Liquidity Asymmetry Under Variation in Short Selling Regimes: A Study under Non-Market-Wide Crisis Settings

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Latest Draft: July 10, 2022

Abstract

I show a near symmetrical adverse effect of shorting flow impediments (caused by an exchange driven short-sale ban or securities lending market-driven constraints) on the buy and sell order flow price impact and liquidity supply dynamics. Overall, I find that the liquidity cost asymmetry is lower than the previously reported outcome with the US 2008 banned stocks in an extreme liquidity crisis. The differential effect is tilted towards sell-initiated order flow impact and bid side liquidity. Utilizing tick-by-tick microstructure data (including depth data) in the Hong Kong market, I conduct ordinary least squares (OLS) and regression discontinuity design (RDD) tests on the Hong Kong market to corroborate my findings. In contrast to Diamond and Verrecchia (1987), my study: a) argues for the importance of informed short sellers (as liquidity suppliers) on the bid and ask side of the market, and b) highlights the juxtaposition between the imperfect competition channel and increased adverse selection due to endogenous information acquisition under an informed short-selling ban. I further report a lower differential effect in buy versus sell under stronger mean reversion properties, a profitable setting for contrarian liquidity provisioning strategies.

Key words: Market Microstructure, Short Selling, Adverse Selection, Order Flow Impact, Liquidity Supply

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I. Introduction

Does a short sale ban (without any effects driven by a market-wide crisis) induce order flow impact costs and liquidity supply distortions on both the buy and sell sides of the market or only on one side? How does the ban's effect compare with that of short selling constraints induced by the lending market? Should regulators adopt the "Hong Kong-style" ban based on market capitalization thresholds?

The extant literature (see, e.g., Boehmer, Jones, and Zhang (2013) and Beber and Pagano (2013)) shows how short sale bans or constraints degrade market quality and highlights the slowing down of price discovery and imperfect competition as factors that deteriorate market quality.[1] However, to the best of my knowledge, the literature is limited in terms of providing insights into a ban's effect by dissecting buy and sell sides while linking bans with liquidity costs, primarily under non-crisis market conditions. Furthermore, I find no literature showing the effects of security lending market dynamics on the buy and sell sides. According to Diamond and Verrecchia's (1987) [DV] settings, short-sellers are only liquidity demanders (and not liquidity suppliers) trading on negative information. Based on DV settings, I bring up two scenarios that lead to a different outcomes for the bid and ask sides of the market. The first scenario is a short sale ban on informed shorting. Considering that shorts are informed,[2] a prohibition of short selling is expected to reduce information content on the sell side, in other words, the sell-initiated order flow. As a result, on the bid side, the equilibrium price (conditional on the sell order flow) goes up because a market maker faces reduced adverse selection[3]. On the ask side, there is no alteration in quoting activity. Why is this so? Since the ban does not prohibit buy order flow, there is no alteration in the buy-side adverse selection (i.e., the risk of losing money while transacting with the buy- initiated order flow). The increase in the bid and no change in the ask result in a narrowing in the bid-ask spread.

The second scenario is a ban on both informed and uninformed shorting alike (i.e., symmetrically). In this scenario, the composition of informed trading does not change. Hence, there is no alteration in sell-side adverse selection costs. This scenario does not result in a change in the bid-ask spread.

In both these scenarios, a ban does not affect market quality, which contrasts with the empirical findings in the short-selling literature. This has motivated further theoretical studies following DV's seminal work on short sale impediments and bid-ask spread. Dixon (2021) extends DV settings by incorporating an endogenous information acquisition channel [4] to show that a short-selling

[1]Non-exhaustive list of measures to quantify market quality include quoted spread i.e., bid-ask spread, effective spread and order book volume or dollar volume-based measures.

[2]It has been documented in literature that short-sellers are informed traders - see, e.g., Boehmer, Jones, and Zhang (2008), Boehmer and Wu (2012).

[3]In a microstructure context, adverse selection is a situation whereby liquidity provider (such as designated market maker) tends to adjust the limit price (lower on bid side and higher on ask side) as compensation for the risk of transacting with informed order flow from the opposite side.

[4]Incentive to acquire information by sellers who own assets vis-a-vis who do not own assets is shown as a key

ban increases only sell-side price impact (proxy for adverse selection). The author finds that the short sale prohibition increases buy-side realized spread, linked to reduced liquidity competition on the ask side because passive informed short-sellers are prohibited. The outcome implies that ban adversely affects the effective spread (proxy for total trading cost)[5] on both the buy and sell-side. The buy-side effect is driven by reduced liquidity competition, and the sell-side is driven by increased adverse selection. The author further finds that ban's impact on the seller-initiated effective spread is more substantial than the buyer-initiated spread and links this outcome to possible dominance of increased adverse selection effect over the imperfect competition. The author considers liquidity providers as risk-neutral in the model. In a different theoretical settings with similar context, Liu and Wang (2019) show that a ban or constraints symmetrically deteriorate spreads and depth on both sides. Their model outcome is driven by an imperfect competition channel where a market maker has a market monopoly in setting a bid price in her favor. In other words, she has a greater market power facing constrained short sellers, and lowers the bid price in equilibrium at a level when short sell constraints start to bind. Such market makers bear the inventory risk and raise ask price with a similar magnitude, to close the position (that is, to net out inventory).

My empirical findings indicate that a ban or constraints (driven by the lending market) adversely affect liquidity and trading costs on both sides of the market. The liquidity asymmetry is lower in my settings, where the ban is not driven by market wide crisis, and my analysis shows that the strength (or magnitude) of the ban's effect is tilted towards bid side liquidity. I run my tests on both level 1 data (trade and quote) and depth data. My study also highlights the importance of short sellers as liquidity suppliers, which is not assumed in the DV model[6]. Comerton-Forde, Jones, and Putnins (2016) claim that short-seller liquidity suppliers are a key ameliorating factor in market quality degradation due to the shorting ban. Using New York Stock Exchange (NYSE) data, the authors find that such types of short-sellers are contrarian, providing liquidity when spreads are wide. When informed liquidity providers cannot take new positions (due to a ban) or take positions cheaply (due to lending market-driven constraints), the alteration in their trading activity may adversely impact both the bid and ask sides of the market. The Financial Conduct Authority (FCA) stated during COVID-19 crisis [7]

A great many investment and risk management strategies rely on the ability to take 'long' and 'short' positions. These benefit a wide range of ordinary investors including the pension funds for employees of companies and local government.

An example is hedge fund managers, who could be informal liquidity providers and need to

factor in an increase in the probability of change in information content in sell initiated order flow post short sale ban. This is discussed in hypotheses Section III.

[5]The effective spread is a proxy for trading or liquidity cost and is captured by adding price impact and realized spread.

[6]DV model assumes short-sellers are only liquidity demanders.

[7]Statement dated:23rd March, 2020 `https://www.fca.org.uk/news/statements/statement-uk-markets`.

cover both bid and ask sides of the market to run active long-short mean reversion strategies or statistical arbitrage strategies on assets. Such investors, under shorting flow impediments, will be driven out of the market, which then results in a reduction in liquidity. This situation results in a shift in informed trading dynamics and could endogenously affect market-making strategies that aim to generate profits trading on spreads while managing inventory risk. From an empirical perspective, the question is: Are the effects of an informed trading shorting ban on one side of the market more substantial/dominant than on the opposite side? Alternatively, is the effect near-symmetrical for both the buy and sell order flow impact and bid and ask sides of the limit order book? Do I see a similar outcome if short -sellers are discouraged from investing in a stock if they are required to pay higher fees due to lending constraints? I formulate my hypotheses and theoretical motivations in section III to discuss my expectations.

To test my hypotheses, I perform OLS tests on a broader set of stocks and identification strategy-driven analysis using RDD tests under stable market conditions, in other words, without the likely presence of confounding effects driven by the crisis. I exploit a unique setting in the Hong Kong market, where stocks are not allowed for short selling based on pre-defined criteria rules. The Hong Kong Exchange provides a list of short sale eligible stocks for a long period, including both bull and bear market periods. This setup provides an ideal test bed to analyze my research questions on a long series of data in this short sale constrained market. In terms of market capitalization, the Hong Kong Exchange has been in top 10 in recent decade and is third largest exchange in the world as at year 2020 [8] and one of the top exchanges for initial public offerings (IPOs)[9]. The Hong Kong Exchange Schedule 11 defines short requirements and regulations and evaluates various rules for designated securities for short selling. The exchange publishes a designated list of short eligible securities (mainly updated every quarter) if stocks fall within, or are otherwise included in, any one or more of the various categories (rules and categories are discussed in appendix section:B). However, some participants are exempted from short-selling regulations. An example list of participants provided by the exchange include "Securities Market Maker Short Selling, Structured Product Liquidity Provider Short Selling, Designated Index Arbitrage Short Selling, Stock Futures Hedging Short Selling, Structured Product Hedging Short Selling and Options Hedging Short Selling"[10]. The Hong Kong Exchange offers three types of designated market maker participants, namely: a) Securities Market Makers trading exchange-traded products (ETPs) which track underlying securities; b) Derivatives Market Makers who provide liquidity for Futures products; and c) Option Market Makers who provide liquidity for Option products.

Based on the research questions, my study:

[8] `https://en.wikipedia.org/wiki/List_of_stock_exchanges`.

[9] `https://www.cnbc.com/2018/09/24/hong-kong-is-set-to-top-global-ipo-market-in-2018-kpmg.html`.

[10] Chapter 1 of the Rules of the Exchange has definitions of these market participants.

- Dissects buy and sell liquidity supply dynamics and the order flow impact to examine the impact of shorting impediments (via exchange-driven ban or lending market-driven constraints) on order book liquidity and trading cost asymmetry – while doing so, I investigate the importance of alteration in the liquidity supplier's ability to trade both the buy and sell sides of the market; and

- Attempts to resolve any open question(s) for the regulators looking to adopt the "Hong Kong style" short ban approach based on a market capitalization-based (size-based) threshold. For example, South Korean authorities have been exploring whether the Hong Kong rule that restricts short selling for stocks whose market capitalization exceeds a certain level is adaptable to the Korean market, which has been vulnerable to short-selling attacks.[11]

In terms of the data sample and the empirical strategy, my study utilizes:

- OLS-based tests as well as quasi-exogenous experiments, covering a long period (a few years) of non-crisis market conditions, unlike the US 2008 ban, which was imposed only for a short period (less than a month) and overlaps with an extreme liquidity crisis period.

- A unique combination of level 1 tick-by-tick trade and quote data, complete with level 2 limit order book data, lending market data, and a periodic short sell eligibility list published by the Hong Kong Exchange.

The paper is organized as follows. I develop the hypotheses in Section III and provide empirical strategies in Section IV. The empirical strategy section provides an implementation approach to tests my hypotheses. Data and sample construction and results are provided in Section V and Section VI, respectively. I discuss robustness using a quasi-exogenous experiment in Section VII and conclude my paper in Section VIII. Data variable definitions are provided in appendix section:A.

[11]Discussion source link:`https://www.kedglobal.com/newsView/ked202008170002`.

II. Literature Review

Empirically, the most recent papers that dissect the buy and sell side for short sell ban analysis are those by Cenesizoglua and Grass (2018) and Dixon (2021). Cenesizoglua et al. (2018) study determinants of the bid and ask side of liquidity using the NYSE limit order book market utilizing 11 years of data covering the US ban period. The authors find a significant imbalance in bid and ask side liquidity with a heavy distortion in liquidity provision, mainly on the ask side during the ban period. However, their study does not address a major counter-factual issue, which is perceived as a critical empirical issue as the ban itself was introduced during an extreme liquidity crisis. Moreover, their outcome is not motivated by theoretical findings and economic channels explaining the expected direction of distortion (if any) on a specific side (bid or ask side) of the market. Dixon (2021) highlights the important of increased adverse selection under the 2008 US ban and finds that the US ban raises the sell adverse selection (i.e., adverse selection initiated from sell order flow). The author claims that market makers face an increased probability of adverse selection from sell-initiated flow and consequently lower the bid side quotes in equilibrium. The ban also reduces liquidity supply competition on the ask side as informed limit short-sellers are potentially driven out from the market. As a consequence, liquidity competition declines. Considering both adverse selection and liquidity competition, the author shows the adverse effect of the ban on both buy and sell trading costs. The author adopts a similar matching algorithm that Boehmer, Jones, and Zhang (2013) proposed for market quality analysis during the US ban period.

I differ from Cenesizoglua and Grass (2018) and Dixon (2021) in the following respects: a) I utilize order flow-based price impact incorporating trade size as a component and order book depth data. b) My Hong Kong (HK) analysis sample period spans three years, unlike the very short US ban period, and is not embedded with any known liquidity crisis or market-wide related effects, to the best of my knowledge. Hence, the trading activity in my sample is unlikely to have significant selling pressure because a market-wide crisis does not drive the Hong Kong exchange's decision to impose a ban on selected stocks. c) In market-wide crises, participants who provide liquidity via derivatives, Exchange-Traded products (ETPs), and in general, index investing may seek to completely withdraw from the market. The counter-factual analysis (with respect to the 2008 US ban) in Dixon (2021)'s study may not completely cover any differences in buying and selling asymmetric behavior in treatment stocks (which were mainly financial firms) as against control stocks. Boehmer et al. (2013) attempt to address confounding events such as news about Troubled Asset Relief Program (TARP) and other government programs including extreme volatility period by incorporating industry match, investigating end-of-ban period and examining subsets of firms that were added to or removed from the banned list post September 19, 2008.

Overall, my Hong Kong sample is not expected to have the obvious risk of crisis-driven endogenous effects (possible in the US ban period), as discussed by Crotty et al. (2018). Crotty et al. (2018), through the adoption of regression discontinuity design (RDD), base their empirical strategy on Hong Kong stocks, perform limited market quality analysis using trade and quote data. However, they primarily focus on asset pricing and crash risk study at a quarterly sampling frequency without going in-depth into microstructure-focused analysis. By contrast, I attempt to perform microstructure analysis of the effect of a ban or lending market constraints on the depth and order flow through OLS tests and quasi-natural experiments utilizing trade and quote data, depth data, and lending market data.

Third, the US ban is imposed on financial firms, whereas the Hong Kong ban is imposed on stocks across industries. However, one caveat is that the Hong Kong banned stock list is not decided on randomized trials but is decided on stocks with lower liquidity thresholds. This implies that banned stocks fall in the category of small market capitalization.

Theoretically, the most recent study concerning my hypotheses is by Liu and Wang (2019). They show that short-sale constraints in an imperfectly competitive market increase bid-ask spread and deteriorate depth symmetrically on both the bid and ask sides of the market. As per their model assumptions, market makers have more power in the presence of short-sale constraints and are risk-averse; they tend to set a lower bid price (against more constrained sellers) and higher ask price to square off the inventory position. They claim that their outcome corroborates with the extant empirical literature that finds that bid-ask spreads significantly increase during the US ban period (as opposed to the prediction from the DV model). The authors further show that their findings are consistent with or without information asymmetry and robust to endogenous information acquisition. Dixon (2021) follows Glosten and Milgrom's (1985) model under assumptions of perfect competition and risk-neutral market makers to show higher sell adverse selection (that is, adverse selection initiated by sell order flow) under impediments to short selling. The author finds that a ban has an asymmetrical and dominant effect only on the sell-side (i.e., seller-trade initiated) adverse selection and this increased adverse selection is the cause for higher transaction costs faced by sell traders as compared to buy traders.

In a separate strand of the literature on short-sale constraints, Diether, Lee, and Werner (2009) examine the effect of temporary suspension of price tests (Regulation SHO Program) on pilot stocks (relative to control stocks) on the bid and ask liquidity for both the NYSE and NASDAQ markets. Their study finds that for the NYSE, the lifting of shorting constraints (the NYSE uptick rule[12]) caused a reduction in asymmetries (i.e., more symmetry) of depth and order flow. This was because: as documented by the authors, in the presence of shorting restrictions, short-sellers became more passive limit sellers, which was a natural consequence of their need to adjust orders to conform to the Uptick rule. Hence, this increased the ask side's depth compared to that of the bid side, generating order book asymmetry. However, when the uptick rules were lifted, short-sellers switched from a more passive to an active strategy, causing greater symmetry in bid/ask depth.

[12]As defined by SEC, "the short must be either at a price above the last traded price of the security or at the last traded price when the most recent movement between traded prices was upward."

In contrast to the NYSE's uptick rule, the NASDAQ had a bid price tests rule [13]. This enabled NASDAQ to have a natural mix of passive and active strategies among short-sellers. Hence, not much asymmetry was observed in the bid/ask depth and order flow on the treatment stocks vis-à-vis control stocks when the bid price tests restriction was lifted.

Overall, context of the study by Diether et al. (2009) is different from this study, as I aim to examine whether short-selling impediments driven by a complete informed short-sale ban or lending market-driven constraints cause or are associated with distortions in both bid and ask depth and buy and sell liquidity supply and order flow. While doing so, I investigate and predict that such a ban or constraints may induce near-symmetric distortions in the buy and sell microstructure dynamics. Our depth measures utilize full limit order book instead of only the best level quote volume in Diether et al. (2009) depth metrics, and our price impact measure captures liquidity order flow impact for the trade-through scenario; in other words, when large trades are executed at multiple bid or ask levels beyond best levels.

Academic literature has also examined implications of US SEC Rule 201[14] short sell restrictions in the US equity market. Using difference-in-differences analysis, Jain, Jain, and McInish (2012) find that US SEC Rule 201 does not significantly impact bid-ask spreads and turnover (as liquidity proxies). In a different empirical settings using RDD tests based on the 10% threshold cut-off (defined by Rule 201) for the short sale restriction, Barardehi, Bird, Karolyi and Ruchti (2020) report that the rule resulted in a 5% decline in the sell-initiated volume (proportional to the traded volume) for treatment stocks (on which the restriction is triggered) relative to control stocks.

Overall, I aim to examine whether a ban or lending market-driven constraints causes distortions in both bid and ask depth and buy and sell order flow. While doing so, I investigate the magnitude of asymmetry (if any) in an alternation in buy and sell microstructure dynamics. I theoretically and economically motivate my analysis related to such distortion in the market's buy and sell-side using various channels discussed in my hypotheses section.

Concerning asset pricing tests on the Hong Kong market, Chang, Cheng, and Yu (2007) utilize short sell eligibility list published by Hong Kong to verify stock overvaluation effects at quarterly intervals and find their overvaluation outcome is consistent with the theoretical claims by Miller (1977) and Lamont and Jones (2002). Crane, Crotty, Michenaud, and Naranjo (2018) point out endogeneity concerns in their empirical strategy since the banned stock list is decided based on criteria rules [15] that are endogenous to dependent variables. They attempt to circumvent the problem by utilizing a quasi-random experiment using the regression discontinuity design approach to find contrasting outcomes concerning stock overvaluation effects. They argue that their outcome is consistent with the theoretical findings from DV. As per DV, in a framework with no uncertainty

[13] "Short sales are not allowed at or below the (insider) bid when the current bid is at or below he previous inside bid".

[14] SEC implemented Rule 201 as an "Alternative Uptick Rule" after previous "uptick rule" was removed in 2007. The rule is triggered based on an intraday price decline of more than 10% from the previous day's closing price.

[15] Criteria is discussed in empirical section VII.A.

about the number of informed traders, any information mispricing should adjust correctly in long-run prices. Hence, prices will not be upwardly biased. My finding on a ban's effect on stock prices is consistent with Crane et al. (2018).

III. Hypothesis Development and Theoretical Motivation

I formulate the following testable hypotheses to study the effect of the Hong Kong short-sell ban and lending market activity on buy and sell supply/demand dynamics in the trading market, in-line with my research objectives.

- **Hypothesis 1**: *A short-sale ban is expected to adversely influence both buy and sell liquidity supply dynamics and order flow impact costs*

  Assume a situation where informed and uninformed traders can short sell without any constraints. Consider this as **scenario 1**. Now the exchange imposes a ban on informed traders, whereas uninformed traders can continue to short sell. Consider this as **scenario 2**. What would happen if there was a transition from **scenario 1** to **scenario 2**?

  Based on DV's rational expectation model settings, where short-sellers are assumed to be liquidity demanders (who trade for immediacy on bad news), if a short-sale prohibition restricts informed traders but not uninformed traders, the percentage of sell-side informed trading to uninformed trading is altered (reduced in this case). This implies that a market maker on the bid side is likely to face a less informed sell "marketable" order; in other words, she will be less likely to be adversely selected. The expected value of the bid price (conditional on selling order flows) goes up. However, the short-ban does not prohibit buy-side trading, and hence, the ban does not alter informed trading initiated by buy order flow. This implies that the ask price remains the same (conditional on buy order flow). Under these assumptions, I expect $bid - ask$ spread to narrow, that is, go down.

  However, the theoretical inference may not be straightforward because various underlying channels could distort liquidity supply dynamics and order flow impact. For example, consider rational expectation model settings, where informed short limit traders co-exist with uninformed market makers as liquidity suppliers. When the ban (under scenario 2) prohibits informed short sellers (as liquidity providers) trading both the ask and bid side of the market, liquidity will decline. Reduction in liquidity competition could result in a shift in uninformed liquidity provisioning dynamics. I refer to this channel as the non-information channel. The informed trading ban may also adversely impact liquidity via the channel of endogenous information acquisition and increased adverse selection. I refer to this as an informational channel. I further discuss these channels below, citing recent theoretical studies.

  a) **Endogenous Information acquisition and adverse selection**:

A ban drives out traders who trade on negative signals without owning the asset. On the sell side, such a ban causes an increase (instead of a decrease) in the probability that a long sell "marketable order" originates from an informed investor. The reason, motivated by Dixon (2021)'s model (see Appendix:C for further discussion), is as follows: Dixon (2021) argues that the distribution of informed sell traders is skewed towards traders who own assets (as against traders who do not own assets). In comparison, the distribution of uninformed traders is not skewed on any one side. Consider a ratio of sell-side sophisticated investors (who trade only on information) and sell-side liquidity (uninformed) traders as: $\frac{informed\_LS+informed\_SS}{uninformed\_LS+uninformed\_SS}$[16]. A short ban on investors (who do not own assets) will have a lesser effect on the numerator than in the case of the denominator. This relative change in the numerator as against the denominator increases the proportion of information content among sellers, because informed trading is skewed towards traders who own assets, that is, long sellers. A market maker on the bid side faces a higher probability of adverse selection due to an order flow originating from the so-called informed long seller. Hence, she tends to lower the valuation on the bid side (conditional on sell order flows) per unit of quantity. Consequently, the bid depth slope flattens, and the half spread widens.

b) **Imperfect competition channel and monopolist market markers**: A ban or constraints drives out informal liquidity providers (informed traders) on ask side of the market. This generates imperfect competition among the formal liquidity providers (such as market makers). Liquidity providers or monopolist market makers would then tend to extract rents from buy traders while executing a liquidity provisioning strategy. She would tend to raise the valuation on the ask side (conditional on buy order flows) per unit of quantity. Consequently, the ask depth slope flattens and half-spread widens.

Once I combine both information-driven and non-information-driven channels (discussed above), I could expect that a short selling ban adversely influences liquidity and trading costs on both the buy and sell-side of the market. This indicates that traders are likely to incur liquidity costs both as buyers and sellers. Figure 1 illustrates flattening of the depth slope (quantity / quote price) and increased order flow impact on both the bid- and ask- side post short selling ban, considering the possibility of both channels linking the shorting ban and market quality.

From empirical perspective: *what is the magnitude of liquidity asymmetry? Can we expect to observe a similar economic impact of shorting impediments on both the bid and ask sides?*

I discuss various possibilities to assess the outcome of the magnitude of liquidity asymmetry.

[16] The term $informed\_LS$ is defined as fraction of informed sellers who own asset and are long sellers, $informed\_SS$ is defined as the fraction of informed sellers who do not own the asset, i.e., they sell via shorting, $uninformed\_LS$ is defined as fraction of uninformed sellers (or liquidity traders) who own the asset, and $uninformed\_SS$ is defined as fraction of uninformed sellers who do not own asset.

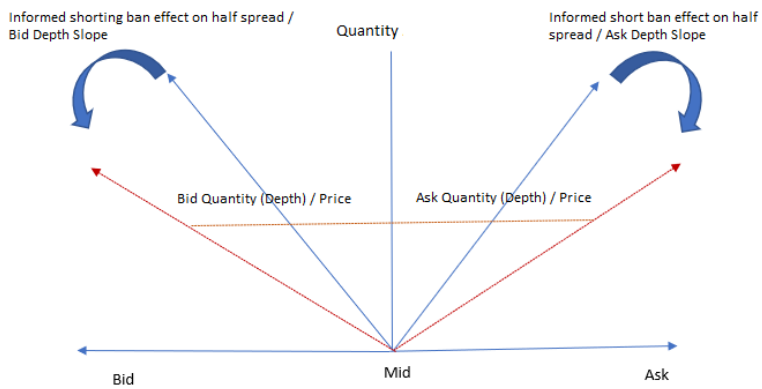

Figure 1. Graph illustrates widening of half spread and the flattening of depth slope (quantity / quote price) on bid- and ask- side post-informed shorting ban.

a) The magnitude of the economic impact on the buy and sell-side may depend on which channel (endogenous information acquisition or imperfect competition) is dominant over the other. For example, suppose endogenous information acquisition channel is more dominant post-ban. In that case, I expect that bid side liquidity (compared to ask side liquidity) will be higher, and seller-initiated trade will generate a higher price impact.

b) Role of informal (informed) liquidity provider. Suppose the market has a significant presence of informal liquidity suppliers (such as active hedge fund managers). To execute mean reversion/market neutral/statistical arbitrage strategies or liquidity provisioning strategy that profits from spread, such market participants need to cover both the long and short sides of the market. They may utilize market states (including order flow data) and other firm characteristics to model positive and negative signals and close position to minimize inventory cost. In the presence of a ban, hedge funds are driven out from taking long buy and short positions in the market, resulting in lower depth on both sides. This could endogenously affect liquidity provider's activity via the channel of imperfect competition. Consequently, depth and liquidity costs (conditional on order flows) are impacted in both buy and sell side (as illustrated in Figure: 1).

In practice, proportion long/short informed limit traders may differ across markets. Various studies argue that informed traders prefer limit orders (see, for example, Anand et al., 2005 and Chakravarty and Holden, 1995). Kaniel and Liu (2006) consider a case in which private information is long-lived, and the number of traders who possess the private information is small. The authors argue that market orders signal impatience and convey too much information, and hence, informed traders prefer limit orders. In reality, it is likely impossible to disentangle various types of informed traders as they trade via brokers using specific execution algorithms, which can result in a mix of order types to meet objectives of optimal execution.

c) Role of monopolist market makers. Liu and Wang (2019) consider imperfect competition channel and risk-averse market makers as key assumptions in showing that short sell constraints cause symmetric deterioration of depth liquidity on both bid and ask sides. They theoretically show that when few market participants are banned from short selling or face short-selling constraints, this generates imperfect competition, giving more power to market markers (who are considered uninformed traders). On the bid side, monopolist market makers would tend to set a lower bid price against more constrained short sellers. On the ask side, assuming market makers are risk-averse, they would set a higher ask price to net out their inventory position. The equilibrium bid price decreases, the ask price increases, and the bid-ask spread goes up.

- **Hypothesis 2:** *Short-sale constraints (induced by the securities lending market) are expected to have an influence on both the buy and sell supply dynamics and order flow impact costs.*

Following my predictions in hypothesis 1 (which mainly concerns a shorting ban imposed by an exchange), hypothesis 2 relates to the effect of changing lending market dynamics. Under this hypothesis setting, if a stock is hard-to-borrow and expensive (due to limited lending supply and borrowing costs), I expect the half spread to widen and the depth slope to flatten on both the bid and ask sides. The economic intuition is as follows: expensive to borrow stocks will constraint short sellers, potentially resulting in decline in demand from short sellers who are not privately informed. Decline in passive short sellers could impact ask side liquidity via non-informational channel (liquidity competition). Whereas a decline in aggressive uninformed short sellers could increase the probability that seller originates from informed trader. In order words, seller initiated adverse selection risk increases, resulting in a potential decline in bid price and depth (Dixon (2021)).

The other likely possibility is when a risk averse informed liquidity supplier tends to set higher ask as a compensation for increased short selling cost and tend to set lower bid to minimize inventory cost, thereby adversely distorting both sides of the market. If informed liquidity suppliers prefer to withdraw stock from their portfolios, I expect an endogenous effect in the uninformed liquidity supplier's liquidity provisioning activity on both the bid and ask sides of the market.

Hypotheses 1 and 2 posit that there would be a degradation in the liquidity and increase in trading costs contributed by distortions in both the buy and sell supply/demand dynamics. I test hypothesis 1 using the Hong Kong short selling ban settings, which presents two kinds of scenarios: a) **Scenario 1:** Both informed and uninformed are eligible to short on the designated list of short sell eligible securities on the designated list of short-sell eligible securities. b) **Scenario 2:** A short sell ban is imposed with the exemption of uninformed traders such as market makers and traders (with motivation to hedge). The list of market participants who are exempted from short selling is summarized in the introduction (Section I).

The ban on a firm causes a transition from scenario 1 to scenario 2.

IV. Empirical Strategy

In this section, I construct an empirical strategy based on hypotheses defined in section III. First, I present an empirical model to study the effect of the Hong Kong short sale ban on the microstructure level supply and demand dynamics by dissecting buying and selling. Second, I extend this study using short constraints induced by the securities lending market. I capture intraday microstructure metrics to perform my analysis.

A. Hypothesis 1: Short sale ban, Liquidity Supply dynamics and Order Flow Impact

To test my first hypothesis, I construct my empirical model using depth and order flow price impact as dependent variables and short sell ban dummy as an independent variable. The short sell eligible dummy variable is set to one if a stock is eligible for short selling. This is based on the short sell ineligibility/eligibility list published by Hong Kong exchange periodic (the construction of this dummy variable is further discussed in the section: V). Depth and order flow impact parameters are dissected into bid and ask side. The construction of the short sell eligibility dummy is discussed in the section: V. The regression is run on a daily firm-day panel using various controls and firm fixed effect. Key control variables include firm $Size$, $Return$, $MarketReturn$, $MarkettoBook$, $QuoteVolatility$ and VIX. The controls are defined in appendix section: A. Empirical models are given as below:

$$Var^B_{i,t} = \beta_0 + \beta_1.ss\_eligible_{i,t|t-1} + \gamma.C_{i,t|t-1} + \epsilon_{i,t|t-1}, \tag{1}$$

$$Var^S_{i,t} = \beta_0 + \beta_1.ss\_eligible_{i,t|t-1} + \gamma.C_{i,t|t-1} + \epsilon_{i,t|t-1}, \tag{2}$$

where “t” (“t-1”) indicates current (one day lag) trading in a daily panel and “i” indicates specific firm in the panel. Left hand side (dependent) variables include buy specific measures

($Var^{B}_{i,t}$) and sell specific measures ($Var^{S}_{i,t}$) to analyze following:

- Change in liquidity supply dynamics. I capture this using order book slope by separating the bid and ask sides. In line with hypothesis 1 Figure: 1, slope captures price sensitivity to changes in quantity supplied on bid and ask side. Similar to the definitions in Cenesizoglu, Dionne and Zhou (2016) and motivated by the concept discussed in Naes and Skjeltorp (2006), slope in this study is simply defined as cumulative quantity available between two levels (in my study level 1 and 5) divided by change in prices - in my study, price component at time "t" is difference between quote at level 5 and mid point price. The values are aggregated by time weights for each quote record update. A greater bid (ask) slope indicates that traders are willing to supply more liquidity at same or higher (lower) bid (ask) prices. The variables are discussed in data definitions in appendix section: A. I take the natural log of these variables to remove skewness in distribution of the slope variables. Log variables are denoted by: *log Bid Slope L*1_5 and *log Ask Slope L*1_5.

- Change in buy and sell order flow impact dynamics. I capture order flow impact using Brennan et al. (2012) lambda price impact measure by separating buy- and sell-initiated trades (The estimation of lambdas is discussed in data definitions in the appendix: A). The metrics are buy-trade initiated lambda: λ_{buy} (hereafter to be referred as "buy lambda") and sell-trade initiated lambda: λ_{sell} (hereafter to be referred as "sell lambda"). The estimation is fundamentally based on Kyle (1985). Under Kyle (1985) settings, a market maker observes order flow revealing information (without being able to distinguish between informed and noise trader) and sets prices which is linear function of the order flow. Market maker and private investor (informed trader) have rational expectations. An alternate option to measure price impact could be to use the simple midpoint price change over an interval. For e.g., Boehmer et al.(2013) measures buy (sell) -initiated price impact as the direction of midpoint movements over 5 minutes from midpoint price as a prevailing quote at the time of buy (sell)-initiated trade. However, in general, this measure is not considered as a direct replacement for price impact conditional on net buy and sell order flow that takes variable trade size into account. Simple midpoint price change over an interval may capture various observed or unobserved factors (including noise).

  One may suggest Amihud (2002) illiquidity as a replacement of lambda price impact. Brennan, Huh, and Subrahmanyam (2013) estimate half-Amihud measure by dissecting Amihud (2002) illiquidity into positive return (UP) days and negative return (DOWN) days dividing by "total share turnover". The denominator "total share turnover" in their measure is aggregated buyer and seller-initiated volume divided by outstanding shares. I, however, choose lambda variables as key price impact variables because I have complete tick data to compute such variables. Moreover, Amihud illiquidity measure may be noisy in high-frequency intervals, i.e., if estimated using the intraday UP and Down returns to come up with a daily measure. Extant literature measures Amihud illiquidity based on a monthly average of daily returns.

B. *Hypothesis 2: Lending constraints, Liquidity Supply Dynamics and Order Flow Impact*

I exploit lending data to construct a firm-day panel to study the effect of short sale constraints driven by securities lending market (extracted from IHS Markit lending market data source) on buy and sell liquidity parameters. The key dependent variables are: *LoanedDemand* (IHS Markit variable: *QuantityOnLoan*), *LendingSupply* (IHS Markit variable: *LendableQuantity*). *LoanDemand* captures the total quantity of stock on loan, and *LendableSupply* captures the quantity of stock inventory available to lend. The Logarithm is taken to remove any skewness in the distribution.

Empirical models are given as below:

$$Var^{B}_{i,t} = \beta_0 + \beta_1.log\ LendingSupply_{i,t} + \beta_2.log\ LoanDemand_{i,t} + \alpha.C + \epsilon_{i,t}, \tag{3}$$

$$Var^{S}_{i,t} = \beta_0 + \beta_1.log\ LendingSupply_{i,t} + \beta_2.log\ LoanDemand_{i,t} + \alpha.C + \epsilon_{i,t}. \tag{4}$$

The analysis is done both at the contemporaneous level ”t” and one period lagged level ”t-1”. “C” is vector of firm characteristics and market condition controls for stock “i”.

I perform panel “Ordinary Least Squares (OLS)” regression independently to examine buying and selling specific dynamics. In addition, I also perform a joint analysis of buy and sell using Seemingly Unrelated Regression (SUR) to allow information from the buy equation to be utilized on the sell equation and vice versa. Hence, residuals (error terms) on equation: 1 and 2 could be contemporaneously correlated. Cenesizoglua and Grass (2018) jointly analyze firm-level determinants of bid and ask liquidity on NYSE market using SUR method.

One may argue about endogenous outcome in OLS or SUR analysis because observed (such as firm characteristics) or unobserved factors may be driving independent variables and dependent variables (order book depth slope and order flow impact) in my model. Also, exchange determines short sale eligibility based on liquidity thresholds. I choose OLS based methods as the key empirical strategy for its simplicity and for the fact that I can apply model specifications uniformly for both my hypotheses 1 and 2. Moreover, I test using lagged dependent variables using various controls and stock fixed effect. However, I provide robustness to my hypothesis 1 testing by exploiting a quasi-exogenous variation in Hong Kong stock short-selling ban using Fuzzy Regression Discontinuity Design (RDD) tests. Out of the various criteria for short sale eligibility discussed in appendix:B, criteria based on liquidity thresholds include stock market capitalization, turnover velocity criteria (stock turnover to market capitalization ratio), and public float capitalization.

Assuming there is informed short selling activity on sample firms (during pre-ban period of those firms), I expect discontinuity in buy and sell liquidity supply and lambda price impact dynamics below cut-off threshold values defined by the exchange. Unlike OLS-based analysis (which is applied on a broader sample comprising large, mid and small market capitalization firms), the RDD analysis effectively uses a smaller sample size, which is local around liquidity threshold cut-off that drives short sell eligibility. The sample comprises both treatment and control groups (counter-factual) based on exchange-driven short sell eligibility. I provide motivation, empirical strategy and results for my RDD analysis in section: VII.

V. Data and Sample Construction

I use stocks listed and traded in the Hong Kong exchange, and my sample includes tick-by-tick level 1 trade and quote data, level II depth data, and end-of-day data. The sample for my regression analysis runs from 27th July, 2013 to 3rd, July 2016. However, the actual sample start date runs from around one year before the regression sample start date (which is 27th July, 2012), so that it receives a full 365 days to compute the turnover velocity. The Hong Kong exchange imposed a threshold criteria change for short sell eligibility effective from 27th July, 2012 and there was no further revision until my sample period end date used in this study. My sample period is between 2012 and 2016 because my lending data ends at December, 2016. Besides, as depth data (based on level 2 order book data) size is relatively larger level 1 trade and quote data), I have computed the data metrics only for a specific period between 2013 and 2016, which I expect to be sufficient to examine my hypotheses.

Construction logic of regression sample including variables are as follows:

Short sale eligibility Sample

Short sell eligible and ineligible stocks are hand collected from the Hong Kong exchange website. Exchange has an archive of periodic insertions and deletions for stocks eligible for short selling. I start with a complete list of short sale eligible securities published by exchange with effective date from 30th December, 2016 and move backwards in time to set the short sell eligibility of stocks to one (1) or zero (0) as and when exchange publishes the eligible list, new additions or deletions on quarterly basis. The list sample from the exchange has the Hong Kong exchange local code. I construct RIC (Reuters Identifier Code) based on the local code.

Buy/Sell Order Flow Impact and Liquidity Supply metrics (as dependent variables)

Microstructure variables include **daily buy lambda and sell lambda** (denoted by λ^{buy} and λ^{sell} respectively) as proxies for order flow impact and **bid and ask depth slope** (denoted by $BidSlopeL15$ and $AskSlopeL15$). These variables are computed based on data from TRTH intraday trade and quotes data and the TRTH depth (level2) data file. The sample per stock is identified in TRTH using Reuters Instrumentation Code (RIC). For each quote and trade, TRTH reports time stamps to the nearest millisecond. These measures (using intraday data) are computed in the continuous trading phase using on-market quotes and trades, and trading halt/suspension are excluded from the computation.

The microstructure panel variables are then merged with short sell eligible panel using the RIC-date identifier.

Control variables - daily data

Control variables include mid-quote based volatility and firm characteristics such as Market-to-Book Ratio. Book value is extracted from Reuters Datastream. Outstanding shares, end-of-day close price and traded volume are extracted Global COMPUSTAT daily security data file. The data is merged using SEDOL and date as identifier and is used to compute variables Market-to-Book Ratio, market capitalization and turnover. The data panel is stamped with RIC code based on reference data code mapping file: ISIN-RIC mapping file. This file is extracted from Reuters and has history of RIC-ISIN changes.

Data Merging

- Merging Lending data with Control variables, which are sourced from Global COMPUSTAT Hong Kong and equities lending data is extracted from IHS Markit source. The lending data has both the SEDOL and ISIN identifiers. SEDOL code is specific to a particular exchange. This, along with the date, is used as a key identifier to merge lending data with data sourced from GLOBAL COMPUSTAT.

- Merging lending data with microstructure variables Microstructure variables, which has RIC, as the primary key identifier, is merged with lending data using ISIN-RIC code mapping file. A RIC can have multiple ISINs. Lending data record, which has ISIN and SEDOL, is stamped with RIC code by tracking the history of ISIN changes for a RIC using ISIN-RIC mapping file. The RIC-date identifier is then used to merge the lending data with the microstructure panel data.

  Stocks in the sample are then flagged with Heng Sang index constituents and derivatives listing (Futures & Options). The final stock-day panel includes microstructure variables, lending data, control variables and firms stamped with short sell eligible dummy (denoted by *ss_eligible*) which is zero or one based on exchange list.

VI. Results

I conduct empirical tests to investigate the effect of short sale selling ban or constraints in Hong Kong market on the liquidity supply and order flow impact dynamics, based on the hypotheses presented in section: III.

Hypothesis 1 is tested based on a short sale ban imposed by the exchange and Hypothesis 2 is tested based on constraints induced by the lending market.

A. *Results 1: Short selling ban, liquidity supply dynamics and order flow impact*

I begin my analysis by comparing various depth and price impact (considered as the inverse of depth) parameters between short sale eligible ($SSeligible$) and ineligible ($SSineligible$) stocks on both the buy and sell-side in my OLS test sample (comprising of large, mid, and small-capitalization stocks). In line with my hypothesis, I expect that the short sell ban reduces the daily depth volume on both bid and ask sides for short-sale in-eligible stocks compared to short-sale eligible stocks. The possibilities of near-symmetric bid- and ask-side distortion (in other words, distortion in the bid and ask with lower asymmetry) could arise via both information-driven and non-information-driven channels when trades are prevented from short selling on a stock. In addition, if a market has a presence of risk-averse informed traders taking positions in both the bid and ask sides of the market to minimize or square-off inventory risk, it is plausible that the informed trading ban may affect both sides of the market. This situation may endogenously affect uninformed liquidity provision trading strategies on both the bid and ask sides due to imperfect competition and greater market power among liquidity providers. Overall, I expect the depth slope flattens because the limit trader is expected to set the price in her favor per unit of supplied quantity. My difference-in-means test outcome shows that the total daily depth volume (up to level 5) is significantly higher for short sale eligible stocks than ineligible stocks on both the bid and ask sides. The “t-statistics” for the difference-in-means test corresponding to the bid and ask sides are 40.45 and 42.72, respectively. The lambda price impact is significantly lower for short sale eligible stocks than ineligible stocks corresponding to both buy-trade initiated and sell-trade initiated flow. The “t-statistics” for the difference-in-means test corresponding to the buy-trade and sell-trade initiated lambda are -43.54 and -47.37, respectively.

I further motivate the use of RDD analysis on a quasi-random sample around size (market capitalization) cut-off in the Empirical strategy section: IV to compare the depth metrics and lambda price impact. The difference-in-means comparison is presented in the Table VII. To investigate the depth volume (which is directly based on the observed data) on the RDD sample, I present the visualization of a near-symmetric increase in the depth volume on both the bid and ask side in Figure:3 (under Section:VII.C).

Following equation:1 and 1, I present ban’s effect on bid/ask depth slope and buy/sell lambda price using OLS results. Table I presents the OLS panel regression estimations of the short sale eligibility dummy on the natural log of the bid depth slope (denoted by *Log Bid Slope* $L1\_5$) and ask depth slope (*Log Bid Slope* $L1\_5$). The regression panel is the same as the one used to test hypothesis 2 based on lending data. The panel includes approximately 1,435 stocks in total. The test presents both contemporaneous and one-day lag results and controls for stock fixed effects, firm characteristics, and volatility and return parameters. Table V demonstrates that short selling eligibility is positively associated with *Log Bid Slope* $L1\_5$ and *Log Ask Slope* $L1\_5$, with near symmetric magnitude at both the contemporaneous level (see columns (1) and (2)) and the one-period lag level (see columns (3) and (4)).

On an average, at the contemporaneous level, the bid and ask depth slope is 3.04% ((exp $\beta -$ 1)*100), beta = 0.03) higher for informed short selling eligible stocks than that for ineligible stocks (i.e. banned stocks). The "t" statistic on the bid depth slope is 3.71 (see column (1)) and the ask depth slope is 3.95 (see column (2)). The one-day lag results indicate that, on average, the bid (ask) depth slope for informed short selling eligible stocks is 3.04% (4.08%), higher than that for ineligible stocks. The "t" statistic is 3.86 (see column (3)) and 4.45 (see column (4)) for results corresponding to the bid and ask depth slope. By contrast, this implies that short selling ineligibility (or a ban), is associated with lower (or flatter) bid and ask slopes. The effect is statistically significant on the both the bid and ask sides. I now turn my attention to the order flow impact, which is considered as the inverse of depth. Lower depth (i.e., flatter depth slope) on the bid and ask sides (refer to slope diagram shown in Figure:1) implies a distortion in liquidity provisioning on both sides of the market, causing an adverse effect on depth. The direct implication is order flow emanating from buy or sell initiated trades is expected to generate a higher price impact. By contrast, a higher (or steeper) depth slope implies a lower impact cost. This result is presented in Table II. In line with my hypothesis 1, I expect that short sell ban, which is shown to be associated with lower or flatter depth slope, generates a higher lambda price impact for buy or sell order flow.

The table indicates that short selling eligibility is negatively associated with a buy-initiated order flow impact (denoted by λ^{buy}) and a sell-initiated order flow impact (denoted by λ^{sell}) at a near similar magnitude. At both the contemporaneous level and the one-day lag level, I find that, on average, the buy and sell lambda for short eligible stocks are 1% lower than that for short ineligible stocks. Overall, Table I and II outcome support my theoretical motivation and hypothesis 1 (discussed in Section III).

While I expect a negative relationship between the short-selling eligibility and the order flow impact, the OLS result is not significant at the contemporaneous level (see column (A) in Table II) and marginally significant at the one-day lag level (see column (C) in Table II). The regression is controlled for firm fixed effects and firm *Size*, *Return*, $MarketReturn$, and $MarkettoBook$, $QuoteVolatility$ and VIX. The intuition with this marginal significance is that λ^{buy} and λ^{sell} capture the order flow impact caused by the information emanating from aggressive trades. Informed traders tend to trade aggressively for firms with a high degree of information asymmetry,

Table I. The effect of short sale eligibility on the bid and ask order book slope

The table presents OLS panel regression results of the short sale eligibility dummy on the bid and ask order book slope. The regression is run on a panel comprising daily microstructure variables, control variables, and short sale eligible dummy variable. The dependent variable in the table is log of the order book slope (denoted by *log Bid Slope L1_5* and *log Ask Slope L1_5*). Independent variables in the table include short sell eligible dummy (*ss_eligible* is one if stock is enabled for short selling, otherwise zero). Models (1) and (2) are based on a contemporaneous short sale eligible dummy. Models (3) and (4) are based on one period lagged short sale eligible dummy. Controls include log of $Size$, $Return$, $MarketReturn$ and $Market-to-Book$, $QuoteVolatility$ and VIX (volatility index). Appendix: A includes the definitions of the controls. The sample period is from 29 July, 2013 to 30 June, 2016 and comprises 1,435 Hong Kong firm codes made up of large, mid, and small-capitalization stocks. The panel regression controls for firm fixed effects.*,**,*** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered at the firm-date level and t-statistics are reported in absolute values.

	(1)	(2)	(3)	(4)
VARIABLES	log Bid Slope L1_5	log Ask Slope L1_5	log Bid Slope L1_5	log Ask Slope L1_5
ss_eligible	0.03***	0.03***		
	(3.71)	(3.95)		
ss_eligible (-1)			0.03***	0.04***
			(3.86)	(4.45)
Observations	703,564	703,564	700,798	700,799
Adjusted R-squared	0.83	0.83	0.83	0.83
Stock Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Table II. The effect of short sale eligibility on buy lambda and sell lambda

The table presents OLS panel regression results of the short sale eligibility dummy on buyer-initiated and seller-initiated price impacts. The regression is run on a panel comprising daily microstructure variables, control variables, and a short sale eligible dummy variable. The dependent variables in the table are buyer- and seller-initiated lambdas (denoted by λ_{it}^{buy} and λ_{it}^{Sell}). The independent variables in the table include the short sale eligible dummy (*ss_eligible* is one if stock is enabled for short selling, otherwise zero). Models (A) and (C) controls include log of $Size$, $Return$, $MarketReturn$ and $Market-to-Book$, $QuoteVolatility$ and VIX (volatility index). Models (B) and (D) exclude "Size" as control. Appendix: A includes the definitions of the controls. The sample period is from 29 July, 2013 to 30 June, 2016 and comprises 1,435 Hong Kong firm codes, consisting of large, mid, and small-capitalization stocks. The panel regression controls for firm fixed effects.*,**,*** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered at the firm-date level and t-statistics are reported in absolute values.

	Contemporaneous				One period Lag			
	(A)	(A)	(B)	(B)	(C)	(C)	(D)	(D)
VARIABLES	λ_{it}^{buy}	λ_{it}^{sell}	λ_{it}^{buy}	λ_{it}^{sell}	λ_{it}^{buy}	λ_{it}^{sell}	λ_{it}^{buy}	λ_{it}^{sell}
ss_eligible	−0.01	−0.01	−0.01*	−0.01**				
	(1.37)	(1.63)	(1.85)	(2.17)				
ss_eligible (-1)					−0.01*	−0.01*	−0.01**	−0.01**
					(1.66)	(1.93)	(2.73)	(2.42)
Observations	147,067	147,067	147,067	147,067	146,310	146,310	146,310	146,310
Adjusted R-squared	0.45	0.40	0.45	0.40	0.35	0.34	0.35	0.34
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes (- Size)	Yes (- Size)	Yes	Yes	Yes (- Size)	Yes (- Size)

which is expected to vary in the cross-sections of firm size. A public firm with larger market capitalization is expected to have a lower degree of information asymmetry and lower adverse selection risk than a firm with smaller market capitalization. However, small and illiquid stocks have the highest execution/impact costs, which are magnified with order aggressiveness (Griffiths et al.(2000)). Overall, I expect order aggressiveness to differ in firm size cross-section. Hence, it may be logical to assume that the short-selling eligibility on buy and sell lambdas is to some extent absorbed by the size effect. Once I exclude *Size* from the control (as shown in column (B) and (D) in Table II), the statistical significance becomes stronger (as I see in column (B) and column (D)). At the contemporaneous level, the absolute 't" statistic for effect on buy lambda is 1.85, and that on sell lambda is 2.17 (see column B). At the lag level, the 't" statistic for the effect on the buy lambda is 2.73 and that on the sell lambda is 2.42 (see column (D)). The magnitude (or power) remains the same in all the model columns, as indicated by the regression coefficient, which is 0.01. One may also argue about the degree of bias in the result as size is endogenous to short sell eligibility (independent variable) and buy/sell lambdas (dependent variable), in other words. size is one of the decision criteria for the short selling eligibility list in Hong Kong. The Section VII further discusses a robustness result using a quasi-random sample where the analysis is conducted on control and treatment stocks around the size cut-off, that is, control and treatment firms are quasi-random in size.

B. *Results 2: Lending market induced short selling constraints, liquidity supply dynamics, and order flow impact*

This subsection presents the OLS analysis outcome of short selling constraints on bid/ask depth and buy/sell order impact variables. Table III and IV demonstrate how lending activity is associated with bid- / ask- depth slope and buy- / sell- lambdas, respectively. The results remain unchanged after controlling for stock fixed effects, firm characteristics, and other market and stock trading controls.

Like Table I, which is based on a short selling eligibility dummy *ss_eligible*, Table III demonstrates that increased lending activity is significantly positively associated with the bid and ask order book depth slope (*Log Bid Slope L*1_5 and *Log Ask Slope L*1_5). The analysis is conducted by taking the natural log of *LoanDemand* and *LendingSupply* to normalize and remove skewness in the distribution. As demonstrated in the Table III, the magnitude of the effect is near symmetric: 1% of the increase in the lending supply is associated with a 0.14% (see columns (1) and (3)) increase in the bid depth slope and a 0.12% (see columns (2) and (4)) increase in the ask depth slope at both the contemporaneous level and the one-day lag level. Concerning the loan demand, the magnitude is near symmetric at both the contemporaneous and the one-day lag level. The outcome is highly statistically significant for all model columns (1) to (4). The outcome is economically significant. One unit of standard deviation in the log of LendingSupply is associated with a 35.6% (standard deviation * coefficient = 2.544 * 0.14) change in the log of the bid depth slope and a 30.5% (2.544 * 0.12) change in the ask depth slope. One unit of standard deviation in the log of LoanDemand is associated with a 38.2% (standard deviation * coefficient = 2.73 * 0.14) change in the bid depth slope and a 32.76% (2.73 * 0.12) change in the ask depth slope. The standard deviation for economically significant numbers corresponding to the *log LendingSupply* and the *log LoanDemand* are extracted from Table XI in Appendix D.

Table III. The effect of loan demand and lending supply on the bid and ask order book slope

The table presents OLS panel regression results of the loan demand and the lending supply on the bid and ask order book slope. The regression is run on a panel comprising daily microstructure liquidity variables, control variables and lending data. The dependent variables in the table are the log of order book slope (denoted by *log Bid Slope L*1 5 and *log Ask Slope L*1 5). The independent variables in the table include the log of loan demand (i.e. shares that are loaned for short selling) denoted by *LoanDemand* and the log of lendable quantity (i.e. shares that are available for lending) denoted by *LendingSupply*. Models (1) and (2) are based on contemporaneous lending and control variables. Models (3) and (4) are based on one period lagged lending and control variables. Controls include log of *Size*, *Return*, *MarketReturn* and *MarkettoBook*, *QuoteVolatility* and *VIX* (volatility index). Appendix: A includes the definitions of the controls.The sample period is from 29 July, 2013 to 30 June, 2016 and comprises 1435 Hong Kong firm codes consisting of large, mid and small-capitalization stocks. The panel regression is controlled for firm fixed effects.*,**,*** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Standard errors are clustered at the firm-date level and t-statistics are reported in absolute values.

	(1)	(2)	(3)	(4)
VARIABLES	log Bid Slope L1_5	log Ask Slope L1_5	log Bid Slope L1_5	log Ask Slope L1_5
log LendingSupply	0.14***	0.12***		
	(29.49)	(24.84)		
log LoanDemand	0.05***	0.04***		
	(36.89)	(35.79)		
log LendingSupply (-1)			0.14***	0.12***
			(30.12)	(25.43)
log LoanDemand (-1)			0.04***	0.04***
			(36.11)	(34.38)
Observations	301,757	301,757	301,436	301,436
Adjusted R-squared	0.91	0.90	0.91	0.90
Stock Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

In line with my hypotheses predictions, I expect that an increased lending supply and a lower shorting demand would result in a steeper (great) depth slope implying a lower order flow price impact. By contrast, higher lending constraints and a lower shorting demand would result in a flatter (lower) depth slope, implying a higher order flow impact . This is depicted in Table IV.

The table indicates that a 1% increase in the lending supply is associated with a 0.01% (see columns (1) to (4)) decrease in both the buy lambda (λ_{buy}) and the sell lambda (λ_{sell}). The magnitude of the effect is the same at both the contemporaneous and the one-period lag levels. With respect to loan demand, a 1% increase in loan demand is associated with a 0.001% decrease in λ_{buy} and λ_{sell} (see columns (1) and (2)) at the contemporaneous level, and a 0.002% decrease in λ_{buy} and λ_{sell} at the one-day-lag period. Overall, the effect of change in lending activity is near symmetric on both the buy and sell lambda and is economically significant. The economic significance indicates that one-unit standard deviation in the log of LendingSupply is associated with a 2.5% (standard deviation * coefficient = 2.544 * 0.01) change in the buy and sell lambda price impact, and one unit standard deviation in the log of LoanDemand is associated with a 6.90% (2.73 * 0.01) change in the buy and sell lambda price impact. I observe this at both contemporaneous and one-period-lag level.

Overall, lending constraints results in higher order flow impact and a flatter depth slope, and the effect is observed to be economically significant for both the bid and ask sides, which is consistent with my hypothesis 2. An increase in lendable shares implies an easing in borrowing shares, and an increase in loan demand suggests higher short interest. The higher short-selling cost naturally results in a decline in demand from short-sellers who trade with public information. The demand for such types of short-sellers is elastic to change in fees. I expect that such constrained short-selling adversely impacts both bid and ask sides of the market, as discussed in hypothesis 2 (Section III).

I further test a sample removing the stocks that are constituents of the "Heng Sang" index in Hong Kong and listed for derivatives trading, to exclude any effects of index investing via exchange-traded products and derivatives hedging on underlying stocks. Only excluding stocks under the "Heng Sang" index may not fully represent stocks that are part of other indices. The entire universe of indices is not captured due to a lack of time series of constituent data covering all the indices. However, I expect that a substantial portion of the effect would be captured by the main Hong Kong index, which comprises most of the market share in Hong Kong. Concerning the short-selling ban analysis (see result discussion in Section VI.A, I find that the depth slope on the bid side is 3.04% ((exp $\beta-1$)*100), beta = 0.03) higher for short selling eligible stocks than for short ineligible stocks (banned stocks). The depth slope on the ask side is 3.04% ((exp $\beta - 1$)*100), beta = 0.05) higher on an average. I observe this at both the contemporaneous and the one-period-lag levels.

With respect to the analysis using the lending market, I find that on the bid side, a 1% increase in the loan demand and the lending supply is associated with 0.15% and 0.04% increases in the bid and ask depth slope, respectively. On the ask side, a 1% increase in the loan demand and the lending supply is associated with 0.13% and 0.04% increases in the bid and ask depth slope, respectively.

C. Joint analysis of buy and sell depth slope and order flow impact

As per my proposal in the empirical strategy section: IV, I further validate above results using joint a SUR analysis of buy and sell variables. Table V presents the joint analysis of buy and sell depth slope and the lambda variables using seeming uncorrelated regression. I mainly present one-period-lag results to summarize the key results in one table. The results are controlled for firm characteristics, stock and market-wide trading conditions ($Size$, $Return$, $MarketReturn$,

Table IV. The effect of loan demand and lending supply on buy lambda and sell lambda

The table presents OLS panel regression results of the loan demand and the lending supply on buyer-initiated and seller-initiated price impacts. The regression is run on a panel comprising daily microstructure price impact variables, control variables and lending data. The dependent variables in the table are buyer- and seller-initiated lambdas denoted by λ_{it}^{buy} & λ_{it}^{Sell} respectively. The independent variables in the table include the log of loan demand (i.e., shares that are loaned for short selling) denoted by $LoanDemand$ and the log of lendable quantity (i.e., shares that are available for lending) denoted by $LendingSupply$. Models (1) and (2) are based on the contemporaneous lending and control variables. Models (3) and (4) are based on one period lagged lending and control variables. The controls include the log of $Size$, $Return$, $MarketReturn$, and $Market-to-Book$, $QuoteVolatility$, and VIX (volatility index). Appendix: A includes the definitions of the controls. The sample period is from 29 July, 2013 to 30 June, 2016 and comprises 1,435 Hong Kong firm codes consisting of large, mid, and small capitalization stocks. The panel regression is controlled for firm fixed effects.*,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Standard errors are clustered at the firm-date level and t-statistics are reported in absolute values.

VARIABLES	(1) λ_{it}^{buy}	(2) λ_{it}^{sell}	(3) λ_{it}^{buy}	(4) λ_{it}^{sell}
log LendingSupply	−0.01***	−0.01***		
	(5.36)	(4.88)		
log LoanDemand	−0.001***	−0.001***		
	(3.85)	(6.18)		
log LendingSupply (-1)			−0.01***	−0.01***
			(6.41)	(5.15)
log LoanDemand (-1)			−0.002***	−0.002***
			(7.19)	(7.42)
Observations	129,129	129,129	128,878	128,878
Adjusted R-squared	0.29	0.25	0.19	0.20
Stock Fixed Effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

$MarkettoBook$, $QuoteVolatility$ and VIX). In addition, the regression is controlled for the Hang Seng index dummy and derivatives listing dummy to exclude any effects that may be driven by trading on the Hang Seng index or derivatives (futures and options).

Panel A presents the analysis based on Hong Kong short selling ban (which is captured by short sell eligible dummy). Columns (1) and (2) show that on an average: a) the bid depth slope is 32.31% ((exp $\beta - 1$)*100), beta = 0.28), and b) the ask slope is 27.12% (((exp $\beta - 1$)*100), beta = 0.24) higher for short selling eligible stocks than that for ineligible stocks (i.e., banned stocks). Columns (3) and (4) (based on lambda price impact, i.e., inverse of depth) indicate that both the buy lambda and the sell lambda are 0.05 (5%) lower for short selling eligible stocks than that for ineligible stocks.

Panel B presents an analysis based on the $LendingSupply$ and $LoanDemand$. Columns (1) and (2) results indicate that on an average: a) a 1% increase in the $LendingSupply$ is associated with 0.70% and 0.69% increases in the bid and ask depth slope, respectively, and b) a 1% increase in the $LoanDemand$ is associated with a 0.21% increase in the bid and ask depth slope. Columns (3) and (4) show that on average: a) a 1% increase in the $LendingSupply$ is associated with 0.01% decrease in buy and sell lambda respectively, and b) a 1% increase in $LoanDemand$ is associated with 0.007% and 0.003% increases in buy and sell lambda respectively. Overall, sign and significance between the short selling eligible dummy or the lending supply and buy/sell lambda and depth slope are consistent with the OLS analysis results (see Table I, II, III, and IV).

Table V. SUR joint analysis of buy and sell depth slope and order flow impact

The table presents joint analysis of Buy and Sell depth slope and order flow impact using seemingly uncorrelated regression (SUR) following the method adopted by Gunnar and Grass (2018). The dependent variables in the table are the log of order book slope (denoted by $logBidSlopeL15$ and $logAskSlopeL15$, see models (1) and (2)), and buyer- and seller-initiated lambdas, denoted by λ_{it}^{buy} & λ_{it}^{Sell}, respectively (see models (3) and (4)). Panel A includes the independent variable: short sale eligible dummy ($ss\_eligible$ is one if stock is enabled for short selling, otherwise zero), and Panel B includes the independent variables: the log of loan demand (i.e., shares that are loaned for short selling) denoted by $LoanDemand$ and the log of lendable quantity (i.e. shares that are available for lending) denoted by $LendingSupply$. All models are run at the one-period lag level. The controls include the log of $Size$, $Return$, $MarketReturn$, and $Market-to-Book$, $QuoteVolatility$, and VIX (volatility index). Firms that are constituents of "Heng Sang" HSI index or have derivatives (futures and options) listing, are excluded from the sample. Appendix: A includes the definitions of the controls. The sample period is from 29 July, 2013 to 30 June, 2016 and comprises 1,435 Hong Kong firm codes consisting of large, mid, and small capitalization stocks. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are reported in absolute values.

Panel A

VARIABLES	(1) log Bid Slope L1_5	(2) log Ask Slope L1_5	(3) λ_{it}^{buy}	(4) λ_{it}^{sell}
ss_eligible (-1)	0.28***	0.24***	−0.05***	−0.05***
	(34.89)	(30.11)	(40.62)	(42.67)
Observations	575,357	575,357	99,385	99,385
Adjusted R-squared	0.13	0.12	0.22	0.21

Panel B

VARIABLES	(1) log Bid Slope L1_5	(2) log Ask Slope L1_5	(3) λ_{it}^{buy}	(4) λ_{it}^{sell}
log LendingSupply (-1)	0.70***	0.69***	−0.01***	−0.01***
	(233.12)	(228.43)	(20.04)	(16.59)
LoanDemand (-1)	0.21***	0.21***	0.0007***	0.0003**
	(121.52)	(122.50)	(4.12)	(2.25)
Observations	238,425	238,425	86,784	86,784
Adjusted R-squared	0.47	0.45	0.09	0.07
Controls	Yes	Yes	Yes	Yes

Panel A SUR columns (1) and (2) indicate the ban's differential effect of 5.19% on the bid depth slope against the ask depth slope. In contrast, the OLS results, corresponding to columns (3) and (4) in the Table I indicate a differential effect of around 1%. Economically, the magnitude of a ban's effect on the bid side depth may be slightly higher than the ask side (I observe similar result in my RDD analysis presented in Table VIII, Section VII.C). A ban can affect the buy-side in various ways: a) drives out informal liquidity providers who may need to take long/short positions. This situation could reduce liquidity competition on the bid side of the market b) possibly increases adverse selection on the bid side via endogenous information acquisition by the long sellers, that is sellers who own assets (Dixon(2021)), and c) may discourage investors from taking new long buy positions due to notion of overpricing and inability to short.

Cenesizoglu and Grass (2018), based on an NYSE market bid and ask ban analysis, find that a ban's effect on ask-side transaction costs is stronger than on the bid side: the cost in their study is estimated using depth data. The authors (refer to Table 4, page 12 in the paper) find that banned stock is associated with a 41.19% ((exp $\beta - 1$)*100, beta = 0.345) higher cost on the ask side and 17.12% (((exp $\beta - 1$)*100, beta = 0.158) higher cost on the bid side. The difference is substantial and a stronger effect is seen on ask side than on the bid side. One key difference is their study is mainly focused around key determinants of bid- and ask- side liquidity using 11 years of data that covers the US ban period. Their US ban outcome does not utilize analysis using counter-factual (i.e., control groups).

Overall, my outcome corresponds to that of Dixon (2021) and past studies regarding the ban's adverse effect on liquidity. Dixon finds that the total trading cost (captured by effective spread) is higher on both the buy and sell-side. Increased adverse selection on the bid side increases seller-initiated price impact, which contributes to sell-side (i.e., seller-initiated) effective spread. Reduced liquidity competition on the ask side due to the ban of short-sellers (as passive limit traders) increases in buyer-initiated realized spread, which contributes to buy-side effective spread. The author, however, finds that seller-initiated effective spread is around 50% higher than buyer-initiated effective spread. In other words, traders are likely to have a significant asymmetric effect in liquidity costs while trading with the buy-side compared to that with the sell-side. My lambda price impact outcome shows that ban adversely affects both buy and sell liquidity (or trading) costs (i.e., captured using buyer and seller-initiated lambda). However, results contrast with that of Dixon (2021) regarding the magnitude of asymmetric effect in liquidity cost. For example, I show 1-5% of asymmetry in ban's impact on buy and sell liquidity supply (see Panel A SUR results for bid and ask depth slope in columns (1) and (2) in Table V). Corresponding regression discontinuity design (RDD) results (see Table VIII) show around 13% of asymmetry. I further show no asymmetry in the ban's effect on buy and sell lambda as per my SUR results (see Panel B SUR results for buy and sell lambda in Table V) and OLS results (see Table II). Regression discontinuity design (RDD) results (see Table IX) however, indicate around 30% of asymmetry in ban's effects on buy and sell lambda.

The difference in Dixon (2021)'s outcome compared to ours may be due to several reasons. First, the author does not test with an order-flow-based price impact measure (that incorporates a size component) and does not utilize depth data. The author utilizes effective spread (as a proxy for trading cost), realized spread (as a proxy for liquidity competition effects), and price impact at multiple intervals (as a proxy for adverse selection), estimated based on the difference between the mid-point at a time "t" and the prevailing midpoint (when trade is executed) to test their findings. I base my outcome on the order-flow-based impact (Kyle lambda price impact) and depth data, and my results are consistent based on both lending market data and short selling ban data. Second, although the author has attempted to perform a difference-in-difference analysis by adopting matching approach proposed by past studies, the liquidity-crisis-driven confounding effects and extreme bear period during Global Financial Crisis may still have a degree of endogenous[17] effect on the outcome. Designated market makers and other liquidity providers may seek to close out positions. Therefore, it is natural to expect higher selling pressure from investors looking to exit from the market during bad times. However, I use a longer sample period without potential crisis-driven effects.

D. Variation in inventory risk and differential effect in buy and sell in the presence of short selling

Based on the theoretical motivations in Section III, if a contrarian informed liquidity supplier (running mean reversion or statistical arbitrage) or a market maker is to make a profit from placing orders in the long and short sides of the market, the markets need to be mean reverting so that their buy and sell orders are matched by aggressive traders, accounting for any adjustments of order processing and adverse selection costs. I could then expect stocks with higher mean-reverting property (which does not follow a random walk) to have lower differential effects in buy and sell order flow impact and supply dynamics. This intuition is straightforward: I expect a high concentration of trading needing both bid and ask sides in markets/stocks with mean-reverting properties. By contrast, momentum-based investing is more profitable with trending price series.

In the absence of private data, I cannot pinpoint investor types and flows; however, the Hong Kong market has a hedge fund presence trading both large, mid and small market capitalization. According to an Hong Kong Securities and Futures Commission (SFC) survey of hedge fund activities dated March 2015[18], the number of hedge funds as at 30 September, 2014 was 778, and equity long/short and multi-strategy were the most popular investment strategies. Equity long/short accounted for approximately 40.8% of hedge fund investment strategies. However, I am unaware of turnover frequency of such investors. Within a multi-strategy, equity long/short and equity hedge market-neutral were the most commonly used underlying strategies. In addition, the market might have received order flows from China mainland investors through the Hong Kong Shanghai or Shenzhen stock connect program –my sample period overlaps with the time when these programs came into effect. These investors faced similar short-selling regulations when trading in Hong Kong stocks.

To test my outcome, I utilize the Lo and MacKinlay's (1988) "Variance Ratio" metric and examine whether the differential effect in the bid and ask order book slope and buy and sell order flow impact is less for firms with stronger mean reversion properties. The classic Lo and MacKinley equation defines the variance ratio as:

[17] In addition, empirical tests in Dixon (2021)'s counterfactual analysis is not seen to be done using using industry match and on sample subsets adopted in Boehmer et al. (2013). It is unclear to what extent author's outcome will change using the approach to minimize confounding effects.

[18] Source link: `https://www.sfc.hk/-/media/EN/files/IS/publications/HF-Survey-Report-EC-2015.pdf`, this is the last report that best overlaps with my sample period.

$$VR(q) = \frac{\sigma^2(q)}{\sigma^2(1)} \tag{5}$$

whereas, $\sigma^2(q)$ is 1/q times the variance of $(X_t - X_{t-q})$ and $\sigma^2(1)$ is the variance of $(X_t - X_{t-1})$. As per the null hypothesis, VR(q) is not statistically different from 1. Traders typically interpret a) VR > 1 as a trending series, which is ideal for a momentum-based strategy profitable for price moving in same direction b) VR = 1 as a random walk series, and lastly c) VR < 1 as an indication of a mean reversion, profitable for a long short contrarian strategy, where traders short when the price moves up and buy when the price moves down.

I utilize one-minute intraday mid-quote returns and estimate five (5) period variance ratios, that is, q = 5, in my variance ratio "VR (q)" estimation. I posit that given that short flow is allowed, a lower variance ratio (i.e., a higher degree of mean reversion) is associated with lower differential depth slope and order flow impact in buy and sell. I expect this outcome, because a high degree of mean reversion is profitable for formal and informal liquidity providers bearing an inventory risk. As liquidity supply on both buy and sell increases, the market is more competitive, and liquidity suppliers are willing to quote at the higher bid and lower ask (in equilibrium) conditional on the sell and buy order flow, respectively. Consequently, the depth increases, the depth slope becomes steeper, and the lambda price impact becomes lower on both sides. This implies that that the differential between the buy and sell depth slope and the lambda price impact reduces.

Tab1e VI presents the effect of an interaction term between the variance ratio and the short selling eligibility on the buy/sell depth slope (column (1)) and lambdas (column (2)). The analysis is done on a cross-section of stocks. At the one-period lag level, the results indicate that in the presence of a shorting flow (i.e., considering short selling is allowed for informed and uninformed investors), one unit of increase in the variance ratio results in a 7% increase in the absolute difference between the bid and ask depth slope (column (1)), and a 1% increase in an absolute difference between the buy and sell lambda (column (2)). The results are statistically significant. Without having to use private data, my outcome, from an empirical perspective, demonstrates a high degree of buy and sell liquidity provision on the bid and ask sides of the market, which is profitable under a mean reversion market, drives the differential effect. Assuming investors look to manage the inventory risk, any effect of a ban or constraints on one side is expected to have a cascading effect on the other side of the market. I also attempt to tie this outcome to the theoretical expectations discussed in the hypotheses section. Figure 5 visualizes the average absolute differential between the buy and sell lambda (λ_{buy} and λ_{sell}) with respect to each bin ranked by the variance ratio. It indicates that a lower variance ratio decile is associated with a lower differential in price impact. With a higher liquidity supply and more competition on both bid and ask side, I expect it to have a lower order flow impact (which is the inverse of depth) on both sides of the market.

Table VI. Fama-MacBeth regression estimates: the effect of variance ratio on differential effect in buy and sell liquidity given short selling is allowed

The table presents Fama-MacBeth (1973)-type OLS cross-sectional regression results, which is run on a panel comprising daily microstructure variables, control variables, variance ratio and short sale eligibility dummy variable. The dependent variables in the table are absolute difference between the bid and ask depth slope (column (1)) and the absolute difference between buy and sell lambda (column (2)). The sample period is from 29 July, 2013 to 30 June, 2016. The independent variables include the one-period lag interaction term between variance ratio and short sell eligible dummy variable (denoted by $vr(5).ss\_eligible$) and the control variables, which include the log of $Size$, $Return$, $MarketReturn$ and $Market-to-Book$, $QuoteVolatility$ and VIX (volatility index). *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The t-statistics are reported in absolute values.

	(1)	(2)
VARIABLES	depth_slope_diff	lambda_diff
vr(5).ss_eligible (t-1)	0.07***	0.01***
	(2.69)	(13.20)
Constant	2.40***	0.04
	(2.78)	(1.53)
Observations	259,320	119,198
R-squared	0.14	0.15
Number of groups	639	631

VII. Robustness to Possible Endogeneity in OLS Tests and "Hong Kong style" Short Selling Ban Analysis

This section presents the outcome of the causal analysis of the short selling eligibility on the liquidity supply dynamics and lambda price impact by exploiting exogenous variations in liquidity threshold cut-offs (imposed by exchange) that drive short selling eligibility.

A. RDD Empirical Setup

Following Crane, Crotty, Michenaud and Naranjo (2018), I use the fuzzy RDD method to exploit the exogenous variation in shorting bans imposed by the Hong Kong exchange. The idea is that short-selling eligible firms that are just above the cut-off threshold criteria (or ineligible firms that are just below the cut-off) should be included by chance and hence, introduce randomization into the sample. The identification assumption implies that there should be local continuity in the buy and sell illiquidity and order book parameters in the absence of the ban. There should be no other observed and unobserved factors that impacts treatment and control stocks differently. Under Hong Kong settings, the underlying assignment rule (based on liquidity/firm characteristics related variables) that drives the eligibility (i.e., treatment), is not perfectly observed. This is because exact date on which exchange measures the eligibility list is not known. Since assignment rule cannot define treatment status (i.e., short selling eligibility) in deterministic way, I am required to use fuzzy RDD (instead of sharp RDD). Fuzzy design models discontinuity in probability of receiving the treatment at cut-off point "c". . To implement fuzzy RDD, my proposed two-stage (2SLS) baseline regression is as explained in following first state and second stage sections:

First stage:

I use cut-off (based on exchange defined criteria) as an instrument and regress on short sell eligibility on firms defined by exchange.

$$cut-off = \begin{cases} 1, & \text{if "}ThresholdCriteria1''or\text{"}ThresholdCriteria2''etc. \\ 0, & \text{otherwise.} \end{cases} \tag{6}$$

Cut-off variable is assignment to treatment. The criteria are published by the Hong Kong Exchange and could be subject to periodic revision [19]. Key liquidity related threshold criteria include:

- Stock market capitalization[20] is greater than exchange defined threshold for market capitalization.

[19] Example exchange news link: `https://www.hkex.com.hk/News/News-Release/2016/160627news?sc_lang=en` highlights a particular threshold criteria that is applicable from 4th July, 2012.

[20] Stock's end-of-day close price multiplied by shares outstanding.

- Stock aggregate turnover during the preceding 12 months to market capitalization ratio (called as turnover velocity) is greater than exchange defined threshold for turnover velocity.

- Stock public float capitalization is greater than exchange defined threshold for public float capitalization.

I focus my experiments on size-based eligibility threshold criteria. Firm size has been a discussion point in the research outcomes on short selling bans and market quality. For example, Boehmer et al. (2013) demonstrates that the US ban impacted market quality/liquidity of larger stocks rather than the smallest quartile of U.S. stocks. By comparison, Beber and Pagano (2013), in their international study, find that short selling bans (during the 2007 –09 crisis) were detrimental to liquidity, primarily for small-capitalization stocks and no listed options. Discontinuity tests around the size cut-off attempt to utilize observations of control and treatment firms similar in size.

The equation below presents the modeling of the probability of receiving the treatment using cut-off variable as an instrument. *ss_eligible* is actual treatment and is an endogenous variable. The coefficient on $cut-off$ measures the difference in the probability of short sell eligibility between firms just below and just above the cut-off. The $\tilde{X}$ is the distance of forcing variable from the cut-off. Consider an example where forcing variable "X" is market capitalization (denoted by $Size$) variable that determines the probability of assignment to short selling eligibility. The $\tilde{X}$ in the equation below is the distance between $Size$ and Cut-off, measured as $Size$ minus cut-off "C"'.

$$ss\_eligible_{i,t} = \gamma_0 + \gamma_1.Cut-off + \gamma_2.\tilde{X} + \gamma_2.Cut-off * \tilde{X} + \gamma.C_{i,t} + \epsilon_{i,t}, \tag{7}$$

where **ss_eligible** is equal to one (1) if stock "i" is eligible for short selling at time "t", otherwise zero (0). C is the vector of controls for stock "i". The controls are discussed in detail in data section V and defined in Appendix section: A.

Second stage:

I regress the predicted value of short-selling eligibility (denoted by $ss\_\hat{eligible}_{i,t}$) from the first stage regression on the liquidity and order flow impact dependent variables (denoted by $DepVar$). $DepVar$ includes the bid and ask depth slope (denoted by $BidSlopeL1\_5$ and $BidSlopeL1\_5$, respectively), and the buyer-initiated lambda and the seller-initiated lambda (denoted by λ^{buy} and λ^{sell} respectively). The assignment to treatment should affect order flow impact and liquidity supply variables through $ss\_\hat{eligible}_{i,t}$ at cut-off.

$$DepVar = \beta_0 + \beta_1.ss\_\hat{eligible}_{i,t} + \beta_2 * \tilde{X} + \beta_3.Cut-off * \tilde{X} + \beta.C + \epsilon_{i,t}. \tag{8}$$

Following Crane et al. (2018), I construct and evaluate thresholds by choosing end-of-month data from two calendar months before the month when the new short sell eligibility list comes into effect every quarter. This is to ensure that the measurement date would precede the announcement date but not be too far ahead. The announcement date could sometimes be in the calendar month before the effective date; hence moving two calendar months back ensures that forcing variables (i.e., market capitalization, turnover velocity, and float capitalization) are measured prior to the announcement date. In theory, I could choose other evaluation dates that are before the announcement date, and the criteria of selecting a particular date could be based on the predictability of cut-off thresholds on the short selling eligibility dummy variable defined in the Equation:7. However, given the announcement and effective dates are irregular, there may not be a single optimal measurement date for the sample. For the sake of simplicity, the two-month procedure is chosen.

B. Sample for RDD Analysis

As per the liquidity threshold criteria (applicable to my sample period), stocks would need to have market capitalization of not less than HKD 3 *billion*, "aggregate turnover during the preceding 12 months" to market capitalization ratio of not less than 60 %, and a public float market capitalization of not less than HKD 1 *billion*, maintained for 60 days of the qualifying period. My sample is based on size eligibility threshold criteria, which is the main focus of the analysis discussed in Section VII.A. Stocks are evaluated for eligibility using the market capitalization threshold values at the measurement date, which is decided two months before the month of the exchange's effective date (as discussed in Section VII.A). I attempt to exclude other effects that drive short sale eligibility. The size-based eligibility sample does not include a) stocks that satisfy the turnover velocity rule, b) Heng Sang index constituents, and c) listed for derivatives trading (futures and options). I further exclude newly listed firms for data continuity across my sample period and simplify the sample construction process. The liquidity criteria for firms listed on the exchange for no more than 60 trading days are different from those of other firms.

Due to floating data quality issues extracted from Reuters Datastream source in my study, the float-adjusted market capitalization rule is not excluded in my market capitalization (size) threshold sample. However, I do not anticipate any notable change in the hypothesis testing outcome after filtering out the float-based market capitalization rule. If float capitalization is filtered out, this may eliminate some bias in the estimation. However, the RDD analysis may have to be conducted on a smaller size sample.

C. RDD Results

Table VII presents a comparison of the mean and difference-in-means estimates between $SSeligible$ and $SSineligible$ stocks, based on the market capitalization threshold sample. The comparison is provided for variables that include a) end-of-day short sale volume (as a fraction of the total volume, denoted by $RellSSVol$), b) the bid and the ask depth volume up to level 5 (denoted by $BidDepthDollarVolL1\_5$ and $AskDepthDollarVolL1\_5$ respectively), c) the trade volume (denoted by $TRADEVOL$), and d) the buyer- and seller-initiated price impact variable (denoted by λ^{buy} and λ^{sell} respectively). The outcome shows that trade and bid/ask depth volume parameters are significantly higher for short-selling eligible stocks than ineligible stocks. By contrast, as we expect, lambda price impact is significantly lower for short-selling eligible stocks. The significance on stock return is marginal at the 10% significance level. However, I do not find a ban affecting returns and volatility, as demonstrated in the RDD analysis outcome in Section VII.D.

Table VII. Analysis of liquidity, trading activity and return-volatility variables: Hong Kong short-sale eligible vs ineligible stocks

The table presents a comparison of the mean and difference-in-means estimates using the market capitalization threshold sample comprising Hong Kong equities. The following firms are excluded from the sample a) constituents of the Heng Sang HSI index, and b) firms that have a derivatives (futures and options) listing. The mean estimates of variables (presented in the table) for *SSeligible* and *SSineligible* stocks are calculated using an equally weighted time series average at daily frequency. The period is from 29 July, 2013 to 30 June, 2016.

	SS eligible	**SS ineligible**	**Difference**
Return	0.0009	0.00133	−.0004*
			(1.7065)
Quote Volatility	0.000708	0.000889	(0.0001)***
			(16.56)
RelSSVol	499755	193894	305861.2***
			(14.95)
Bid Depth Dollar Vol L1_5	1.55E+06	585,892	965207***
			(50.62)
Ask Depth Dollar Vol L1_5	1.69E+06	571,005	1120833***
			(71.97)
TradeVol	6.27E+06	3.62E+06	2648290***
			(21.77)
λ_{buy}	0.0638	0.206	−0.142***
			(24.91)
λ_{sell}	0.063	0.199	−0.14***
			(23.80)

End-of-day Short Volume data

I utilize daily data on short transactions to gauge the extent of short selling trading activity per firm during the pre-ban period. The data is extracted from Reuters history end-of-data transaction data file. The short sell volume (denoted by $RelSSVol$) is plotted below and above cut-off, using market capitalization, that is, size-based eligible sample. Figure 2, using linear and nonlinear polynomial bin plots[21], shows a discontinuity jump in short sell volume above the post- market capitalization cut-off threshold. Based on two stage regression results, I find that the predicted

[21] The plot traces RDD regression function to visualize the treatment effect on shorting activity. The plotting is based on evenly spaced bins and data driven RD regression approach following the method adopted in Calonico, Cattaneo and Titiunik (2015). STATA rdplot package is used for the plotting.

component of short sell eligible dummy ($ss\_\hat{eligible}$) creates a discontinuity effect around the cut-off point. The result is statistically significant at 1% level and coefficient on $RelSSVol$ is around 7. It may be noted that volume is not completely zero for short ineligible stocks because few types of market participants are exempted from short selling regulation (as discussed in introduction section:I). The participants, who are not perceived as informed short sellers, include but are not limited to following: securities market maker, index arbitrage traders, futures and option hedgers. The non zero shorting volume data post ban is likely capturing their trading activity.

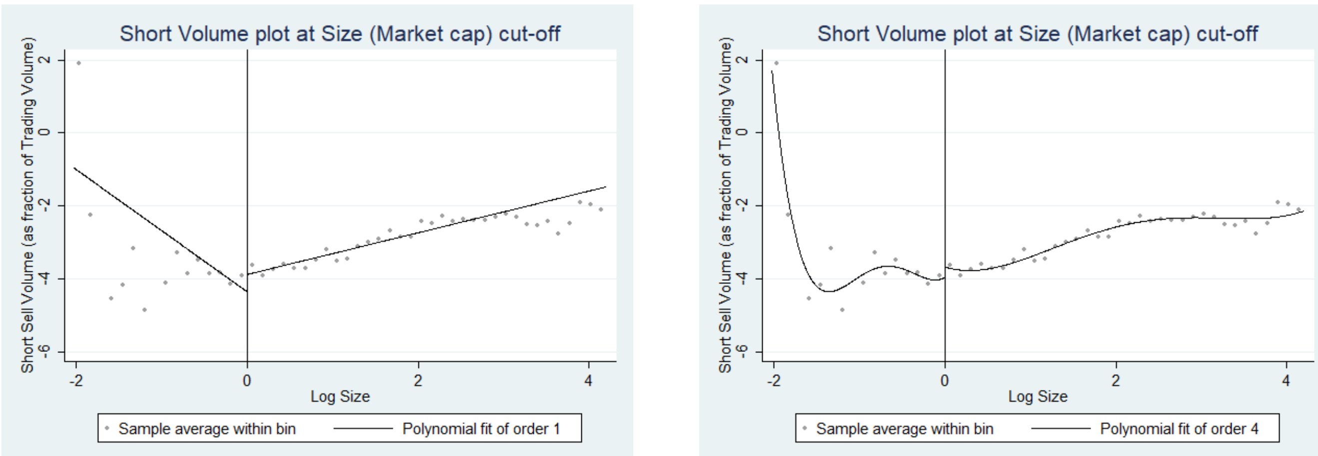

Figure 2. Graphs illustrate the linear and nonlinear sample polynomial bin fitted plots of short selling volume below- and above- market capitalization cut-off threshold.

The sample period is from 29 July, 2013 to 30 June, 2016

Given this paper's context, the data availability across firm-days varies depending on the variables utilized in this study. For example, buy and sell lambdas (denoted by λ^{buy} and λ^{sell}) are based on regression estimated parameters on the intraday order flow and mid-point return (see Appendix A for details), whereas the bid and ask depth slope (denoted by $BidSlopeL1\_5$ and $AskSlopeL1\_5$) are measured using closed form equations from the observed depth data. Moreover, the RDD analysis sample primarily contains small market capitalization firms, as target firms having lower liquidity. Hence, I primarily utilize optimal data-driven bandwidth (proposed by Imbens and Kalyanaraman (2011)) [22] for the fuzzy RDD analysis. Generally, it is perceived as ideal to conduct the analysis using many observations very close to the cut-off, so that the effects can be obtained using non-parametric localized regression on a quasi-random sample. However, there are trade-offs between trying to achieve unbiased estimates (based on quasi-random sample containing treatment assignment close to cut-off) and external validity of the estimates.

I focus on linear polynomial regression results for RDD analysis. Higher polynomial results could be included to check sensitivity of results. Gelman and Imbens (2018), however, argue against the use of high order polynomials (such as third and above) for various reasons. High

[22] I use STATA package "rdbwselect" for optimal bandwidth selection based on Mean Squared Error (MSE)-optimal bandwidth selection method.

order estimation could assign large weights (positive or negative) to extreme values away from the cut-off points. Also, the results could be sensitive, depending on the order of the polynomials. In local linear regression, variables away from the cut-off have less weight.

To test Hypothesis 1 discussed in Section III, Table VIII presents the linear local polynomial fuzzy RDD two-stage regression analysis results, demonstrating the effect of short selling eligibility on *Bid Slope L1_5* and *Ask Slope L1_5*. A natural log is taken on forcing variable to remove any skewness in the distribution of market capitalization below and above cut-off. Optimal bandwidth based on Mean Squared Error (MSE) data-driven selector is estimated as around 6.1% and 6.8% above and below cut-off for analysis on bid and ask depth slope respectively. Panel A in Table VIII presents the fuzzy RDD results, and panel B presents regression kink design (RKD) results. The kink design captures difference between slope of a local linear regression of dependent variables (bid/ask depth slope and buy/sell lambdas) with respect to *Size* as forcing variable minus cut-off below" just below and above the cut-off. This is estimated using coefficient of interaction variable between binary cut-off variable and $\tilde{X}$ in equation, which is the distance between the forcing variable and the cut-off value. The interaction term is denoted by "$Cut-off * \tilde{X}$" in Equation:7 and 8.

I observe that panel A does not have a conclusive outcome in terms of an upward jump/discontinuity in the average treatment effect. Instead of just studying the shift (i.e., discontinuity) in the intercept at the cut-off point, I further report a change in the slope using the RKD approach at the cut-off point. The key motivation for this analysis is to further investigate the depth change of treatment stocks as compared to control stocks comparable in size around the cut-off. The RKD approach (a term first defined by Nielsen et al. (2010)) captures and estimates the change in slope at the likelihood of being treated at the cut-off point, measuring the discontinuity effect in the first derivative of the assignment function. The method enables me to see whether the bid and ask depth liquidity indicate any change in slope in relation to the variable capturing probability of the treatment (predicted short selling eligible/ineligible dummy) at the cut-off point.

Panel B first stage analysis shows that the probability of short sell eligibility for firms above the market capitalization cut-off is 48% (41%) higher than for firms below the cut-off, when analyzed on bid and ask depth slope, respectively. The results remain approximately same post-covariate adjustment – the estimate is adjusted using *Return*, $QuoteVolatility$, and $MktReturn$ to remove the effect of these factors. For valid co-variates, the treatment should have no effect on these variables at the cut-off.

Panel B second stage results indicates that the effect of the short selling eligibility (predicted by the market capitalization threshold) is significantly higher for the short selling eligible group than for the ineligible group (i.e., banned stocks) on both the buy and sell slope. In other words, short selling eligibility causes a steeper slope on the bid and ask sides (with reference to Figure 1)). By contrast, ineligibility causes a flatter slope. The "t" statistic corresponding to the bid depth slope is 4.33 (4.35), and the ask depth slope is 3.86 (3.94) pre (post) the co-variate adjustment. The differential effect between the buy side and the sell side is 1.31 (second-stage regression coefficient of bid depth slope minus (-) that of ask depth slope, that is, that is, 10.93 - 9.62). This is captured in Figure 3, which illustrates the increase in the bid/ask depth volume above the cut-off that drives the short selling eligibility.

Table VIII. The effect of short sell eligibility on bid and ask order book slope

The table presents local polynomial fuzzy regression discontinuity (RD) point estimates (first stage and second stage) using Mean Squared Error (MSE)-optimal bandwidth selector (Imbens and Kalyanaraman (2009)) for the RD treatment effect estimator. The forcing variable - market capitalization is the month-end values, measured two months prior to a quarterly effective date of the short sale eligibility list following Crane et al. (2018). Market capitalization is computed as of the measurement date. The second stage presents estimates of the effect of $ss\_el\hat{i}gible$ on the outcome variables: the log of bid and ask order book slope (denoted by *log Bid Slope L*1_5 and *log Ask Slope L*1_5, respectively). $ss\_el\hat{i}gible$ is the fitted value of the short-sale eligibility as a function of the predicted eligibility at the market capitalization (firm size) threshold. Covariate adjustments are done using the variables: *Return*, *MarketReturn*, and *QuoteVolatility*. The sample comprises the regression variables at a daily sampling frequency and the period is from 29 July, 2013 to 30 June, 2016. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Cluster-robust nearest neighbor variance estimation is done at firm-quarter level to adjust the standard errors. The t-statistics are reported in absolute values.

Panel A: Fuzzy RDD on Market capitalization threshold sample

First Stage	is_eligible	is_eligible	is_eligible	is_eligible
Cutoff	0.01	0.03***	0.01	0.04***
	(1.09)	(5.18)	(1.27)	(6.92)
Second Stage	Log Bid Slope L1_5	Log Ask Slope L1_5	Log Bid Slope L1_5	Log Ask Slope L1_5
$ss\_el\hat{i}gible$	−36.04	−8.61***	−29.81	−4.48***
	(1.09)	(5.00)	(1.28)	(6.06)
Observations	342224	342224	341880	341880
Effect.Observations	42588	97127	43476	75604

Pabel B: Fuzzy Kink RDD on Market capitalization threshold sample

First Stage	is_eligible	is_eligible	is_eligible	is_eligible
CutOff	0.48***	0.41***	0.48***	0.42***
	(5.00)	(4.47)	(5.01)	(4.55)
Second Stage	Log Bid Slope L1_5	Log Ask Slope L1_5	Log Bid Slope L1_5	Log Ask Slope L1_5
$ss\_el\hat{i}gible$	10.93***	9.58***	10.93***	9.62***
	(4.33)	(3.86)	(4.35)	(3.94)
Observations	342224	342224	341880	341880
Effect. Observations	58885	60507	58859	60077
Covariates adjusted	No	No	Yes	Yes

The Figure:3 shows linear and a non-linear RD polynomial fitted bin plots of bid/ask depth volume (in share terms) below/above log of market capitalization cut-off. The bid & ask depth volume slope (with respect to stock market capitalization) is seen to increase above the cut-off point.

To further test hypothesis 1 discussed in section: III, Table IX presents linear local polynomial fuzzy RDD two-stage regression analysis results showing effect of short sell eligibility on buy lambda (λ^{buy}) and sell lambda (λ^{sell}).

As discussed in OLS results section (see Table II results), these lambdas (as proxies for order

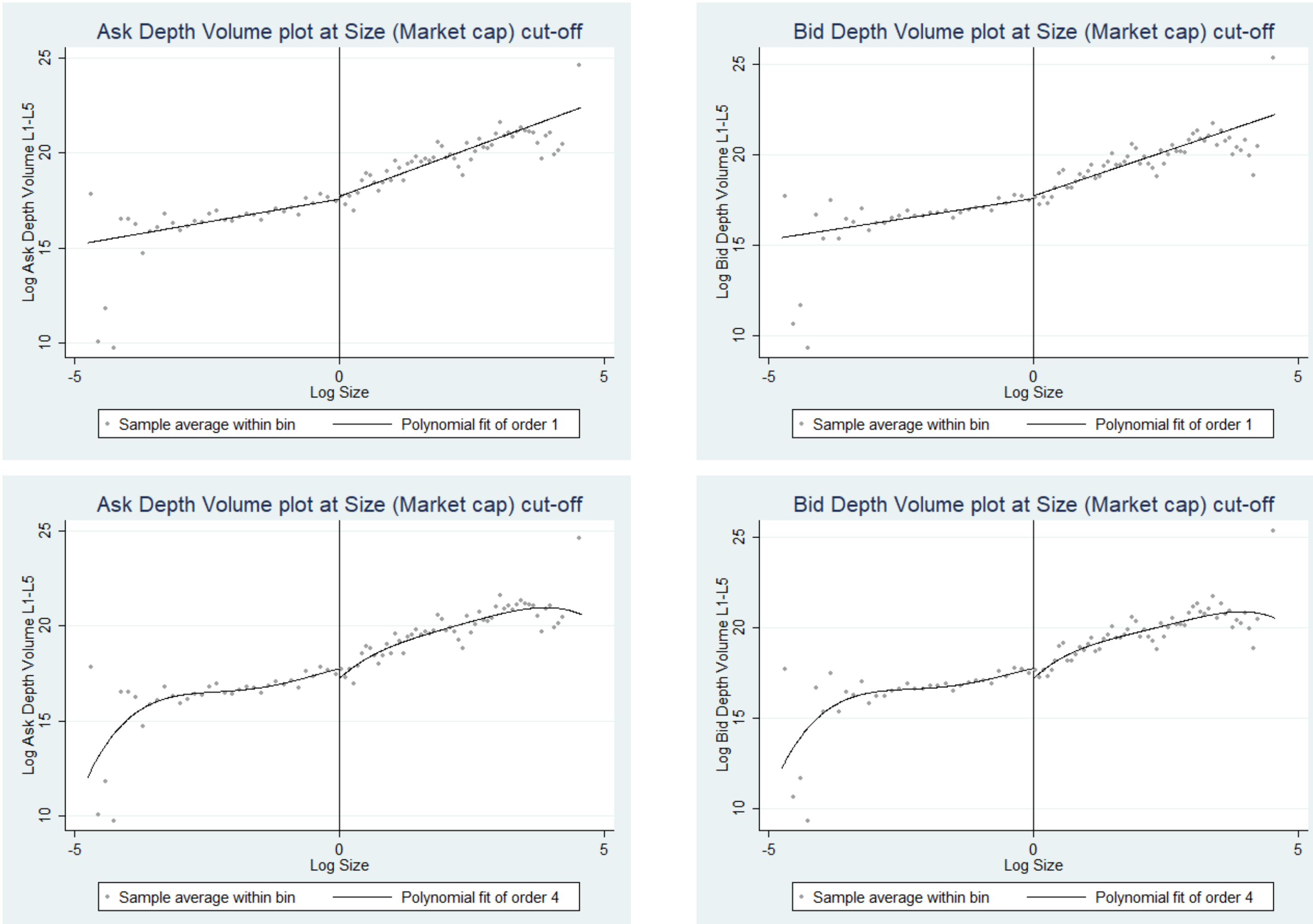

Figure 3. Graphs show linear and non-linear polynomial bin fitted plots of level 2 depth metrics below- and above- market capitalization cut-off threshold sample.

The sample period is from 29 July, 2013 to 30 June, 2016

flow impact) are, by definition, inverse of the depth or depth slope. The first stage in the table results shows significant predictability of the log of the forcing variable: market capitalization on short sell eligibility. The short sell eligibility predicted component caused by the variation in market capitalization around cut-off (denoted by $ss\_el\hat{i}gible$) is then regressed over λ^{buy} and λ^{sell}. Optimal bandwidth based on Mean Squared Error (MSE) data-driven selector is estimated as around 48.2% and 50.2% above and below cut-off for analysis on buy and sell lambda respectively.

The first stage analysis shows that the probability of short sell eligibility for firms above the market capitalization cut-off is 18% (19%) higher than for firms below the cut-off, when analyzed on buy and sell lambda respectively. The magnitude becomes 21% (19%) post-covariate adjustment.

The result shows that $ss\_el\hat{i}gible$ is significantly and negatively associated with λ^{buy} and λ^{sell}, before and after covariate adjustment. The negative result implies that the buy and sell lambda for short eligible stocks are lower than for short ineligible stocks. Buy and sell lambda for short eligible stocks is lower by 49% (coefficient = 0.49) and 64% (0.64) respectively. By contrast, the buy and sell lambdas are higher for banned stocks than for short eligible stocks. As demonstrated

Table IX. The effect of short sell eligibility on buy lambda and sell lambda"

The table presents local polynomial fuzzy regression discontinuity (RD) point estimates using Mean Squared Error (MSE)-optimal bandwidth selector for the RD treatment effect estimator. The forcing variable - market capitalization is the month-end values, measured two months prior to a quarterly effective date of short sale eligibility list following Crane et al (2018) . Market capitalization is computed as of measurement date. The second stage presents the estimates of the effect of $ss\_el\hat{i}gible$ on the outcome variables: *Buy Lambda* (λ_{it}^{buy}) and *Sell Lambda* (λ_{it}^{sell}). $ss\_el\hat{i}gible$ is the fitted value of short-sale eligibility as a function of the predicted eligibility at the market capitalization (firm size) threshold. The covariate adjustments are done using variables: $Return$, $MarketReturn$, and $QuoteVolatility$. Appendix: A includes the definitions of *Buy Lambda*, *Sell Lambda*, and the covariate adjustment variables. The sample comprises regression variables at daily sampling frequency and the period is from 29 July, 2013 to 30 June, 2016. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Cluster-robust nearest neighbor variance estimation is done at firm-quarter level to adjust the standard errors. The t-statistics are reported in absolute values.

Fuzzy RDD on Market capitalization threshold sample

First Stage	ss_eligible	ss_eligible	ss_eligible	ss_eligible
CutOff	0.18***	0.17***	0.21***	0.19***
	(5.80)	(4.75)	(7.21)	(6.22)
Second Stage	λ_{it}^{buy}	λ_{it}^{sell}	λ_{it}^{buy}	λ_{it}^{sell}
$ss\_el\hat{i}gible$	−0.59***	−0.79***	−0.49***	−0.64***
	(5.27)	(4.75)	(6.65)	(3.36)
Observations	49602	49602	49601	49601
Effect. Observations	1984	1710	2097	2013
Covariates adjusted	No	No	Yes	Yes

in the table, the short sell eligibility reduces buy and sell lambda, and the differential effect is 0.2 (0.15) pre (post) the covariate adjustment. The 't' statistic corresponding to the buy lambda is 6.65, and to the sell lambda it is 3.36.

The fact that the supply dynamics and order flow impact costs are significant on both sides corroborates with my outcome discussed in the OLS results Section VI.A. Overall, I observe that the effect on the bid side (shown in results corresponding to bid depth slope and sell lambda) is stronger than that of the ask side. I discuss my intuition in Table V results in Section VI. A ban drives out any informal liquidity providers who may need to take long/short positions in the market. This situation could reduce liquidity competition on the bid side of the market, causing a cascading effect to formal liquidity providers via imperfect competition channel, b) ban could adversely affect depth on bid via endogenous information acquisition channel, and c) ban may discourage investors from taking new buy positions.

The Figure 4 shows linear and nonlinear example of RD polynomial fitted bin plots of λ^{buy} and λ^{sell} below/above log of market capitalization cut-off respectively. The price impact generated from buyers and sellers' order flow shows near symmetrical effect below cut-off as predicted from hypothesis 1.

In line with my overall market quality outcome under Hong Kong RDD settings, Crane et al. (2018) find some evidence of the influence of short sell ban on market quality based on a market capitalization threshold sample. The authors present their results without dissecting buy and sell

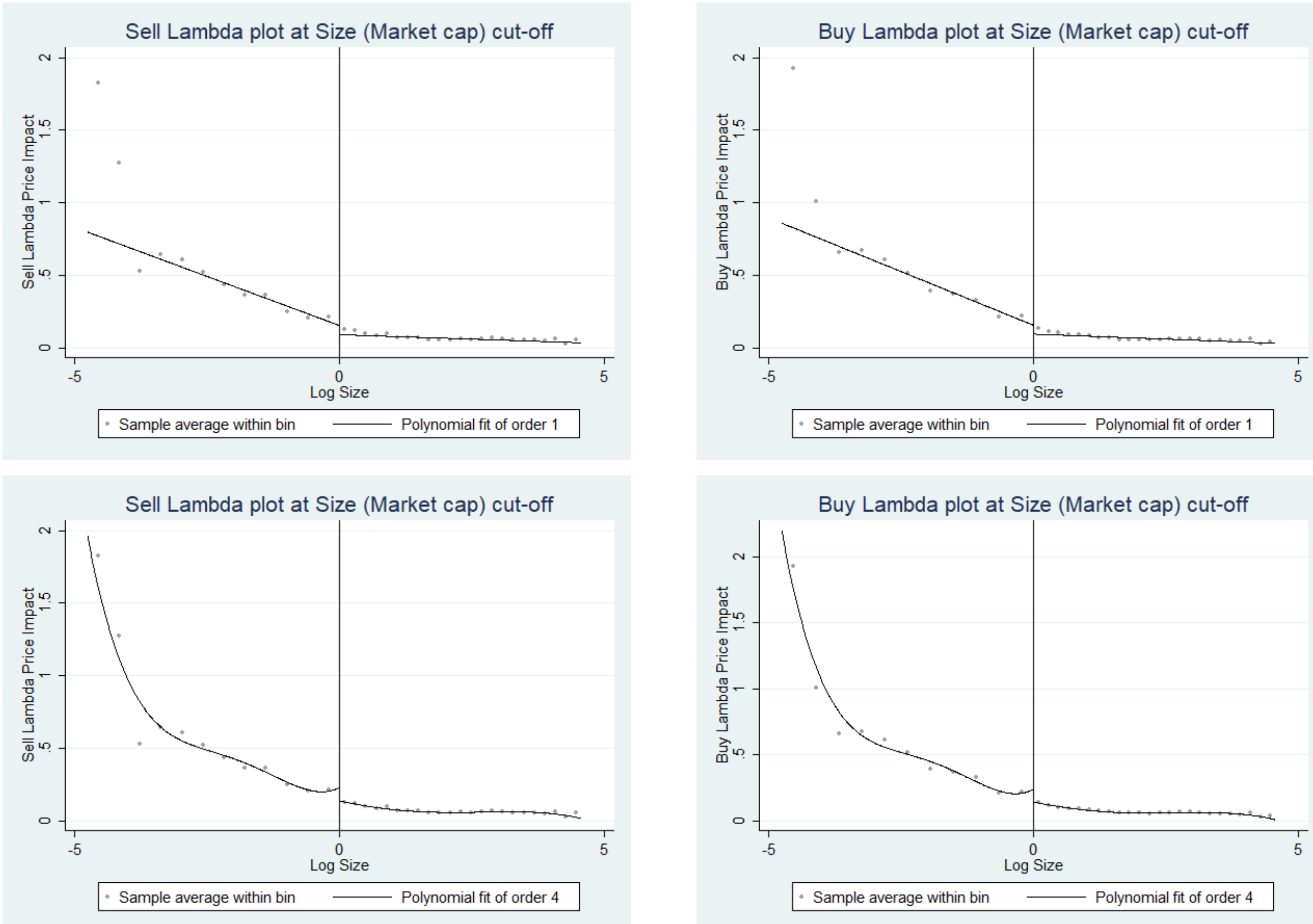

Figure 4. Figure shows first linear and non-linear RD polynomial fitted bin plots of buy and sell lambda impact pre- and post- market capitalization cut-off threshold.

The sample period is from 29 July, 2013 to 30 June, 2016

side. They find that short-sell eligibility is associated with lower transaction costs (utilizing quoted spread) and reductions in zero-trading days in their market-capitalization threshold sample. In contrast, they do not observe similar outcomes in their turnover velocity and float-adjusted market capitalization samples. They conduct combined probability test using multiple thresholds and marginally reject the hypothesis that short sell affects liquidity. Authors, however, reconcile their outcome on market capitalization threshold sample (showing ban deteriorating liquidity costs) with past literature (e.g., Beber and Pagano (2013) and Boehmer, Jones, and Zhang (2013)). The outcome from Beber and Pagano (2013) and Boehmer et al. (2013) differ in size quantiles. For example, Beber and Pagano (2013), in their international study, find detrimental effects of ban on market quality, mainly for stocks with small capitalization and no listed options. Whereas Boehmer et al. (2013) find this effect mainly for large capitalization. My hypotheses and research context differ. Under normal market conditions and utilizing both short sale ban and constraints (driven by lending market), I examine the differential effect of buy and sell order flows and supply dynamics on a broader sample using OLS tests controlling for size effect. I then perform RDD analysis on control and treatment sample quasi-random in size to corroborate my outcome discussed in OLS based results (Section VI.A).

My study further points out that it may be misleading to judge that ban is effective in suppressing volatility and buttress prices for low liquidity (small capitalization) stocks whose volatility is relatively higher than large or mid capitalization stocks. I find both daily returns and volatility are unaffected by short sell ban as shown in Table X. The Figure 6 shows RD polynomial bin plots of stock return, volatility below/above log of market capitalization cut-off respectively. This table shows no significant effect of short sell eligibility: $ss\_el\hat{i}gible$ on stock return (denoted by $Return$) and volatility (denoted by $QuoteVolatility$). The results are consistent with Crane et al. (2018).

Table X. The effect of short sell eligibility on covariate adjustment variables

The table presents local polynomial Fuzzy Regression Discontinuity (RD) point estimates on $Return$, $MarketReturn$ and $QuoteVolatility$ using Mean Squared Error (MSE)-optimal bandwidth selector (Imbens and Kalyanaraman (2009)) for the RD treatment effect estimator. The forcing variable - market capitalization is the month-end values, measured two months prior to a quarterly effective date of short sale eligibility list following Crane et al (2018). The market capitalization is computed as of measurement date. $ss\_el\hat{i}gible$ is the fitted value of short-sale eligibility as a function of the predicted eligibility at the market capitalization (firm size) threshold. Appendix: A includes the definitions of $Return$, $MarketReturn$ and $QuoteVolatility$. The sample comprises regression variables at daily sampling frequency and the period is from 29 July, 2013 to 30 June, 2016. *,**,*** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Cluster-robust nearest neighbor variance estimation is done at firm-quarter level to adjust the standard errors. The t-statistics are reported in absolute values.

Fuzzy RDD on Market capitalization threshold sample

Second Stage	Quote Volatility	Return	Market Return
$ss\_el\hat{i}gible$	-0.004	-0.03	-0.01
	(1.65)	(1.01)	(0.46)
Observations	417945	425904	425917
Effect.Observations	112745	124334	105146

D. Other Tests

I further document sample placebo RDD tests for short selling activity and price impact regression variables used in this study. I run analysis using data driven Mean Squared Error (MSE)-optimal bandwidth. The usual expectation is absence of significant treatment effect at placebo cut-off. Using market capitalization threshold sample used in this study, I set a cut-off (c=0.10) at around 10% above from market capitalization cut-off (defined by exchange), which is 3 billion HKD for the sample period used in this study. Table XIII (in Appendix D) shows sample placebo test for natural log of end-of-day short sale volume as a fraction of total trading volume ($LogRelSSVol$), buyer-initiated lambda (λ^{buy}) and seller-initiated lambda (λ^{buy}).

As I see in the table, the predicted value of short sell eligibility: $ss\_el\hat{i}gible$ (predicted by market capitalization) does not affect short sale volume and lambda price impact at this artificial cut-off. However, one may expect that same artificial cut-off may not apply consistently across all regression (or dependent) variables. This may mainly happen in my study context as the eligibility is based on multiple cut-offs. Moreover, the experiment is done using fuzzy RDD, which is based on the probability of treatment effect. Cattaneo, Idrobo, and Titiunik (2019) suggest to use control and treatment groups separately below and above cut-off to mitigate "contamination" due to real treatment effects. In this paper's context, short sell ineligible stock group (i.e., treatment group) is below cut-off and short sell eligible stock group (i.e., control group) is above cut-off. However, it is unclear that this is appropriate implementation approach for fuzzy RDD tests based on a sample where multiple thresholds determine treatment.

VIII. Conclusion

The paper dissects buying and selling microstructure dynamics in linking shorting impediments with liquidity asymmetry and trading costs. I examine the influence of an exchange-driven shorting ban or lending market-driven shorting constraints on the buy and sell sides of the market utilizing the stocks traded in the Hong Kong market. I apply OLS tests on a Hong Kong stock-day panel controlling for the size effect, in addition to other firm characteristics and trading controls. I further verify my outcome by excluding the effects of index and derivatives listing. I then perform RDD analysis, focusing on treatment and control stocks that are quasi-random around market capitalization, that is, size-based eligibility cut-off defined by the exchange. The sample is constructed based on the unique short-selling regulatory settings in the Hong Kong market, with a longer period of short eligible designated securities updated periodically based on pre-defined criteria. Based on my insights, I provide several implications.

First, I verify the alteration in short selling volumes for banned stocks and provide evidence of a ban causing an adverse effect in buy and sell liquidity supply dynamics and order flow price impact (Kyle lambda). The magnitude of the effect is found to be near symmetrical on both sides with a tilt on the sell-side price impact and bid side order book liquidity.

As per my SUR joint analysis and OLS, I show 1-5% of asymmetry in ban's effect on liquidity supply (based on depth slope metrics) and no asymmetry in ban's impact on buy and sell lambda. My corresponding regression discontinuity design (RDD) results show around 13% of depth slope asymmetry and around 30% of lambda asymmetry. My asymmetry in liquidity supply and trading costs are lower as compared to Dixon (2021)'s outcome using the US 2008 ban period. I suspect the following possible reasons for this effect: First, I capture depth metrics and price impact using trade and quote data that incorporates size information. Second, my Hong Kong sample period spans around three years, and to the best of my knowledge, my sample is not embedded in any known liquidity crisis or market-wide related effects. In a market-wide crisis, informal or formal liquidity suppliers create selling pressure in an attempt to exit from the market. Using the US 2008 ban sample, I acknowledge that researchers have attempted to remove confounding effects via careful evaluation of the counterfactual. However, this may not eliminate the confounding effect (argued by Crane et al.(2018)) in treatment stocks vis-a-vis control stocks before the ban, driving significant asymmetric behavior in buying and selling. In addition, the US ban is imposed on financial firms that span across large, mid, and small-capitalization stocks. In contrast, the Hong Kong ban is imposed on equity stocks across various industries, but mainly on lower market capitalization stocks.

Second, I run OLS and SUR tests using lending market data on a broader firm-date daily sample to find symmetrical effect of lending constraints on buy and sell order flow impact and liquidity supply.

Overall, I draw my theoretical motivations from information and non-information-driven channels (discussed in my hypothesis section) that could drive my results.

Third, I argue against the adoption of the 'Hong Kong-style" short-selling ban approach based on a market capitalization-based threshold. I find that the rule is ineffective in supporting prices and curbing volatility (consistent with Crane et al. (2018)), and at the same time, detrimental to both the buy and sell-side of the market. Hence, regulators should be wary of adopting such a "Hong-Kong" style ban based on size eligibility threshold.

To further study the underlying economic channel of differential effects in liquidity, I attempt to illustrate that stocks with a lower variance ratio have a reduced differential effect on the liquidity supply and order flow impact (given both informed and uninformed short selling are allowed) between buy and sell. The intuition is that a lower variance ratio indicates lower inventory risk for mean reversion-based strategies. This is considered profitable for contrarian trading or market makers who need to place quotes on both bid and ask sides.

Future work may include applying my analysis on the intraday period and during earnings announcements. It may be interesting to see how the differential effect in buy and sell liquidity supply and trading costs changes during intraday and earnings windows. The dominance of a particular channel (for example, imperfect liquidity competition or endogenous information acquisition) and other market-specific nuances, such as the proportion of long/short liquidity providers (informal or formal), may drive time-varying differential effects in buying and selling. The ability to identify short-seller transactions from long sell transactions and account level transactions can further help to precisely analyze channels and liquidity provider's intraday behavior driving the differential effect in buy and sell.

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Appendix A. Key Data Variable Definitions

Buy Lambda (Buyer-trade initiated order flow impact) and Sell Lambda (Seller-trade initiated order flow impact)

This is estimated using a regression model that involves signed order flow as the independent variable and mid-quote change as the dependent variable. This is used to capture how the change in order flow at time "t" observed by the market maker impacts mid-quote price (as proxy for expected value of security conditional on the set of information available at time "t"):

$$\delta m_t = \alpha_t + \lambda_{it}^{buy}(q_t \mid q_t > 0) + \lambda_{it}^{sell}(q_t \mid q_t < 0) + \epsilon_{ti}, \tag{A1}$$

Where δm_t is natural log of mid-quote price at time "t" over mid-quote price at time "$t - 5min$". Following the approach in Brennan et al. (2012), λ_{it}^{buy} is the regression coefficient of buy-initiated order flow $(q_t \mid q_t > 0)$ and λ_{it}^{sell} is the regression coefficient of sell-initiated order flow (denoted by order flow - $q_t \mid q_t < 0$). I measure the order flow as dollar volume. The procedure uses aggregated trade values (for order flow) and mid-quote changes on every 5 minutes. Buyer- and seller-initiated measures are determined using the Lee and Ready (1991) algorithm

Bid and Ask Order Book Slope

$$slope_i^{sell} = \frac{AskDepthAtBest5}{(AskPrice5 - midquote)}. \tag{A2}$$

$$slope_i^{buy} = (-1) * \frac{BidDepthAtBest5}{(BidPrice5 - midquote)}. \tag{A3}$$

$AskDepthAtBest5$ is cumulative volume up to fifth level on ask side and $BidDepthAtBest5$ is cumulative volume up to fifth level on bid side. The slope is computed for each firm "i" on every intraday quote record update and summed up using time-weights for each quote record update to come up with a daily measure.

Size Measures market capitalization of a firm which is calculated by multiplying stock's daily close with shares outstanding.

Return The daily return calculated using close price and adjusted for dividend and share splits using corporate action data sourced from the security daily data files from COMPUSTAT.

Quote Volatility standard deviation of intraday 5 minutes natural log of mid-quote return.

$$mid - quote = \frac{BidPrice + AskPrice}{(2)}. \tag{A4}$$

Market Return Measured using value weighted returns of all Hong kong equity stocks.

Market-to-Book market-to-book is constructed using daily closing prices and shares outstanding in ratio to the most recent book value of equity

Appendix B. Hong Kong Short Selling Key Regulations

1) Short sellers are required to be engaged in a covered short sale, i.e. participants are required to borrow securities under a securities borrowing, and lending agreement or have "obtained a confirmation from the counterparty to the agreement that the counterparty has the security available to lend to him") before shorting.

2) Short selling should be done only on designated securities eligible for short selling.

3) Abide by tick rule, i.e., a short sale on eligible stocks should not be made below the prevailing "Ask Price" during Continuous Trading Session or a "Reference Price" during Closing Auction Session.

The key categories for designated short sell eligibility lists (applicable for my data period from 27th July 2012 to 3rd July, 2016):

"a) all constituent stocks of indices which are the underlying indices of equity index products traded on the Exchange;

(b) all constituent stocks of indices which are the underlying indices of equity index products traded on HKFE;

(c) all underlying stocks of stock options traded on the Exchange;

(d) all underlying stocks of Stock Futures Contracts (as defined in the rules, regulations and procedures of HKFE) traded on HKFE;

(e) stocks eligible for structured product issuance pursuant to Rule 15A.35 of the Main Board Listing Rules or underlying stocks of Structured Product traded on the Exchange;

(f) stocks with market capitalization of not less than HKD 3 billion and an aggregate turnover during the preceding 12 months to market capitalization ratio of not less than 60%;

(g) Exchange Traded Funds approved by the Board in consultation with the Commission;

(h) all securities traded under the Pilot Program;

(i) stocks that have been listed on the Exchange for not more than 60 trading days, with a public float capitalization of not less than HKD 20 billion for a period of 20 consecutive trading days commencing from the second day of their listing on the Exchange and an aggregate turnover of not less than HKD 500 million during such period.

Appendix C. Dixon (2021) Model

Dixon (2021) predicts that short sell ban results in a higher concentration of informed long sellers i.e., sellers who own assets (contributed by sophisticated traders). This type of seller has a higher benefit of acquiring and trading on negative information. Under the model assumptions, a market maker is risk-neutral and places regret free quotes and face perfect competition following Glosten and Milgrom (1985) and Kyle (1985) setup. Market maker set prices based on order flows without an ability to distinguish between the sophisticated trader (who trades on information) and informed liquidity trader (or liquidity trader). Sell orders originate from investors who a) do not own assets and can short orders b) own assets and place long sell orders. Buy orders originate from all types of investors. The order flow events include informed buy, uninformed buy, informed sell, uninformed sell, informed short and uninformed short. Dixon (2021) models the probability of each of order flow events (that include informed buy, uninformed buy, informed sell, uninformed sell, informed short, and uninformed short) based on a probability tree shown in Figure:6.

The ratio of informed (sophisticated investors) to uninformed investors (liquidity traders) is derived as:

$$Ratio = \eta * (\lambda_e + \lambda_n)/(1 - \eta) \tag{C1}$$

λ_e denotes a fraction of sophisticated traders who own asset (i.e., hold long buy position) and become informed. Whereas λ_n denotes a fraction of sophisticated traders who do not own asset. η denotes a fraction of investors who are informed. $(1 - \eta)$ is fraction investors who are uninformed (or liquidity traders) and indifferent to information advantage. While sophisticated traders pay a cost in acquiring information (fundamental value) of an asset, the fraction of the traders who become informed and do not own assets (i.e., λ_n in the equation above) has to pay additional short selling cost to trade on the information. Higher expected costs (cost of acquiring information plus short selling cost) faced by such investors (i.e., who do not own assets) imply that the concentration of information acquisition in investors is lower in traders who do not own assets (as compared to those who owns assets). Hence, in equilibrium, Dixon (2021) states that λ_e will always be *weakly greater* than λ_n.

Given the ratio of sophisticated investors and liquidity investors, and arguments above about costs of acquiring information for traders who do not own assets, the distribution of informed sell traders is skewed towards traders who own assets, i.e., λ_e. Therefore, removal of λ_n (i.e., fraction of investors who does not own assets) post ban will have a lesser effect on the information content of sell orders. On the numerator (as a net effect), the information content of a sell order increases. On the denominator, the distribution of liquidity traders, who own assets vis-a-vis who do not own assets are not skewed - traders, who do not own assets, are indifferent to paying short-selling cost for uninformed hedging (assuming short-selling cost is sufficiently small). If we consider both numerator and denominator, the post ban probability of information content of sell order (which originates from traders who own assets i.e., long sellers) increases. This implies that market makers on bid are more likely to be adversely selected.

Appendix D. Appendix D: Additional Tables

Table XI. Summary statistics: stock-day panel of Hong Kong equities

The table D.1 reports summary statistics for selected variables in daily panel of Hong Kong equities. Appendix: A includes the definitions of *Return*, *Quote Volatility*, *Buy Lambda*, *Sell Lambda*,*Bid Slope L*1_5, and *Ask Slope L*1_5. *ss_eligible* is a short sale eligible dummy variable which is set to one (1) if a stock is in the Hong Kong designated short sell eligibility list, otherwise zero (0). "RelSSVol" is daily short-sale volume as a fraction of total trading volume "TradeVol". The sample period is from 29 July, 2013 to 30 June, 2016 and comprises 1,435 Hong Kong firm consisting of large, mid and small capitalization stocks. *Buy Lambda*, *Sell Lambda*, *Bid Slope L*1_5 and *Ask Slope L*1_5 are winsorized with daily stock cohort at 1 and 99 percentile before applying log of *Bid Slope L*1_5 and *Ask Slope L*1_5. The variables *log LendingSupply* captures log of shares available for lending, and the *log LoanDemand* captures the log of shares loaned for short selling - both these variables are sourced from securities lending data source.

VARIABLES	*N*	**mean**	**sd**	**p5**	**p25**	**p50**	**p75**	**p99**
ss_eligible	819,372	0.388	0.487	0	0	0	1	1
Return	819,098	0.00094	0.0477	−0.0498	−0.0145	0	0.012	0.143
Quote Volatility	806,535	0.00089	0.0029	0.0000	0.0002	0.0005	0.0010	0.0052
log LoanDemand	320,883	15.23	2.730	10.13	13.75	15.66	17.16	20.44
log LendingSupply	553,256	16.54	2.544	11.92	14.89	16.93	18.45	21.00
RelSSVol	131,528	0.125	0.139	0.00324	0.0264	0.0782	0.175	0.657
Bid Depth Vol L1_5 ('000)	819,372	1756	7598	43.807	192.643	504.067	1366	20760
Ask Depth Vol L1_5 ('000)	819,372	1785	5619	45.784	209.459	529.514	1442	21150
TradeVol ('000)	759,393	8785	44960	24	320	1486	5410	119600
Buy Lambda(λ_{it}^{buy})	148,019	0.089	0.107	0.0080	0.0319	0.058	0.103	0.56
Sell Lambda(λ_{it}^{sell})	148,019	0.0883	0.105	0.0082	0.0322	0.0583	0.103	0.549
Log Bid Slope L1_5	708,455	16.24	2.300	12.59	14.72	16.11	17.69	21.99
Log Ask Slope L1_5	708,455	16.20	2.264	12.64	14.69	16.05	17.64	21.81

Table XII. Summary statistics: stock-day panel of Hong Kong equities excluding constituents of Heng Sang index (HSI) and firms having derivatives (futures and options) listing

The reports summary statistics for selected variables in a daily panel of Hong Kong equities, excluding a) constituents of the Heng Sang HSI index, and b) the firms that have a derivatives (futures and options) listing. Appendix: A includes the definitions of *Return*, *Quote Volatility*, *Buy Lambda*, *Sell Lambda*, *BidSlopeL1_5*, and *Ask Slope L1_5*. *RelSSVol* is daily short-sale volume as a fraction of the total trading volume "TradeVol". The sample period is from 29 July, 2013 to 30 June, 2016. The *Buy Lambda*, *Sell Lambda*, *Bid Slope L1_5* and *Ask Slope L1_5* are winsorized with daily stock cohort at 1 and 99 percentile before applying the log of *Bid Slope L1_5* and *Ask Slope L1_5*. The variables *og LendingSupply* captures log of shares available for lending, and *log LoanDemand* captures the log of shares loaned for short selling - both these variables are sourced from securities lending data source.

VARIABLES	*N*	**mean**	**sd**	**p5**	**p25**	**p50**	**p75**	**p99**
is_eligible	677,145	0.354	0.478	0	0	0	1	1
Return	677,092	0.000981	0.0485	−0.0500	−0.0145	0	0.0120	0.145
Quote Volatility	666,036	0.000850	0.00249	0	0.000187	0.000493	0.000980	0.00500
log LoanDemand	255,034	15.06	2.737	9.999	13.58	15.49	17.05	19.69
log LendingSupply	461,100	16.45	2.438	11.96	14.91	16.84	18.31	20.53
RelSSVol	105,141	0.112	0.134	0.00268	0.0211	0.0643	0.153	0.636
Bid Depth Vol L1_5	677,145	1.307e+06	5.511e+06	42,691	185,757	476,145	1.236e+06	1.234e+07
Ask Depth Vol L1_5	677,145	1.335e+06	3.361e+06	42,234	198,359	496,803	1.303e+06	1.298e+07
TradeVol	621,901	8.417e+06	4.113e+07	22,000	296,500	1.390e+06	5.164e+06	1.166e+08
Buy Lambda(λ_{it}^{buy})	100,316	0.0942	0.117	0.00713	0.0317	0.0594	0.108	0.610
Sell Lambda(λ_{it}^{sell})	100,316	0.0932	0.115	0.00727	0.0322	0.0595	0.107	0.596
Log Bid Slope L1_5	581,322	16.43	2.322	12.68	14.91	16.33	17.96	22.04
Log Ask Slope L1_5	581,322	16.38	2.247	12.72	14.86	16.26	17.91	21.65

Table XIII. Placebo cut-off test: the effect of short sell eligibility on daily short-sale volume, buy lambda and sell lambda

The table presents local polynomial fuzzy regression discontinuity (RD) point estimates using MSE-optimal bandwidth selector for the RD treatment effect estimator. The forcing variable - market capitalization is the month-end values, measured two months prior to a quarterly effective date of short sale eligibility list following Crane et al (2018). The market capitalization is computed as of the measurement date. The test is performed using a cut-off (c=0.10) at around 10% above from market capitalization cut-off (defined by exchange), which is 3 billion HKD for the sample period used in this study. Second stage presents estimates of effect of $\hat{ss\_eligible}$ on outcome variables: Short Volume (*RelSSVol*), *BuyLambda* (λ_{it}^{buy}) and *SellLambda* (λ_{it}^{sell}). $\hat{ss\_eligible}$ is the fitted value of short-sale eligibility as a function of the predicted eligibility at the market capitalization (firm size) threshold. The sample comprises regression variables at daily sampling frequency and period is from 29 July, 2013 to 30 June, 2016. *,**,*** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Cluster-robust nearest neighbor variance estimation is done at firm-quarter level to adjust the standard errors. The t-statistics are reported in absolute values.

Fuzzy Kink RDD Market capitalization threshold sample

Second Stage	Log RelSSVol	λ_{it}^{buy}	λ_{it}^{sell}
$ss\_el\hat{i}gible$	−2.66	−0.12	−0.06
	(0.52)	(0.38)	(1.57)
Observations	64797	49796	49796
Effect. Observations	2988	2132	2117

Appendix E. Additional Figures

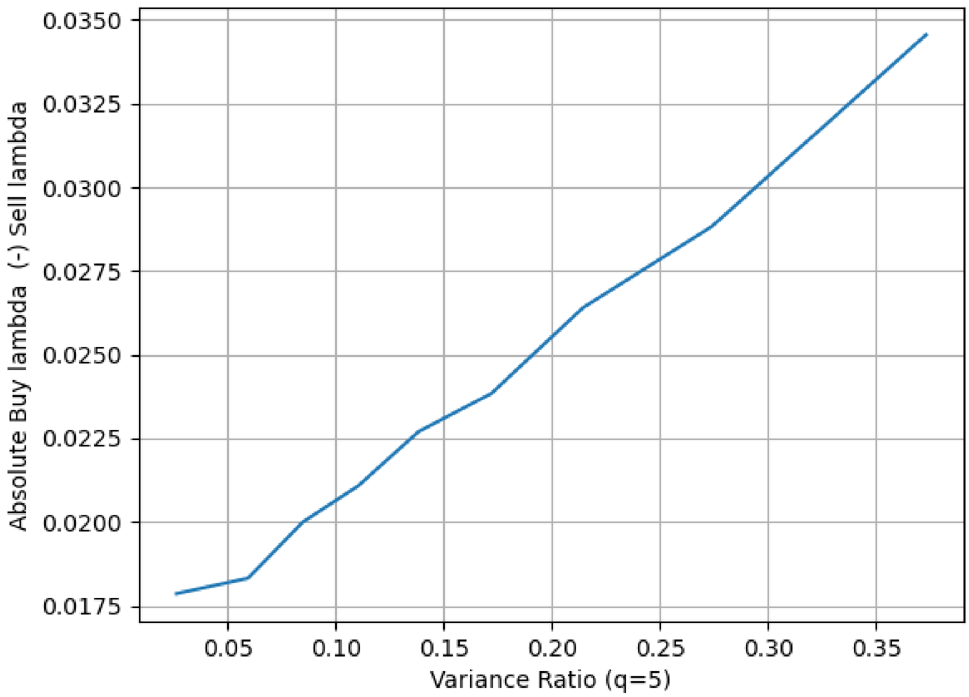

Figure 5. Binned decile bin plots of absolute difference between buy-sell lambda and variance ratio. Variance ratio and buy/sell lambda difference are averaged in each deciles (which are divided into ten equal parts) ranked based on variance ratio values.

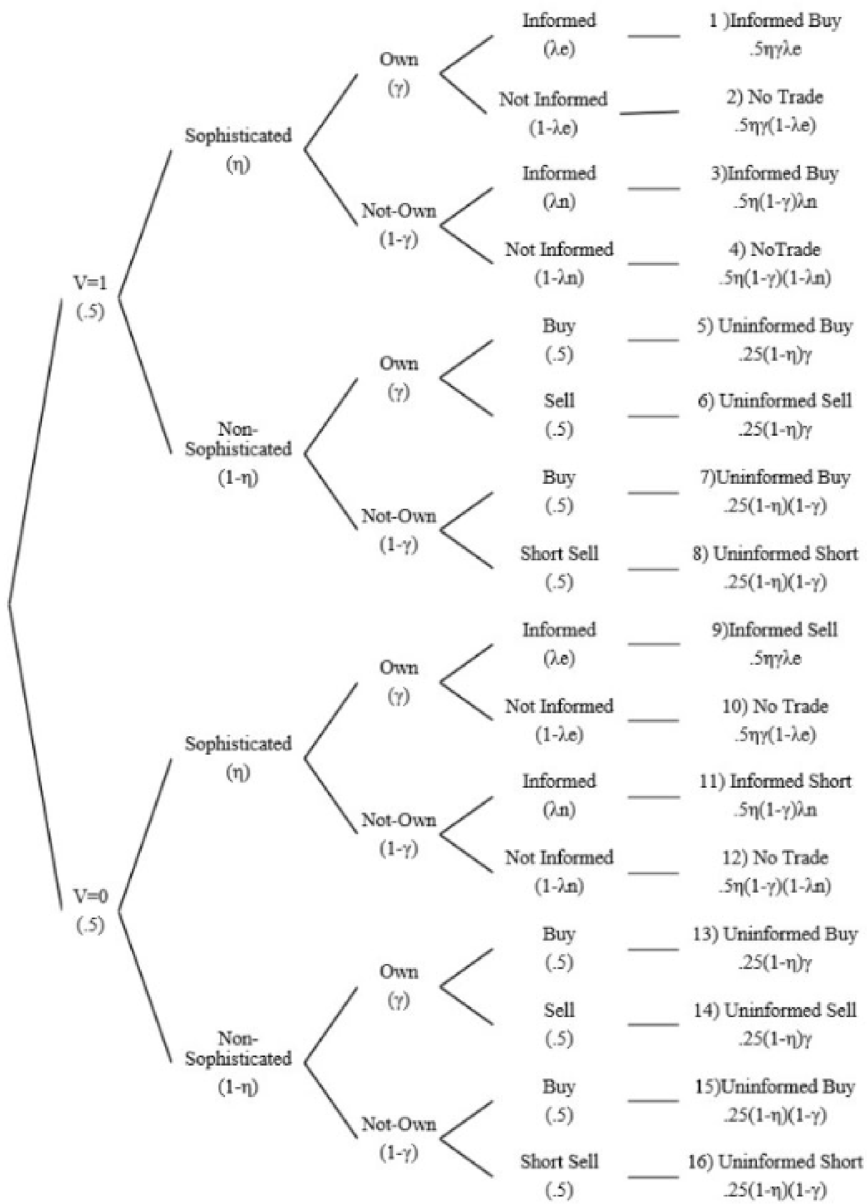

Figure 6. Dixon (2021) probability tree of Sophisticated and Non-Sophisticated trading outcome

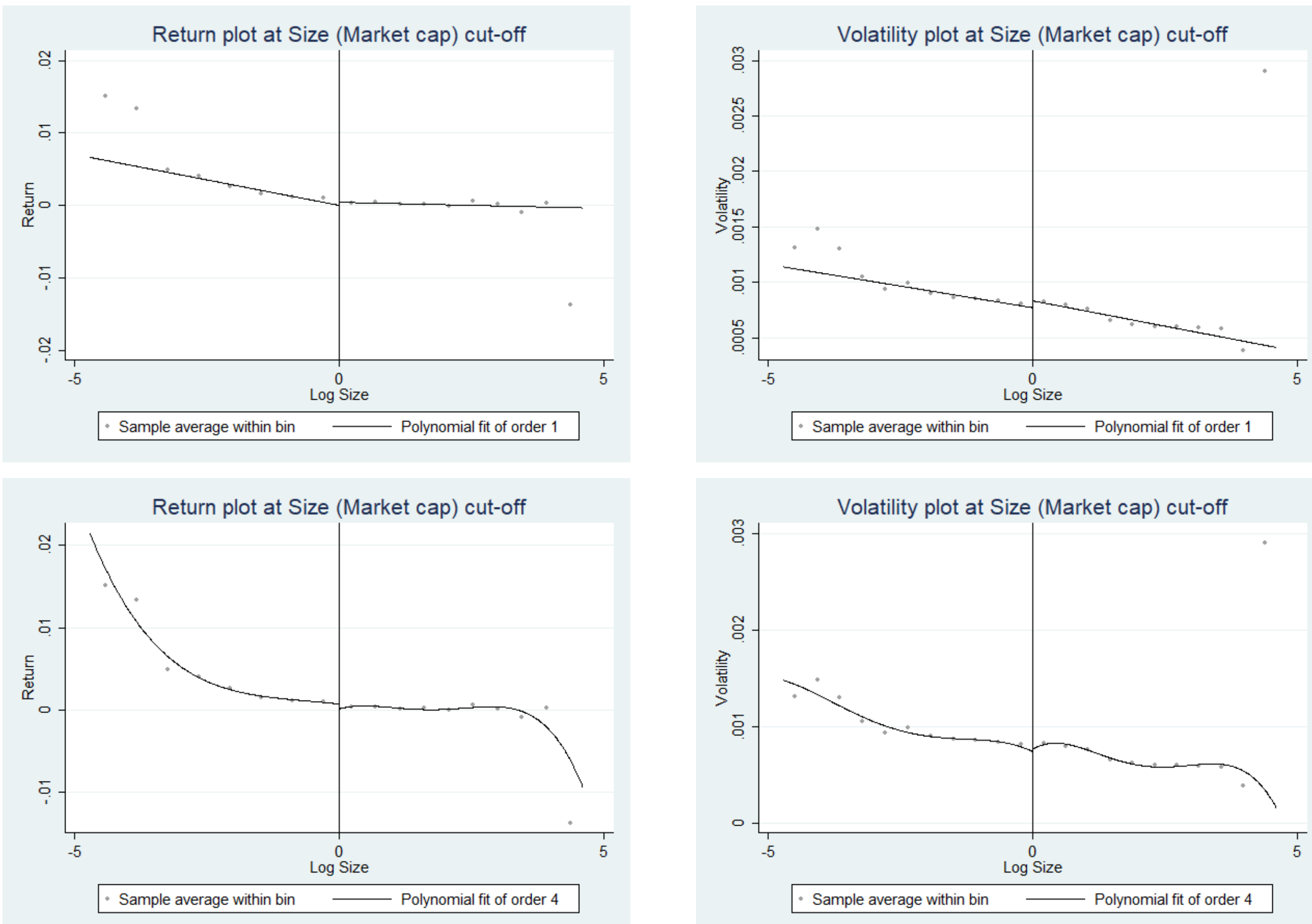

Figure 7. Graphs show first degree (linear) and fourth degree (non-linear) polynomial bin plots of stock return and volatility pre- and post- market capitalization cut-off threshold.

The sample period from 29 July, 2013 to 30 June, 2016.