# An Alternative Event Study Methodology for detecting Dividend Signals in the Context of Joint Dividend and Earnings Announcements

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Warwick Anderson
University of Canterbury
Christchurch
New Zealand

Abstract

This paper has two purposes.  In the first instance, it is an event study which sets out to determine whether or not a dividend signal can be detected, given that earnings and dividends are announced jointly by publicly listed New Zealand companies.  The second purpose is much more important.  In place of the usual simple OLS procedure known as the Market Model to estimate risk-adusted expected returns (and from these, abnormal returns), this paper contributes to event study literature by employing a friction model in which the values of relevant parameters are determined by a maximum likelihood estimation procedure.  This friction modelling approach is more robust than the Market Model when an event study is run on company returns data in the context of a thinly-traded market as it is not immediately reliant on the assumptions underlying the employability of OLS regression.  In addition, given that traditionally a piggy-back procedure involving restricted least squares regresssion has been used by past researchers to sort out the confounding effects of simultaneous dividends and earnings disclosures, this paper further contributes to event study literature and dividend signalling literature by positing several friction models which effectively achieves this same disentanglement.  The models in this study are not necessarily restricted to investigations of dividends and earnings, but are employable (with appropriate specifications of variables) to event studies in general.

# 1 Introduction

This study sets out to provide an alternative methodolgy for investigating the impact of announcements (and simultaneous announcement combinations) on share prices in the context of a market in which many shares are not traded every day the market is open. This methodology is known as friction modelling and employs maximum likelihood estimation in place of the more traditional use of OLS regression. The advantage of using a friction model is that it specifically treats, as a separate category, zero-value daily returns (which are often associated with failures to trade — a phenomenon often called thin trading). In data sets from thinly-traded markets, zero-value returns are very common. The friction model methodology proposed here is demonstrated in terms of a search for evidence of dividend signalling from New Zealand's thinly-traded share market, which has an extra level of complexity added to it by the fact that dividend and earnings disclosures are usually bundled simultaneously in a single announcement. However, the important contribution this paper makes to the literature is that the model has the potential to be employed much more broadly in event study research than in just this one narrow area that concerns dividends.

But given that this study employs the methodology with respect to dividend signalling, a short review of relevant dividend signalling literature is needed. In addition, some commentary will also be furnished on research into correcting for the effects of thin trading.

Research has now been going on for 45 years as to whether the announcement of a change in dividend sends a signal to investors after the concept was considered by Miller and Modigliani (1961). Much of this was in the form of event studies employing the Market Model and focussed on price changes associated with American dividend announcements. But, in the United Kingdom, Australia and in New Zealand, dividends and earnings were and are announced simultaneously. This necessitated a methodology for separating out dividend-related effects from earnings-related effects. Kane Lee and Marcus (1984), working with near- (but not exactly simultaneous) US data, pioneered this methodology, which entailed running a restricted least regression on their event-window cumulative abnormal returns with seven regressor variables. These were percentage dividend change, percentage

earnings change in (the two first-order variables), and five dummies to capture the interaction effects of the six economically plausible pairs of dividend and earnings direction-change (known as interaction variables). This restricted least squares methodology, piggy-backing on an initial Market Model regression run was employed by Easton (1991) on Australian data, Lonie, Abeyratna, Power and Sinclair (1996) on British data, and Anderson (2006) on New Zealand data.

However, the Market Model simply pertains to the running of an OLS regression on a time series to formulate daily expected returns, and from these, abnormal returns and cumlative abnormal returns. In the presence of thin (i.e., periods of total absence of) trading in a particular share, the Market Model will produce outputs that bias expected returns downwards and therefore bias the resulting abnormal returns upwards — thereby exaggerating them. Scholes and Willams (1977) addressed a less extreme form of the same econometric problem, known as non-synchronous trading, which entailed failures to trade precisely at the close of each period. They were followed by a number of papers, which like Scholes and Williams, performed analyses and proposed adjustment mechanisms which did not entail moving away from reliance on on the underlying assumptions of OLS regression (Dimson (1979), Fowler, Rorke and Jog (1979), Dimson and Marsh (1979) and Cohen, Hawawini, Maier, Schwartz and Whitcombe (1983), Fowler, Rorke and Jog (1979). However, it was a moot point as to whether any of these studies offered any improvement on the flawed usage of the simple Market Model. Berglund, Liljeblom and Loflund (1989) on Finnish data, and Barthody and Riding (1994) on New Zealand data, tested the performance of a range of these mechanisms against that of a simple employment of OLS and found OLS to be superior.

The rest of this paper is laid out as follows. In Section 2, the concept of a friction model is explained in broad terms, and I review the literature in economics and in finance in which friction models have been used. In Section 3, the current study's data and variables are explained, while Section 4 goes on to disclose the fine details of the methodology. The study's results are then tabled under various subheadings in Section 5.

## 2  Review of Friction Models and their Literature

Friction models are based on the concept that the a dependent variable, while monotonically changing in response to the behaviour of independent variables over most of their joint ranges, does not change at all over some bounded range in which the values of the independent variables are small.

The insensitivity of a dependent variable to small changes in the state of relevant independent variables has been called 'friction' in economics jargon for well over half a century. The usage was cited as being traditional by Rosett (1959), when he presented the first friction model, and, indeed, coined the term 'friction model' to describe it. He provided a succinct description of what the model does with respect to the embedded employment of the statistical methodology of maximum likelihood estimation[1]:

> *The maximum likelihood method for estimating relationships with limited dependent variables is generalized to include relationships in which the dependent variable, over some finite range, is not related to the independent variables.*

Effectively, the value of a given dependent variable changes in response to changes in value of a particular independent variable over most of its range, but not all of it. Over the finite range Rosett was referring to, the pressures for change on the value of a given dependent variable exert no effective influence on it, and the value does not change. Indeed, the marshaled influences for change cannot overcome the pressures for maintaining the status quo as the 'friction' is too great. However, the range exists between an upper bound and a lower bound. Above the upper bound, the pressure for an upward change in the dependent variable's value overcomes this friction and it moves upward; and conversely, below the lower bound, the pressure for downward change overcomes the friction and the variable takes on new lower values.

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[1] Rosett (1959), p. 263.

**Figure 1:** **Schematic Diagram of a Friction Model.**

YOBSERVED

Independent
Variable

$\alpha_L$

$\alpha_U$
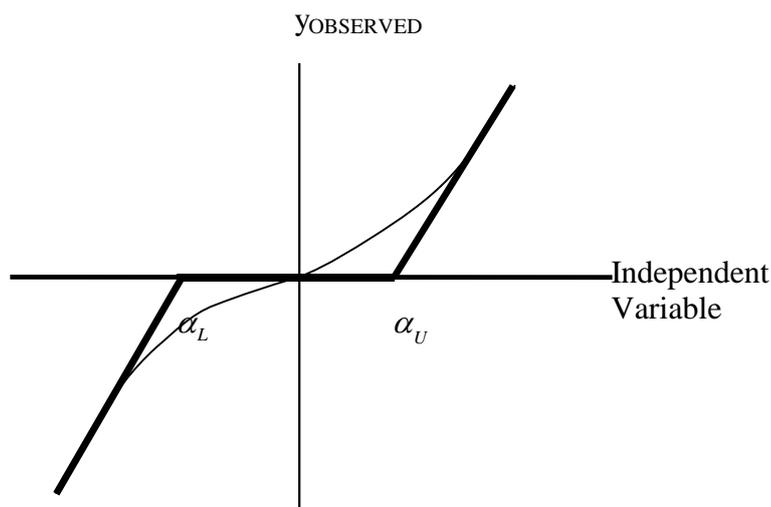
The focus of Rosett's interest was in mapping how changes of yield impacted on how much of an asset would be held by investors in their portfolios. His model is laid out in Figure 1[2] where the observed values of a response variable *Y* (asset holding) are plotted against an independent variable (yield). The observed y values are clustered close to the heavy black line and indeed are zero between the bounds $\alpha_L$ and $\alpha_U$ where pressure for change on *Y* is unable to overcome friction. The thin curve through the origin depicts the theoretical path of *Y* in the absence of that friction.

The bounds, the slope of the line and the standard deviation of the underlying distribution are all parameters of the LDV Friction Model and are determined by maximum likelihood estimation.

Maximum likelihood estimation itself is a technique for determining parameter values that make the pattern of data we have observed most likely to have occurred in that particular pattern. A very useful aspect of it is that it does not require strict adherence to the linearity assumption required by OLS regression. It makes most sense if maximum likelihood estimation is explained from first principles. In terms of basic statistical analysis, we are often interested in determining the probability of an event *Y* conditional on the occurrence of *X*, which is expressed as $P(Y|X)$. *X* may be a variable denoting an event or a state. However, *X* might be replaced by "*p*" (for

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[2] Rosett (1959), Figure 1, p. 263. However, in Figure above, the terminology used follows Figure 6.2 on p. 164 of Maddala (1983) more closely than Rosett's original figure's terminology. However, Rosett's and Maddala's figures and mine are equivalent. Maddala (1983) provided an excellent summary of friction models in general.

parameter), as it may actually be a parameter of the distribution of $Y$ itself. Maximum likelihood estimation is about solving $L(p|Y)$, where L is the likelihood function of $p$ given $Y$.

Rosett's model is adapted for use in the current study. It was also employed with respect to share returns by Lesmond, Ogden and Trzcinka (1999) — albeit not with the intention of estimating abnormal returns to replace those furnished by the Market Model methodology in a thinly-traded market. These authors argued that zero-value share returns occur when transactions costs are higher than the cash return an investor could make if he or she actually traded and interpreted the distance between $\alpha_L$ and $\alpha_U$ as a de facto total transactions cost for buyers and sellers. If these 'round-trip' transactions costs were not going to be exceeded, then either the potential buyer or the potential seller, or both, would have no incentive to transact and no trade would occur. The underlying independent variable, X for Lesmond et al, was returns on the market index ($R_{Mt}$), which they postulated would have near-zero values when companies furnished zero-value daily returns. This assumption makes the model suitable as a replacement for the Market Model in the current study.

However, while Rosett and Lesmond et al employed one independent variable, the current study goes on to develop an LDV friction model employing multiple independent variables to model the trading reaction of investors in response to the event window announcement of dividend and earnings news.

The post-Rozett era of friction-modelling research begins with Dagenais (1969), who developed a model containing horizontal and a vertical calibrations for each of the bounds measured in Rozett's original friction model. Dagenais suggested that his new model would be appropriate for examining the path of the price of newsprint with respect to the paper industry's operating capacity and marginal costs of production. Two other possible applications were the determination of planned factory expansion in the steel industry, given known excess capacity; and household consumption of whiteware given the stock of whiteware already owned and household income. Three years later, Dagenais (1975) applied his model to the American household purchases of automobiles. However, ensuing researchers have tended to prefer Rozett's simpler model over what Dagenais developed.

DeSarbo, Rao, Steckel, Wind and Colombo (1987) developed a friction model to explain and forecast a firm's product-pricing decision. The most interesting aspect of their modelling was in their computation of the upper and lower bounds delimiting the price-no-change continuum and a prediction of by how much a price change would be a price-change decision. Citing Dharmadhikari and Joag-dev (1985)[3] who found that the maximum likelihood function may be multimodal with more than one set of estimates, they calculated their parameter values via a controlled random search procedure modified from Price (1976)[4]. DeSarbo et al then applied their model to 82 weeks of mortgage interest rate information from 15 Philadelphia banks and found that their friction model outperformed equivalent forecasting computations generated from OLS and a Box-Jenkins procedure.[5]

Forbes and Mayne (1989) examined the behaviour of the prime lending rate (compiled as the monthly average of US banks' annualised daily prime rates). The prime rate tends to remain unchanged and therefore apparently unresponsive to changes in money market rates unless these move above or below some pair of tolerance limits. Forbes and Mayne used monthly data that were averaged from daily rates, and which covered US bank figures published in the Federal Reserve Bulletin for the decade from January 1977 to August 1987.

Almekinders and Eijffinger (1996) used friction modelling to shed light on the US dollar – Deutschmark exchange rate (daily data) in the period February 1987 to October 1989 with respect to market interventions by the US Federal Reserve and the Bundesbank. In addition, they observed the US Federal Reserve's interventions in the US dollar – Japanese yen market. These authors stressed that central banks tended not to intervene very often on the ground that the main function of an intervention was to send a signal to private traders, alerting them to the banks' preferred direction of exchange-rate change. Indeed, there were two good reasons behind this. First, while their intervention volumes could be in excess of a hundred million dollars, central banks never traded (and were not able to trade) more than a small fraction, by volume, of overall trading in any given day. Therefore the banks could not determine the market by brute force and had to rely on persuasion. Second, any attempt at

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[3] DeSarbo, Rao, Steckel, Wind and Colombo (1987), p. 308
[4] Ibid, p. 308
[5] Ibid, p. 312. With respect to the comparison with OLS, the friction model produced an Akaike Information Criterion (AIC) of 83.67 versus an AIC from OLS of103.52.

micromanagement by frequent intervention would diminish the efficacy of the signalling function.

Hashimoto and Takatoshi (2004) employed a friction model to examine contagion effects in Asian markets between exchange rates and share prices. Among their results, the authors found that the Thai exchange rate was sensitive to shocks in the stock markets of other Asian countries.

Galpin (2004) investigated the cost of raising capital in a pecking order theory context, used a friction model to map a firm's financing function. The decision to raise new capital (either debt or equity represented by the subscript $i$), or to return it to investors, was dependent on the size of the associated transactions costs.

With respect to the nature of dividend-setting, Cragg (1986) used friction modelling to model dividend-setting behaviour along the path to a perceived target payout ratio. Cragg used 218 US companies whose fiscal years coincided with the calendar year and for which at least 20 years of continuous price information was available between 1959 and 1982. He concluded that firms did indeed only change their dividends when there was only a low probability that the change would have to be reversed in the future. He noted[6] that the firms' lower bound tended to vary to a much greater degree than their upper bound. In a signalling sense, this implied that firms are much more uncertain about when to cut dividends than they are about when to raise them.

Kao and Wu (1994) developed a friction model examining the relationship between changes in a firm's permanent earnings and its dividend policy, and found there was a positive relationship between the two variables. While Cragg's (1986) model was fairly traditional in containing three partitions (change down, no change, change up) and determined its bounds endogenously, Kao and Wu adopted a $K$-level model in which each observed value of the dividend paid, $D_t$ was a discrete level. More generally, Kao and Wu concluded that dividends are strongly related to the estimated level of a firm's permanent earnings, and that dividend changes are reactions to both expected and unexpected changes in the latter. Further, they considered that their friction model had successfully coped with the estimation problem associated with the tendency of firms to leave their dividends unchanged from period to period. In addition, their results showed that the concept of dividend signalling did not conflict

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[6] Ibid, pp. 204-205 and Table 10.4 (lower panel).

with Lintner's (1956) concept of a partial adjustment towards a long-term target payout ratio. Instead, they found that their sample firms' dividend-setting behaviour was consistent with both.

Lesmond, Ogden and Trzcinka (1999) used a friction model to obtain estimates of effective transactions costs associated with marginal traders' buying and selling shares. They argued that the method was a viable alternative to the use of the sum of the bid-ask spread and commission approach that was considered to be current orthodoxy. The friction model approach required only sets of time series of daily security returns. The incidence of zero returns (for days of either no change in price or even days on which the stock fails to trade at all) was a phenomenon that could be turned to good account in terms of a friction model approach as it was in the nature of investor decision-making for zero trades to occur where the potential return to be made was not expected to exceed a threshold imposed by the cost of the trade.[7] It is of interest that Lesmond et al's model assumed that the market model was the correct model of security returns, and that the intercept term captures the effect of any misspecification of the market index relating to mean-variance inefficiency.[8] However, Lesmond et al suppressed the intercept term in their model.

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[7] Lesmond, Ogden and Trzcinka (1999), p.1115. The authors noted that zero returns are a frequent phenomenon, even with respect to firms listed on the NYSE and AMEX in the period they studied which was 1963-1990. They noted, "…[A]s much as 80% of the smallest firms returns are zero and some of the largest firms have 30% zero returns."

[8] Lesmond, Ogden and Trzcinka (1999), p.1120.

# 3   Data and Variables

Because methodology in this paper is proposed as an alternative to a simple Market Model event study methodology, I follow the data requirements that could be considered conventional in event studies.  The announcement event will be deemed to be a single day, $t_0$, seated in the middle of a 21-day test period (days $t_{-10}$ to $t_{10}$).  The test period will be preceded by an expected return estimation period of exactly 100 days, which in turns requires closing price information for the 111 days running from days $t_{-121}$ to $t_{-11}$ (inclusive).  This imposed the restriction that 121 days of closing price information (adjusted for dividend payments and share splits) had to be available running up to each day $t_0$ event; and that these 121 days were required to be clear of any prior dividend and earnings announcement.  In addition, the company had to be either a company that regularly paid ordinary dividends, or was now omitting, initiating or resuming the payment of an ordinary dividend following a phase of not paying them.  This removed firms that never paid dividends from consideration.  Furthermore, the 21-day test period needed to be free of other announcements that might confound the detection of a dividend signal.  These were:

1. Announcements of special dividends
2. Announcements of changes in capital structure with respect to debt
3. Share buybacks and other announcements of capital reduction
4. Earnings forecast announcements
5. Bonus share issue announcements
6. Rights issue announcements
7. Announcements concerning options
8. Announcements of impending take-overs
9. Announcements of company revaluations
10. Follow-up announcements of revisions of erroneous data in an announcement
11. Requests published by the NZX requiring a company to explain unusual (and potentially suspicious) changes in the market price of its shares

The above considerations dropped the number of acceptable announcement events available within the decade starting January 3 1990 and ending December 31 1999 from an initial 1910 to 948.[9]

The joint dividend and earnings events could either be the 'preliminary' report to the New Zealand Stock Exchange made after the end of the company year, or the

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[9] This data is congruent with the data used in the writer's Ph.D thesis, which was an event study employing the Market Model, friction models and state asset pricing models with respect to dividend signalling in a joint dividend and earnings announcement context.

'interim' report produced after the first six months of the company year. In either case, the change in dividend was measured from the equivalent announcement made a year earlier (and likewise for earnings).

The variables of interest were as follows. $R_{jt}$, the observed return on a share in Company $j$ on day $t$, and $R_{Mt}$, the observed return on the market index on day $t$, were required for each day in the estimation and test periods for the computation of an abnormal return, $AR_{jt}$, for each day in the test period. In addition, $DAYSTRADED_j$ reported the count of actual market trading days, out of the 100 available in the estimation period, on which share $j$ actually traded. The thinner the trading, the lower the value this variable would take on.

On the day of the event itself, measures of the change in dividend $\Delta DPS$ and the change in earnings $\Delta EPS$ were required, along with dummy variables modelling the interaction effect between the direction of change in dividends and the direction fo change in earnings. These become relevant in subsection 5.2.5, where I replace the restricted least squares regression procedure with a further set of friction models.

However, some comment on these variables is useful here. The formulation of $\Delta DPS$ as a simple percentage change would have meant giving this variable an infinite value whenever dividends were initiated (or resumed after a non-dividend-paying phase). Hence an alternative measure that was robust to the inclusion of dividend initiation announcements is used:

$$\Delta DPS_j = \frac{DPS_{j\, This\, Announcement} - DPS_{j\, Announcement\, last\, year}}{P_{jt-1}} \tag{1}$$

This variable was in the nature of a dividend yield, where $P_{jt-1}$ was the adjusted closing price of a company $j$'s shares.

The interaction dummies had to be reduced from the five used by Kane, Lee and Marcus (1984) and other studies employing restricted least squares regression) to just two in the context of a friction model containing three regions. These two were GOOD+BADNEWS and MIXEDNEWS$_{DNC}$. GOOD+BADNEWS took on the value

'1' if an announcement entailed an increase in dividend and an increase in EPS (over last year's), or the value '-1' if there was a decrease in both dividend and in EPS, or '0' if the dividend and EPS changes did not move in the same direction. The other dummy variable, $MIXEDNEWS_{DNC}$ took on the value '1' if EPS increased while the dividend remained unchanged, or '-1' if EPS decreased while the dividend remained unchanged. If the dividend changed from the previous year's figure, then $MIXEDNEWS_{DNC}$ took on the value '0'.

# 4  Friction Model Methodology

In this section I will deal with the methodology which replaces the simple OLS regression employed by the Market Model; but will leave discussion of the models that replace the piggy-backed step of restricted least squares regression until subsection 0.  I will start by more closely defining the nature of the observed return, $R_{jt}$.  This may take on positive, zero or negative values, and — depending on the thinness of trading of the particular company share — there may be many zero values. It is assumed that a zero value will be associated with small values of returns on the market index. On average, $R_{jt}$ will take on values that follow the three-part linear (zig-zag) path depicted in Figure 2, which implies it will move in the same direction as changes in the market, $R_{Mt}$ .

**Figure 2:**    **Schematic Diagram of a Friction Model for Calculation of Expected Returns.**
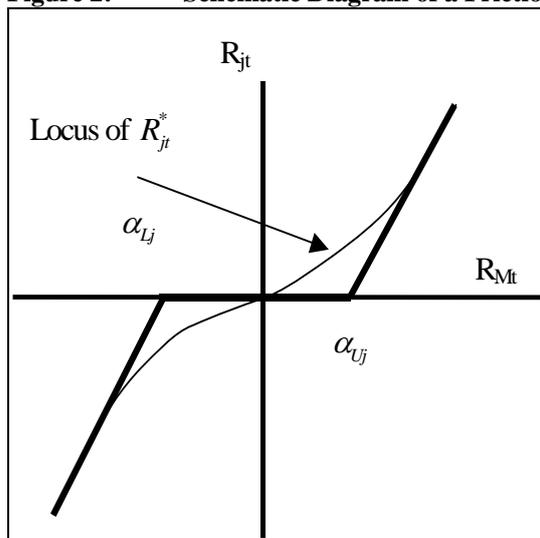


The line segment between $\alpha_{Lj}$ and $\alpha_{Uj}$ explicitly represents the region in which zero-value returns are expected — which means that this initial model sets out to model the effect of these (whether they be generated by prices that fail to shift or by the absence of trading in the share) and therefore impound them into the estimation of expected return parameters.

A "true" daily return for company $j$, is denoted as $R_{jt}^{*}$. Unfortunately this remains unobserved; however it would theoretically furnish near-zero values commensurate

with those small values of market index returns in keeping with the curve that sweeps through the origin in Figure 2. The model is set up as follows:

$$R_{jt}^* = \beta_j R_{Mt} + \varepsilon_{jt}$$

*Where*

$$\begin{cases} R_{jt} = R_{jt}^* - \alpha_{Lj} & \text{if} & R_{jt}^* < \alpha_{Lj} \\ R_{jt} = 0 & \text{if} & \alpha_{Lj} \le R_{jt}^* \le \alpha_{Uj} \\ R_{jt} = R_{jt}^* - \alpha_{Uj} & \text{if} & R_{jt}^* > \alpha_{Uj} \end{cases}$$

(2)

However, the fact that $R_{jt}^*$ is unobservable and $\alpha_{Lj}$ and $\alpha_{Uj}$ are endogenous makes Equation (2) hard to work with. The specification of inputs into the model's maximum likelihood estimation procedure requires some simplification of this.

In the world at large, and in this study's data set, it is quite possible for $R_{jt}$ to be negative instead of positive in a rising market, or positive when the market is falling — hence we can expect a cloud of both positive and negative observations to be associated with increases in the independent variable, $R_{Mt}$. Hence, the assignment of observations to the upper region is not dependent on the sign of the unobservable $R_{jt}^*$ or the observed $R_{jt}$, but on the requirement that $R_{Mt}$ is positive. (However the theoretical locus of $R_{jt}^*$ values in Figure 2 does ordain that $R_{jt}^*$ is positive when $R_{Mt}$ is positive.) Likewise, whatever the sign of $R_{jt}$, the lower region requires the matching $R_{Mt}$ observation to be negative. A practical implementation of the model is as follows[10]:

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[10]This is developed from Lesmond, Ogden and Trzcinka (1999), pp. 1120 – 1122. It will immediately be obvious that Equation (3) differs in its restrictions from those stated in their Equation (1); but Equation (3) has been altered to take into account Lesmond et al's sentence (p.1122) in which they explain that in their likelihood function (Equation (2)) that "…R$_1$ and R$_2$ denote the regions where the measured return, $R_{jt}$ is nonzero in negative and positive market return regions, respectively. R0 denotes the zero returns." This interpretation was confirmed in an email communication with Dr Lesmond, who also kindly made part of his thesis (pertaining to methodology) and his Fortran code available.

$$\begin{cases} R_{jt} = R_{jt}^* - \alpha_{Lj} & \text{if} \quad R_{jt} \neq 0 \text{ and } R_{Mt} < 0 \\ R_{jt} = 0 & \text{if} \quad R_{jt} = 0 \\ R_{jt} = R_{jt}^* - \alpha_{Uj} & \text{if} \quad R_{jt} \neq 0 \text{ and } R_{Mt} > 0 \end{cases} \quad (3)$$

The final embedded assumption is that the non-zero observations of $R_{jt}$ are normally distributed. This was found to be the case with 33.23% of the data sets in terms of a Lilliefors Test with a five percent error, while the returns distributions with zero-value returns included was 3.10 percent. One advantage of assuming a normal distribution of non-zero observations is that the normal probability density function and the cumulative normal density function can be used in the maximum likelihood estimation procedure. Further, it allows for the computation of Z-values (from which confidence intervals can be calculated), and the testing of parameters for significant differences from zero can be performed and the associated p-values can be recorded.

In keeping with Equations (2) and (3) the three-part likelihood function is shown in Equation (4):

$$L = \prod_{t \in R_{LOWER}} \frac{1}{\sigma_j} \phi_1 \left( \frac{\varepsilon_t}{\sigma} \right) \prod_{t \in R_0} \Pr(\text{no change}) \prod_{t \in R_{UPPER}} \frac{1}{\sigma_j} \phi_3 \left( \frac{\varepsilon_t}{\sigma} \right) \quad (4)$$

Here the symbols $R_{LOWER}$, $R_0$ and $R_{UPPER}$ stand for the three regions depicted in Figure and $t$ denotes an observation assigned to a given region. The lower region accounts for decreasing company returns (give or take the presence of some anomalous increasing observations), the zero region contains company returns that are zero in value, and the upper region accounts for increasing returns (allowing for the presence of anomalous decreasing company return observations). In Equation (4), $\phi_L \left( \frac{\varepsilon_t}{\sigma} \right)$ is the standard normal density function of the residuals of the negative returns in the lower region, and $\phi_U \left( \frac{\varepsilon_t}{\sigma} \right)$ the standard normal density function of the residuals of the positive returns in the upper region, where $\sigma$ is the standard deviation estimated from the sample of all observations of observed returns excluding the zero value

observations assigned to the zero region. In accordance with Lesmond et al (1999) and Maddala (1983), the full likelihood function, complete with parameters to be estimated is presented in Equation (5), where $\Phi_L(\cdot)$ and $\Phi_U(\cdot)$ are the cumulative normal density functions of the standard normal distribution for lower and upper regions.

$$
\begin{aligned}
L\left(\alpha_{Lj}, \alpha_{Uj}, \beta_j, \sigma_j \middle| R_{jt}, R_{Mt}\right) \ &= \prod_L \frac{1}{\sigma_j} \phi_L\left[\frac{R_{jt} + \alpha_{Lj} - \beta_j \cdot R_{Mt}}{\sigma_j}\right] \\
&\times \prod_0 \left[\Phi_U\left(\frac{\alpha_{Uj} - \beta_j \cdot R_{Mt}}{\sigma_j}\right) - \Phi_L\left(\frac{\alpha_{Lj} - \beta_j \cdot R_{Mt}}{\sigma_j}\right)\right] \quad (5) \\
&\times \prod_U \frac{1}{\sigma_j} \phi_U\left[\frac{R_{jt} + \alpha_{Uj} - \beta_j \cdot R_{Mt}}{\sigma_j}\right]
\end{aligned}
$$

In natural logarithmic terms, the likelihood function becomes:

$$
\begin{aligned}
\ln L = &\sum_L \ln \frac{1}{\left(2\pi\sigma_j^2\right)^{1/2}} - \sum_1 \frac{1}{2\sigma_j^2}\left(R_{jt} + \alpha_{Lj} - \beta_j \cdot R_{Mt}\right)^2 \\
&+ \sum_0 \ln\left[\Phi_{3j}\left(\frac{\alpha_{Uj} - \beta_j \cdot R_{Mt}}{\sigma_j}\right) - \Phi_{1j}\left(\frac{\alpha_{Lj} - \beta_j \cdot R_{Mt}}{\sigma_j}\right)\right] \quad (6) \\
&+ \sum_U \ln \frac{1}{\left(2\pi\sigma_j^2\right)^{1/2}} - \sum_3 \frac{1}{2\sigma_j^2}\left(R_{jt} + \alpha_{Uj} - \beta_j \cdot R_{Mt}\right)^2
\end{aligned}
$$

The negative of this likelihood function is then minimised to produce solutions for the two bounds, $\alpha_{Lj}$ and $\alpha_{Uj}$, and for the two other parameters, $\beta_j$ and $\sigma_j$. This minimisation process is achieved by a quasi-Newton non-linear numerical optimisation procedure called 'optim' in Scilab.[11] The fact that the process is non-linear liberates friction model methodology from the linear assumption required by the Market Model.

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[11] The computer software which was ultimately used for estimating all friction model procedures was Scilab, which turned out to be far more user-friendly than Matlab for this purpose.

Lesmond, Ogden and Trzcinka (1999) was largely based on Lesmond (1995), which furnished two methods for computing the expected return, E($R_j$) developed from Maddala (1983) — one for an unconditional expected return which includes the zero-return region, and the other for a conditional expected return, which excludes returns falling in the zero region.

Lesmond's unconditional expected return formulation is as follows[12]:

$$
\begin{aligned}
E\left(R_{j}\right) &= \Pr\left(R_{j}<0\right) \cdot E\left(R_{j} \middle| R_{j}<0\right) + \Pr\left(R_{j}=0\right) \cdot E\left(R_{j} \middle| R_{j}=0\right) \\
&\quad + \Pr\left(R_{j}>0\right) \cdot E\left(R_{j} \middle| R_{j}>0\right) \\
&= \left(1-\Phi_{jL}\right)\left[-\alpha_{jL}+\beta_{j}R_{M}\right] + E\left(\varepsilon_{jL} \middle| \varepsilon_{jL}<-\alpha_{jL}+\beta_{j}R_{M}\right) \\
&\quad + \left(\Phi_{jU}-\Phi_{jL}\right)\cdot 0 \\
&\quad + \Phi_{jU}\left[-\alpha_{jU}+\beta_{j}R_{M}\right] + E\left(\varepsilon_{jU} \middle| \varepsilon_{jU}<-\alpha_{jU}+\beta_{j}R_{M}\right) \\
&= \left(1-\Phi_{jL}\right)\left[-\alpha_{jL}+\beta_{j}R_{M}-\sigma_{j}\frac{\phi_{jL}}{\left(1-\Phi_{jL}\right)}\right] + \Phi_{jU}\left[-\alpha_{jU}+\beta_{j}R_{M}+\sigma_{j}\frac{\phi_{jU}}{\Phi_{jU}}\right] \\
&= -\alpha_{jL}\left(1-\Phi_{jL}\right) - \alpha_{jU}\Phi_{jU} + \beta_{j}R_{M}\left(1+\Phi_{jU}-\Phi_{jL}\right) + \sigma_{j}\left(\phi_{jU}-\phi_{jL}\right)
\end{aligned}
\tag{7}
$$

---

[12] Lesmond (1995), Chapter 3, Subsection 3.2.1, Equation 14. This chapter was provided electronically by the author.

Equation (7) shows that the unconditional expected return builds in the influence of market (systematic) risk captured by the Market Model (and by all CAPM models), and in addition incorporates the influence of effective transactions costs — the estimation and nature of which were the primary focus of interest for Lesmond (1995) and Lesmond, Ogden and Trzcinka (1999). Also, the presence of $\sigma$ in the equation indicates that variance in a set of company returns is, in Lesmond's words, "a priced element".[13] With respect to the formulation of conditional expected returns, the zero-returns argument is dropped out of Equation (7) and the specification becomes[14]:

$$
\begin{aligned}
E\left(R_j \middle| R_j \neq 0\right) &= \Pr\left(R_j < 0\right) \cdot E\left(R_j \middle| R_j < 0\right) + \Pr\left(R_j > 0\right) \cdot E\left(R_j \middle| R_j > 0\right) \\
&= \left[-\alpha_{jL} + \beta_j R_M\right] + E\left(\varepsilon_{jL} \middle| \varepsilon_{jL} < -\alpha_{jL} + \beta_j R_M\right) \\
&\quad + \left[-\alpha_{jU} + \beta_j R_M\right] + E\left(\varepsilon_{jU} \middle| \varepsilon_{jU} < -\alpha_{jU} + \beta_j R_M\right) \\
&= -\left(\alpha_{jL} + \alpha_{jU}\right) + \beta_j R_M + \sigma_j\left(\frac{\phi_{jU}}{\left(1 + \Phi_{jU}\right)} - \frac{\phi_{jL}}{\Phi_{jL}}\right)
\end{aligned}
\tag{8}
$$

Both formulations of expected return are useable, with respect to the current study, in the determination of ARs if these are to be employed as the dependent variable in a cross-sectional restricted least squares regression. But only the conditional expected return is useful when an LDV friction model is developed in subsection 5.2 (and onward) for analysis of what happens at the time of the dividend and earnings announcement event, employing $\Delta DPS$ and $\Delta EPS$ as independent variables. The methodological details of that friction model are provided in that later subsection along with its results.

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[13] Ibid, final sentence of Subsection 3.2.2.
[14] Ibid, Chapter 3, subsection 3.2.2, Equation 15.

# 5 Results

## 5.1 Estimation of Expected Returns on the 100-day Period

When the 948 company/event estimation period data sets were passed to the LDV friction model procedure, only 25 of them could not be processed on the ground of insufficient observations in any one region. This dropped the sample size to 923. Given that the company/event sets were scheduled in descending order in terms of the variable, '$DAYSTRADED_j$' (the number of market days on which the company's shares actually changed hands), it became clear that the dysfunctional sets were at the bottom end. Ten of these were the ten most poorly-traded stocks in the study, while the other 15 are all numbered within the poorest-traded 45. The best-transacted of these, event set No. 904, traded on only 28 of the 100 days, while the least, No. 948, traded on a total of 4 days.

Figure 3 summarises the characteristics of the 923 optimised sets of parameters.

**Table 1: Characteristics of the 923 Optimised Sets of Parameters.**

| Parameter | Mean | Minimum | Maximum | Std Deviation |
|-----------|------|---------|---------|---------------|
| $\alpha_L$ | -0.0304 | -0.2499 | -0.0012 | 0.0293 |
| $\alpha_U$ | 0.0297 | 0.0007 | 0.2960 | 0.0291 |
| $\beta$ | 2.0346 | 0.4962 | 19.388 | 1.2279 |
| $\sigma$ | 0.0277 | 0.0069 | 0.2020 | 0.0185 |

The dataset furnishing the highest beta was No. 544, which traded on 89 days, and which contained two large outliers — one negative and one positive. This certainly indicates that the LDV friction model estimates are sensitive to outliers. In the third panel of Figure 3, which contains histograms of the four parameters, it is clear that the betas are quite closely clustered about the mean of 2.03 with some skewing to the right. This mean is much larger than the mean beta of 0.472 furnished by the Market Model on the same data. It is also much more credible given that firms in the sample are not necessarily large firms at all — although the maintenance of a dividend payout policy does argue that the firms will tend to be relatively stable. Arguably this is a function of the exclusion of zero observations. With respect to the bounds $\alpha_L$ and $\alpha_U$, most observations have an absolute value closer to zero than 0.05, while

observations with values in excess of ±0.1 can be considered to be outliers. With respect to the standard deviations in the fourth panel, most appear to be less than 0.05.

**Figure 3:** **Histograms of the Four Parameters of the Friction model.**
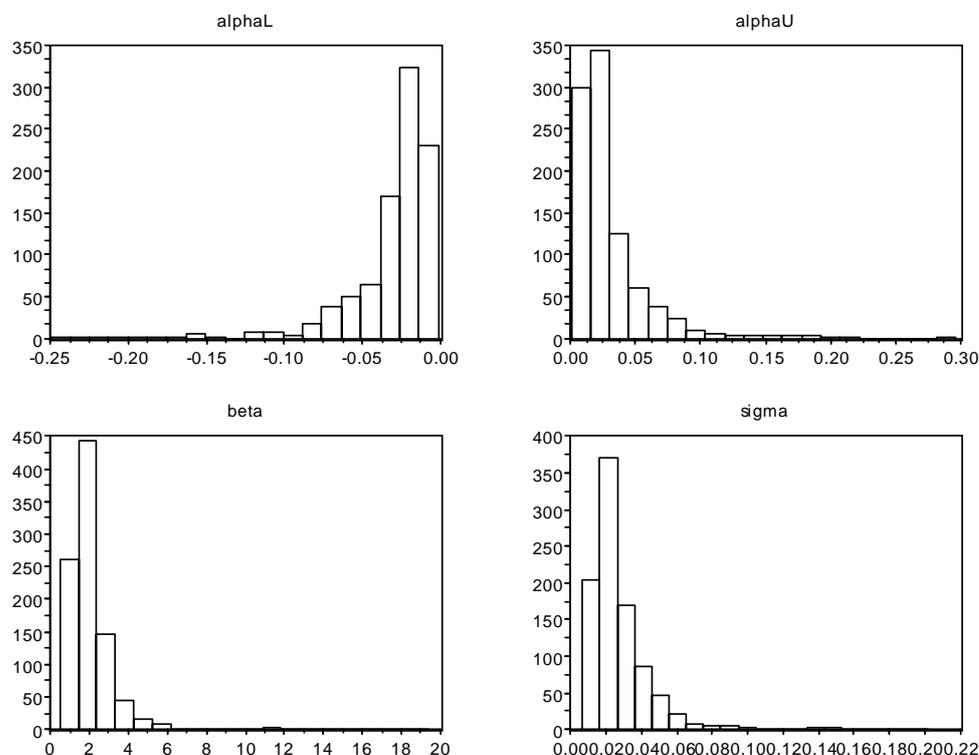


Perhaps more interesting than the estimated parameters themselves are the expected returns generated from them. The summary characteristics of all 923 distributions of unconditional and conditional expected returns (as measured over the 100-day estimation period) are shown in Table 2 along with the equivalent results underlying the OLS estimation procedures calculated here for convenience.

In the first column of Panel A, it is clear that the LDV friction model furnishes expected return distributions that have means that have a higher absolute value, and that these distributions exhibit greater variation. However, with respect to size, the unconditional expected returns have the greatest positive value while the conditional ones are actually negative. The OLS expected returns, on average are positive and closer to zero. This implies that, for observed returns on day $t_0$ that are relatively large and positive, the unconditional expected returns could be predicted to furnish smaller

abnormal returns than the OLS model, while the conditional expected return would actually produce the largest AR.

**Table 2:        Comparison of Expected Returns.**

| Expected Return Distributions[1] | Mean | Maximum | Minimum | Std Deviation |
|---|---|---|---|---|
| **Panel A: Expected Return Distribution Means (100-Day Estimation Period)** | | | | |
| Unconditional | 0.0013 | 0.0290 | - 0.0251 | 0.0044 |
| Conditional | - 0.0062 | 0.0066 | - 0.0436 | 0.0054 |
| OLS Exp. Return Distributions | 0.0004 | 0.0093 | -0.0083 | 0.0022 |
| **Panel B: Expected Return Distribution Standard Deviations (100-Day Estimation Period)** | | | | |
| Unconditional | 0.0165 | 0.0906 | 0.0046 | 0.0084 |
| Conditional | 0.0154 | 0.1203 | 0.0025 | 0.0093 |
| OLS Exp. Return Distributions | 0.0050 | 0.0361 | 3.19E-06 | 0.00485 |
| **Panel C: Expected Return Distribution Means (21-Day Test Period)** | | | | |
| Unconditional Expected Returns | 0.0002 | 0.0252 | - 0.0463 | 0.0060 |
| Conditional Expected Returns | - 0.0073 | 0.0112 | - 0.0577 | 0.0068 |
| OLS Expected. Returns | 9.76E-05 | 0.0118 | -0.0150 | 0.0025 |
| **Panel D: Expected Return Distribution Standard Deviations (21-Day Test Period)** | | | | |
| Unconditional Expected Returns | 0.0158 | 0.1366 | 0.0025 | 0.0113 |
| Conditional Expected Returns | 0.0150 | 0.1826 | 0 | 0.0124 |
| OLS Expected Returns | 0.0044 | 0.0625 | 5.56E-06 | 0.0049 |

[1] 923 sets of Expected Returns data

Also in the 4th column of Panel A, the distribution of unconditional means has a standard deviation that is double that of the OLS means distribution to the four decimal places reported. The conditional mean distribution has yet a larger standard deviation. However, there is no immediate explanation for why the mean of the conditional means distribution should be negative.

When forecasted forward onto market return data available in the 21-day test period, the LDV friction model unconditional expected returns (reported in Panels C and D), again turned out to be larger than those produced by OLS, while the conditional expected returns continued to be smaller. The effect indeed was that the test period ARs based on unconditional expected returns were the smallest; and those based on

the LDV friction model conditional returns were the largest. The AR distributions' mean and standard deviation characteristics are reported in Table 3:

It is a very interesting question as to why the LDV friction model furnishes conditional expected returns that are smaller rather than larger than OLS estimates, and therefore ARs which are larger. When no trade took place on a particular day (or there was at least one trade but the closing price just did not change), the zero value of $R_{jt}$ was assigned to the expected return and also to the AR for that day — and Equation (8) did not apply.

Table 3:        Comparison of Characteristics of Abnormal Returns.

| Expected Return Distributions[1] | Mean | Maximum | Minimum | Std Deviation |
|---|---|---|---|---|
| Panel A: Abnormal Return Distribution Means (21-Day Test Period) | | | | |
| Unconditional Abnormal Returns | -0.0004 | 0.0013 | -0.0016 | 0.0007 |
| Conditional Abnormal Returns | 0.0071 | 0.0092 | 0.0062 | 0.0007 |
| OLS Abnormal Returns | -0.0002 | 0.0009 | -0.0015 | 0.0006 |
| Panel B: Abnormal Return Distribution Standard Deviations (21-Day Test Period) | | | | |
| Unconditional Abnormal Returns | 0.0287 | 0.0560 | 0.0235 | 0.0070 |
| Conditional Abnormal Returns | 0.0285 | 0.0564 | 0.0218 | 0.0074 |
| OLS Abnormal Returns | 0.0239 | 0.0540 | 0.0185 | 0.0078 |

[1] 923 sets of 21-day test period results

One item which surfaced as a result of investigating this question was that there was one company/event data set which furnished nothing but zero values for $R_{jt}$ over the entire test period (the 889th ranked by number of actively traded days, which recorded only 33 trades in the 100-day estimation period.)

## 5.2  Friction Models of the Day Zero Event Window

I now propose a friction model that removes the need to resort to any regression procedure in searching for evidence investor behaviour indicative of a response to a dividend signal. Initially, the 923 observations of day zero conditional abnormal returns derived from the friction model in subsection 5.2.1 will be used as the dependent variable in a friction model procedure in which the independent variable is

$\Delta DPS$ . Then, in a second sweep in subsection 5.2.2, this independent variable will be replaced by $\Delta EPS$ . Following that in subsection 0, both independent variables will be employed together.

## 5.2.1 Conditional Abnormal Returns and ∆DPS

The LDV friction model in the first instance is:

$$AR_j^* = \beta_j \Delta DPS_j + \varepsilon_j$$

*Where*

$$\begin{cases} AR_j = AR_j^* - \alpha_{Lj} & \text{if} & AR_j \neq 0 \text{ and } \Delta DPS_j < 0 \\ AR_j = 0 & \text{if} & AR_j = 0 \\ AR_j = AR_j^* - \alpha_{Uj} & \text{if} & AR_j \neq 0 \text{ and } \Delta DPS_j \geq 0 \end{cases}$$

(9)

The results obtained from this procedure are reported in Table 4. Below a 5.49 percent lower bound, a change in dividend is associated with an increasingly negative AR, while above a 1.53 percent upper bound, the change in dividend is associated with a rising positive AR. The linear approximation of the rate of change ($\beta_{\Delta DPS}$) is strongly significantly different from zero; but the rate of change is quite small (0.0018 per unit change in the dividend variable. The results are reported as point estimates in the table's first column, and in terms of a 95 percent confidence interval in the second and third columns. It must be emphasised that this model is misspecified at least to the extent that it totally ignores the role of the simultaneous earnings announcement information.

**Table 4:** **Conditional Abnormal Returns on Day Zero and ∆DPS.**

| Parameter | MLE | 95% Conf. Int Lower Bound | 95% Conf. Int Upper Bound | p-Values |
|---|---|---|---|---|
| $\alpha_L$ | -0.0549 | -0.0603 | -0.0495 | 0.0000 |
| $\alpha_U$ | 0.0153 | 0.0120 | 0.0186 | 0.0000 |
| $\beta_{\Delta DPS}$ | 0.0018 | 0.0011 | 0.0024 | 0.0000 |
| $\sigma$ | 0.0385 | 0.0361 | 0.0408 | 0.0000 |
| 923 observations | | | | |

## 5.2.2 Conditional Abnormal Returns and ΔEPS

When we replace the change-in-dividend variable with a change-in-earnings variable, the LDV friction model has one subtle change. Because, $\Delta EPS$ never exactly equals zero, the inequalities in the conditions become strict inequalities:

$$AR_j^* = \beta_j \Delta EPS_j + \varepsilon_j$$

*Where*

$$\begin{cases} AR_j = AR_j^* - \alpha_{Lj} & \text{if} & AR_j \neq 0 \text{ and } \Delta EPS_j < 0 \\ AR_j = 0 & \text{if} & AR_j = 0 \\ AR_j = AR_j^* - \alpha_{Uj} & \text{if} & AR_j \neq 0 \text{ and } \Delta EPS_j > 0 \end{cases} \quad (10)$$

The results are very similar to those reported on $\Delta DPS$. There is approximately a 6% range about zero defined by $\alpha_L$ at –4.08% and $\alpha_U$ at 2.15% outside which a change in announced earnings does impact on the size of abnormal earnings; but the rate of change of this impact is again small (0.0008 per unit change in the earnings variable). And again the model is misspecified in the absence of the dividend announcement variable. However, the $\Delta EPS$ coefficient (0.0008) in Table 5 is under half the size of the $\Delta DPS$ coefficient (0.0018) reported above in Table 4**Error! Reference source not found.**.

**Table 5:**         **Conditional Abnormal Returns on Day Zero and ΔEPS.**

| Parameter | MLE | 95% Conf. Int Lower Bound | 95% Conf. Int Upper Bound | p-Values |
|---|---|---|---|---|
| $\alpha_L$ | -0.0408 | -0.0449 | -0.0366 | 0.0000 |
| $\alpha_L$ | 0.0215 | 0.0179 | 0.0252 | 0.0000 |
| $\beta_{\Delta EPS}$ | 0.0008 | 0.0004 | 0.0012 | 0.0000 |
| $\sigma$ | 0.0383 | 0.0360 | 0.0406 | 0.0000 |
| 923 observations | | | | |

## 5.2.3 Conditional Abnormal Returns and both ΔEPS and ΔEPS

Where the friction modelling covered so far in this paper has been developed and adapted from the work of Lesmond (1995) and Lesmond, Ogden and Trzinka (1999), all of the models from here onward have at least two independent variables and were inspired by (but not necessarily closely modelled on) the exchange rate intervention

model employed by Almekinders and Eiffinger (1996). As soon a second independent variable has been brought into consideration, there are two possible ways of defining the model's upper and lower regions. Both are reported in this subection. The first way is to define the prerequisite for upper region membership as $AR_j \neq 0$ and $\sum_{i=1}^{2} X_i \geq 0$ where $\sum_{i=1}^{2} X_{ij} = \Delta DPS_j + \Delta EPS_j$; and for lower region membership, $AR_j \neq 0$ and $\sum_{i=1}^{2} X_i < 0$. This configuration allowed all 923 observations to be used. The model is:

$$AR_j^* = \beta_{1j} \Delta DPS_j + \beta_{2j} \Delta EPS_j + \varepsilon_j$$

*Where*

$$\begin{cases} AR_j = AR_j^* - \alpha_{Lj} & \text{if} & AR_j \neq 0 \; and \; \left( \Delta EPS_j + \Delta DPS_j \right) < 0 \\ AR_j = 0 & \text{if} & AR_j = 0 \\ AR_j = AR_j^* - \alpha_{Uj} & \text{if} & AR_j \neq 0 \; and \; \left( \Delta EPS_j + \Delta DPS_j \right) \geq 0 \end{cases} \tag{11}$$

In the result of the maximum likelihood procedure reported in Table 6, it is strongly clear that the beta of the change in dividend variable is insignificantly different from zero in the presence of an earnings announcement variable.

Table 6: Conditional Abnormal Returns on Day Zero and both ΔDPS and ΔEPS (N = 923).

| Parameter | MLE | 95% Conf. Int Lower Bound | 95% Conf. Int Upper Bound | p-Values |
|---|---|---|---|---|
| $\alpha_L$ | -0.0403 | -0.0443 | -0.0362 | 0.0000 |
| $\alpha_L$ | 0.0206 | 0.0170 | 0.0243 | 0.0000 |
| $\beta_{\Delta DPS}$ | -0.0001 | -0.0007 | 0.0006 | 0.4120 |
| $\beta_{\Delta EPS}$ | 0.0008 | 0.0004 | 0.0012 | 0.0000 |
| $\sigma$ | 0.0374 | 0.0351 | 0.0397 | 0.0000 |
| 923 observations including the DD-EI and DI-ED announcement combinations | | | | |

It can also be seen that the size of the friction region between the two bounds in Table 6 implies that a 6 percent change in the independent variables is necessary before any response is picked up in the AR variable.

However, there is a hidden aspect to this result. Two of the dividend and earnings announcement combinations comprise mixed news in which the two components

move in opposite directions (the DD-EI and DI-ED observations). This means that one had to dominate the other in size in order for the assignment to either upper or lower region to happen. This effectively built in a hidden assumption to the effect that a change in earnings should have the same value as a change in dividend — and that a larger change in one should rightfully dominate the smaller change in the other (even if the difference in size was actually quite small). This assumption can be jettisoned by requiring that the independent variables must each be greater than or equal to zero for assignment to the upper region, and less than or equal to zero for the lower region. However, this altered specification comes at the cost of removing the DD-EI and DI-ED observations from the data set. Nevertheless, it does still allow analysis to occur with respect to observations in which earnings change while dividends do not (the DNC-EI and DNC-ED combinations). The re-specified model looks like this:

$$AR_j^* = \beta_{1j}\Delta DPS_j + \beta_{2j}\Delta EPS_j + \varepsilon_j$$

*Where* (12)

$$\begin{cases} AR_j = AR_j^* - \alpha_{Lj} & \text{if} & AR_j \neq 0 \text{ and } \Delta EPS_j < 0, \Delta DPS_j \leq 0 \\ AR_j = 0 & \text{if} & AR_j = 0 \\ AR_j = AR_j^* - \alpha_{Uj} & \text{if} & AR_j \neq 0 \text{ and } \Delta EPS_j > 0, \Delta DPS_j \geq 0 \end{cases}$$

The result furnished in Table 7 is quite different from that in Table 6. Now, the beta of the change-in-dividend variable is more than four times larger than that of the change-in-earnings variable; and the *p*-values of all parameters indicate the probability of a Type 1 error of much less than one percent.

**Table 7:** **Conditional Abnormal Returns on Day Zero and both $\Delta$DPS and $\Delta$EPS.**

| Parameter | MLE | 95% Conf. Int Lower Bound | 95% Conf. Int Upper Bound | p-Values |
|---|---|---|---|---|
| $\alpha_L$ | -0.0533 | -0.0603 | -0.0463 | 0.0000 |
| $\alpha_U$ | 0.0257 | 0.0193 | 0.0320 | 0.0000 |
| $\beta_{\Delta DPS}$ | 0.0055 | 0.0043 | 0.0068 | 0.0000 |
| $\beta_{\Delta EPS}$ | 0.0017 | 0.0010 | 0.0024 | 0.0000 |
| $\sigma$ | 0.0680 | 0.0640 | 0.0719 | 0.0000 |
| 807 observations that exclude the DI-ED and DD-EI announcement combinations | | | | |
| Minimum Likelihood Estimate = -466.21223 | | | | |

The independent variables in Table 7 exert their effect on the dependent variable, AR above and below a friction region between the upper and lower alphas, which amounts to almost 0.08 in width. This is one third larger than the six percent recorded in Table 6. The results in Table 7 suggest that, both the dividend component of an announcement and the earnings component play a significant role in price change on day zero.

The behaviour of the bounds, $\alpha_L$ and $\alpha_U$ in Table 7 is also of interest. Lesmond, Ogden and Trzcinka (1999) argued, with respect to the relation between company returns and returns on the market index, that investors tend not to transact when the perceived gain from trading does not exceed what they call the round trip effective transaction cost. The fact that $R_{Mt}$ has been replaced in Equation (12) by other independent variables does not change the bounds from being a measure of some form of effective transactions cost. However, we are no longer just dealing with a possible monetary cost, but also with a loss-aversion effect. Kahneman and Tversky (1979), in their promulgation of prospect theory, documented loss aversion as one of the key behaviours identifiable in decision makers making choices under uncertainty; and this was observed, in terms of a 'disposition effect' by Odean (1998) in a study of a brokerage firm's transactions records showing client reluctance to realise losses but greater eagerness to realise gains. More recently, Norsworthy, Gorener, Morgan, Schuler and Li (2004) have confirmed the presence of loss aversion in share market trading behaviour, which they were able to identify in the results generated by their four-state asset-pricing model. Here, in Table 7 we can see evidence of the disposition effect in the fact that the lower bound is approximately twice the distance from zero measured by the upper bound. It appears that investors will trade more readily on the basis of good news, where the seller is able to realise a small profit, than on the basis of bad news where the seller would realise a small loss. The bad news has to be of a greater magnitude before sellers decide to divest. This asymmetry in the values of the bounds has also been apparent in Table 4, Table 5, and in Table 6.

More importantly, the friction region between $\alpha_L$ and $\alpha_U$ can also be interpreted in a more direct manner with respect to dividend and earnings signalling. Between these two bounds the change in the announcement variables is too small for a signal to be sent — of at least too small to be acted upon.

### 5.2.4 Distinction between Day t0 and other Days in the 21-Day Test Period

There is an announcement of dividends and earnings on day $t_0$ only. In all other days of the test period, ARs are either related to other phenomena or to an anticipation of, or maybe a belated reaction to the day zero disclosure. $\Delta DPS$ and $\Delta EPS$ are now applied as leading or lagged independent variables in a series of procedures on the daily ARs — one procedure for each day of the 20 other days of the 21-day test period.

A priori, one would expect very little change in the daily friction regions (between $\alpha_L$ and $\alpha_U$). However, there should be steeper linear associations (captured by the betas) between the day zero ARs and the independent variables than with the ARs of any other day. That is, of course, unless there is leakage of the dividend and earnings information in advance. The summary results are laid out in Table 8 and the next three figures.

**Table 8:** **Parameter Estimates for All Days in the Test Period.**

| Day | $\alpha_L$ | $\alpha_U$ | $\beta_{\Delta DPS}$ | $\beta_{\Delta EPS}$ | $\sigma$ |
|---|---|---|---|---|---|
| -10 | -0.0428 | 0.0222 | 0.0010 | 0.0006 | 0.0389 |
| | (0.0000) | (0.0000) | (0.0034) | (0.0017) | (0.0000) |
| -9 | -0.0398 | 0.0176 | 0.0011 | 0.0008 | 0.0336 |
| | (0.0000) | (0.0000) | (0.0005) | (0.0000) | (0.0000) |
| -8 | -0.0386 | 0.0197 | 0.0013 | 0.0002 | 0.0353 |
| | (0.0000) | (0.0000) | (0.0001) | (0.1967) | (0.0000) |
| -7 | -0.0354 | 0.0175 | 0.0012 | 0.0006 | 0.0312 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0004) | (0.0000) |
| -6 | -0.0335 | 0.0145 | 0.0008 | 0.0001 | 0.0290 |
| | (0.0000) | (0.0000) | (0.0037) | (0.2334) | (0.0000) |
| -5 | -0.0377 | 0.0212 | 0.0019 | 0.0003 | 0.0371 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0574) | (0.0000) |
| -4 | -0.0456 | 0.0228 | 0.0017 | 0.0004 | 0.0401 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0609) | (0.0000) |
| -3 | -0.0340 | 0.0139 | 0.0007 | 0.0006 | 0.0322 |
| | (0.0000) | (0.0000) | (0.0139) | (0.0014) | (0.0000) |
| -2 | -0.0393 | 0.0178 | 0.0008 | 0.0006 | 0.0344 |
| | (0.0000) | (0.0000) | (0.0120) | (0.0019) | (0.0000) |
| -1 | -0.0446 | 0.0225 | 0.0006 | 0.0010 | 0.0405 |
| | (0.0000) | (0.0000) | (0.0674) | (0.0000) | (0.0000) |
| 0 | -0.0533 | 0.0257 | 0.0055 | 0.0017 | 0.0680 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| 1 | -0.0404 | 0.0200 | 0.0022 | -0.0001 | 0.0484 |
| | (0.0000) | (0.0000) | (0.0000) | (0.3333) | (0.0000) |
| 2 | -0.0429 | 0.0211 | 0.0009 | 0.0003 | 0.0396 |
| | (0.0000) | (0.0000) | (0.0124) | (0.0605) | (0.0000) |
| 3 | -0.0351 | 0.0176 | 0.0014 | 0.0006 | 0.0345 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0007) | (0.0000) |
| 4 | -0.0378 | 0.0185 | 0.0015 | 0.0005 | 0.0351 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0084) | (0.0000) |
| 5 | -0.0351 | 0.0155 | 0.0015 | 0.0002 | 0.0299 |
| | (0.0000) | (0.0000) | (0.0000) | (0.1448) | (0.0000) |
| 6 | -0.0364 | 0.0166 | 0.0015 | 0.0004 | 0.0344 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0255) | (0.0000) |
| 7 | -0.0389 | 0.0185 | 0.0009 | 0.0003 | 0.0345 |
| | (0.0000) | (0.0000) | (0.0038) | (0.0988) | (0.0000) |
| 8 | -0.0375 | 0.0178 | 0.0013 | 0.0008 | 0.0314 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0000) | (0.0000) |
| 9 | -0.0366 | 0.0173 | 0.0015 | 0.0004 | 0.0336 |
| | (0.0000) | (0.0000) | (0.0000) | (0.0135) | (0.0000) |
| 10 | -0.0341 | 0.0159 | 0.0008 | 0.0005 | 0.0298 |
| | (0.0000) | (0.0000) | (0.0041) | (0.0027) | (0.0000) |

In each cell, the upper figure is the MLE parameter estimate and the lower figure in brackets is the associated p-value.

In Table 8, all but one of the $\beta_{\Delta DPS}$ are significant at the five percent level of error or better; and there is a strong upward spike (0.0055) on day zero which is close to ten times the size of the beta for the preceding day (0.0006), and is about triple the size on all other days. This is illustrated in Figure 4.

**Figure 4:**   **ΔDPS Coefficients over the 21-Day Test Period.**



Betas for Change in Dividends over the 21 Day Test Period
(Error bars = 95% Confidence Interval)
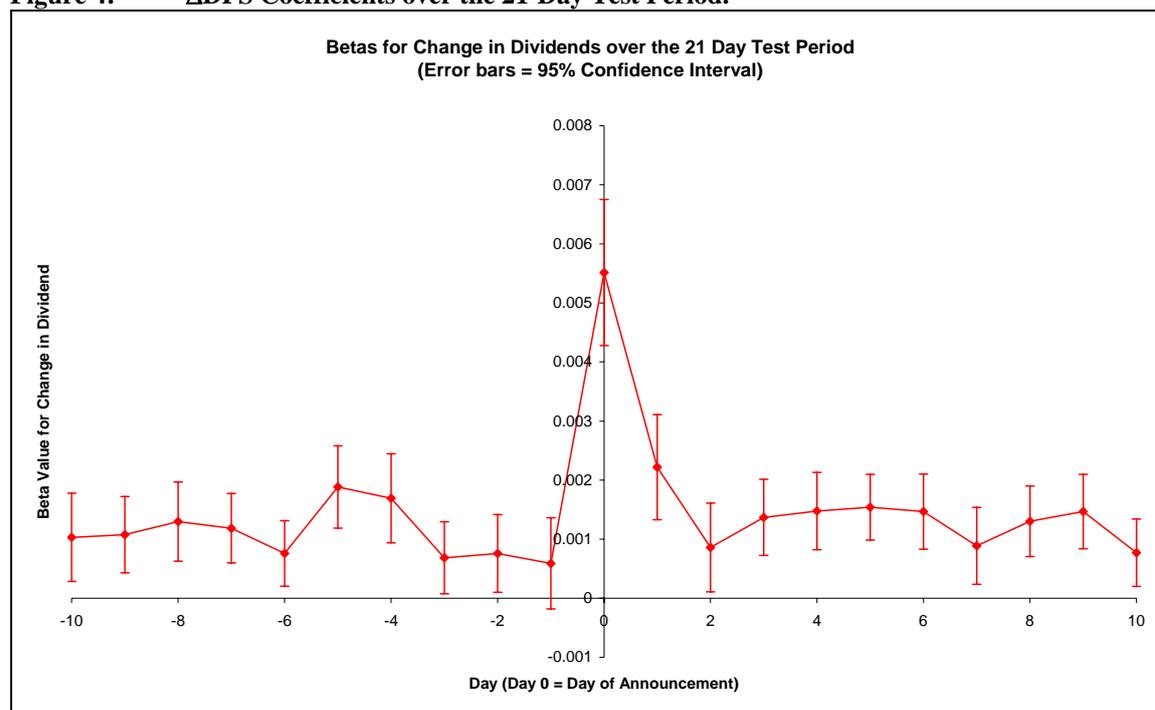
This indicates that investors react to the dividend information and in doing so increase the ARs earned on day $t_0$ in a manner that can be captured linearly (ie, the larger the change in dividend, the larger the associated AR). Arguably, the slight rises on days $t_{-5}$ and $t_{-4}$ could be interpreted as investors acting on either anticipated or insider information; and the day $t_2$ beta, which is the second highest in the test period could be seen as a belated reaction by late receivers of the disclosure.

A similar pattern is observed in Figure 5 with respect to the $\beta_{\Delta EPS}$ results. However, the day zero spike (0.0017) is only one third of the magnitude of the day zero spike observed with respect to $\beta_{\Delta DPS}$ (0.0055). Further, there is a drop on day $t_1$ which suggests that on that day there is next to no association between the earnings news and the new day's trading. This really does suggest that the NZX is an efficient market — at least in the processing of earnings information.

**Figure 5:** ΔEPS Coefficients over the 21-Day Test Period.



Betas for Change in Earnings over the 21 Day Test Period
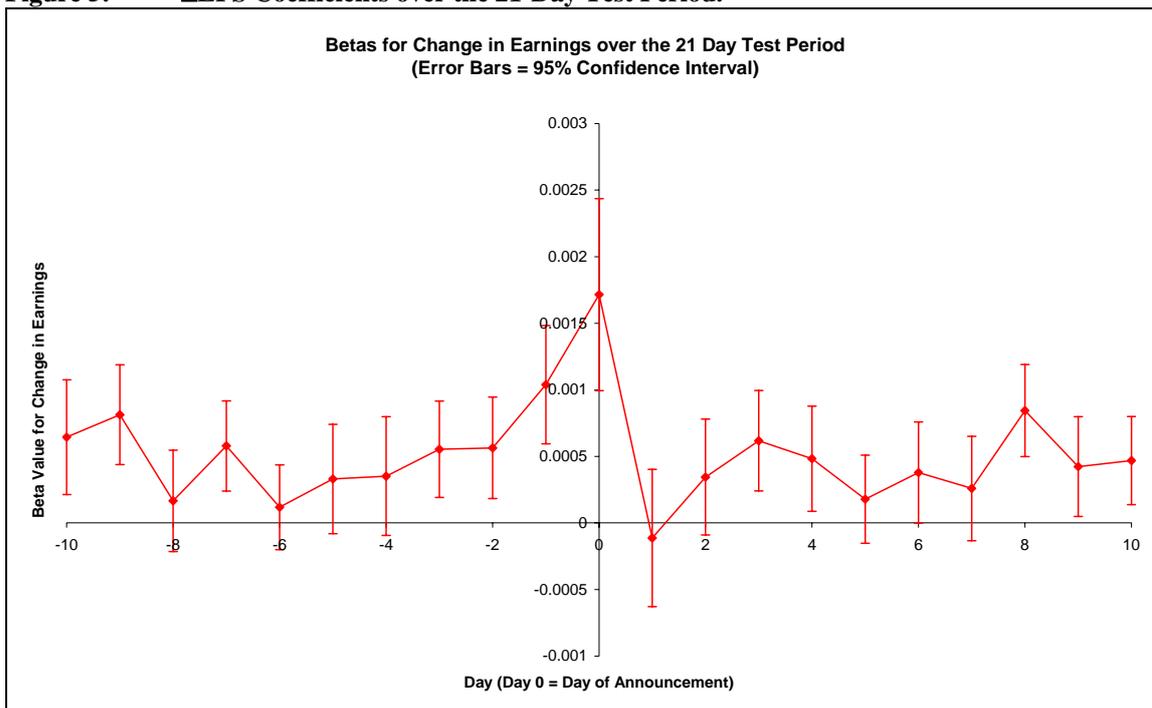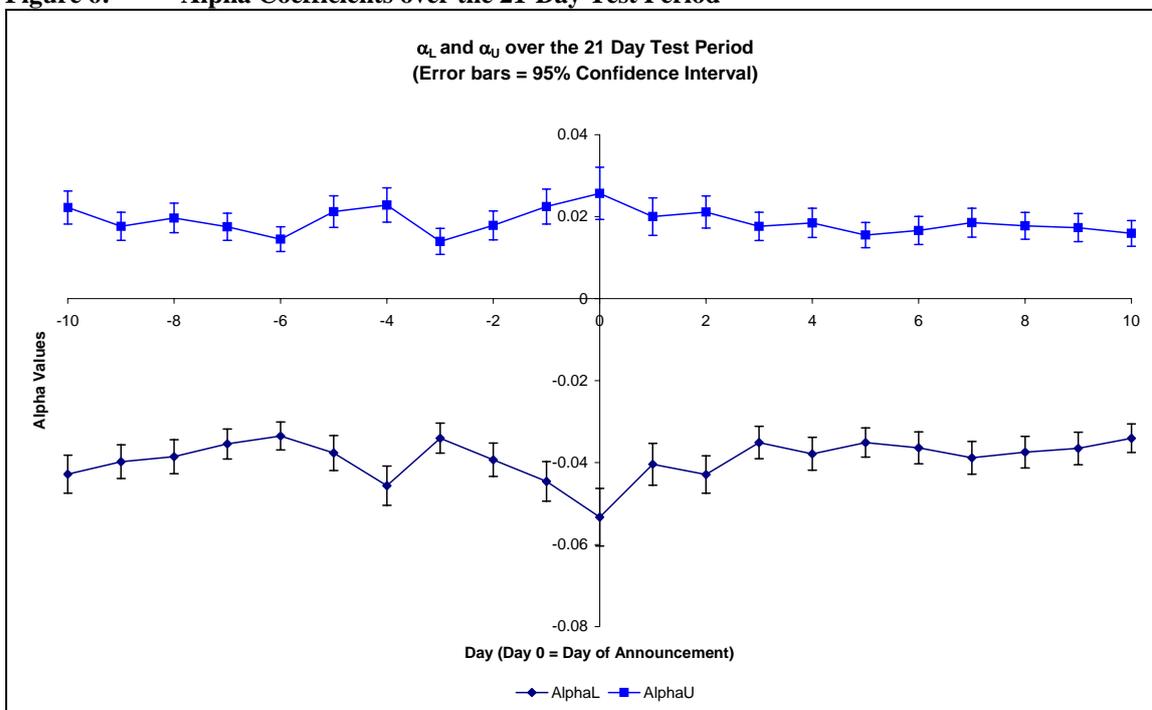(Error Bars = 95% Confidence Interval)

Figure 6 contains the plots of $\alpha_L$ and $\alpha_U$. There is a slight widening of the friction region on day $t_0$; but this widening is hardly significant when one takes the 95% confidence intervals into account.

**Figure 6:** Alpha Coefficients over the 21-Day Test Period



$\alpha_L$ and $\alpha_U$ over the 21 Day Test Period
(Error bars = 95% Confidence Interval)

In the final part of the results, a further LDV friction model configuration is proposed, which brings in several new independent variables in the nature of dummy variables in the RLS regression procedures.

## 5.2.5  Day Zero Friction Model with First-order and Interaction Variables

So far in this chapter, friction models have been employed to consider only the performance of the two first-order variables, $\Delta DPS$ and $\Delta EPS$. A logical progression from this point would be to incorporate into a friction model some version of the dummy variables employed by Kane Lee and Marcus (1984), Easton (1991), Lonie et al (1996) and Anderson (2006) in their RLS regressions.

In the cross-sectional regression procedure, five dummy variables were employed to ascertain the presence (or not) of a significant interaction effect. It was not possible to carry all these dummies over into the maximum likelihood estimation environment. There were several reasons for this. For a start, in a friction model context, we have two alpha values where the restricted least squares regression model furnished only one — which could take on the job of proxying the announcement combination for which no dummy variable was specified. One might ask, which of the MLE alphas would take up this role? More importantly, a dummy variable is binary, taking on the value '1' if an observation belongs to the chosen category, or '0' if it does not; and a binary variable is incapable of furnishing a set of values which fit into all three of the friction model's three regions. The problem arises, that if there are no values present in a given region, then the maximum likelihood estimation procedure furnishes a hessian matrix with negatives present on the leading diagonal, which gives rise to standard errors which are the square roots of negative numbers — and are therefore imaginary. This means that the numerical search mechanism in the maximum likelihood procedure has failed to achieve convergence on an optimal value.

Nevertheless, it is an interesting question as to whether the actual combination of dividend and earnings changes present in an announcement are significantly different from each other. Therefore the friction model was reconfigured to include the 'GOOD+BADNEWS' and 'MIXEDNEWS$_{DNC}$' dummy variables.

The above variables left two dividend-and-earnings combinations unaccounted for. These were DI-ED (dividend increased with earnings decreased) and DD-EI.. These

had to be left out, as all attempts to configure summations of variables to circumvent the same-sign restriction (explained in subsection 0) merely ended up producing results with non-invertible hessian matrices. The implementation of the friction model was as follows.[15]

$$AR_j^* = \beta_{1j}\Delta DPS_j + \beta_{2j}\Delta EPS_j + \beta_{3j}D_{G+B} + \beta_{4j}D_{MIX} + \varepsilon_j$$

*Where* (13)

$$\begin{cases} AR_j = AR_j^* - \alpha_{Lj} & \text{if} \quad AR_j \neq 0 \text{ and } \Delta EPS_j < 0, \Delta DPS_j \leq 0, D_{G+B} \leq 0, D_{MIX} \leq 0 \\ AR_j = 0 & \text{if} \quad AR_j = 0 \\ AR_j = AR_j^* - \alpha_{Uj} & \text{if} \quad AR_j \neq 0 \text{ and } \Delta EPS_j > 0, \Delta DPS_j \geq 0, D_{G+B} > 0, D_{MIX} > 0 \end{cases}$$

When the DI-ED and DD-EI observations were excluded, the data set was now reduced to 807 observations. The results for the expanded model incorporating GOOD+BADNEWS and MIXEDNEWS$_{DNC}$ are in Table 9. In common with the unexpanded friction model, $\beta_{\Delta DPS}$ is about three time the size of $\beta_{\Delta EPS}$, and both are significant. However, both $\beta_{GOOD+BAD\,NEWS}$ and $\beta_{MIXED\,NEWS_{DNC}}$ are much larger than either of the first-order coefficients; and both are supported by p-values with less than a one percent level of error. This strongly supports the contention that investors are indeed reacting to a perception of an earnings signal at the very least. In addition, the fact that β$_{GOOD+BADNEWS}$ has a slightly higher value than β$_{MIXEDNEWSDNC}$ does suggest that the change in the announced dividend does amplify the effect of a change in announced earnings — which does not occur with respect to MIXEDNEWS$_{DNC}$.

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[15] Specification of the restrictions in terms of the dummy variables was actually redundant as these were dependent on the restrictions associated with the two first-order variables. For instance, $D_{GOOD+BAD\,NEWS}$ could only be positive if $\Delta DPS$ and $\Delta DPS$ were both positive.

**Table 9:** **Day Zero Parameters furnished by the Expanded Friction Model with Interaction Variables.**

| Parameter | MLE | 95% Conf. Int Lower Bound | 95% Conf. Int Upper Bound | p-Values |
|---|---|---|---|---|
| $\alpha_L$ | -0.1241 | -0.1645 | -0.0838 | 0.0000 |
| $\alpha_U$ | 0.1030 | 0.0627 | 0.1433 | 0.0000 |
| $\beta_{\Delta DPS}$ | 0.0027 | 0.0013 | 0.0041 | 0.0001 |
| $\beta_{\Delta EPS}$ | 0.0007 | 0.0000 | 0.0015 | 0.0232 |
| $\beta_{GOOD+BADNEWS}$ | 0.1039 | 0.0634 | 0.1443 | 0.0000 |
| $\beta_{MIXEDNEWS}$ | 0.1001 | 0.0598 | 0.1404 | 0.0000 |
| $\sigma$ | 0.0672 | 0.0633 | 0.0711 | 0.0000 |
| This MLE procedure was run on 807 observations | | | | |
| Minimum Likelihood Estimate = -605.26487 | | | | |

But does the expanded model in Table 9 incorporating GOOD+BADNEWS and MIXEDNEWS$_{DNC}$ deliver an improvement in explanatory power over the unexpanded model? A likelihood ratio test was employed in Table 10 to answer this question.

**Table 10**

| | |
|---|---|
| Unrestricted Model (Table 9) MLE = L$_{UNRESTRICTED}$ | -605.26487 |
| Restricted Model (Table 7) MLE = L$_{RESTRICTED}$ | -466.21223 |
| Likelihood Ratio = 2(L$_{UNRESTRICTED}$ - L$_{RESTRICTED}$) | -278.10528 |
| Number of restrictions | 2 |
| $p$-value for a $\chi_2^2$ distribution[16] | 4.07573E-61 |

The two MLE figures are minimum likelihood estimates which need to be multiplied by -1 to be viewed as maximum likelihood estimates. The absolute value of the difference between the unrestricted model with the two interaction dummies and the restricted model without dummies is 278.1053 which is somewhat larger than 9.21, the $\chi_2^2$ critical value with a one percent Type 1 error probability. The $p$-value is 0.0000 to four decimal places, and the expanded model incorporating interaction variables is clearly superior in its explanatory power.

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[16] Excel's CHIDIST function was used for this computation.

# 6 Conclusions and Discussion

This paper set out to do two things. The first was to provide a method for estimating expected returns which did not rely on all of the assumptions that are associated with the Market Model. For instance, the Market Model, by employing OLS regression requires linearity while the friction model's employment of a quasi-Newton optimisation procedure liberates us from the linearity requirement. However, the procedure — as presented — did still make the assumption that the data was normally distributed. But the normality assumption too may be dropped if the normal cumulative density function and the normal probability density functions are replaced by their equivalents furnished by some other distribution such as the asymmetric power distribution (APD). Achieving this would be a logical next step in future employment of friction modelling with respect to event studies.

The second goal of the paper was to provide a method for estimating expected returns which did not rely on sleight of hand or sheer blinkeredness in dealing with the thinness of trading of many of the stocks in the dataset. Far from sweeping non-trading days and zero-value company returns under the carpet, the friction model methodology explicitly sets out to model their impact on the parameters employed in constructing expected returns.

The third goal of this paper was to employ the ARs generated with respect to the expected return output of a friction model procedure on every feasible company/event estimation period dataset, to determine if any evidence of an investor reacting to a dividend signal could be found. When the ARs were constructed from conditional expected returns, evidence of dividend signalling was not clear. With respect to the one-day event window, the two first-order variables were significant together — which is not enough to separate out their signalling effects from one another. The best that could be done was to report that the $\Delta DPS$ coefficient was larger than the $\Delta EPS$ coefficient.

The fourth goal of this paper was to develop friction models which could be used directly to investigate the behaviour in the event window. These models were restricted to either a one-day event window, or a one-day window in the context of the rest of the test period. They certainly showed both $\Delta DPS$ and $\Delta EPS$ to be significant and that $\Delta DPS$ was exerted a greater magnitude impact on the associated ARs. In the

final model, which incorporated two interaction variables modelling the effect of four of the six dividend and earnings interaction effects, some evidence was furnished that indicated that the dividend signal could be separated from the earnings signal — but the degree of separation was very subtle.

But, most important, this paper has demonstrated that friction modelling can be used to replace both the Market Model and restricted least squares regression in event studies where there are two quantifiable variables and a number of possible interaction effects associated with the news that constitutes the study's event.

# 7  Bibliography

ABEYRATNA, G., (1994): *An Empirical Investigation of UK Stock Market Reaction to Dividend Announcements in a Complex Signalling Environment.* PhD Dissertation, University of Dundee.

BARTHOLDY, J. AND A. RIDING, (1994): "Thin Trading and the Estimation of Betas: The Efficacy of Alternative Techniques," *The Journal of Financial Research* 27, no. 2, Summer: 241 – 254.

BEAVER, W. H., (1968): "The Information Content of Annual Earnings Announcements," *Journal of Accounting Research* 6, Empirical Research in Accounting: Selected Studies: 67-92.

BHATTACHARYA, S., (1979): "Imperfect Information, Dividend Policy, and 'The Bird in the Hand' Fallacy," *Bell Journal of Economics* 10, no. 1, Spring: 259-70.

BHATTACHARYA, S., (1980): "Nondissipative Signaling Structures and Dividend Policy," *The Quarterly Journal of Economics* 95, no. 1, August: 1-24.

CAMPBELL, J. Y., A. W. LO, AND A. C. MACKINLAY, (1997): *The Econometrics of Financial Markets*, Princeton University Press, Princeton, New Jersey.

CRAGG, J. C., (1986): "The Relationship of Dividend Payments to the Characteristics of the Earnings Streams of Corporations," Chapter 10, in *Prices, Competition and Equilibrium* by M. H. Preston and R. E. Quandt. Phillip Allen, London.

DAGENAIS, M. G., (1969): "A Threshold Regression Model," *Econometrica*, 37: 193-203.

DAGENAIS, M. G., (1975): "Application of a Threshold Regression Model to Household Purchases of Automobiles," *Review of Economics and Statistics* 57: 275-285.

DESARBO, W. S., V. R. RAO, J. H. STECKEL, J. WIND, AND R. COLOMBO, (1987): "A Friction Model for Describing and Forecasting Price Changes," *Marketing Science* 6: 299-319.

EASTON, S. A., AND N. A. SINCLAIR, (1989): "The Impact of Unexpected Earnings and Dividends on Abnormal Returns to Equity," *Accounting and Finance* 29, no. 1, May: 1-19.

EASTON, S., (1991): "Earnings and Dividends: Is there an Interaction Effect?" *Journal of Business Finance and Accounting* 18, no. 2, January: 255-66.

EDDY, A., AND B. SEIFERT, (1988): "Firm Size and Dividend Announcements," *The Journal of Financial Research* 11, no. 4, Winter: 295-302.

ELIASON, S. R., (1993): *Maximum Likelihood Estimation: Logic and Practice*, Quantitative Applications in the Social Sciences 96, Sage Publications, London.

EMANUEL, D. M., (1984): "The Information Content of Sign and Size of Earnings Announcements: New Zealand Evidence," *Accounting and Finance* 24, No. 2, November: 25-43.

FAMA, E. F., (1965): "The Behavior of Stock-Market Prices," *Journal of Business* 38, January: 34-105.

FAMA, E. F., L. FISHER, M. C. JENSEN, AND R. ROLL, (1969): "The Adjustment of Stock Prices to New Information," *International Economic Review* 10, No. 1, February: 1-21.

FORBES, S. M., AND L. S. MAYNE, (1989): "A Friction Model of the Prime," *Journal of Banking and Finance*: 13, 127-135.

GALPIN, N., (2004): *Can the Pecking Order Explain the Costs of Raising Capital?* Indiana University, Kelley School of Business Working Paper: 1-46.

GRANT, D., (1997): *Bulls, Bears and Elephants: a history o f the New Zealand Stock Exchange*, Victoria University Press, Wellington, New Zealand.

HASHIMOTO, Y., AND I. TAKATOSHI, (2004): *High-Frequency Contagion between the Exchange Rates and Stock Prices*, NBER Working Paper Series Working Paper 10448.

HAW, I., AND W. KIM, (1991): "Firm Size and Dividend Announcement Effect," *Journal of Accounting, Auditing and Finance* 6, no. 3 (New Series), Summer: 325-347.

HOWE, J. S., AND J. LIN, (1992): "Dividend Policy and the Bid-Ask Spread: An Empirical Analysis," *Journal of Financial Research* 15, no. 1, Spring: 1-10.

KAHNEMAN, D., AND A. TVERSKY, (1979): "Prospect Theory: An Analysis of Decision Under Risk," *Econometrica* 47 no. 2: 263-291.

KALLUNKI, J., (1997): "Handling Missing Prices in a Thinly Traded Stock Market: Implications for the Specification of Event Study Methods," *European Journal of Operational Research* 103: 186 – 197.

KANE, A., Y. K. LEE, AND A. MARCUS, (1984): "Earnings and Dividend Announcements: Is there a Corroboration Effect?" *Journal of Finance* 39, no. 4, September: 1091-99.

KAO, C., AND C. WU, (1994): "Tests of Dividend Signalling Using the Marsh-Merton Model: A Generalised Friction Approach," *Journal of Business*, 67: 45-68.

LESMOND, D. A., (1995): *Transaction Costs and Security Return Behavior: The Effect on Systematic Risk and Firm Size*, Unpublished Dissertation, State University of New York at Buffalo.

LESMOND, D. A., J. P. OGDEN, AND C. A. TRZCINKA, (1999): "A New Estimate of Transactions Costs," *Review of Financial Studies*, 12,no 5: 1113-1141.

LONG, J. S., (1997): *Regression Models for Categorical and Limited Dependent Variables*, Advanced Quantitative Techniques in the Social Sciences Series 7, Sage Publications Inc, California.

LONIE, A. A., G. ABEYRATNA, D. M. POWER, AND SINCLAIR C. D, (1996): "The Stock Market Reaction to Dividend Announcements," *Journal of Economic Studies* 23, no. 1: 32-52.

MADDALA, G. S., (1983): *Limited Dependent and Qualitative Variables in Econometrics*, Econometric Society Monographs No. 3, Cambridge University Press, Cambridge, Massachusetts.

MARSH, T. A., AND R. C. MERTON, (1987): "Dividend Behavior for the Aggregate Stock Market," *Journal of Business* 60: 1-40.

NORSWORTHY, J. R., R. GORENER, I. W. MORGAN, R. E. SCHULER JR, AND D. LI, (2004): *Expected Utility, Prospect Theory and Asset Pricing*, Canadian Economics Association Conference, Ryerson University, Toronto, Canada, June: 1-72.

ODEAN, T., (1998): "Are Investors Reluctant to Realize Their Losses," *Journal of Finance* 53: 1775-1798.

PRICE, W. L. (1976): "A Controlled Random Search Procedure for Global Optimization," *The Computer Journal* 20: 48-53.

ROSETT, R. N., (1959): "A Statistical Model of Friction in Economics," *Econometrica* 27: 263-267.

STRONG, N., (1992): "Modelling Abnormal Returns: A Review Article," *Journal of Business Finance and Accounting* 19, no. 4, June: 533-552.

VOS, E., AND R. TONG, (2001): "Dividend Without Signals in New Zealand," *Accounting Research Journal* 14, no. 2: 173-180.