13 | -0.07 | 0.60 |
| EU Energy | 0.1191<br>(2.11)** | -0.0075 | 0.2156 | 4.07 | 51.27 | 0.32 | -0.08 | 0.55 |
| Asia Energy | 0.0937<br>(2.23)** | 0.0000 | 0.1141 | 1.00 | 12.61 | 0.11 | -0.07 | 0.82 |

*Note: This table reports mean, median, standard deviation, skew, kurtosis, maximum, and minimum values of excess returns for pairs trading strategies. We also report (annualized) Sharpe ratios. The t statistics are given in parentheses. The sample period is January 2002 to November 2021. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

### Table 7: Regional Benchmark Stock Index Performance

| | | | | | Percentiles | | | |
|---|---|---|---|---|---|---|---|---|
| **Sector** | **Mean** | **Median** | **Stdev** | **Skewness** | **Kurtosis** | **Max** | **Min** | **Sharpe Ratio** |
| US S&P 500 | 0.0843<br>(1.72) | 0.1372 | 0.1979 | -0.74 | 19.75 | 0.11 | -0.14 | 0.43 |
| EU EuroStoxx 600 | 0.0394<br>(0.83) | 0.1203 | 0.1923 | -0.49 | 14.05 | 0.10 | -0.12 | 0.20 |
| Asia MSCI AC | 0.0399<br>(0.88) | 0.1772 | 0.1834 | -0.7 | 12.56 | 0.09 | -0.12 | 0.22 |

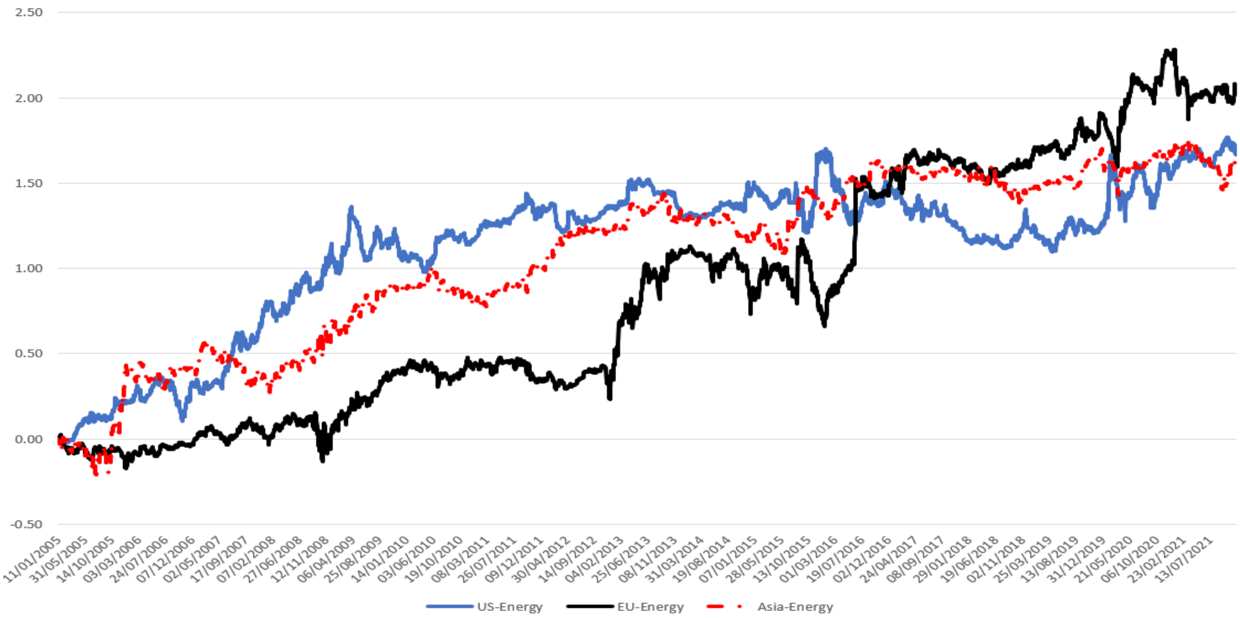
*Note: This table reports mean, median, standard deviation, skew, kurtosis, maximum, and minimum values of regional stock indices performance. We also report (annualized) Sharpe ratios. The t statistics are given in parentheses. The sample period is January 2002 to November 2021. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

Table 6 reports risk-return estimates for the three portfolios considered. For space saving purposes only equal weights are considered. As reported in the literature (see FFPT and references therein) value weighted portfolios lead to lower volatility of returns which implies by relying on equally weighed metrics we are choosing the least conservative weighting scheme. Reported estimates show that all pair's portfolios gain statistically significant positive excess returns. Annualized average return estimates are 9.8%, 11.9% and 9.37% for US, Europe, and Asia respectively. Results therefore show a clear positive performance, which is consistent across different geographical areas. Results in Table 6 may be compared with those reported in Table 7 which reports benchmark equity index performance for the three areas considered. We use the S&P500 as the US benchmark the EU Eurostoxx 600 for the European benchmark and the Asia MSCI index for the Asian benchmark. We can see that the three pair's portfolios outperform their benchmark index counterparts. Moreover, while the reported kurtosis in pairs trading portfolios is of comparable size to those reported by benchmark indexes, pairs trading profitability exhibits a positively skewed distribution while the three market indexes considered show a negative skew in the return distribution. The finding of positively skewed returns in the three pairs trading portfolios is consistent with the literature (see (Figuerola-Ferretti, Paraskevopoulos, and Tang 2018), (Gatev, Goetzmann, and Rouwenhorst 2006) and (Jurek and Yang 2007)).

We next consider the volatility related metrics. Interestingly, we can see that the Asian portfolio exhibits the lowest volatility of returns suggesting that there are diversification benefits from building portfolios with a larger number of pairs. The level of kurtosis is however lowest for the US portfolio suggesting that the US cointegration based portfolios exhibit lower tail risk.

Measures of risk adjusted performance are reported in the last column of Table 6. These are Sharpe ratios constructed assuming zero risk-free interest rates. As it is the case in FFPT we exploit the fact that interest rates have been at historical minimum levels over our sample period. All reported Sharpe ratios are suggesting long-term risk adjusted profitability which beats market index benchmarks and is maximized in the Asian case.

**Figure 1: Time Series Evolution of Pairs Trading Profitability in US, EU, and Asia**




In what follows we analyze the time series evolution of pairs trading profitability. Figure 1 illustrates this evolution for US, Europe, and Asia respectively. We can see that there are four main turning points seen in the patterns of cumulative profitability which correspond to the following global events: the 2008 global financial crisis, the 2010-2012 European sovereign debt crisis, the 2014-2016 crude oil price collapse, and the 2020 pandemic crisis. These global events have been widely documented in the literature. (Figuerola-Ferretti, McCrorie, and Paraskevopoulos 2020), find bubble behavior in crude oil prices in high point of the GFC, and in the last quarter of 2014. While (Cervera and Figuerola-Ferretti 2021) corroborate those findings and suggest that there was also a bubble in Brent crude oil (but not in WTI) in 2011. Moreover, they also demonstrate that there was bubble behavior in energy corporate CDSs during the same documented periods, given special emphasis on the 2014-2015 crude oil price collapse which has been addressed in the literature (see (Kilian 2017) and (Antonakakis et al. 2018) among others). It is interesting to observe that the line representing profitability in the EU crosses the corresponding US and Asian line showing higher profitability for EU in the aftermath of 2016. This suggests that Europe was not as affected by the 2014-2016 episode as the US or Asia. Indeed, this period combined the slowing growth of the Asian economy, the start of the tapering process in the US with the OPEC announcement under an oversupplied shale oil market and the start of the divesting process from fossil fuels. Pairs trading profitability has also been volatile during the 2020 period. Profitability decreases during the COVID crisis reaching minimum levels around March 2020 in Europe and in April 2020 in Asia. This is just around the time that WTI front month future dropped by 306% in a session re reached negative levels. Pairs trading profitability has been volatile in the aftermath of the COVID crisis possibly reflecting supply bottlenecks and the first energy crisis of the green transition.

### 4.2 Sorting portfolios with CAPEX

In what follows we present pairs trading profitability when pairs are sorted by investment in capital expenditure CAPEX as well as by industry and geographical area. The strategy builds on the idea introduced in FFPT under which it is demonstrated that pairs trading profitability increases when sorting cointegrated portfolios by firm fundamentals such as book-to-market ratio, market capitalization, and turnover. Filtering pairs with common corporate fundamentals give rise to stronger stationarity and pairs trading profitability. We consider the CAPEX ratio because we want to capture changes in investment capacity over our sample period. This has varied substantially specially in the aftermath of the 2014 crude oil price shock which coincided with the start of the US tapering period (see (Cervera and Figuerola-Ferretti 2021) and (Sengupta, Marsh, and Rodziewicz 2017)). Here we argue that CAPEX is key measure due to two main arguments: a) firms with similar patterns of CAPEX investment are expected to share common credit constraints; b) under the transition to the net zero objectives initiated with the signature of the Paris Agreement the evolution of CAPEX investment within energy corporates can be used as a measure of adaptation to the energy transition. Energy corporates are expected to set investment policies that are compliant with the green transition. Firms that do not invest in green technologies will find that their assets become stranded (See Atanasova and Schwartz 2019) and will fail to transform their economic models to achieve climate neutrality.

**Table 8: Number of Firms After Controlling for CAPEX**

| Sector | Total |
|---|---|
| US Energy | 40 |
| EU Energy | 48 |
| Asia Energy | 138 |

*Note: This table presents the number of firms after controlling for CAPEX for the period between January 2002 and November 2021.*

**Table 9: Number of Cointegrated Pairs After Controlling for CAPEX**

| Sector | Mean | Standard Deviation | Maximum | Minimum |
|---|---|---|---|---|
| US Energy | 19 | 22 | 110 | 6 |
| EU Energy | 68 | 53 | 186 | 13 |
| Asia Energy | 110 | 79 | 427 | 20 |

*Note: This table presents descriptive statistics of the number of pairs, controlling for CAPEX. Pairs are identified over a 3-year period according to the Johansen cointegration test at the 5% significant level. The Johansen test is conducted on a rolling-window basis. The sample period is January 2002 to November 2021.*

**Table 9** presents the number of cointegrated pairs under each geographical area once the CAPEX filter is imposed. We can see that the European sample falls due to the lack of continuous CAPEX data for 20 of the 68 companies initially considered. The number of cointegrated pairs is therefore also reduced with Europe and Asia reporting 45% and 29% of the number of pairs found under the benchmark case.

Table 10 presents slope coefficient estimations by percentiles while Table 11 presents estimates of trading triggers for the three geographical areas considered. Results demonstrate that there is lower dispersion in the cointegrating vector slope coefficient and higher speed of mean reversion due to increased commonality arising from the CAPEX filter.

### Table 10: Cointegration Slope Coefficient Estimations After Controlling For CAPEX

| | | Percentiles | | | | |
|---|---|---|---|---|---|---|
| Sector | Parameter | $5^{th}$ | $25^{th}$ | Median | $75^{th}$ | $95^{th}$ |
| US Energy | $\gamma_1$ | 0.44 | 0.67 | 0.98 | 3.08 | 13.22 |
| EU Energy | $\gamma_1$ | 0.41 | 0.63 | 1.34 | 3.13 | 18.51 |
| Asia Energy | $\gamma_1$ | 0.07 | 0.39 | 1.28 | 6.17 | 36.53 |

*Note: The summary statistics of the estimated values of $\gamma_1$ are reported. As the Johansen test is conducted on a rolling-window basis, these reported values are an average value computed from a series of estimates of each percentile. The sample period is January 2002 to November 2021.*

### Table 11: Persistency Linked Trading Trigger (ρ) After Controlling For CAPEX

| | | Percentiles | | | | |
|---|---|---|---|---|---|---|
| Sector | Parameter | $5^{th}$ | $25^{th}$ | Median | $75^{th}$ | $95^{th}$ |
| US Energy | ρ | 0.71 | 0.77 | 0.82 | 0.90 | 0.98 |
| EU Energy | ρ | 0.86 | 0.89 | 0.92 | 0.94 | 0.98 |
| Asia Energy | ρ | 0.90 | 0.96 | 0.98 | 0.98 | 0.99 |

*Note: This table presents the values of persistency-linked trading trigger $\rho = 1 + \alpha_1 - \alpha_2$, which is computed using vector error correction model estimates obtained from the Johansen cointegration methodology. As the trading strategy is conducted on a rolling-window basis, these reported values are an average value computed from a series of threshold numbers of each percentile. The sample period is January 2002 to November 2021.*

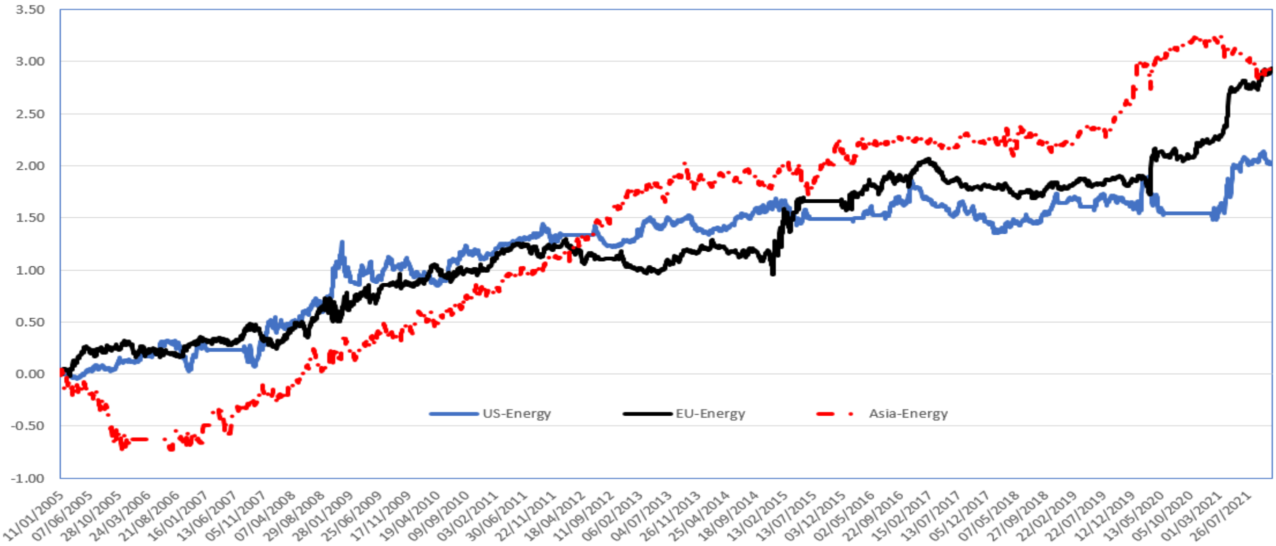
Pairs trading profitability estimates under the CAPEX restriction are reported in Table 12. Results show that filtering by CAPEX ratios deliver significant out-performance when compared to benchmark pairs trading strategies and to corresponding equity indexes. CAPEX restricted pairs trading strategies deliver positive and significant mean returns that outperform the benchmark pairs trading strategies by 2.06%, 5.13% and 7.51%, respectively. Similar conclusions can be obtained when we compare the Sharpe ratios reported in tables 12 and 6 suggesting that the CAPEX measure succeeds in capturing commonalities across energy corporates. This effect is maximized in the Asian portfolio which decreases volatility from 18.5% under the benchmark case to 11.4% under the CAPEX filtered example. The time series evolution of pairs trading profitability for the three areas is depicted in Figure 2. We can see that the cumulative return pattern across EU, US and Asia evolves more closely than in the benchmark case. However, the Asian portfolio outperforms the rest from 2011 up to the end of the sample which shows a decline in profitability possibly driven by the property driven crisis in China. Europe supersedes US profitability since April 2015 and achieves the same level of cumulative returns as its Asian counterpart towards the end of the sample period. The CAPEX factor is therefore highly important in explaining pairs trading profitability.

### Table 11: Pairs Trading Profitability

| | | | | Percentiles | | | | |
|---|---|---|---|---|---|---|---|---|
| Sector | Mean | Median | Stdev | Skewness | Kurtosis | Max | Min | Sharpe Ratio |
| US Energy | 0.1185 (2.03)** | 0.000 | 0.1646 | 0.65 | 12.73 | 0.15 | -0.10 | 0.72 |
| EU Energy | 0.1704 (2.961)** | 0.000 | 0.2077 | 1.27 | 15.91 | 0.16 | -0.08 | 0.82 |
| Asia Energy | 0.1688 (2.23)** | 0.0000 | 0.1851 | 0.60 | 10.58 | 0.17 | -0.09 | 0.91 |

*Note: This table reports mean, median, standard deviation, skew, kurtosis, maximum, and minimum values of excess returns for pairs trading strategies, controlling for CAPEX. We also report (annualized) Sharpe ratios. The t statistics are given in parentheses. The sample period is January 2002 to November 2021. *, ** and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.*

**Figure 2:** Time Series Evolution of Pairs Trading Profitability in US, EU, and Asia with CAPEX Filter Applied




## 5. Conclusions

Recent episodes of turmoil in energy markets have hit companies in the oil and gas sector strongly. The 2014 oil price collapse and the transition away from fossil fuels fostered under the Paris Agreement in (2015) have led to a high degree of uncertainty in the sector. The widespread volatility has only been enhanced by the pandemic in 2020 and during the posterior fast recovery. In this paper, we examine market mispricings in energy corporates applying a pairs trading algorithm. In doing this we shed light to the question of whether there are efficient market valuations of fossil fuels.

This question is of great importance as many regulators and financial institutions have identified the mispricing of stranded asset risk as a potential systemic risk and threat to financial stability.

The pairs trading methodology of FFPT is applied for this purpose to the US, European, and Asian energy stock data.

We find evidence of long-term profitability in the three areas considered. The time series evolution of pairs trading performance is enhanced in the aftermath of the 2008, 2010-2012, 2014-2016, 2020 economic crises.

The performance of the European and Asian portfolios beats its US counterpart in the aftermath of the 2014-2016 crisis suggesting that the shale revolution of the US monetary tightening has negatively affected pairs trading profitability.

CAPEX investment is an important metric for filtering stocks on the basis as fundamentals in a context in which commitments to the net zero objectives has constrained investment in fossil fuels. Sorting portfolios on the basis of CAPEX measures delivers higher profitability than that under the benchmark case.

## References

Antonakakis, Nikolaos, Juncal Cunado, George Filis, David Gabauer, and Fernando Perez De Gracia. 2018. "Oil Volatility, Oil and Gas Firms and Portfolio Diversification." Energy Economics 70: 499–515.

Atanasova, Christina, and Eduardo S Schwartz. 2019. "Stranded Fossil Fuel Reserves and Firm Value." National Bureau of Economic Research.

Cervera, Ignacio, and Isabel Figuerola-Ferretti. 2021. "Credit Risk and Mild Explosivity of Credit Default Swaps in the Corporate Energy Sector."

Figuerola-Ferretti, Isabel, Christopher L Gilbert, and J Roderick McCrorie. 2015. "Testing for Mild Explosivity and Bubbles in LME Non-Ferrous Metals Prices." Journal of Time Series Analysis 36 (5): 763–82.

Figuerola-Ferretti, Isabel, Roderick McCrorie, and Ioannis Paraskevopoulos. 2020. "Mild Explosivity in Recent Crude Oil Prices." Energy Economics 87: 104387.

Figuerola-Ferretti, Isabel, Ioannis Paraskevopoulos, and Tao Tang. 2018. "Pairs-Trading and Spread Persistence in the European Stock Market." Journal of Futures Markets 38 (9): 998–1023.

Frijns, Bart, Alireza Tourani-Rad, and Robert I Webb. 2016. "On the Intraday Relation Between the VIX and Its Futures." Journal of Futures Markets 36 (9): 870–86.

Gatev, E., W. N. Goetzmann, and K. G. Rouwenhorst. 2006. "Pairs Trading: Performance of A Relative-Value Arbitrage Rule." Review of Financial Studies 19 (3): 797–827.

Johansen, Søren. 1995. "Likelihood-Based Inference in Cointegrated Vector Autoregressive Models." New York.

Jurek, Jakub, and Halla Yang. 2007. "Dynamic Portfolio Selection in Arbitrage." In EFA 2006 Meetings Paper.

Juselius, Katarina. 2006. The Cointegrated VAR Model: Methodology and Applications. Oxford University Press.

Kilian, Lutz. 2017. "The Impact of the Fracking Boom on Arab Oil Producers." The Energy Journal 38 (6).

Lane, Philip R. 2012. "The European Sovereign Debt Crisis." Journal of Economic Perspectives 26 (3): 49–68.

Low, Aaron H. W., Jayaram Muthuswamy, and Robert I. Webb. 1999. "Arbitrage, Cointegration, and the Joint Dynamics of Prices Across Discrete Commodity Futures Auctions." Journal of Futures Markets 19 (7): 799–815.

Sengupta, Rajdeep, W. Blake Marsh, and David Rodziewicz. 2017. "Do Adverse Oil-Price Shocks Change Loan Contract Terms for Energy Firms?" Economic Review - Federal Reserve Bank of Kansas City 102.

Webb, R. I. 1985. "The Behavior of Speculative Prices and the Consistency of Economic Models." Journal of Econometrics 27 (1): 123–30.

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