What causes intraday price jumps and co-jump in Gold – Market Psych, Macroeconomic News or Illiquidity?

Neharika Sobti*[1]

Department of Finance, Institute of Management Technology (IMT), Ghaziabad, Delhi-NCR, India

Abstract

What factors drive intraday price jumps and co-jumps in gold markets? Using high frequency data, we examine whether market psych-*attention, sentiments and emotions*, macroeconomic news surprises or illiquidity predicts intraday positive and negative price jumps and co-jumps in gold markets using battery of empirical methods – intraday event analysis coupled with penalised logistic regressions. We find that gold futures witness greater number intraday jumps and ETF, with greater price crash than spikes. News and social media attention and emotions has symmetric impact on price jumps while sentiments have asymmetric impact. US macroeconomic news surprises are dominants predictors of price jumps in gold and illiquidity, trading cost, trading activity, and order imbalance showcase high predictability for jumps and co-jumps.

Keywords- gold, price jumps, co-jumps, market psych, illiquidity, macroeconomic news

Jel Classification- G1, G10, G12, G14

[1] The author is grateful to Sanjay Sehgal for the guidance and support during PhD dissertation work, of which this paper is a part. The author thanks Balakrishnan Ilango and Refinitiv (now LSEG) for the data. The author thanks the discussants at 9th PAN IIM World Conference 2024 and 7th India Gold Policy Conference, IIM Ahemdabad for their valuable feedback and comments.

*Corresponding Author, Email- neharika.sobti@gmail.com

1. Introduction

What factors drives intraday price jumps and co-jumps in gold markets? Surprisingly, no empirical evidence exists despite the fact that gold prices have a history of making several sudden and large single day price spikes and crashes. Some of the notable ones being the famous "$1 trillion crash in gold" of 2013, gold futures trading at Chicago Mercantile Exchange (CME) witness the biggest single day percentage drop in prices of 4.1% ($63.50) on 12th April, 2013, of which gold prices dropped by $25 within 2-minutes due to massive selloff. Recently, due to Covid-19 pandemic induced slowdown and recovery, gold prices witness another dramatic single day fall on 7th August, 2020 to $1,863 from its record high of $2075 due to intense sell offs. In addition, on January 2021, gold prices dropped by 4% in a single day due to rise in the US yields. Strikingly, post the Covid-19 recovery began in 2021, gold price suddenly dropped by $100 on 7th August, 2021 from $1,764 to $1,677, of which 90% price fell in just 15-minutes. This drop is fueled by a combination of technical factors and poor liquidity but the initial trigger came from US non-farm payroll(NFP)[2], whose actual release value beat the analyst expectation.

These multiple instances of sudden and large spikes and crashes in gold prices within minutes due to the reactionary and forward looking nature of gold indicates that gold prices are more prone to frequent extreme price movements or price discontinuities, which are referred to as "price jumps". Price jumps, are high impact events indicating tail risk manifested as discontinuities in prices, which are due to sudden, rare and substantially large upward or downward movement in prices for a short interval of time (Nguyen et al.,2020). Jumps are conduits, which reflect immediate market reaction to information shocks (Frömmel, Han, Gysegem, 2015). Identifying and incorporating jump risk has important implication for volatility forecasting, return predictability (Jiang and Yao,2014; Maheu, et al.,2013; Ornthanalai,2014; Yan, 2011), asset pricing and optimal portfolio allocation (Das and Uppal, 2014; Jin and Zhang, 2012; Bollerslev et al.,2008; Liu and Pan, 2003), risk management and tail risk premium (Christoffersen, et al., 2012; Eraker,2004; Jiang, et al.,2011; Maheu and McCurdy, 2004; Merton, 1976; Liao, 2013). Co-jumps are simultaneous occurrence of price jumps contemporaneously in two or more markets. Co-jumps

---

[2] https://www.bloomberg.com/news/articles/2021-08-09/flash-crash-shows-why-it-s-tough-to-be-bullish-on-gold-right-now High NFP indicates a strong recovery of the US economy, which led to sharp rise in inflation adjusted treasury yields that led to biggest single day hike for US Dollar. It resulted in a sudden fall in gold prices as it has negative relation with US Dollar and gold is regarded as safe haven, hedge and diversifier (Baur and Lucey, 2010; Baur and McDermott, 2010; Capie et al., 2005).

represent non-diversifiable risk Bollerslev et al. 2008 and are important for asset allocation Caporin et al. (2017) and Barunik and Vacha (2018).

The extant literature of intraday jump detection methods has grown extensively but there is no consensus on what factors drive intraday price jumps and co-jumps in gold markets. Only few studies (Evans, 2011; Lee, 2012; Piccotti, 2017; Scaillet et al.2019, Prokopczuk and Simen,2018; Caporin and Poli, 2018; Kapetanios et al.,2019; Boudt and Petitjean, 2013; Baker, Bloom et al.,2021) analyse the nature, determinants and impact of price jumps and co-jumps in stock and bond markets. The unanticipated nature of jumps arises from the fact that some jumps are information driven and are expected to have permanent market effect (Dumitru and Urga (2012, 2016; Frömmel, Han, Gysegem (2015) while purely liquidity driven jump have transitory market effect. Majority studies find that arrival of new information like macroeconomic news announcements are the major driver of price jumps in stocks (Andersen et al.,2007a; Lahaye et al.,2011; Lee,2012; Caporin and Poli, 2018; Baker, Bloom et al.2021 (Andersen, et al.,2003; Chatrath, et al.,2014; Piccotti, 2017(Evans, 2011. While others (Nguyen et al.,2020; Scaillet et al.,2018; Christensen, Oomen, and Podolskij,2014; Boudt and Petitjean, 2013; Sun and Gao (2019; Breedon and Ranaldo, 2013; Mancini et al., 2013) argue liquidity or illiquidity causes price jumps. While others find that investor attention and their heterogeneous beliefs results in asymmetry in stock volatility resulting in jumps.

News analytics has speed up the real-time incorporation of informationally relevant macroeconomic news and social media feeds in asset prices within milliseconds. Today, investor reveal their sentiments, disagreements, opinions, and emotions, via news and social media platforms like StockTwits and Google searches, that enable predictability of returns and volatility (Beschwitz et al.,2018). Some studies argue that most price jumps and crashes occur as a result of investor's overreaction to new information. Moreover, George Soros along with past academic studies (Baur and Glover, 2015; Białkowski, Bohl, Stephan, and Wisniewski, 2015) argue that gold is most susceptible to "madness of the crowds" and claim that more than any other asset, gold price change mainly because of investor perception[3] than fundamentals. However, no study has systematically investigated the high frequency jump dynamics and its determinants for gold, which

[3] The role of perception plays a key role in gold price movements as evident from a sharp drop in gold prices by $800 per ounce to $1050.60 on 17th December 2015 but rose to $1300 by 2017. This sharp rise in gold is majorly due to the perception of possible inflation due to depreciation of dollar, even though there was no inflation and stock markets were also on a bull phase.

is the third largest reserve asset and a strategic financial asset constituting 15% allocation in global portfolios by institutional investors. The extant literature (Nguyen et al.(2020; Piccotti, 2017; Evan, 2011; Caporin and Poli, 2018; Baker, Bloom et al.,2021) provides conflicting evidence and has failed to reach a consensus on what factors cause intraday price jumps and co-jumps. Therefore, the prevalence of these high-impact jump events in gold prices motivated us to examine the dynamics, real-time characteristics and determinants of intraday price jumps and co-jumps in gold markets. We provide first time-evidence for whether intraday gold price jumps are predictable and what are the possible high frequency predictors of intraday price jumps and co-jumps in gold markets. We investigate the "*excess jump puzzle*", as identified by Prokopczuk and Simen (2018), in the context of gold markets to examine whether all jumps in gold prices occur due to news announcements or liquidity.

Our central research question is whether intraday price jumps and co-jumps in gold occur due to (1) market psych, (2) macroeconomic news announcements and surprise, and (3) illiquidity or trading activity. Our novel and central contribution is to examine whether and how market psych triggers intraday price jumps and co-jumps in gold by investigating three dimension of market psych, namely-*attention, sentiments and emotions,* after controlling for news surprises and illiquidity. Another unique contribution of our study is to decipher whether news and social media based market psych dimensions have different impact on the predictability of positive and negative price jumps and co-jumps at high frequency. Hence, to comprehensively investigate our central question, we attempt to find answers to following five research questions- (1) Does news or social media based investor attention to gold improves predictability of intraday price jumps and co-jumps in gold? Is there an attention asymmetry for positive and negative jumps? (2) Does positive (negative) market sentiment for gold increase the predictability of positive (negative) price jumps? (3) Do emotions triumph facts in predictability of intraday price jumps and co-jumps in gold. (4) Which scheduled macroeconomic news surprises can predict intraday price jumps and co-jump in gold markets? And lastly, (5) Does shrinkage in liquidity causes price jumps and co-jumps in gold? In addition, as precursor to our central research question, we also aim to examine – What is the probability of occurrence of price jumps in a trading day in gold futures and ETF markets and does price jumps and co-jumps showcases any intraday patterns. Which hours does jumps occurs the most. Is there any asymmetry in the occurrence of positive and negative price jumps? Does jumps occur more in gold futures or ETF markets? What is likelihood that news announcement causes price jumps and co-jumps? How does liquidity and its dimension behave surrounding price jumps?

In order to address these research question and fill the abovementioned research gaps, we contribute in the following ways to an important area of research in market microstructure literature that is determinants of intraday price jumps and co-jumps, which is still at a nascent stage (Boudt and Petitjean,2013). Firstly, we provide first-time evidence of high frequency jump dynamics in gold markets by identifying intraday price jumps and co-jumps in two major gold trading instruments–COMEX gold futures and SPDR Gold ETF, that have proved to be the major source of price discovery for gold (Sehgal, Sobti et al. (2021); Haupfliesh et al.(2016); Ivanov(2011). Our novel contribution is to draw comparative analysis of characteristics and sources of intraday price jumps and co-jumps between two largest yet different gold trading markets. COMEX futures and SPDR ETF have different levels of liquidity, transaction costs, trading mechanism, settlement procedures, and attract different types of investors. Secondly, we deploy a combination of intraday jump detection techniques, namely- Andersen et al.(2007) and Bollerslev et al.(2013) after controlling for intraweek periodicity patterns in volatility by using weighted standard deviation (WSD) estimator proposed by Boudt et al.(2011), which is a robust estimator of diffusive part of volatility in the presence of jumps. To avoid spurious and fake detection of jumps, we perform additional test of robustness using Lee and Mykland (2008) method. Thirdly, we identify price jumps and co-jumps using high frequency data sampled at 5-minutes for a relative long sample period covering eight years from 1st January, 2010 to 31st March, 2018. As a test of robustness, we detect jumps at 1-/3-/10-minutes at 95% and 99% threshold using multiple intraday jump detection methods.

Fourth, we advance the intraday jump literature by identifying high frequency determinants of price jumps and co-jumps separately for all, positive and negative price jumps and co-jumps for the two largest gold instruments. We are the first study to provide comprehensive analysis of the impact of key behavioural factors (market psych) on intraday gold price jumps and co-jumps by using a unique and proprietary high frequency dataset, Thomson Reuters Market Psych Index (TRMI), which contains data for market attention to gold, market sentiment towards gold and emotions concerning gold at 1-minute interval. What distinguishes our study from past literature is that we analyse whether price jumps are driven by non-fundamental behavioral factors like market psychology, or fundamental factors like macroeconomic news announcement, is what our paper attempts to shed light on by analyzing three key aspects of market psych – attention, sentiments and emotions using both news and social media based indicators along with an exhaustive coverage of 29 US scheduled macroeconomic news surprises. Therefore, we assess whether news or social media based market psych (behavioural) factors showcase different impact of the predictability of positive and negative jumps and co-jumps.

Fifth, our unique contribution in this regard is that we perform a comprehensive intraday event study analysis using constant mean return model for short interval for all classes predictor variables, separately for positive and negative price jumps as identified for both gold instruments. We examine the pre-jump and post-jump market conditions surrounding the positive and negative price jumps by assessing market psych, liquidity, and volatility dimensions from -60 to +60 minutes event window. In addition, we also provide in-depth analysis of the impact of key liquidity and microstructural dimension, namely - *number of trades, depth, effective spread, order imbalance, volatility and ammihud illiquidit*y on positive and negative price jumps and co-jumps.

We perform a predictive regression analysis using penalised (ridge) logistic regression method to identify the which factors are significant predictors of intraday jumps and co-jumps, separately for COMEX futures and SPDR gold ETF. Moreover, using interaction effects regression model, we also assess whether three aspects of market psych for gold has stronger impact during the release of macroeconomic news. We assess asymmetric effect of market sentiment towards gold by analysing whether positive market sentiment drives positive jumps in gold and vice versa. Lastly, we test *news-watcher's hypothesis* using predictive penalised logistic regression using *least absolute shrinkage and selection operator (LASSO)* penalty to identify which among 29 US scheduled macroeconomic news surprises causes intraday price jumps and co-jumps of either signs for COMEX futures and SPDR gold ETF.

We presage our findings here. We find that COMEX gold future experience greater number of intraday jumps (1101) as compared to SPDR Gold ETF (1045) from 2010-2018. We find greater occurrence of negative price jumps than positive jumps for both gold markets, indicating that gold market crashes are more prominent. We observe that US scheduled macroeconomic news is the most dominant predictor of intraday price jumps and co-jumps. We find that US scheduled macroeconomic news announcement causes 18-25% of intraday jumps in COMEX futures while 21-28% jumps in ETF SPDR. Using intraday event study analysis, we find trading activity, trading cost, ammihud illiquidity, and volatility are at elevated level 10-15 minutes prior to both positive and negative jump while buy side orderflow rises during positive price jumps and sell side order flow rises during negative price jump. Next, we find that news attention increases the predictability of negative price jumps and co-jumps while social media attention to gold increases the predictability of positive jumps and co-jumps. We also observe asymmetric effect of market sentiment as positive media sentiment predicts positive price jumps while negative media sentiment predicts negative price jumps. While we find that news and social media emotion have dominant and positive impact on jump and co-jump predictability during macroeconomic news announcement. As price jumps and co-jumps are also preceded by large increase in illiquidity (widening of bid ask spread and ammihud illiquidity ratio), it implies presence of informed traders prior to news and uninformed traders try to avoid trading with them. It implies that informed traders in gold market possess superior skills which results in increase spread by market makers. Lastly, using LASSO logistic regression we find that positive jumps and negative jumps are driven by different set of US scheduled macroeconomic news surprises. We find FOMC Rate Decision is the most dominant and statistically significant US scheduled macroeconomic news, followed by Initial Jobless Claim and Unemployment, which are common and significant predictors for both positive and negative price jump and co-jumps predictability in gold markets. We find that positive price jumps and co-jumps in both gold markets are majorly driven by New Home Sales, Construction Spending, Initial jobless claim and Unemployment. In contrast, negative price jump and co-jumps in gold are predictable from news surprises related to Non-farm payroll, GDP Advance, Capacity Utilisation, Durable Goods, Consumer Confidence, PMI Manufacturing, Initial Jobless Claim and Unemployment. We observe that macroeconomic news which have large surprise index have greater impact on the predictability of intraday price jumps in gold markets.

We organise this paper as follows. Section 2 presents Related Literature and Hypotheses Development. Section 3 reports the Empirical Methods. Section 4 highlights the Data and Descriptive Statistics followed by our detailed empirical findings and implication in Section 5. Section 6 presents robustness tests followed by conclusion in Section 7.

2. Related Literature & Hypothesis Development

What drives intraday jumps and co-jumps in gold is an under-researched yet tricky question as gold is a unique[4] financial asset which is most susceptible to "madness of the crowds" as claimed

[4] Gold's uniqueness stems from its multi-functional role as store of value, medium of exchange, hedge, diversifier and safe haven () which attracts retail and amateur traders to gold.

by George Soros. Past academic studies (Baur and Glover, 2015; Białkowski et al., 2015) argue that more than any other asset, gold price change mainly because of investor perception[5] than fundamentals. The prior literature () has observed that most price jumps and crashes in financial assets occur either due to investor overreaction or under-reaction to the new information occurring due to macroeconomic news announcements, geopolitical events, and supply disruptions, or due to shocks to liquidity. However, it is the market psych i.e. investors attention, sentiments and emotional reaction to news, which alters investor's trading behavior in turn affects asset prices and volatility. Today, investor reveal their real time sentiments, disagreements, opinions, and emotions, via both news and social media sources. Due to lack of evidence and consensus on determinants of intraday price jumps and co-jumps in gold markets, we build five hypotheses on five different high-frequency predictors for intraday jumps in gold, namely- intraday MarketPsych aspects (Attention, Sentiments, Emotions), Macroeconomic News, and shocks to Liquidity, using traditional theories and findings from past academic and practioner's work.

2.1. Does News and Social Media Attention to gold drives intraday jumps in gold?

The pioneering study of Andrei and Hasler (2015) document that investor attention affects asset volatility and argues in their own words that "When investors pay little attention to news, information is only gradually incorporated into prices because learning is slow, resulting in low return volatility. In contrast, attentive investors immediately incorporate new information into prices, and thus high attention induces high return volatility''. Attention is regarded as a scarce cognitive resource (Kahneman, 1973) as investor need to be cautious in allocating their limited attention spans to multitude of information releases arising from multiple sources from news and social media e.g. Reuters, Dow, and Bloomberg), social media messages, Stocktwits, push notifications and emails, as argued by Peng (2005) and Peng and Xiong (2006).

There are two widely accepted theories of investor attention that provides theoretical underpinning to the relationship between investor attention and volatility. First, Odean (1999) and Barber and Odean (2008) postulates a theory based on choice asymmetry which states that since investors are faced with an extremely large investment universe to choose from which asset to buy, so they tend to buy those stocks that grab their attention. While selling they have limited choice as they can sell only those assets which they hold. Hence, high attention typically results in higher buying pressure

[5] The role of perception plays a key role in gold price movements as evident from a sharp drop in gold prices by $800 per ounce to $1050.60 on 17th December 2015 but rose to $1300 by 2017. This sharp rise in gold is majorly due to the perception of possible inflation due to depreciation of dollar, even though there was no inflation and stock markets were also on a bull phase.

which increase prices and induces short term price volatility. Second alterative theory is that greater investor attention generates temporary price pressure but improves market efficiency and induces greater information discovery by reducing return predictability, as observed by some studies (Vlastakis & Markellos, 2012; Vozlyublennaia, 2014; Tantaopas et al., 2016; Smales, 2021). The volatility response to higher investor attention is consistent with mixture of distribution hypothesis (MDH) posited by Smith (2012) which states that increase levels of investor attention may increase the flow of information i.e. the arrival rate of information rises which in turn affects volatility. Investor attention has been a cause of overreaction and underreaction to news (Hirshleifer and Teoh, 2005; DellaVigna and Pollet, 2009), which results price jumps and crashes.

Social media has become the new battlefield for investor and public opinion due to rapid growth in the fully automated high frequency trading coupled with the massive adoption of news analytics, which is an algorithmic processing of news and events by machines, by several institutional investors, as argued by Murphy et al. (2014) and Scholtus, Dijk, and Frijns (2014). A slew of past academic studies (Da et al., 2011, 2015; Renault, 2017; Sun et al., 2016; Zhang et al., 2011; Aouadi et al.,2013; Dimpfl and Jank, 2015; Hamid and Heiden, 2015; Barber and Odean, 2008; Gargano and Rossi, 2018; Arnold et al.,2021) find predictive power of social media attention for stock return volatility as investor attention drives individual investor behavior and risk taking appetite. Past literature uses news word count as a proxy for news attention and find predictive power for stock returns (Tetlock, 2007; Tetlock *et al*., 2008; Garcia, 2013), credit default swaps (Smales, 2016; Cathcart et al., 2020; Narayan and Bannigidadmath, 2021), exchange rate (Narayan et al., 2021), and commodities (Bannigidadmath and Narayan, 2021). Da et al.(2015) proposed google search volume index (GSVI) a measure for investor attention. More recently, Sun et al. (2016) finds predictive ability of attention on stock return by using buzz aspect of Thomson Reuters MarketPsych Index (TRMI) which is a proxy for attention and is based on number of times the unit of study is mentioned in news wires, social media platforms, internet sources. Using deep learning based attention variables, Li et al. (2021) find that investor attention has greater forecasting power for extreme events and volatility in Chinese stock markets and investor attention serves as a channel through which Black Swan events transmits and affects jump risk.

Subsequently, many studies (Barber and Odean, 2008; Da et al.,2011; Cheng et al.,2020; Ibikunle et al.,2020; Li et al.,2021) support the argument that high or excessive investor attention results in heightened volatility and trading volume. Therefore, investor will expect high premium for bearing additional attention induced risk as argued by Andrei & Hasler (2014). However, the attention induced volatility is temporary and reverses back to its original levels because it is driven by net buying pressure of noise traders that diminishes pricing efficiency, as consistent with noise trading hypothesis. More recently, Dzieliński et al.(2018) find that asymmetric attention leads to asymmetric volatility. While Ana et al.(2020) find that a higher media coverage of the stocks results in less probability of stock market crash and find a negative relationship between social media attention and stock market crash (negative jump).

Thus, the reactionary nature of gold makes it the most suscepitible asset to market psych i.e. investor attention. High investor attention are associated with asset price bubbles, market crash, massive selloffs and herding behavior (Li, Ning, and Zhang (2021), which further affects asset price volatility, trading volume, and price jumps. Hence, asset price only respond to new information when investor pay attention to it as argued by Huberman & Regev (2001) and Smales (2021). More specifically, Chen, Jiang and Zhu (2018) and Peng and Xiong (2006) find that limited investor attention enforces category learning behavior due to which investor tend to allocate more attention to macroeconomic news than to firm-specific announcements. **Jiao et al. (**2016) argues that processing information from news and social media sources indicate opposite effects on stock volatility, which highlights that both media sources needs to be separately analysed due to the growing overlap between microblogging networks and trading network (Lin et al.,2016). This motivates us to examine the how investor attention originating from news and social media drives extreme price movements i.e. intraday price jump and co-jump in gold markets. We formulate our first hypothesis H1 as follows:

H1(a): High Attention to gold from News and Social Media predicts intraday price jumps and co-jumps in gold markets.

H1(b): High Attention to gold from News and Social Media during Macroeconomic News announcements predicts price jumps and co-jumps in gold markets.

2.2. Does News and Social Media Sentiments causes intraday jumps in gold?

Traditional behavioral finance theories argue that financial markets are affected by sentiment-driven and irrational investors that are essentially noise traders, who base their decisions and judgement not on the available heuristic sentiments, non-fundamental information, and affective attitudes. (Black, 1986; De Long et al., 1990a, 1990b, 1991; Shiller, 2000; Shleifer & Vishny, 1997). The irrational and sentiment driven behavior of noise traders are considered to be driving force behind extreme and abnormal price fluctuation or volatility, that drive prices away from fundamentals for a very short or long time period. This forms the basis of noise trader's hypothesis in behavioral finance (Kahneman & Tversky, 1979). Market sentiment is a construct which reflects collective mood, beliefs, and reaction of investors towards unscheduled news and events, which are hard to quantify (Gao and Süss, 2018). Miller (1977) and Hong and Stein (2003) argue that sentiments indicate risk and uncertainty that investors perceive during differences of opinion.

The past academic literature (De Long et al.,1990; Cahan et al.,2009; Hwang,2011; Allen et al.,2015; Smales,2017) has documented that investor sentiments play an important role in price formation and volatility forecasting in financial markets as change in noise trader's sentiment result in excess market volatility and deviation in prices from its fundamental value. Barberis, Shleifer, and Vishny (1998) develops a model which exhibit how investor sentiments produce overreaction and underreaction to news. Demers and Vega (2014), Huang et al. (2015) and Chen, Lien and Lin (2021) argue that high (positive) investor sentiment results in optimistic investment decision and judgements as firms increase their investment and price. Studies (Martin and Ventura,2012; Levchenko and Pandalai-Nayar,2015; Angeletos et al.,2018) find that investment sentiment is the cause behind boom and bust in the macroeconomy and explain a sizable portion of fluctuations in business cycles and price bubbles. A slew of studies (Barnuik & Vosvrda, 2009; Siegel, 1992; Wolff, 2013; Zhu et al.,2017) find that investor sentiment is pervasive in predicting stock market crash and collapse find a U-shape relationship between negative sentiment and stock price crash and observe that positive sentiment reduces the probability of stock price crash.

The extant literature considers three measures of investor sentiments. First is *market-based measure* like Baker and Wurglur (2006) sentiment index based market data[6]. The second indicator is *survey-based measures* like the University of Michigan Consumer Sentiment Index, the AAII investor sentiment survey, and the UBS/GALLUP Index for Investor Sentiments, which are widely used by Angeletos et al. (2018) Levchenko and Pandalai-Nayar (2015). These measures also suffer from limitations like these are unavailable at high frequency, become unreliable when non-response rate is high or when there are low incentives for truth telling as argued by Da et al. (2015). Third type of sentiment indicator that have recently gained popularity is *media-based sentiments*,

[6] It is based on closed-end fund discount, IPO first-day returns, IPO volume, trading volume, option implied volatility index, and market state as defined by the sign of lagged three-year or one-year market returns. But some studies (Qiu and Welch, 2006; Da et al.,2015) argues that the main limitation of market based sentiment measures is that these are considered to be equilibrium outcome for many economic forces other than investor sentiments.

which are developed using news analytics. News analytics based sentiment measures are developed using textual analysis of media content from both news (newspaper, news wires of Dow, Wall Street journal) and social media (message boards, twitter, google searches, blogs). The media-based sentiment measures provide the advantage of being available at high-frequency as argued by Da et al. (2015), which is not possible with market based and survey based measures.

Hence, the real time irrationality of noise traders is best reflected in media-based sentiment indices and institutional investors, who are rational (Verma and Verma, 2008) track news and social media sentiment that help them revise their expectations and provide profitable investment strategies, especially during extreme and rare events like jump as observed by Schmeling (2007). Therefore, it is crucial to assess the impact of media-based sentiments (news and social media), which highlight behavioral biases of individual investors as predictor of extreme price movements like price jumps and co-jumps. Tetlock (2007) is a pioneering study to analyse the impact of sentiment and tone of news text messages of Wall Street journal articles on stock prices and prove that media pessimism predicts downward pressure on stock prices for a short period. He finds that investor sentiment surges just before the market crash and results in extreme fall in stock prices when accumulated negative information reaches a tipping point as also observed by Xu, Jiang, Chan & Yi, 2013; Yin & Tian, 2017. One of pioneering study Mao et al. (2011) find both news and social media sentiments significant affect stock volatility. Ho et al. (2013) corroborate the finding that news sentiment greatly affects intraday volatility and find that news sentiments greatly affects volatility persistence of US stocks during high volatility regimes. Using machine learning and deep learning algorithm, Li, Ning, and Zhang (2021) examine the impact of three sentiment aware variables (attention, sentiment, and disagreement) on jump intensity dynamics and jump size variance and observe that sentiment augmented models of GARJI has significantly greater forecasting power for extreme events and volatility than benchmark GARJI model.

Though the studies on gold markets is scant, Smales (2018) use daily news sentiment of unscheduled news index Thomson Reuters News Analytics (TRNA) document a strong empirical evidence that news sentiment has an asymmetric impact on gold volatility such that negative news sentiments triggers a stronger reaction in volatility than positive sentiments. This asymmetric sentiment effect on volatility is corroborated by past studies (Leinweber and Sisk (2011), Smales (2012), and Riordan et al.,2013) that argue that negative news sentiment are more informative and hence more exploitable due to cognitive bias in behavioral finance called negativity-bias hypothesis (Peeters, 1991). It states that sentiment driven investors trade aggressively during low or declining sentiments than during high sentiment. Smales (2016) find that monetary policy announcements have a strong impact on gold volatility during periods of low stock market sentiment (high gold market sentiment), corroborating the safe haven property of gold. Recently, Bannigidadmath and Narayan(2021) find that pessimism risk factor affects risk premium in commodity portfolio, which includes gold, corroborating negativity bias hypothesis in gold. Moreover, gold volatility exhibits initial overreaction by investors which subsequently dies down, indicating the presence of noise traders. Aleksander Fafula () is a first study to use daily TRMI version 1 dataset for gold and find that the most predictive sentiment for gold price is average level of trust expressed for the US Dollar in the previous month. Based on pastacademic literature, we formulate our second hypotheses H2 as follows –

H2(a): Positive (Negative) Sentiment to gold from News and Social Media predicts positive (negative) intraday price jump and co-jump in gold markets.

H2(b): Positive (Negative) Sentiment to gold from News and Social Media during macroeconomic news announcement have higher predictability for positive (negative) intraday price jump and co-jump in gold markets.

2.3. Does News and Social Media Emotions causes intraday price jumps in gold?

Sentiment and Emotions are often used interchangeably but has important differences. The main difference between the two is of dimensionality. Investor sentiment is one dimensional measure while investor emotion is a multi-dimensional construct. For e.g. anger and fear both convey negative sentiment but each of them convey very different meaning. In the world of biased beliefs, Ge et al.(2020) argues that emotions are original, complex yet powerful psychological state, which induces investors to trade on non-fundamental information. The motto of Wall Street "buy on fear and sell on greed" clearly highlights the conventional wisdom the emotions influences investor trading behavior and decisions, which in turn affects price changes and volatility. Several news headlines like '''Gut Feelings' Are Driving the Markets'' or ''How Emotion Hurts Stock Returns'' have become common (e.g., Shiller (2020) and Wolfers (2015)).

The emotions affect individual's cognitive behavior, especially attention, reasoning and memory that produces transient yet powerful triggers, which biases judgement and significantly impacts investor trading decisions as per the affective infusion model (AIM) proposed by Forgas (1995) and observed by past studies (Shleifer et al., 1990; Frijda, 1988; Dolan, 2002; Lo et al., 2005; Fenton-O'Creevy et al., 2011). Taffler (2018) argues that the basic premise of emotional finance is that feelings and short-circuit actions involving emotions of excitement and fear unconsciously influences investor trading, financial and investment decisions. It is emotional reaction of investor to news or new information, which causes prices to change. Studies (Kuhnen and Knutson, 2011; Mayew and Venkatachalam, 2012; Price et al., 2016; Shen et al., 2017) find that emotions play an important role in shaping investor risk perception, decision making ability, information processing capability and trading performance.

Shiller (2003) argues that excessive price volatility in asset prices indicate the investor trading decision are influences by emotions of optimism and pessimism. Tetlock (2007) showcase empirical support to De Long et al. (1990) by documenting that high media pessimism exerts a downward pressure on prices via temporary rise in trading volumes. Past academic studies find significant impact of emotions on stock performance and market crash Zhu et al., 2017 Siegel, 1992. Bollen et al. (2011) is first study that uses emotions in social media (ESM) as carrier of overall investor opinion and find significant stock market predictability. It is important to examine the role of investor emotions is because it fuels noise trading Tetlock, 2007; Sun et al., 2016, which is one of the cause behind extreme or abrupt price movement. Vamossy examine the impact of emotional content of firm specific messages posted on social media on stock return and find that one standard deviation increase in excitement results in 7.8 basis point lower announcement return. Emotions in social media have outperformed those from conventional media and are more useful as information gets instantly available as argued by Yu, Duan & Cao, 2013 and Eickhoff & Muntermann, 2016. Using cognition based framework of "Emotion-Cognition-Market", Ge et al.(2020) find that emotions in social media (ESM) from Weibo significantly affects the probability of stock market crash in China. High arousal increase the market crash risk by 17% while positive valence restores the stability in market cognition much after the crash.

Few studies (Borovkova, 2011; Borovkova and Mahakena, 2015; Smales, 2014) examine the impact of news sentiment on commodity return but. Shen, Najand, Dong, and He (2017) uses TRMI commodity-specific emotions (optimism, fear and joy) on daily basis and find that media based sentiment has significant short term predictive power for the next five days commodity returns for crude oil and gold. They find that the impact of media based emotions is consistent with both valence-arousal approach and cognitive appraisal approach. Our third hypothesis H3 is as follows-

H3(a): Emotions towards gold from News and Social Media have predictive power for intraday price jumps and co-jumps in gold markets.

H3(b): Emotions towards gold from News and Social Media during macroeconomic news announcement predicts intraday price jumps and co-jumps in gold markets.

2.4. Does Illiquidity or liquidity drive intraday price jumps in gold?

The extant literature on jump and co-jump (Sun and Gao, 2019; Jiang et al. 2011; Boudt and Petitjean 2011; Lahaye, et al. (2011; Piccotti, 2017; Kapetanios et al.,2019; Chordia et al., 2017) argue that a sizable portion of jump occur due to abrupt changes in liquidity like trading volume, order imbalance and transaction costs (). Dumitru and Urga (2016; Bajgrowicz and Scaillet (2011)) provide a strong evidence that simultaneous occurrence of macroeconomic news and jumps generate liquidity shocks preceding jumps, which gave rise to "liquidity around the jump price puzzle". Picotti, 2019; Serdengeçti et al.,2021) prove that jumps in liquidity causes jumps in volatility and return for stock, bond and foreign exchange data. Liquidity is the ability to buy and sell (trade) large quantity of assets with no loss of time, value and little price impact. Liquidity is a broad construct and has three key dimension – trading activity[7], trading cost[8] and price impact[9].

Sudden change in liquidity level is observed to be a major sources of price jumps as demonstrated by Serdengeçti et al.(2021) and Boudt and Petitjean (2014) Bajgrowicz and Scaillet (2011). The number of trades play a crucial role in driving price jump predictability as increased trading demand causes price jumps, as observed by (Chan and Fong, 2006); Giot et al.,2010; icotti (2017; Boudt and Petitjean, 2014). Sun and Gao (2019) find that trading volumes showcase predictability of intraday jumps in stock prices of China as it increases by 3 times few minutes before the jumps and revert to normal levels after 10 minutes. The impact of trading volume is more intense for positive jumps than negative jumps. Using intraday data at 5-minute of S&P 500

---

[7] Trading volume, number of trades and depth are regarded as proxy for trading activity dimension of liquidity.

8 Bid ask spread are considered as an indicator of trading costs and reflect repayment for the cost incurred by the market makers to provide liquidity to meet immediacy requirement for trader's demand (Liu, Hua and An (2016).

9 Price impact is best measured using order imbalance, which reflect captures net buying and selling pressure that indicates extreme imbalance, which is a source of illiquidity and volatility (Chordia et al.,2001).

ETF (SPY), Bollerslev et al. (2018) find that the sensitivity of abnormal trading volumes to those of jumps in volatility is significant but less than unity, especially during times of uncertainty.

Trading cost and volatility should have a positive relation if price volatility is driven by shocks to information i.e. informed trading (Foster and Viswanathan (1990), Collin-Dufresne and Fos (2016b). However, the relationship between trading cost and price volatility is negative, when volatility is driven by shocks to uninformed volumes or trading Admati and Peiderer (1988), Collin-Dufresne and Fos (2016a)). Sun, Najand, and Shen (2016) find that market liquidity and noise trading are negatively correlated due to the risk aversion of informed traders, which is consistent with the prediction of Subrahmanyam (1991). Order imbalance contribute significantly to price jumps, as orderflow drives price formation process and volatility (Evans (2002),Evans and Lyons (2002), Green (2004) and Brandt and Kavajecz (2004). Greater orderflow and price impact increases the likelihood of price jumps as markets become one-sided which leads to discrete quote adjustment Glosten and Milgrom (1985). It is believed that trades with extremely high return are driven by buy side orderflow while market crashes are driven by selloffs or sell side orderflow. Lahaye et al. (2011) Scaillet et al.(2020) and Wu, Liu et al.(2020) find that liquidity and order flow contribute more than 80% to the extreme price movements(jumps). Downward EPM are accompanied by liquidity shortages in bid side and vice-versa. Sun and Gao (2019) find that quoted and effective spread increases by 20% and 50% respectively but takes more than 5 minutes to recover to non-jump trading day levels. They find that stronger buyer pressure drives positive jump and seller pressure drives negative jumps.

Illiquidity is a major cause of price jumps as documented by (Jiang & Yao (2013) and Lee (2012)); Mancini, et al. (2013)). Brunnermeier and Pedersen () find that illiquidity exacerbates and generates non-linear amplification for the arrival of news economic information and events. Dungey et al. (2009) find that two-third of the co-jumps coincide with liquidiy shocks. Hence, some studies (Nguyen and Prokopczuk, 2018; Jiang et al.,2011; Jiang & Yao, 2013) document positive relation between illiquidity and jumps for stock, bond and commodity markets. High illiquidity results in high jump intensity (Nguyen and Prokopczuk (2018; Serdengeçti et al. (2021). Some studies find that common illiquidity shocks Mancini, et al. (2013) or illiquidity contagion Cespa and Foucault (2014) are a major cause for jumps and co-jumps. Kapetanios et al.(2019) find that majority of intraday price jumps in stock options markets are driven by shrinkage in liquidity rather than the content of scheduled news. The shrinkage in liquidity is manifested by widening of bid ask spread and greater ammihud illiquidity. Using intraday event study, Zhou and Zhu (2019) find that illiquid stocks with high trading volume and turnover ratio have greater probability of experiencing jumps. Recently, Sun and Gao (2020) find that intraday jump predictability is majorily driven by illiquidity rather than macroeconomic news, in the Chinese stock index futures markets. Kapetanios et al.(2019); Chan et al., 1995; Easley et al., 1998; Chakravarty et al., 2004; Pan and Poteshman, 2006 argue that uninformed traders quote wider[10] bid-ask spread just before the arrival of scheduled macroeconomic news to avoid trading with informed traders. This is consistent with observation of Handa et al.(2003) and Erenburg and Lasser (2009) that bid ask spread and LOB increases around macroeconomic news, which causes information asymmetry resulting jumps due to one sided limit order book.

Die, Xianhua and Xiaoguang (2016) document asymmetric behavior of liquidity for positive and negative price jumps. Positive jumps are preceded by heightened levels of average trade size and trading volume, whereas, negative jumps are preceded by relative lower liquidity. Chordia, Kurov, Muravyev, Subrahmanyam (2017) document that ammihud illiquidity has significant and asymmetric effect on direction of jump as illiquid stocks has greater probability of positive jumps. The only study that examines the role of liquidity in the context of price jumps in gold ETF is Jurdi (2021). They find that shocks to the trading activity and order flow imbalance have highest predictability for gold price jumps, even after controlling for macroeconomic news surprises, Therefore, based on the above discussion and literature support, we formulate our fourth hypotheses H4 as follows-

H4: Greater Illiquidity, high trading activity, high volatility, wider spreads and order imbalance has predictive power for intraday price jumps and co-jumps in gold markets.

2.5. Do Scheduled Macroeconomic News Announcemenets or Surprises causes intraday pricejumps in gold ?

Macroeconmic news announcements are a proxy for public information arrivals, which indicate future state of the economy and it is considered to be predictor of price jumps and extreme volatility. (Andersen et al.,2003). Dumitru and Urga (2016) argues that the only driver of jumps in macroeconomic news as liquidity and jump are endogenously determined and. This is consistent

[10] Investors can increase the bid ask spread due to increase in inventory cost (Muravyev, 2016) or hedging cost of options market (Huh et al., 2014).

with Mixture of Distribution hypothesis[11] (MDH), which states that the asset return volatility is proportional to the rate of information arrival. Several studies (Megaritis, Vlastakis, and Triantafyllou (2021) Bollerslev et al., 2008; Evans, 2011; Lahaye et al., 2011; Miao et al., 2014; Füss, Grabellus, Mager and Stein (2017)) find that only macroeconomic news indicate precise external signals and abnormal information flow conditioned on macroeconomic news announceemnt increases the probability of jumps.The extant literature on jumps (Andersen et al.,2004; Lee and Mykland, 2008; Huang,2007; Evans, 2011; Bradley et al., 2014; Lee, 2012; Miao et al.,2013; Yun, 2019) find strong evidence that macroeconomic news play an important role in the occurrence of price jumps and co-jumps across asset classes. Evans (2011) find that one-third of jumps in US futures market are due to US scheduled macroeconomc news. Many studies (Barndorff-Nielsen and Shephard, 2006; Huang, 2018; Andersen, Bollerslev, Diebold, and Vega, 2003; Andersen, Bollerslev, and Diebold, 2007) document that the number of jumps are higher on days wth scheduled macroeconomic news than on no-news days.

The extant literature on gold documents find that scheduled macroeconomic announcements related to economic activity and interest rate significantly affect gold prices and returns, especially during uncertainty when gold acts as a safe-haven Roache and Rossi (2010). Clements and Todorova (2016) examine the impact of news volume and sentiment on gold volatility and find that positive shocks to rate of news arrival, negative shocks to the news sentiment showcase greatest impact on gold volatility after controlling for shocks in trading activity, depth and trader's position. Elder et al. (2012) find that volatility and volume in gold, silver, and copper futures markets are positively related to economic news. Batten et al. (2010) Rosa (2014) and Glick and Leduc (2012) Basistha and Kurov (2015) show that monetary policy surprises have a significant impact on the level and volatility of gold and energy prices in the period immediately following the announcement. Using high frequency data, Smales (2018) find that the magnitude of liquidity shrinkage in gold is proportional to monetary policy surprise, which is consistent with noise trading hypothesis. Smales and Lucey (2018) find that monetary policy surprises negatively affects gold liquidity and results in lower depth and higher volatility.

The news-watcher's hypothesis attempts to investigate which set of scheduled macroeconomic news is market moving and causes significant changes in asset price, volatility and volumes. In disaggregated news analysis, majority studies examine the impact of US

[11] MDH is proposed by Clark (1973), Tauchen and Pitts (1983) and Harris (1986, 1987)

macroeconomic news on intraday price jump across asset classes. Lahaye et al. (2009; Bauwens et al. 2005; Neely 2011; Evans(2011) Lahaye, Laurent, and Neely (2011) ;Bernanke Miao et al. [11] Serdengeçti et al.(2021; Lee and Wang (2019; Frömmel, Han, Gysegem (2015)-) find that US scheduled macroeconomic news like non-farm payroll, GDP Advance consumer confidence and federal funds target rate announcements of US causes maximum number of co-jumps in stock, bond and exchange rate markets. Some studies (Sun , Najand, and Shen (2016)) find that earlier released 08:30 ET scheduled macroeconomic news in US cause significant price jumps in US equity markets. There is a growing body of literature that analyse the impact of scheduled macroeconomic news announcements on gold prices but failed to establish any consensus on the most important ones. Christie-David, Chaudhry, and Koch (2000) observe that gold volatility is higher during US macroeconomic announcements concerning inflation, employment rate, GDP and industrial production while Cai, Cheung, and Wong (2001) supports the Christie-David et al.(2000) findings but adds that biggest crash in gold prices occur due to massive sale of gold reserve by central banks. Bouri and Gupta (2020) find that macroeconomic news surprises explain most of price jumps in crude oil not metals.

Some studies (Megaritis, Vlastakis, and Triantafyllou (2021) Bomfim, 2003; Rangel, 2011) find that only sign or surprise effect of scheduled macroeconomic news matters while some find that both sign and timing effect causes jumps. Some studies Madura and Tucker (1992) and Aggarwal and Schirm (1998) Evans (2011) Tetlock (2010) find that news announcement with large surprise index tends to drive larger changes in volatility and causes sudden price jumps as it results in high trading volumes. Smales (2016) find that gold price react more strongly to negative news than positive news surprise. In addition, news accompanying with greater dispersion and uncertainty also results in large jump size Kandel and Pearson (1995). However, few studies (Hess (2004), provide evidence that news announcement timing cause price jumps. Hanousek and Kočenda (2011) and Hanousek et al. (2009) argue that local news have limited influence on jumps while global news from US and Europe have maximum impact. Ayadi et al.(2019) document that US scheduled macroeconomic news is the most important news that causes majority price jumps in all three currencies- Euro, Pound and Yen. The only study that investigates the impact of macroeconomic news on price jumps in gold ETF is Jurdi (2020), which find that the probability of macroeconomic news causing jump in gold ETF is 1.11% and observes negative surprise of construction spending and consumer sentiment and positive news surprise for personal income causes jumps in gold ETF. We formulate our last hypotheses H5 as-

H5: Macroeconomic News Surprise and announcement time of US scheduled news causes intraday price jumps and co-jumps in gold markets.

3. Empirical Methods

In this section, we present a brief derivation and explanation of empirical methods we adopt to identify intraday price jumps in Section 3.1. In Section 3.2, we report our identification strategy for intraday co-jumps. Section 3.3. provide the intraday event study methodology we adopt using constant mean return model.

3.1. Intraday Jump Detection Method

To detect intraday jump time and size, we use a combination of jump detection techniques proposed by Andersen et al. (2007, 2012) and Bollerslev et al. (2013), whose brief derivation are provide here. In addition, we correct the intraday jump methods for intraweek volatility periodicity by using weighted standard deviation (WSD) method proposed by Boudt et al.(2011), which we briefly discuss here. We choose to identify intraday price jumps by selecting those jumps which lie at the intersection of two methods, in order to reduce the risk of false detection of jumps as the combination of tests provide more robust results than the usage of the single jump procedure as adopted in the past studies (Dumitru and Urga (2012), 2016).The intuition behind Andersen et al.(2007) jump detection method is that intraday jumps are the large returns compared to a local estimate of volatility. Therefore, the procedure to identify intraday price jumps at time t using Andersen et al.(2007) approach is to simply scale the magnitude of the return of the midquote (r_t) observed at time t by the lagged jump robust local estimate of volatility $\sigma_{t-1}(r)$. If this ratio exceeds the critical value, then we reject the null hypothesis that r_t is a normal return. The derivation of Andersen et al.(2007) intraday jump method is as follows. The logarithmic asset price at time t is p(t). Log price p(t) is assumed to follow a jump diffusion process, which is expressed in the stochastic differential equation (SDE) form as –

$$dp(t) = \mu(t)dt + \sigma(t)dW(t) + \kappa(t)dq(t), \qquad 0 \le t \le T \qquad (1)$$

where, $\mu(t)$ is the instantaneous conditional expected return (locally bounded variation process), $\sigma(t)$ is the instantaneous conditional standard deviation of the returns, $W(t)$ is a standard Brownian motion (Wiener process), $dq(t)$ is the counting process where $dq(t) = 1$, if there jump at time t and $dq(t) = 0$, if there is no jump and $dq(t)$ has time varying jump intensity parameter λ(t) and $\kappa(t)$ is the corresponding jump size. So, the probability of jump event occurring is $P\{dq(t) = 1\} = \lambda(t)$. The quadratic variation of cumulative return process, r(t) = p(t) - p(0) as given in equation (1) is given by –

$$[r, r]_t = \int_0^t \sigma(s) ds + \sum_{0 \le s \le t} \kappa^2(s) \tag{2}$$

Let us denote the discretely sampled Δ-period return as $r_{t,\Delta}$ = p(t) – p(t- Δ). The daily realised volatility is defined as the summation of the corresponding 1/Δ high-frequency intraday squared return, as

$$RV_{t+1}(\Delta) = \sum_{j=1}^{1/\Delta} r^2{}_{t+j.\Delta,\Delta} \tag{3}$$

This realised volatility converges uniformly in probability, under weak regularity, to the corresponding increment to the quadratic variation process, for Δ →0, as

$$RV_{t+1}(\Delta) = [r, r]_{t+1} - [r, r]_t = \int_t^{t+1} \sigma(s) ds + \sum_{0 \le s \le t+1} \kappa^2(s) \tag{4}$$

In the absence of jumps, realised volatility is consistent for integrated variance but in the presence of jumps, realised volatility is consistent for the sum of the integrated variance and cumulative sum of squared jumps. However, Barndorff-Nielsen and Shephard (2006) proved that jump component of the return variance is identified by combining the realised bipower variation proposed by Barndorff-Nielsen and Shephard (2004) with realized volatility, proposed by Andersen et al.(2003) as derived in equation (3. The bipower variation (BV), for Δ →0, is –

$$BV_{t+1}(\Delta) = \mu_1^{-2} \sum_{j=2}^{1/\Delta} \left| r_{t+j.\Delta,\Delta} \right| \left| r_{t+(j-1).\Delta,\Delta} \right| \rightarrow \int_t^{t+1} \sigma^2(s) ds \tag{5}$$

where, $\mu_1 = \sqrt{2}/\Pi$

Bollerslev, Todorov and Li (2013)

Bollerslev et al. (2013) provides a flexible non-parametric estimation procedure for identifying intraday jumps and allows for general dynamic dependence on tails and imposes essentially no restrictions on the continuous part of the price process. Building on the notion of Barndorff-Nielsen and Shephard (2004, 2006) that under weak regularity conditions, RV converges to total variation, which comprises of continuous and jump component, such as –

$$RV_{t+1}(\Delta) = [r, r]_{t+1} - [r, r]_t = \int_t^{t+1} \sigma(s) ds + \sum_{0 \le s \le t+1} \kappa^2(s) \tag{6}$$

The continuous component is called integrated variance (IV) and Barndorff-Nielsen and Shephard (2004, 2006) proves that under weak regularity condition, bipower variation (BV) asymptotically converges to IV, even in the presence of jumps.

$$BV_{t+1}(\Delta) = \mu_1^{-2} \sum_{j=2}^{1/\Delta} |r_{t+j.\Delta,\Delta}| |r_{t+(j-1).\Delta,\Delta}| \rightarrow \int_t^{t+1} \sigma^2(s) ds \quad (7)$$

where, $\mu_1 = \sqrt{2/\Pi}$

Bollerslev et al.(2013) proposed a time-of-the-day (TOD) volatility pattern to develop a truncation factor that will separate realised jumps from the continous price changes that is based on preliminary estimates of the stochastic volatility over the day together with TOD volatility pattern, calculated as –

$$TOD_i = \frac{n \sum_{t=1}^{T} |r_{i_t}^n|^2 1(|r_{i_t}^n| \leq \tau \sqrt{BV_t^{RV_t}} n^{-\omega})}{\sum_{s=1}^{nT} |r_s^n|^2 1(|r_s^n| \leq \tau \sqrt{BV_{s/n}^{RV_{s/n}}} n^{-\omega})}, \quad i_t = (t-1)n + i \quad (8)$$

Where, i=1,,,n is an indicator function, $\omega = 0.49$, $\tau = 3$ is a threshold parameter indicating that price increments beyond three standard deviation of a local estimator of the corresponding stochastic voatility will be classified as jumps. TOD indicates the truncation of price increment impled by τ and ω, which effectively removes jumps. TOD measures the ratio of the diffusive variation over different parts of the day relative to its average value for the day.TOD displays a U-shaped volatility pattern and i-th high frequency jump for the t-th trading day is identified by -

$$BLTJump_{t,i} = r_s^n 1(|r_s^n| \geq \tau \sqrt{BV_{s/n}^{RV_{s/n}} * TOD_{s-\{\frac{s}{n}\}n} n^{-\omega}}), \qquad s=1,,,,,,,nT \quad (9)$$

where, t = [s/n], i=s-tn

Andersen et al.(2007) intraday jumps detction measure

Andersen et al.(2007) developed a popular method for intraday jump detection developed by extending the work the of Barndorff-Nielsen and Shephard (2006) that allows for identification of multiple intraday jumps and their exact timing. Andersen et al.(2007) intraday jump detection measure $\kappa_s(\Delta)$ is –

$$\kappa_s(\Delta) = r_{t+s.\Delta,\Delta} \cdot 1\left(|r_{t+s.\Delta,\Delta}| > \Phi_{1-\frac{\beta}{2}} \cdot \sqrt{\Delta \cdot BV_{t+1}(\Delta)}\right), \qquad s = 1,2,\ldots.,1/\Delta \quad (10)$$

where, $\Phi_{1-\frac{\beta}{2}}$ is the corresponding critical value from the standard normal distribution, 1(x) is an indicator function when x is true and 0, otherwise.

However, the problem with Andersen et al.(2007) jump detection measure as denoted by equation (9) is that it assumes that intraday diffusion component is constant over a trading day. Therefore, Andersen et al.(2007) test will over-reject the null hypothesis of no-jump event, if the intraday volatility of returns exhbit considerable time-variation. Hence, we control for intraweek periodicity in volatility by adjusting the absolute return with weighted standard deviation (WSD), which is a intraweek periodicity estimate proposed by Boudt et al.(2011). We present the derivation of WSD as proposed by Boudt et al.(2011) in Appendix B.

The filtered Jump statistics of Andersen et al.(2007) $\kappa_s(\Delta)$, after controlling for intraweek periodicity using WSD, become $\kappa_s(\Delta)^*$, which calculated as –

$$\text{Filt\_ABD} = \kappa_s(\Delta)^* = r_{t+s.\Delta,\Delta} \cdot 1\left(\frac{|r_{t+s.\Delta,\Delta}|}{\hat{f}^{WSD}_{t+s.\Delta,\Delta}\widehat{BV}^{WSD}_{t+s.\Delta,\Delta}} > \Phi_{1-\frac{\beta}{2}}\right), \qquad s = 1,2, \dots, 1/\Delta \tag{11}$$

where, $\hat{f}^{WSD}_{t+s.\Delta,\Delta} = \frac{WSD_{t+s.\Delta,\Delta}}{\sqrt{\frac{1}{\lambda/\Delta}\sum_{s=1}^{1/\Delta} WSD_{t+s.\Delta,\Delta}{}^2}}$ and $\widehat{BV}^{WSD}_{t+s.\Delta,\Delta}$ is the realised biower varaition scale estimator compted on WSD filtered returns i.e. $\bar{r}_{l,s.\triangle}/\hat{f}^{ShortH}_{t+s.\Delta}$ series.

$$WSD_{t+s.\Delta,\Delta} = \sqrt{1.081 \cdot \frac{\sum_{l=1}^{n} w_{l,s}\bar{r}^2_{l,s\triangle}}{\sum_{l=1}^{n} w_{l,s}}} \tag{12}$$

where, $w_{l,s} = w(\bar{r}_{l,s.\triangle}/\hat{f}^{ShortH}_{t+s.\Delta})$ is a weight function where w(z)=1, $z^2<=6.635$, and w(z)=0, otherwise. 6.635 is the 99% level of the χ^2 distribution with one degree of freedom. The weight function filters out the contribution of the jump return.

$$\hat{f}^{ShortH}_{t+s.\Delta,\Delta} = \frac{ShortH_{t+s.\Delta,\Delta}}{\sqrt{\frac{1}{\lambda/\Delta}\sum_{s=1}^{1/\Delta} ShortH_{t+s.\Delta,\Delta}{}^2}} \tag{13}$$

where, shortest half scale estimator (ShortH) is estimator which has smallest maximum bias in the presence of the jumps as proposed by Rousseeuw and Leroy (1988) and is calculated as –

$$ShortH = 0.7413 \cdot \min\{\bar{r}_{h_s:s\triangle} - \bar{r}_{1:s\triangle}, \bar{r}_{h_s+1:s\triangle} - \bar{r}_{2:s\triangle}, \dots\dots, \bar{r}_{n_s:s\triangle} - \bar{r}_{n_s-h_s+1:s\triangle}\} \tag{14}$$

where, $\bar{r}_{1:s\triangle}, \bar{r}_{2:s\triangle}, \dots.\bar{r}_{n:s\triangle}$ are ordered statistics such that $\bar{r}_{1:s\triangle} < \bar{r}_{2:s\triangle} < \cdots < \bar{r}_{n:s\triangle}$, n_s is the total number of observation of the of sΔth in the intraweek segment in the sample , $h_s=n_s/2+1$.

The term $\frac{|r_{t+s.\Delta,\Delta}|}{\hat{f}^{WSD}_{t+s.\Delta,\Delta}\widehat{BV}^{WSD}_{t+s.\Delta,\Delta}}$ in equation (7) is standard normally distributed random variable under null hypothesis of no jump. Therefore, we identify intraday jump from equation (10), if the magnitude of realized return is significantly higher than what is implied by periodicity–robust estimate of integrated variance. The excess return is attributable to a jump occurance and the observed return over the 5-minute interval is regarded as jump size

Intraday Jump Detection criteria

We identify intraday price jumps in a return series by choosing those price jumps that occur at the intersection of the two methods, namely Andersen et al.(2007) adjusted for periodicity using Boudt et al.(2011) and Bollerslev et al.(2013), as follows-

$$Jump_{i,t} = FiltABDJump_{i,t} \cap BLTJump_{i,t} \tag{15}$$

Gilder et al.(2018) and Dungey 2012 recommend using a combination of intraday jumps detection techniques to avoid detection of spurious jumps.

3.2. Intraday Co-Jump Detection Method

We use the co-exceedance rule to detect intraday co-jumps between two gold markets, namely COMEX gold ETF and SPDR gold ETF. The intuition behind the co-jump detection rule is that we classify that co-jump ($Co - Jump_{i,t}$ when j assets exhibit intraday price jump $Jump_{i,t,j}$ at i-th high frequency return on t-th trading, as derived above in equation (16). Here, j is 2 for COMEX futures and SPDR ETF. Hence, the simultaneous individual jump of assets j (N=2) at same i-th return and t-th trading day is classified as co-jump, as –

$$\boldsymbol{Co - Jump_{i,t} = \sum_{j=1}^{N} \{Jump_{i,t,j} > 0\}} \begin{cases} \boldsymbol{\geq 2} & \boldsymbol{CoJump} \\ \boldsymbol{\leq 1} & \boldsymbol{No - CoJump} \end{cases} \tag{16}$$

$$Co - Jump_{i,t} = {Jump_{i,t}}^{COMEXFUTURES} \cap {Jump_{i,t}}^{ETFSPDR} \tag{17}$$

where, $\boldsymbol{\{Jump_{i,t,j} > 0\}}$ is an indicator function that take value 1, when only one of the two asset exhibit intraday jump and it takes value 2, when both the assets (N=2) exhibit intraday jump at i-th high frequency return at t-th trading day. We use this exceedance rule on the intraday jumps detected using intersection of filtered ABD and BLT jump statistics, shown in equation (14). Thus, we classify co-jump as the intersection of intraday price jumps for both COMEX gold futures (${Jump_{i,t}}^{COMEXFUTURES}$) and SPDR gold ETF (${Jump_{i,t}}^{ETFSPDR}$).

3.3. Intraday Event Study Method

We perform intraday event study to examin the high frequency predictors of intraday price jumps in gold markets, namely, (1) Abnormal Returns, (2) Absolute Returns, (3) Volatility, (4) Liquidity dimensions--trading activity (trades and depth), trading cost (proportional effective spread), ammihud illiquidity, price impact (order imbalance), and (5) Market Psych aspects (Attention, Sentiments, and Emotions) separately for news media and social media, along with return and volatility behaviour. We perform multiple event study for each of different predictors mentioned above separately for positive and negative jumps for COMEX gold futures and SPDR gold ETF. The null hypothesis of event study is that *Jumps have no impact on predictors* while the alternative hypothesis is that *Predictors around the price jumps are abnormally high or low*. We provide details for the five step involved in our intraday event study procedure,

(1) Defining the event and the event window

We define event as the occurrence of intraday price jump (positive/negative) for each of two gold markets. The event window[12] is twelve 5-minutes before the jump interval (-60 minutes) and twelve 5-minutes after the jump interval (+ 60 minutes). We chose a short interval window to reflect and capture the full effect of the jump, as also adopted by Boudt and Petitjean (2013) and Piccotti(2018). Our full event window ranges from -60 to +60 minutes . We denote event time, τ, which indicates number of minutes relative to jump time. The intraday jump time is denoted by τ=0, while t+τ imply τ-th minute counting from t.

(2) Calculating abnormal values of predictors

Following Piccotti (2018), we use constant mean return model to calculate abnormal values of the predictor variables. We denote the total number of 5-minute observation in sample by T and T_j as the total number of 5-minute observation that occurs at intraweek time jΔ. We compute abnormal returns for price as –

$$AR_{i,t+j\Delta} = r_{i,t+j\Delta} - E_{T,j}[r_i] \tag{18}$$

where, $r_{i,t+j\Delta}$ is log return at 5-minute interval, and $E_{T,j}[r_i] = T_j^{-1}\sum_{t=1}^{T_j} r_{i,t+j\Delta}$ is the sample mean return during the intraweek time period, $E_{T,j}[.]$ is the mean conditioned on the full sample of observation i.e. $E_{T,j}[r_i]$ and t represent the week, Δ is the frequency of discretely observed intraweek return, and j ={1,2,3,….,Δ^{-1}}. Similarly, we use same procedure to calculate the abnormal values for the liquidity, volatility and market psych predictor variables, such as –

$$Ax_{i,t+j\Delta} = x_{i,t+j\Delta} - E_{T,j}\left[x_{i,j}\right] \tag{19}$$

where, x = {Trades, Depth, Prop. Effective spread, Ammihud Illiquidity, Volatility, Order Imbalance, NewsM_Attention, SocialM_Attention, NewsM_Sentiment, SocialM_Sentiment, NewsM_Emotion, SocialM_Emotion}.

3) Standardising the abnormal predictors

Next, we standardise all predictor variables to make them comparable across assets, days and intraday time interval. We standardise each of predictor to have mean of zero and variance of one for each intraweek period, such as-

$$SAx_{i,t+j\Delta} = \frac{x_{i,t+j\Delta} - E_{T,j}\left[x_{i,j}\right]}{\sigma_{T,j}[x_{i,j}]} \tag{20}$$

[12] The period over which we examine the impact of the intraday price jumps (positive/negative) on different predictors is referred to as Event window.

Where, $\sigma_{T,j}[x_{i,j}]$ denote standard deviation conditioned on the full sample data i.e. sample mean of $x_{i,j}$ at intraweek time jΔ, which is, ${\sigma_{T,j}}^2[x_{i,j}] = (T_j - 1)^{-1} \sum_{t=1}^{T_j} (x_{i,t+j\Delta} - E_{T,j}[x_{i,j}])^2$

(1) Aggregate individual events

For abnormal returns (AR), we compute cumulative abnormal returns (CAR) such as-

$$CAR_{i,t+j\Delta} = \sum_{m=j*-12}^{j} AR_{i,t+m\Delta} \tag{21}$$

where, j = {j*-12, …, j*-1, j*, j*+1, …., j*+12}

We aggregate each of standardised abnormal values of predictor variables into single one by compute standardised average abnormal values (SAAx) using average of $SAx_{i,t+j\Delta}$ across individual events i.e. positive jumps and negative jumps separately for event window -60 to +60 minutes. SAAx enables us to make general conclusion regarding the impact of intraday positive /negative price jumps. Hence, we aggregate across all years in the sample but distinguish between positive and negative price jumps, separately for CME futures and SPDR ETF.

(2) Evaluate the hypothesis

To test the null hypothesis of *Jumps have no impact on predictors*, we assume by construction that standardised abnormal values of predictor variables in our control sample will be zero at all event window dates when there is no jump. Next, for each time interval in event window, we use Mann-Whitney test to evaluate the null hypothesis that distribution of standardised predictor values on jump days is same as that on no-jump days. Lastly, we also compute the 2.5% and 97.5% quantiles of distribution of standardise predictor variables to visualise the spread of its distribution.

4. Data & Descriptive Statistics

4.1. Data & Variable Operationalisation

We use three different datasets to conduct this study. First, we extract the trade and quote (TAQ) data for two gold instruments, namely- CME gold futures of New York and ETF Gold SPDR traded on NYSE Arca at one-minute interval from Thomson Reuters Tick History database from Refinitiv. This dataset includes best bid and ask quotes, trade price, volume, number of trades, bid and ask size for the most actively traded CME gold futures contract (GC), which is consistent with Fricke and Menkhoff (2011), Hung et al. (2021, Sobti et al.(2021). For this purpose, we choose to work at 5-minute interval as our optimal sampling frequency based on our results from volatility signature plots[13] at 1-/3-/5-/10-minute frequency for two gold instruments, as recommended by Andersen et al. (2000), for CME gold futures and ETF SPDR (see Figure A1 in Appendix A), that showcases that average daily realised volatility converges at 5-minute sampling frequency over the sample period, as adopted by Ma et al.(2019) and Kapetanios et al.(2020). In addition, as a test of robustness, we estimate jumps using different frequency 1-/3-/5-/10-minute and find that the number of intraday jumps detected using various jump detection methods falls at lower frequency of 10-minutes while is higher for high frequencies (see Section 6.2).

We examine the sample period from 1st January, 2010 to 31st March, 2018. We restrict the trading hours of both gold instruments (CME futures and ETF Gold SPDR) to 07:30-16:00 US ET. It is because though CME gold futures trades round-the-clock (24-hours barring 60-minute trading break at 17:00 ET), ETF SPDR starts to trade at 04:00 ET[14] (Opening session) and commence its core trading hours at 09:30 US ET. Hence, we choose to work on the active and overlapping trading hours, in which both gold instruments have trading activity. **Table A1 in Appen**dix document the contract specification, trading hours (timing in US ET), and trading break for two gold instruments. Next, we work with midquotes i.e. average of bid and ask quotes rather than transaction price for estimating price jumps and co-jumps, as the midquotes are least affected by microstructure noise as argued by Grammig et al. (2005). The midquotes of the two gold instruments are measured in USD per troy ounce. We undertake standard data cleaning procedure to ensure accuracy of our sample data using criteria proposed by Brownlees and Galo (2006) and Barndorff-Nielsen et al. (2010). Next, we collect the data for US scheduled macroeconomic news from Bloomberg for the sample period 2010-2018. We extract data for comprehensive list of 29 scheduled macroeconomic news originating from US as enlisted in Table 4. We extract the following variables -news announcement time in US ET, actual release value of news indicator, Bloomberg media analyst forecast for disaggregated (individual) news announcements. Our choice of 29 US scheduled news in based on two criterion-(1) News indicators should have Bloomberg analyst forecast, and (2) news indicator are impactful i.e. have Bloomberg relevance index >50%. Table 4 display that majority of US scheduled news arrive at 08:30 ET, followed by two at 09:15

[13] Volatility signature plots depict realized volatility as a function of the sampling frequency. In the absence of microstructure noise, realized volatility, defined as the squared root of summed squared intraday returns, should be invariant to changes in the sampling frequency provided the data is sampled fine enough

[14] Though ETF Gold SPDR start to trade in Opening session at 04:00 ET, we restrict the trading hours from 07:30 ET because it does not showcase any trading volume till 07:30 ET. Moreover, we need to assess the impact of US scheduled macroeconmic news which arrives at 08:30 ET, hence we did not choose 09:30 ET as the trading time.

ET, one at 09:45 ET, nine at 10:00 ET and FOMC rate decision at 14:15 ET. As market efficiency argues that only unexpected component of the news i.e. news surprises should affect prices than the announcement timing and since each news indicator is measured in different units of measurement, we compute the standardised news surprise index proposed by Balduzzi et al.(2001), which is widely adopted by Elder et al.2011; Sobti et al.,2021), for each disaggregated news announcements (see Table A2 in Appendix).

We gather the high-frequency data on Market Psych of the investor using the proprietary dataset named *Thomson Reuters MarketPsych Indices (TRMI)* from Refinitiv. TRMI[15] is the most comprehensive advanced linguistic index based on textual analysis of financial news and internet messages from wide variety of news media and social media platforms on the real time basis. It deploys machine learning techniques to translate the volume (quantity) and sentiments (emotions) of the financial news and social media post into quantifiable scores for various asset like commodities, stocks and firms. The uniqueness of TRMI dataset is that it provides minute-by-minute attention and sentiment scores for an asset in the form of three major dimension, namely- ***Buzz, Sentiments and Emotions.*** Table A2 in Appendix report the operationalisation of three market psych dimensions- ***Buzz, Sentiment and EmotionVsFact*** as per TRMI. We gather the three above-mentioned aspects of TRMI index – ***Buzz, Sentiment and EmotionVsFact*** for Gold (GOL) from news media, social media sources for the sample period 2010-2018. Since Buzz, Sentiment and Emotion are available on 1-minute frequency, we convert the same into 5-minute interval by taking averages as adopted by Sun, Najand, and Shen, 2016; Gan et al.,2019; Jiao et al.,2016). In order to assess the impact of market psych (attention, sentiment, emotions) along with various microstructural aspects of liquidity, volatility and news surprises as a possible predictor of intraday price jumps and co-jump, we operationalize them in Table A2 in Appendix.

4.2. Descriptive Statistics

Table 1 presents descriptive statistics for two gold instruments namely- COMEX(CME) gold futures and ETF Gold SPDR during jump days and no-jump days in Panel A and Panel B, respectively. We adopt combination of intraday jump detection method namely- Andersen et al.

[15] TRMI uses more than 2000 news sources including leading professional financial newspapers and newswires like The Financial Times, The Wall Street Journal, New York Times, Dow newswire, along with social media platforms like Google News, Yahoo Finance, Factiva, Thomson Reuters News Feed Direct. In addition, TRMI scraps the top 30% of 2 million social media blogs, websites, stock message boards like Yahoo! Finance, SeekingAlpha and StockTwits. Moreover, the linguistic content analytics like term weighting and scoring strategy of TRMI is based on Loughran and McDonald (2011b) dictionary scheme.

(2007), Lee and Mykland (2008) and Bollerselv et al.(2013) after controlling for periodicity using WSD by proposed by Boudt (2011). We categorise jump-day as any day which has atleast one intraday jump, while no-jump day as one in which a day does not have any intraday jump. Table 1 report the mean, median and standard deviation of various market microstructural and market quality aspects of two gold markets, namely- return, effective spread, number of trades, order imbalance, realised variance, depth, ammihud illiquidity, ask size and bid size, which are operationalised in Table A2 in Appendix, for gold markets over the full sample period.

<Insert Table 1 here>

From Table 1, we observe stark differences in market quality dimension during jump days and no-jump days of both gold markets. The average 5-minute return of COMEX gold futures is -0.0036% during jump days while only -0.00001% during no-jump days, which indicates that negative return or negative jumps are more prevalent in CME gold futures from 2010-2018. The variation in average return for COMEX futures is greater during jump days (0.382%) than no-jump days (0.071%). On liquidity aspects, we find similar trend as average number of trades (1710) and depth (1347) of COMEX futures is significantly higher than no-jump days (478 and 550, respectively),which indicates that trading activity is higher during jump days of either signs than no-jump days. Moreover, average transaction cost in terms of effective spread of COMEX gold futures is higher during jump days (0.0163%) than no-jump days (0.012%). In addition, Ammihud illiquidity is also higher during jump days (0.066%) than no-jump days. The average realised variance of COMEX futures is significantly very high during jump-days (0.055%) than no-jump days (0.005%). Lastly, price impact in terms order imbalance display that buy side pressure is very high during jump days (66) than no-jump days.

Similar trends are discernible for ETF gold SPDR from Table 1. We find from Panel A that average 5-minute return is negative (-0.0035%) on jump-days while returns are positive (0.007%) during no-jump days. The variation in average returns of gold ETF is higher on jump days as shown in Panel A. This indicates prevalence of more market crashes or negative jumps than positive jumps. The liquidity of gold ETF is higher during jump days as number of trades (1263), depth (4392), ask and bid size (6422) are quite high. Effective spread is wide during jump days (0.024%) than no-jump days (0.01%). Ammihud Illiquidity is high during jump days. The volatility of gold ETF is significantly higher during jump days (0.0536%) than no-jump days (0.0061%). In contrast to gold futures, the price impact shows that there is net selling pressure as order imbalance is -13134 as compared to buy side pressure during no-jump days (1119). Moreover, comparing the microstructural aspects of COMEX gold futures with ETF gold SPDR in Table 1, we find that number of traders are higher for COMEX futures while depth is greater for ETF SPDR. Effective spread is wide for ETF SPDR which confirms that COMEX futures is more liquid than ETF gold SPDR.

Lastly, we draw a comparative analysis of three Market Psych measures- Attention (Buzz), Sentiments and Emotion from News and Social media during jump days and no-jump days in Panel C of Table 1. We find very interesting insights as news attention to gold is higher during jump-days (19.48) than no jump days (18.3) and the variation in news attention is higher during jump days. We find that average News Sentiment is highly negative on jump days (-0.018) than no-jump days (-0.009), which indicate the dominant impact of negative sentiment to gold that causes negative returns and negative price jumps, as indicated in both gold instruments in Panel A and Panel B in Table 1. We observe that News Emotions index is higher on jump days (0.28) than no-jump days (0.26), which indicates that gold prices are majorly driven by emotion than facts, which corroborates George Soros argument that gold is majorly driven by madness of the crowds. Next, we find that on an average Social media attention to gold is higher during jump days (11.17) than no-jump days (10.54). Social media sentiment is negative during jump days (-0.0215) than no-jump days (-0.019), indicating dominance of negative sentiments to gold during sample period which leads to negative returns in gold. Lastly, Social media Emotions is higher during jump days (0.261) than no-jump days (0.23), implying that emotions from social media dominate over factual information during jump days.

<Insert Table 2 here>

Table 2 reports summary statistics for intraday price jumps characteristics for two gold markets – COMEX futures and ETF SPDR for full sample period 2010-2018. We separately analyse the intraday jump statistics in Panel B, microstructural aspects in Panel C and TRMI indicators in Panel D for All Jump days, Positive Jump Days and Negative Jump Days for COMEX gold futures and ETF SPDR. We find from Panel A that the total number of jumps days for COMEX gold futures is 664 and the probability of having a jump day is 32.15% for COMEX. In contrast, ETF gold SPDR has 687 jump days and the probability of jump day is 33.12% see Panel A of Table 2.

Panel B of Table 2 reports that COMEX gold futures has 1101 intraday jump observations, of which it has greater number of negative jumps (562) while only 539 are positive jumps. Of 2065 days, the probability of having an intraday jump in COMEX futures is 53.3%, while that of positive jump is 26.1% and for negative jump is 27.2%, indicating more price crashes than spikes. Interesting, the expected number of intraday jump in COMEX futures conditional on jump day is 1.658, while that for positive jump is 0.812 and for negative jump is 0.846. From Panel B of Table 2, we find that the average (-0.004%) and median (-0.061%) jump size (average realised return) is negative for COMEX futures full sample period, which indicates that negative jumps (market crashes) dominate over positive jumps. The variation in jump size is greater for negative intraday jump than positive jump. In addition, the probability of observing an intraday jump in COMEX futures conditional on US news is 13.8%, while for positive jump is 7.14% and for negative jump the conditional probability is 6.67%. Similarly, the conditional probability of observing a US news day given all intraday price jump in COMEX futures is 18.62%, for positive jump is 19.67% and 17.67% for negative jump. This indicates that positive price jump in COMEX futures are driven more due to US scheduled macroeconomic news announcement.

From Panel C, we draw a comparative analysis of microstructural aspects of COMEX futures during positive and negative news days. We find that COMEX futures display greater trading activity during negative intraday jump than positive jumps. Number of trades, depth, and realised variance of COMEX futures is higher during negative jump while effective spread and ammihud illiquidity are higher during positive jumps. Moreover, positive jumps have buy side orderflow (positive order imbalance) while negative jump have sell side orderflow (negative orderflow). Next, from Panel D, we observe that both news and social media attention is highest for negative jumps than positive jumps in COMEX futures, which indicates that market crashes in gold (negative jumps) attract greater attention from investor, that is consistent with negativity-bias hypothesis in behavioural finance. Moreover, social media sentiment is highly negative for negative jumps than positive jumps, implying that negative sentiments may cause negative jump or crashes. Lastly, news emotions are greater during positive jumps than negative jumps but social media emotion display opposite behavior as it is higher for negative jumps.

Next for ETF gold SPDR, we observe from Panel B of Table 2 that there are 1045 intraday price jumps, of which there are greater number of negative jump (525) as opposed to positive jumps (520). Of 2074 trading days, the probability of observing all intraday price jump is 50.4%, for positive and negative jump is approx. 25%. The expected number of all intraday price jumps in ETF SPDR conditional on jump days is 1.521. The overall average (-0.003) and median (-0.086) jump size for ETF SPDR is negative, which indicates dominance of negative jumps (crashes) in ETF SPDR over full sample period. The variation in jump size for ETF SPDR is greater for negative jumps than positive jumps. The conditional probability of intraday price jump in ETF SPDR given a US news day is 14.98%, while for positive jump is 7.86% and negative jump is 7.12%. On the other hand, the conditional probability of observing US news day given an intraday price jump in ETF SPDR is 21.34%, for positive jump is 22.50% and for negative news is 20.19%. This indicates that positive jump in ETF SPDR are more likely to occur due to US scheduled macroeconomic news, which similar to the COMEX futures. From Panel C, we observe that liquidity and especially trading activity is higher for negative price jumps in ETF SPDR than positive jump. Trades, Depth, Realised variance and effective spread are higher during negative intraday price jumps. Order Imbalance prove that negative price jumps are accompanied by sell side pressure i.e. negative orderflow, while positive price jumps have buy side pressure i.e. positive orderflow. Lastly, from Panel D, we contrasting results from MarketPsych indicators as New and social media attention is higher during positive intraday price jump. We find that news sentiment is more negative during positive jumps while and social media sentiment is highly negative during negative price jumps than positive jumps. Similarly, news emotion are greater during positive price jumps while social media emotions are greater during negative price jumps.

<Insert table 3 here>

Table 3 provides descriptive statistics for intraday co-jumps, positive co-jumps and negative co-jumps between COMEX gold futures and ETF SPDR during the overlapping trading hours for full sample period 2010-2018. We define co-jump as simultaneous occurrence of intraday jump in two gold instruments. Panel A of Table 3 report that there are 863 intraday co-jumps between COMEX futures and ETF SPDR, of which negative co-jumps (437) are greater than positive co-jumps (426). The probability of a co-jump day is 41%. In addition, the expected no. of co-jump given an intraday jump in COMEX futures is 0.78 while for ETF SPDR it is 0.83. The overall median co-jump size is negative for both COMEX futures (-0.093%) and ETF SPDR (-0.081%), which indicates that on an average, negative co-jumps dominate. The variation in co-jump size is higher for negative co-jump than positive co-jump. Next, from Panel B we find that liquidity, trading activity and volatility is higher during negative co-jumps. Effective spreads and ammihud illiquidity of COMEX futures is higher for positive jumps while for ETF SPDR, these are high for negative co-jumps. Lastly, from Panel C of Table 3, the probability of co-jump given US news day is 12.83%

for all cojumps, while for positive co-jump is 6.45% and for negative co-jump 6.3%. The conditional probability of observing a US news day given intraday co-jump is 22.13% for all co-jumps, while 22.54% for positive co-jump and 21.74% for negative co-jump. This indicates that positive co-jumps are more likely to occur due to US news announcement.

Figure 1 present an intraday (hourly) distribution of price jumps and co-jumps for COMEX gold futures and ETF SPDR from 07:30 -16:00 US ET for full sample period. We find huge intraday variation in number of price jumps and co-jumps in COMEX futures and SPDR ETF during trading day from 2010-2018. We observe interesting insights that majority of intraday price jump (17%) and co-jumps (18%) occur during 08:00-09:00 US ET. This hour constitutes the arrival of majority of US scheduled macroeconomic news announcements as enlisted in **Table 4**. Hence, we find that majority intraday jumps and co-jumps in gold markets takes place during news-intensive timezones, especially 08:30 ET US news hour. The second highest number of price jumps (16%) and co-jumps (17%) takes place during 14:00-15:00 ET, as shown in **Figure 1**. This hour marks the arrival of the Federal Reserve FOMC rate decision news, which is the most important US scheduled macroeconomic news as proved by past studies. Following it, 13% intraday jumps and co-jumps in COMEX futures and ETF SPDR takes place during 09:00-10:00 ET, which also entails arrival of many US scheduled macroeconomic news as mentioned in Table 4. Lastly, we observe that no-news hours have comparatively less number of intraday jumps and co-jumps than news-intensive timezones.

<Insert Table 4>

Table 4 reports the summary statistics for 29 US scheduled macroeconomic news announcements and its corresponding news surprises. We report the actual release time of the news in US ET, name of news indicator, frequency of announcement, total no. of news days, standard deviation of the news surprises, no. of positive surprise days, mean of positive news surprise, no. of negative news surprise and mean of negative news surprise. We find that FOMC rate decision has the highest news surprise size followed by Construction Spending, Unemployment rate, Leading Index, Consumer credit, Building Permit, Capacity Utilisation, and Construction Spending. Moreover, the US scheduled news with large standard deviation in news surprise index is CPI, Personal Income, Durable Goods Sales, Building Permit, Capacity Utilisation, Industrial Production, and Current Account Balance.

5. Empirical Findings

5.1. Intraday Event Study Results

In this section, we present our findings of intraday dynamics of Market Psych aspects (Attention (Buzz), Sentiments, and Emotions) from News Media and Social Media sources along with key microstructural and liquidity aspects around positive and negative jumps, separately, using intraday event study method, which is described in Section 3.3, separately for COMEX gold futures and SPDR Gold ETF in Figures 2 and 3. In addition, we investigate the impact on *Cumulative Abnormal Return (CAR), Absolute Return, Number of Trades, Depth, Realised Variance, Proportional Effective Spread, Ammihud Illiquidity, and Order Imbalance,* which are operationalised in Table A2 in Appendix. We examine the impact of all above-mentioned predictor variables in their standardised abnormal levels. For each variable, we have two plots, one for positive jump and second for negative jump in Figures 2 and 3. All event study graphs have event window timing on the horizontal axis (-60,-55,-50,-45,...,-10,-5,0,5,10,…..,45,50,55,60). The vertical axis mentions the standardised abnormal values of the predictor variables. Each event study graph has two dashed lines which indicate the 5% to 95% quantile interval. The white circles indicate the points when Mann-Whitney null hypothesis gets rejected.

<Insert Figure 2>

5.1.1. **COMEX Gold Futures**

Figure 2 presents intraday event study graphs for positive and negative price jumps in COMEX gold futures across several predictor variables. Fig 2(a) and Fig 2(b) display the intraday return dynamics of COMEX gold futures around positive and negative jumps. In accordance to definition of price jump, we find that returns unsurprisingly rises during positive jump while it falls during negative price jump. Fig 2 (a) reveal that cumulative abnormal returns (CAR), estimated using constant mean return model, sharply rises jump 5-minute prior to positive price jump in COMEX futures, reaches in maximum as it increases by 4 times at the jump time and falls back to normal levels 5-7 minutes after jump. On the other hand, CAR falls sharply 5-minutes before the negative price jump, drops by 4 times at jump time and recover to normal levels 5-7 minutes after the negative jump. In addition, we examine the intraday dynamics of absolute abnormal returns as operationalised in Table A2 rise sharply 5 minutes prior to both positive and negative jump, reaches its maximum by 5 times the normal value (intraweek mean value) at jump time and falls back to normal levels 5-7 minutes after the jump. Second, we observe from Fig 2(c) that there is a huge surge in the intraday realised variance, which rises 5-7 minutes before the positive and negative jump and increase to its maximum of 4 times the intraweek mean level at jump time and then falls back to normal levels 10-15 minutes after the jump. The recovery of realised volatility is quicker during positive jump than negative jump as shown in Fig 2(c).

Third, Fig. 2(d) and 2(e) we observe a surge in the number of trades 5-minutes prior to positive jump and the abnormal trades rises 2 times the intraweek mean at the jump time and falls gradually to reach its normal level 35-40 minutes after the positive jump. This persistence in surge in trades 35-40 minutes after positive jump indicates that market participants need time to satisfy the impending demand, re-balance their portfolio, and adjust their hedging position (Boudt et al.(2011). On the contrary, trades showcase a very significant rise during negative price jump as it abruptly rises 5-minutes prior to the jump and increases by 4 times at jump time, and fall back sharply within 5-7 minutes after the negative jump as shown in Fig. 2(d). In addition, we find that abnormal depth (bid and ask depth) showcases similar intraday patterns around positive and negative jumps as shown in Fig 2(e).

Fourth, we find a sudden rise in transaction costs and illiquidity, which we measure using proportional effective spread (Fig 2(f)) and ammihud illiquidity (Fig 2(g)), respectively, around positive and negative price jumps in COMEX futures. We find that proportional effective spread widens and rises significantly 20-25 minutes before the positive price jump, and falls back to normal levels immediately 5-minutes after the positive jump. In contrast, proportional effective spread surges immediately 15 minutes prior to the negative jump, reaches its maximum and falls back to normal levels within 5-minutes after the jump, as shown in Fig 2(f). The widening of effective spread indicates the transaction cost and any of its three components – order processing cost, inventory costs, and adverse selection costs increases during price jumps of either sign. Next, Fig 2(g) corroborates the above finding that illiquidity surges significantly during both positive and negative price jumps. We find that ammihud illiquidity increases 5-7 minutes before positive and negative jump and reaches its maximum point to be 3 times the intraweek value at the jump arrival and recovers back to normal level 15-20 minutes after the jump. The illiquidity takes more time to recover from a negative price jump (30-35 minutes) than positive price jump, which indicates that traders take more time to adjust their positions after a market crash. Thus, our findings are consistent with those of Boudt (2011) and Piccotti (2018).

Fifth, we observe that positive price jumps are triggered by buy side order as order imbalance rises 5-10 minutes before the positive jump, reaches its maximum of 20% above the intraweek level 5-minutes after the jump and falls back 15-20 minutes after the positive jump, as shown in Fig 2(h). In contrast, we find that negative price jumps are preceded by sell side order flow as order imbalance falls steeply 5-minutes prior to the negative jump and reaches its lowest point by falling more than 10% below intraweek value 5-minutes .Thus, our results are consistent with the findings of Boudt (2011) and Chordia, Roll, and Subrahmayam (2002) that large buyside pressure causes positive jump while large selloffs triggers market crashes.

Sixth, we observe from Fig 2(i) that there is sharp increase in news attention to gold 5-7 minutes prior to positive price jump and falls back to normal levels 10-minutes after the positive price jump. Similarly, news attention to gold rises 10-mins prior to negative price jump, but starts to fall few seconds before the jump time. Corroborating the results of News attention, Fig 2(j) showcases that Social Media Attention starts to rise gradually 15-18 minutes prior to positive intraday jump in COMEX futures, reaches is peak at 5-minutes after the jump and remains elevated even 60-minutes after the positive jump. In contrast, we find that social media attention abruptly rises 10-15 minutes prior to negative price jump and falls to normal levels 55-60 minutes after the negative price jump. We can accurately predict the timing of the positive and negative price jumps in COMEX futures 5-10 minutes before by using TRMI Social Media Attention, while News Attention can predict the timing of positive intraday price jump. Our findings are consistent with the growing popularity and usage of social media platforms like Twitter, Yahoo and Google by investor, which helps to reveal their behavior and trading intentions.

Next, Figure 2(k) we bserve an interesting insight that News Sentiments gradually rises 35-40 minutes before the positive price jump and remains elevated 30-minutes after the jump. In contrast, news sentiment abruptly falls 5-10 minutes prior to negative price jump, reached its lowest point at jump time and recover back to normal levels 10-15 minutes after the negative jump. We observe similar behavior from Social Media Sentiment from Fig 2(l) as *Social Media Sentiment* starts to rise 15-20 minutes before the positive jump, reaches its maximum 5-minutes after the jump and falls abruptly to normal level 15-minutes after the positive and negative jump. Our findings from Sentiment reveal that positive price jumps are predictable and caused by positive sentiments to gold from news and social media, while negative price jumps are predictable and caused by negative sentiments towards gold from news and social media. Lastly, Fig 2(m) and

2(n) we find that News Emotions rises sharply 5-minutes prior to both positive and negative price jump, reaches its maximum at the jump time and falls quickly 5-7 minutes after positive and negative price jumps, as shown in Fig 2(m). Similar behaviour is shown by Social Media Emotions in Fig 2(n) by social media emotions. However, social media emotion increases 5-minutes before the negative jump and reaches its maximum 10-minutes after jump and falls back to normal levels. Our finding highlight that both positive and negative price jumps are driven by Investor Emotions arising from news and social media, which consistent with the argument of George Soros that gold is a forward looking reactionary asset which most susceptible to emotions than fundamentals.

5.1.2. **SPDR Gold ETF**

From Fig 3(a), we find that abnormal return shoots up during positive jump while it drops suddenly within 5-minutes during negative jumps. We further observe that abnormal return display a significant rise and fall by 4 times the intraweek mean value during positive and negative jump, respectively. We observe similar intraday dynamics of absolute abnormal returns (Fig 3(b)) around positive and negative jumps in ETF SPDR. Second, as shown in Fig 3(c) and consistent to definition of price jumps, we find that realised variance display a huge increase 5-7 minutes before the positive and negative jump, reaches its peak at 3 times the intraweek mean value at the jump arrival and falls back to normal levels 10-15 minutes after the jump. Third, in Fig 3(d) we find that number of trades suddenly rises 5 minutes before both the positive and negative jump, and reaches its maximum level at jump arrival. Trades rises by 200% at the positive jump while trades only rise by 100% during the negative jump, which highlights demand for immediacy. While trades fall quickly within 5 minutes after the positive jump but we observe a gradual fall in the trades 50 minutes after the negative jump, indicating traders require more time to adjust their positions after a market crash. Next, Fig 3(e) depicts that average depth also suddenly rises 5-minutes prior to both positive and negative jumps. While depth shoots up to 2 times at positive jump arrival time, it only rises by 1.5 times at negative jump. Moreover, depth remains elevated and gradually falls back to normal levels after 50-55 minutes, this corroborates the argument of Boudt (2011) that jumps are caused due to market’s inability to absorb new orders, without significantly moving the prices up or down.

Fourth, from Fig 3(f), we find that proportional effective spreads surge 15-minutes before the positive price jump, reaches its maximum to 20% higher than intraweek levels at jump arrival and falls down immediately within 5-minutes. While prop. effective spread rises 5 minutes prior to the negative jump, rise to 10% higher than intraweek levels at the jump arrival and falls down 5-minutes after the negative jump. The widening of the proportional effective spreads indicates increase in trading cost after the price jump, which is done by the specialist to compensate for increase in order processing, inventory costs or adverse selection costs. Next, we find a rise in illiquidity from Fig 3(g) as ammihud illiquidity shoots up 5 minutes before the positive price jump and rise to 20% above the intraweek mean value at jump arrival and fall back quickly 5 minutes after the positive jump. In contrast, we find that illiquidity drastically falls at time of negative jump to 20% less than the intraweek mean value and starts to rise after 60-minutes. Fifth, from Fig 3(h), we observe that buy side orders drives positive price jumps as order imbalance rises 5 minute before the jump and reaches its maximum to 20% greater than the intraweek level at jump time and recovers back 10 minutes after the jump. In contrast, we find that sell side order (pressure) drives negative price jumps or crashes as we observe from Fig 3(h) that order imbalance falls abruptly 5 minutes before the jump and reaches 20% less than intraweek level at jump time and recover back quickly with 5 minutes after the jump. Hence, direction of order imbalance can predict the price jump.

Sixth, we observe from Fig 3(i) that news attention surges 20-25 minutes before the positive jump and reaches its peak of 10% higher than intraweek mean value at jump arrival and quickly falls back to normal levels 15 minutes after the jump. In contrast, intraday behavior of news attention around negative price jump does not showcase a clear picture. However, the intraday movement of social media attention indicates that both positive and negative price jump in ETF Gold SPDR can be predicted using TRMI social media attention. Social media attention starts to increase 10-15 minutes prior to the positive and negative jump and increase to more than 20% the intraweek value 10-minutes after the jump and remains elevated 60 minutes after the positive jump. Next, we find from News and Social Media Sentiment that positive sentiments have predictive power for positive jumps while negative sentiments have predictive power for negative jumps. We observe from Fig 3(k) that news sentiments rise 5 minutes prior to positive jump and reaches its peak to 10% higher value than intraweek mean value at jump arrival and falls back to normal level 5-minutes after positive jump. While news sentiments start to fall 10-15 minutes before the negative jump and drop to more than 10% below the intraweek mean at jump arrival and recover back up 10-15 minutes after the jump. Fig 3(l) corroborates the above findings as social media sentiments rises 20-25 minutes before the positive jump and reaches its maximum to more than 20% higher than intraweek mean value 10 minutes after the jump arrival and falls back 15-20 minutes after the positive jump. While social media sentiment falls 20 minutes before the negative jump and drops to 20% below the intraweek value at jump and rises back to normal levels 10 minutes after the jump. Thus, we find that asymmetric behavior of news and social media sentiments can predict intraday jump in gold ETF. Lastly, we find that news based emotions rises suddenly 5 minutes before the positive price jump and increases to more than 10% the intraweek mean value at jump arrival and then recovers back within 5 minutes after the jump. News emotion also rises at the arrival of negative price jumps but does not showcase any significant pre- and post-jump movement, as shown in Fig 3(m). However, we observe that social media emotions display a huge surge just 5-minutes before the negative jump and rises to maximum of 10% higher than intraweek mean value 5 minutes after the jump and recovers after 20 minutes. Thus, we infer from our findings that intraday positive and negative jump in gold ETF are driven by market emotions reflected in news and social media, as we observe for COMEX futures.

5.2. Intraday Price Jumps Predictability in Gold Markets - Baseline Model

In this section, we test our hypotheses H1(a), H1(b), H2(a), H2(b), H3(a),H3(b),H4 and H5 and examine the high frequency predictors of intraday price jumps in COMEX gold futures and SPDR Gold ETF using machine learning technique of penalised logistic regression using ridge and lasso methods. In section 5.2.1, we adopt ridge logistic regression analysis to investigate intraday predictability of All, Positive and Negative price jumps separately for both the gold markets using various high frequency determinants like US aggregate Scheduled Macroeconomic News announcements, Market Psych variables – Attention, Sentiments and Emotions from news media and social media along with different dimension of liquidity and volatility, as operationalised in Table A2 in Appendix. In Section 5.2.2, we assess the interaction effect of US aggregate Scheduled Macroeconomic News announcement with three Market Psych factors from news and social media, respectively using ridge regressions. In Section, 5.2.3, we use least absolute shrinkage and selection operator (LASSO) logistic regression to examine the news-watcher's hypothesis in order to identify which among 29 disaggregate US scheduled macroeconomic news surprise have predictive power for intraday price jumps in COMEX futures and SPDR gold ETF.

5.2.1. High-Frequency predictors of Intraday Price Jumps in Gold

We examine the high frequency sources of predictability of intraday price jumps (All, Positive and Negative) in both the gold markets using penalised (ridge) logistic regression of the form-

$$P(PriceJump_t = 1|X_{t-5min}) = G(\alpha_o + \beta_1 USAgg\_SchMNews_{t-5min} + \sum_{i=1}^{3} \beta_{2,i}\, MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{3,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{2} \beta_{4,k} Liq1\_TradeActivity_{k,t-5min} + \beta_5 Liq2\_TradeCost_{t-5min} + \beta_6 Liq3\_PriceImpact_{t-5min} + \beta_7 Illiquidity_{t-5min} + \beta_8 Volatility_{t-5min} + \varepsilon_t) \quad (22)$$

where, $P(PriceJump_t = 1|X_{t-5min})$ is the conditional probability of observing an intraday price jump (All, Postive or Negative) given 5-minute lagged set of predictors i.e X_{t-5min}. **X** comprises of 5-minute lagged values of the following predictors –(1)US aggregate scheduled macroeconomic news announcements (***USAgg_SchMNews***), which is dummy variable that takes value 1 when any of 29 US scheduled news announcements takes place (as enlisted in Table 4), (2) three dimensions of Market Psych aspects namely, Attention, Sentiments and Emotions from news media (NewsM) and Social media (SocialM), along with (3) three aspects of liquidity - $Liq1\_TradeActivity$, which is trading activity aspect of liquidity that we proxy using total number of trades (Trades) and total depth (Depth) at 5-minute, $Liq2\_TradeCost$ is trading cost aspect of liquidity, which we proxy using Effective spread and $Liq3\_PriceImpact$, is the price impact aspect of liquidity which we measure using order imbalance. In addition, we also assess the impact of (4) $Illiquidity_{t-5min}$ which 5-minute lagged ammihud illiquidity variable and (5) $Volatility_{t-5min}$ which is lagged realised variance. G is logistic function of the form $G(z) = \frac{\exp(z)}{1+\exp(z)}$. We chose to adopt ridge logistic regression framework because many predictor variables have significant correlation and the problem of multicollinearity gets resolved by ridge penalty imposed on ordinary least square method as proposed by Tibsharani (1996). Moreover, our dependent variable is binary, which is 1 when intraday price jumps occurs while 0 otherwise, that makes logistic regression more suitable econometric framework.

Table 6 present our results for equation (22), where we perform separate ridge logistic regression for All, positive and negative price jumps separately for COMEX gold futures and SPDR gold ETF. On the whole, we find that the most dominant and statistically significant predictor of intraday price jumps for both COMEX futures and SPDR ETF is US aggregated scheduled macroeconomic announcements and positively affects jump predictability and hence increases the probability intraday jump occurrence of either signs. We find that US aggregate scheduled news announcements have greater predictive power for All intraday Jump in COMEX futures than ETF SPDR, as evident from higher coefficients. However, we observe an asymmetric news-effect as US scheduled news announcements have greater predictability for negative price jumps in COMEX futures than positive jumps while we observe the opposite for SPDR Gold ETF as positive price jumps are more driven by US scheduled news announcements. Next, we observe that News Attention has positive and significant predictive power for only negative price jump in both COMEX futures and SPDR ETF, as shown in Table 6. This indicates that market crashes trigger greater uncertainty and attracts market attention and hence negative jumps (crashes) can be predicted using news based attention. In contrast Social Media Attention increase the predictability of positive price jumps in both COMEX futures and ETF SPDR. This asymmetric effect of news and social media based attention provides a key insight that sudden large upward movements in gold prices attracts greater social media attention while large market crashes in gold prices attracts greater attention from news based sources. This indicates that since news media based sources are more reliable and disseminates trustworthy information, hence it followed more by market participants during negative price jump (crashes). Social Media Attention also has positive predictive role for All price jumps in gold ETF.

In addition, we observe the asymmetric effect of intraday Sentiments from news and social media on high frequency jump predictability, as shown in Table 6. We find that News Sentiments have negative impact on the intraday predictability of negative and All price jumps in both COMEX futures and ETF SPDR. While we observe that social media sentiments positively impacts the predictability of only positive jumps in both gold markets. Our findings are consistent with past studies which argue that positive sentiments result in buying pressure and leads to upward movement in prices i.e. positive price jump. Moreover, we observe that News Emotions have positive impact on the predictability on all jumps signs but is significant only for positive price jumps in ETF SPDR, while Social Media emotions showcase a negative impact on negative price jumps in ETF SDPR and has no impact for intraday jumps in CME futures of either signs.

Next, we find from Table 6 that trading activity aspect of liquidity – number of trades and depth increases the predictability of positive and negative price jumps for both gold markets. Our findings are consistent with Boudt (2011), Piccotti (2016) and Scaillet (2018) that also find that shocks to trading activity results in price jumps of either signs. In addition, we find that higher trading cost increases the predictability of intraday price jumps of either signs for both COMEX futures and ETF SPDR, which is consistent with noise trading hypothesis. Ammihud Illiquidity has positive impact on the predictability of positive and negative price jumps in COMEX futures and ETF SPDR. Moreover, we find that price impact has positive impact on the predictability of positive price jumps in both gold markets. This corroborates the findings of Boudt (2011) and Evan (2011) that buy side pressures drives positive price jumps while sell side pressure drivers negative price jumps, Lastly, positive shocks to trading activity, order imbalance, effective spreads, illiquidity and volatility greatly increases the predictability of intraday price jumps of either signs, as shown in Table 6.

5.2.2. Interaction Effects of Market Psych and Aggregate US Macroeconomic News Announcements on Intraday Price Jump

In this section, we examine the interaction effect of aggregate US scheduled macroeconomic news announcements with three aspects of Market Psych- Attention, Sentiment and Emotion from News and Social Media separately on intraday predictability of price jumps for both COMEX futures and SPDR ETF. We perform interaction effects using ridge logistic regression on intraday price jump (All, Positive and Negative), after controlling for liquidity and volatility predictors, which is of the following form-

$$\boldsymbol{P(PriceJump_t = 1|X_{t-5min}) = G(\alpha_o + \sum_{i=1}^{3} \beta_{1,i} USAgg_{SchMNews_{t-5min}}\ X\ MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{2,i}\ USAgg_{SchMNews_{t-5min}}\ X\ MarketPsych\_SocialM_{i,t-5min} + \beta_3\ USAgg_{SchMNews_{t-5min}} + \sum_{i=1}^{3} \beta_{4,i} MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{5,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{2} \beta_{6,k} Liq1\_TradingActivity_{k,t-5min} + \beta_7 Liq2\_TradeCost_{t-5min} + \beta_8 Liq3\_PriceImpact_{t-5min} + \beta_9 Illiquidity_{t-5min} + \beta_{10} Volatility_{t-5min} + \varepsilon_t)} \quad \textbf{(23)}$$

where, $\boldsymbol{G}$ is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$, $\boldsymbol{\beta_{1,i}}$ is the coefficient of the interaction terms of 5-minute lagged aggregate US Scheduled Macroeconomic News ($\boldsymbol{USAgg\_SchMNews_{t-5min}}$) with three (i=1 to 3) aspects of Market Psych from News Media ($\boldsymbol{MarketPsych\_NewsM_{i,t-5min}}$) i.e. *Attention_NewsM, Sentiment_NewsM, Emotion_NewsM* and similarly $\boldsymbol{\beta_{2,i}}$ is the coefficient of interaction terms with Social Media ($\boldsymbol{MarketPsych\_SocialM_{i,t-5min}}$) as *Attention_SocialM, Sentiment_SocialM, and Emotion_SocialM, as* shown in Table 7. Table 7 reports the interaction effects results of equation (2) for All Jumps, Positive and Negative Jumps for COMEX futures and SPDR ETF.

We find that during US macroeconomic news announcement, News and Social Media Emotions prove to have a positive and significant on predictability of intraday positive and negative price jumps for both COMEX futures and SPDR ETF. This indicates that emotions overpower facts and are key driving force behind intraday price jumps of either signs during arrival of macroeconomic news. Our findings are consistent with argument that noise traders are more likely to take emotional trading decision during times of uncertainty created by release of macroeconomic news. Next, we observe that increase in positive (net of negative) social media sentiment has positive and significant impact on predictability of intraday positive price jump for both COMEX futures and SPDR gold ETF. This indicates that positive price jumps are driven more by positive sentiment; which investor display on social media platforms at the time macroeconomic news announcements. However, we find that news sentiment does not have significant impact on predictability of price jumps during US news announcements.

Interestingly, we find from Table 7 that News Attention during US scheduled macroeconomic news announcements has positive and statistically significant impact on predictability of intraday negative jumps in both COMEX futures and ETF gold SPDR. Our finding further strengthens our argument that market participants choose to pay more attention to news-based media during market crashes, especially when accompanied by scheduled macroeconomic news announcements from US. On the contrary, we observe from Table 7 that social media Attention during US scheduled macroeconomic news announcements has positive and significant impact on predictability of intraday positive price jumps in both COMEX futures and ETF SPDR. This indicates that investors prefer to pay greater attention to social media platforms during macroeconomic news which may indicate upward price changes in gold.

5.2.3. Impact of Disaggregated US Scheduled News Surprises on Price Jump Predictability

In this section, we examine the news-watcher's hypothesis to identify which out of 29 disaggregate US scheduled macroeconomic news surprises, as enlisted in Table 4, has predictive power for intraday price jumps for COMEX futures and ETF Gold SPDR. We adopt least absolute shrinkage and selection operator (LASSO) logistic regression framework, which has the advantage of selecting optimal predictors from a large number of predictors and account for multi-collinearity among predictors. We perform the following LASSO logistic regression separately for All, Positive and Negative price jumps in COMEX futures and SPDR ETF and control for Market Psych and liquidity predictors, such as-

$$\boldsymbol{P(PriceJump_t = 1|X_{t-5min}) = G(\alpha_o + \sum_{i=1}^{29} \beta_{1,i} USDisagg\_SchMNewsSurp_{i,t-5min} + \sum_{i=1}^{3} \beta_{2,i}\, MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{3,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{2} \beta_{4,k} Liq1\_TradeActivity_{k,t-5min} + \beta_5 Liq2\_TradeCost_{t-5min} + \beta_6 Liq3\_PriceImpact_{t-5min} + \beta_7 Illiquidity_{t-5min} + \beta_8 Volatility_{t-5min} + \varepsilon_t)} \quad \textbf{(24)}$$

where, $\boldsymbol{P(PriceJump_t = 1|X_{t-5min})}$ is the conditional probability of observing an intraday price jump (All, Positive or Negative) given 5-minute lagged set of predictors i.e $\boldsymbol{X_{t-5min}}$. **X** comprises of 5-minute lagged values of the following predictors –(1) Standardised News Surprise for 29 US disaggregate scheduled macroeconomic news announcements ($\boldsymbol{USDisagg\_SchMNewsSurp}$), which are enlisted in Table 4, and news surprise is calculated in Section 4.1 using Balduzzi et al.(2011) approach, (2) three dimensions of Market Psych aspects namely, Attention, Sentiments and Emotions from news media (NewsM) and Social media (SocialM), along with (3) three aspects of liquidity - $\boldsymbol{Liq1\_TradeActivity}$, which is trading activity aspect of liquidity that we proxy using total number of trades (Trades) and total depth (Depth) at 5-minute, $\boldsymbol{Liq2\_TradeCost}$ is trading cost aspect of liquidity, which we proxy using Effective spread and $\boldsymbol{Liq3\_PriceImpact}$ is the price impact aspect of liquidity which we measure using order imbalance. In addition, we also assess the impact of (4) $\boldsymbol{Illiquidity_{t-5min}}$ which is 5-minute lagged ammihud illiquidity variable and (5) $\boldsymbol{Volatility_{t-5min}}$ which is lagged realised variance. $\boldsymbol{G}$ is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$.

Table 8 presents our results for equation (24). We find a strong evidence in support to news-watchers' hypothesis as we observe that not all US scheduled macroeconomic news surprises have statistically significant power for predicting intraday price jumps for COMEX gold futures and SPDR gold ETF. We find that news surprises from FOMC Rate Decision is the most dominant and statistically significant market-moving US scheduled macroeconomic news, as evident from highest coefficients from Table 8. FOMC news surprise has positive impact of intraday jump predictability for all types of jumps and for both COMEX futures and SPDR ETF. Our finding is consistent with Smales (2018) that monetary policy decision has a significant impact on gold prices. Next, we observe that the second most important US scheduled macroeconomic news surprise is GDP Advance as its news surprise positively impacts intraday predictability of all and negative price jumps for both COMEX gold futures and SPDR ETF. Moreover, we observe that GDP Advance news surprise has negative impact on the predictability of positive price jumps in gold ETF. This corroborates the safe haven property of gold as increase in GDP Advance indicates positive outlook for economy but has negative impact on gold prices, which results in sudden trade migration and reversal in flight to safety leading to increase in the likelihood of negative price jumps in gold (market crashes in gold). Similarly, we observe that PMI Manufacturing, ISM Manufacturing, and New Home Sales have positive impact on predictability of negative price jumps while negative impact on positive jump predictability. Next, we observe from Table 8 that news surprises of Non-Farm Payroll, Retail Sales, Capacity Utilisation, Durable Goods, Consumer credit, Leading Index have positive impact of predictability of negative jumps and negatively influences probability of positive jump due to the safe haven argument. In contrast, we find that increase in unemployment and initial jobless claim, which indicate negative future state of the economy, have positive impact on the predictability of positive gold price jump and negative impact on negative price jump due to flight to safe haven to gold.

Moreover, we observe that positive and negative price jumps are predictable by different set of US macroeconomic news surprises. We find that positive price jumps in both gold markets are majorly driven by FOMC, Retail Sales, New Home Sales, Construction Spending, Initial jobless claim and Unemployment. In contrast, negative price jump in gold are predictable from news surprises related to FOMC, Non-farm payroll, GDP Advance, Capacity Utilisation, Durable Goods, Consumer Confidence, PMI Manufacturing, Initial Jobless Claim and Unemployment. Thus, we find that the only three news surprises, namely- FOMC, Initial Jobless Claim and Unemployment prove to be common and significant predictors for both positive and negative price jump predictability in gold markets. In addition, we observe that macroeconomic news which have large surprise index (see Table 4) have greater impact on the predictability of intraday price jumps in gold markets like *FOMC Rate Decision, Retail Sales, Industrial Production, Unemployment, Construction Spending, and ISM Manufacturing*. Moreover, macroeconomic news which have greater dispersion in surprise, as evident from the standard deviation of surprise in Table 4, are more dominant determinants of intraday price jumps, like *Durable Goods Sales, CPI, Non-Farm Payroll, GDP Advance, International Trade, Capacity Utilisation, Leading Index and PMI Manufacturing*.

5.3. Predictors of Intraday Co-Jumps - Baseline Models

5.3.1. High-Frequency Predictors of Co-Jumps in Gold Markets

In this section, we examine the high frequency predictors of co-jumps between COMEX gold futures and SPDR Gold ETF using ridge logistic regression framework. We compute co-jump between two gold markets as the simultaneous occurrence of price jumps in both COMEX futures and SPDR ETF using the combination of Bollerslev et al.(2013) and Andersen et al.(2007) jump detection method as discussed in Section 3.2. We operationalize positive co-jumps as one when both COMEX futures and SPDR ETF observe a positive price jump, while negative co-jump when both COMEX futures and SPDR ETF observe a negative co-jump. We perform separate ridge logistic regression for All, Positive and Negative Co-Jumps of the following form-

$$\boldsymbol{P(CoJump_t = 1|X_{t-5min}) = G(\alpha_o + \beta_1 USAgg\_SchMacroNews_{t-5min} + \sum_{i=1}^{3} \beta_{2,i}\, MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{3,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{5} \beta_{4,i} COMEX\_Liq_{k,t-5min} + \beta_5 COMEX\_RV_{t-5min} + \sum_{k=1}^{5} \beta_{6,i} ETF\_Liq_{k,t-5min} + \beta_7 ETF\_RV_{t-5min} + \varepsilon_t)} \quad \textbf{(25)}$$

where, where, $\boldsymbol{P(CoJump_t = 1|X_{t-5min}}$) is the conditional probability of observing an intraday co-jump (All, Postive or Negative) given 5-minute lagged set of predictors i.e $\boldsymbol{X_{t-5min}}$. **X** comprises of 5-minute lagged values of the following predictors–(1)US aggregate scheduled macroeconomic news announcements (***USAgg_SchMacroNews***), which is dummy variable that takes value 1 when any of 29 US scheduled news announcements takes place (as enlisted in Table 4), (2) three dimensions of Market Psych aspects namely, Attention, Sentiments, and Emotions from news media ($\boldsymbol{MarketPsych\_NewsM_{i,t-5min}}$) and Social media ($\boldsymbol{MarketPsych\_SocialM_{i,t-5min}}$), along with (3) four aspects of liquidity for COMEX futures (***COMEX_LiquidityPredictors***) and ETF SPDR (***ETF_LiquidityPredictors)*** separately in 5-minute lagged form, such as - Liq1_TradingActivity, $Liq2\_TradeCost$ and $Liq3\_PriceImpact$, and Liq4_$Illiquidity_{t-5min}$ Lastly, we also assess the impact of lagged volatility for COMEX futures and ETF SPDR ($\boldsymbol{Volatility_{t-5min}}$). $\boldsymbol{G}$ is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$.

Table 9 presents findings for equation (25) which examines the high frequency predictor for co-jumps in gold markets. We find that aggregate US scheduled macroeconomic news announcements is the most dominant predictor of intraday co-jumps in gold markets and have positive impact, in return, increases the predictability of co-jumps of all kinds between gold futures and ETF. Next, we find that Emotions from News media have positive impact on All and positive Co-jumps in gold markets. We find that positive Social media sentiments drives positive co-jumps in gold markets while negative social media sentiments drive negative co-jumps in gold markets. We observe that both the lagged News and Social Media Attention increases the predictability of All and Negative Co-jumps, which further corroborates our findings that investor prefer to pay attention to news media during gold market crashes or negative co-jumps in gold markets.

Next, we find that increase in liquidity aspects like trades, depth, and ammihud illiquidity increases the predictability of co-jumps of either signs. In contrast, we find that effective spreads widen during positive co-jumps in gold markets and realised volatility in COMEX futures has positive impact in predicting all types of co-jumps. We find that though trades of ETF SPDR only positively impacts intraday negative co-jumps but depth of ETF has positive impact on intraday co-jump predictability of all signs. Similarly, effective spread of ETF has significant and positive impact on All and Negative Co-jumps while ammihud illiquidity has positive impact on the predictability of all Co-Jumps. Lastly, we observe that buy side orderflow has positive impact on the predictability of positive co-jumps.

5.3.2. Interaction Effects of Market Psych and Aggregate US Macroeconomic News Announcements on Co-Jumps

In this section, we examine the interaction effect of US scheduled macroeconomic announcement with the three Market Psych aspects, namely- Attention, Sentiment, and Emotion from news and social media using ridge logistic regression. We control for liquidity and volatility predictors of COMEX futures and ETF SPDR and perform separate regression analysis for All, Positive and Negative Price Jumps, as follows-

$$\begin{aligned}
&\boldsymbol{P(CoJump_t = 1|X_{t-5min}) = G(\alpha_o +} \\
&\boldsymbol{\textstyle\sum_{i=1}^{3} \beta_{1,i}\, USAgg_SchMacroNews\ X\ MarketPsych_NewsM_{i,t-5min} +} \\
&\boldsymbol{\textstyle\sum_{i=1}^{3} \beta_{2,i}\, USAgg_SchMacroNews\ X\ MarketPsych_SocialM_{i,t-5min} +} \\
&\boldsymbol{\beta_3 USAgg_SchMacroNews_{t-5min} + \textstyle\sum_{i=1}^{3} \beta_{4,i}\, MarketPsych_NewsM_{i,t-5min} +} \\
&\boldsymbol{\textstyle\sum_{i=1}^{3} \beta_{5,i} MarketPsych_SocialM_{i,t-5min} + \sum_{k=1}^{5} \beta_{6,i} COMEX_Liq_{k,t-5min} + \beta_7 COMEX_RV_{t-5min} +} \\
&\boldsymbol{\textstyle\sum_{k=1}^{5} \beta_{8,i} ETF_Liq_{k,t-5min} + \beta_9 ETF_RV_{t-5min} + \varepsilon_t)} \qquad \textbf{(26)}
\end{aligned}$$

where, $\boldsymbol{G}$ is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$, $\boldsymbol{\beta_{1,i}}$ is the coefficient of the interaction terms of 5-minute lagged aggregate US Scheduled Macroeconomic News ($\boldsymbol{USAgg\_SchMNews_{t-5min}}$) with three (i=1 to 3) aspects of Market Psych from News Media ($\boldsymbol{MarketPsych\_NewsM_{i,t-5min}}$) i.e. *Attention_NewsM, Sentiment_NewsM, Emotion_NewsM* and similarly $\boldsymbol{\beta_{2,i}}$ is the coefficient of interaction terms with Social Media ($\boldsymbol{MarketPsych\_SocialM_{i,t-5min}}$) as *Attention_SocialM, Sentiment_SocialM, and Emotion_SocialM, as* shown in Table 10. We operationalize positive co-jumps as one when both COMEX futures and SPDR ETF observe a positive price jump, while negative co-jump when both COMEX futures and SPDR ETF observe a negative co-jump.

Table 10 presents our regression results for equation (26). We find that Social media Attention to Gold during US news announcement has the most significant impact on intraday co-jump as it increases the predictability of both positive and negative co-jump. In contrast, we find from Table 10 that News Attention has positive impact on predictability of only negative co-jumps during US macroeconomic news announcements. This indicates that market participants pay greater attention to news media during arrival of macroeconomic news, which indicates fall in gold prices. Next we, observe that positive social media sentiment has positive and significant impact on positive co-jumps during US scheduled macroeconomic announcements. Interestingly, we find that both news and social media emotion have highly positive and significant impact on predictability of positive co-jumps during US news announcements. In contrast, news media based emotions positively impacts positive jumps and negatively impacts negative jumps. Thus, we infer from Table 10 that market psych predictors have stronger impact on predictability of intraday co-jumps in gold when these coincide with US macroeconomic news announcements.

5.3.3. Impact of Disaggregated US Scheduled News on Co-Jumps

In this section, we investigate the news-watcher hypothesis to identify the set of 29 disaggregate US scheduled macroeconomic news surprises, as enlisted in Table 4, causes intraday co-jumps in gold markets of COMEX futures and SPDR ETF. We adopt least absolute shrinkage and selection operator (LASSO) logistic regression. We perform the following LASSO logistic regression separately for All, Positive and Negative co-jumps in CME futures and SPDR ETF, such as-

$$\boldsymbol{P(CoJump_t = 1|X_{t-5min}) = G(\alpha_o + \sum_{i=1}^{29} \beta_{1,i} USDisagg\_SchMNewsSurp_{t-5min} + \sum_{i=1}^{3} \beta_{2,i}\, MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{3,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{5} \beta_{4,i} COMEX\_Liq_{k,t-5min} + \beta_5 COMEX\_RV_{t-5min} + \sum_{k=1}^{5} \beta_{6,i} ETF\_Liq_{k,t-5min} + \beta_7 ETF\_RV_{t-5min} + \varepsilon_t)} \quad \textbf{(27)}$$

where, $\boldsymbol{P(Co-Jump_t = 1|X_{t-5min})}$ is the conditional probability of observing an intraday co-jump (All, Positive or Negative) given 5-minute lagged set of predictors i.e $\boldsymbol{X_{t-5min}}$. **X** comprises of 5-minute lagged values of the following predictors –(1) Standardised News Surprise for 29 US disaggregate scheduled macroeconomic news announcements ($\boldsymbol{USDisagg\_SchMNewsSurp}$), which are enlisted in Table 4, and news surprise is calculated in Section 4.1 using Balduzzi et al.(2011) approach, 2) three dimensions of Market Psych aspects namely, Attention, Sentiments, and Emotions from news media ($\boldsymbol{MarketPsych\_NewsM_{i,t-5min}}$) and Social media ($\boldsymbol{MarketPsych\_SocialM_{i,t-5min}}$), (3) four aspects of liquidity for COMEX futures (***COMEX_LiquidityPredictors***) and ETF SPDR (***ETF_LiquidityPredictors)*** separately in 5-minute lagged form, such as - *Liq1_TradingActivity*, $Liq2\_TradeCost$, $Liq3\_PriceImpact$, and Liq4_$Illiquidity_{t-5min}$. Lastly, we also assess the impact of (4) lagged volatility for COMEX futures and ETF SPDR ($\boldsymbol{Volatility_{t-5min}}$). $\boldsymbol{G}$ is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$.

Table 11 presents our results for equation (27). We observe that not all macroeconomic news surprises cause intraday co-jumps in gold markets. We find that *FOMC rate decision* is the most important US macroeconomic news surprise which predict intraday co-jumps in gold markets and has positive impact on all, positive, and negative co-jumps between COMEX gold futures and ETF SPDR. Moreover, we observe that positive news, which indicates good future state of the economy, have negative impact on positive co-jumps and positive impact on negative co-jumps, like *Non-Farm Payroll, GDP Advance, Retail Sales New Home Sales, Durable Goods Sales Consumer Confidence and ISM Manufacturing.* While we find that negative news, which reflect deterioration in the future state of the economy, have positive impact on positive co-jump and negative impact on negative co-jumps in gold like *Initial Jobless Claim and Unemployment*. This corroborates safe haven and hedging properties of gold.

We also observe from Table 11 that positive and negative co-jumps are predictable by different macroeconomic news surprises. *FOMC Rate Decision, Non-Farm Payroll, GDP Advance, Durable Goods Sales,* which predicts both positive as well as negative co-jumps. We find that majority of positive co-jumps in gold are driven by *New Home Sales, Construction Spending, International Trade, Consumer Confidence, Initial Jobless Claim, and ISM Manufacturing*. In contrast, negative co-jumps in gold markets are predictable by *Factory Order, CPI, PMI Manufacturing, Leading Index, and Unemployment*. In addition, we observe macroeconomic news which have large surprise index (see Table 4) have greater impact on the predictability of intraday co-jumps like *FOMC Rate Decision*, *Retail Sales, Industrial Production, Unemployment, Construction Spending, and ISM Manufacturing*. Moreover, we observe from Table 11 and Table 4 that macroeconomic news which have greater dispersion in surprise, as evident from the standard deviation of surprise in Table 4, are more dominant determinants of intraday co-jumps, like *Durable Goods Sales, CPI, Non-Farm Payroll, GDP Advance, International Trade, Capacity Utilisation, Leading Index and PMI Manufacturing*.

6. Robustness Tests

6.1. Alternative Jump Detection Methods

We undertake several alternative measures of intraday jump detection at 5-minute sampling frequency for both COMEX gold futures and SPDR gold ETF. We identify intraday jumps using the intersection of Andersen et al. (2007) corrected for periodicity using Boudt et al. (2011) method and Bollerslev et al. (2013) method as discussed in Section 3.1. Table 12 reports the number of intraday jumps detected using Andersen et al. (2007) as ABD, Andersen et al. (2007) with periodicity of Boudt et al. (2011) as ABD_BOUDT, Lee and Mykland (2008) as LM, Lee and Mykland (2008) with periodicity correction of Boudt et al.(2011) as LM_BOUDT, Bollerslev et al.(2013) as BLT, along with intersection of BLT ∩ ABD_BOUDT and BLT ∩ LM_BOUDT. As a test of robustness, we identify intraday jumps using Lee and Mykland (2008) method (LM) and also control for periodicity of Boudt (2011) as LM_BOUDT along with intersection of LM with BLT, as shown in Table 12. We present intraday jump detection at 95% and 99% threshold for all measures for the full sample period 2010-2018 in Table 12. We find 2402 intraday price jumps in COMEX futures using ABD_BOUDT method as compared to 2142 using BLT and 956 using LM_BOUDT at 95% threshold. Similarly, we find that 2170 jumps in SPDR ETF using ABD_BOUDT and 2057 jumps using BLT and 866 jumps using LM_BOUDT. We find that the number of intraday jumps detected varies across method and therefore, we use a combination of methods to avoid the problem of false and spurious detection of jumps.

6.2. Alternative Sampling Frequency

We perform jump detection estimation across various sampling frequencies i.e. 1-/3-/5-/10-minutes in order to check variation in the number of intraday jumps detected across sampling frequencies. Table 13 reports the number of intraday price jump during the full sample period using all jump detection methods at 95% threshold across four sampling frequencies. We find that number of jumps detected falls as sampling frequencies increases. We find 8904 jumps at 1-minute interval while 3529 jump at 3-minutes, 2402 at 5-minutes and 1419 jumps at 10-minute for COMEX futures. We find similar results for SPDR ETF. Since our volatility signature plot (Figure A1 in Appendix) justifies the adoption of 5-minute as our optimal sampling frequency, we use the same for the purpose of this study. It is consistent with the past academic studies (Andersen et al. (2003b), Bandi and Russell (2004), Hansen and Lunde (2006) and Aït-Sahalia, Mykland and Zhang (2005**)** which prove that 5-minute sampling frequency strikes a fine balance between the confounding effect of market microstructure noise by sampling too frequently and blurring the price reaction of specific event by sampling too infrequently.

7. Conclusion

We provide first time evidence of real time characteristics, drivers, and impact of intraday jump and co-jumps in global gold markets by using high frequency data sampled at 5-minutes for COMEX gold futures and SPDR Gold ETF. Our main contribution is to analyse whether intraday price jumps and co-jumps in gold occur due to (1) Market Psych-attention, sentiments, emotions, (3) macroeconomic news announcements and surprise or (3) illiquidity or trading activity. Using TRMI high frequency properietory dataset for market psych towards gold, our novel contribution is to examine whether and how market psych triggers intraday price jumps and co-jumps in gold by investigating three dimension of market psych, namely-*attention, sentiments and emotions,* after controlling for news surprises and illiquidity. What makes our study unique is that we decipher whether news and social media based market psych dimensions have different impact on the predictability of positive and negative price jumps and co-jumps at high frequency. We provide comparative analysis of intraday predictability of price jumps and co-jumps in both COMEX gold futures and SPDR gold ETF, separately for postive and negative signed jump and co-jumps. Using intraday event study analysis, we examine pre-jump and post-jump behavior of liquidity, its dimensions and volatility conditions suurounding the postive and negative price jumps. Lastly, to complement the non-parametric event study analysis , we conduct a penalised (ridge and LASSO) logistic regression to examine the intraday predictors of postive and negative price jumps and co-jumps and test news-watcher's hypothesis to identify which scheduled macreconomic news surrpises predicts jumps and co-jumps in gold.

We find that COMEX gold future experience greater number of intraday jumps (1101) as compared to SPDR Gold ETF (1045) from 2010-2018. We find greater occurrence of negative price jumps than positive jumps in both gold markets, indicating that gold market crashes are more prominent. We observe that US scheduled macroeconomic news is the most dominant predictor of intraday price jumps and co-jumps. We find that US scheduled macroeconomic news announcement causes 18-25% of intraday jumps in COMEX futures while 21-28% jumps in ETF

SPDR. Using intraday event study analysis, we find trading activity, trading cost, ammihud illiquidity, and volatility are at elevated level 10-15 minutes prior to both positive and negative jump while buy side orderflow rises during positive price jumps and sell side order flow rises during negative price jump. Next, we find that news attention increases the predictability of negative price jumps and co-jumps while social media attention to gold increases the predictability of positive jumps and co-jumps. We also observe asymmetric effect of market sentiment as positive media sentiment predicts positive price jumps.

Our study have important implication as we observe that a sizeable proportion of price jumps and co-jumps occur due to US scheduled macroeconomic news, which is consistent with the reactionary nature of gold as an asset class. As price jumps and co-jumps are also preceded by large increase in illiquidity (widening of bid ask spread and ammihud illiquidity ratio), it implies presence of informed traders prior to news and uninformed traders try to avoid trading with them. It implies that informed traders in gold market possess superior skills which results in increase spread by market makers. We find that drivers of jumps and co-jumps are similar but vary with sign of jump size. Lastly, using LASSO logistic regression we find that positive jumps and negative jumps are driven by different set of US scheduled macroeconomic news surprises. We find FOMC Rate Decision is the most dominant and statistically significant US scheduled macroeconomic news, followed by Initial Jobless Claim and Unemployment, which are common and significant predictors for both positive and negative price jump and co-jumps predictability in gold markets. We find that positive price jumps and co-jumps in both gold markets are majorly driven by FOMC, Retail Sales, New Home Sales, Construction Spending, Initial jobless claim and Unemployment. In contrast, negative price jump and co-jumps in gold are predictable from news surprises related to FOMC, Non-farm payroll, GDP Advance, Capacity Utilisation, Durable Goods, Consumer Confidence, PMI Manufacturing, Initial Jobless Claim and Unemployment. We observe that macroeconomic news which have large surprise index have greater impact on the predictability of intraday price jumps in gold markets. As a avenue for future research, we can conduct similar analysis for other asset classes for emerging and developed markets to assess whether the sources of price jumps varies across markets and instruments. Another direction for future research is to examine the information spillover during price jumps and assess its causes. Lastly, we can develop trading strategies on the basis significant predictors of postive and negative price jumps in gold to assess the profitability of such trading strategies.

8. References

Aït-Sahalia, Y., & Jacod, J. (2009). Testing for jumps in a discretely observed process. *The Annals of Statistics*, 184-222.

Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling, and forecasting of return volatility. *The review of economics and statistics*, *89*(4), 701-720.

Baker, S. R., Bloom, N., Davis, S. J., & Sammon, M. C. (2021). *What triggers stock market jumps?* (No. w28687). National Bureau of Economic Research.

Bollerslev, T., Law, T. H., & Tauchen, G. (2008). Risk, jumps, and diversification. *Journal of Econometrics*, *144*(1), 234-256.

Bollerslev, T., Todorov, V., & Li, S. Z. (2013). Jump tails, extreme dependencies, and the distribution of stock returns. *Journal of Econometrics*, *172*(2), 307-324.

Boudt, K., & Petitjean, M. (2014). Intraday liquidity dynamics and news releases around price jumps: Evidence from the DJIA stocks. *Journal of Financial Markets*, *17*, 121-149.

Caporin, M., & Poli, F. (2022). News and intraday jumps: Evidence from regularization and class imbalance. *The North American Journal of Economics and Finance*, *62*, 101743.

Das, S. R., & Uppal, R. (2004). Systemic risk and international portfolio choice. *The Journal of Finance*, *59*(6), 2809-2834.

Dumitru, A. M., & Urga, G. (2012). Identifying jumps in financial assets: a comparison between nonparametric jump tests. *Journal of Business & Economic Statistics*, *30*(2), 242-255.

Dungey, M., & Hvozdyk, L. (2012). Cojumping: Evidence from the US Treasury bond and futures markets. *Journal of Banking & Finance*, *36*(5), 1563-1575.

Evans, K. P. (2011). Intraday jumps and US macroeconomic news announcements. *Journal of Banking & Finance*, *35*(10), 2511-2527.

Frömmel, M., Han, X., & Van Gysegem, F. (2015). Further evidence on foreign exchange jumps and news announcements. *Emerging Markets Finance and Trade*, *51*(4), 774-787.

Ivanov, S. I. (2013). The influence of ETFs on the price discovery of gold, silver and oil. *Journal of Economics and Finance*, *37*, 453-462.

Lahaye, J., Laurent, S., & Neely, C. J. (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics*, *26*(6), 893-921.

Lahaye, J., Laurent, S., & Neely, C. J. (2011). Jumps, cojumps and macro announcements. *Journal of Applied Econometrics*, *26*(6), 893-921.

Lee, S. S. (2012). Jumps and information flow in financial markets. *The Review of Financial Studies*, *25*(2), 439-479.

Megaritis, A., Vlastakis, N., & Triantafyllou, A. (2021). Stock market volatility and jumps in times of uncertainty. *Journal of International Money and Finance*, *113*, 102355.

Nguyen, D. B. B., & Prokopczuk, M. (2019). Jumps in commodity markets. *Journal of Commodity Markets*, *13*, 55-70.

Piccotti, L. R. (2017). Financial contagion risk and the stochastic discount factor. *Journal of Banking & Finance*, *77*, 230-248.

Scaillet, O., Treccani, A., & Trevisan, C. (2020). High-frequency jump analysis of the bitcoin market. *Journal of Financial Econometrics*, *18*(2), 209-232.

Sehgal, S., Sobti, N., & Diesting, F. (2021). Who leads in intraday gold price discovery and volatility connectedness: Spot, futures, or exchange-traded fund?. *Journal of Futures Markets*, *41*(7), 1092-1123.

Sun, B., & Gao, Y. (2020). Market liquidity and macro announcement around intraday jumps: Evidence from Chinese stock index futures markets. *Physica A: Statistical Mechanics and Its Applications*, *541*, 123308

TABLES AND FIGURES

FIGURES

Figure 1 : Intraday Distribution of Price Jumps and Co-jumps in Gold Markets across Trading Hours (07:30-16:00 ET)

Figure 1 display hourly distribution of intraday price jumps in CME gold futures and SPDR Gold ETF along with Co-Jumps between the two during core overlapping trading hours from 07:30-16:00 ET over full sample period 2010-2018. To detect intraday price jumps, we use a combination of jump detection techniques proposed by Andersen et al. (2007, 2012) and Bollerslev et al. (2013) corrected for intraweek volatility periodicity by using weighted standard deviation (WSD) method proposed by Boudt et al.(2011). We use the co-exceedance rule to detect intraday co-jumps between two gold markets as explained in Section 3.1.

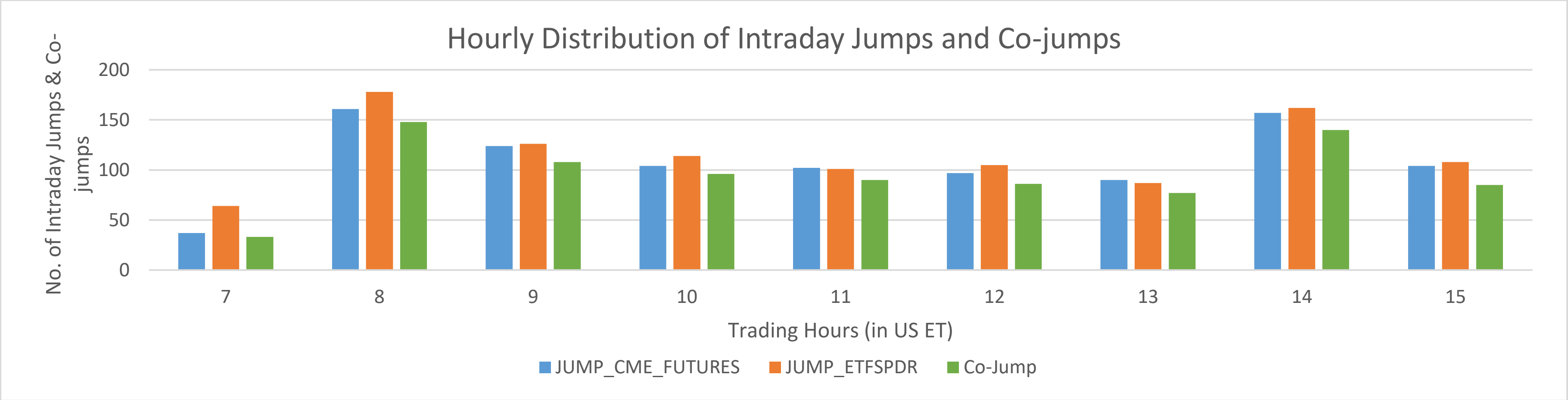


Figure 2 : Intraday Event Study of Positive and Negative Jump for <u>COMEX Gold ETF</u>

Figure 2 display event study graphs using intraday event study analysis for the six possible determinants of intraday postive and negative jumps in CME gold futures namely – three liquidity dimensions of CME gold futures- trading activity (trades and depth), trading cost (proportional effective spread), price impact (order imbalance), ammihud illiquidity and three aspects of Market Psych (Attention, Sentiments, and Emotions) for both news media and social media. In addition, the behavior of intraday Abnormal Returns during occurance of postive and negative jumps is displayed in Fig 2(a), Absolute abnormal return in Fig 2(b), Realised Volatility in Fig 2(c), Number of Trades in Fig 2(d), depth in Fig 2(e), proportional effective spread in Fig 2 (f), ammihud illiquidity in Fig 2(g), order imbalance in Fig 2(h), News Attention to gold in Fig 2(i), Social Media Attention to Gold in Fig 2(j), News Sentiments for gold in Fig 2(k), Social media sentiments for gold in Fig 2 (l), News media based Emotions w.r.t gold in Fig 2 (m), social media based emotions in Fig 2(n).The event window is 12 five-minutes before the jump interval (-60 minutes) and 12 five-minutes after the jump interval (+ 60 minutes). Following Piccotti (2018), we use constant mean return model to calculate abnormal values of the above mentioned predictor variables. Two dashed lines indicate the 5% to 95% quantile interval. The white circles indicate the points when Mann-Whitney null hypothesis gets rejected.

Fig 2(a) Cumulative Abnormal Return (CAR) around Positive Jump and Negative Jump

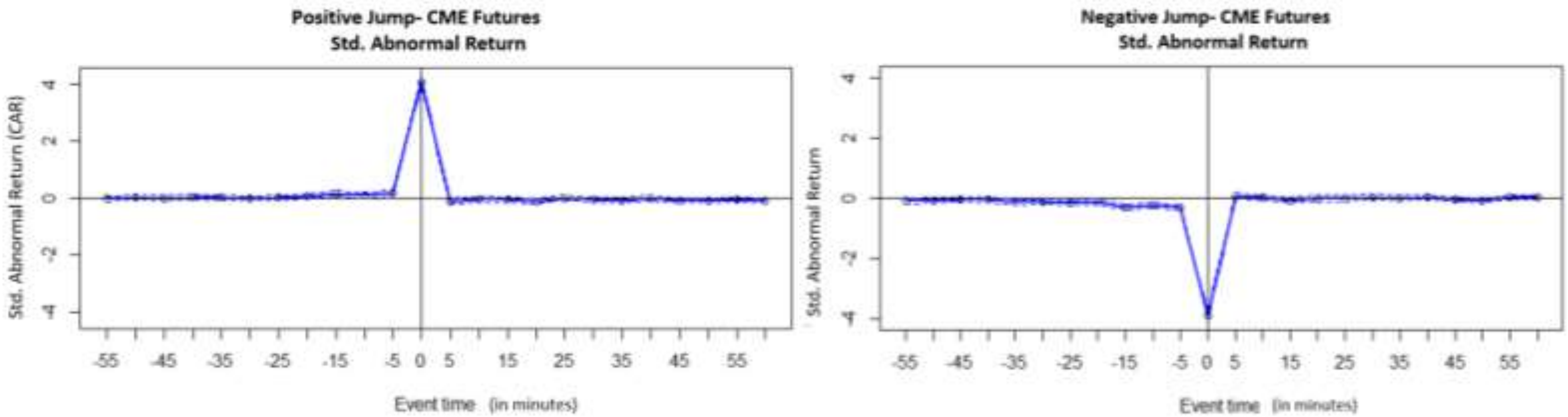


Fig 2(b).Absolute Abnormal Return around Positive Jump and Negative Jump

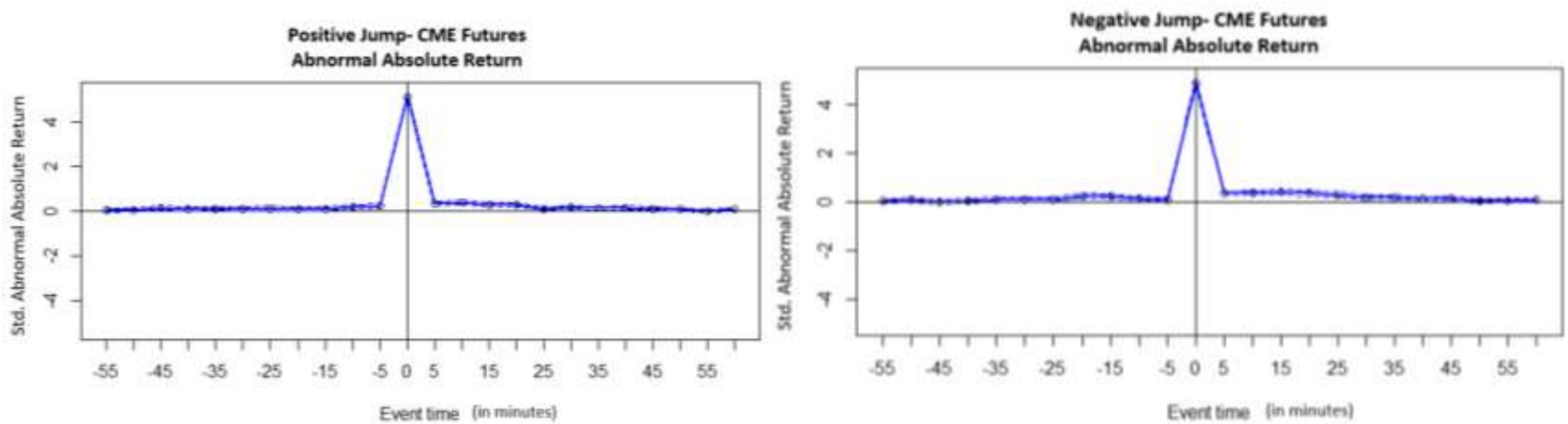
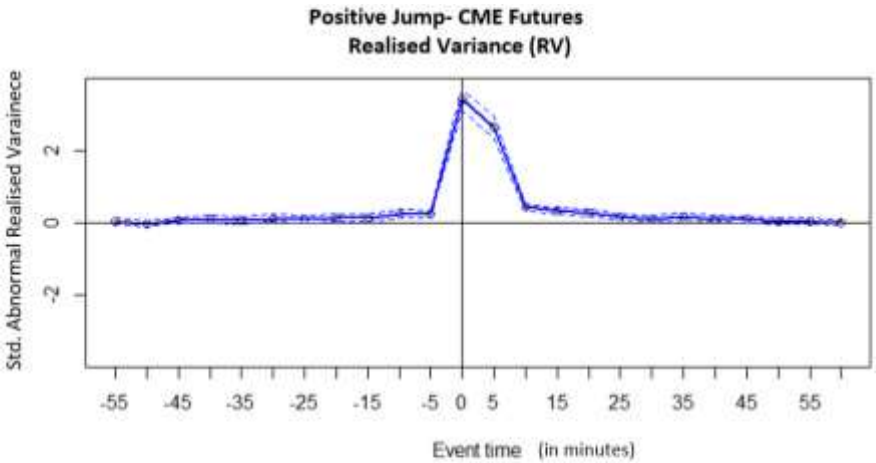


Fig 2(c). Realised Variance around Positive Jump and Negative Jump



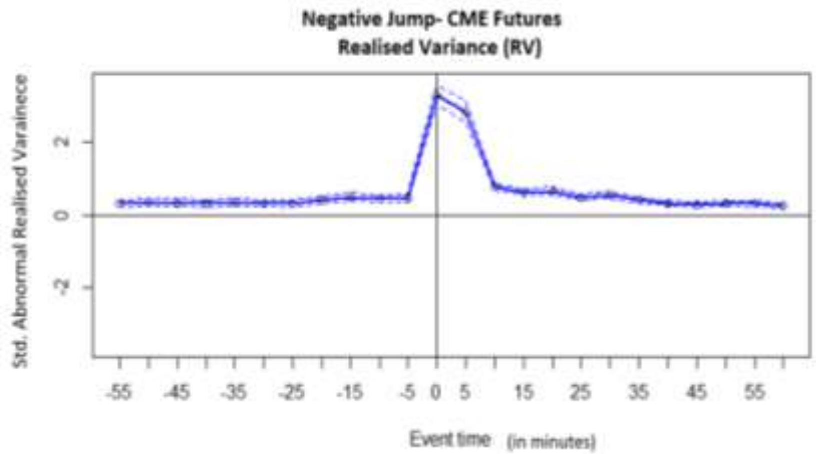
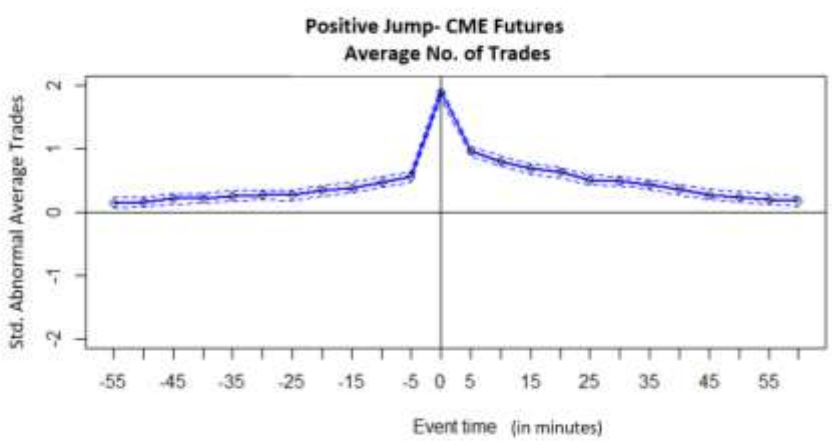


Fig 2(d). Std. Number of Trades around Positive Jump and Negative Jump



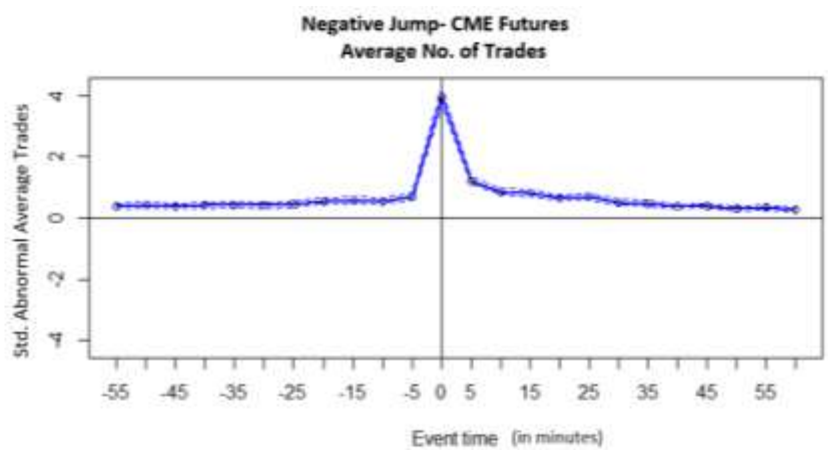


Fig 2(e).Std. Depth around Positive Jump and Negative Jump

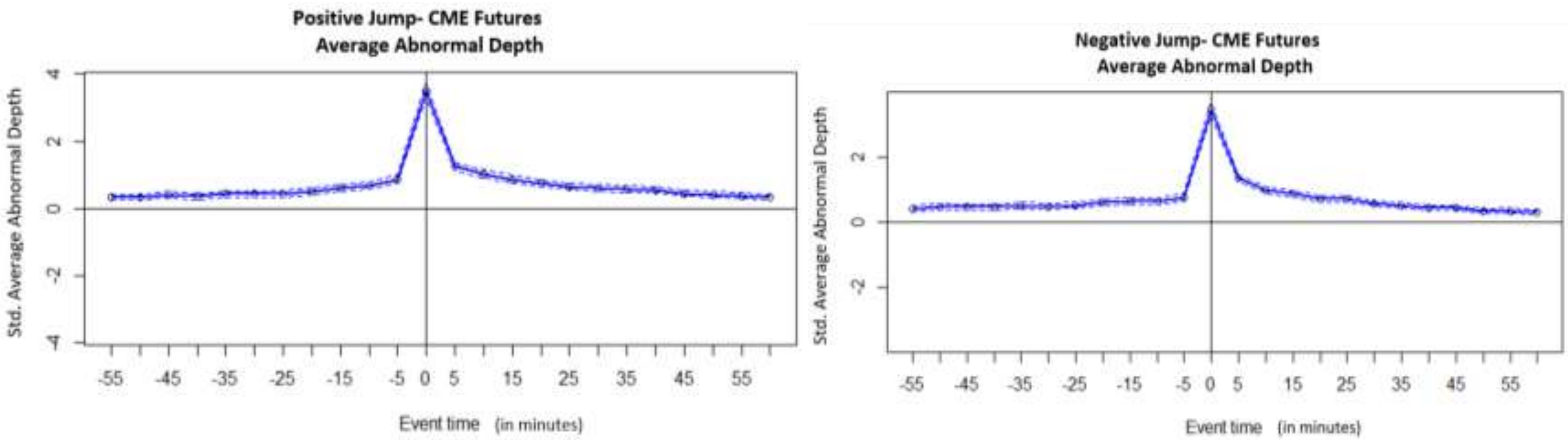


Fig 2(f). Proportional Effective Spread around Positive Jump and Negative Jump

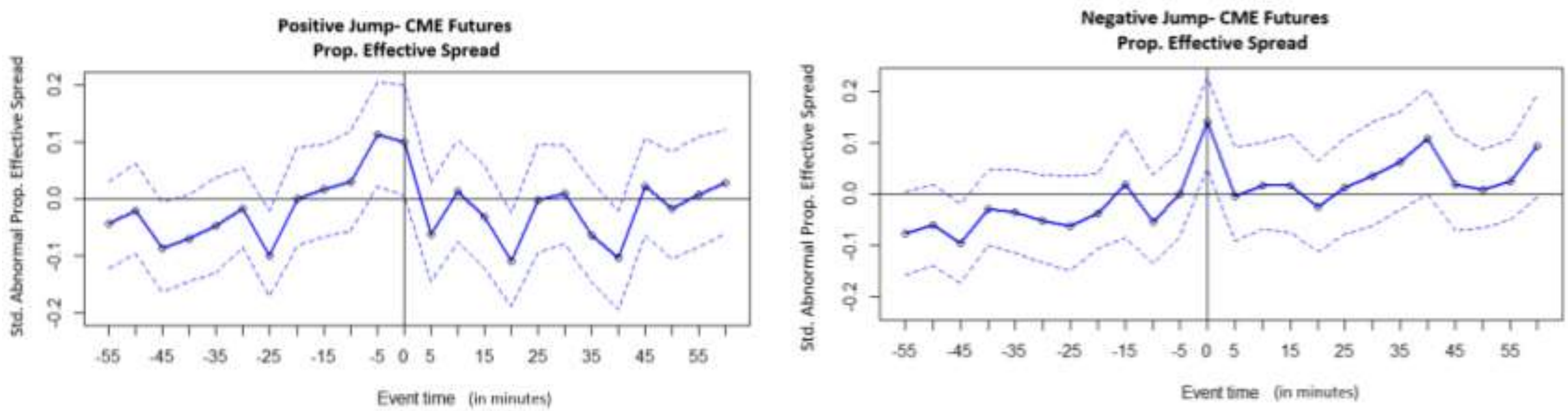


Fig 2(g). Ammihud Illiquidity around Positive Jump and Negative Jump

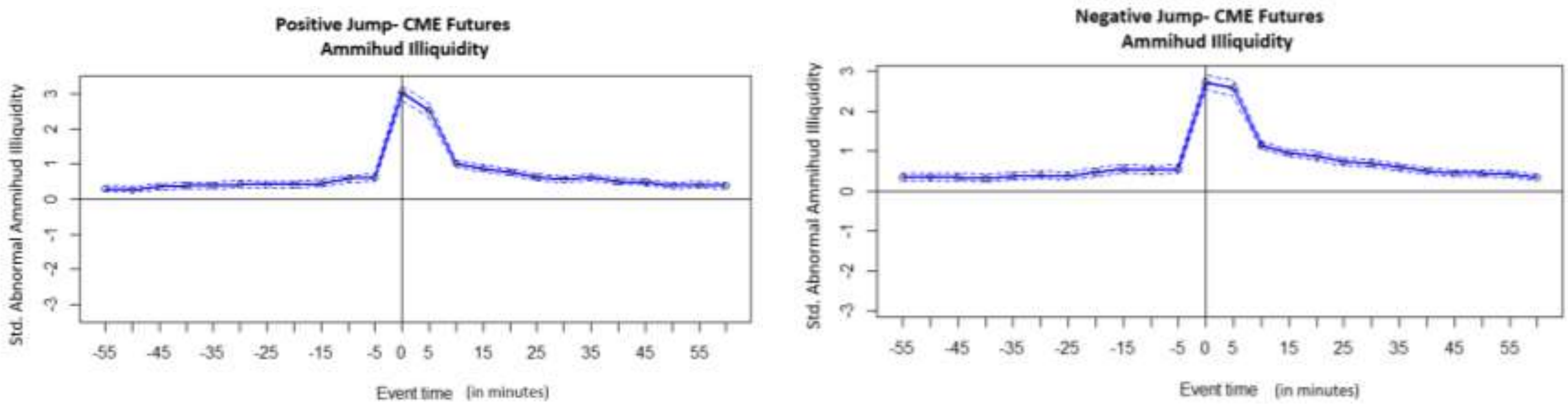


Fig 2(h). Order Imbalance around Positive Jump and Negative Jump

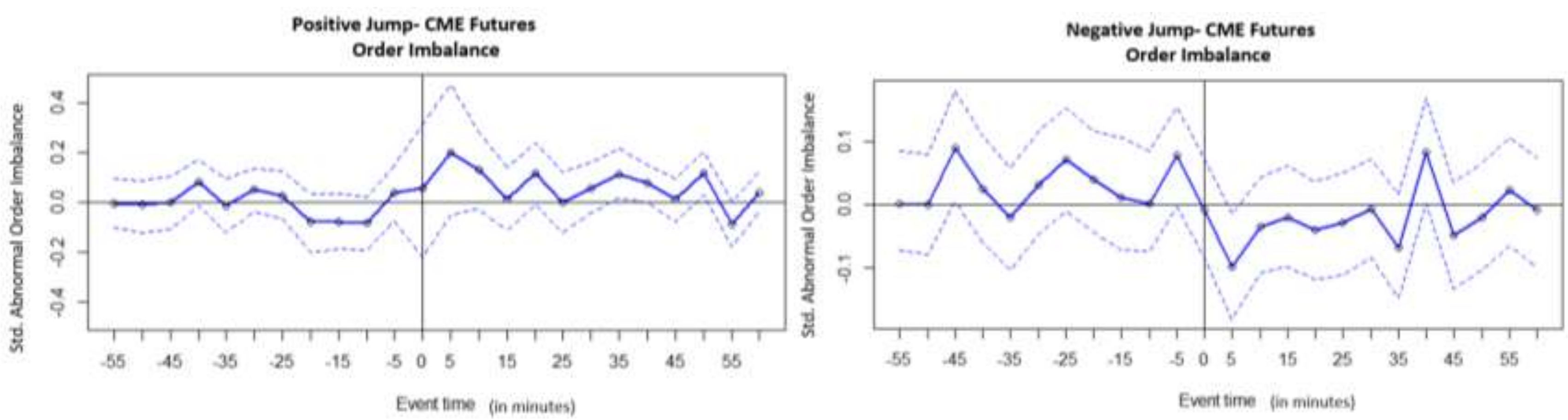
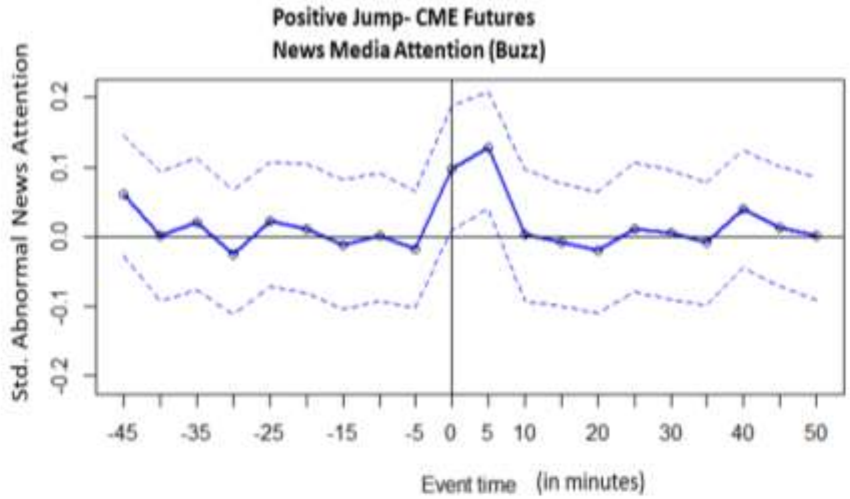


Fig 2(i) News Attention around Positive Jump and Negative Jump



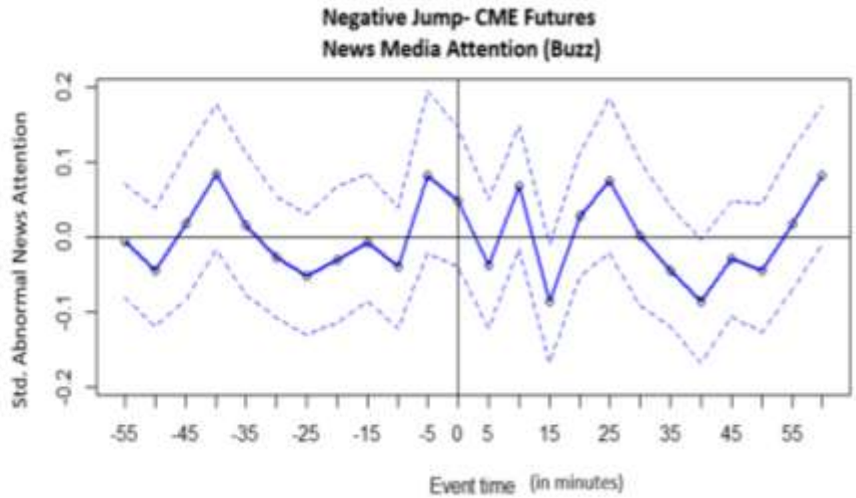
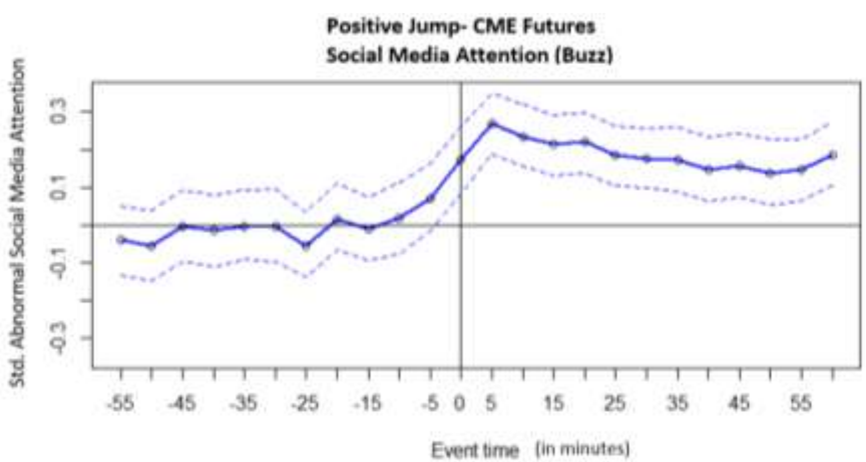


Fig 2(j). Social Media Attention around Positive Jump & Negative Jump



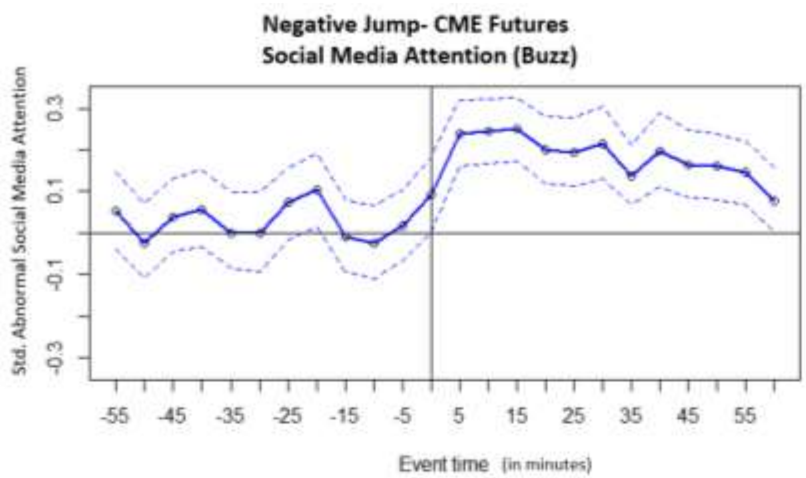


Fig 2(k). News Sentiment around Positive Jump and Negative Jump

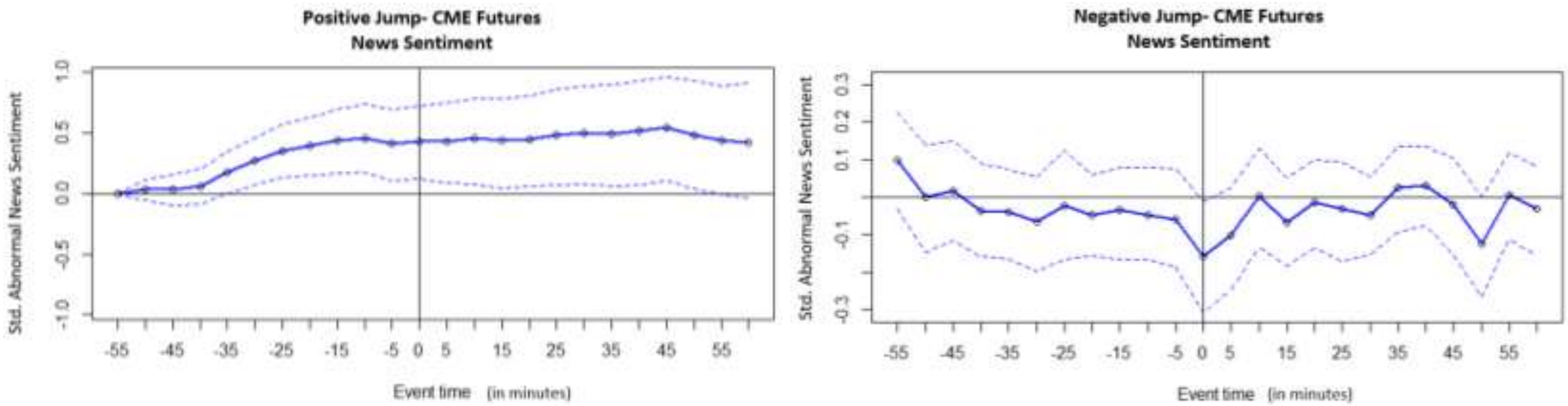


Fig 2(l). Social Media Sentiment around Positive Jump and Negative Jump

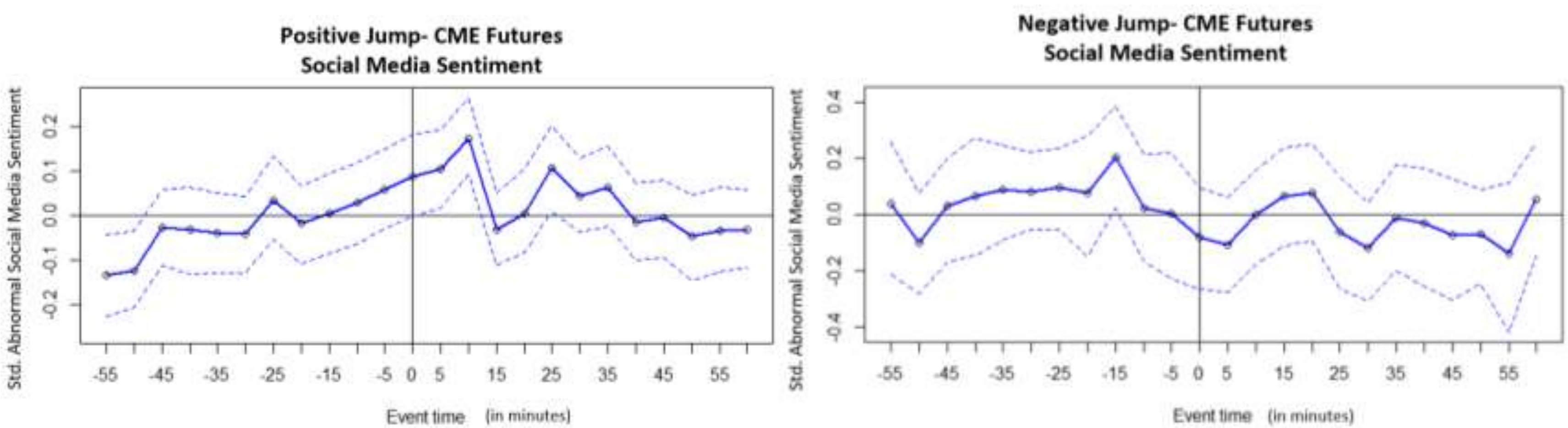


Fig 2(m). News Emotions around Positive Jump and Negative Jump

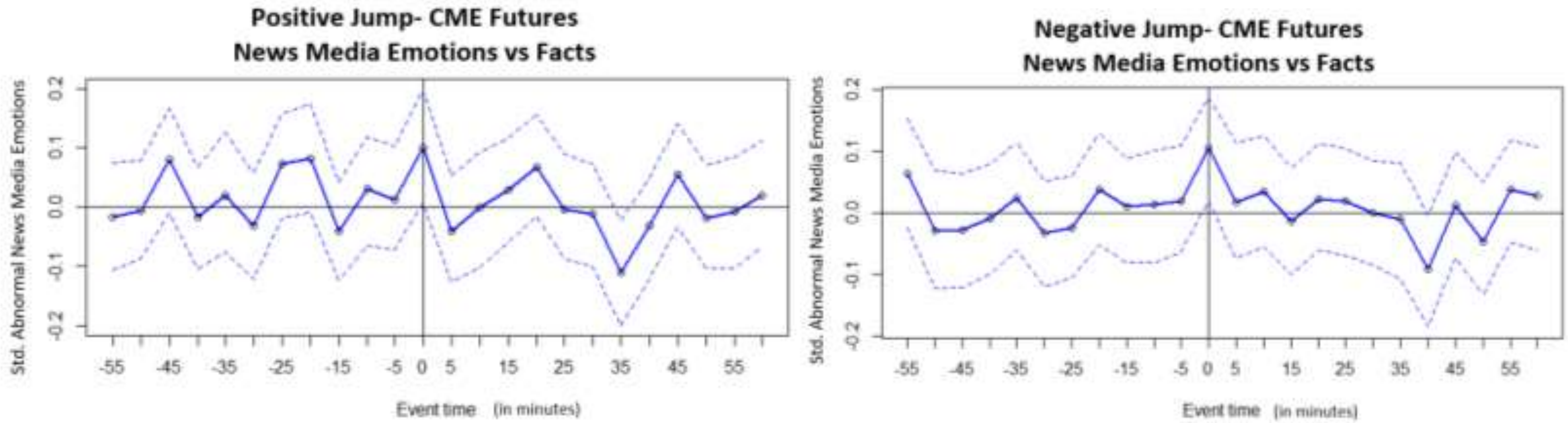


Fig 2(n) Social media Emotions around Positive Jump and Negative Jump

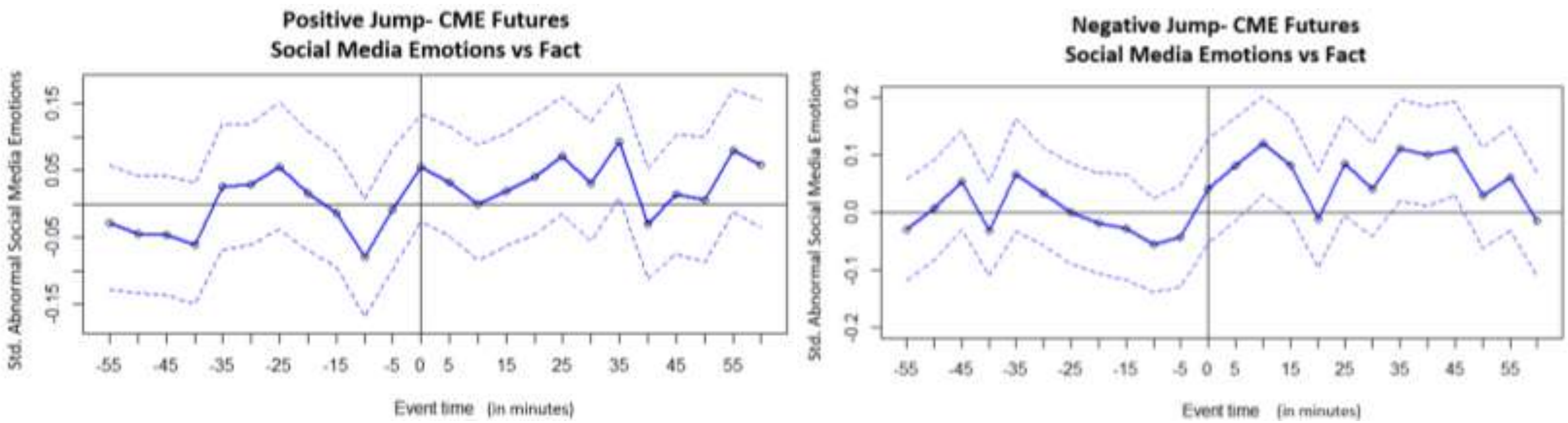


Figure 3 : Intraday Event Study around Positive and Negative Price Jump for Gold ETF SPDR

Figure 3 display event study graphs using intraday event study analysis for the six possible determinants of intraday postive and negative jumps in Gold ETF SPDR namely – three liquidity dimensions of SPDR Gold ETF- trading activity (trades and depth), trading cost (proportional effective spread), , price impact (order imbalance), ammihud illiquidity and three aspects of Market Psych (Attention, Sentiments, and Emotions) for both news media and social media. In addition, the behavior of intraday Abnormal Returns during occurance of postive and negative jumps is displayed in Fig 3(a), Absolute abnormal return in Fig 3(b), Realised Volatility in Fig 3(c), Number of Trades in Fig 3(d), depth in Fig 3(e), proportional effective spread in Fig 3(f), ammihud illiquidity in Fig 3(g), order imbalance in Fig 3(h), News Attention to gold in Fig 3(i), Social Media Attention to Gold in Fig 3(j), News Sentiments for gold in Fig 3(k), Social media sentiments for gold in Fig 3(l), News media based Emotions w.r.t gold in Fig 3(m), social media based emotions in Fig 3(n).The event window is 12 five-minutes before the jump interval (-60 minutes) and 12 five-minutes after the jump interval (+ 60 minutes). Following Piccotti (2018), we use constant mean return model to calculate abnormal values of the above mentioned predictor variables. Two dashed lines indicate the 5% to 95% quantile interval. The white circles indicate the points when Mann-Whitney null hypothesis gets rejected.

Fig 3(a) Cumulative Abnrmal Returns (CAR) around Positive Jump and Negative Jump

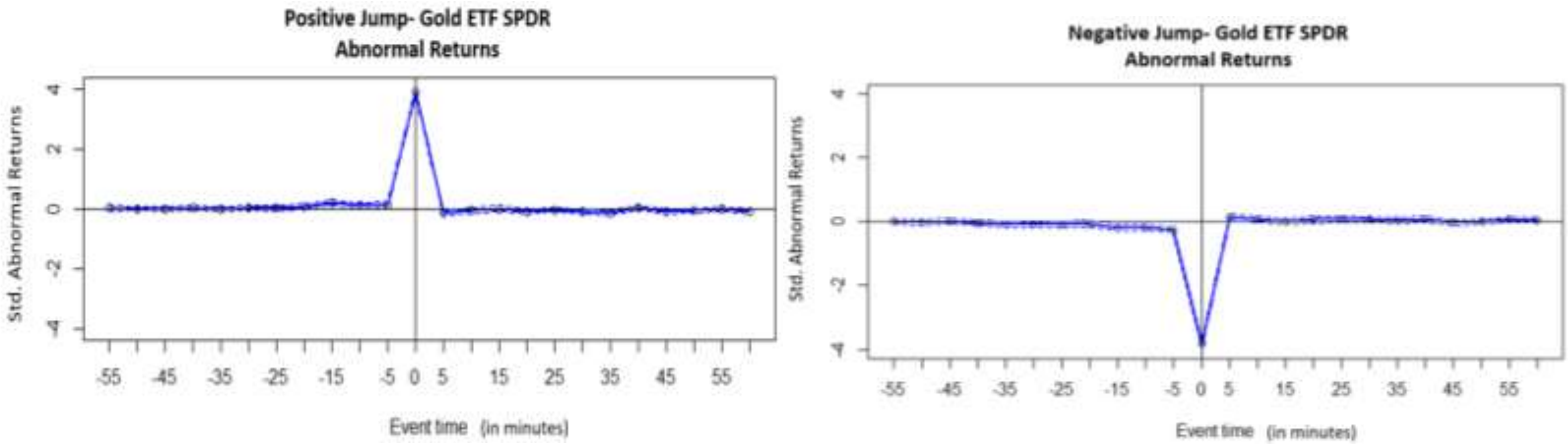


Fig 3(b). Absolute Return around Positive Jump and Negative Jump

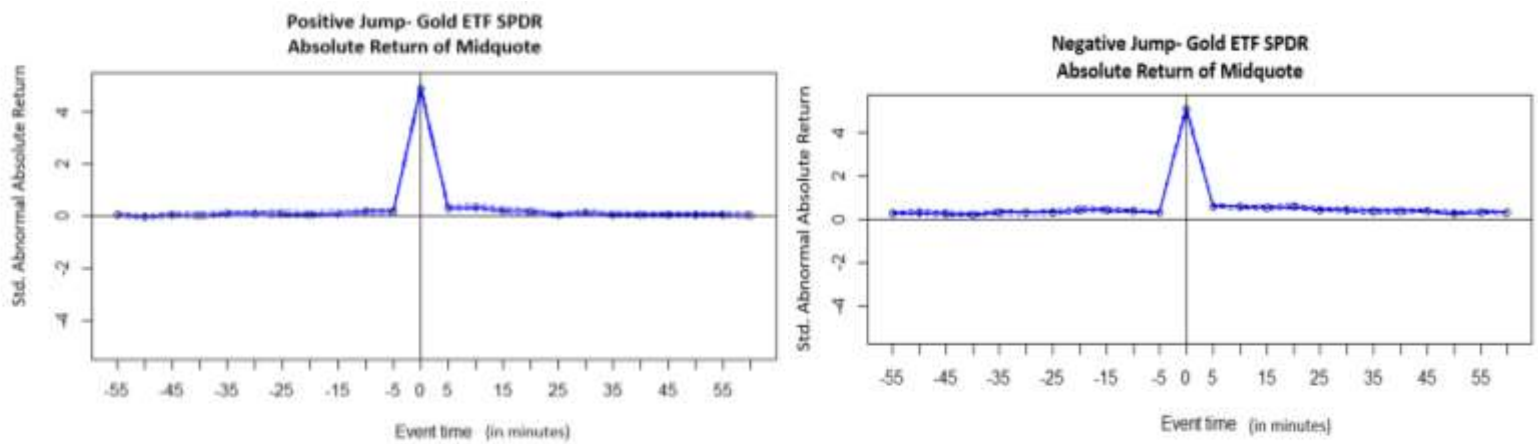


Fig 3(c). Realised Variance around Positive Jump and Negative Jump

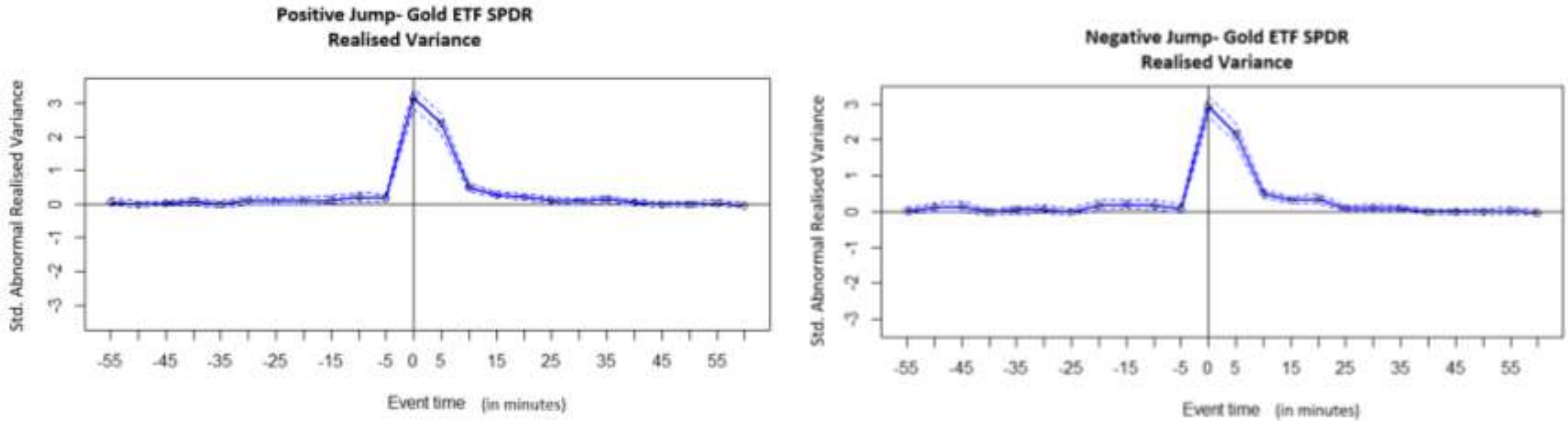


Fig 3(d) Number of Trades around Positive Jump and Negative Jump

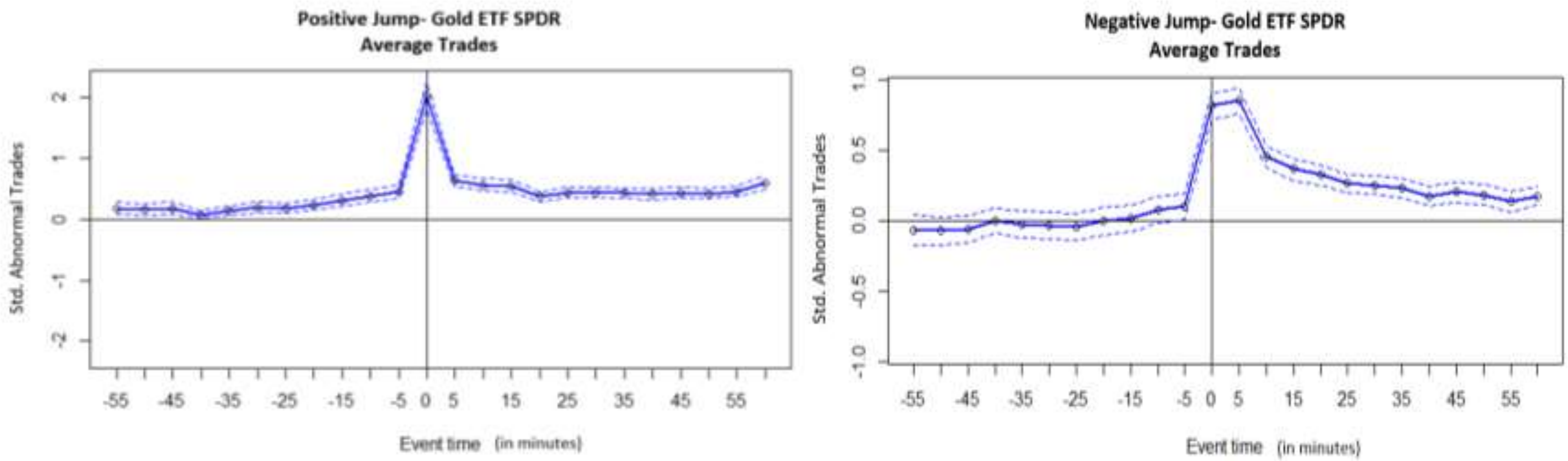


Fig 3(e). Depth around Positive Jump and Negative Jump

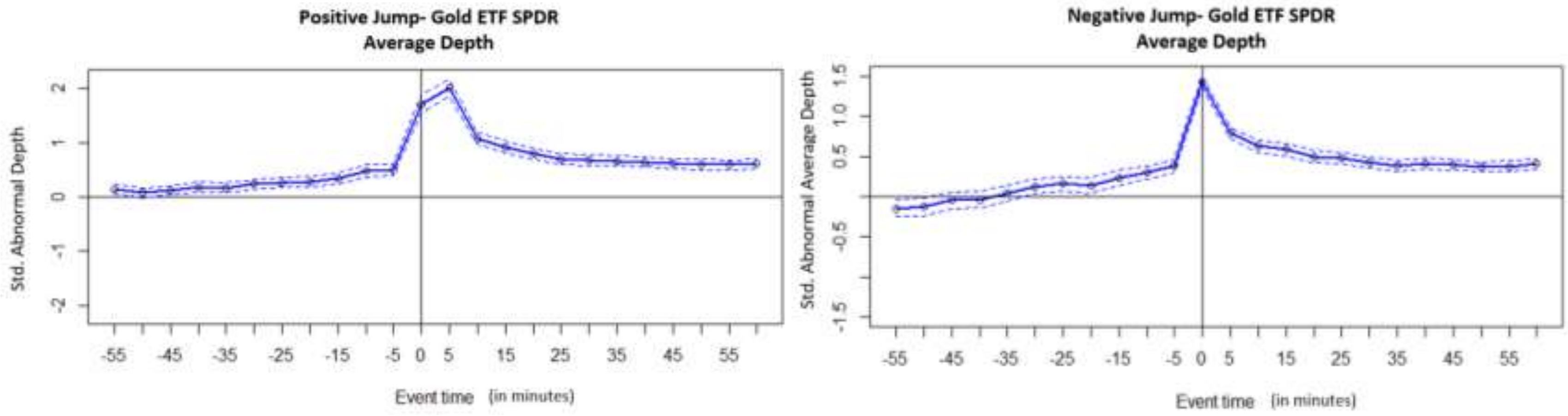


Fig 3(f) Proportional Effective Spread around Positive Jump and Negative Jump

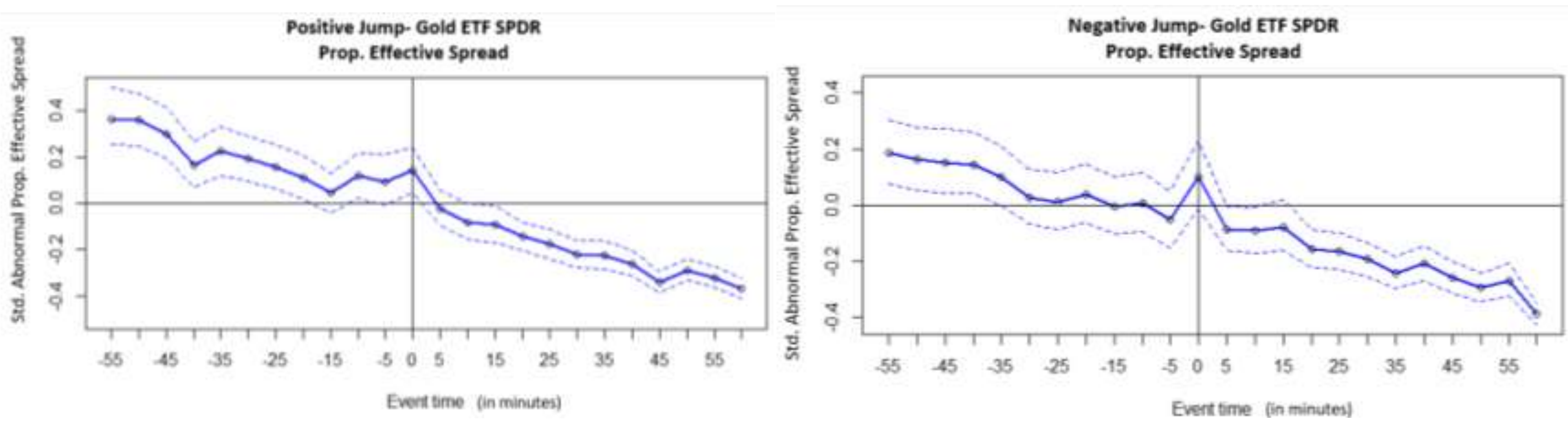
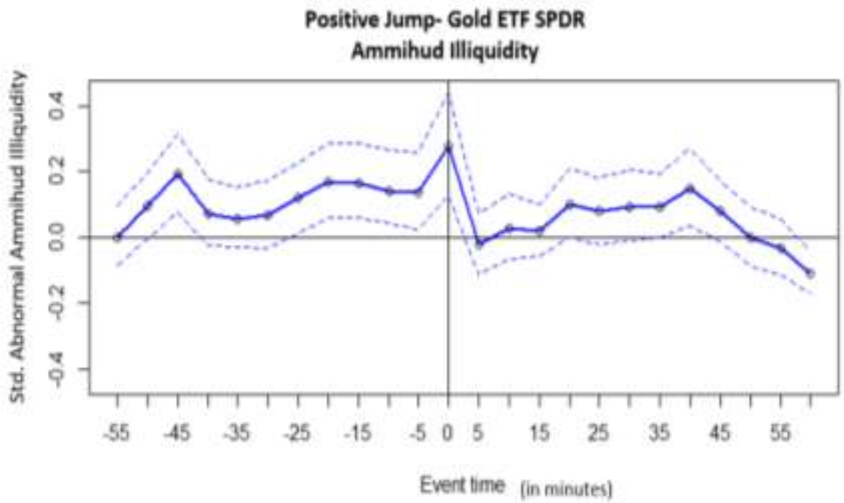


Fig 3(g). Ammihud Illiquidity around Positive Jump and Negative Jump



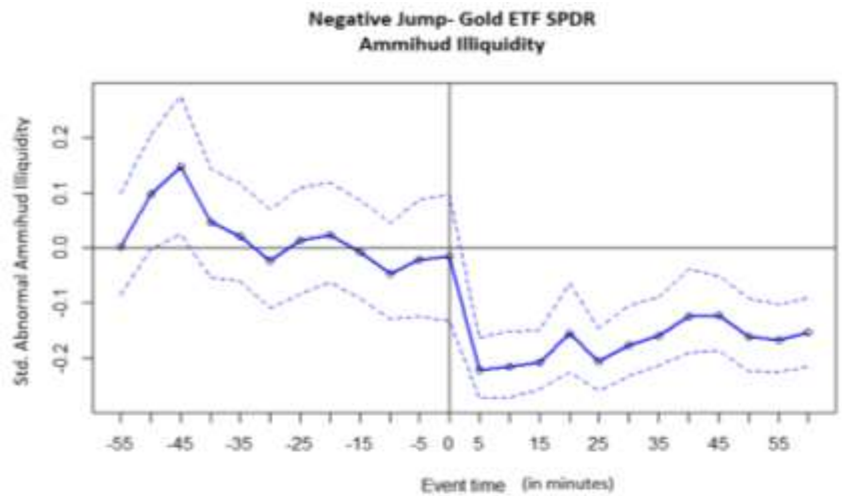
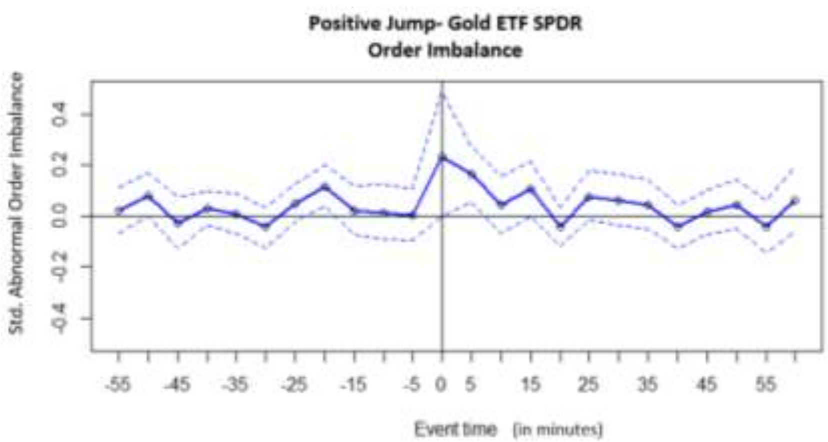


Fig 3(h). Order Imbalance around Positive Jump and Negative Jump



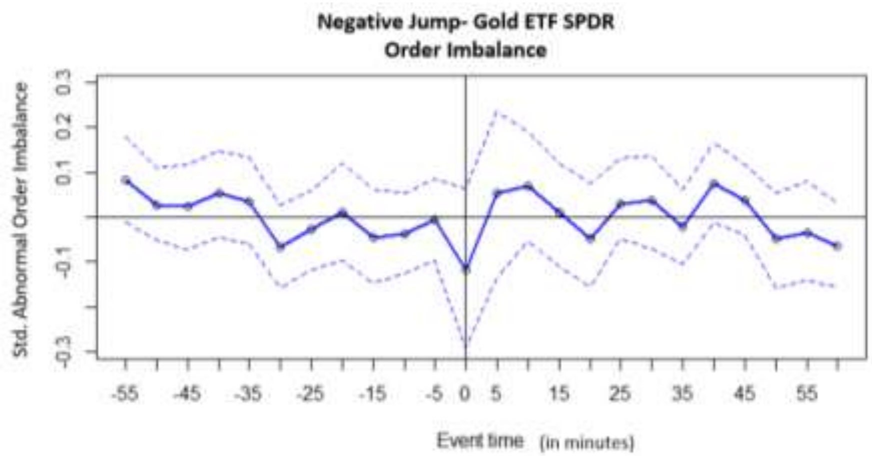


Fig 3(i) News Attention to Gold around Positive Jump and Negative Jump

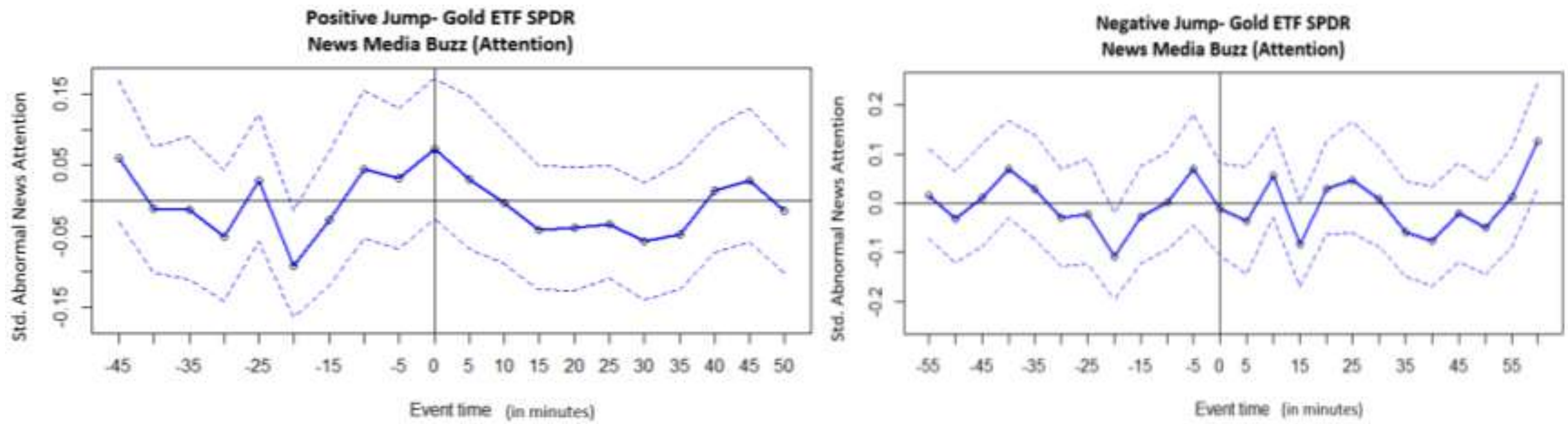


Fig 3(j) Social Media Attentionto Gold around Positive Jump and Negative Jump

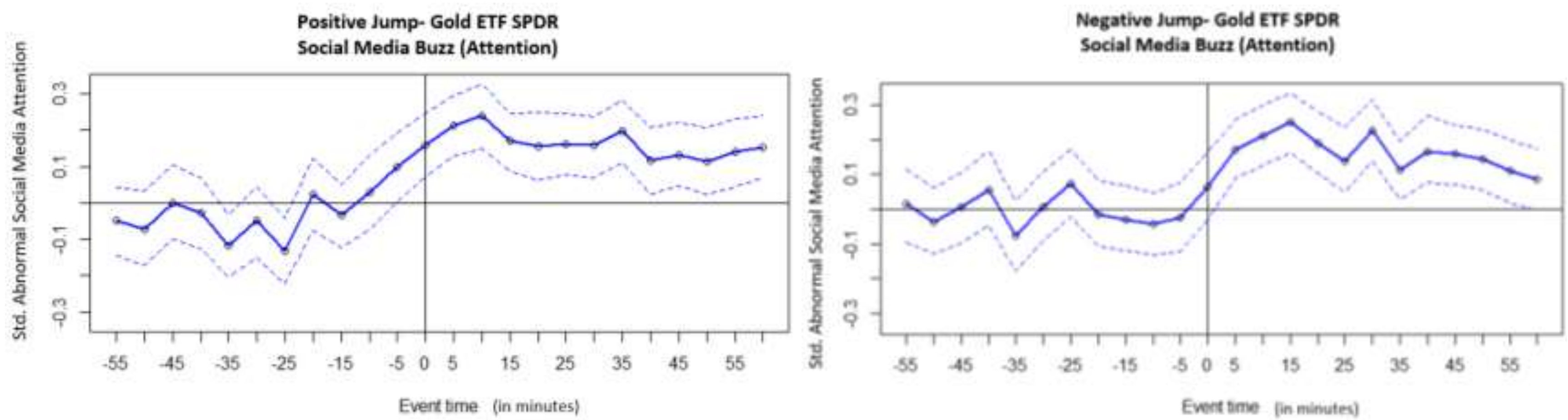


Fig 3(k) News Sentiments for Gold around Positive Jump and Negative Jump

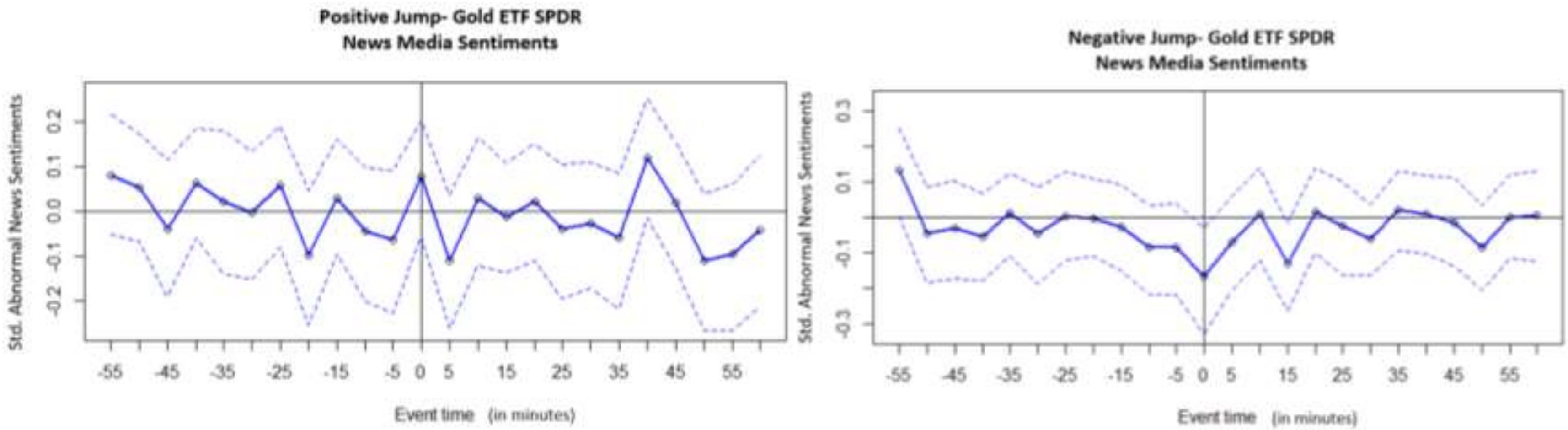


Fig 3(l). Social Media Sentiments for Gold around Positive Jump and Negative Jump

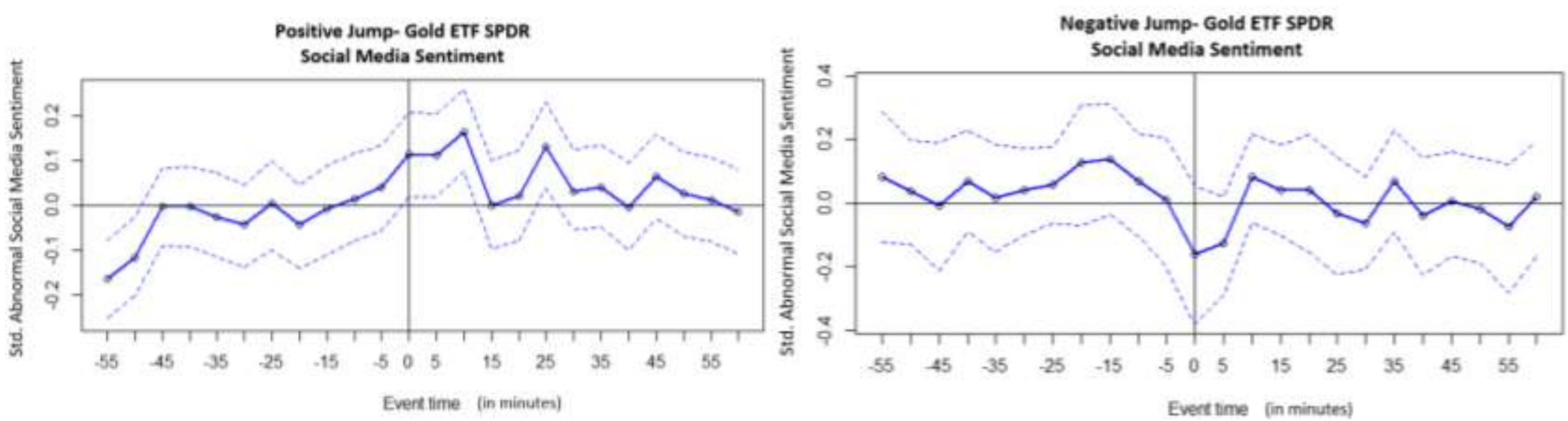


Fig 3(m). News Emotions w.r.t gold around Positive Jump and Negative Jump

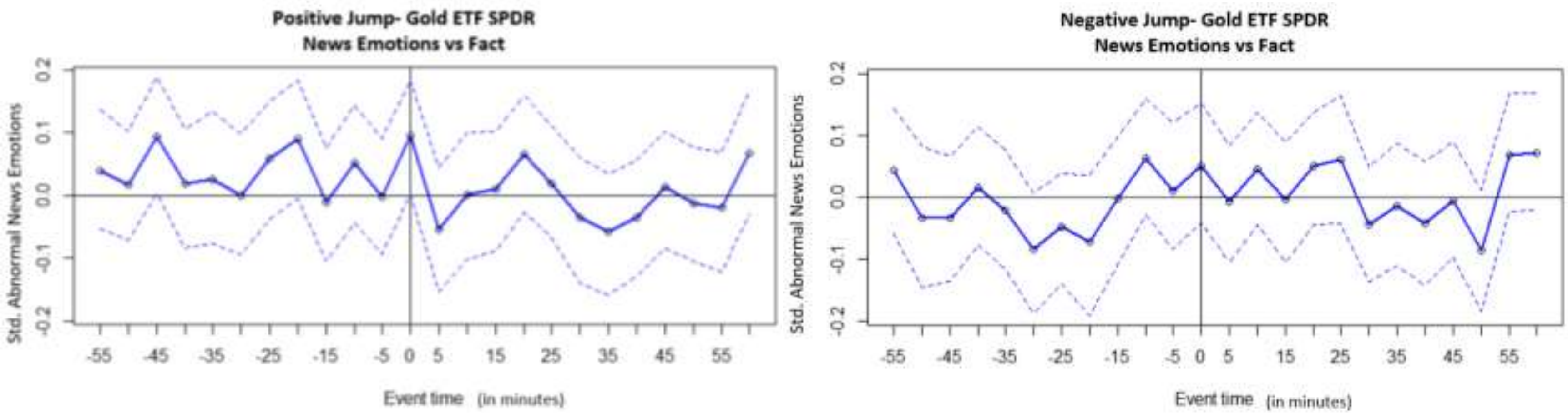
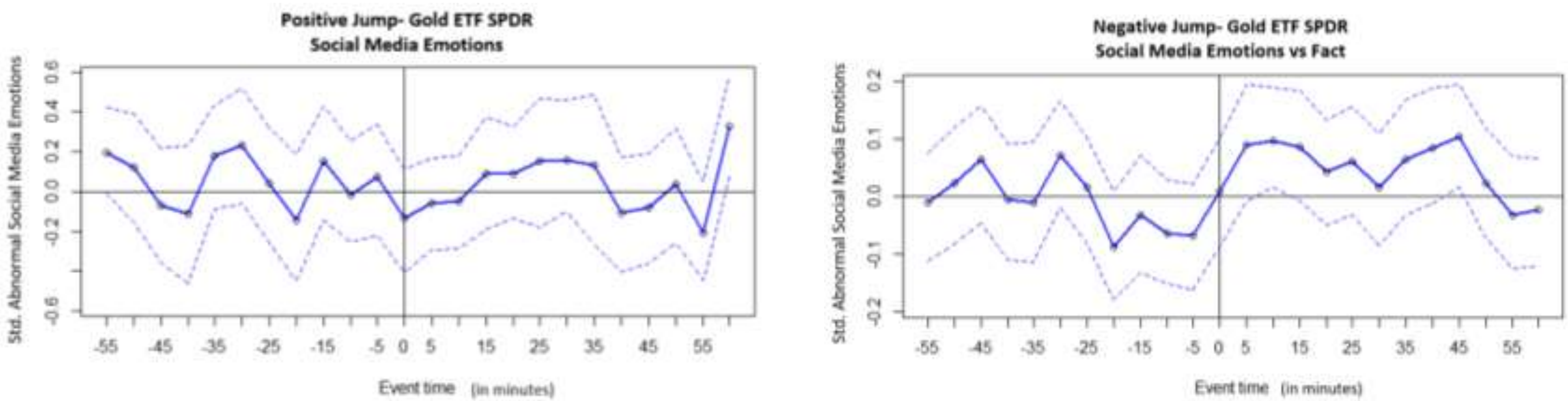


Fig 3(n). Social Media Emotions w.r.t gold around Positive Jump and Negative Jump



TABLES

Table 1- Summary Statistics for Gold & MarketPsych during Jump & No-Jumps Days

This table depicts microstructural and market quality aspects for two major gold markets- CME gold futures and ETF Gold SPDR for JUMP DAYS and NO-JUMP DAYS. Panel A presents descriptives statistics of mean, median, and standard deviation(STD) for the microstructure aspects like return, effective spread, trades, order imbalance, realised varaince, depth, ammihud Illiquidity, Ask Size, and Bid Size during JUMP DAYS. Panle B present the descriptive statistics of the same microstructural aspects on NO-JUMP DAYS. Panel C presents summary statistics for TRMI MarketPsych dimensions of attention, sentiment and emotions from news and social media sources for JUMP DAYS and NO-JUMP DAYS.

Panel A: DAYS WITH JUMPS (JUMP DAYS)

	CME FUTURES (No. of Observation = 664)			ETF SPDR (No. of Observation =687)		
Microstructural Aspects	**MEAN**	**MEDIAN**	**STD**	**MEAN**	**MEDIAN**	**STD**
Return	-0.0036%	-0.0601%	0.3822%	-0.0035%	-0.086%	0.4087%
Effective Spread	0.0163%	0.0079%	0.0410%	0.0241%	0.0090%	0.0415%
Trades	1710	1004	1959	1263	866	1318
Order Imbalance	-66	3	2835	-13	4	2561
Realised Variance	0.0547%	0.0195%	0.127%	0.0536%	0.020%	0.1199%
Depth	1347	820	1660	4392	3288	4133
Ammihud Illiquidity	0.0601%	0.0488%	0.0478%	0.00013%	0.00001%	0.00117%
Ask Size	3348	2017	4161	6422	4810	6190
Bid Size	3383	2038	4155	6422	4810	6190

Panel B : DAYS WITHOUT JUMPS (NO-JUMP DAYS)

	CME FUTURES (No. of Obs.= 233344)			ETF SPDR (No. of Obs.= 208422)		
Microstructural Aspects	**MEAN**	**MEDIAN**	**STD**	**MEAN**	**MEDIAN**	**STD**
Return	-0.00001%	0.000%	0.071%	0.007%	0.000%	0.055%
Effective Spread	0.012%	0.008%	0.027%	0.016%	0.009%	0.028%
Trades	478.4	293	631	515.8	347	579
Order Imbalance	4.05	2	862	11	7	115
Realised Variance	0.00557%	0.0019%	0.0216%	0.0061%	0.0022%	0.0207%
Depth	550	333.6	702	1261	842	1388
Ammihud Illiquidity	0.021%	0.016%	0.017%	0.00011%	0.00001%	0.00176%
Ask Size	1376	833	1762	2953	2071	2986
Bid Size	1374	831	1764	2953	2071	2986

Panel C: Summary Statistics for TRMI (Attention, Sentiments & Emotions)

	JUMP DAYS			NO JUMP DAYS		
TRMI MarketPsych Dimensions	**MEAN**	**MAX**	**STD**	**MEAN**	**MAX**	**STD**
News Attention	19.48	311.47	24.721	18.3	659.8	23.41
News Sentiments	-0.01836	1	0.275	-0.00956	1	0.27
News Emotions	0.2843	1	0.373	0.2618	1	0.37
Social Media Attention	11.167	218.25	20.352	10.54	4414.73	24.99
Social Media Sentiments	-0.02154	1	0.271	-0.0192	1	0.27
Social Media Emotions	0.2611	1	0.408	0.2374	1	0.42

Table 2 : Descriptive Statistics of Intraday Price Jumps (All, Positive, and Negative Jumps)

Table 2 reports summary statistics for intraday price jumps dynamics for two gold markets – COMEX futures and ETF SPDR for ALL intraday jumps, positive jumps and negative jumps over the full sample period 2010-2018. We separately analyse the daily jumps statistics in Panel A, the intraday jump statistics in Panel B, microstructural aspects in Panel C and TRMI indicators in Panel D for All Jump days, Positive Jump Days and Negative Jump Days for COMEX gold futures and ETF SPDR). Positive jumps are those intraday jumps whose realised return (jump size) is greater than zero while negative jump have realised return less than zero.

Panel A: Summary Statistics for Daily Jumps	**CME Futures**	**ETF SPDR**
No. of Obs.	233344	209474
No. of Days	2065	2074
No. of Jump Days	664	687
P(Jump Day)	32.15%	33.12%

	CME Futures			**ETF SPDR**		
Panel B: Summary Statistics for Intraday Jumps	**ALL JUMPS**	**POSITIVE JUMP**	**NEGATIVE JUMP**	**ALL JUMPS**	**POSITIVE JUMP**	**NEGATIVE JUMP**
No. of Intraday Jump	1101	539	562	1045	520	525
P(Intraday Jump) (%)	53.3	26.1	27.2	50.4	25.1	25.3
E(#Intraday Jump | Jump Day)	1.658	0.812	0.846	1.521	0.757	0.764
Average Jump Size (%)	-0.004	0.321	-0.315	-0.003	0.340	-0.344
Median Jump Size(%)	-0.060	0.276	-0.264	-0.086	0.292	-0.278
Max Jump Size (%)	1.593	1.593	-0.039	1.590	1.590	-0.082
Min Jump Size(%)	-1.773	0.046	-1.773	-2.186	0.063	-2.186
Mean Absolute Jump Size(%)	0.318	0.321	0.315	0.342	0.340	0.344
Standard Deviation of Jump Size (%)	0.382	0.202	0.221	0.409	0.200	0.245
Skewness (%)	-0.144	2.053	-2.522	-0.332	2.183	-2.938
Kurtosis (%)	4.24	10.95	13.50	4.61	11.54	16.45
All US News Days	1485	1485	1485	1489	1489	1489
All US News Announcements Obs.	2222	2222	2222	2225	2225	2225
Intraday Jump and US News Day	205	106	99	223	117	106
P(Intraday Jump| US News Day) (%)	13.80%	7.14%	6.67%	14.98%	7.86%	7.12%
P(US News Day| Intraday Jump) (%)	18.62%	19.67%	17.62%	21.34%	22.50%	20.19%
Panel C : Summary Statistics for Microstructural Aspects (Market Quality)						
Trades	1710	1660	1758	1263	1186	1339
Depth	1346	1347	1346	4392	4225	4557
Realised Variance	0.0547%	0.0546%	0.0548%	0.0536%	0.0534%	0.0538%
Ammihud Illiquidity	0.0601%	0.0617%	0.0586%	0.0001%	0.0002%	0.0001%
Effective Spread	0.0163%	0.0173%	0.0154%	0.0241%	0.0240%	0.0243%
Order Imbalance	-66.13	24.71	-153.2	-13	42	-265
Panel D: Summary Statistics for TRMI (Buzz, Sentiments & Emotions)						
News Attention	19.48	19.298	19.66	19.631	19.8	19.47

News Sentiments	-0.018	-0.024	-0.013	-0.009	-0.011	-0.007
News Emotions	0.284	0.289	0.280	0.283	0.288	0.277
Social Media Attention	11.17	11.00	11.33	11.59	11.69	11.48
Social Media Sentiments	-0.022	-0.001	-0.042	-0.018	0.002	-0.039
Social Media Emotions	0.261	0.253	0.269	0.258	0.252	0.264

Table 3 : Descriptive Statistics of Intraday Co-jumps

Table 3 provides descriptive statistics for all intraday co-jumps, positive co-jumps and negative co-jumps between COMEX gold futures and ETF SPDR during the overlapping trading hours for full sample period 2010-2018. We define co-jump as simultaneous occurrence of intraday jump in two gold instruments as widely adopted by Piccotti (2018) and Chatrath et al.(2013). Panel A presents summary statistics like No.of intrday co-jump, Prob of Co-Jump Day, Prob of Co-Jump given intrady jump, average co-jump size, median, maximum and minimum co-jump size, standard co-jump size, skewness and kurtosis for CME futures and ETF SPDR for ALL cojumps, Positive Co-jumps, Negative Co-jumps. Panel B presents microstructural and market quality aspects of CME futures and ETF SPDR during ALL, Positive and Negative Co-Jump. Panel C presents insights on aggregate US macroeconomic news and occurance of intraday co-jumps.

	CME Futures			**ETF SPDR**		
Panel A : Summary Statistics for Co-Jump	**ALL COJUMPS**	**POSITIVE COJUMP**	**NEGATIVE COJUMP**	**ALL COJUMPS**	**POSITIVE COJUMP**	**NEGATIVE COJUMP**
No. of Intraday Co-Jump	863	426	437	863	426	437
P(Co-Jump Day)	41.79%	20.63%	21.16%	41.61%	20.54%	21.07%
E(#Co-Jump| Intraday Jump)	0.78	0.79	0.78	0.83	0.82	0.83
Average Co-Jump Size (%)	-0.002	0.355	-0.350	0.0001	0.355	-0.346
Median Co-Jump Size (%)	-0.093	0.313	-0.291	-0.081	0.312	-0.291
Max Co-Jump Size (%)	1.593	1.593	-0.082	1.589	1.589	0.558
Min Co-Jump Size (%)	-1.773	0.062	-1.773	-1.808	0.063	-1.808
Mean Absolute Co-Jump Size (%)	0.353	0.355	0.350	0.355	0.355	0.354
Standard Deviation of Co-Jump Size (%)	0.413	0.201	0.227	0.416	0.201	0.242
Skewness (%)	-0.159	2.219	-2.571	-0.194	2.206	-1.999
Kurtosis (%)	3.82	11.91	13.38	3.83	11.79	11.93
Panel B – Microstructural Aspects						
Trades	1986	1946	2025	1480	1389	1566
Depth	3808	3842	3733	6990	6845	7132
Realised Variance	0.064%	0.0638%	0.0651%	0.0627%	0.0614%	0.0641%
Ammihud Illiquidity	0.0661%	0.0673%	0.0649%	0.0001%	0.0002%	0.0060%
Effective Spread	0.0153%	0.0162%	0.0145%	0.0213%	0.0207%	0.0218%
Order Imbalance	-112.7	8.9	-231.3	-15	-23.1	-292
Panel C: Summary Statistics for Co- Jumps and US News						
Co-Jump and US News	191	96	95	-	-	-
US News Days	1489	1489	1489	-	-	-
P(Co-Jump|USNews)	12.83%	6.45%	6.38%	-	-	-
P(US News|Co-Jump)	22.13%	22.54%	21.74%	-	-	-

Table 4 – Summary Statistics for Disaggregated US Scheduled Macroeconomics News Announcements & Surprises

This table shows descriptive statistics of 29 individual US macroeconomic news announcements and reports its release time in eastern daylight time of New York, name of news item, frequency of announcement, total no. of news days, mean of the surprise, standard deviation of surprise, total no. of days with positive news surprise, mean of positive surprise, total no. of days with negative news surprise and mean of negative surprise calculated for entire sample period 2010-2018 and extracted from Bloomberg.

US Scheduled Macroeconomic News (Disaggregated)

Release Time in ET	Scheduled Macroeconomic News	Frequency of Announce-ment	Total no. of News Days	Mean of News Surprise	Standard Deviation of News Surprise	No. of Positive Surprise days	Mean of Positive Surprise	No. of Negative Surprise Days	Mean of Negative Surprise
08:30	US_Personal Income	Monthly	87	-0.02	1	29	0.73	34	-0.68
08:30	US_Non Farm Payroll	Monthly	99	-0.03	0.95	48	0.76	51	-0.77
08:30	US_Retail Sales	Monthly	87	-0.13	0.69	29	0.63	45	-0.66
08:30	US_GDP Advance	Monthly	87	-0.07	0.96	36	0.75	39	-0.85
08:30	US_Personal Consumption	Monthly	87	0.09	0.98	43	0.86	36	-0.8
08:30	US_Durable Goods Sales	Twice in a month	109	0.05	1.11	62	0.64	39	-0.87
08:30	US_Imports	Monthly	87	0.07	0.95	44	0.83	33	-0.92
08:30	US_Current Account Balance	Quarterly	29	0.13	1.06	15	0.94	14	-0.75
08:30	US_International Trade	Monthly	87	-0.02	0.97	40	0.72	46	-0.67
08:30	US_PPI	Monthly	87	-0.02	0.86	37	0.76	36	-0.83
08:30	US_CPI	Monthly	87	-0.08	1.05	20	1.42	30	-1.18
08:30	US_Housing Starts	Monthly	87	-0.07	0.98	41	0.76	46	-0.81
08:30	US_Initial Jobless Claims	Weekly	378	-0.04	0.96	168	0.75	205	-0.68
08:30	US_Unemployment_Rate	Monthly	87	-0.36	0.98	24	0.76	40	-1.24
08:30	US_Building Permit	Monthly	87	0.19	1.04	46	0.93	40	-0.66
09:15	US_Capacity Utilisation	Monthly	87	-0.16	1.04	31	0.96	47	-0.92
09:15	US_Industrial Production	Monthly	87	-0.14	1.05	32	0.95	46	-0.92
09:45	US_PMI Manufacturing	Monthly	87	0.13	1.03	45	0.92	41	-0.74
10:00	US_Construction Spending	Monthly	87	-0.37	0.94	34	0.51	51	-0.98
10:00	US_Factory Orders	Monthly	87	0.01	0.87	38	0.77	38	-0.76
10:00	US_Business Inventory	Monthly	87	0.1	0.95	32	1.02	28	-0.87
10:00	US_New Home Sales	Monthly	87	0.04	0.95	43	0.76	43	-0.67
10:00	US_Consumer Confidence	Monthly	87	0.15	0.96	47	0.9	39	-0.74
10:00	US_Leading Index	Monthly	87	0.27	1.01	46	1.04	26	-0.93
10:00	US_ISMAN_Index	Monthly	87	0.12	0.93	50	0.74	35	-0.75

10:00	US_Existing House Sales	Monthly	87	-0.02	0.87	40	0.69	44	-0.66
10:00	US_University of Michigan Sentiment	Twice in a month	174	-0.05	1.05	86	0.73	86	-0.83
14:15	US_FOMC_RateMeeting	6-weeks	58	0.67	0.71	28	0.5	19	-0.31
15:00	US_Consumer Credit	Monthly	87	0.22	0.94	53	0.8	34	-0.67

Table 6: Determinants of Intrady Price Jumps Predictability in Gold Futures & ETF

Table 6 presents results for the high frequency determinants of predictability of intraday price jumps (All, Positive and Negative) in both the gold markets – CME Gold Futures and SPDR Gold ETF using penalised (ridge) logistic regression in equation (22) of the form -

$$\boldsymbol{P(PriceJump_t = 1|X_{t-5min}) = G\,(\alpha_o + \beta_1 USAgg\_SchMacroNews_{t-5min} + \sum_{i=1}^{3} \beta_{2,i}\, MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{3,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{2} \beta_{4,k} Liq1\_TradeActivity_{k,t-5min} + \beta_5 Liq2\_TradeCost_{t-5min} + \beta_6 Liq3\_PriceImpact_{t-5min} + \beta_7 Illiquidity_{t-5min} + \beta_8 Volatility_{t-5min} + \varepsilon_t)} \quad \textbf{(22)}$$

where, $\boldsymbol{P(PriceJump_t = 1|X_{t-5min})}$ is the conditional probability of observing an intraday price jump (All, Postive or Negative) given 5-minute lagged set of predictors i.e $\boldsymbol{X_{t-5min}}$. X comprises of 5-minute lagged values of the following predictors –(1)US aggregate scheduled macroeconomic news announcements (USAgg_SchMNews), which is dummy variable that takes value 1 when any of 29 US scheduled news announcements takes place (as enlisted in Table 4), (2) three dimensions of Market Psych aspects namely, Attention, Sentiments and Emotions from news media (NewsM) and Social media (SocialM), along with (3) three aspects of liquidity - $\boldsymbol{Liq1\_TradeActivity}$, which is trading activity aspect of liquidity that we proxy using total number of trades (Trades) and total depth (Depth) at 5-minute, $\boldsymbol{Liq2\_TradeCost}$ is trading cost aspect of liquidity, which we proxy using Effective spread and $\boldsymbol{Liq3\_PriceImpact}$, is the price impact aspect of liquidity which we measure using order imbalance. In addition, we also assess the impact of (4) $\boldsymbol{Illiquidity_{t-5min}}$ which 5-minute lagged ammihud illiquidity variable and (5) $\boldsymbol{Volatility_{t-5min}}$ which is lagged realised variance. $\boldsymbol{G}$ is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$. The t-statistics are given in parentheses. *,**, and *** indicates statistical significance at 10%, 5% and 1% level.

	CME Gold Futures			Gold ETF SPDR		
Predictor Variables	**All Jumps**	**Positive Jumps**	**Negative Jumps**	**All Jumps**	**Positive Jumps**	**Negative Jumps**
USAgg_SchMacroNews $_{t-5min}$	**1.59*** (10.93)**	**1.493*** (8.45)**	**1.727*** (5.553)**	**1.103*** (7.94)**	**1.476*** (6.88)**	**1.0967*** (4.29)**
MarketPsych_Predictors $_{t-5min}$						
Attention_NewsMedia	0.0071 (0.246)	-0.0255 (-0.80)	**0.007*** (1.88)**	0.0173 (0.874**)**	-0.0148 (-0.329)	**0.060* (1.632)**
Sentiment_NewsMedia	**-0.0492* (-2.04)**	-0.012 (-0.41)	**-0.0492** (-2.38)**	**-0.023* (-1.516)**	-0.0052 (-0.115)	**-0.0661* (-1.622)**
Emotion_NewsMedia	0.0045 (0.086)	-0.0018 (-0.027)	0.0044 (1.066)	0.0024 (0.045)	**0.0456* (1.536)**	0.050 (1.103)
Attention_SocialMedia	-0.0283 (-0.99)	**0.00561* (2.365)**	-0.0283 (-1.25)	**0.0036* (2.166)**	**0.0148* (1.70)**	-0.048 (-0.83)
Sentiment_SocialMedia	0.011 (0.40)	**0.0137* (1.542)**	0.0105 (0.175)	0.024 (1.243)	**0.0498* (1.636)**	0.0254 (0.592)
Emotion_SocialMedia	-0.0126 (-0.384)	0.0032 (0.087)	0.0127 (1.419)	-0.027 (-1.326)	0.005 (0.112)	**-0.0751* (-1.686)**
Liquidity Predictors $_{t-5min}$						

Liq1_TradingAct_Trades	0.0859 (0.632)	**0.0149*** **(1.543)**	0.00085 (0.959)	**0.0678***** **(3.43)**	**0.066**** **(2.259)**	**0.090**** **(2.848)**
Liq2_TradingAct_Depth	**0.1389***** **(4.04)**	**0.088**** **(2.712)**	**0.139***** **(3.187)**	**0.1012*** **(5.088)**	**0.0758**** **(2.55)**	**0.1508***** **(4.23)**
Liq3_TradingCost_EffSpread	0.0186 (0.6578)	**0.046*** **(1.537)**	**0.0186*** **(1.748)**	**0.00669**** **(2.485)**	**0.0079**** **(2.714)**	**0.0053*** **(1.658)**
Liq4_PriceImpact_OrderImb	-0.0022 (-0.077)	**0.0249*** **(1.957)**	0.002 (0.44)	**0.0153*** **(1.971)**	**0.0074*** **(1.776)**	-0.0257 (-1.009)
Amm_Illiquidity $_{t\text{-}5min}$	0.014 (0.30)	**0.069**** **(2.36)**	0.0143 (0.089)	0.0117 (1.358)	0.0101 (0.477)	**0.0215*** **(1.792)**
Realised_Variance $_{t\text{-}5min}$	**0.195***** **(6.23)**	**0.119***** **(3.83)**	**0.125***** **(3.87)**	**0.024*** **(1.62)**	**0.0249**** **(2.96)**	**0.0114*** **(1.606)**
(Intercept)	-5.42*** (-170.4)	-6.113*** (-137.1)	-5.42*** (-141.3)	-5.334*** (-167.2)	-6.047*** (-133.6)	-6.049*** (-133.5)
No. of Observation	**2,34,326**	**2,34,326**	**2,34,326**	**2,09,467**	**2,09,467**	**2,09,467**
McFadden R^2	**4.4%**	**3.1%**	**3.2%**	**2.9%**	**1.7%**	**3.1%**

Table 7: Interaction Effects for Predictability for Intraday Price Jumps in Gold

Table 7 presents the results for interaction effects model using ridge logistic regression on intraday price jump (All, Positive and Negative), the combined effect of aggregate US scheduled macroeconomic news announcements with three aspects of Market Psych- Attention, Sentiment and Emotion from News and Social Media separately, after controlling for liquidity and volatility predictors. The intraday predictability regression model of price jumps for both COMEX futures and SPDR ETF is of the following form-

$$\boldsymbol{P(PriceJump_t = 1 | X_{t-5min}) = G\,(\alpha_o + \sum_{i=1}^{3} \beta_{1,i} USAgg\_SchMNews_{t-5min}\ X\ MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{2,i}\, USAgg\_SchMNews_{t-5min}\ X\ MarketPsych\_SocialM_{i,t-5min} + \beta_3\, USAgg\_SchMNews_{t-5min} + \sum_{i=1}^{3} \beta_{4,i} MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{5,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{2} \beta_{6,k} Liq1\_TradeActivity_{k,t-5min} + \beta_7 Liq2\_TradeCost_{t-5min} + \beta_8 Liq3\_PriceImpact_{t-5min} + \beta_9 Illiquidity_{t-5min} + \beta_{10} Volatility_{t-5min} + \varepsilon_t)} \quad (23)$$

where, G is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$, $\boldsymbol{\beta_{1,i}}$ is the coefficient of the interaction terms of 5-minute lagged aggregate US Scheduled Macroeconomic News ($\boldsymbol{USAgg\_SchMNews_{t-5min}}$) with three (i=1 to 3) aspects of Market Psych from News Media ($\boldsymbol{MarketPsych\_NewsM_{i,t-5min}}$) i.e. Attention_NewsM, Sentiment_NewsM, Emotion_NewsM and similarly $\boldsymbol{\beta_{2,i}}$ is the coefficient of interaction terms with Social Media ($\boldsymbol{MarketPsych\_SocialM_{i,t-5min}}$) as Attention_SocialM, Sentiment_SocialM, and Emotion_SocialM. The t-statistics are given in parentheses. *,**, and *** indicates statistical significance at 10%, 5% and 1% level.

	CME Gold Futures			**Gold ETF SPDR**		
Predictor Variables	**All Jumps**	**Positive Jumps**	**Negative Jumps**	**All Jumps**	**Positive Jumps**	**Negative Jumps**
Interaction Effects $_{t\text{-}5min}$						
USAgg_SchNews X Attention_NewsM	0.0018 (0.119)	-0.0056 (-0.97)	**0.008*** **(1.642)**	0.098 (0.853)	0.1986 (1.026)	**0.0952*** **(1.561)**
USAgg_SchNews X Sentiment_NewsM	0.14 (0.289)	-0.088 (-0.14)	0.449 (0.83)	0.078 (0.534)	-0.044 (-0.185)	0.288 (0.929)
USAgg_SchNews X Emotion_NewsM	**0.801***	**1.002***	0.55	**0.024***	**0.163***	**-0.2658***

	(1.602)	**(1.559)**	(0.684)	**(1.71)**	**(1.799)**	**(-1.340)**
USAgg_SchNews X Attention_SocialM	0.0029	**0.007***	-0.027	0.0819	**0.639****	0.153
	(0.44)	**(1.84)**	(-1.399)	(1.092)	**(2.034)**	(0.89)
USAgg_SchNews X Sentiment_SocialM	**0.992***	**2.173*****	-0.765	0.038	**0.0371***	-0.0506
	(1.72)	**(3.49)**	(-0.63)	(0.82)	**(2.288)**	(-0.133)
USAgg_SchNews X Emotion_SocialM	**0.869*****	**0.908***	**0.90***	**0.0205***	-0.0413	0.1099
	(3.10)	**(2.41)**	**(2.02)**	**(2.088)**	(-1.016)	(0.447)
USAgg_SchNews$_{t-5min}$	**1.35*****	**1.29*****	**1.44*****	**1.313*****	**1.398*****	**1.051*****
	(6.02)	**(4.35)**	**(4.80)**	**(10.76)**	**(7.093)**	**(3.93)**
Market Psych Predictors$_{t-5min}$						
Attention_NewsM	0.00135	-0.0013	-0.0012	0.027	-0.0058	**0.063***
	(1.43)	(-0.097)	(-0.91)	(0.937)	(-0.101)	**(1.721)**
Sentiment_NewsM	-0.0046	-0.049	0.024	-0.040	-0.003	**-0.0779***
	(-0.92)	(-0.122)	(0.34)	(-1.28)	(-0.047)	**(-1.90)**
Emotion_NewsM	0.086	0.108	0.062	0.00178	0.0528	0.056
	(1.23)	(1.08)	(0.69)	(0.054)	(0.874)	(1.219)
Attention_SocialM	-0.0011	-0.0019	-0.00049	**0.026***	**0.017***	-0.0428
	(-1.032)	(-1.156)	(-0.342)	**(1.586)**	**(1.981)**	(-0.793)
Sentiment_SocialM	-0.004	**0.197***	**-0.2007***	0.039	**0.0508***	0.025
	(-0.05)	**(1.697)**	**(-1.299)**	(1.268)	**(1.7479)**	(0.604)
Emotion_SocialM	**0.085***	0.058	**0.11***	**0.052***	0.024	**-0.077***
	(1.69)	(0.705)	**(1.675)**	**(1.66)**	(0.017)	**(-1.71)**
Liquidity Predictors$_{t-5min}$						
Liq1_TradingAct_Trades	**0.13*****	0.067	**0.167*****	**0.0766*****	**0.066*****	**0.090****
	(5.04)	(1.523)	**(5.682)**	**(3.85)**	**(4.75)**	**(2.86)**
Liq2_TradingAct_Depth	0.043	**0.075****	0.007	**0.124*****	**0.0759*****	**0.157*****
	(1.208)	**(2.162)**	(0.218)	**(5.81)**	**(7.84)**	**(4.24)**
Liq3_TradingCost_EffSpread	**0.043***	**0.032***	**0.039***	**0.0071*****	**0.010*****	0.0218
	(1.85)	**(1.175)**	**(1.732)**	**(3.316)**	**(3.29)**	(1.669)
Liq4_PriceImpact_OrderImb	-0.013	-0.0216	-0.0031	**0.0461***	**0.055****	-0.025
	(-0.782)	(-1.115)	(-0.049)	**(1.645)**	**(2.093)**	(-1.02)
Amm_Illiquidity$_{t-5min}$	**0.63***	**0.679***	**0.57*****	**0.0166****	**0.0249*****	**0.0115***
	(4.04)	**(6.81)**	**(6.98)**	**(2.409)**	**(2.175)**	**(1.750)**
RealisedVariance$_{t-5min}$	0.167	**0.1938***	**0.16*****	**0.0194*****	**0.0079*****	0.0053
	(8.63)	**(6.30)**	**(6.76)**	**(4.76)**	**(4.65)**	(0.610)
(Intercept)	-5.79***	-6.58***	-6.44***	-5.348***	-6.05***	-6.05***
	(-109.5)	(-85.15)	(-89.89)	(-163.4)	(-130.9)	(-133.1)
No. of Observation	**2,34,326**	**2,34,326**	**2,34,326**	**2,09,467**	**2,09,467**	**2,09,467**
McFadden R^2	**5.5%**	**3.9%**	**3.6%**	**2.4%**	**2.7%**	**4.1%**

Table 8 : Impact of Disaggregate US Scheduled Macroeconomic News Surprises on Intraday Price Jump Predictability

Table 8 presens the results of the impact of 29 disaggregated US scheduled macroeconomic news surprises on intraday price jumps (All, Positive and Negative price jumps) in COMEX futures and SPDR ETF using least absolute shrinkage and selction operation (LASSO) logistic regression, after controlling for Market Psych and liquidity, of the form -

$$P(PriceJump_t = 1|X_{t-5min}) = G\,(\alpha_o + \sum_{i=1}^{29} \beta_{1,i} USDisag\_SchMNewsSurp_{i,t-5min} + \sum_{i=1}^{3} \beta_{2,i}\, MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{3,i} MarketPsych\_SocialM_{i,t-5min} +$$

$$\sum_{k=1}^{2}\boldsymbol{\beta_{4,k}}\boldsymbol{Liq1\_TradeActivity}_{k,t-5min} + \boldsymbol{\beta_5}\boldsymbol{Liq2\_TradeCost}_{t-5min} + \boldsymbol{\beta_6}\boldsymbol{Liq3\_PriceImpact}_{t-5min} + \boldsymbol{\beta_7}\boldsymbol{Illiquidity}_{t-5min} + \boldsymbol{\beta_8}\boldsymbol{Volatility}_{t-5min} + \boldsymbol{\varepsilon_t}) \quad \textbf{(24)}$$

where, $\boldsymbol{P(PriceJump_t = 1|X_{t-5min})}$ is the conditional probability of observing an intraday price jump (All, Positive or Negative) given 5-minute lagged set of predictors i.e $\boldsymbol{X_{t-5min}}$. **X** comprises of 5-minute lagged values of the following predictors –(1) Standardised News Surprise for 29 US disaggregate scheduled macroeconomic news announcements ($\boldsymbol{USDisagg\_SchMNewsSurp}$), which are enlisted in Table 4, and news surprise is calculated in Table A2 in Appendix using Balduzzi et al.(2011) approach, (2) three dimensions of Market Psych aspects namely, Attention, Sentiments and Emotions from news media (NewsM) and Social media (SocialM), along with (3) three aspects of liquidity - $\boldsymbol{Liq1\_TradeActivity}$, which is trading activity aspect of liquidity that we proxy using total number of trades (Trades) and total depth (Depth) at 5-minute, $\boldsymbol{Liq2\_TradeCost}$ is trading cost aspect of liquidity, which we proxy using Effective spread and $\boldsymbol{Liq3\_PriceImpact}$ is the price impact aspect of liquidity which we measure using order imbalance. In addition, we also assess the impact of (4) $\boldsymbol{Illiquidity_{t-5min}}$ which is 5-minute lagged ammihud illiquidity variable and (5) $\boldsymbol{Volatility_{t-5min}}$ which is lagged realised variance. $\boldsymbol{G}$ is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$. The t-statistics are given in parentheses. *,**, and *** indicates statistical significance at 10%, 5% and 1% level.

	CME Gold Futures			Gold ETF SPDR		
Predictor Variables	**All Jumps**	**Positive Jumps**	**Negative Jumps**	**All Jumps**	**Positive Jumps**	**Negative Jumps**
USDisagg_SchMacro_NewsSurp **t-5min**						
US_FOMC_RateDecision_Surp	**3.45*** (9.76)**	**3.879* (10.09)**	**2.10*** (3.38)**	**0.0603*** (10.253)**	**0.061*** (10.39)**	**0.040*** (3.522)**
US_PersonalIncome_Surp	.	.	.	.	.	.
US_NonFarmPay_Surp	**0.658** (1.927)**	.	**0.879** (2.455)**	.	**-0.0628* (-4.28)**	**0.0298** (2.765)**
US_RetailSales_Surp	**-0.73** (-2.187)**	**-1.1709* (-2.77)**	.	.	**-0.0182** (-2.676)**	.
US_GDPAdvance_Surp	**1.84*** (4.287)**	.	**2.22*** (4.69)**	**0.0337*** (5.423)**	**-0.0414* (-2.944)**	**0.046*** (4.251)**
US_IndusProd_Surp	.	.	.	.	.	.
US_CapacityUtil_Surp	**0.674** (2.001)**	.	**0.74** (2.34)**	.	.	.
US_ConsumerCredit_Surp	.	**-0.198* (-1.70)**	.	.	.	.
US_PersonalCons_Surp	.	.	.	.	**-0.0149* (-2.523)**	.
US_NewHomeSale_Surp	**-1.396* (-2.719)**	**-1.772*** (-3.18)**	.	**-0.0196** (-2.822)**	**-0.0266* (-3.363)**	.
US_DurableGoodSale_Surp	.	**-0.558** (-2.32)**	**0.419** (2.633)**	.	.	**0.0143* (2.727)**
US_ConstructionSpend_Surp	**0.3919* (2.334)**	**0.926** (2.715)**	.	**0.0351** (2.787)**	.	.
US_FactoryOrder_Surp	.	.	.	.	.	.
US_BusinessInventory_Surp	.	.	.	.	.	.
US_Import_Surp	.	.	.	.	.	.
US_InternationalTrade_Surp	**0.3068* (1.555)**	**1.067* (2.465)**	.	.	.	.
US_PPI_Surp	.	.	.	**0.032*** (2.772)**	.	.

US_CPI_Surp	1.796 (1.54)	.	.	.	.	.
US_ConsumerConfidence_Surp	0.378* (1.733)	.	0.3768* (2.29)		-0.012* (-1.77)	0.0178* (2.142)
US_HousingStart_Surp	.	.	.	.	.	.
US_PMIManuf_Surp	1.744*** (3.99)	-0.946* (-1.952)	2.174*** (4.75)	0.035*** (4.68)	.	0.0488*** (5.579)
US_LeadingIndex_Surp	.	-0.311** (-2.40)	.	.	.	.
US_InitialJoblessClaim_Surp	.	0.268* (2.27)	-0.065** (-2.43)	.	0.041*** (3.503)	-0.048* (-2.673)
US_ISM_Surp	-1.068** (-2.65)	-1.437*** (-3.11)	.	.	.	.
US_Unemployment_Surp	-1.02* (-1.65)	0.338** (2.45)	.	.	0.0015* (1.622)	-0.0050* (-2.342)
US_CurrentAccBal_Surp	.	.	.	.	.	.
US_ExtHouseSale_Surp	.	.	.	.	.	.
US_BldPermit_Surp	.	.	.	.	.	.
US_UnivMichiganSenti_Surp	.	.	.	.	.	.
Market Psych Predictors $_{t\text{-}5min}$						
Attention_NewsM	.	.	0.005* (1.618)	.	.	0.027* (1.663)
Sentiment_NewsM	-0.0267* (-1.877)	.	-0.029* (-2.36)	-0.0393 (-1.284)	.	-0.025 (-1.687)
Emotion_NewsM	.	.	.	.	.	0.009 (1.059)
Attention_SocialM	.	.	.	.	.	.
Sentiment_SocialM	.	.	.	0.038 (1.226)	.	.
Emotion_SocialM	.	.	.	.	0.0183* (2.198)	-0.0333 (-1.633)
Liquidity Predictors $_{t\text{-}5min}$						
Liq1_TradingAct_Trades	.	.	0.0298* (1.66)	0.0571*** (3.517)	0.1126*** (2.225)	0.0805* (2.908)
Liq2_TradingAct_Depth	0.097*** (3.362)	0.055** (2.20)	0.093* (2.56)	.	.	.
Liq3_TradingCost_EffSpread	0.0178* (1.791)	0.028* (1.87)	.	0.0997** (2.498)	0.252* (2.53)	0.1389* (1.579)
Liq4_PriceImpact_OrderImb	.	.	.	.	0.034* (1.809)	.
Amm_Illiquidity $_{t\text{-}5min}$	0.169*** (6.032)	0.199*** (6.187)	0.0956*** (3.328)	0.01887* (1.512)	0.072 (0.598)	0.0134* (1.573)
RealisedVariance $_{t\text{-}5min}$	0.0232* (2.07)	0.039*** (3.012)	.	.	.	.
(Intercept)	-5.392*** (-97.83)	-6.111*** (-136.4)	-6.057*** (-139.3)	-5.317*** (-168.23)	-6.143*** (-134.84)	-6.024* (-134.28)
N	2,34,326	2,34,326	2,34,326	2,09,467	2,09,467	2,09,467
MacFadden R^2	5.4%	3.9%	3.8%	2.7%	3%	4.1%

Table 9 – Drivers of Intraday Co-Jumps Predictability in Gold Markets

Table 9 presents the high frequency predictors of co-jumps between COMEX gold futures and SPDR Gold ETF using ridge logistic regression framework. We compute co-jump between two gold markets as the simultaneous occurrence of price jumps in both COMEX futures and SPDR ETF using the combination of Bollerslev et al.(2013) and Andersen et al.(2007) jump detection method as discussed in Section 3.2. We operationalize positive co-jumps as one when both COMEX futures and SPDR ETF observe a positive price jump, while negative co-jump when both COMEX futures and SPDR ETF observe a negative co-jump. The regression equation is of the form-

$$\boldsymbol{P(CoJump_t = 1|X_{t-5min}) = G(\alpha_o + \beta_1 USAgg\_SchMacroNews_{t-5min} + \sum_{i=1}^{3}\beta_{2,i}\, MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3}\beta_{3,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{5}\beta_{4,i} COMEX\_Liq_{k,t-5min} + \beta_5 COMEX\_RV_{t-5min} + \sum_{k=1}^{5}\beta_{6,i} ETF\_Liq_{k,t-5min} + \beta_7 ETF\_RV_{t-5min} + \varepsilon_t} \quad (25)$$

where, $\boldsymbol{P(CoJump_t = 1|X_{t-5min})}$ is the conditional probability of observing an intraday co-jump (All, Postive or Negative) given 5-minute lagged set of predictors i.e $\boldsymbol{X_{t-5min}}$. X comprises of 5-minute lagged values of the following predictors–(1)US aggregate scheduled macroeconomic news announcements (USAgg_SchMacroNews), which is dummy variable that takes value 1 when any of 29 US scheduled news announcements takes place (as enlisted in Table 4), (2) three dimensions of Market Psych aspects namely, Attention, Sentiments, and Emotions from news media ($\boldsymbol{MarketPsych\_NewsM_{i,t-5min}}$) and Social media ($\boldsymbol{MarketPsych\_SocialM_{i,t-5min}}$), along with (3) four aspects of liquidity for COMEX futures (COMEX_LiquidityPredictors) and ETF SPDR (ETF_LiquidityPredictors) separately in 5-minute lagged form, such as - Liq1_TradingActivity, that we proxy using total number of trades (Trades) and total depth (Depth) at 5-minute, $Liq2\_TradeCost$ is trading cost aspect of liquidity, which we proxy using Effective spread and $Liq3\_PriceImpact$ is the price impact aspect of liquidity which we measure using order imbalance, and Liq4_$Illiquidity_{t-5min}$ which is 5-minute lagged ammihud illiquidity variable, lagged volatility for COMEX futures and ETF SPDR ($\boldsymbol{Volatility_{t-5min}}$). G is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$. The t-statistics are given in parentheses. *,**, and *** indicates statistical significance at 10%, 5% and 1% level.

	Co-Jumps		
Predictor Variables	**All Jumps**	**Positive Jumps**	**Negative Jumps**
US_AggSchMNews $_{t-5min}$	**0.277*** (9.23)**	**0.263*** (8.14)**	**0.175*** (8.033)**
Market Psych Predictors $_{t-5min}$			
Attention_NewsMedia	**0.034* (1.163)**	-0.009 (-0.433)	**0.028* (1.65)**
Sentiment_NewsMedia	-0.026 (-0.829)	-0.00059 (-0.107)	-0.0243 (-0.097)
Emotion_NewsMedia	**0.070* (1.979)**	**0.1093* (1.549)**	0.013 (1.219)
Attention_SocialMedia	**0.018** (2.322)**	0.0047 (0.542)	**0.0193* (1.983)**
Sentiment_SocialMedia	0.0048 (0.1483)	**0.018* (1.668)**	**-0.075* (-1.603)**
Emotion_SocialMedia	0.035 (1.05)	-0.0028 (-0.202)	0.029 (0.61)
COMEX_LiquidityPredictors $_{t-5min}$			
Liq1_TradingAct_Trades	**0.0232*** (5.43)**	**0.049** (2.82)**	**0.0365*** (4.846)**
Liq2_TradingAct_Depth	**0.068*** (2.445)**	0.040 (0.56)	**0.0618** (2.168)**
Liq3_TradingCost_EffSpread	0.0246	**0.035***	0.0114

	(1.036)	**(1.792)**	(0.717)
Liq4_PriceImpact_OrderImb	0.0028 (0.371)	-0.021 (-1.231)	0.0096 (0.759)
Liq4_AmmIlliquidity	**0.729*** **(1.686)**	**0.0513*** **(2.72)**	**0.1063*** **(5.024)**
COMEX_RealisedVariance $_{t-5}$	**0.2017***** **(5.556)**	**0.1057***** **(5.14)**	**0.1159***** **(3.433)**
ETF_LiquidityPredictors $_{t-5min}$			
Liq1_TradingActivity_Trades	-0.0223 (-0.943)	0.022 (0.795)	**0.01163*** **(1.720)**
Liq2_TradingActivity_Depth	**0.096***** **(4.139)**	**0.039*** **(0.997)**	**0.0922***** **(4.777)**
Liq3_TradingCost_EffSpread	**0.0264*** **(2.427)**	0.0209 (0.932)	**0.0118*** **(2.474)**
Liq4_PriceImpact_OrderImb	**0.037*** **(1.63)**	**0.027*** **(1.774)**	-0.025 (-1.234)
Liq4_Illiquidity	**0.0137*** **(1.329)**	**0.005*** **(0.336)**	**0.0134***** **(1.698)**
ETF_RealisedVariance $_{t-5}$	0.057 (0.957)	-0.025 (-0.315)	-0.0149 (-0.673)
(Intercept)	-5.581*** (-154.5)	-6.255* (-123.69)	-6.238* (-120.2)
No. of Observation	2,09,467	2,09,467	2,09,467
McFadden R2	5%	3.1%	5.5%

Table 10: Interaction Effects of US Scheduled News announcements and Market Psych on Intraday Co-Jumps prediction

Table 10 presents results of the interaction effects of US scheduled macroeconomic announcement with the three Market Psych aspects, namely- Attention, Sentiment, and Emotion from news and social media using ridge logistic regression. We control for liquidity and volatility predictors of COMEX futures and ETF SPDR and perform separate regression analysis for All, Positive and Negative Price Jumps, of the form which is as follows-

$$\boldsymbol{P(CoJump_t = 1|X_{t-5min}) = G(\alpha_o + \sum_{i=1}^{3} \beta_{1,i}\ USAgg\_SchMacroNews\ X\ MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{2,i}\ USAgg\_SchMacroNews\ X\ MarketPsych\_SocialM_{i,t-5min} + \beta_3 USAgg\_SchMacroNews_{t-5min} + \sum_{i=1}^{3} \beta_{4,i}\ MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{5,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{5} \beta_{6,i} COMEX\_Liq_{k,t-5min} + \beta_7 COMEX\_RV_{t-5min} + \sum_{k=1}^{5} \beta_{8,i} ETF\_Liq_{k,t-5min} + \beta_9 ETF\_RV_{t-5min} + \varepsilon_t)} \quad (26)$$

where, G is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$, $\boldsymbol{\beta_{1,i}}$ is the coefficient of the interaction terms of 5-minute lagged aggregate US Scheduled Macroeconomic News ($\boldsymbol{USAgg\_SchMNews_{t-5min}}$) with three (i=1 to 3) aspects of Market Psych from News Media ($\boldsymbol{MarketPsych\_NewsM_{i,t-5min}}$) i.e. Attention_NewsM, Sentiment_NewsM, Emotion_NewsM and similarly $\boldsymbol{\beta_{2,i}}$ is the coefficient of interaction terms with Social Media ($\boldsymbol{MarketPsych\_SocialM_{i,t-5min}}$) as Attention_SocialM, Sentiment_SocialM, and Emotion_SocialM. The t-statistics are given in parentheses. *,**, and *** indicates statistical significance at 10%, 5% and 1% level.

	Co-Jumps		
Predictor Variables	**All Jumps**	**Positive Jumps**	**Negative Jumps**

Interaction Effects$_{t\text{-}5mins}$			
USAgg_SchNews X Attention_NewsMedia	-0.0012 (-0.135)	-0.283 (-0.472)	**0.132*** **(2.207)**
USAgg_SchNews X Sentiment_NewsMedia	-0.0056 (-0.091)	-0.136 (-0.988)	0.0819 (0.310)
USAgg_SchNews X Emotion_NewsMedia	**0.0258*** **(1.85)**	**0.067*** **(1.694)**	**-0.3786*** **(-1.64)**
USAgg_SchNews X Attention_SocialMedia	0.0052 (0.311)	**0.429*** **(1.522)**	**0.190*** **(1.853)**
USAgg_SchNews X Sentiment_SocialMedia	0.0241 (1.037)	**0.1068**** **(2.976)**	0.1118 (0.318)
USAgg_SchNews X Emotion_SocialMedia	**0.032*** **(2.219)**	**0.0718*** **(1.842)**	0.0036 (0.041)
USAgg_SchMNews$_{t\text{-}5min}$	**0.169***** **(9.783)**	**0.2288***** **(6.030)**	**0.1688*** **(5.62)**
MarketPsych Predictors$_{t\text{-}5min}$			
Attention_NewsMedia	0.0512 (0.589)	-0.0068 (-0.265)	**0.0242*** **(1.653)**
Sentiment_NewsMedia	0.0127 (0.929)	0.00164 (0.150)	-0.0206 (-1.415)
Emotion_NewsMedia	**0.0628*** **(1.566)**	-0.0083 (-0.428)	0.0137 (0.964)
Attention_SocialMedia	-0.0163 (-0.450)	**0.055*** **(1.678)**	-0.011 (-0.669)
Sentiment_SocialMedia	0.00119 (1.194)	0.018 (0.971)	0.0106 (0.559)
Emotion_SocialMedia	0.0168 (0.609)	-0.00172 (-0.149)	-0.0158 (-0.749)
COMEX_LiquidityPredictors $_{t\text{-}5min}$			
Liq1_TradingAct_Trades	**0.137***** **(5.44)**	**0.0197**** **(2.845)**	**0.035***** **(4.80)**
Liq2_TradingAct_Depth	**0.093*** **(2.458)**	0.039 (1.515)	**0.057**** **(2.189)**
Liq3_TradingCost_EffSpread	0.0259 (1.076)	**0.034*** **(1.753)**	0.0098 (0.716)
Liq4_PriceImpact_OrderImb	0.0083 (0.37)	-0.021 (-1.245)	0.0079 (0.764)
Liq4_AmmIlliquidity	0.7283 (0.6809)	**0.049**** **(2.549)**	0.0089 (0.710)
COMEX_RealisedVariance $_{t\text{-}5}$	0.208 (5.53)	**0.1056**** **(2.911)**	**0.113***** **(3.291)**
ETF_LiquidityPredictors $_{t\text{-}5min}$			
Liq1_TradingActivity_Trades	0.0307 (0.922)	0.021 (0.730)	**0.0120*** **(1.624)**
Liq1_TradingAcitivity_Depth	**0.0234***** **(4.118)**	**0.038*** **(2.55)**	**0.0827***** **(4.777)**
Liq2_TradingCosts_EffectiveSpread	**0.044*** **(2.497)**	0.0198 (0.920)	0.0095 (0.87)
Liq3_PriceImpact_OrderImbalance	**-0.0272*** **(-1.609)**	**0.0254**** **(2.765)**	-0.0215 (-1.214)

Liq4_AmmIlliquidity	0.0107 (1.332)	0.0049 (0.143)	**0.0117*** **(1.701)**
ETF_RealisedVariance $_{t-5}$	**0.0932*** **(1.970)**	0.023 (0.14)	-0.011 (-0.665)
(Intercept)	-6.107*** (-154.4)	-6.254*** (-111.0)	-6.234*** (-124.48)
No. of Observation	**2,09,467**	**2,09,467**	**2,09,467**
McFadden R2	**5.5%**	**3.9%**	**6.6%**

Table 11- Impact of Disaggregate Macroeconomic News Surprise on Predictability of Intraday Co-Jumps

Table 11 presents results of the impact of 29 disaggregate US scheduled macroeconomic news surprises, as enlisted in Table 4, on predictability of intraday co-jumps. We adopt least absolute shrinkage and selection operator (LASSO) logistic regression framework separately for All, Positive and Negative co-jumps in COMEX futures and SPDR ETF and control for Market Psych and liquidity predictors, such as-

$$\boldsymbol{P(CoJump_t = 1|X_{t-5min}) = G(\alpha_o + \sum_{i=1}^{29} \beta_{1,i} USDisagg\_SchMNewsSurp_{t-5min} + \sum_{i=1}^{3} \beta_{2,i}\, MarketPsych\_NewsM_{i,t-5min} + \sum_{i=1}^{3} \beta_{3,i} MarketPsych\_SocialM_{i,t-5min} + \sum_{k=1}^{5} \beta_{4,i} COMEX\_Liq_{k,t-5min} + \beta_5 COMEX\_RV_{t-5min} + \sum_{k=1}^{5} \beta_{6,i} ETF\_Liq_{k,t-5min} + \beta_7 ETF\_RV_{t-5min} + \varepsilon_t)} \quad (27)$$

where, $\boldsymbol{P(Co-Jump_t = 1|X_{t-5min})}$ is the conditional probability of observing an intraday co- jump (All, Positive or Negative) given 5-minute lagged set of predictors i.e $\boldsymbol{X_{t-5min}}$. X comprises of 5-minute lagged values of the following predictors –(1) Standardised News Surprise for 29 US disaggregate scheduled macroeconomic news announcements ($\boldsymbol{USDisagg\_SchMNewsSurp}$), which are enlisted in Table 4, and news surprise is calculated in Section 4.1 using Balduzzi et al.(2011) approach, 2) three dimensions of Market Psych aspects namely, Attention, Sentiments, and Emotions from news media ($\boldsymbol{MarketPsych\_NewsM_{i,t-5min}}$) and Social media ($\boldsymbol{MarketPsych\_SocialM_{i,t-5min}}$), (3) four aspects of liquidity for COMEX futures (COMEX_LiquidityPredictors) and ETF SPDR (ETF_LiquidityPredictors) separately in 5-minute lagged form, such as - Liq1_TradingActivity, that we proxy using total number of trades (Trades) and total depth (Depth) at 5-minute, $Liq2\_TradeCost$ is trading cost aspect of liquidity, which we proxy using Effective spread and $Liq3\_PriceImpact$ is the price impact aspect of liquidity which we measure using order imbalance, and Liq4_$Illiquidity_{t-5min}$ which is 5-minute lagged ammihud illiquidity variable. Lastly, we also assess the impact of (4) lagged volatility for COMEX futures and ETF SPDR ($\boldsymbol{Volatility_{t-5min}}$). G is logistic function of the form $\boldsymbol{G(z) = \frac{\exp(z)}{1+\exp(z)}}$. The t-statistics are given in parentheses. *,**, and *** indicates statistical significance at 10%, 5% and 1% level.

	Co-Jumps		
Predictor Variables	**All Jumps**	**Positive Jumps**	**Negative Jumps**
USDisagg_SchMNews $_{t-5min}$			
US_FOMC_RateDecision_Surp	**0.064*** **(10.4)**	**0.0716***** **(10.59)**	**0.0379***** **(3.710)**
US_PersonalIncome_Surp	.	.	.
US_NonFarmPay_Surp	**0.0108*** **(2.161)**	**-0.0642***** **(-4.94)**	**0.0022**** **(2.840)**
US_RetailSales_Surp	**-0.011*** **(-2.371)**	**-0.0215*** **(-2.914)**	.
US_GDPadvance_Surp	**0.038***** **(4.45)**	**-0.0462*** **(-6.077)**	**0.0453***** **(4.672)**
US_IndusProd_Surp	.	.	.

US_CapacityUtil_Surp	**0.010* (2.118)**	.	.
US_ConsumerCredit_Surp	.	.	.
US_PersonalCons_Surp	.	.	.
US_NewHomeSale_Surp	**-0.0308** (-2.73)**	**-0.0403*** (-3.055)**	.
US_DurableGoodSale_Surp	.	**-0.0182* (-2.391)**	**0.004** (2.822)**
US_ConstructionSpend_Surp	**0.00077** (2.371)**	**0.0244** (2.777)**	.
US_FactoryOrder_Surp	.	.	**0.035* (2.830)**
US_BusinessInventory_Surp	.	.	.
US_Import_Surp	.	.	.
US_InternationalTrade_Surp	**0.0006* (1.714)**	**0.0252** (2.581)**	.
US_PPI_Surp	.	.	.
US_CPI_Surp	**0.0388*** (4.18)**	.	**0.0565*** (4.378)**
US_ConsumerConfidence_Surp	**0.0024* (1.799)**	**-0.0468*** (-3.051)**	.
US_HousingStart_Surp	.	.	.
US_PMIManuf_Surp	**0.040*** (4.367)**	.	**0.049*** (5.252)**
US_LeadingIndex_Surp	.	.	**-0.0057* (-2.219)**
US_InitialJoblessClaim_Surp	.	**0.0155* (2.336)**	.
US_ISM_Surp	**-0.0221* (-2.72)**	**-0.0319*** (-3.107)**	.
US_Unemployment_Surp	.	**0.008** (2.580)**	**-0.018* (-2.519)**
US_CurrentAccBal_Surp	.	.	.
US_ExtHouseSale_Surp	.	.	.
US_BuildPermit_Surp	.	.	.
US_UnivMichiganSenti_Surp	.	.	.
MarketPsych Predictors$_{t-5min}$			
Attention_NewsM	.	.	**0.071* (1.813)**
Sentiment_NewsM	.	.	-0.057 (-1.284)
Emotion_NewsM	.	.	.
Attention_SocialM	.	.	.
Sentiment_SocialM	**0.038* (1.179)**	**0.092* (1.722)**	.
Emotion_SocialM	.	.	.
COMEX_LiquidityPredictors $_{t-5min}$			
Liq1_TradingAct_Trades	.	.	0.0176

			(0.110)
Liq2_TradingAct_Depth	**0.066** **(2.142)**	0.0508 (1.47)	**0.0548*** **(1.887)**
Liq3_TradingCost_EffSpread	**0.0167*** **(2.028)**	**0.0286*** **(2.050)**	.
Liq4_PriceImpact_OrderImb	.	.	.
Liq4_AmmIlliquidity	**0.1256***** **(4.198)**	**0.2064***** **(5.390)**	0.0554 (1.457)
COMEX_RealisedVariance $_{t-5}$	**0.011** **(1.783)**	**0.0428***** **(3.481)**	.
ETF_LiquidityPredictors $_{t\text{-}5min}$			
Liq1_TradingActivity_Trades	0.023 (1.359)	.	**0.0324*** **(1.657)**
Liq1_TradingActivity_Depth	**0.0708** **(2.346)**	0.00085 (0.226)	**0.1026***** **(4.275)**
Liq2_TradingCost_EffectiveSpread	.	.	.
Liq3_PriceImpact_OrderImbalance	.	0.0076 (1.275)	.
Liq4_AmmIlliquidity	.	.	.
ETF_RealisedVariance $_{t-5}$	.	.	.
(Intercept)	-5.546* (-155.82)	-6.260*** (-122.52)	-6.215* (-125.15)
N	**2,09,467**	**2,09,467**	**2,09,467**
MacFadden R2	**5.7%**	**3.7%**	**4.4%**

Table 12-Robustness Tests - Alternative Measures of Intraday Jumps Detection

Table 12 reports number of intraday jumps detected using several alternative measures of intraday jump detection at 5-minute sampling frequency for both COMEX gold futures and SPDR gold ETF for full sampleperiod 2010-2018. The number of intraday jumps are detected using Andersen et al. (2007) as ABD, Andersen et al. (2007) with periodicity of Boudt et al. (2011) as ABD_BOUDT, Lee and Mykland (2008) as LM, Lee and Mykland (2008) with periodicity correction of Boudt et al.(2011) as LM_BOUDT, Bollerslev et al.(2013) as BLT, along with intersection of BLT ∩ ABD_BOUDT and BLT ∩ LM_BOUDT at 95% and 99% significance level.

Gold Instrument	Threshold	Andersen et al. (2007): ABD	Andersen et al.(2007) with periodicity factor of Boudt et al.(2011): ABD_BOUDT	Lee and Mykland (2008): LM	Lee and Mykland (2008) with periodicity factor of Boudt et al.(2011): LM_BOUDT	Bollerslev et al. (2013) :BLT	Intersection BLT ∩ ABD_BOUDT	Intersection BLT ∩ LM_BOUDT
CME Futures	95%	2648	2402	1079	956	2142	1101	756
	99%	1847	1628	642	565	1359	756	476
SPDR ETF	95%	2406	2170	959	866	2057	1045	801
	99%	1629	1488	566	526	1300	767	489

Table 13- Robustness Tests - Intraday Jump detection at Alternative Sampling Frequencies

Table 13 presents robustness tests results for intraday jump detection across various sampling frequencies i.e. 1-/3-/5-/10-minutes in order to check variation in the number of intraday jumps detected across sampling frequencies. Table 13 reports the number of intraday price jump during the full sample period 2010-2018 using all jump detection methods, as discussed in Table 12, at 95% threshold across four sampling frequencies for CME gold futures and ETF Gold SPDR.

Gold Instruments	Intraday Jump Methods	1-minute	3-minute	5-minute	10-minute
	ABD	8617	3907	2648	1632
	ABD_BOUDT	8904	3529	2402	1419
	BLT	9764	3362	2142	1034
	LM	3817	1656	1079	557
CME Futures	LM_BOUDT	3975	1499	956	540
	ABD	8200	3540	2406	1450
	ABD_BOUDT	7751	3133	2170	1310
	BLT	7234	3743	2057	1100
	LM	3618	1483	959	505
ETF SPDR Gold	LM_BOUDT	3394	1319	866	487

INTERNAL APPENDIXES

Figure A1 – Volatility Signature Plots

Figure A1 presents eight-figures of volatility signature plots CME gold futures and SPDR gold ETF at one-/three-/five-/ten-minute sampling intervals. The y-axis depicts realized volatility which is the sum of squared log-returns at four different sampling intervals; the x-axis depicts sampling intervals.

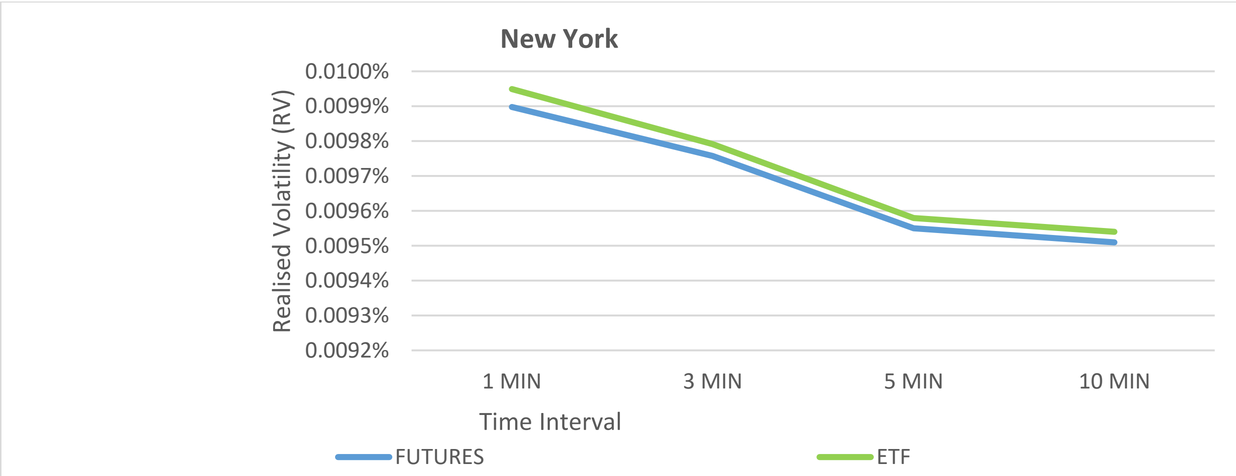


Table A1- Contract Specification

This table present the contract specification of two gold market instruments – CME gold futures and SPDR gold ETF enlisting their symbol, contract size, trading venue, price units, launch year,and trading hours. The data is collect from respective instruments exchange website.

			Contract Specifications				
Gold Markets	**Gold Instruments**	**Symbol**	**Contract Size/ Trading Unit**	**Trading Venue**	**Price Unit**	**Launch Year**	**Trading Hours**
New York	COMEX/CME Gold Futures	GC	100 troy ounces	**Chicago Mercantile Exchange** -CME Globex, CME Clear Port, Open Outcry (New York)	U.S. dollars and cents per troy ounce	1974	Sunday – Friday 18:00 – 17:00 US ET with a 60-minute break each day beginning at 17:00 US ET
New York	SPDR Gold Shares ETF	GLD	1/10th of an ounce of gold	**NYSE Arca**; Singapore Stock Exchange, Tokyo Stock Exchange, The Stock Exchange of Hong Kong and the Mexican Stock Exchange.	U.S. dollars and cents per 1/10 of troy ounce	2004	Pre-Opening Session - 04:00-09:30 US ET; Core Trading Session: 9:30 a.m. TO 4:00 p.m. US ET

Table A2. - Variable Definition and Operationalisation

Table A2 shows the variable definition,operationalisation and measurement of all possible determinants of intraday jumps and co-jumps for COMEX Gold futures and ETF gold futures used in the study. Table A2 presents the definition and operationalisation of different types intraday price jumps used in study – All Jumps, Positive Jumps, Negative Jumps, Co-Jumps, Positive Co-jumps, and Negative Co-jumps. In addition, the measurement of all possible determinants of intraday jumps namely- Number of Trades, Depth, Proportional Effective Spreads , Order Imbalance, Realised Variance, illiquidity, absolute return, all US scheduled macroeconomic news announcements, news surprises for disaggregated news, marketPsych aspects – News Media Attention,News Media Sentiments, News Media Emotions, Social Media Attention, Social Media Sentiments, and Social Media Emotions.

S.No.	**Variables**	**Operationalisation**
1	All Jump	It is dummy variable for All Jump in series , 1 is Jump; 0 is No Jump.
2	Positive Jump	It is dummy variable for Positive Jump in series, 1 is for Positive Jump; 0 is No Positive Jump. Positive jump is when the Jump Size > 0.
3	Negative Jump	It is dummy variable for Negative Jump in series, 1 is for Negative Jump; 0 is No Negative Jump. Negative jump is when the Jump Size < 0.
4	Co Jump_All	It is dummy variable for All Co-Jump Jump between CME Gold Futures and Gold ETF SPDR series. 1 is for Co-Jump; 0 is No Co-Jump.
5	Co Jump_Positive	It is dummy variable for Positive Co-Jump Jump between CME Gold Futures and Gold ETF SPDR series. 1 is for Positive Co-Jump; 0 is No Positive Co-Jump.
6	Co-Jump_Negative	It is dummy variable for Negative Co-Jump Jump between CME Gold Futures and Gold ETF SPDR series. 1 is for Negative Co-Jump; 0 is No negative Co-Jump.
7	Number of Trades(NT)	It is the average of the total number of trades in 5-minute interval from trade and quote (TAQ) dataset at 1-minute. It represents trading activity dimension of liquidity.
8	Depth	It is the average of total bid size and ask size in 5-minute interval, such as $Depth = (SumBidSize + SumAskSize)/2$.

		Depth indicates number of contracts available to buy and sell, and represent trading activity dimension of liquidity
9	Proportional Effective Spreads	Effective Spread (ES) measure the actual transaction cost. We compute it as twice the absolute value of the difference between trade price and midquote divided by the midquote, which is $$ES = \frac{2 * D * (Price - Midquote)}{Midquote}$$ *where*, D is the direction of trade, which indicates buy side (+1) order or sell side order (-1), using Lee and Ready (1991) algorithm. We use proportional effective spread, which facilitates comparison (Boudt et al. (2011). It is calculated as Effective Spread (ES) divided by Depth as proposed by (Venkataraman, 2001), which is $$Prop. Effective\ Spread = \frac{ES}{Depth}$$
10	Realised Variance	It is as the sum of squared log returns of midquotes sampled at 1-minute (r_t^2) for 5-minute interval, widely adopted by Andersen, Bollerslev, Diebold, & Ebens, 2001; Andersen, Bollerslev, Diebold, & Labys, 2003, such as $$RV_t = \sum_{t=1}^{5} r_t^2$$
11	Order Imbalance	**Order Imbalance** is measure of signed trades which is measured as the difference between buy trades and sell trades (assuming that buys are coded positive), thus indicates buying pressure. It indicates the net buy side order, which is as follows- $$OI = \sum D * Trades$$ *where*, D is the direction of trade, which indicates buy side (+1) order or sell side order (-1), using Lee and Ready (1991) algorithm.
12	Ammihud Illiquidity	It is calculated as absolute value of midquote return divided by the total trading volumes. It indicates illiquidity and is widely used. It is computed as- $$AmmihudIlliquidity = \frac{\lvert r_t \rvert}{\sum Volume}$$
13	Absolute Return	It is the absolute value of log return of midquotes. We calculate as follows : $\lvert r_t \rvert = \lvert \log(MQ_t) - \log(MQ_{t-1}) \rvert$.
14	All US News Announcements	Dummy Variable for ALL US Macroeconomic News mentioned in Table 2
15	Disaggregate US scheduled Macroeconomic News Surprise	News Surprise is calculated as the difference between the Actual Release Value and Median Bloomberg Analyst Forecast divided by the standard deviation of this difference as per Balduzzi et al. 2011, for each disaggregated news announcements, k, such as – $$Newsurprise_{t,k} = \frac{Actual_{t,k} - Forecast_{t,k}}{\sigma_k}$$ where, $Actualt,k$ is actual release value of economic news indicator k announced at day t, $Forecastt,k$ is the median analyst forecast from Bloomberg for news indicator k at day t and σt is the sample standard deviation of the surprise component $Actualt,k - Forecastt,k$. As Bloomberg forecast is not available for US Federal fund (FOMC) target rate decision, we calculate its news surprise by using a widely adopted method proposed by Kuttner (2011)– $$NewsSurprise_{t,FOMC} = \frac{D}{D-d}\,(f_t^0 - f_{t-1}^0)$$ where, f_t^0 is FOMC rate implied in the current month using federal funds futures contracts on date t, D is number of days in a month, d is the day of the month when FOMC meeting

		is held, and $\frac{D}{D-d}$ is a scaling factor that accounts for the timing of the FOMC announcement within a given month.
16	News Media Attention	It is TRMI News Buzz for Gold extracted from Thomson Reuters Market Psych Index (TRMI). It indicates the total number of times the name of asset (e.g. gold) is seen in news sources. It indicates media coverage volume metric that reflects the volume of information flow with respect to the asset. Buzz metric for gold represents the investor attention to gold. Buzz is calculated separately for News based Buzz ($BUZZ_N$) and Social Media based Buzz ($BUZZ_S$) as well as combined from both sources ($BUZZ_B$).
17	News Media Sentiments	It is TRMI News Sentiment for Gold extracted from Thomson Reuters Market Psych Index. It is Positive Sentiment net of Negative sentiment. It measures the 24-hour rolling average of the scores by computing the overall positive references net of negative references as a proportion of total references in news media ($SENTI_N$). Sentiment scores are normalized to lie between -1 to 1.
18	News Media Emotions	It is TRMI News EmotionVsFact for Gold extracted from Thomson Reuters Market Psych Index. ***EmotionVsFact*** metric of TRMI dataset, which measures the overall level of emotionality in the news media. EmotionsVsFact is a ratio between all emotional tones in text (fear, anger, joy, optimism etc) versus purely factual information (fundamentals, demandVSsupply, Trade, long/short position, volatility, etc.) or commentaries for each asset as defined by Petersen (2016), who developed TRMI indices.
19	Social Media Attention	It is TRMI Social Buzz for Gold extracted from Thomson Reuters Market Psych Index. It indicates the total number of times the name of asset (e.g. gold) is seen in social media sources. It indicates media coverage volume metric that reflects the volume of information flow with respect to the asset. Buzz metric for gold represents the investor attention to gold. Buzz is calculated separately for News based Buzz ($BUZZ_N$) and Social Media based Buzz ($BUZZ_S$) as well as combined from both sources ($BUZZ_B$
20	Social Media Sentiments	It is TRMI Social Sentiment for Gold extracted from Thomson Reuters Market Psych Index. It is Positive Sentiment net of Negative sentiment. It measures the 24-hour rolling average of the scores by computing the overall positive references net of negative references as a proportion of total references in social media sources ($SENTI_S$). Sentiment scores are normalized to lie between -1 to 1
21	Social Media Emotions	It is TRMI Social EmotionVsFact for Gold extracted from Thomson Reuters Market Psych Index. ***EmotionVsFact*** metric of TRMI dataset, which measures the overall level of emotionality in the social media. EmotionsVsFact is a ratio between all emotional tones in text (fear, anger, joy, optimism etc) versus purely factual information (fundamentals, demandVSsupply, Trade, long/short position, volatility, etc.) or commentaries for each asset as defined by Petersen (2016), who developed TRMI indices