Closing Time: Effects of the closing mechanism and design on market quality*

Nicholas Cordi
University of Sydney

Ester Félez-Viñas
University of Technology, Sydney

Sean Foley†
University of Sydney

Tālis Putniņš
University of Technology, Sydney

First version: August 2015

Abstract

We study the effects that closing batch facilities have on liquidity, price efficiency, and market integrity by exploiting the change in closing mechanism of 43 exchanges around the world. The main analysis supports the idea that the use of batch facilities improves market quality. However, we find evidence of the importance of auction design in explaining the performance of the auction. Closing auctions tend to be more beneficial if they integrate a randomised closing time and price stabilisation systems. Transparency and flexibility are generally detrimental. The results also show that the level of development of the market and the liquidity of the stock are relevant in determining the effects of batch facilities. Our findings have implications for regulators and exchanges seeking to improve the efficiency and integrity of their capital markets.

*The authors acknowledge the generous funding assistance of the Centre for International Financial Regulation. We are thankful for thoughtful comments from participants at the 12th Central Bank Workshop on the Microstructure of Financial Markets and the 26^{th} Finance Forum, and to Michael Aitken, Angelo Aspris, Michael Goldstein, Carole Gresse, Frank Hatheway, Björn Hagströmer, Amy Kwan, Lars Nordén, Richard Phillip, Reuben Segara, Avanidhar Subrahmanyam, Gunther Wuyts, and Caihong Xu. This study was awarded with the Best Paper on Stock Markets award at the 26^{th} Finance Forum in Santander, Spain, 2018.

†Corresponding author: sean.foley@sydney.edu.au

1 Introduction

Closing prices are widely used in financial markets. They are often adopted as the reference price for the settlement of derivatives contracts, for the performance evaluation of brokers and mutual funds, to determine the inclusion of a stock in an index, and to compute portfolio returns. The importance and widespread use of closing prices requires guaranteeing that they reflect the stock's fundamental value. Closing prices have traditionally been tied either to the price of the last trade during the continuous trading session or to the volume-weighted average price (VWAP) of the last trades prior to the close. However, concerns about the ability of *last-trade mechanisms* to generate closing prices that are efficient and resilient to manipulation attempts have led many exchanges to replace them in favour of *batch mechanisms*.[1]

In a batch facility, liquidity is aggregated during a non-trade batching phase in which market participants indicate their trading interests. Orders are then simultaneously executed at the same point in time, the uncross, at a single closing price. There are two main types of closing batch mechanisms: the *call auction* and the *on-close facility*. In the call auction, liquidity is consolidated after the end of the continuous trading session and all marketable orders are accepted. In contrast, the on-close facility runs parallel with continuous trading and, in case of large order imbalances during the pre-close period, it only accepts orders from one side of the book to offset the imbalances. Batch facilities further differ in their design. We identify four distinct design features that are common in batch mechanisms: *flexibility* to modify, submit, or cancel orders during the batching period, *randomisation* of the uncross time, *price stabilisation systems* to curb volatility, and *transparency* of the order book during the batching phase.

We analyse the effects that different closing mechanisms have on market liquidity, the efficiency of closing prices, and market integrity.[2] In particular, we determine

[1]For instance, Pagano and Schwartz (2003) note that the Paris Bourse changed its closing mechanism due to traders' demands to improve price discovery at the close. Pagano et al. (2013) indicate that the change in Nasdaq's closing mechanism resulted from both regulators' requests for more reliable prices and changes in the closing mechanisms at competing venues.

[2]Following the discussion of Austin (2017), we consider that a market has high integrity when

the extent to which batch mechanisms enhance market quality relative to last-trade mechanisms and, given that a batch facility is in use, whether certain design features improve its performance. Additionally, we investigate whether market development and stock liquidity influence the efficacy of batch facilities. To conduct the study, we exploit the change in the closing mechanism of 43 exchanges worldwide from 1999 to 2013. Given that the introduction of a new closing facility represents an exogenous shock for market participants, we are able to attribute the variation in market quality to the change in the closing mechanism.

We find that batch facilities generally improve market quality relative to last-trade mechanisms. Both call auctions and on-close facilities are associated with enhanced liquidity. These results are consistent with the conjecture of Economides and Schwartz (1995) that the aggregation of orders mitigates imbalances and reduces price impacts, and Foucault et al. (2005) and Roşu (2009), who predict that giving liquidity demanders an additional opportunity to trade reduces their aggressiveness. The consolidation of orders should also translate into enhanced price efficiency given that the beliefs of various traders about the stock's fundamental value are brought together. In this vein, our results indicate that both call auctions and on-close facilities are mostly associated with significant improvements, although the latter lead to increased intraday volatility, which could be due to on-close facilities running parallel to the continuous trading session and to the greater participation.

Our results also indicate that batch mechanisms, and especially call auctions, reduce the variability of price distortions around the close and increase synchronicity with the market, which relates positively to market integrity. On the other hand, increases in the probability of manipulation are observed for both mechanisms. Despite the unexpectedness of this result, deeper analyses indicate that the possibility of closing price manipulation is highly dependent on aspects such as the specific design of the batch mechanism, the level of development of the market, or the liquidity of the stock.

its levels of manipulation are low.

In our evaluation of the importance of auction design, our results suggest that randomised closing times provide significant improvements to market quality and integrity. This finding is consistent with the introduction of uncertainty regarding the closing time, which undermines traders' ability to manipulate the close, enhancing price efficiency, encouraging participation, and reducing volatility. Flexibility to enter and cancel orders reduces liquidity and price efficiency but somewhat increases synchronicity with the market. The ability to modify orders allows traders to react to the arrival of new information, which potentially explains the improvement in synchronicity. However, flexibility also facilities gaming behaviour, which deters participation, thus harming liquidity and increasing pricing errors. Transparency of the indicative closing price is largely detrimental to market quality, despite it reducing the probability of manipulation. A transparent auction exposes manipulative orders to market participants, providing them with an opportunity to act against manipulative behaviour, which positively relates to market integrity. However, as noted by Biais et al. (1999), transparency can discourage participation from traders who do not want to reveal their information to other market participants. This decrease in participation harms liquidity and price efficiency. Finally, the use of stabilisation systems improves market integrity, although they do not have much of an impact on closing price efficiency. The lack of effect of stabilisation systems may be explained by their infrequent usage.

Our results also show that the introduction of batch mechanisms largely improves market quality for developed markets, especially for liquid stocks. Both call auctions and on-close facilities enhance liquidity, regardless of the stock's liquidity level. The increased liquidity boosts price efficiency but it also leads to greater intraday volatility for illiquid stocks. While illiquid stocks do not experience much of a change in terms of market integrity, we document a significant improvement for liquid securities. The introduction of batch mechanisms tends to harm market quality for emerging markets. Consistent with the findings of Schwartz (2000) and Ellul et al. (2005), these results suggest an inability of batch mechanisms in emerging markets to attract sufficient order flow to function well. Enhanced regulation and an appropriate auction design are needed in these markets to attract sufficient order flow and fight price manipulation.

When examining the role of auction design for our subsamples, we identify a few key differences from the main analysis. Emerging markets experience a reduction in the probability of manipulation when a transparent auction is in place. They also especially benefit from randomised closing times, which generally improve market quality regardless of stock liquidity. These results are in line with our belief that less developed markets benefit from actions that directly expose manipulative behaviour or hinder gaming the auction. When it comes to developed markets, flexibility appears to be mostly beneficial for liquidity and market integrity. This finding supports the idea that developed markets, where securities regulation is highly enforced and stocks are well monitored by market participants, benefit from giving traders the ability to modify their orders to incorporate new information. Finally, the use of stabilisation mechanisms especially improves closing price efficiency and market integrity for emerging markets.

This paper makes three major contributions to the empirical literature on closing mechanisms. First, a considerable number of studies show that the use of batch mechanisms strengthens the price discovery process (Pagano and Schwartz, 2003, 2005; Barclay et al., 2008) and facilitates the absorption of order imbalances and price impacts at the end of the trading day (Aitken et al., 2005; Kandel et al., 2012; Pagano et al., 2013). Existing research examines the impact of introducing a batch mechanism in a particular exchange and mostly focuses on developed markets and liquid stocks. Instead, we examine the change of the closing mechanism in a comprehensive sample of 43 exchanges around the world for stocks with different levels of liquidity. This setup not only allows us to draw conclusions about the general effects that different closing mechanisms have on market quality but also enables us to extract specific lessons for developed and emerging markets and about liquid and illiquid stocks.

Second, we contribute to the literature by examining how batch mechanisms can help to improve market integrity. The widespread use of closing prices for benchmarking, contracting, and trading purposes gives market participants incentives to manipulate them. Previous literature has indirectly linked the improvements in volatility and price discovery documented after the introduction of batch mechanisms to a reduction in market manipulation (Pagano and Schwartz, 2003; Hillion and Suominen, 2004; Chang et al., 2008). The study of Comerton-Forde and Putniņš (2011a) is one of the few examining the effects of prosecuted manipulation cases on market quality. The authors construct an index that can be used to estimate the probability of closing price manipulation. Our paper is the first to empirically use this measure of closing price manipulation to analyse the effect of different closing mechanisms on market integrity.

Finally, our study relates to the limited literature emphasising the importance of auction design. Previous studies tend to focus on a single design feature (Biais et al., 1999; Domowitz and Madhavan, 2001; Hauser et al., 2012; Félez-Viñas and Hagströmer, 2017). We contribute to the literature by analysing the relative effect that the most common auction design features (i.e., flexibility, randomisation, stabilisation systems, and transparency) have on liquidity, closing price efficiency, and market integrity.

Overall, our empirical evidence indicates that, for the broad market, a call auction that integrates a randomised closing time and a price stabilisation system brings about the greatest improvement in market quality. Transparency is largely detrimental, whereas flexibility only benefits stocks in developed markets. The findings are robust to alternative specifications and have implications for both regulators and exchanges seeking to improve the efficiency and integrity of their capital markets.

2 Literature and hypotheses

Historically, the closing price of a stock was pegged to its last traded price in the continuous trading session. Alternatively, some exchanges used the VWAP of all trades in the last minutes of continuous trading prior to the close. As noted by Cushing and Madhavan (2000), the extensive use of closing prices as benchmarks has increased volume traded at the close, increasing transitory order imbalances in the last minutes of the trading day. Cushing and Madhavan (2000) and Barclay et al. (2008) argue that last-trade mechanisms of price determination have a weak ability to absorb order imbalances. Consequently, in the presence of transitory order imbalances, they are likely to produce biased closing prices and hinder price discovery. Similarly, Easley and O'Hara (1992) present a theoretical model that predicts a negative relation between volume shocks and market liquidity. If their model holds, last-trade mechanisms are vulnerable to large end-of-day trading shocks. These theoretical predictions are empirically confirmed by Lee et al. (1993). For a sample of New York Stock Exchange (NYSE) stocks, the authors document a U-shaped pattern for quoted spreads, effective spreads, and trading volume, demonstrating that liquidity deteriorates at the end of the trading day in response to increasing volumes.

Intending to produce more efficient closing prices, many exchanges have progressively replaced their last-trade mechanisms with batch facilities. In a batch facility, traders indicate their trading interest during a non-trade batching period. Orders are then simultaneously executed at the same time and at a single equilibrium price. Schwartz (1995) argues that the intrinsic characteristics of batch mechanisms facilitate price discovery, since the consolidation of liquidity results in an execution price that more closely reflects the stock's fundamental value. This claim is consistent with the theoretical predictions of Madhavan (1992), who models the process of price discovery under two different market structures, a continuous market and a periodic auction, and shows that the batch mechanism produces more efficient prices. Pagano and Schwartz (2003) empirically confirm these predictions, showing that the introduction of a closing call auction at the Paris Bourse has led to more efficient closing prices. Pagano and Schwartz (2005), Smith (2005), and Barclay et al. (2008) also find that closing prices have become more efficient since the introduction of an on-close facility at Nasdaq.

Pagano et al. (2013) argue that transitory price changes occur due to trading frictions that are dependent on microstructure features, such as transaction costs (i.e. bid-ask spreads and commission fees), tick sizes, price impacts, and order execution based on the arrival sequence. According to Economides and Schwartz (1995), a closing batch mechanism mitigates such trading frictions, with the aggregation of liquidity facilitating the absorption of order imbalances and price impacts generated by the submission of large orders. The absence of bid-ask spreads and the clearing at a single price further reduces transaction costs. Therefore, transitory volatility is reduced and liquidity improves.

Liquidity demanders trade more aggressively at the end of the day because it is their last trading opportunity before market closure. Under a last-trade mechanism, aggressive trading and the sequence of order arrival are likely to produce transitory price changes. In contrast, the theoretical models of Foucault et al. (2005) and Roşu (2009) predict that, by giving traders an additional opportunity to trade, closing batch mechanisms make liquidity demanders less aggressive, which reduces volatility and spreads. A number of empirical studies have analysed the impact of introducing closing batch mechanisms on volatility and liquidity. Pagano et al. (2013) report a significant decline in spreads and volatility since the implementation of the on-close facility at Nasdaq in 2004. Kandel et al. (2012), who study the introduction of a closing call auction at Borsa Italiana and Paris Bourse, also document a reduction in spreads and volatility at the close. However, in contrast with Pagano et al. (2013), they find a redistribution of order flow from the continuous trading session to the call. Such redistribution is also documented by Aitken et al. (2005), who examine the impact of the introduction of a closing call auction at the Australian Stock Exchange.

Based on the discussion above, we formulate our first hypothesis as follows.

Hypothesis 1 *The introduction of a closing batch mechanism improves market liquidity and closing price efficiency.*

The widespread use of closing prices creates incentives for some market participants to manipulate them. Felixson and Pelli (1999) and Hillion and Suominen (2004) show that brokers may attempt to manipulate closing prices to alter the perception that their customers have on their execution quality and increase the prospect of future commissions. Similarly, the remuneration of fund managers usually depends on the performance of their mutual fund, which is evaluated using closing prices. Indeed, Carhart et al. (2002) find evidence consistent with fund managers executing trades in the final minutes before the close to inflate their portfolio's net asset value. Kumar and Seppi (1992) and Ni et al. (2005) show that traders also have incentives to manipulate closing prices in order to profit from open derivatives positions, and Comerton-Forde and Putniņš (2011a) note that traders can also try to manipulate closing prices on index rebalancing days to gain index inclusion. Consistent with this notion, Onayev and Zdorovtsov (2008) document abnormal returns around the rebalancing of the Russell 3000 Index.

Barclay et al. (2008) and Comerton-Forde and Putniņš (2011b) argue that closing price manipulation not only increases trading costs due to trading at an inefficient price, but also undermines investor confidence in the quality of financial markets. Persistent manipulation can discourage market participants from trading in markets susceptible of being manipulated, resulting in insufficient order flow and thus further inhibiting the efficiency of the price discovery process and reducing market liquidity. Studies on known manipulation cases are scarce. Despite this limitation, such studies provide a valuable understanding of the impact of closing price manipulation on market quality. The work of Comerton-Forde and Putniņš (2011a), who examine 184 prosecuted cases of closing price manipulation in the United States and Canada, provides the richest insight on the effects of such manipulation. In the presence of manipulation, the authors document significant increases in end-of-day returns followed by next-day reversals, wider spreads, and greater trading volumes. Similarly, Aggarwal and Wu (2006) analyse 51 litigation cases of market manipulation in the United States and find that instances of manipulation are associated with inflated prices, reversals, and increased volatility.

Given the key role of closing prices, it is important to guarantee that the mechanism used to determine them is resilient to manipulation attempts. In contrast to last-trade mechanisms, batch facilities consolidate liquidity at a single point in time. This feature reduces the possibility of manipulation, since market participants attempting to manipulate closing prices would need to submit larger orders. Besides reducing the influence of manipulative orders, the consolidation of liquidity also reduces the profitability of manipulative strategies by increasing the execution costs and risk for traders trying to game the auction. A number of empirical studies have analysed the impact of introducing batch mechanisms on market quality and have indirectly linked it to the issue of price manipulation. Hillion and Suominen (2004) examine the introduction of a closing call auction at the Paris Bourse and find a decrease in transitory volatility, which they attribute to reduced levels of closing price manipulation. Thomas (1998) and Pagano and Schwartz (2003), who study that same event, also document a reduction in abnormal price volatility and improved price discovery following the introduction of the closing batch mechanism. For the liquid stocks of their sample, Chang et al. (2008) find a decline on the size of price reversals following the introduction of a closing call auction at the Singapore Exchange, which they also attribute to lower magnitudes of price manipulation.

The discussion above leads to our second hypothesis.

Hypothesis 2 *The introduction of a closing batch mechanism enhances market integrity.*

Most of the literature on closing batch mechanisms examines the impact on market quality of ending the trading day with a call auction in contrast to a last-trade mechanism. Studies on the role that auction design plays in the different facets of market quality are limited and tend to focus on a single design feature. The design of the batch mechanism varies considerably across different markets and is likely to contribute to the somewhat mixed empirical evidence regarding the effects of introducing batch mechanisms to end the trading day. Four categories of design features are common in batch mechanisms, either separately or in combination: flexibility to modify orders within the non-trade batching period, randomisation of the uncross time, the use of price stabilisation systems, and transparency of order flow and imbalance information throughout the batching phase.

Within the context of a closing batch mechanism, flexibility refers to the capacity of market participants to freely submit, cancel, or revise their orders. While the effects of flexibility on market quality have not been empirically documented, Biais et al. (1999) and Domowitz and Madhavan (2001) argue that flexibility is likely to prompt gaming behaviour. Such manipulative strategies not only can impair price efficiency and increase volatility but also can deter auction participation, harming market liquidity. On the other hand, Aitken et al. (2005) find that the ability to modify or cancel orders potentially enhances price efficiency, since traders are given the opportunity to react to the arrival of new information. Moreover, if market participants are able to infer gaming behaviour, flexibility can reduce market manipulation and transitory volatility.

Randomisation of the closing time is used with the aim of deterring gaming behaviour during the pre-close. While it is a very common design feature, very few studies have analysed its impact on market quality. Malaga et al. (2010) examine the effects of randomisation in the context of online auction markets. They show that introducing uncertainty regarding the closing time increases execution risk for traders attempting to distort the closing price by entering unrepresentative orders immediately before the close. Since a randomised closing time undermines the ability to mark the close - and thus the profitability of manipulative strategies - it is likely to deter manipulative behaviour overall. This should translate not only into lower levels of manipulation, but also into enhanced price discovery and lower volatility. Consistently, Hauser et al. (2012) find that the introduction of randomisation at the Tel Aviv Stock Exchange has improved price discovery. Medrano and Vives (2001) also argue that the randomisation of the uncross encourages traders to expose their interests early on and reduces the potential for gamed auctions.

Many markets have implemented price stabilisation systems within their batch mechanisms with the aim of minimising large transitory volatility at the close. There are two main types of price stabilisation systems: volatility extensions, which extend the duration of the batching period if the closing price would otherwise fall outside a certain threshold, and price collars, which restrict the closing price to fall within pre-specified thresholds. Félez-Viñas and Hagströmer (2017) empirically study the introduction of a volatility extension in the closing call auction of Nasdaq OMX

Stockholm. They find that the volatility extension reduces certain actions commonly associated with manipulative behaviour, increases the participation of traders in the auction mechanism, and reduces transitory volatility. These findings are in line with the claim of Comerton-Forde and Rydge (2006) that volatility extensions are likely to combat manipulation by giving market participants the opportunity to react to manipulative orders. When it comes to price collars, Schwartz et al. (2007) note that the price restrictions inherent in price collars potentially prevent market participants from trading at an efficient closing price in cases of large fundamental volatility. In such a scenario, price collars undermine the price discovery process within the closing call auction and delay it until the next morning. Therefore, the effects of price stabilisation mechanisms on market quality are likely to depend on the type of stabilisation system and on whether the source of volatility is transitory or fundamental.

Transparency involves the continuous dissemination of order flow and imbalance information throughout the pre-close period.[3] Biais et al. (1999) and Domowitz and Madhavan (2001) argue that transparency could discourage traders from participating in the call auction for fear of revealing their information to other market participants. This lack of participation is likely to impair liquidity and price discovery. However, Domowitz and Madhavan (2001) also point out that the lack of transparency can facilitate the gaming of the auction. A transparent auction reveals the presence of potentially manipulative orders to other market participants, which enhances trader trust in the batch mechanism and potentially attracts liquidity and increases price efficiency.

The scarcity of the literature examining the effects of the different design features on market quality and its mixed conclusions prevent us from developing a clear hypothesis. Hence, the impact that the different auction features have on market quality remains an empirical question.

[3] In our study, a batch facility is classified as transparent if within the batching phase it discloses: i) price and volume information of the buy and sell-side of the limit order book, and ii) indicative closing prices and imbalances.

Most exchanges in both developed and emerging markets have introduced batch mechanisms at market close. Although most studies conclude that batch mechanisms improve market quality, a noticeable limitation is that most of them focus on the effects of introducing batch mechanisms in developed markets. As noted by Camilleri and Green (2009), this limitation is important for several reasons: First, because stocks in emerging markets are commonly less liquid and less actively traded than those in developed countries; second, because batch mechanisms across markets differ in terms of design and studies on emerging markets have not been undertaken; and third, because the trading protocols, market microstructure, and level of development and integrity vary considerably across markets. Given the notable disparities between developed and emerging markets, the conclusions reached in previous literature for developed markets do not necessarily apply to emerging markets.

For illiquid stocks, a trader aiming to manipulate closing prices could find it easier to do so in a batch facility. As noted by Camilleri and Green (2009), less liquid stocks are more sensitive than liquid ones to order imbalances, which facilitates mispricing and gaming behaviour. Schwartz (2000) also claims that batch mechanisms need to attract sufficient order flow in order to function well and, as pointed out by Ellul et al. (2005), this could be an issue for emerging markets if a majority of their stocks are illiquid or inactive. On the other hand, if a certain threshold of order flow is reached, Madhavan (1992) argues that it is precisely the less liquid stocks that benefit the most from a batch facility. This is because the consolidation of orders allows for greater accuracy in the price discovery process, hindering manipulation.

The structural differences between developed and emerging markets could be one of the reasons behind the mixed empirical evidence regarding the effects of batch mechanisms on market quality. Pagano and Schwartz (2003) and Hillion and Suominen (2004) find that the introduction of a closing call auction at the Paris Bourse improves price discovery and reduces volatility. Similar conclusions are reached by Pagano and Schwartz (2005) and Smith (2005) when examining the effects of the introduction of an on-close facility in Nasdaq. However, when turning to the few studies conducted in emerging markets the conclusions change notably. Camilleri and Green (2009) study the impact of the suspension of a closing call auction at the National Stock Exchange of India and find that the suspension improved volatility, price discovery, and liquidity. Suen and Wan (2013) similarly study the suspension of a call auction at the Hong Kong Stock Exchange and conclude that closing prices are more vulnerable to manipulation in the presence of a call auction. For the Thailand Stock Exchange, Shastri et al. (1995) show that prices in the opening call auction are more volatile than during the rest of the day. However, the conclusions from the studies on these emerging markets should be considered with caution. The suspension of call auctions could point to structural problems unrelated to the degree of market development, resulting in nonrepresentative findings.

The scarcity of the literature on emerging markets prevents us from developing a clear hypothesis. The impact that the introduction of batch mechanisms with different design features has on market quality for developed and emerging markets and liquid and illiquid stocks is an empirical question.

3 Empirical setting

3.1 Data and sample

We contacted all 115 exchanges in the World Federation of Exchanges handbook, asking what closing mechanism was currently in use. If a last-trade mechanism was not in place, we also asked for information on when the new mechanism had been introduced and its features.[4] Of the 115 exchanges, we received responses from 86, of which 27 still used the last traded price, 22 had introduced VWAP mechanisms, and 37 had introduced batch mechanisms. We were able to gather usable data from 43 of these exchanges, of which 36 had moved from a last-trade to a batch mechanism.[5]

[4]We initially contacted exchange staff in English. When this was unsuccessful, we tried again in their local language. When neither approach yielded a response, we contacted the local regulatory authority.

[5]To be included, exchanges needed to specify the date of introduction, include sufficient detail around their auction mechanism, and have available tick history data.

For the 43 exchanges in which a change in the closing mechanism is examined, we obtain intraday data on trades and quotes from the Thomson Reuters Tick History (TRTH) database. The quotes dataset contains information on best quotes and associated order volumes, whereas the trades dataset includes the prices and volumes of executed trades. All data are timestamped to the nearest millisecond.

We use a sample period of 500 trading days surrounding the date of the change in the closing mechanism in each of the 43 exchanges. The use of a sample period of 250 days before and after the event is consistent with the work of Pagano and Schwartz (2003) and Comerton-Forde and Rydge (2006) and is adopted for the computation of all liquidity, price efficiency, and integrity measures. A window of 500 trading days allows us to determine the longer-term impact of a change in the closing mechanism, providing sufficient time for market participants to adjust their trading behaviour to the new closing mechanism.

We restrict the sample to include only those stocks listed throughout the whole sample period and that trade a minimum of 80 days in both the pre- and post-event periods. For exchanges that introduced a new closing mechanism only for stocks belonging to an index, we include only those stocks that remained in the index during the entire sample period. We also remove stock-days with no bid or ask quotes at open. Removing these observations avoids inaccurate calculations of price reversals and, therefore, of the closing price manipulation index.

3.2 Sample characteristics

Tables 1 and 2 present an overview of the markets that are part of our sample. We consider a total of 11,912 stocks traded in 43 exchanges from 41 different countries. The different countries are classified as developed (Table 1) or emerging (Table 2) according to the World Bank classification in the year of the country's event, which is based on the country's gross national income per capita.[6] Accordingly, we classify 25 exchanges as developed and 18 as emerging.

[6]World Bank country classifications based on the gross national income per capita are available at `http://databank.worldbank.org/data/download/site-content/OGHIST.xls`.

[Insert Table 1 Here]

[Insert Table 2 Here]

The tables also provide information related to the level of activity of each market. The variable *Stock-Day Count* reports the number of stock-day observations, *Daily Turnover* is the daily average dollar turnover, *Intraday Volatility* represents the average high-low price variation, and *Inactivity* is the average fraction of days with no trades in a particular exchange. Emerging markets tend to be more inactive than developed markets and are thus characterised by a lower stock-day count and daily turnover and a greater intraday volatility. For instance, the Toronto Stock Exchange (TSX), which belongs to a developed market, has a stock-day count of 196,141 for the 159 stocks that experienced a closing mechanism change, an average daily turnover of 15.07, an intraday volatility of 2.90% and an inactivity fraction of 2.05%. In contrast, the Philippines Stock Exchange, which is classified as an emerging market, has a lower stock-day count (168,605) for a similar number of stocks experiencing a change (163). Similarly, its daily turnover is lower (12.68%) and its intraday volatility and inactivity fraction higher (3.75% and 24.18%, respectively).

Table 3 for developed markets and Table 4 for emerging, present details about the change in the closing mechanism together with the design features that were implemented when a batch mechanism was adopted.

[Insert Table 3 Here]

[Insert Table 4 Here]

There are two main categories of closing mechanisms: i) last-trade facilities, which determine closing prices based on the price of the last trade in the continuous trading session (*Last Trade*) or according to a VWAP over the last trades (or minutes) prior to market closure (*VWAP*), and ii) batch facilities, where orders are consolidated during a batching period that starts at the end of the continuous trading session (*Call Auction*), or that runs parallel with continuous trading (*On-close*). The consolidation of orders in a closing call auction occurs after continuous trading ends, resulting in a discontinuity between continuous trading and the close. In contrast, in an on-close facility participation commences immediately after the market opens through market-on-close or limit-on-close orders, which may be entered until a pre-specified time before the close.[7] From that time on, only offsetting orders can be placed to counteract any buy or sell imbalances.

All developed exchanges introduced batch mechanisms, with all on-close facilities belonging to developed markets. Emerging markets changed from a last-trade mechanism to a call auction or a VWAP. It is worth noting that the introduction of the on-close facilities at Nasdaq, the TSX, and the TSX-V was staggered across stocks.[8,9] Exchanges that introduced batch mechanisms chose between four different design features: i) *flexibility* to cancel or modify orders during the batching period, ii) *randomisation* of the time of the uncross, iii) price *stabilisation systems* to curb extraordinary volatility,[10] and iv) *transparency* of the batching phase. The use of a specific design feature is represented by a dummy variable that takes the value of one if such a design feature was implemented and zero otherwise. About 28% of the exchanges that introduced batch mechanisms opted for both, flexibility and price stabilisation systems. About 22% of the remaining exchanges implemented all four design features and another 22% used all but the stabilisation systems. The remaining 28% used less popular combinations or a single feature.

[7] On-close orders are accepted until 15:40 at the TSX and NYSE, and until 15:50 at Nasdaq, at which point imbalance information is disseminated.

[8] Nasdaq staggered the introduction of its on-close facility over a number of months on an as-needed basis (Schwartz et al., 2007). Since the precise date of implementation cannot be individually ascertained for each stock, the post-event period commences in December 2004, once the on-close facility had been fully implemented across all stocks.

[9] The on-close facility at the TSX was first introduced for constituents of the TSX 60 across four dates between March and April 2004. Constituents of the TSX Composite Index were subsequently made eligible for the on-close facility in September 2005, with mid- and small-cap stocks introduced separately across two dates. Further, the TSX-V introduced the on-close facility for the 30 largest stocks in December 2011 and then for the TSX-V Select Index in January 2012.

[10] There are two types of price stabilisation systems: volatility extensions and price collars. Volatility extensions prolong the batching period if the closing price would otherwise fall outside pre-defined volatility bands. Price collars restrict the closing price to fall within certain limits. The two types of price stabilisation systems are likely to have different effects on market quality. However, data limitations do not enable us to distinguish between the two types in this study.

4 Methodology

Exploiting the introduction of different market closing facilities, we conduct a comparative analysis of the closing mechanisms used in 43 exchanges worldwide. For each stock, a number of market quality measures are estimated for both the period before and after the event date. A change in the closing mechanism is considered effective if the majority of measures indicate so. Market quality improvements include greater liquidity, enhanced price efficiency, and lower intraday volatility. Reduced instances of closing price manipulation, reduced reversals, and greater synchronicity with the market indicate improvements to market integrity. First, we analyse whether moving from a last-trade mechanism to a batch mechanism improves liquidity, price efficiency, and market integrity. Second, conditional on the exchange introducing a batch mechanism in the post-event period, we examine the role that different design features play on market quality. To avoid overweighting exchanges with more securities, each market is given an equal weighting in the regression.[11]

4.1 Regression analysis

We conduct our comparative analysis of closing mechanisms in two stages. First, to investigate the effectiveness of the closing batch mechanisms (i.e. call auction and on-close facility) relative to a last-trade mechanism on a variable Y (where Y is a market quality measure as defined in section 4.2), we set up the following regression model

$$Y_{j,t} = \alpha + \beta_1 CALL_{j,t} + \beta_2 ONCLOSE_{j,t} + \sum_{i=1}^{5} \theta_i Control_{j,t,i} + \varepsilon_{j,t}, \tag{1}$$

where j is an index for stocks and t is a time index. The time index only applies to the regressions where Y is a stock-day measure, in which case the time index is days. When Y is instead a stock-only measure, the time index is waived from

[11] For stock-day regressions, the weight factor for each market is determined to be one divided by the number of stock-day observations. For stock-only regressions, the weight factor is calculated as the inverse of the number of stocks.

Equation 1. $CALL_{j,t}$ is a dummy variable that equals one if the security is listed on a market that runs a closing call auction and zero otherwise, and $ONCLOSE_{j,t}$ is a dummy variable that equals one if the exchange operates an on-close facility and zero otherwise. The base case (α) is a market with a last-trade mechanism in place. $Control_{j,t,i}$ is a set of i control variables, including: *Volume* (the natural logarithm of the daily traded dollar volume); *Volatility* (the difference between the daily high and low prices weighted by the high-low midpoint); *Inactivity* (the ratio of days with no trades per stock relative to the maximum number of trading days); $Time$ and $Time^2$ (event time controls to account for linear and nonlinear trends, respectively, in the dependent variable across the sample period).[12] To avoid endogeneity issues, the control variables *Volume*, *Volatility*, and *Inactivity* are calculated as a single average estimated during the pre-event period.

Next, we examine the relative contribution to market quality of four different design features common in call auctions.[13] Conditional on the market having a call auction mechanism in place during the post-event period, we set up the following regression model

$$\begin{aligned} Y_{j,t} = \alpha &+ \beta_1 FLEX_{j,t} + \beta_2 RAND_{j,t} + \beta_3 STAB_{j,t} + \beta_4 TRANS_{j,t} \\ &+ \sum_{i=1}^{5} \theta_i Control_{j,t,i} + \varepsilon_{j,t}, \end{aligned} \tag{2}$$

where, as in Equation 1, the time index t only applies to regressions where the dependent variable is a stock-day measure. $FLEX_{j,t}$ is a dummy variable that equals one if traders have the flexibility to modify or cancel their orders during the batching period; $RAND_{j,t}$ is a dummy variable set to one if the uncross time is randomised; $STAB_{j,t}$ is a dummy variable equal to one if the closing mechanism includes a price stabilisation system; and $TRANS_{j,t}$ is a dummy variable that equals one if the market's closing mechanism is transparent. Each dummy is set to zero in

[12]The time trend controls are only included in the regressions where Y is a stock-day measure.

[13]We exclude on-close facilities from this analysis because only two markets (the United States and Canada), which are, in turn, developed and very liquid, have them in place and because their structure differs significantly from that of the call auction.

the absence of the feature. The base case (α) represents a call auction absent of all features. Accordingly, the dummy variables capture the differences in the liquidity, price efficiency, and market integrity measures due to the inclusion of certain design features within the call auction. To overcome differences across time and markets, we use the same control variables as in Equation 1.

4.2 Measures of market quality

To evaluate our hypotheses that the use of closing batch mechanisms improves market quality, we consider three measures of liquidity, three measures of price efficiency, and four measures of market integrity.

4.2.1 Liquidity measures

Our first measure of liquidity, *Closing Spread*, is calculated for each stock j and day t following Comerton-Forde and Putniņš (2011a). We define *Closing Spread* (measured in basis points, or bps) as

$$Closing\ Spread_{j,t} = \frac{Spread_{j,t,close}}{Midpoint_{j,t,x}}, \tag{3}$$

where $Spread_{j,t,close}$ is the difference between the best ask and bid prices at the closing of the continuous trading session and $Midpoint_{j,t,x}$ is the bid-ask midpoint x minutes before the close of the limit order book. Kandel et al. (2012) find that the effects of the call auction on liquidity are concentrated in the final 10 minutes of the continuous trading session. Comerton-Forde and Putniņš (2011a) also note that manipulators are more likely to act in the final minutes of trading to decrease the costs of sustaining the liquidity imbalance generated when distorting prices. Therefore, we set x to take the minimum of 5, 10, 15, 20, 30, 60 or 90 minutes before the close of continuous trading, such that there is at least one trade during x. For stocks with no trades in the 90 minutes prior to the close, the closing spread is calculated as

$$Closing\ Spread_{j,t} = \frac{Spread_{j,t,close}}{Midpoint_{j,t,y}}, \tag{4}$$

where $Midpoint_{j,t,y}$ is the bid-ask midpoint immediately before the yth last trade. Following Comerton-Forde and Putniņš (2011a), the value of y is taken from the latest transaction set {1, 2, 3, 4} that maximises the return from the midpoint to the close.

Aitken et al. (2005) document a significant relation between the last two hours of trading and participation in the closing batch mechanism. Specifically, they find that traders are willing to delay trading for up to two hours to benefit from the enhanced efficiency achieved when trading in the batching facility. Accordingly, our second liquidity measure, the time-weighted closing spread *(TWCS)*, is computed for each stock and day as the average of the relative quoted spreads calculated at 15-minute intervals in the last two hours of the continuous trading session.[14]

If a change in the closing mechanism improves liquidity at or around the close, *Closing Spread* and *TWCS* should decrease in the post-event period, leading to lower trading costs. However, end-of-day spreads could increase if investors delay their trades to participate in the batching facility. In this case, as argued by Aitken et al. (2005), the closing batch mechanism could induce a negative externality, since the decrease in participation at the end of the continuous trading session could lead to increased trading costs.

To further explore the impact of a change in the closing mechanism on the liquidity of the continuous trading session, we define our last stock-day liquidity measure (computed in natural logarithmic scale) as

$$Value_{j,t} = \frac{V_{j,t}}{\overline{V}_j}, \tag{5}$$

where $V_{j,t}$ is the daily dollar turnover during continuous trading for security j on day t and $\overline{V}_j$ is the average total dollar turnover for security j over the 500 trading days of the sample period. $\overline{V}_j$ includes both the volume traded during the continuous trading session and in the call auction. If a closing call auction does not create new liquidity

[14] The relative spread is estimated as the difference between the best ask and bid prices divided by the prevailing bid-ask midpoint.

but simply redistributes it from the end of continuous trading to the call auction, we expect a negative relation between the batch facility and *Value*. Alternatively, if the closing batch facility positively impacts *Value*, this indicates that the change in the closing mechanism generates new liquidity. The creation of new liquidity is likely to be explained by the greater investor participation due to increased confidence in market efficiency and integrity.

4.2.2 Price efficiency measures

Our first two measures of price efficiency are designed to capture whether the change in the closing mechanism reduces the pricing error (PE) at the close. The two measures are estimated, for each stock and day, as the logarithmic squared difference between security j's closing price ($CP_{j,t}$) and a reference price (Ref) relative to the closing price:

$$PE_{j,t} = \ln\left(100 \times \frac{CP_{j,t} - Ref}{CP_{j,t}}\right)^2. \tag{6}$$

Following Chang et al. (2008), we compute the first of the measures by taking a two-day volume-weighted average price ($VWAP_{j,t-1,t}$) as the reference price. Alternatively, the second measure uses the midpoint one hour after the opening of the following day ($M_{j,t+1}$) as the reference price.[15] In both cases, if the change in the closing mechanism improves price efficiency, the pricing error at the close should decrease in the post-event period.

Our last efficiency measure is designed to capture the broader implications of the change in the closing mechanism for volatility over the entire trading day. We define *Intraday Volatility* as the difference between security j's highest and lowest traded prices on day t divided by the average of the high and low traded prices:

$$\text{Intraday Volatility}_{j,t} = \frac{High_{j,t} - Low_{j,t}}{\frac{High_{j,t}+Low_{j,t}}{2}}. \tag{7}$$

[15] For robustness, we have also computed the latter measure using as reference price the midpoint at the middle of the trading day of the following day. The results are similar to the ones obtained when using as reference price the midpoint one hour after the opening.

We then standardise the measure by dividing it by stock j's full-period average intraday volatility. If a change in the closing mechanism improves investor participation and discourages manipulation, intraday volatility is expected to diminish in the post-event period due to the less extreme price movements at close.

4.2.3 Market integrity measures

In this study, a market with high integrity is one presenting low levels of manipulation. In accordance with our second hypothesis that closing price manipulation decreases with the introduction of batch mechanisms, we use three indirect measures and one direct measure to capture the degree of market integrity.

We define our first measure of market integrity, *Reversal Ratio*, following Madhavan and Panchapagesan (2000)

$$\text{Reversal Ratio}_j = \frac{\text{var}(Reversal_{j,t}^{Post})}{\text{var}(Reversal_{j,t}^{Pre})}, \tag{8}$$

where $Reversal_{j,t}^{Post}$ and $Reversal_{j,t}^{Pre}$ are the variance of return reversals for the post- and pre-event period, respectively. Consistent with Comerton-Forde and Putniņš (2011a), the return reversal for security j on day t is computed as the natural logarithm of the closing price divided by the midpoint one hour after the opening the following day. The variable *Reversal Ratio* is an indirect measure of closing price manipulation. A ratio of less than one indicates reduced volatility around the close and potentially signals an improvement in market integrity after the change of the closing mechanism.

Our next measure, R^2, uses the single index market model approach of Pagano and Schwartz (2003), which compares changes in the synchronicity of price movements with the market. The market model adjusted R^2 is estimated for each stock and period from the following regression[16]

$$r_{j,t} = \alpha_j + \beta_j r_{m,t} + \varepsilon_{j,t}, \tag{9}$$

where $r_{j,t}$ are close-to-close returns for stock j estimated over one-day intervals over the 250 trading days before and after the change in the closing mechanism.[17] The variable $r_{m,t}$ are the close-to-close market returns where, for each of the 43 exchanges, the major local stock index is used as a proxy for the market portfolio. The market model R^2 estimate measures how well a stock's return variation can be explained by broader market movements. If the new closing mechanism reduces closing price manipulation, the unexplained price movements ($\varepsilon_{j,t}$) should be less frequent, indicating a greater price synchronicity. As a result, the estimated adjusted R^2 in the post-period should increase relative to the one estimated in the pre-period.

Pagano and Schwartz (2003) and Hillion and Suominen (2004) document a decrease in volatility after the introduction of a closing call auction at the Paris Bourse, which they attribute to a reduction in closing price manipulation. In this vein, our next measure, idiosyncratic volatility ($IVOL$), evaluates the effect of the change in the closing mechanism on the volatility of closing prices. For each stock and period, the measure is computed as the standard deviation of the lagged market model residuals. Following Peterson and Smedema (2011), we define the lagged market model as

$$r_{j,t} = \alpha_j + \beta_j r_{m,t} + \gamma_j r_{m,t-1} + \varepsilon_{j,t}. \tag{10}$$

$IVOL$ is then calculated by taking the square root of the variance of the residuals:

$$IVOL_j = \sqrt{var(\epsilon_{j,t})}. \tag{11}$$

[16]For a particular stock j, Equations 9 to 11 are estimated for each period (i.e. the pre- and the post-event period) separately. For brevity, the equations do not include an index for the period.

[17] Battig and Chelley-Steeley (2010) note that trading frictions can misrepresent the relationship between stock j's return and the market return in the very short term. Therefore, for robustness, we also compute the measure at two- and three-day intervals to overcome the problems associated with trading frictions, obtaining similar results.

If the change in the closing mechanism improves market efficiency by reducing the variability of price distortions around the close, then $IVOL$ should decline following the introduction of the new closing mechanism. As a result, the $IVOL$ estimated in the post-period should decrease relative to the one estimated in the pre-period.

Finally, we use the probability index of closing price manipulation of Comerton-Forde and Putniņš (2011a) as a direct measure of market integrity. Using a sample of prosecuted manipulation cases, these authors identify trends in four trading variables that are systematically affected by closing price manipulation. They find that, in the presence of closing price manipulation, closing returns increase, there are significant return reversals, trading frequency is higher, and spreads are wider.

Consistent with Comerton-Forde and Putniņš (2011a), we compute closing returns as the natural logarithm of security j's closing price divided by its midpoint before the close. Return reversals are calculated as described in Equation 8 and spreads as in Equations 3 and 4.[18] We then use a difference-in-differences technique to construct the three input variables required to apply the index. Accordingly, each stock's daily observation is compared against a benchmark lagged by 42 trading days to remove time- and stock-specific effects. The application of the index is constrained by the construction of the benchmark period of Comerton-Forde and Putniņš (2011a), who lag the 42-day benchmark by one month. Examining the index more than one month after the event date introduces estimation bias, since the benchmark period partly captures the pre- and post-event periods. To properly estimate the manipulation index for the 250 days before and after the event, we lag the 42-day benchmark period by 250 trading days (approximately one year) to determine the manipulation index for the full sample period without crossing the event date. To remove marketwide effects and the potential bias caused by nonrandom manipulation days, these differences are compared to the market estimate against their respective benchmarks lagged by 42-trading day. The difference-in-differences

[18]We exclude trading frequency from the calculation of the index because, for markets with closing batch mechanisms, it becomes a redundant indicator, given that all trading takes place simultaneously at the uncross.

technique can be expressed as

$$\Delta_i^{diff} = (i_{j,t} - i_{j,t-292,t-250}) - (i_{m,t} - i_{m,t-292,t-250}), \tag{12}$$

where Δ_i^{diff} represents the abnormal component of variable i (returns, reversals, and spreads) for each stock-day, $i_{j,t}$ is security j's estimate for the given variable on day t, $i_{j,t-292,t-250}$ is stock j's variable estimate for each of the 42 trading days in the benchmark period, $i_{m,t}$ is the market estimate on day t, and $i_{m,t-292,t-250}$ is the market benchmark estimate. Hence, there are 42 difference-in-differences observations for each stock-day (i.e. one for each of the 42 days in the benchmark period).

Following Comerton-Forde and Putniņš (2011a), we standardise the difference-in-differences estimators against the security's prior trading characteristics using sign statistics to control for changes in a stock's day-end variable patterns over time and to prevent relatively illiquid and volatile stocks from being unduly penalised by the index measure:

$$S_i = \frac{n_+ - n_-}{2}, \tag{13}$$

where S_i is the sign statistic for variable i (returns, reversals, and spreads) and n_+ (n_-) represents the number of positive (negative) differences between the stock's day-end variable and a 42-trading day benchmark ending 250 trading days prior to day t. Therefore, a stock's sign statistic is bounded between +21 and -21.[19] The sign statistics are expected to be significantly positive for manipulated stock-days and zero, on average, otherwise. Next, to remove marketwide trends, a difference-in-signs estimate is generated by subtracting the cross-sectional median sign statistic:

$$\Delta_i^{sign} = S_i - \mathrm{med}_N\left(S_{N,i}\right), \tag{14}$$

where $\mathrm{med}_N\left(S_{N,i}\right)$ is the median sign statistic across all N other stocks listed on the same exchange (excluding stock j). To construct the index, Comerton-Forde and

[19]A sign statistic of -21 indicates the value of the underlying variable is lower than all the observations in the benchmark period; a sign statistic of $+21$ indicates the value of the underlying variable is higher than all the observations in the benchmark period.

Putniņš (2011a) perform a logistic regression using data from prosecuted cases of closing price manipulation to obtain the factor loadings for each of the four variables and generate a stock-day index for the probability of closing price manipulation:

$$Manipulation\ Index = \frac{1}{1 + e^{-\left(-7.5+4.2\Delta^{sign}_{return}+3.6\Delta^{sign}_{reversal}+1.8\Delta^{sign}_{spread}\right)}}, \qquad (15)$$

where Δ^{sign}_{return}, $\Delta^{sign}_{reversal}$, and Δ^{sign}_{spread} are the stock-day difference-in-sign estimates for the stock's return, reversal, and spread. The key advantage of this index is that it only requires trade and quote data, enabling potential closing price manipulation to be quantified, regardless of prosecution data.[20]

5 Results and discussion

The closing mechanism and its design are investigated in two stages. We first examine the effects of moving from a last-trade mechanism to a closing call auction or an on-close facility, allowing us to comment on the impact of introducing batch facilities on market quality. In the second stage, we investigate the impacts of the four categories of features present in these batch auctions: transparency of the indicative closing price, flexibility to enter and remove orders, randomisation of the uncross, and stabilisation of the closing price via price stabilisation systems. Given the large number of countries and stocks in our sample, we additionally conduct a subsample analysis where we examine how the level of development of the market and the liquidity of the stocks impact our results.

5.1 Impact of the introduction of batch mechanisms

To investigate the impact of introducing batch mechanisms, we first graph the evolution of our market quality variables for 250 days before and after the introduction

[20] Given the definition of returns and reversals, the index is strictly a measure of upward price manipulation. However, Comerton-Forde and Putniņš (2011a) note that upward price manipulation represents the entirety of closing price manipulation cases.

of batch facilities. Figure 1(a) and 1(b) show a noticeable reduction in both measures of closing spreads around the end of the day, indicating reduced transaction costs. Figure 1(c) documents an evident increase in daily traded value, indicating a net migration of new traders. This result is potentially explained by the entry of new market participants encouraged to trade by the lower transaction costs. These changes are immediately coincident with the introduction of the batch mechanisms and persist for the 250 trading days subsequent to the introduction. Figure 2 illustrates the impact of the introduction of closing auctions on our two measures of price efficiency and on volatility. We observe significant and persistent reductions in pricing errors constructed using either the two-day VWAP or the price one hour after opening on the subsequent day. A smaller reduction is observed in intraday volatility, suggesting that batch mechanisms are more effective in improving reference prices than in reducing the overall volatility experienced by securities.

[Insert Figure 1 Here]

[Insert Figure 2 Here]

Table 5 presents the results of more formal tests of the impact of introducing batch facilities in favour of last-trade mechanisms. Consistent with Hypothesis 1, we observe that both call auctions and on-close mechanisms improve market quality via greater liquidity. Closing spreads at the end of the day drop by 0.62 bps for call auctions and by 1.92 bps for on-close facilities. Similarly, the introduction of batch mechanisms reduces trading costs during the last two hours of the day, with the TWCS falling by 0.51 bps and 1.95 bps for call auctions and on-close facilities, respectively. In contrast with the findings of Aitken et al. (2005), our results suggest that liquidity is not redistributed away from the last hours of trading towards the closing auction but, rather, that batch mechanisms are likely to encourage new liquidity to enter the market. Consistent with the creation of new liquidity, we document a significant increase in the daily traded value for both the call auction and the on-close facility.

[Insert Table 5 Here]

Table 5 also documents improved price efficiency after the introduction of batch facilities. Significant reductions are observed in the pricing error relative to the two-day VWAP for the call auction and the on-close facility. Similarly, the pricing error relative to the next day's price one hour after opening also experiences significant decreases for both types of batch facilities. On the other hand, we observe a significant increase in the intraday volatility of the on-close facility, which could be explained by on-close facilities running parallel to the continuous trading session for a large portion of the trading day. The call auction experiences a decrease in intraday volatility, though this result is not statistically significant. As discussed in the next section, the lack of significance for the call auction is potentially due to the greater heterogeneity in its design features, as well as the differences in the levels of development across markets and of liquidity across stocks. Overall, the results are consistent with Hypothesis 1, with batch mechanisms improving market quality via greater liquidity and greater price efficiency.

Table 6 examines the impact of batch mechanisms on a variety of market integrity measures. Consistent with Madhavan and Panchapagesan (2000)'s examination of distortions in the closing returns on the NYSE, we document a significant increase in the adjusted R^2 estimate of one-day close-to-close returns for the closing call auction. The closing call auction provides a non-trading period in which liquidity is aggregated, making it more difficult for manipulators or large trades to distort closing prices away from their fundamental value. The reduction of abnormal imbalances near the end of the day is likely reflected by greater synchronicity with the market. Similarly, we identify a significant reduction in the idiosyncratic volatility $IVOL$ for both the closing call auction and the on-close facility, indicating fewer deviations from the market model. Overall, these results are consistent with the claim of Hypothesis 2 that batch mechanisms improve market integrity.

[Insert Table 6 Here]

Table 6 also presents our findings for the return reversal ratio and the manipulation index. While no significant change is documented for the reversal ratio, increases are observed in both mechanisms for the manipulation index. Contrary to Hypothesis 2, this result suggests that the introduction of batch mechanisms increases the probability of manipulation. While this reasoning is, at first, counterintuitive, it could be driven by three factors: First, the design features employed by the different exchanges differ significantly. If batch mechanisms are introduced with a combination of features that facilitate manipulative behaviour, this could result in greater manipulation. Second, smaller markets and stocks may lack sufficient liquidity to benefit from the beneficial aggregation effects of batch mechanisms, thinning liquidity during the continuous period or exacerbating the impact of large orders. Both explanations are explored in further detail in the remainder of this section. Third, the manipulation index of Comerton-Forde and Putniņš (2011a) is constructed for a market without a closing call auction in place, which poses a limitation for our study.

5.2 Impact of the design features of call auctions

Our second analysis attributes variation in market quality in the period *after* the introduction of call auctions to each of the four identified design features. Overall, our results indicate that randomised closing times improve all facets of market quality and that price stabilisation systems enhance market integrity. In contrast, transparency harms liquidity and price efficiency but somewhat improves integrity, whereas flexibility harms overall market quality.

Table 7 shows that randomisation is the only design feature that is consistently beneficial to liquidity, significantly reducing closing spreads and the TWCS by 0.92 bps and 0.99 bps, respectively, as well as significantly increasing the daily traded value. These results suggest that participants are more willing to trade around the close when the closing time is randomised, since such a feature provides security against attempts to manipulate the price. Our findings are consistent with those of Malaga et al. (2010), who find that randomised closing times in Internet auctions generate execution risk, minimising manipulation ('sniping') at the close. Such an effect could increase investor confidence in the integrity of the closing mechanism, resulting in increased investor participation, as evidenced by the significant increase in daily traded value.

[Insert Table 7 Here]

Table 7 also shows that order flexibility significantly increases spreads around the close by about 1.2 bps, as well as significantly reduces the daily traded value. Giving traders the ability to modify or cancel their orders during the pre-close period increases the risk of gaming behaviour during the auction. Consistent with the findings of Biais et al. (1999), flexibility at the close creates noise and generates uncertainty surrounding the legitimacy of order imbalances and indicative closing prices. This discourages investors from trading around the close, increasing end-of-day spreads. Similarly, a transparent batch mechanism corresponds with a significant drop in traded value and an increase in closing spreads of around 1.7 bps. These results are consistent with the claims of Biais et al. (1999) that traders are generally reluctant to participate in a transparent system, preferring to conceal the information embedded in their orders. This phenomenon is supported anecdotally by the removal of the publication of the indicative calculated closing price from the TSX's market-on-close facility, since it encouraged traders to delay entering their orders until after order information and indicative closing prices were revealed. Consistent with this evidence, a transparent system is found to reduce participation at the close, leading to increased transaction costs.

Surprisingly, stabilisation mechanisms are found to have a significant negative impact on spreads, which increase by approximately 0.8 bps. No effect is documented for the daily traded value. These unexpected results could be due to the limitation of the study to distinguish between price collars and volatility extensions, whose effects could go in opposite directions. The effects of stabilisation mechanisms could also depend on the level of development of the market and the liquidity of the stocks, which we analyse in Section 5.3.

Table 7 also documents that randomisation of the closing time significantly reduces pricing errors and intraday volatility. The impossibility of marking the close discourages manipulators from trading due to the uncertainty in the closing time.

This also discourages gaming activity by participants attempting to distort order imbalances and best bid and ask prices during the pre-auction period, since the potential for costly execution is increased. The drop in gaming behaviour results in a decrease in both pricing errors and in intraday volatility. Flexibility is found to significantly increase pricing errors. This result is indicative of traders' ability to engage in gaming activity by modifying or cancelling manipulative orders during the pre-close period. Similarly, transparency also increases pricing errors. If transparency results in fewer traders participating in the auction, this potentially leads to increased pricing errors, because an auction needs of enough liquidity to generate efficient equilibrium prices. Lack of participation in the auction also hinders its ability to absorb large or manipulative orders, resulting in greater price volatility.

Although evidence of the broad impact of batch mechanisms on integrity suggests they could be somewhat detrimental, Table 8 shows that the design characteristics exhibit a noticeable influence on the prevalence of closing price manipulation. First, stabilisation mechanisms have an insignificant effect on the probability of manipulation, but do significantly reduce the reversal ratio by 0.41 bps, indicating fewer instances of price reversals in subsequent days, consistent with more accurate closing prices. We similarly identify a significant reduction in idiosyncratic volatility ($IVOL$), which indicates fewer deviations from the market model. Our results are in line with those of Félez-Viñas and Hagströmer (2017), who find that volatility extensions deter gaming behaviour. Manipulators are discouraged from distorting prices to avoid triggering the pre-close volatility curb, particularly given the costs associated with maintaining distorted prices over an extended period. The results also indicate the effectiveness of stabilisation mechanisms at moderating large price movements at the close, giving market participants the opportunity to react to trades that distort prices beyond prespecified limits.

[Insert Table 8 Here]

Table 8 also reports a significant increase in the adjusted R^2 estimate of call auctions that have a randomised closing time, as well as a significant decrease in their idiosyncratic volatility. The uncertainty regarding the closing time increases execution risk by undermining the ability of manipulators to mark the close. The inability to pursue manipulative strategies is likely to deter manipulative behaviour, explaining the increase in synchronicity with the market. A less obvious result lies with the coefficient estimates for the transparency design feature. On the one hand, transparency significantly lowers the probability of closing price manipulation by 2.4%. This reduction has two possible explanations. First, in a transparent auction, manipulators risk being detected by fundamental traders, who could subsequently capitalise on their manipulative activity. This would result in a costly execution for manipulators and ultimately reduce their incentives for manipulation. Second, and consistent with the liquidity regressions, the reduction in manipulation could be related to a systematic reduction in the concealment of order information by all traders (including manipulators) at the close. On the other hand, transparency leads to significantly lower synchronicity with the market, with the adjusted R^2 estimate experiencing a significant reduction. This result is supported by the hypothesis that transparency leads to a decrease in participation. For an efficient closing price to be generated, the auction needs sufficient liquidity. A decrease in liquidity could lead to inefficient closing prices and explain the significantly lower synchronicity with the market.

5.3 Subsample analysis by level of development and liquidity

Our analysis encompasses 43 exchanges and differences in how closing auctions impact developed versus emerging markets are possible due to these markets' various levels of enforcement efficacy. The impact of closing batch mechanisms could also differ depending on the liquidity of the stocks, due to the extent to which liquidity is sufficiently aggregated to make closing batch mechanisms efficient. To examine potential differences across stocks and markets, we partition our sample into *developed* and *emerging* market subsamples and *liquid* versus *illiquid* subsamples. A country is categorised as developed or emerging according to the World Bank classification at the time of the change in the closing mechanism. Similarly, a stock is classified as illiquid if both its turnover and the number of days it is not traded are below the exchange's mean.

Table 9 presents the results of introducing a batch mechanism on our two subsamples. Our results are relatively similar across developed markets, especially when focusing on the effects on market liquidity and price efficiency.[21] Consistent with Hypothesis 1, we observe that both call auctions and on-close facilities significantly improve liquidity for developed markets, regardless of the stock's level of liquidity. For call auctions, closing spreads fall by 0.16 bps and 0.60 bps for liquid and illiquid stocks, respectively. Consistent with the creation of new liquidity, we also document a significant increase in the daily traded value of both liquid and illiquid stocks for the on-close facility, with no significant change observed for the call auction. Table 9 also reports an overall decrease in the pricing errors after the introduction of batch facilities for both liquid and illiquid stocks, signalling an improvement in price efficiency. The introduction of call auctions also leads to a decrease in intraday volatility for liquid stocks. However, the intraday volatility of illiquid stocks increases for both types of batch mechanisms, especially for on-close facilities, which could be explained by the entry of new liquidity into the market, as shown in the liquidity results. Consistent with Hypothesis 2, liquid and developed stocks experience a significant improvement in market integrity. The introduction of batch mechanisms significantly decreases the probability of closing price manipulation by 0.8% and 1.8% for the call auction and on-close facility, respectively. Similarly, we also identify a significant reduction in the idiosyncratic volatility for both types of mechanisms and a significant increase in the adjusted R^2 estimate. When it comes to developed but illiquid stocks, the results mostly show that batch mechanisms do not lead to a significant change in market integrity.

[Insert Table 9 Here]

Table 9 also presents the results of introducing batch mechanisms into emerging markets. Consistent with Camilleri and Green (2009) and Suen and Wan (2013),

[21] For brevity, only one measure of spreads, the *Closing Spread*, and one of pricing errors, the *PE (Open)*, are reported for the subsample analyses. The results for the *TWCS* and the *PE (VWAP)* are remarkably close to those of the *Closing Spread* and the *PE (Open)*, respectively.

with a few exceptions, most measures of market quality experience a significant deterioration for liquid stocks. Spreads significantly increase, the daily traded value falls, pricing errors rise, and so do price reversals and the manipulation index. Interestingly, illiquid stocks experience a significant decrease in spreads and intraday volatility, which, consistent with Madhavan (1992), suggests that it is the illiquid stocks that benefit the most from the introduction of call auctions in emerging markets. While batch facilities have a positive impact on market integrity in developed markets, that is not the case for emerging ones. This could reflect the enhanced ability of developed markets to enforce securities regulation, consistent with the results of Bhattacharya and Douak (2000). A change in the closing mechanism does not prove to be enough to improve market integrity on its own in emerging markets. It is likely that both, enhanced regulation and an appropriate auction design are needed in those markets to fight closing price manipulation and enhance market quality and integrity.

Examining the features of batch mechanisms, we report in Table 10 the results for the developed markets. For the liquid stocks, the results mostly mirror those of the main analysis, with a few idiosyncrasies. For instance, for liquid stocks, having a stabilisation mechanism in place decreases spreads by about 0.25 bps, and also reduces idiosyncratic volatility and the reversal ratio. Flexibility to submit, cancel, or modify orders also has a positive effect on the liquidity and market integrity of liquid stocks. Liquid stocks in developed markets are the ones being more closely monitored by market participants. Therefore, traders are more likely to infer the existence of gaming behaviour in these stocks. Giving market participants the flexibility to modify their orders if they believe the auction is being gamed potentially reduces market manipulation. At the same time, if traders believe in the ability of the auction to achieve efficient closing prices, they are more likely to participate in the market, explaining the improvement in market liquidity. As in the main analysis, market transparency is found to be mostly detrimental for market quality.

[Insert Table 10 Here]

When it comes to illiquid stocks in developed markets, the main take away is that market transparency is highly harmful, with almost all measures experiencing a significant deterioration. These results are consistent with the claims of Biais et al. (1999) and Domowitz and Madhavan (2001) that market participants are more reluctant to participate in a transparent system for fears of revealing their information. The lack of participation can facilitate gaming activity and impair liquidity and price efficiency. As is the case for liquid stocks, order flexibility also has a positive effect on market integrity for the illiquid stocks. This supports the idea that developed markets, where securities regulation is highly enforced, benefit from giving traders the ability to modify their orders if they suspect the auction is being rigged.

Table 9 indicates that the introduction of batch mechanisms is mostly detrimental to emerging markets. A possible explanation is that emerging markets lack of sufficient liquidity to gain from the beneficial aggregation effects of batch facilities. The lack of auction participation could be due to an inappropriate choice of design features, offsetting the benefits of batch mechanisms. Table 11 reports the results of the impact of auction design on market quality in emerging markets. The introduction of randomisation in these markets significantly improves almost all measures of market quality for both liquid and illiquid stocks. For example, illiquid stocks with a randomised closing time experience a decrease in closing spreads of 0.79 bps. Similarly, the daily traded value of the liquid stocks also improves significantly. Randomisation also leads to a significant reduction in pricing errors, volatility, and reversals, while it enhances the stock's synchronicity with the market. The presence of stabilisation mechanisms also contributes to a significant reduction in pricing errors, volatility and reversals, as well as to a greater synchronicity with the market for liquid stocks.

[Insert Table 11 Here]

Transparency is mostly detrimental to emerging markets. A transparent auction leads to greater spreads, lower daily trading value, greater pricing errors, and, for illiquid securities, also to higher volatility. However, in contrast with developed markets, we also find that transparency improves the manipulation index. This result could signal that, given sufficient levels of development and liquidity, the visibility of orders and of an indicative closing price allows a potential manipulator to enter and cancel orders to achieve a particular closing price. However, in an emerging market, the display of such a closing price is likely to encourage market participants to counter any potentially manipulative conduct. Finally, in contrast with developed markets, flexibility is mostly detrimental to emerging markets. Although order flexibility reduces reversals and idiosyncratic volatility, it also leads to increased spreads and lower daily traded value, as well as increased pricing errors for illiquid stocks. Of the 12 emerging markets that introduced a closing call auction, 10 allowed for flexibility and 7 also chose a transparent system. On the other hand, stabilisation mechanisms and randomisation were chosen for slightly less than half of the sample. Hence, the detrimental effects of batch mechanisms on emerging markets are, at least to some extent, likely to be due to an inappropriate choice of auction design features.

6 Conclusion

This paper analyses the effects of introducing closing batch facilities on market liquidity, closing price efficiency, and integrity and whether certain design features improve their performance. We conduct the study by exploiting the change in the closing mechanism of 43 exchanges worldwide between 1999 and 2013. Motivated by a commitment to improving market quality, many stock exchanges have introduced closing batch facilities with a variety of design features. This study has implications for both regulators and exchanges seeking to improve the efficiency and integrity of their capital markets.

For the broad market, we find that batch facilities generally improve market quality relative to last-trade mechanisms. Both call auctions and on-close facilities are associated with enhanced liquidity and price efficiency, although on-close facilities also lead to increased intraday volatility. Our results also show that batch mechanisms, and especially call auctions, contribute to greater market integrity by reducing the variability of closing price distortions and by increasing synchronicity with the market. Although we document an increase in the probability of manipulation after the introduction of batch facilities, deeper analyses indicate that the possibility of closing price manipulation depends on aspects such as auction design, the level of development of the market, and the stock's liquidity. In this vein, we document that auction design is important for ensuring a well-functioning batch mechanism. Our findings indicate that randomised closing times and the use of price stabilisation mechanisms largely improve market quality. On the contrary, transparency of the indicative closing price and flexibility to modify orders are mostly detrimental.

The heterogeneity of our sample additionally enables us to extract specific lessons for developed and emerging markets and about liquid versus illiquid stocks. Developed markets strongly benefit from moving from a last-trade mechanism to a batch facility. While illiquid stocks experience a general improvement in liquidity and price efficiency, liquid stocks additionally experience improved market integrity. In contrast to the baseline analysis, flexibility mostly has a positive effect for developed markets, supporting the idea that giving traders the opportunity to act upon the arrival of new information is beneficial in markets where securities regulation is highly enforced. Liquid stocks also benefit from using stabilisation mechanisms.

The introduction of batch mechanisms is mostly detrimental to emerging markets, which likely do not succeed in attracting sufficient order flow into the auction to make it function well. These results suggest that enhanced regulation and an appropriate auction design are needed in these markets in order to attract sufficient order flow and fight price manipulation. Transparency and flexibility are generally strongly detrimental to emerging markets. However, a large fraction of emerging markets have flexibility and transparency within their auction design features. In contrast, while emerging markets especially benefit from randomised closing times and stabilisation systems, only about half of our sample has these features in place.

References

Aggarwal, R. K. and Wu, G. (2006). Stock market manipulations. *Journal of Business*, 79(4):1915–1953.

Aitken, M., Comerton-Forde, C., and Frino, A. (2005). Closing call auctions and liquidity. *Accounting and Finance*, 45(4):501–518.

Austin, J. (2017). What exactly is market integrity: An analysis of one of the core objectives of securities regulation. *William and Mary Business Law Review*, 8(1):215–240.

Barclay, M. J., Hendershott, T., and Jones, C. M. (2008). Order consolidation, price efficiency, and extreme liquidity shocks. *Journal of Financial and Quantitative Analysis*, 43(1):93–121.

Battig, C. and Chelley-Steeley, P. L. (2010). The impact of the closing call auction: An examination of effects in London. *Applied Financial Economics*, 20(4):303–315.

Biais, B., Hillion, P., and Spatt, C. (1999). Price discovery and learning during the preopening period in the Paris Bourse. *Journal of Political Economy*, 107(6):1218–1248.

Camilleri, S. J. and Green, C. J. (2009). The impact of the suspension of opening and closing call auctions: Evidence from the National Stock Exchange of India. *International Journal of Banking, Accounting and Finance*, 1(3):257–284.

Carhart, M. M., Kaniel, R., Musto, D. K., and Reed, A. V. (2002). Leaning for the tape: Evidence of gaming behavior in equity mutual funds. *Journal of Finance*, 57(2):661–693.

Chang, R. P., Rhee, S. G., Stone, G. R., and Tang, N. (2008). How does the call market method affect price efficiency? Evidence from the Singapore Stock Market. *Journal of Banking and Finance*, 32(10):2205–2219.

Comerton-Forde, C. and Putniņš, T. J. (2011a). Measuring closing price manipulation. *Journal of Financial Intermediation*, 20(2):135–158.

Comerton-Forde, C. and Putniņš, T. J. (2011b). Pricing accuracy, liquidity and trader behavior with closing price manipulation. *Experimental Economics*, 14(1):110–131.

Comerton-Forde, C. and Rydge, J. (2006). Call auction algorithm design and market manipulation. *Journal of Multinational Financial Management*, 16(2):184–198.

Cushing, D. and Madhavan, A. (2000). Stock returns and trading at the close. *Journal of Financial Markets*, 3(1):45–67.

Domowitz, I. and Madhavan, A. (2001). Open sesame: Alternative opening algorithms in securities markets. In Schwartz, R. A., editor, *The Electronic Call Auction: Market Mechanism and Trading*, pages 375–393. Springer, Boston, MA.

Easley, D. and O'Hara, M. (1992). Time and the process of security price adjustment. *Journal of Finance*, 47(2):577–605.

Economides, N. and Schwartz, R. A. (1995). Electronic call market trading. *Journal of Portfolio Management*, 21(3):10–18.

Ellul, A., Shin, H. S., and Tonks, I. (2005). Opening and closing the market: Evidence from the London Stock Exchange. *Journal of Financial and Quantitative Analysis*, 40(4):779–801.

Félez-Viñas, E. and Hagströmer, B. (2017). Call auction volatility extensions. *Working Paper*.

Felixson, K. and Pelli, A. (1999). Day end returns-stock price manipulation. *Journal of Multinational Financial Management*, 9(2):95–127.

Foucault, T., Kadan, O., and Kandel, E. (2005). Limit order book as a market for liquidity. *Review of Financial Studies*, 18(4):1171–1217.

Hauser, S., Kamara, A., and Shurki, I. (2012). The effects of randomizing the opening time on the performance of a stock market under stress. *Journal of Financial Markets*, 15(4):392–415.

Hillion, P. and Suominen, M. (2004). The manipulation of closing prices. *Journal of Financial Markets*, 7(4):351–375.

Kandel, E., Rindi, B., and Bosetti, L. (2012). The effect of a closing call auction on market quality and trading strategies. *Journal of Financial Intermediation*, 21(1):23–49.

Kumar, P. and Seppi, D. J. (1992). Futures manipulation with "cash settlement". *Journal of Finance*, 47(4):1485–1502.

Lee, C. M., Mucklow, B., and Ready, M. J. (1993). Spreads, depths, and the impact of earnings information: An intraday analysis. *Review of Financial Studies*, 6(2):345–374.

Madhavan, A. (1992). Trading mechanisms in securities markets. *Journal of Finance*, 47(2):607–641.

Madhavan, A. and Panchapagesan, V. (2000). Price discovery in auction markets: A look inside the black box. *Review of Financial Studies*, 13(3):627–658.

Malaga, R., Porter, D., Ord, K., and Montano, B. (2010). A new end-of-auction model for curbing sniping. *Journal of the Operational Research Society*, 61(8):1265–1272.

Medrano, L. A. and Vives, X. (2001). Strategic behavior and price discovery. *RAND Journal of Economics*, 32(2):221–248.

Ni, S. X., Pearson, N. D., and Poteshman, A. M. (2005). Stock price clustering on option expiration dates. *Journal of Financial Economics*, 78(1):49–87.

Onayev, Z. M. and Zdorovtsov, V. M. (2008). Predatory trading around Russell reconstitution. *Working Paper, State Street Global Advisors.*

Pagano, M. S., Peng, L., and Schwartz, R. A. (2013). A call auction's impact on price formation and order routing: Evidence from the Nasdaq stock market. *Journal of Financial Markets*, 16(2):331–361.

Pagano, M. S. and Schwartz, R. A. (2003). A closing call's impact on market quality at Euronext Paris. *Journal of Financial Economics*, 68(3):439–484.

Pagano, M. S. and Schwartz, R. A. (2005). Nasdaq's closing cross. *Journal of Portfolio Management*, 31:100–111.

Peterson, D. R. and Smedema, A. R. (2011). The return impact of realized and expected idiosyncratic volatility. *Journal of Banking and Finance*, 35(10):2547–2558.

Roşu, I. (2009). A dynamic model of the limit order book. *Review of Financial Studies*, 22(11):4601–4641.

Schwartz, R. A. (1995). The call auction alternative. In Schwartz, R. A., editor, *The electronic call auction: Market mechanism and trading. Building a better stock market*, The New York University Salomon series on financial markets and institutions, pages 3–26. Springer Science + Business Media, New York.

Schwartz, R. A. (2000). Building a better stock market: New solutions to old problems. *Working Paper, AEI-Brookings Joint Center for Regulatory Studies*.

Schwartz, R. A., Byrne, J. A., and Colaninno, A. (2007). *The new NASDAQ marketplace*. Springer Science and Business Media.

Shastri, K. A., Shastri, K., and Sirodom, K. (1995). Trading mechanisms and return volatility: An empirical analysis of the stock exchange of thailand. *Pacific-Basin Finance Journal*, 3(2):357–370.

Smith, J. W. (2005). Nasdaq's electronic closing cross: An empirical analysis. *Working Paper, Nasdaq Economic Research*.

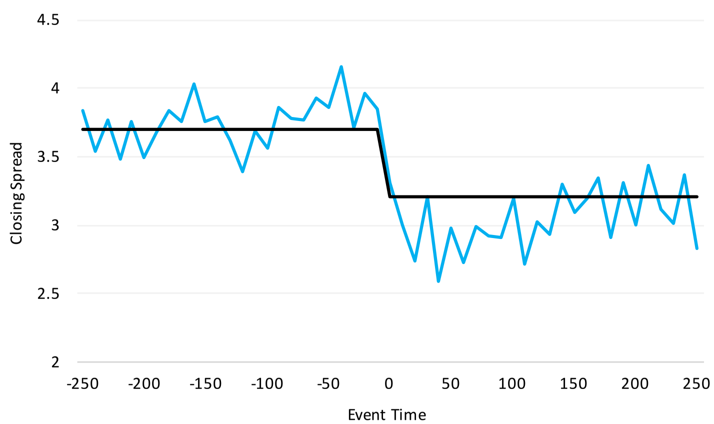
Suen, W. and Wan, K.-M. (2013). Sniping to manipulate closing prices in call auctions: Evidence from the Hong Kong Stock Exchange. *Working Paper, Hong Kong Polytechnic University*.

Thomas, S. (1998). End of day patterns on the paris bourse after implementation of a call auction. In *Global Equity Markets Conference Proceedings, Bourse de Paris-NYSE*.

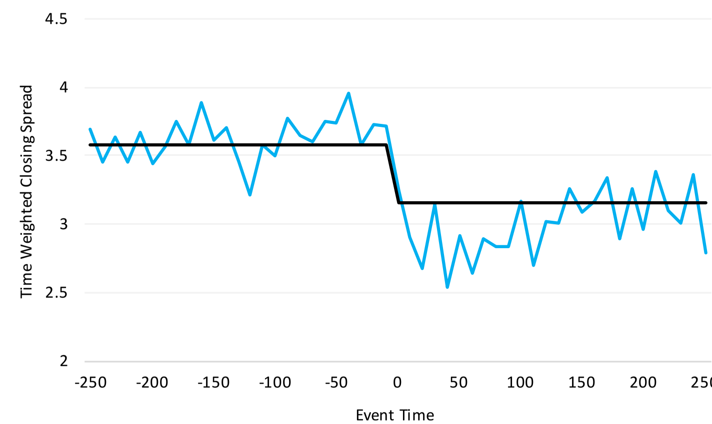
Figure 1: Liquidity measures

This figure presents the evolution of three different liquidity measures. The sample period spans 250 days before and 250 days after the change in the closing mechanism at each of the 43 markets under consideration. The blue lines depict the time series, which have been calculated as the daily average of the corresponding measure across all sample stocks and markets. The black lines show the pre and post-event averages. The three graphed measures of liquidity are: the *Closing Spread*, the *TWCS*, and *Value*. The *Closing Spread* is computed as the difference between the best ask and bid quotes at the closing of the continuous trading session divided by the midpoint x minutes or y trades before the close (x takes the minimum of 5, 10, 15, 20, 30, 60, or 90 minutes before the close of continuous trading such that there is at least one trade during x. For stocks with no trades in the 90 minutes prior to the close, we consider the midpoint immediately before the $y_{th} \in \{1, 2, 3, 4\}$ trade that maximises the return to the close). The *TWCS* is calculated as the average of the relative quoted spread calculated at 15-minute intervals for the last 2 hours of the continuous trading session. And *Value* is defined as the natural logarithm of the ratio between the daily dollar turnover during continuous trading and the total (continuous session and call auction) average dollar turnover for the full sample period.

(a) *Closing Spread*



(b) *TWCS*



(c) *Value*

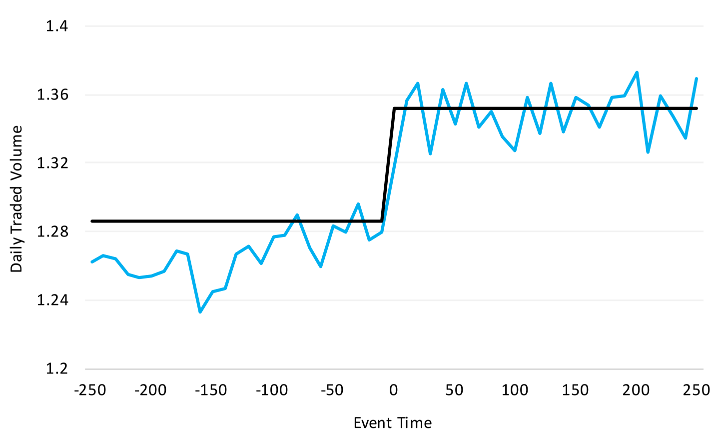
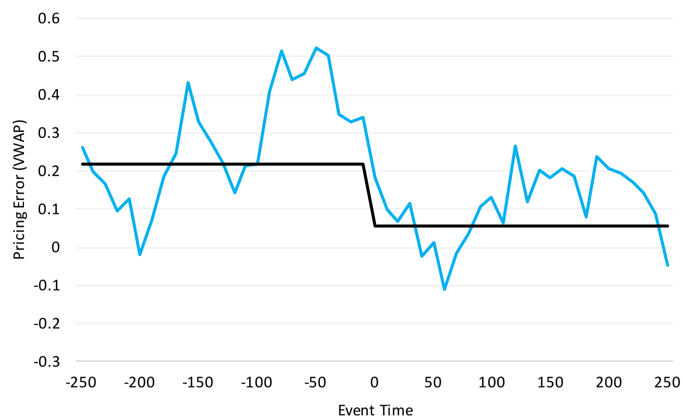


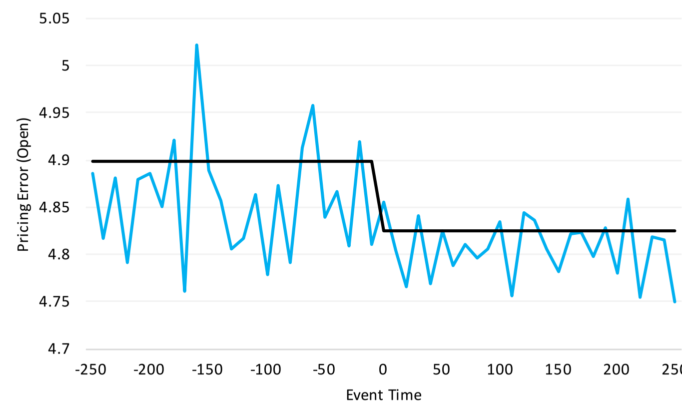
Figure 2: Price efficiency measures

This figure presents the evolution of three different measures of price efficiency. The sample period spans 250 days before and 250 days after the change in the closing mechanism at each of the 43 markets under consideration. The blue lines depict the time series, which have been calculated as the daily average of the corresponding measure across all sample stocks and markets. The black lines show the pre and post-event averages. The three graphed measures of price efficiency are: the *PE (VWAP)*, the *PE (Open)*, and the *Intraday Volatility*. The *PE (VWAP)* is computed as the logarithmic squared difference between a securities closing price and its two-day VWAP, divided by the former. The *PE (Open)* is calculated as the logarithmic squared difference between a securities closing price and its midpoint one hour after the opening of the following day, divided by the former. And the *Intraday Volatility* is calculated as the difference between a securities highest and lowest traded price on a certain day divided by the average of the high and low traded prices. The measure is standardised by dividing it by the stock's full-period average.

(a) *PE (VWAP)*



(b) *PE (Open)*



(c) *Intraday Volatility*

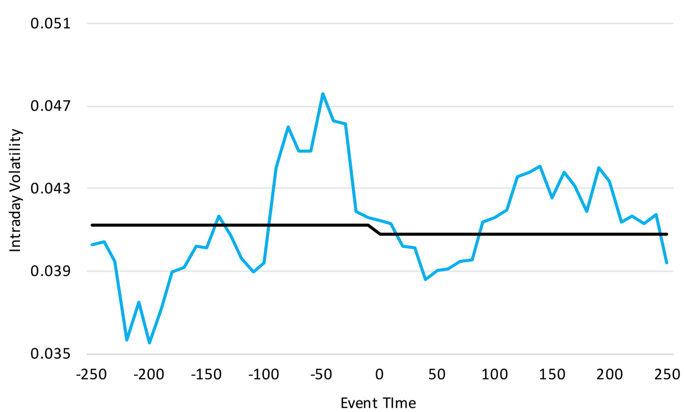


Table 1: Sample data characteristics: Developed markets

This table presents sample characteristics for each exchange in the sample that belongs to a developed country. A market is classified as developed according to the World Bank classification in the year the exchange introduced the change in its closing mechanism *(Event Date)*. The table also provides information on: *Stock Count*, which is the number of stocks on each exchange that experience a change in its closing mechanism. *Stock-Day Count*, which reports the total number of stock-day observations. *Volatility (%)*, computed as the average daily high-low price variation relative to the high-low midpoint. *Daily Turnover*, calculated as the average natural logarithm of daily dollar turnover for all stocks in the sample. And *Inactivity*, which is measured as the average fraction of stock-days with no trades.

Country	**Exchange**	**Event Date**	**Stock Count**	**Stock-Day Count**	**Volatility (%)**	**Daily Turnover**	**Inactivity**
Austria	VSX	05/11/1999	61	29804	1.95	11.91	22.00
Belgium	BRU	01/03/1999	140	95660	2.72	6.65	20.39
Canada	TSX-V	09/06/2005 - 09/12/2005	71	79898	6.43	12.14	5.50
Canada	TSX	03/29/2004 - 04/26/2004	159	196141	2.90	15.07	2.05
Cyprus	CYP	15/06/2009	60	38322	4.91	8.71	26.99
Czech Republic	PRA	11/05/2009	13	6330	4.37	15.26	8.40
Denmark	CPH	04/04/2005	137	129818	2.88	13.02	19.99
England	LSE	30/05/2000	192	212309	4.68	19.48	5.29
Finland	HEX	27/09/2004	112	109100	2.21	10.71	19.10
Greece	ATH	28/11/2005	286	161905	5.01	10.14	3.76
Iceland	ICX	24/03/2003	6	5321	1.88	15.74	39.37
Ireland	ISE	01/07/2002	43	38401	3.76	11.30	17.25
Israel	TASE	29/07/2007	452	316139	2.82	15.83	31.70
Italy	BIA	03/12/2001	288	245632	3.65	12.39	14.60
Netherlands	AEX	29/10/2001	148	144684	3.64	13.02	7.26
New Zealand	NZX	06/07/2007	124	116831	1.36	10.63	18.53
Norway	OSL	14/02/2003	110	115792	4.07	13.37	18.36
Qatar	QAE	10/09/2010	38	40685	3.07	14.21	9.25
Russia	MCX	02/09/2013	278	176935	4.49	12.70	23.99
Singapore	SGX	21/08/2000	319	269420	4.58	11.73	15.55
Slovenia	LJU	06/12/2010	30	16992	2.44	8.47	21.03
Sweden	STO	01/05/2002	276	226511	3.98	13.60	13.33
Taiwan	TWSE	01/07/2002	487	435884	4.28	9.38	4.28
UAE	ADX	02/01/2013	30	30637	2.00	12.68	24.02
USA	NASDAQ	16/12/2004	2958	2444142	5.29	12.40	10.83

Table 2: Sample data characteristics: Emerging markets

This table presents sample characteristics for each exchange in the sample that belongs to an emerging country. A market is classified as emerging according to the World Bank classification in the year the exchange introduced the change in its closing mechanism *(Event Date)*. The table also provides information on: *Stock Count*, which is the number of stocks on each exchange that experience a change in its closing mechanism. *Stock-Day Count*, which reports the total number of stock-day observations. *Volatility (%)*, computed as the average daily high-low price variation relative to the high-low midpoint. *Daily Turnover*, calculated as the average natural logarithm of daily dollar turnover for all stocks in the sample. And *Inactivity*, which is measured as the average fraction of stock-days with no trades.

Country	Exchange	Event Date	Stock Count	Stock-Day Count	Volatility (%)	Daily Turnover	Inactivity
Brazil	BRA	16/06/2008	235	183702	5.41	12.51	34.84
Chile	SGO	02/01/2004	73	58508	1.04	16.26	30.07
China	SHZ	01/07/2006	468	520110	3.17	15.34	8.51
China	SHH	01/12/2001	617	635909	3.74	15.77	8.43
Hungary	BUD	03/10/2005	32	35222	2.72	15.46	12.50
India	NSE	09/06/1999	756	653682	4.65	11.76	7.06
Indonesia	IDX	02/01/2013	326	150678	3.69	19.72	0.14
Jordan	AMM	22/03/2009	167	168412	2.89	9.76	16.29
Macedonia	MKE	03/01/2010	12	9945	1.48	12.81	22.60
Malaysia	KLS	01/12/2008	903	914165	3.58	10.91	33.12
Pakistan	KAR	14/02/2011	432	368721	7.23	10.29	28.63
Peru	LMA	01/01/2011	258	55473	0.98	10.28	66.24
Philippines	PSE	26/07/2010	163	168605	3.75	12.61	24.18
Romania	BUH	23/04/2008	44	32947	3.11	10.82	14.31
South Africa	JNB	13/05/2002	239	202575	2.90	16.75	18.06
Sri Lanka	CSE	01/09/2000	69	23088	1.96	10.71	21.11
Thailand	SET	06/09/1999	265	233864	5.56	8.45	25.00
Ukraine	UAX	12/04/2012	35	32819	3.66	10.19	27.13

Table 3: Closing mechanisms and design features: Developed Markets
This table presents details of the changes in the closing mechanism and the accompanying design features for each exchange in the sample that belongs to a developed country. A market is classified as developed according to the World Bank classification in the year the exchange introduced the change in its closing mechanism. The variables *Last Trade* and *VWAP* denote closing prices based on the last trade of the continuous trading or a VWAP of the last trades, respectively; *CALL* denotes the call auction and *ONCLOSE* the on-close facility. *TRANS*, *FLEX*, *RAND* and *STAB* represent the four design features that could be present in batch mechanisms, namely, transparency, flexibility, randomisation, and stabilisation systems, respectively. The presence of each mechanism and design feature on a particular exchange is coded as a one and the absence as a zero.

Country	Exchange	Last Trade	VWAP	CALL	ONCLOSE	TRANS	FLEX	RAND	STAB
Austria	VSX	0	0	1	0	1	1	1	0
Belgium	BRU	0	0	1	0	1	1	0	1
Canada	TSX-V	0	0	0	1	0	1	0	1
Canada	TSX	0	0	0	1	0	1	0	1
Cyprus	CYP	0	0	1	0	1	1	1	0
Czech Rep.	PRA	0	0	1	0	1	0	1	1
Denmark	CPH	0	0	1	0	1	1	1	0
England	LSE	0	0	1	0	1	1	1	1
Finland	HEX	0	0	1	0	1	1	1	0
Greece	ATH	0	0	1	0	1	1	1	1
Iceland	ICX	0	0	1	0	0	1	1	1
Ireland	ISE	0	0	1	0	1	1	1	1
Israel	TASE	0	0	1	0	1	1	1	0
Italy	BIA	0	0	1	0	0	0	0	1
Netherlands	AEX	0	0	1	0	1	1	0	1
New Zealand	NZX	0	0	1	0	1	1	1	0
Norway	OSL	0	0	1	0	1	1	1	1
Qatar	QAE	0	0	1	0	1	0	0	0
Russia	MCX	0	0	1	0	1	1	1	1
Singapore	SGX	0	0	1	0	1	1	0	0
Slovenia	LJU	0	0	1	0	1	0	1	0
Sweden	STO	0	0	1	0	1	1	1	0
UAE	ADX	0	0	1	0	0	1	0	1
USA	NASDAQ	0	0	0	1	1	0	0	1

Table 4: Closing mechanisms and design features: Emerging markets
This table presents details of the changes in the closing mechanism and the accompanying design features for each exchange in the sample that belongs to an emerging country. A market is classified as emerging according to the World Bank classification in the year the exchange introduced the change in its closing mechanism. The variables *Last Trade* and *VWAP* denote closing prices based on the last trade of the continuous trading or a VWAP of the last trades, respectively; *CALL* denotes the call auction and *ONCLOSE* the on-close facility. *TRANS*, *FLEX*, *RAND* and *STAB* represent the four design features that could be present in batch mechanisms, namely, transparency, flexibility, randomisation, and stabilisation systems, respectively. The presence of each mechanism and design feature on a particular exchange is coded as a one and the absence as a zero.

Country	**Exchange**	**Last Trade**	**VWAP**	**CALL**	**ONCLOSE**	**TRANS**	**FLEX**	**RAND**	**STAB**
Brazil	BRA	0	0	1	0	1	0	0	1
Chile	SGO	0	1	0	0	0	0	0	0
China	SHZ	0	0	1	0	0	0	1	0
China	SHH	0	1	0	0	0	0	0	0
Hungary	BUD	0	0	1	0	1	1	1	1
India	NSE	1	0	0	0	0	0	0	0
Indonesia	IDX	0	0	1	0	0	1	0	0
Jordan	AMM	0	0	1	0	1	1	1	0
Macedonia	MKE	0	1	0	0	0	0	0	0
Malaysia	KLS	0	0	1	0	1	1	0	0
Pakistan	KAR	0	1	0	0	0	0	0	0
Peru	LMA	0	0	1	0	1	1	1	1
Philippines	PSE	0	0	1	0	0	1	0	1
Romania	BUH	0	0	1	0	1	1	0	0
South Africa	JNB	0	0	1	0	1	1	1	1
Sri Lanka	CSE	0	1	0	0	0	0	0	0
Taiwan	TWSE	0	0	1	0	0	1	0	0
Thailand	SET	0	0	1	0	0	1	1	0
Ukraine	UAX	0	1	0	0	0	0	0	0

Table 5: Impact of the closing batch mechanism on market liquidity and closing price efficiency

This table reports the estimated effects on liquidity and price efficiency of moving from a last-trade mechanism to a batch facility to end the trading day. The estimates correspond to the panel regression

$$Y_{j,t} = \alpha + \beta_1 CALL_{j,t} + \beta_2 ONCLOSE_{j,t} + \sum_{i=1}^{5} \theta_i Control_{j,t,i} + \varepsilon_{j,t},$$

where j and t are stock and day indexes, respectively. The regression is estimated for six different dependent variables Y that capture different facets of market quality. All the dependent variables are winsorised at the 2.5% level to avoid capturing the effect of outliers. The variable *Closing Spread* is computed in bps as the difference between the last best ask and bid quotes divided by the midpoint x minutes or y trades before the close. The variable $TWCS$ is calculated as the average of the relative quoted spread at 15-minute intervals for the last 2 hours of the continuous trading session. *Value* is defined as the natural logarithm of the ratio between the daily dollar turnover during continuous trading and the total average dollar turnover for the full sample period. The *PE (VWAP)* is computed as the logarithmic squared difference between a securities closing price and its two-day VWAP, divided by the former. The *PE (Open)* is calculated as the logarithmic squared difference between a securities closing price and its midpoint one hour after the opening of the following day, divided by the former. The *Intraday Volatility* is calculated as the difference between a securities highest and lowest traded price on a certain day divided by the average of the high and low traded prices. The measure is standardised by dividing it by the stock's full-period average. $CALL$ and $ONCLOSE$ are dummy variables equal to one if the market operates a call auction or an on-close facility, respectively. $Volume$ is the natural logarithm of the average daily traded dollar volume for stock j in the pre-event period. $Inactivity$ is the average ratio of days with no trades per stock relative to the maximum number of trading days in the pre-event period. $Volatility$ is the average difference between the daily high and low prices weighted by the high-low midpoint in the pre-event period. The regression includes linear and nonlinear time controls to account for trends in the dependent variables over the sample period. Standard errors are corrected by double clustering by stock and day and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Liquidity			**Price Efficiency**		
	Closing Spread	TWCS	Value	PE (VWAP)	PE (Open)	Intraday Volatility
Intercept	5.527***	5.354***	1.209***	0.804***	0.423***	4.057***
	(0.399)	(0.386)	(0.009)	(0.127)	(0.116)	(0.202)
CALL	−0.621***	−0.512***	0.029***	−0.107**	−0.164***	−0.028
	(0.157)	(0.146)	(0.008)	(0.050)	(0.046)	(0.111)
ONCLOSE	−1.919***	−1.948***	0.287***	−0.717***	−0.674***	0.775***
	(0.188)	(0.176)	(0.010)	(0.059)	(0.052)	(0.126)
Volume	−0.346***	−0.346***		−0.129***	−0.122***	−0.052***
	(0.019)	(0.019)		(0.007)	(0.007)	(0.013)
Inactivity	6.726***	6.783***	−0.524***	2.149***	2.358***	−1.080***
	(0.415)	(0.401)	(0.021)	(0.141)	(0.136)	(0.269)
Volatility	38.988***	39.814***	1.582***	24.536***	27.551***	
	(2.407)	(2.330)	(0.187)	(0.931)	(0.908)	
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,984,331	1,984,331	1,984,331	1,984,331	1,984,331	1,984,331
Adjusted R^2	0.260	0.282	0.183	0.140	0.164	0.007

Note: *p<0.1; **p<0.05; ***p<0.01

Table 6: Impact of the closing batch mechanism on market integrity
This table reports the estimated effects on market integrity of moving from a last-trade mechanism to a batch facility to end the trading day. The estimates correspond to the panel regression

$$Y_{j,t} = \alpha + \beta_1 CALL_{j,t} + \beta_2 ONCLOSE_{j,t} + \sum_{i=1}^{5} \theta_i Control_{j,t,i} + \varepsilon_{j,t},$$

where j and t are stock and day indexes, respectively. The day index only applies to the regression where the dependent variable is the *Manipulation Index*. The regression is estimated for four different dependent variables Y that capture different facets of market quality. All the dependent variables are winsorised at the 2.5% level to avoid capturing the effect of outliers. For each stock, the variable R^2 is the market model adjusted R^2 estimated for one-day return intervals in the pre- and post-event period. The variable $IVOL$ measures the standard deviation of the market model return residuals for each stock and period. The *Reversal Ratio* is calculated for each stock as the variance of price reversals in the post-event period divided by the variance of price reversals in the pre-event period. The *Manipulation Index* measures the probability of closing price manipulation and is computed, for each stock-day, via a difference-in-signs estimation approach. $CALL$ and $ONCLOSE$ are dummy variables equal to one if the market operates a call auction or an on-close facility, respectively. $Volume$ is the natural logarithm of the average daily traded dollar volume for stock j in the pre-event period. $Inactivity$ is the average ratio of days with no trades per stock relative to the maximum number of trading days in the pre-event period. $Volatility$ is the average difference between the daily high and low prices weighted by the high-low midpoint in the pre-event period. For the *Manipulation Index*, the regression includes linear and nonlinear time controls to account for trends in the dependent variables over the sample period. Standard errors (reported in parentheses) are corrected by double clustering by stock and day for the manipulation index, and by clustering on stocks for the remaining three variables. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Integrity Measures			
	R^2	IVOL	Reversal Ratio	Manipulation Index
Intercept	−0.042***	0.840**	2.693***	0.052***
	(0.013)	(0.365)	(0.337)	(0.005)
CALL	0.032***	−0.650***	0.099	0.013***
	(0.008)	(0.172)	(0.145)	(0.002)
ONCLOSE	0.012	−0.385**	−0.157	0.022***
	(0.009)	(0.177)	(0.166)	(0.004)
Volume	0.002***	−0.011	−0.062***	−0.001***
	(0.001)	(0.022)	(0.021)	(0.0003)
Inactivity	−0.004	0.265	−0.056	−0.043***
	(0.009)	(0.275)	(0.251)	(0.005)
Volatility	−0.121**	−6.737***	−5.819***	0.339***
	(0.052)	(2.002)	(1.489)	(0.046)
Time Controls	No	No	No	Yes
Observations	10,573	10,573	10,573	1,984,331
Adjusted R^2	0.014	0.013	0.012	0.006

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7: Impact of auction design on market liquidity and closing price efficiency

This table reports the estimated effects on liquidity and price efficiency of implementing a closing call auction with different design features. Conditional on the market having a call auction mechanism in place during the post-event period, the estimates correspond to the panel regression

$$Y_{j,t} = \alpha + \beta_1 FLEX_{j,t} + \beta_2 RAND_{j,t} + \beta_3 STAB_{j,t} + \beta_4 TRANS_{j,t} + \sum_{i=1}^{5} \theta_i Control_{j,t,i} + \varepsilon_{j,t},$$

where j and t are stock and day indexes, respectively. The regression is estimated for six different dependent variables Y that capture different facets of market quality. All the dependent variables are winsorised at the 2.5% level to avoid capturing the effect of outliers. The variable *Closing Spread* is computed in bps as the difference between the last best ask and bid quotes divided by the midpoint x minutes or y trades before the close. The variable $TWCS$ is calculated as the average of the relative quoted spread at 15-minute intervals for the last 2 hours of the continuous trading session. *Value* is defined as the natural logarithm of the ratio between the daily dollar turnover during continuous trading and the total average dollar turnover for the full sample period. The *PE (VWAP)* is computed as the logarithmic squared difference between a securities closing price and its two-day VWAP, divided by the former. The *PE (Open)* is calculated as the logarithmic squared difference between a securities closing price and its midpoint one hour after the opening of the following day, divided by the former. The *Intraday Volatility* is calculated as the difference between a securities highest and lowest traded price on a certain day divided by the average of the high and low traded prices. The measure is standardised by dividing it by the stock's full-period average. $FLEX$, $RAND$, $STAB$ and $TRANS$ are dummy variables equal to one if the market operates a call auction that permits order flexibility, includes a randomised closing time, integrates a price stabilisation mechanism, or is transparent, respectively. $Volume$ is the natural logarithm of the average daily traded dollar volume for stock j in the pre-event period. *Inactivity* is the average ratio of days with no trades per stock relative to the maximum number of trading days in the pre-event period. $Volatility$ is the average difference between the daily high and low prices weighted by the high-low midpoint in the pre-event period. The regression includes linear and nonlinear time controls to account for trends in the dependent variables over the sample period. Standard errors are corrected by double clustering by stock and day and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Liquidity			**Price Efficiency**		
	Closing Spread	TWCS	Value	PE (VWAP)	PE (Open)	Intraday Volatility
Intercept	5.914***	5.959***	1.252***	0.445*	−0.230	1.953***
	(1.094)	(1.087)	(0.020)	(0.236)	(0.143)	(0.334)
FLEX	1.225***	1.238***	−0.050***	0.557***	0.564***	0.017
	(0.274)	(0.255)	(0.015)	(0.091)	(0.079)	(0.141)
RAND	−0.922***	−0.985***	0.062***	−0.433***	−0.272***	−0.455***
	(0.344)	(0.344)	(0.013)	(0.085)	(0.058)	(0.162)
STAB	0.818**	0.778**	−0.003	0.113	0.017	−0.007
	(0.321)	(0.321)	(0.011)	(0.075)	(0.051)	(0.141)
TRANS	1.754***	1.712***	−0.120***	0.334***	0.304***	−0.053
	(0.221)	(0.222)	(0.014)	(0.082)	(0.068)	(0.175)
Volume	−0.497***	−0.499***		−0.145***	−0.122***	0.083***
	(0.067)	(0.067)		(0.013)	(0.008)	(0.026)
Inactivity	4.668***	4.760***	−0.421***	1.890***	2.054***	−0.260
	(0.621)	(0.611)	(0.025)	(0.145)	(0.137)	(0.265)
Volatility	22.470**	22.705**	2.519***	23.643***	27.525***	
	(8.955)	(8.962)	(0.248)	(1.978)	(1.180)	
Time Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	652,592	652,592	652,592	652,592	652,592	652,592
Adjusted R^2	0.279	0.291	0.148	0.147	0.154	0.016

Note: *p<0.1; **p<0.05; ***p<0.01

Table 8: Impact of auction design on market integrity
This table reports the estimated effects on market integrity of implementing a closing call auction with different design features. Conditional on the market having a call auction mechanism in place during the post-event period, the estimates correspond to the panel regression

$$Y_{j,t} = \alpha + \beta_1 FLEX_{j,t} + \beta_2 RAND_{j,t} + \beta_3 STAB_{j,t} + \beta_4 TRANS_{j,t} + \sum_{i=1}^{5} \theta_i Control_{j,t,i} + \varepsilon_{j,t},$$

where j and t are stock and day indexes, respectively. The day index only applies to the regression where the dependent variable is the *Manipulation Index*. The regression is estimated for four different dependent variables Y that capture different facets of market quality. All the dependent variables are winsorised at the 2.5% level to avoid capturing the effect of outliers. For each stock, the variable R^2 is the market model adjusted R^2 estimated for one-day return intervals in the pre- and post-event period. The variable $IVOL$ measures the standard deviation of the market model return residuals for each stock and period. The *Reversal Ratio* is calculated for each stock as the variance of price reversals in the post-event period divided by the variance of price reversals in the pre-event period. The *Manipulation Index* measures the probability of closing price manipulation and is computed, for each stock-day, via a difference-in-signs estimation approach. $FLEX$, $RAND$, $STAB$ and $TRANS$ are dummy variables equal to one if the market operates a call auction that permits order flexibility, includes a randomised closing time, integrates a price stabilisation mechanism, or is transparent, respectively. $Volume$ is the natural logarithm of the average daily traded dollar volume for stock j in the pre-event period. $Inactivity$ is the average ratio of days with no trades per stock relative to the maximum number of trading days in the pre-event period. $Volatility$ is the average difference between the daily high and low prices weighted by the high-low midpoint in the pre-event period. For the *Manipulation Index*, the regression includes linear and nonlinear time controls to account for trends in the dependent variables over the sample period. Standard errors (in parentheses) are corrected by double clustering by stock and day for the manipulation index, and by clustering on stocks for the remaining three variables. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Integrity Measures			
	R^2	IVOL	Reversal Ratio	Manipulation Index
Intercept	−0.002	−0.304	2.427***	0.060***
	(0.012)	(0.351)	(0.419)	(0.008)
FLEX	0.021**	0.184	−0.145	0.004
	(0.010)	(0.190)	(0.273)	(0.004)
RAND	0.016**	−0.470***	0.135	0.008**
	(0.008)	(0.182)	(0.201)	(0.004)
STAB	0.002	−0.462***	−0.413***	−0.003
	(0.006)	(0.153)	(0.154)	(0.003)
TRANS	−0.048***	−0.015	0.343	−0.024***
	(0.012)	(0.281)	(0.314)	(0.005)
Volume	0.002**	0.047**	−0.034	−0.0003
	(0.001)	(0.024)	(0.024)	(0.0004)
Inactivity	−0.023**	0.831***	0.207	−0.024***
	(0.011)	(0.283)	(0.279)	(0.007)
Volatility	−0.064	−5.403*	−5.299**	0.433***
	(0.072)	(3.060)	(2.361)	(0.085)
Time Controls	No	No	No	Yes
Observations	5,983	5,983	5,983	652,592
Adjusted R^2	0.033	0.016	0.016	0.007

Note: *p<0.1; **p<0.05; ***p<0.01

Table 9: Impact of closing batch mechanisms depending on the level of market development and stock liquidity

This table reports the estimated effects on market quality of moving from a last-trade mechanism to a batch facility when splitting the sample between developed and emerging markets and between liquid and illiquid stocks. The table shows the coefficient estimates of the parameters representing the introduction of the call auction or the on-close facility. The two coefficients of interest are obtained from the panel regression:

$$Y_{j,t} = \alpha + \beta_1 CALL_{j,t} + \beta_2 ONCLOSE_{j,t} + \sum_{i=1}^{5} \theta_i Control_{i,t} + \varepsilon_{j,t},$$

where j and t are stock and day indexes, respectively. The day index only applies to stock-day market quality measures. The regression is estimated for eight different dependent variables Y. All the dependent variables are winsorised at the 2.5% level to avoid capturing the effect of outliers. The variable *Closing Spread* is computed in bps as the difference between the last best ask and bid quotes divided by the midpoint x minutes or y trades before the close. *Value* is defined as the natural logarithm of the ratio between the daily dollar turnover during continuous trading and the total average dollar turnover for the full sample period. The *PE (Open)* is calculated as the logarithmic squared difference between a security's closing price and its midpoint one hour after the opening of the following day, divided by the former. The *Intraday Volatility* is calculated as the difference between a securities highest and lowest traded price on a certain day divided by the average of the high and low traded prices. The measure is standardised by dividing it by the stock's full-period average. For each stock, the variable R^2 is the market model adjusted R^2 estimated for one-day return intervals in the pre- and post-event period. *IVOL* measures the standard deviation of the market model return residuals for each stock and period. The *Reversal Ratio* is calculated for each stock as the variance of price reversals in the post-event period divided by the variance of price reversals in the pre-event period. The *Manipulation Index* measures the probability of closing price manipulation and is computed via a difference-in-signs estimation approach. $CALL$ and $ONCLOSE$ are dummy variables equal to one if the market operates a call auction or an on-close facility, respectively. The regression includes as controls: $Volume$, defined as the natural logarithm of the average daily traded dollar volume for stock j in the pre-event period; $Inactivity$, computed as the average ratio of days with no trades per stock relative to the maximum number of trading days in the pre-event period; and $Volatility$, measured as the average difference between the daily high and low prices weighted by the high-low midpoint in the pre-event period. For stock-day measures, the regression also includes linear and nonlinear time controls to account for trends in the dependent variables over the sample period. Standard errors (in parentheses) are double-clustered by stock and day for all the measures except for R^2, $IVOL$ and *Reversal Ratio*, whose standard errors are clustered on the stock cross-section. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Developed				**Emerging**	
	Liquid		**Illiquid**		**Liquid**	**Illiquid**
	CALL	ONCLOSE	CALL	ONCLOSE	CALL	CALL
Closing Spread	-0.156**	-1.123***	-0.597***	-2.470***	0.654***	-0.814**
	(0.066)	(0.072)	(0.193)	(0.345)	(0.079)	(0.358)
Value	0.019	0.176***	0.004	0.161***	-0.064***	-0.052***
	(0.012)	(0.012)	(0.010)	(0.018)	(0.008)	(0.013)
PE (Open)	-0.049***	-0.338***	-0.246***	-0.798***	0.432***	0.073
	(0.018)	(0.026)	(0.032)	(0.074)	(0.034)	(0.070)
Intraday Volatility	-0.092**	0.300***	0.231***	1.941***	0.096	-0.367***
	(0.046)	(0.061)	(0.077)	(0.192)	(0.079)	(0.109)
R^2	0.057***	0.027***	-0.022	-0.022*	0.025***	0.027***
	(0.008)	(0.008)	(0.017)	(0.013)	(0.007)	(0.005)
IVOL	-0.994***	-1.494***	0.812	-0.408	-0.301***	0.442
	(0.133)	(0.136)	(0.532)	(0.437)	(0.059)	(0.331)
Reversal Ratio	0.448	-0.247	-0.985	-2.644***	1.554***	0.791***
	(2.986)	(3.893)	(0.608)	(0.530)	(0.459)	(0.158)
Manipulation Index	-0.008***	-0.018***	0.009***	-0.003	0.026***	0.019***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.004)

Table 10: Impact of auction design for developed markets depending on stock liquidity
This table reports the estimated effects on market quality of implementing a closing call auction with different design features for developed markets when the sample is split between liquid and illiquid stocks. Conditional on the market having a call auction mechanism in place during the post-event period, the table shows the coefficient estimates of the parameters representing four common auction design features: *flexibility* to cancel, enter or modify orders; *randomisation* of the closing time; use of price *stabilisation systems* to curb volatility; and *transparency* of the batching phase. The coefficients of interest are obtained from the panel regression:

$$Y_{j,t} = \alpha + \beta_1 FLEX_{j,t} + \beta_2 RAND_{j,t} + \beta_3 STAB_{j,t} + \beta_4 TRANS_{j,t} + \sum_{i=1}^{5} \theta_i Control_{i,t} + \varepsilon_{j,t},$$

where j and t are stock and day indexes, respectively. The day index only applies to stock-day market quality measures. The regression is estimated for eight different dependent variables Y. All the dependent variables are winsorised at the 2.5% level to avoid capturing the effect of outliers. The variable *Closing Spread* is computed in bps as the difference between the last best ask and bid quotes divided by the midpoint x minutes or y trades before the close. *Value* is defined as the natural logarithm of the ratio between the daily dollar turnover during continuous trading and the total average dollar turnover for the full sample period. The *PE (Open)* is calculated as the logarithmic squared difference between a security's closing price and its midpoint one hour after the opening of the following day, divided by the former. The *Intraday Volatility* is calculated as the difference between a securities highest and lowest traded price on a certain day divided by the average of the high and low traded prices. The measure is standardised by dividing it by the stock's full-period average. For each stock, the variable R^2 is the market model adjusted R^2 estimated for one-day return intervals in the pre- and post-event period. $IVOL$ measures the standard deviation of the market model return residuals for each stock and period. The *Reversal Ratio* is calculated for each stock as the variance of price reversals in the post-event period divided by the variance of price reversals in the pre-event period. The *Manipulation Index* measures the probability of closing price manipulation and is computed via a difference-in-signs estimation approach. $FLEX$, $RAND$, $STAB$ and $TRANS$ are dummy variables equal to one if the market operates a call auction that permits order flexibility, includes a randomised closing time, integrates a price stabilisation mechanism, or is transparent, respectively. The regression includes as controls: $Volume$, defined as the natural logarithm of the average daily traded dollar volume for stock j in the pre-event period; $Inactivity$, computed as the average ratio of days with no trades per stock relative to the maximum number of trading days in the pre-event period; and $Volatility$, measured as the average difference between the daily high and low prices weighted by the high-low midpoint in the pre-event period. For stock-day measures, the regression also includes linear and nonlinear time controls to account for trends in the dependent variables over the sample period. Standard errors (in parentheses) are double-clustered by stock and day for all the measures except for R^2, $IVOL$ and *Reversal Ratio*, whose standard errors are clustered on the stock cross-section. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Developed Liquid				**Developed Illiquid**			
	FLEX	RAND	STAB	TRANS	FLEX	RAND	STAB	TRANS
Closing Spread	-0.77***	0.26	-0.25**	2.28***	0.61	0.49	0.21	4.67***
	(0.144)	(0.166)	(0.114)	(0.145)	(0.532)	(0.565)	(0.393)	(0.572)
Value	0.33***	0.04***	-0.01	-0.33***	0.08*	0.03*	-0.06***	-0.37***
	(0.027)	(0.014)	(0.012)	(0.018)	(0.040)	(0.019)	(0.017)	(0.032)
PE (Open)	0.47***	0.10	0.08	0.20*	0.74***	0.10	0.15	0.91***
	(0.081)	(0.087)	(0.065)	(0.112)	(0.180)	(0.158)	(0.097)	(0.164)
Intraday Volatility	1.51***	-0.22*	0.30***	-0.84***	1.48***	-0.37	0.68***	-1.26***
	(0.121)	(0.127)	(0.095)	(0.129)	(0.264)	(0.315)	(0.202)	(0.320)
R^2	0.02***	0.05***	0.01*	-0.09***	0.03***	0.04***	-0.00	-0.04***
	(0.008)	(0.006)	(0.005)	(0.007)	(0.011)	(0.006)	(0.004)	(0.010)
$IVOL$	-0.24	0.71***	-0.76***	0.01	-1.61***	-0.08	-0.36	0.31
	(0.160)	(0.132)	(0.103)	(0.138)	(0.396)	(0.375)	(0.272)	(0.356)
Reversal Ratio	-1.52***	0.30	-1.27***	0.30**	0.32	-1.40***	-0.84***	1.92***
	(0.299)	(0.242)	(0.212)	(0.138)	(0.412)	(0.402)	(0.232)	(0.380)
Manipulation Index	-0.02***	0.01**	0.01***	0.02***	-0.02**	-0.03***	0.01**	0.02**
	(0.004)	(0.004)	(0.003)	(0.004)	(0.008)	(0.009)	(0.004)	(0.009)

Table 11: Impact of auction design for emerging markets depending on stock liquidity
This table reports the estimated effects on market quality of implementing a closing call auction with different design features for emerging markets when the sample is split between liquid and illiquid stocks. Conditional on the market having a call auction mechanism in place during the post-event period, the table shows the coefficient estimates of the parameters representing four common auction design features: *flexibility* to cancel, enter or modify orders; *randomisation* of the closing time; use of price *stabilisation systems* to curb volatility; and *transparency* of the batching phase. The coefficients of interest are obtained from the panel regression:

$$Y_{j,t} = \alpha + \beta_1 FLEX_{j,t} + \beta_2 RAND_{j,t} + \beta_3 STAB_{j,t} + \beta_4 TRANS_{j,t} + \sum_{i=1}^{5} \theta_i Control_{i,t} + \varepsilon_{j,t},$$

where j and t are stock and day indexes, respectively. The day index only applies to stock-day market quality measures. The regression is estimated for eight different dependent variables Y. All the dependent variables are winsorised at the 2.5% level to avoid capturing the effect of outliers. The variable *Closing Spread* is computed in bps as the difference between the last best ask and bid quotes divided by the midpoint x minutes or y trades before the close. *Value* is defined as the natural logarithm of the ratio between the daily dollar turnover during continuous trading and the total average dollar turnover for the full sample period. The *PE (Open)* is calculated as the logarithmic squared difference between a security's closing price and its midpoint one hour after the opening of the following day, divided by the former. The *Intraday Volatility* is calculated as the difference between a securities highest and lowest traded price on a certain day divided by the average of the high and low traded prices. The measure is standardised by dividing it by the stock's full-period average. For each stock, the variable R^2 is the market model adjusted R^2 estimated for one-day return intervals in the pre- and post-event period. $IVOL$ measures the standard deviation of the market model return residuals for each stock and period. The *Reversal Ratio* is calculated for each stock as the variance of price reversals in the post-event period divided by the variance of price reversals in the pre-event period. The *Manipulation Index* measures the probability of closing price manipulation and is computed via a difference-in-signs estimation approach. $FLEX$, $RAND$, $STAB$ and $TRANS$ are dummy variables equal to one if the market operates a call auction that permits order flexibility, includes a randomised closing time, integrates a price stabilisation mechanism, or is transparent, respectively. The regression includes as controls: $Volume$, defined as the natural logarithm of the average daily traded dollar volume for stock j in the pre-event period; $Inactivity$, computed as the average ratio of days with no trades per stock relative to the maximum number of trading days in the pre-event period; and $Volatility$, measured as the average difference between the daily high and low prices weighted by the high-low midpoint in the pre-event period. For stock-day measures, the regression also includes linear and nonlinear time controls to account for trends in the dependent variables over the sample period. Standard errors (in parentheses) are double-clustered by stock and day for all the measures except for R^2, $IVOL$ and *Reversal Ratio*, whose standard errors are clustered on the stock cross-section. ***, **, and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Emerging Liquid				**Emerging Illiquid**			
	FLEX	RAND	STAB	TRANS	FLEX	RAND	STAB	TRANS
Closing Spread	1.26***	-0.03	0.56***	0.98***	2.02**	-0.79*	0.08	1.75***
	(0.347)	(0.180)	(0.183)	(0.207)	(0.890)	(0.447)	(0.500)	(0.438)
Value	-0.20***	0.06***	-0.12***	-0.09***	-0.08**	0.02	-0.08***	-0.06***
	(0.028)	(0.012)	(0.011)	(0.012)	(0.033)	(0.014)	(0.013)	(0.013)
PE (Open)	0.01	-0.36***	-0.22***	0.32***	0.67***	-0.66***	0.04	0.76***
	(0.110)	(0.055)	(0.065)	(0.055)	(0.159)	(0.091)	(0.107)	(0.089)
Intraday Volatility	-0.03***	-0.01***	-0.00	-0.01***	0.00	-0.01***	-0.01***	0.01***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.001)
R^2	-0.13***	0.04***	0.02**	-0.03***	-0.05***	0.03***	-0.01	0.00
	(0.009)	(0.007)	(0.007)	(0.007)	(0.010)	(0.007)	(0.007)	(0.006)
$IVOL$	-0.99***	-0.65***	-0.48***	0.15	-1.12***	-0.68***	-0.35***	0.02
	(0.148)	(0.129)	(0.154)	(0.133)	(0.147)	(0.129)	(0.147)	(0.138)
Reversal Ratio	-0.92***	-0.37***	-0.08	0.82***	-1.48***	-0.83***	-0.66**	0.15
	(0.156)	(0.142)	(0.155)	(0.145)	(0.370)	(0.224)	(0.298)	(0.247)
Manipulation Index	-0.01	0.01	0.00	-0.05***	-0.01	0.03***	-0.00	-0.07***
	(0.008)	(0.007)	(0.006)	(0.005)	(0.011)	(0.005)	(0.007)	(0.005)