

Exchange-Traded Barrier Option and VPIN: Evidence from Hong Kong

William M. Cheung

Department of Finance and Business Economics
University of Macau, Macau, China
wcheung@umac.mo

Robin K. Chou

Department of Finance
National Chengchi University, Taiwan
rchou@nccu.edu.tw

Adrian C.H. Lei[☆]

Department of Finance and Business Economics
University of Macau
Avenida da Universidade, Taipa, Macau, China
Tel.: (853) 8822-4162; fax: (852) 2713-4232.
adrianl@umac.mo

forthcoming, Journal of Futures Markets

[☆] Correspondence author, Department of Finance and Business Economics, Faculty of Business Administration, University of Macau, Avenida da Universidade, Taipa, Macau, China. Tel: (853)8822-4162, Fax: (852)2713-4232,e-mail: adrianl@umac.mo

Exchange-Traded Barrier Option and VPIN: Evidence from Hong Kong

Abstract

We study the validity of the *volume-synchronized probability of informed trading* (VPIN) metric in measuring the order flow toxicity around the mandatory call events of callable bull/bear contracts. High VPIN around mandatory call events indicates the existence of large volume imbalances, suggesting high market risk surrounding those call events. In this study, we provide the first direct evidence of the validity of VPIN outside the US market.

Key words: Order flow toxicity, volume-synchronized probability of informed trading, barrier option, mandatory call event

1. Introduction

Understanding high frequency trading behavior in financial markets has become increasingly important. Despite repeated liquidity events, such as the Flash Crash of May 6, 2010, our understanding of the risks associated with liquidity provision remains limited, in part due to the lack of appropriate measures for the risks of liquidity provision in high frequency settings. Recent studies (Easley et al. 2011, 2012) develop a measure for such risks, i.e., the volume-synchronized probability of informed trading (VPIN), which is based on a model of the time-varying arrival rate of informed and uninformed traders, to which they refer to the risk as order flow toxicity (Easley, Engle, O’Hara and Wu, 2008). Andersen and Bondarenko (2014a and b), however, dispute the empirical findings in Easley et al. (2008) and question the validity of measuring order flow toxicity by VPIN.¹

Most of these studies examine the validity of VPIN in relation to specific events, such as the Flash Crash. In this study, we use a unique dataset of exchange-traded callable contracts in Hong Kong to investigate the validity of VPIN as a measure for order flow toxicity. These contracts consist of a barrier price that if reached, triggers a mandatory call event (MCE), at which the contract is immediately terminated. More importantly, the timing of these MCE is uncertain, which offers an ideal setting for testing the validity of VPIN.

The Hong Kong Stock Exchange (HKSE) launched callable bull/bear contracts (CBBCs) on June 12, 2006. CBBCs, consisting of callable bull contracts (bull) and callable bear contracts (bear),² are a structured derivative product most commonly

¹ Easley et al. (2013) extend the debate in their logic behind the VPIN metric.

² A bull contract is similar to a call warrant with underlying stock price S , maturity date T , strike price X and barrier H , where $S > H \geq X$. If the contract is not called back before time T , it matures with a payoff of $S_T - X$.

issued by investment banks. CBBCs must be terminated immediately (MCE) at any time prior to expiry if the underlying asset's price reaches the barrier (call) price. The MCE can significantly influence underlying stocks due to the sheer amount of related shares and hedged positions that must be unloaded in a short period. Therefore, it is interesting to explore the effects of CBBC MCEs on informed stock market trading activities.

CBBC MCEs provide a suitable setting to test the validity of the VPIN. When the underlying stock price is close enough to the barrier price, information about the stock price is less likely to be the major factor affecting it. CBBC issuers have incentives to secure their profits by knocking the CBBCs out before their expiry, which allows them to trade the underlying stock and push the prices to the barrier. Uninformed traders in the market may also observe the CBBC barrier prices and join in trading that drives the prices to the barrier. These barrier prices create a magnetic effect, as discussed in Cho et al. (2003) and Lei (2014), and during this period, trading due to speculation is likely to be larger than that due to information. Furthermore, the timing of MCE is unknown and can occur at any time within a continuous trading session. Thus, we expect that there are higher risks of liquidity provision around the MCE, i.e., a higher order flow toxicity as measured by the VPIN.

Exchange-traded barrier options have become very popular in Hong Kong and around the world.³ From 2006 to 2010, 19318 CBBCs were issued, with a total

However, if the underlying stock price decreases so that $S_t = H$ for any $t < T$, then it triggers the MCE at time t . The contract is then settled with a residual value of $\max[M - X, 0]$, where M is the settlement price, which is the lowest price of the underlying stock price until the end of the *next* trading session after the MCE. A bear contract is defined in the opposite manner.

³ Hong Kong was one of the first countries to launch CBBC exchange-trading in 2006, followed by Taiwan on July 8, 2011, and such trading has rapidly increased. Similar products have been traded off-market in the UK, Germany, Australia, New Zealand, Switzerland, Italy, Korea and Singapore.

amount of HKD1358 billion (approx. USD174 billion). The recent amount of CBBC issuance exceeds that of the exchange-traded derivative warrants (DWs). The market turnover of CBBCs as a percentage of the total market turnover in 2009 reached 10.86%, surpassing the DW turnover of 10.72%. CBBC and DW trading constituted about 25% of the total market turnover throughout the 2006-2010 period. The success of the CBBC provides a unique opportunity to explore the order flow toxicity around the MCE.

We find that the order flow toxicity increases significantly right before the MCE and continues to increase for a short period after the MCE. It then returns to its normal level after the settlement of these contracts. The results are consistent when we separate the CBBCs into bull and bear contracts for the VPIN. In addition, our analysis also shows that there is a substantial amount of uninformed trading activities around the day of the MCE, suggesting significant speculative trading in the underlying assets. In this study, we provide evidence that the VPIN is a valid measure for order flow toxicity and that CBBCs can influence both the informed and uninformed trading of the underlying asset.

We contribute to the literature in the following ways. First, we build on recent research studying liquidity risk in high frequency trading using the VPIN. Unlike previous studies that use the Flash Crash in the US as the main event, we use the MCE events of the CBBCs listed on the Hong Kong stock market. We document the validity of the VPIN to measure liquidity risks in repeated events, such as the MCE, compared with the Flash Crash. Although the Flash Crash is an important event in its

own right, MCE of CBBCs provides a larger set of events for testing the validity of the VPIN as an intraday liquidity risk measure. Second, this study contributes to the literature by empirically detecting the trade imbalances in shorter duration using the VPIN compared with the probability of informed trading (PIN) (e.g. Tay et al., 2009).⁴ Third, we are among the first to document significant speculative trading activities around the CBBC MCE (e.g. Lei, 2014). Our evidence contributes to the literature on the price discovery process of exchange-trade options.

The study most closely related to ours is Lei (2014), who finds substantial intraday price reversals after MCEs and significant abnormal trading volumes of the underlying assets surrounding MCEs. A key difference between this study and that of Lei (2014) is that we identify trade imbalances around the MCEs. The abnormal trading volumes used in Lei (2014) may not be able to accurately identify the risk of liquidity provision, because volumes are not directional and hence cannot adequately measure trading imbalances.

The remainder of this paper is organized as follows. The next section briefly reviews the previous studies related to CBBC, PIN and VPIN, which lead to our hypothesis. Section 3 describes the PIN (Easley et al., 1996) and VPIN (Easley et al., 2012) methods measuring the risk of information trading. Section 4 describes the data, the data processing procedures and the empirical research models. Section 5 presents the empirical results. Finally, we summarize our findings in Section 6.

2. Literature Review and Hypothesis

⁴ Although it seems plausible to put the PIN in an intraday setting, the large amount of non-convergence in the estimations render high-frequency trading analysis with PIN infeasible.

Although CBBs are relatively new to the literature, the price and volatility effects of traditional derivatives on their underlying stocks have been widely studied. Conrad (1989) finds that optioned stocks have a permanent price enhancement. Ni, Pearson and Poteshman (2005) document that option trading changes the prices of underlying stocks. Additionally, some literature explores the effect of the derivatives' issuance and expiration. Detemple and Jorion (1990) and Bansal, Pruitt and Wei (1989) find a positive price effect when option issuing. However, the results are conflicted when the study option expires. Studies such as those conducted by Bhattacharya (1987) and Pope and Yadav (1992) document the negative effect when the option expires. Other studies, such as those of Klemkosky (1978) and Cinar and Vu (1987), do not find any single change in abnormal price and abnormal return.

Chan and Wei (2001) document that the hedging effect created by merchant banks can lead to buying pressure. However, it is unclear how the effect influences informed or uninformed traders, or both. The role of informed and uninformed traders is contentious. Some studies suggest that price moving is induced by informed traders who hold private information and that uninformed traders are liquidity traders (such as Easley et al., 1996, 2008, 2012; Nyholm, 2002; Romer, 1993). Other studies argue that uninformed traders can also cause price movement and that investors bear "noise trader risk" (such as Sias et al., 2001; De Long et al., 1990). Cutler et al. (1989) suggest that uninformed traders are purely trend followers with extrapolative

expectations. Delong et al. (1990) define the noise traders' demand as a function of sentiment, fads, social trends and other random variables. In this study, we fill the gaps using intraday trading data to closely track the trading behavior. We focus on the CBBCs traded in Hong Kong to investigate how they influence the investors' trading behavior.

2.1. Hypothesis

Solt et al. (1988) and De Bondt (1993) find that retail stock speculators trade according to extrapolative expectations, which are mainly based on past returns, and that they appear to be trend followers. In this study, we consider speculators to be uninformed traders who may ask for a higher return if the market is not satisfactory. Many orders caused by retail uninformed traders come into the market with the same price direction and increase the volume imbalance, triggering an MCE. Informed traders who possess new information, together with uninformed traders, enter the market based on the expected trading profit. We observe this change in intraday level using a VPIN metric and predict the short-term risk in the market, as the VPIN is calculated based on the volume imbalance. We conjecture that the VPIN is higher around the MCE.

H1: VPIN is higher around the MCE.

3. VPIN

3.1 The VPIN method

Based on volume imbalance and trading intensity, Easley et al. (2012) produce a VPIN method to overcome the drawbacks met in the high frequency market when applying PIN. This volume-based method fits the high frequency market well and can update in volume-time rather than clock time. This change provides the investor with more efficient and timely access to market information.

To apply the VPIN method, we exogenously define the equal volume buckets with size, denoted as V . We put sequential trades into these buckets. If the volume is larger than the bucket size V , then the extra volume is put into the next bucket until all of the volume has been categorized. We discard the last bucket if its volume is less than V . One of the most important issues is how to classify the volume as buy- or sell-initiated. We discuss this issue in Section 5.

Following the above preparation, the VPIN can be calculated as

$$\text{VPIN} = \frac{\sum_{\tau=1}^n |V_{\tau}^S - V_{\tau}^B|}{nV}, \quad (1)$$

where $\tau = 1, \dots, n$ is the index of equal volume buckets, V is the size for each bucket,

V_{τ}^S and V_{τ}^B are the buy initiated volume in bucket τ and $V_{\tau}^S + V_{\tau}^B = V$.

Easley et al. (2008, 2012) demonstrate the consistency between the PIN and VPIN measures. Easley et al. (2008) show that the expected trade imbalance is $E[|V_t^S - V_t^B|] \approx \alpha\mu$ and that the expected arrival rate of total trades is $E[V_t^S + V_t^B] = V$. The VPIN is the average trade imbalance over n buckets:

$$\text{VPIN} = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} = \frac{\alpha\mu}{V} = \frac{\sum_{t=1}^n |V_t^S - V_t^B|}{nV}. \quad (2)$$

We need to choose the amount of volume V in each bucket and the number of buckets n to calculate the VPIN.⁵ Following Easley et al. (2012), we make V one-fiftieth of the average daily volume and $n = 50$. Thus, the average one-day volume can estimate a daily VPIN. When bucket 51 is filled, we drop bucket 1 and calculate a new VPIN using buckets 2-51. We find that updating the VPIN using volume-time is more convenient than clock time. We can detect the information more efficiently and accurately by observing the volume arrival velocity. Easley et al. (2012) also demonstrate the stability of a wide selection of V and n .

3.2 Applicability in order-driven systems

Previous studies focus on quote-driven markets, in which market makers provide bid-ask prices in the market to supply liquidity, such as with the New York Stock Exchange (NYSE). Easley et al. (1996, 2012) develop their PIN and VPIN metrics

⁵ For more about how to calculate VPIN, please see appendix I.

based on the mechanism in a quote-driven market. However, bid-ask spread is not unique in a quote-driven market (Brockman and Chung, 1999; Huang, 2004; Ahn et al., 2002) and there are no market makers in an order-driven market. However, an order-driven system could be viewed as a platform on which traders supply the liquidity voluntarily by submitting their orders. Spread is determined by the difference in price between the lowest sell order and highest buy order. In this sense, the PIN and VPIN metrics can also be applicable in an order-driven market. Recent studies (e.g., Ma et al., 2001; Aktas, Bodt, Declerck and Van Oppens, 2007) use PIN in order-driven markets. In this paper, we use both PIN and VPIN to study the market behavior of CBBCs and measure their risk around MCEs.

4. Data and methodology

4.1 Data

The intraday data used in this paper are from the tick-by-tick trade records and the bid-ask record of the Hong Kong Exchanges and Clearing Ltd. (HKEx). These records contain transaction price, bid price, ask price and transaction volume with a time stamp to the nearest second. We include all single-stock CBBCs listed from January 2008 to September 30, 2009 for a total of 3136 CBBCs from 36 underlying stocks. The CBBC data are available in the annual HKEx fact book. Table 1 reports the distribution of the CBBCs by their underlying stock. The fact book contains the date of call-back if an MCE occurs before the maturity of the CBBC. The exact timing of

the MCE can be estimated by searching for the first trade that is equal to or over the call price during the last trading day. There are 1935 MCEs during our sample period.

4.2 Data processing for the VPIN and PIN metrics

For the VPIN, we use bulk classification (Easley et al., 2012) to organize buy- or sell-initiated volume in each bucket. Bulk classification categorizes buy or sell volume using standardized price changes (trading price) between the beginning and the end of the interval, such as one-minute bars. Let

$$V_{\tau}^B = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right), \quad (3)$$

$$V_{\tau}^S = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot \left[1 - Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right)\right] = V - V_{\tau}^B, \quad (4)$$

where $t(\tau)$ is the last time bar in the τ volume bucket, Z is the cumulative distribution function of the standard normal distribution and $\sigma_{\Delta P}$ is the estimate of the standard derivation of price changes between time bars. Then, the volume imbalance in bucket τ is $|V_{\tau}^B - V_{\tau}^S|$. If the price does not change during the bucket, then the volume is equally split and the volume imbalance is equal to zero.

After classifying the buy or sell volumes in every bucket, we estimate the VPIN with every n buckets moved (e.g. 50 buckets), as described in equation (2). The VPIN is used to perform a deeper analysis of the market's influence around the exact time at

which the CBBC is called back.

We follow the assumptions in the standard PIN construction. We estimate the daily PIN for all 36 of the underlying stocks over each trading day. Easley et al. (1996) suggest that all trades occurring within five seconds of each other at the same time, with no intervening quote revision, should be collapsed into one trade. We use volume-weighted average price and quotes for the trades occurring within five seconds. We also apply Lee and Ready's (1991) method⁶ to classify the buy and sell orders using quote and tick tests. When using the quote test, orders are classified in "buys" if the trading price is higher than the midpoint of the current bid-ask quotes. If the trading price is below the midpoint, we classify it in "sells." We use the tick test if the quote test fails, as the trading price may equal the midpoint. If the trading price is higher than the last trading price, it is classified as "buys." If the trading price is lower than the last trading price, it is classified as "sells." If they are equal, we compare the trading price with additional price lags until we classify all of the trades. Following Easley et al. (1996), we apply the 5-second rule to match the time between quotes and trades. Thus, bid-ask quotes should have existed five seconds when used. We can derive the parameter vectors and daily PIN using the number of buy and sell orders in each day. We also apply the filters introduced by Brown, Hillegeist and Lo (2004) to eliminate the extreme parameter estimates:

(1) if $50\varepsilon > \mu$ or $50\mu > \varepsilon$;

(2) if $\alpha < 0.02$ or $\alpha > 0.98$;

⁶ Lee and Ready (1991) and Easley (1996) mention that this method may misclassify some trades. Nevertheless, it is commonly used in other studies.

(3) if $\delta < 0.02$ or $\delta > 0.98$; and

(4) if $\min(\varepsilon, \mu) < 1$.

We further investigate the VPIN to study the risk around CBBC MCE. We calculate the VPIN using the bulk classification of one-minute bars. The amount of volume V in each bucket is one-fiftieth of the average daily volume. The VPIN can be calculated for every 50 buckets moved. We also present the VPIN calculated by a different bucket volume V and a different number of buckets n . By studying the VPIN around the moment of CBBC callback, we can find any change or fluctuation in intraday level, which helps us analyze the investors' behavior before and after the CBBC call-back.

4.4 Summary statistic of the sample

Table 1 shows that 1656 bulls and 1474 bears are issued for 36 underlying stocks from January 2008 to September 30, 2009. Nine-hundred and seven bulls and 1028 bears are called back and 227 bulls and 143 bears expired during this period. The number of CBBCs called back is much more than the CBBC expiration, which indicates that most CBBCs are called back before expiration. It is interesting to find that although the number of bear issuances is less than that of bull issuances, the number of bear MCEs is larger than that of bull MCEs. This shows that bear may be more vulnerable to call backs after issue, consistent with Lei (2014).

[Table 1 about here]

5. Results and analysis

5.1 Results of VPIN and PIN

Table 2 presents the statistics related to the VPIN and PIN metrics. Panel A reports the summary statistics of the parameter estimates in the Easley, Kiefer, O'Hara and Paperman (EKOP) (1996) model, along with the summary of percentage spread and daily volume. After data filtering, 11184 of the observations in our sample are valid. The mean probability of events happening (α) is 0.3227. We also note that the probability of the event being bad news (δ) is 0.4779, which indicates an almost equal chance of bad or good news occurring. The arrival rate of informed trade (μ) and that of uninformed traders (ϵ) are 41.46 and 31.45, respectively. The mean of the daily PIN is 0.1642, the minimum daily PIN is 0.042 and the maximum daily PIN is 0.4850.

[Table 2 about here]

In the methodology section, we define bucket volume as one-fiftieth of the average daily volume, with each 50 buckets calculated as one VPIN. This VPIN is a moving average of the 50 buckets, such that in the next period we add one new bucket while deleting the oldest bucket. Panel B of Table 2 reports the summary statistic of the VPIN and describes the detailed bucket information. We find some consistency

between volume-time and clock-time. A bucket duration of 4.88 minutes is about one-fiftieth of the average VPIN duration of 243.98 minutes. However, the time range needed to calculate one VPIN is from one second to 1461.95 minutes. Such a wide interval suggests that intraday trading activities vary significantly. It also demonstrates the rationality of using a VPIN metric in volume-time to measure the risk of informed trading based on volume imbalances.

Table 3 presents the estimated parameters by volume deciles. Previous studies, such as Easley et al. (1996), document that the probability of informed trading is lower for high-volume stocks. Thus, we conjecture that the PIN and VPIN vary when there is a lower volume-level of stocks. We divide the underlying stocks into nine groups by the average daily volume, with each group containing four stocks.

[Table 3 about here]

The average daily volume increases as the decile ascends from 1 to 9. We find that the probability of the event (α), the PIN and the VPIN are obviously lower for decile 9. The probability of the event occurring, the PIN and the VPIN are 10.72%, 18.81% and 21.46% lower, respectively, than the full sample for decile 9, indicating that the overall risk of frequently traded stocks is lower. However, the PIN and VPIN show no obvious difference for relatively lower volume deciles, which is consistent with Easley et al. (1996). Both of the arrival rates of informed and uninformed traders increase as the volume decile ascends. The high arrival rate and low PIN and VPIN

for high-volume deciles confirm the result found in Easley et al. (1996).

5.2 VPIN around MCE

To further investigate the risk surrounding MCEs, we calculate the VPIN, which heralds the short-term risk.

Table 4 displays the mean moving VPIN for the volume buckets around the MCEs. The VPIN significantly increases around the CBBC MCEs from Bucket -3 to Bucket 7, and most of them are significant at the 1% level. The crucial MCE moment embeds in Bucket 0, in which the VPIN is 0.1640—a remarkable increase from 0.1574 at Bucket -1. The increment 0.00658 is much higher than the other increments. As 50 volume buckets are needed to calculate the VPIN, Bucket 0 is removed after Bucket 50. We observe a significant decrease around Bucket 50 that lasts from Bucket 47 to Bucket 55 and then returns to normal. The VPIN shrinks by 0.004158 or 2.43% at Bucket 50 compared with the previous bucket, indicating that there should be a great volume imbalance around Bucket 0, or at the MCE moment. These results support our hypothesis that the VPIN is higher around the MCE.

[Table 4 about here]

The results are similar after dividing the CBBCs into callable bull and bear

contracts. The VPIN increases from 0.006521 and 0.006630 at Bucket 0 to 0.1604 and 0.1672 for callable bull and bear contracts, respectively, compared with the previous bucket. The VPIN decreases from 0.003839 and 0.004439 at Bucket 50 to 0.1674 and 0.1667 for callable bull and bear contracts, respectively, compared with Bucket 49. The increments are significantly different from 0 around the MCEs or Bucket 50, which demonstrates the high risk at Bucket 0 and its surrounding periods.

Easley et al. (2012) document that their results are robust to different choices of bucket volume size (V) and bucket number (n) when calculating the VPIN. Figure 2 shows that there is high consistency in the VPIN, when the bucket volume size and bucket number change. The VPIN continues to rise around Bucket 0 and fall when Bucket 0 is excluded, gradually returning to normal level after n buckets. As intensive trades still come into the market after an MCE, the highest VPIN then occurs immediately after $n/2$ buckets. These results confirm our conjecture that there are large order imbalances around MCEs that increase the risk. Investors should take note of this situation to prevent possible loss.

[Figure 2 about here]

5.3 Does VPIN systematically provide incremental forecast power on MCEs?

Andersen and Bondarenko (2014b) argue that to show validity of VPIN, one must

show the incremental predictive power for volatility and volume. To test whether VPIN provide incremental forecasting power, we test the relation between the underlying stock VPIN and the probability of a MCE event, controlling for lag return volatility (VOLATILITY) and trading volume (VOLUME):

$$MCE_{i,t} = \beta_0 + \beta_1 VPIN_{i,t-1} + \beta_2 VOLUME_{i,t-1} + \sum_{h=0}^j \beta_{h+3} VOLATILITY_{i,t-h} + \epsilon_{i,t}, \quad (5)$$

where $j=1, \dots, 5$. MCE is an indicator variable that equals one if there is a MCE within the volume bucket and is zero otherwise. VPIN is the Volume-Synchronized Probability of Informed Trading (Easley et al, 2011). Definition and construction of VPIN are listed in Appendix I. Stock price volatility ($VOLATILITY_t$) in period t is measured by the ratio of the absolute difference between opening and closing stock prices of the period and the daily opening price. Stock trading volume ($VOLUME_t$) is the total volume traded in period t . First period of each day is filtered to control for autocorrelation of stock returns.

Table 5 displays the probit regression results of the predictability of VPIN on MCE. These results are consistent with our main hypothesis and previous results – the higher the VPIN the higher the probability of MCE. After controlling for volume and volatilities, the coefficients for VPIN are still significantly positive. Volatilities of longer lags are positive and significant, implying that the chance of MCE is higher given a higher volatility. Note that the contemporaneous volatility and MCE is negatively related. Since VPIN metric uses volume-time, the MCE occurs within this

time period, the volatility will become lower as the barrier has been reached. Besides, $VOLATILITY_{t-1}$ is insignificantly negative. This is consistent with the magnet effect of Cho et al. (2007), who show that when the underlying stock price being over a certain threshold, it becomes highly probable that stock price will reach the call price and thus volatility plays a lesser role in triggering the MCE. Our results show that VPIN has significantly incremental predictive power on MCE after controlling for volatility and volume.

[Table 5 about here]

5.4 PIN around MCE

Another question is that whether the quantity of CBBCs influences the probability of informed trading. The following regression is used to test the effect of the CBBCs on the probability of informed trading.

$$\begin{aligned} PIN = & \alpha + \beta_1 Bull + \beta_2 Bear + \beta_3 Bullevent_i + \beta_4 Bearevent_i + \beta_5 Bullexistevent_i \\ & + \beta_6 Bearexistevent_i + \beta_7 Spread + \beta_8 Volume + error, \quad (6) \end{aligned}$$

where Bull, Bear are the number of callable bull and bear contracts, respectively, Spread is the percentage spread and Volume is the natural log of the daily volume. Bullevent contains three conditions; callable bull contract issuance, expiration and MCE. Bearevent also contains callable bear contract issuance, expiration and MCE.

Bullexistevent and Bearexistevent are dummy variables that equal 1 if any condition happens while bull or bear exist. Spread and Volume are control variables.

The percentage spread is calculated using the method documented in McInish and Wood (1992). First, we calculate the percentage spread for each quotation i occurring at time t ,

$$SPREAD_{i,t} = \frac{Ask_{i,t} - Bid_{i,t}}{(Ask_{i,t} + Bid_{i,t})/2}, \quad (7)$$

where $Ask_{i,t}$ and $Bid_{i,t}$ are ask and bid prices at time t . Then, we can use a time-weighted method to aggregate the percentage spread to get the daily percentage spread:

$$SPREAD = \sum_{i=1}^I \frac{D_i}{T} SPREAD_{i,t}, \quad (8)$$

where D_i represents the duration of quotation i in seconds and T and I are the total number of seconds and total number of quotations for any trading day, respectively.

We conjecture that CBBC MCEs or other events could have a longer time effect on the investor behavior due to information leakage and information effects. Thus, we observe the PIN, the arrival rate of informed traders and the arrival rate of uninformed traders during the estimation window $[-15, 15]$ for each CBBC and compare it with

their average level 30 days before and 30 days $[-30, 30]$ after an event such as issuance, expiration or MCE. This provides a closer look at the change around the events, allowing us to study whether the arrival rates of informed or uninformed trades change during the estimation window.

Table 6 reports the daily averages of PIN, the arrival rates of informed traders and those of uninformed traders for each date in the event window $[-15, 15]$ around the CBBC MCEs at date 0. The t-test statistics are computed by comparing the average PIN of an event day with those of all 31 days $[-15, 15]$ around an MCE, which is equal to 0.1443. The results of similar t-tests on the arrival rates of informed traders (μ) and those of uninformed traders (ε) are reported in Columns 5 and 7, respectively. The daily PINs are significantly lower two days before and after the date of the MCEs. The PIN on the date of an MCE is 0.1397, which is significantly lower than the average of 0.1443. The lower PINs around the MCEs imply relatively higher uninformed trading activities such as hedging activities and speculations. The relatively higher arrival rates of uninformed traders to those of informed traders lead to lower PINs. The uninformed trader arrival rates are higher than average after the MCEs, until day +3, because the settlement of a CBBC lasts at least one day, including re-hedging activities related to other CBBC issues.

[Table 6 about here]

Although the daily PIN can identify MCE patterns, similar to Lei (2014), it fails to investigate the trade imbalances around MCEs. The VPIN increases substantially around MCEs, whereas the PIN decreases. The intraday dynamics of MCEs are better

captured by the VPIN, especially when examining minute-by-minute data. Even though the intraday PIN can be estimated, the shorter period significantly lowers trade observations, and convergence is required for PIN estimations. We attempt to estimate shorter intervals of the PIN (e.g. 5-minute PIN), but the majority are invalid results. Thus, the VPIN is a better alternative in intraday analysis, as it consistently generates estimations in all intervals.

Table 7 reports the panel regression results of the probability of informed trading against the number of CBBCs available, transaction volumes and percentage bid-ask spread. We find that the PIN is significantly negatively associated with the number of callable bull and bear contracts, after controlling for market liquidity measures. Both control variables—the daily volume and the percentage spread—are significantly associated with the PIN. Our result suggests that CBBCs are associated with uninformed trading activities, such as hedging or speculation, after controlling for the market liquidity of underlying stocks.

[Table 7 about here]

6. Conclusion

In this study, we apply the VPIN and PIN measures to examine trade imbalances around CBBC MCEs. The VPIN shows a significant increase around MCEs, indicating that activities peak even before an MCE, consistent with Lei (2014). In contrast, the PIN shows a relatively low value around MCEs. This can be misleading because the conventional PIN method does not capture the intraday dynamics of CBBC MCEs. Our results suggest that the VPIN is a good measure for detecting trade imbalances and liquidity risk for stocks, as it is applicable to intraday events. In addition to the evidence from the Flash Crash, we empirically test the validity of the VPIN using CBBC MCEs as alternative events of order flow toxicity.

Our finding also suggests that CBBC activities significantly influence investors' trading behavior. For example, issuers have the incentive to manipulate the underlying stocks in their favor. Speculators may also trade the underlying stock, expecting to knock out the CBBCs. These trades can create noise to the underlying stocks, distorting the price discovery process. The short-term spike in MCE-related trading activities may also increase the liquidity risks of market participants. Regulators can mitigate these undesirable effects of CBBCs by requiring more disclosure of CBBC issuers trading around MCEs, at least to the exchange. Then, less speculative trades will occur around the MCEs to reduce the effects of these types of derivatives on the market.

References

- Ahn, H.J., Cai, J., Hamao, Y., Ho, R.Y., 2002. The components of the bid–ask spread in a limit-order market: evidence from the Tokyo Stock Exchange. *Journal of Empirical Finance* 9(4), 399-430.
- Aktas, N., De Bodt, E., Declerck, F., & Van Oppens, H., 2007. The PIN anomaly around M&A announcements. *Journal of Financial Markets*, 10, 169-191.
- Andersen, T., Bondarenko, O., 2014a. VPIN and the Flash Crash. *Journal of Financial Markets* 17, 1-46.
- Andersen, T. G., & Bondarenko, O. 2014b. Reflecting on the VPIN dispute. *Journal of Financial Markets*, 17, 53-64.
- Bansal, V.K., Pruitt, S.W., Wei, K.C.J., 1989. An empirical reexamination of the impact of CBOE option initiation on the volatility and trading volume of the underlying equities: 1973-1986. *Financial Review* 24, 19-29.
- Bhattacharya, A.K., 1987. Option expirations and treasury bond futures prices. *Journal of Futures Markets* 7, 49-64.

Brockman, P., Chung, D.Y., 1999. Bid-ask spread components in an order-driven environment. *The Journal of Financial Research* 12, 227-246.

Brown, S., Hillegeist, S.A., Lo, K., 2004. Conference calls and information asymmetry. *Journal of Accounting and Economics* 37, 343-366.

Chan, Y., Wei, K.C.J., 2001. Price and volume effects associated with derivative warrant issuance on the Stock Exchange of Hong Kong. *Journal of Banking and Finance* 25, 1401-1426.

Cinar, E.M., Vu, J., 1987. Evidence on the effect of option expirations on stock prices. *Financial Analysts Journal* 43, 55-57.

Cho, David D., Jeffrey Russell, George C. Tiao, and Ruey Tsay, 2003, The magnet effect of price limits: Evidence from high-frequency data on Taiwan Stock Exchange, *Journal of Empirical Finance* 10, 133-168.

Conrad, J., 1989. The price effect of option introduction. *The Journal of Finance* 44, 487-498.

Cutler, D., Poterba, J., Summers, L., 1989. What moves stock prices? *Journal of Portfolio Management* 15, 4-12.

- De Bondt, W.P.M., 1993. Betting on trends: intuitive forecasts of financial risk and return. *International Journal of Forecasting* 9(3): 355-371.
- De Long, J.B., Shleifer, A., Summers, L.H., Waldmann, R.J., 1990. Noise trader risk in financial markets. *Journal of Political Economy* 98: 703-738.
- Detemple, J., Jorion, P., 1990. Option listing and stock returns: an empirical analysis. *Journal of Banking and Finance* 14, 781-801.
- Easley, D., de Prado, Marcos M López, O'Hara, M., 2012. Flow toxicity and liquidity in a high frequency world. *Review of Finance Studies* 25(5), 1457-1493.
- Easley, D., Engle, R.F., O'Hara, M., Wu, L., 2008. Time-varying arrival rates of informed and uninformed trades. *Journal of Financial Econometrics* 6, 171-207.
- Easley, D., Kiefer, N.M., O'Hara, M., Paperman, J.B., 1996. Liquidity, information, and infrequently traded stocks. *The Journal of Finance* 51, 1405-1436.
- Huang, Y.C., 2004. The components of bid-ask spread and their determinants: TAIEX versus SGX-DT. *Journal of Futures Markets* 24(9), 835-860.

- Klemkosky, R.C., 1978. The impact of option expirations on stock prices. *Journal of Financial and Quantitative Analysis* 13, 507-518.
- Lee, C.M.C., Ready, M.J., 1991. Inferring trade direction from intraday data. *The Journal of Finance* 46, 733-746.
- Lei, A.C.H., 2014. Price and volume effects of exchange-traded barrier options: evidence from callable bull/bear contracts. *Journal of Futures Markets*. Forthcoming.
- Ma, T., Hsieh, M., Chen, J.H., 2001. The probability of informed trading and the performance of stock in an order-driven market. EFA 2001 Barcelona Meetings.
- McInish, T.H., Wood, R.A., 1992. An analysis of intraday patterns in bid/ask spreads for NYSE stocks. *The Journal of Finance* 47, 753-764.
- Ni, S.X., Pearson, N.D., Poteshman, A.M., 2005. Stock price clustering on option expiration dates. *Journal of Financial Economics* 78(1), 49-87.
- Nyholm, K., 2002. Estimating the probability of informed trading. *Journal of Financial Research* 25, 485-505.

Pope, P.F., Yadav, P.K., 1992. The impact of option expiration on underlying stocks: the UK evidence. *Journal of Business Finance and Accounting* 19, 329-344.

Romer, D., 1993. Rational asset price movements without news. *American Economic Review* 83, 1112-1130.

Sias, R.W., Starks, L.T., Tinic, S.M., 2001. Is noise traders risk priced? *Journal of Financial Research* 24(3): 311-330.

Solt, M.E., Statman M., 1988. How useful is the sentiment index? *Financial Analysts Journal*, 45-55.

Tay, A., Ting, C., Tse, Y.K., Warachka, M., 2009. Using high-frequency transaction data to estimate the probability of informed trading. *Journal of Financial Econometrics* 7, 288-311.

Tables and Figures

Table 1: CBBC information for each underlying stock

This table displays the distribution of CBBCs as classified by underlying stocks. There are 36 underlying stocks and 3136 CBBCs, among which 3130 CBBCs are new issues from January 1, 2008 to September 30, 2009. The sample covers all of the CBBCs issued, called back and/or expired during this period.

Stock code	Stock name	Bull issuance	Bear issuance	Bull MCE	Bear MCE	Bull expiration	Bear expiration
1	CHEUNG KONG	34	22	15	10	3	2
5	HSBC HOLDINGS	180	158	101	87	10	46
11	HANG SENG BANK	26	18	16	9	1	6
13	HUTCHISON	22	14	10	7	5	4
16	SHK PPT	52	49	23	34	9	3
358	JIANGXI COPPER	32	20	14	12	0	0
386	SINOPEC CORP	58	50	25	34	11	2
388	HKEX	185	214	99	174	25	5
390	CHINA RAILWAY	4	2	3	2	1	0
688	CHINA OVERSEAS	10	11	1	6	1	0
700	TENCENT	5	5	0	5	0	0
728	CHINA TELECOM	25	11	14	6	3	0
762	CHINA UNICOM	9	7	3	3	0	0
813	SHIMAO PROPERTY	15	15	9	7	0	0
857	PETRO CHINA	90	78	56	60	19	7
883	CNOOC	77	77	44	60	18	4
939	CCB	63	72	26	53	19	8
941	CHINA	165	151	108	93	24	25

	MOBILE						
998	CITIC BANK	2	0	2	0	0	0
1088	CHINA SHENHUA	34	23	20	15	3	2
1171	YANZHOU COAL	3	0	3	0	0	0
1186	CHINA RAIL CONS	7	1	5	1	0	0
1398	ICBC	49	51	22	35	12	7
1800	CHINA COMM CONS	17	13	9	10	5	3
1898	CHINA COAL	24	13	15	9	1	0
1919	CHINA COSCO	25	22	16	10	0	0
2318	PING AN	37	28	20	22	5	0
2328	PICC P&C	4	0	4	0	0	0
2388	BOC HONG KONG	16	8	8	5	0	0
2600	CHALCO	28	17	18	9	0	0
2628	CHINA LIFE	239	229	133	188	39	13
2777	R&F PROPERTIES	15	14	9	4	0	0
2899	ZIJIN MINING	5	0	5	0	0	0
3328	BANKCOMM	27	16	15	13	2	0
3968	CM BANK	50	46	30	32	5	5
3988	BANK OF CHINA	22	19	6	13	6	1
		1656	1474	907	1028	227	143
Total		3130		1935		370	

Table 2**Summary statistics for the EKOP model and VPIN**

This table provides the summary statistics related to the PIN and VPIN. Panel A presents the summary statistics of the parameter estimates in the EKOP model along with the percentage spread and daily volume. Parameter α is the probability of events occurring, δ is the probability that the event is bad news, μ and ε are the arrival rates of informed and uninformed traders, respectively, and PIN is the probability of informed trading. The table also shows the statistics for percentage spread and daily volume. Panel B presents the summary statistics related to VPIN. Bucket volume is one-fiftieth of the average daily volume, bucket duration is the duration from the beginning to the end of the bucket, VPIN duration is the period from the first to the fiftieth bucket and VPIN is the *volume-synchronized probability of informed trading* defined by Easley et al. (2011). Bulk classification in one-minute bars is used to classify the buy- or sell-initiated traders.

Panel A: Summary statistics related to PIN

Parameter	Number	Mean	Std. Dev.	Minimum	Medium	Maximum
α	11184	0.3227	0.1484	0.0821	0.2998	0.9744
δ	11184	0.4779	0.2187	0.0203	0.4859	0.9778
μ	11184	41.46	28.20	5.35	33.81	410.22
ε	11184	31.45	18.34	3.85	26.97	224.00
PIN	11184	0.1642	0.0526	0.0420	0.1580	0.4850
Percentage spread (10^{-3})	11184	1.8223	0.7602	0.5609	1.7041	7.6973
Daily volume (10^3)	11184	67948	112094	546	29445	1568239

Panel B: Summary statistics related to VPIN

Parameter	Number	Mean	Std. Dev.	Min	Max
Bucket volume (10^3)	769950	1576.43	2252.41	64.07	8787.39
Bucket duration (minutes)	769950	4.88	6.82	0	392
VPIN duration (minutes)	769950	243.98	131.86	0	1461.95
VPIN	769950	0.1943	0.0904	0	1.0000

Table 3**Summary parameters of the EKOP model and VPIN by volume****decile**

This table presents the means of the parameter estimates by volume decile for the 36 stocks in our sample. Each decile contains four stocks. The average daily volume increases as the decile ascends from 1 to 9. The second and third columns show the probability of the information event (α) and the probability that it will bad news (δ). The fourth and fifth columns show the means of the arrival rates of informed traders (μ) and uninformed traders (ε), respectively. The last two columns show the probability of informed trading (PIN) and the volume-synchronized probability of informed trading (VPIN).

Parameter	α	δ	μ	ε	PIN	VPIN
Full sample	0.3227	0.4779	41.46	31.45	0.1642	0.1943
Decile 1	0.3351	0.4689	30.34	21.55	0.1788	0.1920
Decile 2	0.3319	0.4650	39.96	30.53	0.1692	0.2013
Decile 3	0.3513	0.4940	38.89	29.67	0.1740	0.1832
Decile 4	0.3164	0.4737	43.35	32.68	0.1637	0.1960
Decile 5	0.3405	0.4671	33.27	24.64	0.1763	0.2150
Decile 6	0.3194	0.5029	37.21	28.39	0.1631	0.2043
Decile 7	0.3407	0.4790	36.84	28.25	0.1743	0.2049
Decile 8	0.2731	0.4901	55.09	40.88	0.1383	0.1992
Decile 9	0.2881	0.4619	63.19	50.77	0.1333	0.1526

Table 4: VPIN around CBBC MCE

This table displays the moving mean VPIN, the changes compared with the previous VPIN and its mean-comparison test statistics between this increment and ten volume buckets before and sixty volume buckets after an MCE. VPIN is the volume-synchronized probability of informed trading, as defined in Easley et al. (2012). The CBBCs call back at Bucket 0. Bucket volume size V equals one-fiftieth of the average daily volume and VPIN is calculated with every 50 bucket moves. *, ** and *** represent 10%, 5% and 1% significance levels, respectively.

Bucket/VPIN number	Full Sample			BULL			BEAR		
	Mean VPIN	Mean VPIN change	t statistic	Mean VPIN	Mean VPIN change	t-statistic	Mean VPIN	Mean VPIN change	t-statistic
-10	0.154866	-0.000093	-0.53	0.151973	-0.000097	-0.31	0.157419	-0.000090	-0.48
-9	0.154582	-0.000284	-1.93*	0.151772	-0.000201	-0.79	0.157061	-0.000358	-2.21**
-8	0.154527	-0.000055	-0.4	0.151689	-0.000083	-0.43	0.157031	-0.000030	-0.15
-7	0.154203	-0.000324	-1.84*	0.151298	-0.000392	-1.47	0.156766	-0.000265	-1.13
-6	0.154194	-0.000009	-0.04	0.151118	-0.000179	-0.79	0.156908	0.000142	0.43
-5	0.154270	0.000076	0.42	0.151180	0.000061	0.22	0.156997	0.000089	0.37
-4	0.154443	0.000173	1.17	0.151527	0.000348	1.52	0.157016	0.000019	0.1
-3	0.154967	0.000524	3.33***	0.151829	0.000302	1.41	0.157736	0.000720	3.16***
-2	0.156025	0.001058	6.07***	0.152432	0.000602	2.46**	0.159195	0.001459	5.93***
-1	0.157436	0.001411	7.6***	0.153833	0.001401	4.93***	0.160616	0.001421	5.83***
0 (MCE)	0.164015	0.006579	26.47***	0.160354	0.006521	16.86***	0.167245	0.006630	20.71***
1	0.165737	0.001722	8.86***	0.161978	0.001624	5.17***	0.169054	0.001809	7.57***
2	0.167589	0.001852	9.02***	0.164109	0.002131	6.14***	0.170661	0.001606	6.82***
3	0.168753	0.001163	6.71***	0.164920	0.000811	3.44***	0.172135	0.001474	5.87***
4	0.169167	0.000414	2.49**	0.165408	0.000488	1.83*	0.172483	0.000349	1.68*
5	0.169643	0.000476	3.01***	0.165763	0.000355	1.47	0.173067	0.000583	2.79***
6	0.170215	0.000572	4.07***	0.166313	0.000549	2.45**	0.173659	0.000592	3.36***
7	0.170556	0.000340	2.25**	0.166755	0.000442	1.74*	0.173909	0.000250	1.44

8	0.170733	0.000178	1.29	0.167074	0.000319	1.39	0.173962	0.000053	0.33
9	0.170896	0.000162	1.18	0.167041	-0.000033	-0.15	0.174297	0.000335	2**
10	0.170835	-0.000061	-0.49	0.167095	0.000054	0.28	0.174135	-0.000162	-0.99
11-39
40	0.173993	0.000385	3.09***	0.172414	0.000509	2.7***	0.175382	0.000276	1.67*
41	0.174446	0.000453	3.07***	0.172810	0.000396	2.33**	0.175885	0.000503	2.16**
42	0.174466	0.000020	0.16	0.173100	0.000290	1.62	0.175667	-0.000218	-1.31
43	0.174550	0.000085	0.69	0.173161	0.000061	0.36	0.175772	0.000105	0.6
44	0.174780	0.000229	1.68*	0.173666	0.000506	2.33**	0.175759	-0.000014	-0.08
45	0.174719	-0.000060	-0.43	0.173712	0.000045	0.22	0.175606	-0.000153	-0.79
46	0.174697	-0.000023	-0.18	0.174040	0.000328	1.71*	0.175274	-0.000332	-1.91*
47	0.174432	-0.000265	-1.93*	0.174175	0.000135	0.77	0.174657	-0.000616	-2.98***
48	0.173612	-0.000819	-5.55***	0.173656	-0.000519	-2.36**	0.173574	-0.001083	-5.46***
49	0.171184	-0.002429	-14.34***	0.171285	-0.002371	-9.98***	0.171095	-0.002479	-10.32***
50	0.167025	-0.004158	-22.77***	0.167446	-0.003839	-16.51***	0.166656	-0.004439	-16.12***
51	0.164088	-0.002937	-17.05***	0.164369	-0.003077	-13.23***	0.163842	-0.002814	-11.21***
52	0.162619	-0.001469	-9.83***	0.162975	-0.001394	-6.25***	0.162305	-0.001536	-7.63***
53	0.161678	-0.000964	-6.86***	0.162216	-0.000808	-4.18***	0.161205	-0.001101	-5.46***
54	0.161234	-0.000475	-3.27***	0.161809	-0.000474	-2.5**	0.160729	-0.000475	-2.2**
55	0.160929	-0.000305	-2**	0.161527	-0.000282	-1.41	0.160404	-0.000326	-1.44
56	0.160726	-0.000202	-1.55	0.161474	-0.000053	-0.28	0.160070	-0.000333	-1.86*
57	0.160461	-0.000265	-1.99**	0.161152	-0.000322	-1.6	0.159854	-0.000216	-1.22
58	0.160478	0.000025	0.2	0.161147	0.000011	0.06	0.159892	0.000038	0.22
59	0.160366	-0.000105	-0.62	0.161092	-0.000039	-0.21	0.159731	-0.000162	-0.6
60	0.160519	0.000153	1.1	0.161483	0.000392	1.86*	0.159674	-0.000056	-0.3

Table 5: The predictability of VPIN on MCEs

This table reports the probit regression results on the relation between a firm's stock VPIN and the probability of a MCE event, controlling for lag periods of stock price volatility (*VOLATILITY*) and stock trading volume (*VOLUME*):

$$MCE_{i,t} = \beta_0 + \beta_1 VPIN_{i,t-1} + \beta_2 VOLUME_{i,t-1} + \sum_{h=0}^j \beta_{h+3} VOLATILITY_{i,t-h} + \epsilon_{i,t},$$

where $j=1, \dots, 5$. MCE is an indicator variable that equals one if there is a MCE within the volume bucket and is zero otherwise. VPIN is the Volume-Synchronized Probability of Informed Trading (Easley et al, 2011). Definition and construction of VPIN are listed in Appendix I. Stock price volatility (*VOLATILITY*_{*t*}) in the period *t* is measured by the ratio of the absolute difference between opening and closing stock prices of the period, and the daily opening price. Stock trading volume (*VOLUME*_{*t*}) is the total volume traded in period *t*. First period of each day is filtered to control for autocorrelation of stock returns. Coefficient estimates are shown in bold and their chi-square are displayed in the parentheses. Standard errors are adjusted for heteroscedasticity and clustered by firm. ***, **, * indicates significance at the 1% ,5% ,10% level, respectively.

Variable Name	(1)	(2)	(3)
<i>VPIN</i> _{<i>t</i>-1}	1.165 ^{***} (59.665)	1.093 ^{***} (49.648)	1.075 ^{***} (50.312)
<i>VOLATILITY</i> _{<i>t</i>}	-19.786 ^{***} (124.51)	-21.023 ^{***} (134.215)	-20.804 ^{***} (132.703)
<i>VOLATILITY</i> _{<i>t</i>-1}	-1.345 (0.244)	-0.794 (0.074)	-0.935 (0.104)
<i>VOLATILITY</i> _{<i>t</i>-2}	4.114 (1.601)	2.126 (0.365)	1.944 (0.310)
<i>VOLATILITY</i> _{<i>t</i>-3}	9.214 ^{***} (7.413)	7.250 [*] (3.734)	6.975 [*] (3.494)
<i>VOLATILITY</i> _{<i>t</i>-4}		11.476 ^{***} (8.731)	11.087 ^{***} (8.219)
<i>VOLATILITY</i> _{<i>t</i>-5}		10.323 ^{***} (7.472)	9.800 ^{***} (6.797)
<i>VOLUME</i> _{<i>t</i>-1}			-0.030 ^{***} (20.392)
Number of Observations	708,516	677,799	677,730
Intercept	Included	Included	Included
Firm Fixed effect	Included	Included	Included

Table 6: Daily PIN around CBBC MCE

This table shows the underlying stocks' mean daily PIN, arrival rates of informed traders (μ) and uninformed traders (ϵ) during the event window, from 15 days before to 15 days after the CBBC MCE dates. The t-test statistics are computed by comparing the average PIN of the event day with those of all 31 days ($[-15, 15]$). The results of similar t-tests on the arrival rates of informed traders (μ) and uninformed traders (ϵ) are reported in Columns 5 and 7, respectively. *, ** and *** represent 10%, 5% and 1% significance levels, respectively.

Daily PIN around the period of CBBC MCEs.

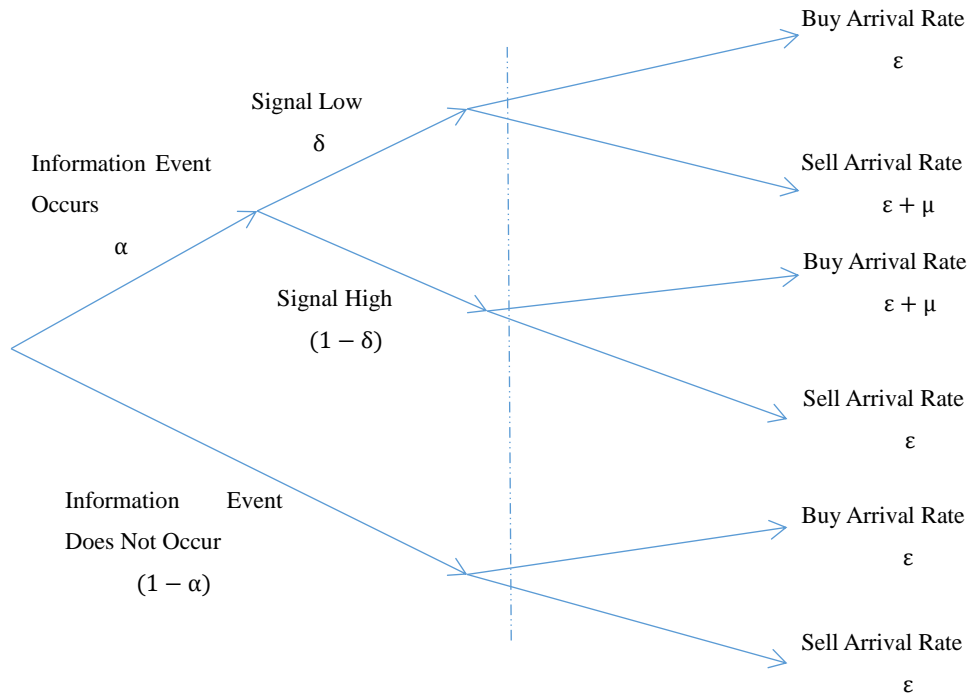
Event	Mean					
day/Window	Daily PIN	t-statistic	Mean μ	t-statistic	Mean ϵ	t-statistic
-15	0.1420	-1.82*	58.12	0.920	45.42	1.66*
-14	0.1435	-0.62	57.16	0.060	44.25	0.01
-13	0.1462	1.55	56.02	-0.920	43.67	-0.85
-12	0.1424	-1.58	58.95	1.540	44.90	0.95
-11	0.1446	0.23	58.93	1.490	45.01	1.13
-10	0.1431	-0.87	55.85	-1.20	44.26	0.03
-9	0.1458	1.08	56.65	-0.410	43.38	-1.42
-8	0.1471	2.11**	56.07	-0.910	43.18	-1.58
-7	0.1471	2.18**	54.30	-2.91***	42.36	-3.24***
-6	0.1464	1.55	54.80	-2.15**	42.87	-2.18**
-5	0.1445	0.16	56.41	-0.620	43.95	-0.42
-4	0.1416	-2.18**	56.66	-0.370	43.81	-0.69
-3	0.1440	-0.24	58.39	1.080	43.51	-1.13
-2	0.1478	2.51**	58.23	0.890	44.15	-0.13
-1	0.1400	-3.41***	59.45	2.02**	46.35	3.17***
0	0.1397	-3.74***	75.11	10.99***	57.01	14.01***
1	0.1398	-3.77***	61.63	4.09***	48.39	6.18***
2	0.1392	-4.21***	58.60	1.450	46.05	2.8***
3	0.1426	-1.33	58.17	1.010	45.67	2.17**
4	0.1420	-1.75*	54.74	-2.47**	43.84	-0.66
5	0.1437	-0.42	56.24	-0.80	44.87	0.96
6	0.1421	-1.73*	56.02	-0.960	44.63	0.58
7	0.1434	-0.71	56.03	-0.980	43.56	-1.04
8	0.1438	-0.35	56.71	-0.330	42.99	-2.04**
9	0.1455	0.9	56.25	-0.780	43.82	-0.65
10	0.1452	0.64	58.42	1.030	44.02	-0.35
11	0.1445	0.19	56.30	-0.660	43.83	-0.62
12	0.1449	0.46	56.51	-0.540	43.65	-0.95
13	0.1466	1.67*	57.64	0.470	44.04	-0.29
14	0.1469	1.92*	54.59	-2.34**	43.66	-0.87
15	0.1417	-1.97**	58.48	1.140	45.82	2.12**

Table 7: Regression of CBBC activities on the daily PIN

This table presents the linear regression of CBBC activities on the PIN. And the regression result of daily PIN on the quantity of CBBC existence. Bull is the number of callable bull contracts existing on that day and Bear is the number of callable bear contracts existing on that day. *, ** and *** represent the 10%, 5% and 1% significance levels, respectively.

Independent Variables	(1) Daily PIN	(2) Daily PIN	(3) Daily PIN
Bull	-0.0007*** (-13.9707)		-0.0003*** (-3.9762)
Bear		-0.0010*** (-14.6919)	-0.0006*** (-6.0128)
Daily volume	-0.0152*** (-36.5271)	-0.0151*** (-36.4281)	-0.0150*** (-36.1670)
Percentage spread	11.1211*** (16.0984)	11.4040*** (16.6946)	11.0040*** (15.9475)
Constant	0.4086*** (60.9787)	0.4071*** (60.7463)	0.4067*** (60.7035)
Observations	11,184	11,184	11,184
R-squared	0.1369	0.1384	0.1397

Figure 1: Trading process in the EKOP model.

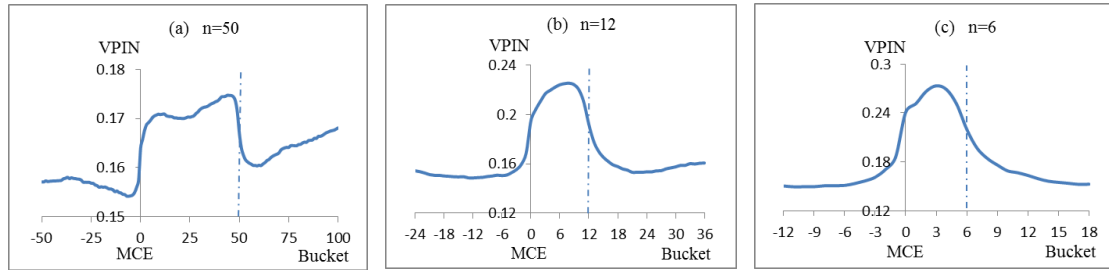


Note: α is the probability of an information event, δ is the probability that this information event is bad news, μ is the arrival rates of informed traders and ε is the arrival rates of uninformed traders.

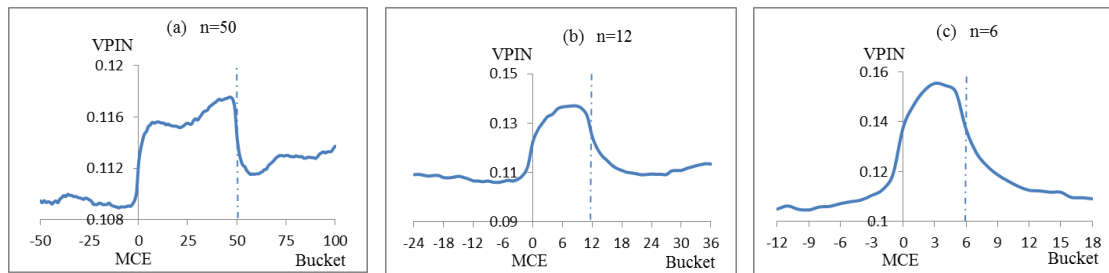
Figure 2: VPIN around MCE.

This figure shows the moving VPIN of the underlying stocks around the MCE moment calculated by different bucket volume size (V), different number of buckets (n) and different time bars. The bucket volume size for Panels A and B is $1/50$ of the average daily volume, and for Panel C is $1/250$ of the average daily volume. Bulk classification is used to process all of the trading data. Panel A uses 1-minute bars and Panels B and C use 10-second bars. The MCEs occur at Bucket 0.

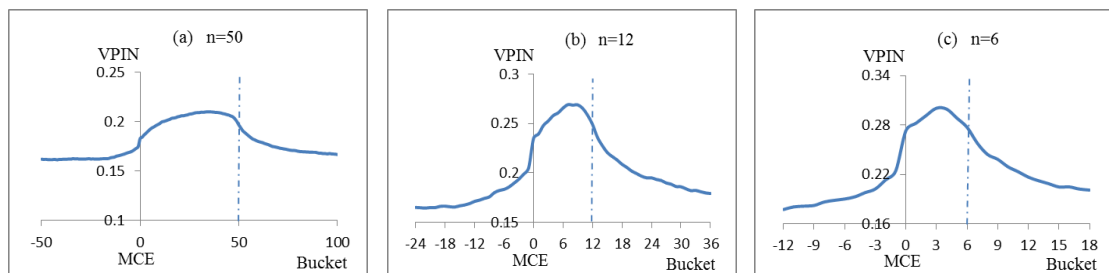
Panel A: VPIN around MCE: $V = 1/50$ average daily volume, 1-minute bars



Panel B: VPIN around MCE: $V = 1/50$ average daily volume, 10-second bars



Panel C: VPIN around MCE: $V = 1/250$ average daily volume, 10-second bars



Appendix I: Estimation of VPIN

This appendix shows the procedure to calculate the volume-synchronized probability of informed trading (VPIN) by Easley (2012).

To calculate the VPIN, we need the following variables:

T_ω : Time of the trade,

P_ω : Price at which securities were traded,

V_ω : Volume exchanged,

V_{ti} : Volume in the i^{th} one-minute bar included in bucket τ ,

$\sigma_{\Delta P}$: Estimate of the standard derivation of price changes between time bars,

V : Volume in each bucket,

n : Buckets used to calculate VPIN.

Note: V and n can be determined by user.

Procedure:

1. Sort transactions by time ascending: $T_{\omega+1} \geq T_\omega, \forall \omega$.
2. Expand the number of observations by repeating each observation P_ω as many times as V_ω . This generates a total of $W = \sum_\omega V_\omega$ observations.
3. Initiate $\tau = 0$.
4. Add one unit to τ .
5. If $W < \tau V$, jump to step 10 (Not enough observations in this bucket).
6. $\forall i \in [(\tau - 1)V + 1, \tau V]$, classify each transaction as buy or sell initiated:
 - a. Classify the transaction in buy initiated using

$$V_\tau^S = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right).$$

- b. Then, classify the transaction in sell initiated:

$$V_\tau^S = \sum_{i=t(\tau-1)+1}^{t(\tau)} V_i \cdot \left[1 - Z\left(\frac{P_i - P_{i-1}}{\sigma_{\Delta P}}\right)\right] = V - V_\tau^B.$$

7. Define V_τ^B as the number of volume in buy initiated and V_τ^S as the number of volume in sell initiated. Obviously, $V = V_\tau^B + V_\tau^S$.
8. Loop to step 5.
9. Set $L = \tau - 1$ (the last bucket is empty or has not enough observation, thus $V_\tau^B + V_\tau^S < V$).

10. For $n \leq j \leq N$, calculate $VPIN_j = \frac{\sum_{\tau=j-n+1}^j |V_\tau^B - V_\tau^S|}{\sum_{\tau=j-n+1}^j (V_\tau^B + V_\tau^S)}$.

Appendix II: Trading characteristics of listed companies in the sample

This table shows the stocks used in this study. Thirty-six stocks are selected, as they are the underlying stocks of CBBCs. Average daily volume, average daily percentage spread, average daily orders, average daily PIN and average VPIN from January 1, 2008 to September 30, 2009 are presented. All of these variables are calculated using the intraday data from the trade record of the HKSE.

Code	Identity	Company name	Average daily volume (10^3)	Average daily percentage spread (10^{-3})	Average daily orders	Average daily PIN	Average VPIN
1	2155010	Cheung Kong (Holdings) Ltd.	6082	1.2608	2367	0.1715	0.1929
5	2034010	HSBC Holdings plc	28616	0.904	9958	0.1356	0.1071
11	2114010	Hang Seng Bank Ltd.	3203	0.9426	3709	0.1821	0.1977
13	2278010	Hutchison Whampoa Ltd.	8498	1.2917	2940	0.1634	0.1932
16	2133010	Sun Hung Kai Properties Ltd.	8605	1.1717	3067	0.1654	0.1864
358	3033010	Jiangxi Copper Co. Ltd. 'H'	31826	1.8902	3922	0.1755	0.2015
386	1009240	China Petroleum & Chemical Corporation 'H'	178450	1.8248	7575	0.1389	0.1987
388	1007640	Hong Kong Exchanges and Clearing Ltd.	10275	0.8823	7476	0.1490	0.1852
390	1152790	China Railway Group Ltd. 'H'	45395	2.0132	4491	0.1686	0.2461
688	2611010	China Overseas Land & Investment Ltd.	37353	1.7097	3736	0.1821	0.2188
700	1035730	Tencent Holdings Ltd.	4496	1.2985	2972	0.1972	0.1844
728	1020510	China Telecom Corporation Ltd. 'H'	143629	2.8267	4981	0.1572	0.2175
762	1007590	China Unicom (Hong Kong) Ltd.	33427	1.799	3257	0.1832	0.2087
813	1074200	Shimao Property Holdings Ltd.	20390	2.1637	2936	0.2019	0.2314
857	1006930	PetroChina Co. Ltd. 'H'	170720	1.6279	7985	0.1309	0.1803

Appendix II-Continued

Code	Identity	Company name	Average daily				
			Average daily volume (10^3)	percentage spread (10^{-3})	Average daily orders	Average daily PIN	Average VPIN
883	1011060	CNOOC Ltd.	122989	1.6624	7754	0.1335	0.1949
939	1058240	China Construction Bank Corporation ‘H’	422515	1.9763	13518	0.1332	0.0850
941	3078010	China Mobile Ltd.	30708	0.8346	10376	0.1309	0.1738
998	1108220	China CITIC Bank Corporation Ltd. ‘H’	49206	2.9335	2602	0.2110	0.2290
1088	1050050	China Shenhua Energy Co. Ltd. ‘H’	29937	1.7914	5541	0.1570	0.1992
1171	1000010	Yanzhou Coal Mining Co. Ltd. ‘H’	29713	2.1307	2919	0.1821	0.2097
1186	1174780	China Railway Construction Corporation Ltd. ‘H’	23806	2.0139	3773	0.1897	0.2362
1398	1084380	Industrial and Commercial Bank of China Ltd. ‘H’	408867	2.1777	13863	0.1245	0.1959
1800	1091300	China Communications Construction Co. Ltd.	43395	1.6733	4762	0.1498	0.1867
1898	1091310	China Coal Energy Co. Ltd. ‘H’	40408	1.9494	4290	0.1639	0.1912
1919	1051020	China COSCO Holdings Co. Ltd. ‘H’	57621	1.9968	6301	0.1632	0.1940
2318	1036030	Ping An Insurance (Group) Co. of China Ltd. ‘H’	16695	1.2875	5369	0.1565	0.2022
2328	1027530	PICC Property and Casualty Co. Ltd. ‘H’	37242	2.592	3031	0.1827	0.2278
2388	1018580	BOC Hong Kong (Holdings) Ltd.	24217	1.6273	3890	0.1717	0.1880
2600	1013210	Aluminum Corporation of China Ltd. ‘H’	59077	2.0877	4842	0.1604	0.1918
2628	1029020	China Life Insurance Co. Ltd. ‘H’	84239	1.869	11028	0.1303	0.2043
2777	1051860	Guangzhou R&F Properties Co., Ltd. ‘H’	25662	2.0343	3886	0.1869	0.2075
2899	1029180	Zijin Mining Group Co., Ltd. ‘H’	41823	2.3405	3728	0.1690	0.1933
3328	1050580	Bank of Communications Co., Ltd. ‘H’	72190	1.7627	5295	0.1598	0.2049
3968	1080540	China Merchants Bank Co., Ltd.	38632	1.7648	5450	0.1560	0.2046
3988	1071410	Bank of China Ltd.	439369	3.3842	9465	0.1353	0.1308