**Call Auction Frequency and Market Quality:
Evidence from the Taiwan Stock Exchange**

Mia Twu and Jianxin Wang

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Abstract

Periodic call auction is the main trading mechanism on the Taiwan Stock Exchange. From 2010 to 2014, the TWSE reduced its call auction interval four times, from 25 to 5 seconds. Using multiple measures for market efficiency, liquidity, and stability, we provide a comprehensive examination on the impact of these reductions on market quality. While different quality attributes have their highest values at different auction intervals, the current 5-second interval is the best for any combination of the three market attributes. We present new empirical evidence on the assumptions and predictions of several theoretical studies. Based on recent theoretical models, we estimate the optimal auction interval to be around 2 seconds for the TWSE.

Mia Twu (twum@nccu.edu.tw) is from the National Chengchi University. Jianxin Wang (Jianxin.wang@ uts.edu.au) is from the University of Technology Sydney and is the corresponding author.

I. Introduction

Call (or batched) auction is a trading arrangement where orders from buyers and sellers are batched for simultaneous execution at a single transaction price at a pre-specified time. The time interval between call auctions is one of the most important features of call auction trading. Based on multiple changes in call auction frequency on the Taiwan Stock Exchange (TWSE), this study conducts a comprehensive examination on how call auction frequency affects stock market efficiency, liquidity, and stability. It provides new empirical evidence on several long-standing theoretical predictions, and sheds new light on the microstructure of call auction trading.

In today's stock markets, call auction is mostly used to conduct the opening and/or closing trade on a trading day. Between the opening and closing calls, the predominant trading method is continuous trading where transactions take place whenever the price of a buyer is equal to or higher than the price of a seller. In recent years, there is a renewed interest in call auction as a replacement for continuous trading. It is motivated by some adverse effects of high-frequency trading on market quality. Everything else being equal, there is always a delay in price reaction to new information due to the latency of electronic data transmission. Budish, et al. (2015) show that in continuous trading, such latency at millisecond level creates mechanical arbitrage profits for high-speed arbitragers at the expense of liquidity providers, thus increasing the cost of liquidity provision. The mechanical arbitrage opportunities come from the serial-processing design of continuous trading, therefore will not be eliminated by the arms race in high-speed trading technology.[1] The solution proposed by Budish, et al. (2015) and many others, e.g. Farmer and Skouras (2012),

[1] If the value change is one cent and is reflected in the next quote change, the fastest trader earns one cent per share by "sniping" the staled quote. Although the arbitrage opportunities declined from 97 milliseconds in 2005 to 7 milliseconds in 2011, the per arbitrage profitability remained stable (Budish, et al. 2015).

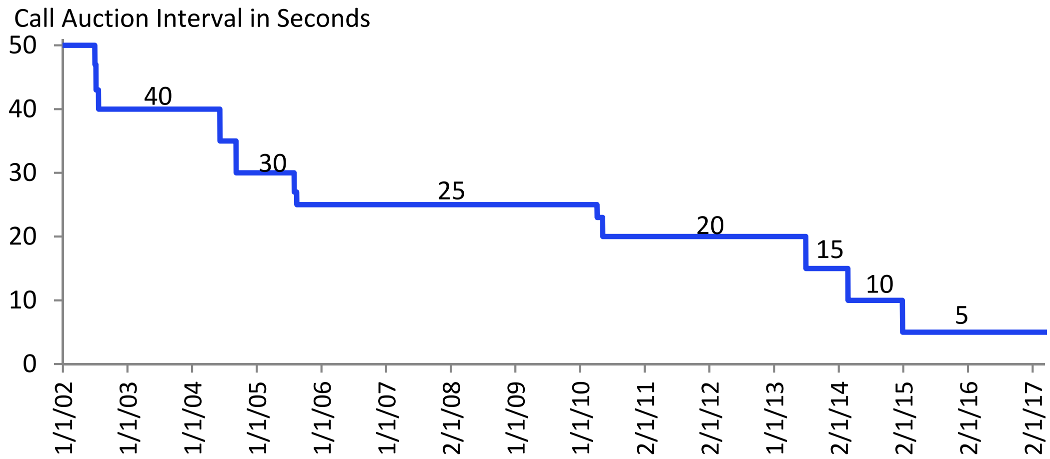
Wah and Wellman (2013), and McPartland (2015), is to replace continuous trading with call auction. The fixed time interval between call auctions, however small, eliminates the speed arms race and forces traders to compete on price.

The literature on call auction frequency is mostly theoretical. Those closely related to the current study can be broadly classified into two topic areas. The first focuses on the optimal auction frequency. Early studies such as Garbade and Silber (1979) and Goldman and Sosin (1979) provide analytical solutions to the optimal auction frequency by minimizing price deviation from the equilibrium value. Motivated by the renewed interest on call auction as a replacement for continuous trading, Fricke and Gerig (2016) derive the optimal auction frequency in a modified and extended model to Garbade and Silber (1979). Du and Zhu (2016) solve the optimal auction frequency for a dynamic model of sequential auctions. We examine the impact of call frequency and explore the optimal frequencies proposed by Fricke and Gerig (2016) and Du and Zhu (2016). The second topic area related to our study examines investor behaviour and equilibrium price under call auction. Ho, et al. (1985) analyse the optimal trading strategy of an individual investor under call auction. Madhavan (1992) show that call auction offers greater efficiency and greater robustness than continuous trading. Brennan and Cao (1996) predict that in call auction, uninformed investors behave as rational trend followers and informed investors follow a contrarian strategy. In a model with dynamic strategic behaviour, Vayanos (1999) shows that agents trade slower and suffer greater welfare loss when the time between auctions decreases. We test some of these theoretical predictions based on multiple changes in auction frequency on the TWSE.

Empirical studies on the impact of call auction frequency are extremely limited. Lang and Lee (1999) examines the switches from 120 to 90 then to 50-second auction intervals on the TWSE and find that the switch was associated with higher volatility and higher liquidity with no significant change in market efficiency. Webb, et al. (2007) studies the reductions of call interval from 30 to 20 to 10 seconds in 1998-1999 on the Taiwan Futures Exchange (TAIFEX). They show volatility increased after the switch from 30 to 20 seconds but had no significant change after the switch to 10 seconds. A number of studies provide empirical comparisons between call auction to continuous trading on the Tel-Aviv Stock Exchange (Amihud, et al. 1997; Lauterback, 2001; Kalay, et al. 2002), the Paris Bourse (Muscarella and Piwowar, 2001), the Frankfurt Stock Exchange (Kehr, et al. 2001), the Warsaw Stock Exchange (Henke and Lauterback, 2005), and the TAIFEX (Cheng and Kang, 2007; Webb, et al. 2007). Many show abnormal returns when stocks are switched to continuous trading. This is partially attributed to enhanced liquidity in continuous trading. Large stocks appear to benefit more from continuous trading. There is no significant change in volatility. Several studies have examined the role of designated market makers in call auction, e.g. Venkataraman and Waisburd (2007) and Theissen and Westheide (2017). There is a growing literature examining the effect of opening and closing calls on investor behaviour and market quality; see references in recent studies by Cordi, et al. (2015) and Bellia, et al. (2016).

In this study, we make three contributions to the limited empirical literature on the impact of call auction frequency. First, we provide a comprehensive examination on the impact of call auction frequency on market efficiency, liquidity, and stability. As indicated in Figure 1, the TWSE reduced the auction interval from 25 seconds to 20 seconds (May 2010) to 15 seconds (July 2013) to 10 seconds (Feb 2014) and to 5 seconds (Dec 2014). These changes provide a unique opportunity to examine investor behaviour and market quality under different auction frequencies. Unlike Lang and Lee (1999) and Webb, et al. (2007), we control for the impact of other factors at individual stocks, the overall market, and the macroeconomic levels in order to isolate the effect of changing auction frequency. Overall we find that market efficiency is the highest when call interval is 25 seconds, liquidity is the highest when call interval is 5 seconds, and stability is the highest when call interval is 10 seconds. The overall market quality is the highest under the current 5-second interval.

Figure 1: Changes in Call Auction Interval on the TWSE



Second, we provide new empirical evidence on the assumptions and predictions of theoretical studies. In almost all theoretical studies, auction frequency and trading frequency are assumed to be the same and the two terms are usually interchangeable. We show that the two are very different: the ratio of the number of trades to the number of auctions monotonically decreases as auction interval decreases: at the current 5-second call interval, only 37% call auctions result in a trade. The evidence provides the first empirical support to the prediction by Vayanos (1999) that investors become less aggressive when there are more opportunities to trade and less (time for) new information between trades. It implies that the process of information arrivals is endogenous to the auction frequency, therefore has direct implications for analysing the optimal auction frequency.

Third, we estimate the optimal auction frequency on the TWSE. After three reductions in 2013 and 2014, the call auction interval has remained at 5 seconds since. Our evidence indicates that the reductions in call auction interval have improved the overall market quality. A natural question is whether the 5-second interval is (close to be) optimal and whether further reductions of the call auction interval are beneficial. We estimate the optimal call auction intervals proposed by Du and Zhu (2016) and Fricke and Gerig (2016) using parameters extracted from Taiwan market data. The analysis indicates that the optimal interval is below the current 5 seconds.

The rest of the paper is organized as the following. Section II explains the data sample, measures for market quality, and the empirical methodology. Section III presents evidence on auction frequency, trading frequency, and market quality. Section IV simulates the optimal auction interval. Section V provides a summary and a discussion on future research.

II. Data, Variable Construction, and Estimation Method

(a) Data and Sample

Our initial sample includes 90 large stocks in the MSCI Taiwan index as of 30 June 2016. These 90 stocks accounted for 85% of the market capitalization of the TWSE. One stock (RIC 8464.TW) had a short trading history and is not included in the study. As we move back in history, some of the 90 stocks were either not listed or under different names. The switching dates of call interval are listed in Table 1 together with the sample periods and the number of stocks used in the analysis. The sample periods are six months before and six months after each change of the call interval. We remove five days before and after the switching dates to avoid any short-term effect from the switch. Because the call interval was 23 seconds from 2010/4/8 to 2010/5/10 (Figure 1), the samples before and after the 20-second interval are 2009/10/1 to 2010/4/2 and 2010/5/17 to 2010/11/10 respectively. For each stock, we obtain transaction price, volume, and millisecond time stamp from Thompson Reuters Tick History.

Table 1: Sample Information

Change in call interval	Switching date	Sample period	Number of stocks
25 to 20 seconds	2010/5/10	2009/10/1 – 2010/11/10	80
20 to 15 seconds	2013/7/1	2013/1/1 – 2013/12/31	87
15 to 10 seconds	2014/2/24	2013/9/2 – 2014/8/31	88
10 to 5 seconds	2014/12/29	2014/7/1 – 2015/6/30	89

(b) Market Quality Measures

Price efficiency

We construct daily measures for market efficiency, liquidity, and stability. Our market efficiency measures include return serial correlation, variance ratio, and price discovery. Daily return serial correlation ρ_t is estimated from intraday 5-minute returns. Daily variance ratio is given by $VR_t = \frac{\mathrm{var}(15\text{−minute return})}{3\times\mathrm{var}(5\text{−minute return})}$. These are efficiency measures often used in studies of financial markets, e.g. O'Hara and Ye (2011). The i^{th} 5-minute return $r_{i,t}$ on day t can be decomposed into a random-walk component $m_{i,t}$ representing the price impact of new information, and a serially-correlated component $n_{i,t}$ representing the price impact of liquidity trading or microstructure noise: $r_{i,t} = m_{i,t} + n_{i,t}$.[2] Let M be the number of 5-minute intervals in a day. Daily information flow is measured by $\sum_{i=1}^{M} m_{i,t}^2$ (Wang and Yang, 2011) and the realized variance on day t is $\sum_{i=1}^{M} r_{i,t}^2$. The daily price discovery measure is given by $PD_t = \frac{\sum_{i=1}^{M} m_{i,t}^2}{\sum_{i=1}^{M} r_{i,t}^2}$.

Stock liquidity

Many liquidity measures have been proposed in the literature to capture different facets of liquidity. For example, Goyenko et al. (2009) compare 24 liquidity measures. Standard measures such as the bid-ask spread are not available in call auctions. We need daily liquidity measures, which rules out regression-based measures that are estimated over

[2] We estimate $r_{i,t} = \sum_{k=1}^{K} A_k r_{i,t-k} + \varepsilon_{i,t}$ via OLS which gives $\Phi(1) \equiv 1 - \sum_{k=1}^{K} \hat{A}_k$ and $\hat{\varepsilon}_t$. The information or permanent component is $m_{i,t} = \Phi(1)^{-1}\hat{\varepsilon}_{i,t}$ and the noise or transitory component is $n_{i,t} = r_{i,t} - \Phi(1)^{-1}\hat{\varepsilon}_{i,t}$.

a longer period, e.g. Lesmond, et al. (1999) and Pastor and Stambaugh (2003). Volume or turnover ratio is more related to volatility than liquidity, e.g. Lesmond (2005) and Barinov (2017). Our liquidity measures are based on the price impact measure of Amihud (2002). Studies have shown that the Amihud measure is priced in stock returns (Korajczyk and Sadka, 2008) and is highly correlated with high-frequency liquidity measures (Hasbrouck, 2009). Let $v_{i,t}$ be the trading value of the i^{th} 5-minute interval on day t. The standard Amihud measure is defined as $\frac{|\sum_{i=2}^{M} r_{i,t}|}{\sum_{i=2}^{M} v_{i,t}} = \frac{|r_t|}{v_t}$. We term this the net price impact (NPI_t) which does not capture the intraday price variations. We define the Gross price impact as $GPI_t = \frac{\sqrt{\sum_{i=2}^{M} r_{i,t}^2}}{\sum_{i=2}^{M} v_{i,t}}$ to capture the volume impact on intraday price changes. We also examine the trade-to-auction ratio (TAR_t) and the average trade size as the auction interval decreases.

Market stability

We use three measures for market stability. The first is the realized variance (RV_t) based on 5-minute returns: $RV_t = \sum_{i=1}^{M} r_{i,t}^2$. The second is a proxy for the ratio of volatility to public information. Since there is no overnight trading and the opening trades have a large number of participants, we take the volatility of overnight returns $\sigma_{N,t}^2$ as a proxy for public information. We define the day-night variance ratio as $DNV_t = \ln(1+\frac{\sigma_{N,t}^2}{RV_t})$ where $\sigma_{N,t}^2$ is estimated via the iterative procedure of Schwert (1990). DNV provides a proxy for the relative importance of public and private information. The third measure for market stability is the volatility sensitivity to negative returns. The following regression is estimated daily:

(1) $$\ln(RV_{i,t}) = \alpha_t + \alpha_t^- r_{i-1,t} D_{i-1,r<0} + \alpha_t^+ r_{i-1,t}(1 - D_{i-1,r<0}) + \gamma_t \ln(RV_{i-1,t}) + \varepsilon_{i,t}$$

where $RV_{i,t}$ is the realized variance in the i^{th} 5-minute interval based on trade-by-trade returns. The dummy variable $D_{i-1,r<0}$ is one if $r_{i-1,t} < 0$ and 0 otherwise. The parameter α_t^- captures the volatility sensitivity to negative news.

(c) Control Variables

As in any event study, it is important to control for the impact of other factors in order to isolate the impact of changing auction frequency. We first control stock-level factors using the overnight stock return and volatility. As mentioned above, the overnight volatility is estimated via the iterative procedure of Schwert (1990). Since there is no overnight trading in Taiwan, overnight return and volatility are not affected by the change in daytime auction interval. We also control for market-level factors using the return and volatility of the index futures traded on the Taiwan Futures Exchange which has continuous trading throughout the sample period. Last but not least, we control for macroeconomic factors using the return and volatility of the TWD/USD exchange rate. The volatilities of the index futures and the exchange rate are calculated as $\frac{1}{2\sqrt{\ln 2}}\ln\left(\frac{P_H}{P_L}\right)$ where P_H and P_L are the intraday high and low values respectively.

(d) Empirical Tests

To estimate the impact of changing auction frequency on a particular market quality variable Y, we estimate the following time-series regression for individual stock k:

(2) $$Y_{t,k} = \alpha_k + \beta_k D_t + \lambda_k Z_{t,k} + \varepsilon_{t,k},$$

where $Y_{t,k}$ is one of the market-quality measures of stock k on day t, D_t = 0 (1) before (after) the switching date, and $Z_{t,k}$ is the set of control variables listed above. The regression is estimated using daily data 6 months before and after the switching date. The coefficient β_k captures the difference in $Y_{t,k}$ while controlling the impact of factors in Z that are unrelated to the change. We note that $\hat{\beta}_k$ is not the difference between the unconditional means of $Y_{t,k}$. Even if $Y_{t,k}$ has higher unconditional mean after the switching date, $\hat{\beta}_k$ can still be negative after taking into the effects of the control variables in Z. The average parameter across all stocks is $\bar{\hat{\beta}} = \frac{1}{N}\sum_{k=1}^{N}\hat{\beta}_k$. We measure the overall impact of the switch by the size and significance of $\bar{\hat{\beta}}$ as well as the percentage of significant $\hat{\beta}_k$ in individual stock regressions. Hameed, et al. (2010) suggest the following standard error measure for $\bar{\hat{\beta}}$:

(3) $$\mathrm{StDev}\left(\bar{\hat{\beta}}\right) = \frac{1}{N}\sqrt{\sum_{k=1}^{N}\sum_{j=1}^{N}\hat{\omega}_{k,j}\sqrt{\mathrm{Var}(\hat{\beta}_k)\mathrm{Var}(\hat{\beta}_j)}}$$

where $\hat{\omega}_{k,j}$ is the correlation coefficient between the estimated residuals $\hat{\varepsilon}_{t,k}$ and $\hat{\varepsilon}_{t,j}$.

(e) Overall Market Quality

We measure the overall market quality as an equally weighted sum of efficiency, liquidity, and stability. Alternative weights can be used to reflect the regulator's priority. Let $E_{t,k}$, $L_{t,k}$, and $S_{t,k}$ be the measures for efficiency, liquidity, and stability respectively. They are defined such that a higher value implies higher market quality: $E_{t,k}$ can be $1/(1+\rho_{t,k})$, $VR_{t,k}$, or $PD_{t,k}$; $L_{t,k}$ can be $TAR_{t,k}$, $1/(1+GPI_{t,k})$, or $1/(1+NPI_{t,k})$; $S_{t,k}$ can be $RV_{t,k}^{-1}$, $DNV_{t,k}$, or $1/(1+|\alpha_{t,k}^{-}|)$. Let $E_{t,k}^{s}$, $L_{t,k}^{s}$, and $S_{t,k}^{s}$ be the corresponding standardized value, e.g. $L_{t,k}^{s} = \frac{L_{t,k}-\bar{L}_{t,k}}{\mathrm{std}(L_{t,k})}$. The overall market quality for stock k on day t is $Q_{t,k} = E_{t,k}^{s} + L_{t,k}^{s} + S_{t,k}^{s}$. We construct two measures for robustness check: $Q_{t,k}^{1} = VR_{t,k}^{s} + (\frac{1}{1+NPI})_{t,k}^{s} + DNV_{t,k}^{s}$ and $Q_{t,k}^{2} = PD_{t,k}^{s} + (\frac{1}{1+GPI})_{t,k}^{s} + (\frac{1}{RV})_{t,k}^{s}$. The impact of changing call interval on $Q_{t,k}$ is estimated from the following time-series regression:

(4) $$Q_{t,k} = \alpha_k + \sum_{j=1}^{4}\beta_{k,j}D_{t,j} + \lambda_k Z_{t,k} + \varepsilon_{t,k}$$

where $D_{t,j} = 1$ after the j^th switch and 0 otherwise. After controlling the effects of variables in Z, $\beta_{k,j}$ captures the impact of the j^th change of call frequency for j = 1,…,4. The average market quality for stock k after the j^th switch is $q_{k,j} = \hat{\alpha}_k + \sum_{s=1}^{j}\hat{\beta}_{k,s}$ with $q_{k,0} = \hat{\alpha}_k$. The overall market quality after the j^th switch is $Q_j = \frac{1}{N}\sum_{k=1}^{N}q_{k,j}$ for j = 0, 1, …, 4. Unlike (2), the dependent variable in (4) is the overall quality of a stock and the regression is estimated over the full sample from 2010/5/10 to 2015/6/30.

III. Evidence on Auction Frequency and Market Quality

(a) Pricing Efficiency

Table 2 reports changes in pricing efficiency. Panel A reports the autocorrelations of 5-minute returns. Panel B reports the variance ratio and Panel C reports the price discovery measure. As mentioned above, the coefficient of the switching dummy in (2) is not the same as the difference of the unconditional averages before and after the change of call frequency. As auction interval decreases from 25 to 5 seconds, the effect on autocorrelation is mixed. The 5- minute return autocorrelation decreased when call interval reduced from 25 to 20 seconds. But it becomes larger (more negative) when call interval reduced from 20 to 15 seconds. Variance ratio improved towards one when call interval decreased from 25 to 20 seconds and from 10 to 5 seconds. Changes in price discovery are not statistically significant except for 25 to 20. Overall there is no significant improvement in market efficiency.

(b) Stock Liquidity

Table 3 reports changes in stock liquidity. Panel A reports the trade-to-auction ratio in percentage. Panel B reports the gross price impact (GPI) and Panel C reports the net price impact (NPI). As the auction interval decreases, the number of auctions increases. However, many auctions do not result in trades. The trade-to-auction ratio dropped from about 80% at 25 seconds per auction to 37% at 5 seconds per auction. This is in contrast to the assumption that a transaction takes place at every auction and auction and trading frequencies are identical.[3] At the current 5-second call interval, more than 60% of auctions do not result in a

[3] See Garbade and Silber (1979), Madhavan (1992), Brennan and Cao (1996), Du and Zhu (2016), Fricke and Gerig (2016), and Hass and Zoican (2016). Only Mendelson (1982) and Toke (2015) examine the probability of

Table 2: Pricing Efficiency

"Ave Before" and "Ave After" are the unconditional average efficiency measures before and after the switch of call interval. "SW Dummy" is the coefficient of the switching dummy in (2). The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%. "t <= -1.96" and "t >= 1.96) are the percentages of stocks with negative and positive significant dummy coefficient.

Panel A: Return autocorrelation

Call Interval (second)	25 to 20	20 to 15	15 to 10	10 to 5
Ave Before	-0.22	-0.222	-0.244	-0.228
Ave After	-0.21	-0.236	-0.244	-0.225
SW Dummy	0.024***	-0.01**	0.002	0.006
t stat	5.47	-2.28	0.576	1.28
t <= -1.96	13%	24%	11%	12%
t >= 1.96	28%	15%	17%	12%

Panel B: Variance ratio

	25 to 20	20 to 15	15 to 10	10 to 5
Ave Before	0.685	0.68	0.667	0.681
Ave After	0.712	0.664	0.662	0.693
SW Dummy	0.052***	-0.015	-0.003	0.022*
t stat	4.49	-1.29	-0.301	1.73
t <= -1.96	8%	18%	11%	7%
t >= 1.96	25%	10%	8%	16%

Panel C: Price discovery

	25 to 20	20 to 15	15 to 10	10 to 5
Ave Before	0.684	0.658	0.656	0.651
Ave After	0.685	0.653	0.655	0.656
SW Dummy	0.018*	-0.01	0.001	0.011
t stat	1.74	-1.05	0.111	1.00
t <= -1.96	0%	9%	2%	3%
t >= 1.96	9%	5%	7%	7%

no trade. Mendelson estimates the probability of no trade to be very small at 0.00032 (page 1513) even in a thin market.

Table 3: Stock Liquidity

"Ave Before" and "Ave After" are the unconditional average liquidity measures before and after the switch of call interval. "SW Dummy" is the coefficient of the switching dummy in (2). The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%. "t <= -1.96" and "t >= 1.96) are the percentages of stocks with negative and positive significant dummy coefficient.

Panel A: Trade-to-auction ratio

	25 to 20	20 to 15	15 to 10	10 to 5
Ave Before (%)	79.8	73.1	63.7	51.8
Ave After (%)	73.5	63.1	53.9	37.3
SW Dummy	-0.084^{***}	-0.164^{***}	-0.207^{***}	-0.357^{***}
t stat	-6.06	-9.03	-9.03	-13.0
t <= -1.96	68%	84%	80%	90%
t >= 1.96	6%	2%	3%	2%

Panel B: Gross price impact

	25 to 20	20 to 15	15 to 10	10 to 5
Ave Before	20.2	20.0	18.0	19.5
Ave After	20.5	18.2	19.0	17.9
SW Dummy	0.054	-0.095^{**}	0.031	-0.043^{**}
t stat	1.07	-2.55	0.835	-2.32
t <= -1.96	23%	15%	21%	18%
t >= 1.96	38%	39%	27%	28%

Panel C: Net price impact

	25 to 20	20 to 15	15 to 10	10 to 5
Ave Before	6.77	6.02	4.48	5.40
Ave After	6.38	4.97	4.30	4.10
SW Dummy	0.12^{***}	-1.07^{***}	-0.147	-1.32^{***}
t stat	2.70	-3.02	-0.998	-6.92
t <= -1.96	19%	14%	30%	43%
t >= 1.96	41%	18%	13%	7%

transaction. On the other hand, the number of transactions has increased from about 510 trades per day at 25 seconds per call to around 1230 trades per day at 5 seconds per call. The average volume per trade has decreased from around 70,000 shares at 20 seconds per call to around 26,000 shares at 5 second per call. Both GPI and NPI decreased as auction interval reduced. GPI dropped by 10% from 20.2 to 17.9 while NPI decreased by almost 40% from 6.77 to 4.1. The smaller trade size and sharp reduction in NPI provide direct empirical support to the prediction by Vayanos (1999, p221): as call frequency increases, investors become less aggressive in both order size and pricing to reduce their welfare loss to strategic behaviour.

(c) Market Stability

Table 4 reports changes in market stability. Panel A reports the daily realized variance (RV). Panel B reports the day-night variance ratio $\ln(1+\frac{\sigma^2_{N,t}}{RV_t})$, and Panel C reports the variance sensitivity to negative news. After controlling stock-specific and the overall market conditions, RV decreased after switching from 20 to 15 seconds and from 15 to 10 seconds. Overall RV decreased from 4.41 (or 2.1% daily return standard deviation) at 25 seconds per call to 3.31 (or 1.8% daily return standard deviation) at 5 seconds per call, after controlling for stock-specific and market-wide variables. The day-night volatility ratio $DNV_t = \ln(1+\frac{\sigma^2_{N,t}}{RV_t})$ also decreased from 0.212 to 0.163 over the four reductions in call interval. It appears that the reduction is largely unrelated to the changes in call frequency. Only the reduction from 15 to 10 seconds is statistically significant after controlling other factors. Volatility sensitivity to bad news increased (more negative) after switching from 20 to 15 seconds but had a mild decrease (less negative) after switching from 10 to 5 seconds. Overall the market stability measures improved over time. But the impact from changing call interval is statistically significant only in a small number of cases.

Table 4: Market Stability

"Ave Before" and "Ave After" are the unconditional average stability measures before and after the switch of call interval. "SW Dummy" is the coefficient of the switching dummy in (2). The asterisks ***, **, and * indicate significance at 1%, 5%, and 10%. "t <= -1.96" and "t >= 1.96) are the percentages of stocks with negative and positive significant dummy coefficient.

Panel A: Realized variance

	25 to 20	20 to 15	15 to 10	10 to 5
Ave before	4.41	3.94	3.18	3.55
Ave after	3.86	3.65	3.24	3.31
SW Dummy	0.050**	-0.038*	-0.044**	-0.013
t stat	2.35	-1.74	-2.14	-0.49
t <= -1.96	19%	25%	26%	28%
t >= 1.96	28%	13%	14%	19%

Panel B: Day-night variance ratio

	25 to 20	20 to 15	15 to 10	10 to 5
Ave Before	0.212	0.178	0.156	0.184
Ave After	0.208	0.167	0.163	0.163
SW Dummy	0.005	0.001	-0.019***	-0.006
t stat	0.497	0.133	-11.2	-0.946
t <= -1.96	3%	6%	53%	15%
t >= 1.96	9%	9%	2%	7%

Panel C: Variance sensitivity to negative returns

	25 to 20	20 to 15	15 to 10	10 to 5
Ave Before	-0.577	-0.41	-0.404	-0.405
Ave After	-0.538	-0.454	-0.396	-0.363
SW Dummy	-0.022	-0.061***	0.002	0.034*
t stat	-1.14	-3.24	0.14	1.89
t <= -1.96	11%	9%	9%	7%
t >= 1.96	9%	5%	8%	15%

Table 5: Overall Market Quality

The overall market quality is the sum of the standardized measures for market attributes. The asterisk indicates the highest value across different call intervals.

Panel A: Market quality based on variance ratio, net price impact, and day-night variance ratio

Call Interval (seconds)	25	20	15	10	5
$E_{i,t}^{s} + L_{i,t}^{s} + S_{i,t}^{s}$	-0.054	-0.027	-0.101	0.053	0.130*
$E_{i,t}^{s} + L_{i,t}^{s}$	0.023	0.009	-0.099	-0.020	0.108*
$E_{i,t}^{s} + S_{i,t}^{s}$	-0.025	0.012	-0.053	0.026	0.029*
$L_{i,t}^{s} + S_{i,t}^{s}$	-0.106	-0.076	-0.050	0.101	0.123*
$E_{i,t}^{s}$	0.052*	0.049	-0.051	-0.047	0.007
$L_{i,t}^{s}$	-0.029	-0.039	-0.048	0.027	0.101*
$S_{i,t}^{s}$	-0.077	-0.037	-0.002	0.074*	0.022

Panel B: Market quality based on price discovery, gross price impact, and volatility

Call Interval (seconds)	25	20	15	10	5
$E_{i,t}^{s} + L_{i,t}^{s} + S_{i,t}^{s}$	-0.411	-0.204	0.121	0.229	0.346*
$E_{i,t}^{s} + L_{i,t}^{s}$	-0.144	-0.064	0.055	0.058	0.177*
$E_{i,t}^{s} + S_{i,t}^{s}$	-0.184	-0.097	0.017	0.123	0.143*
$L_{i,t}^{s} + S_{i,t}^{s}$	-0.494	-0.246	0.170	0.277	0.372*
$E_{i,t}^{s}$	0.083*	0.042	-0.049	-0.048	-0.026
$L_{i,t}^{s}$	-0.227	-0.106	0.104	0.106	0.203*
$S_{i,t}^{s}$	-0.267	-0.140	0.066	0.171*	0.169

(d) Overall Market Quality

Table 5 reports the overall market quality measures under five different call frequencies. They are estimated from the standardized measures for three market attributes: efficiency, liquidity, and stability. A high value indicates better market quality. We estimate the overall market quality when the policymaker cares about all three market attributes, only two of the three attributes, or only one of the three attributes. Panel A reports the average market quality based on variance ratio, net price impact, and day-night variance ratio ($Q_{t,k}^{1}$). It shows that the 5-second call interval has the highest market quality at 0.130 based on all three market attributes or two out of the three attributes. If the policymaker only cares about one of the three attributes, the 5-second interval has the highest liquidity, the 25-second interval has the highest efficiency, the 10-second interval has the highest stability. Overall the 5-second interval has the highest market quality. Panel B reports the average market quality based on price discovery, gross price impact, and volatility ($Q^2_{t,k}$). Although the market quality measures are very different, the 5-second interval still has the highest overall market quality in Panel B.

IV. Optimal Auction Interval

Our analyses show that the reductions in call auction interval on the TWSE have improved the overall market quality. This raises the question whether further reduction will be beneficial or whether the 5-second interval is optimal for the overall market quality. The optimal auction interval was studied by Garbade and Silber (1979) and Goldman and Sosin (1979) and more recently by Du and Zhu (2016) and Fricle and Gerig (2016). We calculate the optimal auction intervals proposed by Du and Zhu (2016) and Fricle and Gerig (2016) using parameters based on the TWSE. The theoretical optimal intervals implied by Taiwan data may shed new light on potential future changes in auction interval.

Du and Zhu (2016) choose the optimal auction interval to balance welfare loss to more strategic trading induced by more frequent auctions and welfare loss to longer trade delay associated with less frequent auctions. They derive an upper bound for the optimal auction interval as $16200\times\left[(\frac{n\alpha}{2}-\frac{1}{3})\mu\right]^{-1}$ where n is the number of traders, α is the confidence level (or 1-α is the probability of adverse information), and μ is the expected arrival frequency of information. The constant 16200 (= 4.5 hours x 60 minutes x 60 seconds) converts the optimal interval to unit of second. Fricle and Gerig (2016) choose the optimal auction interval to minimize the deviation between the equilibrium value and the transaction price, which they term the liquidity risk. Their optimal auction interval in seconds is $\left(\frac{2H(1-\rho^2)}{\sqrt{3}}\right)\frac{\sigma}{\varphi n^{1/2}}$, where H(·) is an increasing function of $1-\rho^2$ and ρ is the return correlation between stock and the market, σ is the volatility of investor reservation prices, φ is the volatility of the stock's equilibrium value, and n is the number of traders.

Table 6 reports the theory-implied optimal auction intervals. Panel A is based on Du and Zhu (2016). The number of traders (n) is estimated by assuming each trade has either 2 or 4 participants. The confidence level (α) is assumed to be 95%, implying a 5% probability of adverse information. Information arrival (μ) is estimated as either trades with non-zero price impact or trades with price impact greater than one tick. Panel A shows that the estimated n and μ increase with auction frequency. We calculate the optimal intervals when the input parameters are taken from different auction intervals. We report two sets of optimal intervals, one based on the low number of traders (# trades x 2) and the low information arrival (# trades with Δp > 1 tick), the other based on the high number of traders (# trades x 4) and the high information arrival (# trades with $\Delta p \neq 0$). In both cases, the optimal intervals are far below one second. The optimal interval is lower if the input parameters are taken from a lower auction interval. Assuming more participants per trade, greater confidence level, or higher information arrival, would further reduce the optimal auction interval. Assuming a lower confidence level α = 0.5 would approximately double the estimated optimal interval.

Panel B is based on Fricke and Gerig (2016). The correlation with the market index (ρ) and the stock volatility (φ) are estimated from daily returns. The number of traders (n) is again estimated as the number of trades multiplied by either 2 or 4. The daily volatility of the reservation price (σ) is set to either 1% or 2%. Panel B shows that n and φ, and most values of ρ, vary systematically with the auction interval. Again we calculate the optimal intervals when the input parameters are taken from different auction intervals, and report a high and

Table 6: Optimal Auction Interval

Panel A: Du and Zhu (2016)

	25	20	15	10	5
# Auctions	637	797	1061	1591	3181
# Trades	508	584	673	841	1187
# Traders (n)					
# Trades x 2	1017	1168	1345	1682	2373
# Trades x 4	2542	2921	3363	4204	5933
Information arrival (μ)					
# trades with $\Delta p \neq 0$	187	209	241	304	428
# trades with $\Delta p > 1$ tick	104	107	112	137	185
Optimal interval (second)					
Low n and low μ	0.322	0.273	0.227	0.148	0.078
High n and high μ	0.072	0.056	0.042	0.027	0.013

Panel B: Fricke and Gerig (2016)

	25	20	15	10	5
$\rho = Cor(r_i, r_M)$	0.533	0.473	0.429	0.423	0.490
$H(1-\rho^2)$	0.877	0.912	0.931	0.933	0.903
# Traders (n)					
# Trades x 2	1017	1168	1345	1682	2373
# Trades x 4	2542	2921	3363	4204	5933
Stock volatility (φ, %)	2.10	1.97	1.85	1.84	1.82
Reserve price volatility (σ, %)	1	1	1	1	1
	2	2	2	2	2
Optimal interval (second)					
Low n and high σ	3.85	3.97	4.04	3.63	2.99
High n and low σ	1.22	1.26	1.28	1.15	0.95

a low estimate for the optimal auction interval based on the combination of n and σ. The optimal intervals from the Fricke-Gerig model are one to four seconds. Unlike in Panel A, the optimal interval peaks when the input parameters are taken from 15-second auctions. When the parameters are taken from the current 5-second interval, the optimal interval is between one and three seconds. Assuming more traders (n) or lower volatility of the reservation price (σ) further reduces the estimated optimal interval.

The results in Table 6 indicate that the TWSE can further reduce the current 5-second auction interval to improve investors' allocative efficiency (Du and Zhu, 2016) and to reduce liquidity risk (Fricke and Gerig, 2016). The optimal interval of 0.013 to 0.078 second implied by Du and Zhu (2016) appears to be a drastic change compared to past changes and the current 5 seconds. It may trigger an arms race in speed since the speed limit implied by the optimal interval is very high. The optimal interval of 2 seconds, the midpoint of 0.95 to 2.99 seconds implied by Fricke and Gerig (2016), appears to be reasonable relative to past changes and the current 5 seconds. However, since only 37.3% of current auctions result in actual transactions (Table 3), further increase in the number of auctions is likely to further reduce the trade-to-auction ratio (TAR). Neither Du and Zhu (2016) nor Fricke and Gerig (2016) has considered the probability of no trade and its effect on investor welfare and market quality.

V. Conclusion

There are very few studies on how call auction interval affects investor behaviour and market quality since almost all major stock markets operate on continuous trading. Using a wide range of market quality measures, this study shows that the overall market quality on the TWSE has improved following four rounds of reductions in the call auction interval. Based on recent theoretical advance and TWSE data, a further reduction from 5 to 2 seconds may be beneficial. We present new evidence on the relationship between auction interval, information arrival, and return correlation that should be considered in future theoretical analysis.

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