Are stock options more informed than Twitter? Evidence from ASX

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Abstract

We study the impact of Twitter information, including activity, sentiment and divergence of sentiment, on option market variables, such as open interest and implied idiosyncratic volatility. We estimate the contemporaneous relationship between Twitter and option market, and we show that open interest is positively correlated with Twitter activity and divergence of sentiment and negatively correlated with sentiment. Implied idiosyncratic volatility is positively correlated with divergence of sentiment. Furthermore, we determine the lead-lag relationship between Twitter information, realized stock volatility and option market variables using time-sequencing tests. Our empirical evidence indicate that whereas stock realized volatility has no predictive power on Twitter information, option market variables present strong predictability on Twitter activity and divergence of sentiment, and weak predictability on Twitter sentiment.

JEL classification: G12; G13; G14

Keywords: Social media, Implied idiosyncratic volatility, Stock volatility

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1. Introduction

Traditionally, the main information sources are company reports, broker reports and newspaper releases. The advent and fast propagation of social media microblogs and networks, in particular Twitter, has created new platforms for an almost real-time dissemination of financial and other information to a large number of users. The guidance published by the US Securities and Exchange Commission (SEC) on the 2nd April 2013, permits companies to use social media including Twitter to communicate corporate announcements,[1] which has reinforced the credibility of Twitter as a platform for disseminating corporate news. With traditional information sources, most news articles are required to be verified by publishers/specialists before they are available to the public; however, with the new social technologies, both factual and inaccurate information can be spread rapidly to a large number of market participants. Social media platforms provide direct access to an unprecedented amount of content and may amplify rumours and questionable information. False rumours and misinformation have been known to affect stock prices and large-scale investments. For example, a false tweet claiming that Barack Obama was injured in an explosion wiped out $130 billion in US stock value.[2] Similarly in the Australian market, during the coronavirus pandemic, Australian Securities and Investments Commission (ASIC) detected a rise in message groups and threads on social media platforms, such as Facebook and Twitter, aimed at unsophisticated retail investors and home to unmoderated commentary on capital markets and investing.[3] Previously, researchers have looked at Twitter as an additional information dissemination platform and this project extends their work by examining whether option traders are more informed on firm specific information than social media users. Specifically we examine the lead–lag structure between social media, stock market variables and option market variables to determine whether social media platforms produce *new* information or only disseminate *existing* information that has already been incorporated into stock and option prices and volumes. Findings from this paper will provide a framework for stock exchanges and

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[1] Press release on April 2, 2013-"The Securities and Exchange Commission today issued a report that makes clear that companies can use social media outlets like Facebook and Twitter to announce key information in compliance with Regulation Fair Disclosure (Regulation FD) provided investors have been alerted about which social media will be used to disseminate such information." https://www.sec.gov/news/press-release/2013-2013-51htm

2 K. Rapoza, "Can 'fake news' impact the stock market?" Forbes, 26 February 2017. https://www.forbes.com/sites/kenrapoza/2017/02/26/can-fake-news-impact-the-stock-market/#37eb20502fac

3 A. Vickovlch, "Social trading fuels market speculation: ASIC" Australian Financial Review, 17 August 2020. https://www.afr.com/markets/equity-markets/social-trading-fuels-market-speculation-asic-20200814-p55lrt

policymakers to develop innovative and effective procedures and regulations to curb "rumourtrage" on social media platforms. An understanding of innovative solutions involving option trading data to regulate the spread of false news will improve the quality of Australian financial markets, with long-term implications for investors, companies and governments.

Global reaching Social microblogs with a global reach, as a real time platforms for free exchange of views and facts about financial markets, have created a massive volume of readily available quantitative and qualitative information on stocks and attracted attention from market participants and academics. Previous studies report a significant contemporaneous relationship between activity in social media activity and the stock market, and also address the role of social media in predicting stock returns (see as examples, Antweiler and Frank 2004; Gannini et al. 2010; Sprenger et al. 2013; Chen et al. 2014; Bartov et al. 2017; Renault 2017; Duz Tan and Tas 2020) and volatility (Glasserman and Mamaysky 2019; Jiao et al. 2020). However, the existing literature almost exclusively tests their hypotheses using data from the US market, and there has been a lack of research on the Australian and other leading financial markets and organizations. Although the SEC requires companies to disclose non-public information simultaneously and promptly, the acceptable methods for public disclosures are rather flexible and may still leave space for selective disclosures and information asymmetry (Miller, 2006; Bushee and Miller, 2012). To circumvent the constraint, this project will collect data from the Australian market, which, unlike the US market, is characterised by a continuous disclosure framework. Continuous disclosure refers to a listed entity's legal obligation to immediately inform the Australian Stock Exchange (ASX) of information likely to have a material impact on the price of its securities[4]. The difference between the two markets can be explained by the materiality requirement of the continuous disclosure regime. Listed entities in Australia are required to disseminate price-sensitive information electronically to ASX, and the information is then announced to the market as soon as possible via the ASX CommNews platform. The platform contains a complete list of company information which has been accurately time stamped with the precise release date and time. The Australian market therefore provides a unique setting to control for the release of price sensitive information.

A number of studies suggest that non-public information is reflected in the options market (Manaster and Rendleman, 1982; Easley et al., 1998; Chakravarty et al., 2004; Pan and

[4] Exceptions, called 'carve-out provisions', are provided for in Listing Rule 3.1A(2) to 3.1A(3). Exceptions include the following circumstances: a reasonable person would not expect the information to be disclosed; the information is confidential; and it is a breach of law to disclose the information.

Poteshman, 2006); therefore, the market provides an ideal environment for investigating the effects of social media activity on financial instruments' prices. Twitter also provides a platform for non-scheduled or non-periodic news to be available to the public. Understanding how these pieces of information are incorporated into market prices, especially how the information flows between social media platforms, option traders and stock market participants, is important to financial market transparency and stability. This paper aims to extend past research by observing the relationship between stock-related social media messages and trading activity in the options market. More specifically, this paper will investigate whether changes in the volume and sentiment of stock-related tweets affect option implied volatility (OIV) and option open interest. OIV has been shown to be a superior predictor for future stock volatility (see Latané and Rendelman, 1976; Chiras and Manaster, 1978; Beckers, 1981; Christensen and Prabhala, 1998; Xing et al., 2010), and follows completely different patterns from the realized volatility that has been examined in existing social media literature (Glasserman and Mamaysky 2019; Jiao et al. 2020).

Antweiler and Frank (2004) present a significant contemporaneous relationship between activity in social microblogs and the US stock market, and also address the role of social microblogs in predicting stock returns and volatility. We extend Antweiler and Frank (2004) by providing the following contributions on social media and financial markets. Firstly, we examine the contemporaneous relationship between Twitter information and stock and option market variables, such as realized stock volatility, idiosyncratic OIV and option open interest. Secondly, we conduct time sequencing tests to determine the lead-lag relationship between Twitter information, stock market volatility and option market variables. Consistent with results presented in extant studies using US market data, we find that realized stock volatility measures are positively correlated with the volume of Twitter messages and the dispersion of Twitter sentiment, but negatively correlated with average Twitter sentiment. Furthermore, we find that the contemporaneous relationship between Twitter information and option market variables is consistent with results using stock market data. We then compare the predictive power of Twitter on stock and option market variables. Our time-sequencing analysis shows that all three Twitter variables predict realized stock volatility but none of them predicts option implied volatility. Interestingly, we also find that option market variables present strong predictability on Twitter volume and divergence of sentiment, and weak predictability on Twitter sentiment, which indicates that option traders are more informed than Twitter users.

3. Data

3.1 Stock and Option Data

Our analysis is based on a dataset of 41 ASX listed stocks with active options trading in the period between 07 March 2016 and 31 March 2021 sourced from Bloomberg. We filter stocks options that are inactively traded and we end up with 73 stocks with active option series, which equivalents to 97,674 stock day observations.

We then source time-series of S&P/ASX 200 and S&P/ASX 200 VIX indices from TRTH and use their log values as proxies for overall market performance and volatility. ASX 200 VIX is a real-time volatility index that provides market participants an insight into investor sentiment and expected levels of market volatility. Figure 1 depicts the Australian stock market performance and market volatility during our sample period. As seen in Figure 1, S&P/ASX 200 has increased by about 40% while the market volatility index has declined by about 35% over our sample period. Before the start of the recent pandemic, a clear upward trend in stock market index and a downward trend in market volatility are observed in Figures 1, indicating that our sample period is relatively bullish before the recent crisis.

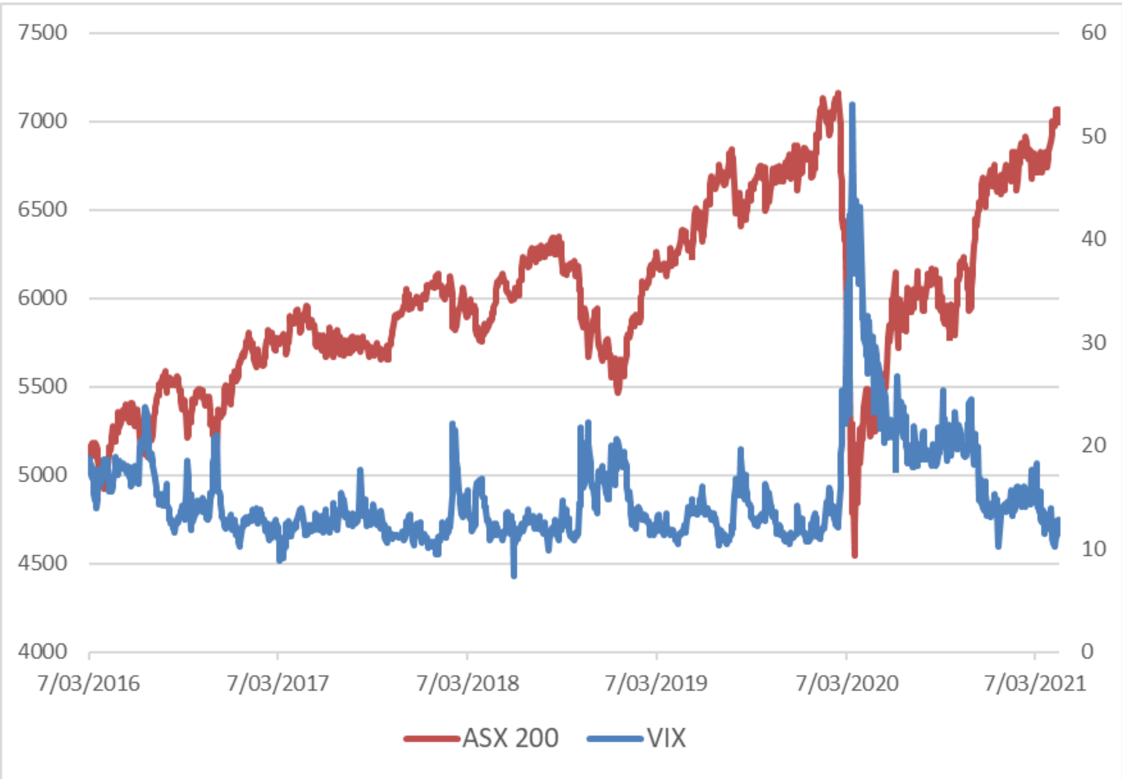

Figure 1: Stock Market index and VIX.

3.2 Social Media Data

The time series of the daily volume and sentiment of Tweets for each stock are obtained from Bloomberg. Using the company name and stock exchange code with $ticker we extract the daily volume and sentiment of Tweets for 64 stocks that match our search criteria. All daily records with no tweets are kept and assigned zero volume. We also extract the minimum and maximum sentiment scores to compute sentiment divergence or disagreement index as the difference between the maximum and the minimum values, divided by 4.

The final sample is created by merging the time series of stocks and options with the time series of tweets and contains 54,858 records of daily financial and social media data for 41 stocks.

3.2 Volatility Measures

Stock volatility variables are calculated based on the high-low range and realized volatility estimators. The high-low measure is the log difference between the highest and the lowest price for each stock each day (Parkinson, 1980). The realized volatility measure is defined as the squared percentage log-returns based on open to close prices for each stock day (Andersen and Todorov, 2010).

We follow Diavatopoulos et al 2008 to compute idiosyncratic implied volatility. We first compute the beta of each sample stocks by regressing firm's monthly returns on market returns:

$$r_{i,m} = \alpha_i + \beta_i Market\_Return_m + e_{i,m} \tag{1}$$

where *Market_Return* is the monthly return of ASX 200 index. For each sample stock, option implied volatilities are collected from Bloomberg. As there are a variety of strike prices and maturities for each stock-day, a standardized implied volatility is calculated by averaging implied volatilities of at-the-money options across all maturities with the largest weight on options closest to 30 days to maturity. Averaging across all options reduces the measurement error associated with inverting option prices to obtain an accurate measure of implied volatility.

S&P/ASX 200 VIX is the market volatility index derived from the near and the next term call and put options on the S&P/ASX 200 market index. We employ beta from Equation

(1) and market implied volatility (VIX) to calculate the idiosyncratic portion of option implied volatility:

$$OIV_{i,t}^2 = \beta_i^2 VIX_t^2 + IDIO\_OIV_{i,t}^2 \tag{2}$$

where $OIV_{i,t}^2$ is the implied total variance for stock i on day t, VIX_t^2 is the implied market variance from VIX on day t, β_i^2 is the squared stock beta from the estimation of Equation (1), and $IDIO\_OIV_{i,t}^2$ is the idiosyncratic portion of implied variance for firm i on day t. The measure of implied idiosyncratic volatility is the square root of the idiosyncratic portion of implied variance. Theoretically, this value should not be less than or equal to zero, but empirically it is possible. A small number of observations have non-positive values which have been set to zero.

4. Methodology

We follow Antweiler and Frank (2004) and conduct a series of contemporaneous and time-sequenced regressions to empirically determine the causality between Twitter variables, stock realized volatility and option market variables, and the ability of tweets to predict stock volatility and OIV.

4.1 Descriptive Statistics

Table I reports average number of tweets, sentiment, disagreement index, implied idiosyncratic volatility, realized stock volatility and market capitalization for each sample stock. As seen in Sentiment column, most stocks present weak negative sentiment, which was expected given that our sample period covers the recent pandemic crisis. The large variability in volatility and market capitalization, as reported in Table I, is indicative of the fact that a wide cross section of firms is utilized in this study.

Table I
Descriptive Statistics

This table provides summary statistics of 41 stocks over the period Mar 2016 to Mar 2021. Messages, Sentiment are the daily average number of tweets and sentiment, extracted from Bloomberg. Disagreement is a proxy of dispersion of opinions and is measured as daily range of twitter sentiment divided by 4. IDIO_OIV is the daily average implied idiosyncratic volatility as computed in Equation (2). Volatility is the squared percentage daily return using open and close prices. Mkt_Cap is the average daily market capitalisation, measured in billion Australian dollars.

RIC	NAME	MESSAGES	SENTIMENT	DISAGREE MENT	IDIO_OIV	VOLATILITY	MKT_CAP (BILLION A$)
AGL	AGL ENERGY	6.96	0.002	0.009	19.03	1.30	12.98
ALD	AMPOL	3.40	0.026	0.018	13.90	1.77	7.62
AMC	AMCOR	4.08	0.057	0.046	18.36	0.84	17.54
AMP	AMP	5.83	-0.001	0.022	24.28	2.44	10.09
ANZ	ANZ BANK	24.31	-0.026	0.053	1.06	1.31	75.17
ASX	ASX	9.94	0.067	0.050	16.45	1.01	14.34
BEN	BENDIGO BANK	3.30	0.039	0.067	8.94	2.08	5.22
BHP	BHP BILLITON	50.61	-0.019	0.104	21.94	1.02	110.52
BSL	BLUESCOPE STEEL	3.54	-0.028	0.044	26.82	3.61	6.87
CBA	CBA	31.97	-0.020	0.033	5.92	0.98	133.69
CSL	CSL LIMITED	3.00	0.059	0.016	21.24	1.55	88.53
CWN	CROWN RESORTS	8.55	-0.037	0.029	18.49	1.53	8.38
FMG	FORTESCUR METALS	7.48	0.027	0.040	38.29	3.95	25.96
HVN	HARVEY NORMAN	4.46	0.048	0.035	21.91	2.57	4.87
IAG	INSURANCE AUSTRALIA	3.24	0.031	0.016	19.22	1.35	15.52
JHX	JAMES HARDIE	4.17	0.028	0.031	12.45	2.01	20.32
MPL	MEDIBANK	4.36	-0.005	0.012	21.48	1.43	8.08
MQG	MACQUARIE GROUP	14.83	0.057	0.060	3.08	1.50	24.57
NAB	NAB	27.90	-0.025	0.054	1.85	1.05	70.13
NCM	NEWCREST MINING	4.85	0.018	0.031	30.23	1.85	18.83
ORG	ORIGIN ENERGY	4.93	0.001	0.034	14.66	2.33	12.16
OSH	OIL SEARCH	3.98	0.013	0.036	1.55	2.44	9.36
OZL	OZ MINERALS	3.29	-0.005	0.046	28.98	2.61	3.16
QAN	QANTAS	112.59	-0.010	0.046	24.90	2.95	8.26
QBE	QBE INSURANCE	4.76	-0.012	0.014	6.91	1.82	14.68

RHC	RAMSAY HEALTH	3.78	0.006	0.026	11.27	1.73	12.91
RIO	RIO TINTO	86.62	-0.633	0.176	24.26	1.15	47.61
RMD	RESMED	10.88	0.017	0.038	24.49	0.73	48.82
S32	SOUTH32	3.86	0.045	0.039	31.32	2.77	14.92
SCG	SCENTRE	3.24	0.522	0.097	2.38	2.08	17.79
SGP	STOCKLAND	3.70	0.008	0.026	2.18	1.95	10.23
STO	SANTOS	3.55	0.008	0.014	8.64	2.75	11.35
SUN	SUNCORP	3.10	0.010	0.013	12.67	1.34	16.14
TAH	TABCORP	3.50	-0.010	0.018	13.32	1.80	4.05
TLS	TELSTRA	218.33	-0.009	0.036	15.15	1.24	68.95
TWE	TREASURY WINE	3.34	-0.001	0.030	29.24	2.62	9.74
VUK	VIRGIN MONEY	3.55	-0.104	0.048	3.97	2.96	5.06
WBC	WESTPAC	46.07	-0.023	0.099	2.88	1.15	100.12
WES	WESFARMERS	4.26	0.006	0.020	12.14	1.01	41.91
WOW	WOOLWORTHS	29.88	-0.007	0.020	16.58	0.93	26.10
WPL	WOODSIDE	6.06	-0.011	0.022	8.21	1.33	25.85

4.2 Regression analysis

Previous research has to some extent explained the impact of social media on financial markets using data from the U.S. market characterised by limited continuous disclosure regime. To analyse the impact of a full continuous disclosure regime on relationship between social media and volatility, we conduct a series of contemporaneous regressions and time-sequencing analysis.

We start our analysis by examining the contemporaneous relation between stock and option market variables and Twitter information. We follow Antweiler and Frank (2004) and conduct the following time series regressions on each stock in our sample. The dependent variable is the average daily volatility for stock *i* and day *t* across sample period, in which realized volatility is measured by *HighLow (HL)* and *SquaredReturns (RET)*, and implied volatility is measured by implied idiosyncratic volatility (IDIO_OIV). Consistent with extant literature, this analysis controls for other factors that affect stock volatility, the overall market-wide price (ASX 200), and the day-of-week effect.

$$Volatility_t^i = \beta_0 + \beta_1 TwMsg_t^i + \beta_2 TwSent_t^i + \beta_3 TwDisagree_t^i + \beta_4\, Mkt_t + \beta_5\, Trend_t + \beta_6 Monday_t + e_{i,t} \quad (3)$$

$TwMsg_t^i$ is the log number of daily tweets for stock *i* on day *t.* A positive and significant β_1 would confirm the finding that posting activity on social media (Twitter) does affect realized and implied volatility. $TwSent_t^i$ is the average daily tweets sentiment for stock *i* on day *t.* A negative and significant β_2 would confirm the finding that posting sentiment on social media (Twitter) does affect realized and implied volatility. $TwDisagree_t^i$ is the range of tweets sentiment divided by 4 for stock *i* on day *t.* A positive and significant β_3 would confirm the finding that sentiment dispersion on social media (Twitter) does affect realized and implied volatility. *Mkt* measures overall stock market volatility, in which *Mkt* is the realized volatility measure of SPI/ASX200 index. The dummy variable $MonD_t$ equals to 1 if the trading day is Monday and 0 if it's not. A negative and significant β_4 indicates that stock volatility is lower on Monday compared to other weekdays.

We examine equation (3) for four different dependent variables, which are implied idiosyncratic volatility, option open interest, realized stock volatility using open and close prices, stock volatility using high and low prices.

To infer predictive ability, we extend our analysis to include time-sequencing tests, as proposed by Antweiler and Frank (2004). The following time series regressions are conducted for each stock in our sample:

$$Volatility_t^i = \beta_0 + \beta_1 TwVariabe_{t-1}^i + \beta_2 TwVariabe_{t-2}^i + \beta_3\, Mkt_t + \beta_4\, Trend_t + \beta_6 Monday_t + e_{i,t} \quad (4)$$

$$TwVariabe_t^i = \beta_0 + \beta_1 Volatility_{t-1}^i + \beta_2 Volatility_{t-2}^i + \beta_3\, Mkt_t + \beta_4\, Trend_t + \beta_6 Monday_t + e_{i,t} \quad (5)$$

5. Results

Table II contains results of contemporaneous regressions. As predicted by Black (1986) and De Long's et al. (1990) and reported by Antweiler and Frank (2004), Koski et al. (2004) and Sprenger et al (2013), all stock volatility measures are significantly positively correlated with posting activity. Open interest is exhibiting similar positive and significant correlation with tweets posting volume, although this correlation, as measured by the magnitude of their correlation coefficient, is significantly weaker.

On the contrary, the relationship between volume of tweets and implied volatility measure is statistically insignificant. Correlation between OIV and tweets sentiment is significantly negative, but weak. The correlation between sentiment dispersion and OIV is positive and significant at 99.9%.

We conclude that a significant contemporaneous correlation between volatilities and volume of message postings reported by Antweiler and Frank (2004) and Sprenger et al. (2013) does exist (3, 4, 7, 8) but that the significant correlation does not hold for implied volatility.

Table II
Contemporaneous Regressions

The table presents the results of contemporaneous regressions of the sample of 41 ASX listed stocks over the period Mar 2016–Mar 2021. IDIO_OIV is the daily implied idiosyncratic volatility as computed in Equation (2). Open_Interest is the daily open interest for both call and put options. Volatility_Ret is defined as the squared percentage log-returns based on open to close prices for each stock day. Volatility_HL is measured as the log difference between the highest and the lowest prices for each stock each day. Messages is the log transformation of (1 + TW) where TW is the number of tweets extracted from Bloomberg. Sentiment is the average daily sentiment score of all tweets. Disagreement is a proxy of dispersion of opinions and is measured as daily range of tweets sentiment divided by 4. Market represents the performance of the S&P/ASX 200 index and is measured as the log value of ASX 200 for regressions (2) and (6), the squared percentage log-returns of ASX 200 for regressions (3) and (7), the log difference between the highest and the lowest prices of ASX 200 for regressions (4) and (8). They are included to control for market volatility and movements in the market value. Monday is a variable that controls for Monday effects. Regressions (1) – (4) use company fixed effects and regressions (5) – (8) do not control for firm fixed effects. The standard errors are reported in parentheses. We denote regression coefficients that are significant at 95%, 99% and 99.9% levels as *, ** and *** respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	IDIO_OIV	Open_Interest	Volatility_Ret	Volatility_HL	IDIO_OIV	Open_Interest	Volatility_Ret	Volatility_HL
Messages	-0.073	0.043***	0.308***	0.332***	-0.687***	0.396***	-0.144***	-0.180***
	(0.049)	(0.003)	(0.026)	(0.019)	(0.045)	(0.005)	(0.015)	(0.011)
Sentiment	-0.504*	-0.140***	-0.457***	-0.336***	-5.623***	0.101***	-0.137	-0.097
	(0.197)	(0.013)	(0.104)	(0.077)	(0.261)	(0.027)	(0.086)	(0.065)
Disagreement	14.276***	0.157***	6.471***	7.501***	5.344***	-0.283*	5.067***	5.752***
	(0.827)	(0.056)	(0.436)	(0.321)	(1.114)	(0.114)	(0.366)	(0.276)
Monday	0.328***	0.006	-0.164***	-0.149***	0.258*	0.036***	-0.203***	-0.193***
	(0.078)	(0.005)	(0.042)	(0.031)	(0.128)	(0.013)	(0.043)	(0.032)
Trend	18.372***	-1.914***	3.974***	3.993***	14.887***	-1.510***	2.971***	2.827***
	(0.393)	(0.036)	(0.210)	(0.155)	(0.632)	(0.087)	(0.210)	(0.159)
Market		0.517***	0.331***	0.693***		0.437***	0.332***	0.695***
		(0.034)	(0.003)	(0.004)		(0.085)	(0.004)	(0.005)
Intercept	-119.000***	20.902***	-29.427***	-29.612***	-95.158***	18.194***	-20.740***	-19.577***
	(2.978)	(0.237)	(1.591)	(1.172)	(4.756)	(0.574)	(1.580)	(1.196)
Observations	54,420	53,789	52,751	52,751	54,420	53,789	52,751	52,751
Firm fixed effect	Yes	Yes	Yes	Yes	No	No	No	No

To test the ability of tweet volume to predict stock volatility and OIV, we conduct time sequencing tests as specified in Eq (4) and Eq (5). Results are reported in Tables III, IV and V. Table III illustrates the effects of a lagged volume of tweets on stock volatility, OIV and open interest and the effects of lagged financial market variables on Twitter volume. Table IV shows the effects of lagged sentiment of tweets on stock volatility, OIV and open interest and the effects of lagged financial market variables on Twitter sentiment. Table V presents the effects of lagged dispersion of tweets sentiment on stock volatility, OIV and open interest and the effects of lagged financial market variables on Twitter sentiment dispersion.

Similar to Antweiler and Frank (2004) we find that the volume of tweets on day (t-1) is significantly positively correlated with stock volatilities on day (t) (Table III). Secondly we show that volume of daily tweets on day (t-1) and day (t-2) predict both measures of stock volatility and option open interest on day (t). The volume of tweets on days (t-1; t-2) does not predict OIV on day (t). Table III as well shows that measures of stock volatility cannot be used to predict the volume of tweets. On the other hand, option market variables, albeit with a different levels of significance, present evidence of predictability on Twitter volume.

In Table IV, we find that the sentiment of tweets on day (t-1) is negatively correlated with stock volatilities and option open interest on day (t), significant at 99.9%. Secondly we show that average sentiment of daily tweets on day (t-2) also predicts option open interest on day (t). The sentiment of tweets on days (t-1; t-2) does not predict OIV on day (t). Furthermore, Table IV shows that measures of stock volatility cannot be used to predict the sentiment of tweets. On the other hand, both option market variables demonstrate weak predictability on Twitter sentiment.

In Table V, we find that the dispersion of Twitter sentiment on day (t-1) is positively correlated with all stock and option market variables on day (t), significant at 99.9%. Secondly we show that sentiment dispersion on day (t-2) predicts option market variables on day (t). Furthermore, Table V shows that measures of stock volatility cannot be used to predict the sentiment dispersion. On the other hand, both option market variables demonstrate strong predictability on sentiment dispersion using the first lag.

Table III
Time Sequencing Tests for Twitter Messages

The table presents the results of time-sequencing regressions of the sample of 41 ASX listed stocks over the period Mar 2016 – Mar 2021 for Twitter messages. IDIO_OIV is the daily implied idiosyncratic volatility as computed in Equation (2). Open_Interest is the daily open interest for both call and put options. Volatility_Ret is defined as the squared percentage log-returns based on open to close prices for each stock day. Volatility_HL is measured as the log difference between the highest and the lowest prices for each stock each day. Market represents the performance of the S&P/ASX 200 index and is measured as the log value of ASX 200 for regressions where Y=Open_Intereset and Messages, the squared percentage log-returns of ASX 200 for regressions where Y=Volatility Ret, the log difference between the highest and the lowest prices of ASX 200 for regressions where Y= Volatility HL. Market is included to control for market volatility and movements in market value. Monday is a variable that controls for Monday effects. All regressions control for company fixed effects. The standard errors are reported in parentheses. We denote regression coefficients that are significant at 95%, 99% and 99.9% levels as *, ** and *** respectively.

Y=f (X-1, X-2, Monday, Trend, Market)

Y	**X**	**X-1**	**X-2**	**Monday**	**Trend**	**Market**
IDIO_OIV	**Messages**	0.109	0.041	0.284***	17.764***	
		(0.059)	(0.059)	(0.077)	(0.390)	
Open_Interest	**Messages**	0.032***	0.030***	0.000	-1.893***	0.484***
		(0.004)	(0.004)	(0.005)	(0.036)	(0.034)
Volatility Ret	**Messages**	0.209***	-0.083***	-0.196***	3.367***	0.333***
		(0.031)	(0.031)	(0.042)	(0.208)	(0.003)
Volatility_HL	**Messages**	0.256***	-0.069***	-0.192***	3.379***	0.697***
		(0.023)	(0.023)	(0.031)	(0.154)	(0.004)
Messages	**IDIO_OIV**	0.002*	0.001	-0.086***	-2.259***	0.323***
		(0.001)	(0.001)	(0.007)	(0.051)	(0.049)
Messages	**Open_Interest**	0.157***	-0.068*	-0.087***	-1.888***	0.172***
		(0.035)	(0.035)	(0.007)	(0.048)	(0.046)
Messages	**Volatility_Ret**	0.000	0.001	-0.086***	-2.107***	0.194***
		(0.001)	(0.001)	(0.007)	(0.047)	(0.046)
Messages	**Volatility_HL**	0.000	-0.000	-0.086***	-2.109***	0.193*
		(0.001)	(0.001)	(0.007)	(0.047)	(0.046)

Table IV
Time Sequencing Tests for Twitter Sentiment

The table presents the results of time-sequencing regressions of the sample of 41 ASX listed stocks over the period Mar 2016 – Mar 2021 for Twitter sentiment. IDIO_OIV is the daily implied idiosyncratic volatility as computed in Equation (2). Open_Interest is the daily open interest for both call and put options. Volatility_Ret is defined as the squared percentage log-returns based on open to close prices for each stock day. Volatility_HL is measured as the log difference between the highest and the lowest prices for each stock each day. Sentiment is the average daily sentiment score of all tweets. Market represents the performance of the S&P/ASX 200 index and is measured as the log value of ASX 200 for regressions where Y=Open_Intereset and Messages, the squared percentage log-returns of ASX 200 for regressions where Y=Volatility Ret, the log difference between the highest and the lowest prices of ASX 200 for regressions where Y= Volatility HL. Market is included to control for market volatility and movements in market value. Monday is a variable that controls for Monday effects. All regressions control for company fixed effects. The standard errors are reported in parentheses. We denote regression coefficients that are significant at 95%, 99% and 99.9% levels as *, ** and *** respectively.

Y=f (X-1, X-2, Monday, Trend, Market)

Y	**X**	**X-1**	**X-2**	**Monday**	**Trent**	**Market**
IDIO_OIV	**Sentiment**	-0.529	-0.01	0.286***	17.845***	
		(0.329)	(0.329)	(0.078)	(0.382)	
Open_Interest	**Sentiment**	-0.095***	-0.084***	0.002	-2.017***	0.523***
		(0.022)	(0.022)	(0.005)	(0.035)	(0.034)
Volatility Ret	**Sentiment**	-0.522***	-0.174	-0.206***	3.026***	0.332***
		(0.173)	(0.173)	(0.042)	(0.204)	(0.003)
Volatility_HL	**Sentiment**	-0.490***	-0.165	-0.199***	2.919***	0.696***
		(0.128)	(0.128)	(0.031)	(0.151)	(0.004)
Sentiment	**IDIO_OIV**	-0.001*	0.000	0.000	-0.161***	-0.008
		(0.000)	(0.000)	(0.002)	(0.012)	(0.012)
Sentiment	**Open_Interest**	0.003	-0.020*	0.000	-0.210***	0.008
		(0.008)	(0.008)	(0.002)	(0.012)	(0.011)
Sentiment	**Volatility Ret**	0.000	0.000	0.000	-0.168***	-0.002
		(0.000)	(0.000)	(0.002)	(0.011)	(0.011)
Sentiment	**Volatility_HL**	0.001	0.000	0.000	-0.168***	-0.004
		(0.000)	(0.000)	(0.002)	(0.011)	(0.011)

Table V
Time Sequencing Tests for Twitter Disagreement

The table presents the results of time-sequencing regressions of the sample of 41 ASX listed stocks over the period Mar 2016 – Mar 2021 for Twitter disagreement. IDIO_OIV is the daily implied idiosyncratic volatility as computed in Equation (2). Open_Interest is the daily open interest for both call and put options. Volatility_Ret is defined as the squared percentage log-returns based on open to close prices for each stock day. Volatility_HL is measured as the log difference between the highest and the lowest prices for each stock each day. Disagreement is a proxy of dispersion of opinions and is measured as daily range of tweets sentiment divided by 4. Market represents the performance of the S&P/ASX 200 index and is measured as the log value of ASX 200 for regressions where Y=Open_Intereset and Messages, the squared percentage log-returns of ASX 200 for regressions where Y=Volatility Ret, the log difference between the highest and the lowest prices of ASX 200 for regressions where Y= Volatility HL. Market is included to control for market volatility and movements in market value. Monday is a variable that controls for Monday effects. All regressions control for company fixed effects. The standard errors are reported in parentheses. We denote regression coefficients that are significant at 95%, 99% and 99.9% levels as *, ** and *** respectively.

Y=f (X-1, X-2, Monday, Trend, Market)

Y	**X**	**X-1**	**X-2**	**Monday**	**Trent**	**Market**
IDIO_OIV	**Disagreement**	8.908***	6.708***	0.280***	18.882***	
		(1.067)	(1.067)	(0.078)	(0.383)	
Open_Interest	**Disagreement**	0.227***	0.226***	0.001	-1.964***	0.531***
		(0.073)	(0.073)	(0.005)	(0.035)	(0.034)
Volatility Ret	**Disagreement**	4.857***	-0.787	-0.202***	3.416***	0.332***
		(0.563)	(0.563)	(0.042)	(0.205)	(0.003)
Volatility_HL	**Disagreement**	5.523***	0.259	-0.197***	3.392***	0.694***
		(0.416)	(0.416)	(0.031)	(0.152)	(0.004)
Disagreement	**IDIO_OIV**	0.001***	0.001***	-0.002***	-0.065***	0.002
		(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
Disagreement	**Open_Interest**	0.007***	-0.005*	-0.003***	-0.043***	-0.019***
		(0.002)	(0.002)	(0.000)	(0.003)	(0.003)
Disagreement	**Volatility Ret**	-0.000	-0.000	-0.002***	-0.044***	-0.017***
		(0.000)	(0.000)	(0.000)	(0.003)	(0.003)
Disagreement	**Volatility_HL**	-0.000	-0.000	-0.002***	-0.044***	-0.017***
		(0.000)	(0.000)	(0.000)	(0.003)	(0.003)

6. Conclusion

In this study we analyse the relationship between the volume, sentiment and sentiment dispersion of tweets and financial market variables in the Australian market, which is characterised by a continuous disclosure regime. Extant literature has almost exclusively analysed the effects of social media on stocks in the US market, where disclosure of new information is more flexible, and not as simultaneous as it is in Australia.

Consistent with past papers analysing the relationship between social media and stocks with US data, we find that contemporaneous stock volatility and option open interest are significantly and positively correlated with social media posting activity proxied by the number of tweets, and sentiment dispersion proxied by the range of Tweets sentiment scores. Contemporaneous regressions also reveal the fact that stock volatility and option open interest are significantly and negatively correlated with social media sentiment.

Extending previous studies, we show that Twitter volume does not correlate with option implied volatility. Time sequencing tests demonstrate that Twitter volume and sentiment predict stock realized volatility but cannot predict OIV. Stock volatility has no predictive ability over Twitter variables. Option market variables present strong predictive power on Twitter volume and sentiment dispersion and weak predictability on Twitter sentiment.

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