Wisdom of Experts and Crowds: Different Impacts of Analyst Recommendation and Online Search on the Stock Market

Completed Research Paper

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Abstract

Sell-side analysts are professional experts while crowds are usually unsophisticated individual investors in the stock market. Understanding the different roles of experts and crowds in the stock market is a fundamental issue for both academia and industry. This empirical study tries to investigate their influences on the stock market by figuring out the following two questions: (1) Will experts and crowds have different impacts on stock prices? (2) Will experts and crowds discriminatively affect stock trading volumes? Adopting the fixed-effect model with panel data from Sogou and CSMAR, we find that experts and crowds have different impacts on the stock market. The wisdom of experts (i.e., analyst recommendation) has a more durable effect on stock prices but a smaller impact on stock turnover compared to the wisdom of crowds (i.e., abnormal search volume index).

Keywords: Analyst recommendation, abnormal search volume index, cumulative abnormal return, abnormal turnover

Introduction

Sell-side security analysts and individual investors are two kinds of important participants in the stock market, and there are significant differences between these two groups in asset size and expertise (Kaniel et al. 2008). Analysts are believed to be experts with excellent abilities of collecting and processing information and preference for stocks of growth companies (Jegadeesh et al. 2004; Womack 1996). However, individual investors are considered as crowds of unsophisticated noise traders with psychological biases (Black 1986; Kyle 1985) and preference for attention-grabbing stocks (Barber and Odean 2008). Therefore, they tilt towards stocks with different characteristics and affect the price formation as well as liquidity provision in the stock market in different ways (Schmeling 2007).

Given the important roles of sell-side analysts and retail investors in the stock market, it is of great significance to study their behavior patterns and effects on stock market. Lots of studies focus on the expert behavior in the stock market (Bradley et al. 2014; Jegadeesh et al. 2004; Womack 1996) or concentrate on the factors that affect analyst recommendation performance (Bradley et al. 2017; Hong and Kacperczyk 2010; Merkley et al. 2017; Mokoaleli-Mokoteli et al. 2009). On the other hand, many studies about the behavior of the crowds in the stock market (Barber et al. 2009; Hvidkjaer 2008; Kaniel et al. 2008; Kelley and Tetlock 2013) and individual investor attention (Da et al. 2011; Gargano and Rossi 2018; Joseph et al. 2011; Liu and Ye 2016) spring up. However, little attention has been paid to the differences between experts and crowds in terms of their impact on the stock market. This study attempts to fill this gap by figuring out the following two questions: (1) Will experts and crowds have different impacts on stock prices? (2) Will experts and crowds discriminatively affect stock trading volume?

Our empirical work provides evidence of impacts of both experts and crowds on stock market. However, there are obvious differences between them. While the expert recommendation affects stock prices in a longer time than the attention of crowds does, the latter has a greater impact on stock turnover. This work makes contributions to theory development by extending research on the behavior of various participants in the stock market and their effects on the stock market. Practically, our findings provide implication about risk management and investment strategy for various participants by demonstrating and comparing the wisdom of experts and crowds.

The rest of this paper is organized as follows. First, we briefly review the previous related research and put forward hypotheses in section II. Section III describes the research methods of this study, including data collection process, the definition and measurement of variables, and the establishment of the model. The descriptive statistics and empirical results are presented in section IV. Finally, we conclude our findings and discuss their implications in section V.

Related Work and Hypotheses Development

Wisdom of Experts

The issue of whether the wisdom of experts is valuable has always been the focus of attention. The experts in this study refer to the analysts from the brokerage houses who contribute to the stock market by facilitating the information distribution, analyzing and forecasting the stock value, and providing analyst recommendations to investors (Brauer and Wiersema 2018; Grossman and Stiglitz 1980; Jegadeesh et al. 2004; Kadan et al. 2009; Loh and Stulz 2011; Womack 1996).

The wisdom of experts derives from their access to specific information and expertise in related industry (Brown et al. 2015), and is delivered to investors through analyst recommendations. Furthermore, their preference towards the stocks of growth companies adds value to their recommendations (Jegadeesh et al. 2004). Therefore, they are professional in evaluating the stock prices and recommending undervalued stocks. Besides, the analyst recommendations will promote investors' transaction, leading to a higher turnover. It has been widely confirmed that the analyst recommendation is influential to stock prices and turnovers, and have some investment value (Brauer and Wiersema 2018; Charitou et al. 2018; Kudryavtsev 2019; Lin 2018; Loh and Stulz 2011). Therefore, we put forward the following hypotheses:

H1a: The analyst recommendation is positively related to stock prices.

H1b: The analyst recommendation is positively related to stock trading volumes.

Wisdom of Crowds

As for another important group of players, the crowds in the stock market are mostly small and unsophisticated investors (Akbas et al. 2015; Frazzini and Lamont 2008) who trade on public information or listen to security analysts (Malmendier and Shanthikumar 2007; Mikhail et al. 2007), transmit their sentiment through the Internet (Wu et al. 2017), and exert pressure on stock prices (Kelley and Tetlock 2013). However, they can't cope with all the information because of scarce attention

(Kahneman 1979). Among thousands of stocks, the crowds of retail investors tend to focus on arresting stocks, such as stocks with extreme absolute returns or huge trading volume. Therefore, the aggregate attention embodies the preference and wisdom of crowds.

Many scholars are wondering whether the wisdom of the crowds has an impact on stock market. Barber and Odean (2008) suggest that the masses are net buyers of attention-grabbing stocks according to attention theory. The collective attention of them will drive the stock prices up and lead to the higher turnovers (Da et al. 2011; Joseph et al. 2011; Liu and Ye 2016). It's worth noting that the crowds in the Chinese stock market are mainly short-term speculators who prefer to realize gains quickly. Therefore, the attention of the crowds will generate positive price pressure in the short term and then result in negative price pressure in the long term as investors realize gains. Based on previous research, we raise the following hypotheses:

H2a: The aggregate attention of crowds is positively related to stock prices in the short term and negatively related to stock prices in the long term.

H2b: The aggregate attention of crowds is positively related to stock trading volumes.

The Comparison of Experts and Crowds

Analysts are significantly different from crowds of individual investors in terms of capital size, financial knowledge and trading patterns (Kaniel et al. 2008).

Sell-side analysts refer to experts who have rich information sources, excellent expertise, and prefer to stocks with long-term investment value (Jegadeesh et al. 2004). In other words, their recommendation will be related to the stock prices over a longer period of time. On the contrary, Hvidkjaer (2008) depicts the crowds as naïve investors who realize gains quickly. His findings suggest that stocks favored by the crowds will suffer prolonged underperformance after a short period of price increases. Therefore, we put forward the following hypothesis:

H3a: The analyst recommendation has an impact on stock prices in a longer period than the aggregate attention of crowds does.

As proved by Mikhail et al. (2007), both large (institutional) and small (individual) investors trade in reaction to analyst reports. However, the inattention and underreaction (Andrei and Hasler 2015; Dellavigna and Pollet 2009) to analyst recommendation due to the limited attention and information explosion may weaken the impact of the analyst recommendation on stock trading volume. As a contrast, the aggregate attention of crowds to particular stocks captures their willingness to trade stocks, resulting in significant increase in trading volume. Therefore, we put forward the following hypothesis:

H3b: The aggregate attention of crowds has a stronger impact on stock trading volumes than the analyst recommendation does.

Research Methodology

Data Collection

The Sogou Index (http://www.zhishu.sogou.com) offers an index of aggregate search frequency of a specific item on daily basis, which reflects the aggregate wisdom of the masses. In order to capture the attention of crowds to listed company stocks more accurately and understand its influence on the stock market, we develop a crawler to collect daily search volume index (*SVI*) based on stock tickers from Sogou Index (see Figure 1, stocker ticker: 300059). We totally obtain *SVI* of 3,791 stocks. The sample period rages from 2016 to 2017.

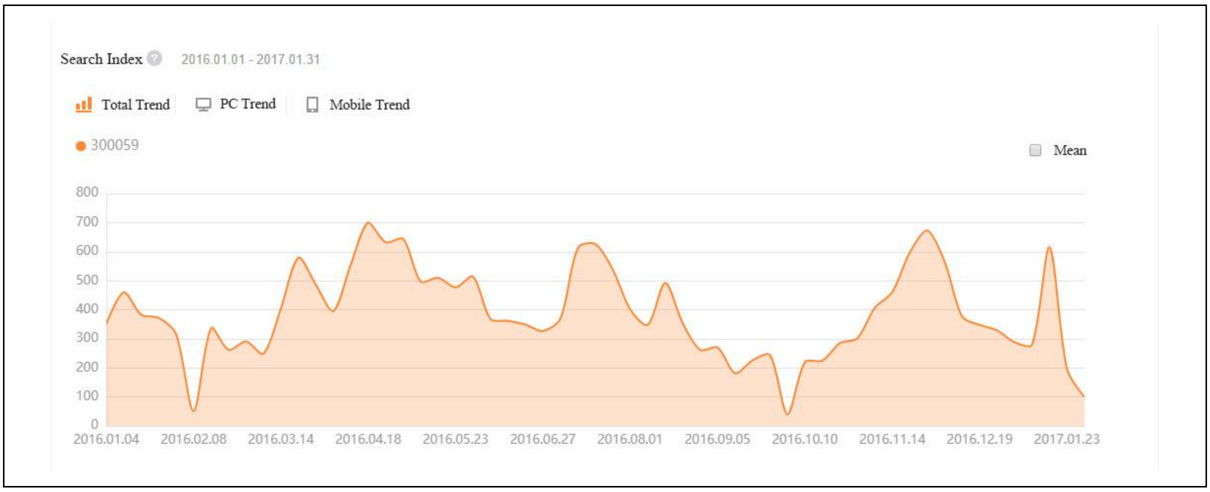

Figure 1. *SVI* from http://www.zhishu.sogou.com

Besides, the data of analyst recommendation, which reflects the expert attitude, is obtained from CSMAR to make a comparison between the wisdom of experts and that of crowds. The analyst recommendation rank in CSMAR is standardized and divided into five categories, with ratings ranging from -2(sell) to +2(buy). We totally obtain 278,389 sell-side analyst recommendations from 2016 to 2017, involving 2,997 stocks.

Following existent studies (Da et al. 2011; Liu and Ye 2016), we also control variables reflecting the firm performance and capital structure. Additional financial characteristics and trading data of A-shares are obtained from CSMAR. After deleting observations with missing data and calculation of variables, our dataset contains 51,848 observations for 2,708 listed firms in the Chinese A-share market from January 4, 2016 to December 29, 2017.

Variables

Dependent Variables

Following Loh and Stulz (2011), we employ the cumulative buy-and-hold abnormal return (*CAR*) to measure stock prices, which reflects the opinion of experts and crowds. The n-day cumulative buy-and-hold abnormal return (*CAR*) is defined as follows:

$$CAR_{it} = \prod_{t=0}^{n}(1+R_{it}) - \prod_{t=0}^{n}(1+R_{it}^{DGTW}) \tag{1}$$

Where R_{it} is the raw return of the stock i on day t; R_{it}^{DGTW} is the return on a benchmark portfolio by capitalization weighting with the same size, book-to-market(B/M), and momentum characteristics as the stock (Daniel et al. 1997). Day 0 is the day when analyst recommendation or online search occurs. We remove the observations when the analysts recommend stocks or the masses search for stock information online on weekends.

We also adopt abnormal turnover (*Abturn*) following the existing study (Llorente et al. 2002) to gauge daily trading volumes, which reflects the expert attitude and the crowd attention. The n-day abnormal turnover is defined as follows:

$$Abturn_{it} = \log(turnover_{it} + 1) - \frac{1}{n}\sum_{s=-n}^{-1}\log\left(turnover_{i(t+s)} + 1\right) \tag{2}$$

Where $\log(turnover_{it} + 1)$ is employed to avoid the situation of zero daily turnover. Day t is the day when analyst recommendation or online search occurs. We remove the observations when the analysts recommend stocks or the masses search for stock information online on weekends.

To observe the fluctuations in stock prices and trading activities over various event windows, we adopt two-day, five-day, twenty-day, forty-day, and sixty-day event windows to incorporate the *CAR* and *Abturn* reflecting the analyst recommendation and individual investor attention.

Independent Variables

Based on previous study, we evaluate the wisdom of experts to a specific stock on day *t* by computing the daily consensus level of analyst recommendation (*CON*) of stock *i* on day *t* (Jegadeesh et al. 2004) as follow:

$$CON_{it} = \overline{All\ recommendations\ for\ a\ given\ firm\ on\ day\ t} \tag{3}$$

Sogou provides the data of aggregate search frequency, allowing us to measure the aggregate attention and wisdom of crowds directly (Da et al. 2011; Mansi et al.). Following Liu and Ye (2016), we crawl the search frequency from Sogou Index based on stock tickers and calculate the abnormal search volume index (*ASVI*) as follows:

$$ASVI_{it} = SVI_{it} - SVI_{i,median} \tag{4}$$

Where

$$SVI_{it} = \log(1 + search\ frequency\ of\ stock\ i\ on\ day\ t) \tag{5}$$

$$SVI_{i,median} = \log(1 + median\ of\ search\ frequency\ of\ stock\ i\ during\ past\ 60\ trading\ days) \tag{6}$$

Control Variables

To control the performance and capital structure of the firm, some control variables are introduced in this study based on related studies. All variables involved in this study are defined in Table 1.

Table 1. Definition of variables

Variable	Definition	Data Source
Dependent variables		
CAR	Cumulative buy-and-hold abnormal return calculated based on *DGTW* benchmark	CSMAR
Abturn	Abnormal turnover calculated based on various event windows	CSMAR
Independent variables		
CON	The consensus level of analyst recommendation which is evaluated by the mean of all recommendations for a given firm on day *t*	CSMAR
ASVI	The *SVI* for firm *i* on day *t* minus the median *SVI* for given firm during the previous 60 trading days	http://www.zhishu.sogou.com
Control variables		
AbsRet	Absolute value of stock returns	CSMAR
ROA	Return on assets which is calculated as net profit/balance of stockholder's equity	CSMAR
EPS	Earnings per share which is calculated as net profit/paid-in capital	CSMAR
CAP	Market capitalization, the log value is used in regressions	CSMAR
DR	Debt ratio which is calculated as total debt/total assets	CSMAR
IH	Institutional holding, the log value is used in regressions	CSMAR
ANA	The number of analysts following stock *i*, the log value is used in regressions	CSMAR

Model Development

Two-way fixed effect regression model with panel data is employed as the base model to explore the difference between the wisdom of experts and crowds in their impacts on the stock market. And standard errors are clustered by firms.

In order to investigate the impact of the recommendations from experts on stock prices and trading volumes, the regressions of cumulative buy-and-hold abnormal return (*CAR*) and abnormal return (*Abturn*) on the consensus level of analyst recommendation (*CON*) are conducted as follows:

$$CAR_{it} = \alpha_i + \beta_1\, CON_{it} + \beta_2\, AbsRet_{it} + \beta_3\, ROA_{it} + \beta_4\, EPS_{it} + \beta_5\, CAP_{it} + \beta_6\, DR_{it} + \beta_7\, IH_{it} + \beta_8\, ANA_{it} + \varepsilon_{it} \tag{7}$$

$$Abturn_{it} = \alpha_i + \beta_1\, CON_{it} + \beta_2\, AbsRet_{it} + \beta_3\, ROA_{it} + \beta_4\, EPS_{it} + \beta_5\, CAP_{it} + \beta_6\, DR_{it} + \beta_7\, IH_{it} + \beta_8\, ANA_{it} + \varepsilon_{it} \tag{8}$$

To understand the effect of the wisdom of crowds on stock prices and trading volumes, and compare their impact on the stock market with the opinion of experts, we estimate the regressions of cumulative buy-and-hold abnormal return (*CAR*) and abnormal return (*Abturn*) on abnormal search volume index (*ASVI*) as follows:

$$CAR_{it} = \alpha_i + \beta_1\, ASVI_{it} + \beta_2\, AbsRet_{it} + \beta_3\, ROA_{it} + \beta_4\, EPS_{it} + \beta_5\, CAP_{it} + \beta_6\, DR_{it} + \beta_7\, IH_{it} + \beta_8\, ANA_{it} + \varepsilon_{it} \tag{9}$$

$$Abturn_{it} = \alpha_i + \beta_1\, ASVI_{it} + \beta_2\, AbsRet_{it} + \beta_3\, ROA_{it} + \beta_4\, EPS_{it} + \beta_5\, CAP_{it} + \beta_6\, DR_{it} + \beta_7\, IH_{it} + \beta_8\, ANA_{it} + \varepsilon_{it} \tag{10}$$

Results

Descriptive Statistics

Our dataset contains 51,848 observations for 2,708 listed firms in the Chinese A-share market from January 4, 2016 through December 29, 2017.

We first present the correlation coefficients between variables and descriptive statistics of key variables in Table 2. The correlation coefficients show that *CON* is positively correlated with both *CAR* and *Abturn*. However, *ASVI* is positively correlated with *CON* in the short term and negatively correlated with *CON* in the long run, while the coefficients between *ASVI* and *Abturn* is positive and larger than the coefficients between *CON* and *Abturn*. Besides, the relationships between two independent variables (*CON* and *ASVI*) and control variables turn out to be quite different, from which we may get a glimpse of the different preferences of experts and crowds.

Based on the key statistics of variables, we find recommendation distribution to be as in Malmendier and Shanthikumar (2014): the analyst recommendations are mostly positive as the mean of *CON* is 1.53 throughout the sample period, which may be the evidence of expert optimistic bias in existing literature (Hong and Kacperczyk 2010; Mokoaleli-Mokoteli et al. 2009). We also show the multicollinearity test results at the bottom of Table 2. It is obvious that the VIF values of all independent variables and control variables are far less than 10, implying that there is no multicollinearity between variables (Marquaridt 1970).

Table 2. Descriptive statistics, correlation coefficient and multicollinearity test of data

	Dependent Variables										Independent Variables		Control Variables						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)
(1)	1.00																		
(2)	0.71	1.00																	
(3)	0.39	0.56	1.00																
(4)	0.26	0.38	0.70	1.00															
(5)	0.21	0.30	0.56	0.80	1.00														
(6)	0.21	0.12	0.05	0.03	0.02	1.00													
(7)	0.20	0.10	0.04	0.02	0.01	0.88	1.00												
(8)	0.17	0.09	0.02	0.00	-0.01	0.70	0.84	1.00											
(9)	0.16	0.08	0.02	0.01	0.00	0.64	0.77	0.94	1.00										
(10)	0.15	0.08	0.03	0.01	0.00	0.61	0.73	0.90	0.97	1.00									
(11)	0.05	0.05	0.03	0.02	0.02	0.02	0.03	0.03	0.04	0.04	1.00								
(12)	0.13	0.07	0.01	-0.02	-0.03	0.27	0.34	0.46	0.52	0.52	0.04	1.00							
(13)	0.28	0.20	0.08	0.03	0.01	0.41	0.41	0.39	0.38	0.38	0.02	0.38	1.00						
(14)	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	1.00					
(15)	0.01	0.01	0.02	0.04	0.05	-0.01	-0.01	-0.01	-0.01	-0.01	0.08	-0.02	-0.03	0.09	1.00				
(16)	0.00	0.02	0.05	0.08	0.09	-0.05	-0.05	-0.05	-0.04	-0.03	0.05	-0.06	-0.10	0.03	0.38	1.00			
(17)	0.01	0.00	0.02	0.01	0.01	-0.02	-0.01	-0.01	0.00	0.01	0.02	-0.02	-0.03	-0.04	0.00	0.31	1.00		
(18)	0.02	0.03	0.06	0.08	0.10	-0.04	-0.05	-0.05	-0.03	-0.02	0.13	-0.06	-0.09	0.04	0.34	0.81	0.23	1.00	
(19)	0.01	0.02	0.05	0.08	0.09	-0.03	-0.03	-0.03	-0.03	-0.02	0.16	-0.03	-0.06	0.05	0.27	0.45	0.03	0.62	1.00
Mean	0.00	0.00	0.00	-0.01	-0.02	0.00	0.00	0.00	0.00	0.00	1.53	0.42	0.02	0.09	0.71	23.45	0.44	4.29	2.69
SD	0.04	0.05	0.10	0.13	0.17	0.02	0.02	0.02	0.02	0.02	0.50	0.56	0.02	1.12	1.23	1.02	0.20	1.03	0.69
VIF											1.04	1.17	1.18	1.01	1.22	3.19	1.14	3.73	1.69

Note: (1): *CAR*2; (2): *CAR*5; (3): *CAR*20; (4): *CAR*40; (5): *CAR*60; (6): *Abturn*2; (7): *Abturn*5; (8): *Abturn*20; (9): *Abturn*40; (10): *Abturn*60; (11): *CON*; (12): *ASVI*; (13): *AbsRet*; (14): *ROA*; (15): *EPS*; (16): *CAP*; (17): *DR*; (18): *IH*; (19): *ANA*.

Empirical Results

To explore whether the attitude of experts or crowds could predict the positive cumulative abnormal return, we conduct regression (7) and regression (9), respectively. The results are presented jointly in Table 3 for a comparison of *CON* and *ASVI*.

As reported in Table 3, the coefficients of *CON* are significantly positive at the level of 0.01 for *CAR*2, *CAR*5, and *CAR*20, but insignificant for *CAR*40 or *CAR*60. It means that the stocks favored by experts will experience positive *CAR* in the following month, which is in line with H1a.

Another interesting fact shown in Table 3 is that *ASVI* has significantly positive correlation only with *CAR*2 and negative correlation with *CAR*20, *CAR*40, and *CAR*60. That is to say, the aggregate attention of crowds is more likely to generate buy pressure and positive *CAR* in the short term; The stock prices then reverse in the long run and yield negative *CAR*, which is consist with Joseph et al. (2011), supporting H2a.

By comparing the regression results in table 3, it is not difficult to find that *CON* is influential to *CAR* in a longer term than *ASVI*, thus H3a is confirmed. As the crowds in the Chinese stock market are speculators rather than value investors, they prefer short-term returns. The experts, however, tilt towards growth firms with a considerable profit and thus yield a higher abnormal return in a relative long period (Jegadeesh et al. 2004).

We also investigate the impact of *CON* and *ASVI* on abnormal turnover by estimating equation (8) and equation (10). The results are presented jointly in Table 4 for the comparison between *CON* and *ASVI*.

Different from the results of equation (7), *CON* is almost always significantly positive related to *Abturn* in Table 4. H1b is partly confirmed, although the coefficients of *CON* are quite small (0.001), which suggests that *CON* has significant but subtle impact on *Abturn*. As the crowds underreact to analyst recommendation due to the information explosion, traditional experts have a slight effect on the abnormal turnover of stocks. On the other hand, the coefficients between *ASVI* and Abturn are significantly positive, strongly confirming H2b. The results shown in Table 4 suggest that the stocks with more attention from the crowds usually have greater turnover, which is in line with Da Silva Rosa and Durand (2008). In another way, the wisdom of crowds, which is measured by *ASVI*, reflects the investor enthusiasm for transactions and leads to the increase in turnover.

H3b is also supported by the joint results in Table 4. As mentioned above, the coefficients of *ASVI* are always positive at the 0.01 level, while the coefficient of *CON* is insignificant for *Abturn*2. Besides, the magnitude of coefficients in Table 4 implies that *ASVI* has a stronger impact on *Abturn* than *CON* does. This is because that *ASVI* captures the crowds' tendency to trade stocks more directly. However, the influence of analyst recommendation on stock turnover depends on whether the crowds listen to the experts.

Conclusion

The purpose of our research is to figure out the differences between the impact of the wisdom of experts and that of crowds on the stock market. We use the consensus level of analyst recommendation and abnormal search volume index to measure the attitude of experts and crowds to stocks, respectively. The cumulative buy-and-hold abnormal return and abnormal turnover are calculated based on various event windows to reflect the impacts of different players on the stock market.

Our study enriches previous studies on the impacts of professional analysts and crowds of retail investors on the stock market. The empirical results suggest that experts and crowds have different impacts on the stock market. While the recommendation of experts has a more durable impact on stock prices, the attention of crowds has a stronger impact on stock trading volumes. It means that the wisdom of experts and crowds has important value to the management of financial risk and investment decisions.

Our empirical findings contribute to both theory development and managerial practice. From the theoretical perspective, we extending research on behavioral finance from a new visual angle. We raise an interesting frontier question and lay the foundation for further studies on the behavior of different

Table 3. Different impacts of experts and crowds on cumulative buy-and-hold abnormal return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	*CAR*2	*CAR*2	*CAR*5	*CAR*5	*CAR*20	*CAR*20	*CAR*40	*CAR*40	*CAR*60	*CAR*60
CON	0.003^{***} (0.000)		0.004^{***} (0.001)		0.004^{***} (0.001)		0.002 (0.001)		0.000 (0.002)	
ASVI		0.002^{***} (0.000)		-0.001 (0.001)		-0.005^{***} (0.001)		-0.010^{***} (0.002)		-0.014^{***} (0.002)
AbsRet	0.493^{***} (0.017)	0.478^{***} (0.017)	0.504^{***} (0.026)	0.515^{***} (0.024)	0.344^{***} (0.035)	0.398^{***} (0.032)	0.159^{***} (0.038)	0.259^{***} (0.038)	0.051 (0.045)	0.189^{***} (0.046)
ROA	-0.000^{**} (0.000)	-0.000^{**} (0.000)	0.000^{**} (0.000)	0.000^{**} (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.001)	-0.000 (0.001)
EPS	-0.000 (0.000)	-0.000 (0.000)	-0.001 (0.001)	-0.001 (0.001)	-0.003 (0.002)	-0.003 (0.002)	-0.005^{*} (0.003)	-0.005^{*} (0.003)	-0.003 (0.004)	-0.003 (0.004)
CAP	0.001 (0.002)	0.001 (0.002)	0.005^{*} (0.003)	0.006^{*} (0.003)	0.021^{**} (0.010)	0.021^{**} (0.010)	0.041^{***} (0.016)	0.041^{***} (0.016)	0.051^{**} (0.020)	0.051^{**} (0.020)
DR	-0.002 (0.004)	-0.002 (0.004)	0.000 (0.007)	0.000 (0.007)	-0.013 (0.023)	-0.012 (0.023)	-0.019 (0.047)	-0.019 (0.047)	-0.102 (0.134)	-0.101 (0.134)
IH	0.002^{**} (0.001)	0.002^{**} (0.001)	0.002 (0.001)	0.002 (0.001)	0.000 (0.004)	0.000 (0.004)	0.002 (0.008)	0.002 (0.008)	0.002 (0.010)	0.002 (0.010)
ANA	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.002 (0.004)	-0.002 (0.004)	-0.005 (0.006)	-0.004 (0.006)	-0.006 (0.009)	-0.006 (0.009)
_cons	-0.034 (0.034)	-0.036 (0.035)	-0.158^{**} (0.068)	-0.161^{**} (0.069)	-0.469^{**} (0.210)	-0.473^{**} (0.211)	-0.936^{***} (0.339)	-0.940^{***} (0.341)	-1.120^{**} (0.454)	-1.125^{**} (0.456)
Observation#	51848	51848	51848	51848	51848	51848	51848	51848	51848	51848
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clusters(firms)	2708	2708	2708	2708	2708	2708	2708	2708	2708	2708
R^2	0.096	0.095	0.054	0.053	0.024	0.024	0.021	0.022	0.021	0.023

Note: Standard errors clustered by firms are in parentheses. ***, **, and * represent the significance at 1%, 5%, and 10% level, respectively.

Table 4. Different impacts of experts and crowds on abnormal turnover

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	*Abturn*2	*Abturn*2	*Abturn*5	*Abturn*5	*Abturn*20	*Abturn*20	*Abturn*40	*Abturn*40	*Abturn*60	*Abturn*60
CON	0.000 (0.000)		0.001*** (0.000)		0.001*** (0.000)		0.001*** (0.000)		0.001*** (0.000)	
ASVI		0.005*** (0.000)		0.008*** (0.000)		0.014*** (0.000)		0.018*** (0.000)		0.019*** (0.000)
AbsRet	0.368*** (0.008)	0.321*** (0.008)	0.376*** (0.009)	0.296*** (0.008)	0.399*** (0.009)	0.254*** (0.008)	0.413*** (0.010)	0.231*** (0.008)	0.421*** (0.010)	0.231*** (0.009)
ROA	-0.000 (0.000)	-0.000* (0.000)	-0.000* (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000** (0.000)	-0.000 (0.000)	-0.000*** (0.000)	-0.000 (0.000)	-0.000*** (0.000)
EPS	-0.000 (0.000)	-0.000 (0.000)	-0.000* (0.000)	-0.000** (0.000)	-0.000 (0.000)	-0.001*** (0.000)	-0.000 (0.000)	-0.001*** (0.000)	-0.000 (0.000)	-0.001** (0.000)
CAP	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.001 (0.001)	0.000 (0.001)	-0.000 (0.001)	0.000 (0.001)	0.000 (0.001)
DR	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.002)	-0.003* (0.002)	-0.004 (0.002)	-0.005*** (0.002)	-0.002 (0.003)	-0.004* (0.002)	-0.000 (0.003)	-0.002 (0.002)
IH	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	-0.001 (0.001)	0.000 (0.000)	-0.001 (0.001)	0.000 (0.001)
ANA	-0.001 (0.000)	-0.001 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.000)	-0.000 (0.001)	-0.000 (0.001)
_cons	0.008 (0.017)	0.009 (0.018)	0.004 (0.016)	0.006 (0.016)	0.006 (0.018)	0.010 (0.017)	-0.009 (0.020)	-0.004 (0.019)	-0.021 (0.024)	-0.015 (0.021)
Observation#	51848	51848	51848	51848	51848	51848	51848	51848	51848	51848
Fixed effects	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Clusters(firms)	2708	2708	2708	2708	2708	2708	2708	2708	2708	2708
R^2	0.209	0.224	0.210	0.250	0.204	0.310	0.205	0.355	0.200	0.357

Note: Standard errors clustered by firms are in parentheses. ***, **, and * represent the significance at 1%, 5%, and 10% level, respectively.

participants in the stock market, such as research on their preference, behavior pattern, and interaction between them. From a practical standpoint, this work furthers the understanding of the effectiveness and credibility of expert recommendation, and highlight the value embedded in wisdom of the crowds. The findings may lead to some specific actions in response to analyst recommendation and online search volume, and may provide implications for risk management and investment strategy.

However, our study has some limitations due to the sample size and measurements employed. Firstly, as the Sogou Index started to present the search volume index from January 1, 2016, the sample spans only two years, which should be extended in future research. Secondly, alternative variables could be introduced to measure the wisdom of experts (e.g., the changes in analyst recommendation) and crowds (e.g., the sentiment of crowds on the Internet) in future research to test the robustness of our results.

Acknowledgements

The authors would like to thank the editor and reviewers for their helpful and constructive suggestions. This research was supported by the National Natural Science Foundation of China (Grant # 71532004, 71801063, and 71850013) and the China Postdoctoral Science Foundation (Grant # 2018M640300).

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