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High Frequency Trading, Information, and Takeovers

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Abstract

This paper (1) proposes new variables to detect informed high-frequency trading (HFT), (2) shows that HFT can help to predict takeover targets, and (3) shows that HFT influences target announcement announcement returns. Prior literature suggests that informed trade may occur before takeovers, but has not examined the role of HFT and has relied on monthly measures of informed trade (such as PIN or the spread components). I propose microstructure-based variables to detect HFT that are derived from hazard modeling and from VWAP trading algorithms. I show that these can help predict takeover targets and are significantly related to target announcement returns. This highlights the existence of pre-takeover informed trade and the need to control for it when analyzing takeover returns.

1 Introduction

This paper proposes measures to detect high frequency trading (HFT), shows that HFT can help predict takeover targets, and finds that HFT influences

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target announcement returns. I contribute to the literature on the detection of HFT and informed trade, takeover returns, and takeover prediction. The intuition for focusing on HFT is twofold. First, high-levels of HFT represent a liquid investor base, implying that there may be a stronger market reaction on the announcement. Second, high levels of HFT might reflect pre-announcement informed speculation, implying the possibility of a takeover and suggesting pre-takeover informed trade. This implies that failing to control for HFT might induce an omitted variable bias in studies that analyze takeover returns, and contributes to the policy debate on the regulation of HFT.

HFT has proliferated and has become a live regulatory issue. HFT and algorithmic trading have increased in popularity (Chew, 2007; Degryse, Van Achter and Wuyts, 2009). Up to 67% of investment managers indicate that they use trading algorithms (Grossman, 2005). They may become more prolific due to the emergence of 'best execution' requirements as in MIFID (following Anolli and Petrella, 2007; Brandes and Domowitz, 2011). Trading algorithms provide one way to for informed traders to shift large blocks of stock while minimizing transaction costs (Humphery-Jenner, 2011; Kissell, Glantz and Malamut, 2004; Kissell and Malamut, 2005, 2006). Subsequently, HFT has been linked to market manipulation and informed trade, raising the possibility of regulating HFT (Bhupathi, 2010; McGowan, 2010; Serritella, 2010). However, there is a dearth of tractable proxies for the presence of HFT, and the literature has not analyzed the relation between HFT and informed trade.

The motivation of this study is to contribute to, and to address gaps in, four strands of literature: informed trade measurement, pre-takeover informed trade, takeover prediction, and the determinants of target returns.

First, I contribute to the 'informed trade' literature. Proxies for the presence of HFT are especially important because traders do not have access to trader IDs; and thus, need ways to transform anonymous trade data into measures of HFT and informed trade. Prior literature focuses on monthly measures such as PIN and the components of the bid ask spread. However, the literature lacks daily measures of informed trade that incorporate intraday trading dynamics. I provide a new daily measure of informed trade. It is based on the intraday frequency of trades. Specifically, it is shape parameter of a Weibull distribution that models the end in a 'lull' in trade. I compute the shape parameter using method of moments. This variable captures the frequency of trades; and thus, represents the presence of high-frequency trade. I also examine intraday deviations from a 'standard' trading volume profile. This provides a measure of the frequency of trading, which represents the existence of HFT.

Second, I contribute to the literature on pre-announcement informed trade. The important finding is that there is some evidence of pre-takeover informed trade. Cumming and Li (2011) find a stock-price run-up in targets and acquirers before takeover announcements. Cao, Chen and Griffin (2005) find significant informed trade in the options market before takeover announcements. Farinós Viñas, Garcia and Ibanez (2003) find that the information asymmetry component of the bid-ask spread increases before a takeover announcement. Further, Aktas, de Bodt, Declerck and Van Oppens (2007) indicate that order-imbalance is higher before a takeover announcement; however, find little relation between PIN and merger announcements. The problem with most of these results are (1) they rely on 'monthly'-type variables. For example, PIN or the decomposition of the bid-ask spread require at least a month of intraday data. (2) The insider trading papers usually rely on information about insider trades,[1] which is non-public and thus not useful to the general market. (3) the daily measures (such as daily order imbalance) ignore intraday trading patterns; and thus, exclude potentially useful information. I show that there is daily 'informed trade' (as proxied by the intraday frequency of trading) in target stock before takeover announcements.

Third, the paper contributes to the takeover prediction literature. Myriad papers have attempted to predict takeover targets. These models aim to predict targets in order to capture abnormal returns on and after the announcement of a takeover. These models are typically based on annual (sometimes quarterly) firm-level data (see Barnes, 1990, 1999; Powell, 2001, 1997). Brar, Giamouridis and Liodakis (2009) incorporate market-based daily returns. The studies have not analyzed pre-takeover informed trade as a prediction

[1]See for example: Bris (2005); Keown and Pinkerton (1981); Meulbroek (1992); Meulbroek and Hart (1997); Seyhun (1990).

mechanism. This is a problem due to the hypothesized presence of informed HFT before takeovers.

Fourth, I show an additional driver of takeover (target) returns. The literature indicates that targets earn significant abnormal returns in the window surrounding a takeover announcement.[2] Prior literature has also examined the drivers of acquirer returns. Prior literature has not examined HFT as a driver of returns. However, HFT might influence returns by (a) representing greater market interest in the stock, suggesting a more liquid market and a potentially greater reaction to news; and (b) indicating pre-announcement informed trade and speculation, which might impound takeover-related information. Thus, failure to properly control for pre-takeover HFT might induce omitted variable bias in cross-sectional regressions of acquirer and/or target returns.

The results confirm the presence of informed trade before takeover announcements and highlight the importance of HFT-based proxies. These proxies are significantly related to the occurrence of takeover events and to takeover returns. I obtain these results by analyzing a sample of firms listed on the Australian Stock Exchange (ASX) between 1998 and 2008. The sample comprises 1014 firm-day observations on which there is a takeover bid, and 1,262,468 firm-day observations on which there is no takeover bid. Advantages of using the ASX are that (a) it has a wide cross-section of both

[2] See for example: Andrade and Stafford (2004); Baugess, Moeller, Schlingemann and Zutter (2009); Campa and Hernando (2004); Franks and Harris (1989); Goergen and Renneboog (2004); Jensen and Ruback (1983); Schwert (1996).

liquid and liquid stocks, (b) it has allowed direct market access for the whole of the sample period (thereby facilitating electronic trading), (c) has had a purely electronic limit order book for the whole of the sample period (as opposed to an open out cry market), (d) it has strong insider trading rules and an effective regulatory. These results should be generalizable to all developed markets that enable direct market access.

The balance of the paper proceeds as follows. Section 2 proposes ways to capture the presence of HFT. Section 3 describes the sample and empirical methodology. Section 4 contains the results and Section 5 concludes.

2 Measuring trade frequency

The first issue is to determine how to measure the presence of HFT. The presence of HFT is not a binary variable (i.e. it is not that either there is HFT or there is not). Rather, the focus should be on high-frequency trading dynamics. The important focuses are the frequency of trades and the presence of intraday volume spikes. Thus, I analyze three HFT variables: the Weibull shape parameter, inspired by hazard modeling; the level of abnormal trade, inspired by VWAP trading, and the intraday order imbalance.

2.1 Weibull Shape Parameter

Here, I observe that there is a time interval between trades. Gourieroux, Jasiak and Le Fol (1999) observe that the duration between trades indicates the level of trade intensity, and imply that it may imply informed trade. I cull this time interval a 'lull' in trading. A shorter time-interval means higher-frequency trade. Thus, one approach is to model the time between trades. I focus on modeling the time until a trading lull ends. The Weibull distribution is particularly appropriate for modeling this trading lull. The Weibull distribution has seen frequent use in the failure prediction literature.[3] Thus, I use the shape parameter for the Weibull distribution.

I compute the shape parameter using a method of moments approach.[4] I assume a two-parameter Weibull model. This model has a scale parameter (α) and a shape parameter (β). The goal is to find an estimate for β. The process is:

1. Define the the first and second moments as:

$$m_1 = \mu = \left(\frac{1}{\alpha}\right)^{1/\beta} \Gamma\left(1 + \frac{1}{\beta}\right) \tag{1}$$

$$m_2 = \mu^2 + \sigma^2 = \left(\frac{1}{\alpha}\right)^{2/\beta} \left(\Gamma\left[1 + \frac{2}{\beta}\right] - \left[\Gamma\left[1 + \frac{1}{\beta}\right]\right]^2\right) \tag{2}$$

Divide the m_2 by the square of m_1 to obtain:

[3] Examples include: Brookman and Thistle (2009); Giot and Schwienbacher (2007); Lee and Urrutia (1996); Wong (1995).

[4] This approach is not new and has seen prior use, see: Cran (1988); Gove (2003); Khalili and Kromp (1991).

$$\frac{\sigma^2}{\mu^2} = \frac{\Gamma\left[1+\frac{2}{\beta}\right] - \Gamma^2\left[1+\frac{1}{\beta}\right]}{\gamma^2\left[1+\frac{1}{\beta}\right]} \tag{3}$$

Equation (3) This implicitly defines shape parameter β.

2. Compute $\frac{\sigma^2}{\mu^2}$ using the actual data. Call this Actual $\left(\frac{\sigma^2}{\mu^2}\right)$. I define μ^2 as the average time between trades for stock i on day t, and σ^2 as variance of the time between trades.

3. Iterate through β values from 0.1 to 10. Compute $\frac{\sigma^2}{\mu^2}$ for each of these β estimates. Call this Estimated $\left(\frac{\sigma^2}{\mu^2}\right)$.

4. Choose the β value that minimizes the squared difference between Actual $\left(\frac{\sigma^2}{\mu^2}\right)$ and Estimated $\left(\frac{\sigma^2}{\mu^2}\right)$.

5. Note that the estimate scale parameter is then,

$$\hat{\alpha} = \text{Scale Parameter} = \left(\frac{\mu}{\Gamma\left[1+(1/\hat{\beta})\right]}\right) \tag{4}$$

2.2 Intraday 'Abnormal' Turnover

The second variable is the intraday abnormal turnover. The basis for this variable is the observation that high trading volumes can signal information.[5] In the presence of HFT, this means that there should be high intraday

[5]See for example: Easley, O'Hara and Srinivas (1998); Kim and Verrecchia (1991)

volume spikes. Thus, the intraday abnormal turnover represents the deviation of intraday trade from that of an ordinary volume profile. A deviation from an 'ordinary' intraday trade profile may convey information (following Bialkowski, Darolles and Le Fol, 2008; Humphery-Jenner, 2011; Lo and Wang, 2000; Manchaldore, Palit and Soloviev, 2010). The ordinary volume profile is the percentage of the stock's daily volume that occurs in any given intraday interval (called a 'bin'). The abnormal turnover is the difference between the actual percent of daily turnover that trades in the interval and the ordinary amount. I define the intraday abnormal turnover in Equation (5).

$$\begin{array}{r}\text{Intraday} \\ \text{Abnormal Turnover}_{i,t_b}\end{array} = \text{Turnover}_{i,t_b} - \text{Expected Turnover}_{i,t_b} \tag{5}$$

$$\text{Turnover}_{i,t_b} = \frac{\text{Volume}_{i,t_b}}{\sum_{b=1}^{N} \text{Volume}_{i,t_b}} \tag{6}$$

$$\text{Expected Turnover}_{i,t_b} = \text{Ave Turnover}_{i,t_b} \text{ over past 30 days} \tag{7}$$

I use five minute intervals and focus on the absolute value of the deviation on grounds that both lulls and spikes in volume can convey information. I define the ordinary amount traded in any five minute interval as the average proportion of turnover traded in that five minute interval over the past month.

2.3 Intraday Order Imbalance

The third variable is the intraday order imbalance. Aktas, de Bodt, Declerck and Van Oppens (2007) show that daily order imbalance is more informative around takeover announcements than are PIN and the spread components. The order imbalance is the number of buy orders less the number of sell orders divided by the total number of buy and sell orders. I focus on the absolute order imbalance (as per Aktas, de Bodt, Declerck and Van Oppens, 2007). I calculate the order imbalance at five minute intervals and control for the moving average of the intraday order imbalance over the past five days.

3 Methods and Materials

3.1 Empirical Strategy

I analyze whether HFT (a) helps to predict takeover activity, and (b) influences takeover returns. The main independent variables are the HFT variables. I measure these over some interval starting 11 days before day t. The baseline HFT variable is just the variable on day $t-11$. However, I also report results for the variable over a 5 day window (from $t-11$ to $t-15$) and a 30 day window (from $t-11$ to $t-40$).

The prediction models use logit regressions. Here, the dependent variable is an indicator that firm i receives a takeover offer within day t and day $t+j$, denoted Bid_t^{t+j}. I focus on the firm receiving a bid over the windows

$(t, t+5), (t, t+10), (t, t+30)$. The binomial logit model is common in the literature (see e.g. Brar, Giamouridis and Liodakis, 2009; Palepu, 1986). The model includes year dummies and standard errors clustered by GICS sector[6] in order to control for takeover waves Almeida and Fernandes (consistent with 2008); Neumayer (consistent with 2008); Petersen (consistent with 2009). [7] The logit model is in Equation (8).

$$\mathbb{I}\left(\text{Bid}_t^{t+k}\right) = f(\text{HFT}_{t-k}^{t-11}, \text{Controls}) \tag{8}$$

The returns models use panel regressions and OLS regressions. There are three sets of models. First, I examine only takeover targets. The sample comprises only firms that receive a takeover offer. The dependent variable is the firm's 'return' on the date of the offer. The return is variously the firm's raw return, the firm's market adjusted return, or the firm's industry (GICS sector) adjusted return. I prefer the industry/market adjusted return to the market-model-based abnormal return because some firms in the Australian market are illiquid;[8] and thus, might have biased and inconsistent market model parameters (Dimson and Marsh, 1983; Scholes and Williams, 1977). The model is in Equation (9).

[6]The results are robust to clustering by the alternative industry definition, the 'GICS group'

[7]The results are robust to using GICS group rather than GICS sector and to using industry dummies. GICs codes, rather than SIC codes, are standard industry classifications for Australian companies.

[8]On the potential illiquidity of the Australian market see (Humphery-Jenner, 2011).

$$\text{Return}_t = f(\text{HFT}_{t-k}^{t-11}, \text{Controls}) \tag{9}$$

Second, I examine takeover targets and non-targets together. The sample comprises all firms in the market. This is an unbalanced panel data set where I observe each firm on each day. Thus, I run a firm-date panel fixed-effects regression that also clusters standard errors by GICS sector.[9] The dependent variables are variously the firm's stock return, GICS sector adjusted return, and market adjusted return. The main independent variables are the HFT variables, an indicator that the firm receives a bid on day t, and the interaction thereof. If pre-announcement HFT drives returns, then the interaction term should be positive and significant. The model is in Equation (10).

$$\text{Return}_t = f(\text{HFT}_{t-k}^{t-11}, \mathbb{I}\left(\text{Bid}_t\right), \text{HFT}_{t-k}^{t-11} \times \mathbb{I}\left(\text{Bid}_t\right), \text{Controls}) \tag{10}$$

3.2 Sample and variables

I analyze the Australian market between 1998 and 2008. The Australian market is an ideal market for this study. First, Australia transitioned from a physical open out-cry market to a fully electronic market between 1987 and 1990. Australia has allowed direct market access and automated trading

[9]The results are robust to using an OLS regression with year and/or GICS sector/group dummies.

since 1997, thereby facilitating algorithmic trading. These combined facts mean that the Australian market has been relatively liquid and automated since before the sample period.[10] Second, the Australian market is of a manageable size, and this allows me to include most stocks on the ASX. This sample-size makes it possible to analyze intraday trading information for all stocks in the market. Third, the Australian market has a wide range of liquid and illiquid stocks. This heterogeneity ensures that the results do not merely apply to a sub-section of liquid stocks. Fourth, Australia has a strong regulatory regime with effective enforcement of insider trading rules.[11]

The ASX is a fully electronic market that allows limit orders. It functions through a continuous order matching process. Normal trading hours are from 10:00 am to 4:00 pm. Stocks commence trading between 10:00 am and 10:30 am. Commencement is staggered by alphabetical order. Trading closes between 4:00 pm and 4:05 pm. A final closing auction determines the closing price. I only include observations that occur between 10:30 am and 4:00 pm.

The stock market variables come from Reuters (as in Humphery-Jenner, 2011). Here, Reuters provides intraday trading information and stock return information. The takeover announcement data comes from SDC platinum as is standard in the takeover literature. The fundamental firm-level data

[10]Full information is available from ASX (2010).

[11]I note that Cumming, Johan and Li (2011) indicate that Australia has relatively poor stock exchange rules. However, in Australia, all relevant rules are in the Corporations Act 2001 (Cth) Division 3 (available here: `http://www.comlaw.gov.au/Details/C2011C00013/Download`). For a detailed discussion see Lyon and du Plessis (2005). Thus, exchange rules are not necessary to govern insider trading in Australia.

is from FinAnalysis (as in Humphery-Jenner and Powell, 2011). The full sample is an unbalanced panel where I have an observation for each stock on each day.[12] I use the panel sample when analyzing the likelihood that a firm receives a bid (Equation (8) and when comparing target-firms' returns to other firms' returns (Equation (10)). I collapse this into a cross-sectional sample when I analyze the sample of targeted firms. Here, I only have one observation for each firm and takeover bid. The sample comprises 1186 companies. Of these, 540 receive a bid at some time. These bids can be of varying sizes and for varying degrees of control. I do not require the bid to be successful.[13]. There are 1014 firm-day observations on which there is a takeover bid, and 1,262,468 firm-day observations on which there is no takeover bid.

3.3 Independent Variables

I use two classes of independent variables. First, the takeover prediction models examine an indicator that equals one if the firm received a takeover offer between day t and $t + k$. I report results for $k = 5, 10, 20$. I obtain the takeover announcement dates from SDC platinum.

Second, the returns-based models examine the stock's return on day t. I examine the raw return, the 'market adjusted' return (the raw return less

[12] I note that some stocks have missing days for days when there were insufficient trades to compute microstructure variables.

[13] Note that requiring the bid to be for 100% control of the company reduces number of bid-observations but increases the ability to detect a takeover

the equally weighted market return) and the 'industry adjusted' return (the raw return less the equally weighted stock return for all stocks in the firm's GICS sector[14]). The stock return data is from Reuters.

3.4 HFT Variables

Section 2 details the variables. I obtain the data to compute these variables from Reuters. I estimate both the raw variable on day $t-11$ and the average of the HFT variable between day $t-11$ and $t-k$, where $k \in \{1, \ldots, 30\}$. For brevity, I only report the 5 day window ($t-11$ to $t-15$) and the 30 day window ($t-11$ to $t-40$). The results hold for the intermediate windows. The intraday data is from Reuters.

3.5 Control Variables

The control variables are factors that might help to predict the likelihood of a takeover. Note that Australia has different governance arrangements from the U.S: Australia forbids (1) anti-takeover provisions (Humphery-Jenner and Powell, 2011), (2) 'frustrating actions' designed purely to resist a takeover rather than to maximize shareholder value (Takeovers Panel, 2010, Guidance Note 12), and (3) dual-class shares in general.[15] Further, Australian compa-

[14]The results are robust to using GICS group rather than GICS sector.

[15]ASX Listing Rule 6.9 mandates that one share has one vote, and Rule 6.10 prevents corporations from removing voting rights (ASX, 2001). It is possible to adopt a dual-class structure in Australia; however, it tends to apply to unusual corporate arrangements. An example is AWB (Australian Wheat Board), which began as a farmer-owned mutual company with a government backed monopoly. AWB attempted to move toward a single-

nies that list on the ASX must comply with the ASX corporate governance principles, which stimulate appropriate internal governance arrangements.[16]

Firm Size ('ln(Assets)'): Large size should weakly decrease the likelihood of a takeover. Large firms are more expensive to acquire; and thus, should be less likely to receive a takeover offer (Powell, 2001, 1997). However, this effect is likely to be weak because: (1) Offenberg (2009) shows that size does not effectively entrench managers and protect them from disciplinary takeovers, suggesting that bidders focus more on the firm's price-to-book than on its mere size. (2) Australian companies tend to be smaller than companies in other countries (Humphery-Jenner and Powell, 2011); and thus, are should benefit less from a size-based entrenchment effect.

Debt/Assets: Financial leverage may influence the likelihood of a takeover. One possibility is that leverage might reduces the likelihood of a takeover. This is for two reasons. First, leverage reduces free cash flows. This reduces Jensen (1986) type agency conflicts (following Harford, 1999; Maloney, McCormick and Mitchell, 1993). This reduces the attractiveness of a disciplinary takeover. Second, leverage reduces available cash holdings. Faleye (2004) shows that cash rich firms are more likely to be taken over. Thus, leverage should reduce takeover likelihood. An alternative possibility is that

class structure in 2008. AWB delisted in 2010. Nenova (2003) and Doidge (2004) report that only 3 Australian companies have dual-class shares.

[16]These principles stipulate matters such as the firm's disclosure obligations and the required number of independent directors (ASX, 2003, 2008). The listing rules are available from `http://www.asxgroup.com.au/asx-listing-rules-guidance-notes-and-waivers.htm`. Different rules have applied at different times; however, year-dummies capture this change.

excess leverage can induce financial distress in industry downturns (see Opler and Titman, 1994). This might motivate distress-motivated takeovers.

Market Cap/Assets: Highly stock prices make firms more attractive; and thus, less likely candidates for a takeover (Powell, 2001, 1997). Thus, I control for the firm's market capitalization on day t divided by its assets reported in the last financial report.

Industry Adjusted Operating Performance (IAOP): Strongly performing companies are less likely to be the subject of a disciplinary takeover, are more likely to trade at higher market prices; and thus, are less likely to be takeover targets. Thus, I control for the industry adjusted operating performance. The firm's operating performance is the its return on assets. The industry adjusted operating performance is the firm's ROA less the median ROA of firms in its GICS sector.

Industry M&A Activity: Takeover activity tends to occur in waves across time and industry (Harford, 2005; Powell and Yawson, 2005). Thus, I control for the number of M&A deals in the firm's GICS sector over the past year scaled by the total number of M&A deals that occurred in the past year.[17]

High Tech Firm Indicator: High tech firms may be more apt takeover targets because (a) they tend to be smaller and (b) they may be subject

[17]Robustness tests replace this variable with the total value of all deals in the firm's industry in the prior year divided by the total value of deals in the prior year. This variable does not significantly influence takeover likelihood and does not change the results for the main microstructure-based variables.

to bids designed to replace internal R&D with external technological acquisitions (Gerpott, 1995; Granstrand, Bohlin, Oskarsson and Sjöberg, 1992; Vanhaverbeke, Duysters and Noorderhaven, 2002). The high tech firm indicator equals one if the firm's GICS group is pharmaceutical, semi-conductor, software, or information technology.

Industry Concentration (HHI): Low industry concentration should increase the takeover likelihood as firms engage in 'roll-up' takeovers designed to maximize market share (Powell and Yawson, 2005). Thus, I control for the HHI of the firm's GICS sector in the year.[18]

Cash Payment: The OLS models in Equation (9) also control for the method of payment. This is based on prior literature that shows that the method of payment influences the takeover premium and/or the market's reaction to the takeover (for acquire-returns results see Chang, 1998; Fuller, Netter and Stegemoller, 2002).

4 Results and Analysis

4.1 Sample Description

The univariate statistics indicate that (a) takeover returns increase with the level of HFT and pre-takeover trading and (b) there are some key differences between target and non-target firms.

[18] I calculate the HHI as the sum of squared market shares for all firms in the GICS sector. The market share is the firm's sales divided by the total sales for all companies in that firm's industry and year.

Table 1 contains the statistics for the HFT variables. The main findings are: (1) The HFT variables are relatively stable over time-horizon; that is, the 1-day, 5-day, 15-day and 30-day moving averages are similar in magnitude. (2) The HFT variables are stable across years. This is relatively unsurprising given that Australia has allowed direct market access for the whole of the sample period. (3) The HFT variables may differ between targets and non-targets. Specifically, Panel C contains statistics sorted by firm-size and whether the firm receives a takeover bid on day t. Small targets (assets in the bottom 50% of the sample) have higher HFT than do small non-targets. However, large targets have lower HFT than do large non-targets. This implies that a multivariate regression framework is necessary to fully analyze the relation between takeovers and HFT.

Table 4 contains the firm-level statistics for targets and non-targets. There are some significant differences between targets and non-targets. The differences quadrate with prior literature (see Brar, Giamouridis and Liodakis, 2009; Powell, 2001, 1997). This implies that it is important to control for these factors when analyzing takeover prediction/returns.

Table 2 and Table 3 focus on takeover targets. Table 2 only examines firm-day combinations on which the firm receives a takeover bid. The main result is that there are positive returns on such days (the raw, market adjusted, and industry adjusted returns are positive). However, the returns are of relatively small magnitude. This is because I do not require the takeover bid to be completed or to be for 100% control of the company. Table 3 contains correlations between the returns and the HFT variables. The key result is that there is a significant positive correlation between most HFT variables and the stock returns.

Overall, the results suggest that there is a relationship between (a) HFT variables, (b) the occurrence of a takeover, and (c) takeover returns. However, when analyzing this relationship it is necessary to control for firm-level characteristics.

4.2 Takeover Return Results

This section discusses the takeover return results. The predictions are that pre-takeover informed trade is positively related to takeover returns. That is, informed trade can predict the market's reaction to the takeover announcement. I analyze this by (a) running a cross-sectional regression on the sample of targets, and (b) running a panel regression on the sample of all firms.

The cross sectional results are in Table 5. The sample comprises takeover targets only. The key result is that the Weibull shape parameter is positive and significant in all models. This implies that pre-takeover informed trade helps to predict target returns. Few control variables are significant. The main findings are that (1) strong pre-takeover performance increases takeover returns. (2) High-tech firms takeovers receive a more negative market reaction. This quadrates with prior evidence that the market tends to under-value high-tech investments Humphery-Jenner (see 2010).

The panel regression fixed effects results are in Table 6 and the panel random effects results are in Table 7. The results are similar in both models. The main independent variable is the interaction term 'Weibull Shape Parameter$_{t-j}^{t-11}$ $\times$ $\mathbb{I}\,(\mathrm{Bid}_t)$'. Here, the interaction term is positive and significant at 1% in all models. This implies that stock returns increase especially with a combination of (a) a bid and (b) pre-takeover informed trade.

The panel regressions yield some other interesting results. First, the mere presence of a bid on day t does not significantly influence returns on day t after controlling for pre-takeover informed trade. That is, while 'Weibull Shape Parameter$_{t-j}^{t-11}$ $\times$ $\mathbb{I}\,(\mathrm{Bid}_t)$' is positive and significant in all models, $\mathbb{I}\,(\mathrm{Bid}_t)$ is not significant.

Second, the level of informed trade in a stock continues to influence returns whether or not there is a bid. That is the term 'Weibull Shape Parameter$_{t-j}^{t-11}$' is positive and significant in most models.

Third, the other informed trade variables (intraday abnormal turnover, and order imbalance) are positively and significantly related to returns in all models. However, unreported results suggest that their interactions with the indicator $\mathbb{I}\,(\mathrm{Bid}_t)$ are not significant.

Overall, the results suggest that the level of informed trade (a) influences stock returns in general, and (b) influences the returns to target firms in especial. This implies that pre-takeover informed trade is an important determinant of takeover returns and that failure to control for it may induce an omitted variable bias.

4.3 Takeover Prediction Results

The main goal is to examine whether intraday variables can help to predict takeover events.

Table 8 contains the prediction results. The key result is that the Weibull shape parameter significantly predicts takeover events. Further, the intraday abnormal trunover is positive and significant at 1% in most models. This implies that there is a high level of intraday-based abnormal trade before takeover announcements.

The control variables have some important implications. First, volatile companies are more likely to be acquired. Companies with a high stock return variance are significantly more likely to receive a bid in all models. This is unsurpising given that high stock variance can represent a high dispersion of opinion and information asymmetry.

Second, high market-to-book ratios reduce takeover likelihood. The coefficient on 'Market Cap/Assets' is negative and significant in all models. This implies that 'expensive' companies are less likely to receive takeover offers. An explanation is that high stock prices deter disciplinary (or opportunistic) takeovers that are designed to acquire cheap assets and/or to remove poorly performing managers.

Third, company size (as proxied by 'ln(Assets)') does not significantly influence the likelihood of a takeover. This appears surprising. However, it quadrates with the findings in Offenberg (2009). A key explanation is a combination of the observations that: (1) large companies are more likely to suffer from agency conflicts and inefficiencies (see Moeller, Schlingemann and Stulz, 2004, 2005); and thus, are more likely to be candidates for disciplinary takeovers. (2) Even large companies in Australia are relatively small (Humphery-Jenner and Powell, 2011). Thus, large companies in Australia may be prime takeover targets.

Fourth, M&A activity in the firm's industry over the prior year is a useful predictor of a firm's takeover likelihood. This quadrates with prior evidence that takeover activity tends to occur in industry waves (see Harford, 2005; Powell and Yawson, 2005, 2007).

Fifth, highly levered companies are more likely to receive a takeover bid. This suggests that for the targets in the sample, high leverage may connote financial distress. This might facilitate restructuring-orientated takeovers.

Sixth, strongly performing companies are less likely to receive a takeover bid. This is consistent with Agrawal and Jaffe (2003) and quadrates with the theory that strong performance deters hostile acquisitions that are designed to remove inefficient managers.

The model diagnostics are encouraging. The R^2 values are low. However, (a) they are only marginally lower than those reported in cross-sectional takeover studies (see Humphery-Jenner and Powell, 2011; Masulis, Wang and Xie, 2007; Moeller, Schlingemann and Stulz, 2004, 2005); and (b) they appear acceptable given that there are few takeover events and the sample comprises all companies that list on the ASX. Further, the ROC areas are reasonable. They are comparable to those reported in Demers and Joos

(2007) in a bankruptcy prediction context.[19] Figure 1 graphs the ROC areas and Table 8 reports them.

4.4 Robustness

This section indicates that the results are robust. (1) The results are robust to time period holding when I split the time period into five-year blocks. (2) The results are robust to clustering, holding when I cluster by year, GICS sector, GICS group, and/or firm. (3) The results (for the HFT variables) are robust to the use of a parsimonious model, which drops all insignificant control variables. (4) The results hold when I replace the bid indicator with an indicator that equals one if the bid was for a complete controlling stake in the company.[20] (5) The results are robust to HFT time horizon (holding when I use moving averages between 5 days and 30 days) and to acquisition time-horizon (being qualitatively the same when I predict a bid in the next 5 to 20 days).

5 Conclusion

I propose new ways to detect HFT, and show that HFT helps to predict takeover targets and influences takeover returns. The literature has documented the presence of a run-up in takeover targets. However, it has not

[19] They are also similar to, and exceed, the ROC areas that Demers and Joos (2007) report for the models in Altman (1968), Zmijewski (1984) and Chava and Jarrow (2004).

[20] I define this as a bid for over 90% of the target, at which point the acquirer can compulsorily acquire the remaining 10% of outstanding shares.

analyzed the existence of HFT before takeovers and the literature on informed trading has generally relied on monthly variables.

I address these issues by proposing three HFT-based variables. First, the Weibull shape parameter models the time between trades. Second, the level of abnormal trade measures deviation from a 'standard' trading pattern. Third, the absolute order imbalance detects the existence of buy or sell pressure. I show that the Weibull shape parameter especially helps to predict takeovers and drives the markets's reaction to a takeover announcement.

These results have important implications. First, they show that failure to control for HFT might induce an omitted variable bias in takeover returns models. Second, they provide an additional input for takeover prediction models. Third, they have implications for regulators by providing an additional way for detect the presence of informed trade. In particular, they show that a high level of HFT might indicate the presence of informed (possibly insider) trading. Future literature can further analyze these variables within the context of acquirer returns and in markets that have less exposure to high frequency algorithmic trading.

6 Figures and Tables

Table 1: Intraday Variable Statistics

Table 1 contains statistics for the intraday variables: the Weibull shape parameter, intraday order imbalance, and intraday abnormal turnover. I compute the moving average variable over 5, 15, or 30 days. The column title indicates the relevant moving average interval. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

HFT Window	1 Day: HFT_{t-11}			5 Day: HFT_{t-15}^{t-11}			15 Day: HFT_{t-25}^{t-11}			30 Day: HFT_{t-40}^{t-11}		
HFT Statistic	Abnormal Turnover	Order Imbalance	Shape Parameter	Abnormal Turnover	Order Imbalance	Shape Parameter	Abnormal Turnover	Order Imbalance	Shape Parameter	Abnormal Turnover	Order Imbalance	Shape Parameter
Panel A: General Statistics												
Mean	0.3211	0.8858	0.2663	0.3495	0.8873	0.2683	0.3654	0.8873	0.2682	0.3739	0.8876	0.2682
Median	0.1285	1.0000	0.2620	0.1674	0.9333	0.2638	0.1839	0.9343	0.2652	0.1928	0.9366	0.2660
Min	0.0081	0.0000	0.1930	0.0155	0.0000	0.1940	0.0169	0.0000	0.1940	0.0175	0.0000	0.1940
Max	3.7255	1.0000	2.0000	3.4571	1.0000	2.0000	3.3853	1.0000	0.9297	3.3431	1.0000	0.6034
Standard Deviation	0.5524	0.1664	0.0357	0.5239	0.1409	0.0289	0.5199	0.1351	0.0172	0.5178	0.1326	0.0134
Panel B: Averages By year												
1998	0.3112	0.9056	0.2652	0.3584	0.9071	0.2675	0.4048	0.9093	0.2678	0.4124	0.9089	0.2679
1999	0.3531	0.8948	0.2640	0.4024	0.8962	0.2663	0.4254	0.8950	0.2661	0.4414	0.8959	0.2659
2000	0.3189	0.8791	0.2661	0.3494	0.8801	0.2679	0.3653	0.8801	0.2679	0.3768	0.8800	0.2677
2001	0.2750	0.8786	0.2660	0.3023	0.8799	0.2683	0.3211	0.8804	0.2682	0.3243	0.8804	0.2681
2002	0.3073	0.9022	0.2675	0.3412	0.9037	0.2696	0.3636	0.9046	0.2696	0.3738	0.9035	0.2695
2003	0.3333	0.9054	0.2669	0.3662	0.9074	0.2690	0.3814	0.9072	0.2688	0.3956	0.9075	0.2688
2004	0.3589	0.9039	0.2671	0.3864	0.9057	0.2691	0.4052	0.9056	0.2689	0.4132	0.9059	0.2689
2005	0.3547	0.8909	0.2663	0.3852	0.8929	0.2683	0.4016	0.8931	0.2681	0.4100	0.8932	0.2680
2006	0.3437	0.8883	0.2659	0.3709	0.8900	0.2679	0.3837	0.8899	0.2678	0.3936	0.8902	0.2677
2007	0.2953	0.8682	0.2666	0.3154	0.8685	0.2684	0.3223	0.8679	0.2683	0.3288	0.8690	0.2682
2008	0.2390	0.8448	0.2657	0.2559	0.8452	0.2682	0.2671	0.8444	0.2679	0.2669	0.8451	0.2678
Panel C: Averages by firm size and whether company receives a takeover bid on day t												
Panel C(i): All Firms												
No Bid on day t	0.3210	0.8858	0.2663	0.3495	0.8873	0.2683	0.3653	0.8874	0.2682	0.3738	0.8877	0.2682
Bid on day t	0.3311	0.8705	0.2662	0.3510	0.8706	0.2685	0.4965	0.8640	0.2670	0.4725	0.8682	0.2677

Panel C(ii): Assets in the bottom 50% of the sample												
No Bid on day t	0.5025	0.9472	0.2707	0.5443	0.9475	0.2728	0.5661	0.9474	0.2726	0.5784	0.9473	0.2724
Bid on day t	0.5475	0.9526	0.2731	0.5612	0.9511	0.2744	0.7473	0.9435	0.2716	0.7271	0.9467	0.2728
Panel C(iii): Assets in the top 50% of the sample												
No Bid on day t	0.1412	0.8262	0.2628	0.1564	0.8276	0.2639	0.1645	0.8273	0.2639	0.1692	0.8280	0.2639
Bid on day t	0.1445	0.8014	0.2618	0.1696	0.8013	0.2635	0.2772	0.7944	0.2629	0.2499	0.7995	0.2632

Table 2: Target Firm Univariate statistics

Table 2 contains univariate statistics for the sample of 1014 days on which firms receive takeover bids. Note that a firm can receive multiple bids (i.e. if the first n takeover bids are unsuccessful).

Variable	Mean	Median	Std Dev	Min	Max	25th Pctile	75 Pctile
Return	0.0269	0.0112	0.0602	-0.1200	0.1500	-0.0056	0.0552
IAR	0.0253	0.0112	0.0585	-0.1243	0.1906	-0.0076	0.0530
MAR	0.0259	0.0111	0.0594	-0.1323	0.1835	-0.0072	0.0547
Intraday Abnormal Turnover$_{t-11}$	0.3311	0.1345	0.5765	0.0081	3.7255	0.0587	0.3451
Intraday Order Imbalance$_{t-11}$	0.8705	0.9583	0.1788	0.0000	1.0000	0.7937	1.0000
Weibull Shape Parameter$_{t-j}^{t-11}$	0.2662	0.2610	0.0346	0.2300	0.8980	0.2560	0.2680
Intraday Abnormal Turnover$_{t-15}^{t-11}$	0.3510	0.1827	0.4991	0.0155	3.4571	0.0778	0.4159
Intraday Order Imbalance$_{t-15}^{t-11}$	0.8706	0.9290	0.1610	0.1950	1.0000	0.8184	1.0000
Weibull Shape Parameter$_{t-15}^{t-11}$	0.2685	0.2632	0.0295	0.2432	0.7840	0.2582	0.2703
Intraday Abnormal Turnover$_{t-25}^{t-11}$	0.4965	0.2426	0.6942	0.0169	3.3853	0.0962	0.5641
Intraday Order Imbalance$_{t-25}^{t-11}$	0.8640	0.9257	0.1574	0.2132	1.0000	0.8204	0.9667
Weibull Shape Parameter$_{t-25}^{t-11}$	0.2670	0.2636	0.0173	0.2330	0.4734	0.2589	0.2698
Intraday Abnormal Turnover$_{t-40}^{t-11}$	0.4725	0.2306	0.6612	0.0175	3.3431	0.0959	0.5330
Intraday Order Imbalance$_{t-40}^{t-11}$	0.8682	0.9317	0.1536	0.2074	1.0000	0.8373	0.9644
Weibull Shape Parameter$_{t-40}^{t-11}$	0.2677	0.2647	0.0145	0.2330	0.4208	0.2594	0.2711

Table 3: Pairwise Correlation Results for Takeover Targets

Table 3 contains the pairwise correlation results for the sample that contains only takeover targets. Here, the sample comprises firms that receive a takeover bid on day t. Brackets contain p-values.

		A	B	C	D	E	F	G
A	Return_t							
B	IAR_t	0.983						
		[0.000]						
C	MAR_t	0.990	0.995					
		[0.000]	[0.000]					
D	Intraday Abnormal Turnover_{t-11}	0.020	0.027	0.021				
		[0.533]	[0.407]	[0.518]				
E	Intraday Order Imbalance_{t-11}	0.042	0.033	0.033	0.121			
		[0.192]	[0.314]	[0.307]	[0.000]			
F	Weibull Shape $\text{Parameter}_{t-j}^{t-11}$	0.108	0.094	0.102	0.043	0.207		
		[0.002]	[0.008]	[0.004]	[0.224]	[0.000]		
G	Intraday Abnormal $\text{Turnover}_{t-15}^{t-11}$	0.011	0.006	0.005	0.725	0.200	0.090	
		[0.741]	[0.843]	[0.869]	[0.000]	[0.000]	[0.010]	
H	Intraday Order $\text{Imbalance}_{t-15}^{t-11}$	0.040	0.032	0.032	0.203	0.882	0.174	0.237
		[0.210]	[0.324]	[0.314]	[0.000]	[0.000]	[0.000]	[0.000]
I	Weibull Shape $\text{Parameter}_{t-15}^{t-11}$	0.098	0.093	0.094	0.090	0.231	0.674	0.105
		[0.002]	[0.004]	[0.003]	[0.005]	[0.000]	[0.000]	[0.001]
J	Intraday Abnormal $\text{Turnover}_{t-25}^{t-11}$	0.036	0.033	0.033	0.473	0.240	0.188	0.662
		[0.256]	[0.306]	[0.299]	[0.000]	[0.000]	[0.000]	[0.000]
K	Intraday Order $\text{Imbalance}_{t-25}^{t-11}$	0.026	0.018	0.018	0.207	0.872	0.177	0.260
		[0.421]	[0.563]	[0.581]	[0.000]	[0.000]	[0.000]	[0.000]
L	Weibull Shape $\text{Parameter}_{t-25}^{t-11}$	0.059	0.052	0.055	0.158	0.349	0.512	0.264
		[0.064]	[0.102]	[0.084]	[0.000]	[0.000]	[0.000]	[0.000]
M	Intraday Abnormal $\text{Turnover}_{t-40}^{t-11}$	0.044	0.040	0.041	0.478	0.249	0.244	0.672
		[0.167]	[0.213]	[0.195]	[0.000]	[0.000]	[0.000]	[0.000]
N	Intraday Order $\text{Imbalance}_{t-40}^{t-11}$	0.028	0.022	0.020	0.215	0.867	0.181	0.265
		[0.372]	[0.498]	[0.524]	[0.000]	[0.000]	[0.000]	[0.000]
O	Weibull Shape $\text{Parameter}_{t-40}^{t-11}$	0.071	0.069	0.069	0.198	0.416	0.404	0.272
		[0.025]	[0.031]	[0.030]	[0.000]	[0.000]	[0.000]	[0.000]
		H	I	J	K	L	M	N

I	Weibull Shape Parameter$_{t-15}^{t-11}$	0.246						
		[0.000]						
J	Intraday Abnormal Turnover$_{t-25}^{t-11}$	0.268	0.148					
		[0.000]	[0.000]					
K	Intraday Order Imbalance$_{t-25}^{t-11}$	0.957	0.250	0.232				
		[0.000]	[0.000]	[0.000]				
L	Weibull Shape Parameter$_{t-25}^{t-11}$	0.355	0.513	0.230	0.386			
		[0.000]	[0.000]	[0.000]	[0.000]			
M	Intraday Abnormal Turnover$_{t-40}^{t-11}$	0.267	0.175	0.947	0.240	0.255		
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]		
N	Intraday Order Imbalance$_{t-40}^{t-11}$	0.958	0.251	0.238	0.990	0.380	0.244	
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	
O	Weibull Shape Parameter$_{t-40}^{t-11}$	0.431	0.497	0.245	0.465	0.757	0.271	0.468
		[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]

Table 4: Univariate statistics

Table 4 contains univariate statistics for the firm-level characteristics. Columns 1-5 contain statistics for firms that receive a takeover bid in year y. Columns 6-10 contain statistics for firms that do not receive a bid in year y. Note that a firm can move from one sample to the other. For example, if a firm receives a bid in 1994 but not 1995, it will be in the target sample for 1994 but not for 1995 (and vice-versa). Superscripts ***, **, and * in Columns 11 and 12 denote significance at 1%, 5%, and 10% in difference in means and difference in medians tests, respectively.

	Takeover Targets (Bid for in year y)					Non Targets (Not Bid For in year y)					Target - Non Target	
	Mean	Median	Std Dev	Min	Max	Mean	Median	Std Dev	Min	Max	Mean	Median
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Debt/Assets	0.164	0.094	0.192	0.000	0.821	0.145	0.054	0.189	0.000	0.821	0.019***	0.041***
Market Cap/Assets	1.921	1.169	2.565	0.093	18.296	2.207	1.255	2.950	0.093	18.296	-0.287***	-0.086*
IAOP	-0.019	0.016	0.268	-1.407	0.523	-0.041	0.010	0.290	-1.407	0.523	0.022**	0.006
ln(Assets)	18.401	17.989	2.525	13.666	25.405	17.564	17.175	2.306	13.666	25.405	0.837***	0.815***
Industry M&A Activity	0.179	0.145	0.111	0.000	0.390	0.161	0.122	0.107	0.000	0.390	0.017***	0.023***
High Tech Firm	0.105	0.000	0.307	0.000	1.000	0.117	0.000	0.322	0.000	1.000	-0.012	0.000
HHI (Sales Based)	0.265	0.180	0.215	0.000	1.000	0.269	0.194	0.205	0.000	1.000	-0.005	-0.014***
Number of Observations			874					7144				

Table 5: OLS Regression Results

Table 5 contains the takeover returns results. The sample comprises takeover targets. The models include year dummies and use robust standard errors clustered by GICS sector. The dependent variable is variously the firm's raw return (denoted 'Return'), the market-adjusted return ('MAR'), or the GICS sector (industry) adjusted return ('IAR'). The main independent variables are the moving average of the Weibull shape parameter, intraday order imbalance, and intraday abnormal turnover. The column title indicates the horizon for the moving average. Brackets contain p-values based upon robust standard errors clustered by vintage. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Model	OLS, year fixed effects, GICS sector clustering								
Sample	Takeover Targets								
HFT Window	1 Day: HFT_{t-11}			5 Day: HFT_{t-15}^{t-11}			30 Day: HFT_{t-40}^{t-11}		
Dependent Variable	Return	MAR	IAR	Return	MAR	IAR	Return	MAR	IAR
Weibull Shape Parameter$_{t-j}^{t-11}$	0.162***	0.152***	0.130***	0.166***	0.157***	0.155***	0.242**	0.235**	0.236**
	[0.006]	[0.008]	[0.005]	[0.003]	[0.006]	[0.002]	[0.012]	[0.025]	[0.012]
Intraday Abnormal Turnover$_{t-j}^{t-11}$	0.005	0.006	0.006	-0.001	-0.001	-0.001	0	0	-0.001
	[0.197]	[0.131]	[0.120]	[0.950]	[0.909]	[0.911]	[0.969]	[0.959]	[0.902]
Intraday Order Imbalance$_{t-j}^{t-11}$	-0.003	-0.007	-0.007	0.005	0	-0.001	-0.008	-0.012	-0.011
	[0.887]	[0.751]	[0.755]	[0.732]	[0.975]	[0.916]	[0.676]	[0.531]	[0.574]
Stock Return Variance$_{t-190}^{t-11}$	0.102	0.085	0.102	0.524	0.516	0.474	0.506	0.493	0.461
	[0.760]	[0.791]	[0.747]	[0.360]	[0.347]	[0.367]	[0.331]	[0.316]	[0.332]
Industry Return Variance$_{t-190}^{t-11}$	-0.654	-0.912	-0.965	0.929	0.657	0.513	0.775	0.5	0.36
	[0.650]	[0.484]	[0.479]	[0.529]	[0.651]	[0.718]	[0.592]	[0.727]	[0.798]
Industry Stock Return$_{t-190}^{t-11}$	-1.429	-1.265	-0.978	-1.434	-1.288	-1.027	-1.312	-1.16	-0.905
	[0.478]	[0.514]	[0.600]	[0.426]	[0.463]	[0.536]	[0.470]	[0.514]	[0.594]
Stock Return$_{t-190}^{t-11}$	0.322	0.341	0.44	-0.406	-0.422	-0.29	-0.357	-0.37	-0.241
	[0.626]	[0.596]	[0.487]	[0.587]	[0.565]	[0.692]	[0.623]	[0.603]	[0.735]
Cash Payment	0.002	0.002	0.002	-0.004	-0.004	-0.004	-0.003	-0.004	-0.003
	[0.503]	[0.575]	[0.491]	[0.298]	[0.248]	[0.289]	[0.341]	[0.287]	[0.339]
Debt/Assets	-0.004	-0.006	-0.004	-0.013	-0.014	-0.012	-0.012	-0.013	-0.011
	[0.782]	[0.694]	[0.804]	[0.439]	[0.380]	[0.481]	[0.500]	[0.436]	[0.530]
Market Cap/Assets	0.001	0.001	0.001	0.002	0.001	0.001	0.001	0.001	0.001
	[0.286]	[0.310]	[0.341]	[0.293]	[0.293]	[0.301]	[0.285]	[0.280]	[0.281]
IAOP	0.020**	0.020**	0.019**	0.022**	0.022**	0.020**	0.022**	0.022**	0.020**
	[0.030]	[0.024]	[0.028]	[0.029]	[0.028]	[0.035]	[0.024]	[0.024]	[0.032]
ln(Assets)	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	[0.492]	[0.495]	[0.451]	[0.669]	[0.550]	[0.519]	[0.552]	[0.509]	[0.511]
Industry M&A Activity	0.007	0.008	0.011	0.017	0.016	0.02	0.016	0.015	0.019

	[0.726]	[0.670]	[0.571]	[0.412]	[0.445]	[0.363]	[0.472]	[0.498]	[0.405]
High Tech Firm	-0.006	-0.004	-0.002	-0.016***	-0.015***	-0.013**	-0.017***	-0.016***	-0.014**
	[0.188]	[0.226]	[0.535]	[0.006]	[0.007]	[0.022]	[0.007]	[0.007]	[0.021]
HHI (Sales Based)	-0.019**	-0.022**	-0.023**	-0.008	-0.01	-0.012	-0.009	-0.011	-0.013
	[0.042]	[0.016]	[0.014]	[0.351]	[0.231]	[0.210]	[0.321]	[0.219]	[0.202]
Constant	0.003	0.007	0.012	-0.016	-0.005	-0.005	-0.015	-0.008	-0.012
	[0.939]	[0.875]	[0.785]	[0.670]	[0.886]	[0.887]	[0.797]	[0.887]	[0.833]
Observations	765	765	765	930	930	930	930	930	930
R-Squared	5.80%	6.10%	6.20%	4.30%	4.50%	4.50%	4.00%	4.20%	4.20%

Table 6: Fixed Effects Panel Regression Results

Table 6 contains panel fixed effects results. The sample comprises all firms listed on the ASX that have the relevant variables. The models are panel fixed effects models with company/date panels and GICS sector clustered standard errors. The dependent variable is variously the firm's raw return (denoted 'Return'), the market-adjusted return ('MAR'), or the GICS sector (industry) adjusted return ('IAR'). The main independent variables are the moving average of the Weibull shape parameter, intraday order imbalance, and intraday abnormal turnover. The column title indicates the horizon for the moving average. Brackets contain p-values based upon robust standard errors clustered by vintage. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Model	Panel Fixed Effects (company/date), industry clustering								
Sample	All firms								
HFT Window	1 Day: HFT_{t-11}			5 Day: HFT_{t-15}^{t-11}			30 Day: HFT_{t-40}^{t-11}		
Dependent Variable	Return	MAR	IAR	Return	MAR	IAR	Return	MAR	IAR
Weibull Shape Parameter$_{t-j}^{t-11}$	0.002	0.002	0.001	0.005***	0.005***	0.005***	0.038***	0.038***	0.035***
	[0.121]	[0.112]	[0.209]	[0.001]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]
$\mathbb{I}(\text{Bid}_t)$	-0.023*	-0.019	-0.016	-0.019	-0.017	-0.017	-0.027	-0.023	-0.022
	[0.070]	[0.136]	[0.145]	[0.138]	[0.186]	[0.144]	[0.249]	[0.305]	[0.292]
Weibull Shape Parameter$_{t-j}^{t-11}$ $\times\ \mathbb{I}(\text{Bid}_t)$	0.182***	0.168***	0.153***	0.170***	0.159***	0.157***	0.199**	0.181**	0.177**
	[0.002]	[0.004]	[0.003]	[0.002]	[0.003]	[0.001]	[0.032]	[0.034]	[0.030]
Intraday Abnormal Turnover$_{t-j}^{t-11}$	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***	0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Intraday Order Imbalance$_{t-j}^{t-11}$	0.003***	0.003***	0.002***	0.007***	0.007***	0.006***	0.011***	0.010***	0.009***
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]	[0.001]	[0.001]	[0.000]	[0.001]
Stock Return Variance$_{t-190}^{t-11}$	0.106***	0.090***	0.089***	0.138***	0.122***	0.120***	0.132***	0.116***	0.114***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Industry Return Variance$_{t-190}^{t-11}$	0.116	-0.046	-0.015	0.149*	-0.018	0.013	0.149*	-0.019	0.012
	[0.154]	[0.328]	[0.479]	[0.087]	[0.654]	[0.594]	[0.076]	[0.608]	[0.646]
Industry Stock Return$_{t-190}^{t-11}$	-0.228*	0.049	0.023	-0.272**	0.009	-0.014	-0.271**	0.011	-0.011
	[0.071]	[0.502]	[0.516]	[0.038]	[0.892]	[0.664]	[0.033]	[0.856]	[0.729]
Stock Return$_{t-190}^{t-11}$	-0.249***	-0.211***	-0.209***	-0.280***	-0.245***	-0.242***	-0.273***	-0.238***	-0.236***
	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]	[0.001]	[0.002]	[0.001]
Debt/Assets	-0.001	-0.001	0.000	-0.001	-0.001	0.000	-0.001	-0.001	-0.001
	[0.315]	[0.365]	[0.487]	[0.203]	[0.215]	[0.317]	[0.109]	[0.108]	[0.155]
Market Cap/Assets	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
IAOP	0.004***	0.004***	0.004***	0.005***	0.005***	0.004***	0.005***	0.004***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(Assets)	0.0000	0.0000	0.0000	0.000*	0.000	0.000	0.001***	0.001***	0.000***

	[0.200]	[0.823]	[0.588]	[0.074]	[0.220]	[0.432]	[0.003]	[0.005]	[0.009]
Industry M&A Activity	0.000	0.001	0.001	-0.002	-0.001	0.000	-0.002	-0.001	0.000
	[0.846]	[0.670]	[0.162]	[0.407]	[0.718]	[0.996]	[0.396]	[0.750]	[0.914]
HHI (Sales Based)	0.002	0.002	0.002**	0.001	0.001	0.001*	0.001	0.001	0.001
	[0.220]	[0.197]	[0.035]	[0.464]	[0.442]	[0.081]	[0.569]	[0.553]	[0.135]
Constant	-0.009***	-0.006***	-0.004***	-0.016***	-0.012***	-0.010***	-0.036***	-0.031***	-0.027***
	[0.000]	[0.004]	[0.009]	[0.000]	[0.001]	[0.005]	[0.000]	[0.000]	[0.000]
Observations	970,811	970,811	970,811	1,163,045	1,163,045	1,163,045	1,163,044	1,163,044	1,163,044
Number of Companies	1,156	1,156	1,156	1,158	1,158	1,158	1,158	1,158	1,158
R-Squared Within	0.300%	0.200%	0.200%	0.400%	0.300%	0.200%	0.400%	0.300%	0.300%
R-Squared Between	1.600%	0.300%	0.200%	0.000%	0.100%	0.100%	0.000%	0.200%	0.300%
R-Squared Overall	0.200%	0.100%	0.100%	0.200%	0.100%	0.100%	0.200%	0.200%	0.200%

Table 7: Random Effeccts Panel Regression Results

Table 7 contains panel random effects results. The sample comprises all firms listed on the ASX that have the relevant variables. The models are panel random effects models with company/date panels. The dependent variable is variously the firm's raw return (denoted 'Return'), the market-adjusted return ('MAR'), or the GICS sector (industry) adjusted return ('IAR'). The main independent variables are the moving average of the Weibull shape parameter, intraday order imbalance, and intraday abnormal turnover. The column title indicates the horizon for the moving average. Brackets contain p-values based upon robust standard errors clustered by vintage. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Model	Panel Random Effects (company/date), industry clustering								
Sample	All firms								
HFT Window	1 Day: HFT_{t-11}			5 Day: HFT_{t-15}^{t-11}			30 Day: HFT_{t-40}^{t-11}		
Dependent Variable	Return	MAR	IAR	Return	MAR	IAR	Return	MAR	IAR
Weibull Shape Parameter$_{t-j}^{t-11}$	0.002*	0.002*	0.002	0.005***	0.005***	0.005***	0.038***	0.038***	0.035***
	[0.077]	[0.069]	[0.157]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
$\mathbb{I}(\text{Bid}_t)$	-0.021*	-0.018	-0.014	-0.021*	-0.018	-0.018*	-0.031	-0.026	-0.026
	[0.066]	[0.152]	[0.178]	[0.077]	[0.118]	[0.078]	[0.152]	[0.188]	[0.173]
Weibull Shape Parameter$_{t-j}^{t-11}$ $\times\ \mathbb{I}(\text{Bid}_t)$	0.176***	0.162***	0.147***	0.174***	0.163***	0.161***	0.212***	0.194***	0.190***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.006]	[0.006]	[0.004]
Intraday Abnormal Turnover$_{t-j}^{t-11}$	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.002***	0.002***	0.002***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Intraday Order Imbalance$_{t-j}^{t-11}$	0.003***	0.003***	0.002***	0.007***	0.007***	0.006***	0.011***	0.010***	0.009***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Stock Return Variance$_{t-190}^{t-11}$	0.102***	0.086***	0.086***	0.133***	0.117***	0.116***	0.127***	0.111***	0.109***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Industry Return Variance$_{t-190}^{t-11}$	0.114	-0.045	-0.011	0.147*	-0.016	0.017	0.146**	-0.018	0.015
	[0.124]	[0.315]	[0.594]	[0.052]	[0.662]	[0.483]	[0.042]	[0.606]	[0.542]
Industry Stock Return$_{t-190}^{t-11}$	-0.228**	0.044	0.014	-0.272**	0.004	-0.023	-0.268**	0.008	-0.019
	[0.040]	[0.523]	[0.678]	[0.013]	[0.951]	[0.463]	[0.010]	[0.895]	[0.546]
Stock Return$_{t-190}^{t-11}$	-0.232***	-0.196***	-0.196***	-0.263***	-0.228***	-0.227***	-0.257***	-0.222***	-0.222***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Debt/Assets	-0.001	-0.001	0.00	-0.001	-0.001	0.000	-0.001*	-0.001*	-0.001
	[0.258]	[0.307]	[0.468]	[0.174]	[0.190]	[0.340]	[0.073]	[0.074]	[0.142]
Market Cap/Assets	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
IAOP	0.004***	0.004***	0.004***	0.005***	0.004***	0.004***	0.005***	0.004***	0.004***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(Assets)	0.000***	0.000	0.000	0.000***	0.000**	0.000**	0.001***	0.001***	0.001***

	[0.008]	[0.135]	[0.150]	[0.002]	[0.013]	[0.019]	[0.000]	[0.000]	[0.000]
Industry M&A Activity	0.000	0.001	0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000
	[0.981]	[0.599]	[0.501]	[0.432]	[0.661]	[0.606]	[0.478]	[0.782]	[0.758]
High Tech Firm	-0.003***	-0.002***	-0.002***	-0.003***	-0.002***	-0.002***	-0.002***	-0.002***	-0.001***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
HHI (Sales Based)	0.001	0.001	0.002**	0.000	0.000	0.001	0.000	0.000	0.001
	[0.313]	[0.234]	[0.012]	[0.746]	[0.701]	[0.103]	[0.821]	[0.776]	[0.154]
Constant	-0.010***	-0.007***	-0.006***	-0.017***	-0.014***	-0.012***	-0.037***	-0.033***	-0.029***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	970,811	970,811	970,811	1,163,045	1,163,045	1,163,045	1,163,044	1,163,044	1,163,044
Number of Companies	1,156	1,156	1,156	1,158	1,158	1,158	1,158	1,158	1,158
R-Squared Within	0.30%	0.20%	0.20%	0.40%	0.20%	0.20%	0.40%	0.30%	0.30%
R-Squared Between	0.90%	0.00%	0.10%	0.00%	0.10%	0.10%	0.00%	0.30%	0.30%
R-Squared Overall	0.20%	0.10%	0.10%	0.20%	0.20%	0.20%	0.30%	0.20%	0.20%

Table 8: Prediction Results

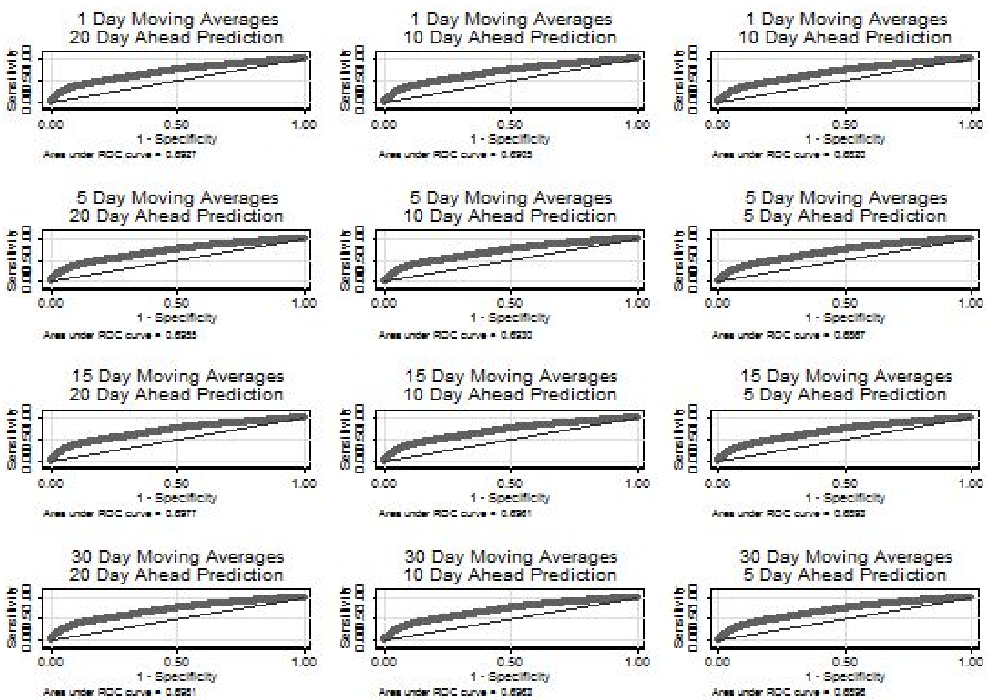
Table 8 contains the takeover prediction results. All models are logit models, include year dummies, and use robust standard errors clustered by GICS sector. The dependent variable is an indicator that equals one if a company becomes a takeover target in the next 20 days (in Columns 1-3), 10 days (in Columns 4-6), or 5 days (in Columns 7-9). The main independent variables are the moving average of the Weibull shape parameter, intraday order imbalance, and intraday abnormal turnover. The column title indicates the horizon for the moving average. The sample comprises all firms that have the relevant independent variables. Brackets contain p-values based upon robust standard errors clustered by vintage. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Model	Logit, year dummies, GICS sector clustering								
Sample	All ASX firms								
Dependent Variable	$\mathbb{I}(\text{Bid}_t^{t+20})$			$\mathbb{I}(\text{Bid}_t^{t+10})$			$\mathbb{I}(\text{Bid}_t^{t+5})$		
HFT Window	HFT_{t-11}	HFT_{t-15}^{t-11}	HFT_{t-40}^{t-11}	HFT_{t-11}	HFT_{t-15}^{t-11}	HFT_{t-40}^{t-11}	HFT_{t-11}	HFT_{t-15}^{t-11}	HFT_{t-40}^{t-11}
Weibull Shape Parameter$_{t-j}^{t-11}$	0.599***	1.307***	7.412***	0.284	0.798**	7.522***	0.398**	0.531	7.412***
	[0.000]	[0.000]	[0.000]	[0.148]	[0.012]	[0.000]	[0.019]	[0.233]	[0.000]
Intraday Abnormal Turnover$_{t-j}^{t-11}$	0.127**	0.207***	0.266***	0.130**	0.214***	0.271***	0.128*	0.216***	0.275***
	[0.042]	[0.001]	[0.001]	[0.043]	[0.001]	[0.000]	[0.064]	[0.000]	[0.000]
Intraday Order Imbalance$_{t-j}^{t-11}$	-0.232	-0.222	-0.211	-0.332**	-0.331	-0.184	-0.392**	-0.406	-0.175
	[0.149]	[0.420]	[0.495]	[0.040]	[0.219]	[0.545]	[0.033]	[0.165]	[0.577]
Stock Return Variance$_{t-190}^{t-11}$	13.535***	15.991***	14.932***	12.427**	15.066***	14.070***	11.588*	15.274***	14.318***
	[0.009]	[0.001]	[0.002]	[0.028]	[0.003]	[0.005]	[0.085]	[0.004]	[0.006]
Industry Return Variance$_{t-190}^{t-11}$	20.652	14.055	13.505	4.531	4.29	4.049	-4.343	-1.313	-1.436
	[0.358]	[0.450]	[0.457]	[0.824]	[0.804]	[0.808]	[0.793]	[0.938]	[0.929]
Industry Stock Return$_{t-190}^{t-11}$	-50.417	-41.279	-38.952	-35.818	-31.886	-29.74	-34.13	-30.046	-27.855
	[0.131]	[0.143]	[0.168]	[0.308]	[0.287]	[0.321]	[0.348]	[0.325]	[0.364]
Stock Return$_{t-190}^{t-11}$	-21.072	-21.972	-21.176	-19.483	-20.289	-19.526	-17.566	-20.272	-19.539
	[0.144]	[0.128]	[0.144]	[0.189]	[0.181]	[0.198]	[0.298]	[0.181]	[0.194]
Debt/Assets	0.435*	0.478**	0.457**	0.433**	0.454***	0.424**	0.465**	0.445**	0.409**
	[0.058]	[0.014]	[0.020]	[0.044]	[0.008]	[0.014]	[0.040]	[0.011]	[0.019]
Market Cap/Assets	-0.065**	-0.073**	-0.064*	-0.061**	-0.068*	-0.056*	-0.060**	-0.064*	-0.051
	[0.022]	[0.044]	[0.065]	[0.029]	[0.053]	[0.088]	[0.029]	[0.067]	[0.111]
IAOP	-0.432***	-0.336***	-0.328***	-0.417***	-0.311***	-0.309***	-0.383***	-0.280**	-0.279**
	[0.000]	[0.003]	[0.004]	[0.000]	[0.007]	[0.006]	[0.001]	[0.013]	[0.014]
ln(Assets)	0.017	0	0.028	0.011	-0.006	0.032	0.009	-0.006	0.038
	[0.602]	[0.998]	[0.489]	[0.724]	[0.871]	[0.399]	[0.763]	[0.886]	[0.312]
Industry M&A Activity	1.469***	1.026***	1.057***	1.398***	0.939***	0.988***	1.366***	0.930***	0.987***
	[0.000]	[0.001]	[0.000]	[0.000]	[0.002]	[0.001]	[0.000]	[0.001]	[0.001]
High Tech Firm	0.01	0.105	0.118	0.004	0.088	0.102	-0.01	0.082	0.097
	[0.932]	[0.317]	[0.241]	[0.977]	[0.455]	[0.369]	[0.942]	[0.486]	[0.392]

HHI (Sales Based)	0.097	-0.103	-0.097	0.108	-0.075	-0.064	0.136	-0.068	-0.055
	[0.669]	[0.631]	[0.639]	[0.661]	[0.760]	[0.786]	[0.627]	[0.787]	[0.818]
Constant	-2.854***	-2.577**	-4.782***	-3.309***	-2.968***	-5.647***	-4.060***	-3.644***	-6.541***
	[0.000]	[0.011]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	971,183	1,163,523	1,163,522	971,183	1,163,523	1,163,522	971,183	1,163,523	1,163,522
Pseudo R-Squared	6.40%	6.60%	6.70%	5.40%	5.60%	5.80%	4.30%	4.50%	4.70%
ROC Area	0.693	0.695	0.698	0.69	0.693	0.696	0.682	0.687	0.69

Figure 1: ROC Curves

Figure 1 contains the ROC curves for logit models that predict the occurrence of a takeover within 5, 10, or 20 days.



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