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Delegated trading and the speed of adjustment in security prices ☆

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ABSTRACT

Institutional trading arrangements often involve the portfolio manager delegating the task of trade execution to a separate division within the firm. We model the agency conflict that arises in this setting and show that optimal performance benchmarks often create an incentive to execute orders contrary to concurrent information flow. We hypothesize that aggregate contrarian trading resulting from widespread application of such benchmarks leads to delays in the assimilation of information in security prices. Using institutional trading data, we document the hypothesized contrarian trading pattern and relate the pattern to price-adjustment delays in the response of individual stocks to index futures returns. The evidence supports the assertion that delegated institutional trading contributes to these delays.

1. Introduction

At many investment firms the portfolio manager delegates the task of implementing changes to the portfolio to a separate division within the firm—a trading desk. The trading desk receives orders from the portfolio manager, but otherwise controls the trading process. This paper shows that agency conflicts inherent in delegated trading arrangements can lead to institutional trading patterns that temporarily impede the incorporation of information into security prices. Our model develops this implication and our empirical analysis provides strong evidence that the impact is material.

Portfolio management and trade execution involve distinctly different skill sets. For example, expertise in portfolio management involves matters such as analysis of accounting statements and product markets, security valuation, and portfolio efficiency. By contrast, expertise in trading involves knowledge of markets and trading venues, analysis of order flow, and locating counterparties without conveying information. Thus, delegating trade execution plausibly improves portfolio performance by allowing agents to develop focused expertise. Our model considers one specific type of trading expertise: analyzing order flow and market conditions to distinguish between transient distortions to price attributable to noise trading and permanent shifts in price attributable to information. Trading counter to transient distortions, i.e., buying (selling) on negative (positive) distortions, lowers transaction costs. However, trading counter to permanent shifts in

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price increases trading costs. We assume that the trader has the expertise to identify transient distortions to price whereas the portfolio manager does not.

The agency problem that the portfolio manager (PM) faces is inducing effort from the trader to identify and respond to transient liquidity opportunities. While there are many approaches the PM could take, they generally involve comparing the trader's execution price to some measure of prevailing market prices. For tractability, we model this process with a formal approach wherein the trader's compensation is based on a quantitative benchmark. We consider the two most widely used benchmarks: the volume-weighted average price of all trades in the security during the trading window (VWAP), and a pre-trade 'strike' or 'arrival' price often referred to as implementation shortfall (I/S).[1]

An important consideration when applying either benchmark is how to handle unexecuted portions of the order (the 'order residual'). In the 'conventional' approach, only the executed portion of the order is evaluated against the benchmark; the order residual may reappear in a subsequent trading window to be evaluated against a reset benchmark, or the PM may choose to cancel it.[2] An alternative approach is to evaluate the PM's full order against the benchmark, even if the trader leaves a portion of the order unfilled. This is done by assigning a hypothetical execution price for the order residual equal to the price at some future time, thus, we refer to it as 'hypothetical' benchmarking. It is often associated with I/S (Perold, 1988), but it is equally applicable to VWAP.

Under the conventional approach, the resetting of the benchmark for order residuals provides the trader with an incentive to accelerate execution when prices move in favor of the order (buy into falling prices, sell into rising prices)—to lock in good performance and delay execution when prices move against the order to reset an unfavorable benchmark. If a price move is transient (i.e., caused by noise trading), this shift in execution quantity benefits the PM by reducing transaction costs. Indeed, this is the motive for granting discretion to the trader. However, if a price move is permanent (i.e., caused by information), then discretionary shifts in quantity provide no benefit. Rather, they generate unwarranted compensation for the trader and may cause the order to be filled when it would be best to delay, or to be delayed when it would be best to fill. Because of this game-playing, it is often argued that conventional approaches are suboptimal.

Hypothetical benchmarking addresses this gaming by evaluating the full order relative to the benchmark, even if the trader leaves a portion unfilled. Under this arrangement the trader has no incentive to shift execution quantities in response to permanent price moves because such a shift would not change expected performance. For this reason, academics and practitioners often argue that hypothetical benchmarking is preferred. However, the elimination of gaming comes at a cost because the hypothetical benchmark introduces risk into the trader's decision. In particular, when the trader leaves an order unfilled, his performance is based on a random (next-day) price. This uncertainty can dissuade the trader from attempting to lower execution costs. Indeed, the trader may choose to execute at a knowingly bad price rather than leave an order unfilled and introduce uncertainty into his evaluation. Thus, in deciding whether to employ conventional versus hypothetical benchmarking, the PM must weigh the potential for gaming against missed opportunities to lower trading cost. Conventional benchmarking grants the trader uninhibited discretion to lower trading costs, but is vulnerable to gaming. Hypothetical benchmarking eliminates gaming, but can inhibit the exploitation of transient liquidity. Neither approach optimizes the trade-off between these competing costs.

We develop a model of delegated trading that balances these two costs. We allow the PM to choose between a conventional and hypothetical approach with either VWAP or I/S. Under the conventional approach, the PM imposes a non-random penalty on order residuals to inhibit gaming, but optimizes the intensity of that penalty so as to not overly inhibit cost-minimization efforts. Because the penalty for the unfilled portion of the order is known, risk aversion does not enter into the trader's decision. Thus, the conventional approach offers an important advantage over the hypothetical counterpart, to the extent that risk (uncertainty) figures into the trader's decision. However, unless the penalty is infinite, conventional benchmarking, remains subject to gaming. The relative merit of a conventional approach is therefore determined by weighing the cost of gaming under the optimal penalty against the expected improvement in trade execution.

Our model shows that conventional benchmarking lowers costs for all but the most extreme assumptions of risk tolerance. The optimality of conventional benchmarking has implications for short-horizon information assimilation in securities prices. As discussed above, under conventional benchmarking the trader alters execution quantities so as to induce a negative correlation with concurrent price moves. When price moves are transient, this trading strategy improves execution costs. But when price moves are information-based (permanent), it inhibits information assimilation.

The relevance of our model in explaining information assimilation delays depends on the extent to which institutions delegate trading. Our model is agnostic to that decision –delegation is optimal if traders' value-added exceeds its cost (including gaming potential). The extent to which this condition holds is unclear. However, anecdotal evidence suggests that delegated trading is common. In a survey of Chief Investment Officers and head traders of asset management firms, Schwartz and Steil (2002) conclude 'As institutions have grown the division of labor between the stock selection and trading function has become greater. Portfolio managers generally have little direct knowledge of the trading process, which makes it difficult for them to evaluate how well

[1] In our model it is not necessary that the trader's compensation be explicitly tied to performance relative to the benchmark. Rather, the trader's job retention, salary, bonuses, etc. are correlated with that performance.

[2] We later discuss evidence suggesting that this is, in fact, the most common or 'conventional' approach.

their trading desks are handling their orders. This leads to a second significant principalagent problem in the operation of collective investment schemes.' More recently, Anne Hartwell, head of trading at $150 billioninassets MFS Investment Management, said, 'Our traders aren't just clerks filling out orders for the portfolio managers anymore.'[3]

The relevance of our model also depends on the extent to which PM's choose conventional versus hypothetical benchmarking. Trade-cost consultants have long offered performance benchmarks that include hypothetical execution (i.e., opportunity costs).[4] However, feedback from executives at these consulting firms suggests that most clients do not employ these metrics. This would explain the absence of these data in databases of institutional trades (Plexus and Abel Noser). Moreover, survey evidence regularly lists conventional VWAP and conventional I/S as the most important considerations in evaluating trade performance, with no mention of hypothetical execution (or opportunity costs).[5] Nevertheless, as with delegation, actual practices are difficult to observe.

Lipson and Puckett (2007) provide direct evidence regarding our model's prediction that institutional traders execute contrary to price changes. They show that institutions are net sellers when market valuations rise and net buyers when market valuations fall. Moreover, they find that this pattern is due to the traders' handling of the order rather than to positioning decisions by the PM. Their study focuses on institutional trading on days with extreme market returns ($\pm 2\%$). We provide additional support in a more general context by documenting institutional trading on all trading days during the period June 1999–2009. We then provide evidence supporting our model's prediction that this contrary pattern in delegated trading inhibits the speed at which information is assimilated into security prices. We do so by showing a statistically and economically significant relation between variation in trade quantities attributable to trader discretion and variation in price-adjustment delays with respect to index futures returns. In particular, we find that price-adjustment delays are roughly 50% larger when traders' aggregate discretionary execution is contrary to market returns.

It is important to emphasize that our model does not presume limited rationality on the part of portfolio managers—as principals in our model, they are well aware of the bias that arises when traders are granted discretion. Indeed, clarifying why rational portfolio managers would *choose* to grant discretion to skilled traders despite this well-known bias is a primary contribution of the model. Intuitively, with a well-calibrated performance benchmark, they can control the magnitude of the bias while inducing sufficient value-added trading to more than offset it.

Our analysis of institutional trading has a number of parallels with other studies of trading. First, the agency conflict in our model is similar to that proposed by Harris and Schultz (1998) to explain the viability of SOES bandit trading. Second, because the price-adjustment delays of our model arise from demand for liquidity, our analysis is consistent with the recognition of technical traders (institutional traders in our model) as providers of liquidity as opposed to exploiters of market inefficiencies; see Kavajecz and Odders-White (2004). Finally, our model demonstrates another way in which market participants can impede the adjustment of prices to information. For example, Hasbrouck and Sofianos (1993) show how specialists or dealers may impede the adjustment of prices because of exchange stabilization obligations or inventory imbalances. Similarly, Admati and Pfleiderer (1988) and Foster and Viswanathan (1993) show how public limit orders and trading strategies may impede the adjustment of prices.

The remainder of our paper proceeds as follows. Section 2 develops the model of the agency conflict inherent in delegating trade implementation and explores its implications. Section 3 discusses the sample selection, data sources, and methodologies used to test the empirical predictions, and presents the empirical results. Section 4 summarizes our findings.

2. Model

Let Q^{PM} denote the portfolio manager's order to the trader. The trading day consists of a morning and afternoon auction (periods 1 and 2, respectively). The quantity that the trader executes in each period is denoted Q_t. The security's price follows the process:

$$P_t = P_t^P + P_t^T + \lambda Q_t, \tag{1}$$

where P_t^P denotes a permanent component to price driven by public and private information flow, P_t^T denotes a transient distortion to price from noise trading; and λQ_t denotes the price impact of trading in period t (again, a transient influence on price). Innovations in both exogenous components of price, ΔP_t^P and P_t^T, are mean zero and i.i.d. The price impact coefficient λ is treated as exogenous.

The trader (but not the PM) can discriminate between permanent and transient price changes by observing P_t^T with effort e (dollar-equivalent). Because P_t^T is not observable to the PM, she cannot directly confirm that the trader applies effort. Instead, she assesses trader performance ex post using one of three benchmarking techniques: conventional VWAP and two variants employing hypothetical execution (VWAP and I/S).

To focus on the trading process rather than portfolio management, we assume that the PM does not wish to change target demands Q^{PM} in response to ΔP_t^P. Typical motives for PM demands include 'fundamental' forecasts of value (i.e., forecasts of $P_{t+j}^P, j \gg 1$); portfolio rebalancing as in Nagel (2006) and Cremers and Mei (2007); shareholder flow as in Edelen (1999), and noise trading as in Dow and Gorton (1997). In each case demands are either: based on an accumulation of many shocks to fair value; predetermined from past shocks to fair value;

[3] Blake and Schack (2002).

[4] For example, Plexus proposes a 30-day post-trade hypothetical execution (Harris, 2003), and ITG proposes a 10% 'clean-up participation rate' (Saraiya and Mittal, 2009).

[5] See, for example, Schwartz and Steil (2002), Blake and Schack (2002), Ramage (2009), and Greenwich Associates (2009).

or independent of fair value. Each implies an inelastic response to contemporaneous shocks to fair value.[6]

In Sections 2.1–2.3 we derive expected execution costs (including trader compensation) using each. In Section 2.4 we compare costs under conventional benchmarking to costs under the hypothetical-execution alternatives, identifying the critical level of risk aversion that equates costs. When risk aversion is above this critical value, conventional benchmarking results in lower costs. We then demonstrate that critical risk aversion is generally very low, consistent with the widespread use of conventional benchmarking in practice. In section 2.5 we derive the implications of conventional benchmarking for the rate of information assimilation into security prices.

2.1. Conventional VWAP

Under C-VWAP the trader is compensated according to

$$A - w(TraderWAP - VWAP)(Q_1 + Q_2) - \kappa Q_R^2 \tag{2}$$

$$Q_R \equiv (Q^{PM} - Q_2 - Q_1); \quad TraderWAP = \frac{P_1 Q_1 + P_2 Q_2}{Q_1 + Q_2}$$

$$VWAP = (P_1 + P_2)/2$$

A ensures that the trader's opportunity costs are met; and w calibrates pay-for-performance. The third parameter, κ, gives the PM a degree of freedom to punish partial execution.[7]

The trader's optimization problem reduces to

$$\max_{Q_{2,1}} \left\{ A - \frac{w}{2} E[\Delta P_2^* \Delta Q_2] - \frac{\lambda w}{2} E\left[\Delta Q_2^2\right] - \kappa E\left[Q_R^2\right] - Effort \right\} \tag{3}$$

where $\Delta P_2^* = (P_2^P + P_2^T) - (P_1^P + P_1^T)$ denotes the exogenous component of price changes. Solving the first-order condition for Q_2 gives (see the appendix for this and other derivations)

$$Q_2 = \Omega^C \left(Q_1 - \frac{\Delta P_2^*}{2\lambda} \right) + (1 - \Omega^C)(Q^{PM} - Q_1) \tag{4}$$

where $\Omega^C = \lambda w/(\lambda w + 2\kappa) \in [0,1]$. Using Eq. (4), the first-order condition for Q_1 gives

$$Q_1 = \frac{1}{2}\left(Q^{PM} + \frac{E_1[\Delta P_2^*]}{2\lambda} \right) \tag{5a}$$

where $E_1[\Delta P_2^*]$ depends on the trader's effort;

$$E_1[\Delta P_2^*] = \begin{cases} E_1[\Delta P_2^P + \Delta P_2^T | P_1^P, P_1^T] = -P_1^T & Effort = e \\ E_1[\Delta P_2^P + \Delta P_2^T | P_1] = -hP_1 & Effort = 0 \end{cases} \tag{5b}$$

with $h = \sigma_T^2/(\sigma_T^2 + \sigma_P^2)$ (subscripts refer to transient and permanent components of price changes). h represents the fraction of return variance that the trader identifies as transient; hence, we refer to it as the Trader R^2. Replacing Eq. (5) into Eq. (4):

$$Q_2 = \frac{1}{2}\left(Q^{PM} - \frac{E_1[\Delta P_2^*]}{2\lambda} \right) - \frac{\Omega^C}{2\lambda}(\Delta P_2^* - E_1[\Delta P_2^*]) \tag{6}$$

The PM chooses w and κ to minimize transaction costs, defined as[8]

$$E\left[(P_1 - P_1^P)Q_1 + (P_2 - P_2^P)Q_2 + \frac{\lambda}{2} Q_R Q_R \right]$$
$$= E\left[(P_1^T + \lambda Q_1)Q_1 + (P_2^T + \lambda Q_2)Q_2 + \frac{\lambda}{2} Q_R Q_R \right] \tag{7}$$

subject to incentive compatibility for the trader (see the appendix). Costs are minimized at

$$\Omega^C = \frac{\lambda w}{\lambda w + 2\kappa} = 2h/3 \tag{8}$$

Replacing Eq. (8) into (7) gives the following: Total costs of execution; Conventional VWAP:

$$= \frac{\lambda}{2} Q^{PM2} - \left(\frac{1}{4} + \frac{h}{3} \right) \frac{\sigma_T^2}{2\lambda} \tag{9}$$

Note that the first term is the cost of trading without a trader (market order for half Q^{PM} in each of the two daily auctions). Net gains from discretionary trading (after compensation and gaming) are proportional to σ_T^2 (transient distortions in price), but these gains decline with larger σ_P^2 because permanent shifts in price induce gaming.

2.2. Hypothetical-execution: VWAP

Now consider hypothetical execution, where trader compensation is specified as

$$A - w\left(\frac{P_1 Q_1 + P_2 Q_2 + P_3 Q_R}{Q^{PM}} - \frac{P_1 + P_2}{2} \right) Q^{PM} \tag{10}$$

P_3 is the next-day hypothetical-execution price applied to the order residual. Note that compensation is a random variable at the time of the last trade decision (period 2) due to the P_3 term, unless the trader chooses $Q_R = 0$. We assume the trader has negative-exponential utility with coefficient of risk aversion ρ, so the trader maximizes

$$\max_{Q_{2,1}} E[Compensation] - \rho Var[Compensation] - Effort \tag{11}$$

given normally distributed price changes. Solving the first-order conditions yields

$$Q_1 = \frac{E_1[\Delta P_2^*]}{4\lambda(1 - \Omega^H)} + \frac{Q_{pm}}{2} \tag{12}$$

$$Q_2 = \frac{1}{2}\left(Q^{PM} - (1 - \Omega^H)\frac{E_1[\Delta P_2^*]}{\lambda} \right) + \frac{\Omega^H}{2\lambda} E_2[\Delta P_3^*] \tag{13}$$

where $\Omega^H = \lambda/(2\lambda + 2\rho w Var[\Delta P_3^*])$. Note that Ω^H is similar to Ω^C except that the choice variable κ is replaced by the exogenous quantity $\lambda w + 2\rho w^2 Var[\Delta P_3^*]$. This highlights the optimization control benefit of conventional benchmarking. With hypothetical execution, the PM has no control over the aggressiveness of trading.

[6] This assumption that portfolio managers do not alter their demands in response to recent price moves is potentially limiting. However, evidence in Section 3.1 suggests that the assumption holds for a large sample of institutional trades.

[7] To simplify, we assume equal market volume in each period.

[8] Note that this expression includes the price impact of executing the order residual over two periods.

The PM minimizes ex ante costs as in Eq. (7), adding a certainty-equivalent payment to compensate for risk borne by the trader. Applying Eqs. (12) and (13) this yields: *Total costs of execution*; *Hypothetical VWAP*:

$$=\frac{\lambda}{2}Q^{PM2}-\left[\frac{(1-\Omega^H-\Omega^{H2})}{2(1-\Omega^H)^2}+\frac{2\Omega^H(1-\Omega^H)}{\lambda}\right]\frac{\sigma_T^2}{2\lambda} \tag{14}$$

Because of the nonlinear dependence on Ω^H we numerically solve Eq. (14) subject to the trader's incentive compatibility constraint.

2.3. Hypothetical-execution: implementation shortfall

The final alternative that we consider is implementation shortfall with hypothetical execution, in which the trader is compensated according to

$$=A-w\left(\frac{P_1Q_1+P_2Q_2+P_3Q_R}{Q^{PM}}-P_0\right)Q^{PM} \tag{15}$$

Demands are formulating as in Eq. (11), using Eq. (15). This yields

$$Q_1=-\frac{1}{(2-\Omega^H)}\frac{P_1^T}{2\lambda}+\frac{(1-\Omega^H)}{(2-\Omega^H)}Q_{PM} \tag{16}$$

$$Q_2=-\Omega^H\frac{P_2^T}{2\lambda}+\frac{(1-\Omega^H)}{(2-\Omega^H)}\frac{P_1^T}{2\lambda}+\frac{(1-\Omega^H)}{(2-\Omega^H)}Q_{PM} \tag{17}$$

where Ω^H is as before. Costs are again determined using Eq. (7) plus a certainty-equivalent payment to offset the trader's risk. This yields—*Total costs of execution*; *Hypothetical-implementation shortfall*:

$$=\lambda\frac{(1-\Omega^H)}{(2-\Omega^H)}Q_{PM}^2-\left(\frac{1}{2-\Omega^H}+\Omega^H\right)\frac{\sigma_T^2}{4\lambda} \tag{18}$$

We numerically solve Eq. (18) subject to the trader's incentive-compatibility constraint.

2.4. Comparison: conventional versus hypothetical benchmarking

The choice of conventional VWAP versus either hypothetical benchmark depends on a comparison of costs under Eq. (9) to costs under Eq. (14) (subject to Eq. (A.13), or Eq. (18)) (subject to Eq. (A.19)). In this section we examine this comparison using a range of plausible parameter values and show that conventional benchmarking is preferred for all but the lowest levels of trader risk aversion. The relevant equations involve four terms: ρ, h, e (which appears in the incentive-compatibility constraints), and the ratio $\lambda Q_{PM}/\sigma_T$. We assert all values but ρ then choose ρ to equate costs under conventional and hypothetical benchmarking.

Transient fluctuations in price (i.e., P_t^T) reflect the price impact of *aggregate* noise trading, and σ_T is their magnitude. λQ_{PM} reflects the price impact of the PM's order. Thus, the ratio $\lambda Q_{PM}/\sigma_T$ should mirror the size of the PM's order in relation to aggregate noise trading. We consider a range of values for this relative order size, from 10% to 100% of average daily volume. Trader R^2 (h) represents the fraction of variance in short-term price changes that a trader can predict using knowledge of current market conditions. Values between 1% and 10% seem plausible; we use 5%. Lastly, we consider a range of values for effort. The maximal per-period benefit to exploiting effort comes from trading the quantity $E[\Delta P^*]/4\lambda$ which maximizes trading revenue at $\sigma_T^2/8\lambda=1/8$. We consider effort costs of 25%, 50%, and 75% of 1/8.

Table 1
Critical value of trader risk aversion.
The table presents the value for trader risk aversion that equates costs under conventional and hypothetical-execution benchmarking strategies. Costs under the indicated benchmarking strategy are compared to costs using conventional VWAP. When trader risk aversion is above the tabulated value, conventional VWAP is the lower-cost method. Values are generated from Eqs. (9), (14), and (18) subject to their respective incentive compatibility constraints, with trader-R^2 (h) set to 5%. Three values are considered for the cost of effort, each representing a fraction of the total potential gains to the trader becoming informed.

	Ratio: Price impact to noise-trader variance $\lambda Q_{PM}/\sigma_T^2$								
	1/10	1/4	1/2	1/1	–	1/10	1/4	1/2	1/1
	Hypothetical VWAP					Hypothetical strike (I/S)			
Effort:									
0.75	0.2	0.6	1.2	2.4		0.2	0.6	1.4	4.2
0.50	0.4	0.9	1.8	3.6		0.3	0.9	2.1	6.3
0.25	0.8	1.9	3.7	7.5		0.7	1.9	4.2	6.5

Table 1 presents the critical risk aversion relating conventional VWAP to hypothetical VWAP and hypothetical I/S. This critical value falls in a plausible, generally low, range. Hypothetical benchmarking becomes relatively efficient only when the PM's relative order size approaches 100%, that is, when the order equals a typical day's volume. Later, in Table 3, we present institutional order summary statistics indicating a typical order size of 10% average daily volume, implying critical risk aversion in the range of 0.2–0.8, depending on effort costs and notably independent of the benchmark used (i.e., VWAP versus I/S). Regarding effort, in a competitive market, one expects effort costs to represent a relatively large fraction of potential gains. From Table 1, this implies critical risk aversion on the order of 0.2 (e=75%). Thus, it is highly plausible that conventional benchmarking is optimal in delegated trading arrangements.

The intuition for the results in Table 1 is as follows. To induce effort, the trader's pay must be tied to performance. For a risk-averse trader, the random influence of hypothetical execution makes this both costly and relatively ineffective (more pay-for-performance means greater compensation uncertainty and hence greater aversion, to exploiting liquidity opportunities). At higher levels of risk aversion the pay-for-performance coefficient required to induce effort (particularly when effort is costly) can impose such a high cost that conventional benchmarking, despite gaming, is preferred.

2.5. Delegated trading, conventional benchmarking, and information assimilation

The preceding analysis demonstrates that relative to first-best trading, delegation involves an agency cost. This cost arises from the incentive that conventional benchmarking creates to trade contra to information flows (i.e., the permanent component of price changes). The following provides a lower bound on this cost[9]: *Agency cost of trade delegation*:

The lower bound for agency costs associated with delegated trading is $h^2\sigma_P^2/8\lambda$

While the existence of this agency cost is a novel observation of the paper, it is the *nature* of the cost that makes the prediction most interesting and relevant. Agency costs arise because the trader sometimes accelerates execution when it would be best to delay, and sometimes delays execution when it would be best to accelerate. In both cases, this short-term deviation from first-best trading is induced by concurrent information flows (changes in value that the trader, but not the PM, knows are permanent).

The most important characteristic of this agency cost is the direction of the temporary deviation in trade quantities induced by delegated trading (contrary to information flow). This has the following implication for market prices: *Delegated trading and price-adjustment delays*.

The price change associated with a permanent shift in value in the afternoon auction (period 2), is less than complete:

$$\frac{\partial}{\partial \Delta P_2^P}\Delta P_2 = 1-\frac{h}{3} \tag{19a}$$

and there is a delayed price reaction in the subsequent period:

$$\frac{\partial}{\partial \Delta P_2^p}\Delta P_3 = \frac{h}{3} \tag{19b}$$

Note that price-adjustment delays arise in the afternoon auction. In the morning auction, the concurrent price reaction is complete and there is no price-adjustment delay. This asymmetry arises because of the nature of a VWAP benchmark: Until the morning trading has transpired, there is no benchmark set for the trader to game, hence, there is no manipulative trading. By contrast, with an I/S benchmark, everything is set and the incentive to game begins immediately. Hence, the asymmetry between morning and afternoon described above is specific to VWAP. However, the overall prediction of a price-adjustment delay holds for either formulation of conventional benchmarking.

It is important to emphasize that the price-adjustment delays generated by delegated trading are highly transient—lasting only until the next evaluation window commences (generally 1 day).[10] We do not assert that institutional trading permanently impedes the market's assimilation of information, or that institutions lower the longer-run efficiency of prices. However, in the short run, the discrepancies from market efficiency induced by delegated trading potentially have a substantial impact on information assimilation.

It is of interest to note the circumstances under which trader discretion is likely to be greatest, and thus, delegated trading has the greatest impact on information assimilation. The PM chooses to delegate when execution costs (Eq. (9) plus compensation for effort, e), are less than execution costs associated with market orders issued under an algorithmic strategy (i.e., default costs, $\lambda Q_{PM}^2/2$). This gives the following condition for delegation: *Conventional VWAP condition*:

$$e < \left(\frac{1}{4}+\frac{h}{3}\right)\frac{\sigma_T^2}{2\lambda} \tag{20}$$

This condition is more likely to be satisfied when noise trading, σ_T^2, is large, both directly and because h increases with σ_T^2. Thus, one expects more trader discretion in illiquid small cap stocks. Conversely, with liquid large cap stocks, one expects greater use of mechanical (algorithmic) trading strategies with no discretion. Finally, traders may not have discretion on certain types of trades such as portfolio transitions (Obizhaeva, 2010).

3. Empirical analysis

This section provides empirical evidence regarding the model's central prediction that institutional traders tend to execute orders contrary to changes in price, and that this contrary execution has an adverse impact on the rate of information assimilation.

3.1. Institutional trade execution

We obtain daily data on institutional trades from Ancerno (parent company Able Noser), a consulting firm that provides transaction cost analysis to brokers, pension funds, and mutual funds.[11] The data consist of 72 million trade summaries in 3,601 U.S. stocks by 1,248 different institutional clients from January 1999 through June 2009.[12] For each trade summary, the data include: a code for the institutional client, a code for the client manager, a code for the brokerage firm executing the trade, the order release date and time, the block size, the execution date, the stock traded, whether the trade is a buy or sell, the number of shares traded, the trade size as a fraction of that day's volume, the execution price, and the volume-weighted average price (VWAP) of all trades during the trading window. A key feature of these data is the direct identification of buyer- and seller-initiated trades—the central focus of our test. One of the limitations of the data is that the anonymity of the client, manager, and broker

[9] The analysis here presumes a C-VWAP benchmark. We justify this with the theoretical conclusion from the previous section that C-I/S is less efficient in inducing effort from the trader, and with evidence from the literature. In particular, Schwartz and Steil (2002) write 'VWAP has in recent years taken on an enormous significance as a benchmark for evaluating trading performance. We find that CIOs rank VWAP performance well above other criteria for evaluating how well their traders handle their orders.'

[10] In the institutional-trading data used in the empirical analysis below, approximately 80% of all trade packages are completed within 1 day, suggesting that this represents a typical window.

[11] Other studies using these data include Goldstein, Irvine, Kandel, and Wiener (2009), and Lipson and Puckett (2007).

[12] A trade summary is an aggregation of all trades by a given combination of client, manager, trader, broker, and 'block' identifier, in a given stock on a given day.

Table 2
Ancerno data representation in CRSP data set.

The table presents percentage of CRSP stocks, share volume, and dollar volume traded by Ancerno clients. 'Cap decile' refers to subsamples by market capitalization decile, with one being the smallest. Correlation refers to the average daily cross-sectional correlation between Ancerno trading volume and CRSP trading volume over the period January 1999–June 2009.

	Stocks	Share volume	Dollar volume	Correlation
Full sample	45%	10.1%	10.8%	0.69
Cap decile:				
1	1.8%	0.8%	1.1%	
2	4.8	1.6	1.9	
3	9.8	2.5	3.3	
4	20.9	4.3	5.5	
5	36.5	5.6	7.3	
6	53.5	7.7	8.7	
7	67.9	8.6	9.7	
8	80.3	9.6	10.6	
9	88.4	10.6	11.1	
Largest	95.5	11.2	10.9	
Year:				
1999	30.3%	9.0%	9.7%	0.61
2000	33.4	8.8	8.8	0.65
2001	35.4	10.1	11.4	0.68
2002	42.0	13.3	14.9	0.66
2003	47.1	11.2	13.2	0.64
2004	52.5	13.7	15.9	0.65
2005	55.3	11.1	12.9	0.66
2006	57.6	10.3	11.2	0.73
2007	60.2	8.9	8.9	0.72
2008	59.1	7.7	7.9	0.71
2009	60.1	7.4	8.2	0.71

Table 3
Characteristics of institutional orders.

The table presents mean (median) values of the indicated variable for 72 million blocks placed by 1,248 institutional investment management clients in 3,601 stocks over the period January 1999–June 2009. A block represents a sequence of daily trade summaries (often 1 day only) connected by a common identifying code. Statistics are reported for the full sample, by market capitalization category, and by block-size terciles within each market capitalization (rank ordered into three equally represented groups). Footprint is trade size divided by the total concurrent trading volume for the stock. Fill rate is the percent of the remaining block filled on a given day. Trade discretion is the average absolute value of the variable *TrDisc*, the difference between the actual fill rate and expected fill rate (as defined in Section 3.1).

		Block size ($millions)	Footprint (% volume)	Fill rate (%block)	Trade discretion
Full sample		1.106	3.8%	77.3%	17.1%
		(0.049)	(0.2)	(100)	(11.6)
SmallCap		0.316	6.9	72.9	20.0
		(0.129)	(1.5)	(97.0)	(15.8)
Block size=	Sml	0.009	2.9	89.1	14.9
	Med	0.055	5.1	72.2	20.1
	Lrg	0.897	12.7	57.9	24.6
MidCap		0.745	3.8	76.8	16.5
		(0.256)	(0.6)	(99.5)	(12.0)
	Sml	0.012	1.4	92.7	11.5
	Med	0.083	2.6	78.3	16.7
	Lrg	2.414	7.3	63.5	20.8
LargeCap		1.836	2.0	80.3	11.6
		(0.477)	(0.2)	(100)	(7.7)
	Sml	0.021	0.5	94.9	7.1
	Med	0.122	1.3	82.1	11.5
	Lrg	5.355	4.2	65.9	15.2

precludes our ability to examine cross-sectional variation along these dimensions. Nor do the data provide information that allows us examine variation related to the type of trade (indexing, shareholder flow, etc).

Summary statistics of the Ancerno data's coverage of stocks in the CRSP database are presented in Table 2. The Ancerno data's coverage of stocks in (CRSP) ranges from 2% for the smallest market capitalization decile to 96% for the largest decile. Coverage of trading volume ranges from 1% to 11%. Overall, Ancerno clients account for 10.1% (10.8%) of CRSP share (dollar) volume. More importantly, the average daily cross-sectional (time-series) correlation between Ancerno volume and CRSP volume is 0.69 (0.52). Finally, while Ancerno volume declines somewhat as a fraction of total (CRSP) volume in the latter half of the sample period, its correlation with total volume increases.[13] Overall, Table 2 suggests that Ancerno volume is a good proxy for aggregate institutional volume and that this volume represents a substantial component of total market volume.

To test the model's prediction of a contrary relation between traders' discretionary execution and changes in market valuation, we first construct a measure of traders' discretionary execution. Our proxy for trader discretion is the difference between the actual and expected execution rate for each block. The expected execution rate is estimated from static characteristics of the order such as manager ID, order size, type of stock, etc. (discussed below). We then test our model's prediction by relating this proxy for traders' discretionary execution to concurrent market returns.

The expected execution rate for each block is taken as the average completion rate of the manager for comparable blocks during the prior year.[14] Specifically, we sort all trade summaries for a given manager during a given year by trade side (buy or sell); block size (small, medium, large); market capitalization of the stock (small, mid, large); and whether the order originated that day or was carried over from a previous day. These factors were chosen from a larger set of candidates that include historical stock-specific attributes (volume, shares outstanding, and return volatility) , as well as contemporaneous market statistics (volume and volatility).[15] We do not include contemporaneous stock-specific measures as they are likely endogenous to the block completion rate,

[13] This trend could reflect the recent emergence of high-frequency trading as a dominant component of market volume. High-frequency traders typically react to, rather than initiate, order flow, and hold positions for less than a day, hence their activity is often characterized as market making. The increasing correlation between institutional trading and total volume suggests that institutions remain an important component of order flow. Whatever the reason, inferences drawn from the latter period are similar to those of the full sample.

[14] The Ancerno data does not report the portfolio manager's original order size but rather the total shares traded as part of the overall block. That is, by the final day of the block, each block is filled exactly 100%.

[15] The four factors explain 43% of the cross-sectional variability in block completion rates and nearly 90% of the variation explained by the larger set of candidate factors.

or contemporaneous market returns as that is the key variable of interest in our tests of trader discretion.

Our proxy for traders' discretionary execution, $TrDisc_{ibt}$, (subscripts denote stock *i*, block *b*, and day *t*) is the difference between the actual fill rate versus the average fill rate for the matched trade sample. We restrict our analysis of trader discretion to orders communicated to the trading desk prior to the market open on the day of the trade. That is, we consider orders carried over from prior days (27% of all orders) and orders submitted prior to the market open on the day of the trade (46% of all orders). Since the block parameters for such orders are set prior to the realization of market returns that day, any correlation between their fill rate and market returns can reasonably be attributed to trader discretion.[16] This restriction removes orders placed after the open on the day of trade (27% of all orders); however, the correlation between the trading volume of this subsample and the full Ancerno sample is 0.94.

Table 3 presents summary statistics for the trading blocks. We report the mean (median) dollar block size, trade footprint, fill rate, and trade discretion for the full sample, by market capitalization, and by block size within each market capitalization. Trade footprint is shares traded divided by total concurrent volume for the stock. Fill rate is the percent of the (remaining) block filled that day. Trade discretion is the absolute value of the difference between the actual fill rate and expected fill rate. From column 2, the average block is roughly 4% of a stock's average daily volume but this varies widely by market capitalization—from 1% for large cap stocks to over 10% for small cap stocks. The average fill rate 77% (column 3) suggests that a sizeable fraction of orders remain unfilled each day. Most relevant to our model is the fact that trade discretion (column 4) is higher for small cap (20.0%) and mid cap stocks (16.5%) than for large cap stocks (11.6%).

Because our interest is the aggregate effect of delegated trading on price-adjustment delays, we aggregate all Ancerno trade data for a given stock on a given day.[17] We compute the aggregate discretionary trader imbalance in stock *i* on day *t*, denoted $TrImbalance_{it}$, by summing $TrDisc_{ibt}$ across all buy-blocks; subtracting the sum of $TrDisc_{ibt}$ across all sell-blocks; and dividing by total CRSP volume:

$$TrImbalance_{it} = \left(\sum\nolimits_{block\ b=Buy} TrDisc_{ibt}\,Volume_{ibt} - \sum\nolimits_{block b=Sell} TrDisc_{ibt}\,Volume_{ibt}\right) / TotalVolume_{it}$$

Our model predicts that exogenous variation in the price/VWAP ratio of a stock (either permanent or transitory in nature) induces contrary variation in $TrImbalance_{it}$. However, the stock's price/VWAP ratio is also endogenous to $TrImbalance_{it}$ due to price impact. Thus, we employ an instrument for the stock's price/VWAP ratio, denoted PV^*, the predicted value from the time-series regression of the stock's price/VWAP ratio on the average price/VWAP ratio of five portfolios of stocks; large cap, small cap, value, growth, and two-digit NAIC industry.

Table 4
Regressions of trade imbalances on price-VWAP ratio.

The table presents coefficient estimates (*t*-statistics) from pooled cross-sectional and time-series regressions with dependent variable listed in the column heading. $TotImbalance_{it}$ is the difference between total institutional buy and sell volume scaled by total (CRSP) volume. $TrImbalance_{it}$ is the difference between traders' discretionary buy and sell volume scaled by total (CRSP) volume, where traders' discretionary volume is actual volume minus the expected volume given the manager, block size, trade side, and market capitalization of the stock traded. Trader buy (sell) is the trader discretionary buy (sell) scaled by total (CRSP) volume. PV^* is an instrument for the stock's price-to-VWAP ratio, calculated as the ratio of the best-fit equity index futures contract price at the time of the stock's last trade, divided by the day's concurrent VWAP for that futures contract. $PV^*>1$ is equal to PV^* if PV^* is greater than one and zero otherwise. $PV^*<1$ is equal to PV^* if PV^* is less than 1 and 0 otherwise. R^{Fut}_{t-1} is the prior day's best-fit futures return. The sample consists of daily observations on 3,601 stocks during the period January 1999–June 2009 (5.3 million observations). Standard errors are corrected for serial correlation using clustering by date.

	Model			
	1	2	3	4
Dependent variable	Trader imbalance	Manager imbalance	Trader buy	Trader sell
PV^*	−0.293	0.091		
	(−9.12)	(3.55)		
$PV^*>1$			0.035	0.285
			(0.66)	(7.22)
$PV^*<1$			−0.246	0.070
			(−7.92)	(2.04)
R^{Fut}_{t-1}	0.028	0.093	0.027	−0.002
	(2.80)	(5.84)	(2.53)	(−0.11)
$TotImbalance_{it-1}$		0.398		
		(11.2)		
$TrImbalance_{it-1}$	0.274			
	(115.5)			
Lag Trader buy			0.272	
			(88.2)	
Lag Trader sell				0.272
				(89.6)
Adj. R^2	0.075	0.157	0.075	0.074

Table 4, column 1 reports coefficient estimates for regressions of $TrImbalance_{it}$ on concurrent PV^*. The strong negative contemporaneous relation between $TrImbalance_{it}$ and PV^* supports the central prediction of our model: an agency conflict inherent in delegated trading causes a contrary relation between traders' discretionary order execution and (exogenous) changes in market valuation.

A natural concern is that our measure of traders' discretion in execution, $TrImbalance_{it,}$ is also influenced by manager discretion. And thus, it may not be the trader who chooses to trade contrary to information flows, but rather the portfolio manager—cancelling orders in response to untoward price moves.

While we calculate our measure of trader discretion using orders submitted prior to the market open specifically to rule out this alternative explanation, this screen might be insufficient.[18] As a robustness check, we

[16] A notable exception is the case of limit orders, which we address later.

[17] Inferences from individual trade summaries are very similar to those from the aggregate stock level.

[18] It is important to emphasize that our analysis of price-adjustment delays involves discretionary responses to high-frequency permanent price moves, not transient fluctuations in liquidity conditions. Such a reaction on the part of the PM would be incongruent with the typical

examine the relation between market returns and the contemporaneous aggregate trade imbalance for orders submitted after the market open:

$$MgrImbalance_{it} = \left(\sum_{PostOpenBuy} Volume_{ibt} - \sum_{PostOpenSell} Volume_{ibt}\right) / TotalVolume_{it}$$

We use the term $MgrImbalance_{it}$ to emphasize the fact that these orders are under the full discretion of the manager at some point during the trading day. Table 4, column 2 reports coefficient estimates for regressions of $MgrImbalance_{it}$ on concurrent PV^*. The significant positive contemporaneous relation between $MgrImbalance_{it}$ and PV^* suggests that manager discretion is not driving the results in column 1. In particular, it is difficult to imagine why managers would impose a negative relation between order execution and market returns on orders submitted prior to the open but a positive relation between order execution and market returns on orders submitted after the open. This provides an empirical basis for the model's assumption that portfolio manager demands do not change with current market conditions.

Another potential explanation for the negative relation between $TrImbalance_{it}$ and market returns is limit orders. As markets rise there is a decrease in limit-buy executions and an increase in limit-sell executions. Conversely, when markets fall there is an increase in limit-buy executions and a decrease in limit-sell executions. In either case, there is a negative relation between order flow imbalance and market returns. Institutional use of such strategies are analyzed in Keim and Madhavan (1996) and Keim (1999).

To address this issue, we conduct an analysis similar to Lipson and Puckett (2007), separately relating discretionary buy volume and discretionary sell volume to positive and negative cases of PV^*. As in Lipson and Puckett (2007), we find an asymmetric relation between trade execution and changes in market valuation. In particular, from Table 4 column 3, discretionary buy volume increases with negative values of PV^*, but is unrelated to positive values. If the results were due to limit orders, there should be a symmetric decline in buy volume with rising markets as those orders go unfilled. A similar asymmetric pattern is found for the case of discretionary sell volume. Thus, limit orders cannot explain the contrary relation we find in column 1.

3.2. Delegated trade execution and information assimilation

We now test the prediction that traders' contrary discretionary order execution inhibits information assimilation by examining the relation between $TrImbalance_{it}$ and delays in the assimilation of information (index futures returns).

Various studies analyze the role of nonsynchronous trading in the serial correlation of observed daily portfolio returns with the general conclusion that roughly half can be attributed to nonsynchronous trading (Kadlec and Patterson, 1999).[19] Because our focus is 'real' price-adjustment delays, we employ a methodology that is free from nonsynchronous trading effects. Specifically, we use NYSE (TAQ) transaction data to identify the time of the last trade for each stock. Our proxy for systematic information is the return on the best-fit index future (either the (S&P 500), Nasdaq 100, or Russell 2000) over the 180 minutes preceding that trade, denoted R^{Fut}.[20] The best-fit index is identified by estimating a single-factor market model for each stock using monthly returns on the S&P 500, Nasdaq 100, and Russell 2000 indexes, and choosing the index with the highest R^2. Delays in the assimilation of that information manifest as a correlation between the next-day (close–close) return on the stock and R^{Fut}.

3.2.1. Univariate price-adjustment results

Table 5 provides an overview of the magnitude of price-adjustment delays and the role of trader discretion in information assimilation. In Panel A we sort observations into three categories of market returns; down market, $R^{Fut} < -0.25\%$, (column 1), neutral market, $-0.25\% < R^{Fut} < 0.25\%$, (column 2), and up market, $R^{Fut} > 0.25\%$, (column 3). Let R^*_{it+1} denote the day $t+1$ factor-adjusted return on the stock (return less predicted return given the concurrent futures return). Price-adjustment delays are evidenced by the average R^*_{it+1} following a negative R^{Fut} (-0.14%) and positive R^{Fut} (0.15%). Consistent with the evidence of contrary patterns in trader execution in Table 4, the average discretionary trade imbalance, $TrImbalance_{it}$, is positive for negative R^{Fut} and negative for positive R^{Fut}.

The remaining panels of Table 5 separately present cases of discretionary buying imbalances (top tercile of $TrImbalance_{it}$) and discretionary selling imbalances (bottom tercile of $TrImbalance_{it}$), and neutral discretionary trading. Consider the case of positive market returns (column 3). The model predicts larger price-adjustment delays (i.e., positive R^*_{it+1}) when delegated traders exercise their discretion with a selling imbalance, and no price-adjustment delays with neutral or buying imbalances. The average R^*_{it+1} is 0.30% when $TrImbalance_{it}$ is negative (Panel D), versus 0.13% in the case of neutral $TrImbalance_{it}$ (Panel C), and 0.04% in the case of positive $TrImbalance_{it}$ in (Panel B). Similar evidence is seen with negative information events (column 1). Overall, Table 5 shows a strong link between the magnitude of price-adjustment delays and the discretionary execution of delegated traders.

3.2.2. Regression price-adjustment results

Table 6 repeats the preceding analysis in a regression context by regressing R^*_{it+1} on

(*footnote continued*)
long (1 year) holding period in equity portfolios. Moreover, survey evidence (Schwartz and Steil, 2002, p. 44) indicates that high-frequency price action rarely (around 8–10%) affects PM decisions on any dimension.

[19] For studies of nonsynchronous trading and serial correlation, see, e.g., Fisher (1966), Lo and MacKinlay (1990), Boudoukh, Richardson, Whitelaw (1994, 2002).

[20] Following Hasbrouck (2003), we use only trades from the primary exchange for each stock. The TAQ database identifies atypical trades. We exclude all trades that are batched, executed as part of a basket trade, or reported out of sequence.

Table 5
Univariate analyses of price-adjustment delays.

The table presents mean (median) values of the variable indicated in the row, conditional on negative, neutral, and positive index futures returns. R^*_{it+1} is the next-day futures-adjusted return on the stock. R^{Fut}_{it} is the return on the best-fit futures contract during the 180 minutes preceding the last trade in stock *i* on day *t*. $TrImbalance_{it}$ is the difference between traders' discretionary buy and sell volume in stock *i* on day *t* scaled by total (CRSP) volume, where traders' discretionary volume is actual volume minus the expected volume given the manager, block size, trade side, and market capitalization of the stock traded. The column heading refers to cases where $R^{Fut}_{it} < -0.25\%$ (negative), $> 0.25\%$ (positive), and between -0.25% and 0.25% (neutral). The sample consists of daily observations on 3,601 stocks during the period January 1999–June 2009 (5.6 million observations). Panels B–D refer to the subsamples where $TrImbalance_{it}$ is in the top, middle, and bottom third by rank ordering, respectively.

	Futures return (R^{Fut}_{it})		
	Negative	Neutral	Positive
Panel A: Full sample			
R^*_{it+1}	−0.0014	0.0003	0.0015
	(−0.0010)	(−0.0001)	(0.0008)
R^{Fut}_{it}	(−0.0090)	0.0001	0.0089
	(−0.0067)	(0.0001)	(0.0066)
$TrImbalance_{it}$	0.0061	−0.0009	−0.0084
	(0.0030)	(−0.0046)	(−0.0052)
Panel B: Trader buy			
R^*_{it+1}	−0.0027	−0.0009	0.0004
	(−0.0023)	(−0.0013)	(−0.0008)
R^{Fut}_{it}	−0.0092	0.0001	0.0087
	(−0.0070)	(0.0001)	(0.0064)
$TrImbalance_{it}$	0.4330	0.4379	0.4375
	(0.3138)	(0.3162)	(0.3104)
Panel C: Trader neutral			
R^*_{it+1}	−0.0010	0.0003	0.0013
	(−0.0011)	(−0.0003)	(0.0004)
R^{Fut}_{it}	−0.0093	0.0001	0.0092
	(−0.0070)	(0.0001)	(0.0063)
$TrImbalance_{it}$	0.0017	0.0006	0.0009
	(0.0000)	(0.0000)	(0.000)
Panel D: Trader sell			
R^*_{it+1}	−0.0002	0.0014	0.0030
	(−0.0002)	(0.0005)	(0.0013)
R^{Fut}_{it}	−0.0091	0.00001	0.0090
	(−0.0069)	(0.00001)	(0.0064)
$TrImbalance_{it}$	−0.470	−0.4647	−0.4717
	(−0.350)	(−0.3570)	(−0.3576)

R^{Fut}_t and the following stock-specific variables[21]:

- R^{Fut}; $TrImbalance_{it}$; $TotImbalance_{it}$.
- $R^{Fut}I_{Tr}$, where $I_{Tr}=1$ if $TrImbalance_{it}R^{Fut} < 0$; 0 otherwise.
- $R^{Fut}I_{Tot}$, where $I_{Tot}=1$ if $TotImbalance_{it}R^{Fut} < 0$; 0 otherwise.
- $R^{Fut}I_{Lrg}$, where $I_{Lrg}=1$ if the stock is in the top market-cap decile.
- *logVolume*=log of daily share volume.
- *logMktCap*=log of market capitalization.

[21] In these regressions we adjust standard errors for serial dependence by clustering on date.

Table 6
Regressions of next-day stock returns on lagged trading characteristics.

The table presents coefficient estimates (*t*-statistics) from pooled cross-sectional and time-series regressions with dependent variable R^*_{it+1}, the next-day futures-adjusted return on the stock. R^{Fut}_{it} is the return on the best-fit futures contract during the 180 minutes preceding the last trade in stock *i* on day *t*. $TrImbalance_{it}$ is the difference between traders' discretionary buy and sell volume in stock *i* on day *t* scaled by total (CRSP) volume for the stock, where traders' discretionary volume is actual volume minus the expected volume given the manager, block size, trade side, and market capitalization of the stock traded. $TotImbalance_{it}$ is the difference between (Ancerno) buy and sell volume in stock *i* on day *t* scaled by total (CRSP) volume. $R^{Fut}_{it}I_{Tr}$, $R^{Fut}_{it}I_{Tot}$, and $R^{Fut}_{it}I_{Lrg}$ are interactive terms with $I_{Tr}(I_{Tot})$ equal to one if $TrImbalance_{it}$ ($TotImbalance_{it}$) is contra to R^{Fut}_{it} and zero otherwise; I_{Lrg} equals one if stock *i* is in the top decile of market capitalization and zero otherwise. LogVolume is the log of stock *i*'s total (CRSP) volume on day *t*. LogMktCap is the log of stock *i*'s market capitalization. The sample consists of daily observations on 3,601 stocks during the period January 1999–June 2009 (5.6 million observations). The column 5 regression is on a restricted sample (June 2007–June 2009). Standard errors are corrected for serial correlation using clustering by date.

Model:	1	2	3	4	5 (last 2 years)
R^{Fut}_{it}	0.177	0.136	0.167	0.175	0.099
	(11.86)	(9.02)	(11.28)	(10.50)	(3.63)
$R^{Fut}_{it}I_{Tr}$		0.087	0.083	0.084	0.041
		(8.68)	(8.89)	(8.92)	(2.79)
$R^{Fut}_{it}I_{Tot}$			−0.060	−0.061	−0.037
			(−5.61)	(−5.71)	(−2.25)
$R^{Fut}_{it}I_{Lrg}$				−0.031	−0.036
				(−2.42)	(−0.47)
$TrImbalance_{it+1}$		−0.007	−0.014	−0.014	−0.015
		(−25.9)	(−53.6)	(−53.7)	(−26.0)
$TrImbalance_{it}$		−0.006	0.001	0.001	0.001
		(−28.2)	(7.71)	(7.71)	(1.92)
$TotImbalance_{it+1}$			0.017	0.017	0.022
			(61.1)	(61.1)	(32.2)
$TotImbalance_{it}$			−0.007	−0.006	−0.008
			(−38.2)	(−38.1)	(−17.0)
logVolume		0.001	0.001	0.002	0.002
		(3.42)	(3.85)	(4.28)	(1.29)
logMktCap				−0.001	−0.001
				(−4.06)	(−0.30)
Adj. R^2	0.003	0.004	0.011	0.012	0.012

The first regressor, R^{Fut}, provides a baseline specification for price-adjustment delays with respect to systematic information. The interactive terms test for the marginal effects of various factors on the speed of price adjustments. I_{Tr} (I_{Tot}) identifies cases in which aggregate discretionary trading imbalances (total imbalances) run counter to the concurrent information signal, R^{Fut}. Our theory predicts that the coefficient on $R^{Fu}I_{Tr}$ is positive: price-adjustment delays are more extreme as a result of the contrary actions of delegated traders. To control for more general order flow effects, we also compute the total buy–sell

imbalance, $TotImbalance_{it}$, for each stock on each day:

$$TotImbalance_{it} = \left(\sum\nolimits_{blockb = Buy} Volume_{ibt} - \sum\nolimits_{blockb = Sell} Volume_{ibt}\right) / TotalVolume_{it}$$

The interactive term $R^{Fut}I_{Tot}$ controls for the potential effects of total buy–sell imbalance on price-adjustment delays. Our theory predicts no relation here because, unlike discretionary trading, total block volume is not endogenous to R^{Fut}. The interactive term $R^{Fu}I_{Lrg}$ controls for the well-documented effects of market capitalization on price-adjustment delays. Finally, we include non-interactive lag terms ($TrImbalance_{it}$, $TotImbalance_{it}$, total volume, and market capitalization) to control for potential spurious relations to other microstructure-related sources of predictability.

Table 6, column 1 presents the base case for price-adjustment delays. The coefficient on lag index returns is 0.18 (t=11.9), indicating that systematic information is not fully assimilated concurrently. While this result is consistent with several other studies documenting lead-lag effects, it is somewhat novel in that we eliminate the confounding effects of nonsynchronous trading by carefully timing lead-lag return calculations.

The impact of delegated trading on information assimilation is seen with the coefficient on the interactive term $R^{Fut}I_{Tr}$ which is, consistent with our theory, positive and highly significant 0.09 (t=9.0) (Table 6, column 2). Comparing the coefficient estimate to that on R^{Fut} suggests that price-adjustment delays are about 50% larger when delegated traders are active in the stock (reacting contrary to factor returns). This confirms that the discretion exercised by delegated traders tends to inhibit information assimilation. By contrast, from column 3, the coefficient on $R^{Fut}I_{Tot}$ is negative and close to zero, consistent with the evidence in Table 4 that PMs do not condition demands on high-frequency, permanent shocks to value. More importantly, the evidence confirming the predicted dependence on discretionary trading imbalances (i.e., the coefficient on $R^{Fut}I_{Tr}$) is unaffected by the inclusion of this control variable.

Note that, the coefficient on $TrImbalance_{it}$ (no interaction with R^{Fut}) is significantly negative. As discussed in the context of Table 5, this is consistent with discretionary trading inhibiting the assimilation of idiosyncratic information, but an exogenous proxy for such information would be needed to more fully test this interpretation. The coefficients on $TotImbalance_{it}$ (no interaction with R^{Fut}) mirror the results in Chordia and Subrahmanyam (2004), who find a negative relation between individual stock returns and lag buy–sell imbalance after controlling for concurrent imbalances.

Finally, in Table 6, column 4 we add controls for the effect of market capitalization. Consistent with prior studies of price-adjustment delays, the coefficient on $R^{Fut}I_{Lrg}$ is negative and significant, −0.03 (t=−2.42). That is, price-adjustment delays are smaller for larger cap stocks. This is consistent with our model's assertion (Eq. (20)) that the net benefit from delegation diminishes with high-frequency pricing efficiency, but it is also consistent with alternative explanations. We note that the adjusted R^2 of these tests of our model (regressions (2)–(5)) are small, however, they are twice that of the baseline regression documenting the well-known lead-lag effect (regression (1)). Moreover, the univariate evidence in Table 5 establishes the economic importance of our results.

3.3. High-frequency trading

A recent phenomenon in financial markets is the explosion in trading volume from high-frequency traders (HFTs) who, by some accounts, now represent as much as 50% of all trading. Because these traders execute via computer algorithms as opposed to trader discretion, a natural question is whether the institutional traders of our model continue to be on the margin, exerting an influence on the speed with which security prices adjust to information.

Many argue that HFTs are best viewed as market makers, *reacting to* distortions in price arising from fluctuations in natural supply and demand, rather than representing natural supply and demand themselves.[22] They elevate reported trading volume, because trade between natural buyers and sellers now passes rapidly through one or several HFT intermediaries.[23] But it is natural volume that sets the price, and the emergence of HFTs does not alter the relative importance of traditional institutions as a source of natural (price-setting) supply and demand. Consistent with this view, the correlation between Ancerno volume and CRSP volume has risen, even as the percentage representation of Ancerno volume has declined (Table 1). Moreover, in results not tabulated, the contrary nature of institutional trade execution (column 2 of Table 4) is largely unchanged in recent periods. The coefficient from regressing $TrImbalance_{it}$ on PV^* is −0.31 (t=−6.2) in the last 2 years of the sample (i.e., June 2007–2009) versus −0.29 (t=−9.12) in the full sample.

Nevertheless, a substantial amount of HFT likely involves arbitrage of short-term predictable price moves, e.g., price-adjustment delays generated by delegated trading. Thus, the net effect of delegated trading, after encountering the arbitrage trading of high-frequency traders, may be reduced, or even eliminated by the price-adjustment delay. To examine the net effect of HFTs on the influence that delegated trading has on the price-adjustment, we estimate regression (4) of Table 6 using data from the last 2 years of the sample. The results, reported in column 5 of Table 6, indicate that the influence of delegated traders has moderated in more recent periods. The coefficient on $R^{Fut}I_{Tr}$ is −0.041 (t=−2.79) in the 2007–2009 period versus −0.084 (t=−8.92) in the full sample. Note that unconditional price-adjustment delays (i.e., the coefficient on R^{Fut}) is also about half the full-sample value. Thus, it appears that HFTs have improved the high-frequency efficiency of stock prices across the board, mitigating the effects of other sources of price-adjustment delays as well as delegated trading. Nevertheless, the effects of delegated trading on price-adjustment remain economically and statistically significant.

4. Summary and conclusions

This paper develops and tests a model of an agency conflict that arises when investment management firms partition labor between portfolio managers who decide on the portfolio composition, and trading desks who

[22] When discussing the role of high frequency traders Gus Sauter, chief investment officer of the Vanguard Group, notes that the stock market has had middlemen for hundreds of years. 'If they were doing what they do without computers, we would call them market makers,' (The impact of high frequency trading' Knowledge@Wharton, September 30, 2009).

[23] See, for example, Lyons (1995) and several later papers.

implement trade decisions. The central result of our model is that in granting discretion to traders to exploit their ability to lower trading costs, portfolio managers implicitly give traders an incentive to execute orders contrary to information flow during the trading window. That is, traders aggressively fill sell orders as a security's price rises and buy orders as the price falls. While such behavior results in lower trading costs when price changes are driven by noise trading, it raises costs when price changes reflect shifts in fair value. A corollary to this result is that widespread use of delegated trading can inhibit information assimilation.

Our model yields several testable implications regarding cross-sectional and time-series properties of trader execution and price-adjustment delays. Using detailed data on a large sample of institutional transactions, we provide empirical support for our model. Specifically, we find that institutional traders execute orders contrary to market returns and that this contrary trading pattern is associated with larger price-adjustment delays. While market returns are but one source of information, they are uniquely suited to testing the predictions of our model because the exogenous information source is easily proxied. Moreover, this form of price-adjustment delay has received much attention in the literature.

Appendix

A.1. Conventional VWAP derivations (Section 2.1)

Period 1 demands: The period-one first-order condition for Eq. (3) is

$$0 = wE_1[\Delta P_2^*](1-\Omega)+2\lambda wE_1[\Delta Q_2](1-\Omega)+4\kappa\Omega E_1[Q_R] \tag{A.1}$$

Noting that $2\kappa\Omega = \lambda w(1-\Omega)$, this can be written as

$$0 = wE_1[\Delta P_2^*](1-\Omega)+2\lambda wE_1[\Delta Q_2+Q_R](1-\Omega) \tag{A.2}$$

$$0 = wE_1[\Delta P_2^*]+2\lambda w(Q^{PM}-2Q_1) \tag{A.3}$$

Incentive compatibility: Applying Eqs. (5) and (6) to (3) yields net expected compensation

$$A+\frac{w}{8\lambda}(E_0\left[E_1[\Delta P_2^*]^2\right]+\Omega Var\left[\Delta P_2^*\right])-effort \tag{A.4}$$

Using Eq. (5b), net expected compensation with effort is

$$A-e+\frac{w}{8\lambda}(\sigma_T^2+\Omega(\sigma_T^2+\sigma_P^2)) \tag{A.5}$$

and without effort:

$$A+\frac{w}{8\lambda}(h\sigma_T^2+\Omega(\sigma_T^2+\sigma_P^2+\sigma_T^2(1-h))) \tag{A.6}$$

Comparing gives the incentive-compatibility constraint on the PM's choice for w and κ:

$$e \le \frac{w(1-h)}{8\lambda}\sigma_T^2(1-\Omega^C) \tag{A.7}$$

Execution costs: Applying Eqs. (5) and (6) to Eq. (7) gives expected transaction costs:

$$= \frac{\lambda}{2}Q^{PM2}-\frac{(1+4\Omega^C)}{8\lambda}\sigma_T^2+\frac{3\Omega^{C2}}{8\lambda}(\sigma_P^2+\sigma_T^2) \tag{A.8}$$

The first term is the default cost of execution (prorating the order evenly over two periods). The σ_T^2 terms reflect the trader's value-added conditional on effort and the σ_P^2 term reflects incremental price impact from asymmetric executions generated by manipulative trading (i.e., the expected cost of gaming).[24] Minimizing this gives Eq. (9).

A.2. Hypothetical VWAP derivations (Section 2.2)

The first-order condition for Eq. (11) with respect to Q_2 is

$$0 = -w\frac{\Delta P_2^*}{2}-\lambda w\Delta Q_2+wE_2\left[\Delta P_3^*\right]+w\frac{\Delta P_2^*}{2}+\lambda wQ_R+2\rho w^2Q_RVar[\Delta P_3^*]$$

$$Q_2 = \Omega^H\left(Q^{PM}+\frac{E_2[\Delta P_3^*]}{\lambda}\right)+(1-\Omega^H)(Q^{PM}-Q_1). \tag{A.9}$$

The period 1 first-order condition is (the expressions for Q_1 and Q_2 then follow):

$$0 = (wE_1[\Delta P_2^*]+2\lambda w\Delta Q_2)(1-\Omega^H)+wE_1[\Delta P_2^*]\Omega^H+2\lambda wQ_R\Omega^H+4\rho w^2Var_1[\Delta P_3^*]Q_R\Omega^H$$

$$0 = \frac{E_1[\Delta P_2^*]}{(1-\Omega^H)}+2\lambda(\Delta Q_2+Q_R) \tag{A.10}$$

Incentive compatibility: Risk-adjusted compensation is given by Eq. (11) using (12) and (13):

$$= A-wE_0\left(\frac{\Delta P_2^*}{2}(\Delta Q_2+Q_R)+\frac{\lambda}{2}\Delta Q_2^2+\Delta P_3^*Q_R\right)-w(\lambda+2\rho wVar_2\left[\Delta P_3^*\right])\frac{Q_R^2}{2}-effort$$

This expression involves several instances of $E_1[\Delta P_2^*]$ and $E_2[\Delta P_3^*]$. Using Eq. (5b),

$effort = e,$	$effort = 0$
$E_0[\Delta P_{t+1}^*E_t[\Delta P_{t+1}^*]] = \sigma_T^2$	$E_0[\Delta P_{t+1}^*E_t[\Delta P_{t+1}^*]] = h\sigma_T^2$
$E_0[E_t[\Delta P_{t+1}^*]^2] = \sigma_T^2$	$E_0[E_t[\Delta P_{t+1}^*]^2] = h\sigma_T^2$

Without effort, risk-adjusted expected compensation reduces to

$$= A+\frac{w}{8\lambda(1-\Omega^H)}(1+4\Omega^H(1-\Omega^H))h\sigma_T^2 \tag{A.11}$$

Similarly, with effort, risk-adjusted expected compensation is

$$= A+\frac{w}{8\lambda(1-\Omega^H)}(1+4\Omega^H(1-\Omega^H))\sigma_T^2-e \tag{A.12}$$

[24] All else equal, price impact is minimized by equally prorating the order across periods. Manipulative trading (in response to permanent price shifts) leads to an asymmetric proration and higher trading costs.

Incentive compatibility requires

$$\frac{w(1-h)}{8\lambda(1-\Omega^H)}(1+4(1-\Omega^H)) \geq e \quad \text{(A.13)}$$

Execution costs: Compensation for risk (using Eqs. (12) and (13)) is

$$\rho w^2 Var[\Delta P_3^*]E[Q_R^2] = \rho w^2 Var[\Delta P_3^*]\frac{\Omega^{H2}}{\lambda^2}\left(1+\frac{1}{4(1-\Omega^H)}\right)\sigma_T^2 \quad \text{(A.14)}$$

Applying demands (Eqs. (12) and (13)) to (7) and adding (A.14) gives

$$= -\frac{\sigma_T^2}{4\lambda(1-\Omega^H)}\left(1-\frac{1}{4(1-\Omega^H)}-\frac{(1-2\Omega^H)^2}{4(1-\Omega^H)} -\frac{\Omega^{H2}}{2\lambda(1-\Omega^H)}(\lambda+2\rho w Var[\Delta P_3^*])\right)$$

$$-\frac{\Omega^H\sigma_T^2}{\lambda}\left(1-\Omega^H-\frac{\Omega^H}{2\lambda}\right)(\lambda+2\rho w Var[\Delta P_3^*])+\lambda\frac{Q^{PM2}}{2} \quad \text{(A.15)}$$

which reduces to Eq. (14).

A.3. Hypothetical-I/S derivations (Section 2.3)

The period-2 first-order condition for Eq. (11) using Eq. (15) is

$$Q_2 = -\frac{\Omega^H}{2}\frac{P_2^T}{\lambda}+(1-\Omega^H)(Q_{pm}-Q_1) \quad \text{(A.16)}$$

The period-1 first-order condition is

$$0 = -wP_1^T - 2w\lambda Q_1 + 2w\lambda Q_R\Omega^H + 2w\lambda Q_2(1-\Omega^H) + 2\rho w^2 Var_1[\Delta P_3]Q_R\Omega^H \quad \text{(A.17)}$$

Using $2w\lambda Q_2(1-\Omega^H) = 2w(\lambda+\rho w Var[\Delta P_3^*])\Omega^H Q_2$, this reduces to Eq. (16).

Trading costs: Applying demands (Eqs. (16) and (17)) to Eq. (7), and adding the risk penalty $\rho w^2 Q_R^2 Var[\Delta P_3^*]$ gives, using $(\lambda+\rho w Var[\Delta P_3^*])\Omega^H = \lambda(1-\Omega^H)$:

$$= -\frac{1}{(2-\Omega^H)}\frac{\sigma_T^2}{2\lambda}+\frac{1}{(2-\Omega^H)^2}\frac{\sigma_T^2}{4\lambda}+\lambda W^2 Q_{PM}^2 -\Omega^H\frac{\sigma_T^2}{2\lambda}+\Omega^{H2}\frac{\sigma_T^2}{4\lambda}+W^2\frac{\sigma_T^2}{4\lambda}+\lambda W^2 Q_{PM}^2$$

$$+\lambda W\frac{\Omega^H}{(2-\Omega^H)}Q_{PM}^2+\lambda(1-\Omega^H)\Omega^H\frac{\sigma_T^2}{4\lambda^2}+\lambda W\frac{\Omega^H}{(2-\Omega^H)}\frac{\sigma_T^2}{4\lambda^2} \quad \text{(A.18)}$$

where $W = (1-\Omega^H)/(2-\Omega^H)$. After much algebra, this reduces to Eq. (18).

Incentive compatibility: Expected compensation is given by the expectation of Eq. (11):

$$= A - effort - wE[(P_1^T+\lambda Q_1)Q_1+(P_2^T+\lambda Q_2)Q_2+\lambda Q_R Q_R]$$

$$-wE[(P_1^P-P_0)Q_1]-wE[(P_2^P-P_0)Q_2]-wE[(P_3-P_0)Q_R] \quad \text{(A.19)}$$

All three of the latter expectations are zero, hence, expected compensation takes the same form as expected costs of execution, which is Eq. (18) with effort, and h times that without effort. This gives incentive-compatibility constraint:

$$-e+w\left(\frac{1}{(2-\Omega^H)}+\Omega^H\right)(1-h)\frac{\sigma_T^{2'}}{4\lambda} > 0. \quad \text{(A.20)}$$

A.4. Agency costs of delegated trading (Section 2.5)

Consider portfolio manager demands given the same information as the trader (know P^T). The aim is to choose deviations from the default quantity $Q^{PM}/2$ so as to minimize

$$\min E\left[(P_1^T+2\lambda q_1)q_1+\left(P_2^T+\frac{3}{2}\lambda q_2\right)q_2\right] \quad \text{(A.21)}$$

$2\lambda q_1$ reflects the round-trip price impact of trading distortions relating to P_1^T (reversed in period 2) and $\frac{3}{2}\lambda q_2$ reflects the round-trip price impact of trading distortions relating to P_2^T (reversed in the two periods of the next day). This yields

$$Q_1 = \frac{1}{2}Q_{PM}-\frac{P_1^T}{4\lambda}$$
$$Q_2 = \frac{1}{2}Q_{PM}+\frac{P_1^T}{4\lambda}-\frac{P_2^T}{3\lambda} \quad \text{(A.22)}$$

Replacing in Eq. (7) to get transactions costs gives

$$= -\frac{\sigma_T^2}{4\lambda}+\lambda\left(\frac{Q^{PM2}}{4}+\frac{\sigma_T^2}{16\lambda^2}\right) -\frac{\sigma_T^2}{3\lambda}+\lambda\left(\frac{Q^{PM2}}{4}+\frac{\sigma_T^2}{16\lambda^2}+\frac{1}{9\lambda^2}(\sigma_T^2)\right)+\frac{1}{18\lambda}(\sigma_T^2) \quad \text{(A.23)}$$

Comparing to Eq. (9) gives the excess costs associated with the agency relation:

$$\text{Agency cost} = \frac{h^2}{8\lambda}\sigma_P^2+\left[\left(-\frac{h}{3\lambda}\left(1-\frac{h}{2}\right)\right)\sigma_T^2\right]-\left[-\frac{1}{6}\frac{\sigma_T^2}{\lambda}\right] \quad \text{(A.24)}$$

Note that $h/3(1-(h/2))$ reaches a maximum of 1/6 at $h=1$. Thus, agency costs $>(h^2/8\lambda)\sigma_P^2$.

Price-adjustment delays: Eq. (19a) follows using Eqs. (5) and (6) and noting that $E_1[\Delta P_2^*] = P_1^T$:

$$\frac{\partial}{\partial \Delta P_2^P}\Delta P_2 = \frac{\partial}{\partial \Delta P_2^P}(\Delta P_2^P+\Delta P_2^T+\lambda\Delta Q_2) = 1+\lambda\left(-\frac{\Omega}{2\lambda}\right) = 1-\frac{h}{3} \quad \text{(A.25)}$$

Similarly, Eq. (19b) follows using Eqs. (5) and (6).

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