Informed trading and price discovery before corporate events

Shmuel Baruch\textsuperscript{a}, Marios Panayides\textsuperscript{b}, Kumar Venkataraman\textsuperscript{c,*}

\textsuperscript{a}David Eccles School of Business, University of Utah, Salt Lake City, UT 84112, USA
\textsuperscript{b}Katz Graduate School of Business, University of Pittsburgh, Pittsburgh, PA 15260, USA
\textsuperscript{c}Edwin L. Cox School of Business, Southern Methodist University, Dallas, TX 75275, USA

\textbf{A R T I C L E I N F O}

\textbf{Article history:}
Received 5 March 2015
Revised 8 June 2016
Accepted 29 June 2016
Available online xxx

\textbf{JEL classifications:}
G11
G12
G14
G18

\textbf{Keywords:}
Informed trader
Insider trading
Limit order
Short selling
Buy–sell asymmetry

\textbf{A B S T R A C T}

Stock prices incorporate less news before negative events than positive events. Further, informed agents use less price aggressive (limit) orders before negative events and more price aggressive (market) orders before positive events (buy–sell asymmetry). Motivated by these patterns, we model the execution risk that informed agents impose on each other and relate the asymmetry to costly short selling. When investor base is narrow, security borrowing is difficult, or the magnitude of the event is small, buy–sell asymmetry is pronounced and price discovery before negative events is lower. Overall, we show that the strategies of informed traders influence the process of price formation in financial markets, as predicted by theory.

© 2017 Elsevier B.V. All rights reserved.

\textsuperscript{*} We thank the editor (Bill Schwert) and, in particular, Gideon Saar (the referee) for many constructive suggestions. For their comments, we thank Amber Anand, Leonce Bargeron, Kerry Back, Indraneel Chakraborty, Jeff Coles, Kevin Crotty, Dave Denis, Diane Denis, Amy Edwards, Robert Engle, Tom George, Hans Heidie, Stacey Jacobsen, Pankaj Jain, Ron Kaniel, Praveen Kumar, Sebastian Michenaud, Bruce Lehman, Ken Leh, Swami Kalpathy, Bige Kahraman, Albert Menkveld, Ling Peng, Gideon Saar, Bob Schwartz, Wing Wah Tham, Erik Thiessen, Shawn Thomas, Rex Thompson, Laura Tuttle, Mathijs Van Dijk, Vish Viswanathan, Sunil Wahal, Ingrid Werner, Chad Zutter, and seminar participants at Arizona State University, Baruch College of the City University of New York, Lehigh University, Rice University, Southern Methodist University, University of Cincinnati, University of Houston, University of Pittsburgh, University of Toronto, Wilfrid Laurier University, the 2013 Erasmus Liquidity Conference, the 2013 Stern Microstructure Conference, the 2013 Northern Finance Association Conference, the 2013 European Finance Association Conference, the spring 2015 Conference of the Multinational Finance Society, and US Securities and Exchange Commission. We thank Laurent Fournier and Carole Huguet of Euronext-Paris for providing data. We are grateful in particular to Hank Bessembinder for helpful discussions during the development of the project.

\textsuperscript{c,*} Corresponding author.
E-mail address: kumar@mail.cox.smu.edu (K. Venkataraman).

1. Introduction

Informed traders play a central role in price formation in financial markets. In microstructure models (see Kyle, 1985; Glosten and Milgrom, 1985), informed traders receive a private signal about the security’s value and build positions before information is widely available. The market participants observe the imbalance created by the informed order flow and move prices in the direction of the signal. Thus, the theoretical literature predicts that the activities of informed traders influence the informational efficiency of prices before news releases.


doi:10.1016/j.jfineco.2017.05.008
http://dx.doi.org/10.1016/j.jfineco.2017.05.008

Please cite this article as: S. Baruch et al., Informed trading and price discovery before corporate events, Journal of Financial Economics (2017), http://dx.doi.org/10.1016/j.jfineco.2017.05.008
In this study, we present an extension of the theory describing informed trader’s strategies and provide relevant empirical evidence on the most basic questions about informed trading: First, how do informed traders build positions, and what explains their strategies? Second, how do their decisions to use aggressive or passive strategies affect the process through which private information is incorporated into security prices? Third, how do their strategies affect the speed of learning before news releases? Understanding the behavior of informed agents is central both to validating the well-developed theoretical literature that relates trading strategies to price discovery and to designing better surveillance systems that monitor and detect insider trading activity.1

Despite the importance of understanding how informed agents build positions, data limitations have left unanswered many important questions about their strategies. In the days leading to corporate announcements, such as those related to mergers and acquisitions (M&As) and earnings releases, prior research presents widespread evidence of insider trading activity and stock price movements.2 Many publicly available data sources, such as the NYSE Trade and Quote (TAQ) database, report all the transactions in a market but do not identify the specific trades of informed agents. Some data on transactions are available from regulatory Form 4 filed by corporate insiders with the US Securities and Exchange Commission (SEC) (see Seyhun, 1986), or from the SEC’s case files of defendants formally charged with insider trading (see Meulbroek, 1992). However, these data sets do not contain order-level information that is necessary to describe the strategies of informed agents.

We examine a data set provided by the Euronext-Paris exchange with information on all orders submitted for all stocks. The Euronext data do not directly identify the orders of informed agents. To identify informed order flow, we employ a research design based on the methodology from Chae (2005), Graham, Koski, and Loewenstein (2006), and Sarkar and Schwartz (2009). Prior studies show that uninformed traders decrease participation in periods leading to news releases with timing that is known in advance, such as earnings announcements. In contrast, uninformed traders cannot anticipate unscheduled news events with timing that is a complete surprise, but informed traders can, if their information concerns the event.3 We examine a sample of unscheduled corporate announcements related to M&As, seasoned equity offerings (SEO), stock re-purchases, dividend initiations, and dividend terminations for Euronext-Paris stocks. We attribute the change in trading activity observed before an unscheduled announcement relative to a control period for the same firm to the actions of informed agents. Using the control period to estimate the shift in order flow before the event reduces the likelihood that the event effect is explained by time-invariant firm attributes that influence order submission on non-event days.

We present a model of the informed agent’s choice of market versus limit orders. The intuition for the model is as follows. Informed agents face a trade-off between transacting with certainty at a current bid or offer price by placing a market order versus managing execution risk in an attempt to get a better price by placing a limit order. In addition to paying the bid-ask spread, market orders tip off market participants about the private signal and increase price impact cost. When other informed agents receive the same signal and trade on the same side of the market, the execution risk of a limit order strategy is particularly high. Our model predicts that informed agents use limit orders when sufficient uncertainty exists about the presence of other informed agents and use market orders if they are certain that other informed agents are present. These predictions follow the Kaniel and Liu (2006) theoretical work showing that informed agents could use limit orders if the mass of informed agents is sufficiently low.

Informed agents face less competition when the nature of private information conveys a decrease in stock price. Corporate insiders face more constraints when they trade on bad news than on good news (see Marin and Olivier, 2008).4 Informed sellers who do not own the stock incur the cost of borrowing shares. When borrowing costs are high, these informed sellers are less likely to trade. Consistent with our model, we report a novel empirical regularity of an asymmetry in informed agents’ order submission strategies before positive and negative events. We find an increase in price aggressiveness of buy orders before positive events and a decrease in price aggressiveness of sell orders before negative events (henceforth, buy–sell asymmetry). As in Diamond and Verrecchia (1987), our model relies on short sale constraints to explain the buy–sell asymmetry observed in the data. However, in our model, the asymmetry emerges not only because some informed sellers decide to abstain, but also because informed sellers become liquidity providers.

Our model yields cross-sectional predictions in buy–sell asymmetry based on the anticipated competition among informed sellers. Informed sellers can be one of two types: the first type already owns the stock and the second type does not. The probability that the informed seller is of the first type increases with breadth of investor base. When investor base is narrow, when the cost of borrowing shares is large, and when the magnitude of news release is small such that the potential gains do not justify the borrowing costs, a limit order equilibrium emerges in which the first

---

1 In this study, the term “informed trader” refers to any person with access to valuable, non-public information before a corporate announcement. Examples include corporate insiders, such as board members, directors, and employees and well-connected participants such as bankers, analysts, lawyers, and institutional investors.


3 A June 6, 2013 Wall Street Journal article reports on the increase in trading activity observed before Smithfield’s acquisition announcement: “When multiple bidders vie for a company, it isn’t unusual for hundreds of people to know about the possible deal before it surfaces—including employees of banks, law firms, and other outside advisors, not to mention the people inside the companies themselves.”

4 Insiders in many markets are prohibited from selling short their own stock (e.g., Section 16 of the US Securities Exchange Act of 1934), or sell stock holdings that are part of a compensation contract below a certain threshold.
type of agent uses limit orders and the second type abstains from trade. On the other hand, when investor base is broad, when borrowing costs are small, or when the magnitude of news release is large, the second type of agent borrows the shares, and both types trade. The competition among informed sellers increases the execution risk of a limit order strategy and leads to usage of market orders. When the private information conveys an increase in stock price, informed buyers always anticipate competition and use market orders. Fig. 1 shows how anticipated competition among informed agents can lead to buy–sell asymmetry before corporate events.

Motivated by prior work, our empirical measures of short sale constraints are stock index membership, availability of exchange-listed stock options, and eligibility for Euronext’s Deferred Settlement Service (SRD, Service de Règlement Différé). Index stocks have broad investor base, active participation by institutions, and lower borrowing cost (see D’Avolio, 2002; Nagel, 2005). Stock options allow informed sellers to establish equivalent positions at a lower cost in short constrained stocks (see Battalio and Schultz, 2011; Hu, 2014). Euronext’s SRD facility allows short positions in eligible stocks to be established more easily (see Foucault, Sraer, and Thesmar 2011).

We find strong empirical support for the model’s predictions. In scenarios in which informed traders anticipate competition (i.e., index constituent stocks, stocks with listed options, SRD-eligible stocks, or large news announcements), we observe an increase in price aggressiveness for buy orders before positive events and for sell orders before negative events. In contrast, when short selling is costly (i.e., non-index stocks, stocks without listed options, or SRD-ineligible stocks) or when news is small, we observe an asymmetry in the mix of order flow before positive and negative events. Specifically, the price aggressiveness of buy orders increases before positive events while the price aggressiveness of sell orders decreases before negative events. Results are robust to different methods for classifying events as positive and negative, as well as alternative model specifications, including panel regressions.

Furthermore, we report the novel empirical result that stock prices incorporate less news before negative events than positive events. Following Blais, Hillion, and Spatt (1999), we estimate the efficiency of price discovery before corporate events using unbiasedness regressions in which we regress the close-to-close return during Days $[-6,+1]$ on the return in the interval $[-6, I]$, where $I$ represents half-hour snapshots in the interval $[-5, I]$. Barclay and Hendershott (2003) interpret the slope of the unbiasedness regressions as the signal:noise ratio. In our research design, as the slope moves closer to one the interpretation is that the security price before the event reflects the security price after the event with increasing precision. For positive and negative events, the slope of the unbiasedness regression at the beginning of the pre-event window is not statistically different from zero. As the event gets closer (i.e., $I = -1$), the slope for positive events is not significantly different from one; for negative events, the slope is lower (between zero and one) and significantly different from one. In addition, consistent with higher price discovery before positive events, we estimate large opportunity costs when limit orders go unfilled before positive events but not before negative events, indicating that employing limit orders before positive events is a costly strategy.

Results based on subsamples suggest that informed traders’ strategies affect the informational efficiency of prices before corporate events. When informed traders employ less price aggressive orders (i.e., negative events in non-index stocks, SRD-ineligible stocks, and stocks without listed options), the slope of the unbiasedness regression toward the end of the pre-event window is between zero and one and is statistically different from one. When informed traders employ more price aggressive orders (i.e., negative events with no short sale constraints and all events. Results are robust to different methods for classifying events as positive and negative, as well as alternative model specifications, including panel regressions.

Furthermore, we report the novel empirical result that stock prices incorporate less news before negative events than positive events. Following Blais, Hillion, and Spatt (1999), we estimate the efficiency of price discovery before corporate events using unbiasedness regressions in which we regress the close-to-close return during Days $[-6,+1]$ on the return in the interval $[-6, I]$, where $I$ represents half-hour snapshots in the interval $[-5, I]$. Barclay and Hendershott (2003) interpret the slope of the unbiasedness regressions as the signal:noise ratio. In our research design, as the slope moves closer to one the interpretation is that the security price before the event reflects the security price after the event with increasing precision. For positive and negative events, the slope of the unbiasedness regression at the beginning of the pre-event window is not statistically different from zero. As the event gets closer (i.e., $I = -1$), the slope for positive events is not significantly different from one; for negative events, the slope is lower (between zero and one) and significantly different from one. In addition, consistent with higher price discovery before positive events, we estimate large opportunity costs when limit orders go unfilled before positive events but not before negative events, indicating that employing limit orders before positive events is a costly strategy.

Results based on subsamples suggest that informed traders’ strategies affect the informational efficiency of prices before corporate events. When informed traders employ less price aggressive orders (i.e., negative events in non-index stocks, SRD-ineligible stocks, and stocks without listed options), the slope of the unbiasedness regression toward the end of the pre-event window is between zero and one and is statistically different from one. When informed traders employ more price aggressive orders (i.e., negative events with no short sale constraints and all
positive events), the slope of the unbiasedness regression is positive and not statistically different from one. Collectively, our results provide support for the well-established theoretical literature that links informed traders’ strategies to level of competition and, further, to the process of price formation in financial markets (Holden and Subrahmanyan, 1992).

In the Diamond and Verrecchia (1987) and also Saar (2001) framework, informed traders trade upon arrival; in other words, they do not employ limit orders. In fact, most theoretical work posits that informed agents exclusively use market orders to exploit their information advantage. Novel exceptions are Kumar and Seppi (1994), Chakravarty and Holden (1995), Kaniel and Liu (2006), Goettler, Parlour, and Rajan (2009), Boulatov and George (2013), and Rosu (2014). In these models, informed traders do find it optimal under certain conditions to submit limit orders. However, none of these theoretical papers relates strategies of informed agents to the direction of the private signal and, further, to asymmetry in competition that is introduced by costly short selling.

In a recent work, Collin-Dufresne and Fos (2015) study a sample of trades reported in the Schedule 13D filings by activist investors. The study shows that activist investors time their trades when liquidity is high and use limit orders when public disclosure of their positions is not imminent. These results support the Kaniel and Liu (2006) prediction that informed traders with long-lived information use limit orders. Other experimental and empirical papers also suggest that informed traders use limit orders (e.g., Barclay, Hendershott, and McCormick 2003, Bloomfield, O’Hara, and Saar 2005, 2015, Anand, Chakravarty, and Martell 2005, Hautsch and Huang (2012), and Zhang (2013)).

Our study points to an unintended consequence of the widespread ban on short selling by regulators around the world in response to the 2007–09 financial crisis. Beber and Pagano (2013) find that the short sale ban lowers the information efficiency of prices, particularly surrounding events with negative information. Because the short sale ban reduces competition among sellers, our model predicts that informed sellers who already own the stock use less aggressively priced orders, which impedes the flow of negative private information into prices. Our study offers a specific mechanism by which short sale constraints impede the price discovery process, as shown by Boehmer and Wu (2013).

The rest of the paper is organized as follows. Section 2 describes the sample, data sources, and summary statistics. In Section 3, we present evidence of buy–sell asymmetry in order price aggressiveness, price discovery, and opportunity cost of non-execution of limit orders before positive and negative events. In Section 4, we present a model that explains the results and provides new testable predictions. We test the model’s cross-sectional predictions in Section 5 and present robustness analyses in Section 6. Section 7 presents the study’s conclusions.

### 2. Sample and data

We examine the Euronext-Paris Base de Donnees de Marche (BDM) database for the year 2003. The BDM database contains detailed information on the characteristics of all orders submitted for all stocks listed on Euronext-Paris: the stock symbol, the date and time of order submission, whether the order is a buy or a sell, the total size of the order (in shares), the displayed size (in shares), an order type indicator for identifying market or limit orders, a limit price in the case of a limit order, and instructions on when the order expires.

We examine the 2003 sample period because more recent order-level data purchased from the Euronext market have important inaccuracies. Orders that never get executed and orders with a hidden size that are partly executed do not get reported to the database. The omission affects the accuracy of the reconstructed limit order book, the analysis of order submission strategies, and the construction of control variables used in some specifications.

The growth in the alternative trading venues in the last decade has caused equity markets in the United States and Europe to be highly fragmented. In a fragmented market, an analysis of the informed traders’ strategies must consider the choice of the trading venue to execute an order, which introduces a layer of complexity due to the inter-market priority rules and the make-take pricing arrangement at each trading venue. During our sample period, the vast majority of trading activity (over 90%) in French stocks was observed on Euronext-Paris. Thus, the market structure in 2003 provides a simple laboratory to test theoretical predictions on informed trader strategies.

The Euronext database does not provide information on trader identity. To identify informed order flow, we examine trading activity before unscheduled corporate events. The timing of information release for scheduled events, such as earning releases, is publicly available in advance of announcement. Chae (2005), Graham, Koski, and Loewenstein (2006), and Sarkar and Schwartz (2009) show that, although traders do not know in advance the information contained in scheduled events, those traders with some discretion on timing of trades alter activity prior to these events. For example, Lee, Mucklow, and Ready (1993) find that market makers widen bid-ask spreads and lower inside depth before earnings releases. In comparison, informed agents alone are aware of the pending news release for unscheduled (surprise) events in which the timing of the information release is not known publicly in advance. Sarkar and Schwartz (2009) show that trading activity before unscheduled events is characterized by one-sided markets, which is consistent with the presence of informed agents. Following the prior literature, we attribute the abnormal trading activity that is observed before unscheduled events to informed agents.

---


6 Evidence on limit order usage in Collin-Dufresne and Fos (2015) is indirect because Schedule 13D filings do not require investors to disclose what type of orders they use. The study matches transaction data disclosed in Schedule 13D filings with TAQ data and uses the Lee and Ready (1991) algorithm to identify limit orders.
We identify unscheduled events using the Securities Data Company (SDC) database compiled by Thomson Financial Securities Data and the Amadeus database provided by Bureau van Dijk. We focus on five types of unscheduled events: M&As, SEOs, repurchases, dividend initiations, and dividend terminations. We use Bloomberg and Factiva search engines to identify the date of the first news announcement about the event (Day [0]). We eliminate Euronext-Paris stocks that switch from continuous trading to call auctions (or vice versa) or were de-listed from Euronext during Days [−30,+10] surrounding the event. The final sample consists of 101 unscheduled corporate events for 95 unique stocks.

In microstructure models, informed agents build positions in the direction of the private signal before the information is widely available. We classify events as positive and negative news based on the announcement (Days [0,+1]) cumulative abnormal returns (CARs), with CAC 40 index return serving as the benchmark. In Table 1, Panel A, the 58 positive events have a mean (median) Days [0,+1] CAR of 4.84% (2.74%) and the 43 negative events have a mean (median) Days [0,+1] CAR of −4.53% (−2.57%). We observe positive and negative news for all event types with the exception of dividend termination.

In Table 1, Panel B, we examine the stock’s price movements over a five-day window before the event. For all event types, the magnitude of Days [−5,+1] CAR in Panel B is larger than Days [0,+1] CAR in Panel A, implying the stock price moves before the event in the direction of the news. The results in Panel C suggest that the stock price incorporates more information before positive events than negative events. For positive events, the Days [0,+1] CAR accounts on average for 44.83% of the Days [−5,+1] CAR, implying that the stock price reflects 55.17% of the news before positive events. In comparison, the stock price reflects 26.48% of the news before negative events.

The descriptive statistics in Table 2, Panel A suggest that the positive event sample has larger market capitalization, higher stock price, lower return volatility, and smaller bid-ask spread than the negative event sample. The median percentage bid-ask spread is approximately 0.80%, indicating that the benefit of using limit orders instead of market orders is economically large.

Panel B presents descriptive statistics for buy orders before positive events and sell orders before negative events. Statistics based on daily averages are reported for event Days [−5,−1], control Days [−30,−10], and tests of the difference between event and control days. We report the total number of orders (marketable and non-marketable), the order size, the percentage of marketable to non-marketable orders (hereafter, market:limit ratio), and the percentage of limit orders with a hidden size. A higher (lower) market:limit ratio on event days relative to control days suggests that informed traders use more (less) aggressively priced orders to build positions before events.

For a sample of French M&A announcements, Aktaş, de Bodt, Declercq, and Ven Oppens (2007) report that trading volume spikes in the five days preceding a merger announcement and that trading volume and bid-ask spreads increase for both acquirers and targets in the Days [−65,−6] before announcement. Informed trading in the control period reduces the power of our research design to detect informed trading. To minimize the impact of leakage, we delete events with rumors reported in press articles based on a Factiva search before the news release.

We identify unscheduled events using the Securities Data Company (SDC) database compiled by Thomson Financial Securities Data and the Amadeus database provided by Bureau van Dijk. We focus on five types of unscheduled events: M&As, SEOs, repurchases, dividend initiations, and dividend terminations. We use Bloomberg and Factiva search engines to identify the date of the first news announcement about the event (Day [0]). We eliminate Euronext-Paris stocks that switch from continuous trading to call auctions (or vice versa) or were de-listed from Euronext during Days [−30,+10] surrounding the event. The final sample consists of 101 unscheduled corporate events for 95 unique stocks.

In microstructure models, informed agents build positions in the direction of the private signal before the information is widely available. We classify events as positive and negative news based on the announcement (Days [0,+1]) cumulative abnormal returns (CARs), with CAC 40 index return serving as the benchmark. In Table 1, Panel A, the 58 positive events have a mean (median) Days [0,+1] CAR of 4.84% (2.74%) and the 43 negative events have a mean (median) Days [0,+1] CAR of −4.53% (−2.57%). We observe positive and negative news for all event types with the exception of dividend termination.

In Table 1, Panel B, we examine the stock’s price movements over a five-day window before the event. For all event types, the magnitude of Days [−5,+1] CAR in Panel B is larger than Days [0,+1] CAR in Panel A, implying the stock price moves before the event in the direction of the news. The results in Panel C suggest that the stock price incorporates more information before positive events than negative events. For positive events, the Days [0,+1] CAR accounts on average for 44.83% of the Days [−5,+1] CAR, implying that the stock price reflects 55.17% of the news before positive events. In comparison, the stock price reflects 26.48% of the news before negative events.

The descriptive statistics in Table 2, Panel A suggest that the positive event sample has larger market capitalization, higher stock price, lower return volatility, and smaller bid-ask spread than the negative event sample. The median percentage bid-ask spread is approximately 0.80%, indicating that the benefit of using limit orders instead of market orders is economically large.

Panel B presents descriptive statistics for buy orders before positive events and sell orders before negative events. Statistics based on daily averages are reported for event Days [−5,−1], control Days [−30,−10], and tests of the difference between event and control days. We report the total number of orders (marketable and non-marketable), the order size, the percentage of marketable to non-marketable orders (hereafter, market:limit ratio), and the percentage of limit orders with a hidden size. A higher (lower) market:limit ratio on event days relative to control days suggests that informed traders use more (less) aggressively priced orders to build positions before events.

We identify unscheduled events using the Securities Data Company (SDC) database compiled by Thomson Financial Securities Data and the Amadeus database provided by Bureau van Dijk. We focus on five types of unscheduled events: M&As, SEOs, repurchases, dividend initiations, and dividend terminations. We use Bloomberg and Factiva search engines to identify the date of the first news announcement about the event (Day [0]). We eliminate Euronext-Paris stocks that switch from continuous trading to call auctions (or vice versa) or were de-listed from Euronext during Days [−30,+10] surrounding the event. The final sample consists of 101 unscheduled corporate events for 95 unique stocks.

In microstructure models, informed agents build positions in the direction of the private signal before the information is widely available. We classify events as positive and negative news based on the announcement (Days [0,+1]) cumulative abnormal returns (CARs), with CAC 40 index return serving as the benchmark. In Table 1, Panel A, the 58 positive events have a mean (median) Days [0,+1] CAR of 4.84% (2.74%) and the 43 negative events have a mean (median) Days [0,+1] CAR of −4.53% (−2.57%). We observe positive and negative news for all event types with the exception of dividend termination.

In Table 1, Panel B, we examine the stock’s price movements over a five-day window before the event. For all event types, the magnitude of Days [−5,+1] CAR in Panel B is larger than Days [0,+1] CAR in Panel A, implying the stock price moves before the event in the direction of the news. The results in Panel C suggest that the stock price incorporates more information before positive events than negative events. For positive events, the Days [0,+1] CAR accounts on average for 44.83% of the Days [−5,+1] CAR, implying that the stock price reflects 55.17% of the news before positive events. In comparison, the stock price reflects 26.48% of the news before negative events.

The descriptive statistics in Table 2, Panel A suggest that the positive event sample has larger market capitalization, higher stock price, lower return volatility, and smaller bid-ask spread than the negative event sample. The median percentage bid-ask spread is approximately 0.80%, indicating that the benefit of using limit orders instead of market orders is economically large.

Panel B presents descriptive statistics for buy orders before positive events and sell orders before negative events. Statistics based on daily averages are reported for event Days [−5,−1], control Days [−30,−10], and tests of the difference between event and control days. We report the total number of orders (marketable and non-marketable), the order size, the percentage of marketable to non-marketable orders (hereafter, market:limit ratio), and the percentage of limit orders with a hidden size. A higher (lower) market:limit ratio on event days relative to control days suggests that informed traders use more (less) aggressively priced orders to build positions before events.

For a sample of French M&A announcements, Aktaş, de Bodt, Declercq, and Ven Oppens (2007) report that trading volume spikes in the five days preceding a merger announcement and that trading volume and bid-ask spreads increase for both acquirers and targets in the Days [−65,−6] before announcement. Informed trading in the control period reduces the power of our research design to detect informed trading. To minimize the impact of leakage, we delete events with rumors reported in press articles based on a Factiva search before the news release.
Table 2

Descriptive statistics on the sample and the order flow before corporate events.

Panel A reports the descriptive statistics on the Euronext-Paris sample firms associated with unscheduled corporate events: acquisitions, targets, seasoned equity offerings, repurchases, dividend initiations, and dividend termination. The sample consists of 95 Euronext-Paris stocks with 101 events. We classify events into positive and negative news based on the two-day (Day [0,+1]) cumulative abnormal returns, with Day 0 denoting the event day. In Panel A, we report market capitalization (in millions of euros, as of January 2003), daily trading volume (shares), quoted bid ask spread (percent), volatility (percent) and stock price (euros) on control Days [−30,−10] before the event. Panel B reports daily statistics on order flow activity on Days [−5,−1] and control Days [−30,−10]. The control period provides a benchmark measure of the order submission process for the firm, absent the event. By holding trading activity on control days in a firm as its own benchmark, our research design reduces the influence of time-invariant firm attributes on the variation in trading strategies across firms.

The null hypothesis is that the event has no impact on order flow or that the event effect is zero. The event’s impact is captured by day coefficients that measure the change in dependent variable on the event days relative to the control days. Extensions of the original Kyle model generate different predictions about the trading intensity of informed agents before news releases (e.g., Kyle, 1985; Back, Cao, and Willard, 2000; Baruch, 2002; Sastry, Smith, and Thompson, 2014). Because theory does not predict that trading intensity is uniform, we estimate separate coefficients for each day in the event period (Days [−5,−1]). This approach allows individual day effects to differ before news releases since informed agents can be active on any of the five days before the event. We then calculate the combined effect of informed trading with a cumulative measure that sums up the individual day coefficients. When interpreting the results, we focus on both the individual day effects as well as the cumulative effect, and the associated t-statistics. In Section 6, we demonstrate

<table>
<thead>
<tr>
<th>Panel A: Sample firms</th>
<th>Positive events</th>
<th>Negative events</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market capitalization (millions of euros)</td>
<td>Mean</td>
<td>Median</td>
</tr>
<tr>
<td>Daily volume (shares)</td>
<td>5114</td>
<td>425</td>
</tr>
<tr>
<td>Quoted spreads (percent)</td>
<td>454,347</td>
<td>6054</td>
</tr>
<tr>
<td>Daily return volatility (percent)</td>
<td>0.18</td>
<td>0.13</td>
</tr>
<tr>
<td>Stock price (euros)</td>
<td>33.3</td>
<td>27.2</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Daily activity descriptive statistics</th>
<th>Panel B: Market activity</th>
<th>Mean</th>
<th>Median</th>
<th>Mean</th>
<th>Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of marketable and non-marketable orders</td>
<td>Days [−5,−1] before corporate event</td>
<td>808.8**</td>
<td>63.9*</td>
<td>995.5*</td>
<td>117.0*</td>
</tr>
<tr>
<td>Control period</td>
<td>638.5</td>
<td>50.7</td>
<td>898.6</td>
<td>87.6</td>
<td></td>
</tr>
<tr>
<td>Average order size</td>
<td>Days [−5,−1] before corporate event</td>
<td>1358*</td>
<td>461.7</td>
<td>2031*</td>
<td>1107</td>
</tr>
<tr>
<td>Control period</td>
<td>1004</td>
<td>436.6</td>
<td>1771</td>
<td>1045</td>
<td></td>
</tr>
<tr>
<td>Percentage marketable or market orders to limit orders</td>
<td>Days [−5,−1] before corporate event</td>
<td>48.1***</td>
<td>46.1***</td>
<td>49.4%</td>
<td>49.0%*</td>
</tr>
<tr>
<td>Control period</td>
<td>45.1%</td>
<td>44.3%</td>
<td>50.0%</td>
<td>51.7%</td>
<td></td>
</tr>
<tr>
<td>Percentage of limit orders with hidden size</td>
<td>Days [−5,−1] before corporate event</td>
<td>18.8%</td>
<td>14.8%</td>
<td>17.1%</td>
<td>16.2%</td>
</tr>
<tr>
<td>Control period</td>
<td>18.4%</td>
<td>15.3%</td>
<td>17.6%</td>
<td>16.3%</td>
<td></td>
</tr>
</tbody>
</table>

The results indicate that informed trades are active before unscheduled events. For both positive and negative events, the daily number of orders and the order size are higher on event days relative to control days. The market:limit ratio increases before positive events (significant at the 1% level) and decreases marginally (significant at the 10% level) before negative events, suggesting that informed agents use a different mix of order flow based on the direction of the news. The percentage of limit orders with a hidden size is similar on event and control days.

3. Analysis of price aggressiveness, price discovery, and opportunity cost of non-execution

Why does the stock price incorporate more information before positive events than negative events? Is price discovery influenced by the informed agent’s choice of active versus passive strategies? We further explore these questions by modeling the order submission strategy in a multivariate regression framework that controls for order attributes and the market conditions at the time of arrival of an order.

3.1. Methodology

The multivariate regressions are estimated on an event-by-event basis using all orders submitted on event Days [−5,+1] and control Days [−30,−10]. The control period provides a benchmark measure of the order submission process for the firm, absent the event. By holding trading activity on control days in a firm as its own benchmark, our research design reduces the influence of time-invariant firm attributes on the variation in trading strategies across firms.

The null hypothesis is that the event has no impact on order flow or that the event effect is zero. The event’s impact is captured by day coefficients that measure the change in dependent variable on the event days relative to the control days. Extensions of the original Kyle model generate different predictions about the trading intensity of informed agents before news releases (e.g., Kyle, 1985; Back, Cao, and Willard, 2000; Baruch, 2002; Sastry, Smith, and Thompson, 2014). Because theory does not predict that trading intensity is uniform, we estimate separate coefficients for each day in the event period (Days [−5,−1]). This approach allows individual day effects to differ before news releases since informed agents can be active on any of the five days before the event. We then calculate the combined effect of informed trading with a cumulative measure that sums up the individual day coefficients.
robustness with a specification that considers a single co-efficient to capture the event’s impact on Days [−5, −1].

We present results that are aggregated across events using the Bayesian framework attributable to DuMouchel (1994) and implemented by Bessembinder, Panayides, and Venkataraman (2009). Similar to Harris and Piwowar (2006), the method assigns larger weight in the cross-sectional aggregation to those events parameters estimated more precisely. Further, the method allows variation in the true parameter estimates across events, thus accommodating the theoretical prediction that informed trader strategies are influenced by firm characteristics, such as short sale constraints. Details of the aggregation methodology are provided in Appendix A. The events are not clustered in calendar time and thus are viewed as cross-sectionally independent. We present robustness analyses based on alternate model specifications, including panel regressions, in Section 6.

### 3.2. Price aggressiveness of informed traders before positive and negative events

We examine the informed agents’ preference of market versus limit orders based on a regression analysis of order price aggressiveness. The regression specification accounts for the impact of market conditions on an order \( O_t \) that arrives at time of submission \( t \) for event \( i \), as follows:

\[
\text{PriceAggressive}_{it} = \gamma_0 + \gamma_1 \text{DayMinus5}_{it} + \gamma_2 \text{DayMinus4}_{it} + \gamma_3 \text{DayMinus3}_{it} + \gamma_4 \text{DayMinus2}_{it} + \gamma_5 \text{DayMinus1}_{it} + \gamma_6 \text{Day08Plus1}_{it} + \gamma_7 \text{DayPlus2}_{it} + \gamma_8 \text{OrderExposure}_{it} + \gamma_9 \text{TotalOrderSize}_{it} + \gamma_{10} \text{Spread}_{it} + \gamma_{11} \text{DepthSame}_{it} + \gamma_{12} \text{DepthOpp}_{it} + \gamma_{13} \text{BookOrderImbalance}_{it} + \gamma_{14} \text{Volatility}_{it} + \gamma_{15} \text{WaitTime}_{it} + \gamma_{16} \text{TradeFreqHour}_{it} + \gamma_{17} \text{PriceAggressive}_{i-1} + \gamma_{18} \text{DisplayOrderSize}_{i-1} + \gamma_{19} \text{TradesSize}_{i-1} + \gamma_{20} \text{HiddenOppSize}_{i-1} + \gamma_{21} \text{FirstHour}_{it} + \gamma_{22} \text{LastHour}_{it} + \gamma_{23} \text{Mkt.Volatility}_{it} + \gamma_{24} \text{Ind.Volatility}_{it}
\]

Following Blais, Hillion, and Spatt (1995) and Bessembinder, Panayides, and Venkataraman (2009), \( \text{PriceAggressive} \) is an ordinal variable that takes the value of one when \( O_t \) is classified in the most aggressive category and takes a value of seven when \( O_t \) is classified in the least aggressive category. The first four categories represent orders that demand liquidity from the limit order book and the last three categories represent orders that supply liquidity to the book.  

To render the results more comparable across stocks, we normalize the continuous (non-dummy) variables by dividing the actual observation by the median for the stock on control days. \( \text{OrderExposure} \) equals one if the order \( O_t \) that arrives at time \( t \) has a hidden size and equals zero otherwise. \( \text{TotalOrderSize} \) is total (displayed plus hidden) size of the order \( O_t \) divided by median order size during the control period.

The variables describing market conditions at time of order submission are defined as follows. \( \text{Spread} \) is the percentage bid-ask spread at time \( t \) divided by the median percentage spread during the control period. \( \text{DepthSame} \) is the displayed depth at the best bid (ask) when \( O_t \) is a buy (sell) order divided by the median depth during the control period. \( \text{DepthOpp} \) is the displayed depth at the best ask (bid) when \( O_t \) is a sell (buy) order divided by the median depth during the control period. \( \text{BookOrderImbalance} \) is the percentage difference between displayed liquidity in the best five prices on the same side versus the opposite side of order \( O_t \) in the limit order book divided by the median percentage difference during the control period. \( \text{Volatility} \) is the standard deviation of quote midpoint returns over the preceding hour divided by the median volatility during the control period. \( \text{WaitTime} \) is the average elapsed time between the prior three order arrivals on the same side as the order \( O_t \) divided by the median time during the control period. \( \text{TradeFreqHour} \) is the number of transactions during the previous hour of trading divided by the median number of transactions for the previous hour of trading during the control period. We also include control variables based on recent transactions observed before submission of the order \( O_t \). \( \text{TradesSize} \) is the size of the most recent transaction divided by the median trade size during the control period. \( \text{HiddenOppSize} \) is the size of the hidden depth at the best ask (bid) revealed in the prior transaction when \( O_t \) is a buy (sell) order divided by the median hidden depth (of the opposite side) revealed in control period. \( \text{DisplayedOrderSize} \) is the exposed size of the previous order \( (O_{t-1}) \) divided by median exposed size of all orders submitted during the control period.

Finally, we include control variables that capture industry volatility, market volatility, and time-of-the-day effects. \( \text{FirstHour} \) (LastHour) is an indicator variable that equals one for orders submitted in the first (last) hour of the trading day and equals zero otherwise. \( \text{Ind.Volatility} \) is the return volatility of the portfolio of all Euronext-Paris stocks belonging to the same industry, and \( \text{Mkt.Volatility} \) is the

---

8 The most aggressive orders (Category 1) represents buy (sell) orders with order size greater than those displayed in the inside ask (bid) and with instructions to walk up (down) the book until the order is fully executed. Category 2 represents buy (sell) orders with order size greater than those displayed in the inside ask (bid) and with instructions to walk up (down) the book, but the order specifies a limit price such that the order is not expected to execute fully based on displayed book. Category 3 represents buy (sell) orders with the limit price equal to the inside ask (bid) and with order sizes greater than those displayed in the inside ask (bid). Orders in Category 2 and Category 3 could execute fully due to hidden liquidity but could also clear the book and convert to a standing limit order. Category 4 represents buy (sell) orders with the limit price equal to the inside ask (bid) and with order size less than those displayed in the inside ask (bid). These orders are expected to immediately execute in full. Category 5 represents orders with limit prices that lie within the inside bid and ask prices. Category 6 represents buy (sell) orders with limit price equal to the inside bid (ask). Finally, Category 7 represents buy (sell) orders with limit price less (greater) than the inside bid (ask). Following Liu and Agresti (2005) and Gelman and Hill (2007), we select a linear specification over a nonlinear specification (ordered probit) because the dependent variable represents a large number of price aggressiveness (seven) categories. When fitting a proportional odds model, little gain in efficiency is achieved when using more than four levels of the category variable over an ordinary least squares. Further, a linear regression specification allows an easy estimation of the economic significance of day-indicator variables and the cumulative measure.
return volatility of the CAC 40 index in the prior hour of trading, both divided by the median volatility numbers during the control period. The last two variables help account for commonality in economic fundamentals (see Chordia, Roll, and Subrahmanyam, 2000).

Columns 1 and 2 of Table 3 report the coefficients of the price aggressiveness regression along with corresponding t-statistics, estimated on an event-by-event basis and then aggregated across events using the Bayesian Aggregation described in Appendix A. The coefficients on the control variables are consistent with those reported in the prior studies. Traders submit less aggressively priced orders (i.e., choose limit orders over market orders) when (1) the inside bid-ask spread is wide, (2) same side book depth is thin, which signals less competition, (3) opposite side book depth is deep or the last trade does not reveal the presence of hidden orders, both of which signal active counterparties, (4) volatility is high, consistent with a volatility capture strategy (see Handa and Schwartz, 1996), (5) book imbalance signals less competition on same side relative to opposite side of the book, and (6) the limit price of the previous order (a proxy for omitted market conditions) is less aggressive. The impact of market volatility and industry volatility is not significant.

We focus on the coefficient estimates of indicator variables, DayMinus5 to DayMinus1. Note that the least aggressive order is categorized as 7 and the most aggressive order is categorized as 1. Thus, a negative (positive) DayMinus3 coefficient suggests the hypothesis that order flow observed on event Day [−3] is more (less) price aggressive than those observed on control days for the same firm. Because the research design attributes abnormal order flow on Day [−3] to informed agents, a negative DayMinus3 coefficient suggests that informed agents use more aggressively priced orders to build the positions.

For buy orders submitted before positive events (Column 1), all five coefficients corresponding to Days [−5,−1] are negative, and DayMinus3 and DayMinus1 coefficients have t-statistics below −2.0. Overall, the cumulative effect coefficient is −0.56 (see Panel B, t-statistic = −2.71), implying that informed traders submit more aggressively priced buy orders before positive events. For sell orders submitted before negative events (Column 2), four of the five coefficients corresponding to Days [−5,−1] are positive and the DayMinus5 coefficient is statistically significant (t-statistic = 2.23). The lack of a clear pattern of price aggressiveness between Day [−5] and Day [−1] points to the possibility that informed agents are not certain about the exact timing of the news release. The cumulative effect coefficient of 0.24 (t-statistic = 1.65) suggests that informed traders submit less aggressively priced sell orders before negative events. The “t-statistic of the difference between positive and negative events” tests the null hypothesis that the event effects for positive and negative news are the same. The highly significant t-statistic (= −3.16) suggests that informed traders strategies are influenced by the direction of the news. The asymmetry in informed trader strategies before positive and negative events is a novel contribution of our study.

In terms of economic significance, the cumulative effect coefficient in linear specification is interpreted as the change in price aggressiveness on Days [−5,−1] relative to control Days [−30,−10] after accounting for other determinants of price aggressiveness. Focusing on all positive events (Column 1), the cumulative coefficient −0.56 implies that, relative to the average price aggressiveness of 5.18 observed on control days, price aggressiveness increases on Days [−5,−1] by 10.8%. For negative events, a similar analysis indicates a decrease in price aggressiveness of 4.8%. We also examine the distribution of the seven categories of price aggressiveness on event days relative to control days. The observed changes in price aggressiveness point to a 8.12% increase in the frequency of aggressive orders (Category 1 to Category 4) on Days [−5,−1] for positive news versus a 4.67% decrease in the frequency of similar aggressive orders on Days [−5,−1] for negative news.

3.3. The speed of price discovery before positive and negative events

Microstructure models predict that stock prices incorporate more information when informed agents use aggressive orders before news releases. In this subsection, we investigate asymmetry in learning and price discovery before positive and negative events using unbiasedness regressions following Blais, Hillion, and Spatt (1999). For each half-hour time period (t) in interval Days [−5,−1], we regress the return from close on Day [−6] to close on Day [t+1] on the return from close on Day [−6] to end of time period t, as follows:

\[ r_{t-6, t+1} = \alpha + \beta \cdot r_{t-6, t} + \epsilon_t. \]  

We separately estimate the cross-sectional regression for each time period t and calculate confidence intervals based on the standard error of the slope. Barclay and Hendrshott (2003) interpret the slope of the unbiasedness regressions as a signal:noise ratio. According to the learning hypothesis, the slope will move closer to one as the pre-event security price reflects the post-event price with increasing precision.

Fig. 2 presents the slope and the confidence intervals for positive and negative events. At the beginning of interval [−5,−1] for both types of events, the slope is not significantly different from zero. In the case of positive events, toward the end of the interval [−5,−1], the slope is significantly different from zero and not significantly different from one. Thus, we cannot reject the learning hypothesis that informational efficiency of the pre-event stock price is no different from the post-event stock price before positive events. Interpretations are similar from the bar chart that shows the ratio of the root mean square error (RMSE) of the unbiasedness regression to the unconditional standard deviation of return from close on Day [−6] to close on Day [t+1]. As the announcement day gets closer, the bar chart shows that the ratio declines.

In the case of negative events, the slope of the unbiasedness regression is significantly lower than one and, in
Table 3

Regression analysis of price aggressiveness and trading costs surrounding unscheduled corporate events.

The table reports the regression coefficients that reflect the change in price aggressiveness and the change in trading costs around unscheduled corporate events (Days [−5, +1], with Day 0 denoting the event day) relative to control days after controlling for order attributes and market conditions. The sample consists of 95 Euronext-Paris stocks with 101 events. We separately investigate buy (sell) orders around positive (negative) events. Price aggressiveness is defined as an ordinal variable that takes the value of one when the order is classified as the most aggressive category and takes a value of seven when it is classified in the least aggressive category. Detailed definitions of the categories and all the explanatory variables are provided in Section 3.2. Columns 3–8 present the coefficients of implementation shortfall, effective spreads and opportunity costs regressions, following the approach proposed by Perold (1988). For a buy order, effective spread cost is defined as the difference between the filled price of each submitted order and the mid-quote price at the time of order submission; opportunity cost, the difference between the closing price on the day of order cancellation or expiration and the quote midpoint at the time of order submission; and implementation shortfall, the summation of the two costs. For effective spread cost, we report regression results conditional on partial execution (effective spread cost ≠ 0, Columns 5 and 6). For opportunity cost, we report regression results conditional on partial non-execution (opportunity cost ≠ 0, Columns 7 and 8).

Panel A reports the regression coefficients (and t-statistic in parenthesis) of market conditions and limit order book variables, as well as individual day coefficients on event Days [−5, +1] that reflects the change in price aggressiveness and trading costs before the event for the same firm relative to control days. Panel B reports cumulative effects (and t-statistic in parenthesis) that sum up the individual day coefficients on Days [−5, −1] relative to control period (Days [−30, −10]) for the same firm. Time series coefficients are estimated on an event-by-event basis. Reported results are aggregated across events using the Bayesian framework of DuMouchel (1994) described in Appendix A. We also report the t-statistic of the difference between positive and negative events.

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Price aggressiveness</th>
<th>Implementation shortfall</th>
<th>Effective spread cost: fill rate &gt;0%</th>
<th>Opportunity cost: fill rate ≤100%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Buy orders, negative events Coefficient</td>
<td>Buy orders, positive events Coefficient</td>
<td>Buy orders, negative events Coefficient</td>
<td>Buy orders, positive events Coefficient</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Intercept</td>
<td>4.8866</td>
<td>4.8747</td>
<td>0.0541</td>
<td>0.0560</td>
</tr>
<tr>
<td></td>
<td>(79.72)</td>
<td>(63.23)</td>
<td>(3.03)</td>
<td>(2.81)</td>
</tr>
<tr>
<td>Price aggressiveness</td>
<td>−0.1933</td>
<td>0.0005</td>
<td>−0.0175</td>
<td>−0.0304</td>
</tr>
<tr>
<td></td>
<td>(−9.80)</td>
<td>(0.43)</td>
<td>(−2.95)</td>
<td>(−0.69)</td>
</tr>
<tr>
<td>Order exposure</td>
<td>0.0030</td>
<td>0.0044</td>
<td>−0.0584</td>
<td>−5.3622</td>
</tr>
<tr>
<td></td>
<td>(−2.87)</td>
<td>(0.46)</td>
<td>(0.83)</td>
<td>(0.11)</td>
</tr>
<tr>
<td>Book order imbalance</td>
<td>−0.0008</td>
<td>−0.0009</td>
<td>−0.0049</td>
<td>−0.0029</td>
</tr>
<tr>
<td></td>
<td>(−1.15)</td>
<td>(−1.17)</td>
<td>(0.19)</td>
<td>(−2.10)</td>
</tr>
<tr>
<td>Volatility</td>
<td>0.0039</td>
<td>0.0016</td>
<td>0.0004</td>
<td>−0.0029</td>
</tr>
<tr>
<td></td>
<td>(0.68)</td>
<td>(0.11)</td>
<td>(0.19)</td>
<td>(−2.10)</td>
</tr>
<tr>
<td>Trade frequency</td>
<td>−0.0612</td>
<td>−0.0531</td>
<td>−0.0035</td>
<td>0.0051</td>
</tr>
<tr>
<td></td>
<td>(−2.58)</td>
<td>(−2.26)</td>
<td>(−1.55)</td>
<td>(1.76)</td>
</tr>
<tr>
<td>Lag (price aggressiveness)</td>
<td>−8.9688</td>
<td>−9.1807</td>
<td>−0.0035</td>
<td>−0.0029</td>
</tr>
<tr>
<td></td>
<td>(−9.18)</td>
<td>(−9.18)</td>
<td>(0.37)</td>
<td>(1.81)</td>
</tr>
<tr>
<td>Lag (displayed order size)</td>
<td>−0.0040</td>
<td>−0.0062</td>
<td>−0.0035</td>
<td>0.0014</td>
</tr>
<tr>
<td></td>
<td>(−1.34)</td>
<td>(1.88)</td>
<td>(1.37)</td>
<td>(1.81)</td>
</tr>
<tr>
<td>Lag (last trade size)</td>
<td>0.0020</td>
<td>0.0059</td>
<td>0.0020</td>
<td>0.0059</td>
</tr>
<tr>
<td></td>
<td>(2.21)</td>
<td>(2.38)</td>
<td>(2.21)</td>
<td>(2.38)</td>
</tr>
</tbody>
</table>

(continued on next page)
Table 3 (continued)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Price aggressiveness</th>
<th>Implementation shortfall</th>
<th>Effective spread cost: fill rate ≥ 0%</th>
<th>Opportunity cost: fill rate ≤ 100%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Buy orders</td>
<td>Sell orders</td>
<td>Buy orders</td>
<td>Sell orders</td>
</tr>
<tr>
<td></td>
<td>positive events</td>
<td>negative events</td>
<td>positive events</td>
<td>negative events</td>
</tr>
<tr>
<td></td>
<td>Coefficient (1)</td>
<td>Coefficient (2)</td>
<td>Coefficient (3)</td>
<td>Coefficient (4)</td>
</tr>
<tr>
<td>HiddenOppSide (norm)</td>
<td>−0.0395 (−7.25)</td>
<td>−0.1111 (−5.61)</td>
<td>−0.0053 (−1.42)</td>
<td>−0.0115 (−0.11)</td>
</tr>
<tr>
<td>First trading hour indicator</td>
<td>0.0028 (0.10)</td>
<td>0.0813 (1.75)</td>
<td>0.0037 (−0.42)</td>
<td>−0.0151 (−0.21)</td>
</tr>
<tr>
<td>Last trading hour indicator</td>
<td>−0.1489 (−5.79)</td>
<td>−0.1785</td>
<td>−0.123 (0.50)</td>
<td>−0.0055 (−0.34)</td>
</tr>
<tr>
<td>Market volatility (norm)</td>
<td>0.0004 (0.16)</td>
<td>−0.0005 (−0.49)</td>
<td>−0.123 (0.50)</td>
<td>−0.0055 (−0.34)</td>
</tr>
<tr>
<td>Industry volatility (norm)</td>
<td>0.0010 (1.51)</td>
<td>0.0001 (0.08)</td>
<td>−0.123 (0.50)</td>
<td>−0.0055 (−0.34)</td>
</tr>
</tbody>
</table>

Panel A2: Individual day dummies

<table>
<thead>
<tr>
<th>Variable</th>
<th>Price aggressiveness</th>
<th>Implementation shortfall</th>
<th>Effective spread cost: fill rate ≥ 0%</th>
<th>Opportunity cost: fill rate ≤ 100%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Buy orders</td>
<td>Sell orders</td>
<td>Buy orders</td>
<td>Sell orders</td>
</tr>
<tr>
<td></td>
<td>positive events</td>
<td>negative events</td>
<td>positive events</td>
<td>negative events</td>
</tr>
<tr>
<td></td>
<td>Coefficient (1)</td>
<td>Coefficient (2)</td>
<td>Coefficient (3)</td>
<td>Coefficient (4)</td>
</tr>
<tr>
<td>DayMinus5 (dummy)</td>
<td>−0.1689 (−1.46)</td>
<td>0.1423 (2.23)</td>
<td>0.0275 (0.88)</td>
<td>−0.0553 (−1.42)</td>
</tr>
<tr>
<td>DayMinus4 (dummy)</td>
<td>−0.0711 (−0.98)</td>
<td>0.0494 (1.01)</td>
<td>0.0037 (0.12)</td>
<td>−0.0115 (−0.42)</td>
</tr>
<tr>
<td>DayMinus3 (dummy)</td>
<td>−0.1032 (−2.04)</td>
<td>0.0138 (2.4)</td>
<td>0.0846 (2.67)</td>
<td>−0.0350 (−2.59)</td>
</tr>
<tr>
<td>DayMinus2 (dummy)</td>
<td>−0.1501 (−1.69)</td>
<td>−0.0034 (−0.07)</td>
<td>0.0161 (0.36)</td>
<td>0.0114 (0.33)</td>
</tr>
<tr>
<td>DayMinus1 (dummy)</td>
<td>−0.1088 (−2.61)</td>
<td>0.0475 (0.54)</td>
<td>0.1018 (2.61)</td>
<td>−0.0142 (−0.48)</td>
</tr>
<tr>
<td>Day0 and DayPlus1 (dummy)</td>
<td>−0.0309 (−0.91)</td>
<td>0.0324 (0.56)</td>
<td>0.0830 (3.51)</td>
<td>−0.0181 (−0.78)</td>
</tr>
<tr>
<td>DayPlus2 (dummy)</td>
<td>−0.0080 (−0.37)</td>
<td>0.0215 (0.27)</td>
<td>0.0011 (0.05)</td>
<td>−0.0381 (1.67)</td>
</tr>
</tbody>
</table>

Panel B: Cumulative effect of day minus 5 to day minus 1 coefficients

<table>
<thead>
<tr>
<th>Variable</th>
<th>Cumulative effect DayMinus5 to DayMinus1</th>
<th>t-statistic of the difference between positive and negative events</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>−0.5617 (−2.71)</td>
<td>−3.16 (−2.62)</td>
</tr>
<tr>
<td></td>
<td>0.2488 (1.65)</td>
<td>2.62 (0.37)</td>
</tr>
<tr>
<td></td>
<td>0.2422 (2.43)</td>
<td>2.62 (0.37)</td>
</tr>
<tr>
<td></td>
<td>−0.0771 (−1.10)</td>
<td>2.62 (0.37)</td>
</tr>
<tr>
<td></td>
<td>0.0107 (0.50)</td>
<td>2.62 (0.37)</td>
</tr>
<tr>
<td></td>
<td>0.0020 (0.19)</td>
<td>2.62 (0.37)</td>
</tr>
<tr>
<td></td>
<td>0.3234 (2.17)</td>
<td>2.62 (0.37)</td>
</tr>
<tr>
<td></td>
<td>−0.1849 (−1.77)</td>
<td>2.62 (0.37)</td>
</tr>
</tbody>
</table>
Fig. 2. The speed of learning before positive and negative events.
This figure plots the speed of price discovery before corporate events based on the coefficients from an unbiasedness regression specification, following Biais, Hillion, and Spatt (1999). For each half-hour time period (i) in the interval Days [−5, −1], we regress the close-to-close return (ret_{i}) in interval Days [−6, +1] on return from the close on Days [−6] to the end of time period i (ret_{-6}). For both positive and negative events, we estimate the unbiasedness regressions cross-sectionally for each time period. The figure plots the beta coefficient and the confidence intervals (dotted line) based on standard error of the beta coefficient. The bar graph shows the ratio of the root mean square error (RMSE) of each unbiasedness regression to the unconditional standard deviation of the close-to-close return (ret_{-6}).

fact, does not reach one by the close on Day [−1]. Similarly, the bar chart indicates that residual variance relative to return variance from close on Day [−6] to close on Day [+1] remains high. Thus, security prices incorporate less news before negative events than positive events.

In a related analysis that links informed trader strategies to the speed of price discovery, we estimate a cross-sectional regression of the event i’s CAR_ratio, defined as \( \text{CAR}_{[0,+1]} / \text{CAR}_{[-5,+1]} \), on event i’s cumulative effect coefficient (AGG_CumEffect) from the event-by-event regression [Eq. (1)]. A higher CAR_ratio indicates that stock prices incorporate less news before the event. A higher value of AGG_CumEffect indicates that informed traders employ less price aggressive orders before the event. The
regressions results are:

\[
\text{CAR}_{\text{ratio}} = \alpha + \beta \text{AGG}_\text{CumEffect}_t + \epsilon_t \\
0.557 \quad 0.449
\]

\[t - \text{stat} = (3.17) \quad (2.13)\]  

(3)

The positive coefficient on \(\text{AGG}_\text{CumEffect}\) suggests that stock prices incorporate more news when informed agents employ more price aggressive orders before news release.

3.4. Opportunity costs of non-execution of limit orders before positive and negative events

The price discovery analysis indicates that stock prices drift more in the direction of news before positive events than negative events. This result has important implications for the informed trader’s choice of a market order versus a limit order. A drift in stock price in the direction of the signal lowers the informed traders’ probability of execution of a limit order because prices tend to gravitate away from the limit price. To prevent limit orders from becoming stale, the informed trader has to keep offering better prices, implying it is more costly to employ limit orders before positive events than negative events.

In this analysis, we estimate the cost of non-execution of a limit order before positive and negative events using the implementation shortfall framework proposed by Perold (1988) and implemented by Harris and Hasbrouck (1996) and Griffiths, Smith, Turnbull, and White (2000). Prior studies note that each order is associated with two cost components: (1) the effective spread cost, which relates to the portion of the order that is executed, is measured as the appropriately signed difference between the fill price and the quote midpoint at the time of order submission, and (2) the opportunity cost, which relates to the portion of the order that goes unfilled, is the appropriately signed difference between the closing price on order expiration or cancellation date and quote midpoint at the time of order submission. The implementation shortfall cost for an order is the weighted sum of effective spread and opportunity cost, in which weights are the proportion of order size that is filled and unfilled, respectively.

Table 3 presents regression coefficients of implementation shortfall costs on the prevailing market conditions and order attributes. For a limit order that goes unfilled, the effective spread cost is zero. Thus, the effective spread regression (Columns 5 and 6) includes only orders with either partial or full execution (fill rate > 0%). Consistent with Harris and Hasbrouck (1996), we find that orders that are more aggressively priced are associated with higher effective spread cost. After controlling for price aggressiveness, the incremental effective spread cost on Days [−5, −1] relative to control days, as reflected in the cumulative effect coefficient, is not statistical significant. Thus, we do not find evidence that trading costs, conditional on execution, are significantly higher before unscheduled events.

We next focus on coefficients of opportunity cost regressions reported in Columns 7 and 8. For an order that is fully executed, the opportunity cost is zero; thus, the analysis considers only orders with partial or full non-execution (fill rate < 100%). When a limit order goes unfilled, the informed trader would need to transact later, possibly at a less advantageous price. The opportunity cost, which captures the cost of the delayed execution, is positive if the stock price moves higher (lower) after a buy (sell) limit order is placed. The results in Columns 7 and 8 suggest that hidden orders are associated with smaller opportunity costs. This result is consistent with Bessembinder, Panayides, and Venkataraman (2009), who show that hidden orders are primarily used by uninformed traders to control order exposure risk.

Results in Table 3 on opportunity costs suggest that employing limit orders on Days [−5, −1] before positive events is costly. For buy orders (Column 7), the cumulative effects coefficient is 0.32 (t-statistic = 2.17), implying that informed traders face a higher cost when a limit order goes unfilled before a positive event relative to control days. The finding is consistent with the price discovery pattern that the stock price incorporates a portion of the good news before positive events. For sell orders (Column 8), the opportunity cost is negative, implying that the stock price does not gravitate away from the limit price before negative events. The difference in opportunity costs between positive and negative events (t-statistic of difference = 2.79) leads to a difference in implementation shortfall costs (t-statistic = 2.62) reported in Columns 3 and 4.

4. Modeling an informed trader’s strategy

The results thus far point to an asymmetry in order flow before positive and negative events. Before positive events, the proportion of aggressively priced orders is increasing; before negative events, the proportion is decreasing. Further, when a limit order goes unfilled, we estimate large opportunity costs prior to positive events but not negative events, indicating that employing an aggressive strategy before positive events is reasonable. The goal of this section is to provide a falsifiable economic rationale for these results; that is, to provide a model that matches the findings and offers novel empirical predictions that are outside our initial findings.

The natural candidate for an explanation of any form of asymmetry in trading patterns between positive and negative news is costly short selling. This is our starting point. In Kaniel and Liu (2006), the lower the probability that the next trader is informed, the more likely the current (informed) trader submits a limit order. We believe that an amalgam of the economics that underlies Kaniel and Liu (2006) together with buy–sell asymmetry in competition that is introduced by costly short selling, as in Diamond and Verrecchia (1987), is a good foundation to build our framework.

We study a two-period Glosten and Milgrom (1985) model with competitive market makers. In the first round of trading, the active (whether noise or informed) trader can submit a limit order or a market order.  

---

\(^{10}\) A related literature on block trading examines buy–sell price impact asymmetry; that is, the well-known result that block purchases of securities convey more information than block sales of securities (see Kraus and Stoll, 1972, Keim and Madhavan, 1998). Saar (2001) motivates the idea that informed sellers could trade for liquidity reasons while informed buyers do not, which is a source of price impact asymmetry.
Because the asset liquidates after the second round, there is no point in submitting a limit order in the second round. Informed traders have identical information and trade in the same direction; that is, buy if the event is positive and sell if the event is negative. The probability of execution of informed limit order is inversely related to the mass of informed trading. Kaniel and Liu show that if the mass of informed trading in the second round is sufficiently small, then an informed trader in round one finds it optimal to submit limit orders. Our model relies on costly short selling to replicate the result in Kaniel and Liu (2006) in a non-symmetric manner. When the event is positive, all informed traders in the second round, constrained or not, are active. When the event is negative, informed sellers can choose to abstain if the borrowing costs are high or the event is small.

4.1. The model

We consider an event period that contains two trading rounds. The timing of the model is as follows: Market makers post bid and ask prices for the first round of trading. A trader is picked at random from a large pool of potential traders, and submits an order (either a market or a limit order). When round two commences, market makers refresh their quotes. A second trader is then picked at random and submits a market order. The asset liquidates.

We denote the asset value by $\tilde{v}$ and assume it is a $0\sim1$ random variable.\(^{11}\) We let $H_0$ denote the history of trade up to the start of the event period and let

$$p_0 = P(|H_0 - 1| = E_g \tilde{v} = E[\tilde{v}|H_0] = P(\tilde{v} = 1|H_0)$$

be the prior. Before the history of trades unfolds, $p_0$ itself is a random variable. However, during the event period, the prior, $p_0$, is common knowledge and, for the remainder of this subsection, we treat $p_0$ as a parameter.

A positive event is $[\tilde{v} = 1]$, and a negative event is $[\tilde{v} = 0]$. We say that an event is small when the magnitude of $\tilde{v} - p_0$ is small. That is, a positive event is small when $p_0$ is close to one, and a negative event is small when $p_0$ is close to zero. When the event is small, the potential gains of informed traders are small.

As in all probability selection models, we need to specify the types of potential traders and their respective masses. All together, our model has four groups of potential traders. There are two groups of noise traders: market order traders and limit order traders. There are also two groups of informed traders: unconstrained and constrained informed traders. The distinction is according to whether or not the traders belong to the firm’s investor base. Unconstrained investors already own the stock before the event period. Constrained investors do not own the stock and can sell only when they pay the borrowing costs associated with short selling.

To simplify our analysis, we assume constrained informed traders are not present in the first round. This assumption can be interpreted as information leakage. Initially (in the first round of trading), information is acquired by traders who are interested in the stock. Later (in the second round of trading), the information leaks to traders who are not part of the firm’s investor base; i.e., constrained traders. That said, this model is not about information leakage, and the assumption is made for simplification.\(^{12}\)

It is natural to assume that the mass of each group of traders is related to the size of the firm’s investor base. We let $\beta \in (0, 1)$ be a measure of the size of the investor base. In each trading round, the mass of noise traders who submit market orders is $2\beta\tilde{v}$, and each of these traders is equally likely to buy or sell. In the first round of trading, the mass of noise traders who submit limit orders is $2\beta$, and each of these traders is equally likely to submit a buy or a sell limit order. We assume that noise limit order traders are absent from the second round of trading.\(^{13}\) The total mass of informed traders in the first round is $\beta\mu$, consistent with our assumption that only unconstrained informed traders are present in the first round. The total mass of informed traders in the second round depends on whether or not constrained informed traders participate. We write the mass of informed traders in the second round as

$$\mu = \mu_1 + \mu_2 = \beta\mu + (1 - \beta)\mu^-,$$

where $\mu^-$ has to be determined in equilibrium. If constrained informed traders choose to abstain, then $\mu^- = \beta\mu$, and if they short sell, then $\mu^- = \mu$.

Let $a_i$ and $b_i$ be the posted ask and bid prices in the ith round of trading. For the first round, $i \in \{1, 2\}$. We let $O_i$ denote the order in round $i$, where $MB$, $MS$, $LB$, $PB$, $LS$, and $PS$ are market buy, market sell, limit buy, and limit sell, respectively, and $PB$ and $PS$ are limit buy and limit sell prices, respectively.

Our notion of equilibrium requires that the following conditions, Eqs. (8)-(13) and Eqs. (18)-(22) hold. First are

---

\(^{11}\) The two point distribution simplifies our analysis and is common in the literature. However, this assumption is a deviation from Kaniel and Liu, who assume that the asset value is drawn from a continuous and symmetric distribution. In Kaniel and Liu (2006), informed traders use limit orders when the asset value is sufficiently close to the unconditional expected value of the asset (i.e., in equilibrium, informed traders use limit orders when the value is between the bid and ask price, or barely outside the quotes ). Also in our model, informed traders end up using limit orders if the value is sufficiently close to the expected value of the asset (though an artifact of the two point distribution assumption is that the asset value is always outside the quotes). Thus, the choice of support is benign.

\(^{12}\) In Kaniel and Liu, there is a positive probability of information leakage, though they assume that in such a case everyone learns the information.

\(^{13}\) Noise limit orders provide camouflage to the informed traders’ limit orders. Limit orders placed in the second round never execute, so we choose to turn off the presence of noise limit order traders in the last round. Kaniel and Liu choose to assume that in the last round of trading, the mass of noise limit order traders is added to the mass of noise market order traders, which increases the proportion of noise trading in the last round. Qualitatively, the choice of assumption has no impact on the asymmetry between positive and negative events.
the rationality conditions for the market makers quotes in the first trading round.

\[ a_1 = E_0[\hat{p}|O_1 = MB] \tag{8} \]

and

\[ b_1 = E_0[\hat{p}|O_1 = MS] \tag{9} \]

Next, we require that limit prices satisfy

\[ PS = E_0[\hat{p}|O_1 = (LS, PS), O_2 = MB] \tag{10} \]

and

\[ PB = E_0[\hat{p}|O_1 = (LB, PB), O_2 = MS] \tag{11} \]

To see why these conditions are natural, consider Eq. (10), which corresponds to the offer (ask) side. If the trader posts at a price strictly higher than the conditional expectation, then market makers will undercut and the limit order will never execute. If the trader posts at a price strictly lower than the conditional expectation, it would be a needless concession. Therefore, condition (10) is natural. A similar argument justifies condition (11).\(^{14}\)

We also require that, in round one, an informed trader optimally chooses between a market order and a limit order, taking into account the execution risk of the limit order. That is, in a positive event, an informed trader prefers a buy market (resp. limit) order over a buy limit (resp. market) order at PB only if

\[ (1 - a_1) \geq (1 - PB) \frac{\beta z}{2 \beta z + \mu} \tag{12} \]

and, in a negative event, an informed trader prefers a sell market (resp. limit) order over a sell limit (resp. market) order at PS only if

\[ b_1 \geq PS \frac{\beta z}{2 \beta z + \mu} \tag{13} \]

The fraction that appears on the right hand side of (12) (resp. (13)) is the execution probabilities of a buy (resp. sell) limit order, conditional on positive (resp. negative) event.

**Lemma 1.** Consider the first round of trading. If informed traders use limit orders, then informed traders and noise traders use the same limit prices, and informed traders are indifferent between limit orders and market orders.

The proof, found in Appendix B, relies only on mutual consistency between conditions (8)–(13). Thus, the lemma is a partial equilibrium result. The first part of the lemma implies that, to find the equilibrium, we need to find a single pair of deterministic limit prices: PS and PB. Moreover, because both noise and informed traders use the same nonrandom limit prices, limit prices do not contain information. Thus, we do not lose any generality if we assume that the first round order, O₁, is in the set \{MB, MS, LB, LS\} and rewrite Eqs. (10) and (11) as

\[ PS = E_0[\hat{p}|O_1 = LS, O_2 = MB] \tag{14} \]

and

\[ PB = E_0[\hat{p}|O_1 = LB, O_2 = MS] \tag{15} \]

The second part of the lemma says that limit orders cannot be strictly optimal for informed traders. This means that whenever informed traders use limit orders, they might as well use market orders. Let \( m_p \) and \( m_n \) be the probabilities that an informed trader submits market orders when the event is positive and negative, respectively. The probabilities that an informed trader submits limit orders for positive and negative events are \( 1 - m_p \) and \( 1 - m_n \), respectively. Because limit orders cannot be strictly optimal, Lemma 1 implies that we do not lose any generality if we replace (12) and (13) with

\[ (1 - a_1) \geq (1 - PB) \frac{\beta z}{2 \beta z + \mu} \quad \text{with} \quad > \quad \text{only if } m_p = 1 \tag{16} \]

and

\[ b_1 \geq PS \frac{\beta z}{2 \beta z + \mu} \quad \text{with} \quad > \quad \text{only if } m_n = 1 \tag{17} \]

The quotes in the second round of trading should depend on the type of order that was submitted in the first round, and we therefore denote them by \( a_2(O_1) \) and \( b_2(O_1) \). We require that

\[ a_2(O_1) = E_0[\hat{p}|O_1 = O_1, O_2 = MB] \tag{18} \]

and

\[ b_2(O_1) = E_0[\hat{p}|O_1 = O_1, O_2 = MS] \tag{19} \]

The above is consistent with conditions (14) and (15); namely, \( a_2(LS) = PS \) and \( b_2(LB) = PB \). The subtle point is that if \( O_1 = LS \), then \( a_2(LS) \) is a limit order trader’s quote and \( b_2(LS) \) is the market makers’ quote. Similarly, if \( O_1 = LB \), then \( b_2(LB) \) is a limit order trader’s quote and \( a_2(LB) \) is the market makers’ quote. If \( O_1 \) is a market order, then both quotes are the market makers’ quotes. Conditions (18) and (19) state that regardless who is quoting, the quotes satisfy the standard rationality condition in round two.

Finally, during a negative event, constrained investors are present only if the bid is greater than the borrowing costs. To emphasize the dependency of the mass of informed trading during negative event on the posted bid, we write \( \mu^-(b_2) \). We denote the borrowing costs by \( c \) and require that

\[ b_2 > c \Rightarrow \mu^-(b_2) = \mu \tag{20} \]

\[ b_2 < c \Rightarrow \mu^-(b_2) = \beta \mu \tag{21} \]

and

\[ b_2 = c \Rightarrow \mu^-(b_2) \in [\beta \mu, \mu] \tag{22} \]

\(^{14}\) The limit prices that satisfy (10) and (11) are the ones that minimize the expected losses from trade of the group of noise limit order traders, subject to the constraint that the limit order is the best quote in the second round. Kaniel and Liu also posit the same price, though they also verify a participation constraint; that is, a noise limit order trader should not prefer market orders. In their Lemma 6, Kaniel and Liu show the constraint is never binding. Also, here the participation constraint is never binding, and we choose not to include it as part of our definition of equilibrium.
Condition (22) is relevant only in a knife-edge situation, in which the constrained investors are indifferent. In that case, any value for \( \mu^-(b_2) \) in the interval \( \{\beta\mu, \mu\} \) is acceptable.

Hereafter, an equilibrium is a tuple 
\[
(a_1, b_1, m_p, m_n, a_2(\cdot), b_2(\cdot), PB, PS, \mu^-(\cdot))
\]
such that, for every \( O_1 \in \{MB, MS, LB, LS\} \), the elements of the tuple
\[
(a_1, b_1, m_p, m_n, a_2(O_1), b_2(O_1), PB, PS, \mu^-(b_2(O_1)))
\]
satisfy conditions (8)-(13) and (18)-(22).

Lemma 2 shows that our model is not vacuous. If borrowing costs are high, the investor base is narrow, and the event is small and negative, then informed traders may submit sell limit orders (i.e., \( m_n < 1 \)), while constrained informed traders abstain.

Lemma 2. Assume the event is negative.

1. If borrowing cost is large or event is small, such that \( p_0 < c \), then constrained informed traders abstain in the second round (i.e., \( \mu^-(b_2(LS)) = \beta\mu \)).
2. If event is small such that \( p_0 < \mu/(z + 2\mu) \), constrained informed traders abstain (i.e., \( \mu^-(b_2(LS)) = \beta\mu \)), and investor base is narrow (i.e., \( \beta \) is sufficiently small), then informed traders in the first round use limit orders (i.e., \( m_n < 1 \)).

The proof of Lemma 2 is in Appendix B.

4.2. Empirical predictions

Recall that \( p_0 = E[p|H_0] \), the prior, depends on the realization of the history up to the start of the event window. Our empirical prediction is based on the assumption that the prior is a symmetric random variable, \( \tilde{p}_0 \). That is, positive events are as likely as negative events, and small positive events are as likely as small negative events. In particular, \( E\tilde{p} = 1/2 \). Thus, the only source of asymmetry between positive and negative events in our model is the need of constrained informed traders to borrow the shares during negative events.

To emphasize the dependency of the equilibrium on the realization of \( \tilde{p}_0 \), we write the equilibrium as \( (a_1(p_0), b_1(p_0), m_p(p_0), m_n(p_0), a_2(p_0, O_1), b_2(p_0, O_1), PB(p_0), PS(p_0), \mu^-(b_2(p_0, O_1))) \) for every \( O_1 \in \{MB, MS, LB, LS\} \).

In preparation for our Theorem 1, in Lemma 3 we compare the probability of informed sell market orders during negative events and informed buy market orders during positive events. To control for the size of the event, the comparison is carried at symmetric values of the prior. That is, we compare \( m_n(p_0) \) with \( m_p(1 - p_0) \).

Lemma 3. Consider the equilibria that correspond to \( \tilde{p}_0 = p_0 \) and to \( \tilde{p}_0 = 1 - p_0 \). Then,

1. \( m_n(p_0) \leq m_p(1 - p_0) \).
2. If both \( \mu^-(b_2(LS)) < \mu \) and \( m_n(p_0) < 1 \) hold, then \( m_n(p_0) < m_p(1 - p_0) \); i.e., the inequality is strict.

Theorem 1. Assume that \( \tilde{p}_0 \) is drawn from a symmetric distribution.

1. Unconditionally (i.e., without reference to the realization of \( \tilde{p}_0 \)), the probability of observing a sell limit order when the event is negative is as high as the probability of observing a buy limit order when the event is positive.
2. [Asymmetry] Consider small events (i.e. \( \tilde{p} - \tilde{p}_0 \) is close to zero). If borrowing costs are sufficiently high and the investor base is sufficiently small, then the probability of observing a sell limit order in a negative event is strictly greater than the probability of observing a buy limit order in a positive event.
3. [Symmetry] When the investor base is large, events are large, or borrowing costs are small, then the probability of observing a sell limit order in a negative event is similar to the probability of observing a buy limit order in a positive event.

Both the proof of Lemma 3 and the proof of Theorem 1 are in Appendix B.

Our model predicts that short sale constraints lead to asymmetry in informed traders’ strategies before positive and negative events. The empirical literature (see Harris and Hasbrouck, 1996; Bloomfield, O’Hara, and Saar, 2005; Hopman, 2007; Bershova, Stephens, and Waelbroeck, 2014) shows that the price impact of a market order is significantly larger than the price impact of a limit order. This evidence is consistent with the patterns in Fig. 2, in which stock prices incorporate more news before positive events than negative events. That is, the usage of more aggressive informed traders’ strategies before positive events leads market participants to incorporate more news before positive events than negative events. We posit the following prediction that relates short sale constraints to price efficiency asymmetry before events:

4. [Price efficiency asymmetry] The stock price incorporates more news before positive events than negative events, particularly when event is small, investor base is narrow, and borrowing costs are high.

5. Cross-sectional evidence on order submission strategies, price discovery, and opportunity cost

Prior research has identified a number of firm attributes that are associated with the ease of short selling. We test our model’s predictions using three cross-sectional measures of short sale constraints. The first measure is the stock’s membership in an index, which influences the broadness of the investor base. Index firms tend to be larger, actively traded, and attract attention from analysts and buy-side institutions (Nagel, 2005). Index stocks are also easier to borrow because index funds are active lenders of securities. We classify stocks based on membership in the SBF 120 index, which represents a broader cross section of stocks than the CAC 40 index (Bessebinder and Venkataraman, 2004).

The second measure is the availability of exchange-listed options contracts in a stock. Battalio and Schultz (2011) show that traders build equivalent short positions using option contracts when short selling is difficult. Because options market makers enjoy special exemptions on inventory-hedging stock trades, they can assume short positions in the underlying stock at low cost and, via
this mechanism, exchange-listed options lower short sale constraints. Hu (2014) shows that options market makers hedge the inventory risk by short selling the underlying stock. Data on the availability of exchange-listed options for sample firms are obtained from the Euronext-Paris BDM database.

The third measure is based on a unique institutional feature on Euronext-Paris that affects the ease of short selling. For certain eligible stocks, the Deferred Settlement Service allows investors the convenience to take long and short positions with deferred settlement of the trade until the end of the month (see Foucault, Sraer, and Thesmar, 2011). Stocks that are eligible for SRD facility are selected by the exchange. An investor who wishes to sell short an SRD-eligible stock must flag the order as deferred execution. On executing the short sale, the broker effectively acts as a lender of the stock until the end of the month. In our setting, the SRD facility offers informed sellers a convenient way to short sell an SRD-eligible stock.15 Foucault, Sraer, and Thesmar (2011) report that short selling a stock that is not eligible for Euronext’s SRD facility is cumbersome because short sellers need to locate shares they want to sell in advance of executing a short sale. Information on SRD-eligibility for sample stocks in 2003 was made available by Euronext-Paris.

Our model predicts that informed traders’ strategy depends on the magnitude of the event. Informed sellers have incentives to locate difficult-to-borrow shares when negative news is large. When the negative news is small, the benefits from short selling might not outweigh the borrowing costs. We classify events as large when the absolute value of announcement day return exceeds 5%.16

Table 4 presents the main results on the cross-sectional analysis of events. Panel A reports the results for index membership and SRD-eligibility, and Panel B reports the results for options listing and announcement return. The model predicts that informed traders employ more aggressive strategies for all positive events (Columns 1, 3, 5, and 7 in Panels A and B), negative events without short constraints (Column 2 in Panels A and B and Column 6 in Panel A), and large negative events (Column 6 in Panel B). In addition, the model predicts that informed traders employ less price aggressive strategies before negative events in short constrained stocks (Column 4 in Panels A and B and Column 8 in Panel A) and small negative events (Column 8 in Panel B). For ease of exposition, we refer to the former category as market order (MO) equilibrium events and the latter category as limit order (LO) equilibrium events.

5.1. The cross section of informed traders’ strategy on price aggressiveness

Table 4 presents univariate statistics on daily market:limit ratio on event and control days. For all LO events, we observe a decrease in the market:limit ratio. As an example, in Column 4 of Panel A, the percentage of market:limit orders declines from 51.5% on control days to 47.4% on events days, indicating that informed traders employ a higher percentage of limit orders relative to market orders. Similar patterns are observed for other LO events reported in Column 8 of Panel A and Columns 4 and 8 of Panel B. In contrast, for all MO events, the market:limit ratio increases from control days to the event days indicating that informed traders employ a higher percentage of market orders relative to limit orders. These results provide preliminary support for the cross-sectional predictions of the model.

Table 4 reports the number of trades on control days and the percentage change (and the associated test of difference) in number of trades on the event days relative to control days. The increase in trading activity on the event days relative to control days is smaller for LO events relative MO events. As an example, the increase in trades for negative events in non-index firms is 11.9% (Column 4 of Panel A) and the increase in trades in Columns 1–3 of Panel A exceeds 20%. These patterns are consistent with the model’s assumption that constrained informed sellers abstain from trading when borrowing shares is difficult, or the benefits of short selling do not outweigh the costs.

In Table 4, we also report the cumulative effects coefficient based on an event-by-event price aggressiveness regression and then aggregated using the Bayesian framework described in Appendix A. The results provide strong support for the model predictions. For all MO events, the cumulative effects coefficient is negative, which indicates that informed order flow is associated with more price aggressive orders. In nine out of 12 columns, the coefficients are statistically significant at the 5% level and, in two columns, the coefficients are significant at the 10% level.

For all LO events, we observe a positive cumulative effects coefficient, which indicates that informed order flow is associated with less price aggressive orders. In two of four columns, the coefficients are statistically significant at the 5% level. For the remaining two columns, the coefficients are significant at the 10% level.

In addition, in the case of short sale constrained firms, we find support for a buy–sell asymmetry in order submission before positive and negative events. Table 4 reports the t-statistic of the difference in cumulative effects coefficient between positive and negative events. We find that the difference is highly significant for non-index stocks, non-SRD-eligible stocks, stocks without listed options, and events with small announcement returns. In contrast, the difference is not statistically significant for index stocks, SRD-eligible stocks, stocks with listed options, and events with large announcement returns. Thus, we observe a buy–sell asymmetry in order flow for stocks that are difficult to short sell but observe a symmetry in order flow for

15 For a typical retail order in June 2001, Foucault, Sraer, and Thesmar (2011) report that online brokers charge an additional fee of 0.2% of the order (with a minimum amount of 6.2 euros) for orders with deferred execution. In comparison, the median announcement returns for negative events reported in Table 1 is −2.57%.

16 In a robustness analysis, we divide the absolute value of the stock’s announcement returns by the stock’s average bid-ask spread on control days, and use this measure to classify events as large (above median) and small (below median). This measure helps incorporate the trade-off between using market orders and paying the spread versus using limit orders and receiving the spread. The sign (and statistical significance) of regression coefficients are similar to those reported in the study.

Please cite this article as: S. Baruch et al., Informed trading and price discovery before corporate events, Journal of Financial Economics (2017), http://dx.doi.org/10.1016/j.jfineco.2017.05.008
The impact of short sale constraints on informed trader strategies and the stock price drift.

The table reports the percentage of marketable or market orders to limit orders, the number of trades, the change in price aggressiveness and the drift in stock price (i.e., opportunity cost of a limit order) surrounding unscheduled corporate events. The table reports the percentage of marketable to limit orders on Days [−5−1] and control Days (Days [−30−10]) for the sample firm, the percentage change in the number of trades on Days [−5−1] from the control period, the cumulative effect measure on Days [−5−1] relative to the control period based on a regression analysis of price aggressiveness that controls for order attributes, market conditions and limit order book, and the cumulative effect measure on Days [−5−1] relative to control days based on a regression analysis of opportunity costs of limit orders that controls for order attributes and market conditions. Variable definitions are provided in Table 3 and Section 3.2. We investigate buy (sell) orders around positive (negative) events based on whether or not the stock belongs to SBF 120 index (Panel A, Columns 1–4), is eligible for Euronext’s Deferred Settlement Services facility (Panel A, Columns 5–8), has exchange-traded options (Panel B, Columns 1–4), and has event period absolute cumulative abnormal returns above and below 5% (Panel B, Columns 5–8). The cumulative effects of DayMinus5 to DayMinus1 coefficients based on price aggressiveness regression analysis and opportunity cost regression analysis are estimated on an event-by-event basis. Reported results are aggregated across events using the Bayesian framework of DuMouchel (1994). For the percentage of marketable or market orders to limit orders, the tests report on differences between Days [−5−1] and the control period. **∗∗∗∗∗** and ∗ indicate statistically significant at the 1%, 5%, and 10% level, respectively. For all panels we report the t-statistic of the difference between positive and negative events.

Panel A: Short sale constraints are SBF120 index membership and eligibility for Euronext’s Deferred Settlement Service (SDR) facility

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Events from companies in SBF120</th>
<th>Events from companies not in SBF120</th>
<th>Events from SDR-eligible companies</th>
<th>Events from SDR-ineligible companies</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of corporate events</td>
<td>Buy orders, positive events Coefficient (1)</td>
<td>Sell orders, positive events Coefficient (2)</td>
<td>Buy orders, positive events Coefficient (3)</td>
<td>Sell orders, negative events Coefficient (4)</td>
</tr>
<tr>
<td>Days [−5−1]</td>
<td>24</td>
<td>16</td>
<td>34</td>
<td>27</td>
</tr>
<tr>
<td>Control period</td>
<td>46.3%</td>
<td>54.7%</td>
<td>44.1%</td>
<td>51.5%</td>
</tr>
<tr>
<td>t-statistic of the difference between positive and negative events</td>
<td>−0.13</td>
<td>2.44</td>
<td>1.08</td>
<td>2.87</td>
</tr>
<tr>
<td>Percentage of marketable or market orders to limit orders</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Days [−5−1] before corporate event</td>
<td>48.4%∗</td>
<td>57.1%∗∗</td>
<td>47.7%∗∗</td>
<td>47.4%∗∗</td>
</tr>
<tr>
<td>Control period</td>
<td>48.4%∗</td>
<td>56.3%∗∗</td>
<td>44.9%</td>
<td>54.8%</td>
</tr>
<tr>
<td>t-statistic of the difference between positive and negative events</td>
<td>−0.13</td>
<td>2.44</td>
<td>1.08</td>
<td>2.87</td>
</tr>
<tr>
<td>Number of trades by type of Event</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Days [−5−1]; percent change from control period</td>
<td>21.3%∗∗∗</td>
<td>26.4%∗∗∗</td>
<td>22.4%∗∗∗</td>
<td>11.9%∗∗∗</td>
</tr>
<tr>
<td>Control period</td>
<td>919.1</td>
<td>975.0</td>
<td>20.9</td>
<td>199.8</td>
</tr>
<tr>
<td>t-statistic of the difference between positive and negative events</td>
<td>−0.47</td>
<td>1.74</td>
<td>−1.29</td>
<td>2.32</td>
</tr>
<tr>
<td>Cumulative effect coefficients based on price aggressiveness regression analysis</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative effect DayMinus5 to DayMinus1</td>
<td>−0.3583</td>
<td>−0.6229</td>
<td>−0.8417</td>
<td>0.3451</td>
</tr>
<tr>
<td>t-statistic</td>
<td>(−2.19)</td>
<td>(−1.63)</td>
<td>(−2.07)</td>
<td>(1.86)</td>
</tr>
<tr>
<td>t-statistic of the difference between positive and negative events</td>
<td>0.64</td>
<td>−2.66</td>
<td>0.33</td>
<td>−2.75</td>
</tr>
<tr>
<td>Control variables in regressions</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Cumulative effect coefficients based on opportunity cost regression analysis</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative effect DayMinus5 to DayMinus1</td>
<td>0.4327</td>
<td>0.2075</td>
<td>0.4180</td>
<td>−0.2347</td>
</tr>
<tr>
<td>t-statistic</td>
<td>(2.25)</td>
<td>(2.08)</td>
<td>(2.21)</td>
<td>−1.72</td>
</tr>
<tr>
<td>t-statistic of the difference between positive and negative events</td>
<td>1.04</td>
<td>2.78</td>
<td>1.13</td>
<td>2.62</td>
</tr>
<tr>
<td>Control variables in regressions</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

continued on next page.
Panel B: Short sale constraints are Exchange-listed options the magnitude of announcement period return

<table>
<thead>
<tr>
<th>Events from companies with Options</th>
<th>Events from companies without Options</th>
<th>Event period absolute return ≥ 5%</th>
<th>Event period absolute return ≤ 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy orders, positive events</td>
<td>Sell orders, negative events</td>
<td>Buy orders, positive events</td>
<td>Sell orders, negative events</td>
</tr>
<tr>
<td>Coefficient (1)</td>
<td>Coefficient (2)</td>
<td>Coefficient (3)</td>
<td>Coefficient (4)</td>
</tr>
<tr>
<td>14</td>
<td>15</td>
<td>44</td>
<td>28</td>
</tr>
<tr>
<td>Control period</td>
<td></td>
<td>19</td>
<td>13</td>
</tr>
<tr>
<td>t-statistic of the difference</td>
<td></td>
<td>39</td>
<td>30</td>
</tr>
<tr>
<td>Number of corporate events</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>14</td>
<td>15</td>
<td>44</td>
<td>28</td>
</tr>
<tr>
<td>Percentage of marketable or market orders to limit orders</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Days [−5,−1] before corporate event</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50.2%**</td>
<td>66.1%***</td>
<td>47.5%**</td>
<td>39.6%**</td>
</tr>
<tr>
<td>Control period</td>
<td></td>
<td>44.0%</td>
<td>45.3%</td>
</tr>
<tr>
<td>t-statistic of the difference</td>
<td></td>
<td>53.5%***</td>
<td>51.7%</td>
</tr>
<tr>
<td>Number of trades by type of Event</td>
<td></td>
<td>43.7%</td>
<td>50.8%</td>
</tr>
<tr>
<td>Days [−5,−1], percent change from control period</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>29.4%***</td>
<td>22.3%***</td>
<td>18.1%***</td>
<td>8.7%***</td>
</tr>
<tr>
<td>Control period</td>
<td></td>
<td>25.4%***</td>
<td>22.3%***</td>
</tr>
<tr>
<td>t-statistic of the difference</td>
<td></td>
<td>12.7%***</td>
<td>8.9%***</td>
</tr>
<tr>
<td>Cumulative effect coefficients based on price aggressiveness regression analysis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative effect DayMinus5 to DayMinus1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>−0.2338</td>
<td>−0.8409</td>
<td>−0.7233</td>
<td>0.4368</td>
</tr>
<tr>
<td>(t-statistic)</td>
<td>(−2.12)</td>
<td>(−2.35)</td>
<td>−1.11</td>
</tr>
<tr>
<td>Control variables in regressions</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Cumulative effect coefficients based on opportunity cost regression analysis</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative effect DayMinus5 to DayMinus1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.2456</td>
<td>−0.2082</td>
<td>0.4511</td>
<td>−0.2052</td>
</tr>
<tr>
<td>(t-statistic)</td>
<td>(1.54)</td>
<td>(2.76)</td>
<td>(−1.44)</td>
</tr>
<tr>
<td>Control variables in regressions</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>
stocks that are easier to short sell. These results provide strong empirical support for the novel predictions of the model.

The economic significance of these results is large. As an example, for large positive events, we estimate an increase of 27.78% in buy order aggressiveness on event days relative to control days, which reflects a 43.59% increase in the frequency of aggressive buy orders (Categories 1–4). The corresponding statistics are 6.37% and 4.67%, respectively, for small positive events. For small negative events, the positive cumulative coefficient translates into a decrease of 4.78% in sell order price aggressiveness and a 4.78% decrease in frequency of aggressive sell orders.

We also examine trading activity in the options market for stocks with listed options. While we observe no significant change in daily options trades relative to control days prior to positive events, we observe an increase in daily options trades prior to negative events. Options activity is nearly twice as large and statistically different on Day −1, which points to informed sellers using options to build short positions (see Battalio and Schultz, 2011).

Our results provide empirical support for several theoretical papers that model a dynamic limit order book with strategic traders. For example, Goettler, Parlour, and Rajan (2009) predict that informed traders use limit orders when volatility is low and Rosu (2014) predicts that informed traders use limit orders when realized signals are close to their expected value. In support of these predictions, and consistent with our model, we find that informed traders use limit orders before negative events with small announcement effects. However, consistent with our model and inconsistent with Goettler, Parlour, and Rajan (2009) and Rosu (2014), we show that informed traders use market orders before positive events with small announcement effects. That said, when event is small, the orders that the informed traders submit are less aggressive than the orders when event is large.

Stocks with small investor base and high borrowing costs can be less liquid. Informed traders face a smaller explicit cost of using market orders (bid-ask spread) in liquid stocks. However, the higher price impact of market orders as compared with limit orders can increase the total cost of building a position. To investigate the interplay between short sale constraints and liquidity, we separately examine informed trader behavior for liquid and illiquid stocks. We classify a stock as liquid (illiquid) if it is placed in the lowest (highest) tercile of stocks based on percentage bid-ask spreads in the control period. In unreported results, we find evidence of buy–sell asymmetry in informed trader strategies for stocks that are difficult to short sell in both the highest and lowest liquidity terciles.

Table 4 reports the number of events for each subsample. Many index stocks have exchange-listed options and are eligible for the SRD facility. We find that the overlap leaves sufficient room for independence across these cuts of the data. For example, for index stocks, ten among 24 positive event stocks and five among 16 negative event stocks do not trade with listed options. Similarly, for stocks without listed options, 13 among the 44 positive events and nine among 28 negative events are eligible for SRD facility.

5.2. Short sale constraints and the speed of price discovery

We investigate the impact of short sale constraints on learning and price discovery before corporate events. We estimate cross-sectional unbiasedness regressions for different subsamples, and calculate confidence intervals based on the standard error of the slope. Fig. 3 reports the slope and the confidence intervals for four subsamples based on SRD eligibility: (1) positive events for SRD-eligible firms, (2) negative events for SRD-eligible firms, (3) positive events for SRD-ineligible firms, and (4) negative events for SRD-ineligible firms. Similar to Biais, Hillion, and Spatt (1999), we plot the ratio of the root mean square error (RMSE) of each unbiasedness regression to the unconditional standard deviation of the close-to-close return (retcc).

For the MO events [i.e., (1), (2), and (3)], the slope of the unbiasedness regression by the end of the pre-event interval is not significantly different from one. We cannot reject the learning hypothesis that informational efficiency of the pre-event stock price is no different from post-event stock price. In contrast, for LO events [i.e., (4)], the slope is significantly less than one and, in fact, not significantly different from zero. These results suggest that LO events incorporate less news before announcement than MO events. The patterns for samples based on index membership and exchange-listed options are similar to Fig. 3 but are not reported in the interest of brevity.

The analysis of the regression residuals also point to lower price discovery for LO events relative to MO events. For MO events, the ratio drops substantially at the end of the interval [−5, −1], indicating that the security price incorporates the informed traders’ private information before the event. For LO events, the ratio does not drop substantially at the end of the interval [−5, −1]. We are unable to reject the hypothesis that noise trading dominates the trading process.

5.3. Short sale constraints and opportunity cost of non-execution of limit orders

The patterns in Fig. 3 suggest that stock prices incorporate more news before MO events than LO events. These patterns raise the possibility that using limit orders before MO events is costly because if the limit order goes unfilled, the informed trader will transact later at a less advantageous price. To empirically estimate the cost of an unfilled limit order, we report cumulative effects coefficients of the opportunity cost regressions in Table 4.

For all MO events (with the exception of Column 2 in Panel B), we estimate a positive cumulative effects coefficient, which indicates that the stock price moves higher before positive MO events (Columns 1, 3, 5, and 7 of Panels A and B) and moves lower before negative MO events (Columns 2 and 6 of Panel A and Column 6 of Panel B). In seven out of 12 columns, the MO coefficients are statistically significant at the 5% level and, in one column, the coefficient is significant at the 10% level. These results suggest that the stock price tends to gravitate away from the limit price and that limit orders face a higher risk of becoming stale. For all LO events, we estimate a negative
cumulative effects coefficient, although only one of four coefficients is statistically significant. The results do not support that stock prices gravitate away from limit price, suggesting that using limit orders to build positions before LO events is a reasonable strategy. In addition, the difference in cumulative effects coefficients between positive and negative events is statistically significant for non-index stocks, non-SRD-eligible stocks, stocks without listed options, and small event returns, and is not statistically significant for index stocks, SRD-eligible stocks, stocks with listed options, and large events.

Overall, the results in Section 5 provide empirical support for the important theoretical prediction that the strategies of informed traders affect the process of price formation in financial markets. When informed traders anticipate competition from other informed traders, they tend to employ aggressive strategies, which are easier to detect by market participants. This causes the stock price...
to move in the direction of the news before the public announcement. When faced with less competition, informed agents employ passive strategies, which are more difficult to detect by market participants, and leads to a smaller stock price adjustment before the public announcement. Our study documents the mechanism that links the activities of informed traders to the price discovery process.

6. Robustness analysis

The analysis thus far classifies events as positive and negative news using announcement period (Days [0,+1]) cumulative abnormal returns (CARs). Results are similar if events are classified as positive and negative news using longer period (Days [−5,+1]) CARs. We also classify events based on the abnormal imbalance in order flow using both nonmarketable and marketable orders. That is, we aggregate the displayed order size each day across all buy orders and all sell orders and then calculate the average daily difference during event and control periods, respectively. Events are classified as positive when abnormal imbalance is greater than zero and negative when abnormal imbalance is less than zero. We observe a significant overlap between the classifications based on announcement period CAR and order imbalance (87 of the 101 events) and near perfect overlap based on longer period CARs and order im-

Please cite this article as: S. Baruch et al., Informed trading and price discovery before corporate events, Journal of Financial Economics (2017), http://dx.doi.org/10.1016/j.jfineco.2017.05.008
balance (97 of the 101 events). For limit order events classified using announcement period CARs, the overlap with other classifications is near perfect.\textsuperscript{17} Thus, the important result that informed agents use limit orders when they anticipate less competition is not sensitive to the classification scheme.

In Table 5, we present robustness analyses based on several alternative specifications of the price aggressiveness regression. In the first set of analyses, the event’s impact is captured by a single event day coefficient, which equals one for orders submitted over the interval [−5,−1] and equals zero otherwise. In comparison with estimating separate event day coefficients, a single coefficient imposes the constraint that informed trading intensity is the same on each of the five days before the news release. We estimate the model for each separate event and aggregate coefficients across events using the Bayesian framework described in Appendix A.

When sample events are not clustered in calendar time, the event study literature commonly estimates the model on an event-by-event basis (see Binder, 1985; Thompson, 1985, 1995). This is because forecast errors are expected to be uncorrelated across events, and the efficiency gain from a panel specification, which imposes additional constraints on parameters, is expected to be small. Since our sample period of one year is relatively short, we present robustness analyses based on panel regression specifications using individual day coefficients for the interval [−5,−1]. Table 5 reports the cumulative effects coefficient and the t-statistics based on robust standard errors with event fixed effects and clustered standard errors by date. In unreported analysis, we find that results are similar in a panel specification using a single event day coefficient for the interval [−5,−1].

Table 5 also reports the cumulative effects coefficient estimated separately for a pooled sample of events that are similar in terms of the direction of news and the proxy for the degree of competition among informed sellers. Pooling similar events helps incorporate the theoretical prediction that true event effects vary by firm attributes, such as short sale constraints, and event attributes, such as the magnitude of the announcement. It also helps alleviate to some extent the difficulty in panel analysis to disentangle the effect of true variation in parameter estimates across events from the variation that is attributable to estimation error. We also estimate the panel regression using the full sample of events and restrict the individual day coefficients for the interval [−5,−1] to be the same for similar events.

Results in Table 5 suggest that the theoretical predictions are strongly supported in the alternative model specifications. For all market order events (Columns 1–3 and 5–7 in Panels A and B), we obtain a negative cumulative effect coefficient, which indicates that informed order flow is associated with more price aggressive orders. We find that 28 out of 36 coefficient estimates are statistically significant at the 5% level and that six estimates are significant at the 10% level. For all limit order events, the cumulative effects coefficient is positive, which indicates that informed order flow is associated with less price aggressive orders. Six of the 12 coefficients are statistically significant at the 5% level, and three more coefficients are significant at the 10% level. In addition, for all subsamples of short constrained firms and for events with small announcement effects, we find support for buy–sell asymmetry in trading strategy before positive and negative events.

The alternative model specifications of the opportunity cost regressions yield results that are similar to those reported in Table 4. In the interest of brevity, these results are not reported in Table 5 but are available upon request.

7. Conclusions

This study extends the theory on the impact of competition among informed traders on the choice of aggressive versus passive trading strategies before news releases. It further shows that the strategies of informed traders affect the process of price discovery before corporate events.

The intuition for the model is as follows. The competition among informed agents increases the execution risk on informed limit orders, which leads an informed agent to preempt and use market orders. Absent competition, an informed agent could prefer a limit order to a market order to lower the cost of building a position. We extend the Kaniel and Liu (2006) framework by incorporating short sale constraints that leads to an asymmetry in competition among informed agents before positive and negative events. When short selling is costly and the magnitude of negative news is small, our model predicts that informed agents use limit orders. When news is positive, short selling is not expensive, or the magnitude of negative news is large, informed agents anticipate competition and use market orders.

For a sample of Euronext-Paris stocks, we show that the order mix of market and limit orders is influenced by anticipated competition among informed agents. We present empirical evidence of an asymmetry in price aggressiveness of informed order flow before positive and negative events. When short selling is costly, when the magnitude of news is small, or when investor base is not broad, informed sellers anticipate less competition and use limit orders before negative events. In all other scenarios, informed traders anticipate competition and use market orders before news releases.

We further show that informed traders’ strategies affect the informational efficiency of prices. In scenarios in which informed agents use aggressive orders, we are unable to reject the learning hypothesis that informational efficiency of the pre-event security price is no different from the post-event security price. In contrast, when informed agents use less aggressive orders, we are able to reject that stock prices incorporate the news before announcement date. The key finding is that stock prices incorporate less news before negative events than positive events, particularly in short constrained stocks.

\textsuperscript{17} For limit order events, the overlap in classification based on announcement period CAR and the order imbalance is 18 of the 19 events for SRO-ineligible stocks, 26 of the 27 events for non-index stocks, and 26 of the 28 events for stocks without listed options. The results using alternative classification schemes are available upon request.
Table 5
Robustness analysis of the impact of short sale constraints on informed trader strategies.

The table reports robustness analysis of informed traders' strategies before unscheduled corporate events. The table reports the change in order aggressiveness observed on Days [−5,−1] relative to control Days [−30,−10] from a regression analysis of price aggressiveness on order attributes, market conditions and limit order book. We report results for buy (sell) orders before positive (negative) events on four samples based on whether or not the stock belongs to SBF 120 index (Panel A, Columns 1–4), is eligible for Euronext's Deferred Settlement Services facility (Panel A, Columns 5–8), has exchange-traded options (Panel B, Columns 1–4), and has event period absolute cumulative abnormal return above or below 5% (Panel B, Columns 5–8). The table reports regression coefficients based on a specification with a single dummy coefficient for Days [−5,−1]. Time series coefficients are estimated on an event-by-event basis and aggregated using the Bayesian framework of DuMouchel (1994). The table also presents the cumulative effect measure based on individual Days [−5,−1] dummy coefficient in a panel regression specification that is estimated separately for each of the 16 event types. This specifications include event fixed effects and cluster the standard errors by date. In addition, the table presents the cumulative effect measure based on individual Days [−5,−1] dummy coefficient in a panel regression specification that is estimated separately for the four sample of events. Within each panel specification, the regression coefficients for subsamples of positive and negative events are obtained using interaction term variables. The specifications include event fixed effects and cluster the standard errors by date. For all panels we report the t-statistic of the difference between positive and negative events.

Panel A: Short sale constraints are SBF120 index membership and eligibility for Euronext's Deferred Settlement Service (SRD) facility

<table>
<thead>
<tr>
<th>Events from companies in SBF120</th>
<th>Events from companies not in SBF120</th>
<th>Events from SDR-eligible companies</th>
<th>Events from SDR-ineligible companies</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Number of corporate events</strong></td>
<td>24</td>
<td>16</td>
<td>34</td>
</tr>
<tr>
<td><strong>Single dummy coefficient for Days [−5,−1]</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual event regression aggregated based on Panayides (2007) and Bessembinder, Panayides, and Venkataraman (2009)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Cumulative effect DayMinus5 to</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DayMinus1</td>
<td>−0.0664</td>
<td>−0.1293</td>
<td>−0.1066</td>
</tr>
<tr>
<td><strong>t-statistic</strong></td>
<td>(−2.48)</td>
<td>(−1.86)</td>
<td>(−2.43)</td>
</tr>
<tr>
<td><strong>r-statistic of the difference between positive and negative events</strong></td>
<td>0.84</td>
<td>−3.35</td>
<td>0.70</td>
</tr>
<tr>
<td><strong>Control variables in regressions</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Cumulative effect of DayMinus5 to DayMinus1 coefficients, panel regression by event type (16 types)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative effect DayMinus5 to DayMinus1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>[t-statistic]</strong></td>
<td>−0.2084</td>
<td>−0.8778</td>
<td>−0.8202</td>
</tr>
<tr>
<td><strong>r-statistic of the difference between positive and negative events</strong></td>
<td>−1.91</td>
<td>(−4.30)</td>
<td>(−3.63)</td>
</tr>
<tr>
<td><strong>Control variables in regressions</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Cumulative effect of DayMinus5 to DayMinus1 coefficients, pooled regression aggregated by short sale measure (four measures)</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cumulative effect DayMinus5 to DayMinus1</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>[t-statistic]</strong></td>
<td>−0.2177</td>
<td>−0.9576</td>
<td>−0.9251</td>
</tr>
<tr>
<td><strong>r-statistic of the difference between positive and negative events</strong></td>
<td>−2.09</td>
<td>(−4.44)</td>
<td>(−4.21)</td>
</tr>
<tr>
<td><strong>Control variables in regressions</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

continued on next page.
Panel B: sale measures, with and without options

<table>
<thead>
<tr>
<th>Events from companies</th>
<th>Event period absolute return ≥ 5%</th>
<th>Event period absolute return ≤ 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Buy orders, sell orders, positive events</td>
<td>Coefficient</td>
<td>t-statistic</td>
</tr>
<tr>
<td>Buy orders, sell orders, negative events</td>
<td>Coefficient</td>
<td>t-statistic</td>
</tr>
<tr>
<td>No options</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Cumulative effect of DayMinus5 to DayMinus1 coefficients, panel regression by event type (16 W)

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>t-statistic</th>
<th>Coefficient</th>
<th>t-statistic</th>
<th>Coefficient</th>
<th>t-statistic</th>
<th>Coefficient</th>
<th>t-statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0612</td>
<td>1.70</td>
<td>0.0946</td>
<td>2.38</td>
<td>0.0950</td>
<td>1.39</td>
<td>0.0612</td>
<td>1.70</td>
</tr>
<tr>
<td>0.317</td>
<td>2.60</td>
<td>0.0810</td>
<td>1.05</td>
<td>0.077</td>
<td>1.05</td>
<td>0.317</td>
<td>2.60</td>
</tr>
<tr>
<td>0.77</td>
<td>1.39</td>
<td>0.0810</td>
<td>1.05</td>
<td>0.077</td>
<td>1.05</td>
<td>0.77</td>
<td>1.39</td>
</tr>
<tr>
<td>0.317</td>
<td>2.60</td>
<td>0.0810</td>
<td>1.05</td>
<td>0.077</td>
<td>1.05</td>
<td>0.317</td>
<td>2.60</td>
</tr>
<tr>
<td>0.77</td>
<td>1.39</td>
<td>0.0810</td>
<td>1.05</td>
<td>0.077</td>
<td>1.05</td>
<td>0.77</td>
<td>1.39</td>
</tr>
</tbody>
</table>

Control variables in regressions

- Single dummy coefficient for Days -5 → -11
- Individual event regression aggregated based on Panayides (2007) and Rosenberg, Panayides, and Venkataraman (2009)
- Control variables in regressions
- Cumulative effects of DayMinus5 to DayMinus1 coefficients, pooled panel regression by event type (16 W)
- Control variables in regressions
- Cumulative effects of DayMinus5 to DayMinus1 coefficients, pooled panel regression by event type (16 W)
- Control variables in regressions
- Cumulative effects of DayMinus5 to DayMinus1 coefficients, pooled panel regression by event type (16 W)
Although our study focuses on informed trading in a centralized limit order market, our theory has implications for informed trading in fragmented markets, in which the strategy space includes the choice of trading platforms with different levels of transparency. Some trading platforms such as Dark Pools are designed to offer lower cost but with lower fill rates (see Zhu, 2014; Buti, Rindi, and Werner, 2017). In the case of Dark Pools functioning as a crossing network, the probability of execution decreases as the number of traders participating on the same side of the market increases. In our theoretical model, this scenario is captured by anticipated competition among informed traders. As some informed traders recognize the low rate of execution in the crossing network, they route their orders to the transparent exchange, despite the higher cost of execution. The price impact of their orders in the transparent exchange increases the execution cost for informed traders remaining in the crossing network because the Dark Pool crossing price is based on quotations from the transparent exchange. Thus, informed traders in fragmented markets face a risk-return trade-off affected by competition that is similar to the one that we have modeled in a centralized market.

Our study points to a specific mechanism by which restrictions on short selling impede the flow of private negative information into prices (see Beber and Pagano, 2013). A short sale ban lowers competition among informed sellers and leads to a limit order equilibrium, which makes it difficult to detect informed order flow. This leads to lower price discovery before negative news relative to positive news. Our study is relevant for regulators interested in the efficacy of short sale regulation, particularly in markets around the world that continue to restrict or impede short sales in one form or another.

Appendix A. Aggregation method

Our aggregation method relies on a Bayesian framework attributable to DuMouchel (1994) and implemented by Panayides (2007) and Bessembinder, Panayides, and Venkataraman (2009). The method assumes that, for each estimated firm $i$ coefficient, $\beta_i$,

$$\tilde{\beta}_i \sim i.i.d. N(\beta_i, \sigma^2)$$

and

$$\beta_i \sim i.i.d. N(\beta, \sigma^2)$$

where $N$ is the Gaussian distribution. The Newey-West corrected standard errors, $s_i$, are estimated using generalized method of moments (GMM) with a Bartlett kernel and a maximum lag length of 10, and $\sigma^2$ is estimated by maximum likelihood.

Harris and Piwowar (2006) emphasize the desirability of assigning larger weights in the cross-sectional aggregation to those securities whose parameters are estimated more precisely. Consistent with the study’s recommendation, the aggregated $\hat{\beta}$ is obtained from $N$ individual firm estimates as

$$\hat{\beta} = \frac{\sum_{i=1}^{N} \tilde{\beta}_i}{\sum_{i=1}^{N} (s_i^2 + \sigma^2)}$$

Assuming independence across firms, the variance of the aggregate estimate is

$$\text{Var}(\hat{\beta}) = \frac{1}{\sum_{i=1}^{N} (s_i^2 + \sigma^2)}.$$ 

where $\hat{\sigma}_{mle}^2$ is the maximum likelihood estimator of $\sigma^2$. The aggregate $t$-statistic is based on the aggregated coefficient estimate relative to the standard error of the aggregate estimate. This method allows for variation across stocks in the true $\beta_i$ and also for cross-sectional differences in the precision with which $\beta_i$ is estimated.18

Appendix B. Proofs of Lemmas 1–3 and Theorem 1

B.1. Proof of Lemma 1

Consider the first part of the lemma. Assume by means of contradiction that informed traders post limit orders and their limit prices are different than the limit prices of noise limit order traders. Then, the only price that satisfies conditions (10)–(11) is $P_S = \tilde{v}$. But, then, optimality conditions (12) –(13) imply that market orders are preferable to limit orders which is a contradiction to the assumption that informed traders use limit orders.

Consider now the second part of the lemma. Assume that informed traders strictly prefer buy limit orders over buy market orders. That is, the right-hand side of (12) is strictly greater than its left-hand side. The right-hand side is strictly smaller than $1/2$. If noise traders submit buy market orders only in round one, the left-hand side of (12) is $a_1 = 1/2$, and a contradiction arises. In a similar manner, we show that informed traders cannot strictly prefer sell limit orders over sell market orders.

B.2. Proof of Lemma 2

Consider the first part. From the equilibrium condition (21) it follows that we only need to show that

$$b_2(LS) < c.$$ 

From equilibrium condition (10), we know

$$b_2(LS) = P_L(\tilde{v} = 1|O_1 = LS, O_2 = MS) < E_0\tilde{v} = p_0.$$ 

where the inequality is because the order flow contains information. Thus, $p_0 < c$ implies $\mu^- (b_2(LS)) = \beta \mu$.

We turn our attention to the second part of the lemma. By way of contradiction, assume that in equilibrium $m_0 = 1$. So, the left-hand side of the equilibrium condition (17) is

18 The aggregated $\beta$ estimate deals with the error-in-variable issue. It also corrects for the variability in the sample selection through $\hat{\sigma}_{mle}^2$. The method does not control for dependence of estimation errors across events. We believe that this dependence should be small because the events are not clustered in time.
\[ b_1 = E_0[\hat{\nu} = 1|\hat{O}_1 = MS] \]
\[ = \frac{\beta z}{2\beta z + \mu z + \mu^2 z} \frac{p_0}{1 - p_0} \]
\[ \geq \frac{\beta z}{2\beta z + \mu z + \mu^2 z} \frac{p_0}{1 - p_0} + \frac{\beta z + m\beta_1}{2\beta z + \mu z + \mu^2 z} (1 - p_0) \]
\[ = \frac{\beta z}{2p_0 + (z + \mu)(1 - p_0)}. \]  

(29)

The right-hand side of the same equilibrium condition, (17), is

\[ PS \frac{\beta z}{2\beta z + \mu - (b_2(LS))} = E_0[\hat{\nu}|O_1 = LS, O_2 = MB] \]
\[ = E_0[\hat{\nu}|O_2 = MB] \]
\[ = \frac{\beta z}{2\beta z + \mu + \mu^2 z} \frac{p_0}{1 - p_0} \times \frac{\beta z}{\beta z + \mu - (b_2(LS))} \]
\[ = \frac{\beta z}{2\beta z + \mu^2 z} \frac{p_0}{1 - p_0} \times \beta z \]
\[ = \beta z(\mu p_0 + 2z) + \mu(\mu p_0 + (1 + p_0)z) \]
\[ \rightarrow \beta \rightarrow 0 \quad \text{for} \quad p_0 < \frac{\mu}{2z + 2\mu}. \]  

(30)

The second equality holds because, under the assumption that \( m_n = 1 \), a limit sell order in round one can come only from a noise limit order trader. Observing a limit sell in round one is uninformative.

Thus, for \( \beta \) sufficiently close to zero, equilibrium condition (17) is violated and a contradiction results.

B.3. Proof of Lemma 3

Given an arbitrary choice of scalars \( m_p, m_n, \mu^- \), and \( b \), the equilibrium conditions (8), (9), (14), and (15) dictate what values \( a_1, b_1, PS, PB, \) and \( b_2(LS) \) are consistent with the arbitrary choice of \( m_p, m_n \) and \( \mu^- \). \( ^{19} \) It is convenient to express these values as

\[ (1 - a_1) = f(1 - p_0, m_p). \]  

(31)

\[ b_1 = f(p_0, m_n). \]  

(32)

\[ (1 - PB) \frac{\beta z}{2\beta z + \mu} = h(g(1 - p_0, m_p), \mu^-, \mu). \]  

(33)

and

\[ PS \frac{\beta z}{2\beta z + \mu^-} = h(g(p_0, m_n), \mu, \mu^-). \]  

(34)

where Bayes rule dictates the functions

\[ f : [0, 1] \times [0, 1] \rightarrow [0, 1]. \]  

(35)

\[ g : [0, 1] \times [0, 1] \rightarrow [0, 1]. \]  

(36)

and

\[ h : [0, 1] \times R^+ \times R^+ \rightarrow [0, 1] \]  

(37)

\[^{19} \) In equilibrium, \( \mu^- \) depends on the realized order at period one. Thus, in equilibrium, (33) holds with \( \mu^- = \mu^- (b_2(LB)) \), and (26) holds with \( \mu^- = \mu^- (b_2(LS)) \).

\[^{20} \) The functions \( f \) and \( g \) also depend on \( \mu \). Because \( f \) and \( g \) do not depend on \( \mu^- \), the dependency on \( \mu \) is of no consequence to our analysis, so we keep it implicit.
Now, if assumption (44) holds, then the inequalities denoted with (46) are both strict. If (45) holds, then the inequality (47) is strict. Either way, we get

\[(1 - a_1p_0) > (1 - PB(1-p_0)) \frac{\beta z}{2\beta z + \mu}.
\]

which implies [see equilibrium condition (16)] that \(m_p = 1\). This is a contradiction because both (44) and (45) imply \(m_p(1 - p_0) < 1\).

**B.4. Proof of Theorem 1**

Under the assumption that \(p_0\) is a symmetric random variable, the first part of the theorem follows from the first part of Lemma 3.

For the second part, let \(p_0\) be such that

\[p_0 < \min \left\{ \frac{c}{z}, \frac{\mu}{z + 2\mu} \right\}.
\]

This condition holds if the event is sufficiently small and borrowing costs are sufficiently high. Because \(p_0 < c\), Lemma 2 implies that \(\mu - (b_2(p_0, L5)) = \beta \mu\). Because \(p_0 < \mu / (z + 2\mu)\), Lemma 2 also implies that \(m_p(p_0) < 1\). From the second part of Lemma 3, it follows that \(m_p(p_0) < m_p(1 - p_0)\). Thus, the probability of observing a sell market order during a small negative event is strictly smaller than the probability of observing a buy market order during a small positive event. This proves the second part of the theorem.

We now consider the third part of the theorem. If \(\beta = 1\), then there are no constrained investors and the model is symmetric, that is, \(m_p(1 - p_0) = m_p(p_0)\). By a continuity argument, it follows that also for \(\beta\) close to one, these probabilities are similar.

In addition, these probabilities are identical whenever constrained investors do not abstain. According to equilibrium condition (20), this is the case whenever the bid in round 2 is greater than the cost of borrowing. This is the case when cost of borrowing is near zero, or \(p_0\) is near one and borrowing cost is less than one; i.e., the event is negative and large.

**References**


Zhang, Z., 2013. Informed liquidity provision and adverse selection measures. City University of Hong Kong, Hong Kong Unpublished working paper.