THE THREAT OF EXIT WITH OPTIMAL CONTRACTING: INSTITUTIONAL CHURNING TRADES AND SUBSEQUENT FIRM PERFORMANCE[*]

David R. Gallagher[† a,c]

Peter A. Gardner[‡ b,d]

Peter L. Swan[§ b]

Current Draft: July 8, 2009

[a] School of Finance and Economics, University of Technology, Sydney NSW 2007, AUSTRALIA
[b]Australian School of Business, The University of New South Wales, Sydney NSW 2052, AUSTRALIA
[c] Capital Markets CRC Limited, Sydney NSW 2000 AUSTRALIA
[d] Plato Investment Management, Sydney, NSW 2000, AUSTRALIA

ABSTRACT

The role of institutional investors on the register constitutes a significant puzzle. Concentrated investors could intervene (i.e., exercise "voice") so as to improve firm governance mechanisms. Alternatively, acting as informed traders, they could effectively discipline management if they adopt the "Wall Street rule" and engage in exit (Edmans and Manso (2009)). We derive the optimal incentive contract for a risk-averse manager in the presence of such traders. Then, utilizing unique daily institutional trading data, we show in conformity with the model: (*i*) a sizeable portion of institutional trading takes the form of "stock churning"; (*ii*) churning is profitable, (*iii*) profitability diminishes in the number of investors trading simultaneously; (*iv*) trading activity is associated with improved pricing efficiency in the form of lower spreads and market impact costs; (*v*) the number of investors trading simultaneously and magnitude of churning swings due to higher noise-trader volatility significantly improve long-term firm performance; (*vi*) when concentrated investors do not churn there is no long-term effect; and (*vii*) investors appear to recognize the benefit of making stock price more sensitive to managerial action since institutional stockholdings are higher in stocks that investors churn. Thus the "threat of exit" speaks more authoritatively than "voice".

JEL Classification: D82, G14, G23, G32
Keywords: Informativeness, Voting with your feet, Wall Street rule, Churning, Governance.

---

[*] Research funding from the Australian Research Council is gratefully acknowledged. The authors also thank Alex Edmans, David Feldman, Ron Giammarino, Jarrad Harford, André Levy, Ernst Maug, Mark Seasholes, Jianfeng Shen, Geoff Warren and seminar participants from the University of Sydney Microstructure Meeting, University of Western Australia, University of Queensland, University of Adelaide, the Reserve Bank of Australia, and the Australasian Finance and Banking Conference for helpful comments and suggestions on earlier versions of the paper.
[†] E-mail: david.gallagher@uts.edu.au
[‡] E-mail: peter.gardner@plato.com.au
[§] Corresponding author. E-mail: peter.swan@unsw.edu.au

1. Introduction

It is well known that concentrated blockholders either attempt to extract private benefits of control (e.g., Zweibel (1995), Barclay and Holderness (1989), and Laeven and Levine (2007)), or improve corporate governance (e.g., Shleifer and Vishny (1986), Admati, Pfleiderer and Zechner (1994), Maug (1998), Kahn and Winton (1998), and Mello and Repullo (2004)). Of critical importance is that both activities require direct intervention in one form or another in an effort to change the way the firm operates. In this paper we analyze a new and alternative form of "monitoring" based on the extraction of trading profits from a common signal of intrinsic future firm value which involves the selling down of stock on receipt of a bad signal. In our framework, direct intervention need never occur.

In the literature cited above in which shareholders exert governance through intervention there are positive externalities with the possibility that insufficient gains are captured to make intervention cost-effective. There exists, therefore, a free-rider problem that can be ameliorated by a blockholder eliminating smaller investors that put in insufficient governance effort. This blockholder monitors firm management by exercising blockholder "voice" (Hirshman (1970)), or via "lobbying", "influence", and other forms of direct intervention.

In contrast to conventional theory, in which it may be advantageous to become larger, a significant literature has developed in which the Wall Street rule and threat of exit discipline firm management.[1] Parrino, Sias and Starks (2003) show that some larger institutional investors are more likely to exit a poorly performing stock prior to a forced CEO departure. Gopalan (2008) shows that institutional selling is a predictor of subsequent poor performance and firm takeover. McCahery, Sautner and Starks (2009) find that 80 percent of responding institutional investors are willing to vote with their feet by selling their shares. Contributions to the theory include Noe (2002), Attari, Banerjee and Noe (2006), Admati and Pfleiderer (2008), Edmans (2008), and Edmans and Manso (2009) (hereafter, EM). EM hypothesize that "blockholders" earn positive returns by trading on a common signal of the future firm value. However, the model does not require that individual informed investors be large or in any sense blockholders. Consequently, we refer to them as simply informed investors or traders. The greater the number of informed investors, the more intensively they collectively trade so as to exploit the common signal. If the signal is good (bad), indicating the future price will increase (decline), it is in both the individual and collective interests of

[1] Lowenstein (1988) refers to the universality of the Wall Street rule (sometimes "walk").

all traders receiving the signal to buy (sell). Buying (selling) brings forward the inevitable price increase (decline) and hence rewards (punishes) the manager who either owns stock in the enterprise or has an incentive scheme in place. This "threat of exit" increases the price sensitivity of the stock to informative signals inclusive of managerial actions. Thus, it credibly rewards (penalizes) the stock-incentivized manager, who *ex ante* has greater incentive to provide effort by means of costly hidden actions.

While EM model a risk-neutral manager holding an exogenous share of the firm's stock for reasons of simplicity and tractability, we introduce a risk averse firm manager rewarded with the optimal equity share holding that maximizes firm value net of managerial cost. Our richer contracting environment provides a number of new insights and hypotheses: first, as stock price sensitivity increases due to more informed investors trading, the equity allocation to the manager falls due to higher stock price volatility (managerial risk). Nonetheless, managerial performance still improves so that stock price rises. Hence, we confirm the major prediction made by EM. Second, since uninformed "noise-traders" must take the other side of informed order flow, the more volatile the "noise-trader" demand, as indicated by the magnitude of the swings from peak to trough in churning trades, the greater will be the manager's equity allocation and hence the firm's subsequent performance. Third, the weaker is the informed investor informational advantage, the higher is the pay-performance sensitivity of the manager and the more aggressive is churning investor trading. Both promote higher firm performance.

In our framework, we interpret informed investors to be a group of institutional investors that set out to maximize short-term trading profits with no desire to monitor or intervene. In this paper, we establish the optimal managerial contract for the manager subject to multiple traders sharing a common signal. Moreover, the empirical predictions from our model are confirmed: more informed short-term trading ("churning") with short-term swings of greater magnitude gives rise to more disciplined firm management with both significantly better long-term firm and institutional investor performance.

We model an endogenous contract to demonstrate that effective monitoring is a serendipitous consequence of the desire by active institutional investors to earn short-term trading profits. Institutional investors, generally in receipt of managerial and broker information, compete to make profitable trading decisions. The signal of future value is rapidly incorporated into the current stock price. This makes stock price exceedingly sensitive to new information inclusive of managerial actions. Even though higher price sensitivity reduces stock allocation to the manager due to higher risk, the manager nonetheless responds with higher effort. Furthermore, we show that this form of trading competition creates long-term shareholder wealth. Alternatively, with conditions that are ideal for blockholder voice, we find that there is no impact on shareholder wealth. This could be due, in part at least, to our sample of investor-managers that does not contain a preponderance of large blockholders.

According to our contracting model, the more volatile are noise-trader demands and the lower the informational advantage of informed investors, the more aggressive is informed trading and the greater will be the beneficial impact of informed trading on the future stock price as the manager puts in more effort. Low informational advantage lowers stock price volatility, thus enabling higher pay-performance sensitivity for the risk-averse manager. This in turn raises managerial effort. In the light of this theory, we define trading that "threatens exit" as "churning" trades that involve short-term sequences consisting of either "buy-sell-buy" or "sell-buy-sell". Our first hypothesis (*H1*) is that this apparently quite irrational and costly churning activity forms a very significant proportion of all investment manager trades. Far from large shareholdings being predominantly stable, as is required for the exercise of the blockholder voice proposition, short-term churning is a major activity which forms a very significant portion of overall stock turnover. We indeed confirm this hypothesis. Second, for the trading view to be substantive, investment managers must be in receipt of valuable information. Thus churning must be profitable to undertake, even after accounting for trading costs and self-selection biases. Hence our second hypothesis (*H2*), which we also confirm, asserts that churning trades are profitable even after these costs are taken into account.

An additional requirement from the perspective of substantive trading is that all investment managers that choose to trade must receive a common signal. The value of this signal, as with the tendency for any underpriced resource to be over-exploited, must be less valuable to each individual investor, the greater the number of investors trading simultaneously on the same information. Hence our third hypothesis (*H3*) which asserts that institutional investor trading profitability is declining monotonically in the number of investors trading simultaneously. Once again, this hypothesis is supported.

Contracting is improved by a less informative signal as the manager bears less idiosyncratic volatility risk. While signal informativeness cannot be observed directly, it can be inferred from increased trade aggressiveness of informed traders as measured by the difference between the peak and trough in stock holdings induced by churning trades and by lower stock return volatility. We find a strong statistical relationship between stock churning activities and lower contemporaneous stock price volatility.

We propose a convergence between microstructure and corporate governance; so as to reveal important common empirical regularities between investment manager behavior and market quality. Hence our fourth hypothesis (*H4*) is that pricing efficiency as captured by lower bid-ask spreads, should be increasing in the number of institutional investors who are trading simultaneously. This decline in trading costs improves the sensitivity of the manager's incentive contract to the stock price, improving managerial performance. To the best of our knowledge, this trading cost hypothesis also provides a new empirical test of the Kyle (1989), Holden and Subrahmanyam (1992) and Foster and Viswananathan (1993) microstructure models utilizing actual data on the number of institutional investors from our representative sample trading simultaneously. We do find that spreads are lowered as more investment managers trade simultaneously.

Our fifth hypothesis is that the more institutional investors there are churning simultaneously (*H5A*), and the larger the magnitude of the swings in these churning trades from peak to trough through the churning sequence (*H5B*), the greater should be the firm's subsequent outperformance. Management is better disciplined when the overall trade aggressiveness (i.e., the collective threat of exit by institutional investors trading simultaneously due to stock churning and the strength in the underlying signal of intrinsic value) is greater. Such precision gives rise to greater aggressivity in our churning sequences as does highly volatile "noise" (i.e. uninformed) trading. Therefore, future performance is enhanced as stock price is now more sensitive to managerial actions. Once again, our findings support these twin hypotheses (*H5 A&B*).

If "voice" is effective in terms of improving governance, for example, then subsequent firm performance should be higher the fewer are the number of institutional investors trading simultaneously. This concentration ameliorates the free-rider problem. Hence our sixth hypothesis (*H6*) asserts that if conditions are ideal for exercising blockholder voice there will be no long-term out- or under-performance. Our criterion for the easy exercise of voice is that there are two or fewer institutional investors holding the stock in our sample and that they be overweight the stock with the absence of churning trades. We find no significant impact under these conditions.

Do institutional investors act as if they understand that churning enables profits to be increased in the longer term by price appreciation of existing stock holdings? Hence our seventh (and final) hypothesis (*H7*) is that existing investor stockholdings are increasing in the degree of churning activity, so as to reap these longer-term profits. We find that institutional investors are more likely to be overweight (relative to index weight) in a stock if the investor is also an intensive churner in that stock. Could investors make unprofitable churning trades and make up for losses on these from long-term holdings? Not according to our theory. Unprofitable and hence uninformed trading does not improve future performance by incorporating new information into stock price.

Our study is organized as follows. Section 2 provides a review of the literature, and 3 provides the theory that forms the basis of our testable hypotheses. Section 4 provides a description of the data and institutional arrangements impacting on the investment management process for our sample of institutional investors. Section 5 exposits our methodology based on churning trades, which we represent as trade package sequences executed within a three-month period. Section 6 presents the empirical results, and the final section makes suggestions for future research.

2. Literature Review

Additional to the theoretical literature on exercising voice cited above, Burkart, Gromb and Panunzi (1997), Bolton and von Thadden (1998), and Faure-Grimaud and Gromb (1997) examine the limits to control of a single blockholder due to other concerns such as liquidity and the free float. In Winton (1993), intervention is most effective with a single blockholder due to the free-riding problem. Bennedsen and Wolfenzon (2000) examine efficiency reasons for coalitions of blockholders. Maury and Pajuste (2005) and Gomes and Novaes (2006) also examine optimal blockholder composition.

The literature on the effectiveness of the exercise of intervention (voice) due to activism or control is mixed. McConnell and Servaes (1990) find some evidence of an impact of institutional ownership on Tobin's q in conjunction with insider ownership. Gillan, Kensinger and Martin (2000), Clifford (2008), Chen, Harford and Li (2007) and Del Guercio, Seery and Woidtke (2008) all find some beneficial impacts of shareholder activism. Becht, Franks, Mayer and Rossi (2008) indicate successful intervention by an activist fund. Cronqvist and Fahlenbrach (2008) find a correlation between blockholders with more monitoring ability and beneficial effects. In the same vein, Hartzell and Starks (2003) and

Almazan, Hartzell and Starks (2005) find a negative impact on the level of CEO compensation but Ferreira, Laux and Markarian (2009) find the reverse.[2] Similarly, Davis and Kim (2007) find for their sample of mutual funds that institutional investors always vote for higher managerial pay in support of management. Karpoff, Malatesta and Walkling (1996), Wahal (1996), Del Guercio and Hawkins (1999), and Gillan and Starks (2000) do not find much evidence of longer-term improvement from blockholder activism.

A difficulty that is commonly neglected by advocates of the efficacy of intervention and voice is that most large firms do not appear to have just one or two major blockholders. Such a structure is required to minimize free-riding. Accordingly, it is implied by the voice hypothesis. In fact, most such firms have a larger number of blockholders (see, e.g., Barca and Becht (2001), Faccio and Lang (2002), Maury and Pajuste (2005), Dlugosz, Fahlenbrach, Gompers, and Metrick (2006), Laeven and Levine (2007), Gregoric, Alekandra, Masten and Zajc (2008), Holderness (2009), and Brockman and Yan (2009)). For example, Dlugosz, Fahlenbrach, Gompers, and Metrick (2006) show that the average U.S. firm in their sample has 2.5 blockholders with a minimum of a 5 percent holding and 70 percent of firms have multiple blockholders.

The theoretical origins of the threat of exit as a disciplinary device lie in the link between stock prices and managerial effort as modeled in the seminal work by Holmstrom and Tirole (1993). More recently, Calcagno and Heider (2008**)** extend the Holmstrom and Tirole model by positing whether more noise trading improves managerial contracting. Noe (2002) provides the first model to propose that multiple blockholders might be beneficial to institutional monitoring and hence firm performance. However, there is no informational signal common to all blockholders forming the cornerstone of our approach.

Admati and Pfleiderer (2008) and Edmans (2008) have each recently proposed models of blockholder exit. Where they differ from us and EM is in only considering the one blockholder. A nice feature of EM's model is that it explains why institutional trading volume is so high. Informed traders in receipt of a common signal will trade excessively from the perspective of any individual trader. When there are multiple investors, all receiving essentially similar private information as in Kyle (1989) and Holden and Subrahmanyam (1992), competition quickly impounds new information into prices. Consistent with these models, Brennan, Jegadeesh and Swaminathan (1993) find that the prices of stocks with more

[2] See also, Smith and Swan (2008a).

analyst-followers adjust more rapidly to new information. Using the number of analyst-followers as a proxy for the number of informed traders, Brennan and Subrahmanyam (1995) find an association between more analyst-followers and market depth in the form of the Kyle lambda. However, apart from these indirect tests, we are unaware of studies utilizing actual data on the number of institutional traders so as to provide rigorous tests of these seminal models.

We now turn to empirical tests of models of exit. Wermers (2000) provides a comprehensive long-term analysis of mutual fund performance, showing that high turnover funds on average out-perform the Vanguard Index 500 fund on a net of transaction costs basis. Garvey and Swan (2002) provide the first empirical tests of the Holmstrom and Tirole (1993) model to show that boards tend to delegate pay to the market through incentives when the stock price is informative due to blockholder trading. Deli (2002) shows that institutional managers with the highest stock turnover receive the highest marginal rewards, indicative of high informational content and profitability of institutional trading. Faure-Grimaud and Gromb (2004) show that higher stock liquidity causes the sensitivity of the firm manager's stake to become greater. This in turn improves incentives. Maury and Pajuste (2005) find that a more equal distribution of investors raises firm value. Sias, Starks and Titman (2006) provide evidence that institutional traders possess information that impacts permanently on prices. Agarwal (2007) finds evidence that it is institutional investors that gives rise to stock liquidity rather than any attraction that liquid stocks may have for such investors. Rubin (2007) finds that institutional ownership is associated with stock liquidity, and institutional concentration with adverse selection and illiquidity. These results are supportive of our hypothesis three (*H3*) on the impact of institutional trading. Smith and Swan (2008b) find that the smaller holdings of active traders – hence relatively short-term investors for whom the threat of exit is highest (not long-term owners) – are associated with an increase in the CEO's incentives. Boehmer and Kelley (2008) show that stocks with greater institutional ownership are more efficient, in that prices more closely follow a random walk, but they do not show how this arises from having more investors sharing the same informative signal. Yan and Zhang (2008) find that that short-term trading by institutions forecasts future returns. These results are supportive of our finding that short-term trading by institutional investors drives both institutional performance and future returns.

As already indicated, the theoretical literature also recognizes the possibility of rent extraction. Thus, not all actions by blockholders need be beneficial to shareholders.

According to Burkart, Gromb and Panunzi (1997), such actions could represent a threat of expropriation that reduces managerial initiative. Zwiebel (1995) builds on the literature related to the private benefits of control. While noting that most firms have multiple blockholders, he shows that there could be controlling coalitions formed to extract these benefits.

3. Optimal Contracting With Informed Traders

Our model is a modified and extended version of EM, who consider the trading behavior of a group of multiple informed investors receiving a signal concerning the firm's future fundamental value that is more reflected in the contemporaneous stock price the larger the number of informed traders. EM take the risk-neutral manager to receive an arbitrary and fixed proportion of the firm's shares only, with no fixed or non-share-price based compensation. This is because for their main predictions they can safely dispense with the compensation contract as we show. We introduce an optimal managerial contract for a risk-averse manager who is rewarded for stock price performance. In the first stage the manager takes actions $a \in [0,\infty]$ that affect firm value, $\tilde{v}$:

$$\tilde{v} = \phi_a a + \phi_b \log \sum_i b_i + \tilde{\eta}\,. \tag{1}$$

Nature determines a value v for the firm's equity from a normally distributed value $\tilde{v}$ with mean $\mu \equiv \phi_a a + \phi_b \log \sum_i b_i$ and variance σ_η^2.[3] The mean μ depends on unobservable effort taken by the firm manager ($\phi_a a$, *i.e.*, costly effort *a*, scaled by productivity, ϕ_a), and public actions taken by *N* symmetric investors ($\phi_b \log \sum_i b_i$, *i.e.*, investor *i*'s costly effort in the form of intervention or voice, log b_i, scaled by investor productivity, ϕ_b) in the first (*action*) period. Investors, observing the drawing *v*, uniquely obtain the true value of the asset[4] and thus receive an informational advantage increasing in the variance, σ_η^2. While a higher variance is beneficial from the perspective of the profitability of blockholder trading, it is costly in terms of providing incentives for management as it disguises the actions of the manager and the higher volatility risk imposed on the manager reduces stockholding.

The manager's total income *I* is:

---

[3] Note that in the EM formulation, firm value depends on the log of effort rather than its level.

[4] It is relatively straight forward to extend the model to one in which each blockholder observes only an imperfect signal, *s*, of the true value such that $s = v + \varepsilon$, where ε is a normally distributed error term with zero mean.

$$I = \alpha_0 + \alpha_p p \,. \tag{2}$$

It consists of a fixed wage, α_0, plus an equity share, α_p, of the stock price, p. The risk averse manager's CARA utility function depends on the manager's income less cost of effort, $U_m(a) = -\exp\left[-\rho_m\left(I - \frac{1}{2}a^2\right)\right]$, where ρ_m is the manager's coefficient of constant absolute risk aversion and $\frac{1}{2}a^2$ is the manager's quadratic cost of effort function.

Risk-neutral owners choose the parameters of the manager's incentive contract so as to maximize the expected value of the firm net of the manager's income:

$$\max_{\alpha_0, \alpha_p} \mathrm{E}\left(\tilde{v} - I\right). \tag{3}$$

This is maximized subject to the incentive compatibility constraint such that the manager's expected utility is maximized:

$$a = \arg\ \max_{a^*} E\left\{-\exp\left[-\rho_m\left(I - \frac{1}{2}a^{*2}\right)\right]\right\}, \tag{4}$$

where the superscripted * indicates the optimal value. In turn, this is equivalent to the manager's certainty equivalent wealth:

$$a = \arg\ \max_{a^*} E\left(I\right) - \frac{\rho_m}{2} Var\left(I\right) - \frac{1}{2}a^{*2}, \tag{5}$$

where $Var(I)$ denotes the variance of managerial income, and subject to the manager's participation constraint:

$$E\left(I\right) - \frac{\rho_m}{2} Var\left(I\right) - \frac{1}{2}a^2 \geq \overline{I} \,. \tag{6}$$

Outside opportunities are reflected in reservation income, $\overline{I}$.

There are *N* symmetric risk-neutral blockholders each with holdings of $\frac{\psi}{N}$ shares in the firm and with each submitting a market order, $x_i\left(\tilde{v}\right)$, after observing the true (common) value of the firm, v. Uninformed risk-neutral (noise) traders submit market orders $\tilde{u}$ with mean zero and variance, σ_u^2. We normalize the price and incentive contract to place it on a gross (i.e., pre-management compensation) basis.[5] The normalization procedure results in the definition of the gross (normalized) share price as $\hat{p} = \alpha_0 + (1+\alpha_p)p$ and normalized manager income as, $I = \hat{\alpha}_0 + \hat{\alpha}_{\hat{p}}\hat{p}$. The first-order condition for maximum manager utility, a^*, yields:

$$a^* = \phi_a \left[\hat{\alpha}_{\hat{p}} E\left(\frac{d\hat{p}}{dv} \right) \right]. \tag{7}$$

We follow EM for our analysis of trading demands. The normalized market-clearing price, $\hat{p}(\tilde{z})$, is set by the competitive market maker who observes only the total order flow, $\tilde{z} = \sum_i \tilde{x}_i + \tilde{u}$, made up of the informed trader demands and normally distributed noise trades, $\tilde{u}$.[6] Competition drives market-making profits to zero. Since traders are symmetric, aggregate informed market orders, $Nx_i(\tilde{v})$, are given by the linear equation:

$$Nx_i(\tilde{v}) = \frac{N}{N+1}\frac{1}{\lambda}(\tilde{v}-\mu) \equiv \frac{\beta}{\lambda}(\tilde{v}-\mu), \tag{8}$$

with variance $Var(Nx_i) = N\sigma_u^2$ increasing in noise trading volatility, where the Kyle (1985) lambda, $\lambda = \frac{\sqrt{N}}{N+1}\frac{\sigma_\eta}{\sigma_u}$, $\mu \equiv \phi_a a + \phi_b \log \sum_i b_i$ as before, $\beta \equiv \frac{N}{N+1}$, $\frac{\beta}{\lambda}$ is the aggregate trade aggressiveness parameter, and $-\frac{\beta}{\lambda}\mu$ is the intercept for the linear equation that informed traders treat as given. Lambda represents the sensitivity of price to market order flow, $\tilde{z}$, with the normalized price, $\hat{p}(\tilde{z}) = \mu + \lambda\tilde{z}$. It is increasing in the value (standard deviation) of the informative signal and decreasing in noise trader volatility. Hence, a low informational advantage is desirable as it reduces market impact costs and thus encourages beneficial churning activity. For $N > 2$ lambda is diminishing in the number of informed traders. Since we proxy lambda by the bid-ask spread, this constitutes our fourth hypothesis (H4). The collective informed order-flow representing our churning trades, Nx_i, is increasing in β, and hence in the number of blockholders at the rate of $\sqrt{N}$ and is diminishing in the Kyle lambda

[5] In the context of a different model, both Holmstrom and Tirole (1993) and Calcagno and Heider (2007) recognize the need to normalize by grossing up.

[6] While the Australian stock market (ASX) does not technically have formal market makers the entire limit order book is visible with no barriers to liquidity provision. These liquidity providers are equivalent to market makers on the NYSE.

as informed trading is more aggressive when market impact costs are low. Swings in churning trades will be of greater magnitude when noise trading is very volatile, market impact costs low, and a large number of informed investors participate. These findings all play a role in hypotheses H5 A and B.

While the overall market order flow observed by the competitive market maker is decomposed into two components, $\tilde{z}(\hat{p}) = \frac{\beta}{\lambda}(\tilde{v} - \mu) + \tilde{u}$, the market maker cannot distinguish between the first informed component and the second that is uninformed.

The normalized price grossed up by payments to the manager becomes:

$$\hat{p} = \alpha_0 + (1 + \alpha_p)p = E[\tilde{v}|z] = \mu + \lambda z = \mu + \beta(\tilde{v} - \mu) + \lambda\tilde{u}, \tag{9}$$

on substituting for the informed blockholder portion of the aggregate order flow, z. The product as shown by EM

$$\beta = \frac{Var(v) - Var(v|\hat{p})}{Var(v)} = E\left[\frac{d\hat{p}}{dv}\right], \tag{10}$$

represents the magnitude of the aggregate informed order flow in equation (9). It specifies the degree of price informativeness in stock price. Informativeness captures the degree to which the informative signal is incorporated in the contemporaneous stock price. This is increasing in the number of informed traders at the rate, $\frac{dE\left[\frac{d\hat{p}}{dv}\right]}{dN} = \frac{d\beta}{dN} = \frac{1}{(N+1)^2} > 0$, hence providing the overall motivation for the paper. The reason that managerial effort only indirectly affects the market clearing price is because only trading activity that affects the informed order flow is acted on by the market maker. Changes in managerial effort that are not reflected in order flow cannot have any direct impact on stock price.

As shown by EM, the expected trading profit for the *i*th blockholder, $\pi_i(N) = E[(\tilde{v} - \mu - \lambda\tilde{y})x_i|\tilde{v} = v]\forall i$, is maximized to yield:

$$\pi_i(N) = \frac{1}{\sqrt{N}}\frac{1}{N+1}\sigma_\eta\sigma_u = \frac{\lambda}{N}\sigma_u^2 > 0, \tag{11}$$

with aggregate trader profitability simply given by $\sum_{i\in N}\pi_i = N\pi_i = \lambda\sigma_u^2$, the product of lambda and the variance of noise trader demand. Hence, we have hypothesis 2 (H2): expected informed blockholder trading profit is profitable as both the standard deviations, σ_η and σ_u, are positive. At the individual trader level, profitability is increasing in the informational advantage of the common signal as to firm value, σ_η, and the volatility of noise trader order flow, σ_u, and diminishing in the number of informed blockholders, *N*. This constitutes our hypothesis three (H3).

The price variance, $Var\left(\hat{p}\right) = \sigma_\eta^2\beta$, computed from the pricing equation (9) is increasing in price informativeness, β, and in the variance of the investor's informational advantage, σ_η^2, and $Corr(v,\hat{p})^2 = E\left[\frac{d\hat{p}}{dv}\right] = \beta$. A low informational advantage is preferable as it enables a higher equity allocation to the manager as a consequence of lower risk.

The transformed components of the incentive contract in gross form can be expressed in terms of the net or observable elements as $\hat{\alpha}_0 = \frac{1}{1+\alpha_p}\alpha_0$ and $\hat{\alpha}_{\hat{p}} = \frac{\alpha_p}{1+\alpha_p}$, with optimal effort, $a^* = \phi_a\beta\hat{\alpha}_{\hat{p}}$, on substituting the relevant values into equation (7). Optimal effort is thus proportional to the normalized equity share allocated to the firm manager. It is also increasing in price informativeness for a given managerial share allocation, as was noted by EM.

The firm's (inside shareholder's) problem is to maximize expected cash flows net of payments and share transfers to management, and subject to the manager's participation constraint given by equation (6), by the appropriate choice of the share allocation, $\hat{\alpha}_{\hat{p}}$:

$$\begin{aligned}&\max_{\hat{\alpha}_{\hat{p}}} E\left(\tilde{v} - I\right)\\ &s.t.\, E\left(I\right) = \frac{1}{2}\left(\phi_a\beta\hat{\alpha}_{\hat{p}}\right)^2 + \frac{\rho_m}{2}Var\left(I\right) + \overline{I}\end{aligned} \tag{12}$$

On simplifying by eliminating $E\left(I\right)$ using the participation constraint, the objective becomes:

$$\max_{\hat{\alpha}_{\hat{p}}}\left[\left(\phi_a\right)^2\beta\hat{\alpha}_{\hat{p}} + \phi_b\log\sum\nolimits_i b_i - \frac{1}{2}\left(\phi_a\beta\hat{\alpha}_{\hat{p}}\right)^2 - \frac{\rho_m}{2}\left(\hat{\alpha}_{\hat{p}}\right)^2\beta\sigma_\eta^2 - \overline{I}\right] \tag{13}$$

since $E(\tilde{v})=(\phi_a)^2\beta\hat{\alpha}_{\hat{p}}+\phi_b\log\sum_i b_i$. The optimal solution to the inside shareholder's allocational problem is:

$$\hat{\alpha}^*_{\hat{p}}=\left[\beta+\frac{\sigma^2_\eta\rho_m}{(\phi_a)^2}\right]^{-1}. \tag{14}$$

Proposition 1: The manager's optimal incentive share allocation is diminishing in his degree of risk aversion, ρ_m, and also in the degree of price informativeness, β, since a larger number of informed traders raises stock price volatility. The allocation is also diminishing in the variance of the informative signal, σ^2_η, as higher stock price volatility due to information increases the manager's risk burden.

Optimal effort is given by,

$$a^*=\phi_a\beta\hat{\alpha}_{\hat{p}}=\phi_a\left[1+\frac{\rho_m\sigma^2_\eta}{(\phi_a)^2\beta}\right]^{-1}. \tag{15}$$

This represents a maximum rather than a minimum, as the second-order condition for a maximum is satisfied. As the manager becomes less risk-averse ($\rho_m\to 0$), the optimal equity allocation, $\hat{\alpha}^*_{\hat{p}}\to\frac{1}{\beta}$. Moreover, optimal effort, $a^*\to\phi_a$, which is the first-best solution. Hence, in a limiting first-best world without risk aversion, firm performance is independent of the degree of price informativeness.

Proposition 2: Since $\frac{\partial a^*}{\partial\beta}=\frac{(a^*)^2\sigma^2_\eta}{\phi_a^3\beta^2}>0$, effort is increasing in price informativeness. This is despite our finding that higher price informativeness reduces the equity-based incentive for the manager to exert effort for a given informational advantage. Moreover, because $\frac{da^*}{d\sigma^2_\eta}=-\frac{(a^*)^2\rho}{\phi_a^3\beta}<0$, effort increases with falls in the informational advantage of informed traders. Recall also from the impact of informativeness on trader aggressiveness that a low informational advantage results in more churning as the adverse price impact of trades is reduced. This establishes hypothesis 5 (H5). Firm performance is increasing in price informativeness, β (H5A). It is also diminishing in the trader informational advantage, σ^2_η. Lower informational advantage increases trade aggressiveness (equation (8) above) so that swings of greater magnitude in churning trades between the peak and trough is associated with reduced informational advantage. This in turn implies higher future firm performance (H5B) as CEO effort increases. Thus in our framework, greater stock market liquidity translates into subsequently higher asset prices but solely through its impact on CEO effort.

While in our propositions we model investors improving performance by trading on the basis of information, Dow and Gorton (1997) explain "excessive" trading by institutional investors with respect to delegated portfolio management, in terms of clients unable to distinguish between managers "simply doing nothing" and "actively doing nothing" by trading to excess, e.g., by "churning". Ours is one of the first studies to adjudicate between the informational hypothesis on the one hand, and the Dow and Gordon client-exploitation hypothesis on the other.

Our model incorporates an important feature of EM's model. If the productivity of direct intervention, i.e., voice, is high, $\phi_b > \phi_a$, and there is little scope for free-riding in the sense that there is very little stock churning, the number of trading participants is small and institutional investors are overweight the stock, then the model predicts subsequent outperformance due to voice. This constitutes hypothesis 6 (H6).

4. Data and Institutional Arrangements

As noted above, in order to provide formal empirical tests of the nested EM hypotheses, together with the first tests of the associated Kyle (1985,1989) and Holden and Subrahmanyam (1992) models, requires identification of the number of agents trading, inclusive of very detailed short-term trading data, replete with trader identities and detailed transactions costs. The *Portfolio Analytics Database* contains proprietary information pertaining to the daily trades and portfolio holdings of Australian investment managers in the domestic equities asset class. It is thus not focused solely on large blockholders. Index fund managers were excluded. The investment managers were each requested to provide information for their two largest institutional pooled Australian equity funds.

The institutional funds data was individually collected from the portfolio managers with the support of Mercer Investment Consulting and contains historical information from 2nd January 1994 to 30th June 2002. Our sample of actively managed institutional Australian equity funds employed in this study comprises 38 funds from 30 unique active institutions. All Australian equity funds in this database are benchmarked to either the S&P/ASX200 or

S&P/ASX300 indices.[7] This database provides a sample that is representative of the Australian investment management industry, and includes data from six of the largest ten fund managers, six from the next ten, four from those managers ranked 21-30 and 14 managers from outside the largest 30 (by funds under management as at 31 December 2001). The sample also includes six boutique firms, which manage less than $A100 million each.

Strictly speaking, our dataset constitutes around ten percent of funds under management in the asset class as reported by the fund performance monitoring firm ASSIRT (now owned by S&P). However, if the data that fund managers provide is representative of their entire Australian operations, as the fund managers' claim, then the effective coverage is over 50 percent as 12 of the top 20 fund managers provide us with data. The magnitude of our sample can be compared with the response rate to the McCahery, Sautner and Starks (2009) governance survey which was also ten percent.

In Table 1 we summarise the holdings according to the number of stocks held by individual managers and the holdings for two managers where they belong to the same family. The latter is shown in Panel B. It can be seen from Panel B that if we adopt the usual definition of a blockholder owning five percent or more of a stock then the mean is only 30 stocks that qualify. At the other extreme, the mean number of stocks held where the fund manager owns 0.5 percent or more is 157. In Panel C we show the number of churned stocks within each category. The mean number of stocks churned in the blockholder category is only 2.4. It rises to 30.5 in the 0.5 percent or more category. Hence, our sample of investment managers does not consist typically of blockholders according to the standard definition. Moreover, stock churning is more likely to occur in stocks where our managers hold less than two percent of the shares on issue. Hence, churning activity is symptomatic of smaller institutional holdings rather than blockholdings. As indicated above, there is no requirement in either EM or our model that the Wall Street rule be confined to blockholders.

The *Portfolio Analytics Database* includes historical month-end portfolio holdings and daily trading data for Australian equity managers. The data fields obtained from the fund managers for their daily trading activities includes the date of execution, ASX stock code and name, quantity traded, daily weighted average price of the trade, the explicit transaction costs

[7] The S&P/ASX 200 (300) Index represents a market capitalization weighted return of the largest 200 (300) Australian stocks. The performance and market capitalization of both indexes are highly similar, given that the additional 100 securities in the S&P/ASX 300 contribute only a very small fractional increase in market coverage over the S&P/ASX 200.

(brokerage) incurred and even the identity of the broker. We received a complete data dump of all trades and holdings for that period (including equities, convertibles, options and futures etc.). The ASX Stock Exchange Automated Trading System (SEATS) data of stocks traded and access to the ASPECT database for the calculation of book-to-market ratios and dividend franking information for each stock was provided by SIRCA Limited.[8]

5. "Churning Trades" Methodology

We seek to identify institutional investors who aim to achieve trading profits rather than the extraction of the private benefits of control or direct intervention to impose better governance. To do this we focus on what appear to be the least explicable (at least up until now) short-term trading sequences made by institutional investors that take the form of "churning" trades.[9] Thus, ironically, we look for investor-client and firm shareholder benefits from what appears, superficially, to be an unlikely quarter, according to the Dow and Gordon (1997) critique of investment mangers. These trades consist of a "buy" package followed by a "sell" package and then a "buy" package ("BSB" sequence), or a "sell" followed by a "buy" and then another "sell" ("SBS" sequence) in a particular stock. We define a trade package sequence following Chan and Lakonishok (1995), which captures all trades over multiple days in the same direction for each stock, and not more than five working days apart from one another. It is the daily nature of our institutional trades that enables us to implement this methodology. The trade package would also be closed off if there is a reversal trade in the same stock, which would then be defined as the first trade in the next trade package. Our methodology requires that these trade sequences be completed within a three-month period of the first trade in the first trade package so as to only capture short-term trading activity that is by its nature hardest to explain.

Why single out only churning sequences as opposed to simple "buys", "sells", "buys" followed by a "sell", "sell" followed by a "buy", and so on? Apart from our theory which states that the greater the precision in the informed signal the greater is trading aggressiveness, the higher is the manager's equity share, and the better the subsequent outperformance, our justification is as follows: a "buy" in isolation may indicate good news and thus subsequent outperformance over the long-term but involves no "threat of exit".

[8] Securities Industry Research Centre of the Asia-Pacific.

[9] We deliberately use the word "churning" because of the pejorative use of the term by critics of active managers, not because we believe that short-term trading is necessarily damaging to investors when there is delegated management.

Similarly, a "sell" in isolation may indicate bad news even in the long-term and thus confound any long-term outperformance due to "threat of exit".[10] Moreover, a "buy" followed by a "sell" sequence may indicate bad news, and *vice versa*, good news, without necessarily providing an unambiguous "threat of exit". By contrast, the churning trade sequences best captures the EM notion of a threat of exit combined with both aggressive buys and sells consistent with large swings and a less advantageous signal. Only our churning trades are relatively "neutral" with respect to net holdings, which change little and thus can encapsulate the threat of exit story while also being inconsistent with a simple "optimism" or "pessimism" informational story. Moreover, the lower are stock holdings at the trough relative to the peak in either of the two sequences (i.e., the greater the swing), the greater is both the threat and the volatility of noise traders taking the other side of these trades. Hence, the magnitude of the swing provides an additional related test (*H5 B).*

In order to test our proposition that churning trade sequences better reflect the threat of exit, we examine two additional subsidiary hypotheses relating to the main hypothesis five (*H5 A*): (*H5 S1): that the short-term trade sequence – "buy followed by a 'sell"* and *(H5 S2): a "sell" followed by a "buy" – each result in significant subsequent outperformance, but considerably less than with a churning sequence*. Both subsidiary hypotheses are empirically supported.

6. Empirical Results

A. Significance of Stock Trading and Short-Term Churning Trades

In this section we determine the nature and significance of equity stock trading by our sample of actively managed institutional equity funds and the significance of short-term churning within this overall pattern of trading. We employ the methodology of Wermers (2000) who decomposes equity mutual fund returns into the transaction costs incurred and net returns after transaction costs.[11] We calculate overall turnover as the average of buys and sells, during a certain period.[12] Transactions costs are calculated using explicit brokerage costs provided by managers. However, given that four of our sample of investment managers

---

[10] For example, Gopalan (2008) uses large acquisitions by a firm possessing a blockholder to identify agency problems. He then relies on "sells" by the dominant blockholder to predict falling returns and poor operating performance followed by acquisition.

[11] A further breakdown of our sample into Wermers (2000)-style characteristics is available from the authors on request but for space reasons has not been included here.

[12] When we calculate turnover as the minimum of buys and sells, we achieve similar results.

did not provide the brokerage costs for their trades, we modeled brokerage costs using the data we did have, thereby estimating the brokerage for the missing values. Missing values comprise less than 8.6 percent of our trades by value (21.5 percent by number). Thus, using the betas from these regressions, we can estimate the brokerage costs for the remaining managers.[13] We subtract the total transaction costs from a manager's gross return to obtain their net return. Excess returns are the calculated returns over the S&P/ASX 300.

Our descriptive statistics on overall turnover and transaction costs for the entire sample of investment funds are shown in Table 2. The average annual turnover rate is 76 percent for our sample of investment managers with the more active investors incurring significantly higher transaction costs than the less active. Investors do not appear to be penalized for this activity as there is no statistically significant net return penalty. This lack of net return penalty suggests that investment managers do not trade to simply keep up appearances, "actively doing nothing", or because of behavioral biases which might favor "excessive" trading. In fact, an overarching aim of this paper is to provide a satisfactory rationale for otherwise puzzling trading and churning activity.

(INSERT TABLE 2 ABOUT HERE)

Table 3 provides descriptive statistics of overall trades for our sample of investment managers and churning trades split into both "all buys" and "all sells" on the one hand and churns commencing with a "buy" (i.e., "BSB") and churns commencing with a "sell" (i.e., "SBS") that are completed within a three month horizon. All daily trades are split up into packages representing the underlying orders following the rules laid down by Chan and Lakonishok (1995). These churning trades make up 33.5 (38.9) percent of our investment manager trades (trade volume), although 65.8 percent of these trades occur in the largest stocks, compared with 52.6 percent of all trades.[14] This establishes our first hypothesis *(H1): that short-term churning trades comprise a significant portion of the overall trading volume for our sample of investment managers*. Moreover, trading volume is itself quite significant. When we analyze the number of days over which these trades are completed, we find similar percentages comparing churning trades with all institutional trades in our database. When we analyze all fund manager trades, we find packages make up on average 85 percent of the average daily trading volume, indicating that active institutional investors are "stealth

[13] The transaction cost regression equation is set out in Appendix B, Table BI.

[14] Table AI in Appendix A provides a breakdown of both buy and sell trades and churns by the number of blockholders trading simultaneously.

traders" that split up the majority of their trades over multiple days so as to more effectively disguise information revealed via trading.

(INSERT TABLE 3 ABOUT HERE)

B. Profitability of Churning Trades and Self-Selection Bias

Our "threat of exit" model requires investors to observe a common signal of future stock value and to trade profitably based on this signal. Hence, our second hypothesis, *H2: both "BSB" and "SBS" churning trades completed within three months are directly profitable to institutional investors, even after taking account of transaction costs and any self-selection bias due to focusing on only a sub-sample of trades, namely churns.*

We now investigate whether the churning trade sequences identified in Table 3 meet our criteria. In Table 4, we measure the excess return around fund manager trades that fit the criteria, such that three successive trade packages (defined according to the Chan and Lakonishok (1995) approach) would be a purchase (sale), sale (purchase) and purchase (sale).[15] These successive three trades must be completed within three months (or the period shown on the left of the table). For example, a trading sequence whereby a manager purchases, then sells, then sells again (after a break of more than five days, so that the trades are not packaged together), before lastly purchasing would not be included, as it does not fit our criteria for our churning sequence. This particular trading sequence would be classified as a purchase, followed by a sale, and then a sale followed by a purchase. We find that, indeed, such sequences do improve future performance but to nothing like the extent of our churning sequences (see Section 6(E) below).

(INSERT TABLE 4 ABOUT HERE)

In addition to the reasons outlined in Section 4 above, which focus on "churning" trade sequences, we wish to include only those trades completed from a short-term perspective. This requirement implies, on the one hand, that fund managers are not building a significant long-term position that could be either strategic or indicate prior knowledge of long-term performance, and on the other, that they are not actually exiting the stock. If managers were to complete multiple purchases (sales) in a row (over a period of more than

[15] Chan and Lakonishok (1995) use a five-day gap definition of a package, implying a new package begins if there is a five-day gap between manager trades (in the same direction), or if the manager executes a trade in the opposite direction.

five days, as trades in the same direction), this suggests they are not engaging in short-term trading so as to threaten exit, but are rather building up (eliminating) a larger strategic position. In Section 6(E) below, we compare the outperformance arising from trading sequences other than churning trades with the long-term performance of churning trades. We show a significantly better performance from churning trades.

We calculate the return using the actual volume-weighted-average-price (VWAP) that the manager obtains for their trades and we subtract (add) the explicit transactions costs from post-purchase (post-sale) excess return.[16] All returns are calculated as excess returns relative to the S&P/ASX 300, although using actual returns yields similar results.

In Panel A of Table 4, we find that fund managers profit from all trades in the "BSB" churning sequence and similarly for the "SBS" sequence in Panel B, which confirms the second hypothesis. We also observe in total, the net excess return to five days after the second purchase is 1.69 percent (0.82 – (-0.59) + 0.28). In Panel B, fund managers profit after the initial sale and the reversing purchase, but not after the subsequent sale. The total net excess return to sales in Panel B is 0.71 percent (- (-0.58) + 0.55 – (0.42)). When these short-term trading sequences are partitioned by the number of days in which they take place, we find that trades which are reversed over intervals of less than five days (a short window indeed) are not profitable. However, trades taking place over a longer window appear to be profitable.

For periods ranging through to five days, and to three months, we not only evaluate the profitability of all the trades that are reversed but we also evaluate all the trades that are not reversed within every three-month horizon. By these means we are able to identify any self-selection bias engendered by focusing solely on trades that are reversed. The profitability of all trades that are not reversed is evaluated by marking-to-market at the end of the three-month period. Similarly, the profitability of non-reversed sale decisions can be assessed by treating as a notional profit the difference between the initial sale price and the repurchase price after the lapse of three months, if this is even lower. If it is higher, then a notional loss can be attributed to the initial sale. If the fund manager has no abnormal trading ability, then the "excess" profit from the self-selected churning sequences will either be offset, or more

[16] Where available, we used the explicit brokerage cost provided by the manager. If it was not provided, we used the cost as predicted by our regression equation included in Appendix B, Table B1.

than offset, by losses from the non-reversed marked-to-market trades at the end of the three month period.

If the fund manager possesses trading ability in terms of the initial purchase or sale decision, yet possesses no additional skills in terms of sequences of churning trades, then there will be no difference in profitability between the churned and non-churned (i.e., non-reversed) trades. Finally, if the fund manager's actions indicate access to valuable information about future firm performance that displays sequences of both good and bad news, then the profitability of the churned trades will be higher than the profitability of the non-churned trades.

In Table 5, we aggregate all buys (sells) that have not been reversed, labeled Buy Only (Sell Only), trades that have been reversed only once, labeled Buy-Sell Only (Sell-Buy Only) and churning trades, labeled Buy-Sell-Buy (Sell-Buy-Sell). We find for both buys and sells that churning trades are more profitable than those trades that managers do not reverse, as well as those trades managers reverse only once, suggesting managers do indeed have sufficient access to information to profit from churning trades as our model requires evidence of informed trading. Hence, we conclude that the profitability of our churning trade sequences is not due to "self-selection" of these sequences when we consider all other possible short-term trading strategies over a three-month window, further supporting our second hypothesis.

(INSERT TABLE 5 ABOUT HERE)

Figure 1 displays the average excess return around all churning trades made over an interval of less than three months, displaying that over short-term intervals managers appear to be able to on average buy when the stock price is low and sell when it is high, just as if they were able to observe a (common) signal of managerial effort.

(INSERT FIGURE 1 ABOUT HERE)

These churning trades are unevenly distributed across fund managers, with four funds executing 70 percent of churning trades (by the number of trades). In unreported results, we complete tests using the trades of these four managers, and also using the trades of the remaining sample, finding the difference between these two partitions is minimal. There is no consistent fund manager style or size difference. There is also no identifiable difference in the performance of these funds. However, due to the increase in volume of these managers, while these trades comprise only 1.4 percent of the average manager's excess performance over the

S&P/ASX300 return (that is, only a very small 1.4 percent of the 2.25 percent out-performance of our sample), they comprise 2.6 percent of the excess performance of those four funds. Note that the subsequent outperformance of the churned stocks is not included in the computation of churning profitability. While churning trades account for 38.9 percent of overall manager trading volume (as measured by the dollar value), they account for a more significant 63.4 percent for our four largest churners.

These findings are surprising as they show that fund managers engage in a substantial quantity of short-term portfolio turnover, which accounts for only a small (yet significant) portion of their overall excess performance. Since we subsequently show (Section 6(F) below) that these funds are more likely to have substantial long-term positions the more they churn, and churning results in subsequent stock out-performance (Section 6(E) below), the true profitability of churning is understated here by a very significant amount. Thus, we confirm that these short-term trades do not detract value, but rather are as a result of superior information on the part of institutional investors, in support of our hypothesis two (*H2*).

C. Impact of the Number of Institutional Investors Trading on Trading Profitability

A crucial requirement of our framework, inclusive of multiple institutional investors trading which compels managerial effort, is the receipt by symmetric investors of a common informational signal. This leads to our third hypothesis, *H3: trading profits of institutional investors should decline with increased numbers of actively trading investors trading simultaneously, as set out in equation* (11) *above.* Moreover, as far as we are aware, this hypothesis represents the first formal empirical testing of the major predictions of the Kyle (1989) and Holden and Subrahmanyam (1992) models using actual trading data. Schnitzlein (2002) uses experimental evidence to show that informed insider trading conforms to the theoretical model when the number of informed insiders is known, but agents in a laboratory fail to behave according to the model when the number of insiders is unknown to participants prior to trade.

In Table 6 we compute the profitability of two different styles of churning trades according to the number of investors simultaneously trading each month. Panel A represents the sequence, buy to sell to buy (i.e., "BSB"), and Panel B, sell to buy to sell (i.e., "SBS"). Column 2 calculates the actual profitability of these churning trades according to whether there is just one investor trading in a given month, two investors, and so on. In column 3, equation (11) above is used to compute the expected profit according to the number of institutional participants trading simultaneously in the Kyle symmetric Cournot equilibrium. For two trading participants, equation (11) is set to be precisely true in both panels. Hence the calibrated impact of the informational advantage and noise trader volatility product $\sigma_\eta \sigma_\varepsilon$ is specified at 7.9552 in Panel A and 7.0359 in Panel B. These relative magnitudes are to be expected given that the trade sequences in Panel A are more profitable than in Panel B.

(INSERT TABLE 6 ABOUT HERE)

It can be observed from column 3 of Table 6, and Figure 2, that the expected profit from trading formula given by equation (11) above predicts the sequence of trading profits for three to five investor participants for each type of churning trade sequence, given that the model is calibrated for two investor participants. These findings support out third hypothesis. For example, in the "BSB" sequence in Panel A with three institutions trading the predicted profit is \$1.15 on a \$100 investment and actual profit, \$1.56, is higher and for four institutions trading, predicted \$0.80 and actual, \$0.73, all with respect to \$100 investment. With sequence "SBS" in Panel B and three institutions trading the predicted profit is \$1.02 and actual, \$1.27, and with four institutions trading the predicted is \$0.70 and actual \$0.92 with respect to a \$100 investment. However, the predicted profitability is too high relative to the actual profitability with only a single institutional participant. Hence actual and predicted values differ significantly. Most likely, this is because the single active institutional trader is unaware *ex-ante* of the absence of competition prior to trading.

(INSERT FIGURE 2 ABOUT HERE)

Table 6 also shows the short-and longer-run profitability of the two types of trade sequence. For example the sequence "BSB" in Panel A does not outperform over the next 250 trading days with one institution trading but considerably out-performs with two institutions trading. Similarly, with just one institution trading in the "SBS" sequence, the long-term performance is very significantly negative but positive for two institutions trading.

In Table 7 we test hypothesis three (*H3*) utilizing regression analyses, rather than simply recording profitability as a function of the number of participating institutional investors as in Table 6. After controlling for a variety of factors including stock size, book to market, and momentum, we find that institutional trading profitability is diminishing in the number of investors trading simultaneously in the stock, as shown in equation (11) above. This is a key feature of the Cournot equilibrium, with multiple investors receiving similar or identical signals of future profitability, and possibly relying on access to firm managers and brokers for such information. Moreover, our findings confirm the intuition underlying the model that more competition results in "excessive" trading from the (short-term) perspective of individual fund managers and their investors. If fund managers could successfully collude, in order to act as a cartel and thereby maximize the value of exclusive information, overall trading volume would be lower and the collective short-term trading profits higher, but it is probable that long-term performance would be worse as less aggressive trading lowers stock price sensitivity and reduces the pressure on management.

(INSERT TABLE 7 ABOUT HERE)

D. Effect of the Number of Institutional Investors on the Bid-Ask Spread

The Kyle (1989) model, together with Holden and Subramayan (1992), predict that market depth should be greater and thus bid-ask spreads lower, as the number of informed investors trading simultaneously increases, as given by the expression for Kyle lambda in equation (8) above. This then constitutes our fourth hypothesis, *H4: the more informed institutional investors actively trading in a stock simultaneously, the lower should be the bid-ask spread.* This is because "excessive" trading more rapidly purges away asymmetric information common to investment managers, the greater is the number of informed traders participating. It is important to understand that each investor trades optimally, given the number of fellow competing investors. For a larger number of participants, N, the smaller is the Kyle lambda, and hence the more closely is the share price $p(\tilde{z})$ tied to both blockholder intervention, b_i, and managerial effort, a, via equation (9). Moreover, according to equations (14) and (15), the greater will be managerial effort, a, and the lower direct investor intervention, b_i.

We calculate the relative time-weighted bid-ask spread for the ith stock and tth period using the following formula:[17]

$$\text{Spread}_{i,t} = \frac{\sum_{j=1}^{n} (\text{Ask}_{i,j} - \text{Bid}_{i,j}) \times \text{Time}_{i,j}}{\sum_{j=1}^{n} \frac{(\text{Ask}_{i,j} + \text{Bid}_{i,j})}{2} \times \text{Time}_{i,j}}. \tag{16}$$

In Table 8 we investigate the impact of investors churning the same stocks on the bid-ask spread utilizing the formula given in equation (16). The presence of informed insiders, in the form of institutional investors, are normally taken to indicate reduced liquidity and depth, due to the higher risk of the market maker meeting an informed trader (see Heflin and Shaw

[17] The relative time-weighted spread was calculated using intraday SEATS data provided by SIRCA.

(2000) for evidence). But the absence of daily investor trading data prior to our study means that very little is known empirically about the impact of the number of simultaneous informed traders on bid-ask spreads. Table 8 shows that bid-ask spreads and excess spreads (defined as the average relative to all stocks) are significantly lower in stocks with more active institutional trading. For example, with a single institution trading, the relative time-weighted bid-ask spread before each churning trade package sequence is 0.654 percent, falling rapidly to only 0.174 percent prior to five or more institutions trading simultaneously. Hence, spreads are initially lower in stocks in which it is likely that more institutional investors are trading. A churning trading sequence by a single institution raises the already high initial spread slightly. With two traders, who now have an incentive to be more aggressive collectively, the spread is reduced. The percentage reduction is 1.82 for two traders, 1.30 for three traders, 1.87 for four traders, and 2.77 for five or more traders.[18]

The Kyle lambda formula, defined in association with equation (8), is used to compute the expected spread reduction as the number of simultaneous traders increases from one to two, two to three, and so on. The results show that while the signs are all correct, the actual magnitudes of the spread reductions are less than predicted by the formula. This contrasts with the actual and predicted trading profit estimates provided in Table 6 that are generally more accurate for two or more investors trading simultaneously.

(INSERT TABLE 8 ABOUT HERE)

E. Impact of Churning on Subsequent Firm Performance

In this section, we implement our major test of either high blockholder intervention (voice) productivity relative to managerial productivity, i.e., $\phi_b > \phi_a$, or *vice versa*, $\phi_a > \phi_b$, with managerial effort productivity boosted by investor churning activity. Assuming for the purpose of hypothesis formulation that the beneficial influence of multiple institutional trading on firm performance dominates the adverse impact of multiple investors on direct intervention, then we arrive at the first component of our fifth (and main) hypothesis, which states (*H5A): long-term firm performance following churning trade sequences will be increasing in the number of institutions trading simultaneously*.

Hence, we aim to determine whether these informed short-term trades are the means by which institutional investors improve stock price sensitivity, thereby improving

[18] Note that Levy and Swan (2008) show using calibrations that even quite small trading cost differences can impact returns.

subsequent firm performance. The intensity with which institutions trade as measured by the high point in the churning sequence relative to the low point, is also an indicator of trading aggressiveness. A low magnitude of the volatility of the informed signal increases the expected magnitude of the subsequent outperformance and the trading aggressiveness. The second component of our fifth hypothesis is, therefore, (*H5B): subsequent firm performance is decreasing in the volatility of the informative signal, as measured by the high stock holding relative to the low over the course of the churning trade sequence.* Hence, we calculate and include in our regressions a variable measuring the proportionate deviation of holdings from peak to trough.

In order to confirm the unique nature of our churning sequence in threatening management, we also create two dummies of alternative short-term trades, that is, where an investor buys (sells) and then sells (buys) within the next three months, without buying (selling) again. If our churning sequences are unique, we expect these dummies to be less significant than our churning dummy.

The sixth hypothesis we test involves the performance of stocks with only one or two institutional investors that are significantly overweight the stock. By the nature of our sample, even though overweight, these investment managers need not be sizeable blockholders. These features admittedly weaken the power of our test. An additional requirement is that they do not engage in churning activity in the prior quarter. This is the most likely instance in which institutional investors may be executing 'voice' with some but not complete immunity to "free-rider" problems and not threatening exit through their actions. (*H6): contrary to the outperformance following churning trades, when conditions are better in supporting "voice", there will be no out- (nor under-) performance in the following twelve months.* This hypothesis is also consistent with a significant portion of the literature on shareholder activism surveyed in Section 2.

In order to test the effect of these actions on firm management, we regress subsequent firm performance over the next twelve months against these short-term trading variables, as well as various control variables.[19] The control variables we use in this regression is the size quintile, book-to-market quintile, and six-month momentum quintile, which have all been shown to be priced risk factors (as in Daniel, Grinblatt, Titman, and Wermers (1997)). The

[19] Descriptive statistics of our sample showing the activity of multiple blockholders trading when broken down by the number of blockholders are presented in Table A1 in the Appendix.

final control variable we use is the change in fund manager weight. We do this in order to isolate the influence of short-term trading behavior on firm performance. Due to the overlapping nature of the monthly observations and 12mthly excess stock returns in this regression, we calculate t-statistics using robust standard errors accounting for clustering in the 12mthly excess stock return variable. This removes the effect of the overlapping sample in biasing t-statistics.

Our results in Table 9 indicate that future firm performance over the subsequent twelve months is both positive and statistically significantly related to whether institutional investors engage in short-term churning trading (at the one percent level). Columns 1 and 4 indicate an economically significant excess return of approximately 4.5 percent due to the completion of a short-term churning sequence in the previous month. This supports the first component of our hypothesis five (*H5A*). Similarly, the larger is the indication of informational precision, in the form of a higher percentage deviation of stock holding from the highest to lowest, raises performance at the rate of 3.25 percent (column 2). Since the mean deviation in stock holding across the two types of churning trades is 51 percent, the outperformance due to the magnitude of this informational effect is 1.66 percent. This finding supports the second component of hypothesis five (*H5B*).

Moreover, the larger is the number of simultaneous short-term institutional investors, the higher is the subsequent level of out-performance (Column 3) at the rate of 0.83 percent per investor trading, after controlling for the magnitude. Since the average number of investors trading simultaneously is 2.9, the outperformance from pure numbers is 2.4 percent. Alternative short-term trades, whether buy-sell or sell-buy, are positively related to subsequent firm performance, but to a lesser degree than churning trades (see column 5). This supports our two subsidiary hypotheses, (*H5 S1)* and (*H5 S2)*, and indicates that these trade sequences are a less successful in terms of threatening management. Lastly, we show in regressions (6) and (7) that, when there are two or fewer investors that are overweight in the stock and who do not engage in churning behavior, there is no significant impact on firm performance. This reduced prospect of free-riding incentives represents the most likely situation where concentrated blockholders are engaging in “blockholder voice”. These results support hypothesis six (*H6*).

(INSERT TABLE 9 ABOUT HERE)

Our findings on subsequent outperformance of churned trades also provide insights as to the relative performance contribution to total return. Over our entire sample, direct churning trade profitability explains only about three basis points of overall outperformance and subsequent performance over the next year, 38 basis points. Hence the quotient of long- to short-term outperformance is approximately 12.67 times. The low direct profitability of churning is consistent with the model's prediction that the informational advantage of traders will be relatively low when churning occurs. The overall churning-related outperformance of 41 basis points represents 18 percent of overall outperformance for our sample. While these figures are overall, for funds more specialized with respect to churning, the one-year outperformance is much higher, peaking at 1.7 percent. For such funds the indirect benefits of churning contribute to a sizeable portion of the overall outperformance.

As additional confirmation, in Table 10, stocks with short-term trading patterns are matched against stocks with no (i.e., zero) short-term trading. The former experience a 3.1 percent higher return significant at the one percent level. Hence, we can conclude that raising the informativeness of the stock price by to informed institutional churning is effective in raising future performance.

(INSERT TABLE 10 ABOUT HERE)

F. Are Institutional Investors Overweight Stocks They Churn?

The threat of exit hypothesis maintains that fund managers will churn stocks, not just because it is profitable to do so, but also because subsequent long-term outperformance will enhance returns on stocks for which investors have a strong incentive to be overweight. Hence our seventh hypothesis, (*H7): we should expect to see higher relative long-term stock holdings, the greater the churning activity in that stock.* This is after controlling for a variety of fund manager and stock characteristics and provided that firm manager productivity is high relative to blockholder intervention productivity.

For each three-month period and stock, we create a churning dummy, equal to one if the manager engaged in churning (when a manager has a trading sequence (*i*) "buy", "sell", "buy" or (*ii*) "sell", "buy", "sell") both during that quarter and in that stock, otherwise zero. For each manager, our sample only includes those stocks in which a manager has traded more than twice (over the life of our sample), as it is unrealistic to expect a manager to churn a stock they have never held. We regress this dummy variable using Logit and Tobit regressions against stock and manager characteristics calculated over both the past period as well as the current period. We do this in order to determine whether, for example, fund manager churning is influenced by past volatility in the stock, or because of current volatility. Recall that the theoretical model (equation (8)) shows that trading aggressivity (taking the form of churning) will be high when stock return volatility is low and precision high. The stock characteristics include size, book-to-market ratio, prior three month (3mth) stock momentum, prior 3mth stock volatility, prior 3mth turnover, prior 3mth spread, all measured as ranks between zero and one, hence the smallest (largest) stock receives a value of zero (one) for each quarter. We also include the prior 3mth S&P/ASX 300 Index return. and stock return volatility. Manager characteristics include the logarithm of fund size (log(fund size)), style (dummy variables for growth, value and style neutral managers), prior 6mth performance, prior 6mth stock turnover and the manager relative weight (difference between manager weight and S&P/ASX 300 Index weight) in the stock.

In Table 11, we find a strong association between churning a particular stock and being overweight in that same stock with a high relative weight, which provides strong support for our seventh hypothesis (*H7*). While this finding is consistent with the threat of exit hypothesis, the reverse causality argument is that fund managers are more likely to be overweight in stocks that they view favorably (given that their investment strategy is to beat the market portfolio)[20]. Moreover, fund managers choose to trade stocks that they know something about. However, this reverse causality story does not explain why fund managers take (on average) substantially smaller positions during the churning sequence if they are simply optimistic about the stock.

(INSERT TABLE 11 ABOUT HERE)

We also find that churning is positively related to stock size and stock turnover, and negatively related to the bid-ask spread. This suggests that this short-term churning is much more likely in highly liquid stocks with low transactions costs (and in stocks which account for larger weights in the benchmark index). This is not surprising, as round-trip transactions costs would be prohibitively expensive in small stocks and, therefore, tend to erode any profit margin. This is also consistent with a trading-related intervention story such as Maug (1998), who shows that increased liquidity is useful for institutional monitoring as it enables fund managers to more easily recover their intervention costs through informed trading activity. Fund manager churning is also positively related to past three month stock volatility, and

[20] This association has been noted by Brands, Brown and Gallagher (2005).

negatively related to book-to-market ratio, momentum, current stock return volatility, and prior index return. These findings are predicted by our theoretical model: a less advantageous informational signal for investors implies a less volatile stock price, more aggressive trading in the form of churning trades which we observe, higher managerial pay-performance sensitivity, and better managerial performance that we also observe. Large fund managers, with high turnover and poor prior performance, are more likely to execute these trades. We also find that style-neutral managers are more likely to execute churning trades. We also use Tobit regressions to regress the number of times managers churn within a quarter (rather than just a dummy variable) in column (3) of Table 11, and the average performance of those churning trades in column (4). From these regressions we identify that value managers tend to profit the most as a result of these strategies, but our results are generally consistent with our logit analysis.

7. Suggestions for Future Research

An important aim of this study has been to show that high levels of short-term trading activity, inclusive of purely "churning" trades by institutional investors, are not evidence of "actively doing nothing" that places a cost burden on the fund manager's clients. Rather, it is fundamental to value-enhancing pressure placed on firm management. This results in longer-term outperformance for both institutional investors and shareholders of the firm in question.

Many extensions to our study are possible. These are likely to integrate market microstructure with agency theory, corporate governance, funds management, and even behavioral finance. A natural extension to our study would be to analyze how different degrees of opacity or transparency in trading mechanisms impact on the nature of trading activity motivated by information. For example, in some stock markets, proxies for the identities of traders in the form of broker identities are revealed, while not in others. Moreover, a number of Exchanges such as Euronext, Tokyo, Australia (ASX), South Korea, and the NASDAQ-OMX group have changed from one system to another, opening up the possibility of examining the impact of these "natural experiments" on "blockholder voice", "managerial voice", churning activity, fund trading behavior, and long-term firm performance.

REFERENCES

Admati, Anat, and Paul Pfleiderer, 2008, The "Wall Street Walk" and Shareholder Activism: Exit as a Form of Voice, *Review of Financial Studies*. Forthcoming.

Admati, Anat, Paul Pfleiderer, and Josef Zechner, 1994, Large Shareholder Activism, Risk Sharing, and Financial Market Equilibrium, *Journal of Political Economy* 102, 1097-1130.

Agarwal, Prasun, 2007, Institutional Ownership and Stock Liquidity, Working Paper, Cornell University.

Almazan, Andres, Jay C. Hartzell, Laura T. Starks, 2005, Active Institutional Shareholders and Costs of Monitoring: Evidence from Executive Compensation, *Financial Management* Winter, 5-34.

Attari, M., S. Banerjee, and T. Noe, 2006, Crushed by rational stampede: Strategic share dumping and shareholder insurrections, *Journal of Financial Economics* 79, 181–222.

Barca, Fabrizio and Marco Becht, 2001. *The Control of Corporate Europe*. (Oxford University Press, Oxford).

Becht, Marc, Julian Franks, Colin Mayer, and Stefano Rossi, 2008, Returns to Shareholder Activism: Evidence from a Clinical Study of the Hermes UK Focus Fund, *Review of Financial Studies*. Forthcoming.

Bennedsen, Morten and Daniel Wolfenzon, 2000, The balance of power in closely held corporations, *Journal of Financial Economics* 58, 113-139.

Bolton, Patrick and Ernst-Ludwig von Thadden, 1998, Blocks, Liquidity, and Corporate Control, *Journal of Finance* 53, 1-25.

Boehmer, Ekkehart and Eric Kelley, 2008, Institutional Investors and the Informational Efficiency of Prices, *Review of Financial Studies*. Forthcoming,

Brands, Simone, Stephen J. Brown and David R. Gallagher, 2005, Portfolio Concentration and Investment Manager Performance, *International Review of Finance* 5, 149-174.

Brennan, Michael J., Narasimhan Jegadeesh and Bhaskaran Swaminathan, 1993, Investment Analysis and the Adjustment of Stock Prices to Common Information, *Review of Financial Studies* 6, 799-824.

Brennan, Michael J. and Avanidhar Subrahmanyam, 1995, Investment analysis and price formation in securities markets, *Journal of Financial Economics* 38, 361-381.

Brockman, Paul and Xuemin Yan, 2009, Block ownership and firm-specific information, *Journal of Banking and Finance* 33, 308-316.

Burkart, Mike, Denis Gromb and Fausto Panunzi, 1997. Large Shareholders, Monitoring, and the Value of the Firm, *Quarterly Journal of Economics* 112, 693-728.

Calcagno, Riccardo and Florian Heider, 2008, Market Based CEO Pay and Stock Price Informativeness, Working Paper, Vrije University, Amsterdam.

Chan, L.K.C. and J. Lakonishok, 1995, The Behavior of Stock Prices Around Institutional Trades, *Journal of Finance* 50, 1147-1174.

Chen, Xia., Jarrad Harford and Kai Li , 2007, Monitoring: Which Institutions Matter? *Journal of Financial Economics* 86, 279-305.

Clifford, C. P., 2008, Value creation or destruction?: Hedge funds as shareholder activists, *Journal of Corporate Finance* 14, 323-336.

Daniel, Kent, Mark Grinblatt, Sheridan Titman and Russ Wermers, 1997, Measuring Mutual Fund Performance with Characteristic-based Benchmarks, *Journal of Finance* 52, 1035-1058.

Davis, Gerald F. and E. Han Kim, 2007, Business ties and proxy voting by mutual funds, *Journal of Financial Economics* 85, 552-570.

Del Guercio, Diane and Jenifer Hawkins, 1999, The motivation and impact of pension fund activism. *Journal of Financial Economics* 52, 293–340.

Del Guercio, Diane, Laura Seery and Tracie Woidtke, 2008, Do boards pay attention when institutional investor activists "just vote no", *Journal of Financial Economics*, Forthcoming.

Deli, Daniel N., 2002, Mutual Fund Advisory Contracts: An Empirical Investigation, *Journal of Finance* 57, 109-133.

Dlugosz, Jennifer, Rudiger Fahlenbrach, Paul Gompers, and Andrew Metrick, 2006, Large blocks of stock: Prevalence, size, and measurement, *Journal of Corporate Finance* 12, 594-618.

Dow, James and Gary Gorton, 1997, Noise Trading, Delegated Portfolio Management, and Economic Welfare, *Journal of Political Economy* 105, 1024-1050.

Edmans, Alex, 2008, Blockholder Trading, Market Efficiency, and Managerial Myopia. *Journal of Finance*. Forthcoming.

Edmans, Alex and Gustavo Manso, 2009, Governance Through Exit and Voice: A Theory of Multiple Blockholders, Working Paper, Wharton School, University of Pennsylvania.

Faccio, Mara and Larry Lang, 2002, The ultimate ownership of Western European Corporations, *Journal of Financial Economics* 65, 365-395.

Ferreira, Miguel A., Paul A. Laux and Garen Markarian, 2009, Institutional Trading, Information and Executive Compensation, Working Paper, Universidade Nova de Lisboa, Portugal.

Faure-Grimaud, Antoine and Denis Gromb, 2004, Public Trading and Private Incentives, *Review of Financial Studies* 17, 985-1014.

Foster, F. Douglas and S. Viswanathan, 1993, The Effect of Public Information and Competition on Trading Volume and Price Volatility, *Review of Financial Studies* 6, 23-56.

Garvey, Gerald T. and Peter L. Swan, 2002, What can Market-Microstructure Contribute to Explain Executive Incentive Pay? Liquidity and the use of Stock-Based Compensation, Working Paper, University of New South Wales.

Gillan, Stuart. L., John W. Kensinger and John D. Martin, 2000, Value creation and corporate diversification: the case of Sears, Roebuck & Co, *Journal of Financial Economics* 53, 103-137.

Gillan, Stuart L., Laura T. Starks, 2000, Corporate Governance Proposals and Shareholder Activism: The Role of Institutional Investors. *Journal of Financial Economics* 57, 275-305.

Gillan, S. and L. Starks, 2007, The evolution of shareholder activism in the United States, *Journal of Applied Corporate Finance* 19 (1), 55-73.

Gomes, Armando and Walter Novacs, 2006, Sharing of Control versus Monitoring as Corporate Governance Mechanisms, Working Paper. Washington University in St. Lousis.

Gopalan, R., 2008, Institutional Stock Sales and Takeovers: The Disciplinary Role of Voting With Your Feet. Washington University, St. Louis working paper.

Gregoric, Aleksandra, Arjana B. Masten and Katerina Zajc, 2008, Exploring Barriers to Coase: Blockholder Identity and Path-Dependency as Determinants of Ownership Dynamics in the Post-Privatization Period, Working Paper. Copenhagen Business School.

Hartzell, Jay and Laura T. Starks, 2003, Institutional Investors and Executive Compensation, *Journal of Finance* 58, 2351-2374.

Heflin, F., and K.W. Shaw, 2000, Blockholder Ownership and Market Liquidity, *Journal of Financial and Quantitative Analysis* 35 (4), 621-633.

Hirshman, Albert, 1970. *Exit, Voice and Loyalty* (Harvard University Press, Cambridge, Mass.)

Holderness, Clifford G., 2008, The Myth of Diffuse Ownership in the United States, *Review of Financial Studies*. Forthcoming.

Holmstrom, Bengt and Jean Tirole, 1993, Market Liquidity and Performance Monitoring, *Journal of Political Economy* 101, 678-709.

Holden, Craig W. and Avanidhar Subrahmanyam, 1992, Long-Lived Private Information and Imperfect Competition, *Journal of Finance* 47, 247-270.

Kahn, Charles and Andrew Winton, 1998, Ownership Structure, Speculation, and Shareholder Intervention, *Journal of Finance* 53, 99-129.

Karpoff, Jonathan, Paul. A. Malatesta, , and Ralf A. Walkling, 1996, Corporate governance and shareholder initiatives: Empirical Evidence, *Journal of Financial Economics* 42, 365-395.

Kyle, Albert S., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53, 1315-1336.

Kyle, Albert S., 1989, Informed Speculation with Imperfect Competition, *Review of Economic Studies* 56 (3), 317-355.

Laeven, Luc and Ross Levine, 2007, Complex Ownership Structures and Corporate Valuations, *Review of Financial Studies* 21, 579-604.

Leland, Hayne E., 1992, Insider Trading: Should It Be Prohibited?, *Journal of Political Economy* 100, 859-887.

Levy, Andre and Peter L. Swan, 2008, The Liquidity Component of the Equity Premium, Working Paper, University of New South Wales.

Lowenstein, Louis, 1988. *What's Wrong with Wall Street?* (Addison-Wesley, Reading, MA).

Maug, Ernst, 1998, Large Shareholders as Monitors: Is there a Tradeoff between Liquidity and Control?, *Journal of Finance* 53, 65-98.

Maury, Benjamin and Anete Pajuste, 2005, Multiple large shareholders and firm value, *Journal of Banking and Finance* 29, 1813-1834.

McCahery, Joseph A., Zacharias Sautner and Laura T. Starks, 2009, Behind the Scenes: The Corporate Governance Preferences of Institutional Investors, ECGI, Working Paper N°. 235/2009, February.

McConnell, John and Henri. Servaes, 1990, Additional Evidence on Equity Ownership and Corporate Value, *Journal of Financial Economics* 27, 595-612

Mello, Antonio and Rafael Repullo, 2004, Shareholder Activism is Non-Monotonic in Market Liquidity, *Finance Research Letters* 1, 2-10.

Noe, Tom, 2002, Investor Activism and Financial Market Structure, *Review of Financial Studies* 15, 289-318.

Parrino, Robert., Richard W. Sias and Laura T. Starks, 2003, Voting with their feet: institutional ownership changes around forced CEO turnover, *Journal of Financial Economics* 68, 3-46.

Rubin, Amir, 2007, Ownership Level, Ownership Concentration and Liquidity, *Journal of Financial Markets* 10, 219-248.

Schnitzlein, Charles R., 2002, Price Formation and Market Quality When the Number and Presence of Insiders Is Unknown, *Review of Financial Studies* 15, 1077-1109.

Sias, Richard W., Laura T. Starks and Sheridan Titman, Changes in Institutional Ownership and Stock Returns: Assessment and Methodology, *Journal of Business* 79, 2869-2910.

Shleifer, Andrei and Robert Vishny, 1986, Large Shareholders and Corporate Control, *Journal of Political Economy* 98, 461-488.

Smith, Gavin and Peter L. Swan, 2008a, To Good to be True: Do Concentrated Institutional Investors Really Reduce Executive Compensation whilst Raising Incentives, Working Paper, University of New South Wales.

Smith, Gavin and Peter L. Swan, 2008b. Will the real monitor please stand up? Institutional investors and CEO compensation, Working Paper. University of New South Wales.

Wahal, S., 1996, Pension fund activism and firm performance, *Journal of Financial and Quantitative Analysis* 31, 1–23.

Wermers, Russ, 2000, Mutual Fund Performance: An Empirical Decomposition into Stock-Picking Talent, Style, Transaction Costs and Expenses, *Journal of Finance* 55, 1655-1695.

Winton, Andrew, 1993. Limitation of Liability and the Ownership Structure of the Firm, *Journal of Finance* 48, 487-512.

Yan, Xuemin and Zhe Zhang, 2008, Institutional Investors and Equity Returns: Are Short-term Institutions Better Informed? *Review of Financial Studies*. Forthcoming.

Zwiebel, Jeffrey, 1995, Block Investments and Partial benefits of Corporate Control, *Review of Economic Studies* 62, 161-185.

Table 1: Descriptive Statistics of Substantial Manager Stock Positions

This table presents a number of descriptive statistics concerning the blockholder status of the investment managers in the PAD sample. In Panel A (D), we measure the average number of stocks (index weight) each month where individual managers in the PAD sample hold over 0.5-5% of the total market capitalisation of a company. In Panel B, we measure the combined holding of all managers in our sample. Panel C (E) measures the average number of stocks (index weight) each month in which our managers have churned and hold over 0.5-5% of the total market capitalisation of a company.

	5%	4%	3%	2%	1%	0.5%
Panel A: Number of Stocks Individual Managers Hold Over x%						
Mean	25	33	44	69	128	209
Median	25	33	47	74	111	182
StDev	10	12	16	23	47	81
Minimum	2	2	2	9	25	46
Maximum	43	52	69	113	225	385
Panel B: Number of Stocks the Sum of our Manager Holdings Hold Over x%						
Mean	30	42	58	86	125	157
Median	33	46	56	78	126	156
StDev	12	17	25	32	36	36
Minimum	2	2	2	13	29	48
Maximum	49	67	99	136	179	208
Panel C: Number of Stocks Churned by Individual Managers which are Held Over x%						
Mean	2.4	3.4	5.0	8.1	16.8	30.5
Median	2.0	3.0	4.0	8.0	15.0	25.0
StDev	2.2	2.7	3.6	5.5	12.0	22.5
Minimum	-	-	-	-	-	1.0
Maximum	11.0	15.0	16.0	22.0	47.0	85.0
Panel D: Index Weight of Stocks Individual Managers Hold Over x%						
Mean	2.8%	6.0%	12.8%	29.9%	51.7%	68.5%
Median	1.2%	2.5%	4.2%	18.0%	61.9%	77.8%
StDev	2.8%	7.9%	15.4%	26.3%	28.7%	19.7%
Minimum	0.1%	0.1%	0.2%	2.1%	6.3%	30.1%
Maximum	13.6%	34.9%	59.3%	80.0%	86.7%	88.9%
Panel E: Index Weight of Stocks Churned by Individual Managers which are Held Over x%						
Mean	0.3%	0.4%	0.7%	1.5%	6.2%	26.0%
Median	0.1%	0.2%	0.4%	1.0%	4.5%	19.5%
StDev	0.4%	0.6%	0.9%	1.3%	6.8%	22.5%
Minimum	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%
Maximum	2.4%	2.9%	3.6%	4.5%	34.1%	82.7%

Table 2: Descriptive Statistics of Institutional Investor Sample Showing the Turnover-Sorted Institutional Investor Return Decomposition

This table provides a decomposition of Australian institutional investor returns, contained in the Portfolio Analytics Database. At the end of each semi-annual period from June-1999 to June 2002, we rank all funds in the database by their prior six month portfolio turnover level (the ranking period). Then we compute average statistics for each quartile (according to their prior portfolio turnover) over the following six months. The statistics calculated are calculated using monthly manager positions: portfolio turnover, gross return, gross excess return (over the S&P/ASX 300 Index Return), transactions costs, net return (net of transaction costs) and net excess return (over the S&P/ASX 300 Index Return). These statistics are annualized and calculated over all semi-annual periods.

Fractile	Avg No.	Turnover (%/year)	Gross Return (%/year)	Gross Excess Return (%/year)	CS (%/year)	CT (%/year)	AS (%/year)	Transactions Costs (%/year)	Net Return (%/year)	Net Excess Return (%/year)
Top 25%	6.6	114.6	9.49	3.07	1.77	1.40	6.32	0.80	8.13	1.71
2nd 25%	5.9	77.8	10.33	3.92	2.92	0.97	6.44	0.54	9.23	2.82
3rd 25%	6.3	62.2	9.93	3.40	2.40	0.52	7.01	0.46	8.91	2.38
Bottom 25%	5.6	44.3	9.83	3.27	2.00	0.74	7.09	0.41	8.86	2.30
Top-Bottom 25%	6.1	70.3***	-0.34	-0.20	-0.23	0.66	-0.77	0.39***	-0.73	-0.59
All Funds	6.1	76.1	9.88	3.40	2.26	0.92	6.70	0.56	8.76	2.28

*,**, and *** display significance at the 90, 95 and 99% confidence interval, respectively.

Table 3: Descriptive Statistics of Institutional Investment Manager Trades

This table measures the percentage of our institutional investor buy, sell churning buy and churning sell trades (trade volume figures are in parentheses), split by stock size quintile and the number of package days over which our trade is split. Churning trades can be defined as the following trade sequences, purchase, sale, purchase and sale, purchase, sale, completed over a period of less than 3 months. Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. Principal refers to the total traded value. The sample comprises all trades of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.

		1 Day	2-3 Days	4-6 Days	7-10 Days	11+ Days
Panel A: All Buys (41,781 Packages, $46.1 Billion Principal)						
All Buys		61.9 (25.3)	13.5 (14.4)	13.2 (18.0)	6.0 (14.6)	5.4 (27.8)
1 (small)	7.0% of packages, 1.9% of principal	69.1 (43.9)	10.7 (12.8)	10.7 (14.9)	5.1 (11.7)	4.4 (16.8)
2	5.5% of packages, 2.0% of principal	65.9 (37.9)	12.5 (15.6)	11.4 (12.7)	4.8 (14.1)	5.4 (19.6)
3	12.5% of packages, 9.1% of principal	61.5 (26.4)	13.7 (12.2)	12.9 (17.1)	6.2 (13.0)	5.7 (31.3)
4	21.9% of packages, 17.3% of principal	60.5 (24.5)	13.9 (13.8)	13.8 (19.4)	6.1 (16.2)	5.7 (26.1)
5 (large)	53.1% of packages, 69.7% of principal	61.0 (24.4)	13.7 (14.8)	13.6 (17.9)	6.2 (14.5)	5.5 (28.4)
Panel B: All Sells (32,609 Packages, $35.4 Billion Principal)						
All Sells		61.9 (27.7)	15.2 (16.5)	12.3 (18.6)	5.9 (14.6)	4.7 (22.6)
1 (small)	7.7% of packages, 2.1% of principal	66.5 (44.1)	12.2 (12.5)	11.4 (14.7)	5.4 (12.7)	4.5 (16.0)
2	5.6% of packages, 2.0% of principal	62.5 (31.0)	14.7 (13.4)	11.9 (20.0)	6.2 (13.5)	4.7 (22.1)
3	12.1% of packages, 8.2% of principal	59.5 (32.9)	15.4 (14.0)	13.5 (20.2)	6.3 (12.9)	5.3 (20.0)
4	22.5% of packages, 18.3% of principal	59.4 (23.0)	15.5 (16.6)	12.3 (18.3)	7.1 (16.5)	5.7 (25.6)
5 (large)	52.1% of packages, 69.4% of principal	62.2 (27.5)	15.6 (17.0)	12.4 (18.6)	5.5 (14.5)	4.3 (22.4)
Panel C: Churning Buys (12,698 Packages, $16.8 Billion Principal)						
All Buys		58.9 (19.3)	13.7 (14.4)	14.8 (17.7)	6.2 (14.5)	6.4 (34.1)
1 (small)	3.0% of packages, 0.6% of principal	71.1 (36.7)	9.0 (10.1)	12.4 (16.6)	4.7 (27.0)	2.8 (9.6)
2	2.9% of packages, 0.8% of principal	71.4 (42.0)	9.0 (19.1)	10.2 (11.7)	5.2 (9.5)	4.2 (17.7)
3	9.3% of packages, 8.4% of principal	57.9 (16.9)	15.3 (12.1)	14.0 (16.4)	6.3 (11.9)	6.5 (42.7)
4	19.0% of packages, 13.6% of principal	58.4 (19.8)	13.3 (14.1)	14.6 (17.9)	6.7 (17.2)	7.0 (31.0)
5 (large)	65.8% of packages, 76.6% of principal	58.0 (19.1)	14.0 (14.7)	15.2 (17.8)	6.2 (14.2)	6.6 (34.2)
Panel D: Churning Sells (12,240 Packages, $14.9 Billion Principal)						
All Sells		61.2 (23.7)	15.9 (16.2)	12.6 (20.2)	5.9 (16.6)	4.4 (23.3)
1 (small)	3.0% of packages, 0.7% of principal	67.8 (56.3)	13.7 (9.2)	10.3 (7.5)	5.9 (14.4)	2.3 (12.6)
2	3.0% of packages, 0.9% of principal	64.4 (28.0)	13.1 (12.8)	9.6 (12.3)	8.0 (18.1)	4.9 (28.8)
3	9.1% of packages, 5.9% of principal	63.8 (28.9)	13.6 (13.3)	12.5 (20.9)	6.2 (14.2)	3.9 (22.7)
4	19.1% of packages, 13.8% of principal	59.7 (21.0)	15.8 (16.3)	12.6 (18.6)	7.2 (20.6)	4.7 (23.5)
5 (large)	65.9% of packages, 78.7% of principal	60.8 (23.4)	16.5 (16.5)	12.8 (20.6)	5.5 (16.1)	4.4 (23.4)

Table 4: Performance of Churning Trades Using Manager Trade Prices After Transaction Costs Over Short- and Long-Term Horizons

This table measures excess stock return (over the S&P/ASX 300) around the following trade sequences, purchase, sale, purchase and sale, purchase, sale. These trade sequences occur over the interval in the left column. The return is calculated using the institutional investment manager's actual average trade package price. Transactions costs are modeled using description in text, and are subtracted from returns after purchases, but added to returns following sales. All figures not in parentheses are in percentages.

Panel A: Buy to Sell to Buy Churning Trade

	Number Trades	Past 5 days	After Buy, Before Sell	After Sell, Before Buy	Next 5 days	Next 10 days	Next 90 days	Next 250 days
<=5WorkingDays	552	0.07	-0.08	0.12	0.40	0.22	0.17	1.56
(t-statistic)		*(0.31)*	*(0.55)*	*(0.70)*	*(1.23)*	*(0.57)*	*(0.22)*	*(1.26)*
6-10 WorkingDays	1,290	0.40***	0.26**	-0.31***	0.03	0.02	1.12**	1.51*
(t-statistic)		*(3.04)*	*(1.97)*	*(2.64)*	*(0.13)*	*(0.08)*	*(2.12)*	*(1.95)*
11-21 Working Days	2,326	0.95***	0.68***	-0.62***	0.36**	0.33*	0.04	0.42
(t-statistic)		*(9.94)*	*(5.10)*	*(5.18)*	*(2.36)*	*(1.91)*	*(0.11)*	*(0.71)*
1-2mths	1,936	1.28***	1.54***	-0.83***	0.32**	0.43**	0.38	0.55
(t-statistic)		*(12.03)*	*(8.16)*	*(5.52)*	*(2.08)*	*(2.40)*	*(0.95)*	*(0.83)*
2-3mths	856	1.11***	1.04***	-0.86**	0.24	0.09	0.17	-0.50
(t-statistic)		*(6.14)*	*(2.64)*	*(2.18)*	*(0.98)*	*(0.30)*	*(0.24)*	*(0.46)*
All trades < 3mths	6,960	0.89***	0.82***	-0.59***	0.28***	0.26**	0.36	0.63*
(t-statistic)		*(15.47)*	*(9.27)*	*(7.40)*	*(3.19)*	*(2.57)*	*(1.62)*	*(1.81)*
Panel B: Sell to Buy to Sell Churning Trade								
	Number Trades	Past 5 days	After Sell, Before Buy	After Buy, Before Sell	Next 5 days	Next 10 days	Next 90 days	Next 250 days
<=5WorkingDays	501	-0.40	-0.16	0.38	0.32	0.26	1.14	1.72
(t-statistic)		*(1.53)*	*(0.91)*	*(1.64)*	*(0.89)*	*(0.65)*	*(1.26)*	*(1.28)*
6-10 WorkingDays	1,399	-0.29**	-0.30***	0.41***	0.48***	0.49**	0.03	-0.80
(t-statistic)		*(2.42)*	*(2.91)*	*(3.53)*	*(2.70)*	*(2.35)*	*(0.06)*	*(1.04)*
11-21 Working Days	2,125	-0.54***	-0.40***	0.44***	0.35**	0.45**	0.89**	1.88***
(t-statistic)		*(5.64)*	*(3.36)*	*(3.60)*	*(2.38)*	*(2.55)*	*(2.16)*	*(2.89)*
1-2mths	1,586	-0.52***	-0.99***	0.58***	0.45**	0.42**	-0.27	-0.13
(t-statistic)		*(4.18)*	*(4.62)*	*(2.84)*	*(2.34)*	*(1.96)*	*(0.60)*	*(0.18)*
2-3mths	735	-0.77***	-1.10**	1.16***	0.47	0.22	-0.03	-0.26
(t-statistic)		*(4.82)*	*(2.53)*	*(3.02)*	*(1.51)*	*(0.51)*	*(0.04)*	*(0.23)*
All trades < 3mths	6,346	-0.50***	-0.58***	0.55***	0.42***	0.41***	0.32	0.52
(t-statistic)		*(8.51)*	*(6.61)*	*(6.46)*	*(4.60)*	*(3.75)*	*(1.35)*	*(1.42)*

*,**, and *** display significance at the 90, 95 and 99% confidence interval, respectively.

Table 5: Aggregate Profitability of a Variety of Multiple Institutional Investor Trade Sequences

This table measures the return of sequences of trades over a three-month window. Buy (Sell) only refers to trades that are not reversed within the three month window. Buy-Sell (Sell-Buy) only refers to trades that are reversed once only during the three month window. Buy-Sell-Buy (Sell-Buy-Sell) refers to trades that are reversed and then re-purchased (re-sold) within the three month window. The excess return is calculated as the difference between the stock return and the S&P/ASX300 Index Return. All figures not in parentheses are in percentages.

	Return	Excess Return	Excess Return (Aft. Trans. Costs)
Profitability of Trade Sequences			
Buy-Sell-Buy	2.72***	1.80***	0.90***
(t-statistic)	*(19.27)*	*(13.83)*	*(6.93)*
Buy-Sell Only	0.37	0.49**	-0.11
(t-statistic)	*(1.49)*	*(2.03)*	*(0.44)*
Buy Only	0.86***	-0.25***	-0.55***
(t-statistic)	*(9.85)*	*(3.06)*	*(6.66)*
Sell-Buy-Sell	1.04***	1.39***	0.49***
(t-statistic)	*(6.75)*	*(9.72)*	*(3.44)*
Sell-Buy Only	0.59***	0.67***	0.07
(t-statistic)	*(3.21)*	*(3.93)*	*(0.41)*
Sell Only	-0.20**	1.06***	0.76***
(t-statistic)	*(2.04)*	*(10.96)*	*(7.87)*

*,**, and *** display significance at the 90, 95 and 99% confidence interval, respectively.

Table 6: Impact of Multiple Institutional Investors Churning the Same Stock on Actual and Predicted Trade Profitability and in the Longer Term

This table measures excess stock return (over the S&P/ASX 300) around the following trade sequences, purchase, sale, purchase and sale, purchase, sale and occur over less than three months. The number of investors that complete their trade sequence in the same month is in the left column. The return is calculated using day-end prices. The computation of transaction costs (brokerage fees) is described in Section 6A in the text. Where transactions costs are not provided they are modeled using the description in Table B1, and are subtracted from returns after purchases, but added to returns following sales. The actual profitability column measures the profitability during the trading sequence and is expressed as a percentage of the value of the trades. The predicted profit column is based on the formula given as equation (11). The constant term in the formula is based on a calibration with two managers trading for each of the two sequences and equals 7.9552 for BSB and 7.0359 for SBS sequence. All figures not in parentheses are in percentages.

Panel A: Buy to Sell to Buy Churning Trade

	Number Trades	Actual Profitability	Predicted Profitability	Actual - Predicted	Past 5 days	After Buy, Before Sell	After Sell, Before Buy	Next 5 days	Next 10 days	Next 90 days	Next 250 days
1 Investor Trading	2,074	1.64***	3.98	-2.34	0.89***	0.81***	-0.83***	0.11	-0.02	-0.56	-0.39
(t-statistic)		*(4.94)*		*(7.04)*	*(7.51)*	*(4.69)*	*(5.20)*	*(0.68)*	*(0.10)*	*(1.17)*	*(0.54)*
2 Investors Trading	1,600	1.88***	1.88	0.00	1.02***	1.16***	-0.72***	0.63***	0.48***	1.09***	3.08***
(t-statistic)		*(5.55)*		*(0.00)*	*(8.96)*	*(6.43)*	*(4.54)*	*(5.07)*	*(3.12)*	*(2.66)*	*(4.53)*
3 Investors Trading	981	1.56***	1.15	0.41	1.10***	1.02***	-0.54***	0.30	0.41*	1.12**	0.89
(t-statistic)		*(3.70)*		*(0.98)*	*(7.84)*	*(4.47)*	*(2.79)*	*(1.45)*	*(1.73)*	*(2.23)*	*(1.13)*
4 Investors Trading	756	0.73	0.80	-0.07	0.83***	0.52**	-0.21	0.38	0.70***	1.17**	-0.43
(t-statistic)		*(1.54)*		*(0.14)*	*(5.26)*	*(1.99)*	*(0.98)*	*(1.63)*	*(2.67)*	*(2.26)*	*(0.52)*
5+ Investors Trading	1,549	0.82**	0.59	0.23	0.68***	0.52***	-0.30**	-0.08	-0.03	-0.20	-0.16
(t-statistic)		*(2.44)*		*(0.68)*	*(6.08)*	*(2.83)*	*(1.97)*	*(0.50)*	*(0.16)*	*(0.60)*	*(0.29)*

Panel B: Sell to Buy to Sell Churning Trade

	Number Trades	Actual Profitability	Predicted Profitability	Actual - Predicted	Past 5 days	After Buy, Before Sell	After Sell, Before Buy	Next 5 days	Next 10 days	Next 90 days	Next 250 days
1 Investor Trading	1,895	1.26***	3.52	-2.26	-0.59***	-0.92***	0.34**	-0.09	-0.22	-1.27**	-2.34***
(t-statistic)		*(3.53)*		*(6.32)*	*(4.98)*	*(4.97)*	*(1.97)*	*(0.49)*	*(0.93)*	*(2.43)*	*(2.94)*
2 Investors Trading	1,469	1.66***	1.66	0.00	-0.56***	-0.80***	0.86***	-0.28**	-0.15	-0.15	1.74**
(t-statistic)		*(4.89)*		*(0.00)*	*(4.90)*	*(4.68)*	*(5.11)*	*(2.23)*	*(0.93)*	*(0.36)*	*(2.53)*
3 Investors Trading	902	1.27***	1.02	0.26	-0.55***	-0.44**	0.83***	0.39*	0.39	1.15**	1.50*
(t-statistic)		*(2.96)*		*(0.60)*	*(3.87)*	*(2.08)*	*(3.82)*	*(1.87)*	*(1.63)*	*(2.23)*	*(1.86)*
4 Investors Trading	733	0.92*	0.70	0.22	-0.33**	-0.14	0.79***	0.80***	1.08***	2.25***	1.25
(t-statistic)		*(1.86)*		*(0.44)*	*(2.10)*	*(0.56)*	*(3.11)*	*(3.53)*	*(4.11)*	*(4.40)*	*(1.49)*
5+ Investors Trading	1,347	0.44	0.52	-0.08	-0.36***	-0.25	0.19	0.37**	0.17	0.09	0.82
(t-statistic)		*(1.14)*		*(0.22)*	*(2.93)*	*(1.31)*	*(0.98)*	*(2.27)*	*(0.89)*	*(0.25)*	*(1.42)*

*,**, and *** display significance at the 90, 95 and 99% confidence interval, respectively.

Table 7: Impact of Multiple Institutional Investors Churning the Same Stock on Short-Term Trade Profitability Utilizing Regression Analysis

In this table, we regress the package profitability against a number of variables. The churning trades must have the following trade sequences, purchase, sale, purchase and sale, purchase, sale. Profitability is calculated as the excess return (over the S&P/ASX 300 Index) earned after the first trade minus the excess return earned after the second trade plus the return earned in the five days following the third trade. The independent variables include a variable (Number of Investors Trading in the Same Month), equal to the number of different investor trading sequences completed over the previous month, and a variable equal to the maximum percentage deviation in stock holdings (from peak to trough). Control variables include size, book-to-market and momentum quintiles, a dummy equal to 1 if the churning sequence was Buy-Sell-Buy (rather than Sell-Buy-Sell) as well as the average change in investment manager weight over the previous month.

	(1)	**(2)**	**(3)**
Constant	0.0240***	0.0267***	0.0263***
(t-statistic)	*(4.12)*	*(4.42)*	*(4.52)*
Size Quintile	-0.0011	-0.0013	-0.0009
(t-statistic)	*(0.95)*	*(1.19)*	*(0.80)*
Book-to-Market Quintile	0.0001	0.0003	0.0001
(t-statistic)	*(0.08)*	*(0.42)*	*(0.15)*
6m Momentum Quintile	-0.0009	-0.0010	-0.0011*
(t-statistic)	*(1.46)*	*(1.48)*	*(1.77)*
Net Investor Change in Position			0.0208***
(t-statistic)			*(5.70)*
Number of Investors Trading in Same Month	-0.0021***	-0.0023***	-0.0021***
(t-statistic)	*(4.41)*	*(4.66)*	*(4.53)*
Buy-Sell-Buy Dummy	0.0065***	0.0065***	0.0018
(t-statistic)	*(3.34)*	*(3.34)*	*(0.83)*
Holdings Percentage Deviation		*-0.0055**	
(t-statistic)		*(1.68)*	
Observations	13,046	13,046	13,046
R-squared	0.29%	0.32%	0.54%

*,**, and *** display significance at the 90, 95 and 99% confidence interval

Table 8: Impact of the Number of Institutional Investors Trading Simultaneously on the Relative Time-Weighted Spread and Comparison with the Predicted Reduction

This table measures the change in relative time-weighted spread before and after our short-term churning trades. The time-weighted spread is computed from the formula given in equation (16). The excess spread is defined relative to the average for all stocks in the sample. The churning trades must have the following trade sequences, purchase, sale, purchase and sale, purchase, sale. The number of investors that complete their trade sequence in the same month is in the left column. All figures not in parentheses are in percentages. The Kyle lambda formula, equation **Error! Reference source not found.**, is used to compute the expected spread reduction in percentage terms which is then contrasted with the actual spread reduction as a percent for each increase in the number of investors trading simultaneously.

		Spread	Excess Spread	Predicted Reduction (%)	Actual Reduction (%)
1 Investor Trading	Spread Before	0.654	-2.714		
	Spread After	0.654	-2.734		
	Difference (basis points)	0.010	-1.960*	NA	-0.020
	(t-statistic)	*(0.01)*	*(1.83)*		
2 Investors Trading	Spread Before	0.358	-3.099		
	Spread After	0.351	-3.111		
	Difference (basis points)	-0.653***	-1.184**	5.720	1.820
	(t-statistic)	*(6.16)*	*(2.01)*		
3 Investors Trading	Spread Before	0.266	-3.189		
	Spread After	0.263	-3.254		
	Difference (basis points)	-0.347***	-6.500***	8.140	1.300
	(t-statistic)	*(4.32)*	*(8.85)*		
4 Investors Trading	Spread Before	0.213	-3.367		
	Spread After	0.210	-3.385		
	Difference (basis points)	-0.399***	-1.846**	7.620	1.870
	(t-statistic)	*(5.81)*	*(2.02)*		
5+ Investors Trading	Spread Before	0.174	-3.538		
	Spread After	0.169	-3.533		
	Difference (basis points)	-0.480***	0.500	6.830	2.770
	(t-statistic)	*(6.99)*	*(0.55)*		

*,**, and *** display significance at the 90, 95 and 99% confidence interval,

Table 9: Impact of Short-Term Institutional Investor Trading on Subsequent Firm Performance

In this table, we regress the 12mth Excess Stock Return (over the S&P/ASX 300 Index) against a number of variables. The independent variables include a dummy variable, equal to 1 when a manager has completed a short-term trading sequence over the previous month (ST Trading Dummy), a variable equal to the number of different managers trading sequences completed over the previous month (ST Trading Number), and a variable equal to the maximum percentage deviation in stock holdings (from peak to trough). Control variables include size, book-to-market and momentum quintiles, as well as the average change in manager weight over the previous month. T-statistics are calculated using robust errors adjusted for clustering in the 12mth Excess Stock Return (due to overlapping intervals).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	-0.0283**	-0.0300**	-0.0295**	-0.0282**	-0.0282**	-0.0276**	-0.0290**
	(2.28)	*(2.29)*	*(2.27)*	*(2.28)*	*(2.27)*	*(2.24)*	*(2.34)*
Size Quintile	-0.0043***	-0.0016	-0.0025*	-0.0042***	-0.0053***	-0.0043***	-0.0042***
	(3.00)	*(1.16)*	*(1.75)*	*(2.99)*	*(3.62)*	*(3.02)*	*(2.98)*
Book-to-Market Quintile	-0.0033**	-0.0038**	-0.0035**	-0.0033**	-0.0032**	-0.0034**	-0.0033**
	(2.09)	*(2.10)*	*(2.13)*	*(2.05)*	*(2.02)*	*(2.10)*	*(2.08)*
6m Momentum Quintile	0.0128***	0.0128***	0.0128***	0.0128***	0.0128***	0.0128***	0.0128***
	(8.29)	*(8.30)*	*(8.29)*	*(8.29)*	*(8.31)*	*(8.29)*	*(8.30)*
Net Blockholder Change in Position	-0.0003	0.0117	0.0044	-0.0182	-0.0023	-0.0003	-0.0003
	(0.02)	*(0.79)*	*(0.74)*	*(1.28)*	*(0.18)*	*(0.02)*	*(0.02)*
Churning Trade Dummy	0.0441***				0.0250***	0.0439***	0.0442***
	(7.62)				*(2.69)*	*(7.58)*	*(7.62)*
Buy-Sell ST Trading Dummy					0.0132**		
					(2.00)		
Sell-Buy ST Trading Dummy					0.0122		
					(1.53)		
Buy-Sell-Buy Dummy				0.0421***			
				(4.80)			
Sell-Buy-Sell Dummy				0.0147*			
				(1.82)			
Number of Blockholders Churning			0.0083***				
			(3.87)				
Holdings Percentage Deviation		0.0325***	0.0162*				
		(3.30)	*(1.76)*				
Single O'weight Mgr W'out Churning						-0.0029	
						(0.57)	
<=Two O'weight Mgrs W'out Churning							0.0017
							(0.39)
Observations	20,945	20,945	20,945	20,945	20,945	20,945	20,945
R-squared	0.82%	0.82%	0.64%	0.82%	0.85%	0.82%	0.82%

*,**, and *** display significance at the 90, 95 and 99% confidence interval, respectively.

Table 10: Impact of Institutional Investor Short-term Trading on Subsequent Firm Performance Based on Matched Firms

In this table, we present the equally-weighted average excess return (over the S&P/ASX 300 Index) over the specified period for stocks where managers have engaged in short-term trading over the prior month. We match these stocks against stocks in the same size, book-to-market and momentum quintiles. The period of this analysis is from Jan-1994 to Jun-2002. All figures not in parentheses are percentages.

	Short-term Trading in Prior Month	No Short-term Trading	Difference
1mth Excess Return	0.28*	-0.15	0.43*
(t-statistic)	(1.68)	(0.86)	(1.78)
3mths Excess Return	0.69**	-0.45	1.14***
(t-statistic)	(2.46)	(1.62)	(2.88)
6mths Excess Return	1.40***	-1.01**	2.41***
(t-statistic)	(3.34)	(2.56)	(4.18)
12mths Excess Return	1.58***	-1.55***	3.13***
(t-statistic)	(2.87)	(2.75)	(3.97)

*,**, and *** display significance at the 90, 95 and 99% confidence interval, respectively.

Table 11: Characteristics of Institutional Investor Churning Trades and Relation to Investor Relative Weight

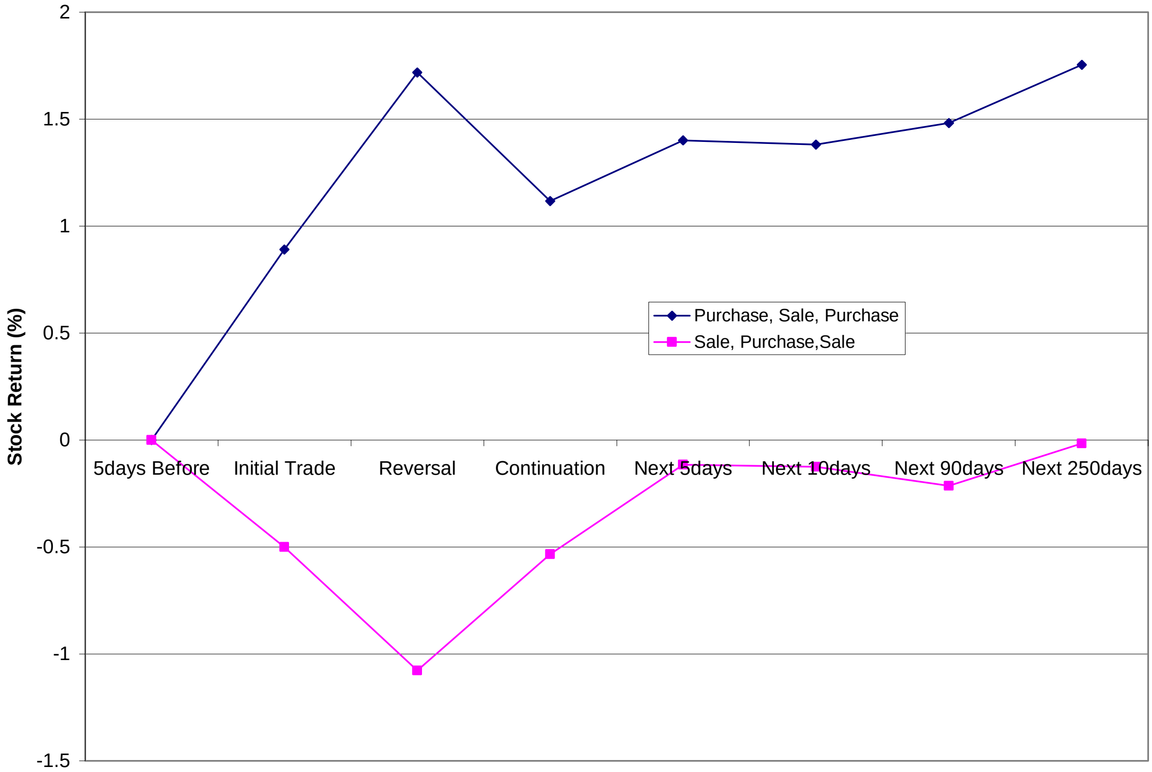
In this table we use regression methodology (listed in the column heading) for the dependent variable (listed in the column headings) regressed against a number of independent variables (listed in the row headings). Regression methodology includes logit and probit for our churning dummy (equal to one in the quarters in which our manager completes the sequence (i) buy, sell, buy or (ii) sell, buy, sell) and Tobit for our churning number (the number of times a manager churns within the quarter) and churning performance (the average performance of the churning sequence). Independent variables include stock size, book-to-market ratio, prior 3 month stock return and volatility, prior 3 month relative bid-ask spread and stock turnover. These variables are all calculated as rank variables between zero and one. We also calculate prior 3 month index return and volatility. Lastly, we include manager variables, such as relative weight in a stock (manager weight minus S&P/ASX 300 Index weight), log (manager size), prior 6mth manager performance and portfolio turnover, and dummy variables equal to one if our manager has a growth or value style. In the first five columns we use past data in order to calculate the independent variables, whereas in the last two columns we use present data, that is calculated during the period with which we measure our dependent variable (churning dummy).

Dependent Variable	Churning Dummy	Churning Dummy	Churning Number	Churning Performance	Churning Dummy	Churning Dummy	Churning Dummy
Regression Methodology	Logit	Probit	Tobit	Tobit	Probit	Logit	Logit
Period Calculation of Independent Variables	Previous	Previous	Previous	Previous	Previous	Current	Current
Constant	-8.98***	-3.72***	-18.56***	-1.16***	-13.22***	-11.32***	-16.29***
(t-statistic)	*(37.40)*	*(43.72)*	*(27.57)*	*(16.16)*	*(43.75)*	*(34.24)*	*(41.56)*
Stock Size	2.54***	0.73***	3.62***	0.18***	8.88***	4.44***	12.80***
(t-statistic)	*(11.07)*	*(8.76)*	*(5.69)*	*(2.59)*	*(32.65)*	*(13.44)*	*(35.06)*
Book-to-Mkt Ratio	-0.48***	-0.28***	-1.50***	-0.05***	-0.52***	-0.50***	-0.37***
(t-statistic)	*(7.38)*	*(8.80)*	*(9.11)*	*(3.45)*	*(8.06)*	*(7.64)*	*(5.55)*
3mth Stock Return	0.01	0.00	0.04	0.00	-0.06	-0.17***	-0.19***
(t-statistic)	*(0.24)*	*(0.13)*	*(0.31)*	*(0.28)*	*(1.13)*	*(3.23)*	*(3.51)*
3mth Stock Volatility	0.04	-0.01	0.08	0.04	2.28***	0.71***	-12.75***
(t-statistic)	*(0.28)*	*(0.12)*	*(0.18)*	*(1.04)*	*(14.77)*	*(3.86)*	*(8.65)*
3mth Index Return	-0.86***	-0.56***	-3.27***	-0.14**	-0.96***	-0.11	-0.17
(t-statistic)	*(2.92)*	*(3.77)*	*(4.37)*	*(2.27)*	*(3.32)*	*(0.39)*	*(0.59)*
3mth Index Volatility	-16.76**	-17.12***	-96.92***	4.95**	-20.27***	0.30	14.90*
(t-statistic)	*(2.29)*	*(4.72)*	*(4.26)*	*(2.18)*	*(2.76)*	*(0.04)*	*(1.92)*
3mth Relative Bid-ask Spread	-0.54***	-0.26***	-1.28***	-0.06***		-0.51***	
(t-statistic)	*(34.70)*	*(37.96)*	*(22.33)*	*(10.96)*		*(30.02)*	
Stock Turnover					0.26***		0.15***
(t-statistic)					*(16.14)*		*(9.87)*
Investor Relative Weight	31.37***	17.53***	80.58***	4.27***	33.54***	31.07***	33.82***
(t-statistic)	*(30.05)*	*(30.66)*	*(24.83)*	*(14.31)*	*(31.30)*	*(30.08)*	*(31.75)*
Manager Size	0.09***	0.03***	0.16***	0.01***	0.08***	0.10***	0.08***
(t-statistic)	*(14.88)*	*(13.50)*	*(11.81)*	*(6.43)*	*(13.46)*	*(14.81)*	*(12.36)*
Growth Investor Dummy	-0.04	0.02	0.47***	0.01	-0.05	0.01	0.02
(t-statistic)	*(0.73)*	*(0.93)*	*(3.54)*	*(1.23)*	*(1.04)*	*(0.27)*	*(0.45)*
Value Investor Dummy	0.03	0.02	0.27**	0.03***	-0.01	0.09*	0.09*
(t-statistic)	*(0.61)*	*(0.65)*	*(1.96)*	*(2.91)*	*(0.28)*	*(1.70)*	*(1.81)*
Style Neutral Investor Dummy	0.16***	0.07***	0.53***	0.02	0.15***	0.18***	0.16***
(t-statistic)	*(2.82)*	*(2.58)*	*(3.54)*	*(1.14)*	*(2.66)*	*(3.20)*	*(2.89)*
Prior 6mth Investor Performance	-0.80**	-0.34*	-2.33***	-0.08	-0.64*	-0.22	0.07
(t-statistic)	*(2.30)*	*(1.82)*	*(2.62)*	*(1.19)*	*(1.85)*	*(0.66)*	*(0.19)*
Prior 6mth Portfolio Turnover	1.98***	1.03***	5.14***	0.26***	1.86***	2.00***	1.76***
(t-statistic)	*(24.63)*	*(24.20)*	*(23.32)*	*(13.94)*	*(23.21)*	*(25.61)*	*(22.24)*
N	8,283,100	8,283,100	8,283,100	8,283,100	8,283,100	8,383,500	8,383,500
R-squared (%)	8.73	8.51	99.83	99.73	7.35	9.15	7.79

*,**, and *** display significance at the 90, 95 and 99% confidence interval, respectively.

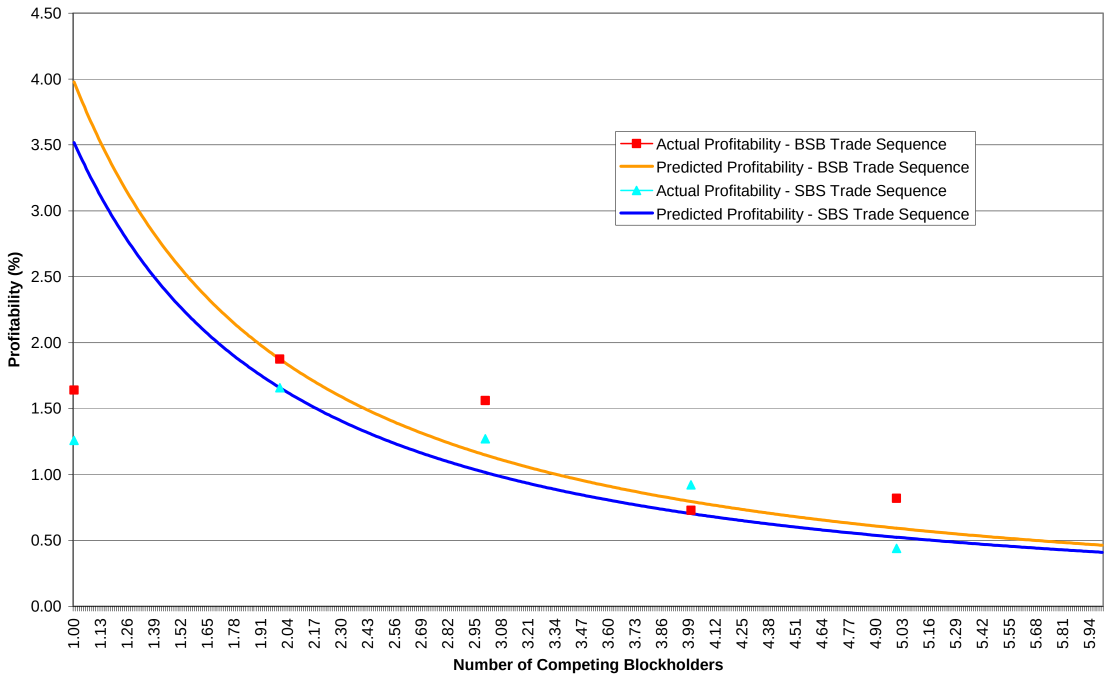
Figure 1

Excess Return (after transactions costs) Around Churning Trades



This figure displays stock excess performance (over the S&P/ASX 300 Index Return) around the following trade sequences, (1) purchase, sale, purchase and (2) sale, purchase, sale. These trade sequences occur over less than three months. We used the volume-weighted-average-price as reported by the blockholder. Transactions costs are subtracted from (added to) the excess return after purchases (sales).

Figure 2
Actual vs Expected Profitability of Institutional Investor Churning Sequences



This figure displays the profitability of two different styles of churning trades according to the number of blockholders simultaneously trading each month. Profitability is calculated as the stock excess performance (over the S&P/ASX 300 Index Return) around the following trade sequences, (1) buy, sell, buy (BSB) and (2) sell, buy, sell (SBS). These trade sequences occur over less than three months. We used the volume-weighted-average-price as reported by the blockholder. Transactions costs are subtracted from (added to) the excess return after purchases (sales). The actual profitability appears as the dots on the chart, which can be compared with the appropriate predicted profitability line. The predicted profitability is the expected profit according to the number of blockholder participants trading simultaneously in the Kyle symmetric Cournot equilibrium. It appears as the continuous lines in the Figure.

Appendix A

Table A1: Descriptive Statistics of Active Institutional Investor Trades including the Number of Churning Investors

This table measures presents a number of descriptive statistics concerning our manager buy and sell trades, as described in the panel titles. Average daily volume and volatiliy is calculated over the past three months. Packages are defined following Chan and Lakonishok (1995), who use a five-day gap definition of a package, implying that a new package begins when there is a five-day gap between manager trades (in the same direction), or when the manager executes a trade in the opposite direction. The sample comprises all trades of 30 active Australian investment managers during the period January 2, 1994 to December 31, 2001.

	All	Number of Investors churning the same stock					All	Number of Investors churning the same stock				
	Buys	1	2	3	4	5	Sells	1	2	3	4	5
	Panel A: Shares Traded (Thousands)											
Mean	168	170	179	155	159	165	161	161	160	162	189	145
Median	21	19	22	19	23	25	25	21	24	26	27	28
StDev	551	626	569	592	424	439	537	694	417	478	603	372
25%	4	3	4	4	4	5	5	3	4	5	4	6
75%	106	98	109	91	102	121	117	105	114	117	120	124
99%	2,263	2,554	2,681	2,073	2,088	2,000	1,982	1,977	1,989	2,402	2,327	1,651
	Panel B: Dollar Value of Package (Thousand $)											
Mean	1,099	639	930	1,027	1,296	1,858	1,052	635	871	1,157	1,259	1,446
Median	162	84	160	176	250	308	192	99	172	220	229	363
StDev	3,157	1,965	2,526	2,829	3,251	4,731	2,709	2,229	1,959	3,032	2,999	3,106
25%	32	16	32	41	41	71	38	17	36	55	44	75
75%	754	391	671	735	1,035	1,574	835	437	722	834	1,054	1,324
99%	15,251	9,117	12,050	13,808	14,394	25,439	12,843	7,948	9,054	14,294	14,146	15,054
	Panel C: Package Size Relative to Normal Trading Volume											
Mean	0.90	1.00	1.00	0.71	0.80	0.82	0.90	0.97	1.02	0.91	0.91	0.72
Median	0.12	0.12	0.15	0.11	0.11	0.11	0.14	0.13	0.16	0.14	0.13	0.14
StDev	2.23	2.44	2.40	1.78	2.06	2.07	2.15	2.36	2.34	2.22	2.18	1.66
25%	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.02	0.03
75%	0.62	0.66	0.71	0.51	0.56	0.60	0.65	0.68	0.74	0.63	0.67	0.59
99%	12.10	13.15	13.05	9.91	10.70	10.91	11.77	13.29	12.64	12.35	11.55	8.70
	Panel D: Package Size Relative to 95th Percentile of Trading Volume											
Mean	0.40	0.40	0.44	0.34	0.38	0.40	0.40	0.39	0.45	0.42	0.42	0.35
Median	0.06	0.05	0.07	0.05	0.05	0.06	0.07	0.05	0.07	0.07	0.07	0.07
StDev	1.00	1.01	1.09	0.84	0.95	1.01	0.96	0.96	1.06	1.04	1.00	0.81
25%	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
75%	0.29	0.27	0.32	0.25	0.28	0.31	0.30	0.29	0.34	0.30	0.33	0.29
99%	5.42	5.22	5.78	4.49	5.32	5.64	4.99	5.07	5.39	5.64	5.43	3.89
	Panel E: Average Daily Volatility (%)											
Mean	4.9	3.7	4.4	5.0	6.0	6.6	4.8	3.7	4.4	4.7	5.0	6.1
Median	2.6	2.4	2.5	2.6	2.8	2.9	2.5	2.3	2.4	2.6	2.6	2.7
StDev	6.8	4.6	6.2	6.9	8.0	8.5	6.7	4.9	6.4	6.5	7.1	8.0
25%	1.7	1.5	1.7	1.8	1.8	1.8	1.7	1.5	1.6	1.7	1.7	1.8
75%	4.4	3.9	3.9	4.2	5.8	7.6	4.2	3.8	4.0	4.2	4.2	5.9
99%	36.8	25.3	34.9	38.2	40.5	40.5	35.7	30.1	37.5	34.4	36.9	38.2

Appendix B
Table B1: Explicit Transaction Costs

Transactions costs are calculated using explicit brokerage costs provided by managers. However, given that four of our sample of investment managers did not provide the brokerage costs for their trades, we modelled brokerage costs using the data we did have, thereby estimating the brokerage for the missing values. Missing values make up less than 50 percent of our trades. In this table, we regress the explicit brokerage costs for trade packages against a number of independent variables: manager style dummies (growth or value), log manager size), broker dummies (for the most popular seven brokers which account for the majority of manager trades). Trade packages are defined according to Chan and Lakonishok (1995), where a package end after a five day period of no trades or a trade is made in the opposite direction. All beta values are in basis points.

Variables	All Trades
Constant	25.63***
Growth Manager	8.51***
Value Manager	-6.13***
log (Manager Size)	-6.18***
Broker 1	7.13***
Broker 2	2.52
Broker 3	-1.10
Broker 4	3.71*
Broker 5	-1.88
Broker 6	3.62
Broker 7	0.26

*,**, and *** display significance at the 90, 95 and 99% confidence interval, respectively.