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 typically vary depending on frequency of the returns data used. However, there is little evidence on how estimates of beta depend on the return frequency used in their estimation and in particular, their relationship to any firm characteristics. This study examines the evidence for Australia, Germany and the UK and broadly shows that longer frequency betas have superior characteristics for regulatory purposes in these countries. We find that differences in beta can be explained by size and liquidity 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.

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".

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 remarkably little attention has been paid to the impact of the choice of the frequency distribution of returns used in estimating beta. In particular, there is a dearth of evidence relating to markets outside the US. 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. A 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 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"[1], 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."[2] 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.[3] 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 Competition and Markets Authority, 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).[4]

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

[1] Private Healthcare Market Provisional Findings Report, August 2014, Appendix 6.14, paragraph 31.
[2] Northern Ireland Electricity Ltd price determination, Final Determination, March 2014.
[3] 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

[4] See https://assets.digital.cabinet-office.gov.uk/media/539b1d28ed915d106c000010/PDL_PFs_Appendices_and_Glossary.pdf Appendix 4.5 paragraphs 111-113.

UK; and the USA.[5] The CAPM is used as the primary model for estimating the cost of equity by the AER in Australia, the principal regulators and the Competition Commission (and its successor body, the Competition and Markets Authority) 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 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.[6] 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 those 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

[5] 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

[6] 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

implies an interest in the analysis of beta well beyond NZ. Accordingly, we limit our analysis in this paper to CAPM betas in Australia, Germany and the UK.

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 main tests are conducted on portfolios formed on the basis of size and book-to-market, but we also run robustness tests using portfolios formed on size alone.

Our findings provide some support for the US-based conclusions of Gilbert et al. (2014), that low frequency betas are superior to high frequency betas, but we find little support for their finding that the differences between high and low frequency betas can be explained by proxies for firm opacity in any of our three countries. Instead, we find that the differences are due to measures of size and liquidity, and that opacity becomes insignificant once size and liquidity are taken into consideration. Whilst in part, this may be due to the fact that we confine ourselves to a sample of larger firms, (as these are likely to be of most interest to regulators) we note that Gilbert et al. (2014) state "our results extend beyond small firms and illiquid stocks. We obtain similar results for large firms and liquid stocks, including firms with an equity market capitalization above $1 billion. Some further support for the use of low frequency (monthly) 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 have a preference for monthly 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. Because of limitations on the length of time series of returns in some of our countries, we are not able to systematically investigate the use of quarterly betas (as in Gilbert et al., 2014), but our analysis is not indicative of any general problem with the use of monthly betas.

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 one of our countries (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 in each of UK, Australia and Germany.

All our estimates use the longest common data period available, so that our regression estimates start in 1984 for monthly data. However, the actual month within 1984 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[7], we follow Gregory et al. (2013) and use end-September portfolio formation dates for UK firms. For Germany, where the fiscal year end is 31st December, we follow Fama and French (1996, 2013) and use end-June formation dates. Finally, 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. As the low frequency beta estimates require 60 monthly observations, and our data start in 1984, our first available beta estimates can be formed in 1989, September in the

[7] This oddity is associated with the fact that the fiscal year end in the UK is 5th April.

case of the UK, June in the case of Germany and December in the case of Australia. Our final year for estimation is 2013. In order to maintain the inter-temporal consistency of the beta estimates, our monthly betas use 60 months of data, ending at the above dates in 1989 to 2013, our weekly beta estimates use 104 weeks of data ending on the 40th week (UK), 52nd week (Australia) and 26th week (Germany), and the daily estimates use 250 trading days of data ending at these dates. These calculations are then repeated each year such that we have estimates of monthly, weekly and daily betas from 1989 to 2013. 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 Germany and Australia. Note, however, that 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.

Our market indices are the total returns on the All-Share Index for the UK, and on the CDAX General 'Performance' Index (DS code CDAXGEN) for Germany. For Australia, there is a problem in identifying a total returns index (as opposed to a price index), and so we 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, the Dealer 90-Day Bill rate (DS code ADBR090) for Australia, and the BD EU-Mark 3 Month Deposit Middle Rate (DS code ECWGM3M) for Germany.

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, with Panel A showing the differences in Monthly and Daily betas, and Panel B showing the difference in Monthly and Weekly betas.

We then investigate whether these beta differences can be explained by size, liquidity and opacity. For size, we use the log of the lagged market capitalisation (*size*). For liquidity we use 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), December (Germany) 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 (Australian $, Euro or £ Sterling) 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) our third measure of liquidity is the trading volume per year per share outstanding (*turnover*), which, in common with the *RtoTR* measure, we winsorise at the 1% level..

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.[8] 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).

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

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.

The absolute value of discretionary (abnormal) accrual is then calculated as the absolute value of the remaining portion of the total current accruals[9].

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

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

Gilbert et al. (2014) 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 simply use DS Level 3 industry dummy variables (modified as described above) in our analysis.

Results

Descriptive statistics

The first thing we note, from Table 1, is that for each of our countries, beta is highest when calculated on a monthly basis. As might be expected, on this basis the mean beta is not

[9] 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.

significantly different from unity for either Australia or the UK, although this is not true for Germany where the mean beta is only around 0.75. Further inspection of the results shows that weekly betas are always higher than daily betas (although we do not formally test this difference). The differences between monthly and daily betas are large and significant for all countries. Indeed, the daily betas are alarmingly low, and inspection of the 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 or monthly 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 each country, and once again the differences between monthly and weekly betas are significant.

Summary statistics for the size, liquidity and opacity proxies are reported in Table 2. Note that there is a slight variation in the number of observations reported in Table 1 and Table 2. This is because missing data for some of our variables means that we cannot obtain estimates for every firm-year observation. These missing data are mainly stock turnover and accounting data needed to estimate abnormal accruals. For space reasons, we do not report full correlation tables[10] for each country and frequency, but we note that the highest absolute correlation between the independent variables is -0.29 between *RtoTR* and *turnover* for the UK sample. 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. We further note that in all cases, the correlation of size and turnover with the difference in betas is negative and that of *RtoTR* and Amihud measure with difference in betas is positive.

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:

[10] Note that at present these can be found in Appendix A3, though in the final version of the paper these could be restricted to a web-based appendix.

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.turnover_{it-1} + \sum IND_{it} + \in_{it}$$

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 for a detailed description). In the first column of each table we run the "full" model described by the above, whilst the second column report the results from this model excluding the industry dummies. The third column includes just the opacity variable, together with industry dummies, whilst columns four to six individually add alternate measures of liquidity (size, the *RtoTR* illiquidity measure and turnover), again including the industry dummies. The final two columns, in the spirit of Gilbert et al. (2014), are regression tests on a sample restricted to only those firms that have a market capitalisation above the median market capitalisation for the year. Once again we run two versions of the full model, the first (in column one) includes industry dummies whilst the second (in column two) does not. 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. We also run the full model without industry dummies.

We start with the Australian results in Table 3, with Panel A showing the monthly vs daily results, and Panel B the monthly vs weekly results. For the full model in Panel A, we see that the opacity measure, *aaa*, although positive as Gilbert et al. (2014) predict, is insignificant in explaining the difference between monthly and daily betas. In column two, where we run the model without industry dummies as in Gilbert et al. (2014) the result of an insignificant *aaa* persists. Further, the effect is also not found in the regressions that are restricted to larger stocks (columns 7 and 8). Size always has a significant negative relationship with the difference, the *RtoTR* illiquidity measure is weakly significant, but turnover is subsumed by other variables in the full model. Of the industry dummies, two of the industries have an impact on beta that is significant at the 5% level or less, whilst a further one is significant at the 10% level.[11] Turning to the monthly vs weekly difference regressions in Table 3, Panel B, we observe similar relationships as in Panel A, with no evidence of any significant relationship between opacity and beta difference. *RtoTR* is still weakly significant and turnover is still subsumed by other variables in the full model. These results also hold in the

[11] Appendix Table A2 shows the coefficients on the Industry dummy variables.

restricted regressions. Surprisingly, industry effects virtually disappear in these regressions, with only one industry dummy being significant at 5% percent level. Therefore in the case of Australia, size and to a lesser degree *RtoTR* are significant determinants of the beta differences.

The results for Germany are reported in Table 4. Panel A reports the monthly vs daily difference regressions. Size is clearly important in explaining the difference, as is *RtoTR* and turnover. We see that twelve out of the thirteen[12] industry dummies are significant at the 1% level. Illiquidity effects remain even with industry dummies and the size effect is stronger with industry dummies. Opacity effects are insignificant in all of the regressions. In the restricted regressions, only *RtoTR* is significant.

For the monthly vs weekly regressions (Table 4, Panel B), we find broadly similar effects. In the full model with industry dummies, both size and illiquidity variables are significant at least at the 5% level. In these weekly regressions, all thirteen industry dummies are significant at the 10% level. For Germany, therefore size and illiquidity measures are important in explaining the differences in betas.

In Table 5 we report the results for the UK. The monthly vs daily regressions in Panel A show that size is the most important determinant of beta difference. The *RtoTR* illiquidity measure is important only when industry dummies are not included or for a size restricted sample. The opacity measure is of no importance in any of the regressions, except when used on its own, when the opacity variable, *aaa*, has the sign predicted by Gilbert et al (2014). Industry differences appear to be of limited importance, with only three industries being significant at least at the 5% level, and further three industries being significant at the 10% level. The restricted regression tests confirm these results, with an increase in the significance of the *RtoTR* variable.

The monthly vs weekly results in Panel B confirm these results, with stronger significance on the RtoTR variable. Two of the industry dummies are now significant at the 1% level, whilst a further two are significant at least at the 10% level. Taken as a whole, the UK results produce strong evidence that beta differences are driven by size and illiquidity effects.

[12] Construction & Materials being the insignificant industry.

To sum up the international evidence, albeit limited to UK, Australia and Germany, we find no substantial support for the Gilbert et al. (2014) result that opacity positively explains beta differences for the samples we consider. This result holds even when we run the full model without industry dummies. We observe remarkably little consistency in the importance industry dummies have in explaining beta differences across the three countries. What *is* highlighted by our results is the importance of size and illiquidity, although the relative importance varies across the countries. Even though we deliberately limit our analysis to larger firms, so eliminating any thin trading problems, it seems that size and/or liquidity measures are important in explaining the large observed differences between high and low frequency betas. The implications of this are clear. If we are able to explain large and systematic differences between high and low frequency betas, it implies that high frequency betas are not capturing some potentially important aspects of risk. In this conclusion, we concur with Gilbert et al. (2014). Where we differ is in what factors are important in explaining the difference and the relative importance of these factors in different markets.

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 December for AU, June for GER and September for UK) we take this sample of top 30% of the firms and we independently sort these into 3 book to market groups by using the 30th and 70th 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 uses value-weighted portfolios formed on the basis of size only. 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 by market capitalisation.

These results are reported for Australia, Germany and the UK in Tables 6-8 respectively, with Panel A reporting the size and book to market results, whilst Panel B reports the size-based results.

The Australian results, in Table 6, show that the model fails the GRS test (i.e. we can reject the hypothesis that the intercepts are jointly zero) for every specification of the CAPM. In short, the CAPM can be comprehensively rejected as a suitable asset pricing model for Australia. However, to the extent that any estimate of beta is preferred, it appears that monthly beta estimates result in marginally lower numbers of intercept terms being significant at the 5% level and higher mean R-squareds.

The German results (Table 7) provide somewhat more comfort for the CAPM, although strictly we can reject the model at the 10% level when size and book-to-market portfolios are employed as the test portfolios. Within the German data, it appears that the number of alphas that are significant tends to increase as we increase the frequency of beta measurement, with the effect being most pronounced at daily frequency. Further, the R-squared decrease with increasing frequency of beta measurement.

The UK results (Table 8) suggest that the CAPM in general does surprisingly well in terms of the GRS tests.[13] When tested against the size and book to market portfolios (Table 8, Panel A) we cannot reject the hypothesis that all the intercepts are jointly insignificant. The same is true for the size portfolios (Table 8, Panel B). Indeed, only in the Panel B results do we see evidence that some individual portfolios have significant alphas, with the daily beta tests having one alpha that is significant at the 5% level and another that is significant at the 10% level. However, in both panels we observe that the mean R-squared falls monotonically as we move from monthly through weekly to daily betas. To sum up the GRS test results, the performance of the CAPM varies across markets. However, there is a consistent tendency for mean R-squareds to be higher for low frequency betas, and for the intercepts to be closer to zero when low frequency betas are used.

Conclusion

Whatever views one might have on the suitability of the CAPM, the model is used extensively by regulatory authorities around the world. Consequently, how they 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 in three markets where we know the CAPM is in major use by regulatory bodies: Australia; Germany; and the UK.

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. Unlike the US position, we showed that in the main these differences cannot be explained by proxies for opacity, but instead are attributable to size and/or illiquidity measures. It is important to stress that this is the case even in the context of a universe of stocks limited to larger firms. We also showed that there is some evidence (though it is not uniform across countries) that intercepts from

[13] 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. Note also that we do not carry out any tests to see if the market factor is priced as the CAPM predicts.

CAPM portfolio regression tests are more likely to be significant when high frequency betas are employed. Finally, we showed that the mean R-squareds from these portfolio tests are inversely related to beta frequency.

Our conclusions, 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 size and illiquidity factors. Further, they should consider what the impact of such factors might be on the cost of equity.

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Table 1 Descriptive statistics for beta

Panel A. Monthly vs Daily Betas

Variable	N	Mean	SD	P25	Median	P75	Min	Max
Australia								
Mβ	2203	1.0175	0.5416	0.6555	0.9559	1.3111	-0.5576	3.5112
Dβ	2203	0.8275	0.4815	0.4880	0.7822	1.1088	-0.5994	3.4533
Mβ-Dβ	2203	0.1900	0.4778	-0.1232	0.1556	0.4745	-1.0794	1.8287
Germany								
Mβ	1708	0.7562	0.4817	0.4043	0.7264	1.0766	-0.6753	2.8232
Dβ	1708	0.6363	0.4213	0.2948	0.6293	0.9342	-0.2146	2.2491
Mβ-Dβ	1708	0.1199	0.4698	-0.1725	0.1020	0.4177	-1.1995	1.4943
UK								
Mβ	4892	0.9983	0.4488	0.7126	0.9831	1.2367	-0.5848	3.4642
Dβ	4892	0.6826	0.4248	0.3452	0.6437	0.9493	-0.1785	2.7669
Mβ-Dβ	4892	0.3156	0.4468	0.0004	0.3154	0.6237	-0.7907	1.5020

This table reports the summary statistics for the Monthly and Daily betas and the difference between them. Mβ is the monthly beta, Dβ is the daily beta, both are calculated as described in the text. Mβ-Dβ is the difference between monthly and daily betas. Note that the sample is based on observations where the extreme percentiles of Mβ-Dβ have been dropped. N is the number of firm-year observations. P25 and P75 are the 25th and the 75th percentile values respectively.

Table 1 (continued) Descriptive statistics for beta

Panel B. Monthly vs Weekly Betas

Variable	N	Mean	SD	P25	Median	P75	Min	Max
Australia								
Mβ	2203	1.0184	0.5477	0.6511	0.9545	1.3111	-0.5576	3.5112
Wβ	2203	0.8846	0.5169	0.5138	0.8122	1.1875	-0.4460	3.2987
Mβ-Wβ	2203	0.1337	0.4517	-0.1544	0.1058	0.3846	-1.1644	1.7074
Germany								
Mβ	1708	0.7572	0.4811	0.4069	0.7264	1.0766	-0.6753	2.8232
Wβ	1708	0.7031	0.4302	0.3792	0.7048	1.0131	-0.2460	2.1652
Mβ-Wβ	1708	0.0541	0.4672	-0.2189	0.0415	0.3142	-1.3087	1.4684
UK								
Mβ	4892	1.0001	0.4551	0.7115	0.9822	1.2378	-0.5848	3.5875
Wβ	4892	0.8089	0.4343	0.5124	0.7723	1.0717	-0.6394	4.0755
Mβ-Wβ	4892	0.1912	0.3663	-0.0538	0.1844	0.4325	-0.8088	1.2369

This table reports the summary statistics for the monthly and weekly betas and the difference between them. Mβ is the monthly beta, Wβ is the weekly beta, both are calculated as described in the text. Mβ-Wβ is the difference between monthly and weekly betas. Note that the sample is based on observations where the extreme percentiles of Mβ-wβ have been dropped. N is the number of firm-year observations. P25 and P75 are the 25th and the 75th percentile values respectively.

Table 2. Descriptive statistics for the size, liquidity and opacity variables

Panel A. Monthly vs Daily sample

Variable	N	mean	p25	p50	p75	min	max	sd	skewness	kurtosis
Australia										
aaa	2203	0.0537	0.0101	0.0263	0.0639	0.0000	0.4673	0.0750	2.9861	13.9267
size	2203	3662.4730	459.9800	1100.0100	3092.2100	19.5300	151862.6000	9675.8340	8.1386	93.4170
turnover	2192	0.6555	0.2490	0.5301	0.9108	0.0008	3.0492	0.5486	1.6449	6.6941
amihud	2193	0.5551	0.0024	0.0165	0.1806	0.0001	14.0527	1.8953	5.4592	35.3896
rtotr	2193	22.7600	0.5637	1.3465	5.7702	0.1478	705.7357	91.3900	6.1597	42.5803
Germany										
aaa	1708	0.0586	0.0096	0.0250	0.0575	0.0000	0.8412	0.1177	4.8731	29.4863
size	1708	5378.4260	398.0000	1093.1700	3547.8600	34.9300	95043.6300	11670.1400	3.6945	18.7833
turnover	1527	0.0501	0.0068	0.0210	0.0586	0.0000	0.4351	0.0767	2.9140	12.5547
amihud	1575	1.8250	0.0557	0.2643	1.4468	0.0011	26.6102	4.0798	3.9074	20.4420
wrtotr	1575	162.3769	12.0386	37.6571	139.4775	1.1979	2365.9440	340.4192	4.0685	22.4276
UK										
aaa	4892	0.0423	0.0110	0.0270	0.0536	0.0000	0.2767	0.0486	2.4349	10.1167
size	4892	3016.0530	272.5865	634.8755	1890.3630	28.0000	141361.7000	9341.8820	7.5907	75.7364
turnover	4049	0.9811	0.4931	0.7894	1.2434	0.0000	3.8840	0.7178	1.6520	6.1515
amihud	4258	0.0544	0.0019	0.0090	0.0452	0.0001	0.9975	0.1335	5.0033	32.0265
rtotr	4244	1.5296	0.3975	0.7077	1.4810	0.1021	26.5347	3.1404	6.1181	45.5407

This table shows the summary statistics for the measures of opacity, size and illiquidity. *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011). For a detailed explanation of the measures and precise descriptions of the year end dates used for each country, see text.

Table 2 (Continued). Descriptive statistics for the size, liquidity and opacity variables

Panel B: Monthly vs Weekly sample

Variable	N	mean	p25	p50	p75	min	max	sd	skewness	kurtosis
Australia										
aaa	2203	0.0537	0.0101	0.0266	0.0638	0.0000	0.4673	0.0752	3.0337	14.3239
lagsize	2203	3683.0980	459.9800	1094.8100	3092.2100	19.5300	151862.6000	9717.6700	8.0593	91.8660
turnover	2192	0.6542	0.2499	0.5338	0.9117	0.0008	3.0492	0.5437	1.6188	6.6095
amihud	2193	0.5585	0.0024	0.0165	0.1700	0.0001	14.0527	1.9115	5.4261	34.8696
rtotr	2193	22.9673	0.5637	1.3456	5.7313	0.1478	705.7357	92.2368	6.1037	41.7445
Germany										
aaa	1708	0.0591	0.0096	0.0250	0.0577	0.0000	0.8412	0.1192	4.8441	29.0324
lagsize	1708	5392.3470	400.0350	1085.5050	3588.7950	34.9300	95043.6300	11671.8700	3.6894	18.7546
turnover	1530	0.0500	0.0067	0.0208	0.0579	0.0000	0.4351	0.0766	2.9146	12.5699
amihud	1577	1.8309	0.0557	0.2715	1.4486	0.0011	26.6102	4.0783	3.9032	20.4231
rtotr	1577	166.3157	12.1592	38.0782	140.3211	1.1979	2365.9440	350.4795	4.0342	21.8411
UK										
aaa	4892	0.0423	0.0109	0.0270	0.0536	0.0000	0.2767	0.0487	2.4375	10.1128
lagsize	4892	3037.6260	273.0000	634.1940	1899.0000	28.0000	155403.1000	9546.9560	7.8762	82.2335
turnover	4049	0.9817	0.4956	0.7891	1.2430	0.0000	3.8840	0.7167	1.6482	6.1227
amihud	4256	0.0538	0.0018	0.0089	0.0444	0.0001	0.9975	0.1321	5.0469	32.6576
rtotr	4242	1.5209	0.3963	0.7049	1.4792	0.1021	26.5347	3.1102	6.1571	46.2799

This table shows the summary statistics for the measures of opacity, size and illiquidity. *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011). For a detailed explanation of the measures and precise descriptions of the year end dates used for each country, see text.

Table 3: Explaining the difference in Betas – Australia

Panel A. Monthly Beta – Daily Beta as Dependent Variable

Mβ-Dβ	full1	full2	opacity	size	rtotr	turnover	sizerestrict1	sizerestrict2
aaa	0.0295	0.0458	0.1220	0.0497	0.1077	0.1385	0.1499	0.1545
	(0.1874)	(0.1945)	(0.1994)	(0.1907)	(0.1941)	(0.1984)	(0.2097)	(0.1951)
lagsize	-0.0912***	-0.0904***		-0.0903***			-0.0904***	-0.0898***
	(0.0129)	(0.0124)		(0.0124)			(0.0162)	(0.0152)
rtotr	0.0002*	0.0003*			0.0004**		0.0003	0.0002
	(0.0001)	(0.0001)			(0.0002)		(0.0002)	(0.0002)
turnover	0.0199	0.0237				-0.0566**	0.0191	0.0173
	(0.0288)	(0.0271)				(0.0272)	(0.0265)	(0.0254)
cons	0.8610***	0.8118***	0.2346***	0.8733***	0.2251***	0.2729***	0.8082***	0.7996***
	(0.1109)	(0.1022)	(0.0585)	(0.1083)	(0.0587)	(0.0664)	(0.1665)	(0.1425)
N	2192	2192	2203	2203	2193	2192	1104	1104
adj. R^2	0.09	0.07	0.02	0.09	0.03	0.03	0.06	0.05
F	15.42	41.13	5.45	17.10	5.83	5.86	7.71	15.90
IND	Y	N	Y	Y	Y	Y	Y	N

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.turnover_{it-1} + \sum IND_{it} + \in_{it}$$

Δβ is Mβ-Dβ, the difference between monthly and daily betas. Standard errors are clustered by firm and year. *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011). Industry dummies are included where indicated. IND is an indicator for inclusion of industry dummies, IND is Y when industry dummies are included and N when it is not. sizerestrict1 and sizerestrict2, are the restriction tests 1 and 2 and require the stock to be above the cross-sectional median size measure in each year. adj. 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. For a detailed explanation of the measures and industry classification see text.

Panel B. Monthly Beta– Weekly Beta as Dependent Variable

Mβ-Wβ	full1	full2	opacity	size	rtotr	turnover	sizerestrict1	sizerestrict2
aaa	-0.1685	-0.1625	-0.1133	-0.1628	-0.1194	-0.0917	-0.0339	-0.0349
	(0.1828)	(0.1808)	(0.1887)	(0.1820)	(0.1868)	(0.1909)	(0.2666)	(0.2598)
lagsize	-0.0662***	-0.0659***		-0.0668***			-0.0611***	-0.0614***
	(0.0126)	(0.0119)		(0.0117)			(0.0193)	(0.0164)
rtotr	0.0002*	0.0002*			0.0003**		0.0002	0.0002
	(0.0001)	(0.0001)			(0.0001)		(0.0002)	(0.0002)
turnover	0.0060	0.0083				-0.0511*	0.0149	0.0145
	(0.0310)	(0.0306)				(0.0273)	(0.0288)	(0.0262)
cons	0.6185***	0.6031***	0.1602***	0.6326***	0.1512***	0.1936***	0.5363***	0.5513***
	(0.1124)	(0.0946)	(0.0575)	(0.1073)	(0.0582)	(0.0632)	(0.1990)	(0.1529)
N	2192	2192	2203	2203	2193	2192	1104	1104
adj. R^2	0.05	0.04	0.02	0.05	0.02	0.02	0.02	0.02
F	9.60	25.12	3.30	10.64	3.70	3.72	3.67	7.96
IND	Y	N	Y	Y	Y	Y	Y	N

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.turnover_{it-1} + \sum IND_{it} + \in_{it}$$

Δβ is Mβ-Wβ, the difference between monthly and weekly betas. Standard errors are clustered by firm and year. *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011). Industry dummies are included where indicated. IND is an indicator for inclusion of industry dummies, IND is Y when industry dummies are included and N when it is not. sizerestrict1 and sizerestrict2, are the restriction tests 1 and 2 and require the stock to be above the cross-sectional median size measure in each year. adj. 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. For a detailed explanation of the measures and industry classification see text.

Table 4: Explaining the difference in Betas – Germany

Panel A. Monthly – Daily Beta as Dependent Variable

Mβ-Dβ	full1	full2	opacity	size	rtotr	turnover	sizerestrict1	sizerestrict2
aaa	-0.0029	-0.1039	-0.0239	-0.0622	0.0066	0.0209	0.1963	-0.0230
	(0.0959)	(0.1094)	(0.0988)	(0.1043)	(0.0962)	(0.0906)	(0.2045)	(0.2513)
lagsize	-0.0465***	-0.0334*		-0.0443***			0.0343	0.0475
	(0.0163)	(0.0179)		(0.0153)			(0.0306)	(0.0350)
rtotr	0.0001*	0.0001*			0.0002***		0.0002**	0.0002*
	(0.0001)	(0.0001)			(0.0001)		(0.0001)	(0.0001)
turnover	-0.6631**	-0.6621***				-0.6428**	-0.2901	-0.2095
	(0.2678)	(0.2282)				(0.2501)	(0.3980)	(0.2957)
cons	0.0245	0.3726***	0.0175	0.3080	-0.3118*	-0.2512***	-0.6834***	-0.3793
	(0.1411)	(0.1378)	(0.4418)	(0.4500)	(0.1853)	(0.0966)	(0.2161)	(0.3039)
N	1527	1527	1708	1708	1575	1527	771	771
adj. R^2	0.09	0.04	0.06	0.08	0.07	0.06	0.20	0.04
F	13.01	14.65	8.60	10.24	10.43	9.87	.	6.94
IND	Y	N	Y	Y	Y	Y	Y	N

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.turnover_{it-1} + \sum IND_{it} + \in_{it}$$

Δβ is Mβ-Dβ, the difference between monthly and daily betas. Standard errors are clustered by firm and year. *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011). Industry dummies are included where indicated. IND is an indicator for inclusion of industry dummies, IND is Y when industry dummies are included and N when it is not. sizerestrict1 and sizerestrict2, are the restriction tests 1 and 2 and require the stock to be above the cross-sectional median size measure in each year. adj. 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. For a detailed explanation of the measures and industry classification see text.

Panel B. Monthly – Weekly Beta as Dependent Variable

Mβ-Wβ	full1	full2	opacity	size	rtotr	turnover	sizerestrict1	sizerestrict2
aaa	0.0756	-0.0286	0.0564	0.0237	0.0891	0.0932	0.0037	-0.2689
	(0.0638)	(0.0871)	(0.0689)	(0.0688)	(0.0686)	(0.0648)	(0.2095)	(0.2517)
size	-0.0410**	-0.0244		-0.0392***			0.0409	0.0596*
	(0.0159)	(0.0185)		(0.0148)			(0.0303)	(0.0358)
rtotr	0.0002**	0.0002*			0.0002***		0.0002**	0.0003**
	(0.0001)	(0.0001)			(0.0001)		(0.0001)	(0.0001)
turnover	-0.5532**	-0.5590**				-0.5917**	-0.3149	-0.2133
	(0.2551)	(0.2390)				(0.2460)	(0.3897)	(0.2822)
cons	-0.2887	0.2267	-0.1430	0.1160	-0.4558	-0.5230**	-1.0515***	-0.5389*
	(0.2408)	(0.1389)	(0.5020)	(0.5092)	(0.2999)	(0.2309)	(0.2622)	(0.3066)
N	1530	1530	1708	1708	1577	1530	773	773
adj. R^2	0.12	0.04	0.07	0.09	0.10	0.09	0.26	0.07
F	11.73	12.40	9.93	10.58	12.12	9.72	.	10.69
IND	Y	N	Y	Y	Y	Y	Y	N

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.turnover_{it-1} + \sum IND_{it} + \in_{it}$$

Δβ is Mβ-Wβ, the difference between monthly and weekly betas. Standard errors are clustered by firm and year. *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011). Industry dummies are included where indicated. IND is an indicator for inclusion of industry dummies, IND is Y when industry dummies are included and N when it is not. sizerestrict1 and sizerestrict2, are the restriction tests 1 and 2 and require the stock to be above the cross-sectional median size measure in each year. adj. 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. For a detailed explanation of the measures and industry classification see text.

Table 5: Explaining the difference in Betas – UK

Panel A. Monthly Beta – Daily Beta as Dependent Variable

Mβ-Dβ	full1	full2	opacity	size	rtotr	turnover	sizerestrict1	sizerestrict2
aaa	-0.1407	-0.1599	0.4166***	-0.1919	0.4435**	0.5164***	-0.0227	-0.1066
	(0.1668)	(0.1664)	(0.1612)	(0.1447)	(0.1781)	(0.1881)	(0.2625)	(0.2531)
size	-0.1521***	-0.1609***		-0.1316***			-0.1523***	-0.1588***
	(0.0143)	(0.0139)		(0.0121)			(0.0222)	(0.0220)
rtotr	0.0058	0.0075*			0.0201***		0.0107**	0.0133**
	(0.0037)	(0.0039)			(0.0045)		(0.0051	(0.0060)
turnover	-0.0049	-0.0095				-0.0675***	0.0052)	0.0054
	(0.0168)	(0.0178)				(0.0202)	(0.0163	(0.0186)
cons	1.3968***	1.4275***	0.1785**	1.2209***	0.1012	0.1985**	1.3703***	1.3927***
	(0.1274)	(0.1084)	(0.0761)	(0.1116)	(0.0798)	(0.0882)	(0.2046)	(0.1895)
N	4035	4035	4892	4892	4244	4049	2237	2237
adj. R^2	0.27	0.24	0.08	0.23	0.11	0.10	0.23	0.20
F	98.29	369.79	33.97	117.50	36.76	34.61	44.99	150.39
IND	Y	N	Y	Y	Y	Y	Y	N

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.turnover_{it-1} + \sum IND_{it} + \in_{it}$$

Δβ is Mβ-Dβ, the difference between monthly and daily betas. Standard errors are clustered by firm and year. *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011). Industry dummies are included where indicated. IND is an indicator for inclusion of industry dummies, IND is Y when industry dummies are included and N when it is not. sizerestrict1 and sizerestrict2, are the restriction tests 1 and 2 and require the stock to be above the cross-sectional median size measure in each year. adj. 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. For a detailed explanation of the measures and industry classification see text.

Panel B. Monthly Beta – Weekly Beta as Dependent Variable

Mβ-Wβ	full1	full2	opacity	size	rtotr	turnover	sizerestrict1	sizerestrict2
aaa	-0.1201	-0.1272	0.1923*	-0.1558	0.2118	0.2555	-0.0463	-0.0934
	(0.1459)	(0.1460)	(0.1158)	(0.1064)	(0.1441)	(0.1558)	(0.1989)	(0.2103)
size	-0.0854***	-0.0940***		-0.0754***			-0.0842***	-0.0889***
	(0.0113)	(0.0110)		(0.0093)			(0.0128)	(0.0130)
rtotr	0.0056**	0.0070***			0.0140***		0.0073**	0.0093**
	(0.0024)	(0.0027)			(0.0032)		(0.0031)	(0.0036)
turnover	-0.0153	-0.0138				-0.0533***	0.0085	0.0145
	(0.0165)	(0.0189)				(0.0161)	(0.0185)	(0.0210)
cons	0.7552***	0.8486***	0.0666	0.6616***	0.0210	0.0950	0.7416***	0.7690***
	(0.1023	(0.0882)	(0.0570)	(0.0810)	(0.0631)	(0.0652)	(0.1229)	(0.1150)
N	4035	4035	4892	4892	4242	4049	2242	2242
adj. R^2	0.17	0.13	0.06	0.14	0.08	0.08	0.12	0.09
F	49.30	162.78	23.42	56.74	25.29	25.24	22.40	65.01
IND	Y	N	Y	Y	Y	Y	Y	N

The full version of the model is:

$$\Delta\beta_{it} = a + b.aaa_{it-1} + c.size_{it-1} + d.RtoTR_{it-1} + e.turnover_{it-1} + \sum IND_{it} + \in_{it}$$

Δβ is Mβ-Wβ, the difference between monthly and weekly betas. Standard errors are clustered by firm and year. *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011). Industry dummies are included where indicated. IND is an indicator for inclusion of industry dummies, IND is Y when industry dummies are included and N when it is not. sizerestrict1 and sizerestrict2, are the restriction tests 1 and 2 and require the stock to be above the cross-sectional median size measure in each year. adj. 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. For a detailed explanation of the measures and industry classification see text.

Table 6: GRS Tests - Australia
Panel A. Based on size and book-to-market test portfolios

	1989m1 to 2013m12		03jan1989 to 31dec2013		1989m1 to 2013m12	
Portfolio	**α**	**t-stat**	**α**	**t-stat**	**α**	**t-stat**
SL	1.91%***	8.01	0.46%***	8.16	0.10%***	8.97
S2	1.57%***	8.24	0.38%***	8.31	0.08%***	8.87
SH	2.32%***	6.94	0.54%***	7.24	0.11%***	7.81
S2L	0.45%**	2.46	0.12%***	2.84	0.03%***	2.97
S22	0.64%***	3.32	0.16%***	3.44	0.03%***	3.55
S2H	0.47%*	1.78	0.13%**	2.25	0.03%**	2.47
M3L	-0.12%	-0.64	-0.01%	-0.18	0.00%	0.11
M32	0.13%	0.82	0.04%	1.01	0.01%	1.25
M3H	-0.10%	-0.39	-0.02%	-0.29	0.00%	-0.06
B4L	0.07%	0.42	0.03%	0.62	0.01%	0.70
B42	-0.10%	-0.65	-0.01%	-0.35	0.00%	-0.43
B4H	-0.14%	-0.81	-0.02%	-0.49	0.00%	-0.46
BL	0.26%	0.99	0.05%	0.80	0.01%	0.78
B2	0.03%	0.32	0.00%	0.11	0.00%	-0.09
BH	-0.12%	-0.91	-0.03%	-1.00	-0.01%	-1.03
GRS	**11.1376**		**11.1878**		**13.4482**	
p-val	**0.0000*** **		**0.0000*** **		**0.0000*** **	
meanR2	0.5555		0.5189		0.4945	
meancon	0.0049		0.0012		0.0003	
meanabscon	0.0056		0.0013		0.0003	
meanse	0.002		0.0005		0.0001	
p<=0.1	6		6		6	
p<=.05	5		6		6	

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

Panel B. Based on size portfolios

	1989m1 to 2013m12		1989w1 to 2013w52		03jan1989 to 31dec2013	
Portfolio	α	**t-stat**	α	**t-stat**	α	**t-stat**
S1	3.86%***	12.17	0.89%***	13.3	0.19%***	14.7
S2	1.56%***	7.77	0.37%***	7.72	0.08%***	8.19
S3	0.74%***	3.70	0.19%***	4.37	0.04%***	4.69
S4	0.78%***	4.20	0.19%***	4.31	0.04%***	4.52
S5	0.32%*	1.65	0.09%*	1.92	0.02%**	2.21
S6	0.15%	0.89	0.05%	1.23	0.01%	1.55
S7	-0.06%	-0.35	0.00%	-0.02	0.00%	0.31
S8	-0.18%	-1.16	-0.03%	-0.84	0.00%	-0.64
S9	-0.11%	-0.83	-0.01%	-0.38	0.00%	-0.37
S10	0.04%	0.31	0.01%	0.39	0.00%	0.4
S11	-0.11%	-0.98	-0.03%	-1.02	-0.01%	-0.98
S12	0.00%	0.06	-0.01%	-0.37	0.00%	-0.68
GRS	20.2608		20.8929		25.106	
p-val	0.0000***		0.0000***		0.0000***	
meanR2	0.6265		0.5955		0.5666	
meancon	0.0058		0.0014		0.0003	
meanabscon	0.0066		0.0016		0.0003	
meanse	0.0017		0.0004		0.0001	
p<=0.1	5		5		5	
p<=.05	4		4		5	

This table reports the results of the time series regression test (GRS test) of the value-weighted returns of 12 size portfolios on the asset pricing model (CAPM) at different frequencies (monthly, weekly and daily). For test portfolios S1-S12, the first character denotes size. 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 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.

Table 7: GRS Tests - Germany

Panel A. Based on size and book-to-market test portfolios

	1989m7 to 2013m6		1989w27 to 2013w26		03jul1989 to 28jun2013	
Portfolio	α	**t-stat**	α	**t-stat**	α	**t-stat**
SL	0.45%*	1.72	0.12%**	2.15	0.03%**	2.40
S2	0.04%	0.20	0.02%	0.48	0.01%	0.97
SH	-0.27%	-1.05	-0.03%	-0.47	0.00%	-0.15
S2L	0.35%	1.59	0.09%*	1.70	0.02%**	2.07
S22	0.25%	1.32	0.07%	1.55	0.02%*	1.85
S2H	-0.32%	-1.01	-0.06%	-0.92	-0.01%	-0.44
M3L	0.64%***	3.10	0.15%***	3.01	0.03%***	3.12
M32	0.22%	1.16	0.06%	1.35	0.02%*	1.66
M3H	0.12%	0.50	0.03%	0.59	0.01%	0.83
B4L	0.33%	1.51	0.09%*	1.65	0.02%	1.52
B42	0.17%	0.98	0.04%	1.10	0.01%	1.24
B4H	-0.10%	-0.40	0.00%	-0.01	0.00%	0.10
BL	0.37%**	2.25	0.08%**	2.04	0.02%*	1.79
B2	-0.13%	-0.96	-0.03%	-0.92	0.00%	-0.51
BH	0.09%	0.38	0.03%	0.52	0.01%	0.60
GRS	1.5293		1.1383		1.1486	
p-val	0.0943*		0.3161		0.3057	
meanR2	0.5602		0.5195		0.4282	
meancon	0.0015		0.0004		0.0001	
meanabscon	0.0026		0.0006		0.0001	
meanse	0.0022		0.0005		0.0001	
p<=0.1	3		5		6	
p<=.05	2		3		3	

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

Panel B. Based on size portfolios

	1989m7 to 2013m6		1989w27 to 2013w26		03jul1989 to 28jun2013	
Portfolio	**α**	**t-stat**	**α**	**t-stat**	**α**	**t-stat**
S1	0.17%	0.88	0.06%	1.29	0.02%*	1.82
S2	0.19%	1.04	0.06%	1.30	0.02%*	1.70
S3	0.28%	1.21	0.07%	1.46	0.02%*	1.82
S4	-0.17%	-0.87	-0.02%	-0.43	0.00%	0.02
S5	0.27%	1.40	0.07%*	1.67	0.02%*	1.95
S6	0.41%**	2.34	0.10%**	2.21	0.03%***	2.58
S7	0.34%*	1.95	0.08%*	1.91	0.02%**	2.19
S8	0.13%	0.77	0.05%	1.16	0.01%	1.26
S9	0.21%	1.26	0.06%	1.50	0.01%	1.63
S10	0.02%	0.09	0.01%	0.32	0.00%	0.39
S11	0.19%	1.33	0.05%	1.31	0.01%	1.43
S12	0.03%	0.31	0.01%	0.35	0.00%	0.40
GRS	1.2384		1.2176		1.3562	
p-val	0.2563		0.265		0.1794	
meanR2	0.6482		0.5914		0.4909	
meancon	0.0017		0.0005		0.0001	
meanabscon	0.002		0.0005		0.0001	
meanse	0.0017		0.0004		0.0001	
p<=0.1	2		3		6	
p<=.05	1		1		2	

This table reports the results of the time series regression test (GRS test) of the value-weighted returns of 12 size portfolios on the asset pricing model (CAPM) at different frequencies (monthly, weekly and daily). For test portfolios S1-S12, the first character denotes size. 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 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.

Table 8: GRS Tests - UK
Panel A. Based on size and book-to-market test portfolios

	1989m10 to 2013m12		1989w40 to 2013w52		02oct1989 to 31dec 2013	
Portfolio	**α**	**t-stat**	**α**	**t-stat**	**α**	**t-stat**
SL	-0.01%	-0.05	0.00%	-0.05	0.00%	0.18
S2	0.10%	0.43	0.03%	0.53	0.01%	0.8
SH	0.14%	0.52	0.04%	0.72	0.01%	0.77
S2L	-0.01%	-0.02	0.01%	0.24	0.01%	0.52
S22	0.21%	1.01	0.06%	1.27	0.01%	1.5
S2H	0.10%	0.39	0.04%	0.62	0.01%	0.65
M3L	-0.09%	-0.36	-0.02%	-0.44	0.00%	-0.24
M32	0.09%	0.48	0.04%	0.75	0.01%	0.92
M3H	0.24%	0.97	0.07%	1.1	0.01%	1.28
B4L	0.23%	0.96	0.05%	0.94	0.01%	1.08
B42	0.21%	1.27	0.05%	1.3	0.01%	1.48
B4H	0.05%	0.23	0.02%	0.39	0.00%	0.33
BL	0.18%	1.26	0.04%	0.92	0.01%	0.87
B2	0.00%	0.01	0.00%	0.06	0.00%	-0.01
BH	0.17%	0.86	0.04%	0.82	0.01%	0.75
GRS	0.7213		0.6608		0.6855	
p-val	0.7624		0.8245		0.8015	
meanR2	0.5789		0.541		0.5117	
meancon	0.0011		0.0003		0.0001	
meanabscon	0.0012		0.0003		0.0001	
meanse	0.0022		0.0005		0.0001	
p<=0.1	0		0		0	
p<=.05	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 (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 $R_{it} - R_{ft} = \alpha_i + \beta_i (R_{mt} - R_{ft}) + \varepsilon_{it}$ 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

Panel B. Based on size portfolios

	1989m10 to 2013m12		1989w40 to 2013w52		02oct1989 to 31dec2013	
Portfolio	**α**	**t-stat**	**α**	**t-stat**	**α**	**t-stat**
S1	0.17%	0.81	0.04%	0.88	0.01%	1.14
S2	0.00%	0.01	0.01%	0.11	0.00%	0.26
S3	0.23%	0.96	0.06%	1.22	0.01%	1.36
S4	0.23%	0.97	0.06%	1.23	0.02%	1.49
S5	0.08%	0.38	0.03%	0.55	0.01%	0.79
S6	0.17%	0.95	0.05%	1.08	0.01%	1.41
S7	-0.06%	-0.35	-0.01%	-0.13	0.00%	0.11
S8	0.34%*	1.85	0.09%*	1.87	0.02%**	2.2
S9	0.12%	0.76	0.03%	0.85	0.01%	0.99
S10	0.11%	0.83	0.02%	0.7	0.01%	0.74
S11	0.10%	0.93	0.03%	1.02	0.01%	0.89
S12	0.03%	0.33	0.00%	0.16	0.00%	0.01
GRS	0.8812		0.8344		0.8877	
p-val	0.5666		0.6149		0.559	
meanR2	0.6715		0.6217		0.5775	
meancon	0.0013		0.0003		0.0001	
meanabscon	0.0014		0.0004		0.0001	
meanse	0.0018		0.0004		0.0001	
p<=0.1	1		1		1	
p<=.05	0		0		1	

This table reports the results of the time series regression test (GRS test) of the value-weighted returns of 12 size portfolios on the asset pricing model (CAPM) at different frequencies (monthly, weekly and daily). For test portfolios S1-S12, the first character denotes size. 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 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.

Appendix Table A1. Industry definitions

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

Appendix A2 Industry Dummy Variable Coefficients

AUSTRALIA

Mβ-Dβ	CNSTM	FDBEV	FINSV	HLTHC	INDGS	MEDIA	OILGS	PERHH	RLEST	RTAIL	TECNO	UTILS
coeff	-0.0954	-0.1652***	0.3066*	-0.1223	-0.0469	0.0849	-0.0990	0.0074	-0.2073	-0.0564	0.0650	-0.1950**
	(0.0633)	(0.0606)	(0.1861)	(0.0825)	(0.0570)	(0.0968)	(0.0776)	(0.0840)	(0.1363)	(0.0787)	(0.1321)	(0.0805)
Mβ-Wβ												
coeff	-0.0201	-0.0912	0.4247**	-0.0531	-0.0326	0.0864	-0.0645	0.0302	-0.0567	-0.0422	0.0610	-0.0257
	(0.0689)	(0.0627)	(0.2105)	(0.0820)	(0.0654)	(0.0992)	(0.0808)	(0.0786)	(0.0573)	(0.0750)	(0.0847)	(0.0536)

GERMAN

Mβ-Dβ	CHMCL	CNSTM	FDBEV	FINSV	HLTHC	INDGS	MEDIA	PERHH	RLEST	RTAIL	TECNO	TRLES	UTILS
coeff	0.6173***	0.3642	0.5316***	0.4131***	0.3757*	0.3478*	0.5589*	0.3812*	0.2298*	0.3880***	0.5721*	0.3498***	0.7128*
	(0.1518)	(0.2434)	(0.1946)	(0.1263)	(0.0849)	(0.0888)	(0.1055)	(0.0970)	(0.0828)	(0.1198)	(0.0979)	(0.0992)	(0.2014)
Mβ-Wβ													
coeff	0.8648***	0.4946*	0.7423***	0.5448***	0.5921*	0.5397*	0.7092*	0.5744*	0.4068*	0.5553**	0.7405*	0.3887*	0.9706*
	(0.2250)	(0.2740)	(0.2559)	(0.2092)	(0.2079)	(0.2137)	(0.2302)	(0.2122)	(0.2097)	(0.2275)	(0.2129)	(0.2152)	(0.2789)

UK

Mβ-Dβ	CHMCL	CNSTM	FDBEV	FINSV	HLTHC	INDGS	MEDIA	OILGS	PERHH	RLEST	RTAIL	TECNO	TELCM	TRLES	UTILS
coeff	0.0351	0.0367	-0.1560**	-0.2584***	-0.1117	0.0282	0.1440*	-0.0911	-0.0068	-0.3424***	-0.1387*	-0.0938	0.2719*	-0.0884	-0.1554
	(0.0795)	(0.0883)	(0.0738)	(0.0955)	(0.0752)	(0.0665)	(0.0795)	(0.0865)	(0.0838)	(0.0849)	(0.0747)	(0.0924)	(0.1645)	(0.0766)	(0.1002)
Mβ-Wβ															
coeff	0.0559	0.0222	-0.0409	-0.2720***	-0.0598	0.0926*	0.2048*	-0.0823	0.0700	-0.2095**	-0.0157	-0.0249	0.3596	0.0290	-0.0550
	(0.0602)	(0.0703)	(0.0592)	(0.0932)	(0.0622)	(0.0488)	(0.0706)	(0.0668)	(0.0621v	(0.0833)	(0.0620)	(0.0673)	(0.2280)	(0.0615)	(0.0779)

The table shows the coefficients and dummy variables for the regressions in Tables 3-5 of the paper. Mβ-Dβ refers to the Monthly vs Daily regressions (reported in Panel A of the respective tables) whilst Mβ-Wβ refers to the Monthly vs Weekly regressions (reported in Panel B of the respective tables). ***, ** and * denotes the significance at the 1%, 5% and 10% levels respectively. Coeff is the coefficient on the dummy variables for the respective industries. Industry definitions correspond to those in Appendix Table A1.

Appendix A3 Correlations Month to Day beta

AUSTRALIA	Mβ-Dβ	Mβ	Dβ	aaa	size	turnover	amihud
Mβ-Dβ	1.0000						
Mβ	0.5609	1.0000					
Dβ	-0.3613	0.5693	1.0000				
aaa	0.0231	0.0612	0.0460	1.0000			
size	-0.1606	-0.0024	0.1567	-0.0346	1.0000		
turnover	-0.0568	0.2537	0.3422	0.0605	0.0654	1.0000	
amihud	0.0971	-0.1024	-0.2118	-0.0075	-0.0956	-0.2668	1.0000
rtotr	0.0724	-0.1326	-0.2212	0.0141	-0.0600	-0.2527	0.7623
GERMANY							
Mβ-Dβ	1.0000						
Mβ	0.6228	1.0000					
Dβ	-0.3773	0.4896	1.0000				
aaa	-0.0342	0.0312	0.0750	1.0000			
size	-0.0108	0.1896	0.2364	-0.0591	1.0000		
turnover	-0.1195	0.0532	0.1961	0.1157	-0.1099	1.0000	
amihud	0.1790	-0.1410	-0.3663	-0.0193	-0.1788	-0.2003	1.0000
rtotr	0.1283	-0.1231	-0.2887	-0.0731	-0.0564	-0.2731	0.4760
UK							
Mβ-Dβ	1.0000						
Mβ	0.5849	1.0000					
Dβ	-0.4625	0.4486	1.0000				
aaa	0.0613	0.0512	-0.0116	1.0000			
size	-0.2585	-0.1054	0.1695	-0.0778	1.0000		
turnover	-0.1289	0.1740	0.3322	-0.0052	0.0062	1.0000	
amihud	0.2000	0.0331	-0.1842	0.1071	-0.1160	-0.2652	1.0000
rtotr	0.1612	0.0345	-0.1400	0.0796	-0.0847	-0.2875	0.8483

The table shows the correlations between our measure of opacity and size and illiquidity. Mβ-Dβ is the difference in monthly and daily betas, Mβ is the monthly Beta, Dβ is the daily Beta, *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011).

Appendix A3 Correlations Month to Week beta

AUSTRALIA	Mβ-Wβ	Mβ	Wβ	aaa	size	turnover	amihud
Mβ-Wβ	1.0000						
Mβ	0.4798	1.0000					
Wβ	-0.3661	0.6409	1.0000				
aaa	-0.0162	0.0651	0.0832	1.0000			
size	-0.1265	0.0001	0.1108	-0.0357	1.0000		
turnover	-0.0582	0.2381	0.3034	0.0646	0.0658	1.0000	
amihud	0.0937	-0.0980	-0.1859	-0.0092	-0.0955	-0.2679	1.0000
rtotr	0.0604	-0.1327	-0.1936	0.0133	-0.0604	-0.2546	0.7662
GERMANY							
Mβ-Wβ	1.0000						
Mβ	0.5986	1.0000					
Wβ	-0.3889	0.5052	1.0000				
aaa	-0.0188	0.0227	0.0464	1.0000			
size	0.0174	0.1884	0.1979	-0.0602	1.0000		
turnover	-0.1150	0.0518	0.1834	0.1164	-0.1102	1.0000	
amihud	0.1825	-0.1383	-0.3556	-0.0214	-0.1786	-0.2008	1.0000
rtotr	0.1561	-0.0976	-0.2804	-0.0761	-0.0513	-0.2717	0.4666
UK							
Mβ-Wβ	1.0000						
Mβ	0.4961	1.0000					
Wβ	-0.3405	0.6475	1.0000				
aaa	0.0406	0.0504	0.0189	1.0000			
size	-0.2047	-0.1058	0.0651	-0.0570	1.0000		
turnover	-0.1142	0.1698	0.2841	-0.0036	0.0032	1.0000	
amihud	0.1501	0.0332	-0.0958	0.1045	-0.1143	-0.2644	1.0000
rtotr	0.1411	0.0345	-0.0865	0.0803	-0.0840	-0.2878	0.8504

The table shows the correlations between our measure of opacity and size and illiquidity. Mβ-Wβ is the difference in monthly and weekly betas, Mβ is the monthly Beta, Wβ is the weekly Beta, *aaa* is the winsorised absolute value of abnormal accruals from the estimation of Modified Jones (1991) model, *size* is the firm's market capitalisation in millions at the end of year t, *turnover*, is the winsorised volume per year per share outstanding and *amihud*, is the winsorised Amihud illiquidity ratio (multiplied by 1000000) from Amihud (2002), and *rtotr*, is the winsorised RtoTR illiquidity ratio from Florackis et al. (2011).