On the Effects of Continuous Trading*

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March 3, 2021

Abstract. The continuous limit order book, in which messages are processed one by one in the order of receipt, is a prominent design feature of modern securities markets. Theoretical models show that this design imposes an adverse selection cost on liquidity providers and suggest that this cost may be reduced by switching to batch auctions. We examine a recent opposite move, whereby a large stock exchange switches from batch auctions to continuous trading. Consistent with theoretical predictions, we find that the move leads to greater adverse selection. Trading costs increase as a result, while displayed liquidity deteriorates.

Key words: liquidity, gains from trade, continuous trading, batch auctions

JEL: G14; G15

*We thank Michael Brolley, Benjamin Connault and Konstantin Sokolov for valuable comments. Pascual acknowledges support of the Spanish DGICYT project ECO2017-86903-P and Generalitat Valenciana Grant Prometeo/2017/158. Shkilko acknowledges support of the Social Sciences and Humanities Council of Canada and the Canada Research Chairs program.

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1. Introduction

The majority of modern equity markets are organized as continuous limit order books. In this design, market participants submit messages in continuous time, and exchange matching engines process the messages one by one in order of receipt. Theoretical literature argues that this design may increase the level of adverse selection (toxicity), because it reduces the ability of liquidity providers to reprice stale quotes before they are picked off (Budish, Cramton, and Shim (2015)). Trading costs increase as a result. As a remedy, the literature proposes replacing continuous trading with frequent batch auctions, in which orders accumulate for a period of time before being matched against each other, thus giving market makers a better opportunity to change stale quotes.

Empirical studies have not yet directly examined these theoretical predictions, largely because switches between the two market designs are rare. We fill this gap by studying a recent decision by the Taiwan Stock Exchange (TWSE) to move all of its activity from batch auctions to continuous trading. In a difference-in-differences (DID) setup, we find that continuous trading is associated with significantly greater adverse selection, a sizeable reduction in displayed liquidity, and an increase in trading costs.

The TWSE is one of the world's 20 largest stock exchanges. Ranked by the U.S. dollar trading volume, it is comparable (ranked 15$^{\text{th}}$) to such markets as the Toronto Stock Exchange (13$^{\text{th}}$) and the Australian Securities Exchange (20$^{\text{th}}$). Until recently, the TWSE was the only large market that used batch auctions as the primary method of matching buyers and sellers. The auctions were relatively frequent, occurring every five seconds, yet recently the exchange joined its industry peers in offering continuous market access. Its new continuous trading platform launched on March 23, 2020.

It is important to acknowledge that the TWSE switched to continuous trading at the onset of the COVID-19 pandemic, and therefore we must be careful with inferences. Notably, the data contain clean and sizeable regime shifts on the day of the switch. For instance, Figure 1 shows that effective spreads, our main trading cost metric, increase sharply on March 23 and stabilize at the new level thereafter. This pattern alone may allay concerns with the confounding effects; however, in subsequent analyses we rely on a formal two-pronged approach to mitigate these concerns even further.

[Figure 1]

First, we use a DID setup with a control sample of stocks trading on the Korean Stock Exchange (KRX). The similarities in infection emergence and pandemic responses undertaken by Taiwan and South Korea allow us to cautiously assert that the DID analysis mitigates the confounding effects of the pandemic onset. Second, we use several event window lengths to assess the sensitivity of our results to possible pandemic effects. The results are preserved regardless of event window lengths and their proximity to the March 23 launch date. Taken together, these analyses give us sufficient confidence that the findings are attributable to the switch to continuous trading rather than the pandemic. We note that due to the one-event nature of the TWSE switch, a DID analysis would have been prudent even in the absence of the pandemic. For such an analysis, the geographic proximity of the two markets and their similar sizes would have made the KRX a sensible source of controls.

The 21st century has witnessed significant changes in the structure of financial markets. Exchanges have largely automated the trading process (Hendershott, Jones, and Menkveld (2011), Hendershott and Moulton (2011)) and considerably improved matching engine connectivity and execution speeds (Conrad, Wahal, and Xiang (2015), Brogaard, Hagströmer, Nordén, and Riordan (2015)). Market participants responded to these changes by adopting the latest technology in a speed race to the exchange engines and between markets (Baron, Brogaard, Hagströmer, and Kirilenko (2019), Shkilko and Sokolov (2020)). One market structure feature that has however remained largely unchanged during this time is the continuous limit order book. In it, orders are fed into the exchange engine one at a time on a first come, first served basis. In the event of two orders arriving simultaneously, chance determines which is processed first.

Budish, Cramton, and Shim (2015) question this design due to its ability to intensify adverse selection. To understand their reasoning, it helps to think of a group of N market participants, who have identical speeds, all reacting to the same information. All N participants may act both as market makers and liquidity takers (snipers). In the former role, they rush to change their posted quotes in response to news, while in the latter role, they attempt to pick off the stale quotes of others. Even though everyone's speeds are the same, chance dictates that one order will be processed by the exchange engine first. Given that there are $N-1$ snipers for each stale quote, the odds of being adversely selected, $(N-1)/N$, are not in favour of the market maker. In the meantime, a batch auction that accumulates orders for a period of time before matching them gives the market maker sufficient time to revise her stale quote before it is picked off. As long as the auctions are not ultra-frequent, she can do so even if the other traders are a little faster. Given this advantage, Budish, Cramton, and Shim (2015) propose that market operators should reduce their reliance on the continuous design.

While Budish, Cramton, and Shim (2015) focus on adverse selection costs, Aït-Sahalia and Sağlam (2017) examine a different market maker concern – inventory management. In their model, the market makers' decisions are characterized by an inventory penalty function, whereby holding inventory comes at a cost. If the market maker can predict future liquidity demand more accurately, she may reduce the risk of taking on unwanted inventory and therefore the penalty cost. Empirical research corroborates this prediction. Brogaard, Hagströmer, Nordén, and Riordan (2015) find that a better ability to predict incoming order flow is associated with lower inventory costs, while Shkilko and Sokolov (2020) suggest that exposure to toxic order flow affects this predictive ability negatively. Following this line of reasoning, continuous trading may have a two-pronged effect on market making costs, by increasing both adverse selection and the risk of unexpected inventory accumulation.

Our analyses support these expectations. In the DID regression setup, we find that adverse selection on the TWSE substantially increases after the switch to continuous trading. Realized spreads too increase consistent with an increase in inventory costs. The total effect is an increase in effective spreads, our proxy for liquidity costs, and a reduction in displayed liquidity represented by quoted spreads and depths. The data also show that continuous trading brings mild improvements in price efficiency, although these results are not always statistically significant, and their economic magnitude appears secondary to that of the liquidity effects.

To date, the proposal to discretize trading has not gained much traction in the exchange industry. Only one U.S. market operator, Cboe Global Markets, has an outstanding application before the Securities and Exchange Commission (SEC) to implement batch auctions on one of its smaller equity exchanges, BYX.[1] Our results help explain the general reluctance of the industry to change the status quo. We show that continuous trading comes with an increase in trading volume, an important revenue driver for modern exchanges. In an industry characterized by high fixed costs, willfully reducing a revenue source is generally inconsistent with profit maximization.

If approved by the SEC, it may be of interest to compare the outcome of discretization on the BYX to the results obtained from the TWSE. We however caution that the multi-market environment that characterizes U.S. equity trading may not be ideal for such an analysis. Adding a batch auction market to the existing continuous markets may result in a clientele migration and therefore confound market quality inferences. Similar concerns may accompany analyses of recent introductions of periodic auctions in Europe. Furthermore, it should be noted that European auction mechanisms are characterized by a limited degree of transparency (e.g., Johann, Putniņš, Sagade, and Westheide (2019)) further confounding design comparisons. In the meantime, the TWSE transition to continuous trading occurs in a market characterised by a high degree of consolidation and without an accompanying change in transparency.

[1] "Cboe Proposes Plan That Could Curb Advantages of Fast Traders," by A. Osipovich, Wall Street Journal, July 28, 2020 (`https://on.wsj.com/3jpZ2KY`).

2. Data and metrics

2.1 Sample

We collect intraday quote and trade data from the Refinitiv Tick History database, the successor to the Thomson Reuters Tick History database. The sample consists of 100 TWSE stocks with the largest market capitalization. The sample period is from November 2019 through July 2020. To establish a baseline, Table 1 reports summary statistics computed prior to the switch to continuous trading.

The average sample stock has a market capitalization of 282 billion New Taiwan dollars (NTD), share price of NTD 182, daily volume of about 9.6 million shares, and daily volatility of 1.43 bps. We compute volatility as the difference between the highest and lowest daily midpoints scaled by the average midpoint. The sample covers a broad cross section, with market capitalizations ranging between NTD 54 billion and 474 billion (respectively, in the 10^{th} and 90^{th} percentiles), prices ranging between NTD 14.73 and 372.05, and daily volumes – between 0.55 and 23.1 million shares.

[Table 1]

Upon switching to continuous trading, the TWSE begins reporting trade and quote data in a format that is similar to that of the Trade and Quote Database often used to examine liquidity in the U.S. The data contain all intraday activity at the top of the limit order book including trades, ask and bid quotes, and quoted depths time-stamped to the nearest millisecond. We bunch trade records that have the same time stamp, trade direction, and price into one trade, as such records typically reflect a trade initiated by one market participant that executes against several standing limit orders. As is common, we omit the first and last five minutes of the trading day.

To assess displayed liquidity, we estimate the *quoted spread* as the difference between the best offer and the best bid. To measure the number of shares available at displayed prices, we compute *quoted depth* as the average of the best quote sizes. To assess trading costs incurred by liquidity demanders, we compute the *effective spread* as twice the signed difference between the traded price and the quote midpoint at the time of the trade. To measure the levels of adverse selection, we compute the *price impact* as twice the signed difference between the quote midpoint at the time of the trade and the midpoint 30 seconds after the trade. Finally, to gauge inventory costs we follow Brogaard, Hagströmer, Nordén, and Riordan (2015) and use the *realized spread*, the difference between the effective spread and price impact.

We drop instances when the best quotes are locked or crossed, that is when the quoted spread is zero or negative. To sign trades, we rely on the Lee and Ready (1991) algorithm. Chakrabarty, Pascual, and Shkilko (2015) show that this algorithm performs well in modern markets. All variables are scaled by the corresponding quote midpoints. In a later section, we show that the results are robust to varying horizons for price impact and realized spread estimates between 10 and 300 seconds.

Panel A of Table 2 reports that the average quoted and effective spreads before the switch to continuous trading are, respectively, 23.41 and 19.12 bps, while price impacts and realized spreads are 10.84 and 8.27 bps. Quoted depth is about 448 thousand shares, or 4.7% of daily trading volume. Again, we observe non-trivial variation in the cross-section, with effective spreads for instance ranging from 10.16 bps in the 10th percentile to 33.89 bps in the 90th percentile, and realized spreads ranging from 0.04 to 18.74 bps.

[Table 2]

2.2 Price efficiency metrics

In addition to understanding the effects of continuous trading on liquidity costs, we are interested in measuring its effects on price efficiency. To measure efficiency, we use two standard metrics: *return autocorrelation* as in Hendershott and Jones (2005) and *price delay* of Hou and

Moskowitz (2005). The former metric relies on the notion that, in a frictionless market, prices should be unpredictable, and as such midpoint returns should have zero autocorrelation. It is defined as the absolute first order midpoint return autocorrelation, and we compute it at several frequencies $s \in \{10\text{s}, 30\text{s}, 60\text{s}, 300\text{s}\}$. Smaller autocorrelation estimates suggest greater efficiency.

The latter metric in turn assumes that efficient prices should instantly incorporate public market information. Accordingly, lagged market returns should have no predictive power for individual stocks returns. To compute this metric, we begin by running the following regression for each stock-day i:

$$r_{i,s} = \alpha_i + \beta_i r_{m,s} + \sum_{k=1}^{10} \gamma_{i,k} r_{m,s-k} + \varepsilon_{i,s}, \tag{1}$$

where $r_{i,s}$ is the quote midpoint return on stock i during time interval s, and $r_{m,s}$ is the return on TAIEX, Taiwan's market index. For consistency, we use the same frequencies for s as we did when computing the autocorrelation metric. We then define the R^2 from regression (1) as unconstrained, R^2_u. Next, we estimate regression (1) without the lagged market returns, effectively constraining γ to zero, and define the corresponding R^2 as constrained, R^2_c. Finally, for each stock-day i, we compute:

$$price\ delay_i = 1 - \frac{R^2_{c\ i}}{R^2_{u\ i}}, \tag{2}$$

which takes values between zero and 1. A smaller delay suggests greater efficiency. Panel B of Table 2 reports the summary statistics for price efficiency metrics. To save space, here and in subsequent analyses, we report both metrics in two ways: (i) computed at the 60-second frequency and (ii) aggregated into the first principal component (PC1) across all above-mentioned frequencies. In a subsequent section, we show that our results are robust to varying horizons for both metrics.

2.3 The control sample

The latter part of our 2019-2020 sample period coincides with the COVID-19 pandemic. To verify that our results are not driven by this global event, we use the DID approach. Specifically, we surmise that the pandemic affected volatility in most equity markets in a similar way. As such, the true effect of the introduction of continuous trading in Taiwan may be observable if juxtaposed against a control market. We note that since continuous trading was introduced for all stocks simultaneously, a DID approach would have been prudent even in the absence of the pandemic.

As a control market, we use the Korean Stock Exchange (KRX), which is well-suited for this purpose due to its geographic proximity to the TWSE as well as similar size. Both Taiwan and Korea faced an onset of COVID-19 cases early in the pandemic and followed similar public health strategies managing to contain the spread of the virus in the spring of 2020. These similarities allow us to cautiously claim that country-specific differences in the pandemic onset and response should not confound the DID results. In addition to DID, in subsequent analyses we use pre- and post-event windows that are sufficiently removed from the month of March to further reduce possible effects of the pandemic-induced global volatility. Our results are however robust, as we show shortly, to various event window lengths.

To match the TWSE and KRX stocks, we use trading volumes and closing prices converted to the same currency for comparability. We then compute the matching score of each TWSE sample stock i and each KRX stock j as:

$$MS_{ij} = \left| \frac{P_i}{P_j} - 1 \right| + \left| \frac{V_i}{V_j} - 1 \right|, \tag{3}$$

where P is the daily average closing price, and V is the daily average dollar volume. We then match, without replacement, each TWSE sample stock with the KRX stock that minimizes the matching score. In the following sections, we report (i) the simple TWSE-only differences in market quality variables and (ii) the DID results. The former give us an understanding of the economic magnitude of changes that follow the switch to continuous trading, and the latter let us zero in on the effects attributable to the switch itself, controlling for possible global confounders.

3. Empirical findings

3.1 Adverse selection

Budish, Cramton, and Shim (2015) show theoretically that continuous trading decreases the ability of liquidity providers to adjust their quotes in response to toxic order flow. As a result, adverse selection increases. The switch to continuous trading by the TWSE gives us a unique opportunity to test this prediction. We begin by computing simple pre- and post-event averages for price impacts, which serve as proxies for adverse selection of liquidity provider quotes. To avoid the effects of the onset of COVID-19 pandemic, the pre-event window includes November 2019 through January 2020, and the post-event window includes May through July 2020. We report the results from alternative windows later in this section. The univariate results in Panel A of Table 3 suggest that adverse selection increases by 27%, from 10.84 bps prior to the switch to continuous trading to 13.78 bps post-switch.

[Table 3]

These results are consistent with the above-mentioned theoretical predictions; however, their univariate nature comes with caveats. First, the univariate analysis does not account for the effects of known adverse selection determinants such as trading volume and volatility. Second, they may be subject to confounding events, particularly the effects of the COVID-19 pandemic. To examine the adverse selection effects more formally, we use the following DID regression setup for each stock i on each day t:

$$\begin{aligned} \textit{price impact}_{it} =& \alpha_i + \beta_1 Post_t + \beta_2 TWSE_i + \beta_3 Post_t \times TWSE_{it} + \delta_1 Volume_{it} \\ &+ \delta_2 Volatility_{it} + \varepsilon_{it}, \end{aligned} \tag{4}$$

where *Post* is an indicator variable that equals to 1 in the post-event period and zero otherwise, $TWSE$ is an indicator variable that equals to 1 for the TWSE stocks and 0 for the KRX stocks, $Volume$ is daily trading volume, and $Volatility$ is the difference between the highest and lowest midpoints scaled by the average midpoint. All continuous variables are winsorized at 1% and normalized, that is, from each stock-day observation we subtract the sample mean and divide this difference by the corresponding standard deviation.

The results in Panel B of Table 3 support previously reported univariate findings in that adverse selection increases upon the switch to continuous trading. In specification 1, the DID specification without the volume and volatility controls, the interaction coefficient $Post \times TWSE$ indicates that price impacts on the TWSE increase by 0.460 standard deviations compared to the KRX, a notable 24% increase over the adverse selection levels that are in place during the discrete regime.[2] In specification 2, which controls for volume and volatility, the interaction coefficient suggests that price impacts increase by 8%.[3]

We note that although the volatility and volume controls do not reduce statistical significance of the $Post \times TWSE$ coefficient, they reduce its economic magnitude. On the one hand, this may

[2] To compute the economic significance of regression coefficients, we use standard deviations from the sample period, for which the coefficients are derived. For instance, the standard deviation for price impacts used to gauge economic significance in Panel B of Table 3 is 5.68. This estimate is from the November 2019 through January 2020 pre-event window and the May through July 2020 post-event window.

[3] We note that the $Post \times TWSE$ coefficient captures the difference between the post-switch effects on the TWSE and the KRX. To measure the full economic effect for the TWSE, one should add the coefficients for *Post* and $Post \times TWSE$. Given that the *Post* coefficient in specification 1 is statistically indistinguishable from zero, we base the economic interpretation on the $Post \times TWSE$ coefficient alone. In specification 2, in which the *Post* coefficient is significant, we use $Post + Post \times TWSE$.

suggest that some of the increase in adverse selection is attributable to changes in volume and volatility, the two known adverse selection determinants. In a subsequent section, we show that both of these determinants increase upon the switch to continuous trading. On the other hand, the price impact, volume, and volatility are all subject to the same structural break that occurs on the day of the switch. As such, the two control variables may mechanically subsume some variation in price impact. While it is not possible to gauge which of the two effects dominates, we suggest that the coefficient in specification 2 likely represents the lower bound of the economic effect, while the coefficient in specification 1 represents the upper bound. In subsequent discussions, we focus on the lower bound coefficients to remain conservative.

To reduce the effect of volatility associated with the onset of the COVID-19 pandemic, our main event window contains three pre-event months (November 2019 through January 2020) and three post-event months (May through July 2020) that are removed from the month of March when it became clear that the virus had spread around the globe, multiple countries announced lockdowns, and markets precipitously declined. To confirm that the results are not driven by the event window choice, we repeat the analyses for two additional periods: (i) the November 2019 through July 2020 period that excludes the month of March and (ii) the entire November 2019 through July 2020 period. The results in Panel C of Table 3 are consistent with those discussed earlier. No matter which sample period we examine, adverse selection for the TWSE stocks substantially increases compared to their KRX matches and compared to the discreet trading regime.

3.2 Displayed liquidity and trading costs

Adverse selection is a cost of market making. In competitive markets, changes in this cost are often relayed to liquidity consumers. With this in mind, we now ask if the increase in adverse selection post-switch affects the cost of liquidity. To answer this question, we examine two related metrics – quoted and effective spreads. The former captures displayed liquidity, that is, prices posted by liquidity providers. The latter accounts for two additional possibilities: (i) that liquidity demanders may choose to trade when liquidity is cheaper, and (ii) that they occasionally receive price improvement over posted prices.

The univariate results in Panel A of Table 4 indicate that quoted spreads increase and quoted depths decline after the switch to the continuous regime. In Panel B, we confirm these results in a DID regression setting of equation (4). Compared to the pre-event period and to the KRX stocks, quoted spreads increase by 0.907 standard deviations, equivalent to 14%. Another notable change is the 0.380 standard deviations decline in quoted depth, equivalent to 10% of the pre-switch depth figure.

In Table 5, we expand the DID regression analysis to effective and realized spreads. Effective spreads, which capture the cost of taking liquidity, increase by 1.149 standard deviations, equivalent to 21%. Next, we turn to the realized spreads that are a composite metric often used to proxy for liquidity provider inventory costs. Brogaard, Hagströmer, Nordén, and Riordan (2015) and Shkilko and Sokolov (2020) show that unpredictable order flow such as that generated in the process of latency arbitrage may impede market maker inventory management. When arbitrageurs pick off stale quotes, market maker inventory may increase unexpectedly, requiring additional efforts to balance it. Inventory holding costs increase as a result. The results corroborate this possibility. Panel B of Table 5 shows that realized spreads increase by 0.545 standard deviations upon the switch to continuous trading. The results for the two alternative sample periods reported in Panel C are consistent with these findings.

[Tables 4 and 5]

Before moving on, it is useful to discuss two issues related to realized spreads. As a residual metric (the difference between effective spreads and price impacts), realized spreads capture not only the inventory costs, but also order processing costs and liquidity provider profits. Our discussion of this metric has so far focused solely on the inventory costs. We cautiously suggest that this focus is justified given that it is difficult to think of ways, in which continuous trading would increase order processing costs per share. If anything, given the greater volumes resulting from continuous trading and the fact that order processing costs have a non-trivial fixed component, these costs could have declined.[4] When it comes to profits, it is again difficult to think of a scenario, in which these could appreciably change in a competitive market for liquidity provision. One possibility is that the switch to continuous trading forced some market makers to exit, resulting in a less competitive environment and therefore greater per-share profits. Nevertheless, a media search and conversations with industry participants do not produce any evidence of market maker exits as a result of the switch.

3.3 Price efficiency

Modern trading strategies that rely on speed and may benefit from continuous trading often improve price efficiency (e.g., Brogaard, Hendershott, and Riordan (2014), Chaboud, Chiquoine, Hjalmarsson, and Vega (2014), Boehmer, Li, and Saar (2018)). While some of these strategies provide liquidity, others – often referred to as *toxic arbitrage* – demand it (Foucault, Kozhan, and Tham (2017)). In the discrete regime, the liquidity-taking strategies may lack profitability, as market maker quotes are not stale often enough. With the switch to continuous trading, the profitability of these strategies is likely to increase, and they may proliferate. Our earlier results are consistent with this possibility, as greater adverse selection is one possible consequence of such a proliferation. In this light, it is of interest to consider the effect of continuous trading on price efficiency. On the one hand, during the discrete regime liquidity providers may have already maintained efficiency at the optimal level by promptly adjusting their quotes. On the other hand, allowing for greater profitability of liquidity demanding strategies may have given price efficiency

[4] We formally discuss increases in trading volume shortly.

a boost. We examine these possibilities by turning to the price efficiency metrics.

Table 6 shows that the effects of continuous trading on price efficiency are somewhat mixed. First, the autocorrelation metric and the principal component of this metric suggest that price efficiency improves, with the DID coefficients of -0.181 and -0.056, respectively. It should be noted that this improvement is economically moderate, between 1.4% and 3.3%. Second, the DID coefficients for the price delay metric are -0.215 and -0.058, translating to improvements between 0.4% and 2.0%. Notably however, changes in the price delay metric are mostly insignificant when we vary the estimation window in Panel C, making price delay the only metric so far that does not show stable results across estimation windows. As such, it appears that continuous trading moderately improves some, but not all, aspects of price efficiency.

[Table 6]

In light of these results, it may be of interest to contemplate the net effect of continuous trading. On the one hand, reductions in return autocorrelations, even on the level of 3.3%, benefit market participants by increasing the probability of trading at the most up-to-date prices. On the other hand, this benefit comes at a cost to liquidity. Consistent with Foucault and Moinas (2019), to justify this tradeoff as welfare-enhancing the benefits of relatively small improvements in price efficiency must be sizeable, and traders must value them exceptionally highly.

3.4 Volatility, volume, and gains from trade

In this section, we seek to better understand the effects of continuous trading on gains from trade. To proceed, we first outline the links between latency arbitrage, volatility, and trading volume proposed by recent theoretical and empirical work and then examine these links in our setting.

Modeling a market in which liquidity takers generate toxic volume, Roşu (2019) shows that such volume is associated with increased adverse selection and volatility. Consistent with these predictions, Shkilko and Sokolov (2020) show empirically that liquidity-taking latency arbitrage indeed generates substantial volume, while increasing adverse selection and volatility. In an earlier section, we find that adverse selection increases upon the switch to continuous trading and relate this increase to the proliferation of latency arbitrage. Given the above-mentioned literature, it is possible that volatility increases as well. We examine this possibility in Table 7. In the DID setting, volatility indeed increases by 0.175 standard deviations after the switch (specification 2). We note that, aside from its standalone significance, this result justifies our use of volatility as a control in all regression specifications.

[Table 7]

We next turn to the volume effects. The theoretical literature emphasizes the role of liquidity in promoting welfare. Improved liquidity allows greater numbers of economic agents to come to the market and benefit from exchanging assets, increasing gains from trade. When liquidity is costly, some agents (we call them the *traditional users* or *end-users* of liquidity) may choose to stay on the sidelines, and gains from trade are reduced. Since the switch to continuous trading results in greater liquidity costs, it is possible that some end-users will leave the market, and trading volume will decline. Still, if the increase in arbitrage activity is substantial, arbitrage volume may compensate for this decline and even result in a net volume increase.

We begin to examine these possibilities in Table 7. At first glance, the univariate results in Panel A and the regression results in specification 3 of Panel B suggest that the switch to continuous trading leads to a volume increase. Notably however, when we control for volatility in specification 4, the change in volume becomes insignificant. This latter result is noteworthy. Insofar as changes in volatility proxy for the proliferation of latency arbitrage discussed by Roşu (2019) and Shkilko and Sokolov (2020), the latter result is consistent with the notion that continuous trading may not lead to greater gains from trade for the traditional users of liquidity.

3.5 Robustness

For several key variables used in this study, we chose estimation horizons that are commonly used in the literature. Specifically, we rely on 30-second horizons when we estimate price impacts and realized spreads and use 60-second horizons for return autocorrelation and price delay metrics. In Table 8, we ask if our results are robust to alternative horizons. The data indicate that they are. In the DID regression specification that uses volume and volatility controls, all above-mentioned variables remain statistically significant and have similar economic magnitudes to those reported in the main tables.

[Table 8]

4. Conclusion

Market structure theory suggests that the continuous limit order book – market design that dominates modern equity trading – is prone to generating adverse selection. For every market maker order that may be attempting to change a stale quote, there likely to be multiple liquidity demanding orders aiming to pick off this quote. Because the continuous limit order book processes orders one by one, and even assuming equal speeds by all market participants, the odds of replacing a stale quote before it is picked off are relatively low. As such, the adverse selection cost born by market makers is high. To compensate for this cost, spreads are kept wider than they would be under an alternative design. Frequent batch auctions, in which orders from all market participants accumulate for a brief period of time before being matched, are often discussed as a superior alternative to the status quo.

The empirical literature has not yet examined this issue directly because transitions from one market design to another are rare. We examine one such recent transition, whereby a large equity market – the Taiwan Stock Exchange (TWSE) – moves all of its equity trading from batch auctions to a continuous book. The data support the above-mentioned theory predictions, in that adverse selection increases significantly. In addition, market maker inventory costs increase, consistent with the notion that latency arbitrage complicates inventory management. The total liquidity effect of the TWSE move is therefore negative; trading costs increase, and displayed liquidity declines.

Our results provide new empirical evidence to the ongoing debate about the costs and benefits of different market designs. On the one hand, the adverse selection cost embedded in the continuous design may be reduced by switching to frequent batch auctions, thereby benefiting the end-users of liquidity. On the other hand, the continuous design comes with increased trading volumes boosted by arbitrage activity, thus benefiting the exchanges. Given the high fixed costs of running an exchange, it is unlikely that market operators will willingly change the status quo, especially if the change will negatively affect trading volumes. In the meantime, it appears that for the continuous order book design to be welfare-improving, the end consumers of liquidity must heavily discount trading costs and put a substantial premium on moderate improvements in price efficiency.

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Table 1
Sample Characteristics

The table reports summary statistics for 100 Taiwan Stock Exchange (TWSE) stocks used in the sample. To establish a baseline, and for comparability with the main regression setup, the statistics are computed during a period prior to the switch to continuous trading: November 2019 through January 2020. *Market cap.* is market capitalization computed as the product of the number of shares outstanding and the share price. *Price* is the daily closing price in New Taiwan dollars (NTD). *Number of trades* and *Volume* are daily averages, and *Volatility* is computed for each stock-day as the difference between the highest and lowest midpoints scaled by the average midpoint. Quote midpoint is the average between the TWSE best bid and best offer prices.

	Mean	Median	Std. Dev.	10th	90th
Market cap., NTD million	282,447	118,614	840,716	54,028	474,412
Price, NTD	181.92	67.65	491.58	14.73	372.05
Number of trades	1,076	972	622	305	1,920
Volume, share thousand	9,550	4,840	16,294	553	23,116
Volatility, bps.	1.43	1.23	0.83	0.52	2.74

Table 2
Liquidity and Price Efficiency Statistics

The table reports liquidity and price efficiency statistics for 100 Taiwan Stock Exchange (TWSE) stocks used in the sample. To establish a baseline, and for comparability with the main regression setup, the statistics are computed during a period prior to the switch to continuous trading: November 2019 through January 2020. Panel A reports statistics for liquidity costs. *Quoted spread* is the difference between the best offer and the best bid. *Quoted depth* is the average of the best bid and best ask quote sizes. *Effective spread* is twice the signed difference between the traded price and the quote midpoint immediately preceding the trade. *Price impact* is twice the signed difference between the quote midpoint immediately preceding the trade and the midpoint 30 seconds after the trade. *Realized spread* is the difference between the effective spread and price impact. To sign trades, we use the Lee and Ready (1991) algorithm. All statistics other than the quoted depths are scaled by the contemporaneous quote midpoints. Quoted spreads and depths are equally-weighted, and all remaining liquidity metrics are volume-weighted. Panel B reports two price efficiency metrics: return autocorrelation and price delay. *Return autocorrelation* is defined as the absolute first order midpoint return autocorrelation computed at the 60-second frequency. In addition, we report the first principal component (PC1) for several estimation frequencies: 10s, 30s, 60, and 300s. *Price delay* is computed by comparing R^2s from two regressions of stock returns on market returns (equation (1)). The first (unconstrained) regression allows for several lags of market returns, while the second (constrained) model does not allow for lagged market returns (Section 2 contains estimation details). The two R^2s are then compared to compute the price delay metric as per equation (2). We report the results estimated using the 60-second frequency, and the first principal component of price delays estimated at 10-, 30-, 60-, and 300-second frequencies.

	Mean	Median	Std. Dev.	10th	90th
Panel A: Displayed liquidity and trading costs					
Quoted spread, bps.	23.41	20.44	10.94	12.09	39.93
Quoted depth, share thousand	447.5	92.7	928.2	8.1	943.9
Effective spread, bps.	19.12	15.63	9.33	10.16	33.89
Price impact, bps.	10.84	9.62	5.46	5.09	19.00
Realized spread, bps.	8.27	6.10	8.15	0.04	18.74
Panel B: Price efficiency metrics					
Return autocorrelation (60s)	0.11	0.11	0.02	0.08	0.14
Return autocorrelation (PC1)	0.33	0.33	0.09	0.23	0.42
Price delay (60s)	0.08	0.06	0.08	0.00	0.19
Price delay (PC1)	0.77	0.86	0.04	0.81	0.89

Table 3
Adverse Selection

The table examines changes in adverse selection of liquidity providers (proxied by the price impacts) around the move to continuous trading. The treatment sample consists of 100 largest TWSE stocks, and the control group is 100 matched KRX stocks. The sample period spans November 1, 2019 to July 30, 2020. To avoid the effects of the onset of COVID-19 pandemic, in Panels A and B, the pre-event window includes November 2019 through January 2020, and the post-event window includes May through July 2020. Panel C examines alternative event windows. Panel A contains univariate results for the TWSE stocks. Panels B and C report the results of a difference-in-differences (DID) regression of the following form:

$$price\ impact_{it} = \alpha_i + \beta_1 Post_t + \beta_2 TWSE_i + \beta_3 Post_t \times TWSE_{it} + \delta_1 Volume_{it} + \delta_2 Volatility_{it} + \varepsilon_{it},$$

where *Post* is an indicator variable that equals to 1 for the post-event period and zero otherwise; $TWSE$ is an indicator variable that equals to 1 for the TWSE stocks and 0 for the KRX stocks; *Volume* is daily trading volume in stock i on day t; and $Volatility$ is the difference between the highest and lowest midpoints scaled by the average midpoint. All continuous variables are winsorized at 1% and normalized, that is, from each stock-day observation we subtract the sample mean and divide this difference by the corresponding standard deviation. White-robust standard errors are in parentheses. *** indicates statistical significance at the 1% level.

	[1]		[2]	
Panel A: Univariate results				
Pre	10.84			
Post	13.78	***		
Panel B: Regression results				
Post	0.010		-0.074	***
	(0.04)		(0.02)	
TWSE	-0.240	***	-0.121	***
	(0.04)		(0.02)	
Post×TWSE	0.460	***	0.235	***
	(0.05)		(0.03)	
Volume			-0.038	***
			(0.02)	
Volatility			0.570	***
			(0.02)	
Incercept	-0.002		0.033	
	(0.04)		(0.03)	
Adj. R^2	0.028		0.310	
Obs.	24,144		24,144	
Panel C: Regression: alternative sample periods				
Post×TWSE: excluding March	0.320	***	0.143	***
	(0.06)		(0.04)	
Post×TWSE: full sample	0.280	***	0.177	***
	(0.05)		(0.04)	

Table 4
Displayed Liquidity

The table examines changes in quoted spread and depth around the move to continuous trading. The treatment sample consists of 100 largest TWSE stocks, and the control group is 100 matched KRX stocks. The sample period spans November 1, 2019 to July 30, 2020. To avoid the effects of the onset of COVID-19 pandemic, in Panels A and B the pre-event window includes November 2019 through January 2020, and the post-event window includes May through July 2020. Panel C examines alternative event windows. Panel A contains univariate results for the TWSE stocks. Panels B and C report the results of a DID regression of the following form:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 TWSE_i + \beta_3 Post_t \times TWSE_{it} + \delta_1 Volume_{it} + \delta_2 Volatility_{it} + \varepsilon_{it},$$

where *DepVar* is the quoted spread or quoted depth, *Post* is an indicator variable that equals to 1 for the post-event period and zero otherwise; $TWSE$ is an indicator variable that equals to 1 for the TWSE stocks and 0 for the KRX stocks; *Volume* is daily trading volume in stock i on day t; and $Volatility$ is the difference between the highest and lowest midpoints scaled by the average midpoint. All continuous variables are winsorized at 1% and normalized, that is, from each stock-day observation we subtract the sample mean and divide this difference by the corresponding standard deviation. White-robust standard deviations are in parentheses. *** and ** indicate statistical significance at the 1% and 5% levels.

	Quoted spread				Quoted depth			
	[1]		[2]		[3]		[4]	
Panel A: Univariate results								
Pre	23.41				447.5			
Post	25.74	***			322.4	***		
Panel B: Regression results								
Post	-0.076	**	-0.045		0.224	***	0.153	***
	(0.04)		(0.04)		(0.05)		(0.04)	
TWSE	-0.468	***	-0.471	***	0.190	***	0.194	***
	(0.03)		(0.03)		(0.04)		(0.03)	
Post×TWSE	0.901	***	0.907	***	-0.375	***	-0.380	***
	(0.06)		(0.05)		(0.06)		(0.05)	
Volume			-0.267	***			0.636	***
			(0.02)				(0.02)	
Volatility			0.178	***			-0.444	***
			(0.02)				(0.01)	
Intercept	0.070		0.042		-0.016	***	-0.096	***
	(0.05)		(0.04)		(0.04)		(0.03)	
Adj. R^2	0.086		0.119		0.01		0.201	
Obs.	24,144		24,144		24,144		24,144	
Panel C: Regression: alternative sample periods								
Post×TWSE: excluding March	0.799	***	0.820	***	-0.358	***	-0.419	***
	(0.05)		(0.04)		(0.06)		(0.04)	
Post×TWSE: full sample	0.751	***	0.703	***	-0.363	***	-0.323	***
	(0.04)		(0.03)		(0.05)		(0.04)	

Table 5
Trading Costs

The table examines changes in effective and realized spreads around the move to continuous trading. The treatment sample consists of 100 largest TWSE stocks, and the control group is 100 matched KRX stocks. The sample period spans November 1, 2019 to July 30, 2020. To avoid the effects of the onset of COVID-19 pandemic, in Panels A and B the pre-event window includes November 2019 through January 2020, and the post-event window includes May through July 2020. Panel C examines alternative event windows. Panel A contains univariate results for the TWSE stocks. Panels B and C report the results of a DID regression of the following form:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 TWSE_i + \beta_3 Post_t \times TWSE_{it} + \delta_1 Volume_{it} + \delta_2 Volatility_{it} + \varepsilon_{it},$$

where *DepVar* is the effective or realized spread, *Post* is an indicator variable that equals to 1 for the post-event period and zero otherwise; *TWSE* is an indicator variable that equals to 1 for the TWSE stocks and 0 for the KRX stocks; *Volume* is daily trading volume in stock i on day t; and *Volatility* is the difference between the highest and lowest midpoints scaled by the average midpoint. All continuous variables are winsorized at 1% and normalized, that is, from each stock-day observation we subtract the sample mean and divide this difference by the corresponding standard deviation. White-robust standard deviations are in parentheses. *** and ** indicate statistical significance at the 1% and 5% levels.

	Effective spread				Realized spread			
	[1]		[2]		[3]		[4]	
Panel A: Univariate results								
Pre	19.12				8.27			
Post	23.01	***			9.23	***		
Panel B: Regression results								
Post	-0.095	***	-0.087	**	-0.187	***	-0.100	***
	(0.04)		(0.04)		(0.03)		(0.02)	
TWSE	-0.609	***	-0.596	***	-0.172	***	-0.281	***
	(0.03)		(0.03)		(0.03)		(0.02)	
Post×TWSE	1.175	***	1.149	***	0.341	***	0.545	***
	(0.05)		(0.04)		(0.04)		(0.04)	
Volume			-0.160	***			-0.066	***
			(0.01)				(0.01)	
Volatility			0.176	***			-0.442	***
			(0.02)				(0.02)	
Intercept	0.045		0.033		0.089	***	0.047	
	(0.04)		(0.04)		(0.03)		(0.03)	
Adj. R^2	0.147		0.162		0.007		0.238	
Obs.	24,144		24,144		24,144		24,144	
Panel C: Regression: alternative sample periods								
Post×TWSE: excluding March	1.083	***	1.072	***	0.422	***	0.595	***
	(0.04)		(0.04)		(0.04)		(0.03)	
Post×TWSE: full sample	0.933	***	0.885	***	0.491	***	0.562	***
	(0.04)		(0.03)		(0.04)		(0.03)	

Table 6
Price Efficiency

The table examines changes in return autocorrelation and price delay metrics around the move to continuous trading. The treatment sample consists of 100 largest TWSE stocks, and the control group is 100 matched KRX stocks. The sample period spans November 1, 2019 to July 30, 2020. To avoid the effects of the onset of COVID-19 pandemic, in Panels A and B, the pre-event window includes November 2019 through January 2020, and the post-event window includes May through July 2020. Panel C examines alternative event windows. Panel A contains univarate results. Panels B and C report results from a DID regression of the following form:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 TWSE_i + \beta_3 Post_t \times TWSE_{it} + \delta_1 Volume_{it} + \delta_2 Volatility_{it} + \varepsilon_{it},$$

where *DepVar* are the autocorrelation and delay metrics for the 60-second intervals and the first principal components (PC1) of these metrics computed for 10-, 30-, 60-, and 300-second intervals, *Post* is an indicator variable that equals to 1 for the post-event period and zero otherwise; $TWSE$ is an indicator variable that equals to 1 for the TWSE stocks and 0 for the KRX stocks; *Volume* is daily trading volume in stock i on day t; and $Volatility$ is the difference between the highest and lowest midpoints scaled by the average midpoint. All continuous variables are winsorized at 1% and normalized, that is, from each stock-day observation we subtract the sample mean and divide this difference by the corresponding standard deviation. White-robust standard deviations are in parentheses. *** indicate statistical significance at the 1% level.

	Return autocorrelation				Price delay			
	60s		PC1		60s		PC1	
	[1]		[2]		[3]		[4]	
Panel A: Univariate results								
Pre	0.112		0.329		0.850		0.767	
Post	0.095	***	0.287	***	0.704	***	0.684	***
Panel B: Regression results								
Post	0.030		0.023	***	-0.329	***	-0.076	***
	(0.02)		(0.01)		(0.04)		(0.01)	
TWSE	0.044		-0.032	***	0.158	***	0.029	***
	(0.02)		(0.01)		(0.03)		(0.01)	
Post×TWSE	-0.181	***	-0.056	***	-0.215	***	-0.058	***
	(0.03)		(0.01)		(0.06)		(0.02)	
Volume	-0.036	***	0.002		0.074	***	0.020	***
	(0.01)		(0.00)		(0.01)		(0.00)	
Volatility	-0.083	***	-0.027	***	-0.112	***	-0.032	***
	(0.01)		(0.00)		(0.02)		(0.01)	
Intercept	0.011		0.351	***	0.287	***	0.806	***
	(0.02)		(0.00)		(0.04)		(0.01)	
Adj. R^2	0.014		0.038		0.069		0.086	
Obs.	24,144		23,353		23,149		23,950	
Panel C: Regression: alternative sample periods								
Post×TWSE: excluding March	-0.179	***	-0.050	***	-0.154	***	-0.031	
	(0.03)		(0.01)		(0.06)		(0.02)	
Post×TWSE: full sample	-0.184	***	-0.051	***	-0.051		-0.010	
	(0.03)		(0.01)		(0.06)		(0.02)	

Table 7
Volatility and Volume

The table examines changes in volume and volatility around the move to continuous trading. The treatment sample consists of 100 largest TWSE stocks, and the control group is 100 matched KRX stocks. The sample period spans November 1, 2019 to July 30, 2020. To avoid the effects of the onset of COVID-19 pandemic, in Panels A and B, the pre-event window includes November 2019 through January 2020, and the post-event window includes May through July 2020. Panel C examines alternative event windows. Panel A contains univariate results. Panels B and C report the results of a pooled DID regression of the following form:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 TWSE_i + \beta_3 Post_t \times TWSE_{it} + \delta_1 Volume_{it} + \delta_2 Volatility_{it} + \varepsilon_{it},$$

where *DepVar* is trading volume or volatility, *Post* is an indicator variable that equals to 1 for the post-event period and zero otherwise; $TWSE$ is an indicator variable that equals to 1 for the TWSE stocks and 0 for the KRX stocks; $Volume$ is daily trading volume in stock i on day t; and $Volatility$ the difference between the highest and lowest midpoints scaled by the average midpoint. All continuous variables are winsorized at 1% and normalized, that is, from each stock-day observation we subtract the sample mean and divide this difference by the corresponding standard deviation. White-robust standard errors are in parentheses. *** indicates statistical significance at the 1% level.

	Volatility				Volume			
	[1]		[2]		[3]		[4]	
Panel A: Univariate results								
Pre	1.43				9,551			
Post	1.96	***			11,795	***		
Panel B: Regression results								
Post	0.116	***	-0.125	***	0.433	***	0.331	
	(0.04)		(0.03)		(0.05)		(0.04)	
TWSE	-0.160	***	-0.113	***	-0.090		0.053	
	(0.03)		(0.02)		(0.06)		(0.04)	
Post×TWSE	0.290	***	0.175	***	0.210	***	-0.044	
	(0.05)		(0.04)		(0.07)		(0.06)	
Volume			0.557	***				
			(0.01)					
Volatility							0.879	
							(0.02)	
Intercept	-0.285	***	-0.052		-0.418	***	-0.167	
	(0.04)		(0.04)		(0.05)		(0.04)	
Adj. R^2	0.036		0.508		0.074		0.527	
Obs.	24,144		24,144		21,144		21,144	
Panel C: Regression: alternative sample periods								
Post×TWSE: excluding March	0.240	***	0.123	***	0.200	***	0.009	
	(0.05)		(0.04)		(0.07)		(0.05)	
Post×TWSE: full sample	0.170	***	0.118	***	0.080		-0.036	
	(0.06)		(0.04)		(0.07)		(0.05)	

Table 8
Robustness

The table contains regression results for price impacts, realized spreads, and price efficiency metrics estimated at various horizons. For price impacts and realized spreads, we use 10, 15, 60, and 300-second horizons. For the price efficiency metrics, we use 10, 30, and 300-second horizons. The treatment sample consists of 100 largest TWSE stocks, and the control group is 100 matched KRX stocks. The sample period spans November 1, 2019 to July 30, 2020. To avoid the effects of the onset of COVID-19 pandemic, the pre-event window includes November 2019 through January 2020, and the post-event window includes May through July 2020. The tables reports the coefficient estimates on the $Post_t \times TWSE_{it}$ variable from a DID regression of the following form:

$$DepVar_{it} = \alpha_i + \beta_1 Post_t + \beta_2 TWSE_i + \beta_3 Post_t \times TWSE_{it} + \delta_1 Volume_{it} + \delta_2 Volatility_{it} + \varepsilon_{it},$$

where *DepVar* are the price impact, realized spread, autocorrelation, and price delay metrics, *Post* is an indicator variable that equals to 1 for the post-event period and zero otherwise; $TWSE$ is an indicator variable that equals to 1 for the TWSE stocks and 0 for the KRX stocks; *Volume* is daily trading volume in stock i on day t; and $Volatility$ is the difference between the highest and lowest midpoints scaled by the average midpoint. All continuous variables are winsorized at 1% and normalized, that is, from each stock-day observation we subtract the sample mean and divide this difference by the corresponding standard deviation. White-robust standard deviations are in parentheses. *** indicate statistical significance at the 1% level.

Panel A: Spread components								
	10 seconds		15 seconds		60 seconds		300 seconds	
Price impact	0.420	***	0.304	***	0.269	***	0.313	***
	(0.04)		(0.03)		(0.03)		(0.04)	
Realized spread	0.535	***	0.572	***	0.447	***	0.272	***
	(0.04)		(0.04)		(0.03)		(0.04)	
Panel B: Price efficiency								
	10 seconds		30 seconds		300 seconds			
Autocorrelation	-0.093	***	-0.222	***	-0.095	***		
	(0.04)		(0.03)		(0.04)			
Price delay	-0.161	***	-0.217	***	-0.242	***		
	(0.05)		(0.08)		(0.08)			

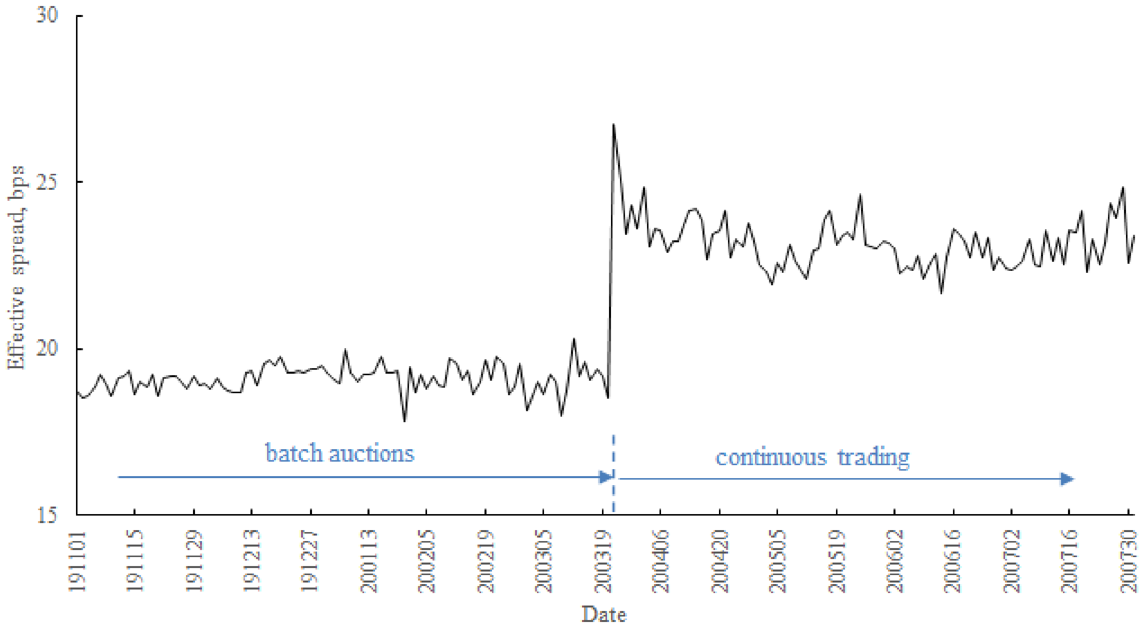

Figure 1

Trading costs around the switch to continuous trading

The figure plots the effective spreads, our proxy for trading costs, from November 2019 through July 2020. The sample consists of 100 largest TWSE stocks. Effective spread is the signed difference between the trade price and the corresponding quote midpoint, scaled by the midpoint. We use the Lee and Ready (1991) algorithm to sign trades. In Section 2, we discuss assumptions required to compute effective spreads in the auction environment. For aggregation, effective spreads are first volume-weighted within each stock-day and then averaged across stocks for each day.