Informed Trading before Unscheduled Corporate Events: Theory and Evidence

Shmuel Baruch
University of Utah

Marios Panayides
University of Pittsburgh

Kumar Venkataraman
Southern Methodist University*

Abstract

Despite widespread evidence that informed agents are active before corporate events, there is little work describing how informed agents accumulate positions and what explains their trading strategies. We use the prisoners' dilemma to model the execution risk that informed traders impose on each other and explain why they forgo the price benefit of limit orders and use instead market orders. However the efficient limit-orders outcome is obtained if there is sufficient uncertainty about the presence of informed traders. We link the level of uncertainty to costly short selling and test theoretical predictions using order level data from Euronext Paris. We find empirical support for the prediction that informed traders use limit orders when the news is negative, especially when (a) the investor base is not broad, (b) security borrowing costs are high, and (c) the magnitude of the event is small so potential profits cannot justify the cost of borrowing. When the news is positive, we show that informed buyers face more competition and use market orders. These results help explain the buy-sell asymmetry in price impact of trades and provide a framework for surveillance systems that are designed to detect insider trading.

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* Baruch can be reached at shmuel.baruch@business.utah.edu, Panayides can be reached at mpanayides@katz.pitt.edu, and Venkataraman can be reached at kumar@mail.com.smu.edu. We thank Leonce Bargeron, Indraneel Chakraborty, Dave Denis, Diane Denis, Charles Jones, Ken Lehn, Swami Kalpathy, Shawn Thomas, Rex Thompson, Chad Zutter, as well as seminar participants at the University of Pittsburgh and Southern Methodist University for comments and discussions. We thank in particular Hank Bessembinder for many helpful discussions during the development of the project.

1. Introduction

Insider trading has been a focus of regulatory efforts in recent years. A large academic finance literature has examined the open market stock trades of corporate insiders (Seyhun (1992), Meulbroek (1992), Agrawal and Jaffe (1995), among others). These studies find that stock price tends to increase following insider purchase and decrease following insider sale and that insider trades are more profitable before corporate events, such as earnings announcements, seasoned equity offerings (SEOs), and earnings restatements. Related empirical work shows that institutional investors build profitable positions before corporate events.[1] Despite widespread evidence that informed traders are active before corporate events, there is little work describing how they accumulate positions and what explains their order submission strategies. In this study, we use the prisoners dilemma framework to model the execution risk that informed traders impose on each other. We examine order level data from Euronext Paris and document informed traders' order submission strategies that are consistent with the model predictions.

The model is based on the following intuition. Informed traders face a tradeoff between transacting with certainty at a current market price by placing a market order versus risking non-execution in an attempt to get a better price by placing a limit order. In addition to paying the bid-ask spread, market orders might tip off market participants about the presence of informed agents and increase market impact cost. On the other hand, the execution risk of a limit order strategy is particularly high when other informed agents receive the same signal and use market orders. In a multiple traders' game, the order submission joint decisions of informed agents fit the prisoners' dilemma framework, i.e., despite the price benefit of limit orders, informed agents use market orders when they anticipate competition from other informed agents receiving the same signal. We posit that informed traders use market orders when the nature of private information conveys an increase in stock price.

Informed traders face less competition when the nature of private information is unfavorable. This is because informed agents are less likely to sell stocks with unfavorable information if they do not

[1] See Bodnaruk, Massa and Simonov (2009), Jegadeesh and Tang (2010), Daouk and Li (2011), Griffin, Shu and Topaloglu (2013), among others.

already own the stock (see Saar (2001)).[2] The model predicts that informed traders use limit orders when there is sufficient uncertainty about the presence of other informed traders, and market orders if they are sure that other informed traders are present.[3] To model the uncertainty about the presence of other informed traders, we extend our model and assume that the informed agent can be one of two types; the first type already owns the stock while the second type does not. The probability that a trader is of the first type increases with the broadness of investor base. When the investor base is narrow, the costs of borrowing shares are sufficiently large, or the event is small so potential gains cannot justify the borrowing costs, a limit order equilibrium emerges in which the first type uses limit orders and the second type abstains from trade. On the other hand, when borrowing costs are sufficiently low or the event is sufficiently large, then the second type borrows the shares, and both types trade. Because of the execution risk they impose on each other, both types use market orders.

The primary objective of insider trading regulation is to prevent corporate insiders and well-connected market participants, such as investment bankers, analysts, and institutions, to trade on material information that is unavailable to the public. If regulations are properly enforced, the amount of asymmetric information in securities market should decline and consequently uninformed investors are willing to participate in a market. However, to detect insider trading, regulators need a framework that describes the ex-ante trading strategies of informed agents, and how strategies vary with firm and event characteristics. Our model provides such a framework for the designers of surveillance systems.

Surprisingly, despite the importance of understanding how informed traders build positions, there is little empirical work describing their trading strategies, mainly because empirical studies need to overcome the lack of useful data. Some data on insider trades are available from regulatory filings, such as Form 4 filed with U.S. Securities and Exchange Commission (SEC); however, the data is not

[2] Studies on insider trading, such as Marin and Olivier (2008), observe that corporate insiders face more portfolio constraints when they trade on bad news than on good news. For example, insiders in many markets are prohibited from selling short their own stock, or corporate managers may be unable to sell stock holdings that are part of a compensation contract below a certain threshold. While insiders face constraints when they are in possession of bad news, they do not face threshold constraints on purchases when they are in possession of good news.

[3] The prisoners' dilemma analogy of this scenario occurs when there is a high likelihood that the accomplice has been released from custody for lack of evidence; i.e., the interrogator is bluffing.

sufficiently detailed to study order submission strategies. Detailed order level data is available from some markets, such as Euronext-Paris, but there is no information on trader identity. We employ a methodology similar in spirit to Chae (2005), Graham, Koski and Loewenstein (2006), and Sarkar and Schwartz (2009), who study information flow surrounding corporate events. These studies document that volume and liquidity decline before scheduled events, such as earnings announcements, because uninformed traders optimize the timing of their trades to lower adverse selection risk. In contrast, uninformed traders cannot anticipate unscheduled events where timing information is unavailable, but informed traders can, if the information concerns the event. Thus the abnormal activity observed before an unscheduled event can be attributed to informed traders.

We examine an Euronext database which contains detailed information on the characteristics of all orders submitted for all stocks listed in the Euronext-Paris market. Since the Euronext data does not contain information on trader identity, we detect informed trader strategies based on abnormal activity observed before an unscheduled event. We identify a sample of 95 French stocks and 101 unscheduled mergers, acquisitions, Seasoned Equity Offerings (SEOs), repurchases, and dividend initiations and terminations in the year 2003.[4] These announcements convey a considerable amount of new information to the market – the absolute value of event day return for our sample exceeds 4.5% - but the timing of the announcements is not public information. We categorize events as positive and negative based on the sign of the announcement return. We rely on an event study research design where event period activity is benchmarked against non-event window for the same firm. The framework holds each firm as its own control and avoids concerns associated with omitted cross-sectional determinants of trading strategies. In our main specifications, we control for order characteristics and market conditions, including the state of the limit order book, following Bessembinder, Panayides and Venkataraman (BPV hereafter, 2009).

[4] Unlike the Trade and Quote (TAQ) database, the Euronext database contains detailed information on all orders sent to the exchange. We examine the 2003 sample period because more recent order-level data purchased from Euronext have important inaccuracies, which we describe in Section 3.1. Further, during the 2003 period, the vast majority of trading in French stocks occurred on Euronext-Paris. The consolidated market structure allows us to abstain from explicitly modeling the trader's choice of the trading venue. Similar to U.S. equity markets, trading in the Euronext-listed stocks has become highly fragmented with the proliferation of alternative trading venues, including dark pool venues, in recent years.

The key model prediction is that informed traders employ more aggressive strategies preceding positive events and less aggressive strategies preceding negative events. We focus on the traders' strategy related to the price aggressiveness of the order (e.g., market versus limit order) but we also examine the trader's decision to expose or hide order size (see Boulatov and George (2013) for theory). We find strong empirical support for theoretical predictions. Preceding positive events, we document an *increase* in aggressively priced buy orders, and further an increase in the magnitude of limit order size that is not hidden. Both using aggressively priced orders and exposing order size increase execution probability and reduce time-to-execution; however, aggressively priced orders signal the presence of informed agents and increase the opportunity cost of non-execution. In contrast, preceding negative events, we observe a *decrease* in aggressively priced sell orders, suggesting that informed sellers prefer to use passive limit orders to build positions. Limit sell orders before negative events are less likely to be hidden and tend to expose more size. The exposure strategy attracts counterparties and increases execution probability and reduces time-to-execution. The latter evidence is consistent with the theoretical framework in Moinas (2006), where informed traders use limit orders to mimic the behavior of uninformed liquidity suppliers.

We develop further tests of the model based on cross-sectional differences in competition among informed sellers before negative events. If there are no barriers to trading, then there will be competition among informed sellers and they will use aggressive (market) orders. We therefore expect that for stocks with broad investor base, or stocks that are easy to borrow, the market order equilibrium is more likely before negative events. If there are restrictions on trading, the competition will be less intense, and informed sellers may consider staying with limit orders to obtain better prices. We therefore expect that a limit order equilibrium will emerge for stocks with narrow investor base or stocks that are difficult to borrow. To classify stocks based on investor base, we rely on prior research showing that institutional investors are active in stocks with index membership. We therefore classify stocks with SBF120 Index membership as those associated with broad investor base (D'Avolio (2002), Nagel (2005)). We proxy for the ease of short selling based on the availability of listed options in the stock. This is because informed seller can avoid costly stock borrowing by trading with the options market maker, who would subsequently post hedging sell orders in the underlying stock.

The model predicts that informed sellers in stocks with index membership or those with listed options will face more competition from other traders. For these stocks, we document an increase in price aggressiveness *symmetrically* for both buy orders before positive events and sell orders before negative events. For stocks with no index membership or listed options, we observe *an asymmetry* in order submission strategies before positive and negative event. Specifically, informed buyers implement more price aggressive strategies while informed sellers implement less price aggressive strategies. We also find that the behavior of informed buyers and sellers are different before events with small announcement return as compared to events with large announcement return. The result supports model prediction that informed sellers face less competition before small news events because the potential gains cannot justify the cost of borrowing the security.

Since informed agents can choose among many potential strategies, our model predicts that the selected strategy reflects an optimization across many dimensions of execution quality, including execution risk, time-to-execution, and trading costs. We show that, although strategies differ, informed agents reduce the limit order time-to-execution for all sub-samples. To investigate whether informed trader strategies impact security prices before the event, we examine the drift in security price subsequent to order submission. For orders that are not fully executed, the opportunity cost for buy (sell) order is positive if the stock price rises (falls) after order submission. The model predicts that, for events associated with intense competition among informed traders (i.e., stocks with index membership and listed options), the opportunity cost is positive because market orders tip off participants about the presence of informed traders. For events where competition among informed traders is less intense (i.e., negative events in non-index stocks and those without traded options), the opportunity cost is small because the limit order strategy reveals less information about the presence of informed agents. We find empirical results that are consistent with these predictions. In index stocks or those with listed options, the opportunity cost is positive both for informed buyers before positive events and informed sellers before negative events. In contrast, for non-index stocks or those without listed options, the opportunity cost is positive for buy orders before positive events but not for sell orders before negative events.

Our results suggest that informed trader strategies influence the price adjustment before corporate events and can contribute, at least in part, to asymmetry in price impact of trades. Past studies on block trading find that security prices reverse after block sale but not after block purchase, suggesting that block purchase conveys more information than block sale.[5] As in Diamond and Verrecchia (1987), our theory uses costly short selling to match the price impact asymmetry observed in the data. However, in our model, the asymmetry is not only because some informed traders decide to abstain, but also because informed agents become liquidity providers; i.e. they use limit orders based on the uncertainty about the presence of other informed traders. An important related paper by Saar (2001) takes a different approach than ours on the buy-sell asymmetry. In his model, informed traders face capital constraints rather than costly short selling. Thus, to finance investment in undervalued securities, informed traders sell securities that are priced correctly; i.e. informed traders may sell for liquidity reasons, which is a source of the price impact buy-sell asymmetry.

Our study extends the growing theoretical literature on informed trader strategies. Most theoretical work posits that informed agents trade aggressively in order to exploit their information advantage.[6] On the other hand, in Kumar and Seppi (1994), Chakravarty and Holden (1995), Kaniel and Liu (2006), Goettler, Parlour and Rajan (2009), and Boulatov and George (2013), informed traders do find it optimal, under certain conditions, to submit limit orders.[7] An important insight from our study is that no single strategy sufficiently describes the behavior of informed agents. We provide a framework for designers of surveillance systems, including exchanges, broker-dealers, and regulators to detect trading

[5] Buy-sell asymmetry is first documented in the seminal work by Kraus and Stoll (1972). Other studies include (a) Holthausen, Leftwich and Mayers (1987), Chan and Lakonishok (1993) and Keim and Madhavan (1996) based on U.S. market, (b) Gemmill (1996) based on London market, and (c) Bessembinder and Venkataraman (2004) based on Euronext Paris.

[6] See Kyle (1985) and Glosten and Milgrom (1985) for studies of strategic trading in a dealer setting and Glosten (1994), Rock (1996), Seppi (1997) and Back and Baruch (2013) for strategic trading in a limit order book setting.

[7] There is also recent experimental and empirical findings that suggest that informed traders do use limit orders (see Barclay, Hendershott, and McCormick (2003); Bloomfield, O'Hara, and Saar (2005); Anand, Chakravarty and Martell (2005), Hautsch and Huang (2012), among others).

activity of informed agents with private information before corporate events.

Recent years have witnessed a proliferation in electronic markets that provide traders with the option to hide orders. Market venues range from stock exchanges that allow "iceberg" orders with some displayed size to opaque dark pool venues that do not display any information.[8] Despite the widespread use of hidden orders, it is still unclear whether informed traders prefer to hide orders. BPV (2009) examine Euronext-Paris data and conclude that hidden orders are primarily used by uninformed traders. However, since most market participants are uninformed, the typical hidden order user is expected to be uninformed. Our research design allows a focused examination of informed agent behavior before corporate events. We find that informed agents who submit limit orders prefer to expose orders which lowers time-to-execution, execution risk, and trading costs. These results suggest that dark pool venues are more likely to attract uninformed investors who hide orders to control exposure risk while 'lit' markets are more likely to attract informed investors who worry about execution risk. Our evidence should inform regulatory initiatives on the impact of dark pools on price efficiency of the market.

The rest of the paper is organized as follows. Section II presents a model on competition among informed traders and identifies testable predictions on order submission strategies preceding positive and negative events. Section III describes the institutional details of the Euronext-Paris, the data sources and sample selection. Section IV presents informed trader strategies on the price aggressiveness attribute and Section V presents the results on the order exposure attribute. Section VI examines the impact of trading strategies on the likelihood of achieving full execution, the time-to-execution, and execution costs. Section VII summarizes the main results and presents the implications of the study.

2. The Model

2.1. The prisoner's dilemma game

When choosing between limit orders and market orders, a trader weighs the price benefit of a limit order against the risk of non-execution. To model the execution risk informed traders impose on

[8] Buti and Rindi (2012) present a theoretical model describing the trader's decision to hide a portion of the order. Recent empirical work on dark pools include Nimalendran and Ray (2011) and Buti, Rindi and Werner (2011). Industry report from the Tabb Group estimates that dark pools account for 8-9% of trading volume in U.S. equities.

each other, we consider a static model with two identically informed traders. The informed traders learn the realization of a signal, v, after which they perceive the asset as either overvalued or undervalued. These informed traders face the choice between using market orders or limit orders to build their position before the information becomes widely known. We model the payoff, which depends on their joint decision to use market or limit order, as a prisoners' dilemma. Trader one's payoff is given by the following payoff matrix, where $\bar{v}$ is the expected value of the signal, and $0<a<b<c<d$.

Trader One's payoff		Trader One: Market Orders	Trader One: Limit Orders
Trader Two	Market Orders	$(v-\bar{v})^2\, b$	$(v-\bar{v})^2\, a$
Trader Two	Limit Orders	$(v-\bar{v})^2\, d$	$(v-\bar{v})^2\, c$

In the following we discuss the payoff order.[9] The assumption $0<a<b<d$ is natural. When trader two uses market orders, then these market orders impose severe execution risk on trader one's limit orders. Therefore, using limit orders when trader two uses market orders should be suboptimal; i.e. $a<b$. Similarly, if trader one uses market orders, these orders should be cheaper to execute if trader two does not compete for available liquidity by employing market orders; i.e. $b<d$.

We still need to motivate the assumption that c lies in the interval (b,d). Stated differently, we assume that if the informed traders could collude, than they would rather use a hybrid of limit orders and market orders. In our static model, the joint payoff when using both types of orders is $a+d$, where a is the payoff generated by the market orders and d is the payoff generated by the limit orders. Similarly, the cost benefit of limit orders means that the joint payoff when using only limit orders, $c+c$, is greater than the joint payoff $b+b$. Put together, we have $b+b< c+c< a+d$. Since we already established that $a<b$, we conclude that $b<c<d$.

[9] For the reader who prefers a more detailed model, we present in the appendix a simple dynamic model with probabilistic arrival of discretionary liquidity traders. The liquidity traders pick off limit orders when the spread is narrow and post limit orders when the spread is wide. We compute the informed traders' payoff for each of the four possible joint actions, and we show that the values of a, b, c, and d, indeed correspond to their alphabetical order.

The inefficient outcome we posit is not a novelty. Using different action spaces, other theoretical papers arrive at the same conclusion. In Holden and Subramanyam (1992) the informed traders can only trade using market orders but they still have a choice between trading on their information gradually or rapidly. If the traders could collude, the optimal behavior is to trade gradually and achieve the monopolist's profit. However, the competition results in an inefficient outcome in which the traders trade so rapidly that their information is revealed to the market instantly. Similarly, in Boulatov and George (2013) informed traders can choose between hidden and visible orders, and though the efficient outcome is to use hidden orders, the equilibrium outcome is to use visible orders.

To sum our discussion thus far: we use the prisoners' dilemma to model the interaction between the informed traders. The outcome of the game is that despite the price benefit of limit orders, informed traders use market orders. What if our assumption is wrong and the values of *a*, *b*, *c*, and *d* do not correspond to their alphabetical order? We ask the reader to suspend disbelief, and for now accept the prisoner's dilemma framework. We are, after all, going to put to the test the predictions of our model.

2.2. Trader competition when short selling is banned

Up until now we assumed that the direction of the information was irrelevant. However, when shares are hard to borrow (either short selling is expensive, prohibited, or the shares are simply hard to locate), then informed sellers might be forced to abstain from trade. In extreme situations, where it is virtually impossible to short, informed traders can sell only if prior to learning that the stock is overvalued, they were long on the stock.

To model the payoff when informed traders may abstain from trade, we extend the payoff matrix:

Trader One's payoff (Type 0)		Trader One		
		Market Orders	Limit Orders	Abstain
Trader Two	Market Orders	$(v-\bar{v})^2\, b$	$(v-\bar{v})^2\, a$	0
	Limit Orders	$(v-\bar{v})^2\, d$	$(v-\bar{v})^2\, c$	0
	Abstain	$(v-\bar{v})^2\, e$	$(v-\bar{v})^2\, f$	0

We posit that numerical values correspond to alphabetical order: $0<a<b<c<d\le e<f$. The assumption that $d\le e$ is natural since the competitor submits a limit order in the former while being absent in the latter. The assumption that $e<f$ is similar to our assumption that absent strategic consideration, informed traders prefer to employ limit orders to market orders.

If the event is negative and short selling is prohibited, traders can sell only if the stock is in their portfolios. Further, we assume each trader perceives the probability that the stock is in the other's portfolio to be p. Then, if p is small enough, limit orders equilibrium emerges. Indeed, let us conjecture trader two, when owns the stock, uses limit orders. Then the expected payoff for trader's one is $(v-\bar{v})^2\,(pd+(1-p)e)$ when using market orders and $(v-\bar{v})^2\,(pc+(1-p)f)$ when using limit orders. Thus, when

$$p < \frac{f-e}{f-e+d-c} \tag{1}$$

the expected payoff when using limit orders is greater than the expected payoff when using market orders, and a limit order equilibrium emerges. Moreover, if p sufficiently small, this is the only equilibrium.[10]

Condition (1) is expressed in terms of the cardinal values of payoff parameters. In a very liquid market, the cost benefit of a limit orders should be marginal, and hence $f-e$ should be small. Similarly, in a liquid market d should be greater than c. Thus, the right hand side of (1), and hence the condition on p is tighter. This is intuitive. In a liquid market, even absent execution risk imposed by other informed traders, informed traders prefer market orders.

2.3. Trader competition when short selling is costly

In this section we extend the above result to a world where traders can short the stock at a cost. The difference between a model with costly short selling and a model without short selling is that now we have to derive the optimal action of a trader that does not own the stock.

[10] We leave it to the reader to verify that when $p<(f-e)/(b-a+f-e)$ then the market order equilibrium breaks down.

We assume each of the informed traders is one of two types; each type faces a different cost of selling. One type corresponds to an informed trader that already located the shares, perhaps because the shares were in the trader's portfolio to begin with. The second type has yet to borrow the shares. We denote the borrowing costs by C>0, with the convention that if the shares are impossible to short or locate then C is infinity. We use the cost of locating the shares, zero or C, to denote the type of the trader. Consistent with the previous discussion, we let p be the probability that a trader is of type zero, and 1-p the probability that a trader is of type C. The payoff of type C trader is

Trader One's payoff (Type C)		Trader One: Market Orders	Trader One: Limit Orders	Trader One: Abstain
Trader Two	Market Orders	$(v-\bar{v})^2 b-C$	$(v-\bar{v})^2 a-C$	0
Trader Two	Limit Orders	$(v-\bar{v})^2 d-C$	$(v-\bar{v})^2 c-C$	0
Trader Two	Abstain	$(v-\bar{v})^2 e-C$	$(v-\bar{v})^2 f-C$	0

To get the payoff of type zero, we replace C in the above with zero, which is exactly the payoff listed in the previous section.

Theorem 1 (Limit Order vs. Market Order Equilibrium): Assume the event is negative, *$0<a<b<c<d\leq e<f$, and $C>0$.*

(I) If inequality (1) *holds, and in addition*

$$C > (v-\bar{v})^2(pc+(1-p)f) \tag{2}$$

then there is a limit order equilibrium in which type 0 *uses limit orders and type C abstains from trade.*

(II) If

$$C < (v-\bar{v})^2 b \tag{3}$$

then, whether or not inequality (1) holds, there is a market order equilibrium in which type C borrows the shares and both types use market orders.

The proof of the theorem goes as follows. Consider the limit order equilibrium and assume that inequalities (1) and (2) hold, and trader two follows the equilibrium strategy; i.e. trader two uses limit orders when two's type is zero, and otherwise abstains from trade. If the type of trader one is zero, then the expected payoff when using market orders is $(v-\bar{v})^2$ $(pd+(1-p)e)$, while the expected payoff when using limit orders is $(v-\bar{v})^2$ $(pc+(1-p)f)$. Inequality (1) ensures that the latter is larger. If the type of trader one is C, then (2) ensures that the cost of borrowing is greater than the expected payoff, and hence trader one abstains when one's type is C. We therefore verified the limit-order equilibrium

When the cost of borrowing is sufficiently low then type C borrows the shares and the market order equilibrium emerges. To verify that this is indeed an equilibrium, we only need to check that the cost of borrowing is lower than $(v-\bar{v})^2$ b, which the payoff when both traders use market orders. This is (3) in the theorem. This concludes the proof of the theorem.

To sum up, when the news is positive the outcome is a market order equilibrium. When the news is negative, depending on parameters, a limit order equilibrium may emerge. This leads to the following testable predictions.

Hypothesis I: *Informed traders use more aggressive (market) orders before positive unscheduled events and less aggressive (limit) orders before negative unscheduled events.*

On the other hand, if the event is sufficiently large; i.e. $(v-\bar{v})^2$ is large, then inequality (3) holds even if borrowing costs are high.

Hypothesis II: *The behavior of informed buyers and sellers is similar when the event is large.*

In addition, when p, the probability that the informed traders owns the stock prior to learning the negative information, is sufficiently high then inequality (1) is violated, and the limit order equilibrium breaks down. It is conceivable that p is high for stocks that belong to an index and low for stocks that are not part of an index. If the cost of borrowing is sufficiently small, then (3) holds, and the informed traders use market orders.

Hypothesis III: *The behavior of informed buyers and sellers is similar for stocks that belong to an index, or stocks that are inexpensive to short.*

3. Data and Methodology

3.1. Sample and data

To understand the trading strategies of informed traders, we examine the Euronext-Paris, Base de Donnees de Marche (BDM) database for the year 2003. The BDM database contains information on the characteristics of all orders submitted for all stocks listed in the Euronext-Paris market. This includes the firm symbol; the date and time of order submission; a buy or sell indicator; the total size of the order (in shares); the displayed size (in shares); an order type indicator for identifying market, open or limit orders; a limit price in the case of a limit order; and instructions on when the order will expire. In addition, each order contains fields that allow tracking of any modifications made to the order prior to the expiration, with the exception of cancellations.[11]

We examine the 2003 sample period because more recent order-level data purchased from the Euronext market have important inaccuracies. In particular, orders that never get executed, or orders with a hidden component 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 control variables used in some specifications (e.g., displayed depth on the same price in the book, or book order imbalance). In addition, an important advantage is that the Euronext market in 2003 is highly consolidated, with the vast majority of orders being submitted and executed in the main exchange. In more recent periods, the European equity markets have become highly fragmented due to the growth in alternative trading venues, including dark pools.

To test the predictions of our model, we focus the analysis on unanticipated corporate events where it is easier to identify informed trading. Following prior literature, "unanticipated" events are those whose timing is not predictable in advance, while "anticipated" events are those whose timing is known

[11] The database contains fields that allow us to track any modifications made to the order (typically order size and limit price) with complete accuracy. Cancelled orders can be identified as of the end of the day with complete accuracy, but cannot always be identified intraday. We are able in many instances to infer the exact time when an order has been cancelled, based on quote updates that do not reflect completed trades or order modifications, as in Bessembinder and Venkataraman (2004). Since the database identifies the cancellation date, any minor errors in the reconstructed limit order book attributable to undetected order cancellations do not accumulate across trading days.

in advance of the event. As shown by Chae (2005), Graham, Koski and Loewenstein (2006) and Sarkar and Schwartz (2009), although market participants do not know in advance the information contained in anticipated events, those traders with some discretion on timing of trades tend to alter behavior before anticipated events in order to lower adverse selection risk. Lee, Mucklow and Ready (1993), for example, show that market makers widen the bid-ask spread and lower the inside depth before earnings announcements. Anticipated corporate events – such as earnings announcements or macro news announcements - are characterized by two-sided markets due to trading motivated by differential information and/or heterogeneous beliefs. Unanticipated events on the other hand are characterized by one-sided markets since order flow reflects trading that is motivated by private information (Sarkar and Schwartz (2009)).

We identify unanticipated events in the year 2003 using both the Global SDC database compiled by Thomson Financial Securities Data and the AMADEUS database provided by Bureau van Dijk. We focus on five types of unscheduled corporate announcements: mergers and acquisitions (M&As), SEOs, repurchases, dividend initiations and dividend terminations. [12] We capture the exact date of these announcements using Bloomberg and Factiva search engines and identifying the date of the first news story about the event. We focus on companies that are publicly traded on Euronext-Paris market. We eliminate stocks that switched from continuous trading to call auctions (or vice-versa) or were de-listed from the exchange during a 40-day period surrounding the event (30 days before and 10 days after). Our final sample consists of 101 unscheduled corporate events for 95 unique stocks.

Table 1 shows the number of the different types of unanticipated corporate events in our sample. We separate the events into positive and negative based on the two day (Days [0,1]) cumulative abnormal returns (CAR). We use the CAC40 daily index return as a benchmark. We report mean and median measures of returns. Overall, the events in our sample have similar magnitude of positive and negative returns. We have 58 positive events with mean (median) CAR of 4.84% (2.74%) and 43 negative events

[12] We eliminate mergers and acquisitions in which the deal value relative to the market value of the acquirer is less than 5%.

with mean (median) CAR of -4.53% (-2.57%). For M&As, SEOs, repurchases and dividend initiation announcements we observe both positive and negative event days (day 0 and day 1) CAR. Only one stock in our sample announced a dividend termination. The most significant announcement effect is observed for M&As followed by SEOs.

For each unscheduled events, we examine order submission around the announcement day 0. Control period is defined as the 20 days preceding the announcement day, starting on day -30 and ending on day -10. We focus our examination on informed trading activity during Days [-5,-1] preceding the announcement day. Specifically, the abnormal activity during Days[-5,-1] benchmarked against control period activity is attributed to informed traders. Table 2 reports descriptive statistics (mean and medians) of order usage characteristics in control and sample period for buy orders before positive events and sell orders before negative events. Reported are the daily number of orders and average order size for all orders, market/marketable orders, and limit orders. We also report the daily ratio of marketable/market to limit orders and daily hidden order usage. A higher value of the market/limit ratio is consistent with the usage of more price aggressive orders.

Table 2 shows that the number of buy orders increase before positive events and the number of sell orders increase before negative events relative to the control period suggesting that informed traders are active before unanticipated events. We also observe similar increases in the average order size of orders submitted. This is particularly true for the less aggressively priced limit orders, where buy (sell) order size increased from 1,095 (1,909) shares in the control period to 1,562 (2,168) shares in the sample period before positive (negative) events. Although large orders increase the risk of front-running by 'parasitic' traders, exposing size attracts the more patient counterparties who react to displayed orders. Consistent with this idea, we observe no increase in the option to hide order size. Importantly, in preliminary support of hypothesis I, we find a marginal increase in proportion of aggressively priced buy orders before positive events and a marginal decrease in proportion of aggressively priced sell orders before negative events.

3.2 *Cross-sectional aggregation*

We estimate all of our subsequent multivariate analyses on an event-by-event basis. In the interest of parsimony, we present results that are aggregated across events. Harris and Piwowar (2006) emphasize the desirability of assigning larger weights in cross-sectional aggregation to those securities whose parameters are estimated more precisely. To do so, we assess statistical significance by relying on a Bayesian framework attributable to DuMouchel (1994) and also implemented by BVP (2009). The method assumes that, for each estimated firm i coefficient, β_i:

$$\hat{\beta}_i \mid \beta_i \sim i.i.d.N(\beta_i, s_i^2) \tag{4}$$

and

$$\beta_i \sim i.i.d.N(\beta, \sigma^2) \tag{5}$$

where N is the Gaussian distribution. The standard errors, s_i, are estimated by use of the Newey-West method to correct for autocorrelation and heteroskedasticity, and σ^2 is estimated by maximum likelihood.[13] The aggregated β estimate is obtained from the N individual firm estimates as

$$\hat{\beta} = \frac{\sum_{i=1}^{N} \frac{\hat{\beta}_i}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}}{\sum_{i=1}^{N} \frac{1}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}} \tag{6}$$

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

$$Var(\hat{\beta}) = \frac{1}{\sum_{i=1}^{N} \frac{1}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}} \tag{7}$$

where $\hat{\sigma}_{m.l.e}^2$ is the maximum likelihood estimator of σ^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 β_i and also for cross-sectional differences in the precision

[13] To estimate the Newey-West corrected standard errors, we use the Generalized Method of Moments (GMM) with a Bartlett kernel and a maximum lag length of 10.

with which β_i is estimated. The key feature of the aggregation method is that it places more weight on those coefficients that are estimated more precisely.[14]

In all of our multivariate specifications of order submission strategies we include daily dummy variables of the sample period (Days [-5,-1]) to identify abnormal order activity –using the control period as our benchmark. We report the daily dummy coefficients and test statistics based on equation (6) and (7). Since informed trading can occur at any time during the five days before the event day 0, we report a cumulative measure, obtained by aggregating individual day dummy coefficients, which captures the abnormal activity without any econometric constraint on each of the days -5 to -1. Throughout the paper, we focus on both the individual day dummy coefficients and cumulative effects and the corresponding t-statistics in our interpretation of the results.

4. Price Aggressiveness of Informed Traders

4.1. Patterns before unscheduled corporate events

In this section we test the model predictions by examining the price aggressiveness of orders submitted before unanticipated corporate events. The regression specification controls for market conditions at the time of order submission and accounts for all orders submitted during the control period of Days [-30,-10] before the event and the event Days [-5,2], as follows:

$$\begin{aligned} PriceAggressive_{it} = {} & \gamma_0 + \gamma_1 DayMinus5 + \gamma_2 DayMinus4 + \gamma_3 DayMinus3 + \gamma_4 DayMinus2 + \\ & \gamma_5 DayMinus1 + \gamma_6 Day0\&Plus1 + \gamma_7 DayPlus2 + \gamma_8 OrderExposure_{it} + \\ & \gamma_9 PriceAggressive_{it-1} + \gamma_{10} HiddenOppSide_{it} + \gamma_{11} DisplayedSize_{it-1} + \gamma_{12} OrderSize_{it} \\ & + \gamma_{13} Spread_{it} + \gamma_{14} DepthSame_{it} + \gamma_{15} DepthOpp_{it} + \gamma_{16} Volatility_{it} + \gamma_{17} WaitTime_{it} + \\ & \gamma_{18} TradeFreqHour_{it} + \gamma_{19} BookOrderImbalance_{it} + \gamma_{20} TradeSize_{it-1} + \\ & \gamma_{21} MktVolatility_{it-1} + \gamma_{22} Ind.Volatility_{it-1} \end{aligned} \tag{8}$$

where the subscript *i,t* refers to the time *t* order for event *i*. *PriceAggressive* is an ordinal variable that takes the value of 1 for the most aggressive order and 7 for the least aggressive, following the approach

[14] The method does not control for dependence of estimation errors across events. We believe that this dependence should be small since the events are not clustered in time.

Biais, Hillion and Spatt (1995) and BPV (2009).[15] DayMinus5 to DayPlus2 are the dummy variables that equal one for each of the event days, and equals zero otherwise.[16]

The control variables are defined as follows. OrderExposure is an indicator variable that equals one if the order has a hidden size and equals zero otherwise. *TotalOrderSize* is total (displayed plus hidden) size of the order divided by average daily trading volume. *Spread* is the percentage bid-ask spread at time t. *DepthSame* is the displayed depth at the best bid (ask) for a buy (sell) order divided by the monthly median. *DepthOpp* is the displayed depth at the best ask (bid) for a buy (sell) order divided by the monthly median. *Volatility* is the standard deviation of quote midpoint returns over the preceding hour. *WaitTime* is the average elapsed time between the prior three order arrivals on the same side, refreshing the time clock each day. *TradeFreqHour* is the number of transactions in the last hour. *TradesSize* is the size of the most recent transaction divided by the average daily trading volume. *DisplayedOrderSize* is exposed size of the order divided by average daily trading volume. *BookOrderImbalance* is the percentage difference between the displayed liquidity in the best five prices on the buy and sell side of the book, suitable signed (i.e., the variable is positive when same size liquidity exceeds opposite side liquidity). *Ind.Volatility* is the return volatility of portfolio of stocks in same

[15] The first four categories represent orders that demand liquidity from the book and the last three categories represent orders that supply liquidity to the book. 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 categories 2 and 3 may execute fully due to hidden liquidity but may 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).

[16] Following Liu and Agresti (2005) and Gelman & Hill (2007), we select a linear specification over a non-linear specification (ordered probit) because the dependent variable represents a large number of price aggressiveness (seven) categories. Liu and Agresti (2005) for example show that, when fitting a proportional odds model, there is little gain in efficiency when using more than 4 levels over OLS (maximum likelihood). Further, a linear regression specification also allows us a) to easily calculate the economic significant of day-dummy variables and b) to appropriately test and interpret the cumulative abnormal price aggressiveness in the week (day minus 5 to day minus 1) before the unanticipated event.

industry in the prior hour. *Mkt.Volatility* is the return volatility of the CAC40 Index in the prior hour.

Table 3 reports regression coefficients along with corresponding *t*-statistics, estimated on an event-by-event basis and aggregated across firms using the approach described in Subsection 5.2. The coefficients on the control variables are consistent with those reported in the prior studies. Specifically, traders submit less aggressively priced orders (i.e., prefer limit orders over market orders) when the inside bid-ask spread is wide; depth on same side of the book is small indicating less competition from other liquidity providers; depth on opposite side of the book is large or that the last trade revealed the presence of hidden orders, both of which signal the presence of counterparties; when volatility is high, consistent with volatility capture strategy (Handa and Schwartz (1996)); book imbalance indicates that there is less competition on same side relative to the opposite side of the book; and the previous order is priced less aggressively which likely captures market conditions that are missing from the model. The coefficients on the market and industry volatility are not statistically significant. However, own-stock volatility is significant and plays an important role in determining price aggressiveness.

The main tests of the theoretical model are based on coefficient estimates on Dummy variables, DayMinus5 to DayMinus1. Because the least aggressive order is categorized as "7" and the most aggressive order is categorized as "1", a negative coefficient on DayMinus dummy is consistent with informed traders using more aggressively priced orders; conversely, a positive coefficient is consistent with informed traders using less aggressively priced orders.

For buy orders submitted in the days preceding positive events (column (1)), we estimate that all the five coefficients corresponding to Days [-5,-1] are negative. Among the coefficients, DayMinus3 and DayMinus1 have t-statistics below -2.0. Focusing on aggregate effects, we estimate a negative coefficient (t-statistic=-2.96) suggesting that informed buyers submit more aggressively priced orders before positive events. For sell orders submitted before negative events (column (2)), we estimate that four of the five coefficients corresponding to Days [-5,-1] are positive and the coefficient on DayMinus5 is highly statistically significant. We also estimate cumulative effect coefficient to be positive (t-statistic=1.70) suggesting that informed sellers submit less aggressively priced orders before negative event. These patterns are consistent with Hypothesis I and supports the idea that trading strategies of informed buyers and informed sellers differ before corporate events.

4.2. Cross-sectional Patterns in Price Aggressiveness

We develop further cross-sectional tests of the model by examining patterns in buy-sell asymmetry along two dimensions. First, we examine corporate events that are characterized by large versus small announcement period returns. Second, we examine sub-samples of firms characterized by the ease of locating shares and the cost of borrowing shares to implement a short sale.

4.2.1. Announcement return and informed trader strategy

Announcement period return influences price aggressiveness in our framework because informed agents weigh the benefits of taking a short position against the cost of borrowing shares. If the information content is large, informed sellers have incentives to locate shares that are difficult or costly to borrow. However, if the information content is small, the benefits of short selling might not out-weight the cost, thus leading informed agents to abstain from trading if they do not already own the stock. The model predicts that informed sellers face more competition from other informed sellers before large negative events relative to small negative events.

Columns (3) to (6) present regression coefficients that are conditional on the magnitude of announcement returns. We use absolute return of 5% to identify large and small announcements. For small announcements, the cumulative effect coefficient on Days[-5,-1] before positive events is negative (coefficient=-0.35 with t-statistic=-2.09), suggesting an increase in price aggressiveness while those before negative events is positive (coefficient=0.31 with t-statistic=1.95), suggesting a decrease in price aggressiveness. For large positive announcements, we observe an increase in price aggressiveness before positive events (coefficient=-1.60 with t-statistic=-2.40). For large negative announcements, the change in price aggressiveness before negative events (coefficient=0.17 with t-statistic=0.45) is not statistically significant. Overall we find that, consistent with model predictions, informed sellers use less aggressive strategies when event conveys less negative information as compared to other scenarios.

4.2.2. Short sale constraints and informed trader strategy

We expect that index membership influences short sale constraints because constituent stocks are owned by index tracking funds who are active participants in the security lending market. Prior work has shown that it is easier to borrow stocks belonging to major indices (D'Avolio (2002), Nagel (2005)). We therefore classify the sample firms based on whether the stock belongs to the SBF120 index. The model predicts that informed sellers are more likely to trade a stock with unfavorable information if the stock is easy to borrow. For these stocks, informed sellers will face more competition from other informed traders and consequently both informed buyers and sellers should implement aggressive strategies. For stocks not belonging to SBF Index, the model predicts that informed buyers face competition from other informed buyers but because of short constraints, informed sellers do not, and consequently, use passive orders.

In columns (1) - (4) of Table 4, we report the regression coefficients for subsamples of firms based on SBF120 index membership. For buy orders preceding positive events (columns (1) and (3)), the cumulative effect coefficients indicate that informed traders increase price aggressiveness in both stocks included in the SBF120 Index and those not included in the index. However, for sell orders preceding negative events (columns (2) and (4)), we observe a strikingly different pattern in informed trading based on index membership. For index stocks, we observe an increase in price aggressiveness by informed sellers before the event while for non-index stocks, we observe a decrease in price aggressiveness by informed sellers before the event. These results provide direct empirical support for the model's central prediction that informed agent strategy is influenced by the degree of trader competition. Specifically, informed buyers and sellers implement similar strategies when short selling is not costly but implement different strategies when short selling is costly.

We build further evidence using another well-know proxy for short sale constraints – the presence of listed option in the stock.[17] For stocks with listed option, informed sellers have the ability to build a

[17] We note that, although many index constituents stocks have listed options, the fit is far from perfect. In particular, for positive events we have 25 stocks in our sample that belong to the SBF120 index where 14 have listed options. Similarly, for negative events we have 17 stocks that belong to the Index and 14 that have listed options. The overlap in both positive and negative events subsamples is less than 70%.

position using the option market. As option market makers hedge their position in the underlying security, the informed order flow in the option market will be transmitted via the market maker trades to the stock market. Although options market makers can use limit orders, they are unlikely to do so because an unexecuted or partially executed limit order will expose them to inventory risk. The model predicts that informed buyers and sellers submit aggressively priced orders in stocks with listed options because both informed buyers and sellers face competition. In contrast, for stocks without listed options, the model predicts that informed buyers will implement price aggressive strategies while informed sellers will implement more passive strategies.

In columns (5) - (8) of Table 4, we report the regression coefficients for firms with and without listed options. The empirical evidence provides support for the model predictions. For firms with listed options (column (5) and (6)), we observe that the cumulative effect coefficient is negative for both buy orders before positive events and sell orders before negative events. These results are consistent with both informed buyers and sellers facing more competition from other informed traders and the execution risk that they impose on each other. In contrast, for stocks without listed option, the coefficient on buy orders before positive events is negative, which indicates more price aggressive orders, but the coefficient on sell orders before negative events is positive, which indicates less price aggressive orders.

5. Order exposure strategies of informed traders

The option to partially or fully hide order size is a widely available feature in many electronic markets. In fact, one important category of trading venues called Dark Pools only accept orders that are fully hidden. Despite the wide-spread usage of hidden orders, only a handful of academic papers have studied empirically the determinants of order exposure.[18] BVP (2009) examine Euronext-Paris data and show that hidden orders are associated with smaller opportunity costs of non-execution, suggesting that hidden orders are primarily used by traders with no information regarding future price movements.

[18] For theoretical studies, see Buti and Rindi (2008), Bloomfield, O'Hara and Saar (2012) and Boulatov and George (2013).

However, since the majority of market participants are likely to be either noise or liquidity traders, the result that the typical hidden order user is not informed is not entirely unexpected.

Do informed traders hide order size? The line of enquiry is important because opaque trading venues, such as dark pools, execute a significant percentage of equity trading volume. Because these venues do not display prices, regulators are concerned whether informed traders prefer such venues and to what extent the lack of transparency impacts the information efficiency of prices. A result that informed traders expose order size implies that dark pools venues are predominantly used by uninformed traders to control order exposure risk. In this section, we use unscheduled corporate events as a setting to study the informed traders' order exposure strategies. Harris (1996) argues that exposing size will attract interest from "reactive" traders, who have not revealed their orders but wait for other traders to post orders at favorable prices. Informed traders might prefer to exposure size when they submit passive orders to attract counterparties. However, exposing order size reveals the presence of informed agents on one side of the market. Some counterparties might react by withdrawing trading interest, or exploit the information content of the order by implementing front-running strategies (Harris (1997)). Building on this reasoning, Moinas (2006) presents a theoretical model where exposing the size of a large limit order lowers the probability of execution.

5.1. The decision to hide an order.

In table 5, we report regression coefficients, along with corresponding t-statistics, of a logistical model on the decision to hide order size, following the approach implemented by BPV (2009). The dependent variable is an indicator variable that equals one for orders that contain hidden size and zero for orders that do not. The model is estimated using limit orders that will stand on the book (those in categories 5, 6 and 7) because the option to hide size is more relevant for such orders. The Day Dummies are defined similar to those described in Section 4 and capture the strategies of informed traders. Consistent with BPV (2009) and De Winne and D'Hondt (2007), we find that market conditions and order attributes at the time of order submission influence the exposure decision. For example, hidden orders are more likely when the depth at the best quote on the same side is greater, or when previous trades have revealed hidden depth on the same side. We also find that traders who submit larger orders are more likely to hide size. Focusing on individual day cumulative effect coefficients, Panel B of Table 5 results indicate that informed buyers are more likely to use the option to hide size before positive events and informed sellers are less likely to use the option to hide size before negative events.

We obtain additional insights by examining the variation across firms in informed trader strategies. Specifically, in Panels C-F of Table 5, we present the individual day cumulative effect coefficients for various subsamples. The following pattern is noteworthy. For buy orders before positive events, the cumulative effect coefficient is positive, suggesting that informed traders are more likely to submit an order with hidden shares. For negative events where short sale constraints are less binding; i.e., stocks in SBF120 Index or those with listed options, the cumulative effect coefficient for sell orders is negative but not statistically significant. From Table 4, note that informed traders in sub-samples discussed thus far use more aggressively priced orders. Collectively, when informed traders face competition, informed traders increase the use of aggressively priced (market) orders; however, conditional on submitting a standing limit order, they are more likely to use the option to hide size.

In contrast, for sub-samples where short sale constraints are more binding; i.e., those stocks not in SBF120 Index (Panel D) or those without listed options (Panel F), the cumulative effect coefficient for sell orders before negative events is negative and statistically significant. Collectively, when informed agents face less competition, the evidence suggests that informed traders increase the use of passive (limit) orders, but conditional on doing so, they are less likely to use the option to hide limit order size.

5.2. The magnitude of hidden order size

In table 6, we report regression coefficients, along with corresponding t-statistics, of a tobit analysis, focusing on the quantity of shares that are hidden. The analysis builds on the logistical analysis above that focuses on whether the incoming order has hidden shares. Similar to Table 5, the empirical specification includes variables that control for the state of the limit order book, the market conditions such as recent volatility and trades, the order attributes such as price aggressiveness and total order size, and Day Dummies that capture informed trader exposure strategies before positive and negative events.

The model is estimated using limit orders that will stand on the book (those in categories 5, 6 and 7). Consistent with prior work, the number of hidden shares is positively associated with the total size of the incoming order.

Controlling for market conditions and order attributes, in Panel B of Table 6, the individual day cumulative effect coefficient is negative and statistically significant for both buy orders before positive events and sell orders before negative events. In Panels C-F of Table 6, we examine the number of hidden shares for sub-sample of firms. For sub-samples with more competition among informed traders – index constituent stocks and those with listed options – the individual day cumulative effect coefficient is negative but not statistically significant both before positive and negative events. For stocks not in the index or those without listed options, the cumulative effect coefficient is negative and statistically significant. The finding that the cumulative effect is negative in all sub-samples suggests that when informed traders submit limit orders, they choose to expose order size. These results are consistent with Harris (1996) prediction that limit order traders who face a large opportunity cost of non-execution will choose to expose order size in order to attract the reactive traders.

In summary, the results thus far point to two types of informed trader strategies, which we broadly classify as “aggressive” and “passive”. Scenarios with more competition among informed traders are characterized by (a) the use of market orders over limit orders, and (b) the exercise more often of the option to hide limit order size, and (c) expose a larger quantity of shares. Scenarios with less competition among informed trades are characterized by (a) the use of limit orders over market orders, and (b) the exercise less often of the option to hide size and (c) expose a larger quantity of shares. With the use of passive strategies, informed traders face a higher execution risk when the price drifts away due to leakage effects. Empirical evidence in BPV (2009) suggests that exposing order size lowers the time to execution and increases the probability of full execution of a limit order. The increased usage of non-hidden limit orders within passive strategies is consistent with strategies that lower the opportunity cost of non-execution.

6. Order submission strategies of informed traders and execution costs

Informed traders have the ability to choose among many possible trading strategies. The analysis thus far identifies two types of strategies based on the degree of trader competition in the stock. Our model predicts that the choice of a specific strategy reflects an optimization across many dimensions of execution quality, including non-execution risk, time-to-execution and trading costs. In this section, we examine the realized outcome on execution quality for the two types of strategies. A rational selection of strategies implies that different strategies achieve favorable outcomes for the informed trader.

6.1. Trader strategies and execution time

In Table 7, we reports results of an econometric model of limit order time-to-execution using survival analysis, as described in Lo, Mackinlay, and Zhang (2002). The model describes an accelerated failure time specification of limit order execution under the generalized gamma distribution. The control variables, which are identical to Lo et. al. (2002), capture the state of the book, market conditions and order attributes. BPV (2009) show that exposing an order lowers execution time We therefore include a dummy variable that equals one for a hidden order and equals zero otherwise. The individual day dummy variable coefficients capture the change in time-to-execution before unanticipated events. A positive coefficient is consistent with an increase in execution time, and vice-versa. Similar to earlier tables, coefficients are estimated for each event and aggregated across events using the Bayesian framework discussed earlier. We find that more aggressively priced orders and orders that are fully exposed are associated with shorter execution time. Consistent with prior work, we also find that execution time increases when there is more competition on the same side of the market, and vice-versa.

More importantly for our investigation, for both buy orders before positive events and sell orders before negative events, we find that individual day cumulative effect coefficient is negative and statistically significant. Thus the abnormal limit order flow, which we attribute to informed traders, are associated with shorter execution time. In Panel C, we report the time-to-execution individual day cumulative effect coefficients for sub-samples of stocks. We find that cumulative effect coefficient is negative for all subsamples and statistically significant in seven of the eight sub-samples. Since execution time is an empirical proxy for price risk associated with a delayed trade, the evidence in Table 7 suggests that informed agents implement trading strategies that minimize execution delay.

6.2. Trader strategies and implementation shortfall

In this section, we investigate how informed trader strategies influenced the price patterns before the event. To measure execution costs, we rely on the implementation shortfall framework proposed by Perold (1988) and implemented by Harris and Hasbrouck (1996), Griffiths, Smith, Turnbull, and White (2000), and BPV (2009). For each order, we estimate two components of the implementation shortfall for each order: (a) effective spread cost is the appropriately signed difference between the fill price and the quote mid-point at the time of order submission, and (b) the opportunity cost is the appropriately signed difference between the closing price on the order expiration or cancellation date and the quote midpoint at the time of order submission.

For a limit order that goes unfilled, the effective spread cost is zero. For an order that is fully executed, the opportunity cost is zero. For orders that are not fully executed, the opportunity cost is positive if the stock price rises for buy orders and falls for sell orders after order submission. The model predicts, when informed agents face more competition from other traders, they employ more aggressive strategies. These strategies reveal the presence of informed traders and cause an adverse price move. We therefore expect that scenarios with more competition among informed agents are associated with higher opportunity costs. The implementation shortfall cost for an order is the weighted sum of effective spread cost and opportunity cost, where the weights are the proportion of the order size that is filled and unfilled, respectively.

Table 8 presents the coefficient estimates of regressions of execution costs on market conditions and order characteristics. Consistent with Harris and Hasbrouck (1996), we find that price aggressiveness is positively associated with effective spread cost. The negative coefficients on hidden order dummy in the opportunity cost regression suggests that hidden orders are associated with smaller opportunity costs. These findings are consistent with BPV (2009) who conclude that hidden orders are primarily used by uninformed traders who use the option to hide order size to control order exposure risk.

To test model predictions, we focus on Day Dummy coefficients in opportunity cost regressions. These coefficients capture the abnormal execution costs before information events relative to the non-event benchmark costs. For buy orders before positive events, the individual day cumulative effect variable is positive and statistically significant (t-statistic=2.17), suggesting that the stock price on average tends to drift upwards before a positive event. For sell orders before negative events, the cumulative effect variable is negative and marginally significant (t-statistic=-1.77), suggesting that the stock price does not drift downwards before negative events. The asymmetry in opportunity cost is consistent with evidence in Table 4 that informed buyers use aggressive strategies before positive events because they face competition from other traders. The aggressive strategies convey more information and are associated with positive drift in stock price. The positive price drift is reflected in the positive opportunity cost of using a buy limit order before positive events.

We next examine the patterns in opportunity cost for sub-samples based on short sale constraints. For stocks included in SBF120 index, the opportunity cost coefficient based on individual day cumulative effects is positive for both buy orders before positive events and sell orders before negative events. In other words, the stock price tends to drift upwards relative to pre-event benchmarks before positive news and tends to drift downwards before negative news. The drift in stock price is consistent with both informed buyers and informed sellers implementing aggressive trading strategies for these stocks. Since both informed buyer and sellers implement aggressive strategies, other participants detect the presence of informed agents in order flow and the price impact of buy and sell orders are similar. The positive opportunity costs results in higher implementation shortfall costs for informed traders relative to a non-event benchmark.

For stocks not included in SBF 120, the opportunity cost coefficient based on cumulative effects is positive (t-statistic=2.21) for buy orders before positive events and negative (t-statistic=-1.72) for sell orders before negative events. The asymmetry in opportunity cost (or the adverse drift in stock price) is consistent with the asymmetry in order submission strategies for this sub-sample documented in Table 4. The point estimates of cumulative effects before positive and negative events are broadly similar for the sub-samples of stocks based on options listing but the statistical significance of the results is smaller. Collectively, the results suggest that aggressive strategies implemented by informed buyers before positive events causes an upward drift in price. In contrast, the stock price does not drift downwards before negative events because informed sellers implement passive trading strategies.

7. Conclusion

In this study, we present a theoretical model that describes the order submission strategies of informed agents. All else the same, an informed agent would prefer to place a limit order in an attempt to get a better price. However the opportunity cost of non-execution is high when other informed traders use market orders and cause an adverse price move. When opportunity costs are present, informed traders have a strong incentive to use market orders before prices can fully adjust to the new information. Thus when the competition among informed traders is high, the equilibrium strategy in the game is to use market orders. In contrast a monopolist informed trader prefers to use limit orders in order to manage order exposure risk and contain the market impact costs. We posit that costly short selling causes an asymmetry in informed trader strategies before positive and negative events. Specifically, when the event is negative, informed agents choose to abstain if (i) the shares are not in their portfolio, (ii) borrowing costs are high, (iii) the event is small so potential profits cannot justify the costs.

Using detailed order level data from Euronext-Paris, we examine whether the optimal response of informed agents is influenced by uncertainty about the presence of other informed agents in the market. Trading activity attributable to informed agents is identified by focusing on unscheduled corporate events where timing information is not available. Our findings are strongly supportive of theoretical predictions. We show that informed agents employ more aggressive strategies preceding positive events and less aggressive strategies preceding negative events. Examining sub-samples, we find that the buy-sell asymmetry in order submission strategies exists only for sub-samples where security borrowing is difficult or too expensive or the announcement returns are small. The model predicts that informed agents will abstain from selling in these sub-samples if they do not already own the stock. For sub-samples where announcement results are large or short sale constraints are less binding, we observe an increase in price aggressiveness symmetrically for both buy orders before positive events and sell orders before negative events. This is supportive of model predictions that both informed buyers and sellers face competition and therefore employ more aggressive trading strategies.

The study contributes to a better understanding of the well-documented asymmetry in the price effects surrounding block purchases and sales. Prior work has shown that block purchases contain more information than block sales. Our results that informed agents with positive private information use aggressive strategies while those with negative information use passive strategies.. We verify that the asymmetry in execution costs exist for sub-samples where short sale constraints are binding but not for sub-samples where stocks are easy to borrow. We propose an explanation for buy-sell asymmetry that the observed price pattern is driven, at least in part, by the extent to which order submission strategies tip off market participants about the presence of informed traders. Intense competition among informed agents signals their presence to other market participants who adjust the security price to reflect the information content of the trade. These price adjustments are captured as higher opportunity costs for buy orders as compared with sell orders, particularly for sub-samples with narrow investor base and short selling costs.

The study provides a framework for detecting unusual trading activity that can be attributed to inside information. An important insight from our model is that informed agents order submission strategies are influenced by the breadth of investor base, the cost of borrowing shares, and the nature of private information. For regulators, broker-dealers, and exchanges interested in detecting patterns attributable to insider trading, our study provides guidance on ex-ante optimal strategies of insiders and how patterns might vary in the cross-section of stocks. Further, we show that informed traders prefer to expose limit order size in order to increase execution probability and lower non-execution risk, suggesting that informed traders are unlikely to be attracted to dark pool venues. Our evidence should inform the debate on the impact of dark pools on informational efficiency of prices.

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Table 1: Unanticipated Corporate Events: abnormal returns

The table reports number of the different types of unanticipated corporate events in our sample. We look at 5 different types of events: acquisitions, targets, season equity offerings, repurchases, dividend initiations and dividend termination. We separate the events into positive and negative based on the two day (day 0 and day plus 1) cumulative abnormal returns. These are calculated by subtracting the CAC40 daily index returns which is used as a benchmark. We report mean and median measures of the returns.

Type of Events		Abnormal Returns					
		Positive			Negative		
	Total	# of Events	Mean	Median	# of Events	Mean	Median
Overall	101	58	4.84%	2.74%	43	-4.53%	-2.57%
Acquisitions	35	26	3.61%	2.56%	9	-3.88%	-4.15%
Targets	25	16	9.52%	7.12%	9	-7.73%	-2.65%
SEOs	22	8	3.41%	3.42%	14	-4.53%	-3.08%
Repurchases	14	6	2.88%	1.59%	8	-1.83%	-1.82%
Divident Initiations	4	2	2.32%	2.32%	2	-5.34%	-5.34%
Divident Terminations	1	-	-	-	1	-1.82%	-1.82%

Table 2: Descriptive Statistics of Order Usage characteristics

The table reports descriptive statistics of order usage characteristics for all 101 unanticipated corporate events in our sample. The relevant characteristics are calculated for each firm-event and the table reports the (cross-sectional) statistics across all firm-events. We report mean and median statistics of order activity and order size of 1) all orders submitted, 2) market/marketable orders submitted and, 3) limit orders submitted. We also report mean and median percentage numbers of the ratio of market/marketable orders to limit orders, and hidden order usage. In Panel A (control period) we report statistics during our control period of 10 days to 30 days before the corporate announcements. Panel B (sample period) reports similar statistics during day minus 5 to day minus 1 before the event announcement.

Daily Descriptive statistics	Positive		Negative Events	
	Mean	Median	Mean	Median
Panel A: Control Period				
Daily Number of Orders	638.5	50.7	898.6	63.9
Average Order Size	1,004.0	436.6	1,771.0	1,045.0
Daily Number of Marketable/Market Orders	147.5	16.0	235.0	24.5
Average Order Size of Marketable/Market Orders	731.0	298.1	1,260.0	705.5
Daily Number of Limit Orders	432.1	45.6	472.2	65.6
Average Order Size of Limit Orders	1,095.0	481.2	1,909.0	1,190.0
Average Percentage Marketable\Market Orders to Limit	45.1	44.3	50.0	51.7
Average Hidden Orders Usage	18.4	15.3	17.6	16.3

Daily Descriptive statistics	Positive		Negative Events	
	Mean	Median	Mean	Median
Panel B: Sample Period				
Daily Number of Orders	808.8	63.9	995.5	117.0
Average Order Size	1,358.0	461.7	2,031.0	1,107.0
Daily Number of Marketable/Market Orders	158.4	15.4	253.3	25.2
Average Order Size of Marketable/Market Orders	703.2	345.0	1,535.0	669.1
Daily Number of Limit Orders	444.5	41.2	507.2	86.2
Average Order Size of Limit Orders	1,562.0	492.5	2,168.0	1,159.0
Average Percentage Marketable\Market Orders to Limit	48.1	46.1	49.4	49.0
Average Hidden Orders Usage	18.8	14.8	17.1	16.2

Table 3: Regressions of Price Aggressiveness and Event Period Returns

The table shows regression coefficients that report changes in price aggressiveness around unanticipated corporate events (5 days before the event to 1 day after the event) controlling for order attributes and market conditions. Detailed definitions of the explanatory variables are provided in Section 4. Our sample is a set of 95 Euronext-Paris stocks around 101 unanticipated corporate events. We investigate buy (sell) orders around positive (negative) events separately and for subsamples of large and small event returns (less or more than 5%). Panel A reports individual day dummy effects and Panel B reports cumulative coefficient effects of the 5 days dummies before the event (day minus 5 to day minus 1). The time series coefficients are estimated on an event-by-event basis. Reported results are aggregated across events using the Bayesian framework of DuMouchel (1994).

	All Events		Event Period Absolute Return <5%		Event Period Absolute Return >5%	
	Buy orders, Positive Events	Sell orders, Negative Events	Buy orders, Positive Events	Sell orders, Negative Events	Buy orders, Positive Events	Sell orders, Negative Events
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Individual Day Minus 5 to Day Minus 1 Day Dummies						
Intercept	4.8742	4.9304	4.9278	4.7356	4.7567	4.9353
(t-statistic)	(75.78)	(23.50)	(70.47)	(60.92)	(34.17)	(48.62)
Day Minus 5 (dummy)	-0.1802	0.0996	-0.0234	0.1553	-0.5875	0.0289
(t-statistic)	(-1.50)	(2.76)	(-0.26)	(2.45)	(-1.89)	(0.25)
Day Minus 4 (dummy)	-0.1036	-0.0066	-0.0412	0.0605	-0.2910	0.1015
(t-statistic)	(-1.07)	(-0.14)	(-0.56)	(0.89)	(-1.21)	(1.59)
Day Minus 3 (dummy)	-0.1069	0.0480	-0.0593	0.1071	-0.2080	-0.3191
(t-statistic)	(-2.08)	(1.30)	(-1.00)	(2.18)	(-2.22)	(-1.38)
Day Minus 2 (dummy)	-0.1524	0.0198	-0.0461	0.0111	-0.4219	0.2013
(t-statistic)	(-1.85)	(0.58)	(1.18)	(0.21)	(-1.69)	(1.53)
Day Minus 1 (dummy)	-0.1147	0.0335	-0.1188	0.1059	-0.1077	0.0167
(t-statistic)	(-2.66)	(0.65)	(-2.43)	(0.86)	(-1.23)	(0.11)
Day 0 & Plus 1 (dummy)	-0.0179	0.0312	-0.0520	0.0432	0.0611	0.1278
(t-statistic)	(-0.48)	(0.82)	(-1.30)	(0.69)	(2.40)	(1.18)
Day Plus 2 (dummy)	0.0412	0.0053	0.0050	-0.0236	0.1523	0.1667
(t-statistic)	(0.74)	(0.09)	(0.09)	(-0.26)	(1.07)	(1.71)
Order exposure	0.7033	0.3215	0.6509	0.6803	0.8131	0.5921
(t-statistic)	(14.79)	(4.95)	(10.80)	(8.21)	(11.52)	(7.14)
Total order size (norm)	-0.0132	-0.0513	-0.0116	-0.0354	-0.0321	-0.0061
(t-statistic)	(-0.75)	(-0.78)	(-0.62)	(-0.71)	(-0.84)	(-0.50)
Bid-ask spread (norm)	26.4288	3.1271	31.9928	30.9306	15.0717	27.5898
(t-statistic)	(3.12)	(0.41)	(2.81)	(3.32)	(1.37)	(1.73)
Depth -same side (norm)	-1.3418	-4.8590	-9.2097	-2.3023	-0.1543	-17.0091
(t-statistic)	(-3.63)	(-2.56)	(-3.05)	(-3.69)	(-2.07)	(-2.90)
Depth - opposite side (norm)	0.5511	2.4014	0.7286	0.3726	0.1437	4.0519
(t-statistic)	(2.60)	(1.58)	(1.90)	(0.80)	(1.65)	(1.66)
Volatility	5.6423	-21.4186	-6.0775	18.3208	18.3363	-19.3126
(t-statistic)	(0.57)	(-0.69)	(-0.44)	(0.82)	(1.45)	(-0.98)
Waiting time	0.0010	0.0007	0.0012	0.0014	0.0004	0.0036
(t-statistic)	(2.23)	(1.32)	(2.34)	(2.04)	(0.54)	(1.89)
Trade frequency	-0.0014	-0.0008	-0.0015	-0.0004	-0.0013	-0.0009
(t-statistic)	(2.00)	(-1.12)	(-1.72)	(-1.01)	(-1.02)	(-0.67)
HiddenOppSide (norm)	-23.4283	-2.7500	-36.8574	-12.4462	-5.5166	-26.0105
(t-statistic)	(-2.85)	(-2.92)	(-3.78)	(-4.29)	(-3.12)	(-2.62)
Book order imbalance (norm)	-0.0351	-0.0673	-0.0425	-0.0782	-0.1328	0.0034
(t-statistic)	(-2.52)	(-2.41)	(-3.09)	(-4.71)	(-0.75)	(0.05)
Lag (price aggressiveness)	-9.0185	-3.7284	-8.0080	-6.4255	-11.0840	-6.7685
(t-statistic)	(-9.20)	(-4.65)	(-8.03)	(-4.27)	(-5.08)	(-2.58)
Lag (displayed order size)	-0.4658	3.7116	-0.1595	1.5042	-0.1126	20.5119
(t-statistic)	(-2.24)	(1.47)	(-0.32)	(1.59)	(-2.49)	(2.40)
Last trade size (norm)	-0.0209	0.4518	1.0078	2.7113	-0.0112	-0.8185
(t-statistic)	(-1.64)	(0.29)	(2.99)	(2.25)	(-2.22)	(-1.32)
Market volatility	0.1982	-0.0653	-0.1107	0.0057	0.9537	-0.1916
(t-statistic)	(0.82)	(-0.79)	(-1.08)	(0.03)	(1.59)	(-1.15)
Industry volatility	0.0454	-0.0111	0.0204	-0.0209	0.0949	0.0043
(t-statistic)	(2.21)	(-1.07)	(1.68)	(-1.17)	(1.63)	(0.88)

	All Events		Event Period Absolute Return <5%		Event Period Absolute Return >5%	
	Buy orders, Positive Events	Sell orders, Negative Events	Buy orders, Positive Events	Sell orders, Negative Events	Buy orders, Positive Events	Sell orders, Negative Events
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Cumulative Effect of Day Minus 5 to Day Minus 1 Coefficients						
Cumulative Effect:						
Day Minus 5 to Day Minus 1	-0.6045	0.1702	-0.3462	0.3138	-1.5966	0.1659
(t-statistic)	(-2.96)	(1.70)	(-2.09)	(1.95)	(-2.40)	(0.45)

Table 4: Regressions of Price Aggressiveness - Inclusion in the SBF120 Index or Presence of Options Market

The table shows regression coefficients that report changes in price aggressiveness around unanticipated corporate events (5 days before the event to 1 day after the event) controlling for order attributes and market conditions. Detailed definitions of the explanatory variables are provided in Section 4. Our sample is a set of 95 Euronext-Paris stocks around 101 unanticipated corporate events. We investigate buy (sell) orders around positive (negative) events for subsamples of companies based on 1) whether or not they belong to the SBF 120 index and 2) have an active options marker. Panel A reports individual day dummy effects and Panel B reports cumulative coefficient effects of the 5 days dummies before the event (day minus 5 to day minus 1). The time series coefficients are estimated on an event-by-event basis. Reported results are aggregated across events using the Bayesian framework of DuMouchel (1994).

	Events From Companies in SBF120		Events From Companies not in SBF120		Events From Companies with Options		Events From Companies without Options	
Variable	Buy orders, Positive Events Coefficient (1)	Sell orders, Negative Events Coefficient (2)	Buy orders, Positive Events Coefficient (3)	Sell orders, Negative Events Coefficient (4)	Buy orders, Positive Events Coefficient (1)	Sell orders, Negative Events Coefficient (2)	Buy orders, Positive Events Coefficient (3)	Sell orders, Negative Events Coefficient (4)
Panel A: Individual Day Minus 5 to Day Minus 1 Day Dummies								
Day Minus 5 (dummy)	-0.0687	-0.0488	-0.2937	0.1799	-0.0713	-0.0442	-0.2265	0.1885
(t-statistic)	(-1.56)	(-0.68)	(-1.31)	(2.21)	(-2.01)	(-0.55)	(-1.38)	(2.26)
Day Minus 4 (dummy)	-0.1212	-0.1221	-0.0705	0.0981	-0.0249	-0.1074	-0.1245	0.0636
(t-statistic)	(-2.27)	(-1.71)	(-0.40)	(1.20)	(-0.53)	(-1.49)	(-0.96)	(0.73)
Day Minus 3 (dummy)	-0.0892	-0.0575	-0.1246	-0.1001	-0.0417	-0.0818	-0.1274	0.0459
(t-statistic)	(-1.67)	(-0.91)	(-1.32)	(-0.61)	(-0.83)	(-1.30)	(-1.80)	(0.42)
Day Minus 2 (dummy)	-0.0877	-0.1014	-0.2018	0.1499	-0.0490	-0.1124	-0.1939	0.0952
(t-statistic)	(-2.50)	(-2.42)	(-1.28)	(1.50)	(-1.51)	(-2.58)	(-1.71)	(1.36)
Day Minus 1 (dummy)	-0.0762	-0.0463	-0.1932	0.0407	-0.0449	-0.0310	-0.1680	0.1272
(t-statistic)	(-1.94)	(-0.87)	(-2.75)	(0.25)	(-1.21)	(-0.71)	(-2.93)	(0.89)
Day 0 & Plus 1 (dummy)	-0.0656	-0.0196	0.0601	0.0882	-0.0529	-0.0186	0.0003	0.1380
(t-statistic)	(-2.20)	(-0.32)	(0.75)	(1.37)	(-3.66)	(-0.31)	(0.01)	(1.80)
Day Plus 2 (dummy)	-0.0681	-0.0828	0.1760	0.0489	-0.0488	-0.0232	0.0825	0.0169
(t-statistic)	(-1.60)	(-1.16)	(1.56)	(0.43)	(-1.02)	(-0.35)	(1.02)	(0.14)
Order exposure	0.6328	0.5981	0.7256	0.6143	0.7312	0.4944	0.6950	0.7589
(t-statistic)	(8.21)	(8.62)	(10.51)	(6.45)	(7.80)	(5.55)	(12.70)	(12.31)
Total order size (norm)	-4.7856	0.1762	0.0016	-0.0230	-10.8506	0.8064	-0.0100	-0.0268
(t-statistic)	(-2.82)	(0.39)	(0.10)	(-0.64)	(-2.93)	(0.99)	(-0.58)	(-0.74)
Control variables	yes	yes	yes	yes	yes	yes	yes	yes
Panel B: Cumulative Effect of Day Minus 5 to Day Minus 1 Coefficients								
Cumulative Effect: Day Minus 5 to Day Minus 1	-0.3781	-0.3521	-0.8574	0.4246	-0.2404	-0.3894	-0.7946	0.5333
(t-statistic)	(-2.31)	(-1.74)	(-2.14)	(2.17)	(-2.04)	(-2.03)	(-2.66)	(2.57)

Table 5: Logistic Regressions of Decision to Hide

The table shows logistic regression coefficients that report changes in the decision to hide for standing limit orders submitted around unanticipated corporate events (5 days before the event to 1 day after the event) controlling for order attributes and market conditions. Detailed definitions of the explanatory variables are provided in Section 4. Our sample is a set of 95 Euronext-Paris stocks around 101 unanticipated corporate events. We investigate buy (sell) orders around positive (negative) events separately. Panel A reports individual day dummy effects and Panel B reports cumulative coefficient effects of the 5 days dummies before the event (day minus 5 to day minus 1). Panels C and D report cumulative coefficient effects of the 5-day dummies before the event (day minus 5 to day minus 1) for subsamples of companies based on whether (or not) they belong to the SBF 120 index. Panels E and F report similar cumulative coefficient effects for subsample of companies based on whether or not they have an active options marker. The time series coefficients are estimated on a event-by-event basis. Reported results are aggregated across events using the Bayesian framework of DuMouchel (1994).

Variable	Decision to hide order size	
	Buy orders, Positive Events	Sell orders, Negative Events
	Coefficient	Coefficient
	(1)	(2)
Panel A: Individual Day Minus 5 to Day Minus 1 Day Dummies		
Intercept	-2.8920	-2.8394
(t-statistic)	(-20.08)	(-13.12)
Day Minus 5 (dummy)	0.0193	-0.2924
(t-statistic)	(0.05)	(-1.24)
Day Minus 4 (dummy)	0.3363	0.0716
(t-statistic)	(1.56)	(0.33)
Day Minus 3 (dummy)	0.4893	-0.3445
(t-statistic)	(2.67)	(-1.03)
Day Minus 2 (dummy)	0.1636	-0.3180
(t-statistic)	(0.85)	(-1.26)
Day Minus 1 (dummy)	0.4417	-0.0341
(t-statistic)	(2.22)	(-0.14)
Day 0 & Plus 1 (dummy)	2.8976	-0.1665
(t-statistic)	(1.41)	(-0.59)
Day Plus 2 (dummy)	0.3199	-0.0425
(t-statistic)	(1.06)	(-0.16)
Price aggressiveness	-0.6754	1.0847
(t-statistic)	(-1.24)	(1.27)
Total order size (norm)	284.7097	187.4860
(t-statistic)	(4.23)	(4.62)
Bid-ask spread (norm)	-14.1272	-21.1568
(t-statistic)	(-1.20)	(-1.41)
Depth -same side (norm)	-20.3182	-18.5887
(t-statistic)	(-4.90)	(-2.88)
Depth - opposite side (norm)	-1.1419	-5.4541
(t-statistic)	(-0.82)	(-1.62)
Volatility	-121.7095	-38.1052
(t-statistic)	(-3.34)	(-1.84)
Waiting time	-6.94E-06	0.0003
(t-statistic)	(-0.01)	(0.52)
Trade frequency	0.2784	-0.0010
(t-statistic)	(1.07)	(-0.03)
HiddenSameSide (norm)	4.4443	6.6096
(t-statistic)	(2.25)	(2.09)
Same price book displayed depth (norm)	0.4473	-1.2861
(t-statistic)	(1.60)	(-2.26)
Book order imbalance (norm)	-0.0449	-0.4683
(t-statistic)	(-1.19)	(-1.69)
Last trade size (norm)	-2.8053	-1.3999
(t-statistic)	(-4.01)	(-0.78)
Market volatility	0.0025	-4.7688
(t-statistic)	(0.01)	(-2.47)
Industry volatility	0.2611	0.0035
(t-statistic)	(0.32)	(0.10)

Variable	Decision to hide order size	
	Buy orders, Positive Events	Sell orders, Negative Events
	Coefficient	Coefficient
	(1)	(2)
Panel B: Cumulative Effect of Day Dummies - Overall		
Cumulative Effect: Day Minus 5 to Day Minus 1	1.4193	-1.7257
(t-statistic)	(2.01)	(-2.34)
Panel C: Cumulative Effect of Day Dummies - Companies in the SBF120 Index		
Cumulative Effect: Day Minus 5 to Day Minus 1	1.1066	-1.9511
(t-statistic)	(1.87)	(-1.55)
Panel D: Cumulative Effect of Day Dummies - Companies not in the SBF120 Index		
Cumulative Effect: Day Minus 5 to Day Minus 1	1.0482	-2.3973
(t-statistic)	(0.85)	(-2.35)
Panel E: Cumulative Effect of Day Dummies - Companies with Options		
Cumulative Effect: Day Minus 5 to Day Minus 1	1.7273	-1.6068
(t-statistic)	(1.85)	(-1.22)
Panel F: Cumulative Effect of Day Dummies - Companies without Options		
Cumulative Effect: Day Minus 5 to Day Minus 1	0.8468	-1.8679
(t-statistic)	(1.02)	(-2.46)

Table 6: Tobit Regressions of Magnitude of Hidden Size

The table shows tobit regression coefficients that report changes of the magnitude of hidden size for standing limit orders submitted around unanticipated corporate events (5 days before the event to 1 day after the event) controlling for order attributes and market conditions. Detailed definitions of the explanatory variables are provided in Section 4. Our sample is a set of 95 Euronext-Paris stocks around 101 unanticipated corporate events. We investigate buy (sell) orders around positive (negative) events separately. Panel A reports individual day dummy effects and Panel B reports cumulative coefficient effects of the 5 days dummies before the event (day minus 5 to day minus 1). Panels C and D report cumulative coefficient effects of the 5-day dummies before the event (day minus 5 to day minus 1) for subsamples of companies based on whether (or not) they belong to the SBF 120 index. Panels E and F report similar cumulative coefficient effects for subsample of companies based on whether or not they have an active options marker. The time series coefficients are estimated on a event-by-event basis. Reported results are aggregated across events using the Bayesian framework of DuMouchel (1994).

Variable	Magnitude of hidden order size	
	Buy orders, Positive Events	Sell orders, Negative Events
	Coefficient	Coefficient
	(1)	(2)
Panel A: Individual Day Minus 5 to Day Minus 1 Day Dummies		
Intercept	-0.1027	-0.2880
(t-statistic)	(-0.67)	(1.79)
Day Minus 5 (dummy)	-0.2054	-0.2451
(t-statistic)	(-1.85)	(-1.41)
Day Minus 4 (dummy)	-0.1493	-0.0001
(t-statistic)	(-1.15)	(-0.00)
Day Minus 3 (dummy)	-0.0442	-0.1186
(t-statistic)	(-0.57)	(-2.14)
Day Minus 2 (dummy)	0.0791	0.0140
(t-statistic)	(0.61)	(0.13)
Day Minus 1 (dummy)	0.0390	0.0765
(t-statistic)	(0.40)	(0.73)
Day 0 & Plus 1 (dummy)	0.0580	-0.0824
(t-statistic)	(0.92)	(-0.42)
Day Plus 2 (dummy)	0.0076	-0.3375
(t-statistic)	(0.05)	(-1.83)
Price aggressiveness	-2.3127	-2.1466
(t-statistic)	(-1.68)	(-1.29)
Total order size (norm)	0.3034	1.3982
(t-statistic)	(4.25)	(3.52)
Bid-ask spread (norm)	-0.1073	-0.7237
(t-statistic)	(-0.08)	(-0.35)
Depth -same side (norm)	-0.1544	-0.2238
(t-statistic)	(-0.91)	(-0.44)
Depth - opposite side (norm)	0.0523	-0.7361
(t-statistic)	(0.33)	(-1.12)
Volatility	-17.4197	5.7855
(t-statistic)	(-1.57)	(0.56)
Waiting time	0.0002	0.0000
(t-statistic)	(0.33)	(0.21)
Trade frequency	0.0050	0.0026
(t-statistic)	(1.25)	(1.18)
HiddenSameSide (norm)	0.3363	1.6736
(t-statistic)	(0.60)	(1.05)
Same price book displayed depth (norm)	-0.0382	-0.5880
(t-statistic)	(-0.56)	(-0.99)
Book order imbalance (norm)	-0.0688	0.0097
(t-statistic)	(-1.69)	(0.16)
Last trade size (norm)	-0.4486	1.1302
(t-statistic)	(-1.29)	(1.68)
Market volatility	-3.3918	0.2542
(t-statistic)	(-2.48)	(1.00)
Industry volatility	0.0944	0.0287
(t-statistic)	(0.68)	(0.27)

Variable	Magnitude of hidden order size	
	Buy orders, Positive Events	Sell orders, Negative Events
	Coefficient	Coefficient
	(1)	(2)
Panel B: Cumulative Effect of Day Dummies - Overall		
Cumulative Effect: Day Minus 5 to Day Minus 1	-1.7683	-1.2516
(t-statistic)	(-3.33)	(-2.44)
Panel C: Cumulative Effect of Day Dummies - Companies in the SBF120 Index		
Cumulative Effect: Day Minus 5 to Day Minus 1	-1.2805	-0.5382
(t-statistic)	(-1.48)	(-1.16)
Panel D: Cumulative Effect of Day Dummies - Companies not in the SBF120 Index		
Cumulative Effect: Day Minus 5 to Day Minus 1	-2.1779	-1.7885
(t-statistic)	(-2.99)	(-2.24)
Panel E: Cumulative Effect of Day Dummies - Companies with Options		
Cumulative Effect: Day Minus 5 to Day Minus 1	-0.3717	-0.7375
(t-statistic)	(-0.61)	(-1.32)
Panel F: Cumulative Effect of Day Dummies - Companies without Options		
Cumulative Effect: Day Minus 5 to Day Minus 1	-2.3479	-1.7502
(t-statistic)	(-3.42)	(-2.38)

Table 7: Order submission strategies and limit order time-to-execution

The table reports parameter estimates of an econometric model of limit order time-to-execution using survival analysis, following Lo, Mackinlay, and Zhang (2002). The model describes an accelerated failure time specification of limit order execution times under the generalized gamma distribution. Our sample is a set of 95 Euronext-Paris stocks around 101 unanticipated corporate events. We investigate buy (sell) orders around positive (negative) events. We report changes in time-to-execution around unanticipated corporate events (5 days before the event to 1 day after the event). Our control variables are: the distance in basis points of the order's limit price from the quote midpoint (*midquote - limit price*); an indicator variable that equals one if the prior trade is buyer-initiated and equals zero otherwise (*last trade buy indicator*); the displayed depth at the best bid (ask) for a buy (sell) order (*same side depth*); the square of the previous measure to account for non-linearity (*same side depth squared*); the displayed depth at the best ask (bid) for a buy (sell) order (*opposite side depth*); the total (exposed plus hidden) size of the order (*order Size*); the number of trades in the last hour (*trade frequency*); an indicator valuable that equals one if the order has hidden size and equals zero otherwise (*hidden order*). Panel A reports individual day dummy effects and Panel B reports cumulative coefficient effects of the 5 days dummies before the event (day minus 5 to day minus 1). Panels C and D report cumulative coefficient effects of the 5-day dummies before the event (day minus 5 to day minus 1) for subsamples of companies based on whether (or not) they belong to the SBF 120 index. Panels E and F report similar cumulative coefficient effects for subsample of companies based on whether or not they have an active options marker. Reported results are aggregated across events using the Bayesian framework of DuMouchel (1994).

Variable	Event regressions: Buy orders, Positive — Coefficient (1)	Event regressions: Sell orders, Negative — Coefficient (2)
Panel A: Individual Day Minus 5 to Day Minus 1 Day Dummies		
Intercept	9.1890	14.7985
(t-statistic)	(13.06)	(13.63)
Day Minus 5 (dummy)	-0.7588	-0.8058
(t-statistic)	(-1.87)	(-2.35)
Day Minus 4 (dummy)	-0.7109	-0.2320
(t-statistic)	(-2.19)	(-0.75)
Day Minus 3 (dummy)	-0.1890	-0.3581
(t-statistic)	(-0.73)	(-1.09)
Day Minus 2 (dummy)	-0.3274	-0.2397
(t-statistic)	(-1.01)	(-1.23)
Day Minus 1 (dummy)	0.1344	0.0637
(t-statistic)	(0.50)	(0.25)
Day 0 & Plus 1 (dummy)	-0.1417	-0.1877
(t-statistic)	(-0.43)	(-1.22)
Day Plus 2 (dummy)	-0.4730	-0.2739
(t-statistic)	(-2.85)	(-0.69)
Midquote - limit price	3.6879	-6.6568
(t-statistic)	(3.02)	(-2.88)
Last trade buy indicator	-0.1330	-0.3285
(t-statistic)	(-2.52)	(-1.72)
Same side depth (norm)	0.0872	0.0478
(t-statistic)	(3.49)	(2.64)
Same side depth squared	0.0029	0.0156
(t-statistic)	(0.03)	(0.36)

Variable	Event regressions	
	Buy orders, Positive	Sell orders, Negative
	Coefficient	Coefficient
	(1)	(2)
Opposite side depth (norm)	-0.2199	-0.3902
(t-statistic)	(-7.18)	(-5.85)
Order Size	0.1884	0.1091
(t-statistic)	(4.81)	(2.83)
Trade frequency	-0.0060	-0.0045
(t-statistic)	(-4.27)	(-4.40)
Hidden order indicator	0.9269	1.2866
(t-statistic)	(5.53)	(6.45)
Scale (fitted distribution)	3.0459	2.0031
(t-statistic)	(8.46)	(5.80)
Shape(fitted distribution)	0.3185	3.6109
(t-statistic)	(0.52)	(3.78)
Panel B: Cumulative Effect of Day Dummies - Overall		
Cumulative Effect: Day Minus 5 to Day Minus 1	-1.7089	-1.2612
(t-statistic)	(-3.17)	(-3.04)
Panel C: Cumulative Effect of Day Dummies - Companies in the SBF120 Index		
Cumulative Effect: Day Minus 5 to Day Minus 1	-1.9295	-1.1736
(t-statistic)	(-2.10)	(-2.88)
Panel D: Cumulative Effect of Day Dummies - Companies not in the SBF120 Index		
Cumulative Effect: Day Minus 5 to Day Minus 1	-1.6231	-1.7499
(t-statistic)	(-2.52)	(-1.89)
Panel E: Cumulative Effect of Day Dummies - Companies with Options		
Cumulative Effect: Day Minus 5 to Day Minus 1	-2.1491	-1.3092
(t-statistic)	(-1.43)	(-3.27)
Panel F: Cumulative Effect of Day Dummies - Companies without Options		
Cumulative Effect: Day Minus 5 to Day Minus 1	-2.0108	-1.2612
(t-statistic)	(-3.34)	(-3.04)

Table 8: Regressions of implementation shortfall, effective spreads trading costs, and opportunity cost

The table shows regression coefficients that report changes in execution costs around unanticipated corporate events (5 days before the event to 1 day after the event) controlling for order attributes and market conditions. Our sample is a set of 95 Euronext-Paris stocks around 101 unanticipated corporate events. We investigate buy (sell) orders around positive (negative) events. Execution costs are based on the implementation shortfall approach proposed by Perold (1988), defined as follows. 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* is defined as the difference between the closing price on the day of order cancellation or expiration and the quote midpoint at the time of order submission. *Implementation shortfall* is the summation of the two costs. We control for three variables that represent order attributes (price aggressiveness, order size, and hidden order indicator) and two variables that represent market conditions during the trading hour prior to order submission (trading frequency and return volatility). For *effective spread cost*, we report regression results conditional on partial execution (*effective spread cost* ≠ 0, Columns 3 and 4). For *opportunity cost*, we report regression results conditional on partial non-execution (*opportunity cost* ≠ 0, columns 5 and 6). Panel A reports individual day dummy effects and Panel B reports cumulative coefficient effects of the 5-day dummies before the event (day minus 5 to day minus 1). Panels C and D report cumulative coefficient effects of the 5-day dummies before the event (day minus 5 to day minus 1) for subsamples of companies based on whether (or not) they belong to the SBF 120 index. Panels E and F report similar cumulative coefficient effects for subsample of companies based on whether or not they have an active options marker. Reported results are aggregated across events using the Bayesian framework of DuMouchel (1994).

	Implementation Shortfall		Effective Spread cost: fill rate >0%		Opportunity cost: fill rate < 100%	
	Buy orders, Positive Events	Sell orders, Negative Events	Buy orders, Positive Events	Sell orders, Negative Events	Buy orders, Positive Events	Sell orders, Negative Events
Variable	Coefficient (1)	Coefficient (2)	Coefficient (3)	Coefficient (4)	Coefficient (5)	Coefficient (6)
Panel A: Individual Day Minus 5 to Day Minus 1 Day Dummies						
Intercept	0.0541	0.0560	0.0651	0.0466	0.0969	0.0775
(t-statistic)	(3.03)	(2.81)	(5.77)	(4.57)	(2.21)	(2.59)
Day Minus 5 (dummy)	0.0275	-0.0553	0.0044	-0.0004	0.0491	-0.1210
(t-statistic)	(0.88)	(-1.42)	(0.39)	(-0.11)	(1.14)	(-2.13)
Day Minus 4 (dummy)	0.0037	-0.0115	-0.0055	0.0032	-0.0197	-0.0406
(t-statistic)	(0.12)	(-0.42)	(-1.23)	(0.50)	(-0.34)	(-0.74)
Day Minus 3 (dummy)	0.0846	-0.0350	-0.0006	-0.0026	0.1338	-0.0691
(t-statistic)	(2.67)	(-2.59)	(-0.10)	(-0.68)	(2.23)	(-3.14)
Day Minus 2 (dummy)	0.0161	0.0114	0.0029	0.0092	0.0008	-0.0152
(t-statistic)	(0.36)	(0.33)	(0.21)	(1.18)	(0.01)	(-0.28)
Day Minus 1 (dummy)	0.1018	-0.0142	0.0327	-0.0080	0.1146	0.0005
(t-statistic)	(2.61)	(-0.48)	(2.14)	(-1.38)	(1.56)	(0.01)
Day 0 & Plus 1 (dummy)	0.0830	-0.0181	0.0005	-0.0042	0.1292	-0.0231
(t-statistic)	(3.51)	(-0.78)	(0.13)	(-1.68)	(3.39)	(-0.54)
Day Plus 2 (dummy)	0.0011	-0.0381	0.0043	0.0001	0.0162	-0.0647
(t-statistic)	(0.05)	(-1.67)	(0.74)	(0.02)	(0.39)	(-1.84)
Price agressiveness	-0.1933	0.0005	22.4275	19.8713	-0.0039	0.0005
(t-statistic)	(-0.80)	(0.43)	(6.05)	(4.09)	(-0.72)	(0.44)
Order size (million shares)	0.0584	-5.3622	-5.9155	-0.0592	-0.5211	2.6222
(t-statistic)	(0.83)	(-0.11)	(-0.13)	(-1.99)	(-0.80)	(0.01)
Hidden order (dummy)	-0.0175	-0.0034	-0.0236	-0.0066	-0.0255	-0.0211
(t-statistic)	(-2.95)	(-0.69)	(-6.15)	(-4.17)	(-2.93)	(-3.28)
Trading frequency	-0.0001	0.0008	0.0000	0.0000	-0.0004	0.0008
(t-statistic)	(-1.77)	(1.36)	(0.02)	(-0.21)	(-2.21)	(1.24)
Volatility	-0.8071	-3.6028	8.1933	7.3242	1.5173	-5.4489
(t-statistic)	(-0.25)	(-2.45)	(1.63)	(3.23)	(0.48)	(-2.48)

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Variable	Implementation Shortfall		Effective Spread cost: fill rate >0%		Opportunity cost: fill rate < 100%	
	Buy orders, Positive Events	Sell orders, Negative Events	Buy orders, Positive Events	Sell orders, Negative Events	Buy orders, Positive Events	Sell orders, Negative Events
	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient	Coefficient
	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: Cumulative Effect of Day Dummies - Overall						
Cumulative Effect:						
Day Minus 5 to Day Minus 1	0.2422	-0.0771	0.0107	0.0020	0.3234	-0.1849
(t-statistic)	(2.43)	(-1.10)	(0.50)	(0.19)	(2.17)	(-1.77)
Panel C: Cumulative Effect of Day Dummies - Companies in the SBF120 Index						
Cumulative Effect:						
Day Minus 5 to Day Minus 1	0.2623	0.1519	-0.0183	0.0255	0.4327	0.2075
(t-statistic)	(3.10)	(1.86)	(-1.13)	(1.54)	(2.25)	(2.08)
Panel D: Cumulative Effect of Day Dummies - Companies not in the SBF120 Index						
Cumulative Effect:						
Day Minus 5 to Day Minus 1	0.2620	-0.0871	0.1007	-0.0079	0.4180	-0.2115
(t-statistic)	(1.83)	(-0.85)	(2.06)	(-0.41)	(2.21)	(-1.72)
Panel E: Cumulative Effect of Day Dummies - Companies with Options						
Cumulative Effect:						
Day Minus 5 to Day Minus 1	0.2430	-0.0777	-0.0135	0.0188	0.2456	-0.2082
(t-statistic)	(3.23)	(-0.57)	(-0.54)	(1.33)	(1.54)	(-0.77)
Panel F: Cumulative Effect of Day Dummies - Companies without Options						
Cumulative Effect:						
Day Minus 5 to Day Minus 1	0.2750	-0.0895	0.0485	-0.0073	0.4511	-0.2052
(t-statistic)	(2.35)	(-0.80)	(1.42)	(-0.34)	(2.76)	(-1.44)

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Appendix

The goal of this appendix is to present a simple model that supports the order of expected payoffs we have postulated; i.e. $a<b<c<d\leq e<f$. To that end, we consider a market for a single asset with a tick size θ. At time zero, the book is populated as follows:

Bid	Price	Ask
	$\beta_{+}4\theta$	*1*
	$\beta+3\theta$	*1*
	$\beta+2\theta$	*1*
1	β	
1	$\beta-\theta$	
1	$\beta-2\theta$	

That is, the bid price at time zero is β, the spread is 2θ, and at each price level the depth is one. In each trading round, a stochastic trader who wants to trade two units shows up. The trader can be either a buyer or a seller with equal probabilities. If the spread is wider than one tick, the trader submits a limit order, otherwise a market orders. Only quotes, but not the depth, are visible.

We assume that two informed traders show up at time zero and see the above quotes. Without loss of generality, we assume the informed traders would like to sell. We further assume that each would like to sell one unit. If both traders use the same strategy, than each received half of combined expected payoff. Thus, when both use market orders, then one unit is sold at β and the second unit at $\beta-\theta$, so the expected payoff is $\beta-0.5\theta$. This value corresponds to $(v-\overline{v})^2b$ in our matrix payoff. When an informed trader uses a limit order, we assume the order sits in the book for two rounds. If after two rounds the order is not executed, it is converted to a market order.

Consider now the case that one trader uses a sell market order while the other uses a sell limit order. After the two orders are submitted, the books look like

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Bid	Price	Ask
	$\beta_{+}4\theta$	*1*
	$\beta+3\theta$	*1*
	$\beta+2\theta$	*1*
	$\beta+\theta$	1
1	$\beta-\theta$	
1	$\beta-2\theta$	

The payoff of the market order strategy is β and this corresponds to $(v-\overline{v})^2d$ in our matrix payoff. To calculate the expected payoff associated with limit orders, we need to consider 4 possible scenarios, according to the arrival of the stochastic trader in the next two periods. If the stochastic trader in the next period is a buyer, then, because the current spread is greater than one tick, he posts a new bid β. Next, if the next stochastic trader is also a buyer, then he buys at the ask price, $\beta+\theta$. Otherwise he is a seller and he hits the bid at β. In that case, the informed trader's limit order was not executed. The limit order is converted to a market order, and executed at $\beta-\theta$. Thus, the expected payoff of using a limit order, conditional on the first stochastic trader being a buyer

$$0.5(\beta+\theta)+0.5(\beta-\theta)=\beta$$

If the stochastic trader is first a seller, then he post an offer β. Regardless of what the type of the second stochastic trader is, the limit order of the informed trader is not executed, and it is converted to a market order. If the second stochastic trader was a buyer, the informed can sell at $\beta-\theta$, otherwise he sells at $\beta-2\theta$. Thus, the expected payoff conditional on the first stochastic trader being a seller is $\beta-1.5\theta$. Therefore

$(v-\overline{v})^2a=0.5(\beta-1.5\theta)+0.5\,\beta=\beta-0.75\theta$

In a similar manner, we compute the expected payoffs of other strategies. The results are

$(v-\overline{v})^2a=\beta-0.75\theta$

$(v-\overline{v})^2b=\beta-0.50\theta$

$(v-\overline{v})^2c=\beta-0.25\theta$

$(v-\overline{v})^2d=\beta$

$(v-\overline{v})^2e=\beta$

$(v-\overline{v})^2f=\beta+0.25\theta$

The order is as we postulated in the payoff matrix, i.e., $a<b<c<d\leq e<f$.