Macroeconomics and Asset Pricing

ICMA Centre

Henley Business School

Thesis submitted in partial fulfilment of the requirements

for the degree of Doctor of Philosophy

Yu Zhang

September 2023

Declaration of Original Authorship

I confirm that this is my own work, and the use of all material from other sources has been properly and fully acknowledged.

Yu Zhang

Acknowledgements

I want to express my heartfelt gratitude to all those who contributed to the successful completion of this thesis. First and foremost, I am deeply thankful to my Ph.D. advisors, Prof. Andrew Urquhart and Dr. Konstantina Kappou, for their unwavering support, guidance, and expertise throughout this journey. Their insights and encouragement were instrumental in shaping this research. I thank Prof. Brian M. Lucey and Dr. Ivan Sangiorgi for agreeing to be my PhD examiners, reviewing my thesis and providing constructive comments.

Additionally, I extend my sincere gratitude to Dr. Ran Tao, whose valuable support and comments significantly contributed to the development of Chapter 3. I also appreciate Ian Dew-Becker and the anonymous referee for their insightful and encouraging comments on my paper titled "*Attention Spillover: Lottery Speculation After Macro Announcements*", included as Chapter 3 in this thesis. My thanks go to the anonymous referees for their helpful comments on my paper titled "*Economic Momentum and Cross-Sectional Stock Market Indices*", included as Chapter 2 in this thesis.

I am also indebted to my family for their unwavering encouragement and understanding during this challenging period. Your belief in me sustained my motivation and determination. I want to acknowledge the numerous friends and colleagues who generously provided comments and assistance and shared their knowledge. Your input was instrumental in refining the ideas presented in this thesis. The list of thanks includes Jian Chen, Michael P. Clements, Zhenghong Ding, Yi Hu, Emese Lazar, Yongda Liu, and Xiaohan Xue.

Finally, I thank the faculty and staff of ICMA Centre for providing an enriching academic environment and invaluable resources that were essential for this study.

Thank you all for your support and for being part of this academic journey.

Abstract

This thesis investigates asset pricing with macroeconomics. Chapter 1 gives an overview of this thesis, including background, motivations and contributions. Chapter 2 documents the economic momentum effects in country-level equity indices. Momentum is a well-known and studied artefact of financial markets. In this paper, we investigate whether momentum in a country's macroeconomic variables is related to the future performance of equities. We find that the past economic trends of a country's fundamentals are positively associated with the equity market index returns, termed the economic momentum effects. Based on that, an economic momentum portfolio of buying (selling) equity index in countries with relatively strong (weak) economic past trends exhibits an annualised Sharpe ratio of 0.87. The economic momentum portfolio outperforms benchmarks regarding rewards to variability and maximum drawdown and yields an annualised alpha of 3.5%

Chapter 3 examines the trading behaviour of noise traders in response to macro-announcements. By employing direct and indirect proxies to capture their attention, we show that noise traders' market-concentrated attention on macro-announcement days spills over to individual firms during post-macro-announcement periods, denoted as attention spillover effects. Both retail and institutional noise traders exhibit rising abnormal attention on stocks following the macro-announcements. Furthermore, we find that the attention spillover effects are more pronounced among stocks without earnings announcements and are particularly noticeable in FOMC announcements.

Chapter 4 examines the performance of equity options surrounding the scheduled

meetings of the Federal Open Market Committee (FOMC). We document significant excess returns on equity options after the FOMC, denoted as the post-FOMC drift, which the standard asset pricing models cannot explain. Upon investigating the mechanisms, we find that this pattern is particularly pronounced in the context of FOMC announcements accompanied by economic surprises, as investors tend to overreact to such shocks. Additionally, we identify that options' illiquidity plays a significant role in driving this drift, as market participants demand higher expected returns to compensate for the heightened illiquidity risk during post-FOMC periods. Furthermore, our analysis leads us to conclude that the observed drift is more pronounced among put options than call options.

Lastly, Chapter 5 concludes the thesis and discusses future research.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Background and Motivations

1.1.1 Momentum

The "momentum effect", a phenomenon where past trends of assets are positively related to their future performance, has been a focal point in financial literature. This effect has been extensively documented, especially concerning cross-sectional stock returns. Portfolios that built on this effect, taking long positions in relative winners and short positions in relative losers, have consistently shown profitability (Jegadeesh & Titman 1993, Rouwenhorst 1998, 1999, Okunev & White 2003, Asness et al. 2013). Beyond equities, the momentum effect has been identified in a broader of asset classes, including but not limited to equity indices, options, commodities, and even cryptocurrencies (Okunev & White 2003, Miffre & Rallis 2007, Zaremba et al. 2019, Hsu & Chen 2021, Li et al. 2021, Heston et al. 2022, Liu, Tsyvinski & Wu 2022). However, most existing research anchore on asset prices as the primary metric for gauging momentum signals.

This predominant focus on asset prices has left a gap in exploring momentum effects based on the fundamental attributes of assets. While studies venture into country-level analyses, linking past economic trends to future currency returns, there remains a vast space for exploration (Dahlquist & Hasseltoft 2020). As documented in prior literature, the established connections between macroeconomic variables and stock markets hint at a more profound relationship yet to be fully understood.

Motivated by this gap in the literature, Chapter 2 of this thesis seeks to explore the momentum effect, not just from the perspective of asset prices but more holistically, considering macroeconomic dynamics. The aim is to investigate if past trends in macroeconomic variables can indeed forecast future stock market returns. By doing so, the research hopes to provide a more comprehensive understanding of momentum within the context of country-level stock market performance, challenging traditional notions and potentially offering novel insights into asset pricing. In addition, policymakers can gain some insights into how global stock markets sluggishly react to their decisions and economic outcomes. As for the market participants, this work can give them some insights into the pricing information embedded in economic trends, sharpening their decision-making.

In our analysis, the fundamental purpose is to answer whether economic trends can cross-sectionally predict stock market returns. To capture the economic trends of countries, we follow Dahlquist & Hasseltoft (2020) to take economic variables with lookback periods of 60 months as momentum signals. We employ index futures rather than price indices to measure market performance for practical purposes. A price index can indicate the performance of a stock market while it is non-tradable. Alternatively, index futures tracking of the stock market index is tradable and is much cheaper than buying the index constituents. If markets digest information efficiently, past trends should not predict future asset performance. To validate our expectation, we regress the stock market returns on the economic momentum signals.

Empirical results suggest that past economic trends positively and significantly affect future stock market returns. Based on this relation, we construct a long-short portfolio, which achieves a Sharpe ratio of 0.87 and outperforms standard momentum strategies documented in the literature. The analysis reveals that some pricing information embedded in the economic trends is not fully priced when announced. It suggests that the markets react sluggishly to macroeconomic announcements, challenging the market efficiency.

1.1.2 Attention Allocation

Chapter 3 studies the asset pricing surrounding macroeconomic announcements with theoretical frameworks in behavioural finance. There's a growing interest in understanding how investors allocate their attention across the stock market. Some studies suggest that macro news can distract investors from micro news, leading to delays in incorporating firm-specific information into stock prices, a phenomenon termed the "crowd-out effects" (Merton 1987, Peng & Xiong 2006). On the other hand, recent literature, such as Hirshleifer & Sheng (2022), argues that macro news can stimulate the incorporation of micro information, termed the "crowd-in effects". However, the role of noise traders in these dynamics is often overlooked.

Chapter 3 aims to bridge this gap by exploring how noise traders respond to macro-announcements. Inspired by the concept of limited attention among investors (Merton 1987) and the theory suggesting that the release of macroeconomic news attracts investor attention to market-level information (Peng & Xiong 2006, Hirshleifer & Sheng 2022), it becomes plausible that the disclosure of macroeconomic news could influence investors' beliefs and subsequent stock trading behaviour. If this premise holds, we hypothesise that the attention primarily focused on the market may overflow to individual firms after macroeconomic announcements.

The primary study in Chapter 3 raises pertinent questions: When a macro-announcement is released, do noise traders focus on the macro-news, reallocating their attention from market-level information to individual stocks? If so, how do they react post-announcement? Answering these questions is crucial to understanding market frictions when significant information enters the market and the subsequent implications for asset pricing. Meanwhile, policymakers can gain some insights into the behaviour of noise traders reacting to their decisions.

In Chapter 3, we employ both direct and indirect proxies to measure investor attention. Specifically, we adopt proxies, as suggested by Da et al. (2011) and Ben-Rephael et al. (2017), to directly capture the attention of retail and institutional investors. Additionally, we identify certain attention-grabbing stocks that exhibit lottery-like characteristics, as outlined by Kumar (2009). These lottery-like stocks are characterised by a slight chance of yielding substantial rewards and display high idiosyncratic skewness. Consequently, we use these lottery-like characteristics as indirect proxies to gauge investor attention. These indirect proxies include the maximum daily returns within the most recent month, as proposed by Bali et al. (2011), the low stock price following the findings of Kumar (2009), high expected idiosyncratic skewness as suggested by Boyer et al. (2010), expected idiosyncratic volatility based on Ang, Hodrick, Xing & Zhang (2006), and the average standardised scores derived from these proxies, as presented in Liu et al. (2020).

Our analysis suggests that our hypothesis holds. That is, the noise traders are attracted to the market-level information when the macro announcements are revealed. Based on the macro information revealed, their market-level-concentrated attention subsequently spillovers to individual firms, and then they make trading decisions. It finally results in heightened speculation in the post-macro-announcement periods.

1.1.3 Options and Macro-Announcements

Aside from examining asset pricing concerning macroeconomic variables trends and investor attention allocation, this thesis also explores asset performance in the context of macroeconomic announcements. Specifically, Chapter 4 investigates options returns surrounding monetary policy announcements.

Numerous studies extensively explore asset returns in the context of scheduled macroeconomic announcements. The existing body of literature demonstrates that considerable portions of total equity premium and fixed income returns are realised on days coinciding with macroeconomic announcements (Savor & Wilson 2013, 2014, Wachter & Zhu 2022). Notably, substantial excess returns on equities have been observed before FOMC meetings (Lucca & Moench 2015). All these studies find the pre-macro announcement premium, and they explain that by suggesting investors require higher expected returns to compensate for higher risk or uncertainty. While many researchers investigate the price reactions of equities and bonds surrounding the FOMC, the behaviour of options, especially straddles, remains relatively unexplored. If the uncertainty compensation theory holds, the options, the instruments naturally reflecting the uncertainty, should theoretically exhibit higher expected returns prior to the announcements.

To fill the gap that little literature mentions regarding the price reactions of straddles to the FOMC, and to validate our hypothesis, Chapter 4 studies the performance of straddles surrounding the FOMC.[1] Answering this question can be an extensive part of asset pricing towards monetary policy events. This work can also give monetary policymakers some insights into how the derivatives market reacts to monetary decisions. For the market participants, they can benefit from this work in terms of the pricing information attributed to the monetary announcements.

Our analysis indicates that returns of straddles have a post-FOMC drift, which is both economically and statistically significant. Such findings go contrary to our hypothesis. We explain the pattern with two mechanisms. First, the drift is more pronounced to the FOMC events with surprises. Investors would overreact to surprising events, leading to over-buying and increasing prices. However, such an overreaction would eventually be corrected. Second, the drift is more profound in the sample with higher illiquidity. Illiquidity of options is changing dynamically from low to high, surrounding the FOMC announcements. Before the announcements, investors tend to hold options for hedging uncertainty. However, the uncertainty reduces after the announcements, leading to lower open interest in the options. Therefore, the illiquidity risk is higher after the events due to the lower open interest. To compensate for the higher illiquidity risk, investors would require higher expected returns.

Overall, this thesis studies asset pricing by taking macroeconomics into consideration. It provides some thoughts for policymakers and market participants, including the information embedded in economic trends predicting the future stock markets across countries, how noise traders allocate their attention surrounding the announcements, and how the derivative market dynamically reacts to the monetary policy announcements. Both agents can utilise that to make optimal decisions.

[1]Straddles comprise call and put options with identical strike prices and expiration dates. We utilise delta-neutral straddles as our main studied objects since they are (1) simple compared with other complected strategies, (2) more informative than individual options (Broadie et al. 2009), (3) pure option strategies and insensitive to underlying stocks.

1.2 Outline of Intended Contributions

Chapter 2 advances the literature on understanding momentum effects in asset pricing by linking the macroeconomic momentum to equity indices. Existing literature such as Jegadeesh & Titman (1993), Moskowitz et al. (2012) and Asness et al. (2013) study the momentum effects on prices. Applying such a concept, emerging literature examines the effects on fundamentals and factors (Ehsani & Linnainmaa 2022, Arnott et al. 2023). Dahlquist & Hasseltoft (2020) link the country's fundamental momentum to currencies, leaving gaps for relations between such momentum effects and other asset classes. Filling this gap, we contribute to the literature by suggesting the macroeconomic momentum effects in country-level equity markets.

Specifically, we find that the past trends in one country's macroeconomic variables are positively related to the future returns on the equity market index. Such predictability is both statistically and economically significant. Based on predictability, we present an economic momentum strategy that buys a country index with stronger macroeconomic past trends and sells a country index with weaker past trends. The strategy achieves a Sharpe ratio of 0.87 with an annualised excess return of 3.60%. Such profitability cannot be subsumed by standard momentum strategies such as time-series momentum, cross-sectional momentum, and value-and-momentum, leaving 95% of the returns unexplained.

Chapter 3 offers several notable contributions to the existing literature. Firstly, it introduces the concept of attention spillover effects, shedding light on how noise traders' attention, influenced by macroeconomic news, spills over from the market to individual firms, a dimension less explored in prior research. Secondly, it advances the understanding of attention dynamics by highlighting that attention spillover effects are more pronounced among firms lacking earnings announcement coverage, building upon the existing crowd-in effects framework. Thirdly, it explores the behaviour of both retail and institutional investors regarding lottery stocks around macroeconomic announcements, revealing that they exhibit varying patterns of abnormal attention, particularly in the lead-up to and after macro-announcements. Lastly, it contributes to the lottery-like assets literature by demonstrating dynamic pricing effects in post-macro-announcement periods, where market returns on macro-announcement days significantly predict subsequent returns on lottery-like stocks, adding depth to our understanding of market-conditional speculation.

Chapter 4, to our knowledge, is the first to document a post-FOMC drift in the options market empirically. While considerable research investigates the behaviour of equities and bonds surrounding macroeconomic announcements, the behaviour of options, particularly straddles, remains relatively unexplored in this context, especially in the post-event period. Moreover, we contribute to the literature by linking this post-FOMC drift to the well-documented investor tendency to overreact to unexpected news, followed by a subsequent correction. This behaviour, supported by psychological frameworks and empirical evidence, demonstrates that investors often assign greater weight to recent surprising information, leading to exaggerated price movements that eventually revert to more rational levels. Our empirical findings corroborate this behaviour, highlighting more pronounced overreactions to unexpected news compared to anticipated news in the context of FOMC announcements. Lastly, our study reveals a positive relationship between option returns and illiquidity, particularly accentuated in the context of FOMC announcements. This aligns with existing research on investors' demand for compensation to mitigate the effects of illiquidity when holding assets. Our contribution lies in uncovering that this effect of illiquidity compensation surrounding FOMC announcements is notably pronounced after the event, indicating a heightened sensitivity of option returns to illiquidity in post-FOMC periods. This finding enriches our understanding of how illiquidity compensation operates within the nuanced setting of FOMC announcements and provides insights into the interplay between market liquidity and option returns.

This thesis is organised as follows. Chapter 2 studies macroeconomic momentum and its prediction on the country index. Chapter 3 investigates investors' behaviours surrounding macroeconomic announcements. Chapter 4 studies options performance surrounding FOMC. Chapter 5 summarises the thesis findings and discusses opportunities for future research.

Chapter 2

Economic Momentum and Cross-Sectional Stock Market Indices

2.1 Introduction

The past price trends of assets have been demonstrated to influence their future performance, a phenomenon commonly called the "momentum effects". Such effects on asset prices are well documented in the literature.[1] As an extensive work exploring such effects with past trends in assets' fundamentals, Huang et al. (2019) demonstrate that the past trends in stock fundamentals contain information affecting the stock's future prices. Expanding from the firm-level to the country-level fundamentals, Dahlquist & Hasseltoft (2020) (DH) link economic past trends to currency future returns.

Given the established connections between macroeconomic variables and stock markets in prior literature (Merton 1973, Roll & Ross 1980, Cox et al. 1985, Chen et al. 1986), our study seeks to investigate whether the past trends of macroeconomic variables can have any cross-sectional impacts on future stock market returns at country level. This investigation aims to shed light on the potential influence of macroeconomic dynamics on country-level stock market performance. Answering this question can give policymakers some insights into how the global stock markets sluggishly react to economic outcomes and their decisions. As for investors, they can gain some insights from this work when allocating their wealth globally by considering the pricing information embedded in past economic trends.

Our findings are threefold. First, we find that the past trends in country fundamentals cross-sectionally and positively predict returns on country indices, which is statistically significant. In detail, we find that one standard deviation increase in

[1] In the context of cross-sectional stock returns, where portfolios that take long positions in relative winners and short positions in relative losers have been consistently profitable (Jegadeesh & Titman 1993, Rouwenhorst 1998, 1999, Griffin et al. 2003). Beyond equities, existing literature also documents price momentum effects in various other asset classes, including equity indices, commodities, bonds, currencies, options, and cryptocurrencies(Okunev & White 2003, Miffre & Rallis 2007, Grobys & Sapkota 2019, Hsu & Chen 2021, Li et al. 2021, Heston et al. 2022, Liu, Tsyvinski & Wu 2022). Moreover, Moskowitz et al. (2012) document such momentum effects in the context of time-series asset prices.

the weights, derived from past economic trends, results in an increase of 24 basis points on country index returns. Second, such a pattern is also economically significant. To elaborate, we form a portfolio by buying (selling) country indices with relatively strong (weak) past trends in fundamentals. This long-short portfolio earns a Sharpe ratio of 0.87 with a return of 3.60%. It still yields a return of 2.14% after transaction costs. Third, this implementable strategy outperforms benchmarks, such as standard momentum strategies and asset pricing models. Nevertheless, the portfolio yields an annualised alpha of 3.72% after controlling for the benchmarks, leaving 95% of the strategy returns unexplained by the benchmarks.

We construct two indices using macroeconomic variables from the Organisation for Economic Co-operation and Development (OECD) to proxy for countries' fundamentals, representing positive and negative influences on stock market returns. One macro index is calculated as the average log growth of the consumer price index, producer price index, and total manufacturing. In contrast, the other macro index is derived from the average log growth of the OECD leading indicator, hourly earnings, and gross domestic production. Our analysis reveals that the former macro index is positively related to future stock market returns, while the latter is negatively related. Consequently, we refer to the former as the "positive macro effect index" and the latter as the "negative macro effect index".

We follow the process outlined by DH to construct portfolios capturing economic momentum returns. First, we calculate the economic momentum signals as cumulative returns over a specific lookback period on the macro indices at the end of every month for each country in our sample period. Second, we form a dollar-neutral sub-strategy that buys (sells) one country's market index when its relative macro index shows stronger (weaker) momentum signals than its peers. The lookback periods we investigate vary from 1 to 60 months, resulting in 120 sub-strategies (60 lookback periods x 2 macro indices). Third, we group these economic momentum sub-strategies into portfolios. To form a portfolio, we aggregate sub-strategies by weighting them based on their inverse volatilities.[2] Specifically, we create positive and negative macro effect portfolios by aggregating all sub-strategies based on the positive and negative macro effect indices. Additionally, we establish short-term, mid-term, and long-term portfolios by aggregating sub-strategies with respective lookback periods of 1-12, 13-36, and 37-60 months. Finally, a combo portfolio aggregates all 120 sub-strategies.

We assign weights to sub-strategies within each portfolio based on the inverse of the volatility of these sub-strategies. We measure ex-ante volatility at the end of every month for each sub-strategy. For the calculation of ex-ante volatility, we follow the approach outlined in Moskowitz et al. (2012) and DH, employing an exponentially weighted moving average (EWMA) method with a lambda of 0.97. Notably, varying lambda from 0.92 to 0.99 does not affect our main results. Then, we use a scaling factor to ensure that the sum of cross-sectional weights equals one. Generally, the scaled-inverse volatility determines the weights assigned to sub-strategies in a portfolio. For robustness, we also examine it with equally weighting strategies within a portfolio, but this does not impact our main results. Therefore, portfolio returns can be calculated by multiplying the lagged-one-month weights with security returns. We refer to these portfolios as the economic momentum portfolios.

The impact of past macroeconomic trends on stock markets is statistically and economically significant. To study the predictability of economic momentum on market returns, we regress country-level stock market excess returns on one-month-lagged weights derived from economic momentum signals. Empirical results demonstrate that this predictability is statistically significant at the 1% level, resulting in a 24 basis point improvement in future stock market excess returns. For the combo strategy, a portfolio built on this predictability exhibits a Sharpe ratio of 0.87 with an annualised return of 3.60%. Similar improvements of 13, 28, 11, 27, and 20 basis

[2] Aside from volatility-weighted constructions, we also examine that in an equal-weighted way.

points are observed for the positive macro effects, negative macro effects, short-term, mid-term, and long-term strategies, respectively, with corresponding Sharpe ratios of 0.49, 0.30, 0.40, 0.96, and 0.66.

We then compare our economic momentum portfolios with standard momentum strategies documented in the literature and passive investment strategies over the sample period. The empirical results show that the economic momentum portfolio outperforms the benchmarks regarding Sharpe ratios and exhibits a lower maximum drawdown. Additionally, the portfolio averages an annualised alpha of 3.72% after controlling for standard momentum strategies, while it also captures benchmark returns.

Moreover, we conduct further analysis on the economic momentum combo portfolio. We find that none of the standard asset pricing factor models can fully explain the profitability of the combo portfolio.[3] Furthermore, none of the countries in the portfolio dominates the returns of the combo portfolio. Regarding transaction costs associated with portfolio trading, the portfolio still yields a Sharpe ratio of 0.52 with annualised returns of 2.14% after accounting for transaction costs, represented by bid-ask spreads. Regarding the robustness of country selection, we find that, based on MSCI indices, the economic momentum effects persist in the G10, developed, and emerging markets.

Our contribution to the literature is fivefold. First, we provide extensive work to the momentum-related literature by suggesting the existence of economic momentum effects in global stock markets. Existing literature predominantly explores price momentum effects such as cross-sectional momentum by Jegadeesh & Titman (1993) and time-series momentum by Moskowitz et al. (2012). Extending these elegant studies and the concept of momentum, emerging research links factor momentum (Ehsani & Linnainmaa 2022, Arnott et al. 2023), and economic momentum

[3]The factor models we study include Fama-French Three Factor (FF3) (Fama & French 1993), Fama-French Five Factor (FF5) (Fama & French 2015), q-Factor (Hou et al. 2021) and relative factors from Jensen et al. (2023).

(DH) to asset prices. Interestingly, all these works reveal that asset prices do not fully incorporate the past public information related to the assets and challenge market efficiency. We extend the work by DH and bridge the gap between economic momentum and cross-sectional stock market indices. Such findings suggest that global stock markets sluggishly incorporate public information, such as free macroeconomic data from the OECD, giving rise to economic momentum effects.

Second, to the best of our knowledge, we are the first to document the cross-sectional predictability of past trends in a country's fundamentals on its future stock market index. This prediction is both statistically and economically significant. We find that stronger past trends in a country's fundamentals are associated with larger returns in that country's stock market. Statistically, a one standard deviation increase in past trends results in 24 basis points higher returns on the equity market index, controlling for country and month fixed effects. A dollar-neutral strategy built on this prediction, buying (selling) the country's index with strong (weak) economic momentum signals, achieves a Sharpe ratio of 0.87 and an annualised return of 3.60%. The mean excess return is statistically significant at the 1% level. This strategy still yields a mean excess return of 2.14% after accounting for transaction costs. The returns of the strategy cannot be explained by popular asset pricing factor models such as FF3 or FF5, and they also cannot be dominated by any of the countries.

In terms of the literature bridging the economics and the financial market, our work is similar to the work by Hong & Yogo (2012) (HY) since both study the relationship between the economic fundamentals and the performance of futures. In addition, both studies mention the influence of open interest in stock market futures. HY provide statistically weak evidence suggesting the prediction of open interest in stock market futures. In this study, open interest is one of the filters taken into consideration when selecting markets and considering liquidity issues. For the robustness of market selection, different market types such as G10, developed and emerging markets are examined as well by ignoring the liquidity issues. Empirical results suggest that liquidity or open interest does not affect the main conclusion, the existence of economic momentum effects.

Nevertheless, this research differs from HY. Firstly, the predictor. The main argument of HY is that open interest in futures contains information predicting future economic activity. HY explain that economic participants such as producers would have abnormal demand for futures to hedge the anticipated higher economic activity. Such abnormal demand would lead to higher open interest. Differing from HY, this study suggests that the economic trends contain information that is not fully reflected in the stock markets, resulting in the economic momentum effects. That is, the economic trends positively predict stock markets. Secondly, the studied markets. Work by HY focuses on the US futures markets across commodities, bonds and stocks, while this work cross-sectionally studies the economic momentum effects at the country-level, covering both developed and emerging markets.

Third, we advance the momentum-related literature by suggesting the outperformance of the economic momentum strategy over benchmarks of momentum strategies such as time-series momentum and value and momentum strategies. Moskowitz et al. (2012) document that past trends in asset returns are positively related to their future performance. Combining cross-sectional momentum and value, Asness et al. (2013) suggest that the effects of half momentum and half value exist across the board. While both studies suggest profitable strategies based on these effects, the economic momentum strategy outperforms them in terms of Sharpe ratios. In comparison, the economic momentum strategy maintains strong persistence, profitability, and stability over time. Especially after the global financial crisis, the benchmarks exhibit higher downside risk and greater volatility. Most importantly, it can explain the benchmarks, while approximately 95% of the returns of it cannot be explained by the benchmarks.

Fourth, we argue the economic and statistical significance of the benchmarks. For the time-series momentum, Moskowitz et al. (2012) find that such effects exist across different asset classes. Doubting that, Huang et al. (2020) reproduce the original work but statistically examine it with time-series and cross-sectional regressions instead of pooled regressions. Consistent with Huang et al. (2020), we find weak evidence of time-series momentum in global stock markets by employing panel regressions with country and month fixed effects. Besides, we also contribute to the literature by providing empirical works questioning the time-varying profitability of the time-series momentum strategy, especially after the financial crisis. As for the value-and-momentum effects, Asness et al. (2013) suggest such effects exist everywhere. However, Hutchinson et al. (2022) argue that the effects diminish over time in the foreign exchange market due to that arbitrageurs learn from the academic and correct the mispricing. Aligning with Hutchinson et al. (2022), we suggest that the value-and-momentum effects are weak in the global stock markets.

Fifth, we contribute to the literature related to the prospect theory by providing pieces of empirical evidence. Under the prospect theory framework by Kahneman & Tversky (1979), investors have different sensitives to risk, separated by gains and losses. In detail, investors have a tendency to hold on to losing stocks due to their attitude of loss aversion. By contrast, they sell winners too soon due to their risk aversion. Such behaviours driving up the spread between fundamental value and market price, would lead to price underreaction to new information. Indeed, this underreaction results in the continuation of past stock price trends so called the momentum effects.

We explain our main findings with this framework. The main finding in Chapter 2 is that economic trends can positively predict future stock market returns, denoted as economic momentum effects. From the perspective of risk-seeking, investors tend to hold on to a stock market index if its country's fundamentals are relatively worse compared with other countries. Suppose an investor has a position on a stock market index. If the country's fundamentals worsen, the investor would decide to keep the position due to its risk-seeking attitude. However, the investor's attitude regarding risk would shift to risk-aversion when the context is set to have outstanding fundamentals. In this situation, the investor would sell the profitable stock market index. Both behaviours would increase the spread between the fundamental and the price, leading to the stock market price underreacting to new macroeconomic announcements. Such underreaction can be the source of driving the economic momentum effects.

Section 2 describes the data. Section 3 discusses methodologies for constructing economic momentum portfolios and benchmarks. Section 4 discusses baseline results and compares them with benchmarks. Section 5 conducts further analysis, including exploring the driving force, transaction costs, and the effectiveness of economic momentum on other types of markets.

2.2 Data

We retrieve daily settlement prices of futures contracts with different maturities from Bloomberg.[4] We study developed markets, namely Australia (S&P/ASX 200), Canada (S&P/TSX 60), France (CAC 40), Germany (DAX), Italy (FTSE/MIB), Japan (TOPIX), Sweden (OMX STKH30), Switzerland (SWISS MKT), United Kingdom (FTSE 100) and the United States (S&P 500). We screen securities by (i) confirming all developed markets based on the classifications of the MSCI;[5] (ii) removing Israel and Ireland as there are no index futures for these markets; (iii) removing Hong Kong and Singapore markets because the OECD has no relevant macro variables for them; (iv) removing Austria, Denmark and New Zealand as the number of data points for these markets are 1752, 788 and 1632, being dramatically smaller than the other markets which have at least 4000 daily observations; (v) removing the index futures with low daily average open interest since we also concern the liquidity issue. Note that samples are from January 1989 to December 2020 due to their availability.

With contract prices, we composite daily continue-series futures returns for each equity market. Since futures have expired dates, we roll over contracts from the most nearby one to the next nearby one by following Bessembinder (1992), De Roon et al. (2000), Paschke et al. (2020) and Koijen et al. (2018). For example, to generate a continuous series for the S&P 500 index, we compute the daily returns on its relative futures contracts. We then merge the first nearby contract with the second nearby contract on the last business day of the rolling month (the month before the previous trading month.). This way, we can avoid "double costs", including

[4]We mainly study index futures rather than the price index since the index is non-tradable. Practically, investors tend to trade index futures for that the futures are cheaper than buying index constituents. For robustness, we also utilise MSCI country indices in Section 2.5.3.

[5]According to the MSCI, developed markets includes Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, United Kingdom and the USA.

re-balancing and rollover costs. Furthermore, we convert daily returns to monthly returns by summing up daily log returns within a month. Lastly, we calculate the excess returns by taking monthly returns on instruments over a one-month Treasury bill rate.[6] All price data in this paper are based on the home currency of the US dollar. Table 2.1 reports descriptive summary statistics for these composited market indices, including names of underlying and tickers of contracts in Bloomberg.

As for macro data, there are tons of macro variables. Including all these variables in predictive models would make the predictability more complex. Moreover, variables can have multicollinearity and would lead to incorrect estimations. One solution for it is to employ the principal component analysis, which reduces the large dimensionality of the dataset. However, it is difficult to economically interpret the relations between the obtained components and the variables when applying such a technique. We, therefore, follow Dahlquist & Hasseltoft (2020) (DH) to select macro variables rather than using all of them.

We obtain macroeconomic variables from the OECD to reflect the fundamentals of countries. We utilise the consumer price index (CPI), and producer price index (PPI) to measure inflation since they can dynamically and complementary reflect the price pressures in the supply chain (DH). We obtain the gross domestic product (GDP) to measure one's economic growth. Moreover, we also employ the OECD composite leading indicator (LOL) as it is found to be highly correlated with economic activity (Ojo et al. 2023). Besides, total manufacturing, a critical component of national and global economies, reflects the overall health and trends in the manufacturing sector. Hourly earnings (HES) measures the labour cost paid in the private and manufacturing sectors of one country.

We construct macro indices measuring fundamentals based on the selected variables. For those variables lacking monthly data, we follow DH to convert the quarterly data into monthly data. In detail, the value observed at the end of quarter

[6]The risk-free data is from the Ken. French library

Q would be repeated monthly in quarter Q+1 to avoid any look-ahead bias. Moreover, this data is one-quarter lagged to ensure our access to economic variables for all countries. Based on the macro-variables, we denote macro index A as the average log growth of the CPI, PPI, and total manufacturing. We also denote macro index B as the average log growth of LOL, GDP and HES. Table 2.1 summarises the descriptive statistics of 12-month log growth on these macro indices, including mean, standard deviation and number of observations. We regress the equity index futures returns on the 12-month log growth of each macro index with country and month fixed effects. Standard errors are clustered by country. Coefficients with the 12-month momentum signals are 0.27% and -3.88% for macro index A and B, respectively (See Table 2.12). It suggests that increases in past macro index A (B) trends might have positive (negative) effects on equity index futures returns. Therefore, we denote the macro index A (B) as the positive (negative) macro effect index. We assign the minus sign to the negative macro effect index for constructing portfolios.

2.3 Methodology

2.3.1 Baseline Portfolios Construction

In this section, we construct baseline portfolios based on economic momentum signals in the following steps.

Firstly, we measure economic momentum signals, which are the cumulative returns on macro indices over a lookback period. Since signals are computed from one of the two macro indices j (positive or negative macro effect index) and lookback periods l of 1-60 months, the amount of momentum signal types is 120.

Secondly, we design a sub-strategy trading on an economic momentum signals type, termed $S(j,l)$. A sub-strategy is to long (short) country indices based on their relatively strong (weak) economic momentum signals. There are 120 sub-strategies in total due to 120 signal types. Within each sub-strategy, we assign weights to each country index by following a cash-neutral-rank-based weighting method towards economic momentum signals. In this way, it can make strategies dollar-neutral and avoid outliers of the macro indices (Dahlquist & Hasseltoft 2020).

In detail, we weight each country index based on their cross-sectional ranking of economic momentum signals by following Asness et al. (2013), Koijen et al. (2018) and Dahlquist & Hasseltoft (2020). Within each sub-strategy, the weight, based on the macro index j and the lookback period l, assigned to country c at month t is

$$\boldsymbol{\omega}_{j,l,c,t} = K_{j,l,t}\Big[Rank(Z_{j,l,c,t}) - \sum_{c=1}^{N_{j,l,t}} \frac{Rank(Z_{j,l,c,t})}{N_{j,l,t}}\Big] \tag{2.1}$$

where $Z_{j,l,c,t}$ denotes a momentum signal for country c at time t within a strategy $S(j,l)$. $N_{j,l,t}$ denotes the total amount of available countries at time t within a sub-strategy. $K_{j,l,t}$ is the scale factor that makes the strategy to have one dollar on the long side and one dollar on the short side.

Thirdly, we aggregate sub-strategies into portfolios in a volatility-weighting method.[7] To avoid look-ahead bias, we estimate ex-ante volatility $\sigma_{j,l,t}$ for each sub-strategy $S(j,l)$ at the end of every month t. $\sigma_{j,l,t}$ is the annualised monthly volatility transformed from daily volatility of $S(j,l)$'s daily log-returns. Specifically, we follow Moskowitz et al. (2012) and Dahlquist & Hasseltoft (2020) to employ the EWMA for calculating the ex-ante volatility with a risk metric λ of 0.97. Note that λ from 0.92 to 0.99 does little difference to the main results. For robustness, we also estimate historical volatility with a rolling window size of three years as an alternative. However, it does not affect our main results. With the weights assigned to sub-strategies, the weights assigned to each country index in portfolio P is

$$\Omega^P_{c,t} = E^P_t * \frac{1}{\sigma_{j,l,t}} * \boldsymbol{\omega}_{j,l,c,t}, \tag{2.2}$$

where E^P_t is a scale factor making the sum of weights within the portfolio P equal to one at the end of every month t.

As for portfolio P, we, first, construct a combo portfolio (CM) by aggregating all the 120 sub-strategies. Second, we form a positive macro portfolio (PM) and a negative macro portfolio (NM) by aggregating sub-strategies, which are developed from positive and negative macro effect indices, respectively. We do it to explore the influence of the macro indices on the portfolio performance. Third, we determine short-term (ST), mid-term (MT) and long-term (LT) portfolios by aggregating sub-strategies $S(j,1-12)$, $S(j,13-36)$ and $S(j,37-60)$ for observing effects of lookback periods in the portfolio performance. Therefore, P could be one of the six portfolios and returns on the portfolios are computed as,

$$r^P_t = r_{c,t} * \Omega^P_{c,t-1}, \tag{2.3}$$

[7]Different sub-strategies may have different volatility. To control the influence of volatility on the portfolio performance, we assign larger (smaller) weights to the sub-strategies with smaller (larger) volatility. For robustness, we also employ an equal-weighting method. Results of that are reported in Table 2.14 in the appendix, while that does not affect the main results.

where $r_{c,t}$ is excess return of country index c over one-month-T-bill at month t.

2.3.2 Benchmarks Construction

To compare the performance of the economic momentum strategies, we employ standard momentum strategies as benchmarks, including time-series momentum (TSMOM), value(VAL), cross-sectional momentum (MOM), value and momentum (VMOM). Apart from active strategies, we also consider the performance of passive investment, buy-and-holding the MSCI world index over a one-month T-bill.

The constructed TSMOM portfolio mainly obeys the methodology mentioned by Moskowitz et al. (2012). However, the dollar-neutral weighting method would be applied to the TSMOM to be consistent with the portfolios designed above. In particular, weights, $w_{c,t}$ assigned to securities are

$$\Omega_{c,t}^{TSMOM} = K_t * sign(r_{c,t-12,t}) * \frac{20\%}{\sigma_{c,t}} \quad , \tag{2.4}$$

where K_t is the scale factor, making the portfolio have one dollar on the long side and one dollar on the short side. $\sigma_{c,t}$ denotes the annualised EWMA volatility of daily log-returns on security c at time t. Besides, $sign(r_{c,t-12,t})$ is the sign of past-12-month cumulative returns on security c. With weights, the calculation of returns on the TSMOM portfolio is

$$TSMOM_t = \sum_c * \Omega_{c,t-1}^{TSMOM} * r_{c,t} \quad . \tag{2.5}$$

Markets covered in the TSMOM are the same as the portfolio created above. Additionally, we also consider the time-series factor data from AQR, denoted as TSMOM_AQR, which has different market selections from this study.

As for value and momentum strategies, we follow Asness et al. (2013) (AMP) to construct portfolios trading based on value and momentum signals but covering the same selected markets in this paper. We term these portfolios value (VAL), momentum(MOM), value and momentum (VMOM). Considering the influence of market selection, we also obtain respective factors data from AQR and label them with VAL_AQR, MOM_AQR and VMOM_AQR. According to AMP, a metric for measuring the value signal on equity indices is the book-to-market ratio of MSCI indices. Meanwhile, we apply 12-month cumulative returns on indices as the momentum signals. When processing these signals, we also employ the weighting method in formula 2.1 so that the main portfolios and benchmarks can be comparable. Therefore, weights for country c at time t within VAL and MOM are

$$\boldsymbol{\Omega}_{c,t}^{VAL} = K_t\Big[Rank(BM_{c,t}) - \sum_{c=1}^{C_t}\frac{BM_{c,t}}{C_t}\Big] \quad \text{and} \tag{2.6}$$

$$\boldsymbol{\Omega}_{c,t}^{MOM} = K_t\Big[Rank(r_{c,t-12,t}) - \sum_{c=1}^{C_t}\frac{r_{c,t-12,t}}{C_t}\Big] \quad , \tag{2.7}$$

where C_t is the total amount of available countries at time t. $BM_{c,t}$ and $r_{c,t-12,t}$ denote the book to market ratio and the past-12-month cumulative returns, respectively. Furthermore, the returns on these portfolios are

$$VAL_t = \boldsymbol{\Omega}_{c,t-1}^{VAL} * r_{c,t} \quad \text{and} \tag{2.8}$$

$$MOM_t = \boldsymbol{\Omega}_{c,t-1}^{MOM} * r_{c,t} \quad . \tag{2.9}$$

Based on that, VMOM, the combination of a half VAL and a half MOM can be calculated as

$$VMOM_t = 0.5 * VAL_t + 0.5 * MOM_t \quad . \tag{2.10}$$

2.4 Empirical Results

This section explores the predictability of a country's past fundamental trends on its equity market index futures returns. We construct economic momentum portfolios, measure their performance, and compare them to benchmark portfolios. The regression results give statistical insights to the policymakers into how stock markets react to macroeconomic announcements. The policymakers can take that into consideration when making announcements. For the market participants, this work gives them some insights into the information embedded in past trends that are not fully priced by the market.

2.4.1 Baseline: Country-Level Regression Analysis

We create 120 sub-strategies using two macro indices (positive and negative effect macro indices) and 60 lookback periods for measuring momentum signals based on a country's fundamentals. These sub-strategies consist of a combo portfolio (CM), which includes all 120 sub-strategies. Additionally, there are two specialised portfolios: the positive macro effect portfolio (PM), which aggregates 60 sub-strategies developed based on the positive macro effect index, and the negative macro effect portfolio (NM), constructed similarly but using the negative macro effect index. Furthermore, we have short-term (ST), mid-term (MT), and long-term (LT) portfolios that combine sub-strategies based on lookback periods of 1-12, 13-36, and 37-60, respectively.

We conduct a panel regression in which we regress the excess returns of equity index futures on lagged-one-month weights, derived from the formula 2.2. We use these weights as the independent variable instead of the momentum signals to mitigate any issues related to outliers in the signals. The panel regression model is represented as follows:

$$r_{c,t} = \beta_0 + \beta_1 * \Omega^P_{c,t-1} + \epsilon_{c,t}. \tag{2.11}$$

In this equation, $r_{c,t}$ signifies the excess return of the security for country c in month t, and $\Omega^P_{c,t-1}$ represents the lagged-one-period-standardised weights, which are the weights of assets within the portfolio P.

We include fixed effects in the model instead of random effects. The random effects model requires a strict assumption of zero correlation between individual unobserved heterogeneity and the independent variables. However, this assumption does not hold for the dataset we study in this paper. First, the dataset has a high correlation between economic variables and stock performance, especially during periods of extreme events, such as the global financial crisis. Second, the country's stock market performance should be affected by its internal characteristics, such as political environment and public policies etc. To control for such internal characteristics, we, therefore, follow Dahlquist & Hasseltoft (2020) to employ fixed effects to be included in the regression models.[8]

The empirical results in Table 2.2 indicate that historical trends in one country's fundamentals have statistically significant predictive power for future equity market returns. To be specific, the coefficient associated with the weight derived from the combo portfolio is 0.24%. This suggests that a one standard deviation increase in the weights derived from the combo portfolio can predict a positive gain of 0.24% on equity market index returns. It's noteworthy that these weights are derived from the momentum signals. Consequently, we can conclude that the historical trends in a country's fundamentals can positively predict that country's equity index returns. This phenomenon is referred to as economic momentum effects.

The statistical significance in asset pricing literature is well debated about the cutoff level in the "Factor Zoo" context today. Existing literature examines and finds tons of factors explaining variations in cross-sectional returns, referred to as "Factor Zoo" by Cochrane (2011). Arguing the issue of Factor Zoo, Harvey et al. (2016)

[8]We also employ a Fama-MacBeth regression which does not affect our findings, please see Table 2.13 in the appendix.

suggest that it is inappropriate to use the traditional threshold of t-statistics applied in asset pricing tests, such as the cutoff of 2.00 employed by Fama & MacBeth (1973). In the past, collecting and handling data was time-consuming and pricy, but the cost of that is "dramatically decreased" today due to the technology development. With the increasing number of empirical works on the same dataset of cross-sectional returns and the same threshold, it is highly to get false discoveries. To measure the rate of false discoveries, Harvey et al. (2016) apply the Family-Wise Error Rate (FWER), which is introduced by Holm (1979) and the False Discovery Rate (FDR) introduced by Benjamini & Hochberg (1995). One issue with using FWER is that it would "*lead to a very limited number of discoveries*" when considering a large number of tests. However, it is not clear how to determine the "large". To determine an appropriate cutoff significance for today's research, Harvey et al. (2016) provide a multiple-testing framework to examine existing factors and derive a benchmark, a t-statistic of 3.00, for future studies. Compared with that benchmark, the main t-statistic of the baseline regression in Chapter 2 is 3.21, displayed in Column 1 of Table 2.2.

The portfolios that aggregate sub-strategies developed exclusively based on one of the macro indexes demonstrate economic momentum effects. More specifically, see columns 1 to 4, when examining the coefficients associated with the lagged-one-period weights for the positive macro effect portfolio (PM) and the negative macro effect portfolio (NM), we find them to be 0.13% and 0.28%, respectively. These coefficients are statistically significant. Furthermore, when conducting regressions of excess returns on both the weights of PM and NM simultaneously, we observe coefficients of 0.15% and 0.29%, respectively. This implies that the responses of excess returns to the negative macro effect index are approximately 93.33% (calculated as 0.29/0.15-1) more significant than those to the positive macro effect index. In essence, this suggests a stronger impact of the negative macro effect on excess returns than the positive macro effect.

The term-based portfolios also display momentum effects, see columns 5 to 7.

Specifically, when examining the coefficients associated with the weights derived from the short-term (ST), mid-term (MT), and long-term portfolios (LT), we find values of 0.11%, 0.27%, and 0.20%, respectively. This suggests that a one standard deviation increase in weights derived from short-term, mid-term, and long-term momentum signals can positively predict gains of 0.11%, 0.27%, and 0.20%, respectively, in stock market index futures returns.

Column 8 of the analysis indicates that economic momentum returns are primarily attributed to mid-term momentum among the term-based portfolios. More specifically, when regressing the excess returns on the lagged weights derived from all three terms (ST, MT, and LT) simultaneously, only the coefficient related to the MT weights is statistically significant, measuring at 0.37%. This magnitude is the largest coefficient among the Panel, indicating that mid-term momentum significantly impacts economic momentum returns among the different terms considered.

To address potential doubts about the robustness of the economic momentum effects, we conducted further analysis by introducing controlling variables that have the potential to affect equity market returns. These control variables were sourced from the Kelly data library and encompass various factors, including accruals, debt issuance, investment, low leverage, low risk, momentum, profit growth, profitability, quality, seasonality, short-term reversal, size, and value, as outlined in the work by Jensen et al. (2023).

Table 2.3 presents the results of our analysis, revealing that the economic momentum effects remain statistically significant even after controlling for various relevant variables. However, the magnitudes of these effects are somewhat reduced, and the predictive model's fitness improves. Specifically, the coefficient associated with the weight derived from the combo portfolio is 19%, which is slightly smaller (by 5%) compared to the coefficient of the same term (24%) in the model without control variables. This suggests that while the effect is slightly diminished, it still holds substantial predictive power.

Additionally, the introduction of control variables leads to a significant increase in the model's explanatory power, as indicated by the rise in the adjusted within R^2 value from 0.49% to 20.48%. This increase implies that economic momentum provides valuable predictive information about equity market returns, and it accounts for a substantial portion of the variance in these returns, even after controlling for other relevant factors. Notably, the control variables related to low risk, probability, quality, and size retain their explanatory power, indicating that these factors contribute to explaining equity market returns alongside economic momentum.

2.4.2 Baseline: Portfolio Analysis

We confirm the predictability of economic momentum on equity index futures returns, but it's worth noting that the profitability of these effects remains unexplored. In this subsection, we delve into an examination of the performance of the economic momentum portfolios.

To compute returns for each portfolio, we utilise the formula 2.3. The results of this analysis are presented in Table 2.4, which provides a descriptive summary of the portfolios. This summary includes key metrics such as annualised means (in percentage), annualised standard deviation (in percentage), skewness, excess kurtosis, first-order autocorrelation, maximum drawdown (in percentage), and Sharpe ratios. Panel A of the table provides a detailed overview of the performance of these portfolios, while Panel B reports on the correlations between the portfolios.

This analysis is crucial in understanding how economic momentum strategies perform compared to various benchmarks and helps assess their risk-adjusted returns, stability, and other essential characteristics.

In Panel A of Table 2.4, it's evident that all economic momentum portfolios demonstrate positive mean returns and Sharpe ratios, underscoring their profitability. Specifically, the annualised mean returns for the economic combo (CM), positive macro effect (PM), negative macro effect (NM), short-term (ST), mid-term (MT), and long-term (LT) portfolios are 3.60%, 3.68%, 3.03%, 2.18%, 4.64%, and 3.16%, respectively, with corresponding Sharpe ratios of 0.87, 0.49, 0.40, 0.40, 0.96, and

0.66. These metrics suggest that these portfolios generate positive returns relative to their risk. It's worth noting that there isn't a strong auto-correlation observed among portfolio returns, indicating that their performance isn't simply driven by recent past performance.

Comparing CM with portfolios based solely on macro indexes (PM or NM), it becomes evident that there are advantages to combining PM and NM. PM exhibits higher mean returns than CM, but CM has a lower standard deviation (4.13%) compared to 7.52% for PM and 7.53% for NM. Moreover, CM offers portfolio diversification and boasts the highest Sharpe ratio (0.87) among them. Additionally, CM shows higher skewness and excess kurtosis but the lowest drawdown.

Interestingly, the analysis suggests that mid-term momentum (MT) plays a crucial role in driving the performance of economic momentum strategies. When comparing CM with term-based portfolios, CM stands out for its lower standard deviation. In contrast, MT demonstrates the highest mean returns (4.64%) and the highest Sharpe ratio (0.96) among all portfolios, along with the lowest maximum drawdown (-5.43%).

Turning to Panel B of Table 2.4, it's clear that CM has a high correlation (0.95) with MT, suggesting a strong relationship between the combo portfolio and mid-term momentum. Correlations between CM and the term-based portfolios (ST, MT, and LT) are also noteworthy, indicating their interconnectedness. On the other hand, correlations between CM and solely macro-index-based portfolios (PM and NM) are lower, highlighting the benefits of aggregating PM and NM into CM. Indeed, the correlations between the portfolios make sense, given that they are constructed from similar sub-strategies or share underlying components.

Furthermore, the analysis explores the time-varying persistence of economic momentum effects. Figure 2.1 illustrates that all economic momentum portfolios exhibit trending behaviour over time and show resilience during recession periods. In Panel A, PM and NM follow opposite routes, emphasising the value of combining them into CM, which appears to be the most promising strategy in terms of growth. Panel B highlights that MT outperforms ST and LT in terms of cumulative returns over the sample period and has a similar pattern to CM but with better volatility-adjusted cumulative returns. This suggests that mid-term momentum signals are likely to drive the profitability and predictability of the economic momentum portfolio.

So why the mid-term momentum strategy is distinguished from the short-term (ST) and long-term (LT) strategies? The ST measures the signals as the past one year trends while it contains the most one-month signals, which can be referred to as the short-term reversal. Therefore, the ST performance would be weaker than the MT. For the LT, it contains the trends covering the past 36-60 months. It can have a momentum reversal phenomenon during the long term and result in weaker performance compared with MT.

2.4.3 Benchmarks

In this section, we conduct a comparative analysis of economic momentum portfolios against standard momentum strategies and other benchmarks. We consider a range of benchmarks widely recognised in the literature to ensure a comprehensive evaluation. These benchmarks include time-series momentum (TSMOM_AQR), value (VAL_AQR), momentum (MOM_AQR), and value and momentum (VMOM_AQR) factors obtained from AQR. Additionally, to align with the markets selected in this paper, we construct equivalent factor data (TSMOM, VAL, MOM, and VMOM) tailored to the specific markets covered in this research. For passive investment comparison, we create a portfolio that involves buying and holding the MSCI world index's excess returns over one-month treasury returns, referred to as Mkt-Rf. This comprehensive set of benchmarks allows us to assess the performance of economic momentum portfolios compared to established strategies and market indices.

Benchmarks: Portfolio Analysis

Panel A of Table 2.5 provides a comprehensive summary of portfolio performance, including risk-adjusted returns, return distribution characteristics, first-order autocorrelation, maximum drawdown, and Sharpe ratios. The analysis indicates that economic momentum portfolios outperform the selected benchmarks regarding risk-adjusted performance.

Among the benchmark strategies, TSMOM_AQR exhibits the highest annualised returns at 12.10%. However, when considering the volatility of its returns, characterised by a standard deviation of 27.18%, its Sharpe ratio is relatively low at 0.45. In contrast, the economic momentum combo portfolio (CM) achieves a much higher Sharpe ratio of 0.93, while the economic mid-term momentum portfolio (MT) boasts an even more impressive Sharpe ratio of 1.01.

Moreover, when examining the maximum drawdown, which represents the peak-to-trough decline in portfolio value, it is notably lower for the economic momentum portfolios (6.53% for CM and 5.43% for MT) compared to the benchmarks, which generally have maximum drawdowns above 20% (except 16.67% for MOM_AQR). This indicates that economic momentum portfolios tend to be more stable and have the potential for lower maximum losses compared to benchmark strategies.

The return distribution characteristics further highlight the superior performance of the economic momentum portfolios. The positive excess kurtosis observed in CM and MT (1.14 and 3.19, respectively) signifies that these portfolios achieve returns that are more "fat-tailed" or exhibit more extreme values than the benchmarks. In contrast, the benchmarks tend to have negative excess kurtosis, indicating that their returns are more "thin-tailed" and cluster closer to the mean. Additionally, the skewness of CM and MT (0.68 and 1.09, respectively) is larger than the skewness of the benchmarks. Positive skewness suggests that these portfolios produce positively skewed returns, indicating the potential for higher returns during favourable market conditions.

The auto-correlations and inter-portfolio correlations for the economic momentum portfolios are low, as shown in Panel A and Panel B of Table 2.5. This indicates that economic momentum portfolios are relatively independent of each other and from the benchmark strategies, further supporting their diversification benefits and potential for risk reduction.

Interestingly, the summary data of the benchmarks we construct and the benchmark factor data obtained from AQR are dramatically different. The main reason for this difference is the market selection. To maintain consistency with our primary studies in this paper, we chose the same country markets when constructing the benchmarks, which differ from those used in the AQR factor data.

Additionally, according to Asness et al. (2013), the value portfolio achieves a mean return of 5.70% and a Sharpe ratio of 0.60 in the sample period from 1978 to 2011. We argue that we find a negative mean return on VAL_AQR when considering the sample period from 1995 to 2020. Therefore, we suggest that the performance of the value factor cannot be sustained over time.

In terms of the time persistence of portfolios, we plot line charts, shown in Figure 2.2, to visualise cumulative returns on both the economic momentum and the benchmarks, exploring the performance of these strategies over time. The drawdown of these portfolios over time is also plotted in Figure 2.3. The NBER recession periods are included in the figures. All portfolio returns are scaled to the same annualised volatility of 6%, which is the average volatility across portfolios. We scale them to control for volatility, allowing for a more meaningful comparison in the visualised line charts.

Panel A of Figure 2.2 compares the cumulative returns of the economic momentum combo portfolio (CM) and passive investment, represented by buying-and-holding the MSCI world index over one-month Treasury T-bills (Mkt-Rf). The figure illustrates that CM consistently outperforms in terms of cumulative returns. Additionally, during recession periods, passive investment performs worse than active investment, CM.

Panel B, which compares the performance of CM with time-series momentum (TSMOM and TSMOM_AQR), indicates that CM performs better than these benchmarks in terms of cumulative returns. Notably, TSMOM_AQR briefly matches CM's cumulative returns around 2008 but fails to maintain its trend afterwards. Particularly after 2018, both TSMOM and TSMOM_AQR experience significant declines in their long-term cumulative returns, raising questions about the persistence of time-series momentum strategies over time.

Panel C reports comparisons between CM and individual cross-sectional momentum strategy (MOM) and value strategy (VAL), as well as their AQR benchmarks (MOM_AQR and VAL_AQR). The benchmarks show slight increases over the sample periods, while CM exhibits significant growth.

Panel D compares CM with the value and momentum strategy (VMOM and VMOM_AQR). CM consistently outperforms the benchmarks. Notably, VMOM_AQR experiences substantial growth before 2008 but a decline in cumulative returns after 2008, suggesting doubts about the time persistence of VMOM.

In conclusion, comparing CM with various benchmarks consistently demonstrates that CM's time-varying cumulative returns outperform the benchmarks, even during recession periods. It's important to note that while time-series momentum and value and momentum strategies perform well in their original paper's sample periods, their profits decline during the extended periods in this paper, casting doubt on their long-term persistence.

From Figure 2.3, it is evident that CM consistently maintains a drawdown of approximately under 4% over time, unlike the other strategies. The drawdown in the passive investment returns widens around recession periods. Additionally, both TSMOM_AQR and VMOM_AQR experience worsening drawdowns after the global financial crisis.

Benchmarks: Regression Analysis

We establish portfolios for both economic momentum and benchmarks and conduct a comparative analysis. Both visually and statistically, our findings lead us to conclude that economic momentum outperforms benchmarks in terms of risk-adjusted returns and risk management. In this section, we delve into a statistical examination of the predictive capabilities of economic momentum and benchmarks on future equity index returns.

From a statistical standpoint, we find strong evidence supporting the superiority of CM over the benchmarks. Utilising the same sample period of 199502:202012 for all portfolios, we conduct panel regression analyses, regressing country index futures' excess returns on lagged one-month portfolio weights.[9] Table 2.6 presents the results of these panel regressions, accounting for both country and month fixed effects, with standard errors clustered by country. Additionally, we incorporate the control variables employed in Section 2.4.1 into these regressions.

Table 2.6 demonstrates that the predictive power of weights derived from CM is the most robust compared to the benchmarks. Specifically, during the sample period 199502:202012, CM maintains its statistically significant predictive power concerning future equity index returns. Even after controlling for relevant variables, the coefficient associated with CM only slightly decreases from 0.24% to 0.18%. Although the magnitude of the coefficient decreases somewhat, it remains solid and significant. The 0.18% coefficient implies that a one standard deviation increase in weights derived from momentum signals corresponds to a 0.18% increase in equity index returns. Conversely, only the VAL strategy exhibits significant coefficients for the benchmarks but bears negative signs, indicating adverse predictive power. The coefficients for the other benchmarks are largely insignificant. Across all columns, it is noteworthy that including control variables in the regressions significantly en-

[9] We select this sample period due to the data availability of all portfolios.

hances the model's goodness of fit. For instance, for CM, the R-squared value increases substantially from 0.56% to 22.30% after controlling for variables in the regressions.

Explanations between Economic Momentum and Benchmarks

By empirically evaluating the performance of economic momentum portfolios and benchmarks, we establish that the economic momentum portfolios consistently outperform the benchmarks in terms of risk-adjusted returns and downside risk. However, it is interesting to confirm whether the superior performance of the economic momentum portfolios can be attributed to the benchmarks, or, conversely, if the economic momentum portfolios influence the benchmarks.

We conduct a regression analysis to examine the relationship between the returns of the economic momentum combo portfolio (CM) and the returns of various benchmarks, including the passive investment strategy (Mkt-Rf), time-series momentum (TSMOM), momentum (MOM), value (VAL), and value and momentum (VMOM), as well as their respective factor data (TSMOM_AQR, MOM_AQR, VAL_AQR, and VMOM_AQR) obtained from AQR. The regression model is specified as follows:

$$ret_t^{CM} = \alpha + \beta \cdot ret_t^P + \epsilon_t, \tag{2.12}$$

where ret_t^{CM} represents the returns on CM. ret_t^P represents the returns on one of the benchmarks denoted as P.

Table 2.7 reveals that none of the benchmarks can fully account for CM's performance. The coefficient associated with Mkt-Rf is -5.22%, indicating a negative relationship between CM and the passive investment strategy. Similarly, CM negatively associates with VAL_AQR, with a coefficient of -11.71%. Except for Mkt-Rf, VAL_AQR, and the insignificant coefficients for TSMOM and VMOM_AQR, all other benchmarks exhibit a positive and statistically significant relationship with CM. Nevertheless, these benchmarks do not entirely explain CM's returns. The average intercept of the model is 0.32, which is statistically significant for all models related to individual benchmarks. Column 10 presents the results of regressing CM returns on all benchmarks. The annualised alpha of the model is 3.72% (0.31% * 12). Considering that the annualised return of CM is 3.95%, we can infer that 94.18% (3.72/3.95) of CM's returns remain unexplained even after accounting for the benchmarks.

Notably, the adjusted R-squared for Column 10 is 9.44%, which is the largest one among the models presented in Table 2.7. This model explains most of the variability of benchmarks around the economic momentum strategy. However, Column 8 provides a negative R-squared, showing the model fails to fit the trends embedded in the data. Economically, the time-varying OLS model does not fit the relationship between "value and momentum factors" and economic momentum appropriately.

On the contrary, we perform regressions of benchmark returns on CM. Specifically, the regression model is defined as follows:

$$ret_t^P = \alpha + \beta \cdot ret_t^{CM} + \epsilon_t, \tag{2.13}$$

where the notations in this formula are the same as in formula 2.4.3.

Table 2.8 shows that CM significantly incorporates returns on the benchmarks, except for Mkt-Rf, VMOM_AQR, and TSMOM_AQR. Intercepts of models related to Mkt-Rf, VMOM_AQR, and TSMOM_AQR are 0.54%, 0.15%, and 1.07%, respectively, all statistically significant. Regarding the coefficients on the term CM, they suggest that MOM, VAL, VMOM, and MOM_AQR have a positive comovement with CM. In addition, we observe no significant relationship between CM and TSMOM and VMOM_AQR.

2.5 Further Analysis

2.5.1 Driving Force Investigation

To explore the driving force of the economic momentum portfolio returns, we employ standard asset pricing factors models to examine if such economic momentum profitability can be explained. The first model, containing the Market, Size and Value factors, is termed the FF3 (Fama & French 1993). The second model is termed the FF5, which requires the Market (Mkt-Rf), Size (SMB), Value (HML), Profitability (RMW) and Investment (CMA) factors (Fama & French 2015). The third model is the q5 factor model with the Market (Mkt-Rf), Size (R_ME), Investment (R_IA), Return on equity(R_ROE) and Expected growth (R_EG) (Hou et al. 2021). The fourth model is from Jensen et al. (2023), which classifies factors into themes (see their appendix for details).

Empirical results in Table 2.9 indicate that none of these standard asset pricing factor models can explain the returns on CM. The alpha (intercept) of factor model FF3, FF5, q-5 and world factors are 0.36%, 0.39%, 0.32% and 0.34%, respectively, statistically significant at the 1% level. These significant alphas imply that none of these factor models can fully explain the returns on CM. However, we note that the market risk premium of FF3 and FF5 can partially explain CM returns but in a negative relationship. Moreover, in the model of world factors, factors of investment, low_leverage, profitability and size have positive explanations on CM returns, while accruals and quality have negative relationships with the CM returns.

Apart from the pricing models, we also decompose the economic momentum combo portfolio returns towards the country for studying if any country domain the combo portfolio returns. In detail, we extract weights for each country index within the combo portfolio. Then, we multiply the weights with the country index futures returns but do not aggregate them, leaving a time-series return for each country.

Table 2.10 shows that no country dominates the combo portfolio returns. In the table, the maximum mean return, 0.85%, is gained by Switzerland, while the minimum mean return is -0.18%, earned by Sweden. Compared with the mean return of 3.95% of CM, country-level portfolio returns are small. Observing the T-statistics of the mean returns, we find that none of the country-level portfolio mean returns are significant. It suggests that none of the countries leads the CM returns. In addition, the Sharpe ratios of these country portfolios are, on average, below 0.30. In contrast, the combination of them, the economic momentum combo portfolio, achieves a Sharpe ratio of 0.93, suggesting the benefits of portfolio diversification.

2.5.2 Transaction Costs

Recent papers discuss the effects of transaction cost on momentum strategy profits. Based on estimation models, Lesmond et al. (2004) and Korajczyk & Sadka (2004) suggest that the profits of momentum strategies are significantly lower than the theoretical world. However, Frazzini et al. (2018) argue their statement using the live data. To examine if the effect of transaction cost on momentum profits is essential, we construct the bid-ask spread ratio as the transaction cost of the trading. We obtain the bid and ask prices of the 1st generic continue series for each country index futures from Bloomberg. Then, we calculate the bid-ask spread ratio (TC) as

$$Spread_{c,t} = 2 * (ASK_{c,t} - BID_{c,t})/(ASK_{c,t} + BID_{c,t}) \quad and \tag{2.14}$$

$$TC_{c,t} = \Omega^{CM}_{c,t-1} * Spread_{c,t}, \tag{2.15}$$

where $ASK_{c,t}$, $BID_{c,t}$ and $Spread_{c,t}$ denote the ask price, bid price, and spread between them for the country c at the month t. Note that $\Omega^{CM}_{c,t}$ is the weights derived from formula 2.2 and $TC_{c,t}$ is the transaction cost of economic momentum combo strategy for country c at the month t. We take the mean basis points of bid-ask spread ratios as the monthly re-balance cost for each market index. Based on that, the economic momentum combo portfolio can still yield a Sharpe ratio of

0.52 with annualised returns of 2.14% even after accounting for transaction costs.

2.5.3 Other Market Indices

The profitability and predictability of the economic momentum portfolio are confirmed in the main results. For robustness, we also study its effectiveness in other general market groups such as G10, developed markets and emerging markets based on MSCI country indices. G10 contains Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, the United Kingdom and the United States. Developed markets are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States. Emerging markets are Brazil, Chile, China, Colombia, Czech Republic, Greece, Hungary, India, Indonesia, Poland, Russia, South Africa, South Korea and Turkey. The descriptive summary statistics of portfolio performance for different market groups are reported in Panel A of Table 2.11, including annualised mean returns in percentage, annualised standard deviation in percentage (Std.), skewness, excess kurtosis, lagged-one-period auto-correlation (AR(1)), maximum drawdown in percentage and Sharpe ratio. Panel B of Table 2.11 presents the results of panel regressions of market indices on the economic momentum portfolio returns for different market groups.

Table 2.11 suggests that economic momentum effects are profitable in different markets. The Sharpe ratios for G10, developed, and emerging markets are 0.66, 0.42, and 0.51, respectively. It's worth noting that the emerging markets portfolio achieves the highest mean return of 7.35%. Still, it lacks stability regarding standard deviation and drawdown, resulting in lower Sharpe ratios compared to the others. All portfolios exhibit low autocorrelation. Furthermore, the predictability of economic momentum in different markets is statistically significant. Therefore, we conclude that economic momentum effects also persist in other markets.

2.6 Conclusion

This paper reveals the substantial predictive power of past trends in a country's fundamentals on its future stock market index performance. It contributes to the literature by providing cross-sectional works suggesting that economic momentum matters to country-level stock markets. Prior work by Dahlquist & Hasseltoft (2020) demonstrate the economic momentum effects in foreign exchange markets. Inspired by them, we suggest a similar pattern in stock markets. Given that macroeconomic variables are free to access by the public, the existence of past trends in economics predicting future stock markets suggests that financial markets do not fully price the macro-level information.

Moreover, such a predictive pattern is economically and statistically significant. Specifically, one standard deviation increase in the weights derived from a country's economic momentum signals leads to a 0.24% increase in the excess returns on the country index futures, which we term as economic momentum effects. A strategy, referred to as the economic momentum combo portfolio, built upon this effect generates a Sharpe ratio of 0.87 and an annualised return of 3.60%. The return remains at 2.14% after accounting for transaction costs. Notably, none of the standard asset pricing models, such as FF3, FF5, q-5 and world factors, can explain its profitability. Also, we find none of the countries solely drive the strategy return.

Furthermore, we find that the economic momentum strategy outperforms popular momentum strategies documented in the literature, such as time-series momentum and value-and-momentum strategies. Comparing the economic momentum strategy with these benchmarks, we observe superior risk-adjusted returns in our strategy. Specifically, our strategy gains an average annualised alpha of 3.72% (calculated as the monthly alpha of 0.31% times 12), even after controlling for benchmarks, leaving around 95% (calculated as 3.72/3.95) of the returns unexplained by the benchmarks. The economic momentum strategy also exhibits lower and more stable time-varying drawdowns than the benchmarks. Moreover, the economic momentum portfolio effectively captures returns on strategies of time-series momentum, cross-sectional momentum, value, and value-and-momentum.

In addition, the economic momentum strategy exhibits economic and statistical significance, whereas the benchmarks do not. In terms of the time-series momentum strategy, our findings are consistent with Huang et al. (2020), who argue that the time-series momentum is statistically weak in their time-series and cross-sectional analysis compared to the pooled regressions utilised by Moskowitz et al. (2012). Apart from the statistical evidence, we also contribute to the literature by providing evidence arguing that the profitability of time-series momentum effects in global stock markets over the sample period from 1989 to 2020 is questionable. As for the value-and-momentum strategy documented by Asness et al. (2013), Hutchinson et al. (2022) doubt the persistence of value-and-momentum effects in currency markets and attribute it to the mispricing corrections by arbitrageurs. To this end, we contribute to the literature by providing empirical evidence arguing its time-varying persistence in global stock markets. However, we do not further conduct works to examine if that is due to similar mispricing corrections since it is not the main purpose of this paper. Future studies extending this could be interesting.

Lastly, regarding the market selection, one may doubt the robustness of the economic momentum effects in other markets. We, therefore, examine the same pattern in G10, developed and emerging markets. We find that the predictability of economic momentum in equity market index returns remains statistically and economically significant. However, this paper mainly studies market indices, which capture large-cap stocks, ignoring the influence of small-cap stocks in the stock markets. Future studies on individual stocks could be interesting.

2.7 Tables

Table 2.1: Data Summary Statistics

This table reports summary statistics on each country's 12-month economic momentum signals and equity index futures. Statistics including observations number, mean, standard deviation, 1st quantile (25%), median and 3rd quantile (75%) are reported. Besides, we also report information about the futures, such as their underlying index and contract symbols. Panel A and B report 12-month momentum signals based on positive and negative macro effect indices. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. Panel C reports monthly returns on the combined futures. We composite the continuing series for a market index by rolling the nearest contracts to the second nearest contracts on the last business day of the month, before the previous trading month. The last three letters, XYY, for the futures contract symbols, can be replaced with the maturity month and year of one contract. For example, the ticker for a contract with a maturity of December 2019 based on the S&P 500 index is SPZ19, where SP is the name of the S&P 500 index futures chain, Z represents December and 19 stands for the maturity year 2019. All prices are converted into USD. The sample period is from January 1989 to December 2020.

	Australia	Canada	France	Germany	Italy	Japan	Sweden	Switzerland	United Kingdom	United States
Panel A: 12-Month Log Growth (%) on Positive Macro Effect Index										
No. of Obs.	373	373	373	373	373	373	373	373	373	373
Mean	1.85	1.40	0.76	1.27	1.30	-0.06	1.75	1.35	1.47	1.86
Standard Deviation	1.92	2.61	2.53	2.62	3.23	3.10	2.86	2.36	2.08	2.61
25%	0.91	0.14	-0.12	0.07	-0.01	-1.21	0.58	-0.20	0.39	0.98
50%	2.01	1.61	0.97	1.59	1.57	0.60	1.90	1.60	1.74	2.48
75%	2.91	2.98	2.29	2.98	2.97	1.76	3.52	2.98	2.78	3.60
Panel B: 12-Month Log Growth (%)on Negative Macro Effect Index										
No. of Obs.	373	373	373	373	373	373	373	373	373	373
Mean	1.16	0.64	0.70	0.81	0.83	0.22	1.02	-0.10	1.03	0.75
Standard Deviation	0.93	1.47	1.40	1.42	1.60	1.73	1.40	1.85	1.67	1.03
25%	0.64	-0.03	0.16	0.13	0.05	-0.44	0.33	-1.27	0.52	0.38
50%	1.17	0.84	0.76	0.89	0.91	0.43	1.14	0.06	1.21	0.84
75%	1.73	1.62	1.57	1.55	1.80	1.20	1.76	1.01	1.93	1.37
Panel C: Monthly Return (%) on Equity Index Futures										
Underlying	S&P ASX 200	S&P TSX 60	CAC 40	DAX	FTSE MIB	TOPIX	OMX STKH30	SWISS MKT	FTSE 100	S&P 500
Symbol	XPXYY	PTXYY	CFXYY	GXXYY	STXYY	TPXYY	QCXYY	SMXYY	Z XYY	SPXYY
No. of Obs.	248	256	383	361	202	368	191	320	384	384
Mean	0.50	0.48	0.26	0.37	0.30	-0.01	0.69	0.71	0.08	0.43
Standard Deviation	6.28	5.79	5.95	6.42	7.32	5.72	6.42	4.68	4.92	4.24
25%	-2.55	-2.25	-3.43	-3.24	-3.66	-3.65	-2.82	-1.89	-2.89	-1.88
50%	1.08	0.85	0.45	0.83	0.63	0.14	0.68	1.08	0.19	0.74
75%	3.87	3.93	4.21	4.43	4.50	3.30	4.18	3.58	3.17	2.97

Table 2.2: Economic Momentum: Country-Level Analysis

This table reports the results of regressing futures returns on weights derived from strategies with country and month fixed effects. The regression model is $r_{c,t} = \beta_0 + \beta_1 \Omega^P_{c,t-1} + \epsilon_{c,t}$, where where $r_{c,t}$ denotes excess return on country index futures c at month t. $\Omega^P_{c,t-1}$ is the lagged-one-period weights within portfolio P for futures c. The weights are cross-sectionally standardised each month. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. Standard errors are clustered by country and month, and T-statistics are reported within parentheses. Intercepts are not reported for brevity. The reported coefficients are in percentage. *, ** and *** indicate the relative parameters are significantly different from zero at the significance level of 10%, 5% and 1%. The sample period is from January 1989 to December 2020.

Dep. = Returns	1	2	3	4	5	6	7	8
Ω^{CM}	0.24**							
	(3.21)							
Ω^{LM}		0.13**		0.15**				
		(2.28)		(2.36)				
Ω^{SM}			0.28**	0.29**				
			(2.62)	(2.63)				
Ω^{ST}					0.11			-0.08
					(1.71)			(-0.80)
Ω^{MT}						0.27***		0.37**
						(3.46)		(2.60)
Ω^{LT}							0.20**	-0.07
							(2.73)	(-0.76)
No. of Obs.	2,944	2,944	2,944	2,944	2,944	2,944	2,944	2,944
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Within R^2(%)	0.53	0.14	0.49	0.67	0.13	0.72	0.35	0.78
Adj. Within R^2(%)	0.49	0.10	0.45	0.59	0.09	0.69	0.31	0.66

Table 2.3: Economic Momentum: Country-Level Analysis with Control Variables

This table reports the results of regressing futures returns on weights derived from strategies and control variables with country and month fixed effects. The regression model is $r_{c,t} = \beta_0 + \beta_1 \Omega^P_{c,t-1} + \lambda X' + \epsilon_{c,t}$, where where $r_{c,t}$ denotes excess return on country index futures c at month t. $\Omega^P_{c,t-1}$ is the lagged-one-period weights within portfolio P for futures c. The weights are cross-sectionally standardised each month. X' is the control variables, the global factors obtained from Kelly data library. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. Standard errors are clustered by country and month, and T-statistics are reported within parentheses. Intercepts are not reported for brevity. The reported coefficients are in percentage. *, ** and *** indicate the relative parameters are significantly different from zero at the significance level of 10%, 5% and 1%. The sample period is from January 1989 to December 2020.

Dep. = Returns	1	2	3	4	5	6	7	8
Ω^{CM}	**0.19*** **							
	(3.98)							
Ω^{LM}		0.12**		0.14**				
		(2.68)		(2.90)				
Ω^{SM}			0.19**	0.21**				
			(2.67)	(2.73)				
Ω^{ST}					0.08			-0.06
					(1.36)			(-0.78)
Ω^{MT}						0.21***		0.29**
						(4.59)		(2.79)
Ω^{LT}							0.16***	-0.04
							(3.33)	(-0.49)
accruals	-5.17	-5.16	-5.05	-5.05	-5.18	-5.16	-5.18	-5.14
	(-0.55)	(-0.55)	(-0.54)	(-0.54)	(-0.56)	(-0.55)	(-0.55)	(-0.55)
debt_issuance	-2.42	-2.56	-2.13	-2.40	-2.48	-2.20	-2.35	-2.01
	(-0.24)	(-0.25)	(-0.21)	(-0.24)	(-0.25)	(-0.22)	(-0.23)	(-0.20)
investment	-5.60	-5.34	-5.78	-5.74	-5.24	-5.69	-5.74	-5.83
	(-0.54)	(-0.51)	(-0.55)	(-0.55)	(-0.50)	(-0.55)	(-0.55)	(-0.57)
low_leverage	-16.96	-16.82	-16.65	-16.92	-16.87	-17.04	-16.74	-16.92
	(-0.94)	(-0.93)	(-0.92)	(-0.93)	(-0.92)	(-0.95)	(-0.92)	(-0.95)
low_risk	-57.52***	-57.88***	-57.24***	-57.39***	-57.65***	-57.48***	-57.64***	-57.47***
	(-5.00)	(-4.99)	(-4.97)	(-4.99)	(-4.99)	(-5.02)	(-4.99)	(-5.02)
momentum	1.37	1.53	1.41	1.39	1.44	1.42	1.43	1.48
	(0.34)	(0.38)	(0.36)	(0.35)	(0.35)	(0.35)	(0.35)	(0.37)
profit_growth	-10.56	-10.60	-10.55	-10.74	-10.44	-10.66	-10.54	-10.70
	(-1.41)	(-1.45)	(-1.41)	(-1.44)	(-1.41)	(-1.42)	(-1.42)	(-1.43)
profitability	25.54*	26.09*	25.33*	25.33*	25.68*	25.71*	25.70*	25.97*
	(2.03)	(2.07)	(1.99)	(2.00)	(2.03)	(2.05)	(2.05)	(2.10)
quality	-50.85***	-51.30***	-51.18***	-50.70***	-51.30***	-50.76***	-51.16***	-50.89***
	(-5.86)	(-5.89)	(-5.90)	(-5.85)	(-5.89)	(-5.88)	(-5.88)	(-5.93)
seasonality	-0.42	-0.37	-0.16	-0.32	-0.38	-0.76	-0.12	-0.84
	(-0.03)	(-0.03)	(-0.01)	(-0.03)	(-0.03)	(-0.06)	(-0.01)	(-0.07)
short_term_reversal	5.48	5.80	5.43	5.36	5.51	5.32	5.79	5.41
	(1.08)	(1.14)	(1.08)	(1.06)	(1.10)	(1.05)	(1.14)	(1.07)
size	-10.59	-10.27	-10.85	-10.75	-10.38	-10.60	-10.59	-10.62
	(-1.65)	(-1.60)	(-1.69)	(-1.68)	(-1.61)	(-1.66)	(-1.64)	(-1.68)
value	8.55	8.80	8.69	8.59	8.75	8.58	8.66	8.63
	(0.74)	(0.77)	(0.76)	(0.75)	(0.76)	(0.75)	(0.76)	(0.76)
No. of Obs.	2,944	2,944	2,944	2,944	2,944	2,944	2,944	2,944
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES
Within R^2(%)	20.91	20.69	20.82	20.96	20.65	21.02	20.81	21.06
Adj. Within R^2(%)	20.48	20.26	20.39	20.50	20.22	20.59	20.38	20.56

Table 2.4: Economic Momentum: Portfolio Analysis

This table reports the results of analysing portfolios constructed on economic momentum signals. Panel A reports portfolio returns' statistics, including mean, standard deviation, skewness, excess kurtosis, one-order autocorrelation, maximum drawdown and Sharpe ratio. Panel B reports correlations between these portfolios. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. We aggregate substrategies based on their inverse volatility in this table while we also consider the equal-weighted methodology, see table 2.14 in the appendix. The sample period is selected from February 1992 to December 2020 for the consistency of the economic momentum portfolio periods.

	CM	PM	NM	ST	MT	LT
Panel A: Portfolio Performance						
Mean(%)	3.60	3.68	3.03	2.18	4.64	3.16
Std(%)	4.13	7.52	7.53	5.50	4.83	4.80
Skew	0.58	0.10	-0.03	-0.20	0.91	0.35
Excess Kurtosis	1.02	-1.39	-1.47	3.43	2.71	-0.16
AR(1)	0.07	0.19	0.06	0.02	0.08	0.00
Max. Drawdown(%)	-6.53	-24.72	-20.86	-19.08	-5.43	-9.36
Sharpe Ratio	0.87	0.49	0.40	0.40	0.96	0.66
Panel B: Correlation						
CM	1.00					
PM	0.57	1.00				
NM	0.54	-0.37	1.00			
ST	0.65	0.41	0.31	1.00		
MT	0.95	0.55	0.50	0.56	1.00	
LT	0.88	0.47	0.50	0.29	0.76	1.00

Table 2.5: Benchmarks: Portfolio Analysis

This table reports the results of comparing economic momentum portfolios and benchmarks. Panel A reports portfolio returns' statistics, including mean, standard deviation, skewness, excess kurtosis, one-order autocorrelation, maximum drawdown and Sharpe ratio. Panel B reports correlations between these portfolios. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. We construct benchmarks to compare our findings. The passive investment (Mkt-Rf) is to buy and hold the MSCI world index over a one-month treasury bill. The time-series momentum portfolio (TSMOM) trades securities according to the macro indices 12-month cumulative returns (Moskowitz et al. 2012). Likewise, value (VAL) and momentum (MOM) buy-sell assets toward relative book values and relative 12-month cumulative returns. Value and momentum (VMOM) is the sum of a half VAL and a half MOM (Asness et al. 2013). TSMOM_ARQ, VAL_ARQ, MOM_ARQ and VMOM_ARQ are similar portfolios as above but employ the original factor data from the AQR. See 2.3.2 for details of benchmarks construction. The sample period is from February 1995 to December 2020 due to data points availability of benchmarks.

	CM	PM	NM	ST	MT	LT	Mkt-Rf	TSMOM	MOM	VAL	VMOM	VAL_AQR	MOM_AQR	VMOM_AQR	TSMOM_AQR
Panel A: Portfolio Performance															
Sharpe Ratio	**0.93**	0.63	0.37	0.48	**1.01**	0.76	0.24	0.05	-0.02	0.21	0.13	-0.10	0.34	0.34	**0.45**
Mean(%)	**3.95**	4.64	2.78	2.34	**4.93**	3.66	3.59	1.37	-0.19	1.66	0.94	-0.81	3.37	1.58	**12.10**
Std(%)	**4.24**	7.32	7.49	4.87	**4.89**	4.82	15.19	28.40	11.49	7.79	7.41	8.49	9.81	4.66	**27.18**
Maximum Drawdown(%)	**-6.53**	-22.64	-20.86	-19.08	**-5.43**	-9.36	-59.78	-73.70	-59.96	-26.23	-25.76	-49.92	-16.67	-20.53	-71.91
Skew	0.68	0.45	-0.16	-0.40	1.09	0.42	-0.68	0.38	-0.01	0.04	0.00	0.09	-0.29	0.24	-0.24
Excess Kurtosis	1.14	-2.35	-1.76	1.05	3.19	0.09	-1.33	0.57	-1.81	-2.61	-2.11	-1.37	-0.36	-0.72	-2.03
AR(1)	0.11	0.17	0.02	0.12	0.12	0.02	0.09	-0.15	0.09	-0.04	-0.01	0.12	0.05	0.01	0.11
Panel B: Correlation Between Portfolios															
CM	1.00														
PM	0.59	1.00													
NM	0.57	-0.31	1.00												
ST	0.64	0.42	0.33	1.00											
MT	0.95	0.57	0.53	0.56	1.00										
LT	0.91	0.50	0.55	0.35	0.79	1.00									
Mkt-Rf	-0.19	0.08	-0.34	-0.11	-0.15	-0.21	1.00								
TSMOM	0.10	-0.08	0.21	-0.01	0.12	0.11	-0.24	1.00							
MOM	0.26	0.16	0.14	0.00	0.26	0.30	-0.21	0.25	1.00						
VAL	0.18	0.31	-0.05	-0.02	0.13	0.27	-0.14	0.11	0.15	1.00					
VMOM	0.29	0.29	0.08	-0.01	0.27	0.37	-0.23	0.25	0.85	0.64	1.00				
VAL_AQR	-0.23	-0.19	-0.11	-0.04	-0.19	-0.29	0.33	-0.16	-0.31	-0.48	-0.49	1.00			
MOM_AQR	0.18	0.13	0.08	-0.02	0.14	0.27	-0.23	0.18	0.53	0.22	0.53	-0.49	1.00		
VMOM_AQR	-0.02	-0.04	-0.01	-0.05	-0.03	0.02	0.06	0.04	0.28	-0.21	0.11	0.40	0.61	1.00	
TSMOM_AQR	0.13	0.08	0.07	0.05	0.14	0.14	0.10	0.34	0.33	0.05	0.28	-0.01	0.35	0.36	1.00

Table 2.6: Benchmarks: Country-Level Regression Analysis

This table reports the results of regressing excess futures returns on weights derived from strategies with country and month fixed effects. The regression model is $r_{c,t} = \beta_0 + \beta_1 \Omega^P_{c,t-1} + \lambda X' + \epsilon_{c,t}$, where where $r_{c,t}$ denotes excess return on country index futures c at month t. $\Omega^P_{c,t-1}$ is the lagged-one-period weights within portfolio P for futures c. The weights are cross-sectionally standardised each month. X' is the control variables, the global factors obtained from Kelly data library. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. We construct benchmarks to compare our findings. The time-series momentum portfolio (TSMOM) trades securities according to the macro indices 12-month cumulative returns (Moskowitz et al. 2012). Likewise, value (VAL) and momentum (MOM) buy-sell assets toward relative book values and relative 12-month cumulative returns. Value and momentum (VMOM) is the sum of a half VAL and a half MOM (Asness et al. 2013). See 2.3.2 for details of benchmarks construction. The reported coefficients are in percentage. Intercepts are not reported for brevity. Standard errors are clustered by country and month, and T-statistics are reported within parentheses. *, ** and *** indicate the relative parameters are significantly different from zero at the significance level of 10%, 5% and 1%. The sample period is from February 1995 to December 2020 due to data points availability of benchmarks.

Dep = Returns	1	2	3	4	5	6	7	8	9	10
Ω^{CM}	0.24***	0.18***								
	(3.01)	(3.73)								
Ω^{VAL}			-1.68**	-1.21*						
			(-2.11)	(-1.86)						
Ω^{MOM}					-0.05	0.10				
					(-0.19)	(0.37)				
Ω^{VMOM}							-0.44	-0.09		
							(-0.96)	(-0.19)		
Ω^{TSMOM}									-0.01	0.01
									(-0.13)	(0.27)
No. of Obs.	2,564	2,564	2,564	2,564	2,564	2,564	2,564	2,564	2,564	2,564
Adj. R^2(%)	0.56	22.30	0.35	22.15	0.00	21.98	0.06	21.98	0.00	21.98
Country Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Month Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Control X	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Table 2.7: Benchmarks: Explaining Economic Momentum

This table reports the results of regressing economic momentum portfolio returns on benchmark returns. The regression model is $ret_t^{CM} = \alpha + \beta \cdot ret_t^P + \epsilon_t$. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. We construct benchmarks to compare our findings. The passive investment (Mkt-Rf) is to buy and hold the MSCI world index over a one-month treasury bill. The time-series momentum portfolio (TSMOM) trades securities according to the macro indices 12-month cumulative returns (Moskowitz et al. 2012). Likewise, value (VAL) and momentum (MOM) buy-sell assets toward relative book values and relative 12-month cumulative returns. Value and momentum (VMOM) is the sum of a half VAL and a half MOM (Asness et al. 2013). TSMOM_ARQ, VAL_ARQ, MOM_ARQ and VMOM_ARQ are similar portfolios as above but employ the original factor data from the AQR. See 2.3.2 for details of benchmarks construction. To adjust for serial correlation, the t-statistics, reported in parentheses, are based on Newey & West (1987) standard errors with the six lags. *, ** and *** indicate the relative parameters are significantly different from zero at the significance level of 10%, 5% and 1%. The sample period is from February 1995 to December 2020 due to data points availability of benchmarks.

Dep = CM	1	2	3	4	5	6	7	8	9	10
Intercept	0.34***	0.32***	0.32***	0.31***	0.31***	0.32***	0.30***	0.33***	0.30***	**0.31*****
	(4.52)	(4.14)	(4.22)	(4.13)	(4.29)	(4.30)	(3.96)	(4.31)	(4.08)	**(4.36)**
Mkt-Rf	-5.22**									-3.81**
	(-2.50)									(-2.26)
TSMOM		1.56								-0.45
		(1.52)								(-0.61)
MOM			9.25**							4.42
			(2.47)							(1.35)
VAL				9.81**						2.65
				(2.42)						(0.74)
VMOM					16.50***					3.53
					(3.27)					(1.62)
VAL_AQR						-11.71***				-5.10
						(-3.38)				(-1.44)
MOM_AQR							7.95***			-0.63
							(3.23)			(-0.28)
VMOM_AQR								-1.55		-2.87*
								(-0.27)		(-1.67)
TSMOM_AQR									2.10*	1.95**
									(1.69)	(2.13)
Adj R^2 (%)	3.08	0.75	5.91	2.97	8.00	4.89	2.91	-0.30	1.45	9.44
No. of Obs.	305	305	305	305	305	305	305	305	305	305

Table 2.8: Benchmarks: Explaining them with Economic Momentum

This table reports the results of regressing benchmark returns on economic momentum portfolio returns. The model is $ret_t^P = \alpha + \beta \cdot ret_t^{CM} + \epsilon_t$. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. We construct benchmarks to compare our findings. The passive investment (Mkt-Rf) is to buy and hold the MSCI world index over a one-month treasury bill. The time-series momentum portfolio (TSMOM) trades securities according to the macro indices 12-month cumulative returns (Moskowitz et al. 2012). Likewise, value (VAL) and momentum (MOM) buy-sell assets toward relative book values and relative 12-month cumulative returns. Value and momentum (VMOM) is the sum of a half VAL and a half MOM (Asness et al. 2013). TSMOM_ARQ, VAL_ARQ, MOM_ARQ and VMOM_ARQ are similar portfolios as above but employ the original factor data from the AQR. See 2.3.2 for details of benchmarks construction. To adjust for serial correlation, the t-statistics, reported in parentheses, are based on Newey & West (1987) standard errors with the six lags. *, ** and *** indicate the relative parameters are significantly different from zero at the significance level of 10%, 5% and 1%. The sample period is from February 1995 to December 2020 due to data points availability of benchmarks.

	Mkt-Rf	TSMOM	MOM	VAL	VMOM	VAL_AQR	MOM_AQR	VMOM_AQR	TSMOM_AQR
Intercept	0.54**	0.25	-0.18	0.06	-0.06	0.09	0.21	0.15**	1.07**
	(2.13)	(0.70)	(-0.86)	(0.40)	(-0.54)	(0.60)	(1.39)	(1.97)	(2.06)
CM	-65.09**	69.12	67.16***	33.54**	50.35***	-44.42**	40.63***	-1.90	84.82**
	(-2.07)	(1.48)	(3.18)	(2.08)	(3.40)	(-2.53)	(3.62)	(-0.26)	(2.07)
Adj. R^2 (%)	3.08	0.75	5.91	2.97	8.00	4.89	2.91	0.00	1.45
No. of Obs.	305	305	305	305	305	305	305	305	305

Table 2.9: Further Analysis: Standard Asset Pricing Factor Models

The table presents the explanation power of standard pricing factors on the economic momentum combo portfolio. The regression model is $ret_t^{CM} = \alpha + \lambda F_t'^X + \epsilon_t$, where ret is the returns on the economic momentum portfolio (CM) and $F_t'^X$ is the factors F of the factor model X. Standard asset pricing factor models we examine include the Fama-French Three Factor (FF3) Fama & French (1993), Fama-French Five Factor (FF5) (Fama & French 2015), q-factors (q-5) (Hou et al. 2021) and theme factors in the world (World Factors) (Jensen et al. 2023). FF3 contains market risk premium, size and value factors, and FF5 adds profitability and investment to FF3. The q5 model requires market, size, investment, ROE and expected growth factors. World Factors include themes of accruals, debt insurance, investment, low leverage, low risk, momentum, profit growth, profitability, quality, seasonality, short-term reversal, size and value. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. To adjust for serial correlation, the t-statistics, reported in parentheses, are based on Newey & West (1987) standard errors with the six lags. *, ** and *** indicate the relative parameters are significantly different from zero at the significance level of 10%, 5% and 1%. The sample period is from February 1995 to December 2020 due to data points availability of benchmarks.

	FF3	FF5	q-5	World Factors
Intercept	**0.36***** **(4.94)**	**0.39***** **(5.35)**	**0.32***** **(5.36)**	**0.34***** **(4.13)**
Mkt-Rf	-5.58*** (-2.75)	-6.31*** (-3.48)	-1.53 (-0.55)	
SMB	-4.11 (-1.20)	-4.98 (-1.36)		
HML	0.24 (0.09)	0.37 (0.08)		
RMW		-5.87 (-0.90)		
CMA		1.63 (0.23)		
R_EG			3.76 (0.66)	
R_IA			1.46 (0.38)	
R_ME			-0.67 (-0.35)	
R_ROE			-0.74 (-0.18)	
accruals				-24.23* (-1.89)
debt_issuance				-31.67 (-1.42)
investment				42.40*** (3.67)
low_leverage				40.23* (1.70)
low_risk				15.00* (1.91)
momentum				3.50 (0.53)
profit_growth				2.88 (0.23)
profitability				57.72*** (3.57)
quality				-54.41*** (-2.89)
seasonality				-8.02 (-0.40)
short_term_reversal				3.90 (0.63)
size				22.24*** (2.62)
value				-23.84 (-1.24)
Adj R^2 (%)	3.80	3.69	0.00	10.34
No. of Obs.	310	308	311	311

Table 2.10: Further Analysis: Decomposition

The table presents the descriptive summary of economic momentum portfolio returns decomposition towards the country, including annualised means in percentage with its T-statistics, annualised standard deviation, skewness, excess kurtosis, the first-order-autocorrelation, the maximum drawdown and Sharpe ratios. Standard errors are adjusted based on Newey & West (1987) with six lags. The economic momentum portfolio combines all the 120 sub-strategies. The sample period is from January 1989 to December 2020.

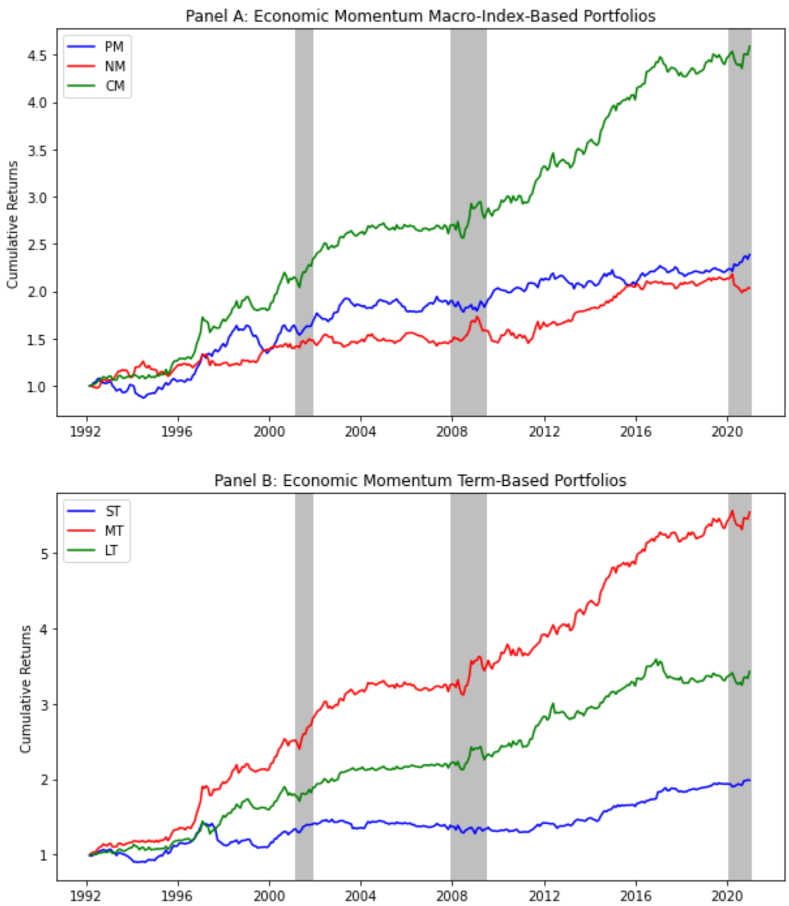
	Australia	Canada	France	Germany	Italy	Japan	Sweden	Switzerland	United Kingdom	United States
Mean(%)	0.08	-0.15	0.31	0.45	0.42	0.59	-0.18	0.85	0.45	0.56
T-Stat. of Mean	1.34	-0.05	-0.60	1.09	0.93	0.42	-0.54	1.03	0.95	-0.41
Std(%)	1.53	3.07	2.37	2.43	3.13	2.42	2.47	3.11	2.74	2.22
Skew.	0.05	-0.20	0.13	-0.09	0.09	0.78	-0.98	-0.05	0.34	-1.03
Excess Kurtosis	3.85	2.94	2.33	0.71	1.52	17.40	2.09	0.68	1.55	7.86
AR(1)	-0.07	0.16	-0.05	-0.06	0.13	0.14	-0.01	0.11	-0.01	0.02
Max. Drawdown(%)	-4.68	-18.05	-10.02	-10.40	-12.66	-7.65	-14.64	-21.17	-13.49	-10.90
Sharpe Ratio	0.05	-0.05	0.13	0.18	0.13	0.24	-0.07	0.27	0.16	0.25

Table 2.11: Further Analysis: Economic Momentum Effects in Other Markets

Based on MSCI country indices, this table summarises the predictability and profitability of the economic momentum effects, represented by the economic momentum combo portfolio, in the selected markets in this paper, G10, developed, and emerging markets. According to OECD, members of G10 are Belgium, Canada, France, Germany, Italy, Japan, Netherlands, Sweden, Switzerland, the United Kingdom and the United States. Developed markets are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom and the United States. Emerging markets are Brazil, Chile, China, Colombia, Czech Republic, Greece, Hungary, India, Indonesia, Poland, Russia, South Africa, South Korea and Turkey. Panel A presents annualized mean return in percentage, annualized standard deviation, skewness, excess kurtosis, lagged-one-period autocorrelation (AR(1)), maximum drawdown and Sharpe ratio for the economic momentum combo (CM) portfolios in different market groups. Panel B reports the results of regressing equity index returns on the lagged weights derived from the momentum signals within CM. The model is $ret_{c,t} = \alpha + \beta\Omega_{c,t-1} + \epsilon_{c,t}$, where $ret_{c,t}$ is the equity index return for country c at month t. $\Omega_{c,t-1}$ is the weight for country c, developed on the momentum signals of the economic momentum combo portfolio. Both country and month fixed effects are included in the regressions. Standard errors are clustered by country and month, and T-statistics are reported within parentheses. *, ** and *** indicate the relative parameters are significantly different from zero at the significance level of 10%, 5% and 1%. This table is based on MSCI market indices obtained from Bloomberg. The sample period is from January 1989 to December 2020.

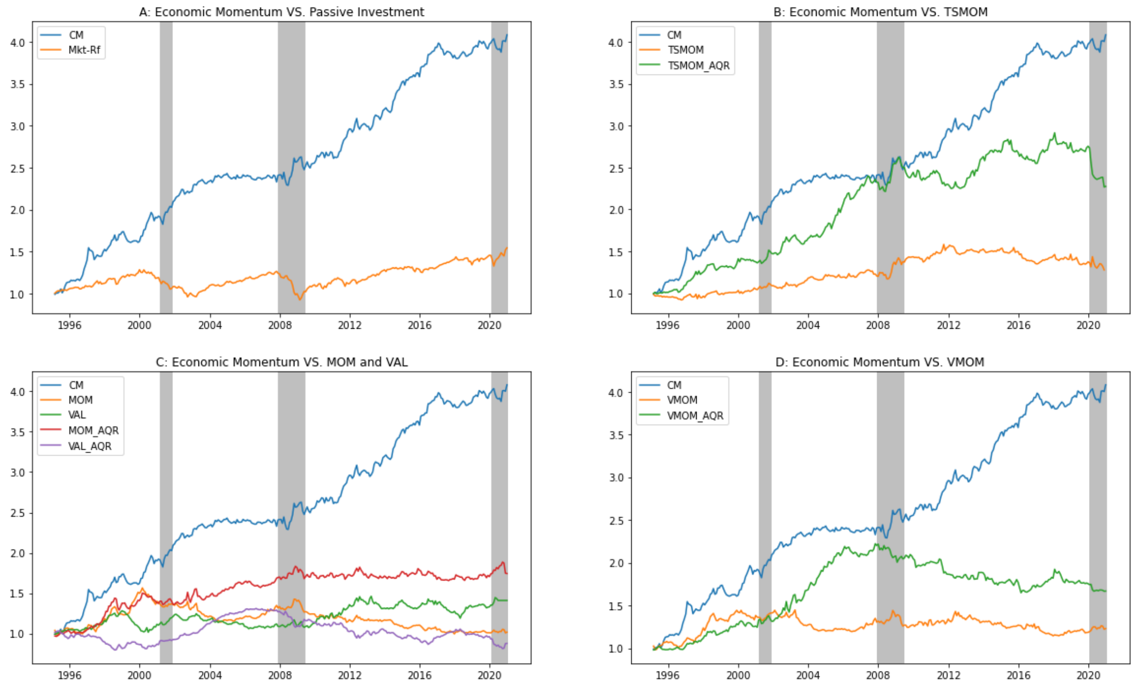
	Selected Markets	G10	Developed	Emerging
Panel A: Portfolio Performance				
Mean(%)	3.27	2.48	1.49	7.35
Std(%)	3.91	3.78	3.57	14.48
Skew.	0.52	0.54	0.23	0.39
Excess Kurtosis	0.01	0.74	-1.11	2.79
AR(1)	-0.01	-0.06	-0.08	-0.07
Max. Drawdown(%)	-6.04	-7.61	-12.30	-34.70
Sharpe Ratio	0.84	0.66	0.42	0.51
Panel B: Regression Analysis				
Ω^{CM}	0.24***	0.18***	0.14**	0.72***
	(3.18)	(2.72)	(2.43)	(4.04)
No. of Obs.	2,946	3,402	6,376	3,162
Adj. Within R^2 (%)	0.14	19.34	21.30	18.52
Country Fixed Effect	YES	YES	YES	YES
Month Fixed Effect	YES	YES	YES	YES

2.8 Figures



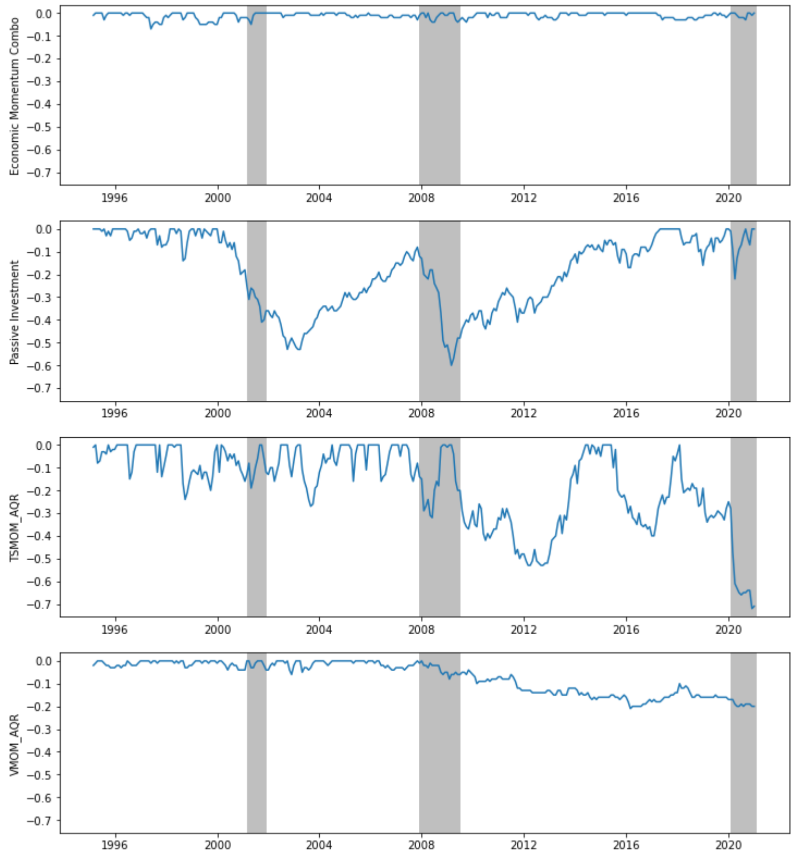
The figure plots the cumulative returns of economic momentum portfolios. Note that all portfolio returns are scaled to the same annualised volatility of 6%, the average volatility across portfolios. We scale them to make their returns comparable. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. Shaded bars indicate the NBER recession periods. The sample period is selected from February 1992 to December 2020 for the consistency of the economic momentum portfolio periods.

Figure 2.1: Cumulative Returns of Economic Momentum Portfolios



The figure plots the cumulative returns of economic momentum combo and benchmark portfolios. Note that all portfolio returns are scaled to the same annualised volatility of 6%, the average volatility across portfolios. We scale them to make their returns comparable. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. We construct benchmarks to compare our findings. The passive investment (Mkt-Rf) is to buy and hold the MSCI world index over a one-month treasury bill. The time-series momentum portfolio (TSMOM) trades securities according to the macro indices 12-month cumulative returns (Moskowitz et al. 2012). Likewise, value (VAL) and momentum (MOM) buy-sell assets toward relative book values and relative 12-month cumulative returns. Value and momentum (VMOM) is the sum of a half VAL and a half MOM (Asness et al. 2013). TSMOM_ARQ, VAL_ARQ, MOM_ARQ and VMOM_ARQ are similar portfolios as above but employ the original factor data from the AQR. See 2.3.2 for details of benchmarks construction. Shaded bars indicate the NBER recession periods. The sample period is from February 1995 to December 2020 due to data points availability of benchmarks.

Figure 2.2: Economic Momentum Vs. Benchmarks: Cumulative Returns



The figure plots the time-varying economic combo and benchmark portfolios drawdown. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. We construct benchmarks to compare our findings. The passive investment (Mkt-Rf) is to buy and hold the MSCI world index over a one-month treasury bill. The time-series momentum portfolio (TSMOM) trades securities according to the macro indices 12-month cumulative returns (Moskowitz et al. 2012). Likewise, value (VAL) and momentum (MOM) buy-sell assets toward relative book values and relative 12-month cumulative returns. Value and momentum (VMOM) is the sum of a half VAL and a half MOM (Asness et al. 2013). TSMOM_ARQ, VAL_ARQ, MOM_ARQ and VMOM_ARQ are similar portfolios as above but employ the original factor data from the AQR. See 2.3.2 for details of benchmarks construction. Shaded bars indicate the NBER recession periods. The sample period is from February 1995 to December 2020 due to data points availability of benchmarks.

Figure 2.3: Economic Momentum Vs. Benchmarks: Drawdown

A Appendix

Table 2.12: Appendix: 12-month Log Growth on Macro Index and Equity Index Futures Returns

This table reports the relationship between futures returns and macro index 12-month log growth. Macro Index A is the average log growth of the consumer price index, producer price index and total manufacturing. Macro Index B is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production.

	1	2	3
Macro Index A	0.27		1.20
	(0.05)		(0.21)
Macro Index B		-3.88	-4.61
		(-0.84)	(-1.13)
No. of Obs.	3,729	3,729	3,729
R^2(%)	0.00	0.01	0.01
Country Fixed Effects	YES	YES	YES
Month Fixed Effects	YES	YES	YES

Table 2.13: Appendix: Country-Level Fama-MacBeth Regression Analysis

This table reports the results of regressing futures returns on weights derived from strategies with Fama-MacBeth regression. The regression model is $r_{c,t} = \beta_0 + \beta_1 \Omega^P_{c,t-1} + \epsilon_{c,t}$, where where $r_{c,t}$ denotes excess return on country index futures c at month t. $\Omega^P_{c,t-1}$ is the lagged-one-period weights within portfolio P for futures c. The weights are cross-sectionally standardised each month. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. To adjust for serial correlation, the t-statistics, reported in parentheses, are based on Newey & West (1987) standard errors with the six lags. Intercepts are not reported for brevity. The reported coefficients are in percentage. *, ** and *** indicate the relative parameters are significantly different from zero at the significance level of 10%, 5% and 1%. The sample period is from January 1989 to December 2020.

Dep. = Futures Returns	1	2	3	4	5	6
Ω^{CM}	0.24***					
	(4.68)					
Ω^{LM}		0.15**				
		(2.29)				
Ω^{SM}			0.14**			
			(2.23)			
Ω^{ST}				0.13**		
				(2.05)		
Ω^{MT}					0.27***	
					(5.31)	
Ω^{LT}						0.20***
						(3.87)
Intercept	0.36	0.37	0.37	0.37	0.36	0.37
	(1.32)	(1.33)	(1.32)	(1.33)	(1.32)	(1.32)
No. of Obs.	2,944	2,944	2,944	2,944	2,944	2,944
Number of Groups	347	347	347	347	347	347
Avg. R^2(%)	13.25	15.09	15.99	14.62	13.56	13.38

Table 2.14: Appendix: Economic Momentum Portfolio Analysis (Equal-Weighted)

This table reports the results of analysing portfolios constructed on economic momentum signals. Panel A reports portfolio returns' statistics, including mean, standard deviation, skewness, excess kurtosis, one-order autocorrelation, maximum drawdown and Sharpe ratio. Panel B reports correlations between these portfolios. The construction of economic momentum portfolios is based on lookback periods of momentum signals and macro indices. We measure the momentum with lookback periods varying from 1 to 60 months. The positive macro effect index is the average log growth of the consumer price index, producer price index and total manufacturing. The negative macro effect index is the average log growth of the OECD leading indicator, hourly earnings and gross domestic production. We then design a sub-strategy that buys (sells) one country index based on its relatively strong (weak) momentum signals. With 60 lookback periods and 2 macro indices, we have 120 sub-strategies. The economic momentum combo portfolio (CM) combines all the sub-strategies above. The positive macro effect portfolio (PM) aggregates sub-strategies trading on momentum signals derived from the positive macro effect index with all lookback periods. Likewise, the negative macro effect portfolio (NM) aggregates sub-strategies constructed on the negative macro effect index. The long-term (LT), mid-term (MT) and short-term (ST) portfolio aggregates sub-strategies built on lookback periods varying between 1-12, 13-36 and 37-60 months, respectively, ignoring the macro index. **We aggregate substrategies in an equal-weighted way.** The sample period is selected from February 1992 to December 2020 for the consistency of the economic momentum portfolio periods.

	CM	PM	NM	ST	MT	LT
Panel A: Portfolio Performance						
Mean(%)	3.37	3.52	2.81	2.78	3.32	3.83
Std(%)	4.21	7.52	7.61	8.84	8.48	7.77
Skew	0.63	0.11	-0.03	-0.17	-0.06	0.41
Excess Kurtosis	0.74	-1.35	-1.43	-0.10	-1.26	-1.85
AR(1)	0.08	0.20	0.06	0.14	0.16	0.18
Max. Drawdown(%)	-6.35	-24.72	-21.58	-36.49	-27.96	-24.07
Sharpe Ratio	0.80	0.47	0.37	0.31	0.39	0.49
Panel B: Correlation						
LM	1.00					
PM	0.55	1.00				
NM	0.56	-0.38	1.00			
ST	0.39	0.76	-0.32	1.00		
MT	0.53	0.97	-0.37	0.72	1.00	
LT	0.53	0.91	-0.31	0.47	0.83	1.00

Chapter 3

Attention Spillover: Lottery Speculation After Macro Announcements

3.1 Introduction

If the Federal Open Market Committee (FOMC) releases an interest rate decision to the public, how do investors allocate their attention surrounding the announcement? Do they digest market-wide information first and react sluggishly to firm-specific news? Inspired by the implication of price inefficiency resulting from higher noise trading when more public information is available (Han et al. 2016), we study how noise traders respond to macro-announcements.[1]

We focus on how noise traders respond to macro-announcements and aim to shed light on the impact of these announcements on investor attention and subsequent trading decisions. By analysing the market and firm-level information surrounding macro-announcements, we aim to uncover new insights into the dynamics of noise trading and its impact on market efficiency. Our findings have important implications for market participants and policymakers by providing insights into how public information is processed and traded in financial markets. Additionally, our research contributes to the broader literature on market efficiency, noise trading, and macro-announcement role in shaping investor attention and behaviour.

Our findings are threefold. First, we document attention spillover effects among noise traders, i.e., their attention on macro-announcement days spreads from the market to the individual firms during post-macro-announcement periods.[2] With indirect proxies capturing their attention, we demonstrate that macro-announcements' arrival significantly impacts noise traders' trading activities. Specifically, market returns that capture macro-announcements positively predict cumulative abnormal

[1]Han et al. (2016) suggests that informed traders trade stocks based on the information before it is publicly available, stimulating the stock price by incorporating such information and promoting price efficiency. In contrast, noise traders tend to drive prices away from their fundamental value, and thus they are uninformed. Throughout the paper, we use the terms "noise traders", "uninformed traders", and "late-informed traders" interchangeably.

[2]In this paper, we use the terms "macro-news", "macro-events", and "macro-announcements" interchangeably to describe events at the macro level, such as FOMC announcements. Similarly, we use the terms "macro-news days", "macro-announcement days", and "macro-event days" interchangeably to refer to days when these macro events are announced.

returns on noise traders' preferred stocks during post-macro-announcement periods. This predictability is both statistically and economically significant at the 1% level, challenging the market efficiency theories. Stocks favoured by noise traders have a 98.75% greater post-macro-announcement reaction than the other stocks to macro-news-day market returns. A long-short portfolio constructed based on this earns 15.81% per annum. Second, we find that the higher the market-level attention on macro-announcement days, the more attention the noise traders pay to stocks during the post-macro-announcement periods with direct proxies introduced by Da et al. (2011) and Ben-Rephael et al. (2017). In addition, we find that retail and institutional noise traders exhibit abnormal attention to stocks during post-macro-announcement periods. Third, we find that the attention spillover effects are more pronounced among firms without earnings announcements. Splitting the sample into an announcing subsample (firms with earnings announcements) and a non-announcing subsample (firms without earnings announcements), we find that the attention spillover effects are significant among the latter subsample. In particular, reactions of stocks preferred by noise traders to macro-news-day market returns are 101.01% stronger than stocks favoured by others, conditioning in the stocks without earnings announcements. Meanwhile, we find no significant evidence suggesting the existence of the effects among the announcing subsample.

There is growing interest in how investors pay attention to the entire stock universe in the market sparks.[3] These studies seem intuitive, while the role of noise traders is barely mentioned. Therefore, a natural extension of the literature is to discuss how noise traders respond to macro-announcements' arrival. We then raise a question: when a macro-announcement is released, are investors (especially noise traders) attentive to the macro-news and, therefore, reallocate their attention from

[3]Macro news distracts investors' attention from the micro news, delaying the market prices of incorporation on micro news, denoted as the *crowd-out effects*(Merton 1987, Peng & Xiong 2006). Arguing with that, Hirshleifer & Sheng (2022) document that the macro news stimulates that incorporation, termed the *crowd-in effects*.

the market-level information to the cross-section of individual stocks? If so, how would the investors react after the macro-announcements? Answering these questions by allowing the participation of noise traders will be crucial to understanding market frictions when important information arrives in the market and subsequent asset pricing implications.

Given the importance of the macro news's informational role, it is less disputed that investors' attention would be drawn to the aggregate-level information when the macro news arrives (Merton 1987, Peng & Xiong 2006, Hirshleifer & Sheng 2022). Since noise traders are unaware of the content of macroeconomic news in advance, disclosing such news can potentially update their trading beliefs concerning stocks. If so, their market-concentrated attention likely spills over to individual stocks during the post-macro-announcement period. Therefore, it is essential to understand and examine the asset pricing implications during the post-macro-announcement periods. Collecting these together, we make the first hypothesis. There is attention spillover from the market to the cross-sectional firms, which would drive those stocks traded by the noise traders during the post-macro-announcement periods.

We explore the impact of firm-level earnings information on noise traders' attention allocation surrounding macro-announcements. Prior research by Liu et al. (2020) suggests that noise traders, who we link to lottery-like stocks below, are more attentive to stocks ahead of earnings announcements. Building on the theory that firm-level earnings information is fully incorporated when macro-announcements are made (Hirshleifer & Sheng 2022), we surmise that noise traders are attentive to announcing firms (firms with earnings announcement coverage) before macro-announcements. Furthermore, the literature suggests that market-level uncertainty accumulates as macro-announcements approach (Hu et al. 2022), which would attract investor attention to announcing firms (Andrei et al. 2023). To this end, from the perspective of either incorporating earnings information or resolving uncertainty, previous research indicates that noise traders are more attentive to announcing firms before macro-announcements. However, where is their attention after macro-announcements? Since the uncertainty is resolved after macro-announcements Hu et al. (2022), and earnings information is fully incorporated (Hirshleifer & Sheng 2022), it is unlikely that noise traders will remain attentive to announcing firms. Alternatively, they might be attentive to non-announcing firms (firms without earnings announcement coverage). Therefore, if the first hypothesis about the attention spillover effects is true, we then make the second hypothesis: the attention spillover effects are more pronounced among non-announcing firms.

Aside from the above hypotheses, we define the clientele of noise traders by utilising lottery-like features documented previously in the literature for three reasons.[4] First, the noise traders have preferences for lottery-like stocks. Peress & Schmidt (2020) suggest that the noise traders seek lottery-like portfolio returns, leading to holding concentrated portfolios and forgoing diversification benefits. Second, assets traded by lottery buyers and noise traders have similar reversal patterns. The higher level of the lottery-like feature a stock has, the lower its return in the future, since lottery-preferred investors are willing to pay more for stocks with higher lottery features (Bali et al. 2011). Similarly, assets traded by the noise traders tend to have subsequent reversals due to their actively buying and selling (Barber et al. 2008). Third, negative impacts on price efficiency and high limits to arbitrage. Noise traders are defined as the clientele that negatively impacts the stock price efficiency by driving stock prices away from their fundamental value (Han et al. 2016). As for lottery-like stocks, they are generally over-valued (Bali et al. 2011, Conrad et al. 2014, Liu et al. 2020). Moreover, both noise traders and lottery buyers face high limits to arbitrage, such as high costs for initialling a transaction and holding position (Han & Kumar 2013). Taking these together, we employ lottery-like stocks as the stocks favoured by noise traders.

Given the characteristics of the lottery-like stocks, we employ the following prox-

[4]Similar to the lottery, lottery-like stocks exhibit a relatively tiny probability of winning a considerable reward (Kumar 2009).

ies. (i) Low price: lottery-like stocks exhibit a characteristic of relatively low price with high potential payoff (Kumar 2009). (ii) High idiosyncratic volatility (IVOL): the payoff of such stocks is very risky, showing extremely high variance (Kumar 2009). (iii) High idiosyncratic skewness (SKEWEXP): they have a relatively small chance of huge profits, showing a payoff distribution with a positive skewness (Boyer et al. 2010). (iv) Extreme daily payoff (MAX): stocks with the most recent extreme daily payoff exhibit lower returns in the future (Bali et al. 2011). Since stocks' price signals vary with these investors, we follow Liu et al. (2020) and employ the (v) ZSCORE, the average individual z-scores on the above price signals, to capture such a stock collection. We then sort all stocks into ten deciles based on the price signals at the most recent month's end. The bottom decile exhibits the most-lottery-like feature, while the top decile shows the least.

We construct the following variables: (1) *Lottery* capturing lottery features represented by ZSCORE (2) Mkt is the CRSP value-weighted market returns, capturing the market-level information; (3) a dummy variable $EA[-1, 1]$ indicating whether a stock has an earnings announcement within a window from one day ahead to one day after a macro event; (4) cumulative abnormal return (CAR), risk-adjusted by the market model for measuring stock response to a macro-announcement by following Hirshleifer & Sheng (2022). Precisely, stock responses to a macro-announcement within pre-, during- and post-period are quantified as $CAR[-5, -1]$, $CAR[0, 1]$ and $CAR[2, 6]$.[5]

Initially, we examine the lottery stocks' performance surrounding the macro-news days by analysing portfolios sorting CAR on lottery features, ZSCORE. Results show that such stocks have strong performance ahead of macro events but no significant reactions after the announcements. Together with our empirical results and the fact that the lottery stocks are "attention-grabbing" stocks (Kumar 2009), we surmise that noise traders' attention is likely distracted by the macro news.

[5]We also examine holding windows varying from 5 days to 60 days with a step of 5 days.

So, where is noise traders' attention? Linking to our first hypothesis, their attention could spill over from the market to the firms. We then examine whether the latest market-level information on the macro-news days can update the noise traders' beliefs and, thus, drive the future returns on stocks that are most likely to be traded by them. We regress CAR on lottery features, market returns, and an interaction term between them. Empirical results show that the market returns on the macro-news days are positively associated with individual stocks' future returns, especially those with noise traders. Specifically, post-macro-announcement lottery-like stocks' reaction to macro-news-day market returns is greater by 98.75% than non-lottery-like stocks. A long-short value-weighted portfolio built on that makes an annual return of 15.62%, which cannot be fully explained by standard asset pricing models such as the Fama-French five-factor model (FF5) (Fama & French 2015) and the capital asset pricing model (CAPM) (Sharpe 1964).

Aside from the indirect methods of capturing investors' attention, we also employ the abnormal search volume index (ASVI), introduced by Da et al. (2011), to measure the attention directly.[6] The higher the ASVI, the higher the attention a stock receives. The upward-sloping pattern in Figure 3.1 illustrates our main finding. The figure visualises a local linear of attention received by the post-macro-announcement lottery-like stocks (value-weighted CASVI[2,6]) relative to the attention received by the macro-news-day market (Market-level ASVI). The figure demonstrates a positive relationship between them, suggesting that the greater attention to the market on the macro-news days, the greater attention to the lottery-like stock during the post-macro-announcement periods. Taking the direct and indirect evidence together, we conclude that there are attention spillover effects among noise traders, consistent with our first hypothesis.

We then examine our second hypothesis that the attention spillover effects are

[6]Lottery-like stocks are attention-grabbing stocks, and therefore we can employ that as an indirect method to capture investors' attention, as suggested by Bali et al. (2021). Alternatively, we employ ASVI introduced by Da et al. (2011) as a direct proxy.

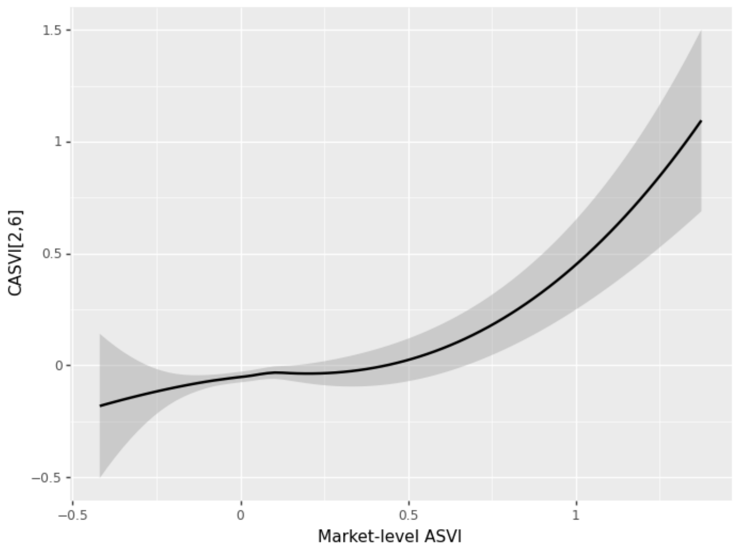


Figure 3.1: Attention Spillover Effects.
The cumulative value-weighted attention received by lottery-like stocks during the post-macro-announcement periods against the value-weighted market's attention on the macro-news day.

more pronounced among firms without earnings announcement coverage. We define a dummy variable identifying whether a firm is covered with an earnings announcement (EA). In detail, EA is one if a firm announces its earnings within a window from one day before and one day ending after a macro-announcement day, denoted as $EA[-1,1]$.[7] We then split the sample into two subsamples, announcing and non-announcing firms, based on whether EA[-1,1] is one. Then, within each subsample, we regress CAR on $Lottery$, mkt and an interaction term between them. The coefficient on the interaction term regarding the post-macro-announcement performance ($CAR[2,6]$) is significantly positive, restricted to the sample including only non-announcing firms. It suggests that the noise traders' market-concentrated attention spillovers to the firms without the earnings announcement coverage after the macro-announcements, which is consistent with our second hypothesis. Overall, our findings suggest that noise traders allocate their attention differently depending on

[7]To ensure that the noise traders have enough time to notice the announcing firms, we relax the announcing window. As robustness checks, we also examine other announcing windows, such as $EA[-2,2]$, $EA[-3,3]$, $EA[-4,4]$ and $EA[-5,5]$, and that does not affect the main results.

the coverage of earnings announcements in the post-macro-announcement periods.

Finally, we conduct a battery of robustness checks. One of the main findings in this paper is that the market return on macro-announcement days can positively predict future returns on lottery-like stocks. However, such predictability disappears ten days after macro-announcements. Moreover, the FOMC events primarily drive such predictability among all these macro event types, and the overlapping events do not affect the baseline results. In addition, we find that the attention spillover effects are more pronounced among stocks with lower prices and stocks with a payoff distribution with more positive skewness.

The contribution of this paper to the literature is fourfold. First, to our best knowledge, we are the first to extend the literature on how investors allocate their attention towards the arrival of the macro news by suggesting that noise-traders attention would spillover from the market to the firms, denoted as the attention spillover effects. Motivated by the limited attention theory (Merton 1987), existing theoretical frameworks have studied how investors allocate their attention to micro news when macro-announcements are released. They infer that macro news distracts the investor's attention from micro information (i.e., crowd-out effects), delaying the incorporation of firm-specific news into stock prices (Peng & Xiong 2006). In contrast, emerging literature reveals that the arrival of the macro news simultaneously stimulates the processing of the micro news (i.e., crowd-in effects), triggering an immediate shift in the investor attention between macro-level and micro-level news (Hirshleifer & Sheng 2022). Both studies suggest that the macro news would attract investors' attention, while the role of noise traders is less emphasised in these studies. By allowing the participation of noise traders, we show that their market-concentrated attention on macro-announcement days would spill over to firms during post-macro-announcement periods. With the revealing of macroeconomic information, their belief is updated, thus driving their trading activities.

Second, regarding the attention transition between macro-level and firm-level information, we advance the literature by suggesting that the attention spillover effects are more pronounced among firms without earnings announcement coverage. Hirshleifer & Sheng (2022) demonstrates that the arrival of the macro-announcements stimulates the incorporation of firm-level earnings information, denoted as crowd-in effects. Suggesting the existence of attention spillover effects, we find it is more pronounced among non-announcing firms due to the crowd-in effects.

Third, we advance the literature on investors' behaviour towards lottery stocks by suggesting that retail and institutional investors have different time-varying abnormal attention to lottery stocks surrounding macro-announcements. Existing literature documents that retail investors are attentive to lottery stocks ahead of earnings announcements (Liu et al. 2020). Arguing with that, Guo et al. (2023) suggest that institutional investors are also attentive to lottery stocks but ahead of FOMC. Filling the gap between these two investor types, we suggest that they have different time-varying demands for lottery stocks surrounding macro-announcements. In detail, consistent with Guo et al. (2023), we find that only institutional investors have abnormal attention on the lottery stocks ahead of the macro-announcements. However, we find that both have similar behaviours during- and post-macro-announcement periods. That is, they seem distracted by the macro-announcements, leading to no significant attention to the lottery stocks when the macroeconomic information is revealed. However, they are abnormally attentive to the stocks during post-macro-announcement periods.

Fourth, we contribute to the lottery-like assets literature by showing the dynamic pricing effects in post-macro-announcement periods. That is, market-conditional speculation increases after the macro-announcements. The existing paper suggests lottery stock drifts ahead of the FOMC (Guo et al. 2023), while they find no evidence of reversals or persistence after such a drift. To this end, we provide extensive evidence showing the market returns on the macro-announcement days positively predict returns on lottery-like stocks during post-macro-announcement periods, which is both economically and statistically significant. The higher the market return on a macro-announcement day, the higher cumulative abnormal returns on the lottery-like stocks over post-macro-announcement periods.

The rest of the paper is organised as follows. Section 2 describes the data and variables. Section 3 provides the baseline results of our empirical analysis towards attention spillover effects. Section 4 presents the results of further analysis towards subsamples regarding earnings announcements. Section 5 conducts robustness checks. Section 6 concludes.

3.2 Data

3.2.1 Data and Variables

We obtain individual U.S. stock data, including open prices, close prices, returns, trading volume, cumulative factors to adjust prices and shares, and the number of shares outstanding, from the Center for Research in Security Prices (CRSP). Our sample includes all common stocks listed on the NYSE, AMEX, and NASDAQ, excluding penny stocks with a share price below $5 at the most recent month's end. Additionally, we obtain fundamental data from Compustat, which includes information such as stockholders' equity, deferred taxes, investment tax credit, preferred stock, and the earnings announcement date.

Following Hirshleifer & Sheng (2022), we construct cumulative abnormal (CAR) stock returns, conditioning on macro-announcement days and based on the market model. We utilise CAR for observing the stock reactions surrounding macro-announcement days. Besides, we follow existing literature to build control variables, including the book-to-market ratio (BM) and the log market capitalization (SIZE) by Fama & French (1993, 1995), the turnover ratio (TURN) by Kumar (2009), the illiquidity (ILLIQ) by Amihud (2002) and Amihud & Noh (2021), and momentum (MOM) by Jegadeesh & Titman (1993). To identify lottery features, we employ proxies, including the log negative stock price (LNP) by Kumar (2009), the idiosyncratic volatility (IVOL) by Ang, Hodrick, Xing & Zhang (2006), the expected idiosyncratic skewness (SKEWEXP) by Boyer et al. (2010), the maximum daily return over the most recent month (MAX) by Bali et al. (2011) and the mean standardised value of the above lottery price signals (ZSCORE) by Liu et al. (2020). For brevity, we employ ZSCORE to represent the lottery features. The higher the ZSCORE, the higher the lottery features. See Appendix A for variable details.

The macroeconomic event data is from the Bloomberg Economic Calendar. We follow Hirshleifer & Sheng (2022) to select events of Federal Open Market Committee decision (FOMC), employment status (UM), purchasing managers index (ISM PMI), and personal consumption (PC). The sample starts in 1997 due to data availability and ends in 2021. The above macro events are chosen because they considerably impact the market. Gilbert et al. (2017) document the importance of macro-announcements, including FOMC, employment status, ISM PMI and Personal Consumption regarding the financial market. Asset pricing implication surrounding the FOMC is well documented(Lucca & Moench 2015, Cieslak et al. 2019). To systematically select events significantly impacting the stock market among 40 different macroeconomic announcements, Hirshleifer & Sheng (2022), event-by-event, regress market returns on a dummy variable indicating if the day is a macro event day, lagged-one-period market returns, and the square of lagged-one-period market returns. Summarising the empirical results, they suggest the aforementioned four events have impacts on the stock markets, which are statistically and economically significant.

3.2.2 Data Summary Statistics

Table 3.1 reports the summary statistics of data. Panel A reports the number of events, including 1,113 macro-announcements and 417,740 firm earnings announcements. Among the macro events, the dates of releasing interest rate decisions (FOMC), ISM Purchasing Managers Index (ISM PMI), Personal Consumption (PC) and Employment Status (EM) are 270, 307, 231 and 305, respectively. Panel B reports cumulative abnormal return (CAR) statistics on universe stocks in percentage, including observations amount (#), mean, standard deviation (Std.), and the 25th, 50th and 75th percentile returns. For instance, $CAR[2,6]$, the mean return of buying stocks at the end of one day after a macro-announcement and holding for five days is 0.10% and the mean amount of $CAR[2,6]$ on a given macro-announcement date is 4378.

[Insert Table 3.1 here]

Panel C reports the mean CAR on portfolios sorting on lottery features. All stocks are sorted into ten deciles based on lottery features, ZSCORE. Then we denote the bottom decile as the lottery-type stocks and the top decile as the non-lottery-type stocks. A hedging portfolio is a difference between the bottom and top decile, showing whether the lottery-type stocks outperform the non-lottery-type stocks. Results indicate that the mean $CAR[-5,-1]$ value-weighted and equal-weighted hedging portfolios are 1.64% and 1.08%, indicating speculative tradings increase before macro-announcements. However, such speculation disappears after the macro-announcements. We find no evidence on the during- and post-event CAR, $CAR[0,1]$ and $CAR[2,6]$. Moreover, Kumar (2009) describes lottery-like stocks as "attention-grabbing" stocks. We, therefore, conjecture that noise traders' attention could be distracted by the arrival of macro events. Panel D reports the mean value of firm characteristics in portfolios sorting on lottery features, ZSCORE. Only lottery, non-lottery, and hedging portfolios are reported for brevity. Results show that lottery-like stocks are highly correlated with momentum, turnover, illiquidity, book-to-market ratio and size (logarithm of market cap).

3.3 Attention Spillover Effects

This section provides empirical results about the attention spillover effects. The policymakers can gain some insights into the mechanism of attention transition by noise traders surrounding macro-announcements, and they can make optimal announcement timing considering their announcement's influence on the noise traders' behaviour. From this work, institutional investors can learn noise traders' behaviour surrounding the announcements that contain rich information and make optimal investment decisions.

3.3.1 Baseline Results

We test whether the revealed market information updates the trading beliefs of noise traders and thus drives their subsequent trading. Specifically, we regress CAR on lottery features (*Lottery*), market return (Mkt), and an interaction term between them. We employ Mkt to capture the market information released on macro-announcement days. The market-level index should incorporate revealed macro information efficiently when the macro-announcement arrives, and thus, theoretically, it has a positive (negative) return if that is positive (negative) news. In addition, *Lottery* would indicate how "lottery-like" a stock is. The higher *Lottery*, the higher the lottery feature a stock has. An interaction term between them is for capturing the response of the noise traders to the latest market information. Theoretically, if noise traders' attention spillovers from the market to the firms during the post-macro-news period, we expect that the market returns positively predict the lottery returns.

In detail, the panel regression model is

$$CAR[h,H]_{i,t} = \beta_0 + \beta_1 Lottery_{i,t} Mkt_t + \beta_2 Lottery_{i,t} + \beta_3 Mkt_t + \lambda' X_{i,m-1} + \epsilon_{i,t}. \quad (3.1)$$

where Mkt is the CRSP-value-weighted market index. We construct lottery proxies, including the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. X are control variables at the end of the most recent month, including the log book-to-market ratio (BM) and log market capitalization (SIZE), momentum (MOM), Turnover (TURN) and Illiquidity (ILLIQ). Note that both firm and year-fixed effects are included. Standard errors are clustered by the macro-event dates.

[Insert Table 3.2 here]

The empirical results in Panel A demonstrate that market returns positively predict the performance of lottery-like stocks after announcements, suggesting that noise traders' attention spillover from the market to firms occurs after macro-announcements. In Column (3) of Table 3.2, the coefficient on the interaction term between $ZSCORE$ and Mkt is 9.54%, which is significant at the 1% level, indicating stronger reactions of lottery-like stocks to the macro announcing information. Compared to the coefficient on non-lottery-like stocks' reaction to revealed macro information (9.66%), the lottery-like stocks' response is greater by 98.75% (9.54/9.66).

Column (1) of Table 3.2 displays an insignificant coefficient on the interaction term, indicating no evidence of how lottery-like stocks react to market information before it is announced. This finding aligns with our expectations since the information is not yet disclosed. Regarding the during-macro-announcement period ($CAR[0, 1]$), the coefficient on the interaction term is 11.75%, which is significant at the 1% level, indicating that lottery-like stocks have a more robust and immediate reaction to the market information. Compared to the coefficient on the non-lottery-like stocks' reactions to the macro news (18.13%), the lottery-like stocks' response is greater by 64.81% (11.75/18.13).

Comparing the greater reactions of 0%, 64.81%, and 98.75% between lottery-like and non-lottery-like stocks regarding pre-, during-, and post-macro-announcement periods, respectively, we conclude that the lottery-like stocks outperform the non-lottery-like stocks the most during post-macro-announcement periods when reacting to macro-announcements. Additionally, the adjusted R-squared for the post-event period regression is the highest among the regression models in Panel A.

The existing literature suggests that noise traders face constraints when short-selling stocks. We expect the noise traders' decisions to be more sensitive to positive market returns. To differentiate between positive and negative macro-announcements, we employ a dummy variable, $PosiMkt$, which indicates whether a market return is positive. We then re-run Regression 3.1 by replacing Mkt with $PosiMkt$ and report the results in Panel B of Table 3.2. In Column (6), the findings indicate that noise traders are more favourable in response to positive market returns. Specifically, the coefficient on the interaction term between $ZSCORE$ and $PosiMkt$ is 0.24%, and the coefficient on the $PosiMkt$ is 0.29%, which are both significant at the 1% level. It suggests that the reactions of stocks favoured by noise traders to positive market returns are 82.76% (0.24/0.29). This finding is consistent with our expectations.

3.3.2 Portfolio Analysis

We follow existing literature to construct portfolios sorted on lottery features but examine their performance during the post-macro-announcement period. Specifically, we buy lottery-like stocks after a macro-news day and hold them over a 5-trading-day window.[8] We employ various proxies, including the high extreme daily return within a month (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL), low price (LNP), and the average Z-score (ZSCORE) for these lottery price signals. We sort all stocks into ten deciles based on the price signals formed at the end of the most recent month. The bottom decile exhibits the most lottery-like features, while the top decile exhibits the least. We then take the hedging portfolio (long the bottom decile and short the top decile) to observe whether lottery-like stocks outperform non-lottery-like stocks during post-macro-announcement periods.

To investigate whether the latest market information updates noise traders' be-

[8] We also examine different windows in the robustness section.

liefs and leads to changes in their trading activities, we refine the lottery portfolios by introducing a trigger condition of market returns called "conditional portfolios". Building on the results of the previous regression analysis, which reveals a positive relationship between lottery-like stock returns during post-macro-announcement periods and market returns on the announcement day, we form conditional portfolios by taking long (short) positions in lottery deciles during the post-event period if the market return on a macro-announcement day is positive (negative).

[Insert Table 3.3 here]

Table 3.3 reports the mean returns on portfolios, alpha of standard asset pricing models and respective T-statistics. Panel A and B of the table report the performance of equal-weighted (EW) and value-weighted (VW) lottery portfolios ("unconditional portfolios"). Panels C and D of the table report the performance of conditional portfolios regarding EW and VW weighting methodologies. To observe the performance of these portfolios over time, we visualise the cumulative returns of the strategies, shown in Figure 3.2.

[Insert Figure 3.2 here]

The empirical results presented in Table 3.3 suggest that adding market returns significantly improves the post-macro-announcement performance of lottery-like stocks. This finding indicates that macro-announcements affect noise traders' beliefs and their post-macro-announcement trading activities. When comparing the mean returns on hedging portfolios (10-1) of Panel A and C, which are -0.21% (insignificant) and 0.44% (significant at the 1% level), we find that the conditional hedging portfolio earns higher returns than the unconditional hedging portfolios, which is economically significant. Furthermore, there is an upward trend pattern in mean returns on conditional deciles from top to bottom, indicating that the post-macro-announcement performance of lottery-like stocks has increased sensitivity to market returns. Considering the size effects, we also construct the portfolios in a value-weighted way, presented in Panel B and D, which does not affect our main conclusions. Importantly, all these findings remain significant even after controlling for standard asset pricing models, including FF5 and CAPM.

The upper part of Figure 3.2 compares the long-term performance of the lottery and conditional lottery strategies. The graph shows that both equal- and value-weighted conditional lottery hedging strategies outperform the original ones. At the same time, their performance is not affected in the NBER-defined recession period (grey shade area in the graph). The lower part of Figure 3.2 plots the cumulative returns of conditional lottery deciles over time. From this graph, we conclude that a decile including the higher lottery feature would perform better over time.

Overall, the results highlight macro-announcements' impact on noise traders' behaviour and suggest that market returns can be utilised as an additional trigger to improve the performance of lottery-like stocks during the post-macro-announcement period. These findings have significant implications for investors and market participants looking to optimise their portfolio strategies and make informed trading decisions.

3.3.3 Capturing Attention Directly

This study employs various proxies, such as MAX, to capture investors' attention towards certain stocks, referred to as "attention-grabbing" stocks, as defined by Kumar (2009). Previously, our research has documented the predictability of macro-news-day market returns on future returns of lottery-like stocks. Given the attention-grabbing nature of these stocks, we infer the existence of attention spillover from the market to these firms during post-macro-announcement periods. However, it is essential to note that these proxies are indirect methodologies for capturing investor attention, as highlighted by (Bali et al. 2021). Therefore, following the approach introduced in Da et al. (2011), we employ the abnormal search volume index (ASVI) and the abnormal institutional investor attention (AIA) as more direct measures of attention.[9]

We follow Da et al. (2011), but at a daily level, to obtain search volume index (SVI) data from Google Trends to proxy for retail investor attention. The SVI captures the search trend for keywords associated with tickers for listed companies within a particular period. The sample is filtered to exclude tickers with synonymous meanings, such as GPS and BABE. To obtain the Abnormal Search Volume Index (ASVI), we compute the logarithmic change of SVI based on the median SVI of the most recent month. The market ASVI, which measures attention on the market, is calculated as the value-weighted ASVI based on stocks' market capitals. For attention received by lottery-like stocks, we sort stocks' ASVI into ten value-weighted deciles based on ZSCORE. The top and bottom deciles are denoted as non-lottery-like ASVI and lottery-like ASVI, respectively.

The mean ASVI for each type, including the market, lottery-like and non-lottery-like ASVI, is calculated surrounding macro-news days (from five days ahead of the macro-event day to five days after that) and visualised in Figure 3.3. We plot the disparity between the two measures as a solid line to visually illustrate the difference between lottery-like ASVI and the market ASVI.

[**Insert Figure 3.3 here**]

In Figure 3.3, the solid line decays when it approaches a macro-announcement day, drifts after the events and eventually climbs over zero. The interesting pattern is aligned with our hypothesis about the attention spillover effects. That is, the macroeconomic announcements draw investors' attention to the market when the day approaches. Then after the announcements, such heightened attention would eventually spill over to stocks. In conclusion, we highlight the possibility of attention spillover effects by taking the evidence of decay in market-level ASVI and the increased attention to lottery-like stocks after the macro-announcements.

[9] The same approach is also adopted by Ben-Rephael et al. (2017), Bali et al. (2021) and Hirshleifer & Sheng (2022)

To this end, we find the negative co-movement between stock-level and market-level ASVI, but the attention spillover question remains open. To further investigate that, we introduce a variable CASVI, capturing the cumulative attention received by stocks during a post-macro-announcement period, which is the sum of ASVI within a post-event window.[10] CASVI also captures the attention allocation of investors when they react to the macro-announcements.

[Insert Figure 3.4 here]

We follow Hartzmark & Shue (2018) to employ local-linear regressions to visualise relationships between the cumulative post-macro-announcement ASVI (CASVI) and the macro-day market ASVI. The top-left grid in Figure 3.4 illustrates that higher attention is allocated to lottery-like stocks during post-macro-announcement periods if the market receives higher attention when it is a macro-news day, which is consistent with our hypothesis about the existence of attention spillover effects. Compared to that, the pattern in the top-left is almost flat, showing no obvious relationship between CASVI and the market-level ASVI. Interestingly, the samples conditioning on non-lottery-type stocks exhibits similar patterns among subsamples conditioning on macro-news and non-macro-news days. That is a 90-degree-clockwise rotated "S". Generally, the grey areas showing 90% confidence intervals are wider in grids conditioning on the macro-news day than on non-macro-news day due to the availability of data points.

Plotted as the up-trend shade of lottery-like ASVI in Figure 3.3, we find that retail investors are attentive to lottery-like stocks after the macro-announcements. However, whether institutions are also attentive to lottery-like stocks after the macro-announcements remains silent. Inspired by Ben-Rephael et al. (2017), we capture abnormal institutional investors' attention with DAIA, a dummy variable

[10] For being consistent with the previous section measuring stocks' reactions during a post-macro-announcement period ($CAR[2, 6]$), we employ the same window capturing the cumulative attention during the post-event period, which is $CASVI[2, 6]$.

indicating if AIA for a firm is scored above and equal to 3 on a specific date.[11] We then follow the study to conduct probit panel regressions, described below,

$$DAIA_{t+j} = \beta_0 + \beta_1 ZSCORE_{i,t} Macroday_t + \beta_2 ZSCORE_{i,t} + \beta_3 Macroday_t + \epsilon_{i,t}, \tag{3.2}$$

where j ranges from -5 to 5, measuring how lagged or ahead DAIA react to explanatory variables. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). $Macroday$ is a dummy variable indicating if any macro-announcements are released on the day. To compare it with retail investors' attention surrounding a macro-announcement day, we follow Ben-Rephael et al. (2017) to construct $DASVI$, a dummy variable built on $ASVI$ indicating if a company receives abnormal attention from retail investors on a specific date. Then we re-run the probit panel regression 3.2 by replacing $DAIA$ with $DASVI$.

[Insert Table 3.4 here]

Table 3.4 indicates the superior attention received by lottery-like stocks over non-lottery-like stocks after macro-announcements for retail and institutional investors. Empirical results present significant coefficients on the interaction term between $ZSCORE$ and $Macroday$ in Column (11) and Column (12), which are 1.11% and 1.03%, respectively. Comparing the above coefficients with coefficients on $Macroday$ accordingly of 1.57% and 0.74%, we find that retail investors pay

[11] As documented in Ben-Rephael et al. (2017), Bloomberg assigns a score ranging between 0 and 4 to measure how strongly a company receives attention from institutions on a date.

70.70% (1.11/1.57) and 139.19% (1.03/0.74) greater attention to lottery-like stocks than non-lottery-like stocks on the 5th and the 6th day after a macro-announcement. We, therefore, suggest that retail investors reallocate a larger proportion of their attention to lottery-like stocks than non-lottery-like stocks after macro-announcement days.

From columns (13) to (24), we find significantly greater attention received by lottery-like stocks, compared with non-lottery-like stocks among pre-and post-macro-announcement periods but insignificant evidence during the macro-announcing period, which is from day zero to day one after the event. As for the pre-event window, the results are consistent with the findings documented in Guo et al. (2023). They find the institutions are chasing lottery-like stocks before an FOMC announcement. However, arguing their insignificant evidence for the post-event period, we raise the significant statistics suggesting that the institutions' attention is greater to the lottery-like stocks than the non-lottery-like stocks during post-macro-announcement periods. For example, Column (20) indicates that lottery-like stocks receive 34.29% (1.32/3.85) greater attention from institutional investors than non-lottery-like stocks on the 2nd day after the macro-announcement.

[Insert Figure 3.5 here]

To summarise such interesting patterns surrounding macro-announcement days, we plot a β_1 to β_3 ratio against a macro-announcement cycle (from -5 to 6 days after a macro-announcement day) in Figure 3.5. The figure illustrates that only institutional investors are attentive to lottery-like stocks before any macro-announcements, while their attention seems to decay when a macro-announcement day approaches. However, retail and institutional investors are increasingly and jointly attentive to lottery-like stocks during the post-macro-announcements, and the retail investors seem to react to it slower than the institutional investors.

Explaining why institutional investors are more attentive to lottery-like stocks than non-lottery-like stocks before macro-announcements, we refer to the findings of Guo et al. (2023), which suggest institutional investors may demand lottery-like stocks for hedging unexpected increases in market volatility. We also explain the post-macro-announcement patterns in the attention of retail and institutional investors by linking them to theories that noise traders can be retail and institutional investors.[12] The noise traders are uninformed about macroeconomic data before it is released and they then place trading orders based on the disclosed macroeconomic information after their releases. Therefore, both retail and institutional investors are increasingly attentive to lottery-like stocks during post-macro-announcement periods.

3.4 Attention Spillover Effects & Earnings Announcements

3.4.1 Regression Analysis

We document the attention spillover effects in the previous section, which is that noise traders' attention spillovers from the market to stocks during post-macro-announcement periods. Linking to theories that earnings-announcing firms are attention-grabbing firms (Liu et al. 2020), we raise a question: would the attention spillover effects be affected by the earnings announcements? Existing literature suggests (i) crowd-in effects, the arrival of the macro-announcement stimulates the incorporation of the firm-level earnings information into stocks' prices (Hirshleifer & Sheng 2022), and (ii) noise traders are more attentive to announcing firms before their earnings announcements (Liu et al. 2020). Taking these together, we posit that the attention spillover effects are more pronounced among non-announcing firms during post-macro-announcement periods. That is because information about an-

[12]Existing literature suggests that retail investors trigger noise trading. However, institutional investors can also be noise traders. They are likely uninformed due to their algorithmic tradings and hedging activities (Skjeltorp et al. 2016, Han et al. 2016)

nouncing firms is fully incorporated into prices when there are macro-announcements (crowd-in effects), leaving non-announcing firms to be noticed after the news.

To examine the hypothesis, we split the sample into two subsamples: only announcing firms (firms announcing their earnings within a window one day ahead of the macro-announcements and one day after that) and non-announcing firms. Then within each subsample, we conduct regression 3.1 to measure whether earnings announcements affect the attention spillover effects. Table 3.5 reports estimated coefficients in percentage with adjusted T-statistics in parentheses.

[Insert Table 3.5 here]

Empirical results indicate that noise traders' market-concentrated attention spillovers to non-announcing firms during post-macro-announcement periods, which is consistent with our hypothesis. Panel A and B present results towards subsample with announcing firms and subsample with non-announcing firms, respectively. Comparing column (6) and column (12), we find that coefficients on the interaction term are statistically significant regarding the subsample with non-announcing firms, while we find no strong evidence for the other subsample. In particular, the reactions of firms favoured by noise traders to the macro-news-day market returns are 101.01% (9.97/9.87) greater than firms favoured by other traders, conditioning in the subsample with non-announcing firms.

In addition, we find that noise traders have an increased demand for stocks ahead of earnings announcements, which is consistent with Liu et al. (2020). Specifically, column (1) presents a significant coefficient of 0.75% on $ZSCORE$, suggesting that one standard deviation increase in the lottery feature results in a 0.55% increase in $CAR[-5, -1]$. While such a phenomenon disappears after the announcements, being reflected on the insignificant coefficients on the same term in column (2) and column (3).

Besides, we present additional evidence suggesting that the crowd-in effects by Hirshleifer & Sheng (2022) are also pronounced in noise traders. Moving our attention from pre-event CAR to post-event CAR simultaneously among Panel A and Panel B (column (1) to column (3) and column (7) to column (9)), we find that the arrival of macro-announcements stimulates the process of incorporating earnings information into prices. In particular, both columns (1) and column (7) present significant coefficients on ZSCORE, suggesting that noise traders have an increased demand for stocks ahead of any macro-news ignoring whether that announces earnings information. However, when we move to the post-event CAR, we find that only the subsample with non-announcing firms has a significant coefficient on $ZSCORE$, presented in column (9). It suggests that the arrival of macro-announcements stimulates the earnings information's incorporation into prices, leaving non-announcing to be noticed by the noise traders during post-macro-announcement periods.

Taking these together, we suggest that earnings announcements affect the attention spillover effects. Such effects are more pronounced among non-announcing firms, indicating that noise traders' attention spills over to non-announcing firms after macro-announcements.

3.4.2 Portfolio Analysis

The regression analysis shows that the attention spillover effects are more pronounced among non-announcing firms, which is statistically significant, while the relative economic significance remains silent. In this section, we examine that by measuring the performance of market-conditional portfolios.

In detail, we first split the sample into two subsamples, announcing firms and non-announcing firms. We denote announcing firms as the firms announcing their earnings one day before and one day ending after a macro-announcement day, in which a macro-announcement is released. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). Then, within each subsample, we sort the stocks into ten deciles based on their lottery proxies in the most recent month. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. We form the lottery-hedging portfolio by taking a long and a short position on the bottom and top decile, respectively, to observe the outperformance of lottery-type stocks over non-lottery-type stocks. To measure the attention spillover effects affecting lottery deciles, we construct conditional lottery portfolios by buying (selling) the deciles if the market returns on the macro-announcement days are positive (negative). Table 3.6 reports the mean CAR on the conditional lottery-hedging portfolios across different earnings announcing windows from EA[-1,1] to EA[-5,5] with Newey & West (1987) adjusted T-statistics reported in parentheses.

[Insert Table 3.6 here]

Empirical results demonstrate that the attention spillover effects are more pronounced among non-announcing firms, which is economically significant at the 1% level. In Panel B of Table 3.6, we present the significant mean $CAR[2,6]$ of 0.45% for non-announcing firms regarding EA[-1,1], suggesting the portfolio buying lottery-type stocks and holding for 5 five days after the macro-announcements is averagely 0.45% greater than buying non-lottery-type stocks in the subsample consists of only non-announcing firms. Regarding the same earnings announcing window in Panel A, there is no significant CAR, suggesting no evidence showing the existence of attention spillover effects in announcing firms. Taking the results of announcing and non-announcing firms regarding EA[-1,1], we conclude that the attention spillover effects are economically significant for non-announcing stocks, consistent with our hypothesis.

However, we find it is limited in the short term. We find no evidence illustrating its long-term persistence in Panel B across different EA windows. Such significant outperformance disappears in longer holding periods, such as 10, 15 and

20 days, since there are no significant results regarding $CAR[2,11]$, $CAR[2,16]$ and $CAR[2,21]$ in Panel B of Table 3.6. Besides, the earnings announcing window size does not affect the main results. We examine the portfolio with different earnings announcing windows, ranging from EA[-1,1] to EA[-5,5], while both of them suggest similar conclusions.

3.5 Robustness

3.5.1 Dominant Macro-Event: FOMC

We document that market returns on macro event days can positively predict future returns on lottery stock. While defining the macro-news days, we follow Hirshleifer & Sheng (2022) to employ days announcing any of FOMC, ISM PMI, EM or PC as that. However, which macro event dominates such predictability? We, therefore, study how lottery stocks respond to the market returns regarding individual macro-news types in this section.

We still employ the regression 3.1 but run it conditionally on the individual macro-news types. Table 3.7 reports coefficients in percentage with adjusted T-stat in the parentheses, observation number (#), and adjusted R-squared. Note that both firm and year fixed effects are included in all regressions, and standard errors are clustered by the macro-event dates. Panel A, B, C and D of Table 3.7 report results of the regressions conditional on FOMC, ISM PMI, EM and PC days.

[Insert Table 3.7 here]

Empirical results show that FOMC dominates the above predictability and persists in the long term. However, it would disappear 16 days after the FOMC announcement. As for the short-term, a five-day window after macro-news days, FOMC and ISM PMI are the leading events for such predictability. Towards $CAR[2,6]$, coefficients on the interaction term between $ZSCORE$ and Mkt indicate that the attention spillover effects mostly exist on the FOMC and ISM PMI announcing days. Specifically, the predictability of market returns on FOMC announcing days on the future lottery-like stock returns is 74.49% (18.69/25.09) greater than on the other stocks' returns. Likewise, the predictability of market returns on ISM PMI announcing days on the future lottery-like stock returns is also greater than on the other stocks' returns. However, we find no similar evidence on EM and PC macro events.

In addition, turning our attention from the short-term ($CAR[2,6]$) to the longer-term CAR ($CAR[2,26]$), we find that such predictability persists longer terms only with FOMC event, although it disappears after the window of [2,16]. Specifically, we find that the predictability of market returns on FOMC announcing days on the future lottery-like stock returns are 74.49% (18.69/25.09), 73.07% (34.56/47.30) and 66.69% (31.58/47.35) greater than on the other stocks' returns, by observing the coefficients on the interaction term towards $CAR[2,6]$, $CAR[2,11]$ and $CAR[2,16]$, respectively.

3.5.2 Different Holding Periods

We examine the attention spillover effects with $CAR[2,6]$. However, whether the effects are related to the holding periods remains silent. We, therefore, conduct empirical work on it in terms of different holding periods in this section. Specifically, we run the regression 3.1 with dependent variables varying from CAR[2,6] to CAR[2,31] with a step of 5 days. Table 3.8 reports the coefficients and respective T-stat in parenthesis for different lottery proxies and holding periods.

[Insert Table 3.8 here]

Empirical results show that the attention spillover effects persist only in the short term. Coefficients on the interaction term and Mkt are 9.54% and 9.66% regarding $CAR[2,6]$, suggesting lottery-like stocks' reaction to the market returns is greater by

98.76% (9.54/9.66) than the non-lottery-like stocks. However, we find no significant coefficients on the interaction term regarding longer buy-and-holding periods.

3.5.3 Non-overlapping Events Test

In previous sections, we confirm the predictability of macro-event-day market returns on future lottery-like stock returns. Based on that, we develop a conditional lottery strategy. That is, when the market returns on the macro-announcement days are positive (negative), we buy (sell) lottery portfolios the next day. Note that we sort all stocks into ten deciles based on their lottery price signals at the end of every month. Under such a strategy, clustering macro-announcements could happen during the portfolio holding periods, leading to overlapping trading. For example, we long the lottery-hedging portfolio today and hold it for the next five trading days if the FOMC released an interest rate decision and the market returns were positive yesterday. In addition, the portfolio can hold another position if triggered by another macro-announcement within the holding period of the last position. That may lead to double or more positions held simultaneously. Considering that, some may doubt the performance of conditional lottery portfolios without overlapping tradings. We, therefore, examine that in this section.

To overcome the overlapping issues, we adopt a constraint to filter CAR: opening new positions during the last position's holding period is prohibited. Table 3.9 reports the results of the non-overlapping test on attention spillover effects across different holding periods. Panel A of the table reports the regression results of regressing non-overlapping CAR on ZSCORE, Mkt, an interaction term between them and control variables including book-to-market ratio (BM), illiquidity (ILLIQ), momentum excluding the most recent month's return (MOM), the logarithm of market capitalization (SIZE) and turnover (TURN). Firm and year fixed effects are included in the regressions. Standard errors are clustered by the macro-news dates. The table reports the coefficients (in the percentage), respective adjusted T-stats (in parentheses), observation number (#) and the adjusted R-squared.

[Insert Table 3.9 here]

Empirical results in Panel A show that the overlapping issues do not affect the main results in this paper. Specifically, the coefficient on the interaction term towards the dependent variable of $CAR[2,6]$ is 8.41%, which is statistically significant, suggesting that lottery-like stocks have greater post-macro-announcement reactions to the macro-news-day market returns than non-lottery-like stocks. It implies the existence of attention spillover effects (noise traders' attention spillover from the market to the firms). In addition, the coefficients on the term ZSCORE are all significantly negative, consistent with the existing literature on lottery-like stocks. That is, the higher the lottery feature a stock has, the worse the future performance of the stock. As for the term Mkt, all coefficients are insignificant, suggesting the non-overlapping CAR has no exposure to the market. That makes sense since the CAR are market risk-adjusted (please see the construction of CAR).

Panel B reports the performance of conditional lottery portfolios, including mean CAR in percentage and Newey & West (1987) adjusted T-stat in the parentheses. In detail, we sort non-overlapping CAR into deciles based on their lottery features, ZSCORE, at the most recent month's end. The bottom (top) decile exhibits the most (least) lottery feature. We then construct a long-short portfolio (10-1) by longing the bottom decile and shorting the top decile. To examine the attention spillover effects, we long (short) the lottery deciles if the macro-news-day market returns are positive (negative), termed the conditional lottery portfolios. Results show that $CAR[2,6]$ on lottery-like stocks are 0.34% greater than non-lottery-like stocks when following the market on macro-news days. Interestingly, we find an uptrend on $CAR[2,6]$ from the top to the bottom decile, suggesting the higher lottery feature a stock has, the greater the stock's reaction to the macro-news-day market returns. However, we find no evidence indicating if such an outperformance would persist or disappear over a longer trading window.

3.5.4 Different Proxies

We employ the ZSCORE summarising all proxies capturing lottery features throughout this paper to demonstrate the attention spillover effects. However, whether different proxies point to different conclusions? We then examine that in this section by intuitively replacing ZSCORE with other specific proxies, including the high maximum daily returns within the most recent month (MAX), the high idiosyncratic volatility (IVOL), the high expected idiosyncratic skewness (SKEWEXP) and the low stock price (LNP). We re-examine the regressions and portfolios based on the other proxies to consider both statistical and economic perspectives. With all the proxies, we sort stocks into ten deciles based on their price signals. The bottom decile exhibits the most lottery features, while the top one shows the least. Since the features across different proxies are not comparable and may lead to incomparable coefficients of regressions, we alternatively adopt the decile number to score how high the lottery feature a decile reflects.

[Insert Table 3.10 here]

Panel A of Table 3.10 reports coefficients of models regressing $CAR[2,6]$ on $lotteryPort$, Mkt and an interaction term between them, where $lotteryPort$ is the decile number indicating the lottery-feature ranking of a stock. The corresponding T-statistics of coefficients are reported within the parentheses. Both observation amount (#) and adjusted R-squared are also reported. Note that control variables, firm and year fixed effects are included in the regressions, and standard errors are clustered by the macro-announcement dates.

In this panel, three out of five proxies provide statistically significant evidence to suggest the existence of attention spillover effects. In detail, coefficients on interaction terms of the regressions regarding proxies LNP, SKEWEXP and ZSCORE are 3.64%, 2.93% and 2.68%. As for remaining proxies, there are positive coefficients on the interaction terms, although they are insignificant.

Panel B of Table 3.10 reports the same statistics of similar regression models as Panel A. Specifically, we take the interaction term and Mkt for observing how stocks react to lottery features during post-macro-announcement periods. Two out of five proxies illustrate that the post-macro-announcement performance of stocks is negatively related to the decile number constructed on LNP and ZSCORE, suggesting the lower (higher) stock price (lottery feature), the lower (lower) post-macro-announcement stock returns. However, there is no significant evidence for the remaining proxies.

Comparing Panel A to Panel B, we find that the market triggers the noise tradings when inserting Mkt and an interaction term between Mkt and $lotteryPort$ into the regressions. In the previous sections, we surmise that is the attention spillover effects, attention of noise traders spillover from the market to the firms during post-macro-announcement periods. Specifically, the delayed reactions of lottery-like stocks to the market returns on the macro-news days are average greater than the general stocks. Such greater lottery-like stock reactions to market returns during post-macro-announcement periods are more pronounced among stocks, exhibiting more features of low prices and small chances of winning potential huge rewards.

Panel C and D report the performance of lottery and conditional lottery portfolios during post-macro-announcement periods. Time-varying average $CAR[2,6]$ of portfolios are reported in the percentage with Newey & West (1987) adjusted T-stat reported in the parentheses. We construct the lottery portfolios by sorting stocks into ten deciles based on price signals of different proxies. The bottom decile exhibits the most lottery features, while the top one shows the least. To observe how strongly the lottery-like stocks react to market returns during post-macro-announcement periods, we long (short) the constructed lottery deciles if signs of the market returns on the macro-news days are positive (negative), denoted the conditional lottery deciles. For brevity, we report only the value-weighted portfolios.

Panel D of Table 3.10 shows a down-trend on the economic magnitude of $CAR[2,6]$ from the top to the bottom deciles across different proxies, reflecting the weaker post-macro-announcement performance of stocks with the higher lottery features. Among the lottery portfolios, results based on only SKEWEXP show that lottery-type stocks significantly underperform non-lottery-type stocks after macro-announcements, although signs of the hedging portfolios (10-1) are all negative across different proxies. That suggests the economic meaning of lottery-type stocks' underperformance during post-macro-announcements is conditional on only the proxy of SKEWEXP.

Interestingly, results on Panel C indicate an up-trend on the mean $CAR[2,6]$ from the top to the bottom deciles across different proxies, suggesting the stronger post-macro-announcements reactions of stocks with higher lottery features to the revealed macro information. Turning to the conditional lottery portfolios' performance, we find that three out of five proxies suggest the outperformance of lottery-type to non-lottery-type stocks during post-macro-announcement periods, which is 0.35%, average.

Taking the results of regressions and portfolios together, we conclude that the attention spillover effects are more pronounced among stocks with lower prices and higher features of small chances of winning huge potential rewards. That implies noise traders prefer lower-priced stocks or stocks with a payoff distribution with more positive skewness when trading on the latest revealed macro information.

3.6 Conclusion

When there is a macro-announcement, noise traders are uninformed about the macro news before it is revealed to the public. They are waiting to disclose such market-level information, and thus, they temporarily neglect the firm-level price signals. However, after the macro news, their attention would spill over to the cross-section of individual stocks since the revealed market-level information would update their belief on their subsequent trading.

We find the attention spillover effects across the market and firms among noise traders, i.e., their attention would spill over from the market to the firms after a macro-announcement. Such attention spillover effects can drive lottery speculation during the post-macro-announcement period, which is statistically and economically significant. It is robust even after controlling for book-to-market ratio, illiquidity, turnover, log capitalization and momentum. Particularly, stocks favoured by the noise traders have 98.75% greater lagged reactions to the market return on the macro-announcement days than stocks traded by others. Based on that, we design a market-conditional strategy of buying (selling) lottery hedging portfolios the next day after a macro-announcement and holding that for five trading days if the market return is positive (negative) on the event day. The value-weighted portfolio gains significant abnormal returns of 35 bp and 34 bp after controlling FF5 and CAPM, respectively. However, such speculation disappears in the longer term due to the price pressure. Moreover, we find the FOMC dominates such effects.

Additionally, we suggest the existence of attention spillover effects with direct proxies capturing investor attention. Specifically, we find that market-level attention positively correlates with firm-level attention to lottery-like stocks. Moreover, we find that retail and institutional noise traders are both abnormally attentive to stocks after macro-announcements, suggesting the attention spillover effects are not solely among the retail or institutional clientele.

Furthermore, we document the attention spillover effects are more pronounced among the stocks without earnings announcements during the post-macro-announcement periods. From the perspective of uncertainty resolution, the market-level uncertainty would be heightened ahead of macro-announcements, and such heightened uncertainty draws investors' attention to firm-level announcing information such as earnings. However, the uncertainty would be fully resolved after the macro-announcement so that investors might switch their attention to the non-earnings-announcing firms during this period. From the perspective of prices incorporating information, the macro-announcement stimulates the incorporation of earnings information into prices, leading to investors focusing on earnings-announcing firms ahead of the macro-announcement. Nevertheless, their attention might eventually switch to non-announcing firms since announcing firms' information is fully incorporated. Empirically, we illustrate that lottery-like stocks have 101.01% greater lagged reaction to macro-news-day market returns than non-lottery-like stocks, conditioning on stocks without earnings announcements. As for the subsample of stocks with earnings announcements, we find no significant results.

3.7 Tables

Table 3.1: Data Summary Statistics

This table reports summary statistics of the data including macro-announcement dates, cumulative abnormal return (CAR) on the macro-announcement days, and lottery CAR on the macro-announcement days are reported. Panel A summarises the amount (#) of event dates we study in this paper. Panel B reports the amount, mean, standard deviation, 25th, median and 75th percentile of CAR. Panel C reports lottery-type stock performance surrounding the macro-announcements. Panel D reports firms' characteristics sorting on lottery features. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. All stocks are sorted into ten deciles on the lottery signals at the end of the most recent month. The bottom decile exhibits the highest lottery feature while the top decile exhibits the least. We denote the bottom (top) decile as the (non-) lottery-type stocks and take the difference between the bottom and top decile as the lottery-hedging portfolio. Firm characteristics are observed at the end of the most recent month, including the book-to-market ratio (BM), Illiquidity (ILLIQ), momentum (MOM), log market capitalization (SIZE) and Turnover(TURN). We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below \$5. Note that the sample period is January 1997 to December 2021.

Panel A: Event

	Earnings Events	Total Macro Events	FOMC	ISM PMI	PC	UM
#	417,740	1113	270	307	231	305

Panel B: Time-varying Mean Statistics on Cross-sectional CAR

	No. of Obs.	Mean(%)	Std.(%)	25th PctTile(%)	Median(%)	75th PctTile(%)
CAR[-5,-1]	4382	0.21	8.56	-3.08	-0.11	2.88
CAR[0,1]	4328	0.09	5.88	-2.04	-0.10	1.86
CAR[2,6]	4378	0.10	8.74	-3.25	-0.20	2.82

Panel C: CAR (%) On Lottery Type Stocks Around Macro-Announcements

	Value-weighted			Equal-weighted		
	Lottery	Non-Lottery	Hedging	Lottery	Non-Lottery	Hedging
CAR[-5,-1]	1.71***	0.07***	1.64***	1.16***	0.08***	1.08***
	(7.05)	(2.62)	(6.59)	(5.76)	(3.02)	(5.22)
CAR[0,1]	-0.03	0.01	-0.04	0.04	0.04***	0.01
	(-0.30)	(0.66)	(-0.38)	(0.55)	(2.69)	(0.07)
CAR[2,6]	-0.20	0.11***	-0.30	-0.13	0.07**	-0.21
	(-1.00)	(3.98)	(-1.42)	(-0.68)	(2.26)	(-1.02)

Panel D: Characteristics On Stocks Sorting On Lottery Features

	Value-weighted			Equal-weighted		
	Lottery	Non-Lottery	Hedging	Lottery	Non-Lottery	Hedging
BM	0.70***	0.42***	0.28***	0.91***	0.56***	0.35***
	(20.30)	(62.91)	(8.54)	(25.58)	(67.74)	(10.35)
ILLIQ	0.03***	0.00***	0.03***	0.06***	0.00***	0.05***
	(6.22)	(9.34)	(6.16)	(14.51)	(8.55)	(13.98)
MOM	-0.10**	0.18***	-0.28***	-0.17***	0.19***	-0.36***
	(-2.46)	(16.77)	(-7.66)	(-4.81)	(17.23)	(-11.80)
TURN	5.57***	1.11***	4.46***	8.40***	1.26***	7.15***
	(12.96)	(36.40)	(10.45)	(5.45)	(36.37)	(4.64)
SIZE	-	-	-	3.80***	8.58***	-4.79***
				(93.86)	(144.17)	(-108.95)

Table 3.2: Attention Spillover Effects: Firm-Level Regression Analysis

This table reports the attention spillover effects. Panel A presents that the market returns on macro-announcement days positively predict the post-macro-announcement returns on lottery-like stocks. Panel B indicates that positive market returns mostly drive such predictability. The regression model is $CAR[h,H]_{i,t} = \beta_0 + \beta_1 Lottery_{i,t} Mkt_t + \beta_2 Lottery_{i,t} + \beta_3 Mkt_t + \lambda' X_{i,m-1} + \epsilon_{i,t}$, where $CAR[h,H]_{i,t}$ is a market model adjusted cumulative abnormal return over a holding window h day(s) and H day(s) after a macro-announcement day t. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. Mkt_t is the CRSP value-weight market returns excluding dividends. Results of the regression regarding the continue market return variable are reported in Panel A. Panel B presents results regarding a dummy variable $PosiMkt$, indicating if the market returns are positive. X are control variables observed at the end of the most recent month, including the book-to-market ratio (BM), illiquidity (ILLIQ), momentum (MOM), log market capitalization (SIZE) and turnover (TURN). Standard errors are clustered by the macro-event date, and adjusted T-statistics are reported in parentheses. Firm and Year fixed effects are included. The intercept is not reported in this table for brevity. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021. Reported coefficients are in percentage.

	Panel A: Continue variable Mkt			Panel B: Dummy variable PosiMkt		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep.	CAR[-5,-1]	CAR[0,1]	CAR[2,6]	CAR[-5,-1]	CAR[0,1]	CAR[2,6]
ZSCORE x Mkt	2.16	11.75***	9.54**	-	-	-
	(0.45)	(4.85)	(2.40)	-	-	-
Mkt	4.42	18.13***	9.66*	-	-	-
	(0.71)	(6.66)	(1.74)	-	-	-
ZSCORE x PosiMkt	-	-	-	0.03	0.24***	0.24***
	-	-	-	(0.45)	(5.71)	(3.23)
PosiMkt	-	-	-	0.03	0.35***	0.29***
	-	-	-	(0.32)	(6.43)	(3.08)
ZSCORE	0.78***	-0.09***	-0.12***	0.76***	-0.21***	-0.25***
	(14.83)	(-3.84)	(-3.31)	(11.80)	(-6.13)	(-4.44)
BM	-0.03	0.15***	0.32***	-0.02	0.15***	0.32***
	(-0.59)	(5.28)	(7.78)	(-0.59)	(5.24)	(7.80)
ILLIQ	-0.14***	0.02	-0.10**	-0.14***	0.02	-0.10**
	(-2.61)	(0.73)	(-2.40)	(-2.60)	(0.85)	(-2.37)
SIZE	0.22***	-0.23***	-0.47***	0.22***	-0.23***	-0.47***
	(4.56)	(-10.18)	(-12.37)	(4.55)	(-10.18)	(-12.46)
TURN	-0.00	-0.00	-0.00***	-0.00	-0.00	-0.00***
	(-0.33)	(-0.70)	(-3.59)	(-0.33)	(-0.68)	(-3.60)
MOM	-0.08*	0.05	0.03	-0.08*	0.05	0.03
	(-1.67)	(1.34)	(0.51)	(-1.67)	(1.33)	(0.51)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
No. of Obs.	2,886,344	2,870,653	2,886,143	2,886,344	2,870,653	2,886,143
Adj. R^2(%)	0.87	0.74	0.93	0.86	0.66	0.94

Table 3.3: Attention Spillover Effects: Portfolio-Level Analysis

This table reports the mean CAR[2,6](%), alphas of standard asset pricing models and relative T-statistics of attention-spillover-lottery portfolios. The unconditional portfolios refer to the deciles obtained by sorting all stocks into ten deciles based on lottery features. The conditional portfolios are the unconditional portfolios adjusted according to market return signs precisely, where buying (selling) the deciles occur if market returns are positive (negative) on macro-announcement days. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. All stocks are sorted into ten deciles on the lottery signals at the end of the most recent month. The bottom decile exhibits the highest lottery feature while the top decile exhibits the least. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021. The t-statistics, reported in parentheses, are based on Newey & West (1987) standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Panel A: Unconditional Portfolios (EW)			Panel B: Unconditional Portfolios (VW)			Panel C: Conditional Portfolios (EW)			Panel D: Conditional Portfolios (VW)		
	Mean (%)	Alpha(FF5) (%)	Alpha(CAPM) (%)	Mean (%)	Alpha(FF5) (%)	Alpha(CAPM) (%)	Mean (%)	Alpha(FF5) (%)	Alpha(CAPM) (%)	Mean (%)	Alpha(FF5) (%)	Alpha(CAPM) (%)
1	0.07***	0.07***	0.07***	0.11***	0.11***	0.11***	0.02	0.02	0.02	-0.01	-0.02	-0.02
	(3.25)	(3.19)	(3.15)	(5.03)	(5.04)	(5.09)	(0.87)	(0.86)	(0.86)	(-0.26)	(-0.88)	(-0.78)
2	0.07***	0.08***	0.07***	0.06***	0.07***	0.07***	0.05*	0.06**	0.05*	-0.01	-0.02	-0.02
	(2.68)	(2.73)	(2.65)	(3.22)	(3.39)	(3.44)	(1.88)	(1.98)	(1.92)	(-0.76)	(-1.23)	(-1.26)
3	0.06*	0.06*	0.06*	0.05*	0.05**	0.05**	0.07**	0.07**	0.07**	0.03	0.03	0.03
	(1.77)	(1.78)	(1.68)	(1.86)	(1.98)	(1.97)	(1.97)	(2.17)	(2.05)	(1.17)	(1.11)	(1.01)
4	0.07**	0.07*	0.07*	-0.00	0.01	0.01	0.09**	0.09**	0.09**	-0.01	-0.00	-0.01
	(1.97)	(1.94)	(1.83)	(-0.05)	(0.15)	(0.18)	(2.27)	(2.39)	(2.25)	(-0.16)	(-0.05)	(-0.17)
5	0.05	0.05	0.04	0.03	0.04	0.03	0.11***	0.13***	0.12***	0.02	0.01	0.01
	(1.12)	(1.02)	(0.87)	(0.51)	(0.67)	(0.64)	(2.64)	(2.85)	(2.66)	(0.43)	(0.26)	(0.26)
6	0.01	0.01	-0.00	0.03	0.03	0.03	0.13**	0.14***	0.13**	0.01	-0.01	-0.02
	(0.25)	(0.13)	(-0.03)	(0.41)	(0.41)	(0.38)	(2.39)	(2.64)	(2.47)	(0.18)	(-0.16)	(-0.24)
7	-0.05	-0.06	-0.06	-0.01	-0.01	-0.01	0.14**	0.16**	0.15**	0.03	0.04	0.03
	(-0.74)	(-0.89)	(-1.03)	(-0.11)	(-0.09)	(-0.15)	(2.26)	(2.55)	(2.39)	(0.38)	(0.44)	(0.33)
8	-0.09	-0.11	-0.12	-0.12	-0.11	-0.12	0.20***	0.23***	0.22***	0.14	0.15	0.14
	(-1.20)	(-1.43)	(-1.58)	(-1.07)	(-1.00)	(-1.07)	(2.70)	(3.03)	(2.86)	(1.25)	(1.37)	(1.27)
9	-0.14	-0.18**	-0.20**	-0.13	-0.17	-0.19	0.27***	0.30***	0.29***	0.24*	0.27**	0.24*
	(-1.59)	(-2.00)	(-2.15)	(-1.02)	(-1.30)	(-1.47)	(3.03)	(3.31)	(3.21)	(1.89)	(2.08)	(1.90)
10	-0.13	-0.20	-0.22*	-0.20	-0.25	-0.26*	0.46***	0.51***	0.49***	0.31**	0.34**	0.32**
	(-1.01)	(-1.51)	(-1.66)	(-1.25)	(-1.61)	(-1.65)	(3.57)	(3.85)	(3.69)	(1.97)	(2.13)	(2.05)
10-1	-0.21	-0.27**	-0.29**	-0.30*	-0.36**	-0.37**	0.44***	0.49***	0.47***	0.31*	0.35**	0.34**
	(-1.50)	(-1.97)	(-2.11)	(-1.80)	(-2.14)	(-2.18)	(3.26)	(3.53)	(3.38)	(1.88)	(2.10)	(2.01)

Table 3.4: Retail VS. Institutional Investors' Attention

This table reports results of probit panel regressions of $Dmy_{i,t+j} = \beta_0 + \beta_1 ZSCORE_{i,t} Macroday_t + \beta_2 ZSCORE_{i,t} + \beta_3 Macroday_t$. The dependent variable of Dmy_{t+i} is either $DAIA_{t+i}$ or $DASVIt + i$, where j is varying from -5 to 6. $DAIA$ is a dummy variable indicating if the institutional investors' attention to stocks is abnormal. Likewise, we employ $DASVI$ to indicate if the retail investors' attention to stocks is abnormal. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample periods for retail investors' attention and institutional investors' attention are 2004:2021 and 2010:2021, respectively, due to their availability. Coefficients are reported in percentage. The intercept is not reported for brevity. Both observation number (#) and Pseudo R^2 in percentage are also reported.

Cycle (j)	-5	-4	-3	-2	-1	0	1	2	3	4	5	6
Panel A: Retail investor clientele's abnormal attention on stocks (DASVI)												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ZSCORE x Macroday	0.22	0.68	0.25	0.25	-0.15	-1.08**	-0.95**	-0.71*	0.44	0.19	1.11***	1.03**
	(0.50)	(1.63)	(0.58)	(0.62)	(-0.35)	(-2.53)	(-2.28)	(-1.87)	(1.11)	(0.50)	(2.61)	(2.48)
ZSCORE	-10.86***	-11.00***	-10.87***	-10.89***	-10.89***	-10.65***	-10.59***	-10.50***	-10.66***	-10.52***	-10.60***	-10.41***
	(-9.65)	(-9.75)	(-9.65)	(-9.67)	(-9.66)	(-9.50)	(-9.49)	(-9.40)	(-9.55)	(-9.41)	(-9.43)	(-9.30)
Macroday	-4.03***	-1.59***	-0.49	0.19	1.28***	3.64***	4.22***	6.10***	6.20***	4.46***	1.57***	0.74**
	(-10.84)	(-4.49)	(-1.39)	(0.55)	(3.45)	(9.98)	(11.71)	(19.28)	(18.81)	(13.92)	(3.96)	(2.09)
No. of Obs.	4,265,680	4,252,855	4,253,030	4,255,303	4,261,828	4,415,351	4,262,778	4,255,066	4,254,220	4,255,113	4,267,540	4,253,258
Pseudo R2(%)	0.40	0.39	0.39	0.39	0.39	0.40	0.40	0.40	0.40	0.38	0.36	0.35
Panel B: Institution clientele's abnormal attention on stocks (DAIA)												
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
ZSCORE x Macroday	1.41***	0.52	1.60***	2.26***	1.38**	-0.78	0.41	1.32**	2.05***	3.96***	3.77***	2.40***
	(2.64)	(1.01)	(3.14)	(4.11)	(2.43)	(-1.49)	(0.81)	(2.50)	(3.80)	(7.25)	(7.44)	(4.93)
ZSCORE	-16.98***	-17.09***	-17.57***	-17.95***	-17.95***	-17.49***	-17.12***	-16.71***	-16.22***	-16.11***	-15.55***	-14.77***
	(-13.00)	(-13.05)	(-13.41)	(-13.59)	(-13.45)	(-13.25)	(-13.11)	(-12.73)	(-12.44)	(-12.31)	(-11.97)	(-11.51)
Macroday	-4.84***	1.83***	3.25***	8.55***	6.72***	-2.73***	5.18***	3.85***	5.22***	2.35***	-3.23***	0.17
	(-9.90)	(3.90)	(7.24)	(19.30)	(14.27)	(-6.04)	(12.68)	(8.63)	(11.36)	(5.11)	(-6.99)	(0.38)
No. of Obs.	2,827,429	2,818,675	2,819,178	2,819,877	2,824,405	2,926,532	2,821,156	2,821,003	2,817,962	2,822,421	2,828,451	2,815,637
Pseudo R2(%)	0.62	0.62	0.64	0.69	0.69	0.66	0.63	0.59	0.55	0.51	0.50	0.45

Table 3.5: Attention Spillover Effects in Non-announcing Firms: Firm-Level Regression Analysis

This table reports the results of regressing stock returns surrounding macro-announcements on lottery features and the coverage of earnings announcements. Panel A presents the analysis results using the full sample. In contrast, Panel B uses a sample restricted to firms covered with earnings announcements, and Panel C uses a sample restricted to firms without earnings announcements (non-announcing firms). The regression model is $CAR[h,H]_{i,t} = \gamma_0 + \gamma_1 Lottery_{i,t} + \lambda' X_{i,t} + \epsilon_{i,t}$. $CAR[h,H]_{i,t}$ is a market model adjusted cumulative abnormal return over a holding window h day(s) and H day(s) after a macro-announcement day t. The earnings announcing dummy variable (EA) is one if a stock has an earnings announcement within a window from one day before a macro-announcement to one day after that, and it would be zero otherwise. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). X are control variables observed at the end of the most recent month, including the book-to-market ratio (BM), illiquidity (ILLIQ), momentum (MOM), log market capitalization (SIZE) and turnover (TURN). Standard errors are clustered by the macro-event date, and adjusted T-statistics are reported in parentheses. Firm and Year fixed effects are included. The intercept is not reported in this table for brevity. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021. Reported coefficients are in percentage.

	Panel A: Announcing Firms (EA==1)						Panel B: Non-announcing Firms (EA==0)					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Dep.	CAR[-5,-1]	CAR[0,1]	CAR[2,6]	CAR[-5,-1]	CAR[0,1]	CAR[2,6]	CAR[-5,-1]	CAR[0,1]	CAR[2,6]	CAR[-5,-1]	CAR[0,1]	CAR[2,6]
ZSCORE x Mkt	-	-	-	8.68	13.44**	1.15	-	-	-	1.76	11.71***	9.97**
	-	-	-	(1.22)	(2.52)	(0.21)	-	-	-	(0.36)	(4.84)	(2.46)
Mkt	-	-	-	4.08	21.03***	4.00	-	-	-	4.31	17.88***	9.87*
	-	-	-	(0.49)	(3.62)	(0.57)	-	-	-	(0.68)	(6.66)	(1.76)
ZSCORE	0.75***	-0.08	-0.10	0.73***	-0.11	-0.10	0.78***	-0.06***	-0.10***	0.78***	-0.08***	-0.12***
	(8.53)	(-1.19)	(-1.34)	(8.11)	(-1.59)	(-1.38)	(14.99)	(-2.66)	(-2.75)	(14.68)	(-3.67)	(-3.24)
BM	0.15	0.33**	0.41***	0.15	0.33**	0.41***	-0.03	0.14***	0.31***	-0.03	0.14***	0.31***
	(1.04)	(2.57)	(3.75)	(1.04)	(2.55)	(3.75)	(-0.80)	(4.73)	(7.46)	(-0.81)	(4.79)	(7.45)
ILLIQ	-0.06	0.05	-0.39*	-0.08	0.02	-0.40*	-0.14***	0.02	-0.10**	-0.14***	0.02	-0.10**
	(-0.28)	(0.25)	(-1.75)	(-0.36)	(0.08)	(-1.76)	(-2.59)	(0.79)	(-2.38)	(-2.60)	(0.68)	(-2.41)
SIZE	0.08	-0.75***	-0.64***	0.08	-0.75***	-0.64***	0.22***	-0.20***	-0.45***	0.22***	-0.20***	-0.46***
	(1.01)	(-9.73)	(-7.05)	(1.01)	(-9.79)	(-7.05)	(4.58)	(-8.87)	(-12.10)	(4.59)	(-8.99)	(-12.08)
TURN	-0.00	-0.01	-0.02***	-0.00	-0.01	-0.02***	-0.00	-0.00	-0.00***	-0.00	-0.00	-0.00***
	(-0.02)	(-0.77)	(-3.35)	(-0.01)	(-0.77)	(-3.35)	(-0.34)	(-0.70)	(-3.52)	(-0.34)	(-0.67)	(-3.51)
MOM	-0.11	-0.01	-0.05	-0.11	-0.00	-0.05	-0.08	0.05	0.03	-0.08	0.05	0.03
	(-1.31)	(-0.09)	(-0.67)	(-1.31)	(-0.05)	(-0.66)	(-1.60)	(1.34)	(0.54)	(-1.61)	(1.35)	(0.52)
No. of Obs.	145,822	145,422	145,822	145,822	145,422	145,822	2,739,247	2,723,954	2,739,048	2,739,247	2,723,954	2,739,048
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R^2 (%)	4.86	3.39	4.68	4.87	3.48	4.68	0.87	0.55	0.90	0.88	0.77	0.93

Table 3.6: Attention Spillover Effects in Non-announcing Firms: Portfolio-Level Analysis

This table reports the mean *CAR* on conditional lottery-hedging portfolios for announcing and non-announcing firms separately. The earnings-announcing window, denoted as EA[h, H], refers to the period starting from h days before and ending H days after a macro-announcement day. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). The sample is then divided into two subsamples, one for announcing firms and one for non-announcing firms, based on whether a firm has such an EA window on a macro-announcement day. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. Within each subsample, stocks are further sorted into ten deciles on the lottery signals at the end of the most recent month. The bottom decile exhibits the highest lottery feature, while the top decile exhibits the least. The lottery-hedging portfolio involves buying the top decile and selling the bottom decile simultaneously. The conditional portfolio involves buying (selling) a decile if the market return on a macro-announcement day is positive (negative). For brevity, the table presents the performance of only conditional lottery-hedging portfolios for different EA windows. The t-statistics, reported in parentheses, are based on Newey & West (1987) standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021.

	Panel A: Announcing Firms					
	CAR[-5,-1]	CAR[0,1]	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]
EA[-1,1]	0.73	-0.07	0.35	0.09	-0.04	0.01
	(1.41)	(-0.24)	(0.78)	(0.15)	(-0.06)	(0.01)
EA[-2,2]	0.73*	0.23	-0.01	-0.16	-0.36	-0.68
	(1.82)	(0.97)	(-0.02)	(-0.33)	(-0.65)	(-0.89)
EA[-3,3]	0.61*	0.25	-0.18	-0.25	-0.27	-0.17
	(1.87)	(1.22)	(-0.54)	(-0.60)	(-0.55)	(-0.25)
EA[-4,4]	0.47	0.18	0.15	-0.30	-0.23	-0.30
	(1.45)	(0.93)	(0.44)	(-0.68)	(-0.46)	(-0.40)
EA[-5,5]	0.39	0.12	0.17	-0.23	-0.06	0.10
	(1.12)	(0.66)	(0.53)	(-0.55)	(-0.13)	(0.15)
	Panel B: Non-announcing Firms					
	CAR[-5,-1]	CAR[0,1]	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]
EA[-1,1]	0.25	0.38***	0.45***	0.26	0.21	0.49
	(1.55)	(5.00)	(2.96)	(1.08)	(0.70)	(1.20)
EA[-2,2]	0.25	0.38***	0.46***	0.28	0.24	0.54
	(1.53)	(4.98)	(3.09)	(1.14)	(0.80)	(1.31)
EA[-3,3]	0.26	0.38***	0.47***	0.28	0.25	0.54
	(1.57)	(4.94)	(3.18)	(1.15)	(0.81)	(1.30)
Ea[-4,4]	0.25	0.38***	0.45***	0.25	0.22	0.54
	(1.49)	(5.03)	(3.12)	(1.03)	(0.73)	(1.34)
EA[-5,5]	0.24	0.39***	0.47***	0.27	0.25	0.57
	(1.50)	(5.05)	(3.30)	(1.14)	(0.83)	(1.40)

Table 3.7: Attention Spillover Effects: Different Macro-Announcement Event Types Analysis

This table reports the predictability of macro-announcement-day market returns on post-macro-announcement returns lottery-like stock, conditioning on a single macro-announcement event type. The regression model is $CAR[h,H]_{i,t} = \beta_0 + \beta_1 Lottery_{i,t} Mkt_t + \beta_2 Lottery_{i,t} + \beta_3 Mkt_t + \lambda' X_{i,m-1} + \epsilon_{i,t}$, where $CAR[h,H]_{i,t}$ is a market model adjusted cumulative abnormal return over a holding window h day(s) and H day(s) after a macro-announcement day t. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). Mkt_t is the CRSP value-weight market returns excluding dividends. X are control variables observed at the end of the most recent month, including the book-to-market ratio (BM), illiquidity (ILLIQ), momentum (MOM), log market capitalization (SIZE) and turnover (TURN). Standard errors are clustered by the macro-event date, and adjusted T-statistics are reported in parentheses. Firm and Year fixed effects are included. The intercept is not reported in this table for brevity. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021.

	Panel A: FOMC					Panel B: ISM PMI				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep.	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]	CAR[2,26]	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]	CAR[2,26]
ZSCORE x Mkt	18.69**	34.56**	31.58*	30.40	31.34	11.58*	-2.91	-2.17	5.38	-7.03
	(2.30)	(2.14)	(1.74)	(1.57)	(1.65)	(1.77)	(-0.25)	(-0.17)	(0.37)	(-0.42)
ZSCORE	-0.15	-0.38***	-0.46***	-0.62***	-0.75***	-0.08	-0.23**	-0.35***	-0.59***	-0.62***
	(-1.59)	(-3.01)	(-2.89)	(-3.53)	(-3.89)	(-1.25)	(-2.37)	(-3.12)	(-4.53)	(-4.16)
Mkt	25.09**	47.30**	47.35**	44.83*	40.76*	10.27	-1.62	-9.51	-5.73	-22.12
	(2.24)	(2.54)	(2.19)	(1.91)	(1.67)	(1.04)	(-0.13)	(-0.77)	(-0.38)	(-1.15)
Control X	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
No. of Obs.	607,922	608,062	606,067	606,067	606,067	893,109	893,370	893,386	893,389	891,394
Adj. R2(%)	1.56	1.93	1.98	2.22	2.52	1.22	1.45	1.82	2.14	3.03

	Panel C: EM					Panel D: PC				
	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Dep.	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]	CAR[2,26]	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]	CAR[2,26]
ZSCORE x Mkt	5.02	1.85	1.44	12.49	25.50	-1.54	-6.38	-14.02	-10.34	-6.28
	(0.59)	(0.13)	(0.10)	(0.77)	(1.37)	(-0.22)	(-0.49)	(-0.99)	(-0.63)	(-0.31)
ZSCORE	-0.21***	-0.36***	-0.51***	-0.64***	-0.82***	-0.06	-0.25***	-0.36***	-0.49***	-0.60***
	(-3.43)	(-3.84)	(-4.68)	(-4.63)	(-5.51)	(-0.82)	(-2.61)	(-2.81)	(-3.87)	(-3.85)
Mkt	3.29	3.75	3.07	8.40	19.21	-4.90	-13.26	-28.20	-13.88	3.26
	(0.38)	(0.30)	(0.23)	(0.48)	(0.95)	(-0.40)	(-0.65)	(-1.30)	(-0.63)	(0.13)
Control X	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
No. of Obs.	876,181	876,439	876,453	874,459	874,459	631,549	629,581	629,581	629,581	627,571
Adj. R^2(%)	1.10	1.50	1.79	2.12	2.88	0.97	1.26	1.59	1.83	2.56

Table 3.8: Attention Spillover Effects: Different Holding Periods

This table reports attention spillover effects towards different buy-and-holding periods after macro-announcements. The regression model is $CAR[2,H]_{i,t} = \beta_0 + \beta_1 Lottery_{i,t} Mkt_t + \beta_2 Lottery_{i,t} + \beta_3 Mkt_t + \lambda' X_{i,m-1} + \epsilon_{i,t}$, where $CAR[h,H]_{i,t}$ is a market model adjusted cumulative abnormal return over a holding window h day(s) and H day(s) after a macro-announcement day t. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEW-EXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. All stocks are sorted into ten deciles on the lottery signals at the end of the most recent month. The bottom decile exhibits the highest lottery feature while the top decile exhibits the least. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). Mkt_t is the CRSP value-weight market returns excluding dividends. X are control variables observed at the end of the most recent month, including the book-to-market ratio (BM), illiquidity (ILLIQ), momentum (MOM), log market capitalization (SIZE) and turnover (TURN). Standard errors are clustered by the macro-event date, and adjusted T-statistics are reported in parentheses. Firm and Year fixed effects are included. The intercept is not reported in this table for brevity. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]	CAR[2,26]	CAR[2,31]
ZSCORE x Mkt	9.54**	7.05	4.92	11.69	12.42	13.73
	(2.40)	(0.96)	(0.63)	(1.36)	(1.29)	(1.28)
ZSCORE	-0.12***	-0.29***	-0.41***	-0.59***	-0.71***	-0.90***
	(-3.31)	(-5.57)	(-6.51)	(-8.09)	(-8.67)	(-10.09)
Mkt	9.66*	9.33	4.15	9.70	8.61	8.36
	(1.74)	(1.16)	(0.46)	(0.97)	(0.74)	(0.68)
Control X	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
No. of Obs.	2,886,143	2,884,803	2,882,831	2,880,808	2,876,809	2,876,809
Adj. R^2(%)	0.93	1.53	2.04	2.61	3.30	4.01

Table 3.9: Attention Spillover Effects: Non-overlapping *CAR* Analysis

This table reports the results of the non-overlapping test on attention spillover effects across different holding periods. To conduct the non-overlapping test, we add a constraint to the *CAR*. Opening a new position during the last position's holding period is prohibited. Panel A reports the coefficients in the percentage of regressing non-overlapping *CAR* on ZSCORE, Mkt, an interaction term between them and X. X are control variables observed at the end of the most recent month, including the book-to-market ratio (BM), illiquidity (ILLIQ), momentum (MOM), log market capitalization (SIZE) and turnover (TURN). Note that firm and year fixed effects are included in all regressions, and the standard errors are clustered by macro-news dates. Adjusted T-stat is reported within the parentheses. Both observation number (#) and adjusted R-squared are also reported. Panel B reports the mean *CAR* on portfolios, and respective Newey & West (1987) adjusted T-statistics are reported in the parentheses. We construct the lottery portfolios with non-overlapping *CAR* first. Specifically, we sort the *CAR* into deciles based on their stocks' lottery feature, ZSCORE, at the most recent month's end. The bottom (top) decile shows the most (least) lottery features. And for each decile, we buy (sell) it based on the sign of market returns on the macro-news days, termed the conditional lottery portfolios. To observe how well lottery-like stocks outperform non-lottery-like stocks, we construct hedging portfolios (10-1), the long-short portfolios formed by simultaneously taking positions in the long bottom and short top decile.Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021.

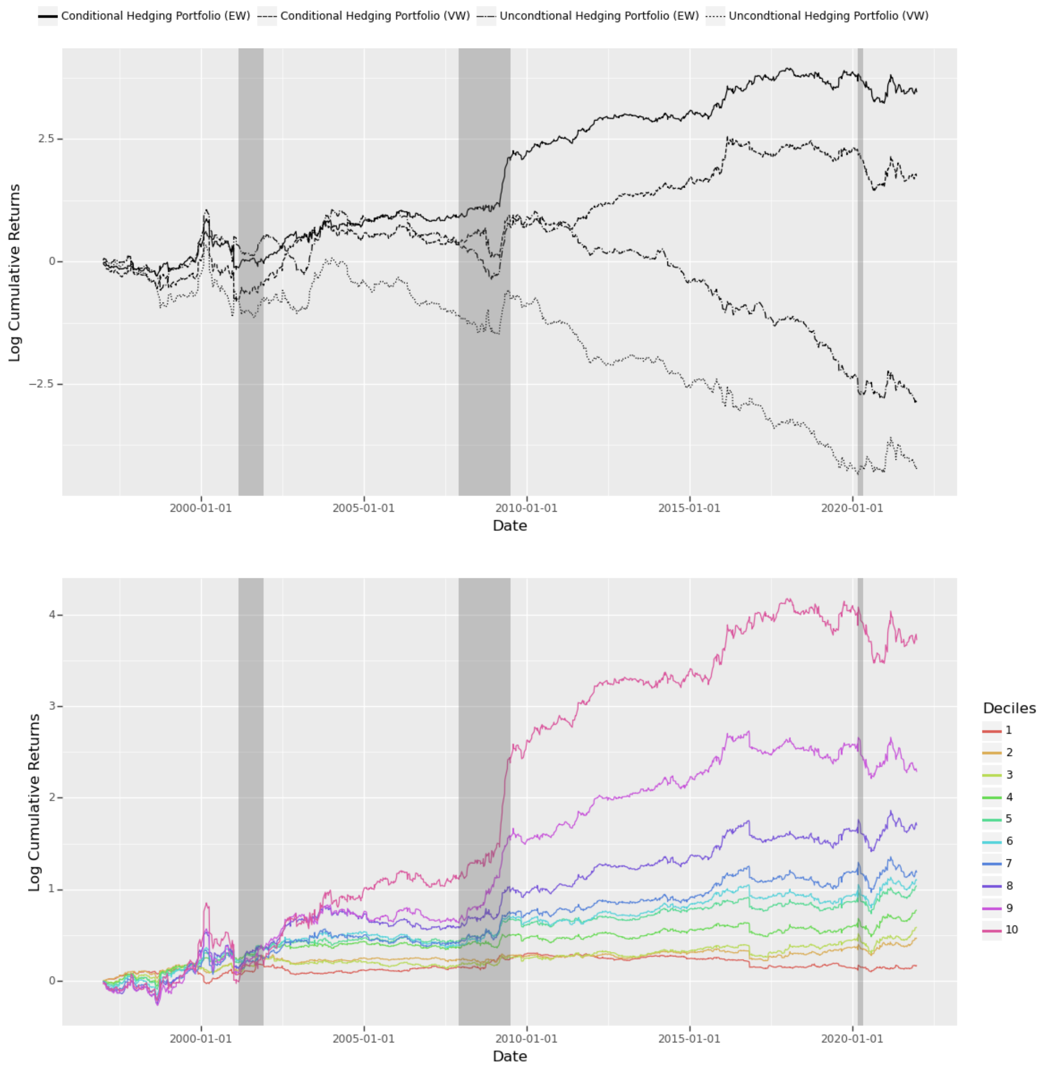
Panel A: Regression Analysis						
	(1)	(2)	(3)	(4)	(5)	(6)
Dep.	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]	CAR[2,26]	CAR[2,31]
ZSCORE x Mkt	8.41*	6.32	12.28	-2.12	-6.73	12.83
	(1.87)	(0.62)	(0.85)	(-0.13)	(-0.35)	(0.56)
ZSCORE	-0.10**	-0.35***	-0.46***	-0.61***	-0.68***	-0.96***
	(-2.05)	(-4.35)	(-4.07)	(-4.80)	(-4.62)	(-5.40)
Mkt	7.13	11.80	17.10	9.26	-6.21	16.95
	(1.06)	(0.94)	(0.94)	(0.55)	(-0.27)	(0.56)
Control X	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
No. of Obs.	1,809,371	1,240,841	1,115,295	913,419	889,714	774,628
Adj. R^2(%)	0.77	1.23	1.64	2.02	2.78	3.48
Panel B: Conditional Portfolios Analysis						
Decile #	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]	CAR[2,26]	CAR[2,31]
1	-0.01	0.07*	0.08	0.02	0.11	0.18*
	(-0.22)	(1.84)	(1.25)	(0.32)	(1.43)	(1.94)
2	-0.03	0.02	0.01	-0.05	-0.09	0.06
	(-1.19)	(0.44)	(0.27)	(-0.58)	(-1.14)	(0.64)
3	0.02	-0.03	-0.00	0.11	0.01	0.06
	(0.55)	(-0.46)	(-0.01)	(1.25)	(0.11)	(0.47)
4	0.01	-0.11	-0.04	0.18*	0.09	-0.19
	(0.23)	(-1.58)	(-0.41)	(1.78)	(0.70)	(-1.45)
5	0.03	-0.20**	-0.24*	-0.07	-0.06	-0.05
	(0.49)	(-2.02)	(-1.74)	(-0.39)	(-0.30)	(-0.21)
6	0.03	-0.03	-0.03	-0.06	-0.15	-0.12
	(0.35)	(-0.23)	(-0.19)	(-0.33)	(-0.71)	(-0.46)
7	0.03	-0.34*	-0.15	-0.19	-0.49	-0.22
	(0.30)	(-1.80)	(-0.66)	(-0.64)	(-1.54)	(-0.64)
8	0.11	-0.31	-0.22	-0.11	-0.37	-0.50
	(0.82)	(-1.34)	(-0.77)	(-0.36)	(-1.08)	(-0.91)
9	0.24*	0.04	0.13	0.12	-0.46	-0.57
	(1.75)	(0.15)	(0.41)	(0.31)	(-0.98)	(-1.09)
10	0.33*	-0.07	0.15	-0.11	-0.86	0.44
	(1.90)	(-0.18)	(0.33)	(-0.16)	(-1.24)	(0.52)
10-1	0.34*	-0.14	0.07	-0.14	-0.97	0.26
	(1.78)	(-0.36)	(0.14)	(-0.18)	(-1.31)	(0.29)

Table 3.10: Attention Spillover Effects: Different Lottery Proxies

This table reports attention spillover effects towards different lottery proxies. Panel A and B report the results of regressions. The regression model is $CAR[2,H]_{i,t} = \beta_0 + \beta_1 Lottery_{i,t} Mkt_t + \beta_2 Lottery_{i,t} + \beta_3 Mkt_t + \lambda' X_{i,m-1} + \epsilon_{i,t}$, where $CAR[h,H]_{i,t}$ is a market model adjusted cumulative abnormal return over a holding window h day(s) and H day(s) after a macro-announcement day t. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. All stocks are sorted into ten deciles on the lottery signals at the end of the most recent month. The bottom decile exhibits the highest lottery feature while the top decile exhibits the least. Since the value of different proxies is not comparable, we replace *lottery* with *LotteryPort*, which indicates the number of deciles that the focal stock is assigned into. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). Mkt_t is the CRSP value-weight market returns excluding dividends. X are control variables observed at the end of the most recent month, including the book-to-market ratio (BM), illiquidity (ILLIQ), momentum (MOM), log market capitalization (SIZE) and turnover (TURN). Standard errors are clustered by the macro-event date, and adjusted T-statistics are reported in parentheses. Firm and Year fixed effects are included. The intercept is not reported in this table for brevity. Panel C and D report the value-weighted portfolios performance. The t-statistics, reported in parentheses, are based on Newey & West (1987) standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021.

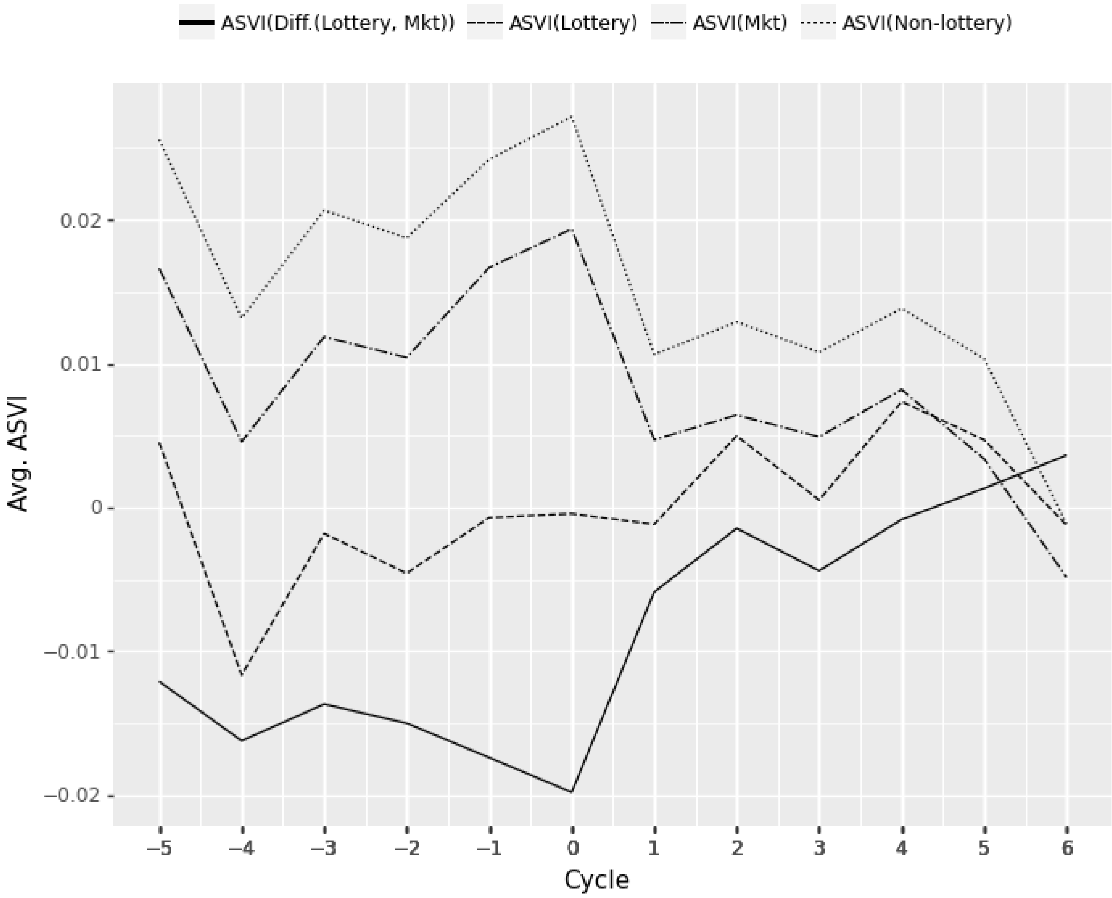
	Panel A: Attention Spillover Effects					Panel B: Lottery Stocks Reacting to Macro-Events				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep.: CAR[2,6]	MAX	LNP	IVOL	SKEWEXP	ZSCORE	MAX	LNP	IVOL	SKEWEXP	ZSCORE
LotteryPort x Mkt	0.77	3.64***	1.61	2.93***	2.68**	-	-	-	-	-
	(0.85)	(3.50)	(1.53)	(4.04)	(2.35)	-	-	-	-	-
Mkt	3.65	-5.17	0.80	-5.69*	-2.46	-	-	-	-	-
	(0.94)	(-1.57)	(0.21)	(-1.71)	(-0.69)	-	-	-	-	-
LotteryPort	-0.02***	-0.01	-0.02***	-0.02*	-0.04***	0.48	-0.09*	2.36	0.01	-0.10***
	(-2.82)	(-0.87)	(-3.23)	(-1.73)	(-3.48)	(1.17)	(-1.92)	(1.25)	(0.92)	(-2.83)
Control X	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
No. of Obs.	2,886,356	2,886,384	2,886,364	2,274,634	2,886,143	2,886,356	2,886,384	2,886,364	2,274,634	2,886,143
Adj. R^2(%)	0.91	0.93	0.92	0.82	0.93	0.90	0.90	0.90	0.79	0.90
	Panel C: Conditional Lottey Portfolios (VW)					**Panel D: Lottery Portfolios (VW)**				
Portfolio	MAX	LNP	IVOL	SKEWEXP	ZSCORE	MAX	LNP	IVOL	SKEWEXP	ZSCORE
1	-0.02	-0.01	-0.03	-0.01	-0.01	0.11***	0.10***	0.11***	0.07**	0.11***
	(-0.57)	(-0.46)	(-1.09)	(-0.40)	(-0.24)	(2.87)	(4.72)	(3.15)	(2.12)	(3.98)
2	0.00	0.01	0.00	-0.01	-0.01	0.08***	-0.03	0.09***	0.06**	0.06**
	(0.04)	(0.42)	(0.10)	(-0.23)	(-0.72)	(3.08)	(-0.98)	(3.75)	(2.18)	(2.49)
3	0.01	-0.02	-0.01	-0.04	0.03	0.09***	0.05	0.06**	0.06*	0.05
	(0.25)	(-0.57)	(-0.29)	(-1.56)	(1.20)	(3.38)	(1.39)	(2.23)	(1.81)	(1.64)
4	-0.03	0.00	0.02	0.00	-0.01	0.01	0.05	0.05*	0.15***	-0.00
	(-1.26)	(0.05)	(0.92)	(0.13)	(-0.16)	(0.22)	(1.04)	(1.66)	(3.38)	(-0.04)
5	-0.00	0.05	0.04	0.04	0.02	0.03	0.13**	0.03	0.13*	0.03
	(-0.04)	(0.94)	(1.16)	(0.73)	(0.42)	(0.88)	(1.99)	(0.86)	(1.95)	(0.43)
6	0.07*	0.12	-0.04	0.05	0.01	-0.01	0.05	-0.00	0.01	0.03
	(1.88)	(1.57)	(-0.86)	(1.07)	(0.16)	(-0.15)	(0.60)	(-0.08)	(0.20)	(0.34)
7	0.01	0.20***	-0.02	0.12**	0.03	-0.01	0.06	0.04	0.07	-0.01
	(0.11)	(2.59)	(-0.28)	(2.03)	(0.33)	(-0.21)	(0.66)	(0.41)	(0.98)	(-0.08)
8	0.01	0.33**	-0.00	0.13*	0.14	-0.01	0.06	-0.08	0.03	-0.12
	(0.16)	(2.38)	(-0.04)	(1.81)	(1.13)	(-0.11)	(0.35)	(-0.85)	(0.33)	(-0.86)
9	-0.14	0.27*	0.06	0.16*	0.24*	-0.05	-0.38**	-0.08	-0.06	-0.13
	(-1.42)	(1.93)	(0.51)	(1.95)	(1.88)	(-0.49)	(-2.20)	(-0.69)	(-0.58)	(-0.84)
10	0.10	0.45***	0.04	0.26**	0.31*	0.03	-0.29	-0.03	-0.34**	-0.20
	(0.95)	(2.64)	(0.31)	(2.24)	(1.82)	(0.29)	(-1.27)	(-0.23)	(-2.50)	(-1.00)
10-1	0.11	0.46***	0.07	0.27**	0.31*	-0.07	-0.39	-0.14	-0.41***	-0.30
	(0.96)	(2.60)	(0.51)	(2.19)	(1.69)	(-0.56)	(-1.63)	(-0.91)	(-2.81)	(-1.42)

3.8 Figures



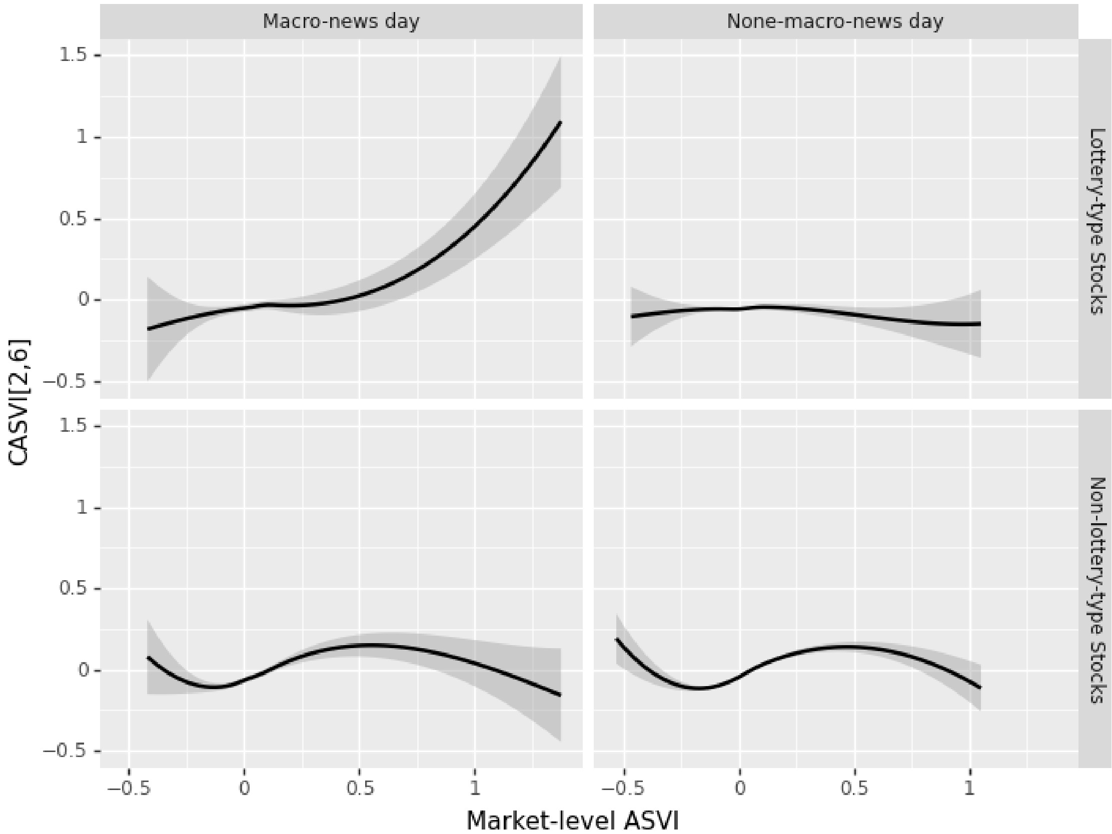
Conditional lottery-hedging portfolios outperform unconditional lottery-hedging portfolios. The figure visualises cumulative returns on the lottery-related portfolios over the long term. The upper part of this figure shows that the value-weighted and equal-weighted conditional lottery-hedging portfolios outperform those unconditional portfolios. The lower part of this figure illustrates the performance of the conditional lottery deciles. The higher the lottery feature, the better the performance of the conditional trading. We sort $CAR[2,6]$ into ten deciles based on the lottery feature, ZSCORE. We then construct the lottery-hedging portfolio by taking the difference between the bottom and top decile. Grey areas indicate the NBER recession periods.

Figure 3.2: Conditional VS Unconditional Lottery Portfolios



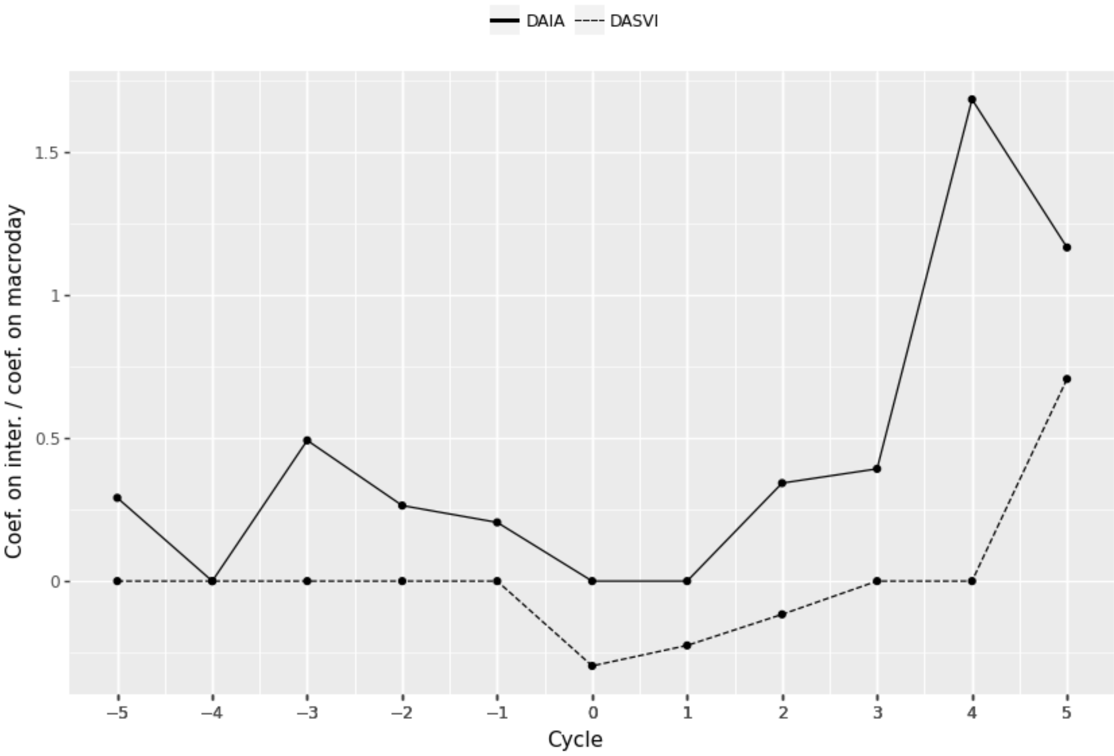
Market-concentrated Attention Spills Over To Lottery Stocks During Post-macro-announcement Periods. The figure reports the mean abnormal Google search volume index (ASVI) towards market and firms classified by lottery features surrounding macro-announcements. Date 0 represents the macro-announcement day. The market ASVI is constructed as the value-weighted ASVI on stocks. The lottery-type ASVI and non-lottery-type ASVI are formed as the value-weighted ASVI on lottery-like and non-lottery-like stocks, respectively. We sort all stocks into ten deciles based on their lottery feature, ZSCORE. The bottom (top) decile is denoted as the lottery-type (non-lottery-type) stocks. The figure shows an increase in abnormal attention on the market approaching the macro-announcements, with such heightened attention on the market dropping dramatically after the events. Meanwhile, there is increased ASVI on lottery-type firms after the events. For brevity, we plot a solid line representing the difference between the lottery-type ASVI and the market ASVI, denoted as ASVI(Diff. (Lottery, Mkt)). This difference has a downtrend pattern ahead of the macro-announcements but is climbing after the events. These findings highlight the attention spillover effects of macro-announcements on individual stocks, particularly on those with lottery-like features.

Figure 3.3: Attention on Market and Firms



The higher attention to the macro-day market, the higher attention to the post-macro-announcement lottery-type stocks. This graph visualises the relation between attention to stocks during the post-macro-announcement period and the market's attention, estimated from local-linear regression with 90% confidence intervals represented as grey areas on the graph. The first row of this grid shows the relation for lottery-type stocks, while the second row shows that for non-lottery-type stocks. The first column shows the relation conditioning on macro-news days, while the second column shows its conditioning on non-macro-news days. The market-level ASVI is the value-weighted ASVI on all stocks in the sample, where ASVI is the log difference between SVI and the median SVI during the most recent month. We calculate CASVI[2,6] as the sum of the ASVI in a window starting two days and ending six days after macro-announcement days.

Figure 3.4: Conditional Attention Spillover



Both retail and institutional investors have increasing attention on lottery-like stocks during post-macro-announcement periods. We respectively run probit panel regressions of DAIA and DASVI on an interaction term between ZSCORE and Macroday, and each of them. We extract coefficients (β_1) on the interaction term and coefficients (β_3) on Macroday. Then we take the ratio of β_1/β_3 to observe how greater lottery-like stocks receive attention on macro-news days than non-lottery-like stocks. Insignificant $\beta 1$ is presented as zero.

Figure 3.5: Attention: Retail VS. Institutions

A Appendix: Variables Construction

A.1 Stock Reaction to Macro-Announcements: CAR

Following Hirshleifer & Sheng (2022), we measure stock reactions to an event with Cumulative Abnormal Return (CAR) based on the market model. That is, given on any day t, the CAR of a company i over period $(t+h, t+H)$ is defined as follows

$$CAR[h,H]_{i,t} = \left[\prod_{j=t+h}^{t+H}(1+R_{i,j}) - 1\right] - \hat{\beta}_{i,t}\left[\prod_{j=t+h}^{t+H}(1+R_{m,j}) - 1\right] \tag{3.3}$$

where $R_{i,j}$ is the stock return of company i on day j, $R_{m,j}$ is the market return on day j, and $\hat{\beta}_{i,t}$ is obtained from the market model regression $R_{i,t} = \alpha_{i,t} + \beta_{i,t}R_{m,t} + \epsilon$ with a rolling window from $t-300$ to $t-46$. Based on that, we quantify the stock performance in the pre-, during- and post-macro-announcements as $CAR[-5,-1]$, $CAR[0,1]$ and $CAR[2,6]$.

A.2 Control Variables

To control for firm characteristics that may affect the main results in this paper, we construct log book-to-market ratio (BM), log market capitalization (SIZE), illiquidity (ILLIQ) and cumulative returns over the recent 12 months but skipping the most recent month (Momentum, denoted as MOM), turnover (TURN). Factors of BM, SIZE and MOM affecting stock prices are documented well in the literature (Fama & French 1993, Jegadeesh & Titman 1993, Carhart 1997).

1. SIZE is the log market capitalization of a stock. Specifically, the market capitalization is the multiplication between share adjusted close prices and adjusted total shares outstanding, where the adjusted close price is the close price divided by the 'cumulative factor to adjust price', and the adjusted shares outstanding is the number of shares outstanding times the 'cumulative factor to

adjust shares'. A company could have several securities with different market values, therefore, we take the sum of the market value of these securities as its market capitalization. It is well known in the literature that smaller firms outperform larger firms (Fama & French 1993, Van Dijk 2011, Zakamulin 2013).

2. BM, the book-to-market ratio is book equity divided by the market capitalization, where book equity is the sum of stockholder's equity, deferred taxes and investment tax credit but minus preferred stock (Daniel & Titman 1997). Capturing the stock value, literature generally documents the BM premium, which is that high-value firms generally outperform low-value firms (Fama & French 1993, 1995, Pontiff & Schall 1998, Caglayan et al. 2018).

3. MOM signal is calculated as the cumulative returns of the past 12 months but skipped returns in the most recent month to exclude the reversal effect. Stocks with past up-trends are believed to outperform stocks with past downtrends (Jegadeesh & Titman 1993).

4. TURN is turnover, the monthly trading volume divided by the monthly total shares outstanding. Kumar (2009) document that stocks with high monthly turnover are more likely to be attention-grabbing.

5. ILLIQ is the absolute monthly returns on a stock divided by the respective monthly trading volume in dollars (the monthly price multiplies the monthly trading). A positive relationship between stock returns and illiquidity is well documented in the literature (Amihud 2002, Amihud & Noh 2021, Cakici & Zaremba 2021).

A.3 Lottery Price Signals

Given that the lottery clientele exhibits the willingness to take a small chance on a large gain (Kumar 2009), we capture the lottery-like stocks by employing proxies of idiosyncratic volatility (IVOL), expected idiosyncratic skewness (SKEWEXP), extreme positive returns (MAX) and Z-score (ZSCORE).

1. MAX: Literature documents the max effects well in stock markets across different countries (Bali et al. 2011, Annaert et al. 2013, Zhong & Gray 2016). That is, investors prefer stocks with extremely positive returns in the most recent month and thus leads to lower future returns on those stocks. We then follow that to employ the maximum daily returns (MAX) in the past month to capture a stock's lottery feature. The larger MAX, the higher the lottery feature a stock has.

2. SKEWEXP: We follow the procedure documented in Boyer et al. (2010) to estimate the expected idiosyncratic skewness. First, we take the time-series residuals of regressions regressing daily stock excess returns on Fama-French-three factor daily data (Fama & French 1993) for every individual stock. Second, we take the standard deviation and skewness on these daily residuals at the end of each month as the monthly idiosyncratic volatility and idiosyncratic skewness. Third, we obtain the estimated coefficients of cross-sectional regressions regressing idiosyncratic skewness on the lagged-60-month variables, including idiosyncratic volatility, idiosyncratic skewness, small and medium size firm dummy variables, Fama-French-17-industry dummies and NASDAQ dummy. Finally, we estimate the expected idiosyncratic skewness for the next-60-month period as the multiplication between the obtained coefficients and the same variables employed in the last step but without lagging.

3. IVOL is the Idiosyncratic volatility. We follow Ang, Hodrick, Xing & Zhang (2006) to estimate the daily residuals by regressing stock daily excess return on Fama-French-three factor daily data (Fama & French 1993) at the end of every month (at least ten non-missing values are required). Then we take IVOL as the standard deviation of the daily residuals within the previous month. Aabo

et al. (2017) document the increasing role of noise traders with the increasing IVOL.

4. LNP is the negative log sum of one and a stock price. Given that the low-priced stock is relative to the highest potential payoff (Kumar 2009, Liu et al. 2020), we then employ the price as one of the measures of lottery price signals.

5. ZSCORE is the average of the individual z-scores of the above lottery price signals for a stock in a month (at least three non-missing lottery price signals are required). Under each lottery measure, the individual z-scores for these stocks are obtained based on the cross-sectional rankings of the lottery price signals (Liu et al. 2020). We employ this methodology since lottery proxies are various and adapt it to represent all proxies.

B Appendix: Other Robustness Check

Table 3.11: Attention Spillover Effects (Subsamples Analysis): Subsample-Firm-Level Regression Analysis

This table presents the attention spillover effects of two subsamples. The left panel reports the regression results based on the subsample starting from 1997 and ending in 2003, while the right panel reports the results based on the subsample starting from 2004 and ending in 2021. We split the sample to be consistent with the attention data sample period (2004:2021)The regression model is $CAR[h,H]_{i,t} = \beta_0 + \beta_1 Lottery_{i,t} Mkt_t + \beta_2 Lottery_{i,t} + \beta_3 Mkt_t + \lambda' X_{i,m-1} + \epsilon_{i,t}$, where $CAR[h,H]_{i,t}$ is a market model adjusted cumulative abnormal return over a holding window h day(s) and H day(s) after a macro-announcement day t. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. Mkt_t is the CRSP value-weight market returns excluding dividends. X are control variables observed at the end of the most recent month, including the book-to-market ratio (BM), illiquidity (ILLIQ), momentum (MOM), log market capitalization (SIZE) and turnover (TURN). Standard errors are clustered by the macro-event date, and adjusted T-statistics are reported in parentheses. Firm and Year fixed effects are included. The intercept is not reported in this table for brevity. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Reported coefficients are in percentage.

	1997:2003			2004:2021		
	(1)	(2)	(3)	(4)	(5)	(6)
Dep.	CAR[-5,-1]	CAR[0,1]	CAR[2,6]	CAR[-5,-1]	CAR[0,1]	CAR[2,6]
ZSCORE x Mkt	6.11	13.66**	18.00*	-0.58	11.34***	6.17*
	(0.69)	(2.37)	(1.84)	(-0.10)	(4.88)	(1.81)
ZSCORE	1.66***	-0.24***	-0.27***	0.64***	-0.07***	-0.11***
	(11.51)	(-4.75)	(-3.90)	(12.55)	(-2.87)	(-2.81)
Mkt	8.39	22.99***	24.13*	2.33	15.86***	2.83
	(0.82)	(4.27)	(1.92)	(0.30)	(5.17)	(0.55)
BM	-0.16**	0.22***	0.34***	0.03	0.13***	0.33***
	(-2.03)	(4.42)	(3.95)	(0.53)	(3.66)	(6.74)
ILLIQ	-0.06	0.03	-0.08**	-0.36***	-0.06	-0.18**
	(-1.52)	(1.11)	(-1.98)	(-3.16)	(-1.04)	(-1.98)
ln(ME)	0.60***	-0.63***	-1.05***	0.14***	-0.24***	-0.52***
	(3.15)	(-8.43)	(-9.00)	(2.98)	(-9.08)	(-11.51)
TURN	-0.03	0.02	0.01	-0.00	-0.00	-0.00***
	(-0.81)	(1.23)	(0.33)	(-0.34)	(-0.78)	(-3.70)
MOM	-0.14	0.12	0.12	-0.08*	0.02	-0.01
	(-1.61)	(1.65)	(0.97)	(-1.79)	(0.80)	(-0.28)
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
No. of Obs.	789,560	777,763	789,483	2,096,782	2,092,888	2,096,659
Adj. R^2(%)	1.45	1.13	1.50	0.63	0.57	0.86

Table 3.12: Attention Spillover Effects: Portfolio Performance Analysis

This table reports the Sharpe Ratios and Sortino Ratios of attention-spillover-lottery portfolios. The unconditional portfolios refer to the deciles obtained by sorting all stocks into ten deciles based on lottery features. The conditional portfolios are the unconditional portfolios adjusted according to market return signs precisely, where buying (selling) the deciles occur if market returns are positive (negative) on macro-announcement days. Both equal-weighted (EW) and value-weighted (VW) portfolios are presented.Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. All stocks are sorted into ten deciles on the lottery signals at the end of the most recent month. The bottom decile exhibits the highest lottery feature while the top decile exhibits the least. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Sharpe Ratio				
	Conditional Portfolio		Unconditional Portfolio	
	VW	EW	VW	EW
1	-0.06	0.20	1.14	0.74
2	-0.17	0.42	0.73	0.61
3	0.27	0.45	0.42	0.40
4	-0.04	0.51	-0.01	0.45
5	0.10	0.60	0.11	0.25
6	0.04	0.54	0.09	0.06
7	0.09	0.51	-0.02	-0.17
8	0.28	0.61	-0.24	-0.27
9	0.43	0.69	-0.23	-0.36
10	0.45	0.81	-0.28	-0.23
10-1	0.43	0.74	-0.41	-0.34
Panel B: Sortino Ratio				
	Conditional Portfolio		Unconditional Portfolio	
	VW	EW	VW	EW
1	-0.09	0.27	1.53	0.94
2	-0.24	0.62	1.05	0.82
3	0.39	0.64	0.62	0.55
4	-0.05	0.76	-0.02	0.62
5	0.14	0.87	0.16	0.37
6	0.06	0.77	0.15	0.08
7	0.10	0.70	-0.04	-0.25
8	0.41	0.81	-0.41	-0.40
9	0.64	0.93	-0.38	-0.55
10	0.63	1.12	-0.51	-0.39
10-1	0.61	1.04	-0.72	-0.59

Table 3.13: Attention Spillover Effects in Non-announcing Firms: Portfolio Analysis (Value-weighted)

This table reports the value-weighted CAR on conditional lottery-hedging portfolios for announcing and non-announcing firms separately. The earnings-announcing window, denoted as EA[h, H], refers to the period starting from h days before and ending H days after a macro-announcement day. Following Hirshleifer & Sheng (2022), we consider macro announcements including FOMC Decisions, Employment Status (EM), ISM Purchasing Manager Index (PMI) and Personal Consumption (PC). The sample is then divided into two subsamples, one for announcing firms and one for non-announcing firms, based on whether a firm has such an EA window on a macro-announcement day. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. Within each subsample, stocks are further sorted into ten deciles on the lottery signals at the end of the most recent month. The bottom decile exhibits the highest lottery feature, while the top decile exhibits the least. The lottery-hedging portfolio involves buying the top decile and selling the bottom decile simultaneously. The conditional portfolio involves buying (selling) a decile if the market return on a macro-announcement day is positive (negative). For brevity, the table presents the performance of only conditional lottery-hedging portfolios for different EA windows. The t-statistics, reported in parentheses, are based on Newey & West (1987) standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021.

Panel A: Announcing Firms						
	CAR[-5,-1]	CAR[0,1]	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]
EA[-1,1]	0.69	0.21	0.57	-0.06	0.03	0.17
	(1.37)	(0.69)	(1.15)	(-0.08)	(0.03)	(0.24)
EA[-2,2]	0.71	0.46*	0.02	-0.34	-0.56	-0.25
	(1.62)	(1.75)	(0.06)	(-0.55)	(-0.66)	(-0.50)
EA[-3,3]	0.13	0.38	-0.04	-0.09	0.40	-0.16
	(0.23)	(1.57)	(-0.12)	(-0.17)	(0.48)	(-0.36)
EA[-4,4]	0.10	0.46**	0.12	-0.32	0.17	-0.37
	(0.20)	(2.09)	(0.32)	(-0.59)	(0.19)	(-0.79)
EA[-5,5]	0.17	0.35*	0.16	-0.15	0.60	-0.21
	(0.32)	(1.76)	(0.45)	(-0.28)	(0.73)	(-0.48)
Panel B: Non-announcing Firms						
	CAR[-5,-1]	CAR[0,1]	CAR[2,6]	CAR[2,11]	CAR[2,16]	CAR[2,21]
EA[-1,1]	0.35	0.45***	0.29	-0.02	0.41	0.04
	(1.54)	(4.36)	(1.54)	(-0.05)	(0.82)	(0.12)
EA[-2,2]	0.35	0.43***	0.31*	0.02	0.48	0.05
	(1.59)	(4.17)	(1.68)	(0.04)	(0.94)	(0.18)
EA[-3,3]	0.42*	0.44***	0.32*	0.01	0.42	0.07
	(1.93)	(4.20)	(1.71)	(0.02)	(0.84)	(0.23)
EA[-4,4]	0.39*	0.42***	0.30*	0.02	0.43	0.05
	(1.78)	(4.04)	(1.71)	(0.04)	(0.85)	(0.15)
EA[-5,5]	0.41*	0.43***	0.34*	0.03	0.40	0.06
	(1.93)	(4.07)	(1.94)	(0.07)	(0.83)	(0.20)

Table 3.14: Attention Spillover: Hausman Test

This table reports the Hausman test results on deciding random effects or fixed effects for regression models. The result suggests that the fixed effects are appropriate to be included in the regression. The regression model is $CAR[h,H]_{i,t} = \beta_0 + \beta_1 Lottery_{i,t}Mkt_t + \beta_2 Lottery_{i,t} + \beta_3 Mkt_t + \lambda' X_{i,m-1} + \epsilon_{i,t}$, where $CAR[h,H]_{i,t}$ is a market model adjusted cumulative abnormal return over a holding window h day(s) and H day(s) after a macro-announcement day t. Lottery proxies are the high maximum daily return (MAX), high expected idiosyncratic skewness (SKEWEXP), high idiosyncratic volatility (IVOL) and low price (LNP). To represent all these proxies briefly, we take the mean value of standardized lottery signals above (ZSCORE). The higher the ZSCORE, the higher the lottery feature a stock has. Mkt_t is the CRSP value-weight market returns excluding dividends. X are control variables observed at the end of the most recent month, including the book-to-market ratio (BM), illiquidity (ILLIQ), momentum (MOM), log market capitalization (SIZE) and turnover (TURN). We include common stocks that are publicly listed on NYSE, AMEX, and NASDAQ stock exchanges and exclude those with prices below $5. Note that the sample period is January 1997 to December 2021.

Dep. = CAR[2,6]	(A) Fixed Effects	(B) Random Effects	(A-B) Difference	Std. Error
Mkt	0.08847470	0.08850720	-0.00003250	0.00018280
ZSCORE	-0.00066240	-0.00100240	0.00034000	0.00002800
Mkt X ZSCORE	0.09695550	0.09461680	0.00233870	0.00022770
BM	0.00355210	0.00394140	-0.00038930	0.00002350
TURN	-0.00001180	-0.00001160	-0.00000020	0.00000005
ILLIQ	-0.00100520	-0.00107630	0.00007110	0.00004840
ME	-0.00335690	-0.00189620	-0.00146070	0.00003990
MOM	0.00016690	0.00005900	0.00010790	0.00001200
chi2(8)		1971.90		
Prob > chi2		0.0000		

Chapter 4

Post-FOMC Drift: Evidence from the Options Market

4.1 Introduction

A large broad literature documents the macro-announcement risk premium (especially the event of the Federal Open Market Committee (FOMC) interest rate decisions) on equity and fixed-income investments, while options are barely explored. To fill the gap, we investigate the dynamic response of options to (FOMC) announcements within an event-time window.[1]

Examining the performance of options surrounding FOMC announcements serves several purposes: (1) it provides market participants insights into the pricing dynamics of options around significant macroeconomic announcements; (2) it offers the opportunity to uncover behavioural biases present in the market following FOMC announcements; and (3) it furnishes valuable insights into how the market perceives and responds to potential shifts in monetary policy and policymakers can gain some insights form that.

Our findings are threefold. First, we establish the presence of large excess returns on straddles after the FOMC, denoted as the post-FOMC drift.[2] By employing an event-time window centred around FOMC announcement days, we observe that straddle returns significantly rise during the post-event period. Both portfolio-level and individual-level analyses offer robust support for these conclusions. Second, this post-event drift is more pronounced among the FOMC announcements that involve surprises followed by a correction. Returns on straddles experience a notable increase during the post-event window when the actual value of the announcements differs from the market's expectations compared to events without surprises. After that, the drift is corrected. This implies that investors have delayed overreactions to economic surprises and followed by a correction. Third, our analysis indicates that

[1] We define the event-time window (-5, +5) as the period from five days leading up to the FOMC announcement to five days following the event.

[2] A Straddle is constructed using a pair of call and put options with identical strike prices and maturities.

investors' heightened illiquidity compensation also explains the post-event returns on straddles. In detail, we observe an inverted 'V' pattern in straddle illiquidity around FOMC announcement days, which aligns with the return pattern. We empirically establish a significant and positive relationship between higher returns and increased illiquidity. Fourth, the post-FOMC drift is mainly attributed to the put options. At the same time, we find no direct evidence linking such attribution to the demand pressure for put options hedging against uncertainty post-FOMC or protection for downside risk of underlying stocks.

Our primary focus in this paper is on delta-neutral straddles. At the end of each formation period, we select a pair of call and put options with the same strike price and expiration date, forming a delta-neutral straddle for a stock. We adjust the weights of these options based on their deltas, which are the binomial-tree deltas, ensuring the straddle's neutrality. We also employ the Black-Scholes delta as a robustness check, which does not affect our main results.

We study delta-neutral straddles for several reasons. Firstly, their simplicity renders them an excellent subject of analysis. Comprising a call and a put with identical specifications solely, delta-neutral straddles are much more straightforward to comprehend and dissect than the more intricate strategies. Secondly, in alignment with Broadie et al. (2009), it's worth noting that straddles tend to offer greater information than individual options. The performance of straddles surrounding events can provide deeper insights into investor behaviour compared to analysing the performance of call or put options in isolation. Thirdly, a delta-neutral option strategy is a pure option strategy and is insensitive to the underlying stock's price movements. Studies such as Cao & Han (2013) and Zhan et al. (2022) study delta-neutral writing call strategy. These studies are elegant but are inappropriate for this paper. Writing call strategy includes positions of long a share and writing a call. Existing literature documents the pre-FOMC drift or macro-announcement risk premium on stocks. Therefore, stock positions can potentially affect the performance of such options strategies surrounding the announcements. By contrast, delta-neutral straddles offer a more distinct and isolated perspective on option performance over the FOMC window. Fourthly, given that straddles capitalise on significant market movements in either direction, analysing their performance can provide valuable insights into the behavioural biases of market participants, including their tendencies towards overreaction or underreaction to the news.

For our study, we make each straddle closest to being at the money (ATM). This entails having the ratio of the stock price to the strike price most relative to one. The rationale behind this requirement is that ATM options typically exhibit higher liquidity than deep-in-the-money or out-of-the-money options. This liquidity advantage facilitates the ease of initiating or closing prominent positions, a particularly crucial factor for institutional investors.

We observe a post-FOMC drift in straddle returns. We observe a distinct pattern by creating an equal-weighted portfolio encompassing universal options for all optionable stocks. The portfolio returns exhibit a distinctive trajectory over a well-defined event-time window ranging from five days before to five days after FOMC announcement days. Specifically, there are large excess returns on straddles post-FOMC. Our empirical analysis underscores that the daily returns of the portfolio are 2.34% higher on the first day after the announcement days compared to other days within the specified event-time window. These heightened returns remain statistically significant and resilient even when controlling for the Fama-French Five factors (FF5) (Fama & French 2015). Beyond the portfolio-level examination, we undertake a granular exploration of individual-level dynamics. Via regressions, we analyse the returns of each straddle for each stock and date against a dummy variable denoting the specific day within the event-time window. Remarkably, these individual-level findings align with the portfolio-level outcomes. Specifically, individual straddles manifest elevated daily returns of 2.15% on the one day following the announcement days. Importantly, these augmented returns sustain their statistical significance even after accounting for the influence of variables impacting option returns.

In order to elucidate the post-FOMC drift observed in straddles, we study potential underlying mechanisms. Firstly, we draw inspiration from the theory of investors' overreaction to surprising news leading to extreme price movement and followed correction (De Bondt & Thaler 1985). Applying the concepts, we hypothesise that investors may be experiencing an overreaction to economic surprises. Should this hypothesis hold, a monetary surprise could potentially stimulate a temporary surge in demand for options, resulting in higher returns. However, due to the price pressure, such higher returns would be corrected after that.

In line with our hypothesis, the post-FOMC drift is more pronounced among economic-surprising FOMC. To elaborate, we visualise the smoothed conditional mean returns on straddles throughout the event-time window. This visualisation is conditioned on the announcements with economic surprise or without. Upon visual inspection, it becomes evident that the inverted "V" pattern is notably steeper within the event-time window of surprising events, in contrast to the event-time window without FOMC surprises. Our regression analysis suggests that the straddle returns on the second day after events exhibit a statistically significant increase compared to the returns observed on other event-time days or on the same days that lack surprises.

Secondly, we link the pattern to the illiquidity compensation. It is well documented that market participants have higher expectations of returns on assets with higher illiquidity (Christoffersen et al. 2018). Observing the higher straddles' illiquidity during post-FOMC periods relative to pre-event periods, we posit that market participants may require higher expected returns on straddles to compensate for the higher illiquidity, leading to the post-FOMC drift.

Consistent with our second hypothesis, the post-FOMC drift comoves with straddles' illiquidity. In particular, we follow Heston et al. (2022) to measure the illiquidity with the weighted average bid-ask spread of the call and put options in the straddle. Empirically, we find that the illiquidity is significantly higher on the announcement day and one and two days following the event than on the other days in the event-time window. By regressing the straddle returns on the illiquidity, conditional on one day of the event-time window, we find that the coefficients are all significant across the window. It suggests that straddle returns are sensitive to illiquidity. We also find that the model's intercept is insignificant after the announcement, implying that straddle returns remain insignificant after controlling for illiquidity. Taking them all together, we conclude that straddles' illiquidity mostly drives the post-FOMC drift.

Thirdly, the post-FOMC drift is more pronounced in the put options. Instead of studying the straddle as a whole, we decompose it and study its components, call and put options. The smoothed conditional mean straddle returns on put options exhibit a more substantial drift than on call options in the event-time window. The individual-level regression analysis results suggest that the drift persists in put option returns on the first, second and third days following the announcements. In contrast, the call option returns are only statistically significant on the third day of the post-event window. In magnitude, the put returns on the first, second and third day after the event remain 20.49%, 20.58% and 12.54%, respectively, higher than on the other event-time window days. The call returns on the first day after the event remains 19.49% higher than on the other days in the event-time window.

We conduct robustness checks, encompassing dynamic-hedged straddles, Black-Scholes delta, and sub-sample analysis. The outcomes of these tests consistently affirm the robustness of our main findings, as they indicate that the Black-Scholes delta, dynamic-hedged straddles, and different periods do not significantly influence our core results.

The contributions of this paper to the literature are threefold. First, to the best of our knowledge, we are the first to document a post-FOMC drift in the options market. In the vast landscape of financial research, the behaviour of assets surrounding macroeconomic announcements, particularly those of the FOMC, is always a topic of keen interest. While many study the price reactions of equities and bonds surrounding the FOMC, the behaviour of options remains relatively unexplored. Moreover, most studies focus on the pre-macroeconomic periods, while few of them study asset performance in the post-event period, leaving a gap.[3] Our research contributes to the literature by filling the gap.

Second, we contribute to the literature by attributing the post-FOMC drift to existing research on investors overreacting to unexpected news, bolstered by empirical studies suggesting such overreactions. Works by Tversky & Kahneman (1974), De Bondt & Thaler (1985), and Stein (1989) offer frameworks and evidence that highlight investors' tendency to assign greater weight to recent information, particularly unexpected news, which in turn leads to an initial overreaction followed by a subsequent correction. In alignment with these insights, our empirical findings corroborate that investors exhibit more pronounced overreactions to unexpected news than anticipated information. This behaviour results in exaggerated price movements that eventually revert to more rational levels.

Third, a significant dimension of our findings reveals a positive relationship between option returns and illiquidity. This pattern aligns with established literature highlighting investors' demand for compensation to counteract the effects of illiquidity. Building upon this existing body of research, our study advances the field by shedding light on the specific context of FOMC announcements, where this compensation for illiquidity appears to be more accentuated. This notion of illiquidity compensation echoes previous works that link the expected returns of assets to their

[3] Numerous studies have extensively explored asset returns in the context of scheduled macroeconomic announcements. The existing body of literature demonstrates that considerable portions of both total equity premium and fixed income returns are realised on days coinciding with macroeconomic announcements (Savor & Wilson 2013, 2014, Wachter & Zhu 2022). Notably, substantial excess returns on equities have been observed before FOMC meetings (Lucca & Moench 2015), and there is evidence of an equity premium being realised during even weeks within the FOMC cycle (Cieslak et al. 2019).

The mechanisms behind these macroeconomic premiums have been elucidated from diverse perspectives within the existing literature. For instance, Hu et al. (2022) present a two-risk model that attributes such premiums to the heightened uncertainty prevalent before the announcements. Alternatively, Wachter & Zhu (2022) introduce a model in which agents learn about the probability of an unfavourable economic state around the time of announcements, thereby accounting for the observed premiums. Additionally, Zhang & Zhao (2023) suggest that a poor information environment can reduce the announcement premium, and it is due to the impact of a noisy environment on uncertainty resolution.

liquidity, underscoring investors' tendency to seek higher expected returns when holding illiquid assets (Pástor & Stambaugh 2003, Amihud 2002, Acharya & Pedersen 2005, Christoffersen et al. 2018, Amihud & Noh 2021). Furthermore, the influence of liquidity on asset prices is dynamic. For instance, Acharya et al. (2013) argue that the pricing of liquidity risk in the bond market depends on the economy's state, with liquidity risk being more significant during times of financial and economic distress. Our contribution reveals that this effect of illiquidity compensation surrounding FOMC announcements is particularly pronounced after the event, indicating an elevated sensitivity of option returns to illiquidity in the post-FOMC periods. This phenomenon finds resonance in the broader literature, highlighting how illiquidity can substantially impact asset pricing and risk premiums, especially in macroeconomic events. Therefore, our study enriches the understanding of how illiquidity compensation operates within the nuanced setting of FOMC announcements, offering insights into the interplay between market liquidity and option returns.

In conclusion, our contributions shed light on a previously unidentified pattern in option returns post-FOMC, offering a fresh perspective on how financial markets process and react to significant macroeconomic information. As the financial industry continues to evolve, insights like these are crucial in refining our understanding of market dynamics and guiding policy decisions and investment strategies.

The rest of the paper is organised as follows. Section 2 describes the data and variables. Section 3 provides the baseline results of our empirical analysis of post-FOMC drift. Section 4 presents the results of inspecting mechanisms for the post-FOMC drift. Section 5 conducts robustness checks. Section 6 concludes.

4.2 Data and Variables

4.2.1 Raw Data

We collect dates announcing FOMC interest rate decisions from the Bloomberg Economic Calendar with the sample period of 1996 through 2021. The amount of meetings is 205. To study the performance of assets surrounding FOMC announcements, we utilise an event-time window (-5, +5) centred on the FOMC announcement day.

We follow Cao & Han (2013) and Zhan et al. (2022) to obtain options data from the OptionMetrics Ivy database, stock price data from CRSP and fundamental data from Compustat. Standard option contracts generally expire on the third Friday of each month (Options before 2015 are expired on the third Saturday of each month). We set straddles' formation and holding periods as two months and one month before the expiration date. e.g., For options expiring on 2018/9/21, their formation and holding periods are July 2018 and August 2018, respectively. For robustness, we also examine buy-and-hold options till their expiration. The sample period is from 1996 to 2021.

We follow the proceeds in the literature (Cao & Han 2013, Zhan et al. 2022) to screen options.[4] In detail, we restrict optionable stocks having share codes of either 10 or 11, which are common stocks, and their previous month's end prices are at least \$5. As for option data, we screen that as follows: (1) exercise style is "A", representing American options; (2) trading volume and bid prices are positive; (3) bid is lower than ask. During formation periods, we further select options contracts as follows: (4) moneyness (underlying stock price divided by strike price) is between 0.8 and 1.2; (5) midpoint of the bid and ask is at least \$1/8; (6) no dividend is paid in options' remaining life; (7) no-arbitrage condition, such as $C \geq S \geq max(0, S - Ke^{-rT})$, where S, K, r and T are the underlying stock price, the option strike price,

[4] We also follow Heston et al. (2022) to filter options, while that does not affect our main results.

the time-to-maturity in years, the annualised risk-free rate (8) extracting pairs of put and call options that are at the same strike price with the same expiration date; (9) take the pairs exhibiting moneyness the closest to one for the same underlying stock for obtaining at-the-money (ATM) pairs.

4.2.2 Variables

We compute straddle prices as the weighted average daily prices of the call and put options with weights as options' Delta at the end of the previous month. We measure daily straddle returns as,

$$ret_d = \frac{StraddlePrice_d}{StraddlePrice_{d-1}} - 1 - r_{f,d} = \frac{\omega_{P,t-1} * C_d + \omega_{C,t-1} * P_d}{\omega_{P,t-1} * C_{d-1} + \omega_{C,t-1} * P_{d-1}} - 1 - r_{f,d}$$
$$\omega_{C,t-1} = -D_{t-1}\Delta_{P,t-1}$$
$$\omega_{P,t-1} = D_{t-1}\Delta_{C,t-1},$$

where C and P are midpoints between the bid and ask price on Call and Put options. Δ is the binomial-tree Delta, which is obtained from OptionMetrics. d and t represent the day and month, respectively. D_t is a scale factor ensuring the sum of weights is one. In this way, the straddle initially has zero Delta. r_f is the risk-free rate obtained from the Ken-French database.

To account for factors influencing option returns, we adopt established practices from the existing literature to construct relevant control variables. Specifically, we consider several control variables related to option returns. One of these control variables is the log difference between the 250-day rolling standard deviation of daily stock returns (HV) and the 30-day equal-weighted implied volatility (IV) of both call and put options with absolute deltas of 0.5, often referred to as HV-IV, as demonstrated by Goyal & Saretto (2009). This variable captures the difference between the historical volatility of the underlying stock and the market's implied volatility for options with moderate deltas. Additionally, we incorporate the implied volatility term spread, calculated as the difference between the 60-day IV and the 30-day IV. This term spread, introduced by Vasquez (2017), serves as another control variable to account for the variation in implied volatility over different time horizons. Furthermore, we consider the implied volatility smirk slope, computed by taking the difference between 30-day call and 30-day put options with absolute deltas of 0.3. This measure, inspired by Heston et al. (2022), helps capture the curvature of the implied volatility smile across different strike prices. By incorporating these control variables, we aim to enhance the robustness and accuracy of our analysis by accounting for various factors that might impact option returns beyond the main variables of interest. See Section A in the Appendix for more details about variables.

4.2.3 Data Summary Statistics

Table 4.1 summarises the dataset we employ in this paper, with Panel A presenting the data summary statistics and Panel B showing straddle performance surrounding FOMC announcements. Our sample covers a period from 1996 through 2021, taking out the days not falling in the (-5,+5) event-time window centred on the FOMC announcement days. 4,754 firms are covered in this sample.

[Insert Table 4.1 here]

Panel A of Table 4.1 suggests that the average straddle excess returns are 1.02% with a median of -1.23% in the event-time window. The 30-day ATM equal-weighted implied volatility (IV) of call and put options has a mean value of 44.62% in the window. The mean historical volatility of 250-day underlying stock daily returns (HV) is 45.64% during the event-time window. The mean log difference between HV and IV is 2.46%. The implied volatility term spread is average -0.07%, suggesting that the 60-day ATM equal-weighted implied volatility of call and put options is lower than the 30-day options during the event-time window. We compute the straddle volume as the weighted-average scaled volume of call and put options, where the scaled volume is the percentage change between the trading volume of an option on a day and the mean trading volume of the option over the recent 90 days. The mean volume of straddles is 1.22%, suggesting that the trading volume of options is 1.22% higher than the volume over the last 90-day window surrounding FOMC announcements.

Panel B of Table 4.1 presents the mean returns of straddles on days within the event-time window. We average straddle daily returns on each day of the window. The mean return on the day following the FOMC announcements is 3.76% with 2.33% and 2.45% on the second and third days after the events. These returns are higher than the returns on the other event-time window days. These findings suggest the potential existence of post-FOMC drift in straddles and prompt us to explore further. Besides the mean excess returns, the table presents the returns after controlling FF5 factors (Fama & French 2015). Results show that the mean returns remain at their significance with slightly lower magnitudes.

Moreover, we employ a univariate portfolio sorting approach to explore the potential relationships between straddle returns surrounding FOMC announcements and various underlying stock characteristics, such as market capitalization, HV, IV, HV-IV, IV Term Spread, and IV Smirk Slope. At the end of every month, this method involves sorting the straddles into five equal-weighted decile portfolios based on a specific characteristic. The deciles exhibit varying levels of the chosen characteristics. We take the difference between the decile with the highest-level characteristics and the decile with the lowest-level characteristics. We then average the daily returns of such difference on each day of the event-time window. We perform this analysis for each of the variables mentioned and report the mean returns of the difference based on the variables on each event-time window day. Panel B of Table 4.1 suggests that the daily straddle returns conditional on each event-time window day are likely related to the IV Term Spread and the HV-IV.

4.3 Post-FOMC Drift

This section provides empirical results suggesting the existence of post-FOMC drift in the option market. It gives policymakers statistical evidence and some insights into the dynamic performance of options surrounding FOMC, showing how the derivative market reacts to the monetary policy announcement. For market participants, this work shows them that the options market does not reflect the monetary policy immediately but sluggishly.

4.3.1 Post-FOMC Drift: Portfolio-Level Analysis

We establish a delta-neutral straddle for each stock on every date. The straddle's formation and holding periods are two months and one month before the expiration date. For instance, for options expiring on 2018/9/21, their formation and holding periods would be July 2018 and August 2018, respectively. At the end of the formation periods, we select a pair of call and put contracts with identical strike prices and the same time-to-maturity. To construct a delta-neutral straddle, we assign weights to the Call and Put contracts, where the weight for the Put contract is the negative of the binomial-tree Put's delta, and the weight for the Call contract is the positive call's delta. As a result, the delta is initially zero at the start of the holding periods.

Afterwards, we analyse the performance of straddles around the FOMC announcement date. We create a portfolio by averaging cross-sectional straddle returns for each date. These returns are then regressed against a dummy variable, $Macroday_{d,j}$, and the FF5 factors (Fama & French 2015). The regression model is,

$$ret_d^{portfolio} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_t. \tag{4.1}$$

$Macroday_{d,j}$ indicates whether date d falls on the day j of the event-time window surrounding the FOMC event, where j varies from -5 to 5. Control variables are

FF5, represented by the vector X'.

In the regression 4.1, the constant β_0 measures the unconditional mean return on the straddle portfolio earned over the event-time window. Excluding X' and the constant β_0 in the regression, β_1 is the portfolio mean return on the day j of the event-time window centred at the FOMC days. Alternatively, β_1 is the portfolio mean return differential on the day j versus other days in the same event-time window when both control variables and the constant are included.

[Insert Table 4.2 here]

Observing the coefficients on $Macroday$ during the post-FOMC window (+1,+5), we conclude that the straddle portfolio exhibits a drift following FOMC announcements. Specifically, the coefficient in column (7) of Table 4.2 illustrates that the coefficient on the first day after the announcement date is 2.34%, which is statistically significant even after controlling for FF5 factors. It suggests that the returns are 2.34% higher one day after the event, compared with the other days. Moving forward to column (9), such a coefficient remains statistically significant, albeit slightly weakened. Notably, the coefficient stands at 1.27% on the third day following the events, which is weaker than the earlier observed value of 2.23%, suggesting that the returns are 1.27% higher three days after the event, compared with the other days. Regarding the fourth day following the event, the outperformance diminishes. In detail, the coefficient on the same term is -1.11%, suggesting that, on the four days following the event, the straddle excess returns are 1.11% lower than on the other days, which is statistically significant.

We find no such drift in terms of the pre-FOMC window (-5,-1). Moving from column (1) to column (6), we observe coefficients on $Macroday$ of -0.74% and -1.03% on the days five and four days prior to the event days, respectively, while the coefficients on the same term are insignificant on the other days. The significant coefficients suggest that, on five and four days before the FOMC announcement days, straddle excess returns are 0.74% and 1.03% lower than on the other days.

Upon observing all columns, it becomes evident that straddle portfolio returns exhibit significant sensitivity to market risk premiums and the size factor (SMB), with negative relationships. Moreover, the adjusted R^2 attains its peak value of 8.32% in column (7), surpassing the values in the remaining columns.

[Insert Figure 4.2 here]

We visualise straddle portfolio returns across the FOMC event-time window (-5, +5). Figure 4.2 depicts a post-FOMC drift. We employ locally-weighted regression to estimate the smoothed condition mean returns over event-time window days. These relationships are presented as solid lines on the graph. Additionally, 95% confidence intervals are illustrated as shaded areas. Notably, an upward trend is observed during the (-5, +1) period, peaking on the first day after the event. Subsequently, the trend diminishes. This pattern serves as a visual representation of our empirical findings.

[Insert Figure 4.3 here]

In addition to visualising portfolio returns over the event-time window, we also plot the portfolio returns for each day, conditioned on a single day within the event-time window. Figure 4.3 showcases these conditioned returns. It's evident from the figure that returns remain relatively flat on the day -5 and -4 of the window. Following this, a noticeable increase in spikes culminating in a peak between the -3rd day and the 1st day of the window. Beyond this point, the returns generally stabilize. The figure effectively highlights the presence of a post-FOMC drift or peak point throughout this period.

4.3.2 Post-FOMC Drift: Individual-Level Regression Analysis

One might think that the post-FOMC drift may also hold for other anomaly characteristics. We, therefore, examine the straddle performance controlling options-related anomalies surrounding FOMC announcements at the individual level in this section.

We mainly conduct panel regression in this paper to study the individual straddle returns against the FOMC event-time window. Specifically, we include both firm and year fixed effects in the regression to control for unobserved, time-invariant individual firm characteristics and time-specific factors constant across firms. Standard errors are clustered by date.

In detail, the regression model is,

$$ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_{d,i}, \tag{4.2}$$

where $ret_{d,i}$ represents the straddle return of stock i on date d. $Macroday$ is a dummy variable indicating whether date d is the day j of the event-time window. Here, j ranges from -5 to +5. X' is the control variables controlling for standard variables affecting option returns. The control variables are implied volatility smirk slope, implied volatility term spread, and the difference between historical volatility and implied volatility.

Empirical findings provide evidence for the presence of a post-FOMC drift. In column (7) of Table 4.3, the coefficient associated with the term $Macroday$ is 2.15% and is statistically significant at the 1% level. This means that holding all else constant, on the day immediately following the FOMC event (when $j = 1$), straddle returns are, on average, 2.15% higher than on the other days in the (-5, +5) window. However, we find no further evidence after that due to insignificant coefficients on the same term. As for the R^2, it is ranging from 0.69% to 0.85% while model results presented in column (7) achieve the highest.

Surprisingly, we observe significantly negative coefficients in the pre-FOMC window (-5,-1). Specifically, coefficients linked to the $Macroday$ term in columns (2) and (5) indicate values of -0.84% and -0.93%, respectively, both significant at a 5% significance level. These coefficients suggest that, during the four and one days leading up to the announcement, straddle returns are, on average, 0.84% and 0.93% lower than the returns observed on other days within the event-time window. It could be that investors are hedging their bets or adopting a wait-and-see approach before the announcements.

Furthermore, coefficients on control variables are mainly aligned with the existing literature but have different signs. Coefficients on the term $HV - IV$ and $IVTermSpread$ are all negatively significant at the 1% level across columns. In literature, Goyal & Saretto (2009) suggest that the difference between historical volatility and implied volatility significantly and positively predicts the future returns on straddles. Besides, Vasquez (2017) presents evidence for the positive relation between implied volatility term spread and future returns on straddles. Therefore, the negative prediction of volatility difference and implied volatility term spread on straddle future returns surrounding FOMC announcements remains a puzzle.

In sum, upon examining the coefficients corresponding to $Macroday$ across columns (1) to (11) in Table 4.3, we observe a pattern of post-FOMC drift. Straddle returns exhibit a significant decrease during the pre-FOMC window days and reach their peak on the day immediately following the announcement. However, the data does not provide evidence to determine whether these elevated returns persist beyond this point.

4.4 Mechanisms Inspection

4.4.1 Economic Surprise

Investors often utilise financial instruments to hedge their exposed positions in response to their anticipated outcomes of FOMC interest rate decisions. Moreover, they may dynamically adjust their positions in these instruments in response to revealed announcements, particularly if any unexpected surprises arise. Based on this rationale, we put forward the hypothesis that the observed post-FOMC drift results from investors' subsequent reactions to economic surprises.

To measure the economic surprise, we obtain the data from the Bloomberg Economic Calendar, including the mean expected value by analysts and actual outcomes of FOMC interest rate decisions. We determine a dummy variable as one when it shows surprise or the actual value differs from the expected value, and zero vice versa.

[Insert Figure 4.4 here]

We visualise the performance of the straddle portfolio in the vicinity of FOMC announcements while considering whether they involve surprises. By contrasting the dashed and solid lines in Figure 4.4, it becomes apparent that returns exhibit a more pronounced response to economic surprises as opposed to announcements that lack surprises. Within the same event-time window, notable differences emerge in returns between days with surprises and those without. This observation indicates that market participants react differently to unforeseen FOMC news.

To further investigate our hypothesis, we introduce a binary variable $Surprise_T$, which indicates whether the FOMC announcement window T contains a surprise. Specifically, $Surprise_T$ takes on a value of one when the actual announcement diverges from the expectations and a value of zero if not. We incorporate this variable into the model described in Equation 4.1. In detail, the model is,

$$ret_d^{portfolio} = \beta_0 + \beta_1 Macroday_{d,j} Surprise_T + \beta_2 Macroday_{d,j} + \beta_3 Surprise_T + \lambda X' + \epsilon_d. \tag{4.3}$$

[Insert Table 4.4 here]

Empirical results suggest that the post-FOMC drift is more pronounced among the FOMC announcements with surprises. The coefficient on the interaction term in column (8) of Table 4.4 provides evidence for that. However, such responses diminish subsequently.

4.4.2 Liquidity Compensation

Investors require higher expected returns for compensating liquidity risk (Pástor & Stambaugh 2003, Amihud 2002, Acharya & Pedersen 2005, Christoffersen et al. 2018, Amihud & Noh 2021). We further examine whether the observed post-FOMC drift is due to illiquidity issues. We proxy for straddle illiquidity with a weighted bid-ask spread of call and put. The weights are identical to the weights forming the straddle. The bid-ask spread is the ratio of the difference between the bid and ask prices over the midpoint between the bid and ask prices.

[Insert Figure 4.5 here]

The illiquidity of the straddle within the (-5, +5) event-time window centred around the FOMC announcement date is depicted in Figure 4.5. Illiquidity exhibits a rise approaching the announcement date, reaching its peak on the first day following the announcement. Subsequently, the illiquidity ratio decreases. Comparing this pattern and the post-FOMC drift on returns documented previously, we posit that investors require higher returns on straddles to compensate for higher illiquidity, leading to the post-FOMC drift.

To empirically test individual straddle's illiquidity changing over an FOMC event-time window, we employ panel regressions with firm and year fixed effects, where standard errors are clustered by date. In detail, we replace ret with $ILLIQ$ in the regression 4.2. The model is,

$$ILLIQ_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_{d,i}, \tag{4.4}$$

where $ILLIQ$ is a variable quantifying the illiquidity of the straddle. It is computed by evaluating the weighted bid-ask spread across both call and put options within the straddle. The same weights employed in the formation of the straddle are used for this calculation.Bid-ask spread refers to the ratio of the difference between the bid and ask over the midpoint between the two.

[Insert Table 4.6 here]

The empirical findings presented in Table 4.6 underscore notable variations in the illiquidity of the Straddle around FOMC announcements. Particularly noteworthy is the substantial surge in illiquidity on the FOMC announcement date itself, as well as on the 1st and 2nd days following the event. After controlling for volatility-related variables, the coefficients associated with the $Macroday$ term in columns (1) and (2) reveal a significant reduction in illiquidity during the initial two days of the event window. However, the illiquidity levels are notably elevated on day 0, +1, and +2 of the event window, with coefficients of 2.43%, 1.34%, and 1.34%, respectively, and all of these coefficients are statistically significant. Subsequent to this period, a gradual decline in illiquidity becomes apparent, as indicated by the negative coefficients corresponding to the same term in columns (9) and (10). Taken together, these findings lead us to the conclusion that illiquidity is notably high at the onset of the event and persists for two days during the post-event period.

Considering the evidence indicating the persistence of high illiquidity during post-event periods, we further investigate whether the straddle returns react to such high illiquidity in the FOMC window. To this end, we employ a similar regression to the regression 4.2 but condition the data on one specific day of the FOMC window for separating data on other days to affect the results on a selected day. Specifically, we run the below regression with data conditioning on j day of the FOMC event window. The regression model is

$$ret_{d,i} = \beta_0 + \beta_1 ILLIQ_{d,i} + \lambda X' + \epsilon_{d,i}. \tag{4.5}$$

[Insert Table 4.7 here]

Empirical results spanning from column (1) to column (11) in Table 4.7 provide compelling evidence that investors demand higher expected returns on straddles as compensation for increased illiquidity throughout the FOMC window. All coefficients associated with the term $ILLIQ$ are positive and statistically significant, even after controlling for variables that impact option returns. In more detail, the coefficient for $ILLIQ$ in column (7), where $j = 1$ representing the day after the FOMC announcement, is 7.81%. This coefficient indicates that a one-standard-deviation rise in a straddle's illiquidity on the first day of the FOMC window corresponds to a 2.04% increase in its returns (calculated as 26.11% * 7.81%).

Interestingly, the average coefficient for $Macroday$ over the post-FOMC (+1, +5) window (averaging across columns (7) to (11)) is 6.97, which is lower than the average coefficients of 10.46 for the same term observed during the pre-FOMC (-5, -1) window (averaging across columns (1) to (5)). This implies that straddle returns display greater sensitivity to illiquidity before the announcements, in contrast to the evidence observed for the post-event period.

4.4.3 Straddle Decomposition

In previous sections, we document a post-FOMC drift on delta-neutral straddles, which are formed with a Call and a Put option with adjusted weights. In this section, we examine whether the pattern is driven by one of the option types. For simplicity, we utilise the individual call and put option, which are the components of the straddles, as our study objectives.

Figure 4.6 plots smoothed conditional mean returns on straddle-decomposed call and put options over the (-5, +5) 11 trading days centred around the FOMC announcement dates. The smoothed conditional mean is estimated with locally-weighted regression. In particular, we form a straddle at the end of every month and observe its performance over the (-5, +5) FOMC event-time window. However, we are particularly interested in its components' performance. Therefore, we focus on the call and put the options' performance here. The dashed and solid lines in Figure 4.6 represent the call and put returns, respectively. The shaded area indicates 95% confidence intervals.

[Insert Figure 4.6 here]

Figure 4.6 demonstrates that both call and put options exhibit post-FOMC drifts, with the pattern being more pronounced in put options. Based on that, we posit that the post-FOMC drift observed in straddles is primarily driven by the behaviour of put options.

We further empirically investigate our hypothesis. In detail, we re-run the regression model 4.2 but replace straddle returns with call and put returns. Results based on call and put returns are presented in Panel A and B, respectively, in Table 4.8.

[Insert Table 4.8 here]

Upon examining the coefficients linked to the $Macroday$ term, we conclude that both call and put options exhibit a post-FOMC drift while put options persist for a longer period with larger coefficients. In Panel A, Column (9) demonstrates that call returns surge by 19.49% on the third day after FOMC announcement days, in stark contrast to the remaining days. This increase is statistically significant at the 1% level. Moving to Panel B, Columns (7), (8), and (9) reveal that returns on put options experience even more substantial increases. Specifically, put option returns soar by 20.49%, 20.58%, and 12.54% on the first, second, and third days following FOMC announcement days, respectively, in comparison to other days. This comparative analysis underscores the observation that put options exhibit more pronounced positive returns over the post-FOMC window, while call options display a comparatively milder response.

Interestingly, we find that call returns are significantly linked to the implied volatility smirk slope, while neither straddle nor put options exhibit a similar relation during the FOMC event-time window. In particular, coefficients on $IVSmirkSlope$ term across columns (1) to (11) in Panel A of Table 4.8 are approximately -18%, implying significant sensitivity of call returns on implied volatility smirk slope. However, we find no such evidence from straddles or put options.

By decomposing the straddles into their constituent call and put options, we unveil a more pronounced post-FOMC drift among put options. The economic mechanisms behind this observation warrant further exploration, with demand pressure emerging as a potential explanatory factor. Previous studies have illuminated the influence of demand pressure on options prices (see Bollen & Whaley 2004, Garleanu et al. 2008, Muravyev 2016, Zhan et al. 2022). In light of this, we inquire whether the post-FOMC drift is attributable to demand pressure. Additionally, investors could employ put options to shield their stock positions from downside risk. With these, we follow Zhan et al. (2022) to construct the variable of the demand pressure and follow Ang, Chen & Xing (2006) to proxy for the downside risk. However, our examination fails to yield significant evidence supporting these rational explanations. Please refer to Appendix C for more details.

4.5 Robustness

4.5.1 Dynamic-Hedged Straddle

The post-FOMC drift we document is on static-delta-hedged straddles, and we study the dynamically delta-hedged straddle in this section to assess the robustness of the pattern. Specifically, the static straddles are initially delta-neutral at the end of formation periods. However, the delta of the straddles may be time-varying during holding periods. We hedge the straddle's delta by utilising its underlying stocks to study the dynamic straddles.

Regarding the detailed construction process, we compute the daily delta of straddles by calculating the weighted average delta of both call and put options. These weights are determined after each formation period, which occurs monthly. To effectively hedge the delta of the straddle during its holding periods, we employ the underlying stocks of the straddle and perform daily rebalancing of the portfolio. The weights assigned to the stocks are, notably, derived from the negative lagged-one-day delta of the straddles. To conduct the empirical work, we replace the static-hedged straddle returns with dynamic-hedged straddle returns in the regression model 4.2.

[Insert Table 4.9 here]

Empirical results suggest the existence of a post-FOMC drift on dynamic-delta-hedged straddles, which is similar to the static-hedged straddles. The coefficient on the *Macroday* term in column (7) in Table 4.9 is 2.15%, which is statistically significant at the 1% level. It indicates that the straddle return on the one day following the FOMC announcement date is 2.15% higher than on the other days within the event-time window, keeping all else constant. However, we find no significant evidence suggesting the persistence of such a drift after that.

Furthermore, we find that the straddle returns are averagely lower during the pre-event window (-5,-1) than on the other days in the event window (-5,+5). Specifically, coefficients associated with the *Macroday* term in columns (2) and (5) of Table 4.9 are -0.83% and -0.92%, respectively. These mean that the straddle returns on the four and one days prior to the announcement date are -0.83% and -0.92% lower than on the other days in the event-time window (-5,+5).

In sum, dynamic-hedged straddles exhibit a similar pattern to the static-hedged straddles. Both straddle types exhibit a post-FOMC drift, and there is no evidence suggesting the persistence of such a drift after the day following the event. Moreover, both of them have lower returns on days in the pre-event window than on the days in the whole event-time window.

4.5.2 Black-Scholes Delta

One may ask whether the delta calculation methodology could affect the main findings of this study, given that the construction of straddles is based on the delta. As noted by Bertsimas et al. (2001) and Zhan et al. (2022), the use of delta-hedged options returns under the Black-Scholes model presents advantages over raw returns with skewed and fat-tailed distributions. Delta-hedged options returns under the Black-Scholes model tend to exhibit a symmetric distribution with a mean of zero, making them more conducive to analysis using normal distribution assumptions. This characteristic enhances their suitability for rigorous statistical analysis and interpretation. We, therefore, study the effects of the Black-Scholes delta in this section.

Employing the Black-Scholes delta rather than the binomial-tree delta, we conduct similar empirical works to previous sections in this paper. Specifically, when constructing the straddle returns in formula 4.2.2, the delta is the Black-Scholes delta. We then run the regression model 4.2.

[Insert Table 4.10 here]

Empirical results suggest similar conclusions to the results based on the binomial-tree delta. In detail, the coefficient on the $Macroday$ term in column (7) in Table 4.10 is 2.15%, which is statistically significant at the 1% level. It implies that the Black-Scholes-straddle returns on the day following the announcements are 2.21% higher than on the other days within the same event-time window. That coefficient is similar to but slightly higher than the results of 2.15% based on the binomial-tree delta, suggesting that the straddle delta calculation methodologies do not affect the main findings on post-Drift in the options markets.

Moreover, the coefficients of the control variables across various columns in Table 4.10 are similar to the results obtained using the binomial-tree delta. The coefficients associated with the "HV-IV" term across different columns average at -4.82%, slightly lower than the -3.47% reported from the binomial-tree model. Concerning the "IV Smirk Slope" term, both sets of coefficients are statistically insignificant, mirroring the results from the binomial-tree model. Regarding the "IV Term Spread" term, the average of the coefficients at -28.07% is lower than the -23.04% observed with the binomial-tree model. Turning to the goodness of fit (R^2), both models indicate that regressions involving the day following the announcements yield the highest R^2 values, 0.97% for the binomial-tree model and 0.85% for the Black-Scholes model.

The conclusion drawn above aligns with expectations, given that the option filtering process eliminates options with the potential for early exercise during both the formation and holding periods. The Black-Scholes model is an appropriate framework for European-style options, as they cannot be exercised before expiration. In contrast, the binomial-tree model is well-suited for American-style options, which can be executed early before reaching maturity. The remaining American options share similarities with European options by excluding option contracts susceptible to early exercise. Consequently, the implied volatility and delta values computed using the Black-Scholes and binomial-tree models are expected to exhibit comparability.

4.5.3 Subsample Analysis

Concerns might arise regarding the enduring nature of the post-FOMC drift in the options market. In addressing this, we undertake a subsample analysis in this section. The existing body of literature examines asset risk premiums leading up to FOMC announcements, with Liu, Tang & Zhou (2022) studying the subject from the perspective of time-varying risk premiums across FOMC meetings. Inspired by this, a question arises regarding the stability of our core findings over time. Drawing inspiration from Boguth et al. (2019), who suggest that investors accord greater significance to FOMC announcements accompanied by press conferences (PC), resulting in amplified market risk premiums on days with PC events, we split our dataset into subsamples using April 2011 as the division point. Since April 2011, the Federal Reserve has conducted press conferences following FOMC announcements. This approach to testing not only highlights the time-evolving persistence of the drift but also evaluates the influence of PC events on the options market.

We conduct the same empirical examination on the subsamples as in the baseline sections. Specifically, we split the sample into two subsamples, the pre-PC subsample and the post-PC subsample, with sample periods of 199601:201103 and 201104:202112, respectively. Subsequently, we run regression model 4.2 on each subsample with results reported in Table 4.11.

[Insert Table 4.11 here]

The results of the subsample analysis are presented in Panels A and B of Table 4.11. Upon examination, we observe that the post-FOMC drift returns are comparatively more minor in the post-PC subsample than the pre-PC subsample. Specifically, focusing on the coefficient on the $Macroday$ term in column (7) across both Panels A and B, we find values of 2.89% and 1.39%, respectively. This suggests that the post-FOMC drift during the pre-PC period is approximately 51.09% lower than the post-PC period (calculated as 1.39/2.89-1). This discovery aligns, to some extent, with the findings of Boguth et al. (2019), who assert that pre-announcement risk premiums are not consistently observed across time but are contingent upon investors' attention. Interestingly, our documented reduction in the post-FOMC drift during the post-PC subsample could indicate diminished co-movement within the options market. This observation can be rationalized by invoking a rational expectations framework put forth by Veldkamp (2006). This framework suggests that asset price co-movement tends to decrease over time due to advancements in information technology and investors' reduced costs in acquiring information. Investors require higher expected returns on assets with less transparency, while the lower cost of obtaining information increases such transparency and thus brings down their expected returns.

However, the coefficient on the $Macroday$ term in column (7) retains its statistical significance across both Panels A and B, despite the variation in magnitude. This suggests that post-FOMC drift remains persistent over time, albeit with some fluctuations in its strength.

4.6 Conclusion

This paper documents a post-FOMC drift in options. We study straddles by buying a pair of call and put options at the same strike price and have the same expiration at the end of every month. The straddles exhibit significant excess returns post-FOMC, which is statistically and economically significant at the portfolio level. Our individual-level analysis remains the same conclusion.

We thoroughly investigate various potential explanations for our observed findings. Our empirical results consistently point towards market participants' overreaction in response to FOMC announcements accompanied by surprises and subsequent price corrections. This phenomenon accounts for the post-FOMC drift observed in the options market. Additionally, our analysis highlights the significant role of illiquidity in driving this drift. Notably, the illiquidity within straddles is considerably higher on post-FOMC days than on pre-FOMC days. Moreover, our results reveal a positive relationship between straddle returns and illiquidity during the event-time window. Considering these findings with the illiquidity compensation theory, we propose that market participants demand higher expected returns on options post-FOMC due to the elevated illiquidity of options during this period.

Furthermore, we comprehensively decompose the straddles into their individual call and put options. This intricate analysis reveals that the observed drift is notably accentuated among put options. This deeper investigation not only strengthens the reliability of our results but also highlights the unique behaviour of put options in response to FOMC announcements. However, it's important to note that while we have empirically identified this phenomenon, a specific theoretical framework or mechanism to explain it remains elusive. This presents an intriguing avenue for future research, where a more detailed examination could provide valuable insights into the underlying dynamics.

Lastly, we ensure the robustness of our findings through a battery of tests. We demonstrate that the post-FOMC drift is not driven by factors such as hedging frequency, delta calculation methodologies, or the choice of sample periods. This reinforces the validity and reliability of our observed patterns across different dimensions of the analysis. However, this work provides no evidence to analyse the post-FOMC drift regarding industries. Industries such as financials and banks show the largest

FOMC-day stock returns among 49 industries (Lucca & Moench 2015). Linking that with post-FOMC drift, future studies on the industries could be fruitable.

4.7 Tables

Table 4.1: Data Summary

This table summarises the main dataset utilised in this paper. Panel A presents summary statistics for only the daily data falling on the (-5,+5) event-time window centred on the FOMC announcement days. Panel B presents straddle performance surrounding the FOMC announcements.At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. Implied volatility (IV) is the equal-weighted IV of call and put 30-day options with absolute deltas of 0.5. Historical volatility (HV) is the standard deviation of daily stock returns over a 250-day window. HV-IV the log difference between HV and IV. IV term spread is the difference between 60-day IV and 30-day IV. IV smirk slope is the difference between the implied volatility of the 30-day call and 30-day put, each with an absolute delta of 0.3. Volume is the percentage change between the option trading volume on a day and the mean volume over the last 90-day window. The straddle volume is the weighted average volume of call and put options. Bid-ask spread refers to the ratio of the difference between the bid and ask over the midpoint between the two. Standard errors are adjusted based on Newey & West (1987) with six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Panel A: Pool Daily Data Summary Statistics

		Number of Obs.	Mean	Std.	10%	25%	50%	75%	90%
Straddle Excess Return	(%)	640,941	1.02	15.48	-11.07	-5.6	-1.23	4.48	14.23
Implied Volatility (IV)	(%)	640,877	44.62	26.62	19.84	26.59	37.71	54.49	77.87
Historical Volatility (HV)	(%)	632,634	45.64	28.2	19.98	26.79	38.46	56.05	80.35
HV - IV	(%)	632,634	2.46	27.55	-29.1	-12.75	2.79	18.39	34.14
Implied Volatility Term Spread	(%)	640,877	-0.07	4.58	-3.72	-1.08	0.05	1.37	3.5
Implied Volatility Smirk Slope	(%)	640,877	-3.21	8.67	-8.8	-5.09	-2.87	-1.24	1.08
Volume		640,941	1.22	6.82	-0.80	-0.56	0.00	1.20	3.57
ln(Open Interest)	(%)	640,941	7.29	1.45	5.42	6.32	7.31	8.26	9.12
Bid-Ask Spread	(%)	640,941	13.11	12.19	3.24	5.68	9.58	16.09	26.49

Panel B: Straddle Performance Surrounding FOMC

Event-Time Window	-5	-4	-3	-2	-1	0	1	2	3	4	5
Mean Return	0.78**	0.34	1.22***	0.86*	0.51	1.53***	3.76***	2.33***	2.45***	0.46	1.02***
FF5-α	0.73**	0.4	1.17***	0.75	0.83*	1.92***	3.43***	2.33***	2.46***	0.29	0.82**
SIZE	-0.23	-0.48**	0.19	-0.19	-0.48	-0.23	-0.65	-1.15**	-0.49	-0.48*	-0.63*
HV	-0.24	0.24	-0.38	0.16	0.01	0.17	0.23	0.15	-0.22	0.27	0.26
IV	-0.53*	0.1	-0.32	0.1	-0.28	-0.09	-0.34	-0.07	-0.77*	-0.19	0.18
HV-IV	0.53**	0.45*	-0.3	0.88***	0.63*	1.02***	1.02***	0.64*	1.77***	0.91**	0.43*
IV Term Spread	0.38	0.48*	0.18	0.87**	1.66***	1.54***	2.19***	2.43***	3.54***	1.10**	0.59
IV Smirk Slope	-0.02	0.11	0.07	-0.28	0.18	-0.80**	-0.01	0.57*	-0.47	0.02	0.01

Table 4.2: Post-FOMC Drift: Portfolio-Level Analysis

This table reports straddle equal-weighted portfolio returns surrounding FOMC days controlling for Fama-French Five Factors (FF5)(Fama & French 2015). The regression model is $ret_d = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_d$. Straddle portfolio returns are mean daily returns across all individual straddles. $Macroday_{d,j}$ indicates if date d is the j day of the FOMC-cycle window (-5,+5). i.e., it is one day after (before) the FOMC date when j is 1 (-1). Control variables FF5 include Market risk premium $(Mkt - Rf)$, HML, SMB, CMA and RMW. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. Reported coefficients are in percentage. The t-statistics, reported in parentheses, are based on Newey & West (1987)'s standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep: Portfolio Ret.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Intercept	1.46***	1.49***	1.42***	1.46***	1.45***	1.35***	1.18***	1.30***	1.28***	1.49***	1.45***
	(9.02)	(9.05)	(8.78)	(9.09)	(8.82)	(8.26)	(7.60)	(8.53)	(8.17)	(9.14)	(8.77)
Macoday	-0.74**	-1.03***	-0.31	-0.73	-0.64	0.52	**2.34*** **	1.01	**1.27***	**-1.11****	-0.63
	(-2.33)	(-3.01)	(-0.70)	(-1.57)	(-1.33)	(0.97)	**(3.01)**	(1.34)	**(1.88)**	**(-2.37)**	(-1.40)
Mkt-Rf	-151.98***	-151.24***	-151.72***	-152.03***	-150.73***	-151.95***	-149.58***	-151.20***	-152.32***	-151.63***	-152.02***
	(-6.57)	(-6.55)	(-6.55)	(-6.57)	(-6.48)	(-6.60)	(-6.57)	(-6.47)	(-6.58)	(-6.57)	(-6.58)
SMB	-70.14**	-71.77**	-70.39**	-69.89**	-70.69**	-70.70**	-69.59**	-72.83**	-69.46**	-71.31**	-70.75**
	(-2.30)	(-2.35)	(-2.30)	(-2.28)	(-2.32)	(-2.32)	(-2.27)	(-2.38)	(-2.29)	(-2.35)	(-2.31)
HML	35.51	36.17	34.99	34.75	33.81	34.83	38.95	34.17	34.58	33.77	35.35
	(1.21)	(1.24)	(1.20)	(1.19)	(1.16)	(1.19)	(1.34)	(1.18)	(1.20)	(1.16)	(1.21)
RMW	-62.86	-61.67	-63.10	-62.42	-61.14	-62.01	-60.73	-61.70	-61.75	-63.21	-64.23
	(-1.61)	(-1.58)	(-1.62)	(-1.60)	(-1.57)	(-1.59)	(-1.57)	(-1.57)	(-1.58)	(-1.62)	(-1.64)
CMA	5.04	4.38	6.92	5.82	7.31	7.56	7.74	6.32	3.54	8.39	7.45
	(0.09)	(0.08)	(0.13)	(0.11)	(0.13)	(0.14)	(0.14)	(0.12)	(0.07)	(0.15)	(0.14)
Adj R2 (%)	7.60	7.68	7.54	7.60	7.58	7.56	8.32	7.67	7.75	7.69	7.58
No. of Obs.	2205	2205	2205	2205	2205	2205	2205	2205	2205	2205	2205

Table 4.3: Post-FOMC Drift: Individual-Level Panel Regression Analysis

This table reports the results of panel regressions with firm and year fixed effects. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_{d,i}$. $ret_{d,i}$ is straddle daily return of firm i. $Macroday_{d,j}$ indicates if date d is the j day of the FOMC-cycle window (-5,+5). i.e., it is one day after the FOMC date when j is 1. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. See appendix A for more details about the construction of the variables. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep: Straddle Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday	-0.52	-0.84**	0.01	-0.58	-0.93**	-0.11	**2.15*** **	0.65	0.81	-0.69	-0.02
	(-1.48)	(-2.40)	(0.01)	(-1.28)	(-2.34)	(-0.23)	**(3.31)**	(1.1)	(1.22)	(-1.49)	(-0.04)
HV-IV	-3.46***	-3.46***	-3.47***	-3.48***	-3.48***	-3.47***	-3.44***	-3.47***	-3.46***	-3.48***	-3.47***
	(-5.24)	(-5.25)	(-5.26)	(-5.27)	(-5.29)	(-5.26)	(-5.24)	(-5.25)	(-5.25)	(-5.28)	(-5.26)
IV Smirk Slope	0.48	0.48	0.48	0.47	0.47	0.47	0.45	0.47	0.49	0.47	0.48
	(0.75)	(0.75)	(0.74)	(0.74)	(0.73)	(0.74)	(0.71)	(0.74)	(0.77)	(0.73)	(0.74)
IV Term Spread	-23.14***	-23.13***	-22.97***	-23.01***	-23.01***	-22.97***	-23.21***	-23.07***	-23.11***	-22.86***	-22.97***
	(-16.40)	(-16.42)	(-16.32)	(-16.39)	(-16.36)	(-16.32)	(-16.60)	(-16.40)	(-16.31)	(-16.34)	(-16.31)
Intercept	1.12***	1.15***	1.07***	1.12***	1.15***	1.08***	0.87***	1.01***	1.00***	1.13***	1.07***
	(7.31)	(7.51)	(7.08)	(7.49)	(7.65)	(7.21)	(6.17)	(6.95)	(7.05)	(7.57)	(7.12)
No. of Obs.	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342
R^2 (%)	0.70	0.71	0.69	0.70	0.72	0.69	0.85	0.70	0.71	0.71	0.69
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.4: Economic Surprise: Portfolio-Level Analysis on Post-FOMC Drift

This table reports the results of regressing daily straddle returns on Macroday and control variables. The regression model is $ret_d^{portfolio} = \beta_0 + \beta_1 Macroday_{d,j} Surprise_T + \beta_2 Macroday_{d,j} + \beta_3 Surprise_T + \lambda X' + \epsilon_d$. Straddle mean returns are aggregated daily returns across all individual straddles. $Macroday$ is a dummy variable indicating whether date d is the day j of the event-time window. Here, j ranges from -5 to +5. $Surprise_T$ is a dummy variable that indicates whether the FOMC announcement event T has a surprise. Control variables are Fama-French Five Factors (FF5), including Market risk premium ($Mkt - Rf$), HML, SMB, CMA and RMW (Fama & French 1995) At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. Reported coefficients are in percentage. The t-statistics, reported in parentheses, are based on Newey & West (1987)'s standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep: Straddle Returns j =	(1) -5	(2) -4	(3) -3	(4) -2	(5) -1	(6) 0	(7) 1	(8) 2	(9) 3	(10) 4	(11) 5
Macroday x Surprise	-1.99**	-2.81***	-1.18	-2.87***	-3.24**	**8.28*** **	0.32	**11.59*** **	**-4.10*** **	**-2.19** **	**-3.13*** **
	(-2.31)	(-3.51)	(-0.64)	(-2.76)	(-2.19)	**(2.70)**	(0.11)	**(2.83)**	**(-2.94)**	**(-2.31)**	**(-3.82)**
Macroday	-0.42	-0.72*	-0.16	-0.36	-0.23	-0.57*	2.30***	-0.56	1.80**	-0.76	-0.24
	(-1.20)	(-1.90)	(-0.38)	(-0.70)	(-0.47)	(-1.76)	(2.89)	(-1.06)	(2.40)	(-1.44)	(-0.48)
Surprise	2.08***	2.16***	2.00***	2.16***	2.19***	1.12**	1.85***	0.81*	2.25***	2.08***	2.17***
	(4.05)	(4.10)	(3.85)	(4.14)	(4.00)	(2.04)	(3.31)	(1.82)	(4.28)	(3.93)	(4.06)
MktRiskPrem	-146.32***	-145.19***	-146.26***	-146.15***	-145.25***	-146.53***	-143.99***	-146.98***	-147.40***	-146.76***	-146.30***
	(-6.33)	(-6.35)	(-6.34)	(-6.34)	(-6.27)	(-6.38)	(-6.33)	(-6.46)	(-6.40)	(-6.38)	(-6.40)
HML	35.35	38.06	37.02	37.71	36.54	31.43	40.82	40.50	37.66	34.64	37.41
	(1.21)	(1.32)	(1.27)	(1.30)	(1.26)	(1.08)	(1.41)	(1.39)	(1.30)	(1.18)	(1.30)
SMB	-68.06**	-70.45**	-68.57**	-68.38**	-67.54**	-68.49**	-67.79**	-70.99**	-66.79**	-69.42**	-70.34**
	(-2.23)	(-2.30)	(-2.24)	(-2.23)	(-2.22)	(-2.26)	(-2.20)	(-2.25)	(-2.18)	(-2.29)	(-2.30)
CMA	4.64	1.36	3.97	2.32	5.34	7.36	4.19	2.18	-2.94	6.46	5.39
	(0.09)	(0.03)	(0.07)	(0.04)	(0.10)	(0.14)	(0.08)	(0.04)	(-0.05)	(0.12)	(0.10)
RMW	-53.84	-52.43	-54.31	-53.09	-53.53	-51.33	-52.31	-52.72	-52.16	-55.75	-55.30
	(-1.40)	(-1.36)	(-1.41)	(-1.38)	(-1.39)	(-1.34)	(-1.37)	(-1.36)	(-1.37)	(-1.45)	(-1.44)
Intercept	1.17***	1.20***	1.15***	1.17***	1.16***	1.19***	0.92***	1.18***	0.98***	1.20***	1.16***
	(7.37)	(7.45)	(7.19)	(7.50)	(7.28)	(7.34)	(6.27)	(7.51)	(6.53)	(7.53)	(7.14)
Adj R^2 (%)	7.25	7.42	7.15	7.33	7.35	8.30	7.92	9.50	7.60	7.34	7.33
No. of Obs.	2,203	2,203	2,203	2,203	2,203	2,203	2,203	2,203	2,203	2,203	2,203

Table 4.5: Economic Surprise: Individual-Level Analysis on Post-FOMC Drift

This table reports the individual analysis results of post-FOMC drift reacting to economic surprise. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} Surprise_T + Macroday_{d,j} + Surprise_T + \lambda X' + \epsilon_{d,i}$. $ret_{d,i}$ is straddle daily return of firm i. $Macroday_{d,j}$ indicates if date d is the j day of the FOMC-cycle window (-5,+5). i.e., it is one day after the FOMC date when j is 1. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. See appendix A for more details about the construction of the variables. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday x Surprise	-2.32**	-2.30**	-0.91	-2.18*	-3.47***	**6.33****	2.74	**10.19*****	**-3.63*****	-0.28	**-2.39****
	(-2.05)	(-2.25)	(-0.63)	(-1.93)	(-3.75)	**(2.44)**	(0.89)	**(3.00)**	**(-3.39)**	(-0.19)	**(-2.02)**
Macroday	-0.11	-0.59	0.15	-0.28	-0.45	-0.84**	1.82***	-0.68*	1.33*	-0.56	0.26
	(-0.27)	(-1.47)	(0.38)	(-0.56)	(-1.03)	(-2.39)	(3.13)	(-1.67)	(1.77)	(-1.11)	(0.51)
Surprise	1.37**	1.36**	1.21**	1.33**	1.44**	0.60	0.90*	0.27	1.44**	1.15*	1.35**
	(2.27)	(2.25)	(2.06)	(2.23)	(2.42)	(1.10)	(1.69)	(0.55)	(2.43)	(1.94)	(2.25)
HV-IV	-4.09***	-4.07***	-4.09***	-4.09***	-4.08***	-4.11***	-4.07***	-4.13***	-4.07***	-4.10***	-4.10***
	(-3.93)	(-3.94)	(-3.94)	(-3.95)	(-3.95)	(-3.94)	(-3.95)	(-3.98)	(-3.92)	(-3.95)	(-3.98)
IV Smirk Slope	0.45	0.47	0.45	0.43	0.42	0.48	0.44	0.49	0.47	0.44	0.44
	(0.59)	(0.61)	(0.59)	(0.56)	(0.55)	(0.62)	(0.57)	(0.64)	(0.61)	(0.57)	(0.57)
IV Term Spread	-22.73***	-22.71***	-22.48***	-22.54***	-22.47***	-22.57***	-22.75***	-22.71***	-22.55***	-22.36***	-22.38***
	(-15.66)	(-15.53)	(-15.35)	(-15.39)	(-15.35)	(-15.42)	(-15.63)	(-15.76)	(-15.29)	(-15.24)	(-15.33)
Intercept	0.90***	0.95***	0.88***	0.92***	0.93***	0.97***	0.72***	0.96***	0.77***	0.94***	0.87***
	(5.75)	(5.99)	(5.53)	(5.88)	(5.91)	(6.11)	(4.82)	(6.09)	(5.28)	(6.04)	(5.56)
No. of Obs.	636,723	636,723	636,723	636,723	636,723	636,723	636,723	636,723	636,723	636,723	636,723
$R\hat{2}$ (%)	0.81	0.83	0.78	0.81	0.86	0.93	0.97	1.19	0.85	0.79	0.80
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.6: Illiquidity Compensation: Illiquidity Over a FOMC Window

This table reports the results of panel regressions with firm and year fixed effects. The regression model is $Illiquidity_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_{d,i}$. $ret_{d,i}$ is straddle daily return of firm i. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. See appendix A for more details about the construction of the variables. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep: Illiquidity	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday	-1.61***	-0.95**	0.23	0.21	0.33	2.42***	1.34**	1.34**	-1.09*	-1.08**	-0.62
	(-3.63)	(-2.24)	(0.48)	(0.40)	(0.65)	(4.16)	(2.52)	(2.46)	(-1.85)	(-2.02)	(-1.16)
HV-IV	-4.84***	-4.86***	-4.88***	-4.88***	-4.87***	-4.87***	-4.86***	-4.87***	-4.89***	-4.89***	-4.88***
	(-3.55)	(-3.56)	(-3.57)	(-3.57)	(-3.56)	(-3.56)	(-3.56)	(-3.56)	(-3.58)	(-3.57)	(-3.57)
IV Smirk Slope	7.43***	7.41***	7.41***	7.42***	7.42***	7.42***	7.40***	7.41***	7.39***	7.40***	7.42***
	(6.58)	(6.55)	(6.54)	(6.54)	(6.56)	(6.56)	(6.53)	(6.56)	(6.52)	(6.54)	(6.56)
IV Term Spread	6.16***	6.48***	6.67***	6.66***	6.65***	6.62***	6.51***	6.45***	6.80***	6.81***	6.72***
	(3.26)	(3.44)	(3.54)	(3.54)	(3.53)	(3.54)	(3.46)	(3.45)	(3.59)	(3.61)	(3.57)
Intercept	29.44***	29.38***	29.27***	29.27***	29.26***	29.07***	29.16***	29.17***	29.39***	29.39***	29.35***
	(178.08)	(176.89)	(178.46)	(181.77)	(177.62)	(180.44)	(178.96)	(179.18)	(182.49)	(181.01)	(180.66)
No. of Obs.	868,950	868,950	868,950	868,950	868,950	868,950	868,950	868,950	868,950	868,950	868,950
R^2 (%)	0.63	0.61	0.60	0.60	0.60	0.65	0.62	0.62	0.60	0.61	0.60
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.7: Illiquidity Compensation: Co-movement between Straddle Returns and Illiquidity During a FOMC Window

This table reports the results of panel regressions with firm and year fixed effects. The regression model is $ret_{d,i} = \beta_0 + \beta_1 ILLIQd, i + \lambda X' + \epsilon_{d,i}$. $ret_{d,i}$ is straddle daily return of firm $i.ILLIQ$ is a variable quantifying the illiquidity of the straddle. It is computed by evaluating the weighted bid-ask spread across both call and put options within the straddle. The same weights employed in the formation of the straddle are used for this calculation.Bid-ask spread refers to the ratio of the difference between the bid and ask over the midpoint between the two. X' are control variables.Control variables are HV-IV, IV Smirk Slope and IV Term Spread. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. See appendix A for more details about the construction of the variables. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep: Straddle Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
ILLIQ	11.89***	11.06***	11.65***	9.44***	8.26***	9.42***	7.81***	5.37***	5.66***	8.16***	7.85***
	(12.75)	(11.84)	(13.79)	(6.65)	(5.63)	(7.45)	(4.92)	(3.85)	(3.16)	(4.56)	(6.75)
HV-IV	-0.94	-2.55*	-3.45**	-6.62***	-2.93	-1.53	-4.61**	-2.91	-2.50	-2.32	-0.98
	(-0.67)	(-1.81)	(-2.10)	(-3.13)	(-1.17)	(-1.07)	(-2.09)	(-1.47)	(-1.19)	(-0.99)	(-0.60)
IV Smirk Slope	-0.40	-0.64	-1.31	-3.26*	1.91	-2.27	-1.22	0.27	0.24	3.11	-1.51
	(-0.21)	(-0.43)	(-0.67)	(-1.65)	(0.78)	(-1.23)	(-0.54)	(0.15)	(0.08)	(1.49)	(-0.99)
IV Term Spread	-21.11***	-23.42***	-25.78***	-20.59***	-21.61***	-28.53***	-16.98***	-22.81***	-34.79***	-28.81***	-25.95***
	(-7.05)	(-7.74)	(-5.27)	(-4.89)	(-5.78)	(-4.85)	(-3.32)	(-4.77)	(-5.12)	(-6.51)	(-5.71)
Intercept	-2.34***	-2.38***	-1.93***	-1.94***	-1.85***	-1.75***	0.90	0.22	0.43	-1.44**	-0.92
	(-7.12)	(-5.90)	(-4.93)	(-3.41)	(-3.52)	(-3.04)	(1.03)	(0.26)	(0.47)	(-2.41)	(-1.63)
No. of Obs.	59,218	58,312	57,603	58,134	57,467	56,684	57,950	58,372	55,520	55,607	55,475
R^2 (%)	1.86	1.95	2.86	2.63	1.18	1.30	0.98	0.56	0.93	1.38	1.05
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.8: Straddle Decomposition: Individual-Level Analysis On Call and Put Options

This table reports the results of regressing decomposed straddle returns on relative variables. Panel A and B report results based on the dependent variable of returns on the Call and Put options, respectively. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_{d,i}$, where $ret_{d,i}$ is either the daily options' return of firm i. $Macroday_{d,j}$ indicates if date d is the j day of the FOMC-cycle window (-5,+5). i.e., it is one day after the FOMC date when j is 1. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. See appendix A for more details about the construction of the variables. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Panel A: Dependent Variable is Call Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday	-3.06	-4.59	-10.14***	-3.78	2.83	0.45	0.13	7.24	**19.49*** **	-1.63	-7.12**
	(-0.65)	(-1.07)	(-3.83)	(-0.87)	(0.55)	(0.13)	(0.04)	(1.09)	**(2.76)**	(-0.28)	(-2.11)
HV-IV	7.75	7.76	7.83	7.63	7.70	7.68	7.68	7.75	7.93	7.66	7.61
	(1.47)	(1.47)	(1.49)	(1.45)	(1.47)	(1.46)	(1.46)	(1.47)	(1.52)	(1.46)	(1.45)
IV Smirk Slope	-18.57***	-18.60***	-18.47***	-18.62***	-18.58***	-18.61***	-18.61***	-18.63***	-18.23***	-18.63***	-18.57***
	(-3.09)	(-3.10)	(-3.08)	(-3.10)	(-3.10)	(-3.10)	(-3.10)	(-3.10)	(-3.08)	(-3.09)	(-3.09)
IV Term Spread	-32.38***	-32.25***	-32.73***	-31.66***	-31.24***	-31.37***	-31.37***	-32.47***	-34.68***	-31.10***	-30.29***
	(-3.32)	(-3.23)	(-3.33)	(-3.21)	(-3.16)	(-3.18)	(-3.18)	(-3.32)	(-3.41)	(-3.19)	(-3.07)
Intercept	10.59***	10.73***	11.24***	10.65***	10.05***	10.26***	10.29***	9.63***	8.59***	10.45***	10.94***
	(7.31)	(7.37)	(7.51)	(7.37)	(6.98)	(6.96)	(7.00)	(7.19)	(6.23)	(7.52)	(7.36)
No. of Obs.	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342
R^2 (%)	0.01	0.02	0.03	0.01	0.01	0.01	0.01	0.02	0.10	0.01	0.02
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Dependent Variable is Put Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday	-11.98***	-13.36***	-8.93***	-1.71	-6.80*	-3.42	**20.49** **	**20.58***	**12.54***	-2.21	-5.47
	(-4.67)	(-5.38)	(-3.01)	(-0.31)	(-1.67)	(-0.62)	**(2.37)**	**(1.71)**	**(1.85)**	(-0.50)	(-1.22)
HV-IV	0.54	0.50	0.38	0.23	0.20	0.24	0.58	0.45	0.41	0.22	0.20
	(0.13)	(0.12)	(0.09)	(0.06)	(0.05)	(0.06)	(0.14)	(0.11)	(0.10)	(0.05)	(0.05)
IV Smirk Slope	3.43	3.31	3.41	3.28	3.22	3.28	3.07	3.23	3.53	3.26	3.32
	(0.38)	(0.36)	(0.37)	(0.36)	(0.35)	(0.36)	(0.34)	(0.35)	(0.39)	(0.36)	(0.36)
IV Term Spread	-75.16***	-73.76***	-72.36***	-71.30***	-71.45***	-71.06***	-73.46***	-74.32***	-73.30***	-70.81***	-70.34***
	(-7.79)	(-7.76)	(-7.68)	(-7.63)	(-7.69)	(-7.65)	(-7.89)	(-7.22)	(-7.84)	(-7.76)	(-7.65)
Intercept	14.18***	14.28***	13.86***	13.20***	13.66***	13.35***	11.15***	11.13***	11.94***	13.24***	13.53***
	(7.92)	(8.00)	(7.80)	(7.68)	(7.79)	(7.78)	(7.18)	(7.30)	(7.17)	(7.60)	(7.77)
No. of Obs.	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342	630,342
R^2 (%)	0.01	0.01	0.01	0.00	0.01	0.00	0.02	0.02	0.01	0.00	0.01
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.9: Robustness: Post-FOMC Drift on Dynamic Straddles

This table reports the results of panel regressions with firm and year fixed effects based on dynamic-delta-hedged straddles. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_{d,i}$. $ret_{d,i}$ is daily-delta-hedged straddle return of firm i. $Macroday_{d,j}$ indicates if date d is the j day of the FOMC-cycle window (-5,+5). i.e., it is one day after the FOMC date when j is 1. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. See appendix A for more details about the construction of the variables. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep: Dynamic Strad.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday	-0.50	-0.83**	-0.05	-0.62	-0.92**	-0.10	**2.15*****	0.65	0.87	-0.66	-0.04
	(-1.45)	(-2.39)	(-0.13)	(-1.37)	(-2.34)	(-0.23)	**(3.29)**	(1.12)	(1.31)	(-1.44)	(-0.08)
HV-IV	-3.41***	-3.41***	-3.42***	-3.43***	-3.43***	-3.42***	-3.39***	-3.42***	-3.41***	-3.43***	-3.42***
	(-5.39)	(-5.40)	(-5.41)	(-5.42)	(-5.44)	(-5.42)	(-5.39)	(-5.41)	(-5.40)	(-5.43)	(-5.42)
IV Smirk Slope	0.36	0.36	0.36	0.36	0.35	0.36	0.33	0.36	0.38	0.35	0.36
	(0.59)	(0.59)	(0.58)	(0.58)	(0.57)	(0.58)	(0.54)	(0.58)	(0.61)	(0.57)	(0.58)
IV Term Spread	-23.43***	-23.42***	-23.27***	-23.31***	-23.30***	-23.26***	-23.50***	-23.36***	-23.41***	-23.15***	-23.25***
	(-17.05)	(-17.07)	(-16.98)	(-17.06)	(-17.02)	(-16.98)	(-17.26)	(-17.07)	(-16.97)	(-17.01)	(-16.96)
Intercept	1.12***	1.15***	1.08***	1.13***	1.16***	1.08***	0.87***	1.01***	1.00***	1.13***	1.08***
	(7.38)	(7.58)	(7.19)	(7.60)	(7.71)	(7.28)	(6.26)	(7.02)	(7.09)	(7.64)	(7.21)
No. of Obs.	624,560	624,560	624,560	624,560	624,560	624,560	624,560	624,560	624,560	624,560	624,560
R^2 (%)	0.70	0.72	0.70	0.71	0.73	0.70	0.87	0.71	0.72	0.71	0.70
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.10: Robustness: Post-FOMC Drift with Block-Sholes Delta

This table reports the results of panel regressions with firm and year fixed effects. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_{d,i}$. $ret_{d,i}$ is straddle daily return of firm i. $Macroday_{d,j}$ indicates if date d is the j day of the FOMC-cycle window (-5,+5). i.e., it is one day after the FOMC date when j is 1. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using the Black-Sholes model. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. See appendix A for more details about the construction of the variables. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep: Straddle Returns j =	(1) -5	(2) -4	(3) -3	(4) -2	(5) -1	(6) 0	(7) 1	(8) 2	(9) 3	(10) 4	(11) 5
Macroday	-0.53	-0.88**	0.03	-0.63	-0.94**	-0.12	**2.21*** **	0.66	0.82	-0.66	-0.03
	(-1.48)	(-2.46)	(0.07)	(-1.42)	(-2.32)	(-0.25)	**(3.34)**	(1.11)	(1.27)	(-1.39)	(-0.07)
HV-IV	-4.81***	-4.81***	-4.83***	-4.84***	-4.84***	-4.83***	-4.79***	-4.82***	-4.82***	-4.85***	-4.83***
	(-4.92)	(-4.94)	(-4.95)	(-4.95)	(-4.98)	(-4.95)	(-4.94)	(-4.94)	(-4.93)	(-4.97)	(-4.95)
IV Smirk Slope	-0.04	-0.04	-0.05	-0.05	-0.06	-0.05	-0.07	-0.05	-0.03	-0.06	-0.04
	(-0.05)	(-0.05)	(-0.06)	(-0.06)	(-0.08)	(-0.06)	(-0.09)	(-0.06)	(-0.03)	(-0.07)	(-0.06)
IV Term Spread	-28.23***	-28.23***	-27.99***	-28.06***	-28.04***	-27.99***	-28.33***	-28.13***	-28.17***	-27.86***	-27.99***
	(-15.60)	(-15.61)	(-15.50)	(-15.59)	(-15.56)	(-15.52)	(-15.77)	(-15.62)	(-15.52)	(-15.54)	(-15.49)
Intercept	1.19***	1.22***	1.13***	1.19***	1.22***	1.15***	0.93***	1.07***	1.06***	1.19***	1.14***
	(7.69)	(7.90)	(7.46)	(7.89)	(8.02)	(7.58)	(6.55)	(7.32)	(7.33)	(7.92)	(7.49)
No. of Obs.	604,054	604,054	604,054	604,054	604,054	604,054	604,054	604,054	604,054	604,054	604,054
R^2 (%)	0.81	0.83	0.80	0.81	0.83	0.80	0.97	0.82	0.82	0.81	0.80
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.11: Post-FOMC Drift: Individual-Level Subsample Analysis

This table reports the results of panel regressions with firm and year fixed effects. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_{d,i}$, where $ret_{d,i}$ is straddle daily return of firm i. $Macroday_{d,j}$ indicates if date d is the j day of the FOMC-cycle window (-5,+5). i.e., it is one day after the FOMC date when j is 1. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. See appendix A for more details about the construction of the variables. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

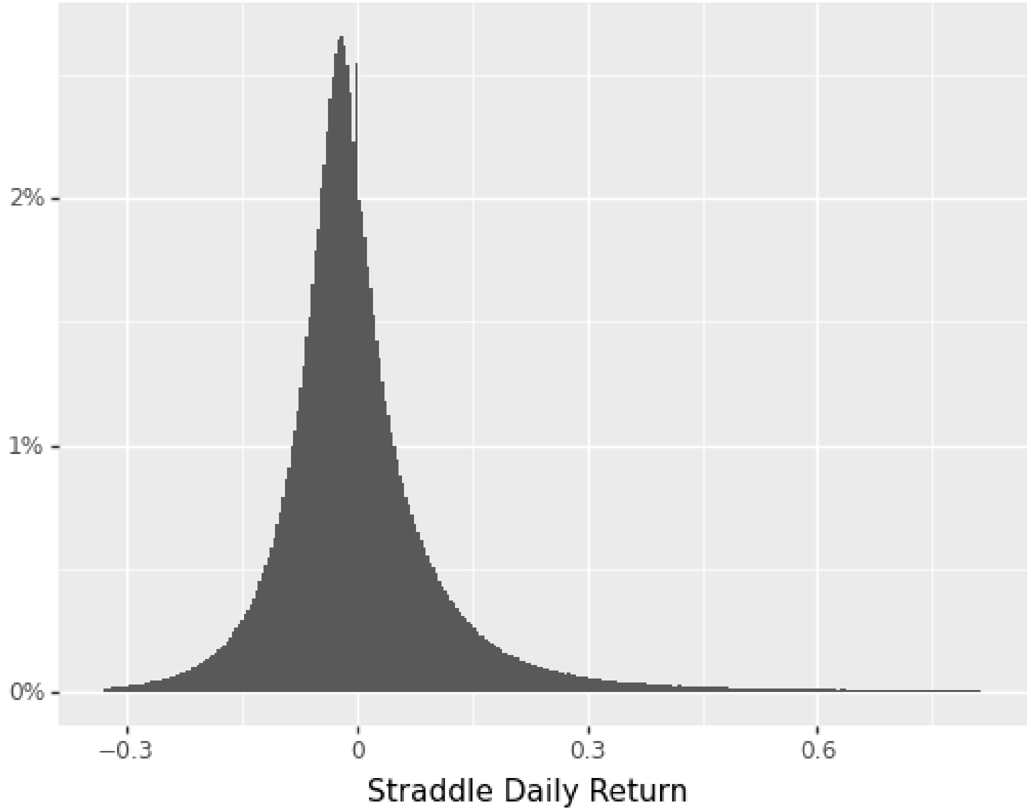
Panel A: Pre-PC Sample (199601:201103)

Dep: Strad. Ret.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday	-0.55	-0.41	0.08	-0.56	-0.82*	-0.91**	**2.89*** **	0.40	0.02	-0.90	0.72
	(-1.16)	(-0.71)	(0.18)	(-0.94)	(-1.65)	(-2.20)	**(2.86)**	(0.51)	(0.03)	(-1.27)	(0.98)
HV-IV	-1.60**	-1.61**	-1.62**	-1.62**	-1.62**	-1.61**	-1.60**	-1.61**	-1.61**	-1.63**	-1.60**
	(-2.30)	(-2.30)	(-2.32)	(-2.33)	(-2.34)	(-2.32)	(-2.33)	(-2.31)	(-2.32)	(-2.34)	(-2.28)
IV Smirk Slope	3.84***	3.84***	3.82***	3.84***	3.83***	3.77***	3.81***	3.83***	3.83***	3.80***	3.82***
	(3.10)	(3.12)	(3.09)	(3.10)	(3.10)	(3.05)	(3.09)	(3.10)	(3.12)	(3.08)	(3.10)
IV Term Spread	-27.83***	-27.75***	-27.63***	-27.67***	-27.63***	-27.53***	-27.71***	-27.68***	-27.64***	-27.48***	-27.82***
	(-12.25)	(-12.22)	(-12.15)	(-12.15)	(-12.14)	(-12.11)	(-12.21)	(-12.16)	(-12.14)	(-12.16)	(-12.10)
Intercept	1.01***	0.99***	0.95***	1.01***	1.03***	1.03***	0.69***	0.92***	0.95***	1.03***	0.89***
	(4.86)	(4.97)	(4.57)	(4.97)	(5.02)	(5.02)	(3.84)	(4.71)	(4.62)	(5.19)	(4.45)
No. of Obs.	332,613	332,613	332,613	332,613	332,613	332,613	332,613	332,613	332,613	332,613	332,613
R^2 (%)	0.53	0.53	0.52	0.53	0.55	0.56	0.85	0.53	0.52	0.55	0.54
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Panel B: Post-PC Sample (201104:202112)

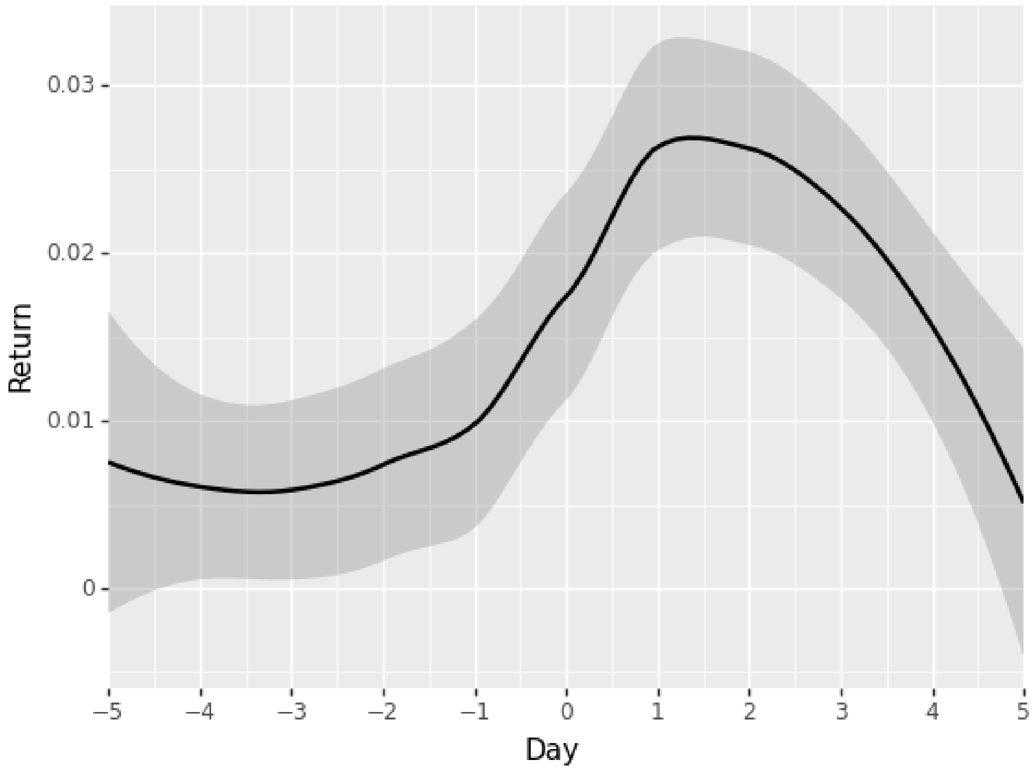
Dep: Strad. Ret.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday	-0.37	-1.51***	-0.05	-0.62	-1.06*	0.96	**1.39***	0.86	1.64	-0.29	-0.99**
	(-0.66)	(-3.60)	(-0.07)	(-0.91)	(-1.65)	(1.10)	**(1.74)**	(0.96)	(1.41)	(-0.46)	(-2.09)
HV-IV	-7.03***	-7.01***	-7.04***	-7.04***	-7.03***	-7.03***	-7.00***	-7.04***	-7.01***	-7.04***	-7.04***
	(-3.54)	(-3.58)	(-3.56)	(-3.56)	(-3.56)	(-3.57)	(-3.56)	(-3.55)	(-3.53)	(-3.56)	(-3.58)
IV Smirk Slope	-1.12	-1.13	-1.12	-1.13	-1.13	-1.13	-1.13	-1.13	-1.11	-1.12	-1.11
	(-1.14)	(-1.16)	(-1.14)	(-1.15)	(-1.16)	(-1.15)	(-1.16)	(-1.15)	(-1.13)	(-1.14)	(-1.14)
IV Term Spread	-19.65***	-19.76***	-19.53***	-19.59***	-19.60***	-19.51***	-19.74***	-19.68***	-19.87***	-19.48***	-19.43***
	(-10.52)	(-10.56)	(-10.44)	(-10.51)	(-10.47)	(-10.54)	(-10.59)	(-10.53)	(-10.50)	(-10.45)	(-10.50)
Intercept	1.29***	1.40***	1.26***	1.31***	1.35***	1.17***	1.13***	1.18***	1.11***	1.28***	1.34***
	(5.37)	(5.69)	(5.23)	(5.42)	(5.59)	(5.01)	(4.81)	(5.04)	(5.03)	(5.41)	(5.53)
No. of Obs.	304,110	304,110	304,110	304,110	304,110	304,110	304,110	304,110	304,110	304,110	304,110
R^2 (%)	0.96	1.02	0.96	0.97	0.99	0.98	1.01	0.98	1.04	0.96	0.98
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

4.8 Figures



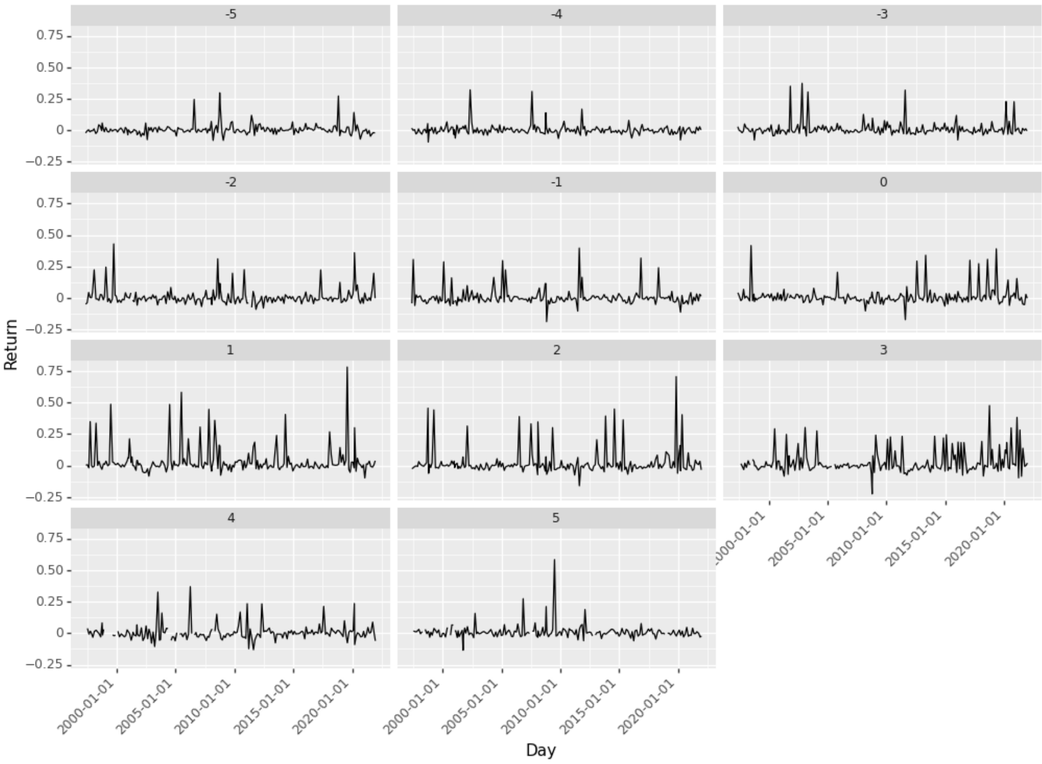
The figure plots the histogram for the pooled distribution of daily straddle returns. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. The sample period is from 1996 to 2021, covering 4,754 firms.

Figure 4.1: The distribution of Daily Straddle Returns.



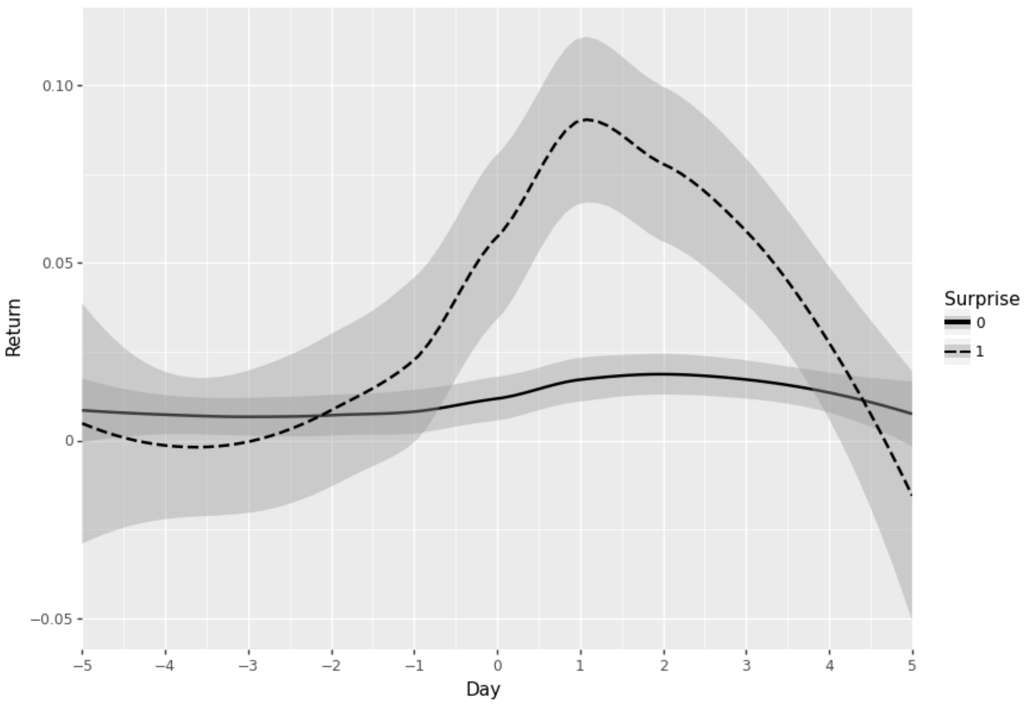
This figure plots smoothed conditional mean returns on straddles during the (-5, +5) event window centred at the FOMC announcement date. The smoothed conditional mean is estimated with locally-weighted regression. The shaded area indicates 95% confidence intervals. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. The sample period is from 1996 to 2021, covering 4,754 firms.

Figure 4.2: Post-FOMC Drift: Event-time Straddle Returns.



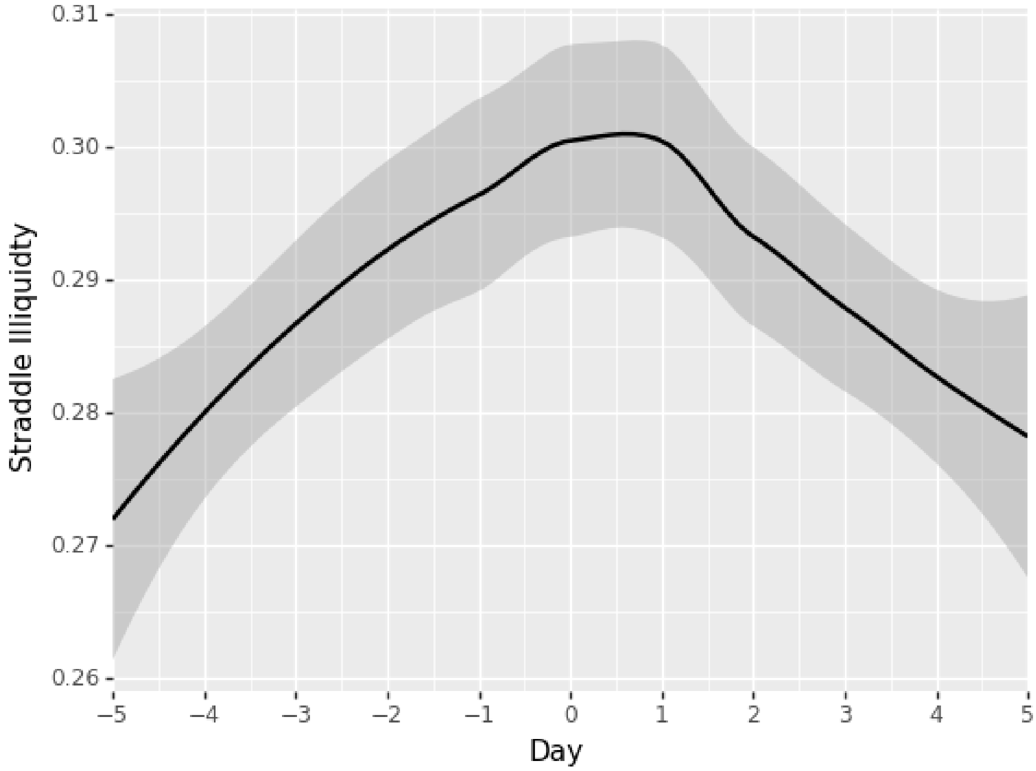
This figure plots daily mean straddle returns on a day of the (-5, +5) event window centred at the FOMC announcement date. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. The sample period is from 1996 to 2021, covering 4,754 firms.

Figure 4.3: Straddle Returns on an Event Date Across Time.



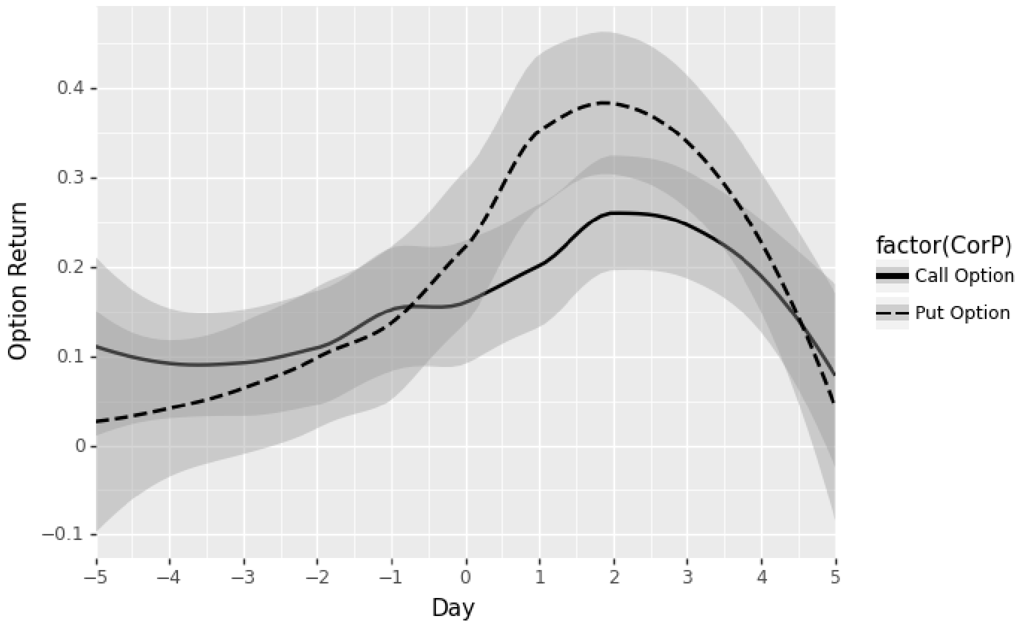
This figure plots smoothed conditional mean returns on straddles during the (-5, +5) event window centred at the FOMC announcement date. The dash and solid line display straddle performance during the event window with and without economic surprise, respectively. The smoothed conditional mean is estimated with locally-weighted regression. The shaded area indicates 95% confidence intervals. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. The sample period is from 1996 to 2021, covering 4,754 firms.

Figure 4.4: Economic Surprise: Event-time Straddle Returns.



This figure plots smoothed conditional mean straddle illiquidity during the (-5, +5) event window centred at the FOMC announcement date. The smoothed conditional mean is estimated with locally-weighted regression. The shaded area indicates 95% confidence intervals. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. $ILLIQ$ is a variable quantifying the illiquidity of the straddle. It is computed by evaluating the weighted bid-ask spread across both call and put options within the straddle. The same weights employed in the formation of the straddle are used for this calculation.Bid-ask spread refers to the ratio of the difference between the bid and ask over the midpoint between the two. The sample period is from 1996 to 2021, covering 4,754 firms.

Figure 4.5: Event-time Straddle Illiquidity.



This figure presents the smoothed conditional mean returns on call options (represented by the solid line) and put options (represented by the dashed line). These options are used in the construction of the straddles. The plotted data covers an event window spanning from five days before to five days after the FOMC announcement date, creating a total period of (-5, +5).The smoothed conditional mean is estimated with locally-weighted regression. The shaded area indicates 95% confidence intervals. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. The sample period is from 1996 to 2021, covering 4,754 firms.

Figure 4.6: Event-time Straddle Return Decomposition.

A Appendix: Variable Definitions

Variable	Description
Panel A: Option Variables	
IV	We obtain implied volatility of 30-day call and put options with absolute deltas of 0.5 from the volatility surface of optionMetrics and then average them for each stock and every date.
HV	250-day rolling standard deviation of stock daily returns (Heston et al. 2022).
HV-IV	Goyal & Saretto (2009) find that the log difference between historical realized volatility and at-the-money implied volatility statistically and economically predicts monthly returns on options.
IV Term Spread	Vasquez (2017) document the slope of the term structure of options is positively related to future returns on options. Based on that, we take the difference between 60-day IV and 30-day IV as the term spread.
IV Smirk Slope	Following Heston et al. (2022), we take the smirk slope as the difference between the implied volatilities of the 30-day call and 30-day put, each with an absolute delta of 0.3.
Option MOM	Heston et al. (2022) explore the predictability of the option's past trends on its future returns and document the existence of momentum effects. They measure the past trends with cumulative returns on options over the past twelve months, ignoring the most recent month.
Option ILLIQ	We measure illiquidity as the bid-ask spread, which is the ratio of the difference between the bid and ask over the midpoint between the two.
Demand Pressure	We follow Zhan et al. (2022) to measure demand pressure on options as the log difference between the market value of options (open interest times option prices) and the market value of the underlying stock at the previous month's end.
Volume	We calculate the volume as the percentage change between the option trading volume on a day and the mean volume over the last 90-day window.
Panel B: Stock Charateristics	
SIZE	It is the log market capitalization of a stock. Specifically, the market capitalization is the multiplication between share adjusted close prices and adjusted total shares outstanding, where the adjusted close price is the close price divided by the 'cumulative factor to adjust price', and the adjusted shares outstanding is the number of shares outstanding times the 'cumulative factor to adjust shares'. A company could have several securities with different market values. Therefore, we take the sum of the market value of these securities as its market capitalization. It is well known in the literature that smaller firms outperform larger firms (Fama & French 1993, Van Dijk 2011, Zakamulin 2013).
BM	The book-to-market ratio is book equity divided by the market capitalization, where book equity is the sum of stockholder's equity, deferred taxes and investment tax credit but minus preferred stock (Daniel & Titman 1997). Capturing the stock value, literature generally documents the BM premium, which is that high-value firms generally outperform low-value firms (Fama & French 1993, 1995, Pontiff & Schall 1998, Caglayan et al. 2018).
TURN	Turnover, the monthly trading volume divided by the monthly total shares outstanding. Kumar (2009) document that stocks with high monthly turnover are more likely to be attention-grabbing.
Stock MOM	It is calculated as the cumulative returns of the past 12 months but skipped returns in the most recent month to exclude the reversal effect. Stocks with past up-trends are believed to outperform stocks with past downtrends (Jegadeesh & Titman 1993).
Stock ILLIQ	Stock illiquidity is the absolute monthly return on a stock divided by the respective monthly trading volume in dollars (the monthly price multiplies the monthly trading). A positive relationship between stock returns and illiquidity is well documented in the literature (Amihud 2002, Amihud & Noh 2021, Cakici & Zaremba 2021).
Downside Risk	We follow Bawa & Lindenberg (1977) and Ang, Chen & Xing (2006) to measure one underlying stock's downside risk with a downside beta, which is the 252-day rolling CAPM beta, conditioning that market returns are smaller than the mean market returns and requiring at least 50 observations.
Panel C: Stock Lottery-Like Charateristics	
MAX	The maximum daily returns of the most recent month (Bali et al. 2011).
Prc	The negative log sum of 1 and stock prices, such as $-log(1 + Price)$ (Liu et al. 2020).
IVOL	Idiosyncratic volatility is the standard deviation of the residuals of a 22-day rolling regression using the Fama & French (1993) factors.
SKEWEXP	Expected idiosyncratic skewness (Boyer et al. 2010).
ZSCORE	The averaged standardised value of above proxies (Liu et al. 2020).

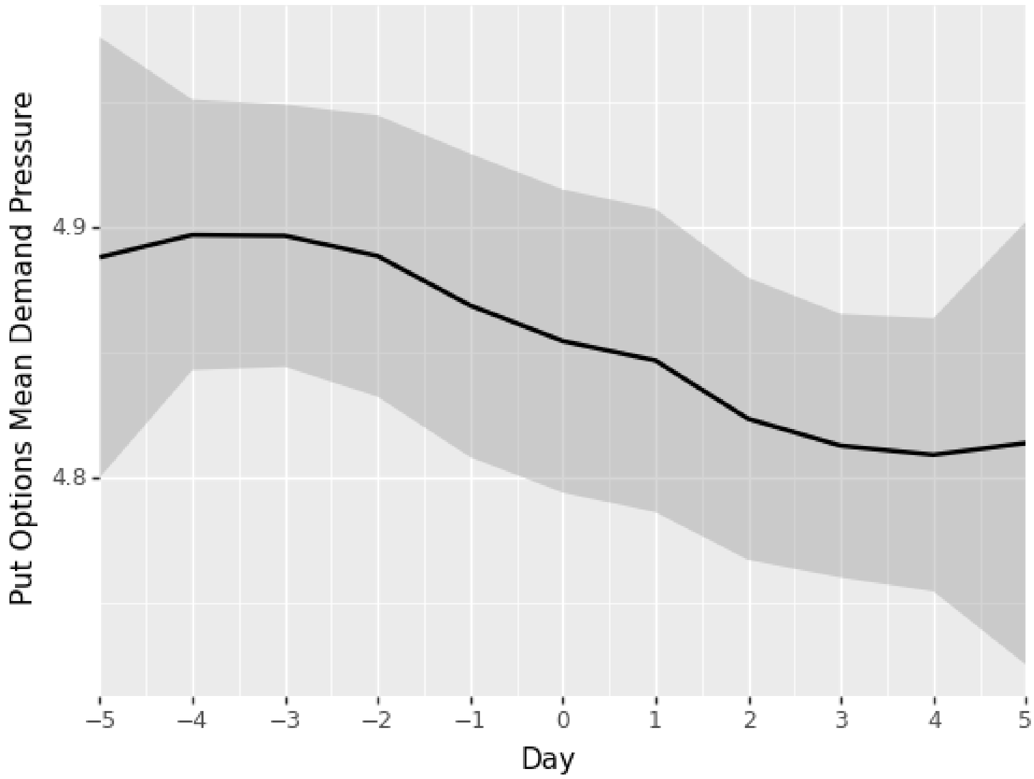
B Appendix: Monthly Portfolios

Table 4.12: Monthly Returns on Straddle Portfolios Sorting on Characteristics

This table reports the monthly returns on straddle portfolios sorting on characteristics. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. At the end of every month, we sort straddles into five equal-weighted deciles based on a specific characteristic. We take the difference between the decile with the highest level characteristics and the decile with the lowest level characteristics. characteristics are varying. Option momentum is the cumulative straddle returns over the past months. Implied volatility (IV) is the equal-weighted IV of call and put 30-day options with absolute deltas of 0.5. Historical volatility (HV) is the standard deviation of daily stock returns over a 250-day window. HV-IV the log difference between HV and IV. IV term spread is the difference between 60-day IV and 30-day IV. IV smirk slope is the difference between the implied volatility of the 30-day call and 30-day put, each with an absolute delta of 0.3. See appendix A for more details about the construction of the variables. The t-statistics, reported in parentheses, are based on Newey & West (1987)'s standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

	Mean (%)						T-statistics					
Portfolio	1	2	3	4	5	5-1	1	2	3	4	5	5-1
Panel A: Option Characteristics												
Option Momentum (1,1)	-5.96***	-7.35***	-7.52***	-7.14***	-6.93***	-0.97**	(-7.55)	(-9.70)	(-9.98)	(-9.67)	(-8.82)	(-2.48)
Option Momentum (1,2)	-6.04***	-7.30***	-6.91***	-7.09***	-5.90***	0.14	(-7.16)	(-9.72)	(-8.66)	(-9.71)	(-7.31)	(0.34)
Option Momentum (1,6)	-5.95***	-6.80***	-6.21***	-6.19***	-5.45***	0.50	(-7.03)	(-8.75)	(-6.80)	(-7.27)	(-6.28)	(0.77)
Option Momentum (1,12)	-6.18***	-6.13***	-6.08***	-5.94***	-4.99***	1.19	(-6.66)	(-6.35)	(-6.51)	(-6.67)	(-5.68)	(1.63)
Option Momentum (2,12)	-6.38***	-6.56***	-5.83***	-5.57***	-5.07***	1.31**	(-6.95)	(-7.52)	(-6.40)	(-6.32)	(-5.90)	(2.15)
Option Momentum (2,24)	-6.52***	-6.23***	-5.88***	-5.59***	-4.35***	2.17***	(-6.04)	(-6.91)	(-5.83)	(-6.21)	(-4.19)	(3.02)
Option Momentum (2,36)	-6.76***	-6.05***	-6.37***	-5.19***	-3.63***	3.14***	(-6.10)	(-6.54)	(-5.88)	(-5.06)	(-3.37)	(3.63)
Option Momentum (13,24)	-6.81***	-5.97***	-6.21***	-5.89***	-4.99***	1.82***	(-7.00)	(-6.53)	(-6.60)	(-6.83)	(-5.23)	(2.93)
Option Momentum (13,36)	-6.56***	-5.94***	-5.90***	-5.35***	-4.61***	1.95**	(-5.90)	(-6.09)	(-5.62)	(-5.60)	(-4.36)	(2.56)
Option Momentum (25,36)	-6.43***	-6.76***	-7.22***	-6.11***	-5.46***	0.96	(-6.51)	(-7.68)	(-8.10)	(-6.42)	(-5.92)	(1.33)
IV	-6.73***	-7.11***	-7.11***	-7.18***	-9.10***	-2.37***	(-7.86)	(-9.05)	(-9.58)	(-10.80)	(-16.00)	(-3.24)
HV	-7.51***	-7.28***	-7.22***	-7.10***	-8.08***	-0.57	(-8.66)	(-9.46)	(-10.18)	(-10.28)	(-12.87)	(-0.74)
HV - IV	-9.87***	-8.07***	-7.47***	-6.63***	-5.33***	4.54***	(-16.36)	(-11.75)	(-10.70)	(-9.20)	(-6.63)	(7.40)
IV Term Spread	-8.80***	-7.39***	-7.29***	-7.40***	-6.48***	2.31***	(-14.68)	(-10.19)	(-10.14)	(-10.06)	(-9.14)	(5.48)
IV Smirk Slope	-7.50***	-7.25***	-6.97***	-7.18***	-8.42***	-0.92**	(-11.96)	(-10.09)	(-9.46)	(-10.02)	(-12.42)	(-2.38)
Panel B: Stock Characteristics												
Stock Return	-8.21***	-6.69***	-6.66***	-7.46***	-8.26***	-0.05	(-10.95)	(-9.52)	(-8.81)	(-11.64)	(-12.60)	(-0.09)
Total Share Outstanding	-7.89***	-7.73***	-7.22***	-7.73***	-6.82***	1.07*	(-13.27)	(-13.03)	(-10.55)	(-10.72)	(-7.94)	(1.95)
Stock Market Cap	-9.17***	-7.37***	-7.21***	-6.87***	-6.90***	2.27***	(-16.82)	(-13.26)	(-10.58)	(-8.70)	(-7.82)	(3.54)
Stock Turnover	-7.61***	-7.42***	-7.49***	-7.42***	-7.32***	0.29	(-9.63)	(-10.29)	(-11.11)	(-10.81)	(-10.74)	(0.45)
Book-to-Market Ratio	-7.65***	-7.77***	-7.55***	-7.85***	-6.82***	0.84	(-10.76)	(-11.25)	(-11.00)	(-11.29)	(-9.36)	(1.53)
Stock Momentum	-6.47***	-7.03***	-7.82***	-8.31***	-7.59***	-1.11*	(-9.95)	(-10.03)	(-9.96)	(-11.20)	(-11.26)	(-1.94)
Stock Dollar Volume	-8.91***	-8.07***	-7.27***	-7.11***	-6.34***	2.58***	(-17.64)	(-13.58)	(-11.48)	(-8.77)	(-7.39)	(4.66)
Stock Illiquidity	-6.17***	-6.89***	-7.35***	-8.14***	-9.08***	-2.91***	(-7.39)	(-8.87)	(-10.57)	(-13.73)	(-17.12)	(-5.20)
MAX	-7.27***	-7.02***	-6.99***	-7.37***	-8.61***	-1.34**	(-9.42)	(-9.10)	(-9.88)	(-10.98)	(-13.80)	(-2.31)
SKEWEXP	-7.37***	-6.91***	-7.46***	-7.41***	-8.41***	-1.04*	(-9.06)	(-8.79)	(-11.48)	(-10.12)	(-13.22)	(-1.81)
PRC	-7.31***	-6.93***	-6.79***	-7.47***	-8.80***	-1.49***	(-8.93)	(-9.48)	(-9.46)	(-12.45)	(-14.64)	(-2.59)
IVOL	-6.88***	-7.03***	-6.94***	-7.49***	-8.95***	-2.08***	(-8.42)	(-9.50)	(-9.91)	(-11.37)	(-14.25)	(-3.12)
ZSCORE	-7.11***	-6.82***	-7.03***	-7.37***	-8.94***	-1.82**	(-8.35)	(-8.89)	(-10.51)	(-11.02)	(-14.54)	(-2.54)

C Appendix: Further Analysis of Post-FOMC Drift in Put Options



This figure plots daily smoothed conditional mean demand pressure on put options during the (-5, +5) event window centred at the FOMC announcement date. The smoothed conditional mean is estimated with locally-weighted regression. The shaded area indicates 95% confidence intervals. The demand pressure is measured as the log difference between the market value of put options (open interest times option prices) and the market value of the underlying stock at the previous month's end. The sample period is from 1996 to 2021, covering 4,754 firms.

Figure 4.7: Demand Pressure On Put Options Over Event-Time Window

Table 4.13: Post-FOMC Drift in Put Options: Demand Pressure

This table reports the individual-level analysis results of post-FOMC drift in put options reacting to demand pressure on options. The influence of demand pressure on options prices has been extensively explored in prior literature (see Bollen & Whaley 2004, Garleanu et al. 2008, Muravyev 2016, Zhan et al. 2022). In our study, we investigate whether the observed post-FOMC drift in put options can be attributed to demand pressure. We adopt the approach of Zhan et al. (2022) to quantify option demand pressure. This involves calculating the ratio of the total market value of options to the market value of the underlying stock. Specifically, the market value of options is computed by multiplying the open interest with the corresponding option price. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} Demand_{d,i} + Macroday_{d,j} + Demand_{d,i} + \lambda X' + \epsilon_{d,i}$, where $ret_{d,i}$ is daily returns on put options of firm i. $Macroday$ is a dummy variable indicating whether date d is the day j of the event-time window. Here, j ranges from -5 to +5. The demand pressure is measured as the log difference between the market value of put options (open interest times option prices) and the market value of the underlying stock at the previous month's end. It is labelled as $Demand$. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. See appendix A for more details about the construction of the variables. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep.: Put Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday x Demand	2.87**	4.60***	3.80***	-1.35	2.51**	-3.22	-0.45	-4.17	-8.53***	1.36	3.50***
	(2.36)	(5.95)	(4.30)	(-0.46)	(1.98)	(-1.05)	(-0.20)	(-1.41)	(-2.70)	(0.95)	(3.53)
Macroday	-26.49***	-37.10***	-28.29***	5.43	-19.65**	13.22	22.57	41.92*	55.49**	-8.98	-23.58***
	(-3.34)	(-7.02)	(-4.16)	(0.27)	(-2.02)	(0.64)	(1.29)	(1.73)	(2.55)	(-0.84)	(-2.87)
Demand	-1.90**	-2.03***	-1.96***	-1.52**	-1.88**	-1.36*	-1.60**	-1.26*	-0.82	-1.78**	-1.96***
	(-2.52)	(-2.69)	(-2.60)	(-2.19)	(-2.49)	(-1.90)	(-2.13)	(-1.73)	(-1.22)	(-2.36)	(-2.59)
HV-IV	-1.60	-1.63	-1.67	-1.87	-1.85	-1.87	-1.51	-1.77	-1.62	-1.87	-1.89
	(-0.41)	(-0.42)	(-0.43)	(-0.48)	(-0.48)	(-0.49)	(-0.39)	(-0.45)	(-0.42)	(-0.49)	(-0.49)
IV Smirk Slope	2.45	2.35	2.31	2.32	2.28	2.25	2.17	2.25	2.47	2.32	2.39
	(0.29)	(0.28)	(0.27)	(0.27)	(0.27)	(0.27)	(0.26)	(0.27)	(0.29)	(0.27)	(0.28)
IV Term Spread	-75.33***	-73.72***	-72.53***	-72.24***	-72.34***	-71.76***	-74.15***	-75.00***	-73.07***	-72.02***	-71.93***
	(-7.57)	(-7.52)	(-7.45)	(-7.44)	(-7.48)	(-7.46)	(-7.62)	(-7.10)	(-7.58)	(-7.55)	(-7.48)
Intercept	23.74***	24.57***	23.77***	20.87***	23.14***	20.17***	19.27***	17.47***	16.00***	22.21***	23.48***
	(4.48)	(4.62)	(4.49)	(4.24)	(4.39)	(4.00)	(3.82)	(3.47)	(3.38)	(4.23)	(4.45)
No. of Obs.	636,403	636,403	636,403	636,403	636,403	636,403	636,403	636,403	636,403	636,403	636,403
$R\hat{2}$ (%)	0.02	0.02	0.02	0.01	0.01	0.01	0.03	0.03	0.03	0.01	0.02
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.14: Post-FOMC Drift in Put Options: Protection for Downside Risk

This table reports the individual-level analysis results of post-FOMC drift in put options reacting to underlying stocks' downside risk. Investors might utilise put options to protect their positions in stocks against the downside risk associated with FOMC announcements. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} DownsideRisk_{d,i} + Macroday_{d,j} + DownsideRisk_{d,i} + \lambda X' + \epsilon_{d,i}$, where $ret_{d,i}$ is daily returns on put options of firm i. $Macroday$ is a dummy variable indicating whether date d is the day j of the event-time window. Here, j ranges from -5 to +5. The downside risk is measured as the CAPM beta, conditioning that market returns are smaller than mean market returns. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. See appendix A for more details about the construction of the variables. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep.: Put Returns	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday x Downside Risk	-1.58	1.03	1.05	-1.70	-0.21	-3.75*	1.80	6.08	-7.98***	3.51	1.92
	(-1.13)	(0.88)	(0.62)	(-1.13)	(-0.10)	(-1.72)	(0.44)	(1.15)	(-2.77)	(1.54)	(0.75)
Macroday	-9.98***	-14.56***	-10.15***	0.43	-6.48	1.27	18.33*	13.18	22.33**	-6.45*	-7.76*
	(-3.09)	(-5.07)	(-2.91)	(0.07)	(-1.28)	(0.18)	(1.85)	(1.60)	(2.32)	(-1.77)	(-1.91)
Downside Risk	1.24	1.03	0.99	1.26	1.11	1.44	0.96	0.51	1.80	0.79	0.93
	(1.10)	(0.92)	(0.89)	(1.12)	(0.99)	(1.25)	(0.95)	(0.54)	(1.58)	(0.71)	(0.84)
HV-IV	-0.11	-0.17	-0.29	-0.47	-0.47	-0.47	-0.08	-0.29	-0.35	-0.47	-0.48
	(-0.03)	(-0.04)	(-0.07)	(-0.12)	(-0.12)	(-0.12)	(-0.02)	(-0.07)	(-0.09)	(-0.12)	(-0.12)
IV Smirk Slope	4.07	3.97	4.05	3.92	3.86	3.92	3.77	3.87	4.12	3.89	3.96
	(0.48)	(0.47)	(0.48)	(0.46)	(0.46)	(0.46)	(0.45)	(0.46)	(0.49)	(0.46)	(0.47)
IV Term Spread	-73.64***	-72.17***	-70.84***	-69.80***	-69.96***	-69.58***	-71.93***	-72.84***	-71.61***	-69.46***	-68.92***
	(-7.94)	(-7.90)	(-7.82)	(-7.78)	(-7.84)	(-7.80)	(-8.02)	(-7.37)	(-7.98)	(-7.93)	(-7.80)
Intercept	12.65***	13.01***	12.64***	11.66***	12.30***	11.58***	9.98***	10.51***	9.74***	12.27***	12.39***
	(6.47)	(6.74)	(6.51)	(6.30)	(6.40)	(5.90)	(6.29)	(5.49)	(5.31)	(6.37)	(6.47)
No. of Obs.	632,781	632,781	632,781	632,781	632,781	632,781	632,781	632,781	632,781	632,781	632,781
R^2 (%)	0.01	0.01	0.01	0.00	0.01	0.00	0.02	0.02	0.01	0.00	0.01
Permno Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

D Appendix: Value-Weighted Portfolio Analysis

Table 4.15: Post-FOMC Drift: Value-Weighted Portfolio-Level Analysis

This table reports straddle value-weighted portfolio returns surrounding FOMC days controlling for Fama-French Five Factors (FF5)(Fama & French 2015). The regression model is $ret_d = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_d$. Straddle portfolio returns are value-weighted daily returns across all individual straddles, based on their underlying stock market capital at the end of the previous month. $Macroday_{d,j}$ indicates if date d is the j day of the FOMC-cycle window (-5,+5). i.e., it is one day after (before) the FOMC date when j is 1 (-1). Control variables FF5 include Market risk premium ($Mkt - Rf$), HML, SMB, CMA and RMW. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. Reported coefficients are in percentage. The t-statistics, reported in parentheses, are based on Newey & West (1987)'s standard errors with the six lags. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep: Portfolio Ret.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Intercept	1.27***	1.28***	1.18***	1.27***	1.22***	1.12***	0.96***	1.11***	1.10***	1.28***	1.24***
	(7.72)	(7.72)	(7.16)	(7.72)	(7.33)	(6.77)	(6.13)	(7.12)	(6.96)	(7.69)	(7.40)
Macroday	-0.91***	-1.06***	0.02	-0.88*	-0.38	0.72	**2.37*** **	0.80	1.00	**-1.08** **	-0.64
	(-2.60)	(-2.82)	(0.04)	(-1.89)	(-0.69)	(1.37)	**(3.10)**	(1.00)	(1.34)	**(-2.04)**	(-1.45)
Mkt - Rf	-217.93***	-217.10***	-217.55***	-217.99***	-216.98***	-217.94***	-215.44***	-217.18***	-218.06***	-217.51***	-217.90***
	(-6.99)	(-6.96)	(-6.96)	(-6.97)	(-6.92)	(-7.02)	(-7.02)	(-6.90)	(-6.98)	(-6.99)	(-6.98)
SMB	-77.54**	-79.27**	-77.90**	-77.24**	-78.05**	-78.27**	-77.04**	-79.79**	-77.13**	-78.75**	-78.22**
	(-2.44)	(-2.50)	(-2.45)	(-2.43)	(-2.46)	(-2.48)	(-2.42)	(-2.50)	(-2.44)	(-2.50)	(-2.46)
HML	24.60	25.14	23.75	23.67	23.15	23.77	27.94	23.25	23.57	22.74	24.30
	(0.86)	(0.88)	(0.83)	(0.82)	(0.80)	(0.83)	(0.98)	(0.81)	(0.83)	(0.79)	(0.85)
RMW	-70.25	-69.13	-70.87	-69.73	-69.53	-68.99	-68.21	-69.55	-69.60	-70.72	-71.75
	(-1.60)	(-1.58)	(-1.62)	(-1.59)	(-1.59)	(-1.58)	(-1.57)	(-1.58)	(-1.59)	(-1.62)	(-1.63)
CMA	-26.81	-27.17	-24.90	-25.84	-24.46	-23.56	-23.74	-25.11	-27.28	-23.16	-24.04
	(-0.51)	(-0.52)	(-0.47)	(-0.49)	(-0.46)	(-0.45)	(-0.45)	(-0.48)	(-0.52)	(-0.44)	(-0.46)
Adj R2 (%)	13.35	13.38	13.24	13.34	13.26	13.31	13.95	13.32	13.36	13.38	13.29
No. of Obs.	2205	2205	2205	2205	2205	2205	2205	2205	2205	2205	2205

E Appendix: Spillover Effects Across Stocks and Options

One may question whether the post-FOMC drift on options is related to the stock market. Existing literature such as Lucca & Moench (2015) document a pattern of pre-FOMC drift on stock returns. Taking that with the post-FOMC drift on options together, we, therefore, investigate whether the options returns surrounding the FOMC announcements can be attributed to the stock performance.

E.1 Momentum Spillover Effects

Using a measure of shared analyst coverage that assesses the connections between firms with similar fundamentals, Ali & Hirshleifer (2020) document that, due to limited attention of investors or analysts paying to a firm, the incorporation of the information about its linked firms into prices of the firm may be sluggish. This phenomenon is referred to as momentum spillovers. Moreover, Gebhardt et al. (2005) and Haesen et al. (2017) suggest the existence of momentum spillover from the equity market to the bond market. They document that firms with high equity returns over the previous years yield high returns on their bonds the following year, and so do their bond ratings. In this section, we explore whether the momentum spillovers from the stock market to the options market. Specifically, whether the past stock price predicts the options price surrounding the FOMC announcements.

Interestingly, in our study, we visually identify a pattern of drift in stocks followed by a similar drift in straddles during the FOMC event-time window, as displayed in Figure 4.8. Both average returns on stocks and options are climbing leading to the FOMC announcement day, marked as day 0 on the figure. Differently, stock returns achieve their peak on the announcement day, while the straddle returns achieve their peak one day after the announcement. Subsequently, they both decline. Such a visual pattern prompts us to question whether the momentum spillover effects statistically drive the post-FOMC drift in the options markets.

However, we find no evidence suggesting such a driving pattern. In detail, Table 4.16 suggests that none of the lagged-one-day stock returns can statistically predict the straddle returns after the announcements. Interestingly, we find that the lagged-one-day stock returns predict the straddle returns on the announcement days.

E.2 Attention Spillover Effects

Apart from the momentum spillover effects, attention spillover effects between the stock and option markets are well documented. For instance, using a categorisation of daily winners and losers based on their daily returns as published in mainstream newspapers such as the Wall Street Journal and New York Times, Kumar et al. (2021) suggest that such attention-grabbing stocks often become overvalued and subsequently underperform due to increased trading activity. Building on this, Choy & Wei (2022) provide evidence that heightened attention to these daily winners and losers triggers additional buying pressure on options, subsequently leading to their overvaluation, denoted as attention spillover effects. Given the assumption that investors have limited attention (Kahneman 1973) and the concept of attention spillover effects, we posit that options prices could react sluggishly to the underlying stock information, such as price, due to the attention spillover effects.

We employ lottery-like proxies capturing stocks, receiving high attention from investors. In real life, the lottery exhibits a small chance of winning huge potential rewards, displaying a highly skewed distribution. Based on that, Kumar (2009) suggest that lottery-like stocks are attention-grabbing stocks. Therefore, we utilise lottery-like characteristics to proxy how stocks receive attention from investors.

In our empirical work, we utilise all proxies documented Liu et al. (2020) representing the attention level paid by investors. However, we find no significant evidence in Table 4.17 suggesting the pattern of the attention spillover effects driving the post-FOMC drift.

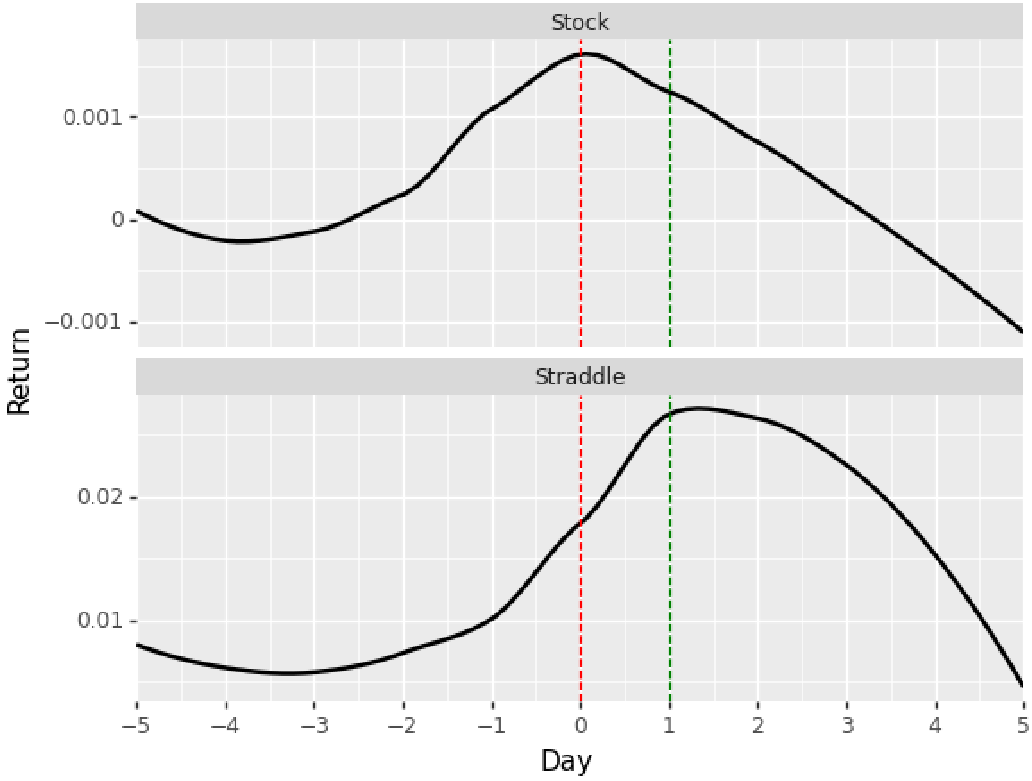


Figure 4.8: Event-time Straddle & Stock Drifts
This figure plots daily returns on straddles and stocks during the (-5, +5) event window centred at the FOMC announcement date. The smoothed conditional mean is estimated with locally-weighted regression. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. The sample period is from 1996 to 2021, covering 4,754 firms.

E.3 Fixed Effects or Random Effects

Table 4.16: Spillover Effects: Individual-Level Panel Regression Analysis

This table reports the results of panel regressions with firm and year fixed effects. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} Stock_{d-1,j-1} + \beta_2 Macroday_{d,j} + \beta_3 Stock_{d-1,j-1} + \lambda X' + \epsilon_{d,i}$. $ret_{d,i}$ is straddle daily return of firm i. $Macroday$ is a dummy variable indicating whether date d is the day j of the event-time window. Here, j ranges from -5 to +5. $Stock$ is the daily stock returns excluding dividends. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. See appendix A for more details about the construction of the variables. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. Standard errors are clustered by date. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep.: Strd. Ret.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
j =	-5	-4	-3	-2	-1	0	1	2	3	4	5
Macroday x Stock	0.22	5.79	-3.89	-17.76*	11.79	29.94***	-7.46	-2.33	-12.61	-6.05	-3.77
	(0.02)	(0.98)	(-0.69)	(-1.88)	(1.26)	(3.31)	(-0.82)	(-0.25)	(-1.57)	(-0.88)	(-0.57)
Macroday	-0.52	-0.85**	0.01	-0.59	-0.93**	-0.08	2.25***	0.64	0.81	-0.68	-0.02
	(-1.48)	(-2.41)	(0.02)	(-1.32)	(-2.33)	(-0.16)	(3.40)	(1.10)	(1.23)	(-1.47)	(-0.04)
Stock	1.28	0.69	1.62	2.58	0.29	-1.37	1.29	1.63	2.45	1.85	1.60
	(0.43)	(0.23)	(0.53)	(0.87)	(0.10)	(-0.52)	(0.49)	(0.55)	(0.82)	(0.62)	(0.54)
HV-IV	-3.97***	-3.97***	-3.99***	-3.98***	-4.00***	-3.95***	-3.94***	-3.98***	-3.98***	-3.99***	-3.98***
	(-4.53)	(-4.56)	(-4.56)	(-4.57)	(-4.59)	(-4.62)	(-4.59)	(-4.54)	(-4.55)	(-4.57)	(-4.56)
IV Smirk Slope	0.23	0.23	0.23	0.23	0.20	0.22	0.20	0.23	0.22	0.21	0.23
	(0.32)	(0.31)	(0.31)	(0.32)	(0.27)	(0.31)	(0.27)	(0.31)	(0.30)	(0.29)	(0.31)
IV Term Spread	-23.15***	-23.14***	-22.97***	-22.98***	-23.01***	-22.98***	-23.24***	-23.07***	-23.11***	-22.87***	-22.97***
	(-16.36)	(-16.36)	(-16.26)	(-16.32)	(-16.30)	(-16.31)	(-16.56)	(-16.35)	(-16.28)	(-16.27)	(-16.26)
Intercept	1.11***	1.14***	1.06***	1.12***	1.15***	1.07***	0.86***	1.00***	0.99***	1.12***	1.07***
	(7.21)	(7.39)	(6.94)	(7.33)	(7.50)	(7.08)	(6.05)	(6.81)	(6.88)	(7.46)	(7.00)
No. of Obs.	632,781	632,781	632,781	632,781	632,781	632,781	632,781	632,781	632,781	632,781	632,781
R^2 (%)	0.73	0.74	0.72	0.74	0.75	0.76	0.89	0.73	0.75	0.73	0.72
Firm Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table 4.17: Attention Spillover: Post-FOMC Drift

This table reports the individual-level analysis results of post-FOMC drift in straddles reacting to stock lottery-like characteristics. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} Proxy_{t-1,i} + Macroday_{d,j} + Proxy_{t-1,i} + \lambda X' + \epsilon_{d,i}$, where $ret_{d,i}$ is daily returns on straddles of firm i. $Macroday$ is a dummy variable indicating whether date d is the day j of the event-time window. Here, j ranges from -5 to +5. $Proxy$ denotes lottery-like characteristics of underlying stocks at the end of the previous month. We employ (1) maximum daily returns within a month (MAX), (2) idiosyncratic volatility ($IVOL$), (3) negative log price ($IVOL$), (4) expected idiosyncratic skewness ($SKEWEXP$) and (5) the mean standardised scores of above proxies ($ZSCORE$), see appendix for more variable construction details. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. See appendix A for more details about the construction of the variables. Reported coefficients are in percentage. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. For brevity, coefficients corresponding to the intercept and the control variables are not reported while they are included when running the regressions. Both firm and year fixed effects are included. Standard errors are clustered by date. The sample period is from 1996 to 2021, covering 4,754 firms.

Dep.: Strd. Ret.	(1) -5	(2) -4	(3) -3	(4) -2	(5) -1	(6) 0	(7) 1	(8) 2	(9) 3	(10) 4	(11) 5
Panel A: Proxy = *ZSCORE*											
Macroday x Proxy	-0.17	0.21	-0.27	0.42	0.02	0.19	**-0.61****	0.04	-0.00	0.17	-0.01
	(-1.00)	(1.39)	(-1.37)	(1.40)	(0.08)	(0.92)	**(-2.42)**	(0.17)	(-0.01)	(0.95)	(-0.05)
Macroday	-0.62*	-0.73**	-0.15	-0.36	-0.93**	0.05	1.88***	0.67	0.81	-0.60	-0.02
	(-1.81)	(-2.10)	(-0.40)	(-0.70)	(-2.43)	(0.11)	(3.05)	(1.17)	(1.16)	(-1.39)	(-0.07)
Proxy	-0.37***	-0.40***	-0.36***	-0.42***	-0.38***	-0.40***	-0.32***	-0.39***	-0.38***	-0.39***	-0.38***
	(-4.23)	(-4.65)	(-4.11)	(-4.67)	(-4.47)	(-4.59)	(-3.89)	(-4.59)	(-4.21)	(-4.56)	(-4.41)
No. of Obs.	632,579	632,579	632,579	632,579	632,579	632,579	632,579	632,579	632,579	632,579	632,579
R^2 (%)	0.72	0.74	0.72	0.73	0.75	0.72	0.89	0.73	0.74	0.73	0.71
Panel B: Proxy = *LNP*											
Macroday x Proxy	0.20	0.23*	-0.08	0.05	0.01	-0.13	-0.33	0.04	-0.22	-0.14	0.41**
	(1.31)	(1.65)	(-0.37)	(0.21)	(0.08)	(-0.68)	(-1.32)	(0.18)	(-0.62)	(-0.65)	(2.24)
Macroday	0.21	-0.00	-0.28	-0.41	-0.88	-0.54	1.00	0.79	-0.01	-1.20	1.50
	(0.34)	(-0.00)	(-0.36)	(-0.42)	(-1.28)	(-0.71)	(0.86)	(0.83)	(-0.01)	(-1.38)	(1.55)
Proxy	-0.22**	-0.23**	-0.20**	-0.21**	-0.21**	-0.19**	-0.17*	-0.21**	-0.19*	-0.19**	-0.24**
	(-2.27)	(-2.30)	(-2.05)	(-2.16)	(-2.10)	(-2.06)	(-1.83)	(-2.14)	(-1.94)	(-1.99)	(-2.45)
No. of Obs.	632,677	632,677	632,677	632,677	632,677	632,677	632,677	632,677	632,677	632,677	632,677
R^2 (%)	0.74	0.75	0.73	0.74	0.76	0.73	0.90	0.74	0.75	0.75	0.73
Panel C: Proxy = *SKEWEXP*											
Macroday x Proxy	-0.05	-0.02	0.10	0.15	0.10	0.09	**-0.36***	-0.16	0.21	-0.11	-0.01
	(-0.33)	(-0.21)	(0.83)	(1.01)	(0.93)	(0.63)	**(-1.76)**	(-0.85)	(1.23)	(-0.84)	(-0.06)
Macroday	-0.46	-0.87**	0.05	-0.72*	-0.96**	-0.04	2.35***	0.69	0.74	-0.74	-0.00
	(-1.23)	(-2.45)	(0.13)	(-1.68)	(-2.35)	(-0.09)	(3.39)	(1.13)	(1.13)	(-1.59)	(-0.01)
Proxy	0.02	0.02	0.01	0.00	0.01	0.01	0.05	0.03	-0.00	0.03	0.02
	(0.39)	(0.33)	(0.12)	(0.02)	(0.11)	(0.14)	(0.95)	(0.62)	(-0.06)	(0.50)	(0.32)
No. of Obs.	545,752	545,752	545,752	545,752	545,752	545,752	545,752	545,752	545,752	545,752	545,752
R^2 (%)	0.73	0.75	0.72	0.74	0.75	0.72	0.90	0.74	0.75	0.74	0.72
Panel D: Proxy = *IVOL*											
Macroday x Proxy	-2.45	7.89	-2.83	20.82**	-2.51	8.67	-23.24	-2.37	-18.44	-3.28	12.33
	(-0.28)	(0.98)	(-0.27)	(1.98)	(-0.23)	(0.63)	(-1.54)	(-0.14)	(-1.09)	(-0.29)	(1.34)
Macroday	-0.49	-1.00**	0.05	-1.00*	-0.89*	-0.22	2.68***	0.69	1.19	-0.61	-0.26
	(-1.20)	(-2.27)	(0.10)	(-1.95)	(-1.71)	(-0.35)	(3.12)	(0.92)	(1.48)	(-0.98)	(-0.47)
Proxy	-24.44***	-25.48***	-24.25***	-26.56***	-24.31***	-25.28***	-22.55***	-24.35***	-23.15***	-24.01***	-25.62***
	(-5.66)	(-5.83)	(-5.69)	(-6.17)	(-5.59)	(-6.14)	(-5.29)	(-5.68)	(-5.54)	(-5.56)	(-5.94)
No. of Obs.	632,613	632,613	632,613	632,613	632,613	632,613	632,613	632,613	632,613	632,613	632,613
R^2 (%)	0.74	0.76	0.73	0.75	0.76	0.73	0.90	0.75	0.76	0.75	0.73
Panel D: Proxy = *MAX*											
Macroday x Proxy	-0.14	2.26	-1.36	4.71	0.34	2.92	**-7.77***	-0.74	-3.60	-1.80	3.86
	(-0.05)	(1.08)	(-0.48)	(1.46)	(0.12)	(0.66)	**(-1.73)**	(-0.16)	(-0.79)	(-0.58)	(1.60)
Macroday	-0.52	-0.98**	0.08	-0.86*	-0.96**	-0.22	2.67***	0.69	1.02	-0.58	-0.25
	(-1.37)	(-2.45)	(0.17)	(-1.78)	(-2.00)	(-0.37)	(3.28)	(0.99)	(1.38)	(-1.01)	(-0.49)
Proxy	-4.87***	-5.11***	-4.73***	-5.32***	-4.88***	-5.11***	-4.20***	-4.80***	-4.58***	-4.67***	-5.21***
	(-4.19)	(-4.31)	(-4.09)	(-4.57)	(-4.16)	(-4.65)	(-3.69)	(-4.12)	(-4.01)	(-4.02)	(-4.42)
No. of Obs.	632,688	632,688	632,688	632,688	632,688	632,688	632,688	632,688	632,688	632,688	632,688
R^2 (%)	0.74	0.75	0.73	0.74	0.76	0.73	0.90	0.74	0.75	0.75	0.73

Table 4.18: Post-FOMC Drift: Hausman Test

This table reports the Hausman test results on deciding random effects or fixed effects for regression models. The result suggests that the fixed effects are appropriate to be included in the regression. The regression model is $ret_{d,i} = \beta_0 + \beta_1 Macroday_{d,j} + \lambda X' + \epsilon_{d,i}$. $ret_{d,i}$ is straddle daily return of firm i. $Macroday_{d,j}$ indicates if date d is the j day of the FOMC-cycle window (-5,+5). i.e., it is one day after the FOMC date when j is 1. Control variables are HV-IV, IV Smirk Slope and IV Term Spread. At the end of every month, we select a pair of call and put option contracts for each stock to construct a straddle. These contracts share the same strike price and expiration date, with their moneyness being the closest to one among the pairs with varying strike prices. The weight assigned to the call contract is $-\Delta_{put}$, while the put contract is assigned a weight of Δ_{call}. The Δ value is calculated using a binomial tree method and is sourced from OptionMetrics. Additionally, we introduce a scaling factor to ensure that the sum of the weights totals one. This ensures the initial delta neutrality of the straddle. See appendix A for more details about the construction of the variables. The sample period is from 1996 to 2021, covering 4,754 firms.

	(A) Fixed Effects	(B) Random Effects	(A-B) Difference	Std. Error
Macroday (j=1)	0.0214639	0.0214175	0.0000465	0.0000496
HV-IV	-0.0298017	-0.0290145	-0.0007872	0.0001606
IV Smirk Slope	0.0061789	0.0052921	0.0008868	0.0006744
IV Term Spread	-0.2179860	-0.2127296	-0.0052563	0.0008977
chi2(8)		119.51		
Prob > chi2		0.0000		

Chapter 5

Conclusion and Future Research

5.1 Summary and Conclusions

This thesis studies asset pricing with macroeconomic-related information, such as macroeconomic variables and announcements. Chapter 2 uncovers the substantial predictive power of past trends in a country's macroeconomic variables on its future stock market index performance, proving it profitable and statistically significant. A strategy based on this effect consistently generates an average annualised alpha of 3.5%, even after controlling for benchmark portfolios. Notably, this predictive power is most pronounced in mid-term look-back periods, particularly within the 13-36 months range. Intriguingly, traditional factor models like FF3, FF5, and q5 fail to establish meaningful relationships with this driving force. Using time-series momentum and value-and-momentum strategies as benchmark portfolios, widely accepted in the literature, we find that the economic momentum strategy consistently outperforms these benchmarks regarding risk-adjusted returns. Furthermore, our strategy exhibits lower and more stable time-varying drawdowns than the benchmarks, demonstrating greater stability. Importantly, our strategy maintains persistent performance over time, contrasting the benchmarks' more variable performance.

Chapter 3 reveals attention spillover effects among noise traders surrounding macro-announcements, leading to increased speculation in lottery-like stocks during the post-announcement period, which is statistically and economically significant. These effects persist even after controlling for various factors. Noise traders initially neglect individual stock prices before the macro-news are public, but their attention shifts to individual stocks post-announcement, impacting trading behaviour. Moreover, the FOMC plays a prominent role in these effects. We also find that market-level attention correlates with firm-level attention to lottery-like stocks, and both retail and institutional noise traders exhibit abnormal attentiveness to stocks after macro-announcements. Additionally, attention spillover effects are more pronounced among stocks without earnings announcements during the post-macro-announcement period, suggesting shifts in investor attention dynamics in response to uncertainty resolution and price information incorporation.

Chapter 4 uncovers a significant post-macro-announcement, FOMC, drift in options, particularly straddles consisting of paired call and put options at the same strike and expiration. This drift is statistically and economically significant, with consistent findings at portfolio and individual option levels. The observed phenomenon is attributed to market participants' overreaction to FOMC announcements, subsequent corrections, and increased illiquidity post-FOMC days. Notably, put options exhibit an accentuated drift. However, we find that the drift in put options is unrelated to demand pressure or downside risk, remaining a puzzle.

5.2 Future Research

Explaining Economic Momentum Chapter 2 delves into the historical trends of a country's fundamentals, including macroeconomic variables and their influence on the future performance of its equity market. Notably, stronger macroeconomic trends in a country correspond to better performance in its equity market, a phenomenon labelled as "economic momentum effects". These effects bear statistical and economic significance. However, the origins of these effects remain undisclosed. Viewing these momentum effects through the lens of behavioural finance, it can be inferred that they stem from initial underreactions to information followed by subsequent overreactions. Future research endeavours that explore the roots of economic momentum effects using theoretical frameworks from behavioural finance could offer intriguing insights.

Attention Spillovers in Different Asset Classes Chapter 3 investigates the response of noise traders to macroeconomic announcements, using both direct and indirect proxies to gauge their attention. The chapter highlights the phenomenon of their attention spilling over from the market to individual firms in the aftermath of macro-announcements. Additionally, it identifies this effect as more prominent among firms without earnings coverage, primarily due to the crowd-in effects. These observations are confined to the equity market, and a logical progression of this study would be to explore whether similar effects persist in other asset classes.

Beyond FOMC Announcements Chapter 4 investigates options behaviour in the context of FOMC announcements and reveals a post-FOMC drift pattern in the options market. This drift is attributed to investors' tendency to overreact to unexpected news and subsequently correct their positions. However, beyond the FOMC, it raises the question of whether options respond to other macroeconomic announcements similarly or if options investors exhibit different trading behaviours in response to various macroeconomic information. While our studies primarily emphasise macro-level information, whether options react similarly to firm-level announcements is worth considering. Future research exploring different announcement events or public information sources could yield valuable insights.

References

Aabo, T., Pantzalis, C. & Park, J. C. (2017), 'Idiosyncratic volatility: An indicator of noise trading?', *Journal of Banking & Finance* **75**, 136–151.

Acharya, V. V., Amihud, Y. & Bharath, S. T. (2013), 'Liquidity risk of corporate bond returns: conditional approach', *Journal of Financial Economics* **110**(2), 358–386.

Acharya, V. V. & Pedersen, L. H. (2005), 'Asset pricing with liquidity risk', *Journal of Financial Economics* **77**(2), 375–410.

Ali, U. & Hirshleifer, D. (2020), 'Shared analyst coverage: Unifying momentum spillover effects', *Journal of Financial Economics* **136**(3), 649–675.

Amihud, Y. (2002), 'Illiquidity and stock returns: cross-section and time-series effects', *Journal of Financial Markets* **5**(1), 31–56.

Amihud, Y. & Noh, J. (2021), 'Illiquidity and stock returns ii: Cross-section and time-series effects', *Review of Financial Studies* **34**(4), 2101–2123.

Andrei, D., Friedman, H. & Ozel, N. B. (2023), 'Economic uncertainty and investor attention', *Journal of Financial Economics* **149**(2), 179–217.

Ang, A., Chen, J. & Xing, Y. (2006), 'Downside risk', *The review of financial studies* **19**(4), 1191–1239.

Ang, A., Hodrick, R. J., Xing, Y. & Zhang, X. (2006), 'The cross-section of volatility and expected returns', *Journal of Finance* **61**(1), 259–299.

Annaert, J., De Ceuster, M. & Verstegen, K. (2013), 'Are extreme returns priced in the stock market? european evidence', *Journal of Banking & Finance* **37**(9), 3401–3411.

Arnott, R. D., Kalesnik, V. & Linnainmaa, J. T. (2023), 'Factor momentum', *The Review of Financial Studies* **36**(8), 3034–3070.

Asness, C. S., Moskowitz, T. J. & Pedersen, L. H. (2013), 'Value and momentum everywhere', *The Journal of Finance* **68**(3), 929–985.

Bali, T. G., Cakici, N. & Whitelaw, R. F. (2011), 'Maxing out: Stocks as lotteries and the cross-section of expected returns', *Journal of Financial Economics* **99**(2), 427–446.

Bali, T. G., Hirshleifer, D., Peng, L. & Tang, Y. (2021), Attention, social interaction, and investor attraction to lottery stocks, Technical report, National Bureau of Economic Research.

Barber, B. M., Odean, T. & Zhu, N. (2008), 'Do retail trades move markets?', *Review of Financial Studies* **22**(1), 151–186.

Bawa, V. S. & Lindenberg, E. B. (1977), 'Capital market equilibrium in a mean-lower partial moment framework', *Journal of Financial Economics* **5**(2), 189–200.

Ben-Rephael, A., Da, Z. & Israelsen, R. D. (2017), 'It depends on where you search: Institutional investor attention and underreaction to news', *The Review of Financial Studies* **30**(9), 3009–3047.

Benjamini, Y. & Hochberg, Y. (1995), 'Controlling the false discovery rate: a practical and powerful approach to multiple testing', *Journal of the Royal Statistical Society: Series B (Methodological)* **57**(1), 289–300.

Bertsimas, D., Kogan, L. & Lo, A. W. (2001), 'Hedging derivative securities and incomplete markets: An ϵ-arbitrage approach', *Operations Research* **49**(3), 372–397.

Bessembinder, H. (1992), 'Systematic risk, hedging pressure, and risk premiums in futures markets', *The Review of Financial Studies* **5**(4), 637–667.

Boguth, O., Grégoire, V. & Martineau, C. (2019), 'Shaping expectations and coordinating attention: The unintended consequences of fomc press conferences', *Journal of Financial and Quantitative Analysis* **54**(6), 2327–2353.

Bollen, N. P. & Whaley, R. E. (2004), 'Does net buying pressure affect the shape of implied volatility functions?', *The Journal of Finance* **59**(2), 711–753.

Boyer, B., Mitton, T. & Vorkink, K. (2010), 'Expected idiosyncratic skewness', *Review of Financial Studies* **23**(1), 169–202.

Broadie, M., Chernov, M. & Johannes, M. (2009), 'Understanding index option returns', *The Review of Financial Studies* **22**(11), 4493–4529.

Caglayan, M. O., Celiker, U. & Sonaer, G. (2018), 'Hedge fund vs. non-hedge fund institutional demand and the book-to-market effect', *Journal of Banking & Finance* **92**, 51–66.

Cakici, N. & Zaremba, A. (2021), 'Liquidity and the cross-section of international stock returns', *Journal of Banking & Finance* **127**, 106123.

Cao, J. & Han, B. (2013), 'Cross section of option returns and idiosyncratic stock volatility', *Journal of Financial Economics* **108**(1), 231–249.

Carhart, M. M. (1997), 'On persistence in mutual fund performance', *The Journal of Finance* **52**(1), 57–82.

Chen, N.-F., Roll, R. & Ross, S. A. (1986), 'Economic forces and the stock market', *Journal of Business* pp. 383–403.

Choy, S. K. & Wei, J. (2022), 'Investor attention and option returns', *Management Science* .

Christoffersen, P., Goyenko, R., Jacobs, K. & Karoui, M. (2018), 'Illiquidity premia in the equity options market', *The Review of Financial Studies* **31**(3), 811–851.

Cieslak, A., Morse, A. & Vissing-Jorgensen, A. (2019), 'Stock returns over the fomc cycle', *Journal of Finance* **74**(5), 2201–2248.

Cochrane, J. H. (2011), 'Presidential address: Discount rates', *The Journal of Finance* **66**(4), 1047–1108.

Conrad, J., Kapadia, N. & Xing, Y. (2014), 'Death and jackpot: Why do individual investors hold overpriced stocks?', *Journal of Financial Economics* **113**(3), 455–475.

Cox, J. C., Ingersoll Jr, J. E. & Ross, S. A. (1985), 'An intertemporal general equilibrium model of asset prices', *Econometrica: Journal of the Econometric Society* pp. 363–384.

Da, Z., Engelberg, J. & Gao, P. (2011), 'In search of attention', *Journal of Finance* **66**(5), 1461–1499.

Dahlquist, M. & Hasseltoft, H. (2020), 'Economic momentum and currency returns', *Journal of Financial Economics* **136**(1), 152–167.

Daniel, K. & Titman, S. (1997), 'Evidence on the characteristics of cross sectional variation in stock returns', *Journal of Finance* **52**(1), 1–33.

De Bondt, W. F. & Thaler, R. (1985), 'Does the stock market overreact?', *The Journal of Finance* **40**(3), 793–805.

De Roon, F. A., Nijman, T. E. & Veld, C. (2000), 'Hedging pressure effects in futures markets', *The Journal of Finance* **55**(3), 1437–1456.

Ehsani, S. & Linnainmaa, J. T. (2022), 'Factor momentum and the momentum factor', *The Journal of Finance* **77**(3), 1877–1919.

Fama, E. F. & French, K. R. (1993), 'Common risk factors in the returns on stocks and bonds', *Journal of Financial Economics* **33**, 3–56.

Fama, E. F. & French, K. R. (1995), 'Size and book-to-market factors in earnings and returns', *Journal of Finance* **50**(1), 131–155.

Fama, E. F. & French, K. R. (2015), 'A five-factor asset pricing model', *Journal of Financial Economics* **116**(1), 1–22.

Fama, E. F. & MacBeth, J. D. (1973), 'Risk, return, and equilibrium: Empirical tests', *Journal of Political Economy* **81**(3), 607–636.

Frazzini, A., Israel, R. & Moskowitz, T. J. (2018), 'Trading costs', *Available at SSRN 3229719* .

Garleanu, N., Pedersen, L. H. & Poteshman, A. M. (2008), 'Demand-based option pricing', *The Review of Financial Studies* **22**(10), 4259–4299.

Gebhardt, W. R., Hvidkjaer, S. & Swaminathan, B. (2005), 'Stock and bond market interaction: Does momentum spill over?', *Journal of Financial Economics* **75**(3), 651–690.

Gilbert, T., Scotti, C., Strasser, G. & Vega, C. (2017), 'Is the intrinsic value of a macroeconomic news announcement related to its asset price impact?', *Journal of Monetary Economics* **92**, 78–95.

Goyal, A. & Saretto, A. (2009), 'Cross-section of option returns and volatility', *Journal of Financial Economics* **94**(2), 310–326.

Griffin, J. M., Ji, X. & Martin, J. S. (2003), 'Momentum investing and business cycle risk: Evidence from pole to pole', *The Journal of Finance* **58**(6), 2515–2547.

Grobys, K. & Sapkota, N. (2019), 'Cryptocurrencies and momentum', *Economics Letters* **180**, 6–10.

Guo, H., Hung, C.-H. D., Kontonikas, A. & Zeng, Y. (2023), 'Flight to lottery ahead of fomc announcements: Institutional investors or retail investors?', *British Journal of Management, Forthcoming* .

Haesen, D., Houweling, P. & van Zundert, J. (2017), 'Momentum spillover from stocks to corporate bonds', *Journal of Banking & Finance* **79**, 28–41.

Han, B. & Kumar, A. (2013), 'Speculative retail trading and asset prices', *Journal of Financial and Quantitative Analysis* **48**(2), 377–404.

Han, B., Tang, Y. & Yang, L. (2016), 'Public information and uninformed trading: Implications for market liquidity and price efficiency', *Journal of Economic Theory* **163**, 604–643.

Hartzmark, S. M. & Shue, K. (2018), 'A tough act to follow: Contrast effects in financial markets', *Journal of Finance* **73**(4), 1567–1613.

Harvey, C. R., Liu, Y. & Zhu, H. (2016), '… and the cross-section of expected returns', *The Review of Financial Studies* **29**(1), 5–68.

Heston, S. L., Jones, C. S., Khorram, M., Li, S. & Mo, H. (2022), 'Option momentum', *Journal of Finance, Forthcoming* .

Hirshleifer, D. & Sheng, J. (2022), 'Macro news and micro news: complements or substitutes?', *Journal of Financial Economics* **145**(3), 1006–1024.

Holm, S. (1979), 'A simple sequentially rejective multiple test procedure', *Scandinavian Journal of Statistics* pp. 65–70.

Hong, H. & Yogo, M. (2012), 'What does futures market interest tell us about the macroeconomy and asset prices?', *Journal of Financial Economics* **105**(3), 473–490.

Hou, K., Mo, H., Xue, C. & Zhang, L. (2021), 'An augmented q-factor model with expected growth', *Review of Finance* **25**(1), 1–41.

Hsu, C.-C. & Chen, M.-L. (2021), 'Currency momentum strategies based on the chinese yuan: Timing of foreign exchange volatility', *Journal of International Financial Markets, Institutions and Money* **72**, 101315.

Hu, G. X., Pan, J., Wang, J. & Zhu, H. (2022), 'Premium for heightened uncertainty: Explaining pre-announcement market returns', *Journal of Financial Economics* **145**(3), 909–936.

Huang, D., Li, J., Wang, L. & Zhou, G. (2020), 'Time series momentum: Is it there?', *Journal of Financial Economics* **135**(3), 774–794.

Huang, D., Zhang, H., Zhou, G. & Zhu, Y. (2019), 'Twin momentum: Fundamental trends matter', *Available at SSRN 2894068* .

Hutchinson, M. C., Kyziropoulos, P. E., O'Brien, J., O'Reilly, P. & Sharma, T. (2022), 'Are carry, momentum and value still there in currencies?', *International Review of Financial Analysis* **83**, 102245.

Jegadeesh, N. & Titman, S. (1993), 'Returns to buying winners and selling losers: Implications for stock market efficiency', *The Journal of Finance* **48**(1), 65–91.

Jensen, T. I., Kelly, B. & Pedersen, L. H. (2023), 'Is there a replication crisis in finance?', *The Journal of Finance* **78**(5), 2465–2518.

Kahneman, D. (1973), *Attention and effort*, Vol. 1063, Citeseer.

Kahneman, D. & Tversky, A. (1979), 'Prospect theory: An analysis of decision under risk', *Econometrica* **47**(2), 263–292.

Koijen, R. S., Moskowitz, T. J., Pedersen, L. H. & Vrugt, E. B. (2018), 'Carry', *Journal of Financial Economics* **127**(2), 197–225.

Korajczyk, R. A. & Sadka, R. (2004), 'Are momentum profits robust to trading costs?', *The Journal of Finance* **59**(3), 1039–1082.

Kumar, A. (2009), 'Who gambles in the stock market?', *Journal of Finance* **64**(4), 1889–1933.

Kumar, A., Ruenzi, S. & Ungeheuer, M. (2021), 'Daily winners and losers', *Available at SSRN 2931545* .

Lesmond, D. A., Schill, M. J. & Zhou, C. (2004), 'The illusory nature of momentum profits', *Journal of Financial Economics* **71**(2), 349–380.

Li, Y., Urquhart, A., Wang, P. & Zhang, W. (2021), 'Max momentum in cryptocurrency markets', *International Review of Financial Analysis* **77**, 101829.

Liu, B., Wang, H., Yu, J. & Zhao, S. (2020), 'Time-varying demand for lottery: Speculation ahead of earnings announcements', *Journal of Financial Economics* **138**(3), 789–817.

Liu, H., Tang, X. & Zhou, G. (2022), 'Recovering the fomc risk premium', *Journal of Financial Economics* **145**(1), 45–68.

Liu, Y., Tsyvinski, A. & Wu, X. (2022), 'Common risk factors in cryptocurrency', *The Journal of Finance* **77**(2), 1133–1177.

Lucca, D. O. & Moench, E. (2015), 'The pre-fomc announcement drift', *Journal of Finance* **70**(1), 329–371.

Merton, R. C. (1973), 'Theory of rational option pricing', *The Bell Journal of Economics and Management Science* pp. 141–183.

Merton, R. C. (1987), 'A simple model of capital market equilibrium with incomplete information', *Journal of Finance* **42**(3), 483–510.

Miffre, J. & Rallis, G. (2007), 'Momentum strategies in commodity futures markets', *Journal of Banking & Finance* **31**(6), 1863–1886.

Moskowitz, T. J., Ooi, Y. H. & Pedersen, L. H. (2012), 'Time series momentum', *Journal of Financial Economics* **104**(2), 228–250.

Muravyev, D. (2016), 'Order flow and expected option returns', *The Journal of Finance* **71**(2), 673–708.

Newey, W. K. & West, K. D. (1987), 'A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix', *Econometrica* **55**(3), 703–708.

Ojo, M. O., Aguiar-Conraria, L. & Soares, M. J. (2023), 'The performance of oecd's composite leading indicator', *International Journal of Finance & Economics* .

Okunev, J. & White, D. (2003), 'Do momentum-based strategies still work in foreign currency markets?', *Journal of Financial and Quantitative Analysis* pp. 425–447.

Paschke, R., Prokopczuk, M. & Simen, C. W. (2020), 'Curve momentum', *Journal of Banking & Finance* **113**, 105718.

Pástor, L. & Stambaugh, R. F. (2003), 'Liquidity risk and expected stock returns', *Journal of Political Economy* **111**(3), 642–685.

Peng, L. & Xiong, W. (2006), 'Investor attention, overconfidence and category learning', *Journal of Financial Economics* **80**(3), 563–602.

Peress, J. & Schmidt, D. (2020), 'Glued to the tv: Distracted noise traders and stock market liquidity', *Journal of Finance* **75**(2), 1083–1133.

Pontiff, J. & Schall, L. D. (1998), 'Book-to-market ratios as predictors of market returns', *Journal of Financial Economics* **49**(2), 141–160.

Roll, R. & Ross, S. A. (1980), 'An empirical investigation of the arbitrage pricing theory', *The Journal of Finance* **35**(5), 1073–1103.

Rouwenhorst, K. G. (1998), 'International momentum strategies', *The Journal of Finance* **53**(1), 267–284.

Rouwenhorst, K. G. (1999), 'Local return factors and turnover in emerging stock markets', *The Journal of Finance* **54**(4), 1439–1464.

Savor, P. & Wilson, M. (2013), 'How much do investors care about macroeconomic risk? evidence from scheduled economic announcements', *Journal of Financial and Quantitative Analysis* **48**(2), 343–375.

Savor, P. & Wilson, M. (2014), 'Asset pricing: A tale of two days', *Journal of Financial Economics* **113**(2), 171–201.

Sharpe, W. F. (1964), 'Capital asset prices: A theory of market equilibrium under conditions of risk', *Journal of Finance* **19**(3), 425–442.

Skjeltorp, J. A., Sojli, E. & Tham, W. W. (2016), 'Flashes of trading intent at nasdaq', *Journal of Financial and Quantitative Analysis* **51**(1), 165–196.

Stein, J. (1989), 'Overreactions in the options market', *The Journal of Finance* **44**(4), 1011–1023.

Tversky, A. & Kahneman, D. (1974), 'Judgment under uncertainty: Heuristics and biases: Biases in judgments reveal some heuristics of thinking under uncertainty.', *Science* **185**(4157), 1124–1131.

Van Dijk, M. A. (2011), 'Is size dead? a review of the size effect in equity returns', *Journal of Banking & Finance* **35**(12), 3263–3274.

Vasquez, A. (2017), 'Equity volatility term structures and the cross section of option returns', *Journal of Financial and Quantitative Analysis* **52**(6), 2727–2754.

Veldkamp, L. L. (2006), 'Information markets and the comovement of asset prices', *The Review of Economic Studies* **73**(3), 823–845.

Wachter, J. A. & Zhu, Y. (2022), 'A model of two days: Discrete news and asset prices', *The Review of Financial Studies* **35**(5), 2246–2307.

Zakamulin, V. (2013), 'Forecasting the size premium over different time horizons', *Journal of Banking & Finance* **37**(3), 1061–1072.

Zaremba, A., Long, H. & Karathanasopoulos, A. (2019), 'Short-term momentum (almost) everywhere', *Journal of International Financial Markets, Institutions and Money* **63**, 101140.

Zhan, X., Han, B., Cao, J. & Tong, Q. (2022), 'Option return predictability', *The Review of Financial Studies* **35**(3), 1394–1442.

Zhang, C. & Zhao, S. (2023), 'The macroeconomic announcement premium and information environment', *Journal of Monetary Economics, Forthcoming* .

Zhong, A. & Gray, P. (2016), 'The max effect: An exploration of risk and mispricing explanations', *Journal of Banking & Finance* **65**, 76–90.