How should we ring the closing bell? Determining optimal closing auction design[*,†]

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This version: March 2022

Abstract

We examine how stock market closing price mechanisms affect liquidity, price efficiency, and market integrity. Using hand-collected data on every major mechanism change in 45 markets during 17 years, we find that replacing simple mechanisms such as the last traded price with a closing auction typically improves market quality. However, auction design substantially impacts auction effectiveness – price stabilization features and randomized closing times are beneficial, whereas transparent indicative closing prices are often detrimental. The effects vary with the level of market development and liquidity, suggesting that when designing optimal closing mechanisms, there is no "one size fits all".

[*]We gratefully acknowledge comments from participants at the 12th Central Bank Workshop on the Microstructure of Financial Markets, the 2018 Monash Workshop on Financial Markets, the 26^{th} Finance Forum, the 2019 New Zealand Finance Meeting, the FMA 2021 European Conference and the 2021 FIRN Annual Meeting. We are also grateful to Michael Aitken, Angelo Aspris, Kingsley Fong, Michael Goldstein, Carole Gresse, Frank Hatheway, Björn Hagströmer, Amy Kwan, Lars Nordén, Richard Phillip, Tavy Ronen, Reuben Segara, Avanidhar Subrahmanyam, Matthijs van Dijk, Gunther Wuyts, and Caihong Xu for comments. We thank Nicholas Cordi for significant research assistance. The authors acknowledge funding from the Centre for International Financial Regulation.

[†]The appendix that accompanies this paper is available online at `https://bit.ly/3BaR0zn`

1 Introduction

Closing prices are the most widely used benchmarks and reference prices for equity markets. They underpin several trillions of dollars of derivatives contracts, managed fund unit prices, index values, index inclusion, the pricing of secondary equity offerings, and daily market news. Moreover, the rise of passive investing has driven an increasingly large share of the day's total trading activity to the closing period: in some markets as much as 40% or more.[1] With the increasing volumes traded at the close come heightened concerns from regulators about the robustness of closing mechanisms, which vary widely around the world, and how such volumes impact the quality of closing prices.[2]

This paper examines closing mechanism design and how it impacts the efficiency of closing prices, market liquidity, and market integrity. To date, most empirical studies of closing mechanisms are confined to a single market — usually examining a single change in the mechanism design. Our contribution is to collect and analyze the most comprehensive sample of closing mechanisms around the world and all their major changes to bring large-scale evidence to the question of what constitutes an optimal closing mechanism. We consider all 115 exchanges reported by the World Federation of Exchanges, from which we hand-collect data on the 45 exchanges that we identify as having substantial mechanism design changes during a 17-year period. For each, we obtain a large time-series of intraday trade and quote data to construct granular measures of market quality and integrity and use difference-in-differences models to quantify the effects of different closing mechanisms and different auction design features.

Our first finding is that, around the world, there is a tendency for stock exchanges to change from simple closing mechanisms, such as halting the market at a specified time and using the last traded price or an average of the last trade prices as the closing price, towards different forms of closing auctions. Almost all developed markets and many emerging countries switch to closing auctions during our sample period.

We find that introducing a closing auction generally improves all facets of market quality. In a closing auction, the consolidation of liquidity mitigates large order imbalances and price impacts (Economides and Schwartz, 1995), and liquidity demanders become less ag-

[1]For example, a recent report from the French market regulator (AMF) estimates that in 2019, closing auctions account for as much as 44% of daily volume in Spain, 41% in France, 40% in the UK, 36% in Germany, 32% in Netherlands, and 24% in Italy (see AMF, 2019). The same report estimates that in the US trading at the close represents around 12% to 14% of daily volume, and that this share is rapidly growing.

[2]For example, Reuters (August 16, 2019): "The growing popularity of passive and index-tracking funds and tougher regulations are driving the shift [to trading on close], ... raising concerns about big price swings and possible disruption to price discovery".

gressive as they are given an additional opportunity to trade (Foucault et al., 2005; Roşu, 2009). As a result, and in line with our findings, liquidity improves, resulting in increased trading volumes and closing spreads which reduce by an economically significant 44%. We also find that closing auctions improve price efficiency and market integrity, as they reduce price pressures, return reversals, and the probability of closing price manipulation.[3] These findings are consistent with Schwartz (1995), who argues that the consolidation of liquidity brings together the beliefs of many traders about the stock's fundamental value and reduces the influence of manipulative orders, contributing to greater price efficiency. At the same time, the aggregation of liquidity also makes it more difficult and costly for manipulators to capitalize on their manipulative strategies, which translates into enhanced market integrity.

However, not all closing auctions are equally beneficial. We show that in our sample there is substantial variation in how exchanges implement closing auctions and these design variations affect how well the auctions work. In all cases, the common feature of closing auctions is that liquidity is aggregated during a non-trade batching phase in which market participants indicate their trading interests. Orders are then executed at a single point in time, the uncross, at a single closing price. There are two main types of closing auctions: the *call auction* and the *on-close facility*, which we collective refer to as *batch facilities*. In call auctions, which are popular in Europe and Asia-Pacific, orders to trade in the auction are collected after the end of the continuous trading session and all orders are accepted. In contrast, on-close facilities, which are predominantly used in North America, run in parallel with continuous trading, accepting orders to trade at the closing price throughout the day. Towards the end of the day, if there is a large order imbalance during the pre-close period, the facility typically accepts only orders which offset the imbalance.

We find that closing call auctions are the more effective of the two batch facilities in terms of increasing liquidity, improving price efficiency, and enhancing market integrity. Their beneficial effects may explain their popularity around the world and why they have become the dominant approach for setting closing prices in most developed markets. In contrast, on-close facilities in the US and Canada are likely the result of designated market makers and "specialists" historically having played a more prominent role in managing the trading of equities in those markets, resulting in a more manual and intermediated closing mechanism that differs from most other developed countries.

Even within the realm of closing call auctions, there are many design features that impact their effectiveness. We classify all closing call auctions in our sample according

[3]Following Austin (2017), we consider that a market has high integrity when its levels of market manipulation are low.

to four distinct design features: *flexibility* to modify, submit, or cancel orders during the batching period; *randomization* of the uncross (closing) time; *price stabilization systems* such as collars that limit price movements and volatility extensions that prolong the auction time if the price would otherwise fall outside of a given range; and *transparency* of the order book and indicative auction price during the batching phase.

We find that price stabilization systems have the largest impact of the four design features. Call auctions that integrate a price stabilization system tend to improve all measures of market liquidity and integrity. Our results support the notion that price stabilization systems diminish the susceptibility to market manipulation by constraining manipulative behavior within certain bounds. The decrease in the risk of manipulation increases the confidence in the ability of the call auction to generate efficient prices, resulting in increased trading at the close and higher liquidity. Closing prices also become more efficient, with significant reductions in variance ratios and in the delays when incorporating information into prices.

For the other design features, we find that randomization of the closing time is also beneficial for market quality and integrity. Randomization introduces uncertainty regarding the exact closing time, forcing traders to submit their orders ahead of time to ensure they are included rather than waiting until the last millisecond before a deterministic closing time. Randomization also makes it more difficult to manipulate closing prices by "punching the close" with an aggressive order submitted just moments before the close. In contrast, we find that transparency of indicative closing prices is largely detrimental for market quality, which is consistent with the arguments of Biais et al. (1999) that transparency discourages participation due to traders' concerns about revealing too much information to the rest of the market.

To examine whether the effects of different closing mechanisms depend on market characteristics, we analyze subsamples of markets categorized according to their levels of development, and stocks categorized by their liquidity. We find that illiquid stocks benefit most from the introduction of a well-designed call auction. These results are consistent with Madhavan (1992), who argues that if illiquid stocks manage to attract sufficient order flow, it is precisely these stocks that benefit the most from a closing auction.

The subsample analysis also shows that both developed and emerging markets benefit on average from call auctions but with some differences. Developed markets benefit from call auctions when they integrate randomized closing times, price stabilization systems, and flexibility to modify and cancel orders. An important takeaway is that the introduction of a call auction *per se* does not always result in improvements for market quality. Rather, call auctions need to have in place certain design features to bring about market-wide benefits. Closing auctions in emerging markets lead to significant improvements in market liquidity and, to a lower extent, to market integrity, especially when the call auction incorporates a price stabilization system. However, flexibility and transparency in the auction generally harm the performance of closing auctions in emerging countries. Overall, these results suggest that "one size does not fit all". What works for developed markets does not necessarily work in emerging countries.

This paper makes three main contributions to the literature on closing mechanisms. First, existing studies examine the impact of introducing a closing auction or on-close trading facility in a single exchange, mainly in developed markets and for liquid stocks. For example, Pagano and Schwartz (2003, 2005); Smith (2005); Barclay et al. (2008) show that in such settings, closing auctions strengthen the price discovery process, while Aitken et al. (2005); Kandel et al. (2012); Pagano et al. (2013) show they facilitate absorption of order imbalances and price impacts at the end of the trading day. Instead, we examine changes of closing mechanisms in a comprehensive global sample of 45 exchanges varying from developed to emerging and including stocks with different levels of liquidity. This broader sample allows us to show that what is optimal in one market is not necessarily optimal in another. Our results provide specific insights for developed and emerging markets as well as for liquid and illiquid securities.

Second, we contribute to the literature by investigating whether closing auctions enhance market integrity. The widespread use of closing prices for benchmarking, contracting, and trading purposes gives market participants many incentives to manipulate them. Previous literature on closing batch facilities have only indirectly analyzed market integrity by attributing improvements in volatility and price discovery to a reduction in market manipulation (Thomas, 1998; Pagano and Schwartz, 2003; Hillion and Suominen, 2004; Chang et al., 2008). However, Comerton-Forde and Putniņš (2011a), who examine 184 prosecuted cases of closing price manipulation in the United States and Canada, construct an index based on returns, reversals, spreads, and trading volumes that can be used to estimate the probability of closing price manipulation. Our paper is the first to empirically use this more specific measure of closing price manipulation to analyze the effect of different closing mechanisms on market integrity.

Finally, our study adds to the limited literature emphasizing the importance of auction design in enhancing the benefits of auctions. Previous studies tend to focus on a single design feature (Biais et al., 1999; Domowitz and Madhavan, 2001; Medrano and Vives, 2001; Hauser et al., 2012; Lin et al., 2019; Félez-Viñas and Hagströmer, 2021) or comparing the Nasdaq and NYSE closing mechanisms (Jegadeesh and Wu, 2022). We contribute to the literature by analyzing the effects of several of the most common auction design features (i.e., flexibility, randomization, stabilization systems, and transparency) and how they influence the auction's effect on liquidity, price efficiency, and market integrity.

The remainder of this paper is organized as follows. Section 2 discusses the theoretical predictions and empirical findings which motivate our hypotheses. The data is presented in Section 3. We introduce the metrics used to measure liquidity, price efficiency, and market integrity in Section 4 as well as our regression modeling. Section 5 presents the effects of closing mechanisms in the full sample while Section 6 presents the varying effects across markets. We conclude in Section 7.

2 Closing Mechanisms and Theoretical Predictions

Historically, most markets have ended their trading day simply by halting trading at a specified time and using either the last traded price or the volume-weighted average price (VWAP) of the last trades as the closing price. This simple mechanism, and the more advanced alternatives to end the trading day, are illustrated in Figure 1. The Figure also illustrates the design features that characterize different implementations of closing call auctions.

[Insert Figure 1 Here]

Despite their simplicity, last-trade mechanisms for setting closing prices have a weak ability to absorb order imbalances, making them more likely to produce biased closing prices in the presence of transitory imbalances (Cushing and Madhavan, 2000; Barclay et al., 2008). In this vein, Easley and O'Hara (1992) present a theoretical model that predicts a negative relationship between volume shocks and market liquidity. If their model holds, last-trade mechanisms are particularly vulnerable to large end-of-day trading shocks.

The extensive use of closing prices as benchmarks and the rise of index funds has increased the volume traded at the close (Bogousslavsky and Muravyev, 2021). Intending to produce more efficient closing prices, many exchanges have 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 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.

According to Pagano et al. (2013), 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 sequential order execution. Economides and Schwartz (1995) argue that closing batch facilities mitigate such frictions because the aggregation of liquidity enables the absorption of 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, contributing to improved liquidity.

Liquidity demanders trade more aggressively at the end of the day because it is their last trading opportunity before the market closes. Under a last-trade mechanism, aggressive trading is likely to produce transitory price changes. In contrast, as predicted in the theoretical models of Foucault et al. (2005) and Roşu (2009), by giving traders an additional opportunity to trade, closing batch facilities make liquidity demanders less aggressive, which reduces continuous market volatility and spreads. Based on the existing theory our first hypothesis is as follows:

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

Another dimension of market quality is market integrity - the extent to which markets are free of securities law violations such as market manipulation. The widespread use of closing prices in contracts and benchmarks creates many incentives to manipulate them. Felixson and Pelli (1999) and Hillion and Suominen (2004) note that brokers may attempt to manipulate closing prices to alter perceptions of their execution quality and increase future commissions. Fund manager remuneration usually depends on the performance of their fund, which is also evaluated using closing prices. 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 derivative positions. Comerton-Forde and Putniņš (2011a) argue that traders can also try to manipulate closing prices on index rebalancing days to gain index inclusion.

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 it also undermines investor confidence in the quality of financial markets. Persistent manipulation can discourage market participants from trading, reducing order flow and thus further inhibiting efficient price discovery.

In contrast to last-trade mechanisms, batch facilities consolidate liquidity, which is likely to reduce the potential for manipulation because larger orders would be needed to successfully influence the closing price. The better the batch facility is at consolidating liquidity, the larger the volume required to manipulate the price and thus the more costly the manipulation. Therefore, our second hypothesis:

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

Closing auctions vary in how they are designed. Studies on how auction design affects different facets of market quality are scarce and tend to focus on a single design feature. The main design features that vary across closing auction implementations are: flexibility to modify orders within the batching period, randomization of the uncross time, price stabilization systems, and the transparency of order flow and imbalance information during the batching phase.

In the context of closing auctions, flexibility refers to the ability of market participants to submit, cancel, or revise their closing auction orders. While the effects of flexibility on market quality have not been empirically examined, Biais et al. (1999) and Domowitz and Madhavan (2001) claim that flexibility may enable gaming behavior, which would not only impair price efficiency and increase volatility, but also deter auction participation. On the other hand, Aitken et al. (2005) argue that flexibility 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 manipulative behavior, flexibility can reduce market manipulation and transitory volatility.

Randomization of the closing time is used to deter manipulative behavior by introducing uncertainty about the exact uncross time (Malaga et al., 2010; Lin et al., 2019). If a randomized closing time makes it more difficult to distort the close, it is likely to improve confidence in the market, thereby enhancing liquidity and price efficiency (Hauser et al., 2012).

Some closing auction implementations include price stabilization systems, such as volatility extensions and price collars, with the aim of curbing large transitory volatility at the close. Volatility extensions prolong the duration of the batching period if the closing price would otherwise fall outside a certain threshold, while price collars restrict the closing price to fall within pre-specified thresholds. Comerton-Forde and Rydge (2006) and Félez-Viñas and Hagströmer (2021) argue that volatility extensions are likely to combat manipulation by giving market participants the opportunity to trade against manipulative orders.

Transparency refers to the dissemination of order flow and imbalance information during the pre-close period.[4] 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, further impairing liquidity and price discovery. However, Domowitz and Madhavan (2001) point out that the lack of transparency can, in turn, facilitate the manipulation of the auction price because traders cannot see and react to manipulative orders, which could harm confidence and liquidity.

Hypothesis 3 *Closing auction design features affect auction performance – randomization of the closing time and price stabilization systems improve liquidity, efficiency and integrity, whereas the effects of flexibility and transparency are theoretically ambiguous.*

The literature on closing auctions focuses on developed markets. As noted by Camilleri and Green (2009), this limitation is important because stocks in emerging markets are generally less liquid and actively traded than those in developed countries and closing auctions could have different effects depending on the level of liquidity and market development. Further, the trading protocols and market microstructure vary across markets with different levels of development. Given the disparities, previous conclusions drawn from the implementation of batch facilities in developed countries do not necessarily apply to emerging markets.

For example, in illiquid stocks, a trader aiming to manipulate closing prices could find it easier to do so in a batch facility (Camilleri and Green, 2009). As discussed in Schwartz (2000), batch mechanisms need to attract sufficient order flow to function well and, as pointed out by Ellul et al. (2005), this could be problematic for emerging markets if a majority of their stocks are illiquid or inactive. Indeed, Chau et al. (2021) show that in Hong Kong illiquid stocks can be manipulated without trading, using only quotes. 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 hinders manipulation and allows for greater accuracy in the price discovery process. The effects of introducing a closing auction and the effects of the different design features for illiquid securities and emerging markets remains an empirical question.

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

3 Empirical Setting

3.1 Data and sample

We consider all 115 exchanges listed in the World Federation of Exchanges handbook. We contacted each of the exchanges asking for details of the closing mechanism that was in place in June 2014 and any major changes to the closing mechanism since 1996.[5] Of the 115 exchanges, we received responses with sufficient information from 87, of which 49 still used a last-trade mechanism, and 38 had moved from a last-trade to a batch mechanism during the sample period.[6] Of the 49 that still used a last-trade mechanism, seven switched from using the last trade price to using the VWAP of trades near the close to set the closing price. For our sample, we keep all 38 exchanges that change from a last-trade to a batch mechanism and the seven exchanges that change from last price to a VWAP closing mechanism. This approach gives us the maximum number of closing mechanism changes in our sample, while making the sample size feasible, considering we process intraday data for all stocks listed on each exchange.

For the 45 exchanges in our sample, we obtain intraday data including trades and quotes from the Tick History database maintained by Refinitiv for every single listed equity security. The trade and quote data span the years 1996 to 2017. 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 before and after the date of the most recent major change in the closing mechanism in each exchange (the "event date").[7] The use of a sample period of 500 days before and after the event date is consistent with Pagano and Schwartz (2003) and is adopted to allow the computation of liquidity, price efficiency, and integrity metrics. A window of 500 trading days allows us to determine the longer-term impact of the introduction of the batch facility, providing sufficient time for market participants to adjust their trading behavior 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 three months in both the pre- and post-event periods.

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

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

[7]Using the most recent major mechanism change ensures the most accurate information about the closing mechanism before and after the change. Although our dataset records closing mechanism changes up until June 2014, the analysis extends beyond that date due to the post-event periods in the exchanges with the most recent changes.

We additionally remove stocks where the number of observations in the pre- and post-period differs by more than 50%.[8] We also exclude weekends and national holidays in each country of our sample. As expected, due to dealing with securities traded on 45 different exchanges, the data contain outliers. To limit their influence, we follow standard practice and winsorize all variables described in Section 7 at the 2.5 and 97.5 percentiles (e.g., O'Hara and Ye (2011)).

3.2 Trends in closing mechanisms and their design

Figure 2 depicts the evolution of the closing mechanisms for our sample of 45 exchanges. The Figure shows an evident decrease in the use of last-trade mechanisms to end the trading day in favor of batch facilities, especially closing call auctions.

[Insert Figure 2 Here]

Tables 1 and 2 present an overview of the markets that are part of our sample. We consider stocks traded in 45 exchanges from 43 different countries. The different countries are classified as developed (Table 1) or emerging (Table 2) in the year of the country's event date according to the World Bank classification, which is based on the country's gross national income per capita.[9,10] Accordingly, we classify 27 exchanges as developed and 18 as emerging.

[Insert Table 1 Here]

[Insert Table 2 Here]

The tables provide information regarding the date (*Event Date*) on which each exchange introduced the new closing mechanism, the number of stocks in our sample for each exchange (*Number of Stocks*), and the total number of stock-day observations in each of the markets (*Number of Stock-Days*). Our sample comprises a total of 11,586 stocks, with 6,770 from developed markets and 4,816 from emerging countries. The number of stock-day observations across all markets is about ten million, with almost six million from developed countries and about four million from those classified as emerging.

The tables also present details of the closing mechanism in place together with the design features implemented when a batch facility is adopted. There are two main categories of closing mechanisms: (i) last-trade facilities, which determine closing prices based on an

[8] For robustness, we repeat the analysis by imposing instead a restriction of 80%. The conclusions remain unchanged. The results for this analysis are found in Section A of the online Appendix.

[9] 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`.

[10] For robustness, we performed an alternative classification of the countries based on their corruption levels as reported by Transparency International (`www.transparency.org/en/cpi`). The country classification based on corruption barely differs from the one based on development levels.

average price (VWAP) of the last trades in the continuous trading session, and (ii) batch facilities, where orders are consolidated during a batching period that starts at the end of the continuous trading session (*Call*), or that runs parallel with continuous trading (*Onclose*).[11]

All developed exchanges introduced batch mechanisms, with the three on-close facilities belonging to developed markets.[12] Of the 18 emerging markets, 11 introduced a closing call auction, with the remaining seven changing from using the last traded price in the continuous trading session to a VWAP of the last trades prior to the close.

Exchanges that introduced closing call auctions are further classified according to four different design features of their auctions: (i) flexibility (*Flex*) to cancel or modify orders during the batching period, (ii) randomization (*Rand*) of the time of the uncross, (iii) price stabilization systems (*Stab*) to curb extraordinary volatility, and (iv) transparency (*Trans*) of the batching phase. The use of a specific closing mechanism and design feature is represented by a dummy variable that takes the value of one if used when the new closing mechanism is introduced, and zero otherwise. Tables 1 and 2 show that flexibility and transparency are the most common design features in our sample exchanges, with randomization and price stabilization systems only being employed in about one-half of the markets.

4 Empirical Models

For each stock-day and each stock-month in our sample, we estimate a range of market quality and integrity metrics. Because market quality is multifaceted, we consider a large variety of measures summarized below. Details of these measures are provided in Appendix A.

We measure liquidity using (i) the quoted bid-ask spread at the close, (ii) a version of the closing spread that is restricted to quote updates within the last three hours, (iii) the time-weighted average bid-ask spread in the last two hours before the close, (iv) the value-weighted effective spread in the last two hours, including and excluding the closing auction,

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

[12]The introduction of the on-close facilities at NASDAQ, the TSX, and the TSX-V was staggered across stocks. NASDAQ staggered the introduction over a number of months (Schwartz et al., 2007). To retain consistency with the single implementation date of other exchanges, the post-event period commences in December 2004, once the on-close facility had been fully implemented across all stocks. The on-close facility at the TSX was first introduced for constituents of the TSX 60 index on 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 on 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.

(v) the dollar value of trading activity, including and excluding the closing auction, and (vi) an end-of-day adaptation of the Amihud (2002) illiquidity metric, capturing price impacts at the close.

We measure price efficiency using (i) intraday high-low range-based volatility, which is expected to decrease if the closing mechanism makes the market more robust to manipulative orders and order imbalances, (ii) a variance ratio introduced by Amihud and Mendelson (1987), which measures transient volatility in closing prices, (iii) absolute autocorrelation of opening and of closing prices, which also capture the presence of transitory price distortions, (iv) an adaptation of the Hou and Moskowitz (2005) *Delay* metric, which captures inefficiency in the form of slow incorporation of market-wide information, and (v) an adaptation of the Lo and MacKinlay (1988) variance ratios, using two alternative time frameworks, that detect deviations from random walk price processes.

We measure market integrity using a range of proxies for closing price manipulation, including (i) a simple, "traditional", day-end return reversal measure that captures the tendency for closing price manipulation to often result in price spikes that subsequently reverse the next day (e.g., Comerton-Forde and Putniņš (2011a)), (ii) an improved reversal measure, using two alternative specifications, that also capture downward price manipulations and remove return continuations, (iii) a version of the reversal measures that eliminates the correlation with volatility, and (iv) the Probability of Manipulation Index (PMI) of Comerton-Forde and Putniņš (2011a) constructed under three different specifications.

In the interest of simplicity given the large number of market quality metrics and variations of them, the main tables in the paper report results for eleven key metrics - four measures of liquidity, four measures of price efficiency, and three measures of market integrity. Additional results for all alternative metrics are reported in Section B of the Online Appendix. The results are qualitatively consistent across the primary and alternative metrics.

We evaluate the effects of changes in closing mechanisms on these market quality metrics using difference-in-differences panel regressions. A potential source of endogeneity is if stock exchanges self-select into a batch facility when they believe the mechanism will be beneficial to them (e.g., when introducing a closing auction is expected to improve market quality) and not adopt such a mechanism if it is not expected to be beneficial. Such selection effects can arise when (i) the treatment has heterogeneous effects, such as auctions being more beneficial in developed or emerging markets or in more/less liquid markets, and (ii) the stock exchanges determine to change their closing mechanisms strategically when it is beneficial.

To a large extent, these selection effects are absorbed by controlling for sources of heterogeneity in closing mechanism effects including exchange fixed effects (subsumed by stock fixed effects), which pick up the level of development and level of liquidity, time fixed effects, which pick up general global economic conditions and the prevailing state of technology, and stock fixed effects. However, we take a further step in the empirical models and apply a two-stage Heckman-style correction (Vella and Verbeek, 1999; Clougherty et al., 2016)

In the first stage, we estimate a probit model of a stock exchange's decision to adopt a closing call auction:[13]

$$Pr(Call_{i,t} = 1) = \Phi(\boldsymbol{\beta} \boldsymbol{Z_{i,t}} + u_{i,t}) \tag{1}$$

where $Call$ is one if the exchange trading stock i at time t has implemented a closing call auction and zero otherwise, Φ is the cumulative standard normal distribution function, and $\boldsymbol{Z}$ is a set of determinants of the choice to introduce a closing call auction. The determinants include: (i) the exchange's region (Asia-Pacific, Europe, Middle East/Africa, North America or South America), (ii) a dummy variable for developed countries,[14] (iii) the lagged average traded dollar volume per stock, (iv) the lagged number of stocks in the exchange, (v) the lagged exchange liquidity computed as the average closing spread of all stocks in the exchange, and (vi) the lagged exchange efficiency, calculated as the average intraday volatility of all stocks in the exchange.

Table 3 reports estimates from the probit model of the likelihood that an exchange selects a closing call auction as their closing mechanism. All coefficient estimates in the probit regression are statistically significant, indicating that the exchange's region, level of development, and trading activity characteristics such as the volume, liquidity and efficiency, are all related to the decision to introduce a call auction.

[Insert Table 3 Here]

From the first-stage model, we construct the inverse Mills ratios using the fitted values ($\hat{\boldsymbol{\beta}}$):

$$\lambda(\hat{\boldsymbol{\beta}} \boldsymbol{Z_{i,t}}) = Call_{i,t} \frac{\Phi(-\hat{\boldsymbol{\beta}} \boldsymbol{Z_{i,t}})}{1 - \Phi(-\hat{\boldsymbol{\beta}} \boldsymbol{Z_{i,t}})} + (1 - Call_{i,t}) \frac{-\Phi(\hat{\boldsymbol{\beta}} \boldsymbol{Z_{i,t}})}{\Phi(-\hat{\boldsymbol{\beta}} \boldsymbol{Z_{i,t}})} \tag{2}$$

In the second stage, we estimate difference-in-differences regressions that incorporate the

[13] Given that only two countries implement on-close facilities, we limit the probit selection equation to call auctions.

[14] A country is categorized as either developed or emerging according to the criteria of the World Bank in the year of the change in closing mechanism.

selection-corrected inverse Mills ratios:[15]

$$\begin{aligned} Y_{i,t} = {} & \alpha_i + \gamma_t + \beta_1 Call_{i,t} + \beta_2 Onclose_{i,t} + \beta_3 Call_{i,t} \times Rand_{i,t} + \\ & \beta_4 Call_{i,t} \times Stab_{i,t} + \beta_5 Call_{i,t} \times Flex_{i,t} + \beta_6 Call_{i,t} \times Trans_{i,t} + \\ & \beta_7 \lambda(\hat{\boldsymbol{\beta}} \boldsymbol{Z_{i,t}}) + \varepsilon_{i,t}, \end{aligned} \tag{3}$$

where $Y_{i,t}$ is a market quality measure for stock i on day or month t (for daily metrics the time index are days and for monthly metrics the index are months). α_i and γ_t are stock and time fixed effects. $Call_{i,t}$ 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 $Onclose_{i,t}$ is a dummy variable that equals one if the exchange operates an on-close facility and zero otherwise. $Rand_{i,t}$ is a dummy variable set to one if the uncross time is randomized; $Stab_{i,t}$ is a dummy variable equal to one if the closing mechanism includes a price stabilization system; $Flex_{i,t}$ is a dummy variable that equals one if traders have the flexibility to modify or cancel their orders during the batching period; and $Trans_{i,t}$ is a dummy variable that equals one if the market's closing mechanism is transparent.[16]

Because the different markets in the sample change closing mechanisms at different times, adding stock and time fixed effectively provides a difference-in-difference estimator. For a given chance in closing mechanism, all other markets that do not experience a change at the same time serve as the implicit control markets.

5 Effects of closing mechanisms in the full sample

We first analyze the effects of introducing batch facilities on market quality for our entire sample, which allows us to draw general conclusions. In the next section, we analyze various partitions of the sample.

Table 4 presents the results of the fixed effects panel regressions for the market liquidity measures using the full sample. Following Petersen (2009) and Thompson (2011), the standard errors (reported in parenthesis) in this and all subsequent tables are robust to within-cluster error correlation in both the stock and time dimensions. To avoid over-

[15]In Section C of the Online Appendix we report the regression results for the simpler difference-in-differences regression model that excludes the selection-corrected inverse Mills ratios. The conclusions about the effects of batch facilities remain qualitatively unchanged.

[16]Equation 3 analyzes the effects of introducing batch facilities and, conditional on the market having a call auction in place, the relative contribution to market quality of the four different design features. In the regression, we exclude the interaction of the on-close facility variable (*Onclose*) with the design features due to the lack of variability in design across the two countries employing the on-close mechanism.

weighting exchanges with more securities, all regressions are weighted to limit the influence of countries with many stocks.[17]

[Insert Table 4 Here]

Consistent with Hypothesis 1, Table 4 shows that call auctions improve liquidity. Spreads experience a significant reduction: for the average call auction, the time weighted closing spread (*TWCS*) and the value-weighted *Effective Spread* fall by 13.3 bps and 11.7 bps, respectively. These reductions represent economically significant reductions in transactions costs - in comparison to the 'typical' stock, these represent reductions of 16% and 44%, respetively. In contrast to the findings of Aitken et al. (2005), our results also suggest that liquidity is not redistributed away from the last hours of trading towards the closing auction but, rather, that the introduction of a call auction is 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 of approximately 13%, both when accounting for the volume traded in the auction and, as reported in appendix results, also when excluding it.

In contrast, the introduction of an on-close facility appears to be mostly detrimental for market liquidity, with closing spreads significantly widening and daily trading values experiencing a significant reduction. The deterioration of liquidity further manifests in an increase in the impact of closing trades (*Closing Impact*), which comes as a result of the larger spreads and lower trading volumes. These detrimental effects could be explained by on-close facilities running parallel to the continuous trading session, which splits the order flow for a large portion of the day leading to larger spreads. Moreover, given that orders in on-close facilities are not executed until market close, the results potentially signal an inability of on-close facilities to attract sufficient activity early in the trading day.

Table 4 also provides evidence of the importance of auction design in explaining the impact of the auction on market quality. A call auction with a randomized ending time and, especially, with a price stabilization system in place, greatly improves the performance of the auction, consistent with Hypothesis 3. A closing call auction with a randomized closing time significantly increases daily traded volumes, leading to a reduced impact of closing trades. These results are consistent with the notion that market participants are more willing to trade at the close when the closing time is randomized because this feature makes it more difficult

[17] For exchanges with a number of stocks below 150 (the sample median), we assign a weight of one to each stock in that market. For exchanges where the number of stocks is 150 or greater, we set each stock's weight to 150/N, where N is the number of stocks in that particular market. This ensures the weight of each country is scaled so that its overall influence is as if it had 150 stocks. For robustness, we repeat the analysis using a threshold of 250 (the sample mean) obtaining similar results. The results for the robustness analysis are found in Section D of the online Appendix

to manipulate the closing price. Our findings are consistent with Malaga et al. (2010), who find that randomized closing times in internet auctions generate execution risk, minimizing manipulation ('sniping') at the close. Increased investor confidence in the integrity of the closing mechanism can lead to increased investor participation, as evidenced by the significant increase in daily traded values.

Price stabilization systems consistently benefit all measures of market liquidity and seem to be the most important design feature in improving auction performance. Relative to a closing call auction lacking any design features, the introduction of a call auction with a price stabilization system brings further reductions to all spread measures, increases daily trading volumes and decreases closing price impacts. Price stabilization systems constrain manipulative behavior within certain bands, diminishing the scope for price manipulation.

Flexibility is mostly beneficial, resulting in significant reductions for both spread measures and closing price impacts. The results are consistent with traders valuing the potential to freely react to the arrival of new information by canceling, submitting, or modifying their orders. However, our results also show that flexibility significantly reduces daily traded dollar volumes. As noted in Biais et al. (1999), giving traders the ability to modify or cancel their orders increases the risk of manipulative behavior during the auction, which generates uncertainty about the legitimacy of order imbalances and indicative closing prices. As a result, investors may be discouraged from participating, leading to a decrease in trading volume. That said, while flexibility decreases the daily traded volumes, the overall effect of introducing a flexible call auction is positive, as the reduction in trading volumes brought by flexibility is lower than the increase prompted by the introduction of the closing call auction. Further, the effects of flexibility are highly dependent on the level of development of the market, which we analyze in Section 6.

Lastly, Table 4 shows that transparency of orders and prices within a closing call auction is largely detrimental to market liquidity. A transparent auction, compared to a non-transparent one, is associated with large and significant increases in spreads and closing price impacts, as well as significant decreases in daily traded values. These results are consistent with the arguments of Biais et al. (1999) that traders are generally reluctant to participate in transparent auctions, preferring to conceal the information 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 tends to reduce participation at the close, leading to increased transaction costs.

Table 5 reports the results of the fixed effects regressions for price efficiency using the full sample. In line with Hypothesis 1, both call auctions and on-close facilities improve price efficiency by means of a reduction in the levels of intraday volatility. This result is consistent with the predictions of Foucault et al. (2005) and Roşu (2009) that by giving traders an additional opportunity to trade, closing batch facilities make liquidity demanders less aggressive, which reduces volatility. The drop in intraday volatility is also in line with Economides and Schwartz (1995), who note that the aggregation of liquidity in batch mechanisms facilitates the absorption of order imbalances and price impacts generated by large orders, leading to lower volatility. This reduction is not only statistically significant, but is also economically significant, representing a reduction of 9.8%.

[Insert Table 5 Here]

Table 6 reports regression results for the market integrity metrics. The consolidation of liquidity in call auctions makes it more difficult for either manipulators or large trades to distort closing prices away from their fundamental value. This aggregation of liquidity also reduces the profitability of manipulative strategies by increasing the execution costs and risk for traders attempting to manipulate the auction. In this vein, and consistent with Hypothesis 2, we find that the introduction of closing call auctions improves market integrity, with the *Reversal* metric experiencing a significant reduction of 6 bps (a reduction of 8.5% from the mean of 70 bps) and the probability of manipulation (*Manipulation Index*) experiencing a significant drop of 8.2% (representing a reduction of 20% when compared to the average probability of manipulation).

[Insert Table 6 Here]

In contrast, on-close facilities do not appear to be beneficial for market integrity. The previously-reported drop in liquidity and activity levels is probably driving this result given that, as argued in Ellul et al. (2005), a batch facility needs to attract enough order flow in order to function well. Failure to do so makes the mechanism sensitive to order imbalances and facilitates manipulative behavior.

When it comes to auction design, randomization and price stabilization systems increase volatility levels, which is likely explained by the greater trading activity and increase in liquidity brought about by these two design features. While the mere introduction of a closing call auction does not lead to a significant drop in the variance ratios (*Amihud VR* and *LoMacKinlay VR*) or the rate at which information is incorporated into prices (*Delay*), Table 5 shows statistically significant reductions in these metrics when the call auction incorporates a randomized closing time or a price stabilization system. The impossibility of marking the close due to the uncertainty in the closing time, and the constraints to manipulation brought about by price stabilization systems, are likely to discourage manipulative activity. As a result, price efficiency improves, as evidenced by the reduction in price pressures (*Amihud VR* and *LoMackinlay VR*) and the faster incorporation of information into prices (*Delay*).

The use of price stabilization mechanisms additionally brings large and significant improvements to market integrity. Price stabilization systems not only reduce price pressures from large order imbalances (as indicated by the reduction in the reversal metrics), but it also further reduces the probability of manipulation by about 9.0%, relative to a call auction with no design features in place. These results are consistent with the arguments of Félez-Viñas and Hagströmer (2021) that manipulators are discouraged from distorting prices when stabilization systems are in place as they wish to avoid triggering the pre-close volatility curbs, particularly given the costs associated with maintaining altered prices over an extended period of time.

Flexibility to cancel and amend closing auction orders tends to be beneficial for both price efficiency and market integrity. Flexibility in a call auction is associated with lower intraday volatility, reduced delay in information incorporation, and a decrease in price reversals. These results are consistent with the notion that allowing traders to modify and cancel closing orders encourages them to reveal more information with their closing orders, leading to improved price discovery.

On the other hand, flexibility increases the probability of manipulation by 4.1% compared to an inflexible closing call auction. The net effect of introducing a flexible call auction is still positive, given that the increase in the *Manipulation Index* brought by flexibility is lower than the drop prompted by the introduction of the closing call auction. The increase in the probability of manipulation implies that it provides manipulators with a greater ability to pursue manipulative strategies. While flexibility allows traders to react to new information, it also enables them to game the auction, which may be especially problematic in poorly monitored markets with low levels of regulatory enforcement.

Finally, the results presented in Tables 5 and 6 show that transparency of closing auction prices and orders is largely detrimental for price efficiency and market integrity. If, as previously reported, transparency results in a reduction of liquidity and discourages traders from participating in the auction, this is likely to harm the price discovery process because an auction needs sufficient liquidity to generate efficient closing prices. In this vein, the significant increase in *Delay* indicates that, with a transparent auction, it takes a longer time for prices to incorporate new information. The increase in the *LoMackinlay VR* also tells us that closing prices become more inefficient, given that they experience greater price pressures. The lack of participation also hinders the ability of the auction to absorb large order imbalances and facilitates manipulative behavior, as indicated by the significant increase in all reversal measures and the *Manipulation Index*.

6 Do the effects of closing mechanisms vary across markets and stocks?

Our analysis includes 45 exchanges in a wide variety of global markets. Differences in how closing mechanisms impact developed versus emerging markets are likely to be driven by their varied levels of regulatory enforcement and differences in trading protocols and market participants. The effects of closing 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 such potential differences across stocks and markets, we partition our sample into *developed* and *emerging* markets, and we further partition stocks into *liquid* versus *illiquid* securities. A country is categorized as either developed or emerging according to the criteria of the World Bank in the year of the change in closing mechanism. Similarly, a stock is classified as liquid or illiquid based on the pre-period trading volumes and number of inactivity days. A stock is classified as liquid if its inactivity levels are below the exchange's mean and its trading volume above, otherwise the stock is categorized as illiquid.[18] We use the same difference-in-differences panel regression models as in the full sample, but here we estimate the models using subsamples: developed and emerging markets and liquid and illiquid securities.

Table 7 reports the effects of introducing batch mechanisms on market liquidity for the liquid and illiquid securities of developed markets. Consistent with Hypothesis 1, and in line with the results obtained for the broad sample, Table 7 confirms the overall positive effects on market liquidity of introducing a call auction in developed countries. The results make evident the importance of auction design in developed markets, especially for their illiquid securities, where it is the design features, rather than the introduction of a call auction alone, that drives the beneficial effects on market liquidity. When it comes to on-close facilities, only developed markets employ them, and the results are in line with those of the main analysis without any large differences emerging between liquid and illiquid stocks.

[18]For robustness, we partition stocks into liquid and illiquid based on medians rather than means, and using volatility rather than inactivity levels. The conclusions remain unchanged.

[Insert Table 7 Here]

Liquid securities in developed countries especially benefit from a randomized closing time, with this design feature being consistently associated with enhanced performance of the call auction. The use of price stabilization systems is also beneficial, as it significantly reduces $TWCS$ and contributes to the creation of new liquidity as shown by the positive and significant estimates of the daily trading volumes. However, the magnitude of the effects are smaller than those observed in the full sample. Price stabilization systems are only triggered in cases of extreme price movements. In developed markets, where securities regulation is highly enforced and volatility is lower than in emerging countries, stabilization systems are seldom triggered, which is likely why this feature makes a relatively lower contribution. The results are consistent with the notion that in a highly monitored and regulated market, traders are less likely to perceive flexibility as a tool to manipulate markets, and rather as an instrument that allows them to modify their orders in the event that new information arrives at the market immediately prior to the close. As in the main analysis, transparency remains largely detrimental to market liquidity.

Illiquid securities in developed countries strongly benefit from having randomization, price stabilization systems, and flexibility in the closing call auction. Transparency, in contrast, is harmful for illiquid stocks, with all measures experiencing a large and significant deterioration.

Table 8 reports the price efficiency results of introducing batch mechanisms in developed markets for both liquid and illiquid securities. While the results show noticeable similarities with those from the full sample, this subsample analysis generates two additional takeaways: (i) auction design is important, as it is the design features (rather than the mere introduction of a call auction), that drives the improvements in closing price efficiency and (ii) illiquid stocks benefit the most from having in place appropriate design features. While a call auction devoid of the four features does not generally bring significant gains in the price efficiency of illiquid stocks, it drives significant improvements when the call auction incorporates randomization, flexibility or price stabilization systems. As argued by Schwartz (2000), an auction requires sufficient liquidity to generate efficient prices, which could prove particularly difficult for illiquid stocks. As reported in the liquidity regressions, randomization, flexibility and price stabilization systems bring significant liquidity improvements for illiquid securities. Finally, transparency continues to be associated with significantly less efficient prices for illiquid stocks.

[Insert Table 8 Here]

The importance of auction design is similarly underscored in Table 9, which reports the results of the market integrity regressions for developed markets. Randomization, price stabilization systems, and flexibility remain important contributors to market integrity for both liquid and illiquid stocks. The results support the notion that having in place a closing call auction with randomization, price stabilization systems and flexibility, alleviates price pressures from large order imbalances at the close (as shown by the reversal estimates), and reduces the probability of closing price manipulation (as reported by the *Manipulation Index*).

[Insert Table 9 Here]

Lastly, we examine the effects of introducing closing auctions in emerging markets.[19] Table 10 presents the effects on market liquidity for the liquid and illiquid securities. Consistent with Hypothesis 1, Table 10 corroborates the beneficial impact on market liquidity of introducing a call auction in emerging markets. Both liquid and illiquid stocks experience large and statistically significant improvements from the change in closing mechanism. With the introduction of a call auction devoid of design features, all spread measures fall, closing price impacts diminish, and new liquidity enters into the market as signalled by the increase in daily traded volumes. Although all securities are better off with the new closing mechanism, consistent with Madhavan (1992), it is the illiquid stocks that benefit the most, experiencing overall larger effects relative to liquid securities.

[Insert Table 10 Here]

When it comes to auction design, an important takeaway is that what works for developed markets does not necessarily apply to emerging ones. Compared to developed countries, the use of price stabilization systems plays a more central role than randomization in improving the performance of the auction in emerging markets. This difference may be explained by the lower levels of regulatory enforcement and monitoring by market participants in these countries. As a result, emerging markets benefit particularly from an auction design that actively constrains manipulative behavior without the need for regulatory oversight, as is the case for price stabilization systems.

In contrast with the results for developed markets, flexibility is not a desirable design feature in emerging markets, especially for illiquid securities, where it significantly contributes to wider spreads, lower trading volumes, and increased price impacts. This result is consistent

[19] As discussed in Section 3.2, some exchanges in the emerging countries of our sample changed from using the last traded price in the continuous trading session to a VWAP of the last trades prior to close. As an additional test for our emerging markets subsample, Section E in the Online Appendix shows regression results for an alternative specification of our Difference-in-Differences regression model that includes a VWAP dummy.

with the idea that in countries with limited enforcement of securities regulation and minimal monitoring, flexibility is likely perceived by market participants as a tool that facilitates the manipulation of the auction, which discourages overall market participation. In line with the arguments of Biais et al. (1999) and Domowitz and Madhavan (2001), transparency is found to be detrimental for market liquidity in emerging countries, as the fear of revealing information to other market participants discourages participation. As shown in Table 2, a majority of the emerging markets that introduced call auctions have transparency or flexibility in place, which when used in combination, completely undermine the performance of the auction, negating its associated benefits.

Table 11 reports the price efficiency results of introducing closing auctions in emerging markets for both liquid and illiquid securities. The introduction of closing auctions enhances price efficiency for emerging markets, although the coefficient estimates are predominantly weakly statistically significant. Moreover, while auction design plays an important role in improving price efficiency for developed markets, these findings do not translate to emerging ones. A possible explanation is that despite the increase in market liquidity, emerging markets still lack enough liquidity to fully realize gains from the beneficial aggregation effects of closing auctions, which is needed in order to generate efficient closing prices (Schwartz, 2000). Given the preference of emerging markets to adopt transparency and flexibility features in their auctions, the lack of auction participation could, in many cases, be due to an inappropriate choice of design features.

[Insert Table 11 Here]

Lastly, Table 12 reports the results of the market integrity regressions for emerging markets. The introduction of a call auction in emerging markets, absent any design features, is associated with a significant improvement in the integrity measures, with all return reversal metrics experiencing a significant decline and, for the liquid securities, the probability of closing price manipulation also diminishing.

[Insert Table 12 Here]

When it comes to auction design, the results are less conclusive than in the liquidity regressions, but generally point in the same direction. Price stabilization systems are associated with a significant reduction in *Reversal*s and in the probability of price manipulation in liquid securities of about 10.5%. Randomization appears to be detrimental, although the overall net effect is generally positive, as the reduction in market integrity brought by randomization tends to be small enough to not wipe out the benefits of the auction. The results for randomization potentially reflect the lack of the liquidity required in these markets to take full advantage of the benefits reported for developed countries. If an auction does not attract enough liquidity, it is likely that the design features do not bring about improvements in its performance. Finally, the results suggest that flexibility and transparency are undesirable design features, as they commonly lead to increased reversals and a higher probability of manipulation (*Manipulation Index*). Adopting these design features discourages participation, making the call auction more sensitive to the effects of large order imbalances and manipulative behavior.

7 Conclusion

Many stock exchanges around the world have moved from simple closing mechanisms such as using the last trade price(s) at a specific time to closing auctions with a variety of design features. In a global sample of 45 exchanges we find that call auctions generally improve market quality relative to last-trade mechanisms. In contrast, we do not find similar benefits for the on-close facilities, although we caution that we have far fewer observations in which on-close facilities are adopted. These findings help explain why so many exchanges are choosing to adopt closing call auctions and why they have become the most popular approach to closing stock exchanges in almost all developed markets and many emerging markets too.

The second key takeaway is that auction design matters. Not all auctions are effective. For example, we find that randomized closing times and price stabilization systems significantly enhance the performance of closing auctions with respect to market liquidity, price efficiency and market integrity. Flexibility is also generally beneficial for market quality, although a deeper subsample analysis indicates that this is mainly the case for developed markets. In contrast, our results suggest transparency in closing auctions is generally detrimental for most measures of market quality.

The third main takeaway is that when it comes to closing mechanisms, it is not the case that "one size fits all". In developed countries, all aspects of market quality are improved on average by the introduction of a call auction that incorporates randomization, stabilization systems, and flexibility, especially in illiquid securities. In emerging markets, closing call auctions substantially improve market liquidity but have less of an effect on market integrity and price efficiency. The commonly used features of flexibility and transparency tend to decrease the performance of closing auctions in emerging countries.

Our results provide guidance to global exchanges and regulators on how to structure call auctions. Our results may also provide guidance for design considerations in other types of auctions such as new venues that abandon traditional continuous double-auction designs in favor of frequent batch auctions. Our results suggest that it is not sufficient to "ring" the closing bell, rather it is imperative that consideration is given to the details around how it is "rung".

Appendix A: Measures of market quality

A.1: Liquidity measures

Our first measure of liquidity, *Closing Spread*, is calculated for each stock i and day t in basis points. We define *Closing Spread* as

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

where $Spread_{i,t,close}$ is the difference between the best ask and bid prices at the closing of the continuous trading session and $Midpoint_{i,t,close}$ is the bid-ask midpoint at the closing of the continuous trading session. We also calculate a restricted version of the *Closing Spread* (*Restricted Closing Spread*), where we only include the spread observation if the quotes are updated within the last three hours of the continuous trading session. We include these two measures of liquidity in our robustness estimations.

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 first key metric of liquidity, the time-weighted closing spread ***(TWCS)***, is computed for each stock and day as the average relative quoted spreads in the last two hours of the continuous trading session.[20]

To estimate the transaction costs for liquidity demanding traders we use the value-weighted ***Effective Spread*** as our next measure of liquidity. The *Effective Spread* is calculated in basis points for trades that occur in the last two hours of the continuous trading session both including and excluding the auction. The specification of *Effective Spread* that includes (excludes) auction trades constitutes another of our key (robustness) liquidity metrics. We define the effective spread for transaction τ as

$$Effective\ Spread_{\tau} = \frac{|Price_{\tau} - Midpoint_{\tau}|}{Midpoint_{\tau}} \tag{5}$$

where $Price_{\tau}$ is the transaction price and $Midpoint_{\tau}$ is the prevailing midpoint at the time of the trade. As transactions during the auction will have a transaction price equal to the midpoint, the effective spread will be zero. The effective spread is then weighted by the

[20] Metrics in bold constitute our "key metrics" of market quality and integrity. Regression tables in the main paper report estimates using these metrics. We calculate the remaining metrics for robustness and their regression results are reported in Section B of the Online Appendix.

dollar value of the transaction.[21] If liquidity demanding traders trade less aggressively after the implementation of a closing auction, we expect the value-weighted effective spread to decrease in the post period. Traders would therefore pay lower transaction costs as predicted by Foucault et al. (2005) and Roşu (2009).

The next metric we use to measure liquidity is a measure of the value of trading activity that we refer to as ***Value***. We include this metric to estimate whether the introduction of the closing auction creates new trading activity or simply shifts activity from the continuous trading session to the auction. We calculate *Value* including and excluding the auction volume, the former (later) being another of our key (robustness) liquidity metrics, as:

$$Value_{i,t} = \frac{V_{i,t}}{\overline{V_i}} \tag{6}$$

where $V_{i,t}$ is the daily dollar volume traded during continuous trading, including or excluding the auction, for security i in day t and $\overline{V_i}$ is the average dollar volume for security i during the pre- and post-event periods.

If a closing call auction does not create new liquidity but simply redistributes it from the end of continuous trading to the call auction, we expect a negative relation between the batch facility and trading activity excluding the auction volume. Alternatively, if the closing batch facility positively impacts trading activity, this indicates that the change in the closing mechanism generates new liquidity.

Finally, we use an adaptation of the Amihud (2002) illiquidity metric, the ***Closing Impact***, as our last key measure of liquidity:

$$Closing\ Impact_{i,t} = \frac{|R_{i,t,close}|}{Value_{i,t,close}} \tag{7}$$

where $R_{i,t,close}$ is the return from the prevailing midpoint two hours before the close to the closing price. The closing price is the transaction price of the last trade during the continuous trading session or the auction price. $Value_{i,t,close}$ is the dollar volume of trading during the last two hours of the day, including the auction if there is one.

If the introduction of a closing auction consolidates liquidity and mitigates large order imbalances and price impacts, we expect a negative relation between *Closing Impact* and the introduction of the auction.

[21] To reduce the effects of large outliers we limit the values of all our spread measures to 2,000 bps.

A.2: Price efficiency measures

Our first key measure of price efficiency is ***Intraday Volatility***, which we define as

$$Intraday\,Volatility_{i,t} = \frac{(High_{i,t} - Low_{i,t})}{\frac{(High_{i,t}+Low_{i,t})}{2}} \tag{8}$$

where $High_{i,t}$ and $Low_{i,t}$ are security i's highest and lowest daily trade prices on day t. The metric is normalized by the average intraday volatility of the stock during the pre- and post-event periods.

Schwartz (1995) notes that consolidated liquidity incorporates the beliefs of many traders, which reduces the influence of manipulative orders and individual noise trades and contributes to greater price efficiency. Additionally, the consolidation of liquidity diminishes large order imbalances further improving price efficiency (Economides and Schwartz, 1995). If the consolidation of liquidity in a closing auction improves price efficiency, we expect the intraday volatility to decrease, as the effect of manipulative orders and the impact of order imbalances and noise trades should decline.

In the absence of transitory volatility, the variance of 24-hour stock returns should be the same, regardless of the time of the day when stock prices are sampled. To test if this holds we estimate our second key metric of price efficiency, the variance ratio introduced by Amihud and Mendelson (1987) (***Amihud VR***), which is defined as

$$Amihud\,VR_{i,m} = \frac{VAR(ln(Price^{Close}_{i,t+1}) - ln(Price^{Close}_{i,t}))}{VAR(ln(Price^{Open}_{i,t+1}) - ln(Price^{Open}_{i,t}))} - 1 \tag{9}$$

where $Price^{Close}_{i,t}$ is the price of the last trade during the continuous trading session or the auction price for security i on day t and $Price^{Open}_{i,t}$ is the midpoint one hour after the market opens. The variance is calculated based on daily returns resulting in a variance ratio for month m.

A variance ratio greater than unity indicates that the transitory volatility in the closing price returns exceeds that of the opening price returns. If the introduction of a closing batch auction makes prices more efficient, we expect transitory volatility in the closing price to decrease and the *Amihud VR* to converge towards unity.

Our next measures of price efficiency are the *Closing* and *Opening Autocorrelation*, which are metrics that we calculate for robustness and that we define as the absolute autocorrelation of close-to-close or open-to-open returns. For the *Closing Autocorrelation*, returns are calculated in basis points using the price of the last trade during the continuous trading session or the auction price. For the *Opening Autocorrelation*, the opening price used to calculate returns is defined as the prevailing midpoint one hour after the opening of the continuous trading session. The autocorrelation is computed using daily returns for each stock-month *i,m*. If price efficiency improves after introducing a closing auction, we expect a decrease in the autocorrelation metrics.

Our third key metric of price efficiency measures the extent to which lagged market returns predict a stock's closing returns by adapting the *Delay* metric by Hou and Moskowitz (2005) to an intraday setting. To calculate ***Delay*** we first estimate the following regression:

$$\begin{aligned} Return_{i,t} = \beta_0 + \beta_1 MarketReturn_t + \beta_2 MarketReturn_{t-1} \\ +\beta_3 MarketReturn_{t-2} + \beta_4 MarketReturn_{t-3} + \epsilon_{i,t} \end{aligned} \tag{10}$$

where $Return_{i,t}$ is the close-to-close return in basis points using the last traded price during the continuous trading session or the auction price for security i on day t, and $MarketReturn_t$ is the close-to-close return of the market index. The regression is estimated with (*Unconstrained*) and without (*Constrained*) the lagged market returns. We save the R^2 estimates of the two regressions $R^2_{Constrained}$ and $R^2_{Unconstrained}$ from which we calculate *Delay* as:

$$Delay_{i,m} = 1 - \frac{R^2_{Constrained}}{R^2_{Unconstrained}} \tag{11}$$

The *Delay* metric takes a value between zero and one. The higher the *Delay* the more variation in stock returns can be explained by lagged market returns, indicating that market-wide information is only slowly incorporated into the stock's price, suggesting lower informational efficiency. If the introduction of a closing auction improves price efficiency, we expect a decrease in *Delay*.

The last price efficiency metric measures whether stock prices follow a random walk and thus whether the variance of the stock returns is a linear function of the measurement frequency. We estimate ***LoMacKinlay VR***, the variance ratio introduced by Lo and MacKinlay (1988) and applied to intraday data by Foley and Putniņš (2016):

$$LoMacKinlay\, VR_{k,l} = \left| \frac{\sigma^2_{kl}}{k\sigma^2_l} - 1 \right| \tag{12}$$

where σ^2_l and $\sigma^2_{k,l}$ are variances of the *l-day* and *kl-day* close-to-close returns in basis points for a given stock day. The closing price is the last traded price during continuous trading or the auction price. We use the *k,l* combination of 1-day and 3-day returns for our last key metric of price efficiency, and of 1-day and 5-day returns for our robustness metric.

If the variance of three-day (five-day) returns is higher or lower than three (five) times the variance of one-day returns, price dynamics depart from a random walk, indicating inefficiency in prices. Given the predicted improvement in price efficiency following the introduction of a call auction, we expect the *LoMacKinlay VR* to decrease in the post-event period.

A.3: Integrity measures

We use four measures of market integrity, the first of which is the *Traditional Return Reversal*, a metric that we calculate for robustness. *Traditional Return Reversal* measures the price change between the closing price on day t and the opening price on day t+1. If market manipulation is present, closing prices usually display an upward spike that reverses the following day, resulting in a return reversal. We define *Traditional Return Reversal* as

$$Traditional\ Return\ Reversal_{i,t} = ln(\frac{Price_{i,t}^{Close}}{Price_{i,t+1}^{Open}}) \tag{13}$$

where $Price_{i,t}^{Close}$ is the last traded price of the continuous trading session or the auction price of security i on day t and $Price_{i,t+1}^{Open}$ is the midpoint one hour after the market opens for security t on day *t+1*. If the introduction of a closing auction consolidates liquidity, large trades will have a smaller price impact and the price will deviate less from the fundamental value. This makes it more costly and risky for manipulators to attempt to manipulate the closing price. We therefore expect the *Traditional Return Reversal* measure to decrease when a closing auction is introduced as the price should deviate less from the fundamental value at the time of the close and thus reverse less at the open the next day.

To capture the possibility that closing prices could also be manipulated downward, and to eliminate close-to-open returns that are the result of return continuations rather than reversals, we construct a new ***Reversal*** metric that constitutes our first key measure of market integrity:

$$Reversal_{i,t} = max(Reversal^{+}, Reversal^{-}) \tag{14}$$

where the components are defined as follows:

$$Reversal^{+} = min(max(0, R_1), max(0, R_2)) \tag{15}$$

$$Reversal^{-} = min(max(0, -R_1), max(0, -R_2)) \tag{16}$$

$$R_1 = log(Price_{i,t}^{Close}) - log(Price_{i,t}^{Midday}) \tag{17}$$

$$R_2 = log(Price^{Close}_{i,t}) - log(Price^{Midday}_{i,t+1}) \tag{18}$$

$Price^{Close}_{i,t}$ is the price of the last trade during the continuous trading session or the auction price for security i and day t and $Price^{Midday}_{i,t}$ is the prevailing midpoint halfway through the continuous trading session. We expect the *Reversal* measure to be negatively related to the introduction of a closing auction if manipulation of the closing prices becomes more difficult as liquidity is consolidated.

As the *Reversal* metric may be positively related to volatility we create a measure based on the *Reversal* but removing the reversals caused by volatility to isolate the reversals that are due to manipulation. Since closing price manipulation usually occurs in the upward direction (Comerton-Forde and Putniņš, 2011a), we construct our second key metric of integrity, ***Reversal Asymmetry***, which measures the extent to which the reversals occur disproportionately for positive closing returns for security i, in month m:

$$Reversal\ Asymmetry_{i,m} = \frac{mean(Reversal^{+})}{mean(Reversal^{+}) + mean(Reversal^{-})} \tag{19}$$

where $Reversal^{+}$ and $Reversal^{-}$ are defined in Equation (15) and (16) respectively. We expect the *Reversal Asymmetry* measure to decrease in the post-event period if the introduction of a closing auction reduces closing price manipulation. For robustness, we construct an alternative measure of *Reversal* and *Reversal Asymmetry* by substituting $Price^{Midday}_{i,t}$ by $Price^{VWAP}_{i,t}$ in Equations (17) and (18). $Price^{VWAP}_{i,t}$ is the daily volume weighted average price during the continuous trading session and the closing auction, if there is one.

Lastly, we use the probability index of closing price manipulation of Comerton-Forde and Putniņš (2011a) as our last key metric of market integrity. Using a sample of prosecuted manipulation cases, the authors identify four trading variables that are systematically affected by closing price manipulation: closing returns, trading frequency, spreads, and return reversals. Consistent with Comerton-Forde and Putniņš (2011a) we calculate *Return Reversal* following equation (13), *Closing Spread* following equation (4) and *Closing Returns* as the natural logarithm of security i's closing price divided by its midpoint at the close.[22]

To remove time- and stock-specific effects we use the difference-in-difference technique adopted by Comerton-Forde and Putniņš (2011a). Each stock's daily observation is compared against a benchmark period of 42 trading days lagged by 250 trading days (approximately one year), which ensures that each stock's daily observation in the post-event period is always compared to a benchmark day in the pre-event period. Again following Comerton-Forde and

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

Putniņš (2011a), we standardize the difference-in-difference indicators against the security's prior trading characteristics using sign statistics. The sign statistic controls for changes in a stock's day-end variable patterns over time and prevents relatively illiquid and volatile stocks form being unduly penalized by the manipulation index measure:

$$S_j = \frac{n_+ - n_-}{2} \tag{20}$$

where S_j is the sign statistic for variable j (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 days prior to day t. Therefore, a stock's sign statistic is bound between +21 and -21. 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. The sign statistics are expected to be significantly positive for manipulated stock-days and zero, on average, otherwise.[23]

From the sign statistics we compute the ***Manipulation Index*** similar to Comerton-Forde and Putniņš (2011a):

$$ManipulationIndex = \frac{1}{1 + e^{-(-7.5 + 4S_{return} + 4S_{reversal} + 4S_{spread})}} \tag{21}$$

where S_{return}, $S_{reversal}$, and S_{spread} are the stock-day sign statistics for the stock's *Closing Returns*, *Return Reversal*, and *Closing Spread*. To compute the manipulation index, Comerton-Forde and Putniņš (2011a) estimate 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. While the methodology by Comerton-Forde and Putniņš (2011a) is calibrated for the US and Canadian equity markets, our analysis uses global data from 45 markets. To avoid biasing the results for, or against the US and Canadian markets, we use instead equal factor loadings for each of the index components for our key metric.

If closing auctions makes it more difficult, costly, and risky for manipulators to affect the closing price, we expect the manipulation index to have a negative relation with the introduction of a closing auction.

[23] Comerton-Forde and Putniņš (2011a) also remove any market wide trends by taking the difference between the stock-day sign statistic and the market wide sign statistic for that day. However, our analysis aims to capture changes in market wide manipulation and then relate it to changes in the closing price mechanism. We therefore skip this step in constructing the manipulation index.

Finally, for robustness, we use two alternative specifications of the *Manipulation Index* developed by Comerton-Forde and Putniņš (2011a). The first one, the *Original Manipulation Index*, uses as input to construct the index the four original coefficients used in Comerton-Forde and Putniņš (2011a). The second one, *Simple Manipulation Index*, excludes trading frequency as one of the coefficients given that in the auction all trading takes place simultaneously. The metrics are calculated as follows:

$$Original\ Manipulation\ Index = \frac{1}{1 + e^{-(-7.5+4.2S_{return}+3.6S_{reversal}+8.5S_{frequency}+1.8S_{spread})}} \quad (22)$$

$$Simplified\ Manipulation\ Index = \frac{1}{1 + e^{-(-7.5+4.2S_{return}+3.6S_{reversal}+1.8S_{spread})}} \quad (23)$$

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Figure 1: Types of closing mechanisms

This figure illustrates the three alternative mechanisms that are used to end the trading day. Panel A depicts the structure of a *last-trade mechanism*, where the closing price is based on the price of the last trade in the continuous trading session. Panel B shows the functioning of *on-close facilities*. When an on-close facility is in place, the continuous trading session runs parallel to the batch facility, where market-on-close (MOC) and limit-on-close (LOC) orders may be entered until a pre-specified time before the close where the order imbalance is disseminated. From that time on, only offsetting orders can be placed to counteract any buy-sell imbalances. Panel C presents the structure of a *call auction* together with its possible design features. The non-trade batching phase of the call auction starts immediately after the end of the continuous trading session. Liquidity is consolidated during this phase. If *transparent*, the batching phase depicts order book and indicative price information to market participants and if *flexible*, traders have the ability to modify and cancel their orders. The batching phase may also incorporate *stabilization systems* such as volatility extensions, which extend the duration of the batching period if the closing price would otherwise fall outside a certain threshold. Orders are executed at the same point in time, the uncross, at a single closing price that balances supply and demand. The uncross time may be *randomized*, in which case the closing time falls within a pre-specified interval of time.

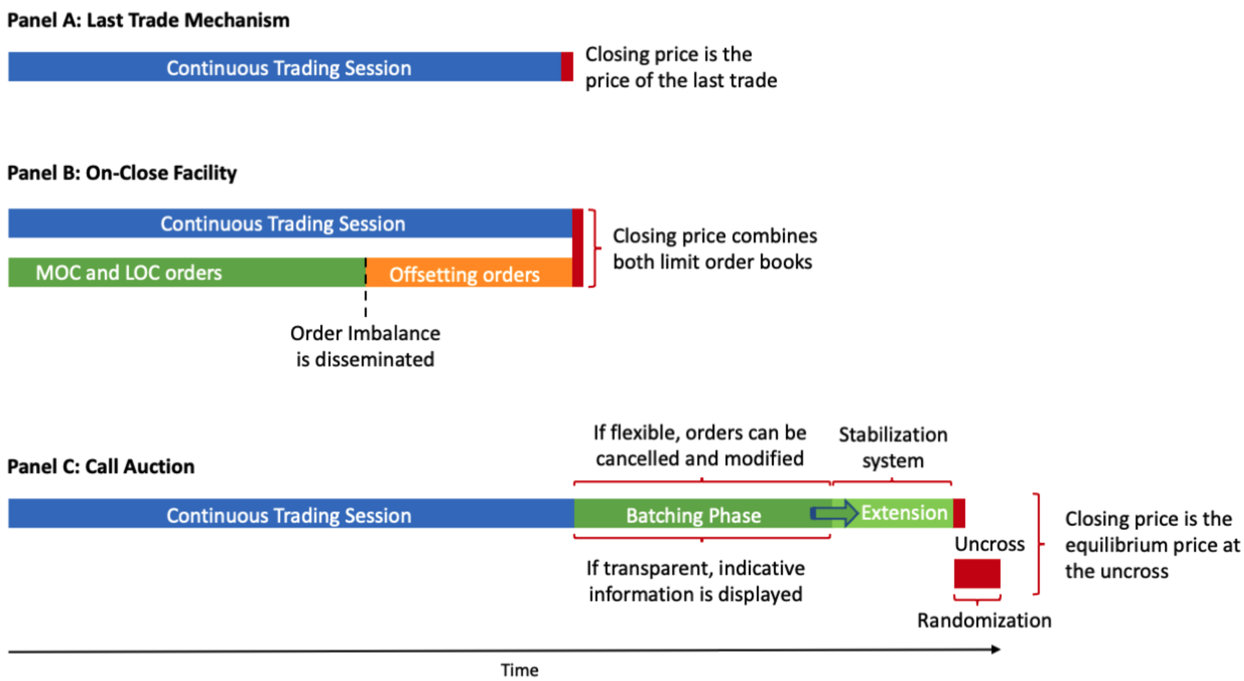

Figure 2: Evolution of closing mechanisms
This figure presents the evolution from 1996 until 2014 of the closing mechanism in place across the 45 markets of our sample.

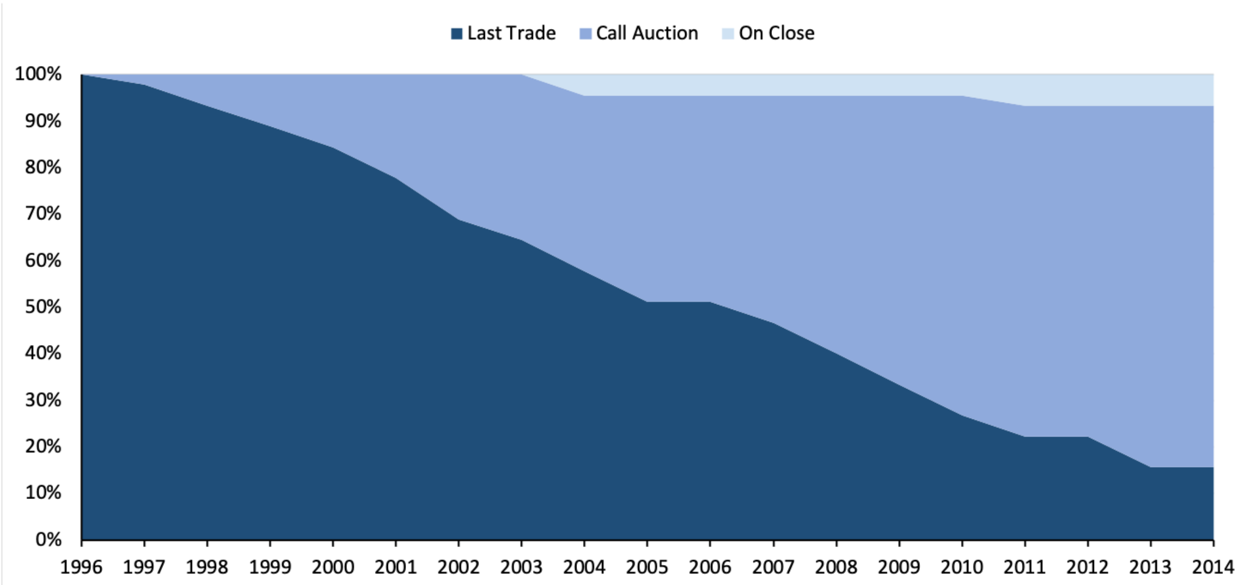

Table 1: Sample characteristics of developed markets

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. *Event Date* is the date when the exchange made the most recent substantial change to their closing mechanism. The table provides information on the number of stocks in our sample for each exchange (*Number of Stocks*) and the total number of stock-day observations (*Number of Stock-Days*). The table also presents details of the closing mechanism for each exchange as at June 2014 and the accompanying design features. The variable *VWAP* denotes a closing mechanism based on a VWAP of the last trades of the continuous trading session. *Call* denotes a call auction and *Onclose* the on-close facility. *Stab*, *Rand*, *Flex* and *Trans* correspond to the four design features that are potentially in place in a batch mechanism; namely, stabilization systems, randomization, flexibility and transparency, 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	Event Date	Number of Stocks	Number of Stock-Days	VWAP	Call	Onclose	Stab	Rand	Flex	Trans
Australia	ASX	10/02/1997	771	311399	0	1	0	0	0	1	0
Austria	VSX	5/11/1999	60	50659	0	1	0	0	1	1	1
Canada	TSX-V	12/12/2011 - 09/01/2012	69	64679	0	0	1	1	0	1	0
Canada	TSX	29/3/2004 - 12/09/2005	154	148604	0	0	1	1	0	1	0
Cyprus	CYP	15/06/2009	57	44159	0	1	0	0	1	1	1
Czech Republic	PRA	11/05/2009	13	12368	0	1	0	1	1	0	1
Denmark	CPH	4/04/2005	132	124309	0	1	0	0	1	1	1
England	LSE	30/05/2000	184	163556	0	1	0	1	1	1	1
Finland	HEX	27/09/2004	111	104797	0	1	0	0	1	1	1
France	XPAR	2/06/1998	163	156051	0	1	0	0	0	1	1
Greece	ATH	28/11/2005	285	271995	0	1	0	1	1	1	1
Iceland	ICX	24/03/2003	6	4875	0	1	0	1	1	1	0
Ireland	ISE	1/07/2002	42	36502	0	1	0	1	1	1	1
Israel	TASE	30/07/2007	441	304709	0	1	0	0	1	1	1
Italy	BIA	3/12/2001	267	242726	0	1	0	1	0	0	0
Netherlands	AEX	29/10/2001	146	137144	0	1	0	1	0	1	1
New Zealand	NZX	6/07/2007	121	106896	0	1	0	0	1	1	1
Norway	OSL	14/02/2003	107	100741	0	1	0	1	1	1	1
Qatar	QAE	10/09/2010	37	28349	0	1	0	0	0	0	1
Russia	MCX	2/09/2013	271	249985	0	1	0	1	1	1	1
Singapore	SGXI	21/08/2000	310	276795	0	1	0	0	0	1	1
Slovenia	LJU	6/12/2010	26	22071	0	1	0	0	1	0	1
Sweden	STO	1/05/2002	251	235327	0	1	0	0	1	1	1
Switzerland	SIX	2/11/1998	331	311571	0	1	0	1	1	0	1
Taiwan	TWSE	1/07/2002	485	458185	0	1	0	0	0	1	0
UAE	ADX	2/01/2013	30	22145	0	1	0	1	0	1	0
USA	NASDAQ	16/12/2004	1900	1835480	0	0	1	1	0	0	1
Total	27	-	6770	5826077	0	24	3	14	16	21	20

Table 2: Sample characteristics of 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. *Event Date* is the date when the exchange made the most recent substantial change to their closing mechanism. The table provides information on the number of stocks in our sample for each exchange (*Number of Stocks*) and the total number of stock-day observations (*Number of Stock-Days*). The table also presents details of the closing mechanism for each exchange as at June 2014 and the accompanying design features. The variable *VWAP* denotes a closing mechanism based on a VWAP of the last trades of the continuous trading session. *Call* denotes a call auction and *Onclose* the on-close facility. *Stab*, *Rand*, *Flex* and *Trans* correspond to the four design features that are potentially in place in a batch mechanism; namely, stabilization systems, randomization, flexibility and transparency, 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	Event Date	Number of Stocks	Number of Stock-Days	VWAP	Call	Onclose	Stab	Rand	Flex	Trans
Brazil	BRA	16/06/2008	206	172243	0	1	0	1	0	0	1
Chile	SGO	2/01/2004	72	60335	1	0	0	0	0	0	0
China	SHZ	3/07/2006	581	528011	1	0	0	0	0	0	0
China	SHH	3/12/2001	461	413971	0	1	0	0	1	0	0
Hungary	BUD	3/10/2005	31	28657	0	1	0	1	1	1	1
India	NSE	9/06/1999	746	654891	1	0	0	0	0	0	0
Indonesia	IDX	2/01/2013	323	299494	0	1	0	0	0	1	0
Jordan	AMM	23/03/2009	164	114281	0	1	0	0	1	1	1
Macedonia	MKE	4/01/2010	12	10078	1	0	0	0	0	0	0
Malaysia	KLS	1/12/2008	875	835825	0	1	0	0	0	1	1
Pakistan	KAR	14/02/2011	423	367894	1	0	0	0	0	0	0
Peru	LMA	3/01/2011	121	72053	0	1	0	1	1	1	1
Philippines	PSE	26/07/2010	162	148671	0	1	0	1	0	1	0
Romania	BUH	23/04/2008	44	38317	0	1	0	0	0	1	1
South Africa	JNB	13/05/2002	231	204957	0	1	0	1	1	1	1
Sri Lanka	CSE	1/09/2000	69	53386	1	0	0	0	0	0	0
Thailand	SET	6/09/1999	260	230034	0	1	0	0	1	1	0
Ukraine	UAX	12/04/2012	35	33224	1	0	0	0	0	0	0
Total	18	-	4816	4266322	7	11	0	5	6	9	7

Table 3: Selection Equation

This table presents estimates from the probit model of the likelihood an exchange introduces a call auction as its closing mechanism. The dependent variable *Call* is a dummy variable equal to one if the exchange introduces a closing call auction and 0 otherwise. The variable *Volume* is the lagged average dollar traded volume per stock. *Developed* is a dummy variable that equals one for exchanges that belong to developed countries and zero for emerging. *Number of Stocks* is the lagged number of stocks in an exchange. *Exchange Liquidity* is computed as the lagged average closing spread of all stocks in an exchange on a certain day and *Exchange Efficiency* as the lagged average intraday volatility of all stocks in an exchange on a certain day. *Europe*, *Middle East - Africa*, *North America* and *South America* are the exchanges' regions, with the omitted category being *Asia-Pacific*. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Call
Intercept	-0.447^{***}
	(0.037)
Volume	0.009^{***}
	(0.002)
Developed	0.291^{***}
	(0.022)
Number Of Stocks	0.0001^{**}
	(0.0001)
Exchange Liquidity	0.0003^{***}
	(0.00005)
Exchange Efficiency	-1.984^{***}
	(0.485)
Europe	0.062^{**}
	(0.028)
Middle East - Africa	-0.112^{***}
	(0.026)
North America	-5.254^{***}
	(0.036)
South America	-0.103^{**}
	(0.043)
Observations	11,025,277
R^2	0.087
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 4: Impact of closing batch mechanisms on market liquidity for the full sample
This table reports the estimated effects on liquidity of introducing batch facilities with certain design features to end the trading day. The estimates are from a fixed effects regression model that incorporates selection-corrected inverse *Mills Ratio*s to estimate the impacts of closing call auctions and on-close facilities relative to last-trade mechanisms. The regression includes stock fixed effects and time fixed effects and is estimated for four different dependent variables Y that capture different aspects of market liquidity. *TWCS* is the time weighted closing spread in basis points during the last two hours of the continuous trading session. *Effective Spread* is the value weighted effective spreads in basis points during the last two hours of trading considering the auction trades. *Value* measures the total daily turnover, including the closing auction, and is standardized by the average daily turnover during the four year sample period. *Closing Impact* is the last two hour return of the trading session relative to the turnover during the same time period, including the auction, in basis points. *Call* and *Onclose* are dummy variables equal to one if the market operates a call auction or an on-close facility, respectively, or zero otherwise. *Rand*, *Stab*, *Flex* and *Trans* are dummy variables equal to one if the market operates a call auction that includes a randomized closing time, integrates a price stabilization mechanism, permits order flexibility, or is transparent, respectively. Each dummy is set to zero in the absence of the feature. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	TWCS	Effective Spread	Value	Closing Impact
Call	−13.300*	−11.700***	0.135***	0.002
	(7.431)	(2.486)	(0.031)	(0.002)
Onclose	32.350***	−4.099	−0.233***	0.009***
	(7.095)	(3.052)	(0.029)	(0.002)
Call × *Rand*	−17.080**	−3.711	0.371***	−0.004***
	(7.516)	(2.784)	(0.023)	(0.002)
Call × *Stab*	−53.780***	−12.540***	0.204***	−0.006***
	(6.551)	(2.156)	(0.021)	(0.001)
Call × *Flex*	−36.410***	−13.460***	−0.093***	−0.017***
	(8.264)	(2.959)	(0.028)	(0.002)
Call × *Trans*	107.300***	33.780***	−0.484***	0.027***
	(8.713)	(3.090)	(0.024)	(0.002)
Mills Ratio	−1,092.000***	−131.500***	−2.789***	0.061***
	(57.920)	(18.500)	(0.236)	(0.010)
Stock and Time FE	Yes	Yes	Yes	Yes
Observations	9,893,219	7,806,021	9,021,081	7,763,722
Adjusted R^2	0.619	0.508	0.085	0.405

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

Table 5: Impact of closing batch mechanisms on price efficiency for the full sample
This table reports the estimated effects on price efficiency of introducing batch facilities with certain design features to end the trading day. The estimates are from a fixed effects regression model that incorporates selection-corrected inverse *Mills Ratio*s to estimate the impacts of closing call auctions and on-close facilities relative to last-trade mechanisms. The regression includes stock fixed effects and time fixed effects and is estimated for four different dependent variables Y that capture different aspects of price efficiency. *Intraday Volatility* is the daily high-low spread relative to the high-low midpoint standardized by the average intraday volatility during the sample period. *Amihud VR* is the variance ratio introduced by Amihud and Mendelson (1987) using close-to-close returns relative to open-to-open returns. *Delay* is the short-term predictability measure introduced by Hou and Moskowitz (2005). *LoMacKinlay VR* is the variance ratio of 1-day and 3-day close-to-close returns introduced by Lo and MacKinlay (1988). *Call* and *Onclose* are dummy variables equal to one if the market operates a call auction or an on-close facility, respectively, or zero otherwise. *Rand*, *Stab*, *Flex* and *Trans* are dummy variables equal to one if the market operates a call auction that includes a randomized closing time, integrates a price stabilization mechanism, permits order flexibility, or is transparent, respectively. Each dummy is set to zero in the absence of the feature. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Intraday Volatility	Amihud VR	Delay	LoMacKinlay VR
Call	-0.053^{***}	0.040	0.010	-0.002
	(0.015)	(0.027)	(0.016)	(0.007)
Onclose	-0.081^{***}	0.047^{*}	-0.021	0.013^{**}
	(0.013)	(0.025)	(0.014)	(0.006)
$Call \times Rand$	0.094^{***}	-0.040^{**}	-0.043^{***}	-0.010^{*}
	(0.012)	(0.019)	(0.011)	(0.005)
$Call \times Stab$	0.042^{***}	-0.046^{***}	-0.014	-0.006
	(0.012)	(0.017)	(0.010)	(0.004)
$Call \times Flex$	-0.047^{***}	0.011	-0.027^{**}	0.002
	(0.015)	(0.026)	(0.013)	(0.006)
$Call \times Trans$	-0.023	0.039^{*}	0.052^{***}	0.012^{**}
	(0.015)	(0.021)	(0.014)	(0.005)
Mills Ratio	1.667^{***}	0.787^{***}	-0.701^{***}	0.006
	(0.116)	(0.263)	(0.130)	(0.070)
Stock and Time FE	Yes	Yes	Yes	Yes
Observations	9,019,394	417,139	416,975	445,529
Adjusted R^2	0.055	0.115	0.280	0.119
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 6: Impact of closing batch mechanisms on market integrity for the full sample
This table reports the estimated effects on market integrity of introducing batch facilities with certain design features to end the trading day. The estimates are from a fixed effects regression model that incorporates selection-corrected inverse *Mills Ratio*s to estimate the impacts of closing call auctions and on-close facilities relative to last-trade mechanisms. The regression includes stock fixed effects and time fixed effects and is estimated for three different dependent variables Y that capture different aspects of market integrity. *Reversal* is the largest reversal of close to same day or next day midpoint return, measured in basis points. *Reversal Asymmetry* measures the extent to which the reversals occur disproportionally on the upside. *Manipulation Index* represents the probability of manipulation and is based on the metric by Comerton-Forde and Putniņš (2011a). *Call* and *Onclose* are dummy variables equal to one if the market operates a call auction or an on-close facility, respectively, or zero otherwise. *Rand*, *Stab*, *Flex* and *Trans* are dummy variables equal to one if the market operates a call auction that includes a randomized closing time, integrates a price stabilization mechanism, permits order flexibility, or is transparent, respectively. Each dummy is set to zero in the absence of the feature. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Reversal	Reversal Asymmetry	Manipulation Index
Call	-6.030^{***}	-0.013	-0.082^{***}
	(1.408)	(0.010)	(0.012)
Onclose	4.356^{***}	0.011	0.021^{**}
	(1.451)	(0.009)	(0.009)
Call × *Rand*	-1.474	-0.002	0.003
	(1.434)	(0.009)	(0.011)
Call × *Stab*	-2.379^{**}	-0.024^{***}	-0.090^{***}
	(1.167)	(0.007)	(0.009)
Call × *Flex*	-5.838^{***}	-0.026^{***}	0.041^{***}
	(1.440)	(0.010)	(0.013)
Call × *Trans*	14.557^{***}	0.059^{***}	0.074^{***}
	(1.494)	(0.010)	(0.011)
Mills Ratio	-16.608^{*}	0.149	0.291^{***}
	(9.526)	(0.114)	(0.065)
Stock and Time FE	Yes	Yes	Yes
Observations	8,773,504	482,388	3,599,655
Adjusted R^2	0.211	0.174	0.087
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 7: Impact of closing batch mechanisms on market liquidity for developed markets

This table reports the estimated effects on market liquidity of introducing batch facilities for both liquid (first four columns) and illiquid stocks (last four columns) in developed markets. The estimates are from a fixed effects regression model that incorporates selection-corrected inverse *Mills Ratios* to estimate the impacts of closing call auctions and on-close facilities relative to last-trade mechanisms. The regression includes stock fixed effects and time fixed effects and is estimated for four different dependent variables Y that capture different aspects of market liquidity. $TWCS$ is the time weighted closing spread in basis points during the last two hours of the continuous trading session. *Effective Spread* is the value weighted effective spreads in basis points during the last two hours of trading considering the auction trades. *Value* measures the total daily turnover, including the closing auction, and is standardized by the average daily turnover during the four year sample period. *Closing Impact* is the last two hour return of the trading session relative to the turnover during the same time period, including the auction, in basis points. *Call* and *Onclose* are dummy variables equal to one if the market operates a call auction or an on-close facility, respectively, or zero otherwise. *Rand*, *Stab*, *Flex* and $Trans$ are dummy variables equal to one if the market operates a call auction that includes a randomized closing time, integrates a price stabilization mechanism, permits order flexibility, or is transparent, respectively. Each dummy is set to zero in the absence of the feature. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Liquid Stocks				**Illiquid Stocks**			
	TWCS	Effective Spread	Value	Closing Impact	TWCS	Effective Spread	Value	Closing Impact
Call	−17.840	−14.380*	0.124*	0.005	43.930***	−0.948	−0.085	0.005
	(16.340)	(7.983)	(0.069)	(0.003)	(16.080)	(5.938)	(0.058)	(0.004)
Onclose	20.820***	−9.696**	−0.178***	0.003**	37.320***	−6.822**	−0.045	0.009***
	(6.910)	(4.676)	(0.043)	(0.001)	(10.240)	(3.364)	(0.039)	(0.002)
Call × *Rand*	−32.230**	−22.750**	0.500***	−0.015***	−69.240***	−12.390**	0.479***	−0.038***
	(16.240)	(9.015)	(0.050)	(0.003)	(15.650)	(5.747)	(0.043)	(0.004)
Call × *Stab*	−19.370*	4.081	0.137***	−0.001	−55.670***	−5.799	0.229***	0.001
	(10.870)	(5.785)	(0.040)	(0.002)	(12.010)	(4.257)	(0.034)	(0.003)
Call × *Flex*	0.514	1.550	−0.011	−0.012***	−51.420***	−12.100**	0.184***	−0.044***
	(12.830)	(5.476)	(0.068)	(0.002)	(14.950)	(4.854)	(0.058)	(0.004)
Call × $Trans$	68.590***	35.140***	−0.478***	0.023***	96.260***	19.350***	−0.503***	0.070***
	(19.480)	(10.300)	(0.069)	(0.004)	(17.980)	(6.711)	(0.060)	(0.006)
Mills Ratio	−435.800***	−93.210**	−2.447***	0.033***	−1,565.000***	−187.000***	−4.848***	0.240***
	(76.200)	(39.160)	(0.412)	(0.013)	(106.900)	(29.190)	(0.399)	(0.024)
Stock and Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,582,546	2,416,651	2,568,707	2,412,220	3,117,539	2,115,445	2,736,934	2,092,710
Adjusted R^2	0.557	0.654	0.115	0.347	0.564	0.402	0.087	0.407

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 8: Impact of closing batch mechanisms on price efficiency for developed markets

This table reports the estimated effects on closing price efficiency of introducing batch facilities for both liquid (first four columns) and illiquid stocks (last four columns) in developed markets. The estimates are from a fixed effects regression model that incorporates selection-corrected inverse *Mills Ratios* to estimate the impacts of closing call auctions and on-close facilities relative to last-trade mechanisms. The regression includes stock fixed effects and time fixed effects and is estimated for four different dependent variables Y that capture different aspects of price efficiency. *Intraday Volatility* is the daily high-low spread relative to the high-low midpoint standardized by the average intraday volatility during the sample period. *Amihud VR* is the variance ratio introduced by Amihud and Mendelson (1987) using close-to-close returns relative to open-to-open returns. *Delay* is the short-term predictability measure introduced by Hou and Moskowitz (2005). *LoMacKinlay VR* is the variance ratio of 1-day and 3-day close-to-close returns introduced by Lo and MacKinlay (1988). *Call* and *Onclose* are dummy variables equal to one if the market operates a call auction or an on-close facility, respectively, or zero otherwise. *Rand*, *Stab*, *Flex* and *Trans* are dummy variables equal to one if the market operates a call auction that includes a randomized closing time, integrates a price stabilization mechanism, permits order flexibility, or is transparent, respectively. Each dummy is set to zero in the absence of the feature. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Liquid Stocks				Illiquid Stocks			
	Intraday Volatility	Amihud VR	Delay	LoMacKinlay VR	Intraday Volatility	Amihud VR	Delay	LoMacKinlay VR
Call	−0.152***	0.258***	−0.012	−0.004	−0.081***	0.202**	0.027	0.004
	(0.032)	(0.073)	(0.023)	(0.011)	(0.029)	(0.095)	(0.020)	(0.011)
Onclose	−0.009	0.050	−0.006	0.011	−0.065***	0.194***	−0.010	0.006
	(0.019)	(0.040)	(0.020)	(0.007)	(0.019)	(0.066)	(0.017)	(0.008)
$Call \times Rand$	0.057**	−0.127***	−0.032*	−0.020**	0.129***	−0.326***	−0.048***	−0.031***
	(0.027)	(0.042)	(0.018)	(0.008)	(0.027)	(0.064)	(0.015)	(0.008)
$Call \times Stab$	0.034	−0.129***	−0.016	0.007	0.060***	−0.123**	−0.035***	−0.018***
	(0.023)	(0.032)	(0.016)	(0.006)	(0.020)	(0.052)	(0.013)	(0.007)
$Call \times Flex$	0.029	−0.141*	0.0001	0.007	0.079***	−0.254***	−0.067***	−0.025**
	(0.028)	(0.077)	(0.020)	(0.009)	(0.026)	(0.097)	(0.018)	(0.010)
$Call \times Trans$	0.026	0.012	0.047*	0.014	−0.091***	0.332***	0.085***	0.040***
	(0.033)	(0.064)	(0.028)	(0.012)	(0.032)	(0.081)	(0.025)	(0.012)
Mills Ratio	1.565***	1.114**	−0.685***	−0.107	1.026***	2.640***	−0.733***	0.075
	(0.196)	(0.554)	(0.202)	(0.104)	(0.182)	(0.743)	(0.177)	(0.113)
Stock and Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,568,707	120,587	118,663	128,533	2,735,470	127,299	125,146	132,738
Adjusted R^2	0.108	0.130	0.280	0.108	0.056	0.142	0.173	0.111

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

Table 9: Impact of closing batch mechanisms on market integrity for developed markets
This table reports the estimated effects on market integrity of introducing batch facilities for both liquid (first three columns) and illiquid stocks (last three columns) in developed markets. The estimates are from a fixed effects regression model that incorporates selection-corrected inverse *Mills Ratio*s to estimate the impacts of closing call auctions and on-close facilities relative to last-trade mechanisms. The regression includes stock fixed effects and time fixed effects and is estimated for three different dependent variables Y that capture different aspects of market integrity. *Reversal* is the largest reversal of close to same day or next day midpoint return, measured in basis points. *Reversal Asymmetry* measures the extent to which the reversals occur disproportionally on the upside. *Manipulation Index* represents the probability of manipulation and is based on the metric by Comerton-Forde and Putniņš (2011a). *Call* and *Onclose* are dummy variables equal to one if the market operates a call auction or an on-close facility, respectively, or zero otherwise. *Rand*, *Stab*, *Flex* and *Trans* are dummy variables equal to one if the market operates a call auction that includes a randomized closing time, integrates a price stabilization mechanism, permits order flexibility, or is transparent, respectively. Each dummy is set to zero in the absence of the feature. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Liquid Stocks			**Illiquid Stocks**		
	Reversal	Reversal Asymmetry	Manipulation Index	Reversal	Reversal Asymmetry	Manipulation Index
Call	−7.693*	0.058***	0.155***	−5.587*	0.047***	0.119***
	(4.298)	(0.017)	(0.025)	(3.096)	(0.017)	(0.030)
Onclose	2.348	−0.008	−0.002	3.852**	0.041***	−0.030**
	(2.042)	(0.014)	(0.013)	(1.935)	(0.012)	(0.013)
Call × *Rand*	−12.653***	−0.039**	−0.074***	−11.079***	−0.031**	−0.057**
	(4.313)	(0.015)	(0.020)	(2.990)	(0.012)	(0.028)
Call × *Stab*	0.173	−0.042***	−0.196***	1.304	−0.017	−0.110***
	(3.008)	(0.012)	(0.016)	(2.318)	(0.011)	(0.017)
Call × *Flex*	−3.029	−0.055***	−0.193***	−5.104*	−0.081***	−0.046
	(2.686)	(0.018)	(0.030)	(2.749)	(0.018)	(0.031)
Call × *Trans*	21.710***	0.052**	0.155***	15.678***	0.094***	0.023
	(5.175)	(0.025)	(0.030)	(3.548)	(0.021)	(0.034)
Mills Ratio	−27.818	0.080	−0.144	−62.832***	0.388**	0.589***
	(18.030)	(0.202)	(0.103)	(15.201)	(0.156)	(0.109)
Stock and Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,557,052	130,097	1,128,181	2,657,097	149,361	1,000,753
Adjusted R^2	0.189	0.161	0.096	0.191	0.185	0.079

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

Table 10: Impact of closing batch mechanisms on market liquidity for emerging markets

This table reports the estimated effects on market liquidity of introducing batch facilities for both liquid (first four columns) and illiquid stocks (last four columns) in emerging markets. The estimates are from a fixed effects regression model that incorporates selection-corrected inverse *Mills Ratio*s to estimate the impacts of closing call auctions and on-close facilities relative to last-trade mechanisms. The regression includes stock fixed effects and time fixed effects and is estimated for four different dependent variables Y that capture different aspects of market liquidity. $TWCS$ is the time weighted closing spread in basis points during the last two hours of the continuous trading session.*Effective Spread* is the value weighted effective spreads in basis points during the last two hours of trading considering the auction trades. *Value* measures the total daily turnover, including the closing auction, and is standardized by the average daily turnover during the four year sample period. *Closing Impact* is the last two hour return of the trading session relative to the turnover during the same time period, including the auction, in basis points. *Call* is a dummy variables equal to one if the market operates a call auction or zero otherwise. *Rand*, *Stab*, $Flex$ and $Trans$ are dummy variables equal to one if the market operates a call auction that includes a randomized closing time, integrates a price stabilization mechanism, permits order flexibility, or is transparent, respectively. Each dummy is set to zero in the absence of the feature. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Liquid Stocks				Illiquid Stocks			
	TWCS	Effective Spread	Value	Closing Impact	TWCS	Effective Spread	Value	Closing Impact
Call	−65.020***	−35.730***	0.265***	−0.021***	−253.900***	−128.700***	0.369***	−0.061***
	(17.380)	(6.217)	(0.098)	(0.004)	(34.170)	(14.010)	(0.101)	(0.006)
$Call \times Rand$	47.730***	25.930***	−0.010	0.015***	26.590	8.758	0.019	0.040***
	(11.910)	(4.170)	(0.065)	(0.003)	(17.890)	(6.777)	(0.060)	(0.006)
$Call \times Stab$	−61.020***	−27.980***	0.531***	−0.008***	−83.610***	−18.640**	0.311***	−0.008
	(12.680)	(4.069)	(0.061)	(0.002)	(22.870)	(9.365)	(0.058)	(0.006)
$Call \times Flex$	2.646	3.494	−0.185**	0.002	123.500***	54.740***	−0.265***	0.015***
	(16.560)	(5.497)	(0.087)	(0.002)	(32.690)	(12.850)	(0.092)	(0.005)
$Call \times Trans$	116.600***	31.270***	−0.363***	0.013***	179.100***	67.870***	−0.173***	0.024***
	(13.680)	(4.193)	(0.065)	(0.003)	(22.990)	(9.984)	(0.060)	(0.006)
Mills Ratio	105.200	99.380***	−6.067***	0.093***	−858.400***	52.040	−6.140***	0.178***
	(77.790)	(27.600)	(0.599)	(0.019)	(121.300)	(44.750)	(0.514)	(0.035)
Stock and Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,752,267	1,623,894	1,717,670	1,619,342	2,440,867	1,650,031	1,997,770	1,639,450
Adjusted R^2	0.535	0.374	0.120	0.266	0.608	0.401	0.124	0.446

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 11: Impact of closing batch mechanisms on price efficiency for emerging markets

This table reports the estimated effects on closing price efficiency of introducing batch facilities for both liquid (first four columns) and illiquid stocks (last four columns) in emerging markets. The estimates are from a fixed effects regression model that incorporates selection-corrected inverse *Mills Ratios* to estimate the impacts of closing call auctions and on-close facilities relative to last-trade mechanisms. The regression includes stock fixed effects and time fixed effects and is estimated for four different dependent variables Y that capture different aspects of price efficiency. *Intraday Volatility* is the daily high-low spread relative to the high-low midpoint standardized by the average intraday volatility during the sample period. *Amihud VR* is the variance ratio introduced by Amihud and Mendelson (1987) using close-to-close returns relative to open-to-open returns. *Delay* is the short-term predictability measure introduced by Hou and Moskowitz (2005). *LoMacKinlay VR* is the variance ratio of 1-day and 3-day close-to-close returns introduced by Lo and MacKinlay (1988). $Call$ is a dummy variable equal to one if the market operates a call auction or zero otherwise. $Rand$, $Stab$, $Flex$ and $Trans$ are dummy variables equal to one if the market operates a call auction that includes a randomized closing time, integrates a price stabilization mechanism, permits order flexibility, or is transparent, respectively. Each dummy is set to zero in the absence of the feature. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Liquid Stocks				**Illiquid Stocks**			
	Intraday Volatility	Amihud VR	Delay	LoMacKinlay VR	Intraday Volatility	Amihud VR	Delay	LoMacKinlay VR
$Call$	−0.061	−0.184**	−0.020	−0.025*	−0.189***	−0.178	−0.032	−0.030*
	(0.046)	(0.088)	(0.043)	(0.015)	(0.052)	(0.153)	(0.036)	(0.017)
$Call \times Rand$	0.039	0.176**	−0.097**	0.019	−0.001	0.203*	−0.076**	0.009
	(0.032)	(0.078)	(0.040)	(0.012)	(0.029)	(0.110)	(0.033)	(0.013)
$Call \times Stab$	0.140***	−0.014	−0.028	−0.012	0.183***	0.015	0.009	−0.016
	(0.031)	(0.073)	(0.028)	(0.010)	(0.032)	(0.114)	(0.019)	(0.015)
$Call \times Flex$	−0.084**	0.088	−0.010	0.014	0.021	0.133	0.032	0.020
	(0.042)	(0.076)	(0.030)	(0.012)	(0.048)	(0.131)	(0.025)	(0.014)
$Call \times Trans$	0.003	0.111*	0.004	0.016	0.006	−0.075	−0.019	0.026
	(0.034)	(0.065)	(0.031)	(0.011)	(0.033)	(0.113)	(0.027)	(0.017)
Mills Ratio	1.125***	2.470***	−0.180	0.284**	0.447**	4.541***	−0.711***	0.255*
	(0.220)	(0.950)	(0.295)	(0.124)	(0.180)	(1.437)	(0.272)	(0.140)
Stock and Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,717,670	86,339	79,906	86,941	1,997,547	97,272	93,260	97,317
Adjusted R^2	0.082	0.112	0.284	0.082	0.057	0.166	0.317	0.124

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

Table 12: Impact of closing batch mechanisms on market integrity for emerging markets
This table reports the estimated effects on market integrity of introducing batch facilities for both liquid (first three columns) and illiquid stocks (last three columns) in emerging markets. The estimates are from a fixed effects regression model that incorporates selection-corrected inverse *Mills Ratio*s to estimate the impacts of closing call auctions and on-close facilities relative to last-trade mechanisms. The regression includes stock fixed effects and time fixed effects and is estimated for three different dependent variables Y that capture different aspects of market integrity. *Reversal* is the largest reversal of close to same day or next day midpoint return, measured in basis points. *Reversal Asymmetry* measures the extent to which the reversals occur disproportionally on the upside. *Manipulation Index* represents the probability of manipulation and is based on the metric by Comerton-Forde and Putniņš (2011a). *Call* is a dummy variable equal to one if the market operates a call auction or zero otherwise. *Rand*, *Stab*, *Flex* and *Trans* are dummy variables equal to one if the market operates a call auction that includes a randomized closing time, integrates a price stabilization mechanism, permits order flexibility, or is transparent, respectively. Each dummy is set to zero in the absence of the feature. Standard errors are corrected by double clustering by stock and time and are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Liquid Stocks			**Illiquid Stocks**		
	Reversal	Reversal Asymmetry	Manipulation Index	Reversal	Reversal Asymmetry	Manipulation Index
Call	−18.319***	−0.121***	−0.104***	−44.982***	−0.120***	−0.045
	(4.598)	(0.031)	(0.039)	(7.195)	(0.028)	(0.039)
Call × *Rand*	18.693***	0.106***	0.153***	12.765***	0.064***	0.102***
	(2.785)	(0.023)	(0.020)	(3.583)	(0.018)	(0.021)
Call × *Stab*	−6.956**	−0.008	−0.105***	−8.295*	−0.009	0.007
	(2.908)	(0.019)	(0.026)	(4.538)	(0.017)	(0.024)
Call × *Flex*	−5.206	0.030	−0.035	15.227**	0.045*	−0.024
	(4.287)	(0.026)	(0.036)	(6.608)	(0.024)	(0.038)
Call × *Trans*	19.623***	−0.008	0.126***	26.518***	0.031	0.028
	(2.887)	(0.025)	(0.022)	(4.542)	(0.019)	(0.023)
Mills Ratio	72.326***	0.130	0.744***	74.584***	0.268	1.199***
	(19.984)	(0.216)	(0.123)	(25.322)	(0.177)	(0.109)
Stock and Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,697,832	88,371	798,770	1,893,774	114,559	671,951
Adjusted R^2	0.182	0.182	0.137	0.250	0.206	0.109

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$