

Price Impact Asymmetry of Block Trades: An Institutional Trading Explanation

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This article develops a theoretical model to explain the permanent price impact asymmetry between buyer- and seller-initiated block trades (the permanent price impact of buys is larger than that of sells). The model shows how the trading strategy of institutional portfolio managers creates a difference between the information content of buys and sells. The main implication of the model is that the history of price performance influences the asymmetry: the longer the run-up in a stock's price, the less the asymmetry. The intensity of institutional trading and the frequency of information events affect the asymmetry differently depending on recent price performance.

Empirical research on block transactions and institutional trades has produced a seemingly puzzling result: Markets react differently to buy and sell orders. Beginning with Kraus and Stoll (1972), researchers have found that block purchases have a larger permanent price impact than block sales [Holthausen, Leftwich and Mayers (1987, 1990), Gemmill (1996), Keim and Madhavan (1996)]. The same result is documented for institutional trades [Chan and Lakonishok (1993)] and for institutional trade packages [Chan and Lakonishok (1995)]. While prices go up on buys and down on sells, they revert after sells but remain high after buys, creating a permanent price impact asymmetry.

Two explanations appear in the literature to account for the permanent price impact of block trades: inelastic demand and supply curves, and information effects. If a stock does not have sufficiently close substitutes, the excess demand and supply curves for its shares will not be perfectly elastic, and block trades will have a permanent price impact. No obvious story, however, can explain why the long-term elasticity of demand in a secondary market should differ from that of supply. Hence it is unclear why the permanent price impact should depend on whether the initiator of a transaction is a buyer or a seller.¹ On the other hand, if informed traders are active in the

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¹ Short-run liquidity costs are used in the literature to explain the *temporary* impact of block trades. Temporary asymmetry between buys and sells is attributed to the willingness of block positioning firms to accommodate sales but not purchases [Kraus and Stoll (1972)] and to difficulty in locating potential sellers as opposed

market, and their trading strategy makes buy orders convey more information than sell orders, equilibrium prices should adjust more for buys than for sells.

Chan and Lakonishok (1993) propose one possible reason for differences in the information content of trades: "Since an institutional investor typically does not hold the market portfolio, the choice of a particular issue to sell, out of the limited alternatives in a portfolio, does not necessarily convey negative information As a result, there are many liquidity-motivated reasons to dispose of a stock. In contrast, the choice of one specific issue to buy, out of the numerous possibilities on the market, is likely to convey favorable firm-specific news" (p. 185). Implicit in this argument are numerous assumptions about both the set of feasible investment strategies and the optimal trading strategy of mutual funds.² Without being specific about the underlying mechanism that generates information differences between buys and sells, we cannot hope to test the information explanation. An investigation of the permanent price impact asymmetry therefore requires setting forth a basic set of assumptions on the behavior of institutional investors, generating information differences between buys and sells, and relating them to other market phenomena in order to produce new testable implications. The objective of this article is to pursue this line of investigation.

More specifically, I make four observations concerning the behavior and constraints of mutual funds.³ First, they often devote substantial resources to gathering and analyzing information. Second, most mutual funds limit their investment to money they receive from shareholders (rather than borrow). Hence, investing in one stock has the opportunity cost of not investing in another. Third, mutual funds do not concentrate their holdings in only a few stocks. Fourth, they hold assets in nonnegative amounts. In other words, they seem to be averse to selling short. These four characteristics of institutional behavior create a situation in which portfolio managers are predominantly engaged in searching for stocks whose prices are expected to rise. They rebalance their portfolios frequently to sell stocks that do not fit this description.

I model an institutional trading strategy consistent with these four observations. The model highlights the considerations of portfolio managers who

to potential buyers [Chan and Lakonishok (1993)]. Holthausen, Leftwich, and Mayers (1987) report that discussions with block traders suggest that they do in fact often accommodate block purchases. Analysis of commissions by Keim and Madhavan (1994) suggests that differences in the cost of locating counterparties cannot explain the asymmetry in the price impact of buys and sells. While it may be that short-run liquidity concerns affect the prices at which blocks trade, these concerns cannot explain why the *permanent* price impact of buys and sells differs.

² A similar intuition appears in Keim and Madhavan (1995), who find that it takes more time to execute buyer-initiated institutional trades than seller-initiated trades. They suggest that buys are more informationally motivated than sells because institutional traders can choose from among many potential assets to buy but usually limit themselves to selling those assets they already own due to restrictions on short sales. Keim and Madhavan (1997) offer additional evidence consistent with information differences by showing that trading costs for buyer-initiated trades exceed those of seller-initiated trades.

³ I use the terms "institutional investors" and "mutual funds" interchangeably. A more elaborate discussion of these observations (with references) is provided in Section 2.1.

are looking to exploit information in a multiple-stock context and are subject to some constraints on their trading strategies. Their expected profit-maximizing trading strategy involves always searching for information about stocks already in their portfolios in order to sell stocks whose prices are expected to go down or on which there is no special information. Their search for information continues among stocks not in their portfolios in order to buy stocks on which they discover favorable information. If the market knows that institutional investors may be informed about the prospects of stocks, such a dynamic rebalancing strategy creates a difference between the information content of buys and sells.

I use a simple intertemporal trading model to investigate how the behavior of institutional investors affects the market. The expected permanent price impact of a block trade in the model corresponds to the change in the market's expectations of the true value of a stock brought about by the block transaction. I derive an expression for the expected permanent price impact asymmetry between buyer- and seller-initiated block transactions, and explore its relationship with the economic environment. The model demonstrates how the price impact asymmetry that has been documented can arise. More important, the model produces new empirical implications concerning the influence of price performance, institutional following, information intensity, and volatility on the asymmetry phenomenon.

The main implication of the model is that a stock's history of price performance influences the asymmetry. The longer the run-up in a stock's price, the less the permanent price impact asymmetry between buys and sells. In fact, the model predicts no asymmetry or even negative asymmetry—sells have a greater permanent price impact than buys—following a long (abnormal) price run-up.

In addition, past price performance affects the way other elements of the economic environment relate to the asymmetry phenomenon. For example, the greater the trading intensity of institutional investors, the more pronounced the asymmetry when the stock's price has not been rising or when the stock is at the beginning of a price run-up. The opposite result appears after a long period of (abnormal) price appreciation. A similar relationship also exists between the frequency of information events concerning the stock and the asymmetry: The more "informationally active" a stock, the greater the asymmetry if the stock's price has not been going up or is at the beginning of a series of price appreciations. The opposite result appears after a long price run-up. While the required return always increases the asymmetry, greater dispersion of a stock's price intensifies the asymmetry at the beginning of a price run-up, but diminishes it after a long period of price appreciation.

The model is further examined using numerical analysis. A calibration exercise shows that reasonable parameter values can produce asymmetry of the extent reported in the empirical literature. Moreover, the implications of

the model are shown to hold when asymmetry is defined in terms of the net order flow during the day and not just in terms of individual blocks.

The implications of the model concerning the relation between the permanent price impact asymmetry and the economic environment have not been tested by the empirical articles that have documented this phenomenon. Hence they provide an opportunity to test the hypothesis that the asymmetry phenomenon arises due to the behavior of institutional investors. Previous theoretical models of block trades, such as Easley and O'Hara (1987) and Seppi (1990), focus on a trader's choice of trade size but make no attempt to explain the price impact asymmetry. Other related articles are Bhattacharya and Krishnan (1999), who explore how suspicion in capital markets may alleviate moral hazard in managerial disclosure and produce a difference in the information content of buys and sells, and Allen and Gorton (1992), who investigate market manipulation using exogenous asymmetry in the arrival rates of uninformed buyers and sellers.

The rest of the article is organized as follows. Section 1 defines the permanent price impact asymmetry. Section 2 describes the trading strategy of institutional investors and sets up the trading model. Section 3 investigates the asymmetry phenomenon in this economy. Section 4 concludes.

1. Permanent Price Impact Asymmetry

The empirical literature on the price impact of block trades focuses on three basic prices: a proxy for the equilibrium price prior to the block trade (P_{-1}^e), the price at which the block trade is executed (P^T), and a proxy for the equilibrium price following the block trade (P_{+1}^e). The permanent price impact of a buyer-initiated block trade is defined as $\Delta B = \frac{P_{+1}^e - P_{-1}^e}{P_{-1}^e}$ conditional on the execution of a block trade in the period bracketed by these two equilibrium prices. Hence the permanent price impact is not a function of the block's actual trading price. Instead, it is a random variable assumed to represent the possible changes in equilibrium value conditional on the information that can be inferred from the block. The fact that an investor wants to trade a block alters beliefs about the value of the stock. If some investors have private information and use it optimally, the expected permanent price impact of a buyer-initiated block trade will most likely be positive. To make the comparison of magnitudes easier, the permanent price impact of a seller-initiated block trade is defined as $\Delta S = \frac{P_{-1}^e - P_{+1}^e}{P_{+1}^e}$. Hence the expected permanent price impact of seller-initiated block trades is also likely to be positive.

A theoretical investigation of the price impact asymmetry requires more specific definitions of the value process of stocks and the pre- and posttrade equilibrium prices. There are N stocks in the economy, each representing a claim to the assets of a firm. To streamline the notation, all parameters will be specified in terms of a single firm. It should be understood that these parameters can differ across stocks. The true value of a stock is defined as

the discounted value of all future gains or losses of the firm. A bad event on date t implies a loss of Z (a strictly positive number) and occurs with probability δ . A good event on date t implies a gain of the same magnitude, Z , and occurs with probability $1 - \delta$.⁴ Information about the gains or losses reaches the market with probability α . On dates without information, the market assumes that gains (or losses) are at their expected value, $(1 - 2\delta)Z$.⁵ Private information is short-lived, and the nature of an information event is revealed to all after the end of trading on date t . For ease of exposition, each date is referred to as a “day.”⁶

The required return on the stock, r , is the result of an equilibrium along the lines of traditional asset pricing models. In other words, investors in the market agree on the model for long-term valuation of stocks. Every evening when all investors have the same information set, they reach the same conclusions as to the values of all stocks.⁷ Investors value each stock under the assumption that α , δ , and r are constant for a finite horizon of T days.⁸

Let $\mathcal{F}_t$ be the information set the market uses to value stocks at the end of each day (i.e., $\mathcal{F}_t$ includes all parameters of the economy and past realizations of the information events). Then, the true value of the stock on date $t < T$ is

$$V_t = (1 - r)^t E \left[C + \sum_{s=1}^T \frac{e_s}{(1 + r)^s} \middle| \mathcal{F}_t \right],$$

where e_s is the gain or loss on date s , and for $s > t$,

$$e_s = \begin{cases} Z & \text{with probability } \alpha(1 - \delta) \\ -Z & \text{with probability } \alpha\delta \\ (1 - 2\delta)Z & \text{with probability } 1 - \alpha. \end{cases}$$

The role of C is to capture accrual earnings, investment costs prior to date zero, and the market’s best-effort assessment of the discounted value of future cash flows beyond T . Under this structure, the discounted true value process

⁴ Z can change over time without affecting any of the results in this article.

⁵ This information structure is similar to the one used in Easley and O’Hara (1992) and includes event uncertainty in addition to uncertainty with respect to the nature of the event.

⁶ If one believes that relevant information arrives only once a week or once a month, one can simply relabel the time intervals accordingly. What is important to the analysis is the discrete nature of information arrival and that old information is completely revealed before new information arrives.

⁷ While the model that gives rise to the required return is not explicitly written down in this article, it can be thought of as one of the standard asset pricing models that describe a world of homogeneous information.

⁸ T depends on how strong beliefs are in the market that the firm will continue to perform according to the current parameters.

is a martingale with respect to $\mathcal{F}_t$, and the expression for the value of the stock can be rearranged to emphasize the change in value over days:

$$V_t = V_{t-1}(1+r) + e_t - (1-2\delta)Z. \quad (1)$$

Equation (1) shows how, in addition to the required return earned by the stock every day, the stock's value will go up by $2\delta Z$ on days with good information events, go down by $2(1-\delta)Z$ on days with bad information events, and stay the same on days without information events.

The empirical articles mentioned in the introduction differ in terms of the proxies used for equilibrium prices. Following Kraus and Stoll (1972), I define P_{-1}^e as the closing price on day $t-1$. In the context of the model presented here, the actual price of the last trade of the day is not known for sure. Hence P_{-1}^e is taken to be the price after the close on day $t-1$, V_{t-1} . Similarly, the equilibrium price following the block transaction, P_{+1}^e , is defined as the price after the close on day t , V_t . Using these definitions, the permanent price impact of a block buy at the opening of the market on day t can be written as

$$\Delta B_t = \frac{V_t - V_{t-1}}{V_{t-1}} = \begin{cases} \frac{V_{t-1}(1+r) + Z - (1-2\delta)Z - V_{t-1}}{V_{t-1}} \\ \quad = r + 2\delta \frac{Z}{V_{t-1}} & \text{w.p. } P(H|B) \\ \\ = \frac{V_{t-1}(1+r) - V_{t-1}}{V_{t-1}} = r & \text{w.p. } P(O|B) \\ \\ \frac{V_{t-1}(1+r) - Z - (1-2\delta)Z - V_{t-1}}{V_{t-1}} \\ \quad = r - 2(1-\delta) \frac{Z}{V_{t-1}} & \text{w.p. } P(L|B), \end{cases} \quad (2)$$

where the events H , O , and L represent good information, no information, and bad information, respectively, about the firm; B in the conditioning information set represents the arrival of a buy order for a block of the firm's stock; and all probabilities are conditional on the history $\mathcal{F}_{t-1}$. The price impact of seller-initiated blocks can be defined in a similar fashion:

$$\Delta S_t = \frac{V_{t-1} - V_t}{V_{t-1}} = \begin{cases} -r - 2\delta \frac{Z}{V_{t-1}} & \text{w.p. } P(H|S) \\ \\ -r & \text{w.p. } P(O|S) \\ \\ -r + 2(1-\delta) \frac{Z}{V_{t-1}} & \text{w.p. } P(L|S), \end{cases}$$

where S in the conditioning information set represents a block sell.

Let the *expected permanent price impact asymmetry expression* of the stock at the opening of the market on day t be defined as

$$J_t = E[\Delta B_t|B] - E[\Delta S_t|S]. \quad (3)$$

J_t is positive, zero, or negative if and only if the expected permanent price impact of buyer-initiated block trades is greater than, equal to, or less than that of seller-initiated block trades, respectively.

Note that while the unconditional increase or decrease in the value of a stock over a day can be symmetric, the arrival of a block trade provides information, so the resulting conditional distribution may be skewed in one direction or the other. The empirical literature investigating the price impact of blocks conditions on the execution of these trades and then looks at the changes in the proxies for equilibrium prices. Similarly, I condition on the arrival of a block trade and then ask what the expected change in the value of the stock is. If the magnitude of the expected change in value conditional on the arrival of a buy block is greater than that magnitude conditional on the arrival of a sell block (as documented by the empirical articles), the asymmetry expression will be positive.

Following Easley and O'Hara (1987), I define $\delta(B)$ as

$$\delta(B) = P(L|B) + \delta P(O|B). \quad (4)$$

Hence $\delta(B)$ is the probability that the true value of the stock reflects a loss conditional on the arrival of a block buy, whether or not information about the loss arrives in the market. $\delta(S)$ can be defined in an analogous manner.

Plugging ΔB_t and ΔS_t into the permanent price impact asymmetry expression and using the definitions of $\delta(B)$ and $\delta(S)$ yields

$$J_t = 2 \frac{Z}{V_{t-1}} [\delta - \delta(B) + \delta - \delta(S)] + 2r. \quad (5)$$

The asymmetry expression in Equation (5) comprises two separate effects. The first term of the expression is the difference between the information content of buys and sells. $[\delta - \delta(B)]$ can be thought of as a "distance" between the prior probability (for the day) and the posterior probability (conditional on observing a block buy) of a loss. The more (good) private information is associated with a buy, the smaller $\delta(B)$, and the greater the distance between the prior and the posterior. Similarly, $[\delta - \delta(S)]$ is the negative "distance" between the prior probability (for the day) and the posterior probability (conditional on observing a block sell) of a loss. The more (bad) private information is associated with a sell, the larger $\delta(S)$, and the more negative the distance between the prior and the posterior. Hence, heuristically, if buys convey more information than sells, the first "distance" dominates the term,

and the information effect gives rise to a positive asymmetry. If sells convey more information than buys, the second “distance” dominates the term, and the information effect is negative.

The second term of a Equation (5) is the required return—the time value of money adjusted for risk. If investors expect a positive return on their investment, prices (cum dividend) will move up on average regardless of the trades that arrive in the market. This effect, however, can be small for short time intervals. Nonetheless, stocks with more systematic risk would *ceteris paribus* exhibit a greater permanent price impact asymmetry between buys and sells. Most empirical articles that document the permanent price impact asymmetry control, using various methods, for the effect of the required return. Hence the key to understanding the permanent price impact asymmetry lies in understanding the “information” term of J_t .

2. The Market

2.1 Institutional investors

There are four observations about the way institutional investors behave that are central to modeling their trading strategy. While not all mutual funds behave according to them, many operate in a manner consistent with these observations. Hence, these observations can be viewed as describing a “prototypical” mutual fund. The first observation is that institutional investors devote substantial resources to the tasks of gathering and analyzing information. Portfolio managers make investment decisions based on predictions and recommendations produced by research departments.⁹ Also, it is no longer considered sufficient for analysts to determine the long-term prospects of firms. Reports in the popular press claim that predicting the short-term movements of stocks is viewed as central in an analyst’s job [see, e.g., Nocera (1997)]. I model this observation by allowing institutions to invest in building a research infrastructure. This enables them to follow certain stocks that fit their preferred investment profile or that offer a cost advantage with respect to information gathering. Let $\mathcal{G}^j$ be the set of stocks followed by institutional investor j . For each stock in $\mathcal{G}^j$, the research department of the institution has determined that the cost of finding private information on the stock does not exceed the expected profit from knowing the private information.¹⁰

The second observation is that mutual funds primarily invest money received from shareholders. The Securities and Exchange Commission (SEC) limits the ability of mutual funds to use leverage.¹¹ Even more important,

⁹ Mutual funds that do not have their own in-house research infrastructure pay substantial amounts in commissions to “sell side” institutions in exchange for research and analysis.

¹⁰ Each institutional investor may have its own cost advantage in different industries, so the set $\mathcal{G}^j$ depends on characteristics of the institutional investor that are not modeled explicitly.

¹¹ See Investment Company Act (1940) 80a-18 and Investment Company Act Release No. 7221 (1972).

many mutual fund charters restrict the use of leverage. Reports in the popular press indicate that portfolio manager investment styles are indeed shaped by these restrictions [e.g., Barnhart (1997)]. The investment of limited sums of money creates the notion of an opportunity cost; money invested in one stock cannot be used to invest in another stock. To model this observation, I assume that each institutional investor manages a portfolio with a certain number of stocks and cannot borrow money in order to invest in more stocks. The number of stocks held by a mutual fund (and hence its size) can change due to trading profit, cash inflows and outflows, and dividends the mutual fund pays to its shareholders.

The third observation is that mutual funds hold relatively diversified portfolios consisting of many stocks. A mutual fund will not invest a large portion of its money in one stock, as such behavior will be hard to justify to shareholders (many of whom invest in mutual funds with the explicit objective of diversifying their holdings). Moreover, SEC rules that apply to most mutual funds limit the percentage holdings of any one stock and hence *de facto* require diversification. In order to model the notion that mutual funds do not concentrate on only a few stocks and that the trades modeled here are large (i.e., block trades), I assume that a mutual fund's holding of a stock is equivalent to a block trade. This assumption is referred to as the "diversification constraint."¹²

The fourth observation is that most mutual funds hold stocks in nonnegative amounts [see Falkenstein (1996)]. Most mutual funds do not sell short as a matter of policy because it involves the risk of unlimited losses if the stock price goes up, and the charters of many mutual funds explicitly restrict the usage of short sales [see Smith (1985)]. Sharpe (1991) notes that some of this aversion is due to the implicit threat of suit for violation of fiduciary standards. The regulatory environment also discourages short sales. The SEC limits the amount of short sales a mutual fund can undertake [see Investment Company Act Release 7221 (1972)], and there are additional regulatory constraints on short selling (the up-tick rule) and on profit from short selling (the "short-short rule"). The end result is that institutions are looking for stocks to hold and not stocks to sell short.

I restrict mutual fund short sales in this article in a manner that resembles the true situation in the market. Unlike in Diamond and Verrecchia (1987), there is no fraction of sales that is arbitrarily assumed to be short sales. Instead, a mutual fund is prevented from selling a stock only when the stock is not in its portfolio. Hence, any inference on institutional trades will necessitate assessing the probability that a stock is in the portfolios of

¹² This constraint can be somewhat relaxed at the cost of additional complexity, but without materially affecting the results. Institutional investors may hold multiple blocks of the same stock as long as they are increasingly averse to acquiring more of the same stock.

mutual funds. While a simple restriction on sells always creates an asymmetry, the true short sale constraint in this model allows for no asymmetry and even negative asymmetry (when sells have a greater price impact than buys).

These four observations—the constant search for information, the investment of specific amounts, the holding of diversified portfolios, and the aversion to short selling—shape the optimal investment strategy of institutional investors.¹³ What should a mutual fund do in order to maximize expected profit? A simple buy-and-hold strategy will earn on average the required return on each stock. An uninformed dynamic strategy will do even worse (on average), since it involves transaction costs (e.g., the bid-ask spread) with no expected gain. With the ability to search and trade on the basis of information, an institutional investor can hope to do better. Let $\mathcal{P}_t^j$ be the portfolio held by institutional investor j at the beginning of day t (before any rebalancing), and consider a trading strategy as follows:

- Step 1. Search for information on all stocks in $\mathcal{P}_t^j$.
- Step 2. Sell all stocks in $\mathcal{P}_t^j$ with bad information events.
- Step 3. Search among stocks in $\mathcal{G}^j \setminus \mathcal{P}_t^j$ for stocks with good information events. Buy the stocks you find until you replace all the stocks sold, and use whatever money that is carried forward from previous days (if you exhaust all stocks in that set, hold money, and skip Step 4).
- Step 4. Continue to search in $\mathcal{G}^j \setminus \mathcal{P}_t^j$ for stocks with good information events. Upon finding such stocks, sell stocks in $\mathcal{P}_t^j$ with no information events, and replace them with good information event stocks (continue until you replace all stocks with no information events in $\mathcal{P}_t^j$, or until you exhaust searching all stocks in $\mathcal{G}^j \setminus \mathcal{P}_t^j$, whichever comes first).¹⁴

The essence of this trading strategy is that portfolio managers rebalance their portfolios often to sell stocks that are viewed as going down or not moving anywhere, and replace them with stocks on which they discover good information.¹⁵ This strategy is consistent with all four assumptions about the

¹³ One may wonder whether the emergence of hedge funds (which face fewer constraints than mutual funds) has affected the information content of trades and the permanent price impact asymmetry. Since there is a much greater amount of assets under mutual fund management than under hedge fund management, it may be that the trading strategies of mutual funds exert more influence on the information content of the order flow, sustaining the information differences between buys and sells. On the other hand, finding that the price impact asymmetry weakens with greater hedge fund participation may in fact lend support to a model that shows how the information differences are related to mutual fund constraints. Further empirical work is needed to shed light on this issue.

¹⁴ Step 4 is carried out only if there are good information event stocks in $\mathcal{G}^j \setminus \mathcal{P}_t^j$. Otherwise it is never profitable to sell stocks with no information events because holding them earns the required return, while replacing them entails trading costs (in the form of the bid-ask spread) and the newly purchased stocks can also earn at most the required return.

¹⁵ The popular press attributes the high turnover of stocks in the portfolios of mutual funds to the constant search for “winning” stocks [Blumstein (1984)]. The average turnover rate of stocks in the portfolios of mutual funds in 1996 was 91% [Quinn (1997)].

behavior of institutional investors, but is it profit maximizing? The answer to this question must depend on the cost of information in the economy and the way market makers set prices. It is possible to derive a set of sufficient conditions for this trading strategy to be expected profit maximizing among all allowable trading strategies (where allowable strategies are those in which a mutual fund invests in a portfolio of stocks without borrowing or short selling).¹⁶ This set of sufficient conditions can be interpreted to characterize a world in which (1) information costs are not too high (i.e., the cost associated with searching for information on the gain or loss on any given date is low); (2) the mutual funds' optimal search for stocks with good information events is not too lengthy (i.e., they do not spend too much money in the optimal search before finding a good stock); and (3) information is not impounded into prices too quickly (i.e., there is enough uninformed trading). The first two conditions constitute a requirement on the research technology of institutions whereby the process of finding stocks in which to invest is not too costly. The last condition is a requirement on the trading environment: Without a sufficient number of uninformed investors, spreads will be very wide [see also Glosten and Milgrom (1985)] and therefore transaction costs will make this dynamic trading strategy unprofitable.

The first observation about the behavior of mutual funds is that they constantly search for information about stocks. This behavior would not make sense if information costs or the costs of the optimal search in the real world were too great. Hence, I will assume in the rest of the article that institutional investors in the market follow this trading strategy.¹⁷

Note that this trading strategy implicitly assumes that institutional investors would rather hold cash than buy stocks on which they have no information. Another implicit assumption is that mutual funds can always meet redemption needs by selling stocks that experience either bad information or no information events. In other words, they will not sell stocks on which they discover good information. If mutual funds in the real world sometimes behave in a manner that violates these assumptions, the trading strategy described here can be viewed as an approximation of the one actually employed by mutual funds. Controlling for noise that may be introduced by these implicit assumptions is important for empirical tests of the model. In the spirit of the quote from Chan and Lakonishok (1993), I also make the simplifying assumption that there are enough stocks with good information events in the universe of stocks followed by a mutual fund to replace all stocks with bad

¹⁶ A derivation of these sufficient conditions appeared in a previous version of this article. The derivation assumes that institutions use their experience to perform an optimal search among the stocks in $\mathcal{G}^I$ and that prices are set by risk-neutral and competitive market makers. The assumptions on the behavior of the market makers are similar to those in Glosten and Milgrom (1985) and Easley and O'Hara (1987, 1992).

¹⁷ Transaction costs (beyond the information asymmetry-driven bid-ask spread that is determined endogenously) could make step 4 of the trading strategy (selling stocks that are not moving to buy stocks that will go up) less profitable. It can be shown that if mutual funds carry out only steps 1–3 of the trading strategy, the results in Section 3.1 remain intact though the magnitude of the effects may be smaller.

information and no information events in its portfolio. This assumption is not necessary for deriving the results in Section 3.1, but it simplifies the presentation considerably.¹⁸

2.2 Uninformed traders

Besides institutional investors, the market also includes uninformed traders. They are called uninformed because they do not know the realization of the gain or loss of a firm during the trading day, but rather discover it when the information is publicly revealed at night. The identity of the uninformed traders is by default all traders who are not information-intensive institutional investors. Some institutional investors in the real world, like index funds, fit the characterization of uninformed traders. Individuals and portfolio managers who believe they have real information but in fact trade on pure noise satisfy the description of uninformed traders as well. If inflows or outflows of money cause portfolio managers of mutual funds to buy or sell stocks without the support of research, these transactions will be part of the uninformed order flow.¹⁹ I do not differentiate buys from sells on noninformation (e.g., liquidity) grounds. Hence, uninformed traders are assumed to buy or sell with equal probabilities.

For the sake of parsimony, I consider only uninformed block trading, but the model can be extended to include small uninformed trades.²⁰ This extension produces practically identical results to those presented here. Also for parsimony, the arrival of uninformed traders to the market is assumed rather than derived from a larger set of investment strategies. Note, however, that if we let uninformed investors choose between investing through mutual funds and coming to the market separately, they will come to the market only if they are indifferent between these two strategies.²¹ Therefore, any profit mutual funds make as a result of trading on information (beyond the required return) should be exhausted by the cost of maintaining the research infrastructure and searching for information.²² Uninformed investors who choose to invest through mutual funds would ultimately bear the cost of information

¹⁸ Relaxing this assumption is straightforward in that it involves only modifying the inference the market draws from trades on no information days. If there are not enough stocks with good information events in $\mathcal{G}^j \setminus \mathcal{P}_t^j$, institutions will still sell stocks with bad information events (step 3) but will no longer sell stocks with no information events (step 4). Similar results to those presented in Section 3.1 can be derived in this case, though at the cost of some additional complexity.

¹⁹ The trading strategy of institutional investors in Section 2.1 can therefore be viewed as describing only a part of the trading strategy of an institution—the part that is based on information.

²⁰ The parameters of such an extension can then be set to reflect the fact that block trades are indeed not as common as small trades.

²¹ This argument requires the assumption that uninformed investors are large enough so that investing through mutual funds does not provide them with benefits, such as diversification, that they cannot replicate by directly trading in the stocks.

²² A previous version of this article presented an equilibrium condition where the expected trading profit of an institutional investor was set equal to the expected information gathering costs. For some recent evidence of the “competitive market for information” see Gasparino (1997) and Waggoner (1997).

gathering as part of the management fees, and hence would not be making excess returns.²³ Therefore the presence of uninformed traders in the market alongside informed mutual funds can be consistent with a more elaborate model in which the investment strategy of the uninformed traders is endogenized.

2.3 The trading model

Every day is divided into L trading periods. Each period allows for at most one trade. Most stock exchanges in the world have a mechanism and a set of procedures that facilitate the execution of individual orders. This mechanism can take the form of a specialist (NYSE), multiple dealers (NASDAQ), an electronic limit order book (the Paris Bourse), and so on. Since the permanent price impact of a trade is not affected by the actual price paid for the shares, I need not be specific about the manner in which prices are set in this economy. The only assumption I make is that trading is anonymous: Observing an order does not reveal to the market the identity of the trader (i.e., whether it comes from an informed institutional investor or an uninformed trader). Hence the market cannot separate institutional investors from uninformed traders and has to resort to probabilistic inference on the information content of any particular order.

The probability that an institutional investor that follows the stock arrives in the market at any period during the day is given by ν . Since each trading period can accommodate only one trader, the probability that an uninformed investor arrives in the market is $1 - \nu$.

If a mutual fund that follows the stock arrives in the market on date t , the probability that it will buy or sell the stock depends on the nature of the information event about the stock and whether the stock is in the mutual fund's portfolio. When the stock is in its portfolio and a good information event takes place, the mutual fund cannot load more of the stock due to the diversification constraint. If bad information or no information events occur, the mutual fund can sell the stock since the short-sale constraint is not binding. When the stock is *not* in its portfolio and bad information or no information events occur, the mutual fund cannot sell the stock since the short-sale constraint is binding. If a good information event takes place, the mutual fund can buy the stock since the diversification constraint is not binding. Whether the mutual fund in fact buys the stock depends on whether it searched for information on that particular stock on that day. A priori, therefore, the diversification constraint works to limit informed buys, and the short-sale constraint works to limit informed sells. The degree to which these

²³ This property ties into the extensive literature on the performance of mutual funds. While some research finds that mutual funds trade as if they have information, it does not appear that they can deliver better performance than some benchmarks, especially after management costs are taken into consideration. For a review of this literature, see Grinblatt and Titman (1995).

constraints are expected to bind the trading of informed institutional investors is the key to understanding the price impact asymmetry of trades.

Define $\Omega_t \in [0, 1)$ as the market's assessment of the probability that a mutual fund will search for information about the stock on date t if the stock has a good information event day and is not in the mutual fund's portfolio.²⁴ Denote the probability that a stock is in the portfolio of an institutional investor by $\gamma_{t,q}$. The subscript q (on date t) is the length of the current run of good information event days that is known to the market, or the number of consecutive days in which the stock had good information events up to date $t - 1$. For example, $q = 0$ means that there was either a bad information event or a no information event on date $t - 1$. Given the trading strategy of mutual funds, the stock cannot be in the portfolio of a mutual fund on date t since it would have been sold at $t - 1$ if it had been in the portfolio then and would not have been bought otherwise. Hence, to calculate the probability that the stock is in the portfolio of a mutual fund on date t , we need not consider the entire history of information events, but rather only what has happened from the beginning of the current run of good information events.

Since a mutual fund will buy a stock only once during any given run of good information events (due to the diversification constraint), and will not sell that stock until the run ends, the probability that the stock is in the portfolio of a mutual fund that arrives in the market equals the probability that the stock was bought by the mutual fund in all previous days during the current run. More specifically, $\gamma_{t,q}$ is given by

$$\begin{aligned}\gamma_{t,0} &= 0 \\ \gamma_{t,1} &= \Omega_{t-1}(1 - \gamma_{t-1,0}) = \Omega_{t-1} \\ \gamma_{t,2} &= \Omega_{t-2}(1 - \gamma_{t-2,0}) + \Omega_{t-1}(1 - \gamma_{t-1,1}) = \Omega_{t-1} + \Omega_{t-2}(1 - \Omega_{t-1}) \\ &\vdots \\ \gamma_{t,q} &= \sum_{p=1}^q \Omega_{t-p}(1 - \gamma_{t-p,q-p}).\end{aligned}$$

Fixing t , $\gamma_{t,q}$ is increasing in q (since we are adding nonnegative terms to the expression).

The trading probabilities and the associated trading outcomes are depicted in Figure 1. On a bad information event day, an institutional investor will sell a block with probability $\gamma_{t,q}$. With probability $1 - \gamma_{t,q}$, the stock is not in its portfolio, so the short-sale constraint is binding and the institution does not trade in the stock. On a good information event day, an institutional investor will buy if the stock is not in its portfolio and if it searches for information

²⁴ Ω_t is strictly less than one as it is possible that all stocks in the portfolio of an institution will have good information events, in which case the institution will not search for information on any additional stock.

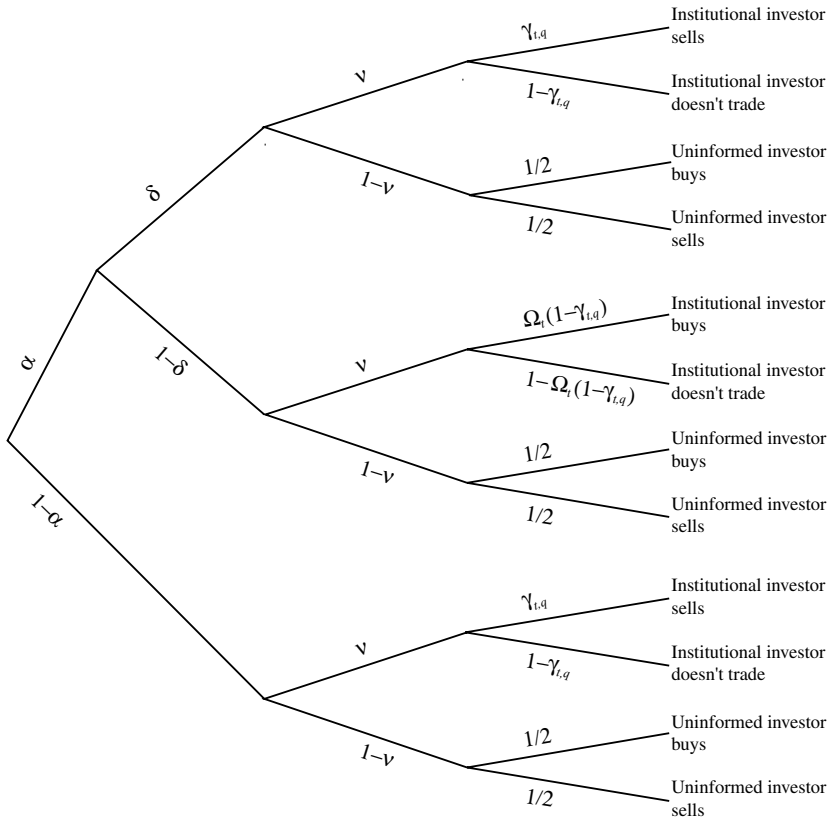


Figure 1
Probability tree of the trading model

This figure depicts the probabilities and trading outcomes for an arbitrary stock. α is the probability of an information event. δ is the probability of bad information, and $1 - \delta$ is the probability of good information. v is the probability that an institutional investor arrives in the market. $\gamma_{t,q}$ is the probability that the institutional investor's portfolio contains the stock. Ω_t is the probability that the institutional investor buys the stock on a good information day if the stock is not in its portfolio.

on the stock. Since these events are independent (due to the independence of information events across days), the institution will therefore buy a block with probability $\Omega_t(1 - \gamma_{t,q})$. Otherwise it does not trade in the stock. On a no information event day, an institutional investor sells if the stock is in its portfolio (with probability $\gamma_{t,q}$) and it otherwise does not trade in the stock.

3. Properties of the Price Impact Asymmetry

The next step is to examine the properties of the expected permanent price impact asymmetry expression. My goal is to derive properties that can translate into useful empirical implications that will allow the model to be tested.

Almost all articles that examine the price impact of trades focus on individual blocks.²⁵ The usual methodology identifies a set of blocks, establishes the pre- and postequilibrium prices for each block, and computes the price impact. These articles construct their samples so that the issue of multiple blocks between the pre- and postequilibrium prices is, to a large extent, either avoided or ignored.²⁶ This emphasis on individual blocks has motivated the construction of the model in this article, which considers the price impact of a single trade. The main intuition of the results, however, carries over to the situation where one considers multiple blocks between the pre- and postequilibrium prices. This point is addressed using numerical analysis in Section 3.2.

While the permanent price impact asymmetry expression in Section 1 was developed for the opening of the market, the empirical articles use block trades that occur at different times during the day. To generalize the asymmetry expression to apply to each of the $l \leq L$ periods in a day, we need to specify the time that the analysis of the price impact is conducted. Assume that we stand before the beginning of the trading day, and we would like to calculate the expected permanent price impact asymmetry in each of the l periods during the day. Let Q^l be the sequence of trading outcomes up to and including period l . It can be shown that the expectation of the permanent price impact of a block buy in period $l + 1$ with respect to both Q^l and the information events is equal to the expected price impact of a block buy at the opening of the market.²⁷ Therefore the expected permanent price impact asymmetry expression of a block in period $l + 1$ is the same as the expected asymmetry at the opening of the market that is specified by Equation (3).

The picture changes when we consider the price impact of a block one period ahead, conditioning on the history of trades up to that point [where the probabilities have the form $P(H|Q^l, B_{l+1})$]. In this case it is possible to derive an asymmetry expression that allows conditioning on each and

²⁵ An exception is Chan and Lakonishok (1995), who look at the price impact of trade packages.

²⁶ For example, Holthausen, Leftwich, and Mayers (1987) use the price of the trade prior to the block as the preequilibrium price and the closing price on the same day as the postequilibrium price. To avoid the possibility of multiple blocks between the equilibrium prices, they eliminate from the sample blocks that have "trailing" blocks on the same day. So if there is a day with two block trades, the first one will be eliminated and the second one will be used in the analysis.

²⁷ Let ψ be the information event. The joint probability of H and the history of trades Q^l given a buy block in period $l + 1$ can be written as

$$P(H, Q^l | B_{l+1}) = \frac{P(B_{l+1} | H, Q^l) P(H, Q^l)}{P(B_{l+1})} = \left[\frac{P(B|H) P(H)}{\sum_{\psi} P(B|\psi) P(\psi)} \right] P(Q^l | H),$$

where $P(B_{l+1} | H, Q^l) = P(B|H)$ due to the independence of the arrival of trades conditional on the information event. Note that the term in brackets is the conditional probability $P(H|B)$ that has been used to derive the expected asymmetry expression at the opening of the market in Section 1. The probabilities $P(O, Q^l | B_{l+1})$ and $P(L, Q^l | B_{l+1})$ can be decomposed in a similar fashion. When the expectation over all possible sequences is taken, $P(Q^l | L)$, $P(Q^l | O)$, and $P(Q^l | H)$ disappear and the expression is therefore the same as the one derived for the opening of the market. The same applies to the expected permanent price impact of a block sell in period $l + 1$.

every possible combination of outcomes in Q^I .²⁸ However, it is unclear what additional insights we can gain by analyzing the asymmetry conditional on each combination of histories of trades. When we examine the asymmetry from the viewpoint of the opening of the market, we essentially form an expected asymmetry expression summing over all possible trade combinations. The discussion in Section 2.3 emphasizes that the asymmetry in the information content of trades is driven by differences in the portfolio positions of institutional investors *across* days. The parameters of the trading model change with q , the sequence of realizations of good information events, but do not change throughout the day. Thus to investigate the influence of institutional investors it is sufficient to consider the expected asymmetry expression in an arbitrary period during the day from the viewpoint of the opening of the market.²⁹

To facilitate the investigation, the asymmetry expression in Equation (5) needs to be rewritten in terms of the parameters of the trading model. Using Equation (4), $\delta(B)$ and $\delta(S)$ can be written as

$$\begin{aligned}\delta(B) &= \delta \left[\frac{\frac{1}{2}(1-v)}{\alpha(1-\delta)v\Omega_t(1-\gamma_{t,q}) + \frac{1}{2}(1-v)} \right] \\ \delta(S) &= \delta \left[\frac{v\gamma_{t,q} + \frac{1}{2}(1-v)}{[1-\alpha(1-\delta)]v\gamma_{t,q} + \frac{1}{2}(1-v)} \right].\end{aligned}$$

The expected permanent price impact asymmetry then has the simple form

$$\begin{aligned}J_t &= 2 \frac{Z}{V_{t-1}} \alpha \delta (1-\delta) v \left[\frac{\Omega_t(1-\gamma_{t,q})}{\alpha(1-\delta)v\Omega_t(1-\gamma_{t,q}) + \frac{1}{2}(1-v)} \right. \\ &\quad \left. - \frac{\gamma_{t,q}}{[1-\alpha(1-\delta)]v\gamma_{t,q} + \frac{1}{2}(1-v)} \right] + 2r.\end{aligned}\quad (6)$$

Equation (6) can now be used to analyze the relation between the expected permanent price impact asymmetry and the economic environment.

3.1 Results

The first two results focus on the importance of conditioning on past price performance of a stock to understand the expected permanent price impact asymmetry:

Result 1. *The asymmetry expression of a stock that did not experience significant price appreciation on the previous day is always strictly positive.*

²⁸ This expression was derived in a previous version of the article and is available from the author upon request.

²⁹ Another approach is to define the asymmetry over the aggregate number of block buys and sells that trade in a day. This approach is investigated numerically in Section 3.2.

Result 2. *The longer the run of price appreciations a stock experiences (the higher q), the less positive the price impact asymmetry expression.*

Proofs of all the results in this section appear in the appendix. For low q (and especially for $q = 0$), the probability that any institutional investor owns a block of the stock is low. Hence it is unlikely that the diversification constraint is binding on a mutual fund that follows the stock, but the short-sale constraint is most likely binding. In this case, good information about the stock may prompt many mutual funds to buy it, resulting in a high probability of an informed buy. Since most mutual funds do not own the stock, they cannot sell it on a bad information event day, so the probability of an informed sell is low. This creates a positive permanent price impact asymmetry.

As q increases and the stock price rises, more mutual funds buy the stock. After a long period of abnormal price appreciation (above and beyond the required return), which is equivalent to saying that q is high, the probability that a stock is in an institutional portfolio is also high. A mutual fund that holds the stock will not buy more blocks of the same stock, so the probability of an informed buy decreases. Yet since many mutual funds own the stock, the short-sale constraint is not binding and bad information will result in informed sells. Hence the probability of an informed sell increases. This effect makes the asymmetry expression less and less positive. If the stock price has been going up for a sufficiently long period, we may see a negative asymmetry expression.

Still, the probability of a high q is very low, so the implications of the model are consistent with the empirical findings of positive asymmetry. For example, a stock with probability of information events $\alpha = 0.25$ and conditional probability of bad information $\delta = 0.5$ will have $q = 0$ with probability 0.875; $q = 1$ with probability 0.109; $q = 2$ with probability 0.014; and $q \geq 3$ with probability of only 0.002. Whether J_t will be positive or negative for $q \geq 1$ depends on the values of the parameters of the stock. Section 3.2 presents numerical analysis that examines the asymmetry expression more closely for the case of $q \geq 1$, and evaluates the expected value of the asymmetry expression taking the distribution of q into account.

Results 1 and 2 imply that stocks that generate more and shorter runs (e.g., with $\alpha(1 - \delta) \approx \frac{1}{2}$) will have on average more days with low q , and hence will more often exhibit a large permanent price impact asymmetry. Note, however, that q is always known. Hence analysis of the influence of the other fundamentals of the economy on the asymmetry expression takes q as given and conditions on being at a particular point in the run of good information events.

Result 3. *When a stock's price has not risen recently ($q = 0$), the greater the trading intensity of institutional investors (the higher v), the more positive the asymmetry expression. For a sufficiently long price run-up (high enough*

q), the greater the trading intensity of institutional investors, the less positive the price impact asymmetry expression.

What affects the price impact asymmetry most at the beginning of a good run is the probability of an informed buy. The greater the trading intensity of institutional investors, the more informed buy orders will arrive in the market, and hence the greater the price impact asymmetry. As the number of consecutive price appreciations increases, the probability that the stock is in an institutional portfolio increases as well. When the good run ends, more institutional ownership means more informed sells. Hence the higher ν , the less positive the price impact asymmetry expression for a high enough q .

Result 4. *When a stock's price has not risen recently ($q = 0$), the more informationally active a stock (the higher α), the more positive the asymmetry expression. For a sufficiently long price run-up (high enough q), the more informationally active a stock, the less positive the price impact asymmetry expression.*

The more information events, the higher the probability that there has been a good information event, so it is more likely that a buy is informed. At the same time, the probability of bad information events increases as well. For low q , the increase in the probability of an informed buy is larger than the increase in the probability of an informed sell (especially for $q = 0$ when sells cannot be informed). For high q , the opposite result occurs since sells are more likely to be informed than buys.

Result 5. *When a stock's price has not risen recently ($q = 0$), the greater the stock's price dispersion (measured by $\frac{Z}{V_{t-1}}$), the more positive the asymmetry expression. For a sufficiently long price run-up (high enough q), the greater the stock's price dispersion, the less positive is the asymmetry expression.*

In general, a block trade will have a greater price impact the greater the dispersion of the value process of a stock. If the information term of the asymmetry expression is positive, greater dispersion will make the asymmetry even more positive. When a stock is far into the run of good information events, the information term of the asymmetry expression will be negative, and greater dispersion will make the asymmetry expression less positive by increasing the influence of the negative information term.

3.2 Numerical analysis

The analytical results presented in the previous section provide new implications for testing the permanent price impact asymmetry. Additional insights can be gained by evaluating the model numerically. The first question to address is whether reasonable parameter values provide a reasonable amount

of asymmetry. The model is calibrated using daily data to maintain the conventions used in the analytical results.³⁰ Easley, Hvidkjaer and O'Hara (2000) (henceforth EHO) estimate the parameters of a structural trading model for a sample of all NYSE common stocks for the years 1983–1998.³¹ While the model they use is not identical to the one presented here, the information structure is similar, and their procedure yields estimates of both the daily probability of an information event (α) and the conditional probability of bad information (δ). EHO use daily data to estimate the information parameters separately for each year in the sample period. Their results show that the parameter estimates are very stable over time, so to calibrate the model I use the means of their 1997 estimates: $\alpha = 26.76\%$ and $\delta = 31.89\%$.

For consistency, the value of the stock (V_{t-1}) is estimated as the mean daily closing price of all common stocks traded on the NYSE and AMEX in 1997 with records in the CRSP database.³² The mean closing price of stocks in the sample is \$29.7875.

Using the estimate of δ from EHO and Equation (1), I calculate the average daily gain or loss (Z) as the mean of the variable

$$\hat{Z}_t = \begin{cases} \frac{\hat{V}_t - \hat{V}_{t-1}}{2(0.3189)} & \text{if } \hat{V}_t - \hat{V}_{t-1} > K \\ \frac{\hat{V}_{t-1} - \hat{V}_t}{2(1 - 0.3189)} & \text{if } \hat{V}_t - \hat{V}_{t-1} < K, \end{cases} \quad (7)$$

where K is a positive constant, and $\hat{V}_t$ and $\hat{V}_{t-1}$ are closing prices of the stock from the CRSP database. Hence Z is calculated using days when the absolute change in prices from the previous close is greater than a certain magnitude. The reason for introducing K is twofold. First, it reduces the chance that differences in closing prices simply reflect bid-ask bounce. Second, it allows a calibration of the relative number of days that are identified as information days to approximately match the parameter estimate of α from EHO.³³ Using $K = \$0.5$, the estimate of the average daily gain or loss (Z) is \$1.3251. The average number of days that satisfy the criterion in Equation (7) for the

³⁰ To make the model more parsimonious, I use a single time interval—a “day”—for three different purposes. First, it is the interval between the pre- and postequilibrium prices that are used to evaluate the price impact of blocks. Second, it is the horizon for creation and revelation of private information. Third, it is the period over which institutional investors rebalance their portfolios. The model can accommodate (although at the cost of additional complexity) separate periods for the measurement of price impacts and the creation of information (or portfolio rebalancing).

³¹ Their methodology, developed in Easley, Kiefer, and O'Hara (1997a, 1997b), uses as input signed trade data (buy and sell orders).

³² The only stock excluded from the analysis is Berkshire Hathaway Inc. due to its abnormal price range.

³³ The expression in Equation (7) omits the daily expected return (r) from the calculation of Z . Incorporating r will affect only the magnitude of the constant K that will be needed to identify days with information events. Since K is chosen to make the fraction of days with information events close to the value of α from EHO, the exclusion of r should not affect the estimate of Z .

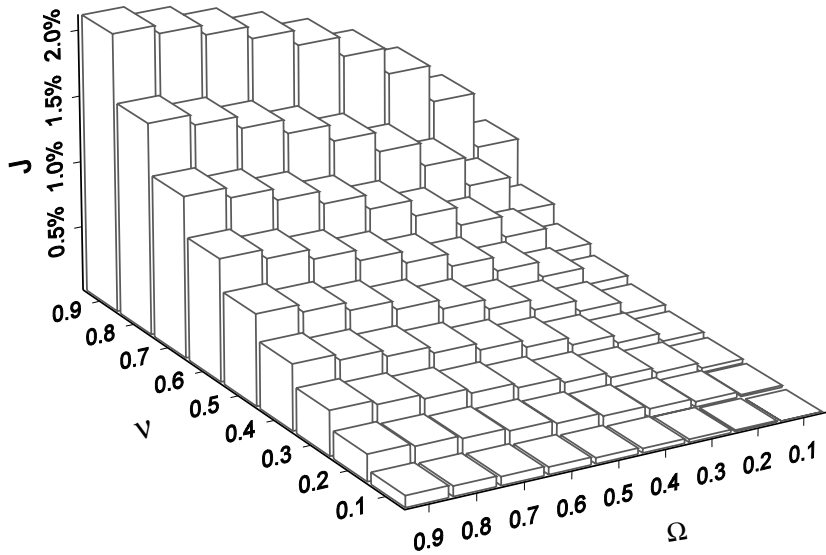


Figure 2

Permanent price impact asymmetry for $q = 0$

This figure shows how the permanent price impact asymmetry (J_t) changes with the probability that an institutional investor arrives in the market (v) and with the probability that the institutional investor buys the stock on a good information day if the stock is not in its portfolio (Ω_t). The calibrated parameters used for the numerical analysis are $\alpha = 0.2676$, $\delta = 0.3189$, $V_{t-1} = 29.7875$, and $Z = 1.3251$. The asymmetry expression is evaluated at $q = 0$ (when the stock price did not go up the previous day).

stocks in the sample is 55.2. The average number of days in which stocks in the sample were listed in 1997 is 238.3. Hence this value of K results in identifying approximately 23.15% of the days as containing information events, which is quite close to the parameter estimate from EHO.

Simulation results with the parameters ($\alpha = 0.2676$, $\delta = 0.3189$, $V_{t-1} = 29.7875$, $Z = 1.3251$) and setting $q = 0$ are presented in Figure 2. It is clear that the expected permanent price impact asymmetry increases with both v , the probability that an institutional investor arrives in the market, and Ω_t , the probability that an institutional investor buys the stock on a good information event day if the stock is not in its portfolio. The magnitude of the asymmetry varies considerably depending on the values of these two parameters. In Kraus and Stoll (1972), for example, the magnitude of the permanent price impact asymmetry (adjusted for the required return) is 0.14%, and is within the range of the simulated asymmetry expressions in Figure 2.³⁴ In fact, such an asymmetry requires relatively small values of both v and Ω_t . For example, asymmetry estimates with either ($v = 0.4$, $\Omega_t = 0.2$) or ($v = 0.3$, $\Omega_t = 0.3$) are around 0.13%. The permanent price impact asymmetry

³⁴ I simulate only the information term of Equation (6) without the required return (that contributes $2r$ to the asymmetry expression) to allow comparisons with empirical studies that control for the expected return.

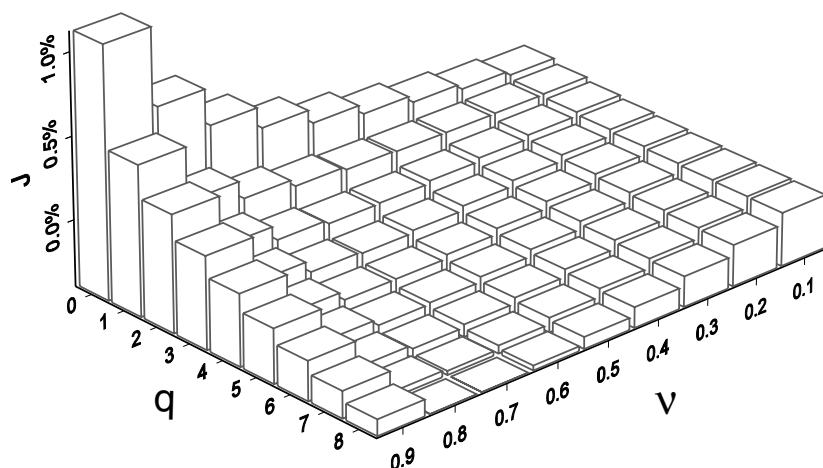


Figure 3

Permanent price impact asymmetry for $q \geq 0$

This figure shows how the permanent price impact asymmetry (J_t) changes with the length of the current run of good information events (q) and with the probability that an institutional investor arrives in the market (v). The parameters used for the numerical analysis are $\alpha = 0.2676$, $\delta = 0.3189$, $V_{t-1} = 29.7875$, $Z = 1.3251$, and $\Omega_t = 0.2$.

in Keim and Madhavan (1996) is 0.10%, which is similar to that reported in Kraus and Stoll (1972) and which can be achieved by many combinations of reasonable values of v and Ω_t . Hence the model seems able to replicate the asymmetry, at least for the case of $q = 0$ (when the stock price did not go up the previous day).

However, as noted in the previous section, the asymmetry decreases monotonically with q . To investigate how the extent of the asymmetry changes with q , Figure 3 presents the results of the numerical analysis for zero to eight consecutive days with good information events. The parameters (α , δ , V_{t-1} , Z) have the same values as before, and I fix $\Omega_t = 0.2$. For all values of v , the asymmetry decreases with the number of successive good information events (q). Also, the asymmetry increases monotonically with the probability that an institutional investor arrives in the market (v) for $q = 0$. As q increases, however, the relation between the asymmetry and v becomes nonmonotonic (the asymmetry is decreasing for low v and increasing for high v). Result 3 tells us that the relation between the asymmetry and v becomes monotonically decreasing for sufficiently high q .

Since the asymmetry becomes negative as the number of successive days with good information events (q) increases, the question remains whether we should observe a positive or a negative asymmetry in the market. The empirical articles that document the asymmetry do not condition on the history of prices, and hence we need a measure of expected asymmetry that takes into account the probability of any given day having q equal to zero, one, two,

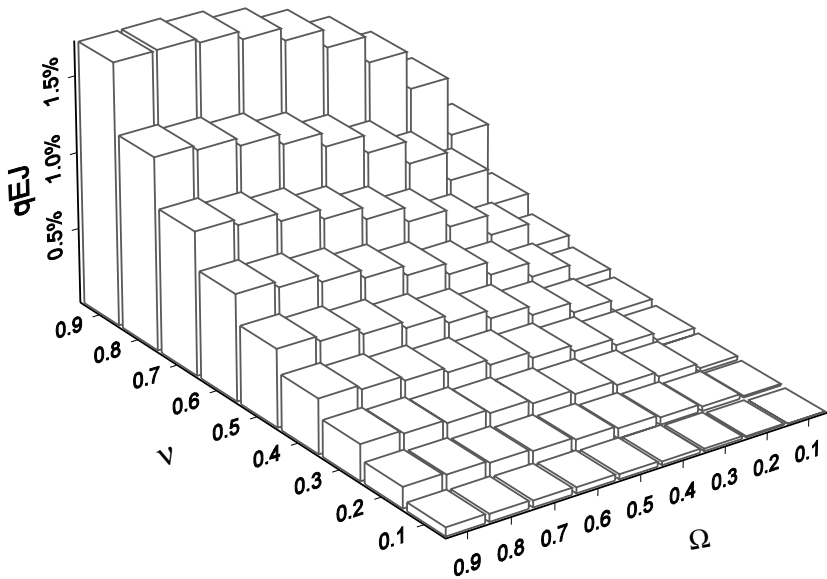


Figure 4
 q -expected permanent price impact asymmetry

This figure shows how the q -expected permanent price impact asymmetry (qEJ_t) changes with the probability that an institutional investor arrives in the market (v) and with the probability that the institutional investor buys the stock on a good information day if the stock is not in its portfolio (Ω_t). The calibrated parameters used for the numerical analysis are $\alpha = 0.2676$, $\delta = 0.3189$, $V_{t-1} = 29.7875$, and $Z = 1.3251$.

and so on. This measure is straightforward to evaluate numerically because the information events on different days are independent. The probability of $q = 0$ is equal to the probability that the previous day was either a bad information or a no information event day, $1 - \alpha(1 - \delta)$. The probability of $q = 1$ is equal to the joint probability that the previous day had a good information event and the day before it had either a bad information or a no information event, $[1 - \alpha(1 - \delta)]\alpha(1 - \delta)$. The probability of observing an arbitrary q is $[1 - \alpha(1 - \delta)][\alpha(1 - \delta)]^q$.

Hence I define the q -expected asymmetry expression (qEJ_t) as

$$qEJ_t = \sum_{q=0}^{\infty} J_t [1 - \alpha(1 - \delta)][\alpha(1 - \delta)]^q.$$

For the sake of the numerical analysis, the sum ends at $q = 10$, since the probability becomes extremely low for larger values of q .³⁵ Figure 4 provides the results of the simulation of qEJ_t using the calibrated parameters (α , δ , V_{t-1} , Z) and varying v and Ω_t . The pattern is similar to that

³⁵ Using the parameter estimates from EHO ($\alpha = 0.2676$ and $\delta = 0.3189$), the probability that $q = 10$ is $3.3E-8$.

in Figure 2 (which describes the case of $q = 0$), with magnitudes that are slightly lower. For example, the q -expected asymmetry estimates for the pairs ($v = 0.4, \Omega_t = 0.2$) and ($v = 0.3, \Omega_t = 0.3$) are about 0.10%, as compared with 0.13% for $q = 0$. These results are therefore consistent with empirical findings of an unconditional positive expected permanent price impact asymmetry.

Numerical analysis can also aid in looking at whether the results carry over to the case where we consider the price impact of multiple blocks between the pre- and postequilibrium prices. Let M be the number of block buys and N be the number of block sells that are traded during the day. If there are more buys than sells ($M > N$), we would expect a positive permanent price impact. Similarly, if there are more sells than buys ($N > M$), we would expect a negative permanent price impact. The multiple-block expected permanent price impact asymmetry expression (JMN_t) can therefore be written as³⁶

$$JMN_t = E[\Delta(M > N)_t | M > N] - E[\Delta(N > M)_t | N > M],$$

where $\Delta(M > N)_t$ and $\Delta(N > M)_t$ are the multiple-block equivalents of ΔB_t and ΔS_t , respectively.³⁷ This expression can be reduced to

$$JMN_t = 2 \frac{Z}{V_{t-1}} [\delta - \delta(M > N) + \delta - \delta(N > M)] + 2r, \quad (8)$$

where $\delta(M > N) = P(L|M > N) + \delta P(O|M > N)$, and $\delta(N > M)$ is defined analogously. These probabilities can be evaluated numerically.

To simplify the numerical analysis, I ignore nontrading periods and set the sum of buy and sell blocks equal to the number of trading periods during the day, $M + N = L$. For example, if there are three periods in a day ($L = 3$), the net buy order flow involves the combinations of blocks $(M, N) \in \{(3, 0), (2, 1)\}$, while the net sell order flow involves the combinations of blocks $(M, N) \in \{(0, 3), (1, 2)\}$. The asymmetry expression now depends on the number of periods in a day, as there are different combinations of buys and sells for days with different numbers of periods. Figure 5 presents a numerical analysis of the multiple-block asymmetry expression with parameters $\alpha = 0.2676$, $\delta = 0.3189$, $V_{t-1} = 29.7875$, $Z =$

³⁶ I thank the editor for suggesting this form of the price impact asymmetry.

³⁷ We can write the price impact of a positive net order flow as

$$\Delta(M > N)_t = \frac{V_t - V_{t-1}}{V_{t-1}} = \begin{cases} r + 2\delta \frac{z}{V_{t-1}} & \text{w.p. } P(H|M > N) \\ r & \text{w.p. } P(O|M > N) \\ r - 2(1 - \delta) \frac{z}{V_{t-1}} & \text{w.p. } P(L|M > N). \end{cases}$$

The price impact of a negative net order flow is defined in an analogous fashion.

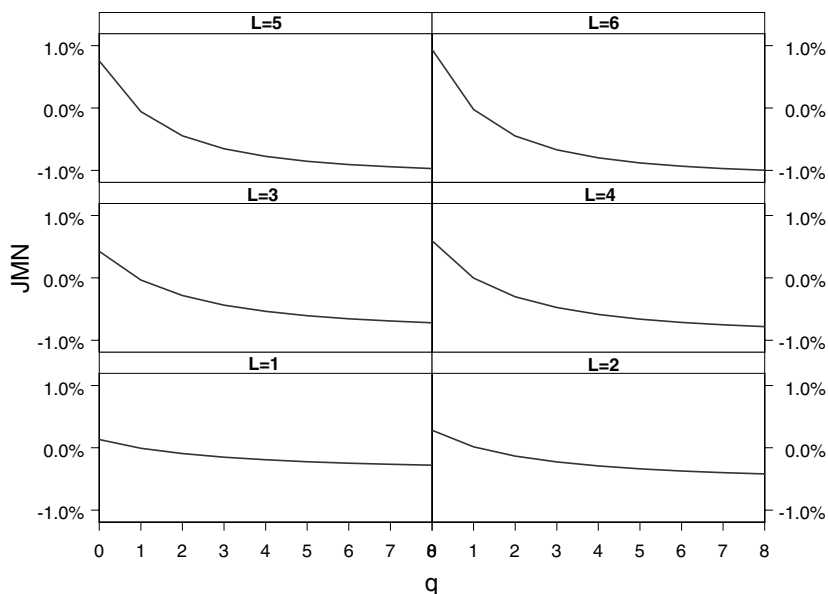


Figure 5
Multiple-block permanent price impact asymmetry for $q \geq 0$

This figure shows how the multiple-block permanent price impact asymmetry (JMN_t) changes with the length of the current run of good information events (q). Each panel presents the results for a single value of L (the number of periods in a day). The parameters used for the numerical analysis are $\alpha = 0.2676$, $\delta = 0.3189$, $V_{t-1} = 29.7875$, $Z = 1.3251$, $\nu = 0.4$, and $\Omega_t = 0.2$.

1.3251, $\nu = 0.4$, $\Omega_t = 0.2$. Each panel shows how the asymmetry expression changes with q for a single value of L . The figure demonstrates that Result 1 and Result 2 from the single-block case hold for the multiple-block asymmetry expression as well.³⁸ The asymmetry expression is positive at $q = 0$ and is monotonically decreasing in q for all L . Thus the implications of the model seem robust to the exact manner in which the price impact of trades is considered. Note that the dispersion of JMN_t seems to increase with L . As the number of periods in a day increases, JMN_t becomes more positive for a low q and more negative for a high q .

4. Conclusion

Empirical research in finance documents a permanent price impact asymmetry between buyer- and seller-initiated block transactions (and institutional trades). This article contributes to the literature by developing a theoretical model to explain and investigate the asymmetry phenomenon. The model is based on the premise that the profit-maximizing behavior of institutional

³⁸ Note that the figure nests the single-block asymmetry expression, which is equivalent to $L = 1$.

investors creates a difference between the information content of buys and sells. There are two driving forces behind the asymmetry phenomenon. The first is the way portfolio managers optimally use information when they have the ability to search for private information about multiple stocks. The second is a set of constraints on the allowable trading strategies of portfolio managers. Incorporating the dynamic trading strategy of mutual funds in a simple trading model allows for the explicit derivation and investigation of the expected permanent price impact asymmetry.

The main insight that comes out of the model is the relation between the history of price performance and the expected permanent price impact asymmetry. Block trades during periods of poor price performance or little price appreciation should exhibit stronger positive asymmetry. Block trades that come after a price run-up should exhibit less asymmetry or even negative asymmetry.

The model identifies several parameters of the environment that should influence the asymmetry, like the intensity of institutional trading or how “informationally active” a stock is. When implementing an empirical investigation, however, identification of proxies for informed institutional investors may be far from trivial. The number of institutional shareholders or the percentage holdings of a stock by institutions can be very misleading proxies, as they can include many uninformed institutions (e.g., index funds).

Designing appropriate controls for the empirical analysis becomes an important issue if mutual funds in the real world trade for reasons not accounted for in the model. One reason could be the volatile flow of money into and out of funds [see Chevalier and Ellison (1997) and Del Guercio and Tkac (1998)]. The model here assumes that managers can always search for information on stocks and find enough stocks with good information events. This may not hold at times if cash inflows are so large as to overwhelm the research capabilities of an institution. Similarly, large outflows may require selling stocks on which the institutional investor discovers good information. Since empirical tests of the model should focus on the information-based part of the trading strategy of institutional investors, controlling for inflows and outflows could help the investigation considerably.³⁹

The advantage of looking at the behavior of institutional investors to explain the permanent price impact asymmetry lies in the additional insights that come out of the model. While the model indeed shows how a positive asymmetry expression can arise, it goes further to detail the influence of elements in the economic environment on the asymmetry. Testing the model is equivalent to testing these additional implications. Thus the model provides a framework for further empirical analysis of the asymmetry phenomenon.

³⁹ For a discussion of this point see Edelen (1999).

Appendix

Proof of Result 1. If the stock's price did not go up substantially on the previous day, it must be that the previous day was either a bad information or a no information event day. Hence $q = 0$, which implies $\gamma_{t,q} = 0$.

$$J_{t|q=0} = 2 \frac{Z}{V_{t-1}} \alpha \delta (1 - \delta) v \frac{\Omega_t}{\alpha (1 - \delta) v \Omega_t + \frac{1}{2} (1 - v)} + 2r > 0. \quad \text{Q.E.D.}$$

Proof of Result 2. Note that the only parameter affected by q is $\gamma_{t,q}$, which monotonically increases with q . Hence it suffices to show that J_t is decreasing in $\gamma_{t,q}$.

$$\begin{aligned} \frac{\partial J_t}{\partial \gamma_{t,q}} = & - \frac{Z}{V_{t-1}} \alpha \delta (1 - \delta) v (1 - v) \left[\frac{\Omega_t}{[\alpha (1 - \delta) v \Omega_t (1 - \gamma_{t,q}) + \frac{1}{2} (1 - v)]^2} \right. \\ & \left. + \frac{1}{[1 - \alpha (1 - \delta)] v \gamma_{t,q} + \frac{1}{2} (1 - v)]^2} \right] < 0. \end{aligned} \quad \text{Q.E.D.}$$

Proof of Result 3.

$$\begin{aligned} \frac{\partial J_t}{\partial v} = & \frac{Z}{V_{t-1}} \alpha \delta (1 - \delta) \left[\frac{\Omega_t (1 - \gamma_{t,q})}{[\alpha (1 - \delta) v \Omega_t (1 - \gamma_{t,q}) + \frac{1}{2} (1 - v)]^2} \right. \\ & \left. - \frac{\gamma_{t,q}}{[1 - \alpha (1 - \delta)] v \gamma_{t,q} + \frac{1}{2} (1 - v)]^2} \right]. \end{aligned} \quad (9)$$

For $q = 0$,

$$\left. \frac{\partial J_t}{\partial v} \right|_{q=0} = \frac{Z}{V_{t-1}} \alpha \delta (1 - \delta) \frac{\Omega_t}{[\alpha (1 - \delta) v \Omega_t + \frac{1}{2} (1 - v)]^2} > 0. \quad (10)$$

For $q \geq 1$, the sign depends on the values of the other parameters. As q increases, the second term of Equation (9) begins to dominate and the expression becomes negative. We can use infinity as an approximation for a high q to show that the expression will become negative for all values of the other parameters (note that $\gamma_{t,q}$ approaches one as q approaches infinity as all institutions have already bought the stock after an infinite number of good information event days).

$$\lim_{q \rightarrow \infty} \frac{\partial J_t}{\partial v} = - \frac{Z}{\alpha} \delta (1 - \delta) V_{t-1} \frac{1}{[1 - \alpha (1 - \delta)] v + \frac{1}{2} (1 - v)]^2} < 0. \quad (11)$$

Q.E.D.

Proof of Result 4.

$$\begin{aligned} \frac{\partial J_t}{\partial \alpha} = & 2 \frac{Z}{V_{t-1}} \delta (1 - \delta) v \left[\frac{\frac{1}{2} (1 - v) \Omega_t (1 - \gamma_{t,q})}{[\alpha (1 - \delta) v \Omega_t (1 - \gamma_{t,q}) + \frac{1}{2} (1 - v)]^2} \right. \\ & \left. - \frac{(\gamma_{t,q})^2 v + \frac{1}{2} (1 - v) \gamma_{t,q}}{[1 - \alpha (1 - \delta)] v \gamma_{t,q} + \frac{1}{2} (1 - v)]^2} \right]. \end{aligned} \quad (12)$$

For $q = 0$,

$$\left. \frac{\partial J_t}{\partial \alpha} \right|_{q=0} = 2 \frac{Z}{V_{t-1}} \delta (1 - \delta) v \left[\frac{\frac{1}{2} (1 - v) \Omega_t}{[\alpha (1 - \delta) v \Omega_t + \frac{1}{2} (1 - v)]^2} \right] > 0.$$

For $q \geq 1$, the sign depends on the values of the other parameters. As q increases, the second term of Equation (12) begins to dominate and the expression becomes negative. We can use infinity as an approximation for a high q to show that the expression will become negative for all values of the other parameters (note that $\gamma_{t,q}$ approaches one as q approaches infinity as all institutions have already bought the stock after an infinite number of good information event days).

$$\lim_{q \rightarrow \infty} \frac{\partial J_t}{\partial \alpha} = -2 \frac{Z}{V_{t-1}} \delta(1 - \delta)v \left[\frac{\frac{1}{2}(1 + v)}{[1 - \alpha(1 - \delta)]v + \frac{1}{2}(1 - v)]^2} \right] < 0. \quad \text{Q.E.D.}$$

Proof of Result 5. The dispersion of a stock's price at any given date can be represented by the range $\frac{2Z}{V_{t-1}}$. It is clear from Equation (6) that an increase in $\frac{Z}{V_{t-1}}$ will intensify the effect of the information term on the asymmetry expression. If this term is positive, greater dispersion implies a more positive asymmetry expression. If this term is negative, greater dispersion implies a less positive asymmetry expression. Q.E.D.

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