Informed Trading Before Corporate Events: Theory and Evidence *

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Abstract

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Abstract

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"The cases we bring are ones in which people are being paid, sometimes cash money, to provide before the public release of revenue numbers those revenue numbers to people trading on the information. That's called insider trading, and that's very clearly criminal…. The scope of the insider trading problem generally, I think we've discovered, has been quite broad and quite deep. Fair to say that insider trading has been for a while, on Wall Street and elsewhere, rampant."

Preet Bharara, U.S. Attorney for the Southern District of New York
Interview in PBS-Frontline documentary "To Catch a Trader"

1. Introduction

Insider trading has been a focus of regulatory efforts in recent years. Academic research on the trades of corporate insiders finds that (a) the stock price tends to increase following insider purchases and decrease following insider sales (see Seyhun (1992), Meulbroek (1992), Agrawal and Jaffe (1995), among others), and (b) insider trades are particularly profitable before corporate events, such as earnings announcements, accounting restatements and seasoned equity offerings (see Bodnaruk, Massa and Simonov (2009), Jegadeesh and Tang (2010), Griffin, Shu and Topaloglu (2012)). 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 prisoner's dilemma framework to model the execution risk that informed agents impose on each other.[1] Using data from Euronext-Paris, we study the informed agent's order submission strategies and document several patterns of behavior that are consistent with the model's 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 the 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. We posit that the joint order submission

[1] In our framework, informed agents include corporate insiders such as board members, directors and employees as well as well-connected market participants such as bankers, analysts and hedge fund managers. A recent WSJ article dated 06/06/2013 that describes abnormal trading activity before Smithfield's acquisition announcement says "*When multiple bidders vie for a company, it isn't unusual for hundreds of people to know about the possible deal before it surfaces – including employees of banks, law firms, and other outside advisors, not to mention the people inside the companies themselves.*"

decisions of informed agents fit the prisoner's dilemma framework, i.e., despite the price benefit of limit orders, informed agents use market orders when they anticipate competition from other informed agents.

Informed agents face less competition when the nature of private information conveys a decrease in stock price. This is because informed agents are less likely to sell stocks with unfavorable information if they do not already own the stock (see Saar (2001)).[2] Our model predicts that informed agents use limit orders when there is sufficient uncertainty about the presence of other informed agents,[3] and market orders if they are certain that other informed agents are present. To incorporate the uncertainty about the presence of other informed agents, 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 the informed agent is of the first type increases with the broadness of investor base. When the investor base is narrow, when the cost of borrowing shares is sufficiently large, or when the event is small such that potential gains cannot justify the borrowing costs, a limit order equilibrium emerges in which the first type of agent uses limit orders and the second type abstains from trade. On the other hand, when borrowing costs are sufficiently low or when the event is sufficiently large, the second type of agent borrows the shares, and both types trade. Because of the execution risk they impose on each other, both types use market orders. When the nature of private information conveys an increase in stock price, informed agents always anticipate competition from other informed agents and therefore informed buyers always use market orders.

Surprisingly, despite the importance of understanding how informed agents build positions, there is relatively little empirical work describing their trading strategies, mainly because the available data sources are not sufficiently detailed to identify informed trading. Publicly available data sources, such as NYSE's Trade and Quote (TAQ) database, report all the transactions in a market but do not identify the

[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. Moreover, corporate managers may be unable to sell stock holdings that are part of a compensation contract below a certain threshold.

[3] The prisoner's 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.

specific trades of corporate insiders. 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 sufficiently detailed to study order submission strategies.

We examine a dataset provided by the Euronext-Paris exchange that contains detailed information on all orders submitted for all stocks. However the Euronext data do not identify the orders of informed agents. We therefore employ a research design based on Chae (2005), Graham, Koski and Loewenstein (2006), and Sarkar and Schwartz (2009), who study information flow surrounding corporate events. These studies show that trading volume and liquidity decline before scheduled corporate events, such as earnings announcements, because uninformed traders alter the timing of trades to lower adverse selection risk. In contrast, uninformed traders cannot anticipate unscheduled events where timing information is unavailable in advance, but informed traders can, if their information concerns the event. Thus the abnormal activity observed before an unscheduled corporate event can be attributed to informed agents.

We examine 95 French stocks and 101 announcements related to M&As, SEOs, repurchases, dividend initiations and dividend terminations in 2003.[4] These announcements convey new information – the absolute value of event day return exceeds 4.5% - but the timing of the announcements is not known to the public in advance. The median percentage bid-ask spread for sample firms is economically large (approximately 0.80%) implying that the implementation cost of a market order strategy is non-trivial. In our framework, informed agents receive a private signal about the nature of the event and build positions before the event in the direction of the signal. We therefore categorize positive and negative news events based on the sign of the announcement return and identify informed trading based on abnormal buying activity before positive events and abnormal selling activity before negative events. Abnormal activity is measured by comparing pre-event activity with non-event activity for the same firm. By holding each firm as its own control, our approach reduces the influence of omitted firm characteristics on the cross-

[4] We examine the Euronext-Paris data in 2003 because more recent order-level data obtained from NYSE-Euronext have important omissions, which we describe in Section 3.1. Moreover, in 2003, the 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 Euronext-listed stocks has become highly fragmented with the proliferation of alternative trading venues, including dark pool venues, in recent years.

sectional variation in order submission strategies (Lee, Mucklow, and Ready (1993)). Nonetheless, in the regression analysis, we explicitly control for market conditions at the time of the order following the approach in Bessembinder, Panayides and Venkataraman (BPV hereafter, 2009).

The model predicts that informed agents use more aggressive orders before positive events and less aggressive orders before negative events. We focus on the order's price aggressiveness attribute (i.e., market versus limit order), but we also examine the decision to expose or hide the order (see Boulatov and George (2013) for theory). Before positive events, we observe an *increase* in aggressively priced buy orders. Using aggressive orders increases execution probability and lowers time-to-execution; however, they signal the presence of informed agents and impose execution risk on informed agents using limit orders. Before negative events, we observe a *decrease* in aggressively priced sell orders, which supports the model's prediction that informed sellers use more limit orders to build positions. The limit orders are more likely to expose order size, consistent with evidence in BPV (2009) that exposing size attracts counterparties and increases execution probability.

We develop further tests of the model based on cross-sectional differences in competition before negative events. If there are no barriers to trading, competition among informed sellers is intense; thus, for stocks with a broad investor base, or for stocks that are easy to borrow, the market order equilibrium is more likely to emerge. If there are short sale constraints, competition is less intense,[5] and the model predicts that informed sellers stay with limit orders to obtain better prices. Motivated by prior work, our measures of short sale constraints include (a) membership in a major stock index, (b) availability of exchange-listed stock options, and (c) eligibility for Deferred Settlement Service. Stocks that belong to an index have a broad investor base and active participation by institutional investors (see D'Avolio (2002), Nagel (2005)). Informed agents can establish equivalent short positions at lower cost using stock options in short constrained stocks (see Battalio and Schultz (2011), Hu (2013)). Euronext's Deferred Settlement

[5] For roughly one-third of their sample of NYSE and NASDAQ stocks, Diether and Werner (2011) show that a limited supply of loanable shares reduces the ability of short sellers to trade on mispricing. Boehmer and Wu (2013) show that stock prices are more accurate when short sellers are more active.

Service (called "SRD") facility allows traders to locate shares and hold short positions until the end of the month, thus easing borrowing constraints (see Foucault, Sraer and Thesmar (2011)).

The results provide broad support for the model's predictions. For stocks with few trading barriers – index constituent stocks, stocks with listed options, and stocks eligible for SRD facility – we observe an increase in price aggressiveness for both buy orders before positive events and sell orders before negative events. In contrast, for stocks that face short constraints – non-index stocks, stocks without listed options, and stocks not eligible for SRD facility – informed buyers and sellers do not use similar strategies. Specifically, informed buyers submit more price aggressive orders before positive events while informed sellers submit less price aggressive orders before negative events.[6] Along similar lines, when the magnitude of the event announcement is large, both informed buyers and sellers submit more price aggressive orders. When the magnitude of the event announcement is small, we find that informed sellers submit less price aggressive orders before negative events while informed buyers do not before positive events. These results support the model's prediction that informed sellers face less competition before small news events because potential gains from short selling do not justify the borrowing cost of the security.

One implicit assumption of the model is that when some informed agents use market orders, their trades tip off market participants about the forthcoming event. This leads the security price to drift in the direction of the signal and imposes severe execution risk on other informed agents using limit orders. We test this assumption by examining the opportunity cost of using limit orders. A limit order that is fully executed has zero opportunity cost. A partially- or un-executed buy (sell) limit order has positive opportunity cost if the security price drifts upwards (downwards) after the order is submitted. For stocks with few trading barriers, we find that the opportunity cost of using limit orders is positive before both positive and negative events. This evidence is consistent with the execution risk that informed agents

[6] Besides being more difficult to short sell, short-constrained stocks might differ from less short-constrained stocks in important ways. For example, the former group of stocks is likely to be smaller and less liquid. However, as discussed in Section 2.3, any difference in market capitalization (or stock liquidity) should not generate difference in informed trader behavior before positive and negative events. The asymmetry in informed trader behavior observed for stocks that are short constrained is a key testable prediction of our model.

impose on each other in a market order equilibrium. For stocks that face short constraints, the opportunity cost of using limit orders is positive before positive events but not before negative events. Note that our model predicts a limit order equilibrium for the latter event alone. Thus the results support that a limit order equilibrium reveals less information while a market order equilibrium tips off market participants about the forthcoming event.

Our study points to an unintended consequence of the widespread ban on short selling by regulators around the world in response to the 2007-09 financial crisis. Because the short sale ban lowers competition among informed sellers, our model predicts that insiders who already own the stock are better off after the ban and that the limit order strategy that they implement makes it difficult to detect insider trading. Beber and Pagano (2013) document that the global ban on short sales lowers the information efficiency of prices, particularly surrounding events with negative information (see also, Boehmer, Jones and Zhang (2013)). Our study points to a specific mechanism by which a short sale ban impedes the flow of negative information into prices.

A well-established finding in the block trading literature is that security purchases convey more information than security sales (see Kraus and Stoll (1972)). Our results suggest that informed agents contribute, at least in part, to this asymmetry in the price impact of trades. 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 emerges not only because some informed agents decide to abstain, but also because informed agents become liquidity providers; i.e. they use limit orders when the expected level of competition from other informed agents is low. An important related paper by Saar (2001) takes a different approach than ours on the buy-sell asymmetry. In his model, informed agents face capital constraints rather than costly short selling. 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 asymmetry.

Our study provides guidance for designing surveillance systems that monitor insider trading activity surrounding corporate events. Properly enforced regulations deter insider trading, lower adverse selection risk, improve investor trust, and facilitate capital raising in financial markets. To detect insider trading, regulators need a framework that describes the strategies of informed agents and how these strategies vary with firm and event characteristics. Most theoretical work posits that informed agents exclusively implement aggressive strategies and use market orders to exploit their information advantage.[7] Novel exemptions are Kumar and Seppi (1994), Chakravarty and Holden (1995), Kaniel and Liu (2006), Goettler, Parlour and Rajan (2009), and Boulatov and George (2013). In these models, informed traders do find it optimal, under certain conditions, to be less aggressive and submit limit orders.[8] We extend this literature by showing that informed trader strategies are different before positive and negative news. In particular, when the news is negative and the stock is short constrained, informed sellers extract more rents from the public by using passive strategies.

Further, regulators are interested in understanding the impact of opaque "dark pool" venues on price efficiency and whether informed agents use such venues to hide their activity. We document that informed agents, when provided the option to hide, choose to expose orders to attract counterparties and lower execution risk. The results suggest that dark pool venues attract patient traders with low opportunity cost of non-execution while 'lit' markets attract informed traders who worry about execution risk.

The rest of the paper is organized as follows. Section 2 presents a model on competition among informed traders and identifies testable predictions on trader strategies before positive and negative events. Section 3 describes institutional details of Euronext-Paris, the data sources and the sample selection. The informed traders' choice of the price aggressiveness and order exposure are presented in Section 4 and Section 5 respectively. Section 6 presents the estimates of implementation shortfall costs, the time-to-execution, and opportunity costs. Section 7 presents the conclusions.

2. The Model

2.1. The prisoner's dilemma game

[7] 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.

[8] Recent experimental and empirical work suggests that informed traders use limit orders. See Barclay, Hendershott, and McCormick (2003); Bloomfield, O'Hara, and Saar (2005, 2013); Anand, Chakravarty and Martell (2005), Hautsch and Huang (2012), among others.

To model the execution risk that informed traders impose on 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 prisoner's dilemma. Trader One's payoff is given by the following payoff matrix, where $\bar{v}$ is the expected value of the signal, and $0<a<b<c<d$. The payoff to Trader Two is symmetric.

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

In the following we discuss the payoff order.[9] The assumptions $0<a<b<d$ are natural. When Trader Two uses market orders, then these market orders impose severe execution risk on Trader One's limit orders. Therefore, when Trader Two uses market orders, using limit 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). The assumption that $c>b$ means that if the informed traders could collude, they would rather use limit orders than market orders. Indeed, the combined payoff when both traders use market orders is $b+b$ whereas the combined payoff when they use limit orders is $c+c$. The assumption that $c<d$ means that if Trader Two populates the book with limit orders, then Trader One prefers extracting liquidity (i.e. market orders). That said, the assumption $c \in (b,d)$ is strong in the sense that one should not expect that this assumption always holds.

[9] Adding a layer of complexity, the appendix presents a 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 spread is the wide. We compute the informed traders' payoff for each of the four possible joint actions, and show that the numerical order of a, b, c, and d, corresponds to their alphabetical order, as in the main model presented in Section 2.

However, as we point out in Section 2.3, the empirical implications we draw from the model only require that this assumption holds for some stocks.

To sum our discussion thus far: we use the prisoner's 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 due to the execution risk that they impose on each other.

The inefficient outcome we posit is not a novelty. Using different action spaces, other theoretical papers arrive at the same conclusion. In Holden and Subrahmanyam (1992), though informed traders can only trade using market orders, they still have a choice between trading on their information gradually or rapidly. If 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 instantly to the market. 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.

2.2. Trader competition when short selling is banned

Up until now we assumed that the direction of the information is not relevant. However, when shares are hard to borrow (either short selling is expensive, prohibited, or shares are simply hard to locate), then informed sellers might choose 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 hold a long position in the stock.

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

		Trader One		
Trader One's payoff (Type 0)		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: $0<a<b<c<d\leq e<f$. The assumption that $d\leq e$ 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 uses limit orders when he owns the stock. Then, Trader One's expected payoff 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, when p is sufficiently small, this is the only equilibrium.[10]

Next, 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. 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 who has 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 is -

[10] In particular, when $p<(f-e)/(b-a+f-e)$ then the market order equilibrium breaks down.

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

For type zero, we replace C in the above with zero.

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

On the other hand, if

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

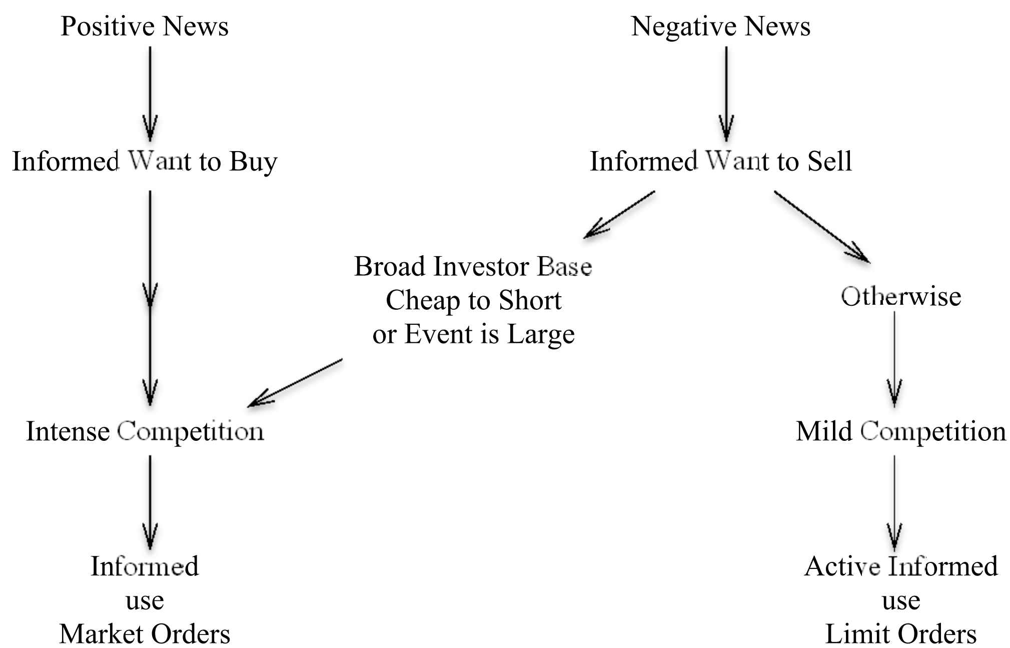
then, whether or not inequality (1) holds, there is a market order equilibrium in which type C borrows the shares and both types use market orders.

Equations (2) and (3) are the exclusions/participation conditions for the type C trader. The proof of the theorem goes as follows. 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 abstains from trade when the type is C. 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.

The second part of the theorem applies when the cost of borrowing is sufficiently low so both traders participate, regardless of their types. In that case, we are back at the prisoner's dilemma setting 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 $(v\text{-}\bar{v})^2\, b$, which is the payoff when both traders use market orders. This is (3) in the theorem. This concludes the proof of the theorem.

2.3. Empirical Implications

The following figure summarizes the results: when the event is positive, despite the price benefit of limit orders, the competition among informed agents leads to a market order outcome. When the news is negative, depending on parameters, we may see limit orders. This is because the high likelihood that some informed traders abstain from trade reduces the execution risk of limit orders.



So far, we relied on the assumption that the parameter c lies in the interval (b,d). What if $c<b$? When we repeat the analysis we have carried above, we find that the only possible outcome is market orders. Market orders can be a dominant strategy, for example, when information is short lived or the market is sufficiently liquid. Thus, regardless of the direction of the news, we should see market orders.

What if $c>d$? This can happen, for example, when the market is sufficiently illiquid. In this case, when the news is positive, two equilibria exist, one with a limit order outcome and one with a market order outcome. The limit order outcome is more desirable (because $c>d$ also implies $c>b$). Whether we consider the limit order equilibrium as focal or accept that our theory cannot pick an equilibrium, we cannot use our model to predict differences in strategies when the news is positive or negative. In conclusion, if the assumption that $c \in (b,d)$ is violated, our theory does not predict differences between positive and negative news. However, when the assumption $c \in (b,d)$ holds, our theory does predict differences. This discussion leads to the following testable predictions:

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

If the event is sufficiently large; i.e. $(v-\overline{v})^2$ is large, then inequality (3) holds even if borrowing costs are high. In addition, when p, the probability that informed traders own the stock prior to learning the negative news, is sufficiently large then inequality (1) is violated and the limit order equilibrium breaks down. It is conceivable that p is high for stocks with broad investor base.

Hypothesis II: *When the magnitude of event is large, both informed buyers and sellers use more aggressive (market) orders. When the magnitude of the event is small, informed buyers use more aggressive (market) orders while informed sellers use less aggressive (limit) orders.*

Hypothesis III: *When (a) investor base is narrow, and (b) borrowing cost is large, then informed buyers use more aggressive (market) orders while informed sellers use less aggressive (limit) orders. In other cases, both informed buyers and sellers use more aggressive (market) orders.*

3. Data and Methodology

3.1. Sample and data

We examine the Euronext-Paris, Base de Donnees de Marche (BDM) database for the year 2003. The BDM database contains detailed information on the characteristics of all orders submitted for all stocks listed on Euronext-Paris. This includes the stock symbol; the date and time of order submission; whether the order is a buy or a sell; the total size of the order (in shares); the displayed size (in shares); an order type indicator for identifying market or limit orders; a limit price in the case of a limit order; and instructions on when the order will expire.[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 reconstructed limit order book, the analysis of order submission strategies, and construction of control variables used in some specifications. Another advantage of 2003 sample period is that trading in Euronext stocks is highly consolidated with the vast majority of orders being submitted and executed on the main exchange. With the explosion in alternative trading venues, European equity markets in recent years have become highly fragmented. In a fragmented market, the informed agent's choice of the trading venue needs to be modeled, thus introducing a layer of complexity in the interpretation of results.

The Euronext database does not provide any information on trader identity. We therefore focusing on trading activity before "unanticipated" events, whose timing is not known in advance. In contrast, the timing of release of anticipated events such as earning announcements is publicly available in advance. Chae (2005), Graham, Koski and Loewenstein (2006) and Sarkar and Schwartz (2009) document that, 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. Lee, Mucklow and Ready (1993) show that market makers widen bid-ask spread and lower inside depth before earnings announcements. In contrast, informed agents alone are aware of the timing and information content of unanticipated events. Sarkar and Schwartz (2009) show that trading activity before unanticipated events is characterized by one-sided market. Following prior literature, we attribute the abnormal activity observed *before* unscheduled events to informed agents.

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

We identify unanticipated events using 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 events: M&As, SEOs, repurchases, dividend initiations and dividend terminations.[12] We use Bloomberg and Factiva search engines and identify the date of the first news story about the event. We eliminate Euronext-Paris stocks that switch from continuous trading to call auctions (or vice-versa) or were de-listed from Euronext during Days [-30,+10] surrounding the event (Day[0]). The final sample consists of 101 unscheduled corporate events for 95 unique stocks.

In Table 1, Panel A reports the announcement returns and Panel B reports the characteristics of the sample. In our model, informed agents build profitable positions before the event in the direction of the private signal. We therefore classify events as positive and negative news based on the announcement (Days [0,1]) cumulative abnormal returns (CAR), where the CAC40 Index daily return serves as the benchmark. The 58 positive events have a mean (median) CAR of 4.84% (2.74%) and the 43 negative events have a mean (median) CAR of -4.53% (-2.57%). For M&As, SEOs, repurchases and dividend initiation, we observe both positive and negative events.[13] The largest announcement returns are observed for M&As followed by SEOs. The positive event sample has on average larger market capitalization, higher stock price, lower return volatility and smaller bid-ask spread than the negative event sample. The median percentage bid-ask spread for the sample firms is economically large (approximately 0.80%) suggesting that the cost of implementing a market order strategy is non-trivial.

For each unscheduled event, we compare trading activity before the event - Days [-5,-1] - with the control period activity - Days [-30,-10] – for the same firm, where Day [0] is the event day. We measure informed trading as the change in trading activity for buy orders before positive events and sell

[12] We eliminate M&As in which the deal value relative to the acquirer's market value is less than 5%.

[13] Asquith and Mullings (1986) and Graham et al. (2006) find negative announcement returns for 28% and 36%, respectively, of their dividend initiation sample. The former study notes that "for these firms investors are anticipating the initiation of dividends and were disappointed by the amount of the initial dividend." Consistent with the idea, the Factiva dividend announcement of one of our firms with negative returns says "However, this is a special dividend. It is not expected to pay a regular dividend."

orders before negative events.[14] In Table 2, we report descriptive statistics of the order characteristics in the event and control periods. Relative to control period, the number of buy orders increase before positive events and the number of sell orders increase before negative events. These patterns support that informed agents are active before unanticipated events. We also observe an increase in average size of orders submitted before the event. This is particularly true for limit orders that are expected to stand in the book, where buy (sell) order size before positive (negative) events increases from 1,095 (1,909) shares in control period to 1,562 (2,168) shares in event period. We also observe an increase in market/limit ratio before positive events and a decrease in market/limit ratio before negative events. A higher (lower) market/limit ratio is consistent with the usage of more (less) price aggressive orders.

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 the 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 BPV (2009). The method assumes that, for each estimated firm i coefficient, β_i:

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

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

where N is the Gaussian distribution. The Newey-West corrected standard errors, s_i, are estimated using Generalized Method of Moments (GMM) with a Bartlett kernel and a maximum lag length of 10, and σ^2 is estimated by maximum likelihood. The aggregated β is obtained from N individual firm estimates as -

[14] For a sample of French M&A announcements, Aktas et al. (2007) report that trading volume spikes in the five days preceding the merger announcement. They also show that trading volume and bid-ask spreads increase for both acquirers and targets in the Days [-65,-6] before the announcement. This raises the possibility that our control period captures some activity by informed agents. If so the change in trading activity that we attribute to informed agents is understated and therefore the empirical tests are biased against finding support for the model.

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

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 with which β_i is estimated.[15]

In all of our multivariate specifications of order submission strategies we include daily indicator variables for each day of the event period (Days [-5,-1]). For example, variable *DayMinus5* equals one for orders submitted on Day [-5] and equals zero otherwise. We also include all orders submitted on the control period Days [-30,-10] for the same firm. Thus the *DayMinus5* coefficient captures abnormal order activity on Day [-5] relative to the control days. We report the Day coefficients and test statistics based on equation (6) and (7). Because informed agents can be active on any of the five days before the event, we estimate a cumulative measure that aggregates individual day indicator coefficients. The cumulative measure captures the activities of informed traders over the five days before the event without any econometric constraint on each of the Days [-5,-1]. In interpreting the results, we focus on both individual day indicator coefficients and the cumulative measure and the associated t-statistics.

[15] The aggregated β estimate deals with the error-in-variable issue. It also corrects for the variability in the sample selection through $\hat{\sigma}_{m.l.e}^2$. 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.

4. Price Aggressiveness of Informed Traders

4.1. Patterns before unscheduled corporate events

We begin our investigation by examining the price aggressiveness attribute of buy orders before positive events and sell orders before negative events. The regression specification controls for the impact of market conditions on an order that arrives at time of submission 't' for event 'i', as follows:

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

Following Biais, Hillion and Spatt (1995) and BPV (2009), *PriceAggressive* is an ordinal variable that takes the value of 1 for the most aggressive order and 7 for the least aggressive order.[16] The market conditions capture (1) the state of the limit order book, including bid-ask spread and displayed depth at the inside quotes, cumulative order book imbalance, standing limit orders at the same price as the incoming order, and revelation of hidden orders at the inside quotes by the most recent transaction; (2) trading conditions for the stock, such as recent volatility, the trading frequency, and the waiting time between recent order arrivals; (3) order attributes, such as size and exposure; and (4) control variables such as recent industry volatility, market volatility, and time-of-the-day effects. The inclusion of industry and market volatility variables helps to control for any commonality in economic fundamentals, as in Chordia, Roll and Subrahmanyam (2000). A detailed description of the variables is provided in Appendix B. To render results more comparable across stocks, we normalize some variables. The depth and spread variables are each normalized by dividing the actual observation by the median for that stock during the control period, while order size and trade size are normalized by dividing the actual observations by the

[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 of the category variable over an OLS (maximum likelihood). Further, a linear regression specification allows us to a) easily calculate the economic significant of day-indicator variables and b) appropriately test and interpret the cumulative abnormal effect before the event.

stock's average daily trading volume during the control period.

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 3.2. 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 (a) the inside bid-ask spread is wide, (b) same side book depth is thin, which signals less competition (c) opposite side book depth is deep, or the last trade reveals the presence of hidden orders, both of which signal the presence of strategic counterparties, (d) when volatility is high, consistent with a volatility capture strategy (see Handa and Schwartz (1996)), (e) book imbalance signals less competition on same side relative to opposite side of the book, and (f) the limit price of the previous order is less aggressive which is a proxy for omitted market conditions. We find that the impact of market volatility and industry volatility are not statistically significant; however, own-stock volatility has a significant influence.

The main tests of the theoretical model are based on coefficient estimates on indicator variables, *DayMinus5* to *DayMinus1*. Note that the least aggressive order is categorized as "7" and the most aggressive order is categorized as "1". Thus a negative (positive) coefficient on *DayMinus3* is consistent with an increase (decrease) in price aggressiveness on Day [-3] relative to control days for the same firm. The usage of same-firm order flow attributes during the control days reduces the influence of unobservable firm characteristics on the order submission strategies. Since the research design attributes abnormal activity on Day [-3] to informed agents, a negative *DayMinus3* coefficient implies that informed agents use more aggressively priced orders to build positions before the event.

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 cumulative effect presented in Panel B, the negative and significant coefficient (t-statistic=-2.96) suggests that informed buyers submit more aggressively priced buy orders before positive events. For sell orders submitted before negative events (column (2)), four of the five coefficients corresponding to Days [-5,-1] are positive and the DayMinus5 coefficient is statistically significant. The cumulative effect (column (2) of Panel B) is positive (t-statistic=1.70) suggesting that informed sellers submit less aggressively priced sell orders before negative events. These patterns are consistent with Hypothesis I – informed agents use more aggressive orders before positive events and less aggressive orders before negative events.

In Panel C, we estimate the economic significance of the aggregate results presented in Panel B. Because we use a linear specification, the aggregate coefficient can be interpreted as the change in price aggressiveness in Days [-5,-1] relative to control days [-30,-10], after controlling for other determinants of price aggressiveness. Focusing on all positive events (column (1)**),** the cumulative effect captured by coefficient -0.6045 suggests that, relative to average price aggressiveness of 5.1796 observed over control days, we observe an increase in price aggressiveness on Days [-5,-1] by 11.67%. For negative events the aggregate coefficient for Days [-5,-1] represents a decrease in price aggressiveness of 3.27%. We also examine the distribution of the seven categories of price aggressiveness in control days to uncover how informed agent behavior is reflected in each of the seven categories. Controlling for market conditions and order characteristics, we document a 8.74% increase in frequency of aggressive orders (categories 1 to 4) during Days [-5,-1] for positive news versus a 2.90% decrease in frequency of similar aggressive orders during Days [-5,-1]) for negative news. Overall, these results support that informed agents have an economically significant impact on the price aggressiveness of incoming orders before corporate events.

4.2. Cross-sectional patterns in price aggressiveness

We examine cross-sectional patterns in buying and selling behavior to test model predictions along two dimensions. First, we identify corporate events that are characterized by large versus small announcement period returns. Second, we examine trading strategies based on the broadness of investor base and the ease of implementing a short position.

4.2.1. Announcement return and informed trader strategy

In our model, informed agents weigh the benefits of taking a short position against the cost of borrowing shares. If the information content of the event is large, then informed sellers have more 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 sellers to abstain from trading if they do not already own the stock. The model predicts that heightened competition leads to a market order equilibrium before (a) positive events – both large and small, and (b) large negative events. In contrast, the reduced competition leads to limit order equilibrium before small negative events.

Columns (3) to (6) present the results of the regression analysis for large and small events. Large events are defined as those with absolute value of announcement day return exceeding 5%.[17] Focusing on Panels B, we see that for positive events, the cumulative effect coefficient on Days [-5,-1] is negative for both large (coefficient=-0.35 with t-statistic=-2.09) and small (coefficient=-1.39 with t-statistic=-2.40) events. The economic effects, reported in Panel C suggest that before large positive events we observe an increase of 26.80% in average order aggressiveness of buy orders, which reflects a 42.06% increase in the frequency of aggressive buy orders (categories 1-4). Before small positive events, the corresponding increases are 6.68% and 4.91%, respectively. These results suggest that informed buyers increase the order price aggressive before positive events, consistent with a move towards a market order equilibrium. In contrast, the cumulative effect coefficient before small negative events is positive (coefficient=0.31 with t-statistic=1.95). This translates into a decrease of 6.05% in price aggressiveness of sell orders, which reflects a 6.05% decrease in frequency of aggressive sell orders. For large negative events, the cumulative effect coefficient is not statistically significant (t-statistic=0.45). Overall the results support that informed sellers use less aggressive strategies when information event is small (Hypotheses II).

4.2.2. Index constituent stocks and informed trader strategy

Stock membership in an index influences the broadness of investor base because index firms tend to be larger and actively traded and attract interest from analysts and buy-side institutions (Nagel (2005)).

[17] We also classify events as large (above median) or small (below median) after normalizing the absolute value of announcement return by the stock's average bid ask spread estimated in the control period. The normalized measure captures the trade-off between using market orders and paying the spread versus using limit orders and receiving the spread. The coefficient signs and statistical significance are similar using the normalized measure.

We classify stocks that belong to the SBF120 index as those with a broad investor base, and vice-versa.[18] Informed agents, both buyers and sellers, face more competition in index stocks and consequently employ aggressive strategies before the event. For stocks outside the index, our model predicts that informed buyers use market orders because they face more competition. In contrast, informed sellers who own the stock use limit orders because they are less likely to face competition when the investor base is narrow.

In columns (1) - (4) of Table 4, we report regression coefficients for subsamples of firms based on index membership. Before positive events, the cumulative effect coefficients reported in Panel B are negative and statistically significant for both index (column (1)) and non-index (column (3)) stocks. These results are consistent with an increase in usage of price aggressive orders. In contrast, before negative events, the cumulative effect coefficient is negative and marginally significant for index stocks (column (2)) alone. For non-index stocks (column (4)), the coefficient is positive and statistically significant, which is consistent with the usage of less price aggressive orders; i.e. limit order equilibrium. We conclude that informed buyers and sellers implement aggressive strategies when investor base is broad but informed sellers implement less aggressive strategies when the investor base is narrow.

4.2.3. Listed Options and informed trader strategy

Exchange-listed options serve as a possible substitute for short sale in the stock market. Battalio and Schultz (2011) for example show that, when short selling in the stock market is constrained, informed sellers increase the usage of options contracts to build position. This creates in buy-sell imbalance in the options market. The options market makers hedge their (long) inventory positions by implementing short sale in the stock market. Options market makers enjoy special exemptions from locate requirements on their inventory-hedging trades and therefore short sale constraints do not significantly affect their ability to implement a short position. For this reason, an options market lowers the cost of establishing short positions in constrained stocks.

[18] Compared to CAC40 Index, the SBF120 index represents a broader cross-section of stocks (see Bessembinder and Venkataraman (2004)). For our sample of French stocks in 2003, the availability of useful data on institutional ownership and borrowing cost appears to be limited.

In our framework, one implicit assumption is that options market makers use market orders in the stock market to hedge their inventory. This assumption seems reasonable since the use of limit orders will impose additional execution risk on hedging trades. For stocks with listed options, our model predicts that both informed buyers and sellers face competition and submit more aggressive orders before the event. For stocks without listed options, informed buyers use aggressive orders but informed sellers face less competition and therefore use less aggressive orders before the event.

Results in Table 4 are broadly supportive of these predictions. For stocks with listed options, the cumulative effect coefficient is negative and statistically significant for both buy orders before positive events (column (5)) and sell orders before negative events (column (6)). For stocks without listed option, the coefficient is negative and significant for buy orders before positive events (column (7)). All these results are indicative that informed agents using more aggressive orders when they face competition from other informed agents. In contrast, the cumulative effect coefficient for sell orders before negative events is positive and statistically significant (column (8)). The result indicates that informed sellers submit less price aggressive orders when options market is not available.

In an unreported analysis, we examine trading activity in the options market for stocks with listed options. We find no evidence of a statistically significant increase in the number of daily trades before positive events. Before negative events, we find that the average number of daily trades increase in the Days[-5,-1] as compared to the control period. In particular, we estimate that options trading activity on Day [-1] is nearly twice as large and the increase is statistically significant as compared to the control days. Thus informed agents are active in the options market primarily before negative events. This can be partly driven by synthetic short strategies implemented by informed sellers as a substitute to short sale.

4.2.4. Deferred Settlement Service and informed trader strategy

Euronext-Paris offers a unique mechanism, the Deferred Settlement Service ("Service de Règlement Différé", henceforth SRD) that allows investors to take long and short positions with deferred settlement of the trade until the end of the month (see Foucault, Sraer and Thesmar (2011)). Stocks that are eligible for SRD-facility are chosen by the exchange. Specifically, an investor who wishes to sell short an SRD-eligible stock must flag the order as *deferred execution* when submitting to the broker. On executing the short sale, the broker effectively acts as a lender of the stock until the end of the month and charges an additional fee for the service. Thus the SRD facility lowers the cost of locating the shares by allowing informed agents to sell stocks that they do not own as long as they cover the short position by the end of the month. In contrast, anecdotal evidence indicates that short selling a stock that is not eligible for Euronext's SRD facility is cumbersome as short sellers need to locate the shares they want to sell in advance of executing a short sale. Our model predicts that informed sellers in SRD-ineligible stocks face less competition before the event and submit less price aggressive orders. In all other cases, informed agents face more competition and submit more price aggressive orders.

Table 4, Panels C and D, report the results for SRD-eligible and SRD-ineligible stocks. Before positive events, the cumulative effect coefficient for buy orders is negative and significant for events from SRD-eligible stocks (column (1)) and SRD-in-eligible stocks (column (3)). Before negative events for SRD-eligible stocks (column (2)), the negative cumulative effect coefficient for sell orders indicates that informed agents submit more price aggressive orders. However, for negative events in SRD-ineligible stocks (column (4)), the cumulative effect coefficient is positive and statistically significant. Thus the results support that when shares are more difficult to borrow, informed sellers anticipate less competition and therefore submit less price aggressive orders. Overall the evidence in Table 4 provides strong support for the key testable predictions of our model (Hypothesis III).

It is important to note that many stocks that belong to the SBF120 Index have exchange-listed options and are eligible for the SRD facility. In an unreported analysis, we find that the overlap leaves sufficient room for independence across these cuts of the data. For example, focusing on SBF120 index stocks, 10 among 24 positive event stocks and five among 16 negative event stocks do not trade with listed options. Similarly, focusing on stocks without listed options, 13 among the 44 positive events and nine among 28 negative events are eligible for SRD facility.

5. Order exposure strategies of informed traders

The option to hide an order is a widely available feature in many electronic markets. In a laboratory setting, Bloomfield, O'Hara and Saar (2013) show that both uninformed and informed investors use hidden orders. They also find that informed traders make higher profits in an opaque market when their private information is valuable. Using data from Euronext-Paris, BPV (2009) document that hidden orders are associated with a smaller post-order price drift in the direction of the order. This evidence leads them to conclude that hidden orders tend to be used primarily by uninformed traders to control their risk of order exposure (see Aitken, Berkman and Mak (2001), De Winne and D'Hondt (2007), and Kumar, Thirumalai and Yadav (2010) for related evidence).

However it is still unclear based on the prior literature whether informed agents prefer to hide or expose orders. This is because the empirical research on order exposure strategies is based on all of the orders that are submitted to a market. On a typical day, it is reasonable that trading activity is dominated by uninformed or noise traders and therefore it is difficult to isolate the trading activity of informed agents in a general setting. Our model does not provide testable predictions on informed trader's order exposure strategies; however the event-study design helps isolate the trading activity of informed agents and therefore provides a setting to understand their preference for the order exposure attribute.

The theoretical predictions on informed trader's usage of hidden orders are ambiguous. Moinas (2010) predicts that when informed agents are restricted to supplying liquidity and cannot use market orders, they select an limit order exposure strategy that increases execution probability (see Buti and Rindi (2013) and Balatov and George (2013) for related work). Harris (1996) argues that exposing size will attract interest from "reactive" traders who monitor markets and respond to orders posted by other traders. However exposing size might cause other traders to withdraw trading interest, or implement front running strategies if they infer the presence of informed agents by observing a large order.

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 in BPV (2009). The dependent variable is an indicator variable that equals one for orders that contain hidden size, and equals zero otherwise. We only consider standing limit orders (those in categories 5, 6 and 7) for this analysis because the exposure attribute is economically relevant only for these orders. Consistent with BPV (2009) and De Winne and D'Hondt (2007), we find that order exposure is influenced by the prevailing market conditions at the time of order submission and the attributes of the order. Specifically, hidden orders are more likely when quoted inside depth on the same side is high, when previous trades reveal hidden depth on the same side, and when the order size is large.

While prior literature documents exposure strategies across all traders, our analysis isolates the activity of informed agents by focusing on unanticipated events. Similar to Section 4, we include Day indicator variables and report Day cumulative effect coefficients in Panel B of Table 5. The results suggest that informed buyers are more likely to hide orders before positive events and informed sellers are less likely to hide orders before negative events. To obtain better insights, we examine the cross-sectional variation in exposure decision across firms in Table 5, Panels C to H. Across all positive events, the cumulative effect coefficient for buy orders is positive, suggesting that informed buyers who submit limit orders prefer to hide orders; however none of the results are statistically significant at the 5% level. Before negative events for stocks with few restrictions (i.e., SBF120 Index stocks (Panel C), those with listed options (Panel E), or SRD-eligible stocks (Panel G)), the cumulative effect coefficient for sell orders is negative but none of the coefficients are significant. Significant cumulative Day coefficients are observed only before negative events when short constraints are binding (i.e., non-index stocks (Panel D), those without listed options (Panel F) or SRD-ineligible stocks (Panel H)). In all these cases, the cumulative effect coefficient is negative suggesting informed sellers prefer to fully expose limit orders.

These patterns support the interpretation that informed agents use order attributes to manage both price and execution risk. Informed agents facing less competition submit more limit orders to obtain a better price but choose to fully expose more limit orders to improve execution probability. This interpretation is supported by results in Table 4 as well as Panels D, F and H in Table 5. On the other hand, informed agents facing more competition submit more price aggressive (market) orders due to the execution risk that they impose on each other.

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. Similar to Table 5, the empirical specification examines standing limit orders and includes control variables that account for market conditions and other attributes of the order. We also include Day dummy coefficients to examine informed agent behavior.

For both buy orders before positive events and sell orders before negative events, the Day cumulative effect coefficient in Panel B of Table 6 is negative and statistically significant. Further, in all sub-samples, the cumulative effect coefficient is negative both before positive and negative events. In the case of index stocks (Panel C), stocks with listed options (Panel E) or SRD-eligible stocks (Panel G), the coefficient is negative but statistically insignificant while for non-index stocks (Panel D), stocks without listed options (Panel F) or stocks that are SRD-ineligible (Panel H), the cumulative effect coefficient is negative and statistically significant. Based on these results, we conclude that, when provided with the option to hide order size, informed agents prefer to increase the number of shares that are exposed to the market. The results support Harris (1996) prediction that informed agents (with high opportunity cost of non-execution) expose their orders to attract reactive counterparties.

In relation to the prior literature, BPV (2009) and De Winne and D'Hondt (2007)) document that hidden orders are typically used by uninformed agents to lower order exposure risk. BPV (2009) also documents that order exposure depends in part on the order's price aggressiveness, since market participants are likely to infer the presence of informed agents based on price aggressiveness of the incoming orders. Our results are broadly consistent with these interpretations. We extend the literature by specifically showing how the degree the competition influences informed agents usage of "aggressive" and "passive" strategies. When faced with more competition, informed agents increase usage of aggressively priced (possibly, market) orders. When faced with less competition, informed agents increase usage of less aggressively priced (possibly, limit) orders but more often fully expose the limit orders and expose a larger quantity of shares. Both strategies reflect an active tradeoff between the desire to obtain a better price using limit orders and the execution risk imposed by other informed traders.

6. Informed trader strategies and execution costs

Informed agents have the ability to choose among many possible trading strategies. The analysis thus far relates trading strategies to the degree of competition in the stock, which influences price impact, the execution risk, and the time-to-execution. A rational selection implies that, although strategies might differ based on competition, they achieve favorable outcomes for informed agents. In this section, we examine whether informed agents obtain outcomes consistent with this idea.

6.1. Trader strategies and limit order's 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). Execution time is an empirical proxy for the price risk associated with a delayed trade. The model describes an accelerated failure time specification of limit order execution under the generalized gamma distribution. Following the literature, we include control variables that capture the prevailing conditions in the book and attributes of the order. We find that more aggressively priced orders and orders that are fully exposed are associated with shorter execution time. We find that execution time increases when there is more competition on the same side of the market. These results are consistent with the results in Lo, Mackinlay, and Zhang (2002).

To test our framework, we include Day indicator variables to assess time-to-execution of limit orders on days when informed agents are active. A positive Day coefficient indicates that limit orders take longer to execute in Days [-5,-1] before the event, and vice-versa. The model is estimated for each event and the coefficients are aggregated across events using the Bayesian framework.

In Table 7, Panels B to H, we report the cumulative effect coefficient for both buy orders before positive events and sell orders before negative events. For the overall sample in Panel B, the coefficient is negative and statistically significant for both positive and negative events. Further, the cumulative effect coefficient is negative for all subsamples in Panels C to H and statistically significant in ten of the twelve sub-samples. The results reveal that limit orders submitted on trading days when informed agents are active are associated with shorter time to execution.

6.2. Trader strategies and Opportunity costs

To measure opportunity costs, we rely on implementation shortfall framework proposed by Perold (1988) and implemented by Harris and Hasbrouck (1996) and Griffiths, Smith, Turnbull, and White (2000). Each order is associated with two components of implementation shortfall: (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 order expiration or cancellation date and 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 (falls) for buy (sell) orders after order submission. The implementation shortfall cost for an order is the weighted sum of the effective spread cost and the opportunity cost, where the weights are the proportion of the order size that is filled and unfilled, respectively.

An important assumption of our model is that informed agents using market orders tip off participants about the information event and thus impose execution risk on other informed agents who use limit orders. This leads to the prisoner's dilemma outcome. To test this assumption, we separately examine sub-sample of events that are associated with a market order equilibrium. For these events, the model predicts that opportunity costs for limit orders submitted during Days [-5,-1] will be significant because the market order equilibrium causes the stock price to drift in the direction of the private signal.

Table 8 presents the results of a regression of the order's implementation shortfall on prevailing market conditions and various order attributes. Consistent with Harris and Hasbrouck (1996), we find that price aggressiveness is positively associated with effective spread cost. The negative coefficients for hidden order dummy in the opportunity cost regression suggest 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 to control order exposure risk.

To test model predictions, we focus on the cumulative effects Day coefficients in the opportunity cost regressions (columns (5) and (6)). The coefficients capture the change in opportunity costs on days when informed agents are active before the event relative to control days for the same firm. In Panel B, for buy orders before positive events (column (5)), the Day cumulative effect coefficient is positive and statistically significant (t-statistic=2.17). Further, in sub-samples (Panels C to H), we obtain *positive* coefficients in all the panels and the coefficients are statistical significant in five out of six panels. Thus, before positive events, the evidence supports that stock price drifts upwards after limit order submission. The positive price drift is consistent with the results in Table 4 where we document that informed buyers submit more price aggressive orders before the event. Aggressive buy orders convey good news and cause a positive price drift, which imposes significant execution risk on informed agents using buy limit orders.

For sell orders before negative events (column (6)), the cumulative effect variable is negative and significant at the 10% level (t-statistic=-1.77); however, we observe variations across sub-samples based on the ease of short selling. For stocks with few barriers (index stocks in Panel C and SRD-eligible stocks in Panel G), the cumulative effect coefficients are *positive* and statistically significant (t-statistic=2.08 for index stocks and t-statistic=1.60 for SRD-eligible stock) suggesting that stock price tends to drift lower before the negative event. For stocks that face short constraints (non-index stocks in Panel D, those without listed options in Panel F and SRD-ineligible stocks in Panel H), the opportunity costs are *negative* with marginal significance. Recall that the latter sub-samples are associated with usage of less price aggressive orders in Table 4. Thus the results support the model's prediction that limit order equilibrium conveys less information and imposes lower execution risk on informed agents. Finally, for negative events in stocks with listed options (Panel E), the model predicts a positive opportunity cost but the estimate is negative and statistically insignificant.

Collectively, the results indicate that, when informed agents face competition, they use aggressive strategies which cause a significant drift in stock price in the direction of the private signal and the price drift impose execution risk on other informed traders using limit orders. When informed agents face less competition, they use passive strategies which hides the presence of informed agents from market participants. The use of passive strategies is associated with an insignificant drift in stock price. Figure 1 plots the stock price movements before positive and negative events and Figure 2 plots the drift based on index membership. The patterns in price drift are broadly supportive of our main results – the weakest drift is observed for negative events in non-index firms while other sub-samples in Figure 2 are associated with significant price drifts in the direction of the signal.

7. Conclusion

Aggressive market orders used by some informed agents impose an execution risk on the limit orders of other informed agents. This leads to a prisoner's dilemma outcome in which informed agents forgo the price benefit of limit orders and instead use market orders. In this paper we extend the classic prisoner's dilemma game by incorporating the possibility that some informed traders choose to abstain from trade. In equilibrium, our model predicts that informed agents who don't have the shares in their portfolio may abstain if (i) the nature of private information conveys a decrease in stock price (negative event), (ii) borrowing costs are high, (iii) the investor base is not broad, and (iv) the event is small so potential profits cannot justify the costs. In this equilibrium, informed sellers who do have the shares in their portfolio use limit orders.

Using detailed order level data from Euronext-Paris, we examine whether the strategies of informed agents are influenced by the expected level of competition in the stock. We measure informed trading by examining unscheduled corporate events whose timing is not known in advance. We find that informed agents employ more aggressive orders preceding positive events and less aggressive orders preceding negative events. Examining sub-samples, we find that when short selling is costly, when event returns are small, or when the investor base is not broad, informed sellers face less competition and use less price aggressive orders. In all other cases, both informed buyers and sellers increase their usage of price aggressive orders. These empirical results are strongly supportive of the model's predictions.

The study contributes to a better understanding of the price impact asymmetry surrounding block purchases and sales; i.e., the well-documented result that purchases convey more information than sales.

Our results indicate that the price impact asymmetry can be influenced, at least in part, by competition among informed agents. Intense competition among informed agents signals their presence to the market and causes the stock price to drift in the direction of the private signal. We show that such an outcome is more likely when informed agents have positive news than in situations when they have negative news, thus contributing to asymmetry in the price impact of purchases and sales.

The study provides a framework to form expectations ex-ante on insider trading strategies before corporate events and how strategies vary in the cross-section of stocks. Specifically, we show that insider strategies are influenced by both firm characteristics, such as breadth of investor base and the ease of short selling, and event characteristics, such as the direction and information content of corporate announcements. Our results provide specific guidance to designers of insider trading surveillance systems at broker-dealers, stock exchanges and regulators such as U.S. Securities and Exchange Commission.

The study also highlights an unintended consequence of the global ban on short selling in equity markets imposed by regulators in response to the 2007-09 financial crisis. Beber and Pagano (2013) document that the ban on short selling lowers the information efficiency of prices, particularly in relation to negative information. Our study points to a specific mechanism by which a short sale ban can impede the flow of information into prices. Specifically, the short sale ban lowers competition among informed sellers and thereby leads to a limit order equilibrium that makes it more difficult for market participants to detect the presence of informed sellers. These insights are topical because more than a dozen stock markets around the world continue to restrict or impede short sales in one form or another.

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Table 1: Unanticipated Corporate Events: Abnormal Returns and Sample Characteristics

The table presents descriptive information on the sample and reports abnormal returns for the different types of unanticipated corporate events. We separate the events into positive and negative news based on the two day (Day[0,1]) cumulative abnormal returns. In Panel A we report returns for the five different types of anticipated events: acquisitions, targets, season equity offerings, repurchases, dividend initiations and dividend termination. These are calculated by subtracting the CAC40 daily index returns which is used as a benchmark. In Panel B we report the following sample characteristics: market capitalization (as of January 2003) and daily volume, percentage quoted spread, volatility and price during the control days [-30,-10] before the announcement of the event. We report mean and median measures in both panels.

Panel A: Abnormal Returns

		Positive			Negative		
Type of Events	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%

Panel B: Sample Characteristics

	Positive		Negative	
Variables	Mean	Median	Mean	Median
Market Capitalization (Euro mill)	5,114	425	2,805	227
Benchmark Daily Volume (shares)	454,347	6,034	996,291	45,526
Benchmark Quoted Spreads (Prc)	1.32	0.78	1.45	0.88
Benchmark Daily Volatility (Prc)	0.18	0.13	0.25	0.16
Benchmark Average Price (Euro)	33.29	27.21	24.08	17.97

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 for all orders, market/marketable orders and limit orders. 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 event 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: Price Aggressiveness and the Magnitude of Event Return

The table shows regression coefficients that estimate the change in price aggressiveness before unanticipated corporate events (Days[-5,+1] with Day 0 denoting the event day) after controlling for order attributes and market conditions. Detailed definitions of the explanatory variables are provided in Appendix B. The sample is a set of 95 Euronext-Paris stocks around 101 unanticipated corporate events. We separately investigate buy (sell) orders around positive (negative) events 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 five days dummies before the event (day minus 5 to day minus 1). In Panel C, we report economic effects of the cumulative coefficients reported in Panel B by translating them into percentage changes in average order aggressiveness and the frequency of incoming aggressive orders (categories 1 to 4). 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)

Variable	All Events: Buy orders, Positive Events Coefficient (1)	All Events: Sell orders, Negative Events Coefficient (2)	Event Period Absolute Return <5%: Buy orders, Positive Events Coefficient (3)	Event Period Absolute Return <5%: Sell orders, Negative Events Coefficient (4)	Event Period Absolute Return >5%: Buy orders, Positive Events Coefficient (5)	Event Period Absolute Return >5%: Sell orders, Negative Events Coefficient (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	-1.3859	0.1659
(t-statistic)	(-2.96)	(1.70)	(-2.09)	(1.95)	(-2.40)	(0.45)
Panel C: Economic Interpretation of the Cumulative Effect of Day Minus 5 to Day Minus 1 Coefficients						
Comparisons with benchmark period:						
%Change in Average Aggressiveness	11.67	-3.27	6.68	-6.05	26.80	-3.18
% Change in the Frequency Of Aggressive Orders	8.73	-2.90	4.90	-6.05	42.06	-2.78

Table 4: Price Aggressiveness and Short Sale Constraints

The table shows regression coefficients that estimate the changes in price aggressiveness around unanticipated corporate events (Days[-5,+1] with Day 0 denoting the event day) after controlling for order attributes and market conditions. Detailed definitions of the explanatory variables are provided in Appendix B. The 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 whether or not (a) the stock belongs to SBF 120 index, 2) the stock has exchange traded options, and 3) the stock is eligible for SRD-facility. Panels A and C report individual day dummy effects and Panels B and D report cumulative coefficient effects of the five days dummies before the event (day minus 5 to day minus 1). 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	
	Buy orders, Positive Events	Sell orders, Negative Events	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	Coefficient	Coefficient
Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
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)

	Events From SDR-Eligible Companies		Events From SDR-Ineligible Companies	
	Buy orders, Positive Events	Sell orders, Negative Events	Buy orders, Positive Events	Sell orders, Negative Events
	Coefficient	Coefficient	Coefficient	Coefficient
Variable	(1)	(2)	(3)	(4)
Panel C: Individual Day Minus 5 to Day Minus 1 Day Dummies				
Day Minus 5 (dummy)	-0.1656	-0.0662	-0.2509	0.2419
(t-statistic)	(-1.87)	(-1.05)	(-1.09)	(2.17)
Day Minus 4 (dummy)	-0.1130	-0.1334	-0.0478	0.2383
(t-statistic)	(-2.24)	(-2.06)	(-0.25)	(1.97)
Day Minus 3 (dummy)	-0.1186	-0.1111	-0.1264	-0.0234
(t-statistic)	(-2.10)	(-1.52)	(-1.33)	(-0.12)
Day Minus 2 (dummy)	-0.0839	-0.1680	-0.2507	0.0058
(t-statistic)	(-2.04)	(-2.24)	(-1.49)	(0.66)
Day Minus 1 (dummy)	-0.0783	-0.1143	-0.1850	0.1479
(t-statistic)	(-2.28)	(-1.54)	(-2.24)	(0.66)
Day 0 & Plus 1 (dummy)	-0.0570	-0.0883	0.0348	0.1107
(t-statistic)	(-1.82)	(-1.43)	(0.42)	(1.16)
Day Plus 2 (dummy)	-0.0660	-0.1305	0.2066	0.1872
(t-statistic)	(-1.50)	(-1.89)	(1.75)	(1.28)
Order exposure	0.6543	0.5313	0.7231	0.7708
(t-statistic)	(8.79)	(7.85)	(10.55)	(7.92)
Total order size (norm)	-3.8650	0.1554	-0.0092	-0.0212
(t-statistic)	(-2.83)	(0.48)	(-0.47)	(-0.59)
Control variables	yes	yes	yes	yes
Panel D: Cumulative Effect of Day Minus 5 to Day Minus 1 Coefficients				
Cumulative Effect: Day Minus 5 to Day Minus 1	-0.4532	-0.8868	-0.5692	0.5484
(t-statistic)	(-2.26)	(-2.09)	(-2.19)	(2.04)

Table 5: Logistic Regressions of Decision to Hide and Short Sale Constraints

The table shows logistic regression coefficients that estimate changes in the decision to fully hide a standing limit order 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 Appendix B. The sample is a set of 95 Euronext-Paris stocks around 101 unanticipated corporate events. We separately investigate buy (sell) orders around positive (negative) events. 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) for the full sample. Panels C and H 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 (a) the stock belongs to SBF 120 index, (b) the stock has exchange traded options, and (c) the stock is eligible for SRD-facility. 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)
Panel G: Cumulative Effect of Day Dummies - SRD-Eligible Companies		
Cumulative Effect: Day Minus 5 to Day Minus 1	0.878	-1.0922
(t-statistic)	(1.51)	(-1.24)
Panel H: Cumulative Effect of Day Dummies - SRD-Ineligible Companies		
Cumulative Effect: Day Minus 5 to Day Minus 1	1.6064	-2.5014
(t-statistic)	(1.80)	(-2.39)

Table 6: Tobit Regressions of Magnitude of Hidden Size and Short Sale Constraints

The table shows tobit regression coefficients that estimate 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 Appendix B. The 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) for the full sample. Panels C and H report cumulative coefficient effects of the 5-day dummies before the event for subsamples of companies based on whether or not (a) the stock belongs to SBF 120 index, (b) the stock has exchange traded options, and (c) the stock is eligible for SRD-facility. 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)
Panel G: Cumulative Effect of Day Dummies - SRD-Eligible Companies		
Cumulative Effect: Day Minus 5 to Day Minus 1	-0.1341	-1.1560
(t-statistic)	(-0.43)	(-0.49)
Panel H: Cumulative Effect of Day Dummies - SRD-Ineligible Companies		
Cumulative Effect: Day Minus 5 to Day Minus 1	-3.3938	-2.5758
(t-statistic)	(-2.84)	(-4.83)

Table 7: Limit Order Time-to-Execution and Short Sale Constraints

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) for the full sample. Panels C and H report cumulative coefficient effects of the 5-day dummies before the event for subsamples of companies based on whether or not (a) the stock belongs to SBF 120 index, (b) the stock has exchange traded options, and (c) the stock is eligible for SRD-facility. 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	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)
Panel G: Cumulative Effect of Day Dummies - SRD-Eligible Companies		
Cumulative Effect: Day Minus 5 to Day Minus 1	-0.6324	-1.0176
(t-statistic)	(-1.02)	(-2.18)
Panel H: Cumulative Effect of Day Dummies - SRD-Ineligible Companies		
Cumulative Effect: Day Minus 5 to Day Minus 1	-2.3863	-1.6689
(t-statistic)	(-3.44)	(-2.26)

Table 8: Implementation Shortfall and Short Sale Constraints

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 days dummies before the event (day minus 5 to day minus 1) for the full sample. Panels C and H report cumulative coefficient effects of the 5-day dummies before the event for subsamples of companies based on whether or not (a) the stock belongs to SBF 120 index, (b) the stock has exchange traded options, and (c) the stock is eligible for SRD-facility. 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).

	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)

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)
Panel G: Cumulative Effect of Day Dummies - SRD-Eligible Companies						
Cumulative Effect:						
Day Minus 5 to Day Minus 1	0.2018	0.1114	-0.0076	0.0198	0.3627	0.1303
(t-statistic)	(2.20)	(1.92)	(-0.48)	(1.09)	(1.92)	(1.60)
Panel H: Cumulative Effect of Day Dummies - SRD-Ineligible Companies						
Cumulative Effect:						
Day Minus 5 to Day Minus 1	0.3050	-0.0693	0.0445	0.0083	0.4408	-0.3548
(t-statistic)	(2.17)	(-0.38)	(0.78)	(0.06)	(2.15)	(-1.58)

Figures: Price drift before unanticipated events

The figures plot the drift in the stock price surrounding the unanticipated corporate announcement. The stock price before the event is normalized by the average stock price in the control period (Days [-30,-10]), which is denoted by the horizontal line (black at 1.00). Figure 1 plots the stock price for the overall sample of positive and negative events. Figure 2 plots the stock price for sub-samples based on SBF120 Index membership.

Fig 1. Price movements before unanticipated events

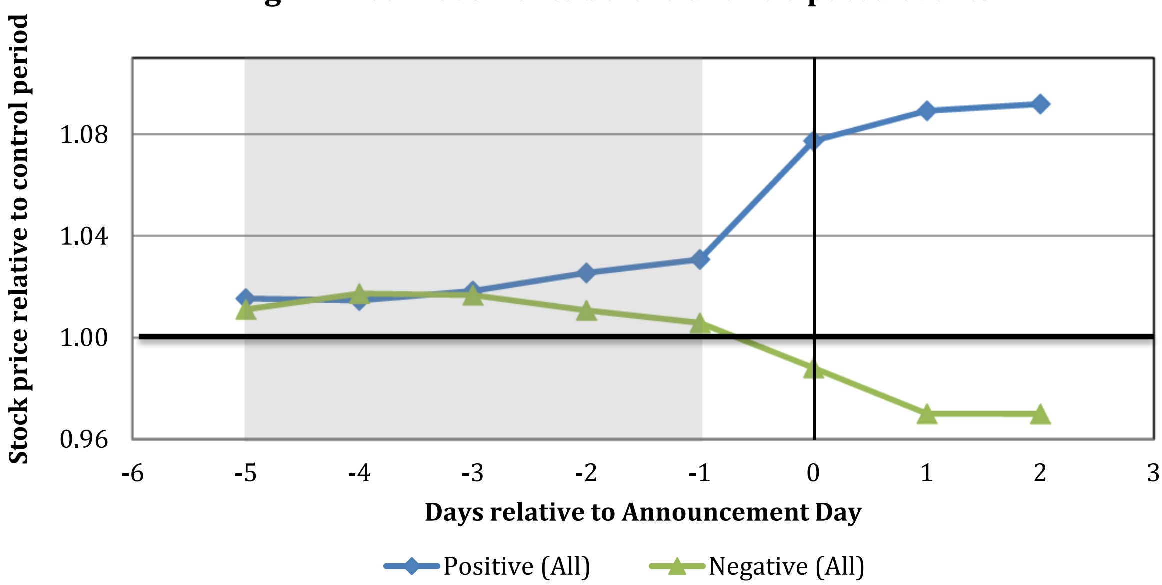
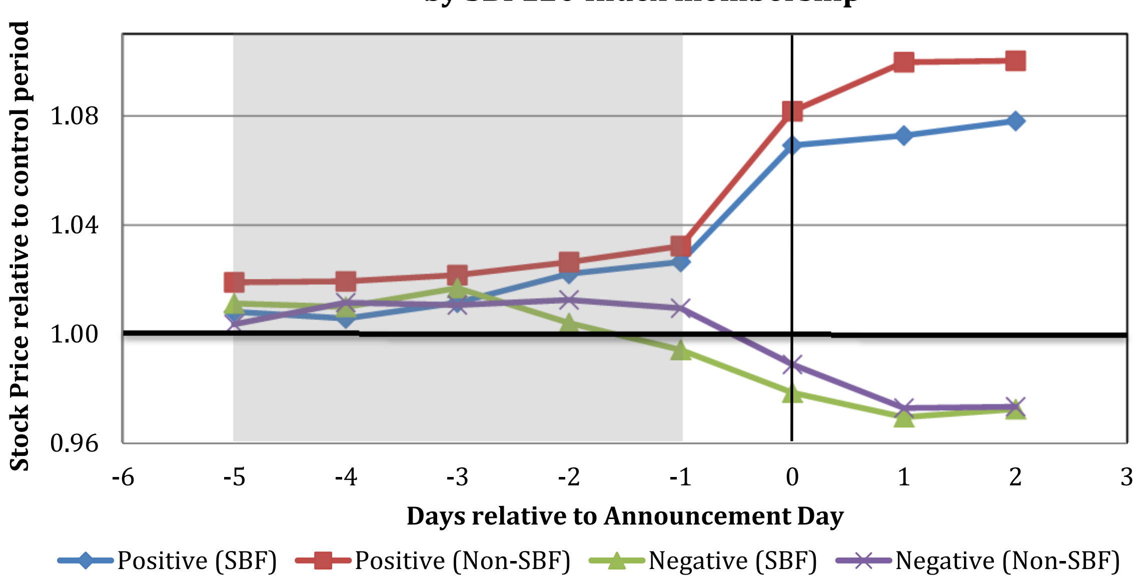


Fig 2. Price movements before unanticipated events by SBF120 Index membership



Appendix A: Model Extension

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 $(v-\bar{v})^2b$ 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

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 $(v-\bar{v})^2d$ 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

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

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

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

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

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

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

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

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

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

Appendix B: Variable Definitions

Following Biais, Hillion and Spatt (1995) and BPV (2009), *PriceAggressive* is an ordinal variable that takes the value of one for the most aggressive order and seven for the least aggressive. The first four categories represent orders that demand liquidity from the limit order book and the last three categories represent orders that supply liquidity to the book.

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).

The remaining variables are defined as follows. *OrderExposure* equals one if 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 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 industry in the prior hour. *Mkt.Volatility* is the return volatility of the CAC40 Index in the prior hour.