Bulk Volume Classification Under the Microscope: Estimating the Net Order Flow [*]

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September 2018
(Preliminary and incomplete draft)

* Funding: This paper is supported by the Spanish DGICYT project ECO2017-86903-P, and the Generalitat Valenciana Grant Prometeo/2017/158. Any errors are entirely our own.

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Abstract

We evaluate the bulk volume classification (BVC) method of Easley et al. (2016). Our focus is on markets where algorithmic trading strategies govern the order flow and trade initiation no longer signals informed trading. So, we account for all sources of buying or selling pressure (order submissions, revisions, and cancellations) to gauge BVC's accuracy in estimating the net order flow (NOF). We show that the BVC accuracy could be as high as 92.4% for 5-minute time bars, and as low as 50.9% for 1-second time bars. The BVC renders more accurate estimates of the NOF than of the trade-based order imbalance (OI). Indeed, for relatively small bars the OI is itself a pretty poor proxy of the NOF. The BVC-based NOF is a better proxy for the HFT-related NOF component than for the non-HFTs'. Finally, the BVC accuracy rate decreases with pre-trade opacity, monitoring intensity, the non-ATs' contribution to the NOF, the HFTs' message-to-trade ratio, and the absolute magnitude of the price change between bars.

In posterior versions of this paper, we will also evaluate the BVC's capacity to (i) capture the information embedded in the net order flow, and (ii) signal order flow toxicity.

Keywords: BVC, trade classification, net order flow, toxicity, order imbalance, liquidity, VPIN, limit orders, limit order book.

JEL Classification: G10, G11, G14, G15,

1. Introduction

The bulk volume classification (BVC) is a probabilistic method to assign direction to pre-aggregated volume. To apply the BVC, one need to aggregate volume into bars of a pre-determined size, compute standardized price changes between bars and, given a probabilistic distribution for those price changes, estimate the probability of buyer-initiated volume within each bar. In a series of related papers, Easley, López de Prado, and O'Hara (hereafter, ELO) use the BVC to estimate volume imbalances within the VPIN approach, a new procedure to measure order-flow toxicity.[1]

Provided that the researcher has access to pre-compressed volume data, the BVC is undoubtedly more efficient than traditional tick-based algorithms (e.g., Lee and Ready, 1991) in terms of data processing time and computational requirements. But, is the BVC accurate? Andersen and Bondarenko (2015), Chakrabarty, Pascual, and Shkilko (2015), Pöppe, Moos, and Schierek (2016), and ELO (2016) have all independently addressed the accuracy issue using the so-called order imbalance (OI) as the BVC's target. The OI is the relative difference between buyer- and seller-initiated volumes; therefore, it relies exclusively on aggressive orders. Overall, the studies cited above conclude that tick-based algorithms are more accurate than the BVC in estimating the OI. Yet, is the OI the proper target for the BVC?

In this paper, we investigate the accuracy of the BVC in estimating the net buying pressure or net order flow (NOF). We define the NOF as the relative imbalance between all sources of buying and selling pressure: trades, of course, but also limit submissions, revisions, and cancellations. Building on extant theoretical and empirical research, we

[1] See ELO (2011a,b, 2012a,b, 2014, 2015, 2016). Independent studies about the VPIN include Abad and Yagüe (2012), Wei, Gerace, and Frino (2013), Wu et al. (2013), Andersen and Bondarenko (2014, 2015), Low, Li, and Marsh (2016), Yildiz, Van Ness, and Van Ness (2017), and Abad, Massot, and Pascual (2018). Empirical applications of the VPIN include Bhattacharya and Chakrabarti (2014), Borochin and Rush (2016), and Cheung, Chou, and Lei (2015).

argue next that in modern high-frequency markets dominated by algorithmic trading strategies, where both limit and market orders convey information, the BVC's proper target should be the NOF rather than the OI. Our contribution is twofold. Using detail-rich order level data from one of the world fast-growing equity markets, the National Stock Exchange of India (NSE), we firstly assess the accuracy of the BVC in estimating the NOF and, secondly, we evaluate the BVC's capacity to capture the information embedded in the NOF and signal order flow toxicity.

In seminal market microstructure models of adverse selection, traders endowed with perishable positive (negative) private signals are expected to aggressively buy (sell).[2] Accordingly, empirical research attaches a pivotal role to the trade initiator (e.g., Hasbrouck, 1991) and the initiator-based OI (e.g., Easley et al., 1996) in signaling informed trading. Examining ultra-high frequency futures data, ELO (2016) find that BVC-based volume imbalances are strongly and positively correlated with Corwin and Schultz's (2012) high-low spread. However, the corresponding correlation for the tick-based OI is weak or even negative. What may explain this puzzling finding?

A variety of theoretical, empirical, and experimental research studies posit that traders that have a private signal about the fundamentals of the firms (i.e., informed traders) might frequently choose to make rather than take liquidity.[3] Insofar as limit orders convey information, trade-based estimates of the net buying pressure (such as the OI) might perform poorly in signaling toxic order flow. Thus, ELO's (2016) finding echoes Kim and Stoll (2014), who find that trade imbalances do not reflect private information about posterior corporate information events, or Collin-Dufresne and Fos

[2] See, for example, Glosten and Milgrom (1985), Kyle (1985), Easley and O'Hara (1987), Easley, O'Hara, and Paperman (1992), and Glosten (1994).
[3] Theoretical models include Harris (1998), Kaniel and Liu (2006), Rindi (2008), Goettler, Parlour, and Rajan (2009), and Rosu (2009). For supportive empirical studies see, Anand, Chakravarty, and Martell (2005), Cao, Hansch, and Wang (2009), Pascual and Veredas (2010), and Collin-Dufresne and Fos (2015). Finally, for reinforcing laboratory experiments see Bloomfield, O'Hara, and Saar (2005).

(2015), who show that initiator-based measures of adverse-selection, like the PIN (e.g., Easley et al., 2008) or the cumulative impulse-response (Hasbrouck, 1991), do not reveal the presence of informed trading.[4]

Nowadays, financial markets are populated by high-frequency traders (HFTs) (e.g., O'Hara, 2015; Menkveld, 2016). These proprietary traders use low latency technologies to run computer algorithms that optimally design, route, monitor, execute, and cancel thousands of orders at extraordinary high speed (e.g., Hasbrouck and Saar, 2009, 2013).[5] HFTs account for most of the message traffic and participate in half of the trades (e.g., SEC, 2014). They are also responsible for the rapid growth in order-to-trade ratios and cancellation rates over the last decade (e.g., Angel, Harris, and Spatt, 2011; Khomins, and Putnins, 2017). Accordingly, HFTs have become the main driving force behind the NOF.

Are the HFTs better informed? Numerous empirical studies conclude that the HFTs' market and limit orders convey information and substantially contribute to make prices more efficient.[6] So, low latency technology (e.g., co-location, direct access to data feeds) apparently grants HFTs with some sort of informational advantage (e.g., Brogaard et al., 2015; Easley, O'Hara and Yang, 2018). However, as pointed by O'Hara (2015), in the high-frequency world information-based trading does not necessarily relate to fundamental information. Rather than produce new information, HFTs free ride on information acquisition by slower fundamental investors (e.g., Biais and Foucault,

[4] Two mechanisms contribute to explain their finding. Firstly, the informed traders they identify trade when liquidity is high. Secondly, and more important for our purposes, they use limit orders to trade.
[5] Some HFTs engage in market making, while others pursue opportunistic strategies (e.g., directional trading, anticipatory trading, cross-market arbitrage etc.) or even predatory and manipulative practices (e.g., Hagströmer and Nordén, 2013; SEC, 2014, Egginton, Van Ness, and Van Ness, 2016, and Boehmer, Li, and Saar, 2018).
[6] See Riordan and Storkenmaier (2012), Brogaard, Hendershott, and Riordan (2014, 2018), Benos and Sagade (2016), and Chakrabarty et al. (2018).

2014, Yang and Zhu, 2018).[7] Moreover, HFTs have the ability to process and react faster to market events and public news, which induces adverse selection costs for slow traders (e.g., Biais, Foucault, and Moinas, 2012).[8] In general, HFTs contribute to order-flow toxicity because they are capable of turning publicly available information into valuable private signals, albeit for a very short time.

With the advent of this new type of informed traders, the trade initiator might no longer relate to the information embedded in the order flow, which may explain ELO's (2016) finding. In the HFT era, order flow toxicity should be better captured by metrics that consider all sources of buying and selling pressure. ELO (2016) claim that the BVC relies on order flows rather than individual trades or orders, accommodates all sources of underlying information (e.g., fundamental, order flow, public news etc.), and is less sensible to high-frequency data difficulties (e.g., order splitting, hidden orders, orders out of sequence, differences in latency across trading platforms, etc.). Accordingly, BVC is expected to render accurate estimates of the NOF.

Overall, our findings show that for those interested in assigning direction to data pre-aggregated into relatively large intraday time intervals, the news are good. When the focus is on relatively small bars, however, we find that the BVC-based NOF estimates can be pretty noisy. Thus, the BVC accuracy increases with the bar size from about 50% for 1-second time bars to more than 92% for 5-minute time bars. Supporting ELO's (2016) claim that BVC relies on all sources of buying and selling pressure, we find that BVC renders more accurate estimates of the NOF than of the trade-based OI. For example, the BVC accuracy in estimating the OI for 1-second time bars is just 22.6%.

[7] Supportive evidence of order anticipation or pattern recognition strategies is provided by Korajczyk and Murphy (2016), van Kervel and Menkveld (2017), and Hirshey (2018).

[8] Brogaard et al. (2014) show that HFTs can anticipate short-term price movements, while Foucault, Hombert, and Rosu (2016), Chakrabarty, Moulton, and Wang (2018), and Chordia, Green, and Kottimukkalur (2018) show that HFTs trade ahead of (or react faster to) incoming public news.

Indeed, for relatively small bars the OI turns out to be an unreliable proxy of the NOF. We also find that BVC-based NOF estimates approximate the HFTs' component of the NOF much better than the non-HFTs' component, especially for relatively small bar sizes. As the bar size increases, the correlation the HFTs' and non-HFTs' NOF components increases.

We identify market-related determinants of the BVC accuracy rate. We focus on factors that can potentially change the informativeness of the standardized price changes between bars, the main input of the BVC approach. We show that the BVC accuracy decreases with the use of hidden volume (our proxy for pre-trade opacity), the number of revisions and cancellations of standing limit orders (our proxy for monitoring intensity), the non-ATs' contribution to the NOF (our proxy for unsophisticated retail trading), and the absolute magnitude of the price change between bars. For relatively small bars, the BVC accuracy benefits from rising price volatility and trading activity. For relatively large bars, however, the BVC accuracy declines during more volatile markets, as suggested by Andersen and Bondarenko (2015). Finally, the HFTs' order flow intensity enhances (dampens) BVC accuracy for relatively small (large) bars, where their message-to-trade ratios are relatively lower (higher).

The rest of the paper is organized as follows. In Section 2, we define the NOF and describe the BVC approach. In Section 3, we provide the market background and describe our database. In Section 4, we evaluate the accuracy of the BVC approach in estimating the NOF. In Section 5, we study the determinants of the BVC accuracy. In section 6, we evaluate the accuracy of the BVC approach in estimating the HFT-related component of the NOF. In section 7, we examine how much explanatory power on posterior returns, volatility, and liquidity is lost by using BVC-based NOF estimates rather than the actual NOF. In section 8, we analyze the capacity of the BVC approach in signaling order flow toxicity. In Section 9, we conclude.

2. Net order flow (NOF) and the BVC approach

The BVC approach is a probabilistic method to assign direction to volume that has been pre-aggregated into equally-sized bars. We consider time, trade, and volume bars. Time bars are uniform across stocks. The shortest bars we consider last one second and the longest comprise the whole trading session. Volume and trade bars are stock-specific. For volume bars, the size is a given percentage (v) of stock i's daily average volume (in shares) over the preceding month (V_i). The smallest v we consider is 0.1% (i.e., 1000 bars per day, in average) and the largest one is 40% (i.e., 2.5 bars per day in average). Trade bars are defined analogously but with respect to stock i's daily average number of trades over the preceding month (T_i). For practical reasons, we define the size of the volume (trade) bar as the closest integer to vV_i (vT_i).

For each bar b, we compute the buying pressure for stock i as

$$BP_{i,b} = V_{i,b}^{MB} + V_{i,b}^{LB} + V_{i,b}^{CS} \qquad [1]$$

where V^{MB} (V^{LB}) represents the accumulated size of all the market or marketable limit (non-marketable limit) orders to buy submitted between the beginning and the end of bar b. V^{CS} is the accumulated size of the standing limit orders to sell cancelled within bar b. Revisions of standing limit orders to buy that increase the order size are treated as new non-marketable limit order submissions and therefore added to V^{LB} by the amount of the revision. Similarly, revisions of limit orders to sell that decrease the order size are treated as cancellations and therefore added to V^{CS} by the amount of the revision. Revisions or standing limit orders that do not change the order size are ignored. The selling pressure for stock i and bar b is computed analogously,

$$SP_{i,b} = V_{i,b}^{MS} + V_{i,b}^{LS} + V_{i,b}^{CB} \quad [2]$$

with V^{MS} (V^{LS}) being the accumulated size of all the market or marketable limit (non-marketable limit) orders to sell and V^{CS} being the accumulated size of the standing limit orders to buy cancelled within bar *b*. We define the total order flow volume for stock *i* and bar *b* as the sum of [1] and [2],

$$V_{i,b}^{OF} = BP_{i,b} + SP_{i,b} \quad [3]$$

and the NOF as the relative difference between [1] and [2],

$$NOF_{i,b} = \frac{BP_{i,b} - SP_{i,b}}{V_{i,b}^{OF}} \quad [4]$$

Finally, we define the order imbalance for stock *i* and bar *b* as

$$OI_{i,b} = \frac{V_{i,b}^{TB} - V_{i,b}^{TS}}{V_{i,b}^{T}} \quad [5]$$

where V^{TB} (V^{TS}) represents the accumulated buyer- (seller-) initiated volume and V^{T} is the total volume traded,

$$V_{i,b}^{T} = V_{i,b}^{TB} + V_{i,b}^{TS} \quad [6]$$

Notice that V^{TB} in [5] and V^{MB} in [1] are not necessarily equal, since marketable limit orders may not be fully executed.

In former applications, the BVC approach has been used to split V^{T} in [6] into buyer- and seller-initiated volume, that is, to provide estimates of V^{TB} and V^{TS}, and then of the *OI* in [5]. However, ELO (2016) claim that BVC relies on order flow rather than trades and that BVC-based *OI* estimates are actually capturing the *NOF* in [4] or, equivalently, that BVC-based estimates of V^{TB} and V^{TS} are actually proxies for *BP* and *SP* in [1] and [2], respectively. Notice that given the bar type and size, the price change, and the CDF, the BVC approach will render the same estimate for NOF in [4] than for OI in [5] no matter the difference between V^{OF} and V^{T}. In this paper, we evaluate the accuracy of the BVC approach in assigning direction to the V^{OF} in [3].

To apply the BVC approach, we need the standardized price changes between bars, $\Delta p_{i,b}/\sigma_{\Delta p}$, where $\Delta p_{i,b} = p_{i,b} - p_{i,b\text{-}1}$, p_{ib} is the price at the end of bar b, and $\sigma_{\Delta pi}$ is the volume-weighted standard deviation of $\Delta p_{i,b}$ over the sample period. The probability of buyer-initiated pressure for stock i and bar b is given by $\Phi(\Delta p_{i,b}/\sigma_{\Delta pi})$, where $\Phi(.)$ is the presumed CDF for the standardized change in prices. Following the extant literature, we consider three options for $\Phi(.)$: the normal distribution (e.g., ELO, 2011a; Andersen and Bondarenko, 2014), and the t-student distribution with 0.1 and 0.25 degrees of freedom (e.g., ELO, 2012, 2016; Wu et al., 2013). The accuracy of the BVC approach to estimate the *OI* in [5] has been shown to depend on the choice of $\Phi(.)$, and the type and size of bars (e.g., Chakrabarty et al., 2015; Andersen and Bondarenko, 2015).

The intuition behind the BVC approach is simple: the larger and positive $\Delta p_{i,b}/\sigma_{\Delta pi}$, the larger the proportion of buyer-initiated volume within bar b. Accordingly, the BVC-based estimate of the $BP_{i,b}$ in [1] would be,

$$\widehat{BP}_{i,b} = V_{i,b}^{OF}\Phi\left(\Delta p_{i,b}/\sigma_{\Delta p_i}\right) \qquad [7]$$

and the BVC-based estimate of $SP_{i,b}$ would be the complementary amount,

$$\widehat{SP}_{i,b} = V_{i,b}^{OF} - \widehat{BP}_{i,b} \qquad [8]$$

Similarly, the buyer-initiated and seller-initiated volumes in [5] would be given by

$$\hat{V}_{i,b}^{TB} = V_{i,b}^{T}\Phi\left(\Delta p_{i,b}/\sigma_{\Delta p_i}\right),\ \hat{V}_{i,b}^{TS} = V_{i,b}^{T} - \hat{V}_{i,b}^{TB} \qquad [9]$$

In our analysis, we exclude overnight returns by dropping the last volume or trade bar of each trading session when it is only partially filled. We also drop time bars for which there are no trades.[9]

Our database (see next section for details) contains trader-type flags, hidden-volume flags, and order-initiator flags, which allows us to compute the actual NOF and OI in [4] and [5] for the whole market and also for particular types of traders, such as HFTs, and also distinguish between hidden and displayed liquidity.

3. Market background, database, and sample

NSE is the 4th largest exchange in the world in terms of number of trades and 10th largest exchange in the world in terms of dollar volume.[10] Indian equity markets have a near non-fragmented structure. With only two exchanges where any meaningful trading takes place, the NSE accounts for 80% of the total domestic trading volume.[11] The NSE is a fully electronic order-driven market with no designated market makers. Structurally, it is similar to the Hong Kong Stock Exchange, Tokyo Stock Exchange, or NYSE-Euronext. The market opens with a 15-minute pre-opening session. Continuous trading then takes place from 9:15 a.m. till 3:30 p.m. The trading system follows the price-exposure-time priority. For the benefit of the market participants, the exchange publicly displays on its website real-time information of the top five ask and bid quotes (price and depth).

Like every important modern stock market, NSE is characterized by the prominent presence of algorithmic traders (ATs). Although AT has been allowed since April 2008, it became widespread once the co-location service was introduced in January 2010.

[9] In the Appendix, we show that our findings do not substantially change if we include empty time bars or if we filter the sample by imposing a minimum number of non-zero time bars per stock.
[10] https://www.world-exchanges.org/home/index.php/statistics/annual-statistics
[11] https://www.sebi.gov.in/sebi_data/attachdocs/1463726488005.pdf

Nawn and Banerjee (2018), for example, report that 95% of the order messages and 43% of the trading volume in the 50 largest 2013 NSE-listed stocks comes from AT.

In this study, we use four months, from April to July 2015, of high-frequency data on the fifty constituents of the NSE's benchmark market index, the NIFTY-50, as on April 30, 2015. These stocks are the largest in terms of market capitalization. Together, they account for approximately 60% of the total market value.

The data is provided by the exchange itself. For each trading day, we have an order file and a trade file. The order file contains detailed information on every order message, including submissions of market and limit orders, and cancellations and revisions of standing limit orders. The database identifies orders with special conditions, such as hidden volume (iceberg orders), on-stop, or immediate-or-cancel. Each order is identified with a unique code, meaning that we can track each order's history overtime. The most common type of order by far is that of limit orders, for which we know the limit price, the displayed size, and the hidden size. The trade files provide information on each individual trade, including the size, the price, the code of the orders involved, and the time at which the trade took place. An incoming aggressive order can be executed against several standing limit orders on the opposite side of the book. In such a case, the trade is reported in several entries, one for each passive order executed.

Orders and trades are time-stamped in jiffies (one jiffy is 1/2^^{16}th of a second). We use the codes developed by Chakrabarty et al. (2018) to match the order and the trade files, collapse the trades reported in fragments, assign direction to trades, and rebuild the LOB of each NSE-listed stock in our sample at every point in time.

The database includes two exchange market flags that allow us to identify the orders placed by HFTs. On the one hand, the algorithmic trading flag identifies the orders placed by algorithms. On the other hand, the client flag indicates whether an order is for a proprietary or a client account. Based on these two flags, we can classify each order as coming from one of three mutually exclusive and exhaustive groups of traders: algorithmic orders from a proprietary account are attributed to HFTs (e.g., SEC, 2010); algorithmic orders from a client account are attributed to other or "agency" ATs (AATs), and finally orders not placed by algorithms are attributed to non-ATs (NATs).

In Table I, we provide some descriptive statistics. In Panel A, we show that there are economically meaningful differences across the fifty stocks in our sample in terms of market capitalization, activity, liquidity, volatility and price. In Panel B, we provide the contribution of each type of trader to the order flow. Averaged across stocks, HFTs account for 83.5% of the daily message traffic, 48.3% of the daily order submissions, and 86.6% of the daily revisions and cancellations. In contrast, NATs contribution is much lower: 4.7%, 22%, and 3.2%, respectively. In Panel C, we show that the HFTs' message-to-trade ratio is 13.8 (41) times larger than of AATs (NATs), and their cancellation-to-trade ratio is 16.2 (61.5) times larger. These ratios are frequently used in the literature as proxies for HFT (e.g., Chakrabarty, Moulton, and Pascual, 2017), suggesting our identification of HFT is highly precise.

[Table I]

4. BVC's accuracy in estimating the NOF

In this section, we evaluate the accuracy of the BVC approach for our sample of 50 large NSE-listed stocks. For comparative purposes, we first gauge the performance of the BVC in assigning direction to traded volume and, thus, in estimating the OI in [5]. As Chakrabarty et al. (2015), we measure the percentage of volume correctly classified for stock *i* and bar *b* as

$$Ar_{i,b}^{T} = \frac{\min\left(V_{i,b}^{TB}, \hat{V}_{i,b}^{TB}\right) + \min\left(V_{i,b}^{TS}, \hat{V}_{i,b}^{TS}\right)}{V_{i,b}^{T}} \quad [10]$$

The average performance of BVC for stock *i* across all bars is given by

$$Ar_{i}^{T} = \frac{1}{N_i}\sum_{b=1}^{N_i} Ar_{i,b}^{T} \quad [11]$$

where N_i is the total number of bars for stock *i*. Finally, our summary accuracy measure is the cross-sectional average of [11]. Regarding the estimation of the OI, Chakrabarty et al. (2015) measure BVC accuracy for stock *i* as

$$ArOI_{i}^{T} = 1 - \sum_{b=1}^{N_i} \frac{\left|\widehat{OI}_{i,b} - OI_{i,b}\right|}{V_{i,b}^{T}} \quad [12]$$

which can also be computed from [11] as

$$ArOI_{i}^{T} = 2Ar_{i}^{T} - 100 \quad [13]$$

The corresponding summary measure is the cross-sectional average of [13].

In Table II, we report our findings. Firstly, the accuracy of the BVC is worse under the normal distribution than under the t-student distribution for all trade and volume bar sizes. For time bars, the normal works slightly better for relatively small bars but it renders lower accuracy rates for relatively large bars. Additionally, the t-student with 0.1 degrees of freedom (hereafter, d.f.) works marginally better than with 0.25 d.f. Secondly, the lowest accuracy rates correspond to the smallest bars. For 1-second time bars, under the normal, the accuracy rate is 61.32%, which means a poor 22.63% accuracy rate in estimating the OI. For 1% trade (volume) bars, the accuracy rate is 76.38% (73.78%), that is, a 52.76% (47.57%) accuracy rate in estimating the OI. As the bar size increases, the BVC accuracy improves. Under the t-student, the relationship between bar size and BVC accuracy is linear, while under the normal is non-linear (the highest accuracy rate is 68.83% for 10-minute bars).

[Table II]

In Panel A of Table AI of the Appendix, we compare the accuracy of BVC across time, trade, and volume bars of similar duration for the t-student with 0.1 d.f. We show that the BVC accuracy in estimating the OI is actually quite similar across bar types. BVC works slightly better with trade bars as we shorten the bar size, and slightly worse with volume bars as we lengthen it.

Chakrabarty et al. (2015) apply the BVC approach on a representative sample of 2011 Nasdaq-listed stocks. Using Nasdaq quote and trade data only, 60-second time bars, and the normal distribution, they report a 31.3% accuracy rate in estimating the OI. Using consolidated data from the DTAQ database, the accuracy rate falls to 19.1% (see Table 5, p. 65). We report a 61.6% accuracy rate, suggesting that market fragmentation could be a major concern for the precision of the BVC, at least for relatively small bars. Thus, ELO (2016) evaluate the accuracy of the BVC for non-fragmented index and commodity futures. From their Tables 2-4 (p. 279), we can estimate a 63.2% to 80.64% accuracy rate for 60-second time bars. For the NSE, we report a 63.33% accuracy rate in that case.

We have already argued that in modern high-frequency markets, where HFT strategies dominate the order flow and both market and limit orders are informative, the relevant target for the BVC should be the NOF rather than the OI. Moreover, ELO (2016) imply that BVC-based OI estimates are actually estimates of the (unobservable to them) NOF. Accordingly, the accuracy rates in Table II would be somewhat irrelevant unless the OI itself was a good proxy for the NOF. In Table III, we address this issue. For different bar types and sizes, we gauge the accuracy of the OI in estimating the NOF as follows. First, we measure the precision of buyer-initiated and seller-initiated volume as proxies for the buying and selling pressure in [1] and [2]. In particular, for each stock *i* and bar *b*, we use the percentage of buyer-initiated volume over the total trading volume as our estimate of the relative weight of BP on the order-flow-based volume,

$$V_{i,b}^{BP} = \left(\frac{V_{i,b}^{TB}}{V_{i,b}^{T}}\right) V_{i,b}^{OF}; \; V_{i,b}^{SP} = V_{i,b}^{OF} - \hat{V}_{i,b}^{BP} \qquad [14]$$

Next, we obtain the correctly classified order-flow-based volume as

$$Ar_{i,b}^{OF} = \frac{\min\left(V_{i,b}^{BP}, \hat{V}_{i,b}^{BP}\right) + \min\left(V_{i,b}^{SP}, \hat{V}_{i,b}^{SP}\right)}{V_{i,b}^{OF}} \qquad [15]$$

Averaging [15] across bars, as in [11], we obtain the average accuracy ratio for stock *i*, Ar_i^{OF}, and from [13] we obtain the summary accuracy metric Ar^{OF} reported in Table III.

[Table III]

We find that for relatively small bars OI is a bad proxy for the NOF. For 1-second time bars, for example, the OI accuracy rate is just 33.04%. For 1% trade bars, which have an average duration of 20 seconds, the accuracy rate is only 56.18%. As we increase the bar size, however, the OI becomes a better proxy for the NOF. From 1-second to 1-minute bars, the accuracy rate increases a significant 28.72%, while from 1-minute to daily bars, increases an additional 27.48%, to reach a relatively good 89.24% accuracy rate. Similarly, for 40% trade bars (about half-a-day-long in average) the accuracy is 87.4%. Additionally, in Panel B of Table A1 in the Appendix, we show that for short-lasting bars, the OI approximate the NOF better when we choose trade or volume bars than when we choose time bars. This is because the OI accuracy improves with the number of trades per bar (see the next section) and trade and volume bars guarantee a higher average number of trades per bar duration. For long-lasting bars, the choice of bar type becomes irrelevant.

The above findings suggest that for large bars, no matter the type, the BVC could provide relatively good estimates of the NOF. For small bars, however, the performance of the BVC approach is totally uncertain. We address this issue in Table IV, where we provide accuracy rates of the BVC in estimating the NOF. In this case, we use eq. [15] to obtain the accuracy rate of the BVC in assigning direction to V^{OF} for each stock and bar, and eq. [13] to obtain the accuracy of BVC to estimate the NOF. Conveniently averaged across bars and then across stocks, we obtain the summary metrics reported in Table IV.

[Table IV]

As in Table II, we find that the BVC accuracy rate is significantly larger under the t-student distribution than under the normal, but in this case for all bar types and sizes. Moreover, it is increasing, although not strictly, with bar size. The highest accuracy rate in assigning direction to V^{OF} is an impressive 96.22% for 5-minute time bars, which results in an accuracy ratio of 92.44% in estimating the NOF. The lowest accuracy rate corresponds to 1-second time bars, for which the precision in estimating the NOF falls to a 50.97%. In Panel C of Table A1 of the Appendix, we compare the BVC accuracy across bar types using bars of similar duration. For bars lasting 10 seconds or more in average, BVC with time bars renders higher accuracy rates than with volume bars; for bars lasting 30 minutes or more, BVC with time bars renders better estimates of the NOF than BVC with trade or volume bars.

Our results thus far suggest that with the appropriate choice of bar type, bar size, and CDF, the BVC can perform reasonably well as a proxy for the NOF. How to choose ex-ante the BVC parameters is a concern that has not yet been convincingly addressed in the literature (e.g., Abad et al., 2018). Our findings, however, shed some light on the issue. Firstly, long-tailed leptokurtic distributions, such as the t-student, outperform the normal case. Secondly, the BVC approach does not make the grade when bars are of short average duration. For other bar sizes, the BVC approach should be implemented using time bars rather than volume or trade bars.

In Table V, we compare the BVC accuracy in estimating the NOF with the BVC accuracy in estimating the OI. We find that the BVC approach renders more precise NOF estimates than OI estimates. For example, for 1-second time bars, the BVC accuracy in estimating the NOF is 37.36 percentage points higher than in estimating the OI (30.19 for 1% trade bars, and 30.51 for 1% volume bars). Our findings support ELO's (2016) claim that BVC relies on order flow rather than just trades and, therefore, BVC-based OI estimates are actually proxies of the NOF. We have already shown (Table III) that the OI improves as a proxy for the NOF as we aggregate the data into larger bars. Consistently, we show now that for relatively large bars, the BVC renders estimates of the OI that are as accurate as the estimates of the NOF.

[Table V]

5. Determinants of the BVC accuracy in estimating the NOF

In this section, we use a pooled regression approach to evaluate the determinants of the BVC accuracy in estimating the NOF bar by bar. Extant empirical literature provides some hints on this issue. Andersen and Bondarenko (2015) find that, in assigning direction to trades, raising volatility induces systematic classification errors on the BVC approach. In a preliminary version of Chakrabarty et al. (2015), cited by Andersen and Bondarenko (2014) and ELO (2016), it is shown that the BVC accuracy in estimating OI decreases with volatility, trading frequency, and hidden volume.

However, there is no formal theory that could guide us in selecting potential determinants. Therefore, we provide a comprehensive empirical analysis that relies on previous empirical work and our own intuition to identify potential determinants.

The fundamental input of the BVC approach is the standardized price change between bars. So, we focus our attention on factors that can either enhance or dampen the informativeness of the standardized price changes. Moreover, we have already shown that BVC classification errors are more severe for bars of a relatively short duration. Thus, we focus on 1-second to 600-second time bars, and 0.1% to 10% trade bars. For each stock-bar, we compute the following potential determinants of the BVC accuracy:

- Volatility and trading activity: Our proxy for volatility is the high-low trade price ratio ($HL_{i,b}$). As for trading activity, we use the trade volume in shares ($VOL_{i,b}$) for time and trade bars, and the number of trades ($TRD_{i,b}$) for volume bars. Periods of raising volatility and trading activity are likely associated with intensive price discovery. By adding these covariates to our regression model, we can study how the BVC approach responds to information-intensive or turbulent scenarios, as predicted by Andersen and Bondarenko (2015).

- Hidden volume: we use the percentage of hidden volume over total volume submitted ($HVOL_{i,b}$) to measure pre-trade opacity. Limit order traders might choose not to expose their orders if they perceive a high risk of being picked-off by faster traders, front-run by parasitic traders, or adversely-selected by informed traders (e.g., Bessembinder et al., 2009; Chakrabarty et al., 2018). By means of this covariate, we investigate if the BVC accuracy is adversely impacted when a meaningful fraction of the NOF is concealed.

- Monitoring: we use the number of order cancelations and revisions ($CR_{i,b}$) as a proxy for monitoring intensity (e.g., Liu, 2009). High order cancellation rates are often claimed to be a symptom of predatory and manipulative behavior by HFTs (e.g., Egginton et al., 2016). Thus, cancelation-to-trade ratios are a common proxy for HFT (e.g., Chakrabarty, Moulton, and Pascual, 2017). However, Khomyn and Putnins (2018) point to the increasing market fragmentation and the decreasing monitoring costs as the main drivers behind the increasing cancelation-to-trade ratios in the last decades. The literature suggests that limit order traders manage picking off risk by closely monitoring their standing orders, which results in frequent cancellations and revisions (e.g., Fong and Liu, 2010). As seen in Table I, in our NSE sample HFTs account for most of the revisions and cancellations of orders. We empirically investigate how the BVC accuracy is affected by the intensity of monitoring.
- HFT: Some recent empirical research concludes that HFTs contribute to price discovery and make prices more efficient (e.g., Brogaard et al., 2014, 2018; Chaboud et al., 2015). Boehmer, Li, and Saar (2018) find also that competition between HFTs lead to faster revelation of information, lower adverse selection costs, and reduced volatility. Yet, HFTs' intensive quotation injects noise and generates excess quote volatility (e.g., Hasbrouck, 2018). We include the HFTs' share of V^{OF} ($HFT_{i,b}$) in our regression model to empirically test whether more intense HFT activity enhances BVC's accuracy.
- Retail trading: NATs are the least sophisticated of the NSE's trader types, and include mostly retail traders (e.g., Nawn and Banerjee, 2018). There exists mixed evidence on whether the trading of individual investors is mainly informative or noisy (e.g., Barber and Odean, 2000; Kaniel, Saar, and Titman, 2008; Kelley and

Tetlock, 2012). We include the NATs' share of V^{OF} ($NAT_{i,b}$) in our regression model to empirically investigate whether and how the performance of the BVC approach depends on the incidence of retail trading.

- Extreme price changes: For bars with extremely large price increases (decreases), the BVC will assign a probability of one to V^{OF} being buyer- (seller-) initiated, meaning an estimated NOF of 1 (-1). For bars with no price change, BVC will assign a ½ probability to V^{OF} being buyer- (seller-) initiated, meaning a NOF of 0. If extreme or zero price changes are a good signal of the order flow net direction, then the BVC approach should be particularly accurate when they happen. In our regression, we control for extreme price changes by including the dummies $LargePC_{i,b}$ and $ZeroPC_{i,b}$. $LargePC_{i,b}$ equals one whenever the standardized price change is above the 90% percentile or below the 10% percentile, zero otherwise; $ZeroPC_{i,b}$ equals one whenever the standardized price change is zero, zero otherwise.
- Intraday patterns: we control for regular unusual trading conditions during the first and the last 30 minutes of the NSE trading session by including the dummies $First30_{i,b}$ and $Last30_{i,b}$, respectively. $First30_{i,b}$ ($Last30_{i,b}$) equals one whenever the bar *b* of stock *i* overlaps with the [9:15 9:45] ([15:00 15:30]) time interval, zero otherwise.

We estimate a pooled regression model for each bar type and size. For time bars, we drop bars with no trades. We reduce the effect of possible spurious outliers by winsorizing all the time series per stock. We replace the top (bottom) 0.5% of the sorted observations by the 99.5% (0.5%) percentile. The model is estimated by OLS with

White-robust standard errors clustered by stock. Our findings for the selected time (Panel A) and trade (Panel B) bar sizes are reported in Table VI.[12]

[Table VI]

As volatility regards, our findings are contingent on bar size. Along with Andersen and Bondarenko (2015), we find that BVC accuracy significantly drops with volatility ($HL_{i,b}$) when bar sizes are relatively large (i.e., 60-second time bars or longer). For the smallest bar sizes, however, volatility enhances accuracy. Similarly, when we focus on the more volatile initial 30 minutes of the NSE trading session, as captured by the $First30_{i,b}$ coefficient, we observe that BVC accuracy goes from regularly larger to regularly lower as the bar size increases. Consistently, for small bar sizes the $ZeroPC_{i,b}$ coefficient is negative and significant, suggesting that price stability wrongly signals a balanced NOF. As the bar size increases, zero price changes become less noisy and, as a result, the BVC improves its performance. In contrast, the $LargePC_{i,b}$ coefficient is significantly negative no matter the bar size, meaning that extreme absolute price changes mistakenly signal one-sided order-flow, decreasing BVC accuracy rates.

By construction, BVC relies on trades to assign direction to the order flow. Consistent with the volatility findings, for small bar sizes, raising trading volume enhances accuracy. However, as we increase the bar size, trading volume becomes irrelevant in determining the BVC performance.

Our estimates in Table VI also reveal that BVC accuracy tends to deteriorate with pre-trade opacity ($HVOL_{i,b}$) and monitoring intensity ($CR_{i,b}$). Using hidden-limit orders and engaging in intensive order monitoring are means to reduce the risks of supplying liquidity (i.e., picking-off risk, adverse-selection costs, front-running etc.). Popular

[12] For volume and trade bars our findings are similar. Volume bar regressions are available from the authors upon request.

order flow toxicity metrics such as the PIN (e.g., Easley et al., 1996) or the VPIN (e.g., ELO, 2012a) build on the presumption that a large absolute NOFs signal the presence of information-motivated trading. Our findings suggest that BVC might underperform precisely when the perceived risk of toxic order flow is high. As a result, the BVC-based VPIN (or VPIN-BVC) might fail to signal actual toxic events. Thus, Abad et al. (2018) find that VPIN-BVC rarely signals abnormal illiquidity and only occasionally anticipates intraday trading halts triggered by price limits. Pöppe et al. (2016) conclude that VPIN-BVC cannot predict the flash crash of the German blue chip stock K+S on July 30, 2013. In section 8, we investigate this issue in more detail.

As the activity of particular traders regards, we find that the more NATs contribute to message traffic, the less accurate BVC becomes. Our findings are therefore in line with previous studies concluding that unsophisticated individual traders inject noise in prices (e.g., Barber and Odean, 2000), which leads to imprecise BVC-based NOF estimates.

The impact of HFTs on the BVC accuracy is contingent on bar size. For the smallest bars, the more the HFTs contribute to the order flow, the higher the BVC accuracy rate. As the bar size increases, however, the $HFT_{i,b}$ coefficient becomes negative and statistically significant. In Table VII, we provide a plausible explanation for this finding. We report the contribution of HFTs, AATs, and NATs to the total buying plus selling pressure (V^{OF}) and to the trading volume (V^{T}) per bar type and size. We find that, in average terms, across bar sizes, HFT's contribution to V^{OF} is much higher than to V^{T} (63.8% vs. 13.6% for time bars), consistent with their higher message-to-trade ratios. Moreover, as the bar size increases, the contribution of HFTs to V^{OF} increases from 46.58% for one-second time bars to 70.25% for daily time bars. In contrast, their contribution to V^{T} increases from 9% to 15% only. As a result, the HFTs' message-to-trade ratios increase with the bar size, which, according to Hasbrouck (2018), might exacerbate quote midpoint volatility and, then, reduce BVC accuracy. The variability in the contribution of AATs and NATs to V^{OF} across bar sizes is much lower, and their message-to-trade ratio is much more stable.

[Table VII]

6. BVC accuracy and the HFT's NOF

In Table I, we have already shown that HFTs account for most of the message traffic at the NSE. In Table VII, we have also seen that the HFTs contribution to the overall NOF is increasing with the bar size. Given the prominent role that HFTs' trades and orders play in liquidity supply and price discovery in modern security markets (e.g., Brogaard et al., 2018), we investigate to what extent BVC renders particularly accurate estimates of the HFTs' contribution to the overall NOF. We compute the NOF in [4] for each of our three types of traders. Then, we obtain the BVC accuracy ratio in [15] for each trader type's NOF. In Table VIII, we report our findings for a few select bars.

[Table VIII]

We find that, for the majority of bar type and size combinations, BVC-based NOF estimates are better aligned with the NOF component attributable to the HFTs than to the NOF component attributable to either the AATs or the NATs. For time bars, for example, the average BVC accuracy rate across bar sizes in estimating the HFTs' NOF is 82.22%, falling to 72% and 62.67% for the NOF components attributable to the AATs and the NATs, respectively. Moreover, the variability in the BVC accuracy rate, as measured by the standard deviation across bar sizes, is much lower for the case of the HFTs' NOF. The later finding is mostly explained by relatively small bar sizes, for which the BVC is particularly inaccurate in estimating the non-HFTs component of the NOF. For example, for 0.1% trade bars, the BVC accuracy in estimating the HFTs'

NOF is 82.74%, while for the NATs' NOF is just 59.81%. Differences in accuracy rates across trader types decline as we increase the bar size and the absolute correlation between the NOF components attributable to the different types of trades increases. For 20% trade bars, for example, the BVC accuracy rates for estimating the HFTs', AATs', and NATs' NOF components are, respectively, 88.17%, 87.74%, and 84.42%. We can therefore conclude that BVC offers NOF estimates that mostly reflect the HFTs' trades and orders, especially for relatively small bar sizes.

7. BVC-based NOF estimates relative explanatory power

In this section, we evaluate BVC-based NOF estimates in the context of a particular empirical application. Namely, we investigate how much explanatory power on concurrent and short-term liquidity, returns, and volatility is lost by using BVC-based NOF estimates rather than the actual NOF. [Work in progress]

8. Order flow toxicity: VPIN-BVC vs. VPIN-NOF

As a second suitable empirical application for the BVC, we look at the VPIN approach of ELO (2012a) to measure order flow toxicity. VPIN is the acronym for Volume-synchronized Probability of Informed Trading, an indicator of short-term toxicity-driven volatility that is supposed to perform better when implemented in a high-frequency environment, such as the NSE case we are studying. Conceptually, the VPIN is turns out to be a function of the usually unobservable NOF. In previous empirical applications, VPIN has been estimated either using OI estimates obtained using tick-based trade classification algorithms, like the tick rule, BVC-based NOF estimates, or the actual OI (e.g., Abad et al., 2018). In this section, we compare the BVC-based VPIN (hereafter, VPIN-BVC) with the VPIN based on the actual NOF (hereafter, VPIN-NOF) in two different ways. Firstly, we look at how closely the VPIN-

BVC tracks the VPIN-NOF by computing cross-sectional average correlations between the two metrics for different bar types and sizes using our sample of 50 NSE-listed stocks. Secondly, we look at the cross-sectional average proportion of highly toxic events that are not flagged by the VPIN-NOF but flagged by the VPIN-BVC, that is, the type II error, and the proportion of highly toxic events that are flagged by the VPIN-NOF but not flagged by the VPIN-BVC, that is, the type I error. [Work in progress]

9. Conclusion

We have evaluated the accuracy of the BVC approach of ELO (2016) in estimating the net order flow (NOF). The NOF for a given stock is defined as the relative imbalance between the buying and the selling pressure, which we compute taking into account the order flow volume (in shares) being submitted, revised, and cancelled. Brogaard et al. (2018) have recently shown that in high-frequency markets populated by algorithmic traders, limit orders are the main contributor to price discovery. Since the BVC is intended to capture order flow toxicity, the NOF should be a better benchmark with which to gauge it than the trade-based order imbalance (OI) considered thus far. Besides, ELO (2016) argue that BVC actually accounts for all sources of order-flow-related information; consequently, BVC is presumably giving NOF rather than OI estimates.

In this preliminary and incomplete version of the paper, we show that BVC performs relatively well in estimating the NOF for relatively large intraday time, trade, or volume bars. The highest cross-sectional average accuracy rate we report is 92% for 5-minute time bars. For relatively small bars, however, the BVC accuracy substantially declines. For 1-second time bars, for example, we report a 50% cross-sectional average accuracy rate. We do find that BVC renders more accurate estimates of the NOF than of the trade-based OI. For 1-second time bars, for example, the BVC accuracy rate is a poor

22.6% across all our stock-days. Our findings therefore back ELO's claim that BVC relies on all sources of buying and selling pressure, not only trades. Moreover, we show that the frequently unobservable OI is an unreliable proxy for the also unobservable NOF, most notably when we consider relatively small bars.

The BVC-based NOF estimates are more accurate in estimating the HFT-related NOF component than the non-HFT-related NOF component. For example, for 1-second time bars, the BVC accuracy rate in estimating the HFT-related (NAT-related) component is 68.52% (35.13%). As the bar size increases the NOF components become increasingly correlated, and differences in BVC accuracy fall. For example, for 5-minute time bars, the BVC-accuracy in estimating the HFT-related (NAT-related) component is 91.95% (85.36%).

We also find that the BVC accuracy is sensitive to changes in market conditions. Namely, the BVC accuracy rate decrease with pre-trade opacity, monitoring intensity, and unsophisticated retail trading. Large absolute price changes between bars turn out to be a noisy signal of one-sided order flow, causing systematic classification errors on the BVC approach. Additionally, for relatively small bars the BVC approach benefits from rising price volatility and trading activity. For relatively large bars, however, the BVC accuracy declines with volatility, in line with the findings of Andersen and Bondarenko (2015). Finally, we find that the HFTs' message-to-trade ratio increases with bar size. Consistent with higher message-to-trade ratios exacerbating quote midpoint volatility (Hasbrouck, 2018), we find that HFT intensity enhances (dampens) BVC accuracy for relatively small (large) bars.

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TABLE I
Descriptive Statistics

This table provides descriptive statistics for our sample, which consists of the 50 largest stocks listed at the NSE in 2015. We use order, trade, and quote data from January to March 2015. In Panel A, we report cross-sectional average statistics on market capitalization, trading activity, volatility and liquidity. Market capitalization is the market value of the company shares in billions of rupees in May 2015. "Volume" is the daily average accumulated traded volume in shares. "Trades" is the daily average accumulated number of trades. Volatility is the daily average high-low ratio. The relative bid-ask spread is averaged weighting by time. In Panel B, we provide cross-sectional average daily statistics on the order flow composition for all traders together and for three subsets of traders: high-frequency traders (HFTs), agency algorithmic traders (AATs) and non-algorithmic traders (NATs). "Total messages" (or message traffic, "MT") is the sum of all submissions, revisions, and cancellations of orders. "New submissions" is the number or market and limit order submitted. "C&R" is the number of cancellations and revisions (of either the limit price or the order size) of standing limit orders. "MT/Trades" is the ratio of MT to trades. For the trader types, "MT/Trades" is the ratio of all messages to all trades initiated by the corresponding type of trader. "C&R/Trades" is the equivalent ratio of C&R to trades. Statistical tests compare the equality of the cross-sectional daily means across types of traders.

Panel A: Sample statistics	Mean	Min	Max
Market capitalization (billions of rupees)	1134955.80	195071.30	4871797.20
Volume (/10000)	304.30	5.39	1257.82
Trades	21815.25	3214.55	49271.94
Volatility ((high/low-1)x100)	2.61	1.73	3.78
Relative bid-ask spread			
Displayed depth (5 best quotes) (/10000)			
Hidden depth (5 best quotes) (/10000)			
Price (Rupees)	949.92	73.40	3895.18

Panel B: Order flow statistics	All	HFTs	AATs	NATs
Messages (MT)	1287202.9	1074794.8	152138.5 ***	60269.6 ***
(%)		(83.5)	(11.8)	(4.7)
New submissions	104199.7	50345.9	30942.7 ***	22911.1 ***
(%)		(48.3)	(29.7)	(22.0)
Cancellations & revisions (C&R)	1183003.2	1024449.0	121195.8 ***	37358.5 ***
(%)		(86.6)	(10.2)	(3.2)

Panel C: Common HFT proxies	All	HFTs	AATs	NATs
MT/Trades	68.67	310.41	22.51 ***	7.40 ***
(d.t.)	(29.8)	(159.4)	(11.6)	(2.2)
C&R/Trades	63.37	295.68	18.28 ***	4.81 ***
(d.t.)	(28.7)	(154.0)	(10.4)	(2.1)

***, **, * means statistically different than the HFT's statistic at the 1%, 5%, and 10% level respectively.

TABLE II
Classification accuracy: OI

This table provides accuracy rates for the BVC algorithm in assigning direction to traded volume and estimating the order imbalance (OI). The OI is the difference between the buyer- and the seller-initiated volume divided by total volume. Accuracy rates are computed for the three-month period of May-July 2015 on the 50 NSE-listed stocks constituents of the NIFTY-50. We aggregate trading volume into time (Panel A), trade (Panel B), and volume (Panel C) bars. We use time bars from 1 second to a full trading session. We drop time bars with no trades. The size of a trade (volume) bar is a given proportion of the average daily number of trades (volume) over the preceding month. We use trade and volume bars from 0.1% (200 bars per day, in average) to 40% (2.5 bars per day, in average). We report our findings for select bar sizes. We consider three alternative distributions for the standardized prices change between bars: normal, and t-student with 0.1 and 0.25 degrees of freedom. The accuracy rate ("AR") is the cross-sectional daily average of the percentage of trading volume correctly classified by the BVC. The accuracy with which the BVC estimates the OI equals 2AR-100. We gauge differences in accuracy across the presumed statistical distributions for the price changes using the non-parametric Wilcoxon rank-sum test.

	Normal		t (0.1 df)		t (0.25 df)	
Size	AR	OI	AR	OI	AR	OI
Panel A: Time bars						
1	61.32	22.63	56.81	13.61 ***	58.00	16.00 ***
5	66.74	33.48	64.15	28.30 ***	64.99	29.97 ***
10	70.60	41.21	68.95	37.90 **	69.64	39.29
30	77.25	54.50	76.95	53.90	77.48	54.96
60	80.68	61.36	81.26	62.51	81.67	63.33 *
300	84.30	68.60	87.72	75.43 ***	87.61	75.23 ***
600	84.42	68.83	89.39	78.79 ***	88.96	77.92 ***
1800	83.77	67.54	91.19	82.39 ***	90.12	80.25 ***
Daily	78.67	57.34	93.20	86.39 ***	90.15	80.30 ***
Avg.	76.42	52.83	78.85	57.69	78.74	57.47
Std.	(8.36)	(16.73)	(13.03)	(26.05)	(12.02)	(24.03)
Panel B: Trade bars						
0.10	76.38	52.76	77.41	54.82 *	77.99	55.99 ***
0.50	80.21	60.42	85.72	71.43 ***	85.70	71.40 ***
1	80.40	60.80	87.88	75.76 ***	87.45	74.90 ***
5	79.52	59.03	90.82	81.65 ***	89.20	78.40 ***
10	78.99	57.97	91.56	83.12 ***	89.43	78.86 ***
15	78.50	57.00	91.88	83.77 ***	89.45	78.89 ***
20	78.29	56.59	92.12	84.23 ***	89.51	79.02 ***
30	77.74	55.48	92.40	84.80 ***	89.47	78.95 ***
40	77.34	54.67	92.58	85.16 ***	89.46	78.92 ***
Avg.	78.60	57.19	89.15	78.30	87.52	75.04
Std.	(1.33)	(2.67)	(4.98)	(9.96)	(3.80)	(7.61)
Panel C: Volume bars						
0.10	73.78	47.57	73.62	47.24	74.54	49.07
0.50	76.49	54.53	80.12	65.01 ***	80.41	64.95 ***
1	77.75	55.63	84.76	70.22 ***	84.35	69.24 ***
5	77.96	55.43	87.05	77.75 ***	86.07	74.44 ***
10	77.46	54.93	89.88	79.75 ***	87.74	75.47 ***
15	77.45	54.36	90.11	80.62 ***	87.86	75.77 ***
20	77.19	54.38	90.66	81.33 ***	88.08	76.17 ***
30	76.96	53.85	90.87	82.13 ***	88.16	76.50 ***
40	76.91	53.53	91.29	82.78 ***	88.37	76.79 ***
Avg.	76.88	53.80	86.49	74.09	85.06	70.93
Std.	(1.25)	(2.43)	(6.06)	(11.72)	(4.73)	(9.12)

***, **, * means statistically different than the normal at the 1%, 5%, and 10% level, respectively

TABLE III
The OI as a proxy for the NOF

This table provides accuracy rates for the order imbalance (OI) as an estimator of the net order flow (NOF). The OI is the difference between the buyer- and the seller-initiated volume divided by total volume. Therefore, the OI is trade-based. The NOF is the difference between buying pressure (*BP*) and the selling pressure (*SP*), divided by order-flow-based volume (*V*), *NOF* = (*BP*-*SP*)/*V*. *BP* (*SP*) is the accumulated size of all market and limit order to buy (sell) submitted plus the size of all standing limit orders to sell (buy) cancelled. Therefore, the NOF is order-flow-based. Accuracy rates are computed for the three-month period of May-July 2015 on the 50 NSE-listed stocks constituents of the NIFTY-50. We aggregate trading volume into time, trade, and volume bars. We use time bars from 1 second to a full trading session. We drop time bars with no trades. The size of a trade (volume) bar is a given proportion of the average daily number of trades (volume) over the preceding month. We use trade and volume bars from 0.1% (200 bars per day, in average) to 40% (2.5 bars per day, in average). We report our findings for select bar sizes. We evaluate differences in accuracy across bar sizes and bar types of similar duration using the non-parametric Wilcoxon rank-sum test.

	Bar type			
Size	Time	Size	Trade	Volume
1	33.04	0.10	56.18	57.03
5	32.55	0.50	70.10	67.44
10	39.57	1	74.28	71.43
30	53.79	5	81.07	78.72
60	61.76	10	83.35	81.16
300	74.16	15	84.55	82.42
600	77.64	20	85.43	83.32
1800	81.88	30	86.62	84.46
Daily	89.24	40	87.40	85.27
Avg.	60.40		78.78	76.80
Std.	(21.74)		(10.28)	(9.58)
1 vs. 60	28.72 ***	0.1 vs 1	27.16 ***	24.13 ***
60 vs. Daily	27.48 ***	1 vs. 40	4.05 ***	4.10 ***

***, **, * means statistically different at the 1%, 5%, and 10% level, respectively

TABLE IV
Classification accuracy: NOF

This table reports accuracy rates for the BVC algorithm in assigning direction to pre-aggregated order-flow-based volume and estimating the net order flow (*NOF*). Accuracy rates are computed for the three-month period of May-July 2015 on the NSE-listed stocks constituents of the NIFTY-50. The order-flow-based volume (*V*) is the sum of the buying pressure (*BP*) and the selling pressure (*SP*), while the *NOF* = (*BP*-*SP*)/*V*. *BP* (*SP*) is the accumulated size of all market and limit order to buy (sell) submitted plus the size of all standing limit orders to sell (buy) cancelled. We compute *SB*, *SP*, *V*, and *NOF* for given time (Panel A), trade (Panel B), and volume (Panel C) bars. We use time bars from 1 second to a full trading session, and trade (volume) bars from 0.1% to 40% of the average daily number of trades (volume) over the preceding month. We report our findings for select bar sizes. We assume three distributions for the standardized changes in prices between bars: normal, and t-student with 0.1 and 0.25 degrees of freedom. The accuracy rate ("AR") is the cross-sectional daily average of the percentage of buying and selling pressure correctly classified by the BVC. The accuracy with which the BVC estimates the *NOF* can then be obtained as 2AR-100 (reported as "NOF"). We drop time bars with no trades. We gauge differences in accuracy across alternative BVC implementations using the non-parametric Wilcoxon rank-sum test.

	Normal		t (0.1 df)		t (0.25 df)	
Size	AR	NOF	AR	NOF	AR	NOF
Panel A: Time bars						
1	73.22	46.44	75.49	50.97 ***	75.19	50.39 ***
5	81.25	62.49	86.10	72.20 ***	85.19	70.38 ***
10	84.01	68.02	89.94	79.87 ***	88.74	77.49 ***
30	86.79	73.58	94.04	88.08 ***	92.44	84.88 ***
60	87.52	75.05	95.40	90.80 ***	93.58	87.16 ***
300	86.82	73.65	96.22	92.44 ***	93.91	87.82 ***
600	85.86	71.73	96.09	92.17 ***	93.55	87.10 ***
1800	84.34	68.68	95.72	91.45 ***	92.89	85.78 ***
Daily	78.13	56.26	94.24	88.47 ***	90.30	80.60 ***
Avg.	83.10	66.21	91.47	82.94	89.53	79.07
Std.	(4.78)	(9.56)	(6.88)	(13.75)	(6.09)	(12.19)
Panel B: Trade bars						
0.10	81.34	62.68	92.51	85.01 ***	90.16	80.32 ***
0.50	80.66	61.31	94.79	89.59 ***	91.47	82.93 ***
1	80.13	60.27	94.90	89.81 ***	91.35	82.70 ***
5	78.89	57.77	94.60	89.19 ***	90.76	81.51 ***
10	78.40	56.80	94.42	88.85 ***	90.50	81.00 ***
15	77.92	55.84	94.29	88.58 ***	90.28	80.57 ***
20	77.71	55.43	94.23	88.46 ***	90.19	80.38 ***
30	77.22	54.43	94.10	88.20 ***	89.98	79.96 ***
40	76.73	53.46	93.97	87.94 ***	89.77	79.53 ***
Avg.	78.78	57.55	94.20	88.40	90.49	80.99
Std.	(1.60)	(3.21)	(0.71)	(1.41)	(0.59)	(1.18)
Panel C: Volume bars						
0.10	78.56	57.12	88.88	77.75 ***	86.84	73.69 ***
0.50	79.39	58.79	92.92	85.84 ***	89.84	79.67 ***
1	79.27	58.53	93.55	87.11 ***	90.19	80.39 ***
5	78.38	56.76	93.87	87.74 ***	90.11	80.22 ***
10	78.05	56.11	93.89	87.77 ***	90.02	80.05 ***
15	77.79	55.58	93.90	87.80 ***	89.97	79.94 ***
20	77.71	55.42	93.90	87.81 ***	89.95	79.90 ***
30	77.29	54.57	93.87	87.74 ***	89.82	79.65 ***
40	76.97	53.95	93.83	87.67 ***	89.72	79.44 ***
Avg.	78.16	56.31	93.18	86.36	89.61	79.21
Std.	(0.83)	(1.65)	(1.64)	(3.29)	(1.05)	(2.09)

***, **, * means statistically different than the normal at the 1%, 5%, and 10% level, respectively

TABLE V
Classification accuracy: NOF vs OI

This table reports cross-sectional average differences in accuracy for the BVC algorithm in estimating the net order flow (*NOF*) and the order imbalance (*OI*). To perform this analysis, we use order-level data for the period May to July 2015 on the 50 NSE-listed stocks constituents of the NIFTY-50. We compute the *NOF* and the *OI* for given time (Panel A), trade (Panel B), and volume (Panel C) bars. For the NOF, the accuracy rate is the percentage of buying and selling pressure correctly classified. For the OI, the accuracy rate is the percentage of buyer-initiated and seller-initiated volume correctly classified. We compute the accuracy rates per bar, and the average accuracy rate per stock-day (*AR*) averaging across bars. Next, we obtain $2(AR_{NOF} - AR_{OI})$, the difference in accuracy per stock-day. Averaging across days we obtain the average difference in accuracy per stock, and averaging across stocks, we obtain the reported statistic. We gauge whether the cross-sectional average daily difference in accuracy is statistically different from zero using the non-parametric Wilcoxon rank-sum test. We use time bars from 1 second to a full trading session, and trade (volume) bars from 0.1% to 40% of the average daily number of trades (volume) over the preceding month. We report our findings for select bar sizes. We assume three distributions for the standardized changes in prices between bars: normal, and t-student with 0.1 and 0.25 degrees of freedom. We drop time bars with no trades.

Size	Normal	t (0.1 df)	t (0.25 df)
Panel A: Time bars			
1	23.81 ***	37.36 ***	34.39 ***
5	29.01 ***	43.90 ***	40.41 ***
10	26.81 ***	41.97 ***	38.20 ***
30	19.07 ***	34.18 ***	29.92 ***
60	13.69 ***	28.28 ***	23.83 ***
300	5.04 ***	17.01 ***	12.60 ***
600	2.90 ***	13.38 ***	9.18 ***
1800	1.13	9.06 ***	5.53 ***
Daily	-1.08	2.08 ***	0.30
Avg.	13.38	25.25	21.59
Std.	(11.75)	(15.29)	(15.06)
Panel B: Trade bars			
0.10	9.92 ***	30.19 ***	24.33 ***
0.50	0.89	18.16 ***	11.53 ***
1	-0.54 *	14.04 ***	7.80 ***
5	-1.26 ***	7.55 ***	3.11 ***
10	-1.18 ***	5.73 ***	2.14 ***
15	-1.16 **	4.82 ***	1.68 ***
20	-1.16 **	4.23 ***	1.36 ***
30	-1.05 **	3.40 ***	1.01 **
40	-1.21 **	2.77 ***	0.61
Avg.	0.36	10.10	5.95
Std.	(3.65)	(9.16)	(7.80)
Panel C: Volume bars			
0.10	9.55 ***	30.51 ***	24.61 ***
0.50	4.26 ***	20.83 ***	14.72 ***
1	2.90 ***	16.88 ***	11.15 ***
5	1.33 *	9.98 ***	5.77 ***
10	1.18	8.02 ***	4.58 ***
15	1.22 *	7.18 ***	4.17 ***
20	1.03	6.48 ***	3.73 ***
30	0.72	5.62 ***	3.14 ***
40	0.42	4.89 ***	2.65 ***
Avg.	2.51	12.27	8.28
Std.	(2.90)	(8.72)	(7.35)

***, **, * means statistically different from zero at the 1%, 5%, and 10% level, respectively

TABLE VI
Classification accuracy: determinants

This table reports the estimated coefficients of a pooled regression model for the accuracy rate of the BVC approach in estimating the net order flow (NOF) per time bar (Panel A) or trade bar (Panel B) on a set of potential determinants. The accuracy rate is the percentage of buying and selling pressure correctly classified within each bar. As explanatory variables, computed per stock-bar, we consider: the high-low trade price ratio, our proxy for volatility (HL); the volume traded in millions of shares (VOL); the number of cancellations and revisions, in millions (CR), our proxy for monitoring intensity; the percentage of hidden volume over the total volume submitted (HVOL), our proxy for pre-trade transparency; the relative contribution of HFTs to the order flow (HFT); the relative contribution of NATs to the order flow (NAT); a dummy for extreme absolute price changes between bars (LargePC); a dummy for zero price changes between bars (ZeroPC); a dummy for the first 30 minutes of trading (First30), and a dummy for the last 30 minutes of trading (Last30). We report estimates for time bars of 1, 5, 60, 300, and 600 seconds, and trade bars of 0.1%, 0.5%, 1%, 5% and 10% of the average daily number of trades over the preceding month. To apply the BVC, we assume that the standardized price changes between bars follow a t-student distribution with 0.1 degrees of freedom. We drop time bars with no trades. The pooled regression is estimated by OLS with White-robust standard errors and clustered by stock.

Panel A: Time bars

	1s	5s	60s	300s	600s
Intercept	0.3602 ***	0.6203 ***	0.9458 ***	0.9847 ***	0.9839 ***
HL	134.5527 ***	64.5123 ***	-6.1452 ***	-6.6736 ***	-5.7053 ***
V	27.7613 ***	9.7531 ***	0.6820 ***	0.0340 *	0.0036
CR	714.4254 ***	89.4303 ***	-0.8206 ***	-0.1724 **	-0.0774 **
HVOL	0.0239 ***	-0.0081	-0.0449 ***	-0.0357 ***	-0.0322 ***
HFT	0.2742 ***	0.2045 ***	0.0231 ***	-0.0176 ***	-0.0208 **
NAT	-0.1043 ***	-0.2080 ***	-0.2107 ***	-0.0886 ***	-0.0529 ***
LargePC	-0.0137 ***	-0.0426 ***	-0.0466 ***	-0.0645 ***	-0.0713 ***
ZeroPC	-0.0536 ***	-0.0409 ***	-0.0087 *	0.0178 ***	0.0281 ***
First30	0.0567 ***	0.0346 ***	-0.0033 ***	-0.0068 ***	-0.0052 ***
Last30	0.0353 ***	0.0386 ***	0.0066 ***	-0.0011	-0.0013
Obs.	31020281	11936376	1208901	242465	119621
F	1409.34	716.12	106.52	439.16	589.51
Adj. R^2	0.3076	0.2722	0.2088	0.423	0.5364

Panel B: Trade bars

	0.10%	0.5%	1%	5%	10%
Intercept	0.7667 ***	0.9432 ***	0.9622 ***	0.9551 ***	0.9537 ***
HL	23.8265 ***	-8.1883 ***	-9.3149 ***	-6.4234 ***	-4.9801 ***
V	0.9594 ***	0.0329 ***	0.0025	0.0009 *	0.0007 **
CR	-1.9504 **	-0.7089 ***	-0.2434 ***	-0.0357 ***	-0.0113 *
HVOL	0.0306 *	-0.0409 ***	-0.0419 ***	-0.0195 **	-0.0165 *
HFT	0.1365 ***	-0.0016	-0.0206 ***	-0.0144 **	-0.0139 *
NAT	-0.1678 ***	-0.0930 ***	-0.0510 ***	-0.0095	-0.0102
LargePC	-0.0561 ***	-0.0606 ***	-0.0654 ***	-0.0736 ***	-0.0746 ***
ZeroPC	-0.0351 ***	0.0154 **	0.0322 ***	0.0586 ***	0.0662 ***
First30	0.0083 ***	-0.0066 ***	-0.0068 ***	-0.0016	0.0001
Last30	0.0127 ***	0.0001	-0.0015	0.0001	0.0005
Obs.	3121805	623319	310806	60864	29630
F	357.84	528.14	690.23	662.28	898.1
Adj. R^2	0.1774	0.2063	0.3478	0.5338	0.554

***, **, * means statistically significant at the 1%, 5%, and 10% level respectively

TABLE VII
Trader types: relative contributions

This table shows the contribution of high-frequency trading (HFT), agency algorithmic trading (AAT), and non-algorithmic trading (NAT) to the buying pressure (BP) and selling pressure (SP), components of the net order flow (NOF), and to the buyer-initiated volume (BV) and seller-initiated volume (SV), components of the order imbalance (OI). Namely, $NOF = (BP\text{-}SP)/(BP+SP)$ and $OI = (BV\text{-}SV)/(BV+SV)$. *BP* (*SP*) is the accumulated size of all market and limit order to buy (sell) submitted plus the size of all standing limit orders to sell (buy) cancelled. We report the average contribution to the buy and sell side component of each metric per bar. We use three months of data (May-July 2015) on the NSE-listed stocks constituents of the NIFTY-50. We compute *SB*, *SP*, *BV*, and *SV* for given time (Panel A), trade (Panel B), and volume (Panel C) bars. We use time bars from 1 second to a full trading session, and trade (volume) bars from 0.1% to 40% of the average daily number of trades (volume) over the preceding month. We report our findings for select bar sizes. For time bars, we drop bars with no trades. We test for differences in contribution across trader types using the non-parametric Wilcoxon rank-sum test.

	Buying and selling pressure (NOF)			Buyer- and seller-initiated volume (OI)		
Size	HFT	AAT	NAT	HFT	AAT	NAT
Panel A: Time bars						
1	46.54	26.98 ***	26.48 ***	8.97	42.92 ***	48.11 ***
5	57.30	22.27 ***	20.43 ***	10.13	41.19 ***	48.68 ***
30	64.55	19.15 ***	16.30 ***	13.58	39.75 ***	46.67 ***
60	66.17	18.41 ***	15.42 ***	14.71	39.36 ***	45.93 ***
300	68.47	17.32 ***	14.21 ***	16.00	39.25 ***	44.74 ***
1800	70.12	16.50 ***	13.37 ***	16.33	39.32 ***	44.35 ***
Daily	70.34	16.53 ***	13.13 ***	15.09	40.16 ***	44.76 ***
Avg.	63.36	19.59	17.05	13.54	40.28	46.18
Std.	(8.65)	(3.82)	(4.84)	(2.89)	(1.35)	(1.72)
Panel B: Trade bars						
0.10	63.55	19.90 ***	16.55 ***	16.00	40.94 ***	43.06 ***
0.50	66.16	18.45 ***	15.39 ***	15.72	40.75 ***	43.53 ***
1	66.92	18.06 ***	15.02 ***	15.70	40.73 ***	43.57 ***
10	68.91	17.08 ***	14.01 ***	15.67	40.42 ***	43.91 ***
20	69.56	16.71 ***	13.73 ***	15.70	40.16 ***	44.15 ***
30	69.91	16.51 ***	13.57 ***	15.69	39.95 ***	44.37 ***
40	70.17	16.35 ***	13.48 ***	15.67	39.75 ***	44.57 ***
Avg.	67.88	17.58	14.54	15.73	40.39	43.88
Std.	(2.45)	(1.29)	(1.15)	(0.12)	(0.45)	(0.53)
Panel C: Volume bars						
0.10	56.08	23.15 ***	20.76 ***	14.67	41.04 ***	44.28 ***
0.50	60.04	21.04 ***	18.92 ***	14.49	40.84 ***	44.67 ***
1	61.29	20.46 ***	18.25 ***	14.45	40.79 ***	44.76 ***
10	64.73	19.10 ***	16.17 ***	14.57	40.55 ***	44.88 ***
20	65.81	18.61 ***	15.58 ***	14.65	40.38 ***	44.97 ***
30	66.44	18.29 ***	15.27 ***	14.69	40.25 ***	45.06 ***
40	66.72	18.11 ***	15.16 ***	14.67	40.04 ***	45.29 ***
Avg.	63.02	19.82	17.16	14.60	40.55	44.84
Std.	(4.00)	(1.84)	(2.17)	(0.10)	(0.36)	(0.32)

***, **, * means statistically different than HFTs at the 1%, 5%, and 10% level, respectively

TABLE VIII
Classification accuracy: trader types

This table contains accuracy rates for the BVC in estimating the net order flow (NOF) of particular types of traders. We consider three types of traders: high-frequency traders (HFTs), agency algorithmic traders (AATs), and non-algorithmic traders (NATs). Let BP (SP) be the buying (selling) pressure. *BP* (*SP*) is the accumulated size of all market and limit order to buy (sell) submitted plus the size of all standing limit orders to sell (buy) cancelled. We compute the *NOF* as (*BP*-*SP*)/(*BP*+*SP*). We use three months of data (May-July 2015) on the NSE-listed stocks constituents of the NIFTY-50. We compute *SB*, and *SP* for given time (Panel A), trade (Panel B), and volume (Panel C) bars. We use time bars from 1 second to a full trading session, and trade (volume) bars from 0.1% to 40% of the average daily number of trades (volume) over the preceding month. We report our findings for select bar sizes. For time bars, we drop bars with no trades. We test for differences in accuracy across trader types using the non-parametric Wilcoxon rank-sum test.

Size	HFTs	AATs	NATs
Panel A: Time bars			
1	68.52	46.00 ***	35.13 ***
5	72.92	56.27 ***	39.84 ***
60	89.35	82.12 ***	71.06 ***
300	91.95	86.62 ***	81.95 ***
Daily	88.38	89.45 ***	85.36 ***
Avg.	82.22	72.09	62.67
Std.	(10.70)	(19.65)	(23.65)
Panel B: Trade bars			
0.10	82.74	73.49 ***	59.81 ***
1	88.78	84.26 ***	80.18 ***
10	88.45	87.13 ***	84.30 ***
20	88.17	87.74	84.42 ***
40	87.77	88.27 ***	84.07 ***
Avg.	87.18	84.18	78.56
Std.	(2.51)	(6.17)	(10.63)
Panel C: Volume bars			
0.10	78.67	67.01 ***	57.42 ***
1	87.49	80.95 ***	76.27 ***
10	88.07	85.56 ***	82.40 ***
20	88.05	86.56 ***	82.92 ***
40	87.79	87.46	83.07 ***
Avg.	86.01	81.51	76.42
Std.	(4.11)	(8.48)	(10.99)

***, **, * means statistically different than HFTs at the 1%, 5%, and 10% level, respectively

TABLE IX
Explanatory power: returns, liquidity, and volatility

This table will answer the question of how much explanatory power we lose by using the BVC-based NOF estimates rather than the actual NOF and, therefore, if the BVC can capture the information embedded in the NOF.

[Work in progress]

TABLE X
VPIN-BVC vs VPIN-NOF

Panel A: Correlations
Panel B: Toxic events

This table will answer the question of whether the BVC-based NOF estimates signal toxic order flow by comparing the VPIN-BVC time series with the VPIN-NOF (the “true” and unobservable VPIN) time series (Panel A), and the type I and type II errors of the BVC approach in identifying truly toxic events, as signaled by the VPIN-NOF (Panel B).

[Work in progress]

TABLE A1
Classification accuracy: Bar types of equal duration

In Panel A, we provide accuracy rates across time, trade, and volume bars of equal average duration (in seconds). In Panel A, we gauge the accuracy of the BVC approach in assigning direction to traded volume ("Direction") and in estimating the order imbalance (OI). In Panel B, we study the accuracy of the OI as a proxy for the NOF. In Panel C, we look at the accuracy of the BVC approach again but in assigning direction to order-flow-based volume and in estimating the net order flow (NOF). Let BP (SP) be the buying (selling) pressure. *BP* (*SP*) is the accumulated size of all market and limit order to buy (sell) submitted plus the size of all standing limit orders to sell (buy) cancelled. Let BV (SV) be the buyer-(seller-) initiated volume. The *NOF* = (*BP*-*SP*)/(*BP*+*SP*) and *OI* = (*BV*-*SV*)/(*BV*+*SV*). We use three months of data (May-July 2015) on the NSE-listed stocks constituents of the NIFTY-50. We consider time bars of 10, 20, 1800, 4500, and 9000 seconds. For each of those duration, we look for trade and volume bars of equal average duration. Trade (volume) bars are defined as a percentage of the the average daily number of trades (volume) over the preceding month. For time bars, we drop bars with no trades. We test for differences in accuracy across trader types using the non-parametric Wilcoxon rank-sum test.

Panel A: BVC accuracy in estimating the OI

Time bars			Trade bars			Volume bars	
Size	Direction	OI	Size	Direction	OI	Direction	OI
10	68.95	37.90	0.05	72.38	44.76 ***	68.82	37.64
20	74.06	48.13	0.1	77.41	54.82 ***	73.62	47.24
1800	91.19	82.39	12	91.71	83.42	90.11	80.22 **
4500	92.15	84.30	20	92.12	84.23	90.66	81.33 ***
9000	92.65	85.30	40	92.58	85.16	91.39	82.78 **

Panel B: OI accuracy in estimating the NOF

Size	Pressure	NOF		Pressure	NOF	Pressure	NOF
10	69.78	39.57	0.05	74.49	48.99 ***	76.46	52.91 ***
20	74.25	48.50	0.1	78.09	56.18 ***	78.51	57.02 ***
1800	90.94	81.88	12	91.96	83.93 ***	90.86	81.71
4500	92.47	84.95	20	92.72	85.43	91.66	83.32 **
9000	93.54	87.07	40	93.70	87.40	92.63	85.26 **

Panel C: BVC accuracy in estimating the NOF

Size	Pressure	NOF		Pressure	NOF	Pressure	NOF
10	89.94	79.87	0.05	89.71	79.41	85.75	71.49 ***
20	92.82	85.63	0.1	92.51	85.01	88.88	77.75 ***
1800	95.72	91.45	12	94.37	88.73 ***	93.93	87.86 ***
4500	95.19	90.39	20	94.23	88.46 ***	93.90	87.81 ***
9000	94.75	89.50	40	93.97	87.94 ***	93.83	87.67 ***

***, **, * means statistically different than the time bars case at the 1%, 5%, and 10% level, respectively

TABLE A2
Classification accuracy: Aggressiveness

This robustness table will show whether the accuracy of the BVC improves when we compute the targeted NOF using only trades and aggressively priced orders, that is, when we restrict our analysis to the best levels on the limit order book.

[Work in progress]

TABLE A3
Classification accuracy: NOF without hidden volume

This robustness table will show whether the accuracy of the BVC improves when we ignore hidden volume in computing the targeted NOF.

[Work in progress]

TABLE A4
Classification accuracy: quote midpoint changes

This robustness table will show whether the accuracy of the BVC improves when instead of using standardized trade price changes between bars to apply the methodology, we use quote midpoint changes between bars, eliminating the bid-ask bounce and controlling for non-synchronous trading when using time bars.

[Work in progress]

TABLE A5
Classification accuracy: alternative time bars

In applying the BVC with time bars we drop bars with no trading. In this table, we consider alternative approaches to deal with no-trade time bars, and we test the robustness of our findings.

[Work in progress]