In Search of Beta

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Abstract

Despite the arguments that can be made against using the CAPM, it is very widely used in regulation. In particular, it is relied upon in setting utility prices in each of Australia, New Zealand and the United Kingdom, and also features in this context in Germany. In addition, UK competition authorities make use the CAPM to assess profitability in the case of "market investigations". All of these applications require beta as an input into the CAPM, but the beta estimates employed typically vary depending on frequency of the returns data used in their estimation. Given the implication of returns frequency for estimates of beta noted in the literature, and in particular the role of firm characteristics in this, this study undertakes a detailed examination of the evidence for the UK and shows that longer frequency betas have superior characteristics to high frequency betas. We find that differences in beta can be explained by opacity, size, liquidity and book-to-market factors. Our conclusions are unequivocal and have important policy implications for regulatory use of the CAPM, as they imply that low frequency beta estimates should always be preferred to high frequency beta estimates. They also have important implications for academic researchers using the market model in empirical investigations.

In Search of Beta

Whilst the CAPM has been subject to considerable criticism (most recently by Dempsey (2013a), who catalogues the empirical failings of the model), the model retains a core role in modern finance and, in particular, is extensively used by regulators globally. Whether or not this is desirable is clearly debateable. One can argue, as in Dempsey (2013a, 2013b), Cai, Clatcher and Keasey (2013) and Moosa (2013) that it is time to move on to another paradigm altogether, or one can argue the case for an alternative factor model, such as the Fama-French model (Fama and French, 1993, 1996) or some form of conditional asset pricing model (Durack, Durand and Maller, 2004; Fletcher and Kihanda, 2005; Schrimpf, Schröder and Stehle, 2007). Alternatively one can adopt the position of Brown and Walter (2013) and Smith and Walsh (2013) that the CAPM is defensible, and indeed according to the latter, despite being "half right" is "the only game in town". Whatever one's views on this, pragmatically it is hard to disagree with Partington (2013) who predicts that "the reign of the CAPM is unlikely to end anytime soon".

In all this it is absolutely critical to recognise that whatever the academic debate on asset pricing, in the UK the CAPM is the only model currently accepted by the regulatory authorities in the UK. These include the Competition and Markets Authority (CMA), OFCOM, OFWAT, OFGEM and the CAA.[1] A broadly similar utility regulatory regime exists in Australia and New Zealand. However, in the UK the CMA also has the power to conduct "Market Investigations", which were introduced by the Enterprise Act (2002). These investigations give wide-ranging powers to the CMA to investigate whether there are features in the market that result in a so called "adverse effect on completion" (AEC).[2] As part of its investigation, the CMA will typically look at prices and profitability in the relevant market. Annex A of *Guidelines for Market Investigations: Their role, procedures, assessment and*

[1] In the UK, monopoly utility services are subject to price regulation: telecommunications access prices are set by OFCOM, water and sewerage prices are set by OFWAT, electricity and gas network prices are set by OFGEM and monopoly airport landing charges are set by the CAA in conjunction with the CMA. The CMA has the role of being the appeals body for the regulated utility companies. Additionally, it has a key role in undertaking market investigations. For a full description see: https://www.gov.uk/government/organisations/competition-and-markets-authority

[2] See: https://www.gov.uk/government/uploads/system/uploads/attachment_data/file/284390/cc3_revised.pdf

Remedies[3] makes clear that profitability will be assessed using either adjusted accounting data and an ROCE analysis, or an IRR/Truncated IRR approach, and critically (Appendix A, paragraph 16):

> *In assessing levels of profitability the CC will have regard to its view of firms' cost of capital. The CC will generally look to the capital asset pricing model (CAPM) when considering the cost of capital, since this is a widely understood technique with strong theoretical foundations. However, the CC will have regard to alternative models where appropriate.*

Yet despite thus expression of openness to such alternatives, the CMA and its predecessor body (the Competition Commission) has always rejected any "alternative model". It may "consider" such models, but only in so far as it consistently rejects them. As such, the CAPM is the only model that it has ever used in either regulatory appeals or market investigations.

However, the use of the CAPM in a regulatory (or indeed any other) context requires an estimate of beta. Discussions of the techniques of beta estimation, the suitability of alternative analogues for beta and the treatment of leverage in deriving asset betas are standard fare in both textbooks and regulatory reports. Early research also considered issues such as the effects of non-synchronous trading (Dimson 1979, Scholes and Williams, 1977) and intertemporal parameter stability (Blume, 1971, 1975), but little attention has been paid to the impact of the choice of the frequency distribution of returns used in estimating beta. An early work was by Levhari and Levy (1977) who show that the impact on beta of lengthening the investment horizon (i.e. the return interval) depends on the riskiness of stock, Cohen et al. (1980) show that the effect of the lengthening of the return interval may depend on the severity of thin trading problems. Handa, Kothari, and Wasley (1989) specifically consider firm size and show that portfolio betas of small (large) cap firms rise (fall) as the return interval is lengthened. However, there appears to have been little interest in investigating what firm-specific characteristics, apart from size and liquidity, might influence the way in which beta estimates vary with the frequency of their estimation. A notable exception is the recent study is that of Gilbert et al. (2014), who show that estimates of beta are frequency-dependent, and that differences between high and low frequency betas can be explained by proxies for opacity of the firm. Opaqueness creates uncertainty about the effect of systematic news on the firm and this uncertainty affects how quickly such information is

[3] See footnote 2 for link

impounded into the prices. This coupled with the risk averseness of investors affects the returns of opaque firms at higher frequencies. At lower frequencies however, the effect of the systematic news is reflected in the returns of all firms (Gilbert et al., 2014). The consequence is that high frequency betas are particularly problematic in that they do not fully reflect risk characteristics. By contrast, low frequency betas will not suffer from this difficulty. Thus for opaque firms, using shorter return intervals results in a beta estimate that does not accurately reflect the riskiness of the stock.

This simple finding has potentially huge regulatory implications, as regulatory authorities sometimes assume that high frequency data is more desirable than low frequency data. For example, in its recent investigation of the UK Healthcare market, the UK Competition Commission (CC) asserts that "[weekly data] permits a more statistically robust estimation due to the larger number of data points available for the calculation and hence the lower standard errors"[4], although they then go on to consider both weekly and monthly betas in reaching their conclusions. However, in the recent Northern Ireland Electricity case, the CC goes much further: "Daily data is usually preferred as it is likely to have the smallest standard errors and may be regarded as more statistically robust (providing the share's trading frequency is sufficient) but monthly betas may be more reliable, particularly for thinly traded stocks. We have concentrated on betas calculated from daily data in this inquiry."[5] The Australian Energy Regulator considers both weekly and monthly estimates in reaching its conclusions, although does not appear to regard either as having any superior characteristics.[6] However, the cases above (except for Healthcare) took place before the publication of the Gilbert et al. (2014) paper. It is noticeable that in its latest published investigation material at the time of writing, the "Payday Lending" case, the CC (by now superseded by the CMA) does not express a preference for high frequency betas and indeed includes an estimate of quarterly betas in its analysis, in addition to weekly and daily betas (though curiously, it does not refer to monthly betas).[7]

[4] Private Healthcare Market Provisional Findings Report, August 2014, Appendix 6.14, paragraph 31.
[5] Northern Ireland Electricity Ltd price determination, Final Determination, March 2014.
[6] For an extensive discussion, see "Better Regulation: Equity Beta Issues Paper" October 2013 available at: http://www.aer.gov.au/sites/default/files/AER%20-%20equity%20beta%20issues%20paper%20-%20rate%20of%20return%20guideline%20-%20October%202013.PDF

[7] See https://assets.digital.cabinet-office.gov.uk/media/539b1d28ed915d106c000010/PDL_PFs_Appendices_and_Glossary.pdf

Internationally, the use of the CAPM in regulation appears to be widespread, and Sudarsanam, Kaltenbron and Park (2011) surveys practice in six countries: Australia; Canada; Germany; New Zealand; the UK; and the USA.[8] They find that the CAPM is used as the primary model for estimating the cost of equity by the AER in Australia, the principal regulators and the CC in the UK, and by the New Zealand Commerce Commission. In addition, it is described as "informing" the cost of equity estimates in Germany. The CAPM is not used in the Canadian case reviewed (the Ontario Energy Board), and its use in the USA is varied, as there are a multiplicity of federal and state regulators. Nonetheless, it appears that *some* weight is given to the CAPM in the USA, although a dividend discount model appears to be a key input.

The implication of this widespread use of the CAPM in the regulation of utilities is that fairly small variations in beta can have a very large economic impact when multiplied by the CAPM risk premium, given the size of utility companies. For example, Buckland, Williams and Beecher (2014) cite an Ofwat report that "in the case of water, it has been estimated that a 0.5 percentage point variation in the cost of capital might translate into a change of £10.00 in the average annual bills of the 28 million households served by water companies in England and Wales (Ofwat, 2014: 2)." With a market risk premium of 5%, such a variation is equivalent to a change of only 0.1 in the estimate of the beta for a firm financed entirely by equity. Not surprisingly, regulated firms invest heavily in consultants and academics who argue the case for variations in the beta estimates, and regulatory bodies often employ others who argue for variations in the other direction.[9] Consequently, research that objectively establishes how beta should be estimated has important policy implications and considerable economic impact.

Given that Gilbert et al. (2014) have analysed the position in the USA, in this paper we focus upon the UK, firstly because of the added importance of market investigations in the UK, and

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Appendix 4.5 paragraphs 111-113.

[8] See http://webarchive.nationalarchives.gov.uk/20140402141250/http:/www.competition-commission.org.uk/assets/competitioncommission/docs/pdf/non-inquiry/our_role/analysis/cost_of_equity_comparison_of_international_regulatory_practice.pdf

[9] Note that in the UK, cost of capital is an important parameter in market investigations. The UK's approach to such investigations differs from that in many other countries. See, for example, the UK and Australian positions set out in the OECD paper on excessive prices: http://www.oecd.org/competition/abuse/49604207.pdf

secondly because we have a much longer run of data for the UK than for the other countries where Sudarsanam et al. (2011) show that the CAPM is a key input. Unfortunately, New Zealand's stock market is too small to allow us to do any detailed analysis of the differences between daily, weekly and monthly betas, in addition to which we note that in the case Sudarsanam et al. (2011) investigate, "New Zealand estimated a beta based on data from 79 listed utilities in New Zealand, Australia, the UK and the USA", which implies an interest in the analysis of beta well beyond NZ. Additionally, we found that data available for Australia and Germany were rather limited. Indeed, were we to try and estimate betas on the same basis as for the UK, we would have six years less data. Nonetheless, given the central importance of the CAPM in Australian regulation, we report basic monthly vs daily betas for Australia and footnote how our results differ between the UK and Australia.

We add to the Gilbert et al (2014) investigation in two ways. First, we consider other firm-specific risk factors, apart from opacity, that might make it more difficult to quickly interpret the impact of systematic news on the firm. Specifically, we consider the extent to which gearing (leverage) and BE/ME may be important in this respect. Additionally, we consider whether these risk factors have explanatory power in the presence of controls for industry membership. Second, in addition to investigating the differences between high and low frequency betas, as in Gilbert et al. (2014), we also run the F-test of Gibbons, Ross, and Shanken (1989, hereafter GRS) in order to check whether or not the pricing errors from the CAPM at each beta frequency are jointly zero. In a well-specified version of the CAPM, the alphas from regression tests conducted on a set of test portfolios should be jointly zero. Following Fama and French (2012) our tests are conducted on portfolios formed on the basis of size and book-to-market, but additionally, following the suggestion of Lewellen, Nagel and Shanken (2010) we run tests based on portfolios formed on either industries or volatility. Such tests are also run in Gregory, Tharyan and Christidis (2013) who provide an additional motivation for such portfolio by noting that recent work by Brooks, Li and Miffre (2011) raises the possibility that idiosyncratic risk may be priced in the US.

Our findings provide support for the US-based conclusions of Gilbert et al. (2014), that low frequency betas are superior to high frequency betas. For the UK, we find that the differences are due to measures of opacity, size, liquidity and BE/ME. There is also clear evidence that industry effects are important in explaining differences. However, opacity becomes less significant when the sample is partitioned on the largest and most liquid firms, although it should be noted that in our main results we deliberately confine ourselves to a sample of larger firms, as these are likely to be of most interest to regulators. Some further support for the use of low frequency betas comes in the form of the GRS tests. The important policy implications are that regulators (and indeed other users of the CAPM) should avoid the use of daily betas, and in general should have a preference for monthly or even quarterly betas over weekly or daily betas. Our results also have important implications for academic studies that employ the market model or the CAPM using daily data.

Research design

Our objectives in this paper are first to establish whether estimates of beta vary with the frequency distribution of the returns used to estimate those betas. Our second objective is to investigate whether we can explain the differences between high and low frequency betas using proxies for size, liquidity and opacity. Finally, our objective is to establish the best specification of the CAPM based on different frequency returns using the time series asset pricing test of Gibbons, Ross and Shanken (1989).

Our basic research method is different from that of Gilbert et al. (2014), in that we do not form portfolios based on differences between high and low frequency betas. Further, we deliberately focus on larger firms and exclude small ones for three reasons. First, in pragmatic terms, regulation is typically concerned with large firms rather than small ones. To the extent that small firms are regulated, they are typically subsidiaries of larger firms (see, for example, the recent Bristol Water appeal case to the UK's Competition Commission). Second, we know that asset pricing models for the UK perform more successfully when limited to larger firms (Gregory, Tharyan and Christidis, 2013) and that pricing small value stocks in particular is a general challenge for asset pricing models (Fama and French, 2012). Finally, it is well-known that smaller stocks suffer from thin trading problems (Dimson, 1979). Including such stocks in our test portfolios would effectively be loading the experiment in favour of finding that high frequency betas are problematic. To avoid this problem, we limit our portfolios to the top 30% of firms by market capitalisation.

All our estimates use the longest common data period available. For the UK, our major restriction is the availability of returns data on the LSPD daily database. To run our regressions, we need a sufficient run of data to estimate monthly and quarterly betas (which respectively use five years' and ten years' of returns data from the monthly LSPD), 250 trading days of data to estimate daily beta and 104 weeks to estimate the weekly betas. Additionally, we need lagged values of our opacity measure (which are formed using the accounting data described below), market capitalisation, liquidity, book equity to market equity and gearing/leverage. The Gilbert et al. (2014) measure of opacity (based on the Jones 1991 model) can only be measured at annual intervals, so that the only betas we run regressions for are those calculated six months after the financial year end.

These requirements mean that our first regression to explain the *difference* between monthly/quarterly and daily beta estimates can be run in 1988, and the final regression in 2013. The month within the year that we start is affected by the availability of accounting data needed to estimate our measure of opacity (which is based on the Jones 1991 model) and the way we form our book-to-market portfolios for the GRS test portfolios. Following Fama and French (1996), it has become standard practice to allow at least 6 months between the financial year end (FYE) and the portfolio formation date. Because of the prevalence of March year financial year ends in the UK[10], we follow Gregory et al. (2013) and use end-September portfolio formation dates for UK firms.[11] In order to maintain the inter-temporal consistency of the beta estimates, our monthly betas use 60 months of data (120 months in the case of quarterly betas), ending in September, whilst our weekly beta estimates use 104 weeks of data ending on the 40th week, and the daily estimates use 250 trading days of data ending in the same week.[12] These calculations are then repeated each year such that we have estimates of quarterly, monthly, weekly and daily betas for the period 1988-2013 for the UK.[13] If any observations are missing such that a beta cannot be estimated for a particular date-frequency, we drop that firm-date observation from the sample. Our returns data come from the LSPD for the UK, and from Datastream for Australia.

Our market indices are the total returns on the All-Share Index for the UK. For Australia, there is a problem in identifying a total returns index (as opposed to a price index), and so we

[10] This oddity is associated with the fact that the fiscal year end in the UK is 5th April.
[11] For Australia, where the fiscal year end is 30th June, we follow Chan et al. (2010) and form portfolios as at the end of December. In the case of Australia, we cannot go back as far as 1978 to estimate quarterly betas, and indeed the regressions for monthly data have one year's less data than the UK.
[12] The 52nd week for Australia.
[13] For Australia we have only monthly and daily estimates from 1989 on.

construct a value-weighted total return index based on the largest 50% of firms by market capitalisation. The risk-free rates of return were the 3-month Treasury Bill Rate for the UK, and the Dealer 90-Day Bill rate (DS code ADBR090) for Australia.

We estimate betas by running OLS, time series regressions of the form

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it}$$

Where R_{it} is the return on the stock, R_{ft} is the risk-free rate, R_{mt} is the return on the market portfolio. To avoid outliers unduly influencing the regression tests for differences in beta, we then drop any observations where the differences between the high and low frequency betas are in the extreme percentiles of the distribution. The resultant beta estimates and their differences are reported in Table 1.

We then investigate whether these beta differences can be explained by size, liquidity and opacity. For size, in order to avoid time trends due to increases in market capitalisation, we use the market capitalisation of the firm as a percentage of the total capitalisation of the market. This variable (*size*) is lagged by one year. For liquidity we consider three measures. The first is the Amihud illiquidity ratio, A_{it} (scaled by 1 million), from Amihud (2002), calculated over the prior year ending June (Australia) and September (UK). We Winsorise this measure at the 1% level. This measure captures the average daily price response associated with one currency unit of trading volume and is defined as:

$$A_{it} = \frac{1}{D_t} \sum \frac{|r_{idt}|}{VOL_{idt}}$$

Where r_{idt} is the return on stock i for day d of year t, VOL_{idt} is the daily volume in the local currency unit on stock i for day d of year t and D_t is the total number of trading days in year t. However, there is a problem with this measure of illiquidity as the return to volume ratio (the summed term on the RHS) is inevitably influenced by size. It further ignores the frequency of trading. These limitations motivate Florackis, Gregoriou and Kostakis (2011) to develop an alternative measure, based on return to turnover ratio, TR_{idt}, defined as the stock's turnover divided by the number of shares outstanding. Formally, the measure is:

$$RtoTR_{it} = \frac{1}{D_t} \sum \frac{|r_{idt}|}{TR_{idt}}$$

We use *RtoTR* as our main measure of illiquidity. Florackis et al. (2011) show this measure to be free of size bias in the UK and we also find that it has a lower correlation with size in our data across all three countries we investigate. Additionally, we find it has better explanatory power in our regression tests. Nonetheless, in unreported robustness checks, we obtain broadly similar conclusions when the Amihud measure is used. Finally, following Gilbert et al. (2014) we investigated a third measure of liquidity, the trading volume per year per share outstanding (*turnover*), which, in common with the *RtoTR* measure, we Winsorised at the 1% level. As we find we get lower R-squareds in regressions using this measure of liquidity, we treat it as a robustness check only and do not report results using this measure. Our key results are unaffected by the use of this measure in place of *RtoTR* and similarly are unaffected by including both measures simultaneously, despite the obvious (negative) correlation between the measures.

Our proxy for opacity is a measure based on discretionary (abnormal) accruals computed using a modified Jones (1991) model. This measure reflects accruals management and works as a good proxy for firm opacity. As Hutton, Marcus and Tehranian (2009 p.69) notes *"Considerable evidence indicates that accruals management obscures at least some information about firm fundamentals (see, e.g., Sloan, 1996) and is thus a direct, firm-specific measure of opacity. In addition, aggressive earnings management is likely to proxy for management's general proclivity to hide information from the capital market and thus captures less easily quantifiable or observable aspects of opacity".*

The specific model that we use follows Mouselli, Jaafar and Goddard (2013) and our specific measure of opacity is the absolute value of abnormal accruals, which is the absolute value of the discretionary component of total current accruals.

The total current accrual for each firm TCA_{it} is defined as

$$TCA_{it} = (\Delta CA_{it} - \Delta Cash_{it}) - (\Delta CL_{it} - \Delta STD_{it})$$

Where, ΔCA_{it} is the change in current assets, $\Delta Cash_{it}$ is the change in cash and short-term investment, ΔCL_{it} is the change in current liabilities and ΔSTD_{it} is the change in short-term debt.

We then run a cross-sectional OLS regression across all the firms in each industry for each year with the following specification and obtain industry year specific estimates of α_1 and α_2.

$$\left(\frac{TCA_{it}}{TA_{it-1}}\right) = \alpha_1 \left(\frac{1}{TA_{it-1}}\right) + \alpha_2 \left(\frac{\Delta REV_{it}}{TA_{it-1}}\right) + \varepsilon_{it}$$

where, TA_{it-1} is lagged total assets, ΔREV_{it} is the change in revenue.

Since this approach estimates an annual cross-sectional industry level model, it has the advantage of avoiding survivorship bias and also allows for variations through the business cycle.[14] Further, applying the model at an industry level avoids the considerable loss of power associated with applying the model at a firm level (Dechow et al., 2012, p.290). In order to ensure we have sufficient firms in each industry sector, we start with Datastream Level 3 industry classifications (19 industries) but in some cases have to combine industries to give enough observations in each sector. Precise details are set out in the Appendix (Table 1A).

Using the estimates of α_1 and α_2, for each firm the non-discretionary part of its total current accruals, $NDAC_{it}$, is calculated as

$$NDAC_{it} = \hat{\alpha}_1 \left(\frac{1}{TA_{it-1}}\right) + \hat{\alpha}_2 \left(\frac{\Delta REV_{it} - \Delta AR_{it}}{TA_{it-1}}\right)$$

where, apart from the variables as defined earlier, ΔAR_{it} is the change in accounts receivable.

[14] Unfortunately, there is no guidance in Gilbert et al (2014) on exactly how the Jones (1991) model is applied in their paper.

The absolute value of discretionary (abnormal) accrual is then calculated as the absolute value of the remaining portion of the total current accruals[15].

$$|DAC_{it}| = \left|\left(\frac{TCA_{it}}{TA_{it-1}}\right) - NDAC_{it}\right|$$

Finally, to avoid undue influence from outliers we Winsorise this at the 1% level.

Gilbert et al. (2014) also uses an alternative measure of opacity which comes from the questionnaire based research of Hambrick and Abrahamson (1995). As Gilbert et al. (2014) describe the process, the questionnaire "*focuses on managerial discretion at the industry level between 1985 and 1989 for 31 industries as defined by two-digit SIC codes. We assign the managerial discretion measure to all firms in our sample between 1969 and 2010, based on the firm's two-digit SIC code. All firms in the same industry therefore receive the same score.*" We do not directly use this measure as there are several issues with applying this measure for our purposes. The first is that the 31 industries surveyed do not constitute a comprehensive sample, so that some industries simply have no data. The second is that these 31 industries do not map neatly on to the Datastream industry level categories that we can observe. For these reasons, as an alternative, we use DS Level 3 industry dummy variables (modified as described above) in our analysis.

In addition to the variables considered by Gilbert et al (2014) we additionally consider variables that may be predicted to influence beta (though not necessarily the difference in magnitude between daily and weekly betas). First and most obviously, we consider the impact of gearing, or leverage. This we measure as total debt to market capitalisation of equity (TD/MC). Our prior would be that indebted firms may be more complex. For example, Manconi and Massa (2009) suggest that firms characterised by higher complexity tend to fund their financial deficit with more debt and less equity. So if leverage has such an impact, we might expect a positive association between leverage and the difference between low frequency and high frequency estimates.

A second variable that might influence the CAPM beta is the book-to-equity ratio (BE/ME). There are two plausible reasons why there could be an association between BE/ME and beta.

[15] In unreported robustness tests, we ran our regressions using the variance of the discretionary accruals over the prior three years rather than the lagged value itself. The results of doing so were qualitatively similar to those reported.

Pope and Stark (1999) provide a model, based upon real option theory and costly reversibility, which shows that the CAPM beta will be a function of the BE/ME ratio. In a similar vein, Zhang's (2005) model of costly reversibility combined with a counter-cyclical costs of risk proposes that value firms are riskier than growth firms. In a CAPM world the corollary would be that beta should be associated with BE/ME. Finally, Campbell, Polk and Voulteenaho (2010) provide a useful review of CAPM beta decomposition. "Value" stocks (i.e. those with high BE/ME) have a higher sensitivity to so-called "bad" beta, which captures cash flow shocks. The implication is that BE/ME captures an important risk exposure. Whilst the common theme here is that BE/ME is a proxy for risk, if that risk is particularly difficult to interpret we might expect a positive association between BE/ME and the difference between low frequency and high frequency estimates.

Results

Descriptive statistics

We start with an analysis of basic betas. The first thing we note, from Table 1, is that beta decreases with the frequency of estimation. This is a striking result. However, the mean beta is not significantly different from unity whether it is estimated on a monthly or quarterly basis in the UK, and neither is it for Australia when estimated on a monthly basis. Further inspection of the results shows that weekly betas are higher than daily betas in both countries (although we do not formally test this difference). The differences between monthly and daily betas are large and significant for both countries, as is the difference between quarterly and daily betas for the UK. Indeed, the daily betas are alarmingly low, and inspection of the (unreported) medians show that this is not driven by a few outliers. Whilst the point made by the UK Competition Commission in the Northern Ireland Electricity case, namely that daily betas have lower standard errors, is borne out by the data, this is not entirely surprising since we use a larger number of observations to estimate daily betas when compared to weekly , monthly or quarterly betas. However, it is clear that daily betas seem to be downward biased, and this is something we turn to in the next section. Finally, we note that weekly betas are also significantly less than unity for both countries, and once again the differences between monthly and weekly betas are significant.

We now focus our attention firmly on the UK, and summary statistics for the size, liquidity and opacity proxies for the monthly vs daily beta sample, together with beta differences, gearing (TD/ME) and BE/ME variables are reported in Table 2, whilst the quarterly vs daily sample data are reported in Table 3. Panel A reports summary statistics whilst Panel B shows the correlations between variables. For space reasons, we do not report the equivalent tables for the equivalent *versus* weekly samples.[16] In unreported figures, we find that consistent with the evidence in Florakis et al. (2011), in all cases we observe that the correlation between the Amihud and *RtoTR* measures of illiquidity are reasonably strong. Furthermore, the correlation of *RtoTR* with size is lower than the correlation of the Amihud measure and size. None of the correelations reported are particularly remarkable. Consistent with *RtoTR* being a measure of *illiquidity* (i.e. as opposed to liquidity) it is negatively correlated with size. Rather more strikingly, beta differences in both Table 2 and Table 3 are inversely correlated with size and positively correlated with illiquidity.

Regression results

To explain the difference in the beta estimates, we run the following regression model, for each country and each of the weekly and daily beta difference specifications:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.BE/ME_{it-1} + e.TD/MC_{it-1} + \sum IND_{it} + \in_{it}$$

Where in addition to the variables described above, $\Delta\beta$ is the difference between monthly and weekly betas or monthly and daily betas, IND_{it} is an industry dummy (see Appendix A1 for a detailed description). In all cases "Basic Resources" forms the base case industry. All standard errors are estimated using the two-way cluster robust standard error (or CL-2) approach of Petersen (2009), which Gow et al. (2010) show to yield well-specified standard errors in accounting panel data simulations.

Table 4 presents the results from our regression of UK monthly betas minus UK daily betas on our variables of interest. The first two columns show what happens when we include just the opacity variable (column 1) or the opacity variable plus industry dummies (column 2). The final two columns show what happens when we include our full set of variables, with and without industry dummies respectively. In line with the findings of Gilbert et al (2014) we find that opacity has power to explain the difference in betas. This is consistent with the conjecture that markets need more time to fully interpret new information for more "opaque"

[16] Because we Winsorise on the *differences* in betas, the samples have (very) minor differences in their statistical properties.

companies than less opaque ones. This effect remains once we include industry dummies, though it is clear that industry effects are important in explaining beta differences. Once we include all our variables of interest, opacity retains its explanatory power at the 5% level. As might be expected, size effects have an important role to play, in so far as larger companies show less difference between monthly and daily betas than smaller ones, and the less liquid a firm's stock is, the greater the difference between monthly and daily betas. For gearing, there are no significant effects, but intriguingly BE/ME is associated with beta differences, which is consistent with BE/ME capturing information about real options that markets need time to interpret. Finally, the last column of Table 4 shows that these effects are robust to the inclusion of industry dummies, but the adjusted R-squared figures also demonstrate the explanatory power of industry effects. Although we do not report industry coefficients in detail, we note that of the 16 industry dummies, four are significantly positive, with a further one being positive at the 10% level, whilst two are significantly negative, with a further one being negative at the 10% level.

In Table 5 we report the results from similar regressions that take the difference between quarterly betas and daily betas as the dependent variable. Broadly, the results are similar to the monthly beta differences, with the exception that in the "full" model regressions opacity only has significant explanatory power at the 10% level. What both the monthly and quarterly beta difference regressions confirm is that there are large differences in betas, arising from estimation frequency, that are associated with opacity, size, liquidity, BE/ME and industry effects. The important regulatory implication is that daily betas are not reliable indicators of the CAPM beta, as the fact we can explain the differences between high and low frequency betas by factors that can be viewed as proxies for risk suggests that the high frequency (daily) beta estimates omit important risk characteristics.

So if this is the case for daily betas, a natural question is whether the use of weekly betas might be helpful. Having demonstrated that quarterly minus daily and monthly minus daily betas as dependent variables lead to similar inferences, to answer this question we concentrate on the differences between monthly and weekly betas. The relevant regressions are reported in Table 6. When we do so, the first thing to note, in the first two columns, is that opacity now plays only a weak role in explaining these differences. Indeed, when we include all our other variables of interest, opacity ceases to have any power in explaining differences. Size and liquidity remain important, and BE/ME is weakly significant when industry effects are excluded, but significant when they are included. Inspection of the unreported industry dummies reveals four industries have significant positive coefficients whilst one has a significant negative coefficient. The conclusion is that whilst weekly betas seem to be less problematic than daily betas, the differences in betas can still be explained in terms of size, liquidity, BE/ME and industry effects which again suggests they are not to be relied upon as indicators of the CAPM beta.

Robustness tests

Recall that by design in this paper we have limited our analysis to the largest companies by market capitalisation. Nonetheless, in the spirit of Gilbert et al. (2014), we run our regression tests on a sample restricted to only those firms that have a market capitalisation above the median market capitalisation for the year. We also run the regressions on firms which have below median illiquidity (that is, the most liquid stocks). The results are reported in Tables 7-9. In each table the first group of models restricts the sample to cases where size is above the median. The model "Opacity 3" includes only the opacity variable, whilst "Opacity 4" includes this plus industry dummies. Similarly the model "Restrict 1" includes all control variables but no industry dummies, whilst "Restrict 2" includes all control variables plus industry dummies. The second group of models restricts the sample to cases where the illiquidity measure is below the median. "Opacity 5" includes only the opacity variable, and "Opacity 6" includes this plus industry dummies. Similarly "Restrict 3" includes all control variables but no industry dummies, whilst "Restrict 4" includes all control variables plus industry dummies. .

Table 7 runs the regressions with the monthly minus daily beta as the dependent variable. Looking at the large company group of regressions (columns 1-4) we observe that opacity only has an explanatory role when looked at alone. In the presence of other variables, its significance disappears. But despite being limited to just the largest firms, size and illiquidity are still important in explaining beta differences, as is BE/ME in the presence of industry dummies. Industry effects are again important in explaining differences. Similar conclusions can be drawn when we limit the sample to the most liquid stocks. There is some hint that gearing may matter in this sub-sample. Overall, the message from these regressions is that our main results are not attributable to features in the smallest or most illiquid stocks, and that even the largest and most liquid ones exhibit important differences in betas estimated at high and low frequencies.

Table 8 reports the regressions using quarterly minus daily betas as the dependent variable. Results are broadly similar to those reported in Table 7 for the large firm group, except we now find that gearing matters in the presence of industry effects but BE/ME does not. However, when we turn our attention to the sub-sample of the most liquid stocks (columns 5-8), opacity plays an important role in all the regressions, along with size and liquidity. Gearing has a role to play in explaining the differences in this subgroup (at least in the presence of industry effects) but BE/ME loses its significance.

In conclusion, then, differences between high and low frequency betas exist in the largest and most liquid stocks, and even in these groups size and illiquidity have important roles to play in explaining these differences, as do industry effects. Quite whether opacity, gearing and BE/ME are important depends on which frequency difference we are trying to explain, and which sub-sample is being investigated.

Finally, for the sake of completeness, we analyse the beta differences between monthly and weekly betas for the largest and most liquid stocks in Table 9. In these regressions it is clear that opacity has no explanatory power, and size has important explanatory power. Illiquidity is important in the large firm sub sample, with BE/ME having some role here in the presence of industry dummies, and once again industry effects themselves are important. For the most liquid stocks, illiquidity and BE/ME have only weak explanatory power, and again industry effects are important.

Our final robustness check uses Australian data. Recalling that we have less years of data for Australia, these results are reported in Table 10. We only report the full model results as the opacity regression proves to be insignificant. In these full regressions we see that the opacity measure, *aaa*, although positive as Gilbert et al. (2014) predict, is wholly insignificant in explaining the difference between monthly and daily betas. Size always has a significant negative relationship with the difference, and whilst the *RtoTR* illiquidity measure is weakly significant, it is subsumed when industry effects are included. Curiously, gearing has a weak role to play but the relationship between TD/ME is negative. Of the (unreported) industry dummies, two of the industries have an impact on beta that is significant at the 5% level or less, whilst a further two are significant at the 10% level. The only strong conclusion that can be drawn from the Australian data is that there are important differences between high and low frequency beta estimates, and that size and industry effects have an important role to play in explaining these differences. So despite the modest explanatory power of these regressions, the message for regulation is the same as for the UK. That is, high frequency betas cannot be relied upon as estimates of the CAPM beta, because they omit some known risk characteristics.

GRS Test Results

Our final set of tests involve standard GRS tests of the CAPM. The GRS F-statistic tests whether the time-series intercepts (pricing errors) are all zero when excess returns on assets under consideration are regressed against the risk factors of any particular asset pricing model. With N number of test assets, the test is whether the N intercepts are jointly indistinguishable from zero. In testing the CAPM, the GRS test proceeds by running OLS time series regressions of the form

$$R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it}$$

for each test asset portfolio. R_{it} is the return on the test portfolio, R_{ft} is the risk-free rate, R_{mt} is the return on the market portfolio. The form of the test is

$$T\left[1+\left(\frac{E_T(f)}{\hat{\sigma}(f)}\right)^2\right]^{-1} \hat{\alpha}' \, \hat{\Sigma}^{-1} \, \hat{\alpha} \sim {\chi_N}^2$$

Where $E_T(f)$ denotes the sample mean of the factor, $\hat{\sigma}(f)$ denotes the sample variance and $\hat{\alpha}$ is a vector of estimated intercepts. $\hat{\Sigma}$ is the residual covariance matrix and T is the number of time periods. The GRS test statistic is then

$$\frac{T-N-1}{N}\left[1+\left(\frac{E_T(f)}{\hat{\sigma}(f)}\right)^2\right]^{-1} \hat{\alpha}' \, \hat{\Sigma}^{-1} \, \hat{\alpha} \sim F_{N,T-N-1}$$

If we are correct in being troubled by the "missing risk" component of high frequency betas, this should show up in two ways. First, the GRS tests of the CAPM should be less anomalous when we use low frequency betas rather than high frequency betas. Second, the explanatory power of the regressions (as measured by the mean R-squared of the portfolio regression tests) should be higher for low frequency betas compared to high frequency betas.

In conducting these tests, we report two sets of results. The first uses the "standard" Fama-French value-weighted portfolios formed using the intersection of size (market capitalisation) and book-to-market. These portfolios are formed from the top 30% of firms by market capitalisation each year. Every year (in September) we take this sample of top 30% of the firms and we independently sort these into 3 book to market groups by using the 30^{th} and 70^{th} percentile of the (BTM) ratio and quintiles by size. The intersection results in fifteen size and book-to-market portfolios. The second set of tests, following the suggestion of Lewellen et al. (2010, p.182), uses value-weighted portfolios formed on the basis of volatility (the standard deviation of returns). Similar to the formation of the size and book- to -market portfolios, using the sample of the top 30% of firms by market capitalisation, every year we sort firms into twelve size groups based on the standard deviation of returns over the previous 12 months.

The UK results based on the size and book-to-market sorts (Table 11) suggest that the CAPM in does surprisingly well in terms of the GRS tests.[17] When tested against the size and book to market portfolios (Table 11) we cannot reject the hypothesis that all the intercepts are jointly insignificant for any of the beta frequency estimates. None of the alphas is significant. Nonetheless, we observe that the mean R-squared falls monotonically as we move from quarterly through monthly through weekly to daily betas. Allowing for differences in return periods, there is also a tendency for intercepts to be closer to zero when low frequency betas are used.[18] However a very different picture emerges when test portfolios are formed on the basis of the standard deviation (Table 12). Whilst we cannot reject the joint significance of the intercepts for any of the frequency estimates, we see evidence that some individual portfolios have significant alphas, and that this propensity increases with the frequency of estimation. For quarterly betas, only one alpha is significant at the 10% level, and none at the 5% level. When betas are estimates monthly, one intercept (the low volatility portfolio) has an alpha that is significantly positive at the 5% level, with a further one being significant at the 10% level. Once we move to weekly and daily frequencies, we observe that two alphas are significant at the 5% level, with a further one being significant at the 10% level. Further, these portfolios are at the extremes, with the low volatility portfolios exhibiting significant positive alphas but the high volatility portfolios exhibiting significant negative alphas. Taken as a whole, these results suggest that the CAPM may be better specified as a risk pricing model when betas are calculated on a low frequency basis.

Conclusion

[17] This is likely to be attributable to the restriction of the model to larger firms - see Gregory, Tharyan and Christidis (2013), and also Fletcher (2010) for a rather more pessimistic analysis of UK asset pricing. Additionally, in unreported tests using Fama-MacBeth regressions we find that the market risk factor is never priced.

[18] Note that the mean alphas reported in the table are, of course, quarterly, monthly, weekly and daily returns respectively so cannot be compared without multiplication.

Whatever views one might have on the suitability of the CAPM, the model is used extensively by regulatory authorities around the world. Consequently, how theses authorities assess beta in such regulatory cases is economically significant on a large scale. As we have shown, there has been a tendency for these regulatory bodies to regard high frequency beta estimates as useful, and indeed in some cases judgements have been made that daily betas are superior to monthly betas. The research question that this paper has addressed is whether there is any validity in the use of high frequency betas. We already know, from Gilbert et al. (2014), that high frequency betas are problematic in the US, and so the focus in this paper has been on assessing whether beta estimates are frequency dependent the UK market where we know the CAPM is in major use by regulatory bodies, and where we know there has been a preference for high frequency estimates over low frequency ones. We also provide a more limited analysis of the Australian market.

We have shown that high frequency betas have significantly lower mean and median values than low frequency (monthly) betas, and that mean high frequency betas are significantly less than unity. We then investigated the cause of these differences. We have shown that these differences can be explained by opacity, size, illiquidity and market to book effects, along with industry effects. Whilst opacity is less important when we explain the difference between weekly betas and low frequency estimates, the other effects remain. These results all apply in our full sample, which by design we limited to just the largest stocks in order to avoid known thin trading problems in small stocks. This decision was also motivated by us noting that typically only larger firms are subject to regulation or market investigations. Nonetheless, in robustness tests we showed that most of these effects remain even when we run tests on sub-samples of the largest stocks and most liquid stocks.

These analyses reveal something very important about high frequency beta estimates. They are systematically lower than beta estimates obtained from low frequency data, and this difference can be explained by factors that are known to be associated with risk: opacity (as measured by abnormal accruals); size; illiquidity, and; BE/ME. Industry effects are also important. The corollary is that high frequency beta estimates do not fully reflect the likely risk characteristics of stocks, and so their use in a CAPM, in preference to a low frequency beta estimate, is likely to under-estimate the cost of equity capital.

We also showed that there is some evidence that intercepts from CAPM portfolio regression tests are somewhat more likely to be significant when high frequency betas are employed, and that the mean R-squareds from these portfolio tests tend to be inversely related to beta frequency. These results are consistent with low frequency betas giving better estimates of the true CAPM beta.

Our findings, therefore, are unequivocal and have important policy implications for regulators and other users of the CAPM. In general, low frequency betas should always be preferred to high frequency betas. If users still wish to use high frequency betas in their analysis, then it is important to check whether those high frequency beta estimates are being biased downwards by opacity, size, illiquidity and BE/ME factors, together with industry effects.

Of course, for much of this paper we have focussed on regulatory activity, simply because the large economic impact of the CAPM beta is directly observable in such activity. But our findings on beta go far beyond this. Most obviously, many academic event studies use estimates of daily betas derived from either a market model or CAPM. Our evidence, together with that from Gilbert et al (2014) would suggest that the use of such estimates is seriously questionable. Based on our analysis, we would call for robustness checks using low frequency beta estimates in such studies (or, alternatively, a simple market adjusted returns model which implicitly assumes beta is unity). Many corporates and investment analysts use beta estimates in their cost of capital model that are often derived from a commercial source rather than estimated. Again, our analysis would encourage the adoption of low frequency beta estimates in such models.

In conclusion, our findings would suggest that on average, a cost of equity estimated using the CAPM and daily or weekly betas is likely to under-estimate the true cost of equity by not properly considering the impact of known risk factors. Besides the importance of this for users of the CAPM in general, this is a result with particularly important policy implications for all utility regulators and competition authorities.

References:

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, *5*(1), 31-56.

Blume, M. (1971). On the assessment of risk, *Journal of Finance*, 26, 1-10.

Blume, M. (1975). Betas and Regression tendencies. *Journal of Finance*, 30, 785-795

Brooks, C., L. Xiafei and J. Miffre (2011), 'Idiosyncratic Risk and the Pricing of Poorly-Diversified Portfolios', Available at SSRN: http://ssrn.com/abstract=1855944

Buckland, R., Williams, J. & Beecher, J. (2015). A cross-country comparison of evidence from the CAPM, *Journal of Regulatory Economics*, 47(2)., pp 117-145

Bradshaw, M. T., Hutton, A. P., Marcus, A. J., & Tehranian, H. (2009). Opaque Financial Reports, R-square, and Crash Risk," *Journal of Financial Economics*, 94, 67-86.

Brown, P., & Walter, T. (2013). The CAPM: theoretical validity, empirical intractability and practical applications. *Abacus*, 49, Supplement , 44-50.

Cai, C. X., Clacher, I. & Keasey, K. (2013). Consequences of the capital asset pricing model (CAPM)—a critical and broad perspective, *Abacus*, Supplement, 49, 51–61.

Chan, H., Chang, X., Faff, R., & Wong, G. (2010). Financial constraints and stock returns—Evidence from Australia. *Pacific-Basin Finance Journal*, *18*(3), 306-318.

Cohen, K., Hawawini, G., Mayer, S., Schwartz, R., & Whitcomb, D. (1980). Implications of microstructure theory for empirical research on stock price behavior. *Journal of Finance*, 35, 249-257.

Dechow, P. M., Hutton, A. P., Kim, J. H., & Sloan, R. G. (2012). Detecting earnings management: A new approach. *Journal of Accounting Research*, *50*(2), 275-334.

Dempsey, M. (2013a). 'The Capital Asset Pricing Model (CAPM): The History of a Failed Revolutionary Idea in Finance?', Abacus, 49, Supplement, pp. 7–23.

Dempsey, M. (2013b). 'The CAPM: A Case of Elegance is for Tailors?', Abacus, 49, Supplement, pp. 82–87.

Dimson, E. (1979). Risk measurement when shares are subject to infrequent trading. *Journal of Financial Economics*, 7(2), 197-226.

Durack, N., Durand, R. B. *&* Maller R. A. *(*2004). A best choice among asset pricing models? The conditional CAPM in Australia, *Accounting and Finance* 44, 139–162.

Fama, E. F., & French, K. R. (1993). Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), 3-56.

Fama, E. F., & French, K. R. (1996). Multifactor explanations of asset pricing anomalies. *The journal of finance*, *51*(1), 55-84.

Fama, E. F., & French, K. R. (2012). Size, Value, and Momentum in International Stock Returns, *Journal of Financial Economics*, 105, 457-472.

Fletcher, J. (2010), 'Arbitrage and the Evaluation of Linear Factor Models in UK Stock Returns' **,** *The Financial Review*, Vol. 45, No.2, pp. 449-468.

Fletcher, J. & J. Kihanda (2005), 'An examination of alternative CAPM-based models in UK stock returns', *Journal of Banking & Finance*, 29, No. 12, pp. 2995-3014

Florackis, C., Gregoriou, A. & Kostakis A. (2011). Trading Frequency and Asset Pricing on the London Stock Exchange: Evidence from a New Price Impact Ratio. *Journal of Banking and Finance*, Vol. 35, 3335-3350.

Gibbons, M. R., Ross, S. A., & Shanken, J. (1989). A test of the efficiency of a given portfolio. *Econometrica: Journal of the Econometric Society*, 1121-1152.

Gilbert, T., Hrdlicka, C., Kalodimos, J., & Siegel, S. (2014). Daily Data is Bad for Beta: Opacity and Frequency-Dependent Betas. *Review of Asset Pricing Studies*, *4*(1), 78-117.

Gow, I.D., Ormazabal, G. & Taylor, D.J. (2010). Correcting for Cross‐Sectional and Time‐Series Dependence in Accounting Research. *The Accounting Review*, 85(2), 483–512.

Gregory, A., Tharyan, R., & Christidis, A. (2013). Constructing and testing alternative versions of the Fama–French and Carhart models in the UK. *Journal of Business Finance & Accounting*, 40(1-2), 172-214.

Handa, P., Kothari, S.P., & Wasley, C. (1989). The relation between the return interval and betas: Implications for the size effect. *Journal of Financial Economics*, 23, 79-100.

Hambrick, D. C., & Abrahamson, E. (1995). Assessing managerial discretion across industries: A multimethod approach. *Academy of Management Journal*, 38(5), 1427-1441.

Jones, J. J. (1991). Earnings management during import relief investigations. *Journal of accounting research*, 193-228.

Levhari, D., & Levy, H. (1977). The capital asset pricing model and the investment horizon, *Review of Economics and Statistics*, 59, 92-104.

Lewellen, J., S. Nagel and J. Shanken (2010), 'A Skeptical Appraisal of Asset-Pricing Tests', *Journal of Financial Economics*, Vol. 96, pp. 175-194.

Manconi, A and Massa, M. Modigliani and Miller Meet Chandler: Organizational Complexity, Capital Structure, and Firm Value (September 1, 2009). Available at SSRN: http://ssrn.com/abstract=1359762

Moosa, I. A. *(*2013). The Capital Asset Pricing Model (CAPM): The History of a Failed Revolutionary Idea in Finance? Comments and Extensions, *Abacus*, 49, Supplement, 62-68.

Mouselli, S., Jaafar, A., & Goddard, J. (2013). Accruals quality, stock returns and asset pricing: Evidence from the UK. *International Review of Financial Analysis*, *30*, 203-213.

Partington, G. (2013). Death Where is Thy Sting? A Response to Dempsey's Despatching of the CAPM, *Abacus*, 49, Supplement, 1–6.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *Review of financial studies*, *22*(1), 435-480.

Scholes, M., & J. Williams (1977). Estimating Betas from Nonsynchronous Data, *Journal of Financial Economics* ,5 ,309-327.

Schrimpf, A., Schroder, M. & Stehle, R. (2007). Cross-sectional tests of conditional asset pricing models: evidence from the German stock market', *European Financial Management*, 13(5), 880–907.

Sloan, R. G. (1996). Do Stock Prices Fully Reflect Information in Accruals and Cash Flows about Future Earnings? *The Accounting Review*, 71, 289-315

Smith, T. & K. Walsh (2013). 'Why the CAPM is Half-right and Everything Else is Wrong', *Abacus*, 49, Supplement, 73–78.

Sudarshanam, S., Kaltenbronn, U. & Park, P. (2011). Cost of Equity for Regulated Companies: An international Comparison of Regulatory Practices, available at : http://webarchive.nationalarchives.gov.uk/20140402141250/http:/www.competition-commission.org.uk/assets/competitioncommission/docs/pdf/non-inquiry/our_role/analysis/cost_of_equity_comparison_of_international_regulatory_practice.pdf last accessed: 01/04/2014

Table 1: Summary beta statistics

UK Betas					
Estimation interval	**No Obs.**	**Mean**	**Std Dev**	**Min**	**Max**
Quarterly	3447	1.028	0.469	-0.586	3.972
Monthly	4355	1.023	0.455	-0.457	3.498
Weekly	4355	0.843	0.443	-0.675	4.075
Daily	4355	0.720	0.425	-0.176	2.657
Qtr-Day	3447	0.286	0.452	-0.758	1.428
Qtr-Wk	3447	0.187	0.472	-1.443	2.561
Mon-Day	4355	0.303	0.460	-0.783	1.492
Mon-Wk	4355	0.180	0.390	-1.975	1.706
Australian Betas					
Estimation interval	**No Obs.**	**Mean**	**Std Dev**	**Min**	**Max**
Monthly	2208	1.028	0.545	-0.558	3.459
Weekly	2208	0.908	0.547	-0.620	5.097
Daily	2208	0.848	0.494	-0.599	3.453
Mon-Day	2208	0.180	0.473	-1.082	1.724
Mon-Wk	2208	0.120	0.467	-2.985	2.137

Note that the sample is based on observations where the extreme percentiles of Monthly/Quarterly β-Daily β have been dropped. N is the number of firm-year observations.

Table 2: Descriptive statistics, UK Monthly vs Daily Sample

Panel A: Means, standard deviations and medians

Variable	Obs	Mean	SD	Median
ΔBeta	4355	0.303	0.460	0.293
size	4355	0.26%	0.64%	0.06%
aaa	4355	0.041	0.048	0.026
RtoTR	4355	1.422	2.633	0.713
TD/ME	4355	0.335	0.489	0.226
BE/ME	4355	0.485	0.437	0.394

Panel B: Correlations:

Variable	ΔBeta	size	aaa	RtoTR	TD/ME	BE/ME
ΔBeta	1.00					
size	-0.29	1.00				
aaa	0.07	-0.09	1.00			
RtoTR	0.19	-0.10	0.07	1.00		
TD/ME	0.04	-0.04	-0.09	-0.01	1.00	
BE/ME	0.08	-0.03	-0.10	-0.02	0.43	1.00

This table shows the summary statistics for the measures of opacity, size and illiquidity, plus control variables. Where *aaa* is the Winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation as a percentage of total market capitalisation, *RtoTR*, is the Winsorised RtoTR illiquidity ratio from Florackis et al. (2011), TD/ME is the gearing ratio calculated as total debt/market value of equity, and BE/ME is the book value of equity to the market value of equity. For a detailed explanation of the measures and precise descriptions of the year end dates used, see text.

Table 3: Descriptive statistics, UK Quarterly vs Daily Sample

Panel A: Means, standard deviations and medians

Variable	No. Obs	Mean	SD	Median
ΔBeta	3447	0.286	0.452	0.271
lagsize	3447	0.28%	0.69%	0.07%
aav	3447	0.037	0.042	0.024
RtoTR	3447	1.294	2.046	0.688
TD/ME	3447	0.346	0.505	0.235
BE/ME	3447	0.492	0.439	0.404

Panel B: Correlations:

Variable	ΔBeta	lagsize	aav	RtoTR	TD/ME	BE/ME
ΔBeta	1.00					
lagsize	-0.29	1.00				
aav	0.07	-0.08	1.00			
RtoTR	0.22	-0.12	0.10	1.00		
TD/ME	0.05	-0.05	-0.05	-0.01	1.00	
BE/ME	0.09	-0.05	-0.05	-0.01	0.43	1.00

This table shows the summary statistics for the measures of opacity, size and illiquidity, plus control variables. Where *aaa* is the Winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation as a percentage of total market capitalisation, *RtoTR*, is the Winsorised RtoTR illiquidity ratio from Florackis et al. (2011), TD/ME is the gearing ratio calculated as total debt/market value of equity, and BE/ME is the book value of equity to the market value of equity. For a detailed explanation of the measures and precise descriptions of the year end dates used, see text.

Table 4: Explaining the difference in Betas – UK Monthly vs Daily betas

Model	Opacity 1	Opacity 2	Full 1	Full 2
aaa	0.628***	0.528***	0.360**	0.361**
	(0.176)	(0.171)	(0.160)	(0.168)
size			-19.12***	-17.67***
			(5.690)	(5.482)
RtoTR			0.0286***	0.0238***
			(0.005)	(0.005)
TD/ME			-0.0134	-0.00738
			(0.027)	(0.030)
BE/ME			0.0868**	0.117***
			(0.037)	(0.036)
_cons	0.278***	0.153**	0.260***	0.165*
	(0.038)	(0.074)	(0.045)	(0.084)
N	4355	4355	4355	4355
R^2	0.004	0.096	0.118	0.181
Industry Dummies?	N	Y	N	Y

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.BE/ME_{it-1} + e.TD/MC_{it-1} + \sum IND_{it} + \epsilon_{it}$$

Opacity 1 includes only the opacity variable, and Opacity 2 includes this plus industry dummies. Similarly Full 1 includes all control variables but no industry dummies, whilst Full 2 includes all control variables plus industry dummies. Δβ is Mβ-Dβ, the difference between monthly and daily betas. Standard errors are clustered by firm and year. Where *aaa* is the Winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation as a percentage of total market capitalisation, *RtoTR*, is the Winsorised RtoTR illiquidity ratio from Florackis et al. (2011), TD/ME is the gearing ratio calculated as total debt/market value of equity, and BE/ME is the book value of equity to the market value of equity. For a detailed explanation of the measures and precise descriptions of the year end dates used, see text. Industry dummies are included where indicated. For a detailed explanation of the measures and industry classification see text. R^2 is the adjusted R-Squared. For each independent variable, we show the coefficient in the first row and standards errors (in parenthesis) in the second row. ***, ** and * denotes the significance at 1%, 5% and 10% respectively.

Table 5: Explaining the difference in Betas – UK Quarterly vs Daily betas

Model	**Opacity 1**	**Opacity 2**	**Full 1**	**Full 2**
aaa	0.692***	0.592***	0.318*	0.310*
	(0.213)	(0.190)	(0.190)	(0.174)
size			-17.23***	-15.70***
			(5.456)	(5.098)
RtoTR			0.0405***	0.0336***
			(0.007)	(0.007)
TD/ME			-0.00129	0.0211
			(0.030)	(0.033)
BE/ME			0.0787**	0.0959**
			(0.040)	(0.037)
_cons	0.260***	0.184**	0.232***	0.198**
	(0.039)	(0.083)	(0.045)	(0.082)
N	3447	3447	3447	3447
R^2	0.004	0.115	0.126	0.200
Industry Dummies?	N	Y	N	Y

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.BE/ME_{it-1} + e.TD/MC_{it-1} + \sum IND_{it} + \epsilon_{it}$$

Opacity 1 includes only the opacity variable, and Opacity 2 includes this plus industry dummies. Similarly Full 1 includes all control variables but no industry dummies, whilst Full 2 includes all control variables plus industry dummies. Δβ is Qβ-Dβ, the difference between quarterly and daily betas. Standard errors are clustered by firm and year. Where *aaa* is the Winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation as a percentage of total market capitalisation, *RtoTR*, is the Winsorised RtoTR illiquidity ratio from Florackis et al. (2011), TD/ME is the gearing ratio calculated as total debt/market value of equity, and BE/ME is the book value of equity to the market value of equity. For a detailed explanation of the measures and precise descriptions of the year end dates used, see text. Industry dummies are included where indicated. For a detailed explanation of the measures and industry classification see text. R^2 is the adjusted R-Squared. For each independent variable, we show the coefficient in the first row and standards errors (in parenthesis) in the second row. ***, ** and * denotes the significance at 1%, 5% and 10% respectively.

Table 6: Explaining the difference in Betas – UK Monthly vs Weekly betas

Model	Opacity 1	Opacity 2	Full 1	Full 2
aaa	0.292**	0.220*	0.119	0.109
	(0.128)	(0.120)	(0.117)	(0.119)
size			-12.04***	-10.65***
			(3.296)	(3.455)
RtoTR			0.0194***	0.0161***
			(0.004)	(0.003)
TD/ME			-0.0201	-0.0209
			(0.020)	(0.021)
BE/ME			0.0493*	0.0692**
			(0.027)	(0.028)
_cons	0.170***	0.0553	0.164***	0.0663
	(0.024)	(0.062)	(0.029)	(0.068)
N	4354	4354	4354	4354
R^2	0.001	0.071	0.072	0.120
Industry Dummies?	N	Y	N	Y

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.BE/ME_{it-1} + e.TD/MC_{it-1} + \sum IND_{it} + \epsilon_{it}$$

Opacity 1 includes only the opacity variable, and Opacity 2 includes this plus industry dummies. Similarly Full 1 includes all control variables but no industry dummies, whilst Full 2 includes all control variables plus industry dummies. Δβ is Mβ-Wβ, the difference between monthly and weekly betas. Standard errors are clustered by firm and year. Where *aaa* is the Winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation as a percentage of total market capitalisation, *RtoTR*, is the Winsorised RtoTR illiquidity ratio from Florackis et al. (2011), TD/ME is the gearing ratio calculated as total debt/market value of equity, and BE/ME is the book value of equity to the market value of equity. For a detailed explanation of the measures and precise descriptions of the year end dates used, see text. Industry dummies are included where indicated. For a detailed explanation of the measures and industry classification see text. R^2 is the adjusted R-Squared. For each independent variable, we show the coefficient in the first row and standards errors (in parenthesis) in the second row. ***, ** and * denotes the significance at 1%, 5% and 10% respectively.

Table 7: Explaining the difference in Betas – UK Monthly vs Daily betas, restricted sample

Model	Opacity 3	Opacity 4	Restrict 1	Restrict 2	Opacity 5	Opacity 6	Restrict 3	Restrict 4
aaa	0.457*	0.514**	0.254	0.371	0.747**	0.651**	0.484*	0.380
	(0.269)	(0.254)	(0.255)	(0.247)	(0.300)	(0.268)	(0.287)	(0.265)
size			-12.92***	-11.96***			-17.04***	-17.20***
			(4.252)	(4.167)			(4.748)	(5.416)
RtoTR			0.0256***	0.0212***			0.353***	0.320***
			(0.008)	(0.007)			(0.098)	(0.094)
TD/ME			0.0361	0.0365			0.0722*	0.0848*
			(0.051)	(0.050)			(0.042)	(0.044)
BE/ME			0.0620	0.105**			0.0663*	0.0756**
			(0.050)	(0.051)			(0.039)	(0.036)
_cons	0.130***	0.0599	0.136***	0.0496	0.166***	0.178***	0.00714	0.0136
	(0.035)	(0.073)	(0.049)	(0.078)	(0.033)	(0.062)	(0.055)	(0.079)
N	2184	2184	2184	2184	2183	2183	2183	2183
R^2	0.002	0.091	0.095	0.155	0.006	0.070	0.136	0.178
Industry Dummies?		Y		Y		Y		Y

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.BE/ME_{it-1} + e.TD/MC_{it-1} + \sum IND_{it} + \epsilon_{it}$$

The first group of models restricts the sample to cases where size is above the median. Opacity 3 includes only the opacity variable, and Opacity 4 includes this plus industry dummies. Similarly Restrict 1 includes all control variables but no industry dummies, whilst Restrict 2 includes all control variables plus industry dummies. The second group of models restricts the sample to cases where liquidity measure is below the median (that is, the most liquid companies). Opacity 5 includes only the opacity variable, and Opacity 6 includes this plus industry dummies. Similarly Restrict 3 includes all control variables but no industry dummies, whilst Restrict 4 includes all control variables plus industry dummies. Δβ is Mβ-Dβ, the difference between monthly and daily betas. Standard errors are clustered by firm and year. Where *aaa* is the Winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation as a percentage of total market capitalisation, *RtoTR*, is the Winsorised RtoTR illiquidity ratio from Florackis et al. (2011), TD/ME is the gearing ratio calculated as total debt/market value of equity, and BE/ME is the book value of equity to the market value of equity. For a detailed explanation of the measures and precise descriptions of the year end dates used, see text. Industry dummies are included where indicated. For a detailed explanation of the measures and industry classification see text. R^2 is the adjusted R-Squared. For each independent variable, we show the coefficient in the first row and standards errors (in parenthesis) in the second row. ***, ** and * denotes the significance at 1%, 5% and 10% respectively.

Table 8: Explaining the difference in Betas – UK Quarterly vs Daily betas, restricted sample

Model	Opacity 3	Opacity 4	Restrict 1	Restrict 2	Opacity 5	Opacity 6	Restrict 3	Restrict 4
aaa	0.628*	0.601*	0.343	0.346	1.100***	0.933***	0.864***	0.678**
	(0.351)	(0.347)	(0.338)	(0.331)	(0.340)	(0.325)	(0.331)	(0.293)
size			-11.36***	-10.80***			-16.52***	-17.23***
			(4.014)	(3.703)			(4.544)	(5.009)
RtoTR			0.0390***	0.0288***			0.341***	0.293***
			(0.011)	(0.010)			(0.118)	(0.112)
TD/ME			0.0565	0.126**			0.0852	0.147***
			(0.065)	(0.059)			(0.052)	(0.046)
BE/ME			0.0252	0.0402			0.0526	0.0462
			(0.055)	(0.050)			(0.042)	(0.035)
_cons	0.103***	0.0811	0.113**	0.0924	0.141***	0.184***	-0.00698	0.0352
	(0.037)	(0.078)	(0.049)	(0.070)	(0.038)	(0.062)	(0.061)	(0.079)
N	1730	1730	1730	1730	1730	1730	1730	1730
R^2	0.003	0.116	0.094	0.182	0.010	0.093	0.132	0.200
Industry Dummies?	N	Y	N	Y	N	Y	N	Y

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.BE/ME_{it-1} + e.TD/MC_{it-1} + \sum IND_{it} + \epsilon_{it}$$

The first group of models restricts the sample to cases where size is above the median. Opacity 3 includes only the opacity variable, and Opacity 4 includes this plus industry dummies. Similarly Restrict 1 includes all control variables but no industry dummies, whilst Restrict 2 includes all control variables plus industry dummies. The second group of models restricts the sample to cases where liquidity measure is below the median (that is, the most liquid companies). Opacity 5 includes only the opacity variable, and Opacity 6 includes this plus industry dummies. Similarly Restrict 3 includes all control variables but no industry dummies, whilst Restrict 4 includes all control variables plus industry dummies. Δβ is Qβ-Dβ, the difference between quarterly and daily betas. Standard errors are clustered by firm and year. Where *aaa* is the Winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation as a percentage of total market capitalisation, *RtoTR*, is the Winsorised RtoTR illiquidity ratio from Florackis et al. (2011), TD/ME is the gearing ratio calculated as total debt/market value of equity, and BE/ME is the book value of equity to the market value of equity. For a detailed explanation of the measures and precise descriptions of the year end dates used, see text. Industry dummies are included where indicated. For a detailed explanation of the measures and industry classification see text. R^2 is the adjusted R-Squared. For each independent variable, we show the coefficient in the first row and standards errors (in parenthesis) in the second row. ***, ** and * denotes the significance at 1%, 5% and 10% respectively.

Table 9: Explaining the difference in Betas – UK Monthly vs Weekly betas, restricted sample

Model	Opacity 3	Opacity 4	Restrict 1	Restrict 2	Opacity 5	Opacity 6	Restrict 3	Restrict 4
aaa	0.218	0.258	0.149	0.187	0.272	0.238	0.135	0.0773
	(0.217)	(0.195)	(0.190)	(0.180)	(0.226)	(0.197)	(0.218)	(0.197)
size			-8.213***	-7.643***			-10.22***	-10.67***
			(2.479)	(2.672)			(2.444)	(3.012)
RtoTR			0.0146**	0.0120**			0.161*	0.151*
			(0.006)	(0.006)			(0.093)	(0.087)
TD/ME			0.0390	0.0456			0.0213	0.0261
			(0.037)	(0.039)			(0.036)	(0.037)
BE/ME			0.0506	0.0693*			0.0500*	0.0486*
			(0.035)	(0.042)			(0.026)	(0.027)
_cons	0.0764***	0.00611	0.0692**	-0.0144	0.105***	0.111*	0.0368	0.0448
	(0.024)	(0.067)	(0.031)	(0.070)	(0.023)	(0.057)	(0.046)	(0.073)
N	2183	2183	2183	2183	2182	2182	2182	2182
R^2	0.001	0.063	0.060	0.104	0.001	0.054	0.063	0.105
Industry Dummies?	N	Y	N	Y	N	Y	N	Y

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.BE/ME_{it-1} + e.TD/MC_{it-1} + \sum IND_{it} + \epsilon_{it}$$

The first group of models restricts the sample to cases where size is above the median. Opacity 3 includes only the opacity variable, and Opacity 4 includes this plus industry dummies. Similarly Restrict 1 includes all control variables but no industry dummies, whilst Restrict 2 includes all control variables plus industry dummies. The second group of models restricts the sample to cases where liquidity measure is below the median (that is, the most liquid companies). Opacity 5 includes only the opacity variable, and Opacity 6 includes this plus industry dummies. Similarly Restrict 3 includes all control variables but no industry dummies, whilst Restrict 4 includes all control variables plus industry dummies. Δβ is Mβ-Wβ, the difference between monthy and weekly betas. Standard errors are clustered by firm and year. Where *aaa* is the Winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation as a percentage of total market capitalisation, *RtoTR*, is the Winsorised RtoTR illiquidity ratio from Florackis et al. (2011), TD/ME is the gearing ratio calculated as total debt/market value of equity, and BE/ME is the book value of equity to the market value of equity. For a detailed explanation of the measures and precise descriptions of the year end dates used, see text. Industry dummies are included where indicated. For a detailed explanation of the measures and industry classification see text. R^2 is the adjusted R-Squared. For each independent variable, we show the coefficient in the first row and standards errors (in parenthesis) in the second row. ***, ** and * denotes the significance at 1%, 5% and 10% respectively.

Table 10: Explaining the difference in Betas – Australian Monthly vs Daily betas

Model	**Full 1**	**Full 2**
aaa	0.00151	-0.0520
	(0.191)	(0.192)
size	-7.614***	-8.156***
	(2.145)	(2.244)
RtoTR	0.0003*	0.0003
	(0.000)	(0.000)
TD/ME	-0.00003*	-0.00003*
	(0.000)	(0.000)
BE/ME	0.0000660	0.0000568
	(0.000)	(0.000)
_cons	0.186***	0.242***
	(0.038)	(0.065)
N	2207	2207
R^2	0.040	0.067
Industry Dummies?	N	Y

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.BE/ME_{it-1} + e.TD/MC_{it-1} + \sum IND_{it} + \epsilon_{it}$$

Full 1 includes all control variables but no industry dummies, whilst Full 2 includes all control variables plus industry dummies. Δβ is Mβ-Dβ, the difference between monthly and daily betas. Standard errors are clustered by firm and year. Where *aaa* is the Winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation as a percentage of total market capitalisation, *RtoTR*, is the Winsorised RtoTR illiquidity ratio from Florackis et al. (2011), TD/ME is the gearing ratio calculated as total debt/market value of equity, and BE/ME is the book value of equity to the market value of equity. For a detailed explanation of the measures and precise descriptions of the year end dates used, see text. Industry dummies are included where indicated. For a detailed explanation of the measures and industry classification see text. R^2 is the adjusted R-Squared. For each independent variable, we show the coefficient in the first row and standards errors (in parenthesis) in the second row. ***, ** and * denotes the significance at 1%, 5% and 10% respectivel

Table 11: GRS Tests – UK Based on size and book-to-market test portfolios

FF3F	Quarterly		Monthly		Weekly		Daily	
	α	t	α	t	α	t	α	t
SL	-0.20%	-0.26	-0.04%	-0.16	-0.01%	-0.15	0.00%	0.14
S2	0.06%	0.09	0.04%	0.18	0.01%	0.3	0.01%	0.60
SH	0.08%	0.09	0.09%	0.34	0.03%	0.52	0.01%	0.59
S2L	-0.17%	-0.18	-0.02%	-0.07	0.01%	0.19	0.01%	0.51
S22	0.60%	0.87	0.18%	0.91	0.05%	1.19	0.01%	1.45
S2H	0.40%	0.46	0.11%	0.44	0.04%	0.64	0.01%	0.71
M3L	-0.33%	-0.43	-0.09%	-0.35	-0.02%	-0.42	-0.00%	-0.20
M32	0.18%	0.33	0.07%	0.37	0.03%	0.62	0.01%	0.85
M3H	0.71%	0.85	0.21%	0.90	0.06%	1.05	0.01%	1.23
B4L	0.40%	0.50	0.14%	0.62	0.03%	0.57	0.01%	0.71
B42	0.59%	1.13	0.19%	1.18	0.05%	1.19	0.01%	1.40
B4H	0.15%	0.19	0.01%	0.06	0.01%	0.22	0.00%	0.17
BL	0.59%	1.41	0.21%	1.48	0.04%	1.09	0.01%	1.08
B2	0.03%	0.08	-0.00%	-0.02	0.00%	0	-0.00%	-0.06
BH	0.64%	1.00	0.18%	0.93	0.04%	0.91	0.01%	0.81
GRS	0.9385		0.7074		0.6434		0.6777	
p-val	0.5260		0.7767		0.8403		0.8090	
meanR2	0.5963		0.5840		0.5437		0.5142	
meancon	0.0025		0.0009		0.0003		0.0001	
meanabscon	0.0034		0.0011		0.0003		0.0001	
meanse	0.0070		0.0021		0.0005		0.0001	
p<=0.1	0		0		0		0	
p<=.05	0		0		0		0	

This table reports the results of the time series regression test (GRS test) of the value-weighted returns of 15 (5×3) intersecting size and book-to-market (BTM) portfolios on the asset pricing model (CAPM) at different frequencies (quarterly, monthly, weekly and daily). For test portfolios SL-BH, the first character denotes size, the second the BTM category. For the GRS test of Gibbons, Ross and Shanken (1989), we run time series regression of the form $R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt}\text{-}R_{ft}) + \varepsilon_{it}$ where R_{it} is the return on the test portfolio, R_{ft} is the risk-free rate, R_{mt} is the return on the market portfolio. We test for the rejection of the null hypothesis that all the intercept terms are jointly zero using the GRS test. The table reports the α (the intercept) and its associated t-statistic for the individual portfolios. GRS is the GRS test statistic, p-val. is its p-value, mean R2 is the mean adjusted R-squared from the regressions, meancon is the mean α, meanabscon is the mean absolute α, meanse is the mean standard error of the α, p <= 0.05 is the number of intercept terms that are significant at the 5% level, and $p <= 0.1$ is the number of intercept terms that are significant at the 10% level. $***$, $**$ and $*$ denotes the significance at 1%, 5% and 10% significance levels respectively. The time period is from the beginning of Octorber1988 to the end of September 2013.

Table 12: GRS Tests – UK Based on Standard Deviation test portfolios

FF3F	Quarterly		Monthly		Weekly		Daily	
	α	t	α	t	α	t	α	t
SD1	0.65%	1.43	0.45%***	2.83	0.08%**	2.18	0.01%*	1.80
SD2	0.45%	0.92	0.30%*	1.88	0.07%*	1.77	0.02%***	2.64
SD3	1.16%*	1.88	0.12%	0.65	0.00%	-0.01	0.01%	1.11
SD4	0.60%	1.27	0.18%	1.14	0.03%	0.73	0.01%	0.68
SD5	0.50%	0.88	-0.19%	-1.11	0.03%	0.59	0.01%	0.90
SD6	-0.04%	-0.09	0.04%	0.23	0.04%	0.87	0.01%	0.74
SD7	-0.49%	-1.12	-0.10%	-0.51	0.04%	0.85	0.01%	0.68
SD8	0.11%	0.17	0.14%	0.71	0.03%	0.59	0.01%	1.34
SD9	0.08%	0.12	0.17%	0.77	0.02%	0.43	0.01%	0.83
SD10	0.22%	0.37	-0.32%	-1.41	-0.05%	-0.75	0.00%	0.36
SD11	-0.60%	-0.87	-0.42%	-1.55	0.00%	0.04	-0.00%	-0.30
SD12	-0.94%	-0.80	-0.25%	-0.73	-0.20%**	-2.54	-0.03%**	-2.36
GRS	1.2195		1.3862		1.2043		1.4608	
p-val	0.2830		0.1715		0.2743		0.1311	
meanR2	0.6421		0.6063		0.5685		0.5839	
meancon	0.0014		0.0001		0.0001		0.0000	
meanabscon	0.0049		0.0022		0.0005		0.0001	
meanse	0.0060		0.0020		0.0005		0.0001	
p<=0.1	1		2		3		3	
p<=.05	0		1		2		2	

This table reports the results of the time series regression test (GRS test) of the value-weighted returns of 12 standard deviation portfolios on the asset pricing model (CAPM) at different frequencies (quarterly, monthly, weekly and daily). For test portfolios SD1-SD12, the first character denotes standard deviation. For the GRS test of Gibbons, Ross and Shanken (1989), we run time series regression of the form $R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt}-R_{ft}) + \varepsilon_{it}$ where Rit is the return on the test portfolio, Rft is the risk-free rate, Rmt is the return on the market portfolio. We test for the rejection of the null hypothesis that all the intercept terms are jointly zero using the GRS test. The table reports the α (the intercept) and its associated t-statistic for the individual portfolios. GRS is the GRS test statistic, p-val. is its p-value, mean R2 is the mean adjusted R-squared from the regressions, meancon is the mean α, meanabscon is the mean absolute α, meanse is the mean standard error of the α, p <= 0.05 is the number of intercept terms that are significant at the 5% level, and p <= 0.1 is the number of intercept terms that are significant at the 10% level. ∗∗∗, ∗∗ and ∗ denotes the significance at 1%, 5% and 10% significance levels respectively. The time period is from the beginning of Octorber1988 to the end of September 2013.

Appendix Table A1. Industry definitions

Mnemonic	Datastream description	UK category	Australian category
MEDIA	Media	MEDIA	MEDIA
RTAIL	Retail	RTAIL	RTAIL
CHMCL	Chemicals	CHMCL	CHMCL
CNSTM	Construct. & Material	CNSTM	CNSTM
UTILS	Utilities	UTILS	UTILS
INSUN	Insurance	**FINSV**	**FINSV**
FINSV	Financial Services	FINSV	FINSV
PERHH	Personal & Household Goods	PERHH	PERHH
FDBEV	Food & Beverage	FDBEV	FDBEV
INDGS	Ind. Goods & Services	INDGS	INDGS
BRESR	Basic Resources	BRESR	BRESR
BANKS	Banks	**FINSV**	**FINSV**
AUTOP	Automobiles & Parts	**PERHH**	**PERHH**
TELCM	Telecommunications	TELCM	**TECNO**
HLTHC	Healthcare	HLTHC	HLTHC
TECNO	Technology	TECNO	TECNO
OILGS	Oil & Gas	OILGS	OILGS
TRLES	Travel & Leisure	TRLES	**PERHH**
RLEST	Real Estate	RLEST	RLEST

This table shows the basic Datastream Level 3 industry classifications. Merged groupings (needed to give a reasonable number of observations in each industry for the purpose of calculating the Modified Jones (1991) measure (see text for a full explanation) are shown in **bold**. For example, for the UK Insurance and Banks have been merged into Financial Services.