ENDOGENEITY IN THE CAPM

Can OLS regression yield unbiased beta estimates when using the CAPM to estimate the cost of equity for a FTSE 100 firm?

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Abstract

This study uses data from the FTSE 100 to look at the extent to which the market return is an endogenous variable when using the CAPM and the problems that this causes in beta estimation. The ordinary least squares method of beta estimation is compared to an unbiased "instrumental variable" estimate and the bias is then tested for significance using a form of the Hausman test. A simple model for the bias is then formed, that takes into account changing market conditions through shifts in the covariance matrix. The implications of the endogeneity on beta stability, a major area of previous research, are then investigated. This paper finds that endogeneity is a significant problem in the FTSE 100 and that this may have serious implications for studies of beta stability. By using data from a market in which there is no lack of liquidity, the distinction between thin-trading bias and endogeneity bias is made clearer than it has been in previous literature.

[1] Main body-text only, excludes abstract, contents, tables, references, appendices and boxed text.

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I: INTRODUCTION

The Capital Asset Pricing Model (CAPM) is perhaps the most celebrated development in modern financial theory, with its findings concerning the risk-return trade-off being the foundations upon which four decades of financial theory has been based.

Fama and French (1992) found significant evidence that the CAPM had little predictive ability and that the securities market line (SML), relating beta to expected return, was flat. However, as emphasised by Black (1998), if the SML is flat, it becomes optimal to actively seek out the portfolio with the lowest possible beta. This leads us to the conclusion that even if the CAPM is dead, beta is still very much alive!

Whatever the relative merits of the CAPM, it is clear that accurate beta estimation is still a highly important area of research. Inaccurate beta estimates can lead investors to make sub-optimal asset allocation decisions or cause a firm to miscalculate their cost of equity and pursue unprofitable ventures.

The literature has focused on two major sources of error in beta estimation: thin-trading bias and beta stability over time. However, there is a third source of error in beta estimation that may be at least as significant as the two aforementioned sources and has not received nearly as much attention. This is the bias caused by the endogeneity of market returns.

The standard method of beta estimation is to use the ordinary least squares method to regress the excess returns to the asset on the excess returns to the market. However, in the CAPM "the market" should be representative of "all wealth", something that is almost impossible to measure.[3] Instead, market indices are used as a proxy. However, when looking at shares, this is often the index of which they are a constituent. The ordinary least squares regression then involves regressing the

[3] See (Roll 1976), commonly known as "The Roll Critique" for a full explanation of the inadequacy of using a market index as a proxy for "all individual assets".

returns to the share on the returns to the index, which are, to some extent, decided by the returns to the share! Clearly, this leads to the market returns being endogenous and beta estimates to be biased.

It has been shown by Woo, Cheung and Yan-Ki Ho (1994) that this represents a serious problem on emerging Asian stock markets (EASMs). Their discussion of the causes of this bias is vague in differentiating between endogeneity caused by thin-trading (a lack of liquidity) and the endogeneity caused by high index weightings. By adapting their methods and applying them to the shares of one of the most actively traded markets in the world, the FTSE 100, this paper provides a number of further insights into the problem of endogeneity bias in beta estimation as well as its effects on attempts to investigate beta stability over time.

II: THEORY & LITERATURE REVIEW

II.1: A BRIEF INTRODUCTION TO THE CAPM

The CAPM[4] is used to determine a theoretically appropriate required rate of return for an asset. It is the simplest version of a family of equations that express expected returns as a linear function of one or more macro-economic variables.

The CAPM model

$$E(r_a) - r_f = \beta_a [E(r_m) - r_f]$$

Where r_a is the return on the asset, r_f is the risk free rate of return, $E(.)$ denotes an expected value and β_a measures the sensitivity of the asset's returns to the returns of the market.

[4] The CAPM is often credited solely to Sharpe (1964). This ignores, however, the important contributions of Treynor (1961), Lintner (1965) and Mossin (1966). Sharpe was the only one of the four to receive a Nobel Prize for the contribution.

It assumes that the asset is to be added to an already well-diversified portfolio and therefore that only market risk should be rewarded with higher returns. Having made some broad assumptions, the CAPM goes on to reach some rather startling conclusions, namely that no possible portfolio of assets can *be expected* to outperform the market portfolio.

The equation has many practical uses for both firms and investors. Firms can use the CAPM as a tool for estimating their cost of equity, the amount that new shareholders would demand for taking on the risk of the firm. Investors can use the CAPM to determine the rate of return that they can expect from an asset. This will be particularly useful to them if they are adding the asset to an already well diversified portfolio as they will have no reason to be concerned with any kind of idiosyncratic risk, which is ignored by the CAPM.

II.2: BETA ESTIMATION

The most common method of beta estimation is to estimate the following equation using an ordinary least squares (OLS) regression:

Estimating beta using OLS

$$[r_{Jt} - r_{ft}] = \beta_J [r_{mt} - r_{ft}] + \varepsilon_J$$

Given that this method is to be used, there are still two important decisions to be made; the frequency of returns and the length of the time period to be used.

Daves, Ehrhardt and Kunkel (2000) emphasise the trade-off between the two issues; the use of more observations in the sample has the advantage of a reduced standard error, but if it involves a longer estimation period then it has the disadvantage of being more likely that beta has changed during the period. They use a large data-set to attempt to reach a definitive answer to the two issues.

With regard to the frequency of returns, they find that daily returns provide the optimal results for all liquid shares[5] due to meaningful reductions in standard error.

The caveat that the shares must be liquid for daily data to be optimal is in line with the findings of Cohen, Hawawini, Maier, Schwartz & Whitcomb (1983), who were the first to examine the effect of micro-structural issues on the appropriate return interval to use. They stress that the most important of these issues is the price adjustment delay and where this is significant, daily data can lead to biased results. They also suggest that where these delays are short or non-existent, shorter return intervals were appropriate.

With regard to the optimum estimation period, Daves, Ehrhardt and Kunkel (2000) go on to find that a period of three years is optimal, as it captures the majority of the reduction in the standard error of the estimate, as well as minimising the risk that beta has changed during the time period. This stands in contrast to much of the earlier literature[6], such as that contributed by Gonedes (1973) and Baesel (1974), that recommend periods of seven and nine years respectively.

II.3: SOURCES OF ERROR IN BETA ESTIMATION

There are three main sources of error in beta estimation. These are beta instability during the time period, thin trading bias caused by large differences in liquidity between shares and the bias caused by the endogeneity of market returns. When two or more of these are affecting estimates simultaneously, it can be hard to differentiate

[5] They recognise that the findings may not apply directly to less liquid shares for which micro-structural issues such as stale prices may exist.

[6] We cannot take this as strong evidence that there has been a dramatic change in the level of beta stability in the last few decades. This is because it could easily be a result of the switch to using daily data; when using weekly data, nine years provides a substantial advantage to three years but when using daily data, the advantage is smaller.

between them. This study is investigating the effects of only one of these sources of error, endogeneity, but it is crucial to understand the nature of the other two in order to properly separate them.

Endogeneity of market returns

This paper was largely influenced by the work of Woo, Cheung and Yan-Ki Ho (1994). They show that beta estimates in "small stock markets" are biased upwards due to the endogeneity of market returns. They do this by applying the Hausman (1978) specification test for endogeneity to the returns of stocks in two small stock markets, Hong Kong and Thailand.

They find that every share that they examined has significant evidence of endogeneity according to the Hausman test and that comparing the OLS estimates to unbiased IV estimates results in biases of up to 7%.

There are many reasons why the findings of Woo, Cheung and Yan-Ki Ho (1994) should be taken further. Most importantly, they fail to make a clear distinction between the effects of the endogeneity of market returns and the effects of thin trading bias. This is partly due to the nature of the South-East Asian exchanges, in which a few shares account for the majority of trading activity as well as having very high index weightings.

Their lack of separation between the two issues greatly detracts from their ability to reach a firm conclusion and to predict which other exchanges may suffer from similar problems. They state that the endogeneity issues that they have found to be problematic on the Asian exchanges would also affect any other exchange in which a few shares "become dominant in the market index", pointing to the Milan and Amsterdam exchanges as possible cases in Europe. It is clear from their statements that they have not been able to clearly define when a share is "dominant"; in this case it could mean that it dominates the trading activity (liquidity related bias) or that it has a particularly high index weighting (endogeneity bias).

In addition, their form of the Hausman test appears to be inadequate; it finds overly strong evidence of endogeneity, to the point where the test gives no indication of which shares may be experiencing a real problem with it.[7] If a more appropriate test could be applied, it may give a better indication of which shares experience problems with endogeneity.

Once the tasks of separating the sources of bias and finding more appropriate testing methods have been accomplished, there is potential to explore the implications of the endogeneity on other issues such as beta instability.

Beta Instability

It is well known that beta can change whenever there are fundamental changes to the characteristics of the firm or market, such as spin-offs, mergers and tax law. If these changes occur during an estimation period for beta, the estimate will be influenced by the value before the changes, which is no longer valid.

Blume (1971) was the first to investigate the issue of beta instability, paving the way for a wealth of literature to be developed on the topic. He suggested that mean reversion could be the cause of beta instability as well as a range of other possible reasons. Dejong and Collins (1985) reach several interesting conclusions about beta instability; they find that beta coefficients are more unstable during times of high interest rate volatility and also that firms with higher levels of leverage have more unstable beta estimates.

Many studies have attempted to identify systematic shifts in instability due to changing market conditions. Fabozzi and Francis (1977) found that beta estimates were wholly unaffected by the "alternating forces of bull and bear markets". They also went on to show in Fabozzi and Francis (1979) that mutual funds did not

[7] They use a test that is closer in its construction to the Hausman-Wu test. However, the appropriateness of their test is debatable as the Hausman-Wu test is useful only in models with multiple independent variables.

exhibit any differences in beta values for bull and bear markets.[8]

Their work has been followed by many subsequent studies by other academics, most of which have confirmed their findings. Those that have found contrasting results have generally done so outside of the world's most developed exchanges; Woodward and Anderson (2003), for example, find significant evidence of changing beta behaviour in bull and bear markets in Australian shares. Many of the studies that stand in contrast to the work of Fabozzi and Francis also use alternative definitions of bull and bear markets, which can be manipulated to give different results.

Another important point of consideration in beta stability is whether or not beta estimates exhibit mean reversion. Where present, mean reversion affects the way in which historical estimates must be translated into future forecasts. Blume (1975) finds strong evidence that "extreme" beta estimates (those that are furthest from one) have a high probability of being closer to one in the next period. He also paves the way for an explanation of this tendency, speculating that it is because firms with extreme beta estimates are likely to be undertaking projects with extreme characteristics which, once completed, cause the beta estimate to revert to a more normal level. Kolb and Rodriguez (1989), building on the work of Blume, find that although extreme betas tend to move towards one, betas that started near to one tended to move away from it, leaving the distribution approximately stationary.

The implication of mean reversion is that it is prudent to take a beta estimate as an upper or lower bound depending on whether it is above or below one, especially for extreme values.

[8] This is even more surprising, as a mutual fund has far more control over its beta value than a firm does and could easily reallocate its capital to low beta assets during market downturns.

Thin trading bias

Thin trading bias is caused by a lack of liquidity for an asset within a group of assets. If an asset is not traded very often, it will exhibit little or no price movement in some periods. This causes it to seemingly be uncorrelated with the market in these periods and therefore it will have a lower beta estimate than it otherwise would. As the average of all beta values in a market index has to be one, the downwards bias on the low liquidity shares also leads to an upwards bias on the more liquid shares. This issue is linked to many of the micro-structure problems discussed in Cohen, Hawawini, Maier, Schwartz and Whitcomb (1980) which come under the general category of market frictions.

Many studies have looked at the effects of this problem on various exchanges across the world. In perhaps the most cited of these studies (and certainly the most relevant to this paper), Dimson and Marsh (1983) look at the problem of thin trading in the UK stock market. They find that thin trading bias is a serious practical problem in the UK market and that this detracts from the reliability of any study of instability of beta estimates in the UK.

It may appear that this finding stands in contrast to assertions made in this paper that by using data from the UK FTSE 100, all thin trading bias is removed leaving only endogeneity bias. However, this is not the case, as Dimson and Marsh (1983) uses data from "all UK companies for which data was available", a very different proposition to using data only from the most actively traded shares.

III: EMPIRICAL STRATEGY

III.1: SELECTING THE DATA

In order to fully separate the issues of thin-trading bias and endogeneity bias, this study uses data from the UK FTSE 100 index of leading shares. This index is one of the most liquid in the world; every share in the index is actively traded in large volumes on every single business day. We can therefore attribute any bias in beta estimates to the endogeneity of market returns, rather than having the issue confused by the presence of thin-trading as occurred in Woo, Cheung and Yan-Ki Ho (1994).

Due to the nature of the index, there are very few micro-structural issues with using daily data. There are small bid-ask spreads, no stale prices and instantaneous information transmission. The benefits of using daily data, in terms of the reduction in standard error, can therefore easily justify using daily data in this case.

The time period used spans from July 2006 to January 2008. This has been selected due to the contrasting market conditions observed during this period and has been divided into two intervals to reflect this. The first, spanning from July 2006 to July 2007, saw a “bull market” in which the FTSE 100 gained 16.5%, the second, from July 2007 to January 2008, is the period in which we saw the effects of the so-called “credit crunch”, during which the FTSE 100 recorded an annualised loss of 30%.

III.2: CONSTRUCTING THE INDEX

There exist several problems with using the raw data for the returns to the FTSE 100. Firstly, the constituents of the index change on a fairly regular basis.[9] Secondly, in order to get accurate estimates, one needs to know the weightings of the shares in the same frequency as the observations. However, there are no daily weightings published for the FTSE 100.

[9] Only 83 of the constituents at the end of the observation period of this study had been present at the start.

Both of these problems can be solved by "constructing" a replica of the FTSE 100, using the observed data for returns and keeping the constituent firms constant.[10] This is done by taking the constituents from the end of the observation period, calculating appropriate weightings for them at the start of the observation period and then proceeding using the two formulae explained below.

Constructing the Index

$$I_{t+1} = I_t \,.\, (\Sigma_J (r_{J\,t+1}\, w_{J\,t})) \qquad w_{J\,t+1} = w_{J\,t}\,[(1 + r_{J\,t+1}) / (1 + r_{I\,t+1})]$$

Where I is the value of the index, r_J is the return to firm j, w_J is the weighting of firm j and r_I is the return to the index.

Two step procedure for each time period:

1. At the end of each day the index is calculated as the previous value multiplied by the sum of weighted returns to the constituents, using the previous day's weightings.

2. The new weighting is calculated as the previous day's weighting multiplied by the ratio of the return to that share divided by the return to the index.

III.3: DETERMINING THE SIZE OF THE BIAS

The size of the bias inherent in using an OLS estimate of beta is found by comparing it to an unbiased "instrumental variable" (IV) estimate[11]. In this case, there is a highly effective instrument available to us. Instead of having the return to the index as the

[10] This should have a high correlation to the real index as the firms that come and go have small weightings.

[11] An instrumental variable is used when it is suspected that one of the independent variables in a regression model is endogenous. The instrument that is chosen should be highly correlated to the suspected endogenous variable but uncorrelated to the error terms.

independent variable, we use:

The Instrumental Variable

$$r^*_{m\,j\,t} = \frac{\Sigma_k (r_k \, w_{k\,t-1})}{1 - w_{j\,t-1}} \qquad \text{for all k not equal to j.}$$

This variable is specific to each share; it is the weighted sum of the returns to all other shares, which is then increased to reflect the fact that it will be strictly less than the index returns.

This variable removes the effects of the particular share on the index returns. Essentially, it gives the market returns if the performance of the share in question were in line with that of all the other shares. This is precisely what a beta estimate should be based upon; the correlation of a share to a diverse group of other shares of which it is not a part. For this reason, this method can be considered to give a true, unbiased beta estimate.

Calculating the size of the bias

$$\textbf{BIAS} = ((\beta_{j\,OLS} / \beta_{j\,IV})\text{-}1).100\%$$

It is clear that the OLS beta estimate should always be greater than the IV estimate. We should therefore observe that:

$$\beta_{OLS} > \beta_{IV} \longrightarrow \textbf{BIAS} > 0$$

III.4: TESTING THE SIGNIFICANCE OF THE BIAS

The presence of endogeneity can be tested for using a form of the Hausman test. The test computes the significance of the bias by comparing the OLS estimates to the unbiased IV estimates.[12]

The Hausman Test

$$H = \frac{(\beta_{IV} - \beta_{OLS})^2}{se_{IV}^2 - se_{OLS}^2}$$

The test statistic, H, corresponds to the Chi- Square distribution with one degree of freedom.

Null hypothesis: Market returns are not endogenous.

Alternative hypothesis: Market returns are endogenous.

Critical value of H (5%): 3.841

It should also be noted that this form of the Hausman test is different to the one used by Woo, Cheung and Yan-Ki Ho (1994). As mentioned earlier, the appropriateness of their test is debatable as it seems to find overly strong evidence of endogeneity; this will also be investigated by employing their form of the test on the data.

III.5: MODELLING THE SIZE OF THE BIAS

Once the bias has been calculated for each share in both time periods, it will be useful to be able to determine the factors that affect it. This can be achieved using a simple regression of the cross-sectional data. There will be one hundred observations for each of the two time periods. This should be sufficient to gain a valuable insight into the factors that affect the size of the bias. For a list of variables please see Appendix 1.

[12] This test is only appropriate when $se_{IV} > se_{OLS}$. If this condition is not satisfied, it indicates that there are problems with the data and the test is not suitable.

III.6: THE EFFECT OF THE BIAS ON BETA STABILITY

We can test whether the beta coefficient of a particular share has changed between two sampling periods by using a Chow test for structural change. The test statistic refers to the F-distribution and is given by:

The Chow Test for Structural Change

$$F = \frac{(RSS_T - RSS_1 - RSS_2) / \text{DoF used}}{(RSS_1 + RSS_2) / \text{DoF remaining}}$$

Null hypothesis: Beta is constant over the two time periods

Alternative hypothesis: Beta has changed between the two periods

Critical value of F: 3.86

The numerator degrees of freedom will in this case be one and the denominator degrees of freedom will be 378.

By performing this test twice for each share, once using the OLS data and once using the IV data, we will be able to see whether the bias influences the results in any meaningful way. Percentage changes in beta estimates will also be compared for the OLS and IV methods in order to see if there is a systematic difference between them.

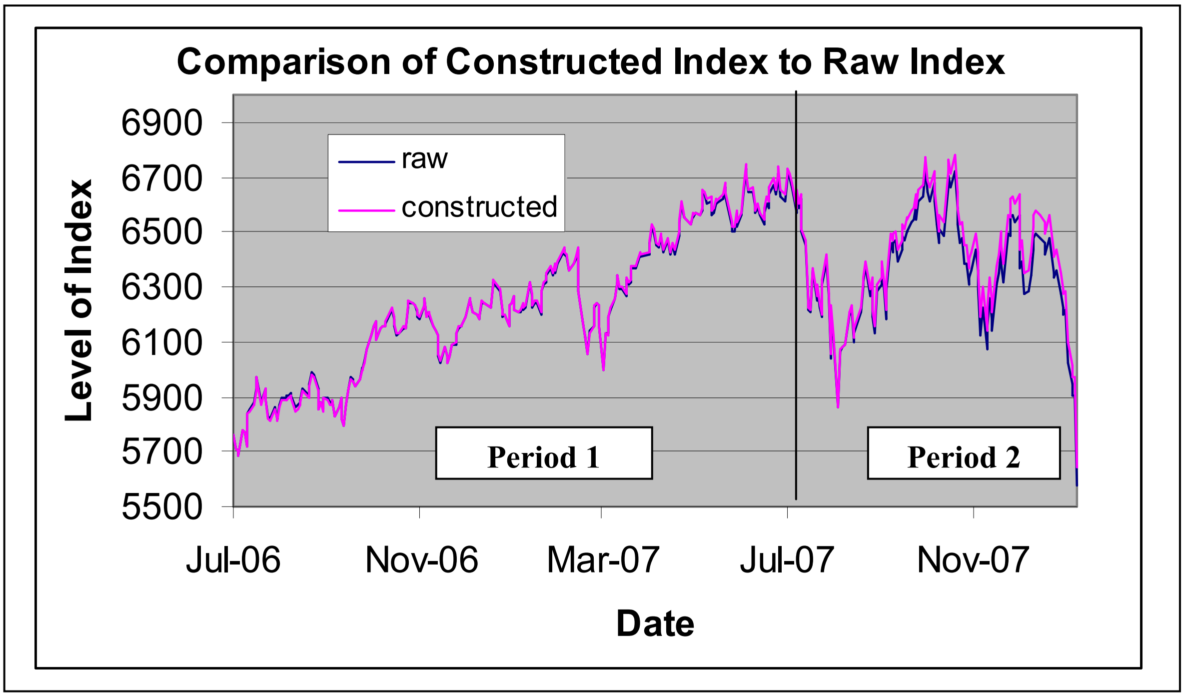
IV: DATA AND RESULTS

IV.1: PRELIMINARY DATA ANALYSIS

Analysing the constructed index and weightings

Figure 1 shows the constructed index and the raw index over the observation period. It is clear that the constructed index is a highly effective proxy for the raw data. They have a correlation coefficient of 0.996 for the absolute level of the index and 0.9995 for the daily returns. This shows that there is almost no loss in accuracy from using this method, but it has the advantages of keeping the constituent firms constant and giving the daily weightings.

Figure 1[13]**:** *Comparing the raw index to the constructed index*

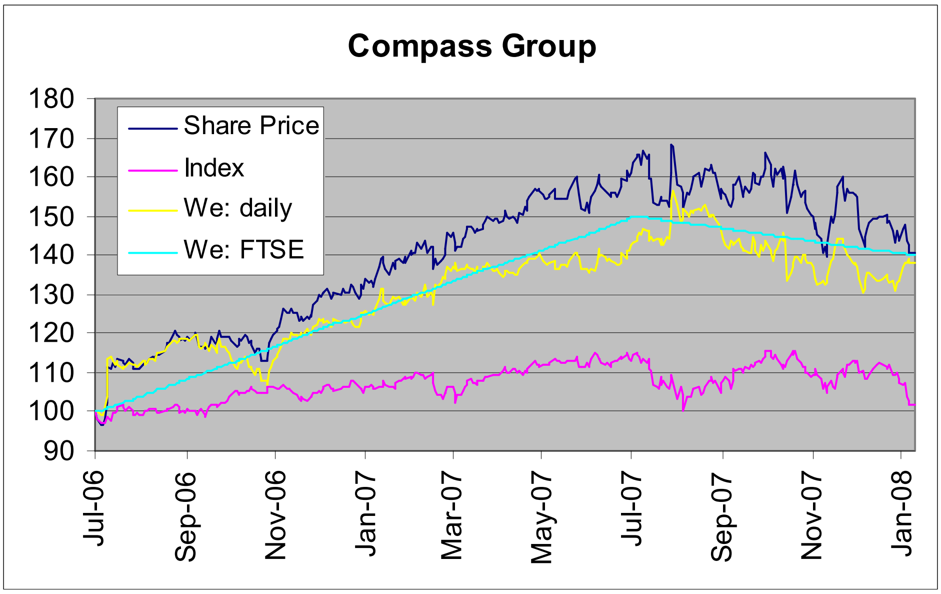


One of the main advantages of constructing the index is that it gives the daily weightings of the share, which are otherwise not available. Figure 2 demonstrates

[13]It is clear from inspection of figure 1 that the constructed index fits the raw data better during the first part of the observation period than it fits it in the second part. When using this technique to construct an index, the longer that it is used, the further the constructed index will depart from the raw index as the difference is the sum of all previous errors. This is not the case for the returns to the index, which should have a decreasing error. Since this study is only concerned with the returns, this is insignificant.

this advantage by plotting information relating to the weighting of one particular share, Compass Group.

Figure 2: *Demonstrating the advantage gained by using daily weightings*



Note: *All variables are standardised to have an initial value of 100. "We: daily" is the weighting as calculated from the constructed index. "We: FTSE" is the weighting implied by a smooth transition between the limited points supplied by FTSE on request.*

It is clear from figure 2 that the weighting does not change smoothly over time and that it deviates substantially from the weightings implied by a smooth transition between the three known points. Due to this, a significant advantage is gained from being able to calculate the daily weightings.

Contrasting the two periods: Summary statistics

From inspection of figure 1, it is clear that there are some very important differences between the two periods.

Period 1 represents a classic bull market. There is a clear upward trend throughout the period, with prices rising on 54% of the days. The mean daily return was 0.0573%.

However, although period two has been referred to by some commentators as being a "bear market", it is not clear that this is an appropriate label. Although the index does lose almost 17% of its value during the period, there is no obvious trend and it is likely that this loss is purely a result of the choice of dates.

Formalising the trends in each period

Estimating the following regression model for each time period gives a good indication of the market trend during the period:

$$\textbf{Index} = \alpha + \gamma \ \textbf{(time)} + \varepsilon$$

γ **significant and positive:** strong evidence for a bull market

γ **significant and negative:** strong evidence for a bear market

The results are given in figure 3

Figure 3: *Testing the slope coefficients of the index in each period*

	α			γ		
	coefficient	**t-stat**	**Probability**	**Coefficient**	**t-stat**	**probability**
Period 1	5798.6** (11.68)	496.2	0.000	3.459** (0.0813)	42.513	0.000
Period 2	6404.7** (36.32)	176.3	0.000	0.129 (0.474)	0.272	0.786

Note: *** indicates significance at 1% level. Standard errors in parentheses.*

As expected, the slope coefficient in period one is highly significant and positive; strong evidence for a bull market. However, in period 2, not only is the slope coefficient insignificant, it is not even negative! This is strong evidence that the label of "bear market" is not appropriate for period 2.

Whilst it may not be a standard transition from a bull to a bear market, there are important differences between the two periods. These are summarised in figure 4:

Figure 4: *Summary statistics showing the changes between the two periods*

	Period 1	Period 2	% change
Average Volatility	1.427	2.277	59.566
Index Volatility	0.701	1.463	108.702
Average Liquidity	0.758	0.824	8.707
Average Weighted Correlation	0.281	0.454	61.566
Average Return	0.057	-0.121	N/A
% days on which index rises	53.600	50.700	N/A

The main differences between period 1 and period 2 are the change in volatility and the shift in the covariance matrix between shares. This is shown in figure two by the fact that index volatility rose by 109% and the average weighted correlation rose by 62%. In fact, there is a direct link between these two variables; when the correlation between shares increases, the volatility of the index is also likely to increase as more shares will be moving in the same direction on any given day.

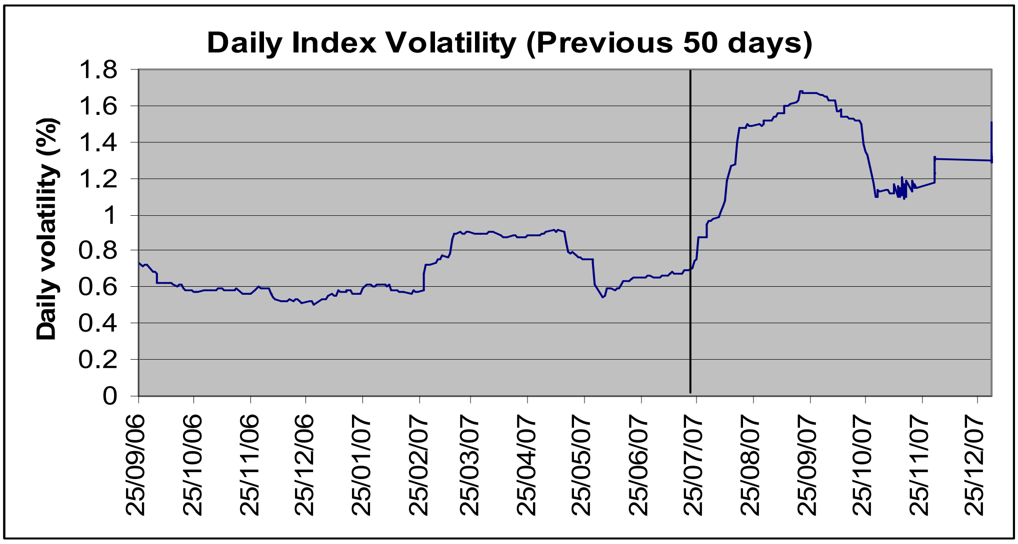
Finding the break in the sample[14]

Given that there is clear evidence of changing market conditions, it is important to determine the optimal position to separate the sample. This optimal position is where there exists a structural break in the correlation and volatility variables.[15]

Figure 5 shows the 50-day moving average of the daily index volatility. The vertical line marks the presence of a structural break at around the 20th of July 2007. This corresponds fairly well to the date that was chosen to divide the sample, the 13th of July 2007.

[14] This is not intended to be a rigorous investigation into the exact location of the break, only a brief justification that the sample is divided in a suitable position.
[15] Since these two variables are linked, we need only to determine the position of the break in one variable, with the most appropriate one being the volatility.

Figure 5: *A fifty day moving average of the daily volatility*



IV.2: SUMMARY STATISTICS

The IV estimates were in every case less than the OLS estimates, confirming that there exists a positive bias in the beta estimate of every share of the FTSE 100. The size of the bias ranges from 0.05% to over 22%. Figure 6 shows the ten shares with the highest percentage bias in each period, as well as their ranking in terms of weight for that period (1 = highest weight).

Figure 6: *The ten companies with the highest percentage bias in each period*

Period 1		
Company	**Bias (%)**	**Weighting Rank**
GlaxoSmithKline	22.75	5
Shell	15.55	1
BP	14.61	2
Vodafone	13.14	4
Astrazeneca	12.55	7
HSBC	10.56	3
Tesco	7.65	11
RBS	7.46	6
Rio Tinto	6.08	13
BT	5.65	17

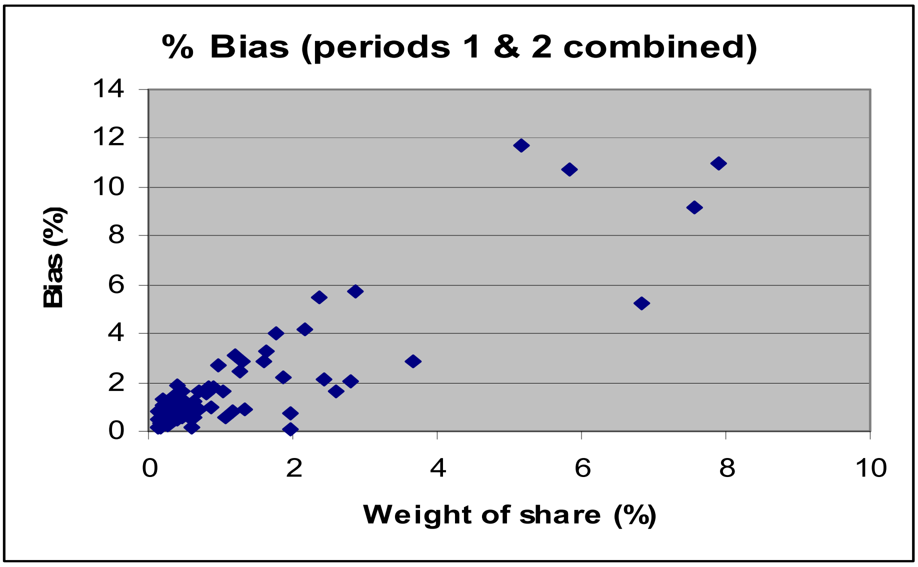
Period 2		
Company	**Bias (%)**	**Weighting Rank**
Vodafone	9.18	3
Shell	8.98	1
GlaxoSmithKline	6.86	5
BP	6.65	2
Rio Tinto	5.13	7
BG Group	3.83	14
HSBC	3.34	4
Tesco	2.98	12
Astrazeneca	2.78	11
British American Tobacco	2.61	17

This indicates that the weighting of the share plays a large role in determining the size of the bias; most of the ten highest biases are for shares with the ten highest weightings. It does show, however, that the weighting is not the only factor affecting the size of the bias; if it were then there would be no way of accounting for shares with lower weightings (eg BT in period 1 and British American Tobacco in period 2) having biases that place them in the top ten.

It is also clear that there exist differences between the biases in each period; the biases in period 1 were far higher than those observed in period 2. This was not merely a pattern observed in the largest shares; on average, across all shares, the bias in period 1 was 2.7 times that in period 2. Additionally, in period 1, 39% of shares had a bias of less than 1%, in period 2 this figure rose to 70%.

Figure 7 plots the size of the bias against the weighting of the share for the combination of the two periods. It is immediately apparent that there is a great deal of "bunching" of data at low levels of bias. This will be particularly important when using regression analysis to model the size of the bias, especially as it is more important to be able to model accurately the shares which have the *most* bias, not the least.

Figure 7: *Scatter graph of the percentage bias against the weighting of the share*



IV.3: HAUSMAN TEST RESULTS

The form of the Hausman test used is only appropriate when the standard error of the IV estimate is larger than the standard error of the OLS estimate. Of the three hundred observations (100 shares in period 1, 2 and combined) this condition was satisfied 98% of the time.

Figure 8: *The results of the Hausman test for endogeneity. The table shows the number of shares for which the null hypothesis is rejected as well as their ranking by weight.*

	Period 1 (Jul-06 – Jul-07)	**Period 2 (Jul-07 – Jan-08)**	**Combined (Jul-06 – Jan-08)**
Number with endogeneity	29	10	25
Rankings of shares with evidence of endogeneity. Ranked by weight in index. (1=highest weight)	1, 2, 3, 4, 5, 6, 7, 9, 11, 12, 13, 14, 16, 17, 18, 20, 22, 23, 26, 28, 30, 33, 34, 41, 47, 55, 73, 88, 97	1, 2, 3, 5, 11, 15, 17, 21, 22, 40	1, 2, 3, 4, 5, 7, 11, 12, 15, 16, 17, 18, 20, 21, 22, 26, 27, 29, 30, 31, 41, 42, 46, 54, 58

Note: *The rejections of the null hypothesis are at the 5% significance level.*

We can see that the Hausman test tends to find evidence of endogeneity in shares with higher weightings and that it supports the finding that endogeneity was far more prevalent in period 1 than in period 2; the null hypothesis is rejected for 29 shares in period 1 and only ten in period 2.

In period 1, it finds evidence of endogeneity in 80% of the shares with the twenty highest weightings, which indicates that the test is working somewhat efficiently. It is worth noting, however, that the test finds evidence of endogeneity in some shares with a relatively low weighting. For example, in period 1, the Hausman test finds endogeneity in four shares that are in the bottom half of the index in terms of weighting.[16]

[16] It is not clear whether this is due to the Hausman test being less than perfect or whether there is a genuine reason for the rejection of the null hypothesis for these shares.

On inspection of the test results for the two periods combined, we can say that if a share is in the top thirty in terms of weight, then there is a strong chance (around 63%) of the test finding evidence of endogeneity.[17]

It was noted in section III.4 that this form of the Hausman test is different from that used by Woo, Cheung and Yan-Ki Ho (1994). When their form of the test is applied to this dataset, it finds strong evidence of endogeneity in every share of the FTSE 100; clearly this is not a useful result.[18]

IV.4: MODELLING THE SIZE OF THE BIAS

It was expected that the two main factors affecting the size of the bias would be the weight (positive effect) and the weighted average correlation (negative effect).

When considering the optimal functional form of the regression, it became apparent that including these two variables linearly caused unfavourable results in the estimation. A preliminary regression was run using only these two main variables:

Preliminary regression with two main variables

$$\mathbf{BIAS}_i = \alpha + \gamma_1\,\mathbf{weight}_i + \gamma_2\,\mathbf{w.a.c}_i + \varepsilon$$

[17] This figure is a general estimate of the probability and could only be applied to other time periods with an allowance for a margin of error.
[18] One possible reason that this was not perceived as a problem in their study, is that they only looked at shares that they *suspected* had biased estimators. They therefore saw these test statistics as evidence in favour of their selection. However, when using data comprising an entire index, it soon becomes clear that their form of the test gives very little insight into the problem as by its very construction it will find evidence of endogeneity in any share.

Figure 9: *Results of preliminary regression with the two main variables*

	Period 1		Period 2		Combined	
Variable	**Coefficient**	**T-stat**	**Coefficient**	**T-stat**	**Coefficient**	**T-stat**
Intercept	5.136** (0.619)	8.297	3.236** (0.408)	7.927	3.936** (0.476)	8.274
Weight	2.167** (0.0919)	23.578	1.027** (0.0399)	25.736	1.357** (0.0543)	24.975
Average Correlation	-16.819** (2.157)	-7.794	-6.919** (0.898)	-7.701	-9.897** (1.254)	-7.893

Note: ** & ** indicate significance at the 5% and 1% levels respectively*

One aspect of the model that is slightly troubling is the intercept coefficient. At 3.936 (for the combined time periods), it stands at a level above 91% of the values.[19]

Testing has shown that the model performs better over multiple periods by combining the two variables into a single variable, which in this case is the weighting divided by the average weighted correlation. Using this variable, along with all other relevant variables, we arrive at the following model.

Main regression model for the size of the bias

$$\mathbf{BIAS}_i = \alpha + \gamma_1 (\mathbf{weight}_i / \mathbf{w.a.c}_i) + \gamma_2\, \mathbf{vol}_i + \gamma_3\, \mathbf{liq}_i + \gamma_4\, \mathbf{bank}_i + \gamma_5\, \mathbf{ind}_i + \gamma_6\, \mathbf{util}_i + \gamma_7\, \mathbf{cs}_i + \gamma_8\, \mathbf{ogbm}_i + \gamma_9\, \mathbf{fin}_i + \varepsilon$$

For an explanation of the variables see Appendix A

Figure 10 summarises the results

[19] Whilst intercepts can be considered to be of little interpretative importance, a regression model of this form, in which there are two main variables with opposite signs, has the unfortunate tendency to produce extreme coefficient estimates when using the ordinary least squares method and as such, it will rarely hold over more than one period.

Figure 10: *Regression results for the model introduced above over each time period*

	Period 1		Period 2		Combined	
Variable	**Coefficient**	**T-stat**	**Coefficient**	**T-stat**	**Coefficient**	**T-stat**
Intercept	-0.714 (0.479)	-1.49	-0.022 (0.250)	-0.09	-0.103 (0.338)	-0.31
Weight / WAC	0.682** (0.020)	34.04	0.503** (0.020)	24.86	0.567** (0.020)	28.55
Volatility	1.233** (0.313)	3.94	0.174 (0.109)	1.58	0.458* (0.186)	2.46
Liquidity	-0.129 (0.394)	-0.33	-0.067 (0.209)	-0.32	-0.242 (0.282)	-0.86
Bank	-1.980** (0.371)	-5.34	-1.179** (0.235)	-5.01	-1.784** (0.262)	-6.81
Industrial	-0.857* (0.386)	-2.22	-0.198 (0.229)	-0.87	-0.265 (0.264)	-1.00
Utility	-0.438 (0.325)	-1.35	0.0214 (0.192)	0.11	-0.0357 (0.220)	-0.16
Consumer Services	-0.663* (0.300)	-2.21	-0.262 (0.175)	-1.50	-0.388 (0.203)	-1.91
Oil, Gas, Mining	-1.782** (0.332)	-5.36	-0.486* (0.200)	-2.43	-0.803** (0.234)	-3.43
Finance	-0.942** (0.280)	-3.37	-0.361* (0.164)	-2.20	-0.559** (0.190)	-2.94

Note: ** & ** indicate significance at the 5% and 1% levels, respectively.*

As expected, the weight of the share divided by the weighted average correlation is highly significant across all time periods. Clearly this is a logical starting point for assessing the endogeneity present in any share and it performs very well as a standalone estimator.[20]

It can be argued that volatility should have a positive effect on endogeneity bias, as greater volatility will likely result in greater price movements and therefore have a greater effect on the returns to the market. There is some evidence that volatility has a positive effect on the size of the bias; it is significant at the 1% significance level in period 1 and at the 5% level overall.

[20] The hypothesis that this is the most important of all the variables is confirmed by running a regression of the bias in both periods combined against this variable alone, with the resulting R-squared being 0.89.

As expected, the liquidity of the share is not a significant variable when estimating the size of bias in shares from the FTSE 100.[21] This evidence is crucial to the results; it shows that the bias that has been found to exist is not due to differences in liquidity between shares and therefore allows us to assume that the bias that is present is due to the endogeneity of market returns.

The sector dummy variables show that there exist differences in the size of the bias for different market sectors. The regression uses consumer goods companies as its reference variable and finds that every other market sector has a lower bias than it does. Looking at the results for period one and two combined, we can see that at the 1% significance level, there are three sectors that have lower biases than would otherwise have been predicted. These are the finance sector, the energy & mining sector and the major banks in the FTSE 100.[22] One possible explanation for this is that the firms in these sectors have a far greater correlation to one-another than the firms in other sectors. This would then increase their average weighted correlation with all other shares and would therefore decrease the bias.

This explanation fits well with the sectors in question. For example, there are many reasons why banking shares tend to move together in any time period; if interest rates change, this is likely to affect all banks in similar ways, whether positive or negative. The same cannot be said, to the same extent, for the consumer goods sector, in which the effect is likely to be more firm specific.

Whilst we cannot say for sure whether some sectors have permanently lower biases, these results provide reliable evidence that the market sector can have an effect on the size of the bias and should not be ignored.

[21] It should be noted that this is in no way considered as evidence that liquidity is not a relevant variable to consider when looking at the problem of endogeneity in beta estimation in general or on other exchanges; it is merely a result of choosing the data from an index in which every share is very liquid and there are only small differences in liquidity between shares.

[22] The banks were separated from the rest of the finance sector for two reasons. Firstly the sector as a whole was very dominant in the index, which could have caused problems in the results. Secondly, the banks in the FTSE 100 were found to have very different characteristics to the other finance companies, such as insurance companies, brokerages and financial information providers.

IV.5: EFFECT OF BIAS ON BETA STABILITY

General Results

The changes in beta between the two time periods were tested for significance using a Chow test for both the IV and the OLS estimates for each firm. The percentage change in the beta estimates was also calculated for the IV and OLS methods in order to see if the bias affected the size of the change in a systematic or random way.

The OLS and IV estimates agreed on the direction of the change in beta for 98 of the 100 shares. The two shares for which the two techniques did not agree were Glaxosmithkline and Astrazeneca, two of the largest shares in the index. In the case of Astrazeneca, the OLS estimate had beta falling by 5.6%, whereas the IV estimate had beta rising by 3.6%. However, since in these two cases neither of the F-statistics were significant for either estimation technique, this result is of little interpretative significance.

At the 5% level, the OLS and IV methods agreed on the significance of changes in beta between the two periods for 98 of the 100 shares.[23] The two shares for which the two methods disagree are HBOS and Vodafone, which again are two heavily weighted shares.

In trying to determine the effects of endogeneity on beta stability, it is far more illustrative to look at the difference in the percentage changes of beta for each estimation technique. In doing this, it shows whether the OLS estimates have a consistent bias (upwards or downwards) on beta stability, or whether the direction of the bias is different for different shares.

[23] Looking at which shares have OLS and IV F-statistics that fall on either side of any particular value (as we just have for F equal to 3.866) is a fairly fruitless endeavour. The F-statistics for every share are different for the IV and OLS methods and so picking some arbitrary point does not give a good indication of how the results differ for the two methods.

It was found that the percentage change between the OLS estimates for periods 1 and 2 were less than those of the IV estimates in 98 of the one hundred shares. This shows that the OLS technique gives a consistently downwards bias on beta stability.[24]

A case study: banking shares

In order to gain a greater insight into the errors that are caused by using OLS estimation techniques in studies of beta stability, it is more illustrative to look at a single group of shares. Figure 11 looks at the 8 banking stocks in the sample. It shows all of the data that someone investigating the effects of the credit-crunch on banking stock betas would have found for both the IV and OLS techniques.

Figure 11: *Percentage changes and F-statistics for banking share betas*

	Alliance & Leicester	Barclays	HBOS	HSBC	Lloyds	RBS	Standard Chartered	Standard Life
β OLS P 1	1.075	1.305	1.026	0.659	0.827	0.941	1.275	1.037
β OLS P 2	1.726	1.454	1.266	0.900	1.157	1.509	1.393	1.278
β IV P 1	1.068	1.267	0.990	0.595	0.801	0.876	1.258	1.022
β IV P 2	1.706	1.430	1.246	0.872	1.150	1.490	1.384	1.270
F-stat OLS	4.388*	1.113	3.668	11.384**	12.270**	18.561**	0.847	2.657
F-stat IV	4.185*	1.223	3.964*	14.011**	13.292**	19.882**	0.924	2.779
% Ch. OLS	60.56	11.43	23.35	36.72	39.97	60.37	9.26	23.21
% Ch. IV	59.74	12.91	25.87	46.58	43.70	70.06	10.02	24.31

Note: *The first four rows are the beta estimates for the OLS and IV techniques for periods 1 and 2 . The next two rows show the F stats, representing the certainty with which we can say that beta changed between the two periods. The bottom two rows show the percentage changes in beta between periods 1 and 2 for each estimation technique. * & ** indicate significance at the 5% and 1% levels, respectively*

[24] When beta has fallen, the OLS technique overstates the fall and where beta has risen, the OLS technique understates the rise.

The beta estimates for all eight banking shares went up between periods 1 and 2, showing that there were differences between the two periods that affected all of the banks in the same way. The increases were significant at the 5% level for four of the banks using the OLS technique and five of the banks using the IV technique.

The F-statistics and percentage changes in beta were greater using the IV technique than the OLS technique for each of the shares except for Alliance & Leicester.[25]

The average percentage change in beta for the eight shares was 33.1% using the OLS technique and 36.7% using the IV technique. This represents a proportional error of 10.7%, an error that is likely to be highly significant in any study of the effects of the credit crunch on banking shares.

Interpreting the results of the beta stability test

It is clear from the evidence above that endogeneity bias *can* have an effect on studies of beta stability. However, it is important to address whether these results will always apply between any two time periods or whether the results found are specific to the time periods chosen for this study.

In this case, the OLS estimates consistently underestimated the change in beta between period one and two. However, this is merely a result of the fact that the bias was far greater in period one. The following examples show how the effect on beta instability is related to the *change* in bias between the periods, not the overall level.

[25] This was one of only two shares in the sample of 100 in which the OLS percentage change was higher than the IV percentage change.

<u>Examples to show how *relative* bias affects beta instability</u>

Example 1: Bias is 20% in period 1, 10% in period 2. "True" (IV) beta changes 50%

$$\beta_1^{OLS} = 1.2 \; , \; \beta_1^{IV} = 1.0 \qquad \beta_2^{OLS} = 1.65 \; , \; \beta_2^{IV} = 1.5$$

$$\%\ \text{change (OLS)} = ((1.65/1.2)-1)*100\% = 37.5\%$$

$$\%\ \text{change (IV)} = ((1.5/1.0)-1)*100\% = 50\%$$

As was the case in this study, the OLS technique understates the percentage change in beta between the two periods

Example 2: Bias is constant at 20%. "True" (IV) beta changes 50%

$$\beta_1^{OLS} = 1.2 \; , \; \beta_1^{IV} = 1.0 \; , \; \beta_2^{OLS} = 1.8 \; , \; \beta_2^{IV} = 1.5$$

$$\%\ \text{change (OLS)} = ((1.8/1.2)-1)*100\% = 50\%$$

$$\%\ \text{change (IV)} = ((1.5/1.0)-1)*100\% = 50\%$$

This shows that when the bias remains constant between two time periods, there is no bias on the results of a beta stability test.

This study does not therefore make any broad statements about exactly how endogeneity bias affects beta stability, it only says that it should be borne in mind that changes in bias over time may have an unwanted effect on the results of a beta stability study. This is especially relevant as studies of beta stability often focus on periods of contrasting market conditions, such as a transition from a bull to a bear market, precisely the time when conditions such as the covariance matrix and volatility may be shifting and causing changes in the bias.

V: CONCLUSIONS AND EXTENSIONS

V.1: CONCLUSIONS

In selecting data from an index in which all shares are highly liquid, this study has separated the effects of endogeneity bias and other types of bias attributed to liquidity issues. It finds that the endogeneity of market returns in the CAPM causes a strong upwards bias on beta estimates when using the OLS estimation technique, reaching a maximum of over 20% for the most highly weighted shares.

This study has shown that whilst tests such as the Hausman test can be useful in detecting endogeneity bias in beta estimates, the bias is really only significant when it would affect the decisions of those who use the CAPM to estimate rates of return or the cost of equity. Consider the following example:

<u>Example of a Cost of Equity Calculation</u>

Assume that the market risk premium is 10%. A bias of 1% in the beta estimation would translate into an error in the cost of equity calculation of 10 basis points. This is likely to be wholly insignificant in investment decisions. However, if the bias is 10%, the error in the cost of equity calculation is 100 basis points. This is likely to be very significant; it is higher than the profit margin of many large banks!

This study has found that the size of the bias can be attributed to a few main factors. Unsurprisingly, the weight of the share in the index is the main factor. However, the effect that the average weighted correlation of the share with all other shares has is particularly interesting; it shows that shifts in the covariance matrix (as we saw at the start of the credit crunch) lead to large changes in the size of the bias that we observe. This is the variable that leads to the changing bias over time and is therefore the reason that the bias may have an effect on beta stability.

In addition, the volatility was found to have a weak effect on the size of the bias and crucially, the liquidity of the share was ineffectual on the size of the bias in both periods. Interestingly, the results also found strong evidence that the size of the bias in different shares is affected by the market sector in which the firm operates.

Finally, the study found that endogeneity bias can have a significant effect on studies of beta stability. The effect that it has is related to *changes* in bias between time periods rather than the absolute level; if there is a high level of bias but it is constant over the observation period then it will not have an effect on studies of beta stability.

V.2: LIMITATIONS AND EXTENSIONS

The main limitation to the findings of this study is the fact that they do not contain data from enough time periods to be applicable to the general case or to be used to predict current or future biases.

Essentially, the model is likely to be "over-fitted" to the time periods used and therefore lacks the robustness required to use it to predict biases in other periods. In addition, the findings on beta stability can only be viewed as proof that endogeneity *has the potential* to affect studies of beta stability, not that it always does so.[26]

It was , however, never the intention of this paper to form a robust model that could predict levels of endogeneity bias in any time period or to say exactly how past studies of beta stability have been affected by it. It was only the intention to indicate that endogeneity bias does exist as a standalone phenomenon, independent of any form of liquidity related bias and to indicate the effect that this *may* have on studies of beta stability. To this extent, it has been relatively successful.

[26] For example, if the last 100 years had been split into 100 time periods, we cannot be sure that the two time periods examined in this study would not have been the only time that endogeneity bias would have caused problems in the results.

The main way to extend the study would be to use data from many more time periods, which together would represent every market condition and from which, a usable model could be derived that was capable of predicting the size of the bias in any market condition. From this, a technique could be found to remove the bias from OLS beta estimates without having to go to the trouble of calculating an IV estimate. If such a technique could be developed, it would be a useful tool for anyone who uses the CAPM to estimate rates of return or the cost of equity.

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APPENDICES

A.1: DESCRIPTION OF VARIABLES

Given below is a very brief discussion of the various factors that may be expected to affect the size of the bias.

The weighting of the share: This should be the most important factor in determining the size of the bias. The higher the weighting of the share, the more effect it has on the index returns and therefore the more endogeneity will be present in the estimate.

The covariance matrix: This represents the relationships that the return to the share has with those of all the other shares. As it has to be captured in a single variable, it is best represented by the weighted average correlation with all other shares. This is given by:

weighted average correlation = $\boldsymbol{\rho^*_j = \Sigma_k (\rho_{kj}\, w_k)}$, for all k not equal to j.

It is clear that the higher that this variable is, the smaller the bias will be. This is because when the share is more correlated to all other shares, the consequences of removing the share from the index (which is essentially what you do when you calculate an IV estimate) become smaller. As the correlation approaches one, the bias approaches zero.

The liquidity of the share: The literature has focused heavily on this variable and it is generally accepted that a lack of liquidity leads to a downwards bias on beta estimates. However, the reason that the FTSE 100 was selected was to remove the effects of this bias. For this reason, it would be expected that this variable would be insignificant in this case. If it were significant, it would detract from the clarity of the results as thin-trading bias and endogeneity bias are easily confused when both present.

The volatility of the share: This could potentially have an effect on the size of the bias. As the volatility increases, it is likely that the share will have a greater effect on the market index as it is likely to experience greater price movements.

The sector in which the firm operates: This could have an effect on the size of the bias, particularly if there exist higher or lower than average correlations for some industries. If this is the case then sector dummies will add explanatory power to the model.

This resulted in the final regression model:

$$\mathbf{BIAS}_i = \alpha + \gamma_1 (\mathbf{weight}_i / \mathbf{w.a.c}_i) + \gamma_2 \mathbf{vol}_i + \gamma_3 \mathbf{liq}_i + \gamma_4 \mathbf{bank}_i + \gamma_5 \mathbf{ind}_i + \gamma_6 \mathbf{util}_i + \gamma_7 \mathbf{cs}_i + \gamma_8 \mathbf{ogbm}_i + \gamma_9 \mathbf{fin}_i + \varepsilon$$

A key to the variables is given below:

Weight / w.a.c: This is the weight of the share divided by the average weighted correlation of the share to all other shares.

Vol: This is the daily volatility of the share over the time period. It is given by the standard deviation of the daily returns.

Liq: This is the liquidity of the share. It is calculated as the average number of shares traded per day divided by the total amount outstanding.

Bank: This is the sector dummy variable for the banking sector.

Ind: This is the sector dummy variable for the industrial sector.

Util: This is the sector dummy variable for the utility sector.

Cs: This is the sector dummy variable for the consumer services sector.

Ogbm: This is the sector dummy variable for the oil, gas and basic materials sector.

Fin: This is the sector dummy variable for the finance sector (other than banks).

The sector which was not represented by a sector dummy was the consumer goods sector.

A.2: REGRESSION RESULTS

Period 1: 13th July 2006 – 12th July 2007

Dependent Variable: BIAS1				
Method: Least Squares				
Date: 04/07/08 Time: 13:01				
Sample (adjusted): 1 100				
Included observations: 100 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.714114	0.478723	-1.491705	0.1393
W_C1	0.681627	0.020024	34.04092	0.0000
V1	1.233394	0.312680	3.944593	0.0002
L1	-0.128794	0.393569	-0.327247	0.7442
BANK	-1.980437	0.370594	-5.343952	0.0000
IND	-0.856909	0.385669	-2.221875	0.0288
UTIL	-0.438255	0.324842	-1.349131	0.1807
CS	-0.663113	0.299896	-2.211141	0.0296
OGBM	-1.782253	0.332205	-5.364925	0.0000
FIN	-0.942148	0.279821	-3.366971	0.0011
R-squared	0.943998	Mean dependent var		2.578302
Adjusted R-squared	0.938398	S.D. dependent var		3.589501
S.E. of regression	0.890904	Akaike info criterion		2.701479
Sum squared resid	71.43384	Schwarz criterion		2.961996
Log likelihood	-125.0739	F-statistic		168.5663
Durbin-Watson stat	2.065289	Prob(F-statistic)		0.000000

Period 2: 13th July 2007 – 21st January 2008

Dependent Variable: BIAS2				
Method: Least Squares				
Date: 04/07/08 Time: 13:16				
Sample (adjusted): 1 100				
Included observations: 100 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.022116	0.250232	-0.088384	0.9298
W_C2	0.503178	0.020244	24.85582	0.0000
V2	0.173538	0.109966	1.578107	0.1180
L2	-0.067049	0.209183	-0.320528	0.7493
BANK	-1.178748	0.235348	-5.008528	0.0000
IND	-0.198461	0.229369	-0.865248	0.3892
UTIL	0.021374	0.192158	0.111229	0.9117
CS	-0.261842	0.175039	-1.495901	0.1382
OGBM	-0.485762	0.199955	-2.429351	0.0171
FIN	-0.361233	0.164267	-2.199057	0.0304
R-squared	0.908164	Mean dependent var		1.124643
Adjusted R-squared	0.898981	S.D. dependent var		1.656762
S.E. of regression	0.526578	Akaike info criterion		1.649803
Sum squared resid	24.95555	Schwarz criterion		1.910320
Log likelihood	-72.49016	F-statistic		98.89005
Durbin-Watson stat	2.126761	Prob(F-statistic)		0.000000

Periods 1 & 2 combined: 13th July 2006 – 21st January 2008

Dependent Variable: BIAST				
Method: Least Squares				
Date: 04/07/08 Time: 12:46				
Sample (adjusted): 1 100				
Included observations: 100 after adjustments				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.103025	0.337641	-0.305133	0.7610
W_CT	0.566988	0.019863	28.54514	0.0000
VT	0.458202	0.186244	2.460225	0.0158
LT	-0.242349	0.282380	-0.858237	0.3930
BANK	-1.784626	0.262216	-6.805934	0.0000
IND	-0.264561	0.263973	-1.002229	0.3189
UTIL	-0.035676	0.219828	-0.162291	0.8714
CS	-0.387523	0.202711	-1.911702	0.0591
OGBM	-0.803242	0.234242	-3.429108	0.0009
FIN	-0.559075	0.190023	-2.942146	0.0041
R-squared	0.930064	Mean dependent var		1.551524
Adjusted R-squared	0.923070	S.D. dependent var		2.188313
S.E. of regression	0.606955	Akaike info criterion		1.933915
Sum squared resid	33.15548	Schwarz criterion		2.194432
Log likelihood	-86.69575	F-statistic		132.9877
Durbin-Watson stat	2.020037	Prob(F-statistic)		0.000000

A3: BETA INSTABILITY RESULTS

	F Statistics		Beta: up/down?		Significant?		% changes in beta		
	OLS	IV	OLS	IV	OLS	IV	OLS	IV	OLS<IV
3I Group	0.339	0.279	down	down	No	No	-6.10	-5.58	yes
Admiral Group	1.870	1.780	down	down	No	No	22.41	22.11	yes
Aliance & Leicester	4.388	4.185	up	up	5%	5%	60.51	59.71	no
Amec	0.020	0.027	up	up	No	No	2.62	3.08	yes
Anglo American	0.370	0.211	down	down	No	No	-5.51	-4.60	yes
Antofagasta	0.155	0.144	down	down	No	No	-4.10	-3.98	yes
Associated British Food	2.309	2.333	up	up	No	No	36.17	36.63	yes
Astrazeneca	0.131	0.039	down	up	No	No	-5.68	3.57	yes
Aviva	1.482	1.718	up	up	No	No	12.65	14.03	yes
BskyB Group	0.001	0.009	up	up	No	No	0.71	1.82	yes
BAE Systems	7.401	6.776	down	down	1%	1%	32.64	32.21	yes
Barclays	1.113	1.223	up	up	No	No	11.43	12.91	yes
BG Group	1.501	1.314	down	down	No	No	17.25	17.09	yes
BHP Billiton	1.617	0.972	down	down	No	No	10.48	-8.77	yes
BP	1.357	0.167	down	down	No	No	11.85	-5.05	yes
British American Tobacco	0.020	0.001	down	down	No	No	-2.40	-0.44	yes
British Land	0.062	0.078	up	up	No	No	3.61	4.13	yes
British Airways	0.060	0.037	down	down	No	No	-3.22	-2.57	yes
British Energy	1.109	1.307	up	up	No	No	41.58	47.17	yes
BT Group	0.194	0.412	up	up	No	No	7.12	11.05	yes
Cable & Wireless	1.574	1.424	down	down	No	No	13.95	13.46	yes
Cadbury Schweppes	4.843	5.315	up	up	5%	5%	48.38	52.85	yes

Cairn Energy	0.059	0.073	up	up	No	No	4.43	4.99	yes
Capita Group	1.337	1.400	up	up	No	No	19.52	20.18	yes
Carnival	0.458	0.387	down	down	No	No	11.17	10.42	yes
Carphone Warehouse	0.431	0.384	down	down	No	No	13.09	12.48	yes
Centrica	2.561	2.248	down	down	No	No	24.23	23.36	yes
Compass Group	0.902	0.955	up	up	No	No	14.23	14.85	yes
Diageo	0.512	0.385	down	down	No	No	-8.38	-7.52	yes
Enterprise Inns	5.984	6.092	up	up	5%	5%	44.54	45.44	yes
Experian	7.017	7.299	up	up	1%	1%	59.04	62.10	yes
Firstgroup	5.571	5.663	up	up	5%	5%	40.03	40.84	yes
Friends Provident	3.629	3.533	down	down	No	No	25.23	25.12	yes
G4S	0.219	0.191	down	down	No	No	-6.35	-5.99	yes
Glaxosmithkline	0.456	0.012	down	up	No	No	11.35	2.30	yes
Hammerson	0.011	0.007	down	down	No	No	-1.62	-1.33	yes
HBOS	3.668	3.964	up	up	No	5%	23.35	25.87	yes
Home Retail Group	8.311	8.396	up	up	1%	1%	62.53	63.98	yes
HSBC	11.384	14.011	up	up	1%	1%	36.72	46.58	yes
ICAP	0.508	0.492	down	down	No	No	-9.80	-9.70	yes
Imperial Tobacco	0.176	0.063	down	down	No	No	-8.42	-5.34	yes
ITV	5.165	4.962	down	down	5%	5%	34.88	34.59	yes
Intercontinental Hotels	4.251	4.440	up	up	5%	5%	33.22	34.40	yes
International Power	2.421	2.251	down	down	No	No	19.18	18.76	yes
Johnson Matthey	12.160	12.061	down	down	1%	1%	34.60	34.65	no
Kazachmys	0.510	0.542	up	up	No	No	8.22	8.54	yes
Kelda Group	11.927	11.686	down	down	1%	1%	49.90	49.75	yes
Kingfisher	0.148	0.154	up	up	No	No	7.94	8.21	yes

Land Sec	0.650	0.569	down	down	No	No	10.55	10.05	yes
Legal & General	2.127	1.962	down	down	No	No	12.76	12.45	yes
Liberty International	0.008	0.010	up	up	No	No	1.05	1.22	yes
Lloyds TSB	12.270	13.292	up	up	1%	1%	39.97	43.70	yes
Lonmin	2.894	2.772	down	down	No	No	18.03	17.87	yes
LSE Group	2.566	2.519	up	up	No	No	41.05	41.22	yes
Man Group	1.191	1.051	down	down	No	No	10.90	10.46	yes
Marks & Spencer	0.701	0.773	up	up	No	No	17.23	18.62	yes
Morrison Supermarkets	3.306	3.601	up	up	No	No	38.25	41.08	yes
National Grid	2.975	2.579	down	down	No	No	26.73	25.87	yes
Next	9.316	9.611	up	up	1%	1%	63.40	65.59	yes
Old Mutual	0.224	0.156	down	down	No	No	-3.64	-3.09	yes
Pearson	0.453	0.376	down	down	No	No	-8.36	-7.71	yes
Persimmon PLC	0.077	0.074	down	down	No	No	-4.65	-4.58	yes
Prudential	1.025	1.280	up	up	No	No	9.78	11.32	yes
Reckitt Benckiser	0.142	0.076	down	down	No	No	-7.49	-5.73	yes
Reed Elsevier	0.210	0.274	up	up	No	No	6.65	7.74	yes
Rentokil Initial	1.285	1.310	up	up	No	No	25.25	25.72	yes
Resolution	7.564	7.288	down	down	1%	1%	40.93	40.78	yes
Reuters Group	12.555	11.409	down	down	1%	1%	54.14	53.19	yes
Rexam	2.011	4.447	up	up	No	No	24.78	40.50	yes
Rio Tinto	0.153	0.093	down	down	No	No	-5.05	-4.43	yes
Rolls-Royce Group	4.431	4.146	down	down	5%	5%	22.31	21.95	yes
Royal Bank of Scotland	18.561	19.882	up	up	1%	1%	60.37	70.06	yes
Royal Dutch Shell	0.921	0.146	down	down	No	No	10.49	-5.10	yes
Royal Sun Aliance	0.085	0.065	down	down	No	No	-2.87	-2.53	yes

Sabmiller	0.130	0.080	down	down	No	No	-4.08	-3.28	yes
Sage Group	6.440	6.323	down	down	5%	5%	32.19	32.11	yes
Sainsbury	0.382	0.416	up	up	No	No	19.42	20.84	yes
Schroeders	0.500	0.479	down	down	No	No	-7.45	-7.33	yes
Scottish & Southern Energy	4.767	4.316	down	down	5%	5%	29.16	28.46	yes
Scottish & Newcastle	0.914	0.869	down	down	No	No	21.08	20.91	yes
Severn Trent	1.719	1.645	down	down	No	No	17.32	17.09	yes
Shire	2.053	1.846	down	down	No	No	21.91	21.16	yes
Smith & Nephew	0.306	0.254	down	down	No	No	10.38	-9.62	yes
Smiths Group	7.459	7.130	down	down	1%	1%	31.61	31.28	yes
Standard Chartered	0.847	0.924	up	up	No	No	9.26	10.02	yes
Standard Life	2.657	2.779	up	up	No	No	23.21	24.31	yes
Taylor Wimpey	0.663	0.773	up	up	No	No	16.27	18.07	yes
Tesco PLC	1.532	1.986	up	up	No	No	23.11	28.54	yes
Thomas Cook Group	1.042	1.150	up	up	No	No	39.35	42.41	yes
Tui Travel	0.022	0.037	up	up	No	No	3.26	4.37	yes
Tullow Oil	1.771	1.627	down	down	No	No	23.37	22.92	yes
Unilever	0.929	0.724	down	down	No	No	14.04	12.90	yes
United Utilities	0.026	0.016	down	down	No	No	-2.07	-1.63	yes
Vedanta Resources	1.375	1.323	down	down	No	No	13.00	12.85	yes
Vodafone Group	4.417	2.424	down	down	5%	No	23.25	20.75	yes
Whitbread	0.715	0.814	up	up	No	No	14.16	15.36	yes
Wolsely PLC	5.911	5.582	down	down	5%	5%	25.86	25.52	yes
WPP Group	0.032	0.016	down	down	No	No	-1.96	-1.40	yes
Xstrata	3.850	3.370	down	down	No	No	21.01	20.61	yes
Yell Group	0.546	0.666	up	up	No	No	17.90	20.27	yes