Zero-value Company Returns, Thin Trading and the Use of State Asset Pricing Models in Event Study Research

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Abstract

The calculation of expected returns is a necessary ingredient in data processing for an event study. The method most commonly used, the market model, often fails to meet the OLS requirement of normally distributed residuals, and tends to furnish regression output (low R^2, and insignificant *t*- and *F*-statistics) that, in other contexts, one would not rely on. A family of state asset pricing models may offer improved performance in this respect. This issue becomes important when a listed company's stocks are thinly traded and missing data is proxied by zero-value returns whose rate of occurrence impacts on the ability of the market model to cope. A 3-state asset pricing model has superior performance characteristics when applied to thinly-traded data sets.

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1 Introduction

Event studies traditionally employ the market model for calculating abnormal returns that determine if a particular event's news content significantly impacts on share value or not.[1] This paper considers state asset pricing models as an alternative method. Why is this a good idea? This is a question addressing the issue of how to deal with thinness and/or absence of trading for stretches in the estimation period of the market (or any other) model you want to use in your study. Additionally, the market model's simple OLS procedure usually furnishes expected returns with a tiny R^2 statistic implying relatively low explanatory power. Intuitively, one would want expected returns, given that they are deemed to be market-risk adjusted, to be associated with R^2 statistics that are not vanishingly small. State asset pricing models offer much greater explanatory power, which makes an investigation of them enticing. Further, their regression procedures furnish larger, statistically more significant *F*-statistics along with residuals that are more likely to conform to a normal distribution. This is especially useful because, the less often shares change owners in a company's event study estimation period, the less likely it is that the regression inputs or outputs are going to be normally distributed. While the market model has been found by researchers such as Brown and Warner (1985) to be robust on data that is not necessarily normally distributed, models that do more closely meet the best linear unbiased estimator requirements of OLS regression must surely be attractive. Therefore this paper rates a set of candidate models on their performance in generating expected return parameters for future service in an event study, where the rating criteria are R^2 and *F*-values, and the incidence of normally distributed residuals. In particular, we are interested in how useful the models are when operating on data sets where thinness of trading is increasingly the norm.

Various methods for dealing with the thin trading problem have been suggested, among which those of Scholes and Williams (1977), and Dimson (1979) stand out as early examples. Subsequent research into thin trading (Dimson and Marsh, 1983,

[1] The methodology entails three simple steps. The first is to collect parameters from an OLS regression of return on the market on a data set of company returns (the dependent variable) spanning a timeframe known as the estimation period. The second is to use these parameters to forecast return expectations onto data in a test period containing the occurrence of the event of interest (the event window); and the third is to determine the magnitude of abnormal returns as the discrepancy between observed returns and their expected values.

Fowler, Rorke and Jog, 1979 and 1989; Martikainen, Perttunen, Yli-Olli and Gunasekaran, 1994 among others) has provided methodological solutions that are perhaps too complicated to have been widely accepted or adopted. Indeed, if any adjustment is made at all when dealing with data sets containing instances of zero trading observations, event study researchers have tended to make use of Scholes and Williams (1977). However, many have tended to ignore the issue of thin trading entirely. This may be reasonable given that Bartholdy and Riding (1994) found, on data for thinly-traded New Zealand securities, that the conventional market model (a simple ordinary least squares regression) produced betas that were as consistent as those of Scholes and Williams, while superior in efficiency and smallness of bias. But the problem of missing trades still gives rise to the need for a decision on how to best deal with it. With respect to data sets from the United States, CRSP provides a fix before researchers get their hands on them. An appendix to Lesmond, Ogden and Trzinka (1999) provides an excellent insight into the quite complex manner in which CRSP decides what to put in the gaps left by missing trades. Elsewhere in the world, time series of closing prices often have these gaps left in them. Kallunki (1997) describes and assesses three hole-filling methodologies in preparation for OLS processing, one of which is simply to plug the gap with a zero-value return. Utilizing zero-value returns, Anderson (2009) proposes a friction modeling approach in which maximum likelihood estimation is used on data that are segregated into three zones including one for zero values and the other two according to the sign of the daily return on the market. The current paper sets out to use state asset modeling in a similar manner.

A state asset pricing model is one in which either company or market returns, or both sorts of return are compartmentalized by whether they are positive or negative. The simplest model in the family would be a 2-state model in which company returns that are greater than or equal to zero in value are segregated into the first state, and the second state contains company returns that are negative. A dummy variable in the OLS regression procedure distinguishes the states. An alternative 2-state model might segregate company and market return pairs likewise by the sign of the market return. A second, more cogent alternative in the context of thin trading, is a two-state model that segregates zero-value company returns from returns that are non-zero in value.

Norsworthy, Gorener, Morgan, Schuler and Li (2004) set up a 4-state asset pricing model which partitions daily company returns into four quadrants depending on whether they are positive or negative in conjunction with the sign (positive or negative) of the market return for the same day. They noted that their four-way partition "doubles the explanatory power of the conventional asset pricing model (APM), the market model" (p.3). However Norsworthy et al's purpose was quite removed from an event study focus. They were looking for decision-framing effects posited by Prospect Theory (Kahneman and Tversky 1979 and 1991). Further, their study employed only 40 sets of daily returns data that were each 15 years in length.

Norsworthy et al were not the only authors to consider 4-state models. On French data, Jokung and Meyfredi (2003) investigated both unrotated and rotated versions as alternative tools to the market model for asset valuation. They found both produced a reduction in non-systematic risk and an improvement in the stability of betas. But while Jokung's and Meyfredi's time-series of daily observations at five years were only one third the length of those of Norsworthy et al, the time-series of both sets of authors were somewhat long for employment in a standard event study, of, say dividend announcements, where announcements are made as frequently as twice or even four times a year.

The current study sets out to investigate the performance of a 2-state model (segregating zero-value from non-zero company returns), two 3-state models and a four-state model, and compare this performance with that of the market model on the same data. But the data sets employed are of a more conventional length for event study purposes. The estimation period for generating expected returns is restricted to the 100 days of company log returns that precede a test period of 21 days centered about a day zero, (the day of a targeted event). There is an actual event underlying the data sets. This is a joint dividend and earnings disclosure. But the paper does not set out to examine the nature of dividend (or earnings) signaling, and looks instead at the quality of the expected returns underlying the abnormal returns employed in such an examination. The 948 data sets used in the study are from New Zealand Stock Exchange-listed shares 1990-1999[2].

[2] The analysis of day zero abnormal returns (and of cumulative abnormal returns for a three-day window spanning day zero) is reported by Anderson (2006, 2009). It entailed analysis of the

Of the models considered, it is the 3-state model with partitioning by sign of company return that turns out to be the most useful for efficiently processing event-study estimation-period data sets. In this model, company returns are assigned to the positive region when they are positive, to the negative region when negative; and isolated from the model's dummy regression procedure when they are zero in value.

The roadmap for the paper is as follows. Section 2 explains the mechanics of the 3-state models. In Section 3 the data is described. Additionally, this section explores the characteristics of the data sets furnished by the market model, which is the study's base case. In Section 4, the models are compared. This is mainly in terms of the characteristics of their regression outputs – keeping in mind that OLS regression ideally should be performed on data that is normally distributed. Section 5 presents the paper's conclusions.

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interaction effects arising from different dividend and earnings combinations, following the methodology of Kane, Lee and Marcus (1984).

2 Methodology

The methodology used in this paper is very simple. Four state asset pricing models are compared with the market model on an identical portfolio of data sets. The criteria for assessment are the OLS regression outputs provided by each model with respect to that portfolio. In particular, the mean recorded F-statistics and p-values are considered along with the R^2 statistics. In addition, the residuals for the regressions are subjected to both Jarque-bera and Liliefors tests for normality. With respect to the output of the normality tests, the data sets in the study are partitioned into bands of trading thinness. Further, because all zero-value returns have the same impact on models, zero-value returns from both liquidity-trading and from absence of trading are lumped together. However, in Appendix 1, the effect of separating out the two types of zero-value return is examined in terms of the 3-state (by company) asset pricing model. The remainder of this methodology section describes the specifications of each candidate model, starting with the market model.

2.1 Market Model

The market model is the traditional workhorse for computing a measure of reaction by investors to a given news event occurring on a known date, t_0, or over a specified number of days (event window) spanning that day. This entails the specification of the reactivity measure, which is usually an abnormal return (AR) or a cumulative abnormal return (CAR). These are calculated as a measure of how much an observed return departs from expectation as predicted by the model. Hence, a time series of closing price data is required that is long enough to furnish a span over which an expected return can be calibrated (estimation period), and a portion left over (known as the test period) for comparing and contrasting observed returns nett of that expectation. If the news has an impact on investors, then investor trading activity will show up as an AR spike in the 'event window' portion of the test period, the rest of which should contain ARs that are small and insignificant.

In this study, the event window will be defined as day t_0, embedded at the centre of a 21-day test period, which is preceded by a 100-day estimation period.

The basic building blocks for the calculation of expected returns are the daily log return, R_{At} (the return on company A on day t) and the return on the market index for the same day, R_{Mt}:

$$R_{At} = \ln\left[\frac{P_{At}}{P_{At_{-1}}}\right] \quad (1)$$

$$R_{Mt} = \ln\left[\frac{Index_t}{Index_{t_{-1}}}\right] \quad (2)$$

Because closing price data series should be free of the effects of share splits and dividend payments, P_{At} characteristically comes from an index of adjusted closing prices. The expected return, E(R_{At}) is calculated from the parameters estimated in the OLS regression[3]:

$$R_{At} = \beta_{1A} + \beta_{2A} R_{Mt} + \varepsilon_{At} \quad (3)$$

Return expectations can be forecasted for each day (t) of the test period by applying these regression parameters:

$$E\left(R_{At}\right) = \beta_{1A} + \beta_{2A} R_{Mt} \quad (4)$$

Test period ARs and CARs are then:

$$AR_{At} = R_{At} - E\left(R_{At}\right) \quad (5)$$

And:

$$CAR_{AT} = \sum_{t=1}^{T} AR_{At} \quad (6)$$

An alternative version of CAR_{AT} is an averaged CAR which entails scaling the right-hand side of Equation (6) by $1/T$

2.2 2- and 3-state Models

The 2-state model is simply the market model with a dummy variable employed to pick up the impact of zero-value returns.

[3] The numbering of the intercept term and slope coefficient β_{1A} and β_{2A} instead of the more traditional α and β is to facilitate the scheduling the outputs of a model per column in Table 4 and later tables.

There are two possible 3-state models, both of which partition returns into a positive state, a negative one, and a state in which returns are zero in value. This zero-value state pertains to zero-value company returns in both models. This is because the underlying purpose is to bring an adjustment for thin trading explicitly into the calculation of expected returns; and it is the absence of trading in a company's stocks that is of interest rather than the liquidity of a stock market as a whole. Aside from that, it is also extremely unlikely that the return on the market index will ever be zero unless the stock exchange happens to be extremely small with only a few dozen companies listed on it.

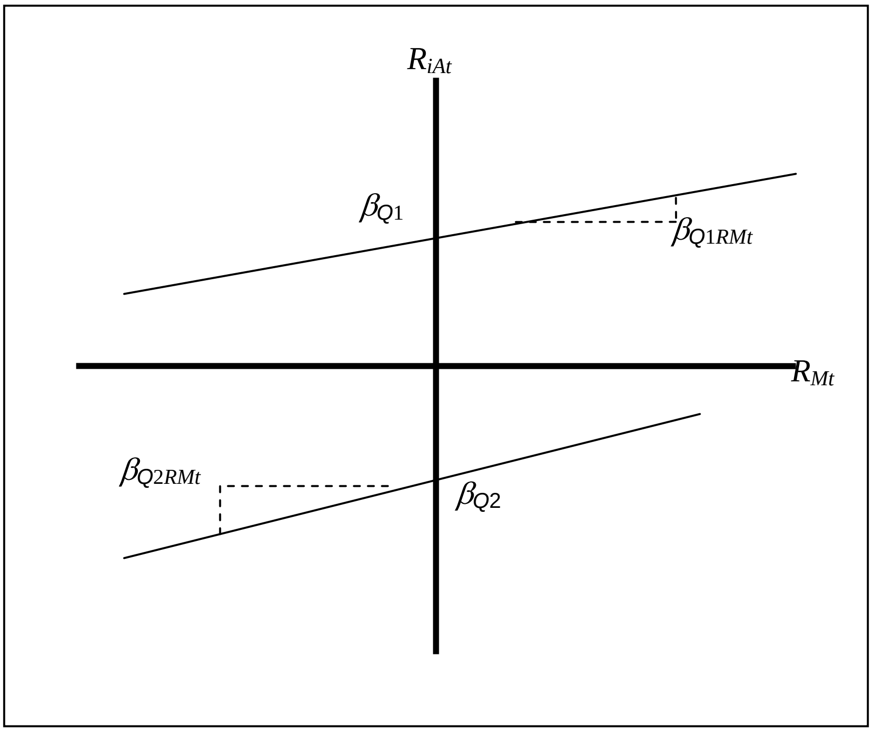
2.2.1 3-state (by Company) Model

The three states of the 3-state model partitioned by company depend on the sign of R_{iAt}, which can be positive, negative or neither (zero). The model employs two dummy variables. These are Q_1, which takes on the value '1' when R_{iAt} is positive, and zero otherwise, and Q_2, which takes on the value '1' only when R_{iAt} is negative. $\beta_{Q1}Q_1$ and $\beta_{Q2}Q_2$ are both intercept terms.

$$R_{iAt} = \beta_{Q1}Q_1 + \beta_{Q2}Q_2 + \beta_{Q1RMt}Q_1R_{Mt} + \beta_{Q2RMt}Q_2R_{Mt} + \varepsilon_{jt} \tag{7}$$

The zero state is dropped out of the dummy regression procedure in Equation 7 on the ground that a zero company return is deemed to be both its own expected return and abnormal return. The slopes of the positive and negative company returns, as shown in Figure 1, are independent of each other.

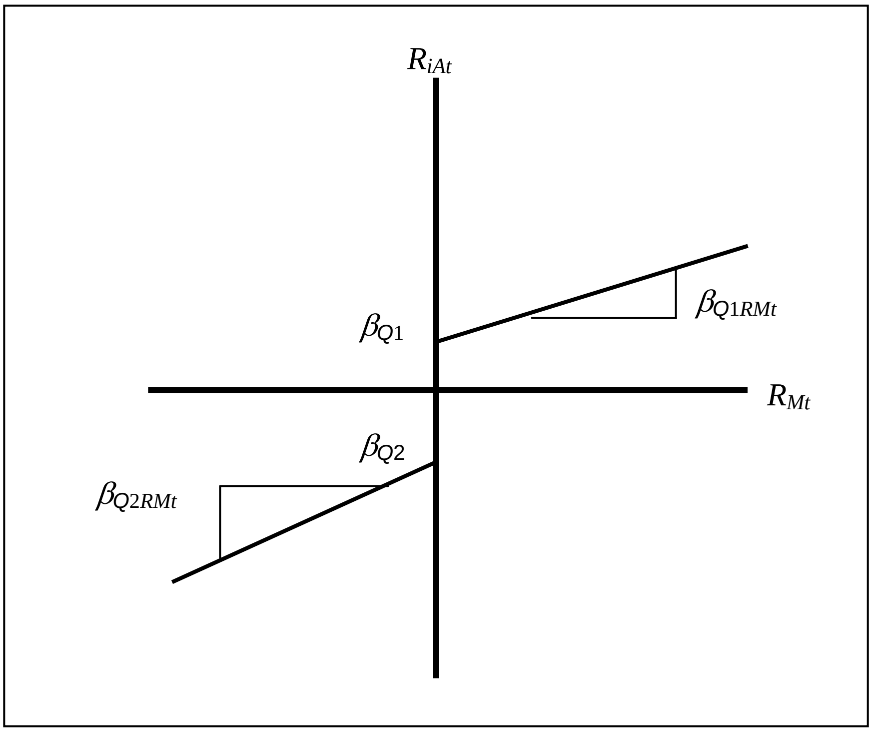
Figure 1: 3-state (by Company) Model



2.2.2 3-state (by Market Index) Model

The second 3-state model also employs Equation (7). What is different is that it assigns returns to the positive and negative states depending on the sign of the associated return on the market. This makes for quite a different diagram. In Figure 2 there are two intercept terms, although it is extremely unlikely there will be a market return observation sited precisely on the vertical axis. Further, a negative market return does not necessarily imply that its matched company return is also going to be negative. The model's fitted line relating to the negative region may be either below, straddling or above the horizontal axis. However, it will most definitely not pass through the origin.

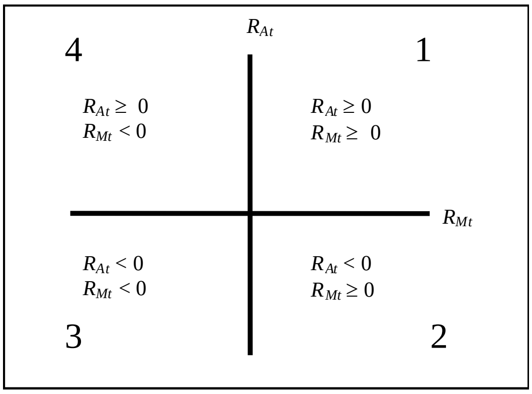
Figure 2: 3-state (by Market Index) Model



2.2.3 4-state Model

Norsworthy et al (2004) develop a 4-state model by using both the horizontal and vertical axes to partition time-series data into four quadrants by the combination of signs of the company return and matched market return. With this additional information coding, the daily return on company 'A' becomes R_{iAt} where, in the t^{th} instance, the return falls into quadrant *i*. The four quadrants are labelled in Figure 3.

Figure 3: Classification of Quadrants used by the 4-state Model.



Investors do not know in advance where an observation (R_{iAt}, R_{Mt}) will be recorded relative to the axes; but they *will* have a pretty good idea of the nature of each particular quadrant. Jokung and Meyfredi (2003, p.3) note the two quadrants in which R_{Mt} is positive are indicative of a rising market, while the other two with a negative R_{Mt} show the market falling (at least over the period of day t). Therefore, investors with an eye on price movements will have a sense of whether their intended transaction is likely to be moving with (same signs) the market or (contrary signs) against it. In statistical terms, this is impounded in a much higher R^2 in the regression procedure calculating the expected returns.

This regression is run with dummy variables so that, for each of the four quadrants, a unique intercept term (α_{iA}) and also a unique beta β_{iA} are calculated.

$$R_{iAt} = \sum_{i=1}^{4} \alpha_{iA} + \sum_{i=1}^{4} \beta_{iA} R_{Mt} + \varepsilon_i \quad (8)$$

This equation expands to Equation 9 where the dummies (Q_i) take on the value '1' for the i^{th} quadrant, otherwise zero, and $\beta_{iA} Q_i$ (with four states) replaces α_{iA}[4]:

$$\begin{aligned} R_{iAt} = {} & \beta_{1A} Q_1 + \beta_{2A} Q_2 + \beta_{3A} Q_3 + \beta_{4A} Q_4 \\ & + \beta_{5A} Q_1 R_{Mt} + \beta_{6A} Q_2 R_{Mt} + \beta_{7A} Q_3 R_{Mt} + \beta_{8A} Q_4 R_{Mt} + \varepsilon_t \end{aligned} \quad (9)$$

For each day of an event study's test period, an abnormal return would be generated by subtracting the right-hand side (excluding the error term) of Equation 9 from the day's observed return – just as for the market model. However, there is one extra requirement. For this and all other state asset pricing models, the quadrant membership of the observed return needs to be calculated so that the dummy variables can be valued at 1 or zero appropriately in the test period expected return forecast.

[4] Note that the subscript 'i' is not carried through for the independent variable, R_{Mt} in either this or the immediately preceding equation. This is because the observation has already been assigned with respect to the company share return in conjunction with it per the decision table embedded in Figure 3.

3 Data and Preliminary Analysis

The initial data set consists of 948 events between April 1990 and December 1999 where companies listed on the New Zealand Stock Exchange announced dividend-and-earnings news. Adjusted closing-price series, the value-weighted NZX Gross All Companies Index, announcement dates, and also earnings per share and dividend-per-share information were all provided by the Investment Research Group Ltd, a New Zealand financial data archive. Each announcement event had to have daily price data available from at least 111 days before till at least 10 days after the day of the event. These data sets comprise the population of 1990s New Zealand observations of this sort of news event with test periods free of extraneous announcement phenomena. But an exploration of dividends and earnings disclosures is not the focus in this paper.

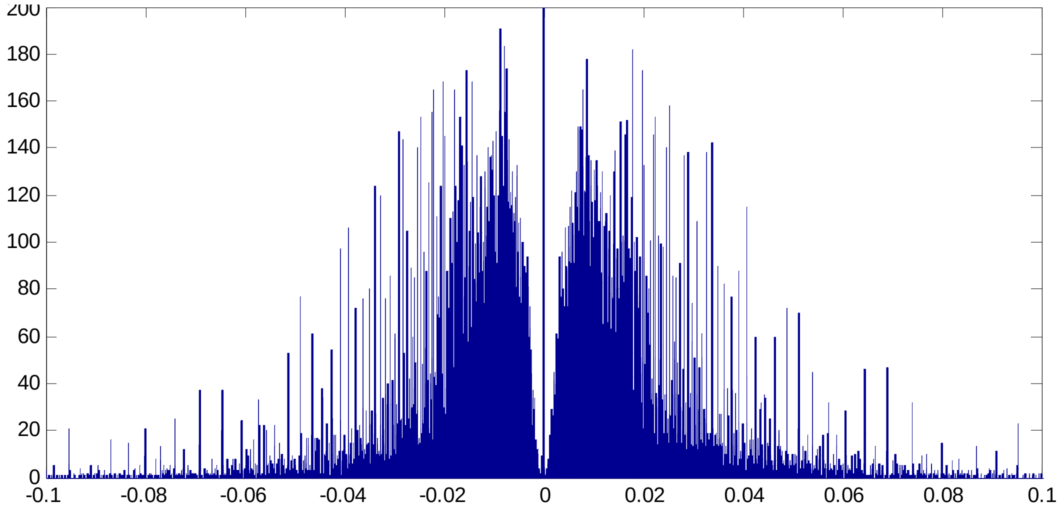
However, the trading frequency characteristics of both the estimation periods and the test periods of the 948 data sets are both interesting and salient. While 211 have estimation periods in which trading occurred every day, the sample tails down to five instances in which the estimation period furnished less than 10 actual days of trading. With respect to the day of the event, t_0, 847 recorded trades and 101 (or just under 11%) did not. These 101 instances of failure to trade on day zero amount to 37.13% of 272 zero-value returns that were recorded on the day of the announcement event.

However, if the event window is redefined as a three-day span, then the number of traders rises to 910 (96%) with the remaining 38 being non-traded over the three-day span. However the 910 traders contain 53 instances of zero price change in the span. At the extreme end of the sample's spectrum were four company/event data sets with no trading at all in the 21-day test period (days t_{-10} to t_{+10}).

With respect to the overall incidence of zero-value returns, it is recognised that they can be the result of either an absence of trading activity or from liquidity trading that fails to shift the price. Failure to trade can be diagnosed from observing that the daily trading volume is also zero. The percentage of zero-value returns that are due to no trading (from all 121 available days from the estimation period and the test period combined) is 59.62%.

Frequent absence of trades over stretches of time inside the Market Model estimation period is strongly likely to give rise to daily returns that are not normally distributed.

Figure 4: Distribution of Log Returns with Both Axes Truncated



The default method for handling these absences of trading is to assign each one of them a zero-value return; but the prevalence of zero-value returns drives the behaviour of the OLS regressions used in Market Model estimation. Figure 4 shows the distribution of returns with the horizontal axis (return value) restricted to –0.1 and +0.1 and the vertical axis (count) cut off at 200. This is a very artificial view because the free-standing spike at zero has a count of 41,655.

Of interest also is the absence of values that are close to zero — which causes the zero-return spike to rise from the bottom of a deep valley. This implies that the returns change in discrete steps relating to the price changes in dollars and cents on a share; and that there is a minimum step-size.

Initially in the study, the 948 data sets are assessed with respect to analysis of the performance of the market model. But then the number is reduced to 794 in the processing of the main body of results. This is done in order to provide absolutely identical input data in the assessment of all of the competing models.

The use of 794 data sets was originally determined by the inclusion of two versions of the 4-state model. The 4-state model still in the paper is capable of processing 801 data sets, while the 2-state model handles 938 of the data sets. In the middle ground between these, the 3-state (by company) model is able to process 900, and the 3-state (by market) can be used on 906 data sets. The usable data is lower than the 801 by seven data sets as a result of the processing requirements of the alternative 4-state model that was dropped.[5] It turns out that four of the dropped data sets are furnishers of trades on every day of the 100-day trading period. This drops that subset from 211 data sets to 207.

4 Results

4.1 The Market Model

In this subsection, the market model is assessed in terms of the normality of its residuals, and then in terms of the mean characteristics of its OLS regression statistics. In ensuing subsections, the market model's performance is compared with that of the family of four state asset pricing models.

Table 1: Normality Tests on Market Model Estimation Period Residuals.

Days Traded		Incidence of Normality					
Band	Count	Jarque-Bera Test		Lilliefors Test		Kurtosis	Skewness
Panel A: Full sample							
0-100	948	22%	(207)	17%	(163)	8.847026	0.211914
Panel B: Partitioning by 20-day bands							
81-100	648	31%	(204)	25%	(162)	6.133884	0.239446
61-80	138	2%	(3)	1%	(1)	8.660193	0.416425
41-60	77	0%	(0)	0%	(0)	13.9152	-0.18276
21-40	60	0%	(0)	0%	(0)	20.72871	0.36279
1 -20	25	0%	(0)	0%	(0)	36.07696	-0.77714
Panel C: More than 80 days traded							
91-100	519	34%	(179)	30%	(155)	5.7831	0.2516
81-90	129	19%	(25)	5%	(7)	7.5450	0.1904
Panel D: Trading every day of the 100-day estimation period							
100	211	42%	(89)	47%	(100)	5.5613	0.2644

948 sets of estimation period residuals generated by the market model are partitioned by thinness of trading. The estimation period contained 100 days of company returns and returns on the value-weighted NZX All Companies Index. Counts and percentage results are provided for two tests for normality — the Jarque-bera Test and the Lilliefors Test, along with averaged kurtosis and skewness statistics. Jarque-bera and Lilliefors tests detect departures from normality. The table furnishes the incidence of normality directly by reporting the incidence of failure to detect non-normality at a 5% level of error.
Panel A contains results for the full sample. Panel B partitions the sample into 20-day bands. Panel C re-partitions the top band into two 10-day bands; while Panel D furnishes results for estimation sets where there was trading on all 100 available days.
All data sets are from firms listed on the NZX that happened to make joint dividend and earnings announcements falling between April 1990 and the end of December 1999 and whose date of trading commencement on the Exchange enabled them to furnish a 100-day estimation period.

[5] With the dropping of the alternative 4-state model, which employed rotation as described and tested in Norsworthy et al (2004), the feasible uniform set of data sets applicable to all this paper's models rises to 801. Although it is intended that this will be incorporated into the next draft of this paper, it is unlikely that the extra seven sets of observations will make any material difference to the results tabled in this current draft.

Given that returns are not generally found to be normally distributed, thinness exacerbates the problem. When the 100-day estimation sets are separated, in Table 1, into bands by the number of days on which trading actually occurs, there is a gradation in the incidence of non-normality of market model residuals with respect to two tests for non-normality — the Jarque-Bera and Lilliefors tests. Table 1 shows that where estimation sets contain at least 81 days of actual trading, the incidence of normally distributed residuals was 31%. However, as the number of actual trading days approached the full 100, non-normality did indeed trend downward. This is visible towards the bottom of the table where the top 20% band was split into two narrower bands, and then the 100% group recorded in isolation.

There is another noteworthy feature in Table 1. As more and more of the 100 available days become days of actual trading, the mean kurtosis monotonically reduces from 38.88 to a minimum (for 100-day traders) of 5.56. While this is still far from the kurtosis value for a normal distribution, it is a big drop. There is no similar trend in the skewness figures.

Table 2: Unmodified Market Model Results.

	Mean	Min	Max	St Dev
F	15.1694	0.0000	490.8003	34.0293
Sig. F	0.2109	0.0000	0.9983	0.2837
R^2	0.0968	0.0000	0.8336	0.1385
Adj R^2	0.0875	-0.0102	0.8319	0.1400
Variance	0.0005	0.0000	0.0252	0.0011
Durbin-Watson	1.9900	0.8880	2.9990	0.2530
β_{A0}	0.0001	-0.0101	0.0095	0.0020
t-Stat	0.1008	-3.0969	3.3023	1.0121
p-Value	0.4944	0.0013	0.9991	0.2919
β_{A1}	0.4720	-0.8982	2.7031	0.4441
t-Stat	2.6507	-2.7792	22.1540	2.8552
p-Value	0.2109	0.0000	0.9983	0.2837
N		948		

This table contains the summarised market model regression results of all 948 100-day estimation period data sets. The inputs were NZX-listed company log returns and matched market index log returns series from between early 1990 and December 1999.

Table 2 shows the behaviours of market model parameters. On average, no parameter is significant, although the mean *F*-stat does register a healthy 15.17. The mean R^2 is a relatively lowly 9.68%. This indicates that market model-generated returns do not embody very much of the information about the market available to investors – that is, relative to the degree of capture provided by the state asset models in the next section. Table 3 furnishes the actual count and percentage incidence of market model parameters associated with a Type I error of 5 percent or less. While just over half of the slope coefficients β_{A1} have an acceptably small error, only 4.85 percent of the 948 intercept terms do likewise.

Table 3: Incidence of significant Market Model Parameters

Coefficient	N ($\alpha \leq 0.05$)	% ($\alpha \leq 0.05$)
β_{A0}	46	4.85%
β_{A1}	483	50.95%

With respect to the market model, this table provides the count (out of 948) and percentage of data sets furnishing betas associated with a Type I error of less than 5% ($\alpha \leq 0.05$).

4.2 The Regression Output of State Asset Models

So how well do the various state asset models perform, relative to the market model benchmark? We first look at the mean values of the models' parameters. The two panels of Table 4 deal with the regression results for the 2-state model, the two 3-state models and the 4-state model. Although the market model could process all 948 data sets, the number that all models could process in common was 794, as explained earlier. Table 5 then furnishes the rates at which parameters are found to have acceptably low rates of a Type I error. The benchmark for this is the 5% level. These two tables include market model information from above for convenience.

Consider the R^2 information in the third row of Panel A in Table 4. The market model furnishes the lowest R^2 (0.1078) while those of the 2-state model and the 3-state model partitioned by market index are slightly higher (0.1409 and 0.1724 respectively). However, the 3-state model partitioned by company returns has an R^2 (0.7004) that is almost seven times larger than that of the market model. This 3-state model also furnishes the highest mean F-statistic (87.7387), which is, on average, the most strongly significant F-stat as well.

Table 4: Summary Results for all Models

Panel A: Means and Standard Deviations of Model Regression Statistics and Intercept Coefficients										
	Market Model		2-state Model		3-state Model by Company		3-state Model by Market		4-state	
	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
No. of Data Sets	794		794		794		794		794	
F	16.2165	29.5506	21.4846	33.412	87.7387	49.1672	8.5811	11.6208	17.3968	9.1543
Sig. F	0.174	0.264	0.0819	0.1658	0	0.0009	0.086	0.1756	0.0003	0.0049
R^2	0.1078	0.1395	0.1409	0.1476	0.7004	0.0975	0.1724	0.1455	0.5417	0.1056
Adj. R^2	0.0987	0.1409	0.1322	0.1491	0.691	0.1005	0.1465	0.1501	0.5068	0.1137
Variance	0.0005	0.0012	0.0005	0.0012	0.0002	0.0011	0.0004	0.0012	0.0003	0.0011
β_{Q1}^{*}	0	0.002	0	0.0036	0.0205	0.0106	0.0003	0.008	0.0077	0.0054
t-Stat	0.0408	0.9842	0.0476	1.2804	9.7403	3.014	0.0941	1.3492	2.2504	1.2621
p-Value	0.4998	0.2879	0.4183	0.303	0.0003	0.0051	0.4099	0.2993	0.1281	0.2091
β_{Q2}^{**}					-0.0193	0.0098	0.0005	0.0101	-0.0186	0.0141
t-Stat					-9.6178	2.9402	0.0841	1.3783	-2.8471	1.2421
p-Value					0.0004	0.0061	0.4134	0.3088	0.0625	0.138
β_{Q3}									-0.0179	0.0127
t-Stat									-3.2321	1.3877
p-Value									0.0433	0.1181
β_{Q4}									0.0081	0.0056
t-Stat									1.9253	0.9399
p-Value									0.1474	0.1984

Panel B: Means and Standard Deviations of Model Slope Coefficients										
	Market Model		2-state Model		3-state Model by Company		3-state Model by Market		Unrotated 4-state	
	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev	Mean	St Dev
β_{Q1RMt}*	0.5305	0.4313	0.7353	0.6052	0.2784	0.5063	0.6846	1.1967	0.4127	0.6048
t-Stat	2.9486	2.7445	3.4477	2.9565	1.5185	2.2021	1.5616	1.9982	1.4389	2.0252
p-Value	0.1741	0.264	0.1278	0.2348	0.2654	0.3006	0.2477	0.2957	0.3296	0.3213
β_{Q2RMt}**					0.2121	0.4994	0.7963	1.3469	-0.0035	1.619
t-Stat					1.3119	2.5697	1.7074	2.1014	-0.0168	0.9867
p-Value					0.3255	0.3183	0.2547	0.2954	0.5528	0.2891
β_{Q3RMt}									0.3682	1.2273
t-Stat									1.075	2.1985
p-Value									0.4062	0.3306
β_{Q4RMt}									0.1476	0.6442
t-Stat									0.2425	0.8792
p-Value									0.5391	0.2769
Zero Region?	**NO**		**NO**		**YES**		**YES**		**NO**	

The means and standard deviations for all coefficients generated on all five models are lined up in this table. The input data is 948 100-day estimation period data sets of NZX-listed company log returns and matched market index log returns (from between early 1990 and December 1999). The market model processes all of these. However, the requirement that each state of the state models must contain a minimum of 6 observations for successful processing reduces the number of eligible data sets as the number of states grows. The number of datasets able to run all five models is only 794. However, the 3-state model (by company) is able to use 900 while the 4-state model is able to use 801. The four states of the 4-state model are explained in Figure 1. The 3-state model (by market) partitions company returns by whether the matched market return is positive or negative and quarrantines zero-value company returns in a zero region. The 3-state model (by company) partitions company returns by whether it is positive or negative and quarrantines zero-value company returns in a zero region.

* The intercept (Panel A) and slope (Panel B) for first quadrant observations in the 4-state model but the sole intercept (slope in Panel B) for the market model ($b_{Q1} = b_{A0}$, $\beta_{Q1RMt} = \beta_{A1}$) and the intercept when market returns are positive in the 3-state model (by market), and the intercept when company returns are positive in the 3-state model (by company).

** the intercept (Panel A) and slope (Panel B) for second quadrant observations in the 4-state model; and the intercept or slope (depending on panel) when market returns are negative in the 3-state model (by market), or when company returns are negative in the 3-state model (by company).

This suggests that segregating company returns by sign might make this model a better compiler of expected returns. In addition, by segregating zero-value returns into the third 'state' and leaving them out of the expected return calculation, the 3-state model avoids the market model's problem of setting up understated parameters (as pointed out by Scholes and Williams (1977) among others) that get used in forecasting spurious levels of abnormal return in an event study's event window.

Interestingly, only one model consistently furnishes intercept coefficients that, on average, yield p-values indicative of a Type I error of less than the benchmark five percent. The p-values of both intercept coefficients for the 3-state (by company) model (0.0003 and 0.0004 respectively) are significant at less than the 1% level of error. However, the third state of the 4-state model does produce an intercept coefficient out of its four that scrapes in at the 4% level of error. No other intercept coefficient of any other model meets the benchmark. The nature of the apparently well-performing 3-state (by company) model is explored further with respect to its full 900 usable data sets in Appendix.

However, the explanatory power of the individual slope coefficients in Panel B is uniformly low. Neither the market model nor any other model manages to achieve significance within any acceptable benchmark level for a Type 1 error. In this instance, the 2-state model has the least unacceptable Type I error (12.78%), with the market model coming in second with a 17.41% error. All of the slope coefficients for the remaining state asset pricing models have p-values that range from just under 25% to 55%.

The actual incidence of acceptable Type I errors for each of the models is reported in Table 5. Of strong interest here is the extremely high incidence of acceptable Type I errors associated with the intercept terms of the3-state (by company) model (99.75%). The only other instances of high incidence rates are furnished by the 4-state model intercepts. In the case of the 4-state model, the high rate may possibly have occurred because two of the four states have had zero-value company returns segregated out of them. In the case of the 3-state (by company) model the reason is clearly because the zero-value company returns that have dampened down the fitted line of the market model (in accordance with Scholes and Williams' (1977)) do not dampen down the fitted lines for positive rturns and negative returns. By contrast, the relatively low incidence of acceptable Type I errors associated with the 2-state model (13.22%)

Table 5: Incidence of Coefficients with Type I Errors of 5% or less

Coefficents by Type	Market Model		2-state Model		3-state Model by Company		3-state Model by Market		4-state	
	N	%	N	%	N	%	N	%	N	%
Intercept										
β_{Q1}	33	4.16%	105	13.22%	792	99.75%	110	13.85%	462	58.19%
β_{Q2}					792	99.75%	118	14.86%	604	76.07%
β_{Q3}									654	82.37%
β_{Q4}									366	46.10%
Slope										
β_{Q1RMt}	460	57.93%	537	67.63%	298	37.53%	327	41.18%	242	30.48%
β_{Q2RMt}					233	29.35%	312	39.29%	40	5.04%
β_{Q3RMt}									182	22.92%
β_{Q4RMt}									23	2.90%
No. of Data Sets	794		794		794		794		794	

This table provides, for each model, the incidence of parameters that furnsih a Type I error of no greater than 5%. The row headings are the quartile designations for the 4-state model. Because the market model has only one intercept and one slope coefficient, it is slotted for convenience, into the first quadrant rows. Similarly, the various state asset pricing models have intercept and slope coefficients slotted into the first two quadrant rows. N is the number of data sets (out of 794) that furnish a Type I error within the 5% benchmark and this is accompanied by its incidence in percentage terms.

captures the effect of the removal of zero-value company returns while still permitting negative returns to dampen down positive returns. The fact that the 3-state (by market) model furnishes a low incidence of acceptable errors relative to the 3-state (by company) model is indicative of there being both positive and negative company returns in both this model's positive and negative states – which have a dampening effect within each of the states.

With respect to the incidence of Type I errors in slope coefficients, the market model's single slope coefficient (57.93%) handily outperforms all coefficients furnished by the 3-state and 4-state models. However, the superior incidence of an acceptable Type I error in the single slope coefficient of the 2-state model (67.63%) is evidence of the effect of removing the influence of zero-value returns keeping all else constant.

4.3 Trading Thinness and Normality Tests

Table 6 presents normality test results on the residuals for all the models discussed. The market model results furnished in Table 1 are repeated in the two columns labeled MM. The patterns furnished by the Jarque-Bera and Lilliefors Tests are similar, with the Lilliefors figures tending to be higher for the 3-state asset pricing models, while slightly more conservative for the market model and 2-state asset pricing model. Therefore the Jarque-Bera results will be discussed, with the Lilliefors findings mostly left in a corroborative role.

In Panel A, which where the two tests were performed on the full sample for each methodology, all of the state asset pricing models except the 4-state perform better than the market model. The 3-state (by company) shows a small improvement at 33.12% over the market model's 26.2%; but the 2-state and 3-state (by market) models both furnish just over a 72% incidence of normality. The Liliefors test, however doubles the market model's incidence of normality (29.56%) in the 3-state (by company) model's case (52.27%). In Panel C, where the top trading band is diced into two ten-day bands (i.e., between 81 and 90 days trading, and between 91 and 100 days) this pattern in each of them. Further, when the 207 full-traded data sets are considered in isolation, the 2- and 3-state (by market) models produce close to double the incidence of normality (67.15% and 68.60%) found in the market model's 42.03%, while the 3-state (by company) model dips to only 29.95% normality.

However, the Liliefors test rates the 3-state (by company) model at marginally more normally distributed than the market model by just under half a percentage point (53.62% versus 53.14%).

For every band in Panel B, the number of datasets with normally distributed residuals is furnished for each model along with the model's incidence of normality in that trading range. On 636 data sets in the most heavily-traded band (81-100 days), the market model achieves a 32.39% incidence. This drops to 28.62% for the 3-state (by company) model while remaining at 70.75 for the 2-state and 3-state (by market) models. The Liliefors test, again however, is kinder on the 3-state (by company) model with a finding of 49.21% normality versus the market model's 29.56%

With respect to all more thinly traded bands, the Jarque-Bera incidences of normality for the all of the state asset pricing models climb, while those for the market model drop towards (and then to) zero. In the 41-60 trading days band, for instance, there are 35 data sets but for the market model the incidence of normality is zero. By contrast, the 3-state (by company) model achieves an incidence of 65.71, while the 2-state and 3-state (by market) register just over 77% each. The 4-state model continues to perform more poorly, registering a 39% incidence of normality in this instance. And, although there are only 5 data sets in the 21-40 trading day bracket, the market model's zero incidence of normality is in stark contrast to the 3-state model's 60% incidence and an 80% incidence over all of the other three state asset pricing models

In Table 7, the pattern evident in Table 6 is repeated. The mean kurtosis figures for the state asset pricing models run on the full sample of data sets (Panel A) are all lower than the 6.7026 furnished by the market model; but the market model does perform better than the 3-state (by company) and 4-state models when there are 91 or more actual trading days (Panels C and D).[6] On the other hand, where there are 80 or less days of trading, all of the state asset pricing models furnish lower kurtosis figures than does the market model. However, the 2-state and 3-state (by market) models furnish uniformly lower mean kurtosis figures over all trading bands than do either the market model or the 3-state (by company) asset pricing model.

[6] A normal distribution has a kurtosis of 3.0000, while the skewness value will be zero.

Table 6: Normality Tests on Model Residuals

Band	JARQUE-BERA					LILLIEFORS				
	MM	2-State	3-State by Co	3-State by Mkt	4-State	MM	2-State	3-State by Co	3-State by Mkt	4-State
Panel A: Full sample										
0 - 100	26.20%	72.29%	33.12%	72.67%	22.92%	23.68%	69.77%	52.27%	70.15%	26.83%
(Obs)	208	574	263	577	182	188	554	415	557	213
Panel B: Partitioning by 20-day bands										
81 - 100	32.39%	70.75%	28.62%	70.75%	18.87%	29.56%	68.71%	49.21%	67.61%	24.53%
(Obs)	206	450	182	450	120	188	437	313	430	156
61 - 80	1.69%	78.81%	46.61%	81.36%	33.05%	0.00%	74.58%	62.71%	79.66%	33.90%
(Obs)	2	93	55	96	39	0	88	74	94	40
41 - 60	0%	77.14%	65.71%	77.14%	54.29%	0%	74.29%	68.57%	80.00%	40.00%
(Obs)	0	27	23	27	19	0	26	24	28	14
21- 40	0%	80.00%	60.00%	80.00%	80.00%	0%	60.00%	80.00%	100.00%	60.00%
(Obs)	0	4	3	4	4	0	3	4	5	3
0 - 20										
(Obs)										
Panel C: More than 80 days traded										
91 - 100	35.42%	70.65%	27.59%	70.84%	18.59%	34.44%	70.45%	51.08%	68.30%	25.44%
(Obs)	175	355	135	356	89	170	354	255	343	124
81 - 90	20.00%	71.20%	32.80%	70.40%	20.00%	9.60%	61.60%	41.60%	64.80%	20.80%
(Obs)	25	89	41	88	25	12	77	52	81	26
Panel D: Trading every day of the 100-day estimation period										
100	42.03%	67.15%	29.95%	68.60%	21.26%	53.14%	74.40%	53.62%	65.70%	33.82%
(Obs)	87	139	62	142	44	110	154	111	136	70

The incidence of normality in the event-study estimation-period residuals calculated from four versions of state asset pricing models are tabulated alongside that of the market model (MM) with respect to the Jarque-bera Test and the Lilliefors Test. The estimation period was set at 100 days in length and contained all available daily company returns and their associated returns on the value-weighted NZX All Companies Index. The Jarque-bera and Lilliefors Tests for normality are both set up to detect departures from normality. The table furnishes the incidence of normality directly by reporting the incidence of failure to detect non-normality at a 5% level of error. All data sets are from firms listed on the NZX that happened to make joint dividend and earnings announcements falling between April 1990 and the end of December 1999 and whose date of trading commencement on the Exchange enabled them to furnish a 100-day estimation period.

The percentages (and observations) in each column show the proportion (number) of observations in a band that are normal in that band for that model. The total number of datasets is 794. The total number processed at each level of trading thinness is shown in Table 7 for each band for each model.

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Table 7: Kurtosis and Skewness of Residuals

	Average Kurtosis					Average Skewness				
	MM	2-State	3-State by Co	3-State by Mkt	4-State	MM	2-State	3-State by Co	3-State by Mkt	4-State
Band										
Panel A: Full sample										
0 - 100	6.7026	4.0717	6.5816	4.0169	7.1649	0.2182	0.1528	0.2667	0.1447	0.4334
(Obs)	794	794	794	794	794	794	794	794	794	794
Panel B: Partitioning by 20-day bands										
81 - 100	6.1122	4.1924	6.8787	4.1433	7.4539	0.2286	0.1594	0.3057	0.1496	0.4408
(Obs)	636	636	636	636	636	636	636	636	636	636
61 - 80	8.0425	3.4760	5.3684	3.3837	6.0973	0.3254	0.1835	0.2694	0.1651	0.5072
(Obs)	118	118	118	118	118	118	118	118	118	118
41 - 60	11.9765	4.0423	5.5841	3.9423	5.8627	-0.4066	-0.1045	-0.3950	-0.0513	0.0230
(Obs)	35	35	35	35	35	35	35	35	35	35
21- 40	13.2684	2.9801	4.3973	3.4126	4.7111	0.7373	0.3947	-0.1267	0.4185	0.6291
(Obs)	5	5	5	5	5	5	5	5	5	5
0 - 20										
(Obs)										
Panel C: More than 80 days traded										
91 - 100	5.7664	4.1759	6.8260	4.1357	7.3939	0.2343	0.1624	0.3025	0.1522	0.4299
(Obs)	511	511	511	511	511	511	511	511	511	511
81 - 90	7.5256	4.2600	7.0942	4.1742	7.6992	0.2051	0.1472	0.3187	0.1390	0.4855
(Obs)	125	125	125	125	125	125	125	125	125	125
Panel D: Trading every day of the 100-day estimation period										
100	5.5355	4.3481	6.9479	4.2948	7.3973	0.2396	0.1857	0.3533	0.1654	0.4231
(Obs)	207	207	207	207	207	207	207	207	207	207

The average kurtosis and skewness in the event-study estimation-period residuals calculated from four versions of state asset pricing models are tabulated alongside that of the market model (MM). The estimation period was set at 100 days in length and contained all available daily company returns and their associated returns on the value-weighted NZX All Companies Index. All data sets are from firms listed on the NZX that happened to make joint dividend and earnings announcements falling between April 1990 and the end of December 1999 and whose date of trading commencement on the Exchange enabled them to furnish a 100-day estimation period.

The upper figure in each row is kurtosis (left half) and skewness (right half) for the given band of the model in that column. The total number of data sets (observations) is 794. The total number processed at each level of trading thinness for each band for each model is shown as the lower figure in each row.

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With respect to skewness, there is yet again a similar pattern. The 2-state and 3-state (by market) asset pricing models outperform the market model and the 3-state (by company) model over all trading ranges. The 3-state (by company) model only outperforms the market model, however, when the number of days traded drops below 81 days.

In summary, the residuals of the 2-state and 3-state (by market) models conform better to a normal distribution than those of the 3-state (by company) model. This stands in contrast with the superiority of the 3-state (by company) model in terms of the *F*-stat and R^2 values over those for these other models shown in Table 4 back in Section 4.2. The 4-state model turns out generally to be the worst performer of all of the state asset pricing models examined with respect to incidence of normally distributed residuals. Nevertheless, both of these models outperform the market model on the normality criterion when trading occurs on less than 81 days. It is clear then, that state asset pricing models perform better than the market model as the number of trading days in an event study expected-return estimation period tails off.

5 Conclusions and Limitations

The paper has focussed, in particular on the role of zero-value company returns. Although they may be instances of liquidity trading, rafts of zero-value returns over extended periods of time are strongly associated with no trading taking place, especially with respect to the smaller firms on stock exchanges everywhere. In this paper, 59.62% of the zero-value returns were instances of absence of trading.

This paper applied a 2-state, two 3-state and a 4-state asset pricing model to the task of compiling expected returns for use in an event study context. Of particular importance was the question – would they offer an improvement over the market model with respect to event study data sets from markets with thin trading? A portfolio of 794 New Zealand data sets associated with 1990s dividend-and-earnings announcement events provided the raw material. Further, the estimation period was restricted to a standard 100 days, which is a common length for studies of events that recur twice yearly.

The best state asset pricing model for event study purposes turned out to be the 3-state (by company) model. The adoption of three states — negative, positive and zero — caused three things to happen. First, the mean *F*-statistic and adjusted R^2 values increased over both the market model and the 4-state model. Second, the number of usable data sets increased markedly, allowing 94 percent (rounding down) of the company/events to be processed, which made the loss in available data quite small. The third was the effect of segregation of zero-value returns from both 3-state models' regressions. This was doubly advantageous. With these segregated out, they could no longer furnish spurious abnormal returns (potentially of various sizes and statistical significance) and instead, the associated abnormal return was free to be assigned a zero value for event-related hypothesis testing. In addition, the 3-state (by company) model's residuals (by Liliefors test evidence although not by Jarque-bera Test evidence) tended to be normally distributed more often and to a greater degree than those of the market model.

The paper has several clear limitations. The first is that there is a clear benefit in separating out the two types of zero-value returns (liquidity-trading-based and absence-of-trading-based). This has only been done for the 3-state (by company) model in Appendix 1. Arguably it is perfectly reasonable to retain liquidity-trading-based zero-value returns without segregation. However, a strong impact is observable in the table in Appendix 1 when non-trading zero-value returns alone are segregated.

The second issue that limitation is that it does not continue on into an exploration of the distributions of abnormal returns, or investigate what really did happen with respect to the joint dividend and earnings phenomenon underlying this particular collection of data sets . These were left out on the ground that dividend-and-earnings announcements come in basic six categories that can be briefly summarised as good-news rises in both earnings and dividends, bad news reductions in both, or mixed news contrary movements in each, or failure of a dividend to change coupled with a movement (up or down) in earnings. Any discussion of abnormal returns would, with little added benefit, have greatly increased the complexity of the discussion of each model. Any discussion of dividend or earnings signalling would have blown the paper's dimensions out even more so. But those aspects are irrelevant to the topic at hand. It would, however, be interesting to investigate them further on data with artificial levels of impact imposed to simulate a fictional event. Alternatively, one could run an equivalent study on, say, the data sets associated earnings-only announcements in a small market that is not New Zealand. Both look reasonable and exciting.

6 Bibliography

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Appendix 1

Although only 794 data sets were used in much of this study, it was possible to run the 3-state (by company) model on 900 data sets, which is a loss of only 48 data sets. Of these, 23 are from the set of the 25 firms trading 20 days or less ; and a further 22 belong to the range from 21 up to 40 trading days. The final 3 data sets belong to the 41 to 60 trading days bracket. Consequently 3-state model can run on datasets with fewer than 40 days of trading in a 100-day estimation period. The following table furnishes mean OLS regression results based on all 900 data sets. In addition, the definition of zero-value trades is varied to show what happens when the non-traded zero-value observations are separated out from zero-value observations from days when a a non-zero volume was recorded.

	3-state Model (by company) (zero state = all zero-value returns)		3-state Model (by company) (zero state = when no trades occurred)	
	Mean	St Dev	Mean	St Dev
No. of Data Sets	900		900	
F	88.0833	49.4516	40.3244	19.2703
Sig. F	0	0.0009	0.0001	0.0028
R^2	0.7001	0.0992	0.5338	0.1006
Adj. R^2	0.6908	0.1023	0.5192	0.1038
Variance	0.0002	0.001	0.0003	0.001
β_{Q1}^{*}	0.0221	0.0131	0.0106	0.0058
t-Stat	9.8019	3.0816	5.4729	1.2107
p-Value	0.0003	0.0048	0.0008	0.0094
β_{Q2}^{**}	-0.0207	0.0119	-0.0207	0.0119
t-Stat	-9.5527	3.0023	-7.4068	1.7362
p-Value	0.0004	0.0058	0.0005	0.0065
β_{Q1RMt}	0.2655	0.8105	0.3131	0.4528
t-Stat	1.3837	2.3042	1.6694	1.9333
p-Value	0.2625	0.299	0.2668	0.3044
β_{Q2RMt}	0.1964	0.7138	0.1965	0.7138
t-Stat	1.2105	2.6451	1.0124	2.1645
p-Value	0.3136	0.3175	0.3767	0.3236

In this table it is clear that the zero-value trades from liquidity trading do dampen down the mean regression output. The mean F-statistic for the procedure in which all zero-value returns were segregated is 88.0833 with a mean level of Type I error that is zero in at least the first four decimal places. This drops to less than half in the case where only non-trading zero-value returns are segregated (and liquidity-trading based zero-value returns are treated as if they positive in sign in the model. Nevertheless, this lower F-statistic (40.3244 with a mean p-value of 0.0001) is still higher than the market model manages in Table 2 (15.1694 with a mean p-value of 0.2109) and in Table 4 on the standardised meta-data set (16.2165 with a mean p-value of 0.174).

There is a similar drop in the mean R2 statistic when non-traded zero-value returns alone are segregated in the model (from 0.6908 to 0.5192); but again these R2s remain much higher than their equivalents for the market model in Table 2 (0.0968) and in Table 4 (0.1078).