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ON FREQUENT BATCH AUCTIONS FOR STOCKS

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ABSTRACT

I show that frequent batch auctions for stocks have the potential to reduce the severity of stock price crashes when they occur. For a given sequence of orders from a continuous electronic limit order book market, matching orders using one second apart batch auctions results in nearly the same trades and prices. Increasing the time interval between auctions to one minute significantly reduces the severity stock price crashes. In spite of this and other advantages pointed out in the literature, frequent batch auctions have not caught on. There is a need for carefully designed market experiments to understand why, and what aspect of reality academic research may be missing.

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How stocks are traded has dramatically changed during the past two decades[1]. Technological innovations have made continuous trading through anonymous electronic order book markets become the preferred mechanism for securities trading, as foreseen by Glosten, 1994, and now accounts for a major share of trading in stocks.[2] There is some concern that this may have increased some of the *indirect costs*. For example, electronic continuous trading has led to the rise of algorithmic High Frequency Traders (HFTs). Weller, 2017 finds that algorithmic trading decreases the incentives for gathering pre- earnings announcement information. Budish, Cramton, and Shim, 2015a show that competition among HFTs has led to an arms race for speed, resulting in socially wasteful investment in speed-trading infrastructure, and advocate using frequent, just milliseconds apart, batch auctions instead of continuous trading.

I argue that frequent batch auctions have another important advantage that has been overlooked. Allowing for sufficient time interval between successive auctions facilitates enough orders to arrive before the clearing price is set thereby reducing the severity of stock price crashes[3].

I find that for a given sequence of orders that traders had placed in a continuous limit order book market, prices and trading volumes will be the same when orders are matched using periodic batch auctions instead of using a continuously updated limit order book provided the auction frequency is sufficiently high. Consequently, traders may not have an incentive to change their behavior when moving to very frequent batch auctions[4].

When the time interval between auctions is increased to one minute, prices, volumes,

[1]See Fox, Glosten, and Rauterberg, 2015 for an excellent discussion

[2]This is evidenced by the fact that 65% of the 5-day average notional trading volume in U.S. equities on 8/1/2018 of about $366 billion was due to trading in electronic limit order book markets, i.e., other than NASDAQ (DQ) and NYSE (DN).

[3]Technological innovations has made it feasible for making the time interval between batch auctions a function of market conditions like the depth of the aggregate order book.

[4]This is not necessarily true. The set of profitable trading strategies under continuous trading may become infeasible under frequent batch auctions and vice verse. For example, as mentioned earlier, Budish, Cramton, and Shim, 2015b show that investing in speed would become less attractive under frequent batch auctions

and order fill rates change; crash severity and volumes come down, and some traders find better execution of their orders. Further, short term traders who carried very little inventory overnight and contributed to a significant fraction of the volume are worse off during crashes. Hence we should expect traders' order submission behavior to change when moving to one minute apart periodic auctions from continuous trading. However, even when the change in trader behavior is taken into account, the conclusion that trading volume would be lower under periodic auctions is likely to hold, since natural buyers and sellers are more likely to cross without the need for an intermediary. Crashes are likely to be less severe to the extent they were due to lack of order book depth, since the time interval between auctions would allow more new orders to come in.

My analysis ignored information gathering and informativeness of prices, which could be adversely affected. To provide a definitive answer we need a better understanding of the types of traders in the stock market, their motives for trading, and the difficulties they face in learning and developing their trading strategies. For example, small and infrequent impatient traders may feel that learning to bid in auctions involves formidable set up costs when compared to trading against the limit order book using a marketable limit order.[5]

The rest of the paper is organized as follows. I examine how trading volume, trader surplus, and crash severity change when moving from continuous trading to a batch auction in Section I. In Section II, I describe the data. I discuss the findings in Section III and conclude in Section IV.

I. Batch Auction vs Continuous Trading in a Model Economy

In this section I explain why we are likely to see lower trading volumes, higher trader surplus (ignoring the benefits to immediacy), and less severe crashes under batch auctions

[5] See Jagannathan, Jirnyi, and Sherman (2015) for related observations.

when compared to continuous limit order book trading, using numerical examples.

Consider a short interval of time during which the following four orders arrive.

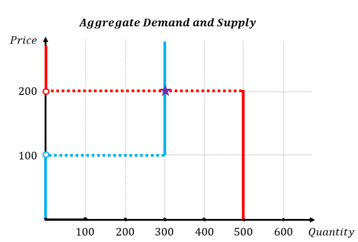
Table 1: A List of the Limit Orders

ord_no	Buy_or_Sell	price	quantity
1	S	100	100
2	S	200	500
3	B	100	100
4	B	200	500

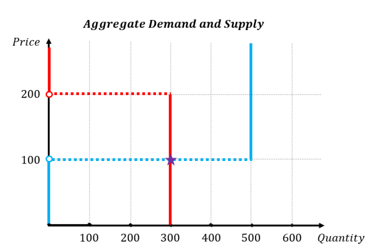
Notes:

Single End of the Time Interval Batch Auction

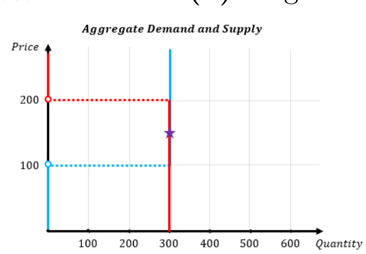
Orders are collected as they arrive and the clearing price is determined using a uniform price auction at the end of the time interval. Figure 1 illustrates the auction clearing price determination procedure that will be used when prices and quantities in the orders submitted are in discrete intervals, as in our example. When the aggregate demand and supply curves cross, the crossing point gives the clearing price, as shown in Panels (a) and (b). When the aggregate demand and supply curves overlap, the mid point is chosen as the clearing price, as shown in Panel (c) of the figure.



(a) Single Cross: A



(b) Single Cross: B



(c) Vertical Overlap: C

Figure 1: Aggregate Demand and Supply Curves

Figure 2 gives the plot of the aggregate demand and supply curves. The market-clearing price is 200, trading volume is 500, and trader surplus ($\sum(P_{limit} - P_{auction}) \cdot \Delta Q$) is $10,000$. After the auction, there will be two orders left in the limit order book.

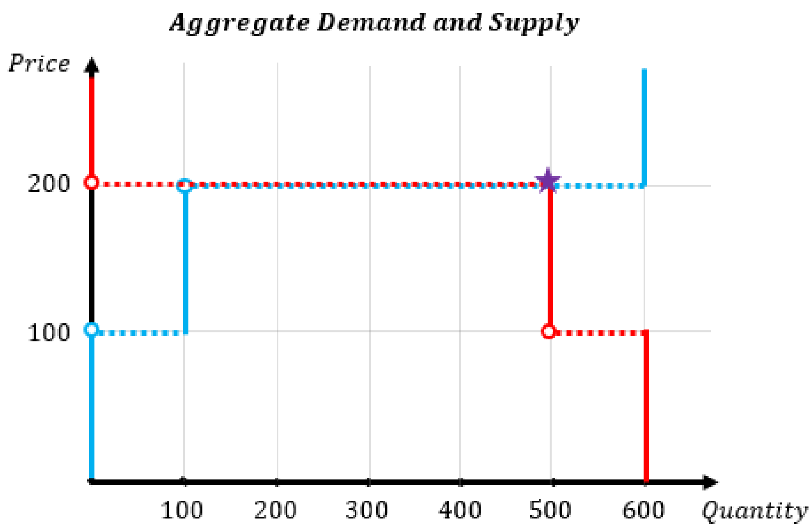


Figure 2: Aggregate Supply and Demand

Table 2: Unexecuted Orders – Batch Auction

ord_no	Buy_or_Sell	Price	Quantity
2	S	200	100
3	B	100	100

Notes:

Continuous Trading, Price Priority, Followed by Time Priority

Now consider the case where orders are crossed continuously as they arrive to the extent possible. There are $4 \cdot 3 \cdot 2 \cdot 1 = 24$ possible order arrival sequences. The 24 possible order sequences can be classified into three categories based on the set of prices at which trades took place as given in Table 3. Notice that when compared to the single end of period batch auction outcomes, the trading volume is higher, prices are more volatile and lower on average, and trader surplus is lower.[6]

[6]Trade surplus in the case of a buy order is the amount the buyer was willing to pay based on the

Table 3: Market Dynamics of Different Sequences

category	# of cases	price	vw price	volume	trader surplus
1	8	200	200	500	10000
2	8	100→200	183.3	600	0
3	8	200→100	183.3	600	0

Notes: Volume μ = 566.7, trader surplus μ = 3333.3, vw price: μ = 188.9 and σ = 7.9. Continuous trading sequence creates volatility

Effect of Panic Sell & Opportunistic Buy Orders

Suppose the following two orders arrive simultaneously after the four orders have been cleared using end of time interval batch auction or continuous trading: a panic sell order at a price of 1 or above and an opportunistic buy order at a price of no more than 1 as given in Table 4.

Table 4: Orders Following Fourth Order

ord_no	Buy_or_Sell	Price	Quantity
1*	S	1	1
2*	B	1	1

Notes:

In the case of batch auction, the price will drop from 200 to 100, and an associated trader surplus of 99. Under continuous trading the order book is depleted after the first four orders, for order arrival sequences in categories 2 and 3. So in cases where the order arrival sequences fall into categories 2 and 3, the two orders will be crossed at a price of 1 – a drop of 182.3 from the weighted average trade price of 183.3 prevailing just before the two orders arrived; and the trader surplus for the last trade will be zero. For sequences of orders that fall into category 1, there will be one order to buy at a limit price of 100 and one order to sell at a limit price of 200 on the book, and the order to sell at the limit price of 1 will be executed at 100, a drop of 100 from the previous trade price of 200, and

limit order prices and quantities minus the amount the buyer actually paid. Trader surplus is defined in a similar manner for a sell order. This measure ignores immediacy.

the associated trader surplus will be 99. These results are summarized in Table 5. This results in increased crash severity and lower trader surplus on average under continuous trading.

Table 5: Effect of Panic Sell Order & Opportunistic Buy Order

category	# of cases	price	vw price	volume	trader surplus
1	8	100	100	1	99
2	8	1	1	1	0
3	8	1	1	1	0

Notes:

The results in this example model economy can be generalized.

Trading volume is higher and trader surplus is lower under continuous trading

In what follows, I show that in general moving from continuous trading to an auction will in general reduce the trading volume, but at the same time increase the trader surplus – defined as the difference between the reservation bid price and paid by a buyer, and the difference between the price obtained and the reservation ask price for a seller. For the purpose of discussions in this section I will consider a more general aggregate supply and demand curves given in Figure 3 – not the specific aggregate and supply curves generated by the orders considered in the example we discussed earlier.

I will first consider the demand and supply in a batch auction, and then consider continuous trading where the sequence in which the orders arrived matter. I will assume that there are no order cancellations. The line M, D_0 represents the aggregate demand curve in the batch auction, and the line N, S_0 represents the aggregate supply curve. Assume that the aggregate demand curve is downward sloping and supply curve is upward sloping and both are linear[7]. The aggregate demand curve is the consist of segments MA, AB, BF, and FD_0 – and the aggregate supply curve consists of segments NJ, JK, KG, GF, FC, CL,

[7]This assumption can be relaxed

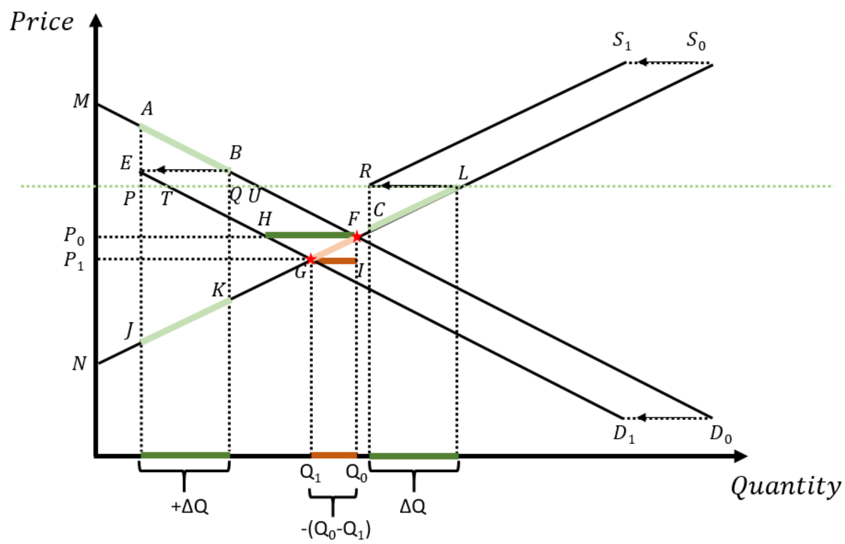


Figure 3: Continuous trading vs Batch Auction - Volume and Trader Surplus

and SL_0. The auction clearing price is P_0 and the corresponding quantity traded is Q_0, i.e., represented by the point F.

Now consider the case of continuous limit order book trading where the sequence in which orders arrive matter. Assume that the buy and sell orders arrived sequentially in the following order: the buy corresponding to the segment AB and sell order corresponding to CL arrived first and were matched. The orders then arrive incrementally alternating between buy and sell orders as follows: MA, NJ, EG, JG. The last trade price will be given by the point G. The orders corresponding to RS_1 and GD_1 arrive but they will remain on the book unexecuted.

Trading volume

Notice that,

- Increase in Volume $= EB = RL = PQ = TU = HF$
- Decrease in Volume $= GI \leqslant HF$
- Increase in Volume $\geqslant$ Decrease in Volume

So the volume increases.

Trader surplus

Assume supply CD instead of supply in NC is matched with demand AB:
Notice that,

- Increase in Trader Surplus = $ABE + BEPQ + CLR \leqslant ABE + BETU + TUFH$
- Decrease in Trader Surplus = $AEGF = ABE + BETU + TUFH + FHG$
- Increase in Trader Surplus $\leqslant$ Decrease in Trader Surplus

So trader surplus declines.

II. Data

I use data for the period 3 April 2006 to 30 June 2006 for a representative liquid large firm stock traded in the National Stock Exchange of India. The firm was a constituent of both NIFTY-50 and Sensex/BSE-30, the two major Indian stock indexes. The data has orders, cancellations and transactions information along with trader-broker identities. This is the same data used in Getmansky, Jagannathan, Pelizzon, and Schaumburg, 2015 and Getmansky, Jagannathan, Pelizzon, Schaumburg, and Yuferova, 2018 to examine liquidity provision/demand by different types of traders in the stock market during normal times and during crashes, and we use their method for classifying traders into different types based on their behavior, and identifying crashes. During the April 2006/June 2006 sample period normal market opened at 9:55am and closed at 3:30pm. The closing session started at 3:40pm and closed at 4:00pm. Trading during normal trading hours occurred through the limit order book. The closing price represented the weighted average of transaction prices during the last half hour of the normal trading session. All orders during the closing session were crossed at the closing price established earlier for that day.

There are 56 trading days in the sample with 108,542 traders and a trading volume of 115.6 million shares, with interesting features. There are two fast crashes, identified by Getmansky, Jagannathan, Pelizzon, and Schaumburg, 2015, where the stock price dropped more than 3% and recovered by more than 3% within a 15 minute interval on two of the days, 19 May and 22 May. Further, there was a trading halt on 22 May. Table 6 provides descriptive statistics about the number of traders and trades, trade and order sizes, trading volume, fill rates etc., for the two days with crashes and other days.

Table 6: Descriptive Statistics

	May 19th	May 22nd	Other Days
N of Days	1	1	54
Daily Volume (K)	3457.9	2273.6	2037.4
Regular Session (K)	3457.2	2270.0	2035.7
Closing Session (K)	0.7	3.6	1.8
Daily N of Trades	48719	34671	31914
Daily N of Traders	8349	6957	5475
Trade Size	71.0	65.6	63.2
Order Size	204.2	171.9	198.4
Log high-low-range	0.16	0.26	0.05
Daily Return	-17.3%	-3.3%	0.5%
Fill Rate	53.6%	58.7%	46.5%

Notes: Volume is number of shares. K denotes thousands. Log high-low-range is the natural logarithm of the highest price divided by the lowest price in a day. Fill rate is the quantity-weighted order-level traded volume divided by initial order size.

As can be seen, the first crash day, 19 May, has 50% more trades and traders and 70% higher trading volume than other days. However, the trades and order sizes were not much different. The price declined by 17.3% during 19 May - whereas it rose by 0.5% on other days on average. Trading was halted on 22 May, the second crash day in the sample. While the number of trades, traders, and trading volume were higher by 11%, 27%, and 11% respectively when compared to other days, they did not rise as much as on 19 May, probably due to the trading halt. The fill rates were higher on crash days than other days. The price declined by 3.3% during the day. The closing sessions had very little volume during crash days as well as other days.

A. Trader Categories

The objective of this exercise is to understand how moving from continuous trading through limit order books to periodic batch auctions would affect different *types of traders*, if they were to place the same sequence of orders. To facilitate the analysis I use the procedure in Getmansky, Jagannathan, Pelizzon, and Schaumburg, 2015 and classify traders into different types of traders: Domestic Mutual Funds (MF) and Foreign Institutional Investors (FII) [8] are kept as distinct types, and the rest of the traders are put into the following five types, for each trading day.

Trader Types

- Small: Traders who trade volumes less than or equal to 750 shares on a given day. Small traders can not offset/hedge their spot position using single stock futures since the futures contract size was 750 shares.

- Short Term Traders (STT) Retail: Traders who are not legally classified as proprietary traders and whose day end inventory to traded volume ratio is less than 10%.

- STT Prop: Trading on own account and with day end inventory to traded volume ratio is less than 10%.

- Other Long Term Traders (OLTT) Retail: Traders who are not legally classified as proprietary traders and whose day end inventory to traded volume ratio is greater than 10%.

- OLTT Prop: Traders who trade on their own account, and whose day end inventory to traded volume ratio is greater than 10%

- Mutual Funds: Traders who are legally classified as mutual funds.

[8] MF and FII are generally patient and opportunistic investors. Further, MFs have a natural advantage in making a market in the stocks that they follow, and have long term market making capital that gives them the ability to withstand inventory shocks that last for several days.

- Foreign Institutional Investors(FII): Traders who are legally classified as Foreign Institutional Investors.

The daily classifications means that a particular trader active on multiple days can get classified differently depending on the trading behavior for that particular day. To achieve a consistent classification for each trader, I follow the algorithm in Getmansky, Jagannathan, Pelizzon, and Schaumburg, 2015 given below:

- Compute the mode of the behavioral classifications for a particular trader across all active trading days.
- If the mode of the behavioral category is not *Small* then assign the obtained modal category to that trader for the entire sample period (Apr, 2006 - Jun, 2006).
- If the modal category for a trader is *Small* and the "*Small*" days cover more than 67% active trading days, assign that trader to category *Small*.
- Finally, there are cases where the modal category for a trader is *Small* but the "*Small*" days do not cover more than 67% active trading days. In such cases, pick the modal category for the days where the trader did not behave as *Small*.

III. Findings

In this section I compute the properties of prices, trades, and trading volumes under periodic auctions. I assume that the sequence of orders and cancellations will remain the same as in the data. Orders that are not executed in an auction are carried forward to the next auction unless they are canceled in the data, or the end of the trading day is reached.

A. One Second Apart Auctions

I first consider periodic auctions that take place every second, i.e., they are one-second apart. The time stamp in the data is fine only up to a second. However the orders and trades and cancellations are arranged in the the sequence in which they arrived within each second. Therefore it is feasible to construct the limit order books of each trader and the aggregate limit order book as they evolve over the course of a day and identify who trades with whom. For details regarding how the limit order books are constructed, the reader is referred to Getmansky, Jagannathan, Pelizzon, Schaumburg, and Yuferova, 2018.

The time series of auction prices and actual transactions prices in the data are very close even during the most severe of the two crash days, i.e., the 15 minutes time period leading to the crash on 22 May when trading was suspended. Figure 4 plots the time series of minute level average auction clearing prices and the corresponding prices in the data.

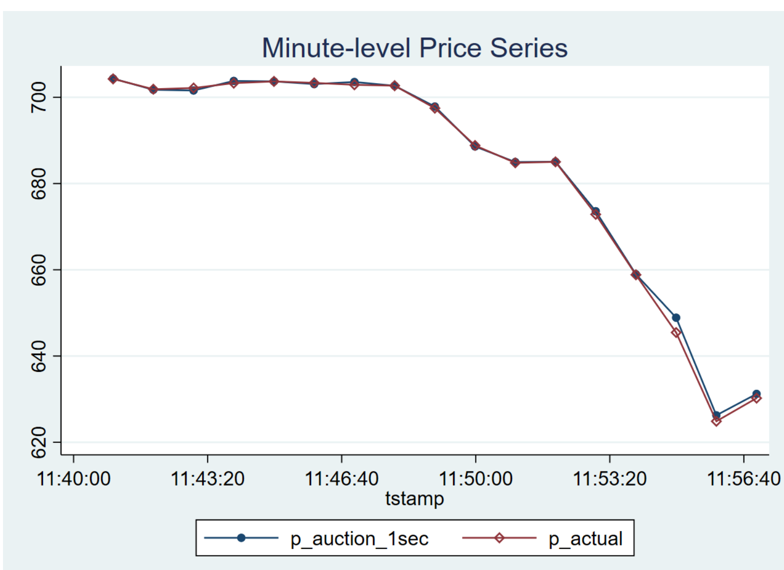


Figure 4: Minute-level Average Price Before the Market Suspension at May 22nd

Figure 5 gives the minute level buy and sell volumes by various trader types before market suspension on 22 May, for the one second apart auctions and the data. As can be seen, the price and volume series for the data and the one second apart auctions are very close.

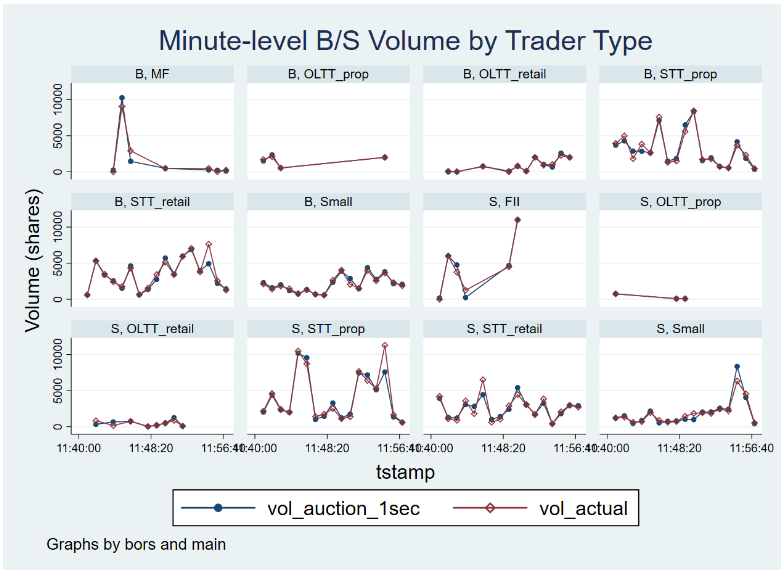


Figure 5: Minute-level Buy and Sell Volume by Trader Type Before the Market Suspension at May 22nd

This finding also supports Budish, Cramton, and Shim, 2015b who argue in favor of very frequent periodic batch auctions. If very frequent periodic auctions had replaced continuous limit order book trading, in the sample considered in this study, trades and profits to various types of traders would have been about the same, except for taking away the incentives for investing in higher speed technology and the associated sniping strategies.

Next I examine what would happen when the time period between auctions is increased to one minute.

B. One minute apart auctions

Table 7 gives the classification of traders based on trading outcomes under batch auctions that are one minute apart. STT_retail classification is affected significantly. About 35%

of those who were classified as STT_retail using the actual data, are now reclassified as OLTT_retail, and about 18% are reclassified as Small. Most of the traders in other trading types remain in the same trading type categories.

Table 7: Migration of Trader Types in Moving to 1-min Apart Auctions

Actual Trader Type	Trader Type under 1-min Batch Auctions						
	FII	MF	OLTT_prop	OLTT_retail	STT_prop	STT_retail	Small
FII	133	-	-	-	-	-	2
MF	-	301	-	-	-	-	18
OLTT_prop	-	-	48	-	1	-	4
OLTT_retail	-	-	-	1,083	-	21	138
STT_prop	-	-	104	-	57	-	11
STT_retail	-	-	-	2,253	-	3,009	1,113
Small	-	1	1	120	1	36	91,483

Table 8 gives the ratio of end of the inventory to trading volume for various trader categories. The end of the day inventory position of FII and MF are hardly affected. The inventories as a percentage of trading volume increases for all other types of traders. STTs are affected most: there end of the day inventories increase by a factor of 3.5 for STT_prop and 5.7 for STT_retail resulting in several of them being reclassified under one minute trading outcomes. Clearly, those who ended up almost flat at the end of the day would not be able to do so if they did not alter their order placement strategies when moving to 1-minute apart auctions. Such traders will necessarily have change their strategies if they were to come out with little inventory at the end of the day. We will keep this in mind while we summarize our findings and their implications for future research in the concluding section.

Figure 6 plots how the trading volumes change as the time between auctions changed, for the two crash days and the days before and after. While the trading volumes for 1-second apart batch auctions and the actual trading volumes are very close[9], the volume

[9]I argued earlier that trading volume should weakly decline when moving from continuous trading to frequent batch auctions, when there were no order cancellations. In the figure, some times the volume

Table 8: End-of-the-Day Inventory to Trading Volume Ratio

	Continuous Trading (Actual)			1-min Auction		
Avg. EoD Inv. to Vol.	May 19th	May 22nd	Other Days	May 19th	May 22nd	Other Days
FII	100%	100%	100%	100%	100%	100%
MF	100%	99%	96%	100%	99%	96%
OLTT_prop	37%	76%	35%	38%	82%	39%
OLTT_retail	80%	79%	68%	85%	82%	72%
STT_prop	0%	1%	4%	9%	11%	14%
STT_retail	1%	2%	3%	14%	15%	17%
Small	18%	22%	13%	27%	33%	25%

is lower by 20% in 1-minute apart batch auctions. The trading volumes continue to drop significantly (by about 40%) as the time between auctions is increased to 15 minutes, suggesting that exchanges that depend on trading volume for revenue may change the way they charge for providing trading related facilities.

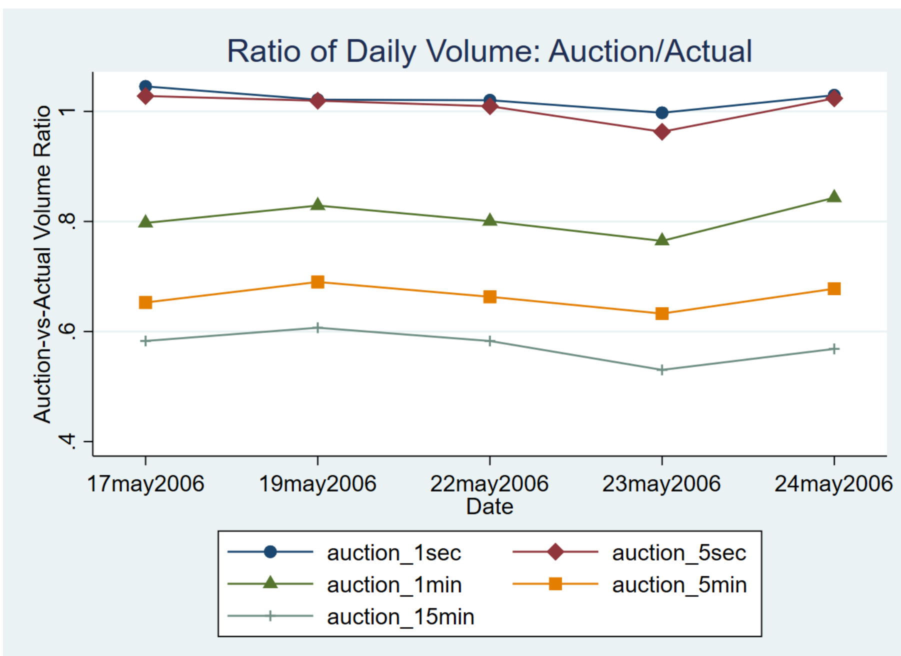


Figure 6: Trading Volume and Frequency of Batch Auctions

As can be seen from Table 9, the price volatility as measured by the difference between

is higher for one second apart batch auctions. This is due to orders that were cancelled or partially cancelled in the data but filled or partially filled in the high-frequency auctions.

the logarithm of high and low prices is largely reduced under the 1-minute batch auction, especially during the crash days – one on May 19th and one on May 22nd that led to a brief suspension of trading. We examine trading during regular sessions only in Table 9 and subsequent tables since the volume during closing sessions are small, for convenience.

Table 9: Market Descriptive Statistics Under Different Rules, Regular Sessions

	Continuous Trading (Actual)			1-min Auction		
	May 19th	May 22nd	Other Days	May 19th	May 22nd	Other Days
Daily Regular Volume (K)	3457.2	2270.0	2035.7	2865.3	1821.7	1672.3
log high-low-range	0.16	0.26	0.05	0.12	0.13	0.04
Daily Return	-15.2%	-4.3%	0.4%	-15.8%	-4.3%	0.4%
Fill Rate	53.8%	58.6%	46.6%	44.9%	47.2%	38.7%

Table 10: Minute-level Statistics Under Different Rules, Regular Sessions

	Continuous Trading (Actual)		
	Crash May 19th	Crash May 22nd	Other
Avg. Regular Volume (K)	19.8	10.4	6.8
Avg. Ineff. Cancel. Vol. (K)	0.2	0.2	0.4
log high-low-range	0.83%	2.24%	0.43%
Avg. Trader Surplus (K)	38.3	17.8	5.7
	1-sec Auction		
Avg. Regular Volume (K)	19.9	10.3	7.0
Avg. Ineff. Cancel. Vol. (K)	0.4	0.4	0.3
log high-low-range	0.69%	1.75%	0.38%
Avg. Trader Surplus (K)	46.1	38.6	10.9
	1-min Auction		
Avg. Regular Volume (K)	15.6	9.1	5.6
Avg. Ineff. Cancel. Vol. (K)	-	-	-
log high-low-range	-	-	-
Avg. Trader Surplus (K)	98.1	144.5	24.3

Table 10 compares the sample averages of volume, cancellations, log high-low range under continuous trading, in second apart auctions and one minute apart auctions during one minute intervals. Crash 1 is from 10:25:00 to 10:55:00 on May 19th; Crash 2 is from

11:40:00 to 13:10:00 on May 22nd. Ineffective cancellation volume is the volume of the cancelled orders submitted after their full execution under 1-min auction. Trader surplus is the sum of buyer surplus and seller surplus of all the transactions.

Profit by Trader Type: Actual vs. 1-min Auction

Because of the effects of 1-minute batch auction on on price and volume, the profits earned by different trader types are affected as given in Table 11. As can be seen, Small, STT_retail, and MF are worse off on crash days. Some traders in those classes provided liquidity in the actual data and earned a reward for doing so, but that opportunity was reduced in one minute auctions.

Table 11: Daily Profit by Trader Type Under Different Rules

	Continuous Trading (Actual)			1-min Auction		
Daily Profit (M)	May 19th	May 22nd	Other Days	May 19th	May 22nd	Other Days
FII	-145.9	-24.7	-3.7	-117.9	-18.0	-2.8
MF	173.3	34.5	-0.1	148.8	29.6	-0.1
OLTT_prop	32.7	6.7	-0.3	32.2	8.1	-0.2
OLTT_retail	-52.5	-10.0	5.2	-19.7	-6.6	4.2
STT_prop	35.2	4.9	-0.3	56.5	11.8	-0.3
STT_retail	6.4	1.1	-0.6	-18.1	-4.0	-0.6
Small	-49.2	-12.6	-0.3	-81.7	-20.8	0.0

Notes:

Behavior of Prices in Crashes

Figure 7 and Figure 8 plot the prices during the two crashes, the one on May 19, 2006 and the other on May 22, 2006. While the one minute apart auctions reduced the crash severity on both days, the effect was much more for the crash on May 22 that led to a trading halt.

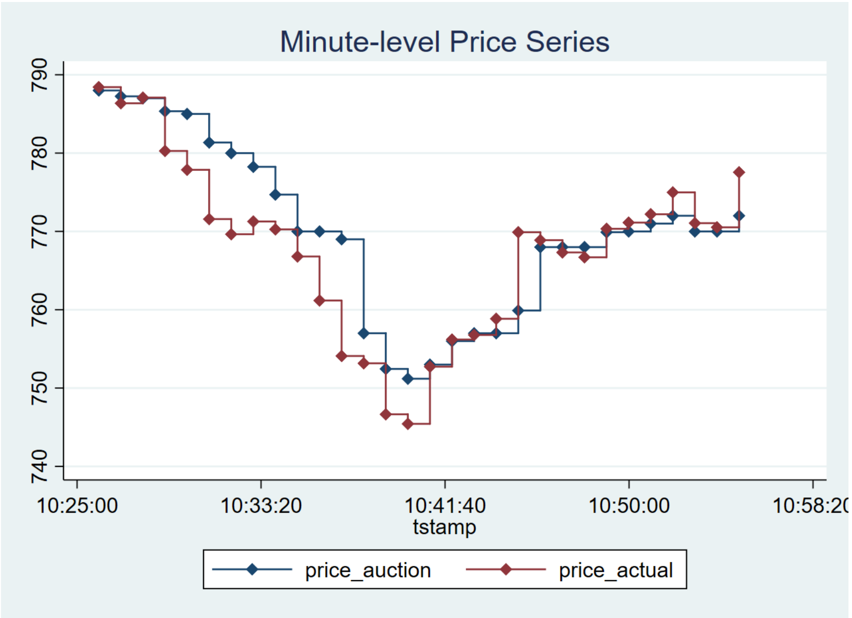


Figure 7: May 19th Crash 1

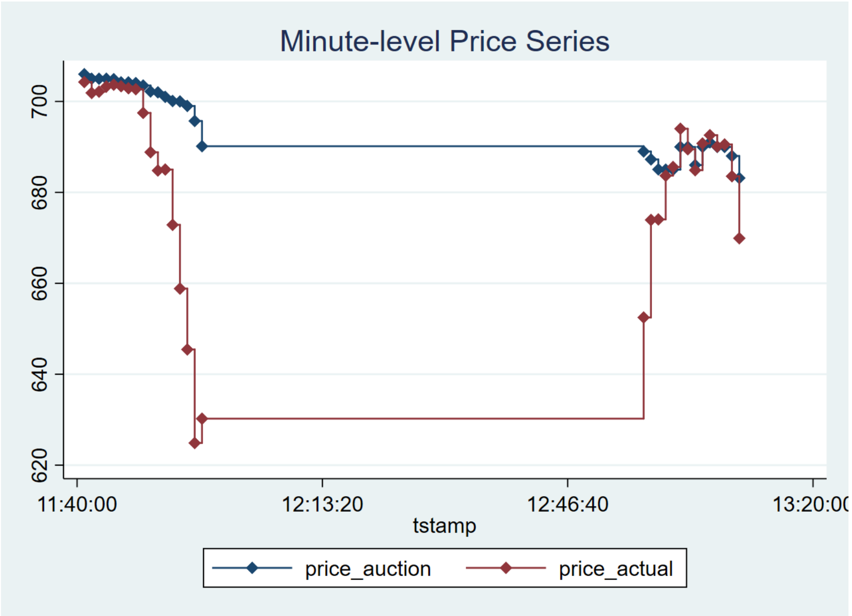
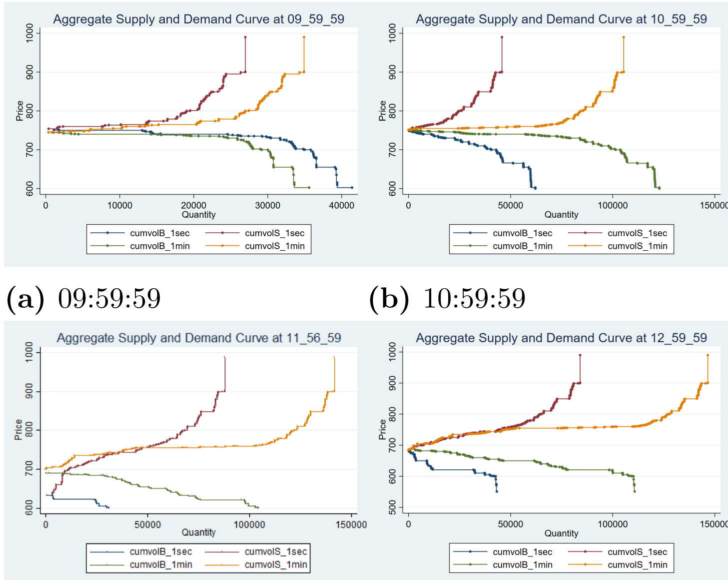


Figure 8: May 22nd Crash 2



(a) 09:59:59 **(b)** 10:59:59

(c) 11:56:59 **(d)** 12:59:59

Figure 9: Unfilled Demand and Supply after Auctions - May 22nd

Crash 2 (May 22nd)

To understand the significantly lower crash severity on May 22, I plot the orders that remain unfilled after the batch auctions at four points in time leading up to the crash in Figure 9. As can be seen, the order book has more depth at the four points in time leading to the crash and market suspension on May 22, 2006 under the one minute apart auctions.

C. Conclusion

I provide some evidence showing that frequent batch auctions have the potential to attenuate the severity of stock price crashes when they occur provided the time interval between auctions is sufficiently large, about a minute. This complements Budish, Cramton, and Shim, 2015a who advocate more frequent batch auctions, just milliseconds apart. Given the current state of the technology available, it may be feasible consider frequent batch auctions where the time interval depends on market conditions.

Theory alone can not say what the trading frequency should be if batch auctions were to be used, and whether they are preferred to continuous trading, without taking a stand on the tradeoff among various social goals. Vayanos, 1999 and Du and Zhu, 2017 show that optimal trading frequency depends on trade-offs among competing interests and under certain conditions lowering the frequency of auctions can lead to better allocative efficiency.[10] Rostek and Weretka, 2015 finds that under a different set of assumptions, a higher trading frequency leads to welfare improvement.

In spite of the advantages of frequent batch auctions few stock exchanges use frequent batch auctions, except for the opening and closing sessions, and for stocks that are illiquid with low trading volumes.[11] An exception is the Taiwan Stock Exchange (TSE), where stocks are traded in periodic frequent call auctions. Even at TSE, the batch interval has come down steadily, from 25 to 20 seconds in 2010 to 5 seconds in December 2014, [12] and there are reports in the Taiwanese press mentioning that TSE may move to continuous trading in the future.

Since the introduction of Markets in Financial Instruments Directive II (MiFID II) in January 2018, use of periodic auctions for trading in European stocks has increased. Periodic auctions contributed to as much as 22% of the average daily trading volume (Euro 37 billion) in European stocks for the month ending 22 August 2018.[13] However, it is too early to take a stand on whether periodic auctions will displace continuous limit order book trading since many of the auction platforms use European Best Bid Offer (EBBO) collar from continuously updated limit order books, and in that sense rely on

[10] This is consistent with the empirical findings reported in Lauterbach, 2001, Muscarella and Piwowar, 2001, citealpkehr2001anatomy and Kalay, Wei, and Wohl, 2002.

[11] Periodic call auctions are used for illiquid stocks in the Bombay Stock Exchange and the National Stock Exchange of India, as required by the Securities and Exchange Board of India. In Paris Bourse, securities with relatively low trading volumes are traded twice daily in batch auctions and others are traded continuously.Muscarella and Piwowar, 2001 examine stocks that move across the two trading systems.

[12] See Twu and Wang, 2018 for a discussion of how various measures of market quality changed when the call auction frequency came down over time at the TSE.

[13] Source: Cboe Services - Market Data - Cboe Global Markets.

price discovery in the continuous limit order book market.

For explaining why frequent batch auctions have not caught on it is necessary to have a better understanding of who the various market participants are and their motives for trading[14]. Further, the issues involved may be too complex to be addressed by theoretical models. Carefully designed market experiments may be necessary to evaluate how informational efficiency of prices, market liquidity, and severity of crashes would change across different market structures.

[14] A better understanding of who the market participants are and their motives for trading may help build models that capture reality better. An example is Baruch and Glosten, 2019 who find that order cancellation by traders might be thought of as an aspect of equilibrium rather than manipulation or some other nefarious purpose.

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