International Journal of Economics and Financial Research
ISSN(e): 2411-9407, ISSN(p): 2413-8533
Vol. 7, Issue. 3, pp: 82-89, 2021
URL: https://arpgweb.com/journal/journal/5
DOI: https://doi.org/10.32861/ijefr.73.82.89

Academic Research Publishing Group

Original Research | Open Access

The Relation Between Trading Volume Concentration and Stock Returns

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Article History
Received: 26 April, 2021
Revised: 17 June, 2021
Accepted: 1 July, 2021
Published: 7 July, 2021

Abstract

The Taiwan Stock Exchange discloses data on daily trading volume across brokerage firms for each listed stock. Market practitioners suggest that the concentration of trading volume contains information on the trading behaviors of big players. We use the Gini Coefficient to measure the degree of concentration, upon which a trading strategy is proposed. We conduct an event study to examine whether such a strategy will yield abnormal returns. Our sample contains 375 listed companies with events identified during the sample period from February 2020 to August 2020. The empirical results show that the trading signal based on the Gini coefficient is informative and that most of the average abnormal returns after the event date are significantly positive with the cumulative average abnormal returns increasing almost monotonically up to the end day of the event window. Consistent with prior studies in which different measures of concentration are utilized, our findings provide additional evidence that the Gini Coefficient could help investors to develop profitable stock selection and market timing strategies.

Keywords: Trading volume concentration; Gini coefficient; Big players; Event study.

1. Introduction

Investors and financial practitioners in the stock market use many indicators for stock selection and trading decisions. In addition to fundamental and technical indicators, a third group of indicators related to stock ownership, dubbed as chip/stake indicators, is also popular with Taiwanese investors. Some Taiwanese investors compare investing in the stock market to participating in a game, where shares or stakes are regarded as chips in gambling. The stake indicators are constructed mainly by utilizing trading and/or shareholding data by type of investors with the purpose to assess the moves of certain investor groups, especially those of "big players". There is no clear definition of a big player, who conceptually is similar to a sophisticated investor with a high net-worth and sufficient financial knowledge and experience to evaluate the return/risk profile of investments. Generally speaking, the three major institutional investors (foreign institutions/ securities investment trust companies/ dealers), company insiders, major shareholders, and large individual investors may be considered big players. In this paper, we first construct a chip/stake indicator, named the Gini coefficient of stake concentration, to measure the inequality of daily trading volume distribution across brokerage firms for each listed firm in the sample. Market practitioners suggest that trading volume concentration can shed light on the trading behaviors of big players. An event is set to occur when the Gini coefficient is greater than a threshold value. Event-study methodology is applied to examine whether there are significant abnormal returns. The whole distribution of trading volume across brokerages is used to construct the Gini coefficient of stake concentration, which should be more informative on trading concentration than the measures adopted by prior studies where partial distribution of trading volume is utilized.

Investors in the securities market can generally be divided into institutional investors and individual investors. The former can be further subdivided into foreign institutions, investment trusts, and proprietary dealers. Market participants can also be classified into informed traders and uninformed traders. Informed traders are those who possess the information about the real value of the asset, through either access to private information or skillful processing of public information, while uninformed traders do not have such information. Prior literature provides evidence that institutional investors gain while retail investors lose in the Taiwan stock market (Barber *et al.*, 2009) and that not only are institutional investors informed traders, but large individual investors may also be informed traders (Lee *et al.*, 1999). It then makes sense to track what stocks the big players are buying or selling.

Individual investors in Taiwan's stock market account for the largest percentage of securities trading value, approximately 60% on average over the period 2011 to 2020. Individual investors are considered to be in a disadvantageous position in gathering and processing information. In order to protect individual investors and to narrow the information gap, the competent authorities of the Taiwan government require investment service providers to make available to the public certain trading and shareholding data by investor type, upon which chip/stake indicators are constructed. The Taiwan Stock Exchange (TWSE) provides pre-market, intra-market, and after-market transaction data on the company's website. The after-market trading data include, for example, stock-level daily trading reports of the three major legal entities, and the daily report of foreign shareholding percentage. Although some data are not disclosed by investor type, they are considered to reflect the trading behavior of a certain investor group. For example, the data on margin trading/short selling is usually considered to be related to the sentiments of retail investors. The Taiwan Depository & Clearing Corporation (TDCC) discloses the weekly "Table for Spread of Shareholdings under TDCC Custody", in which the shareholding structure of each listed stock is tabulated into 15 brackets. For each bracket, the range of the number of shares, the number of shareholders, total number of shares, and the shareholding percentage are disclosed. The distribution of equity stakes, the level and change of shareholding of insiders and major shareholders over time may provide useful information on these big players' prospects of the company.

Except the summary trading data of the three major institutional investors, we cannot directly observe trading data of other big players. All investors, except dealers, have to place their orders through brokers. For each stock, TWSE provides free access to the daily trading report, containing data on trading volume across brokerage firms for each listed stock, after the trading closes in each trading day. The brokerage firms (or branches for simplicity) denote the places of business, including head-offices and branches. As of January, 2020, there were 1,013 members of securities firms registered with Taiwan Securities Association, including 129 main offices and 844 branches. In the daily trading report, trading volume of each stock is disclosed at a stock-brokerage branch-transaction price level. For each record in the report, it contains brokerage firm code, transaction price, the number of shares purchased (buy volume), and the number of shares sold (sell volume). Many securities firms and financial websites provide an abridged version of daily trading reports at a stock-branch level by aggregating trading volume over all transaction prices. For any security, the buy volume and sell volume aggregated across brokerage firms are the same in a given day. But this relation mostly does not hold at a particular brokerage firm. Practitioners often analyze the net-buy or net-sell volumes of pivotal brokerage firms that are related to big players for a listed firm, due to business relation or geographic proximity. As investors do not change their brokers often, analysts sometimes deem a key broker as a representative investor for big players under this brokerage. Furthermore, the distribution of the unsigned trading volume (net buy/net sell) across brokerage firms may also shed light on the big players' trading behavior at a firm level. For example, if the buy volumes are large and concentrated in a few brokerage firms, while sell volumes are small and scattered in most branches, it may be a signal that informed big players are on the buy side of the market. Practitioners borrow the concept of Gini coefficient in economics to measure the concentration of trading volume across securities firms. Investors can then formulate trading strategies based on this indicator.

Few prior studies examine the relation between stake concentration ratio and stock returns. These studies generally provide evidence that strategies based on stake concentration ratio may generate abnormal returns, though different measures of the stake concentration ratio are used (e.g.Chan (2017), Liao (2014)). Despite the popularity of the Gini coefficient of stake concentration with market practitioners, virtually no academic paper provides evidence on its viability for picking stocks. In this paper, we use the Gini coefficient to measure the extent of stake concentration of trading volume and examine whether a trading strategy based on it can benefit investors. Consistent with previous studies, our findings reveal that investors can earn positive abnormal returns if they follow the trading signal to purchase stocks the first day after the event day.

The remainder of the paper is organized as follows. Section 2 presents an overview of related literature. Section 3 describes the data and methodology. Section 4 reports the empirical results and discussion. Section 5 concludes the paper.

2. Related Literature

Our study is related to the literature on the relation between informed trading and trade size. There are three alternative predictions from theoretical models and empirical studies on the order size that informed traders will use. In the model of Kyle (1985), a monopolistic informed trader would split trades over time favoring small trade size for their private information to be gradually incorporated in the prices. In contrast, Holden and Subrahmanyam (1992) develop a model where multiple informed traders are more likely to aggressively trade with their private information by utilizing large trade size. Barclay and Warner (1993), provide supporting evidence for a joint hypothesis, called stealth trading hypothesis, that privately informed traders concentrate their trades in medium sizes, and that these information-based trades account for the largest proportion of price movements. Chakravarty (2001) provides further evidence that medium size trades by institutions are the driving force for the price impacts.

Easley and O'Hara (1987), explicitly addressing the issue of the choice of trade size, posit that informed traders prefer trading larger quantities at any given price; however, the expected price impact of the trades (price reductions) increases with trade size. In equilibrium, the choice of the trade size for informed traders depends on three market conditions, without taking into the consideration the impact of transaction costs and risk aversion attitude of informed traders. These conditions are the ratio of large to small trade size that uninformed traders desire to use (market width), the fraction of uninformed traders who want to trade in large quantities (market depth), and the probability of information-based trading. In a wide and deep market, with few information-based trades, a separating equilibrium exists where informed traders choose to use a large trade size. Otherwise, a pooling equilibrium will prevail, where informed traders choose to trade both large and small quantities, with large trades transacting at less favorable prices.

There is evidence that informed traders in Taiwan stock market tend to trade medium to large orders, which is consistent with the predictions of Easley and O'Hara (1987), Holden and Subrahmanyam (1992) and Barclay and Warner (1993). Lee *et al.* (1999), examine the trading patterns of various investor groups (e.g., institutions, big/small individual investors), where a trade size of 10,000 shares or 10 round lots is used as the dividing point for the big/small players. With intraday order book and transaction data of the 30 most actively traded stocks in Taiwan Stock Exchange for the period from March through May 1995, the results of the VAR analysis show that big individual investors are the most informed group followed by institutional investors, while individual investors tend to be noise traders. Lee *et al.* (2004), cross-tabulate daily marketable limit order imbalance by investor type (individuals/domestic institutions/ foreign institutions) and order size (large traders/small traders) for the period from September 1996 through April 1999 and investigate the trading profits of the six trader classes. The results show that domestic institutions are most likely to engage in profitable informed trading with low price impact, possibly via splitting orders over time. Lee *et al.* (2004), also find that institutions have more persistent order imbalances, which may be due to rational herding among institutions or orders splitting by institutional traders. Using intraday data from 2005 and 2010, Lin *et al.* (2013) find that not only are institutional investors likely to be informed traders, but they also tend to herd rationally, as their buy (sell) herding are positively (negatively) correlated with future market returns.

Barber *et al.* (2009), investigate whether there are investor groups that are consistent winners and losers from trading in the Taiwan stock market for the period 1995 to 1999. The results indicate that all institutional groups, with better information and skills, make gains while individual investors incur losses. Barber et al. attribute the gains of institutional investors more to stock selection than market timing. Gibson and Safieddine (2003), use quarterly dada and a sample that includes all NYSE, AMEX, and Nasdaq stocks to investigate the relationship between institutional ownership changes and same-period return. The empirical results indicate that except for small capitalization stocks, the increase of institutional ownership is correlated with the positive return of stocks, while the decrease of institutional ownership is correlated with the negative return. Gibson and Safieddine conclude that the positive relationship is consistent with the notation that institutional investors play a price-setting leadership role in equity markets. Tsai (2014), uses the event study method to examine the trading behaviors of individual traders in Taiwan before and after the annual earnings announcement. The results reveal that individual investor as a whole are not informed about the imminent earnings announcement, but some smart individual traders place aggressive orders like informed and earn positive profits, except for periods in financial crisis. There is evidence that big players are informed traders, institutional trades lead stock price, and institutional investors tend to herd rationally in Taiwan stock market. Therefore, individual investors could collect information on the trading activities of institutional investors, such as their net-buy/net-sell positions, to follow their moves and make profits.

Few previous studies examine the profitability of trading strategies based on stake concentration indicators, despite their popularity among investors and practitioners. Chan (2017) investigates whether a stake concentration ratio (SCR), serving as an additional filter for picking stocks, can enhance the performance of momentum strategies over different holding horizons in Taiwan stock market using monthly data for the period from January 2011 through March 2017. The monthly SCR for each individual stock is defined as the average of daily SCR for the most recent 20 days. The daily SCR is computed on the basis of trading volume at brokerage houses, as top 15 net-buy volume minus top 15 net-sell volume and then divided by total trading volume. Long-short portfolios with individual stocks sorted by momentum and/or SCR are constructed. The results reveal that positive abnormal returns can be achieved by momentum strategies, SCR strategies and combined strategies.

Using data in daily trading reports for the period from October 2012 to January 2013, Liao (2014) selects top 15 brokerage firms sorted by the absolute relative trade imbalance (RTI) for each sample firm. Each of these brokerage firms is considered a representative of a big player. An event is defined to occur when the signed RTI is greater than a threshold value of 0.2. (RTI = (B-S)/(B+S)) where B and S refers to the buy volume and sell volume for a given stock at a particular brokerage branch. For the net-buy events, they are further classified into 5 subsamples according to the market capitalization of the firm. Event study is carried out for each subsample, with an event window covering 5 trading days before and after the event date. Except the subsample with the lowest market capitalization, the CARs are positive for all subsamples. A similar analysis is conducted for the net-sell events, where CARs for all subsamples are negative.

3. Data and Methodology

This section describes the sample construction, the definition of variables of interests and the methodology used in this study.

3.1. Data Source and Sample

The initial sample include all companies listed on the Taiwan Stock Exchange in 2020 subject to data availability. Firms newly listed after June 30, 2018 are excluded, as there tend to be a large short-run initial return for initial public offerings. Financial firms are also excluded from the sample because their high leverage characteristic is different from that of non-financial firms. The final sample contains 375 listed companies with events identified during the sample period from February 2020 to August 2020.

The daily returns of individual stocks come from the database of Taiwan Economic Journal (TEJ). The data for the daily trading volume by securities firm for each stock for the calculation of Gini coefficient is accessed from the trading platform of Yuanta Securities Co., Ltd. with a user-defined program. Yuanta provides a simplified version of TWSE daily trading reports at a stock-branch level which make the calculation of Gini coefficient more efficient.

3.2. Sample Descriptive Statistics

Table 1 shows the descriptive statistics of the number of outstanding shares of the 375 listed companies in the sample, which indicates that there is an adequate spread of company size.

Table-1. Descriptive statistics of the number of outstanding shares (Thousand shares)

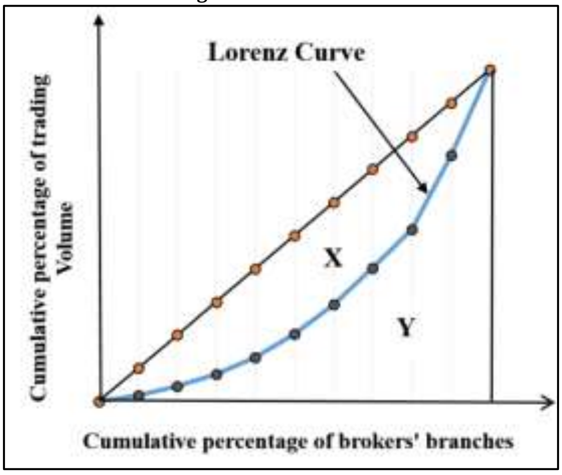
Mean	**591,469**
Median	274,367
Standard deviation	2,475,689
Kurtosis	308
Skewness	17
Minimum	30,000
Maximum	46,120,000
Number of companies	375

3.3. Variable

We obtain data on daily trading volume of each listed firm in the sample at the brokerage branch level. Many practitioners view the brokerage branch with substantial net-buy or net as a representative of big player. The concentration of trading volume across brokers may reveal the future moves of the big players. To measure the extent of stake concentration, we utilize the Gini's coefficient, which has been widely used in many academic fields notably in economics as a measure of degree of concentration (or inequality) in the distribution of non-negative values of some attribute (e.g. income).

For measuring household income inequality, the Gini coefficient is usually illustrated with the Lorenz curve, which plots the cumulative percentage of income on the vertical axis against the cumulative percentage of households on the horizontal axis. In our case, the Lorenz curve plots the cumulative percentage of net-buy/net-sell volume (number of shares) against the cumulative number of branches. The 45-degree line represents the case of a perfect equality. The Gini coefficient can then be defined as the ratio of the area that lies between the line of equality and the Lorenz curve (marked area X in Figure 1) over the total area under the line of equality (market area X+Y in Figure 1). The value of the Gini coefficient is between 0 (perfect equality) and 1 (perfect inequality). The larger the Gini coefficient, the higher the trading concentration.

Figure-1. Lorenz Curve



We can calculate the Gini coefficient without referring to the Lorenz curve. Glasser (1962), shows that the Gini coefficient is one half of the mean absolute difference divided by the population mean. For a population of n (n>2) observations with an attribute Y sorted in ascending order ($Y_1 \leq Y_2 \leq \ldots \leq Y_i \leq \ldots \leq Y_n$), the population Gini coefficient, G, for the distribution of Y can be calculated using the following formula in Sen (1977):

$$G = \frac{1}{n}\left(n + 1 - 2\frac{\sum_{i=1}^{n}(2i - n - 1)Y_i}{\sum_{i=1}^{n} Y_i}\right) \tag{1}$$

In case of a sample, the sample Gini coefficient can be calculated using the above formula, and then multiplied by an adjustment factor of n/(n-1) to be a consistent estimator.

We construct the Gini coefficient of stake concentration using trading volume records by brokerage branches. For each stock, we sort the daily net position (buy volume minus sell volume) of all branches with transactions. We compute the buyer's Gini coefficient for net-buy volume among net-buy branches and the seller's Gini coefficient for the absolute value of net-sell volume among net-sell branches. We then define the Gini coefficient of stake concentration to be the buyer's Gini coefficient minus the seller's Gini coefficient, which then serves as a filter for events.

3.4. Event Study Methodology

To examine whether a trading strategy based on the Gini coefficient of stake concentration can generate abnormal returns for investors, we apply the standard event-study methodology outlined in Brown and Warner (1980;1985) and MacKinlay (1997). An event is defined to occur when in a trading day the Gini coefficient of stake concentration is greater than a threshold value of 0.2. For each event, the calendar time is converted to event time with reference to the event day, i.e. day[0]. The event period is the period from 20 days before and after the event day (i.e. day[-20] to day[+20]) and the estimation period is the period from 21 days to 200 days before the event day ([i.e. day[-220] to day[-21]].

The daily actual rate of returns of an individual stock j, R_{jt}, over the estimation and event periods are downloaded from TEJ. Abnormal returns for any given point in time for each stock are the difference between actual returns and normal returns.

$$AR_{jt} = R_{jt} - E(R_{jt}) \quad (2)$$

AR_{jt} : Abnormal rate of return of security j on day t

R_{jt} : Actual rate of return of security j on day t

The normal or expected returns can be estimated by several models, like mean adjusted returns model, market adjusted returns model, and the OLS market model. We choose to use mean adjusted returns model as Brown and Warner (1980;1985) document that empirical results are often not sensitive to the choice of models. The mean adjusted model assumes the expected rate of return of an individual security during the event period is a constant, and could be estimated by the average rate of return of the security during the estimation period. In our study, stock returns in 200 trading days prior to the event window are used for the estimation of constant mean.

$E(R_{jt})$: Expected rate of return of security j in period t

$$E(R_{jt}) = \bar{R}_J \quad (3)$$

$\bar{R}_J$: Mean of return of security j in estimation period

Average abnormal return (AR) in a given day t in event window is computed by averaging abnormal returns across all event firms.

$$AR_t = \frac{1}{N}\sum_{j=1}^{N} AR_{jt} \quad (4)$$

To understand whether the price impact of the event last for more than one day, we compute cumulative abnormal returns during the event period. Cumulative average abnormal return (CAR) in a given day T in event window is computed by aggregating average abnormal returns from the start of the event window up to and including day T.

$$CAR_T = \sum_{t=-20}^{t=T} AR_t \quad (5)$$

We test whether a AR at a given day or a CAR up to a given day in event window are significantly different from 0. The null hypothesis (H_0) and the alternative hypothesis (H_1) are as follows:

$H_0: AR_t = 0$

$H_1: AR_t \neq 0$

$H_0: CAR_T = 0$

$H_1: CAR_T \neq 0$

We apply the traditional no dependence adjustment test (t test) in Brown and Warner (1980;1985) to test whether ARs and CARs are significantly different from zero. It has been shown that this method is sensitive to non-normal returns and event-induced increases in variance (Brown and Warner (1985) and Boehmer *et al.* (1991)). Therefore, we also employ cross-sectional standard deviation test and sign test (nonparametric test) to check for robustness.

4. Empirical Results and Discussion

4.1. Empirical Results

Table 2 reports the ARs and CARs for all event-firms within the event period [-20, +20]. The t-statistics of the two-tailed no dependence adjustment test are displayed next to the ARs and CARs. We observe that there are some significantly positive and negative ARs on days [-20] through [-1] and there is a run of negative ARs on days [-12] to [-6]. Overall, the ARs do not show a price run-up or drop-off during the period [-20, -1], indicating that there is no information leakage to the market. The AR on the event day [0] is -0.36%, the minimum value of all ARs, and significant at 1% level. This result indicate that the signal based on the Gini coefficient is informative. It is consistent with a situation that big players are on the buy side when the stock prices of event firms fall. As the buy signal based on the Gini coefficient can only be observed after market close on the event day, investor can only buy the stocks of events firms starting from day [1], on which a positive and statistically significant AR of 0.38% is observed. Furthermore, 16 out of the 20 ARs after the event day are positive and statistically significant, with only two insignificant and negative ARs.

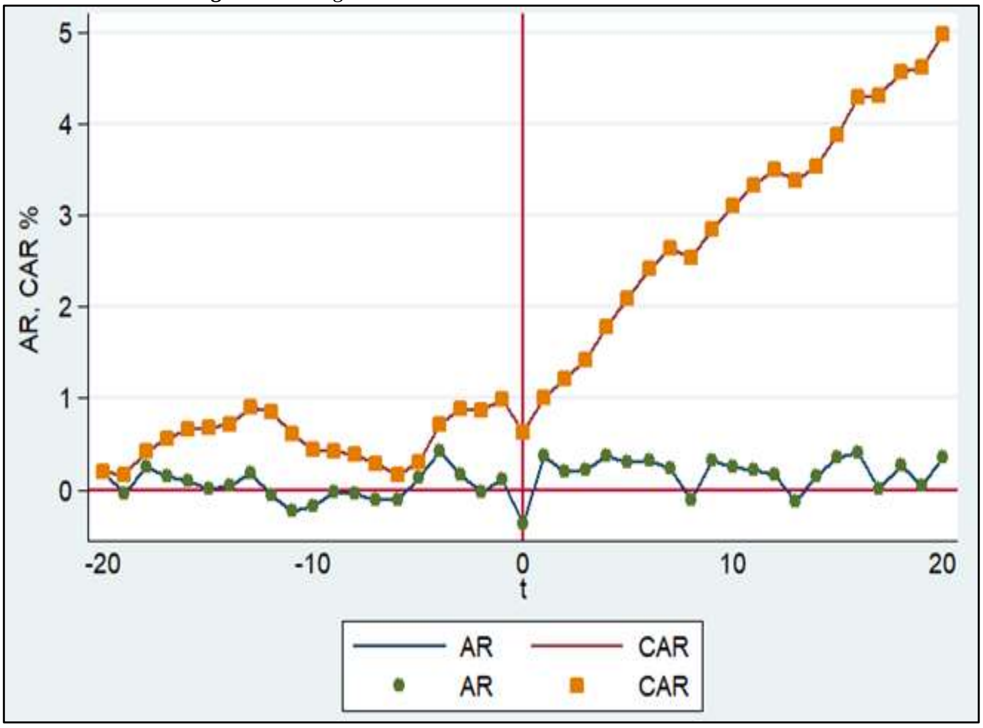
CARs provide the aggregate effect of the abnormal returns. Figure 2 plots the ARs and CARs around the event date. Although statistically significant positive CARs start before the event day, the noticeable increase in CARs is observed from day [1] and the CARs increase almost monotonically up to day [20] with a maximum value of 4.98%, indicating that the information on the buy signal may be incorporated into prices gradually. Overall, the results suggest that following the buy signal filtered by the Gini coefficient of stake concentration might be both an achievable and profitable strategy especially for small investors and early aggressive investors make the most of the profits.

Table-2. Average abnormal returns and cumulative average abnormal returnS

t	AR	t-stat		CAR	t-stat	
-20	0.21	(2.61)	***	0.21	(2.61)	***
-19	-0.05	(-0.59)		0.16	(1.43)	
-18	0.26	(3.21)	***	0.42	(3.02)	***
-17	0.14	(1.82)	*	0.56	(3.52)	***
-16	0.11	(1.33)		0.67	(3.75)	***
-15	0.01	(0.11)		0.68	(3.47)	***
-14	0.04	(0.53)		0.72	(3.41)	***
-13	0.19	(2.37)	**	0.91	(4.03)	***
-12	-0.05	(-0.66)		0.85	(3.57)	***
-11	-0.23	(-2.94)	***	0.62	(2.46)	**
-10	-0.17	(-2.14)	**	0.45	(1.70)	*
-9	-0.03	(-0.32)		0.42	(1.54)	
-8	-0.03	(-0.44)		0.39	(1.36)	
-7	-0.10	(-1.31)		0.28	(0.96)	
-6	-0.11	(-1.39)		0.17	(0.56)	
-5	0.13	(1.60)		0.30	(0.95)	
-4	0.42	(5.27)	***	0.72	(2.19)	**
-3	0.17	(2.07)	**	0.89	(2.62)	***
-2	-0.02	(-0.21)		0.87	(2.50)	**
-1	0.12	(1.54)		0.99	(2.78)	***
0	-0.36	(-4.55)	***	0.63	(1.72)	*
1	0.38	(4.72)	***	1.00	(2.69)	***
2	0.20	(2.56)	**	1.21	(3.16)	***
3	0.21	(2.63)	***	1.42	(3.63)	***
4	0.37	(4.61)	***	1.78	(4.48)	***
5	0.30	(3.80)	***	2.09	(5.14)	***
6	0.32	(4.05)	***	2.41	(5.83)	***
7	0.23	(2.93)	***	2.64	(6.27)	***
8	-0.11	(-1.33)		2.54	(5.92)	***
9	0.32	(3.99)	***	2.86	(6.55)	***
10	0.25	(3.17)	***	3.11	(7.01)	***
11	0.22	(2.75)	***	3.33	(7.39)	***
12	0.17	(2.17)	**	3.50	(7.65)	***
13	-0.12	(-1.53)		3.38	(7.27)	***
14	0.15	(1.91)	*	3.53	(7.49)	***
15	0.35	(4.41)	***	3.88	(8.12)	***
16	0.40	(5.07)	***	4.28	(8.85)	***
17	0.02	(0.23)		4.30	(8.77)	***
18	0.26	(3.30)	***	4.57	(9.18)	***
19	0.05	(0.62)		4.61	(9.16)	***
20	0.36	(4.53)	***	4.98	(9.76)	***

Note: ***, **, * denote significant at the 1%, 5%, 10% levels, respectively.

Figure-2. Average abnormal returns and cumulative abnormal returns



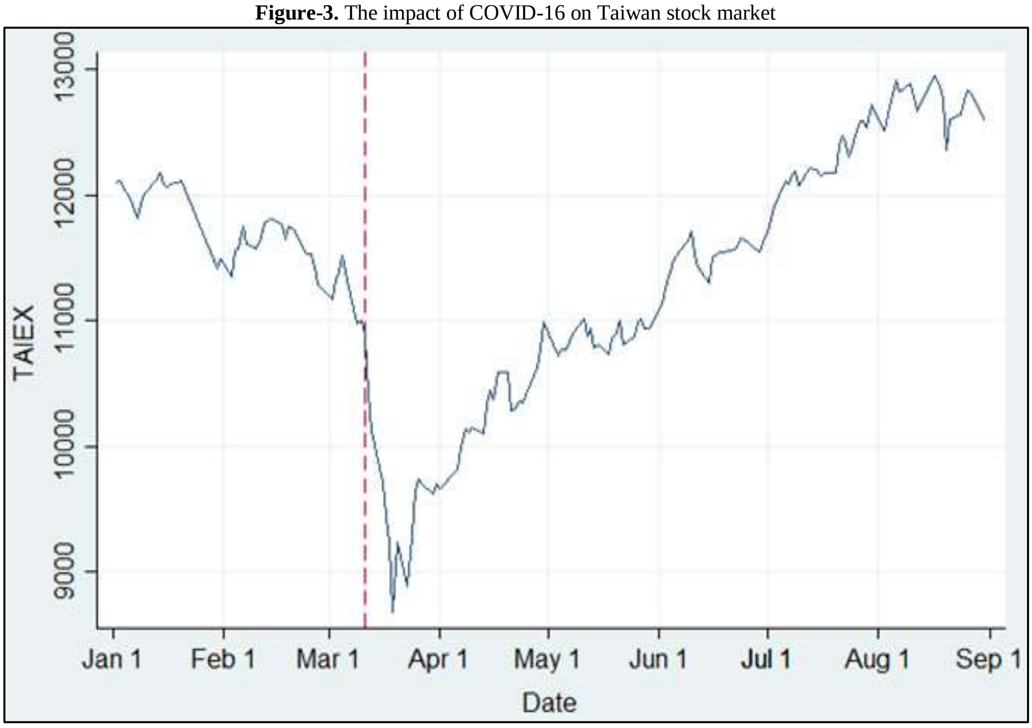
4.2. Discussion

Taiwan stock market experienced an initial downturn and a subsequent upturn during the sample period, which coincided with COVID-19 pandemic. The coronavirus disease was first reported at the end of 2019 and declared a global pandemic by the World Health Organization on March 11, 2020. The pandemic substantially affected the economies and stock markets all over the world. The benchmark index of TWSE, TAIEX index, fell from the year-start level of 12,100 points to a low of 8,681 points on March 19, as shown in Figure 3. To boost local investors' confidence, Taiwan government announced its decision to activate the National Financial Stabilization Fund, a sovereign wealth fund established since 2000 to maintain stability in capital markets and other financial markets in response to significant events with a maximum available funds up to TWD 500 billion. Following the announcement, TAIEX index rebounded steadily and returned to the year-start level in early July, with the aid of the successful containment of COVID-19 at an early stage and the bailout measures adopted by governments across the world. The National Financial Stabilization Fund announced its withdrawal from Taiwan's stock market on October 12, 2020, with a sixth consecutive profitable outcome out of the seven interventions since its establishment. In fact, it was reported that only TWD 757 million were utilized to support the market, where the average daily trading value was about TWD193.5 billion during the sample period. To sum up, the Taiwan government served as an ultimate big player whose interventions, direct or indirect, could change investors' beliefs or expectations of the stock market even without affecting much of the trading volume of the market.

All industries virtually have been affected by the COVID-19 pandemic, whereas the magnitude and duration of the impacts vary across industries. Due to the border controls and quarantine measures implemented worldwide, some industries, e.g. retail, transportation, and tourism, have been badly affected. Still, there are industries, including computers, communication, and semiconductors, that suffered a temporary negative impact at the initial stage but have benefited from the surge in demand as people were forced to study and work from home in most countries. Furthermore, firms in medical supplies actually have gained a lot from the start of the pandemic. Future research could examine the stock performances by industries or sectors when applying the Gini coefficient of stake concentration.

In addition, there are several limitations to utilizing the stake concentration ratio to infer big players' trading behaviors. First, the daily trading report does not include the trading data of dealers. Second, informed traders may split orders over time and across brokerage firms, or time their trading when the market is liquid in high volume (Admati and Pfleiderer, 1988; Blau *et al.*, 2009). Third, not all large trades are information-based. Furthermore, there could be trade-based manipulation, where informed or uninformed traders may buy and sell the same security at the same time to pump up trading volume to manipulate the beliefs of other investors to make profits (Allen and Gale, 1992; Foster and Viswanathan, 1994).

Figure-3. The impact of COVID-16 on Taiwan stock market



5. Conclusion

We examine the relation between trading volume concentration and stock returns buy testing whether a trading strategy based on the Gini coefficient of stake concentration can generate abnormal returns for investors. We conduct an event study using a sample of 375 event firms during the sample period from February 2020 to August 2020. An event is defined to occur when the Gini coefficient of stake concentration is larger than threshold value of 0.2. The mean adjusted returns model is used to compute to the normal returns. We find that the signal based on the Gini coefficient is informative and that most of the average abnormal returns after event date are significantly positive with the cumulative average abnormal returns increasing almost monotonically up to the end day of event window. Our results are consistent with those of prior studies where other measures of concentration are utilized

Nevertheless, we want to caution investors that the empirical evidence is based on a specific sample from the Taiwan stock exchange for a chosen period of 6-month. Our conclusions may not extend to other time periods or other stock markets. Despite its limitations, the Gini-coefficient of trading volume inequality among brokerage branches may still serve as a useful analytical tool. It could enhance investment performances when combined with the use of other indicators.

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