NERA
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Review of UKRN report recommendations on beta estimation

Prepared for National Grid

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Executive Summary

National Grid plc (NG plc) commissioned NERA Economic Consulting (NERA) to review the recommendations on estimating betas for UK regulated companies presented in the report by Wright, Burns, Mason and Pickford prepared for the UK Regulators Network ("UKRN report").[1]

We gratefully acknowledge support by Professor Ania Zalewska of the University of Bath in preparing this report.[2]

Three of the UKRN report authors, Mason, Pickford and Wright (MPW) recommend estimating betas using a methodology which substantially departs from common regulatory practice. Specifically, they recommend betas should be estimated using: i) very long-run estimation periods going back to 2000; ii) aggregated or low frequency data (e.g. quarterly returns); and iii) statistical models from the GARCH[3] family. On this basis, the authors estimate *equity betas* for United Utilities (UU) and Severn Trent (SVT) between 0.3 and 0.5, which according to the authors are distinctly lower than the equity betas allowed at recent price controls of between 0.8 and 0.9.[4]

In this report, we show that the first two MPW recommendations regarding the time period and data frequency are not appropriate for estimating betas for UK utilities and that high frequency data (e.g. daily) and recent time periods (e.g. two to five years) should be used. Once these issues are corrected, we find that asset beta estimates for UU and SVT and indeed other UK and European comparators are consistent with asset beta estimates at recent reviews, irrespective of the statistical model used (OLS vs. GARCH).

We note that our conclusions appear to be consistent with the view of the fourth author of the UKRN report, Burns, who disagrees with MPW recommendations and highlights that MPW's results are driven by their decision to "*adopt the highly unusual practice of estimating the CAPM on quarterly data, which is the key factor that drives the lower estimates of beta"* while *"MPW's results based on higher frequency data are recognisably similar to existing regulatory estimates over the relevant time frames"*.[5]

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1 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), Estimating the cost of capital for implementation of price controls by UK Regulators, An update of Mason, Miles and Wright (2003).

2 Professor Zalewska has published widely on the topic of beta estimation in the regulatory context in the UK. Relevant references to her work have been cited throughout this report.

3 We note that the specific model suggested by MPW is a multivariate GARCH model (MGARCH), as it describes the evolution of the market return and one individual stock return simultaneously. In this report we use the term "GARCH" as a catch-all phrase for the family of models that allow for time-varying distributions, including multivariate models.

4 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. 9.

5 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. 9.

Relying on data since 2000 for estimating betas ignores changes in risk over time and leads to downward biased beta estimates for UK water and energy comparators

MPW recommend using long time periods for estimating beta, going back to 2000 for listed UK water stocks.

We disagree with MPW's recommendations. Estimating betas over long horizons going back to 2000 as a basis of determining beta risk going forward ignores material changes in UK (and other comparator) companies' business and financial risk, changes in market conditions as well as changes in the regulatory regime and risk, resulting in beta estimates that fail to reflect regulated companies' risk profile for the upcoming price control periods.

Our estimates of asset betas for the five listed UK utilities (UU, SVT, Pennon, National Grid and SSE) using the recommended MPW approach (GARCH model and low frequency data) over different timeframes shows that asset betas increase substantially as we move to the more recent periods, in particular for periods starting after 2011, which shows a potential structural break. We therefore conclude that the use of long time-series data since 2000 leads to downward biased beta estimates, as it fails to reflect the increase in UK water and energy companies' risk over time. To avoid biased estimates, we recommend asset betas are estimated based on recent data, e.g. a period of 2 to 5 years, consistent with standard practice of UK regulators over many years.[6]

Relying on low frequency (e.g. quarterly) data leads to less precise beta estimates, aggregation rules are arbitrary and aggregation of returns is inconsistent with the GARCH model

MPW recommend the use of low frequency (e.g. quarterly) data for estimating beta. We disagree with MPW's recommendations.

The use of low frequency data requires extending the estimation period to ensure sufficient observations, leading to very long estimation periods that are not relevant in terms of risk profile, as noted above. Even when all available data is used (in the case of MPW that is data from 2000-2017), the number of observations is still considerably smaller compared to common practice of using daily data,[7] leading to less precise beta estimates as measured by standard errors.

Moreover, there are a number of ways of aggregating daily returns to lower frequency data, e.g. there are 60 different specifications of quarterly returns depending on the choice of the starting day. MPW only present one estimate out of the 60 possible. We show that MPW's results change dramatically when the aggregation rule, i.e. the choice of the starting day for each quarter, is changed in a trivial manner, demonstrating the volatility of MPW results.

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6 For example, periods ranging from 2 to 5 years have recently been used in Ofwat PR14, CMA Bristol Water 2015, CAA Airports 2014 and Ofcom LLCC 2016 decisions, as shown in Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., Appendix F, Figure F.2, pp. F-129 – F-130.

7 Using an estimation period of 17 years, quarterly data provides 17*4=68 observations while daily data provides around 17*250=4,250 observations.

Finally, the use of quarterly data by MPW appears inconsistent with the reasons for adopting a GARCH model in the first place. There is evidence in academic literature that stock returns may not be independent, which is the standard assumption of the OLS model. One way to address these issues within a standard OLS framework is to lower the frequency of the data, but this inevitably leads to fewer observations and less precise beta estimates as noted above. Models such as GARCH allow the explicit modelling of the time-varying properties of stock returns, thus avoiding the issue of losing valuable information by aggregating data to lower frequencies. It is therefore puzzling that MPW first propose to use GARCH models to reflect time-varying properties of asset returns (such as time-varying volatility) but at the same time they also remove these very properties from the data that GARCH is designed to deal with by aggregating returns to quarterly frequencies. In addition, we note that MPW apply the same MGARCH model to daily returns as well as lower data frequencies. We believe their application of the same model across all data frequencies is inconsistent with academic literature, which shows that if the MGARCH model proposed by MPW is the appropriate model to apply to daily data, it cannot be the appropriate model for lower data frequencies at the same time.

In summary, we consider that the GARCH model, if applied, should be applied to daily data, where we observe the MPW results are substantially higher than using quarterly data.[8]

Correcting MPW estimates using shorter time periods and high data frequency produces asset betas in line with recent determinations using a GARCH model

MPW estimate equity betas for UU and SVT of 0.3 to 0.5 and argue that these are substantially lower than allowed equity betas at recent reviews of 0.8 to 0.9.[9] We note that this comparison is misleading, as equity betas are affected by differences between the empirical gearing for comparators and the notional gearing assumed by regulators. The correct comparison is therefore using un-levered or asset betas, which MPW estimate at 0.15 to 0.25 for UU and SVT.[10]

Figure 1.1 below shows asset betas estimated using the MPW preferred approach (long-run data, quarterly returns) compared to our recommendation (short-run data, daily returns). [11]

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8 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. G-148.

9 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. 9.

10 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. G-152.

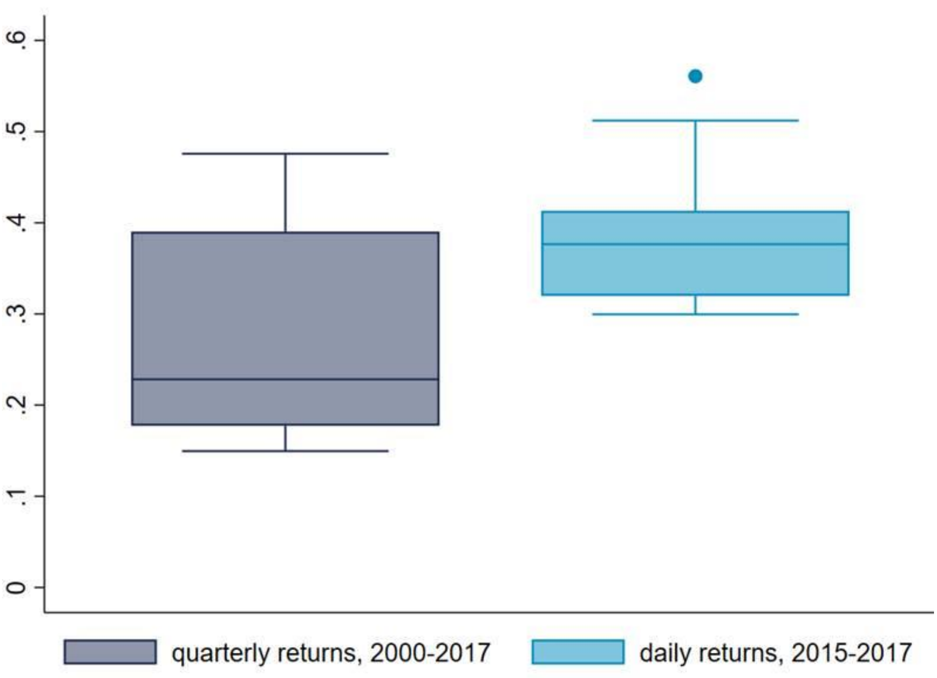
11 This figure shows the distribution of MPW "short-run" asset betas from the MGARCH model for 11 UK and EU comparators (National Grid (UK), SSE (UK), United Utilities (UK), Severn Trent (UK), Pennon (UK), Red Electrica (Spain), TERNA (Italy), ACEA (Italy), Gas Natural SDG (Spain), SNAM (Italy), and Enagas (Spain)). The left panel shows figures based on the MPW recommended approach, i.e. quarterly returns estimated over the period 2000Q1-2017Q3. The right panel shows figures based on daily returns and a two year period 1 October 2015 to 25 September 2017. In each panel there is a central rectangular shape with a horizontal bar. The horizontal bar represents the median estimate, whereas the lower and upper edges of the rectangles represent the 25th and 75th percentile, respectively. This implies that the central 50 per cent of beta estimates are contained in the rectangular shape. The highest and lowest "cross-bars" represent the range of beta estimates that are not considered as outliers. Outliers are defined as those estimates which are higher /lower than the 75th / 25th percentile +/- 1.5 times the inter-quartile range and are indicated as dots.

We use a sample of 11 UK and European comparators,[12] as we consider MPW's focus on two water stocks is too restrictive and a wider range of comparators should be used.

We find that asset betas estimated using a GARCH model applied to daily data and recent time period for UU and SVT and indeed other UK and European comparators are substantially higher than MPW estimates and consistent with asset betas determined at recent reviews.[13] This demonstrates the lower beta estimates MPW claim to find are primarily driven by their choice of estimation period and the data frequency, not by the introduction of a new GARCH model.

We therefore conclude that we find no evidence for lower asset betas compared to previous reviews as argued by MPW.

Figure 1.1
Correcting MPW estimates using shorter time period (2 years) and daily data produces asset betas in line with UK precedent using an MGARCH model



Source: Bloomberg, NERA calculations

[12] Our sample includes five listed UK companies (National Grid, SSE, United Utilities, Severn Trent, Pennon) and six European energy networks (Red Electrica (Spain), TERNA (Italy), ACEA (Italy), Gas Natural SDG (Spain), SNAM (Italy), and Enagas (Spain)).

[13] For example, at RIIO-1, Ofgem determined asset betas in the range of 0.32 to 0.43. See NERA (2012) Cost of capital estimation for RIIO-ED1, a report for WPD. Link: https://www.westernpower.co.uk/docs/About-us/Stakeholder-information/Our-future-business-plan/Supporting-Financing-plan/NERA-Cost-of-Capital-Estimation.aspx

GARCH produces similar results as OLS when same time frames and data frequency used, which questions the benefit of more complex GARCH approach for regulation

We also show that once consistent time periods and data frequencies are used, the results from standard OLS estimation and the MGARCH model proposed by MPW become very similar. This confirms the above conclusion that the lower beta estimates MPW claim to find are primarily driven by their choice of time frame and aggregation of returns, not by the introduction of a new MGARCH model. This is consistent with the view presented by Burns.[14]

We note that GARCH models do not represent the only alternative to OLS for modelling time-varying properties of asset returns. We also estimate betas using the so called Kalman-filter technique, and find that this produces similar results to OLS and MGARCH on average, while showing a greater variation of estimates within the comparator group.

While we do not object to the use of GARCH models for the purpose estimating betas, we note that GARCH-type models are complex and difficult to implement and reproduce by stakeholders, which may introduce arbitrariness in regulatory decision making and increase perceptions of regulatory risk. Given we find that MGARCH and OLS models produce consistent results, we consider that the benefit of a more complex MGARCH model relative to standard OLS appears questionable in the regulatory context.

[14] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. F-136

1. Introduction

National Grid plc (NG plc) commissioned NERA Economic Consulting (NERA) to review the recommendations on estimating betas for UK regulated companies presented in the report by Wright, Burns, Mason and Pickford prepared for the UK Regulators Network ("UKRN report").[15].

Wright et al. (2018) were asked to advise UK regulators on the appropriate methodology for setting the cost of capital at future price controls. The UKRN report makes ten recommendations on the cost of capital at future reviews, including on the appropriate approach for estimating betas for UK regulated networks. In its RIIO-2 Framework Consultation, Ofgem proposes to incorporate eight of these recommendations within the RIIO-2 methodology, including the methods of estimating betas referenced in the UKRN report.[16]

This report has been prepared to support National Grid's response to Ofgem's RIIO-2 Framework Consultation on the appropriate methodology for estimating betas at RIIO-2. We do not comment on the other recommendations presented in the UKRN report.

We gratefully acknowledge support by Professor Ania Zalewska of the University of Bath in preparing this report.[17]

This report is structured as follows:

- Section 2 presents the key recommendations of the UKRN report in relation to beta estimation;
- Section 3 assesses the UKRN report recommendation, made by three of the authors Mason, Pickford and Wright (MPW) of using long-horizon time series data to estimate betas;
- Section 4 assesses the UKRN-MPW recommendation of using low-frequency data to estimate beta and shows that the UKRN-MPW beta results are largely driven by the estimation period and data frequency as opposed to the new MGARCH model and that using high frequency data and recent time periods produces betas in line with precedent;
- Section 5 discusses the role of advanced time series models (e.g. GARCH) in the regulatory context and shows that results for OLS and MGARCH are very similar for UK and EU comparators for consistent time periods and data frequencies, questioning the need for employing complex statistical methods in the regulatory context.

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[15] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), Estimating the cost of capital for implementation of price controls by UK Regulators, An update of Mason, Miles and Wright (2003).

[16] Ofgem (March 2018), RIIO-2 Framework Consultation, para 7.32 -7.33.

[17] Professor Zalewska has published widely on the topic of beta estimation in the regulatory context in the UK. Relevant references to her work have been cited throughout this report.

2. Key recommendations on beta estimation presented in the UKRN report

The authors of the UKRN report agree that betas should be estimated based on robust econometric evidence. However, the authors do not agree on the exact methodology to be used for estimating empirical betas for comparator companies.

Three of the authors, Mason, Pickford and Wright (MPW), propose to estimate betas using a methodology which is in stark contrast with existing regulatory precedent in the UK. Their recommendations deviate from current regulatory standard practice in three key areas:

- Firstly, MPW suggest that regulators should choose a **long horizon** in estimating betas, going back to 2000. They argue that if regulators are concerned with long-horizon risks, longer-term data provide evidence that is better aligned with this objective.[18]
- Secondly, MPW favour beta estimation based on **low frequency data**. In particular, they adopt the unconventional approach of estimating betas based on quarterly data, rather than making use of daily data – the most granular information available – as is more common in academic, regulatory and commercial settings. MPW, referring to their own calculations, argue that quarterly data estimates yield more consistent results than higher-frequency approaches when using different estimation techniques.[19] In addition, they emphasise that the use of high frequency data would be inconsistent with regulators' general aim to capture systematic long-term components of equity returns.[20]
- Thirdly, MPW advocate the use of models from the family of **Generalised Autoregressive Conditional Heteroscedasticity (GARCH) models** to derive beta values rather than the ordinary least squares (OLS) approach that dominates regulatory practice in the UK. A crucial difference between the two estimation approaches is that GARCH, unlike OLS, takes into account the potential conditional heteroscedasticity of returns, making it possible to estimate time variation in beta. To date, this approach has not been adopted for the purpose of regulatory beta estimation in the UK.

In Appendix G of the UKRN report, MPW present beta estimates for the two listed water stocks United Utilities (UU) and Severn Trent (SVT), using the FTSE All-share Index as the market index. Implementing their three key recommendations, they estimate equity betas between 0.3 and 0.5, which according to the authors are distinctly lower than the equity betas allowed at recent price controls of between 0.8 and 0.9.[21]

In contrast, the fourth author of the UKRN report, Burns, remains sceptical regarding the three key recommendations of his co-authors with respect to the beta estimation methodology.

He highlights that MPW's results are driven by their decision to "*adopt the **highly unusual practice of estimating the CAPM on quarterly data**, which is **the key factor that drives the***

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[18] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. G-139.

[19] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. 53, and appendix G.

[20] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. G-139.

[21] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. 9.

lower estimates of beta. *"* while *"MPW's* ***results based on higher frequency data*** *are recognisably* ***similar to existing regulatory estimates*** *over the relevant time frames".*[22]

In contrast to MPW, Burns recommends that *"[…] regulators should continue to use the CAPM on a wide range of comparator stocks, using* ***higher frequency data*** *(subject to testing for thin-trading and serial correlation), over* ***different sample sizes****, and interpret that body of evidence judiciously, in line with practice to date. The continuation of this holistic approach is important because it has been an important contributor to regulatory stability which itself has contributed to reducing investor risk premiums over the past 25 years."*[23]

In the following sections, we contest the first and second recommendations by MPW and highlight potential issues with employing advanced statistical methods in the regulatory context.

We note that the specific model suggested by MPW is a multivariate GARCH model (MGARCH), as it describes the evolution of the market return and one individual stock return simultaneously. In this report we use the term "GARCH" as a catch-all phrase for the family of models that allow for time-varying distributions, including multivariate models. We briefly describe our implementation of the GARCH model recommended by MPW in Appendix A.

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[22] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. 9.

[23] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. 54.

3. The use of long-horizon data for beta estimation at future reviews

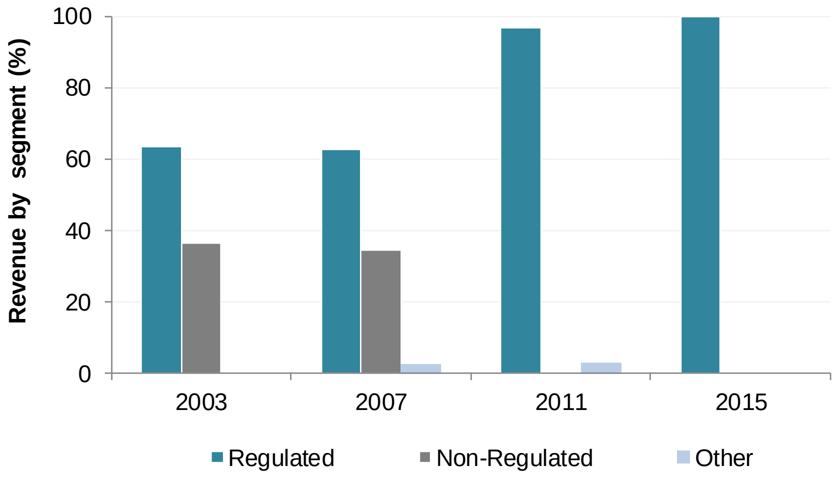
In this section, we explain that there are a number of issues with relying on long-horizon data for estimating betas at future price controls. In summary, the use of long-horizon data fails to take into account changes in UK regulated networks' risk over time arising from changes in companies' business models, changes in regulation as well as changes in the market itself, all of which affect the beta. We show that estimates from the more recent periods support higher betas and therefore relying on data since 2000, as MPW suggest, would lead to downward biased beta estimates.

3.1. UK regulated companies' business models changed substantially over time

A closer look at the evolution of business activities of National Grid and the two UK water companies (Severn Trent and United Utilities) analysed by MPW over the 18-year period 2000 to 2017, the period over which MPW estimate their betas, reveals that there have been substantial changes in the companies' business activities and therefore risk over time.

Figure 3.1 illustrates that UU's revenue sources since 2000 have changed substantially. While in 2003, 36 percent of the company's revenues were generated through activities in its "non-regulated" business segments, including UU's international businesses, its UK non-regulated businesses and its investment in UK energy networks. Following the sale of these activities in 2010, UU started focusing almost exclusively on its UK water regulated business.

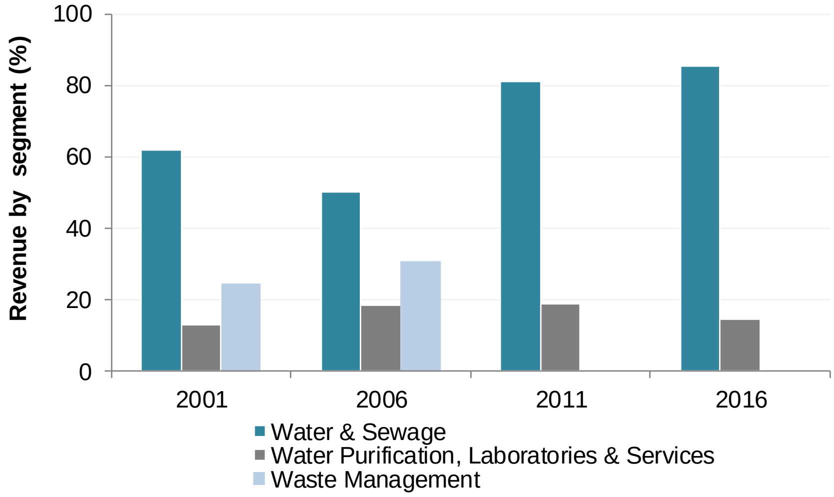
Figure 3.1
United Utilities' revenue composition has changed substantively since 2000



Source: UU annual reports, NERA analysis
Note: United Utilities activities classified as "non-regulated" include investments in Northern Gas Networks and Manila Water, electricity operations and maintenance business in the North West of England, holding in Meter Fit, the Australian business, UK and European non-regulated water interests, contract with Northern Gas Networks, gas and electricity metering installation contract and municipal solid waste related interests. (Annual Report 2011, p.3) as well as Vertex (sold in March 2007), a leading provider of business process outsourcing (BPO) services specialising in the front and back-office management of customer relationships. (Annual Report 2003, cover page 4). Revenue split between different non-regulated activities is not available.

Similarly to UU, Severn Trent has also seen a substantial shift in its business focus, as illustrated in Figure 3.2. In 2007, it disposed of its waste management business which generated a quarter of its revenues in 2001. Its UK water regulated business now accounts for the vast majority of its revenues, while in 2006 it produced only half of SVT's revenue.

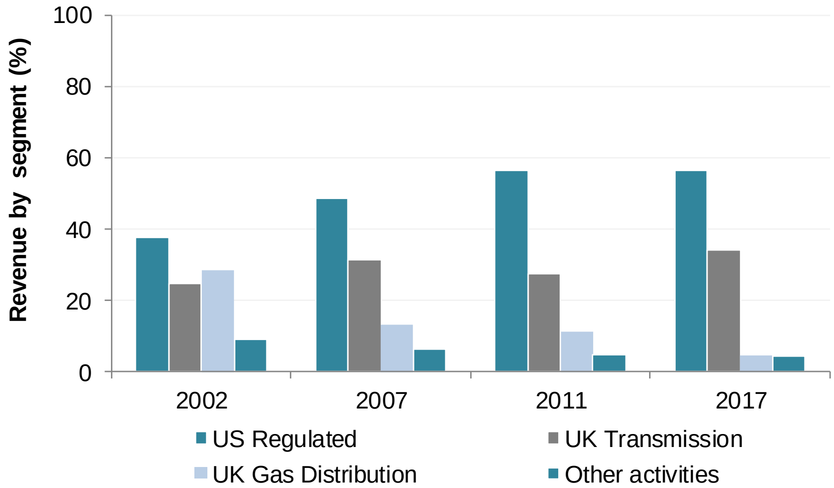
Figure 3.2
Severn Trent's revenue composition has changed substantively since 2000



Source: SVT annual reports, NERA analysis

National Grid's business activities have seen both a geographical and sectoral shift over the last 18 years. Figure 3.3 shows that the company's US regulated energy segment has gradually gained importance at the expense of UK regulated operations (e.g. with the partial sale of NG plc's gas distribution business in 2017).

Figure 3.3
National Grid has seen increasing importance of its US business



Source: NG plc annual reports, NERA analysis

The above observations highlight two important issues relevant for beta estimation:

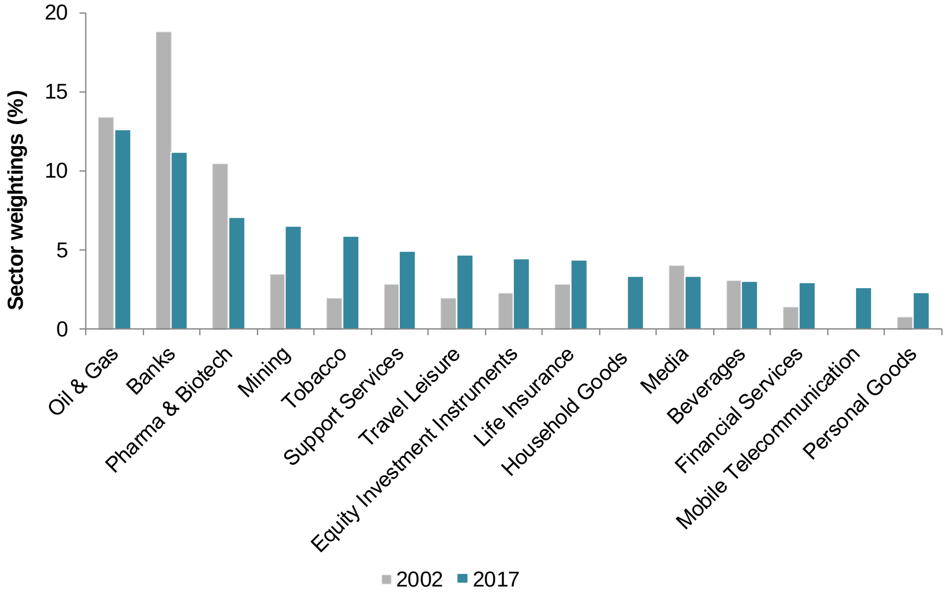
- Firstly, as the comparator companies' business models evolve over time, so does their risk profile and the co-movement of their stock returns with the overall market (i.e. the beta). Hence, a company with a higher beta today may have had a lower beta 15 years ago and vice versa. By estimating the beta over very long time frames, the business models and risk profiles from the historical period will affect the empirical beta estimate, although the associated risks may no longer be relevant going forward. Thereby, using very long time frames may lead to biased beta estimates.
- Secondly, finding an appropriate set of comparator firms may become increasingly difficult the longer the estimation time frame. Firms who are close comparators today need not have been close comparators more than a decade ago.

3.2. Market composition and general market conditions have changed considerably since 2000

Even if firms' business models and thereby the relative importance of different revenue sources had remained constant for different comparator companies since 2000, considerable changes in market conditions suggest that betas would have changed significantly nevertheless.

Changes in the sector weightings of the FTSE All-Share Index (see Figure 3.4) suggest a considerable shift in market fundamentals. While the financial sector is still among the biggest components, its importance has waned over the last 15 years. At the same time, other sectors such as mining or consumer-centred sectors have made big gains in their share of the index.

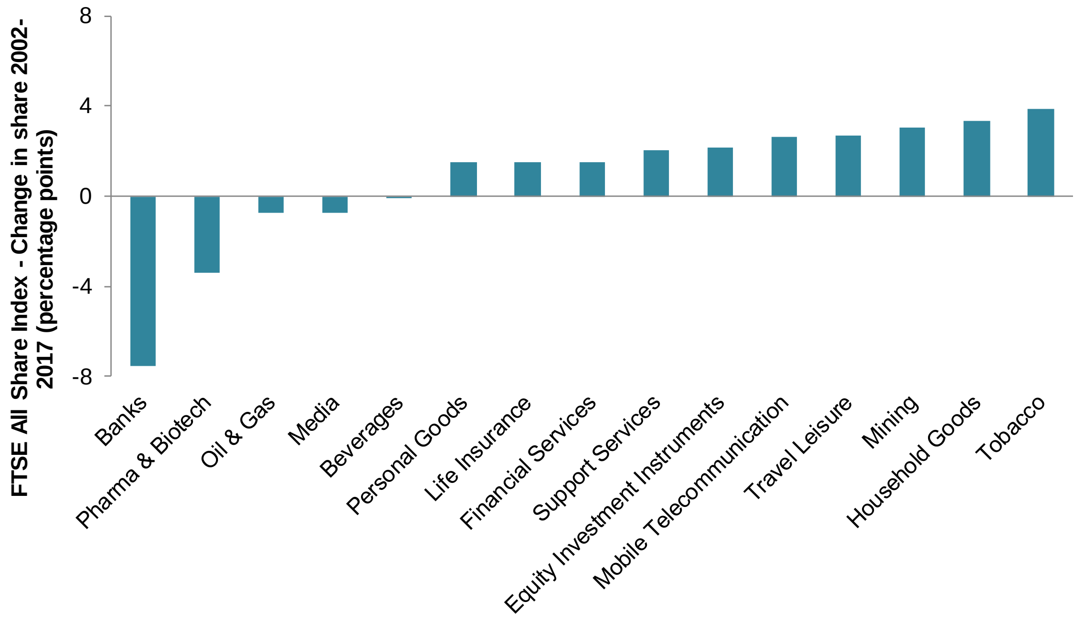
Figure 3.4
FTSE composition has changed substantially over the last 15 years: Top 15 components of the FTSE-All Share Index in 2002 vs. 2017



Source: Bloomberg, NERA analysis

Figure 3.5 shows by how much the share of the top 15 industries in the FTSE All-Share Index in 2017 changed relative to 2002. The changes in share range from about minus 8 percentage points for banks to about plus 4 percentage points for Tobacco.

Figure 3.5
Top 15 components of the FTSE All Share Index by share of 2017 and their change relative to 2002



Source: Bloomberg, NERA analysis

As the sectoral composition of the market index changes, the co-movement of any given company's share price with the market changes as well. Therefore, the beta of any given company versus the 2017 composition of the market index is mechanically different from its beta versus the 2002 composition of the market, even if the business model and other factors are held constant.[24]

The longer the time frame used for estimating betas, the more will results be biased by market conditions that no longer reflect the present. Therefore, betas based on an 18-year estimation window must be considered inadequate for the current price reviews.

3.3. The UK regulatory regime changed considerably since 2000

The regulatory regime and associated regulatory risk is a key determinant of the risks faced by UK regulated companies.

The UK regulatory regime for utilities has changed in substantial ways over the 2000-2018 period. In particular, the UK regulatory frameworks have undergone substantial changes

24 Grout and Zalewska (2016) show that equity betas of industrials and utilities in 11 mature equity markets were affected by the decreasing share of bank stocks in the market index during the global financial crisis. Grout, P.A. and Zalewska, A. (2016), Stock market risk in the financial crisis, International Review of Financial Analysis, vol. 46, pp. 326-345.

with the introduction of high-powered incentives under the output-based RIIO framework for energy and PR14 framework for water as well as an increasing role of competition, e.g. through liberalisation of non-household retail at PR14 and plans to open up further parts of the value chain to competition at future reviews.

Political risk, another determinant of the risk profile of UK utilities, has also increased over the period since 2000, e.g. the introduction of an energy price cap and recent nationalisation threats are among the factors driving an increase in political uncertainty.

As a consequence of increased regulatory and political risk, as cuts to allowed returns are looming, rating agencies have recently assigned a negative outlook to the UK water sector.[25]

As such, regardless of the choice of estimation technique, a long-horizon beta estimation period subjects beta estimates to market and regulatory conditions that were prevalent more than a decade ago and no longer resemble current conditions.

3.4. Long time period leads to downward biased betas for UK stocks compared to recent periods

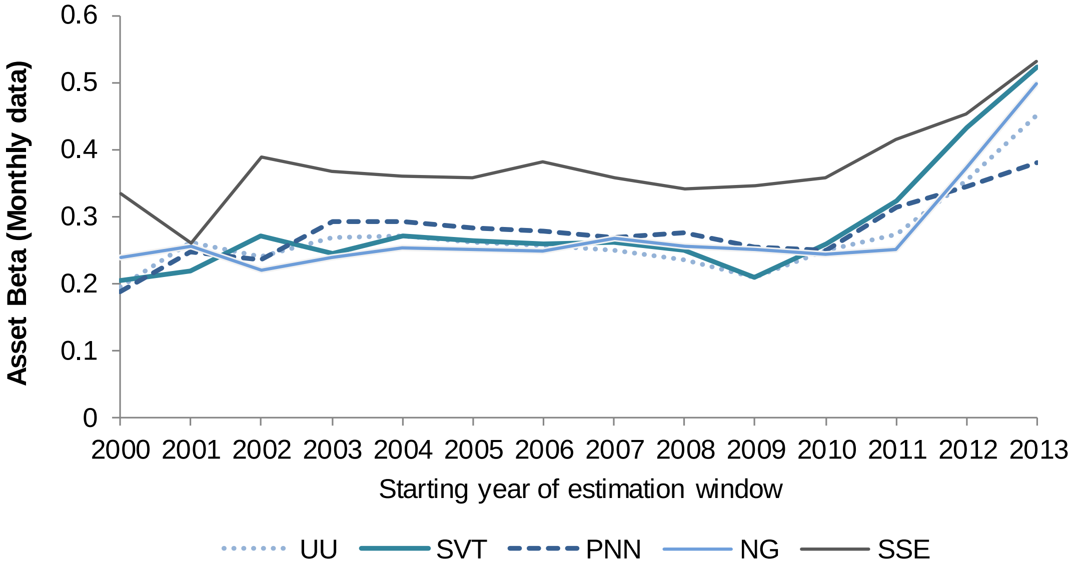
As argued in the previous sections, estimating betas over long horizons ignores changes in companies' business and financial risk, changes in market conditions as well as changes in the regulatory regime, resulting in beta estimates that fail to reflect regulated companies' risk for the upcoming price control periods.

To illustrate the potential bias introduced in beta estimates through relying on an excessively long estimation period, in Figure 3.6 we show estimates of the MPW "Short-Run" asset beta based on monthly returns for the five UK listed comparators (United Utilities, Severn Trent Pennon, National Grid and SSE). [26] The betas are estimates using MPW's recommended GARCH-model.

[25] For example, in January 2018 Moody's assigned negative outlook to UK water sector following Ofwat's proposed cut of allowed returns in PR19. Link: https://www.moodys.com/research/Moodys-changes-UK-water-sector-outlook-to-negative-as-Ofwat--PR_378176

[26] We use monthly instead of quarterly returns as quarterly returns do not provide sufficient number of observations to estimate betas over shorter time frames.

Figure 3.6
MPW "Short-Run" asset betas show increase in most recent period (based on monthly returns for five UK comparators)



Source: Bloomberg, NERA calculations.
Note: Following the terminology of MPW, this figure shows "Short-Run" asset betas for five UK comparators estimated using the MPW recommended MGARCH model. Each figure is calculated based on monthly returns and a time frame where the end date is fixed at 2017Q3 and the start date is the first quarter of the year indicated on the horizontal axis. We use the average net debt to market capitalisation ratio over the given time frame to un-lever the equity betas into asset betas, using the Miller formula.

The leftmost values in Figure 3.6 are based on the entire 18-year time period of 2000 to 2017, as advocated by MPW. As we move right along the x axis, the end date of the time period is kept fixed at 2017, but the start date gradually increases in annual increments. Hence, the second entry value from the left reflects betas estimated over the period 2001 to 2017. The rightmost values show beta estimates based on the five-year period 2013 to 2017.

As Figure 3.6 shows, we estimate substantially higher asset betas as the beginning of the estimation period is gradually shifted towards more recent times. While the full period 2000 to 2017 yields an average asset beta of 0.23 across the five comparators, we calculate an average asset beta of 0.48 as the calculation window is shortened to the most recent five year period.

The significant joint increase in asset betas for starting years between 2009 and 2011 suggests a potential structural break during that period. A potential explanation of this result would be that betas of UK utilities as "defensive stocks" fell in the aftermath of the Global Financial Crisis (GFC), depressing beta estimates for estimation windows which include the GFC period.[27] Once the GFC period is excluded from the sample, more recent estimation windows show substantially higher beta estimates.

We consider that the most straightforward way to avoid biased beta estimates is to rely on time series that are sufficiently recent such that results are not biased by shifts in fundamentals. This use of more recent time series of data, typically of 2 to 5 years, has been the standard practice of UK regulators over many years.[28]

3.5. Conclusion: beta estimates should be based on recent periods

In summary, in our view, OLS and GARCH models are only appropriate for estimating betas for estimation of regulatory cost of capital when applied using more recent data. There are many fundamental reasons why we have reached this conclusion, discussed in sections 3.1 to 3.3 above concerning changes in business models over time, changes in market composition and conditions as well as changes in regulation over time. In section 3.4 we have presented statistical support for the use of shorter run time series data for application in OLS or GARCH models, since we have shown that betas change significantly over time and are particularly sensitive to the inclusion of the period around the Global Financial Crisis. The change in betas over time, and sensitivity of the beta estimate to the inclusion of the GFC period, was not explored at all by MPW in their report.

We conclude that a more recent time frame should be considered when estimating betas for the purpose of regulatory determinations, to ensure the beta estimates reflect the risks companies face going forward. Such time frames may include very recent data (2 years) as well as medium term estimates (e.g. 5 years). This is consistent with the approach taken by Burns as well as with established UK regulatory precedent.[29]

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[27] It is likely that equity betas of UK comparators dropped during the crisis and that therefore any time frame including the 2009-2011 period underestimates equity betas and consequently asset betas as well. Grout and Zalewska (2006) document that the betas of US and UK utilities declined in the aftermath of the dotcom-bubble burst and similar dynamics may have played out in the financial crisis as well. Grout, P.A. and Zalewska, A. (2006), The impact of regulation on market risk, Journal of Financial Economics, vol. 80(1), pp. 149-184.

[28] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p.49

[29] See e.g. Burns in Appendix F, pp.F-129-130 which includes precedent from Ofwat PR14, CMA Bristol Water 2015, CAA Airports 2014, and Ofcom LLCC 2016 decisions.

4. The use of low-frequency data for beta estimation at future reviews

In this section, we explain that there are a number of issues with relying on low frequency data, such as quarterly returns, as proposed by MPW. In summary, we explain that smaller sample size associated with the use of low frequency data leads to less precise beta estimates. We also demonstrate that there are a number of ways for aggregating returns to lower frequencies, producing volatile results when the aggregation rule is changed in a trivial manner. We also highlight that the use of low frequency data together with GARCH models appears inconsistent. Finally, we show that once low frequency data and recent time periods are used, the MPW GARCH beta estimates are consistent with asset betas determined at recent reviews.

4.1. Low frequency data and associated smaller sample size leads to less precise beta estimates

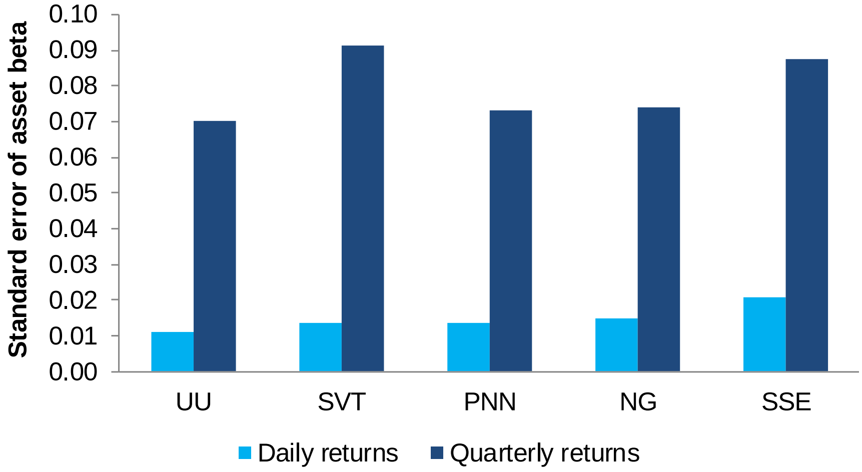
MPW estimate betas for United Utilities and Severn Trent using a range of data frequencies, including daily, weekly, monthly and quarterly data, although they advocate the use of low frequency data for the estimation of betas at future reviews.

An important obstacle to estimating betas at lower frequencies is the associated reduction in sample size compared to when higher-frequency data is used. When moving from high to low-frequency data, one is forced to use relatively long time-series to obtain enough observations.

This is particularly true for the use quarterly data. Using quarterly data for a relatively long estimation window of 10 years, we would be left with a small sample of 40 observations. A 5-year estimation window would give a mere 20 observations to analyse. Even when all available data is used (in the case of MPW that is data from 2000-2017), the number of observations is still considerably smaller compared to common practice of using daily data.[30] As a result, beta estimates are substantially less precise due to loss of valuable information in aggregating returns data to lower frequencies. Figure 4.1 below shows that the standard error of the beta estimate for the five UK listed comparators increases around six times when moving from daily to quarterly data frequency.

30 Using an estimation period of 17 years, quarterly data provides 17*4=68 observations while daily data provides around 17*250=4250 observations.

Figure 4.1
Standard errors of betas for UK comparators increase six times when moving from daily to quarterly data frequency



Source: NERA analysis based on Bloomberg data
Note: The figure shows the standard errors of the asset beta from an OLS regression estimated over the period 1 Jan 2000 – 25 Sept 2017 based on daily and quarterly data. Standard errors are calculated using the Huber/White/sandwich estimator (robust estimator) for the variance-covariance matrix of parameter estimates.

4.2. Changes to aggregation method for low frequency returns produces volatile results

The process of aggregating from daily to lower frequency returns requires decisions on the exact aggregation rules. Table 4.1 shows a stylised example of how the choice of the specific weekday used as the starting point of the weekly return affects the calculated weekly return. The same issue applies to the setting of start dates for months and quarters.

Table 4.1
The choice of starting point greatly affects returns calculated at lower frequencies

Week	Trading Day	Share Price	Weekly Return^{Monday}	Weekly Return^{Wednesday}
	Monday	10.0		
	Tuesday	10.5		
1	Wednesday	10.0		
	Thursday	10.5		
	Friday	11.0		
	Monday	12.0	20%	
	Tuesday	11.5		
2	Wednesday	11.0		10%
	Thursday	11.5		
	Friday	12.0		

Source: NERA illustration

For weekly returns, there are five possible definitions, one for each day of the week, of how to calculate weekly returns from daily data. For monthly returns there are around 20 possible definitions, corresponding to the number of trading days per month. For quarterly returns, there are about 60 possible definitions.

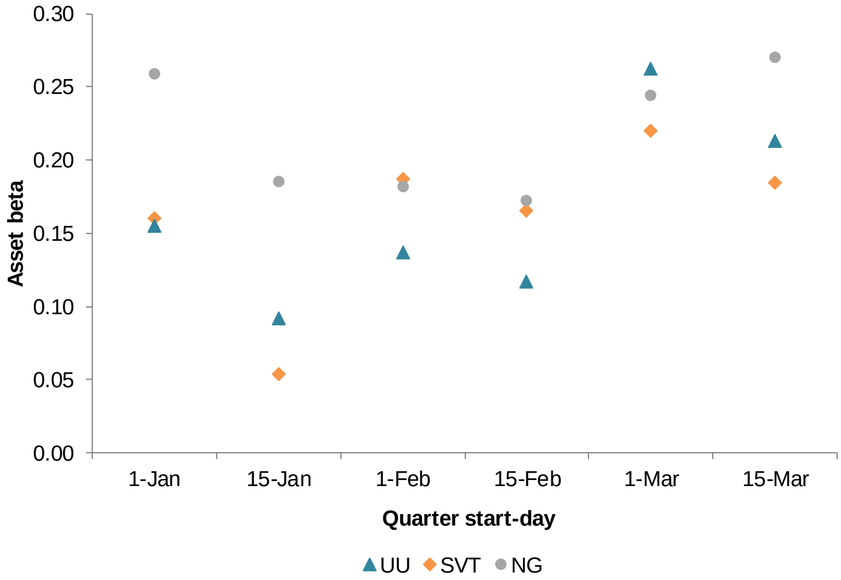
When aggregating returns from the most granular frequency available to a lower frequency for beta estimation, regulators are faced with the decision of how to define the aggregation interval. As the number of possible choices increases the more aggregated returns get, the regulator’s choice may seem increasingly arbitrary as the frequency is lowered.

MPW do not explain how they aggregate daily to quarterly returns. We assume they use end-of-quarter stock returns and we use this aggregation method ourselves, unless otherwise stated in this report. However, we note that there is no theoretical reason to calculate quarterly returns starting from the last day of the quarter instead of any other day of the quarter.

Below, we demonstrate that changing the starting point for aggregating returns at lower frequencies may have dramatic effects on the beta estimate when using quarterly returns, both based on OLS as well as the MPW recommended MGARCH model, highlighting the volatility of MPW results.

In Figure 4.2 we show the estimates of asset beta for UU, SVT and NG plc obtained by OLS using quarterly returns over the period of 2000Q1 to 2017Q3. We show betas for six possible definitions of a quarterly return out of the ca. 60 possible definitions available.

Figure 4.2
OLS-based asset betas for UU, SVT and NG plc exhibit substantial volatility depending on quarter definition



Source: Bloomberg, NERA calculations
Note: This figure shows asset betas for UU, SVT and NG plc when the start date of the first quarter is the one given on the horizontal axis. Betas are estimated using OLS based on quarterly returns and a period of 2000Q1-2017Q3.

The leftmost values represent the asset beta estimates for UU, SVT and NG plc when the aggregation quarter is defined using a start date on 1 January (1 April, 1 July, 1 October) and an end date of 31 March (30 June, 30 September, 31 December). This corresponds to the end-of-quarter definition we employed elsewhere in this report. As we move rightwards in the graph, the start date (and corresponding end date) of the quarter are shifted forward. For example, the second set of values from the left represents the asset betas estimated for UU, SVT and NG plc when the aggregation quarter has a start date on 15 January (15 April, 15 July, 15 October) and an end date of 14 April (14 July, 14 October, 14 January). The rightmost set of values represents the asset beta estimate when the aggregation period has a start date of 15 March (15 June, 15 September, 15 December) and an end date of 14 June (14 September, 14 December, 14 March).

Appendix B shows similar analyses for beta estimates obtained using GARCH-type models.

Figure 4.2 highlights that asset beta estimates for a given firm vary in a large range when the definition of the quarter is changed. This problem is independent of the modelling choice (OLS or GARCH), but is a general problem of aggregating returns.

Focusing on the OLS results only, the asset beta estimate for UU varies between 0.09 and 0.26, for SVT the range is 0.05 to 0.22, and for NG plc the range is 0.17 to 0.27. These ranges are very substantial and show how volatile beta estimates are depending on the aggregation rule. A similar concern applies to the GARCH results, as shown in Appendix B. Importantly, one of the implications of this analysis is that these ranges could still be much wider if all 60 possible definitions of a quarter were investigated, as the choice of the six definitions considered above is entirely arbitrary.

It should be emphasised that all of the asset beta results above are generated using quarterly data over the whole sample period 2000-2017. For the reasons discussed in section 3 above, we do not regard the use of this time period to be appropriate, since it likely leads to downwardly biased beta estimates for UK regulated companies, especially if the analysis is focused only on a limited set of two comparator companies UU and SVT, as MPW have done. However, the analysis in this section provides an additional reason not to rely on quarterly data over this time period since the beta estimates are highly sensitive to the start dates of the chosen intervals.

4.3. MPW use of low-frequency returns in conjunction with models of the GARCH family appears inconsistent

In the previous chapter we have pointed out problems that arise from aggregating returns from higher to lower frequencies. The issues presented so far apply in any case, irrespective of the econometric model used to estimate betas, e.g. OLS or GARCH.

In the academic literature, higher frequency data is preferred over low frequency data, provided that there is sufficient variation between observations. For instance, Morse (1984) examines the choice between monthly and daily return data. He finds:

> *"The most powerful estimate of mean abnormal returns is generated by the return series that minimizes bias and maximizes efficiency. The results generally support the use of daily return data to estimate information effects, with the possible exception of cases in which there is uncertainty about the date of the information release. Even with this uncertainty, however, daily returns may still be preferred to monthly returns in some situations."*[31]

In the remainder of this section we comment on the use of low-frequency returns in conjunction with models of the GARCH family.

It is well documented in literature that stock returns may not be independently distributed.[32] One way to address this issue under an OLS framework would be to lower the frequency of the data to reduce the problem of autocorrelation or heteroscedasticity. However, this necessarily reduces the number of available observations, as we discuss above.

Models such as ARCH, GARCH, and MGARCH allow for explicit modelling of the time-varying properties of stock returns empirically observed in financial data, thus avoiding the issue of losing valuable information by aggregating returns to lower frequencies.

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[31] Morse, D. (1984), An Econometric Analysis of the Choice of Daily Versus Monthly Returns in Tests of Information Content, Journal of Accounting Research, vol. 22(2), p. 606.

[32] See for example Zalewska, A., Grout, P.A. (2006), The impact of regulation on market risk, Journal of Financial Economics, vol. 80(1), pp. 149-184.

MPW propose to use GARCH models for estimating betas to reflect time-varying properties of asset returns (such as time-varying volatility) but at the same time they also propose to remove those very properties that GARCH models are designed to deal with from the data by aggregating returns. Therefore, we find the simultaneous recommendation for the use of GARCH-type models and the aggregation of returns inconsistent.

There is a second, more technical argument against the use of GARCH-type models in conjunction with aggregate returns as MPW propose. MPW apply the same (M)GARCH model to daily, weekly, monthly, and quarterly returns. However, it is not immediately apparent that a GARCH-type model that is a suitable representation of returns at a given frequency is still a suitable representation when the returns are aggregated to a lower frequency. This issue has received continued attention in academic literature.

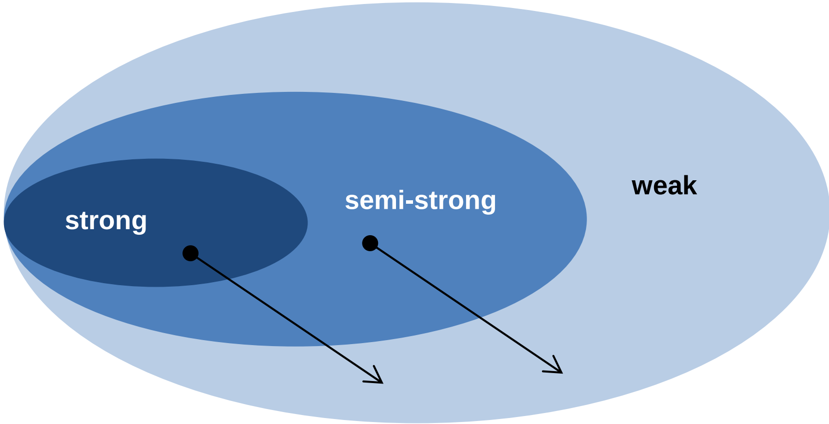
Drost and Nijman (1993)[33] have analysed the case of univariate GARCH processes and Hafner (2008)[34] has extended this analysis to the multivariate case which is relevant for the model MPW suggest. Hafner (2008) defines three families of MGARCH models. These are the "strong", the "semi-strong", and the "weak" family. These families are not mutually exclusive, but the strong family is contained in the other two families and the semi-strong family is contained in the weak family. We illustrate this in Figure 4.3. For instance, any model that belongs to the semi-strong family also belongs to the weak family, but not vice versa. There are models that belong to the weak family, but not to the semi-strong family.

One of the central findings of Hafner (2008) is that only MGARCH models of the weak family have the property of closedness with regard to time aggregation. In this context closedness means that if a model of the weak type is the right model of returns at a given frequency, the right model for aggregate returns is of the weak type as well. This property does not hold for semi-strong and strong models in general. For instance, if the right model for daily returns belongs to the semi-strong family, the right model for weekly returns belongs to the weak, not to the semi-strong family. We indicate these relations with the black arrows in Figure 4.3.

33 Drost, F.C. and Nijman, T.E. (1993), Temporal aggregation of GARCH processes, Econometrica, vol. 61, pp. 909-927.

34 Hafner, C.M. (2008), Temporal aggregation of multivariate GARCH processes, Journal of Econometrics, vol. 142(1), pp. 467-483.

Figure 4.3
Classification of MGARCH models following Hafner (2008)



Source: NERA illustration.

Given the technical appendix to the UKRN report, we believe the specification of MPW is not of the weak, but of the semi-strong type.[35]

We therefore believe that it is inconsistent for MPW to argue that their proposed model can be a suitable description of high frequency and low frequency returns at the same time. By applying the same model to all four data frequencies, MPW claim that the daily, weekly, monthly, and quarterly data are of the semi-strong type. However, Hafner (2008) shows that once the daily data is assumed to be of the semi-strong type, this implies that any lower frequency data should be of the weak type. Therefore, MPW appear to contradict themselves through applying the same model to all four frequencies at the same time. We consider this as yet another reason not to apply a GARCH-type model to low frequency returns if daily data is available.

4.4. Using shorter time periods and high data frequency produces asset betas in line with recent determinations using a GARCH model

As we explain in this and the previous section, we disagree with MPW recommendations of using long time frames since 2000 and low frequency data (e.g. quarterly) for estimating betas for UK regulated utilities at future reviews. In line with standard practice, we consider beta estimates should draw on high frequency data (e.g. daily) and recent time periods (e.g. two to five years) to ensure precise and relevant estimates.

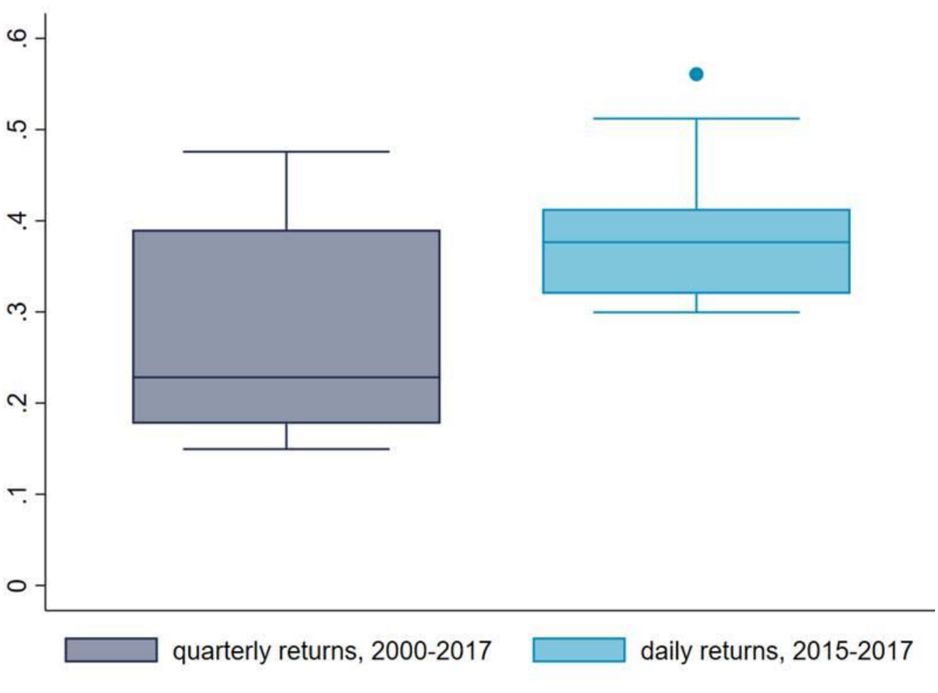
Figure 4.4 below shows asset betas estimated using the MPW preferred approach (long-run data, quarterly returns) compared to our recommendation (short-run data, daily returns). We use a sample of 11 comparators, including five listed UK companies (National Grid, SSE,

[35] On page 2 of the technical appendix of the UKRN report, the authors provide a parametric expression for the conditional variance-covariance matrix of the stock and market return innovations that resembles Hafner's definition 3.2 for a semi-strong MGARCH process.

United Utilities, Severn Trent, Pennon) and six European energy networks (Red Electrica (Spain), TERNA (Italy), ACEA (Italy), Gas Natural SDG (Spain), SNAM (Italy), and Enagas (Spain)), as we consider MPW's focus on two water stocks is too restrictive and a wider range of comparators should be considered for beta estimation.

Figure 4.4 shows a range of asset beta estimates for the 11 comparators using the MPW preferred approach (left-hand side) versus our preferred approach (right-hand side). In each panel there is a central rectangular shape with a horizontal bar. The horizontal bar represents the median estimate, whereas the lower and upper edges of the rectangles represent the 25th and the 75th percentile, respectively. This implies that the central 50 per cent of beta estimates are contained in the rectangular shape. The highest and lowest "cross-bars" represent the range of beta estimates that are not considered as outliers. Outliers are defined as those estimates which are higher /lower than the 75th / 25th percentile +/- 1.5 times the inter-quartile range and are indicated as dots.

Figure 4.4
GARCH-based short-run asset beta estimates for 11 comparator companies



Source: Bloomberg, NERA calculations
Note: This figure shows the distribution of MPW "short-run" asset betas from the MGARCH model for 11 UK and EU comparators(National Grid (UK), SSE (UK), United Utilities (UK), Severn Trent (UK), Pennon (UK), Red Electrica (Spain), TERNA (Italy), ACEA (Italy), Gas Natural SDG (Spain), SNAM (Italy), and Enagas (Spain)). The left panel shows figures based on the MPW recommended approach, i.e. quarterly returns estimated over the period 2000Q1-2017Q3.

Figure 4.4 reveals a number of key observations regarding MPW's results:

- The lower beta estimates MPW claim to find are primarily driven by their choice of time frame and the aggregation of returns, not by the introduction of a new MGARCH model.

Using more recent data (2 years) and daily frequency we estimate asset betas which are substantially higher than MPW's, and in line with betas determined at recent reviews.[36]

- When applied to the wider set of 11 comparators, the MPW recommended approach of using long-time periods and low frequency data yields a substantially wider range of betas (as measured by the inter-quartile range, or the width of the "box" in each panel) compared to the approach of relying on recent data and daily frequency. This is surprising, given the comparator group includes broadly similar companies, and casts further doubt on the reliability of MPW results. We also note that if MPW had expanded their comparator set to include other UK and EU comparator energy and water companies, the results of their analysis would have changed substantially.

In summary, as we explain in this and the previous section, we do not consider the use of long time frames since 2000 and low frequency data (e.g. quarterly) is appropriate for estimating betas for UK regulated utilities at future reviews. Figure 4.4 shows that asset betas estimated using the MGARCH model based on more recent time periods and daily data frequency are consistent with asset betas determined at recent reviews. We therefore conclude that we find no evidence for lower asset betas for the upcoming price control reviews, as argued by MPW.

Finally, we note that MPW compare their estimated *equity* betas for UU and SVT of 0.3 to 0.5 with allowed *equity* betas at recent reviews (e.g. 0.8 by Ofwat at PR14).[37] However, this comparison is misleading, as the equity betas are affected by the differences in empirical gearing for the comparators and the notional gearing assumed by Ofwat.[38] The correct comparison is therefore using un-levered or asset betas, which MPW estimate at 0.15 to 0.25 for UU and SVT.[39] The allowed asset beta by Ofwat for water companies at PR14, the most recent review, has been 0.3.[40] The correct comparison of *asset* betas therefore shows that the difference between MPW asset beta estimates (0.15 to 0.25) and UK precedent (0.3) is less extreme than presented by MPW.

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36 For example, at RIIO-1, Ofgem determined asset betas in the range of 0.32 to 0.43. See NERA (2012) Cost of capital estimation for RIIO-ED1, a report for WPD. Link: https://www.westernpower.co.uk/docs/About-us/Stakeholder-information/Our-future-business-plan/Supporting-Financing-plan/NERA-Cost-of-Capital-Estimation.aspx

37 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. 9.

38 The beta from stock market data reflects the so called levered or equity beta, which reflects the impact of financial leverage on equity risk. The greater financial leverage (i.e. debt), the greater the equity beta, as the fixed payments to debt holders accentuate the volatility of residual cash-flows which accrue to equity holders. Equity betas are therefore different for different levels of financial leverage even for companies with the same underlying business risk. To estimate the stand-alone business risk of the comparator firm, the estimated equity betas should be un-levered using an estimate of the company's gearing to obtain the corresponding asset beta.

39 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. 55

40 Ofwat (December 2014), Setting price controls for 2015-2020, Final price control determination notice: policy chapter A7 – risk and reward, Table A7.10, p. 41.

5. Role of advanced time series models for estimating betas in the regulatory context

In this section, we analyse asset beta estimates obtained using different estimation methods and discuss the role of more advanced models in the regulatory context.

In summary, we find that once consistent time periods and data frequencies are used, the beta estimates produced by MPW's proposed MGARCH model and standard OLS become very similar for our comparator set. We therefore conclude that the benefit of a more complex MGARCH model relative to standard OLS is questionable in the regulatory context. We further note that time-varying properties of betas can be captured using the OLS model and a rolling-window estimation approach, which is substantially less complex and may be more suitable for regulatory purposes.

5.1. Beta estimates using alternative estimation methods

We estimate asset betas for the 11 comparator companies discussed in the previous section using three different estimation methods:

- the traditional OLS model;
- the BEKK-MGARCH model suggested by MPW; and
- a state space model estimated using the Kalman Filter (KF).[41]

For each of the estimation methods, we estimate asset betas using two alternative estimation periods and data frequencies:

- The MPW recommended approach of relying on quarterly data and an estimation period since 2000; and
- Our preferred approach of relying on daily data and recent time periods (for illustration, we use a 5-year estimation period).

The resulting asset beta estimates for the different estimation methods as well as estimation periods and data frequencies are shown in Table 5.1 below. We note that due to the low number of observations under the quarterly specification, the KF model could not be estimated over the MPW preferred period since 2000. For daily data, the KF model could also not be estimated using a 5-year period. We therefore estimate the KF using a 10-year period instead. However, we report asset betas averaged over the same 5-year period as the OLS and MGARCH results.

[41] We provide a more detailed discussion of alternative models besides OLS in the next section.

Table 5.1
Asset betas for 11 comparator firms from OLS, Kalman Filter, and MGARCH under two time period/data frequency specifications

	Quarterly returns 2000Q1 – 2017Q3 (18 years)		Daily returns 26 Sep 2012 – 25 Sep 2017 (5 years)		
	MGARCH	**OLS**	**MGARCH**	**OLS**	**KF***
National Grid	0.25	0.24	0.38	0.37	0.29
SSE	0.21	0.16	0.54	0.56	0.43
United Utilities	0.15	0.15	0.34	0.32	0.26
Severn Trent	0.18	0.15	0.35	0.35	0.29
Pennon	0.15	0.17	0.38	0.38	0.32
Snam (GT)	0.21	0.17	0.39	0.41	0.52
Terna (ET)	0.23	0.22	0.39	0.40	0.50
Acea (ED)	0.48	0.42	0.31	0.30	0.39
Enagas (GT)	0.39	0.36	0.41	0.38	0.44
Red Electrica (ET)	0.28	0.39	0.40	0.39	0.50
Gas Natural (GD)	0.42	0.49	0.50	0.48	0.60
Range	**0.15-0.48**	**0.15-0.49**	**0.31-0.54**	**0.30-0.56**	**0.26-0.60**
Average	**0.27**	**0.26**	**0.40**	**0.40**	**0.41**

Source: Bloomberg, NERA calculations
*Note: * We estimate the KF model using a 10-year period as the model could not be estimated using a 5-year timeframe. The betas reported in the table are the average KF betas over the period 26 September 2012 to 25 September 2017, the same period which we use to estimate the OLS and MGARCH betas using daily returns.*

Considering the long time period since 2000 and using quarterly returns as advocated by MPW, asset betas estimated using the MGARCH model lie in the range of 0.15-0.48 with a mean of 0.27. Using the same period and data frequency, but instead using a standard OLS model, we estimate asset betas which lie in the range of 0.15-0.49, with a mean of 0.26. The results further confirm our earlier conclusions that the "alternative" equity beta estimates presented by MPW are not driven by the use of a more sophisticated estimation method (an MGARCH model) but rather by the use of a very long time frame and quarterly data frequency for estimating betas.

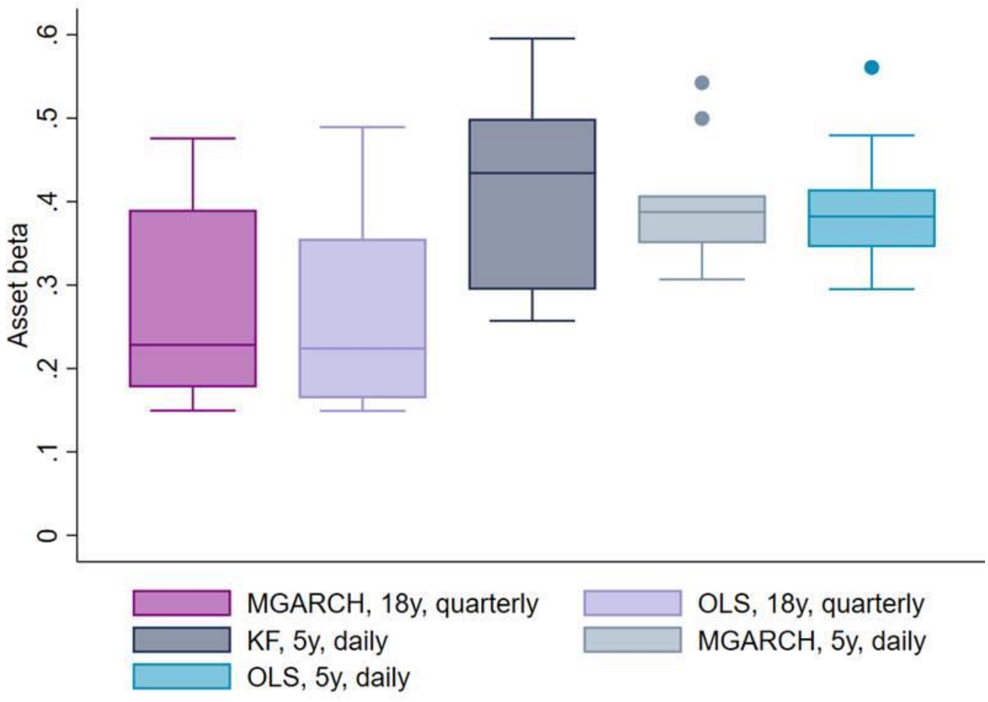
Using our alternative daily returns frequency and a shorter time frame (last 5 years for illustration), asset betas estimated using the MGARCH model lie in the range of 0.31-0.54 with a mean of 0.40. Asset betas from the OLS model lie in a very similar range of 0.30-0.56 and a mean of 0.40. The asset betas from the KF model lie in a slightly wider range of 0.26-

0.60, but the average of 0.41 is consistent with the OLS and MGARCH results. As is the case for the longer time period and lower data frequency, the betas estimated using different econometric methods are fairly consistent with each other when daily data and shorter estimation periods are used.

The dispersion of asset beta estimates from all models under both time period and data frequency specifications is shown in Figure 5.1.

Notably, the estimates from the MGARCH and the OLS model under the alternative specification (5-year estimation window using daily returns) exhibit the smallest dispersion across firms as measured by the interquartile range.

Figure 5.1
Dispersion of asset betas from OLS, Kalman Filter, and MGARCH under two time period/data frequency specifications



Source: Bloomberg, NERA calculations
Note: This figure shows the distribution of asset betas as obtained from the MGARCH model recommended by MPW, OLS, and KF models for 11 UK and EU comparator firms in the form of box plots. The two left panels show figures based on the MPW recommended approach of relying on quarterly returns and a time period of 2000Q1-2017Q3. The three right panels show figures based on daily returns and a time frame spanning the five years from 26 September 2012 to 25 September 2017. In each panel there is a central rectangular shape with a horizontal bar. The horizontal bar represents the median estimate, whereas the lower and upper edges of the rectangles represent the 25th and the 75th percentile, respectively. This implies that the central 50 per cent of beta estimates are contained in the rectangular shape. The highest and lowest "cross-bars" represent the range of beta estimates that are not considered as outliers. Outliers are defined as those estimates which are higher /lower than the 75th / 25th percentile +/- 1.5 times the inter-quartile range and are indicated as dots.

Figure 5.1 reveals that the average as well as ranges of asset betas estimated using the MGARCH model are remarkably close to the results estimated using OLS, irrespective of the time period and data frequency used. The KF betas produce similar results to MGARCH and OLS on average, but exhibit greater volatility within the sample of comparator companies.

In summary, we show that once consistent time periods and data frequencies are used, the results from standard OLS estimation and the MGARCH model proposed by MPW become very similar. This confirms our earlier conclusion that the lower beta estimates MPW claim to find are primarily driven by their choice of long time period, aggregation of returns to low frequencies, and by focussing on a sample of only two comparators, not by the introduction of a new MGARCH model. This is consistent with the view presented by Burns.[42]

While we do not object to the use of GARCH model for the purpose estimating betas, we note that GARCH-type models are complex and difficult to implement and reproduce by stakeholders, which may introduce arbitrariness in regulatory decision making and increase perceptions of regulatory risk. Given we find that MGARCH and OLS models produce consistent results, we consider that the benefit of a more complex MGARCH model relative to standard OLS appears questionable in the regulatory context.

In the next section, we include a short discussion of the potential role of different models for the purpose of estimating betas in the regulatory context.

5.2. Use of advanced time series models in the regulatory context

We consider that in the future more advanced time series models may prove useful insight for beta estimation in the regulatory context. In particular, they may help understand and assess variation in betas over time.

Beta is defined as the covariance between returns on the asset and returns on the market portfolio, divided by the variance of returns of the market portfolio. In academic literature, there are several econometric methods available for estimating the CAPM beta.

The earliest and possibly the most widely used method to date is the standard linear regression model, estimated by ordinary least squares (OLS). One of the potential restrictions of the OLS model is that it assumes the beta is constant over time. However, there is a body of empirical evidence showcasing that betas may vary over time.[43]

There are a number of models which allow analysing time variation in beta. Variants from the GARCH family provide a framework to explicitly model how the variance and covariance of stock returns changes over time. State-space models relying on the Kalman filter (KF) represent another class of models besides GARCH which also accommodate time-varying betas. The KF is widely employed in academic literature, but also in engineering

[42] Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. F-136-137

[43] For example, Engle and Patton (2001) survey the most important stylized facts about the volatility of asset returns.[43] They present evidence of so called volatility clustering, which means that large moves in returns (of either direction) are typically followed by large moves and small moves are typically followed by small moves, creating persistence in volatility. They also show that volatility is mean reverting, i.e. a period of high volatility will eventually give way to a more normal level of volatility and conversely a period of exceptionally low volatility will eventually reverse, too. These stylised observations about asset returns' volatility imply that beta may vary over time. (Source: Engle, R.F., Patton, A.J., 2001. "What good is a volatility model?" Quantitative Finance, vol(1), pp. 237-245)

technical applications where results can be tested experimentally. The OLS model using a rolling window (RW) estimation approach is a much simpler model that may incorporate time variation in beta as well.

Hollstein and Prokopczuk (2016) provide a comprehensive survey of market beta estimation techniques comparing a broad range of models, including GARCH, Kalman Filter and even more advanced, option-based models.[44] They find that:

> *"estimators using historical information perform well only if they do not make too strong structural assumptions, like the simple historical beta and the Kalman filter approach with a random walk parametrization. In contrast, models that make strong assumptions on the volatility and correlation processes (like the GARCH-based DCC) are shown to produce very large errors."*[45]

By *simple historical beta* the authors refer to an OLS regression with a rolling window of one year. The rolling window OLS approach also appears to be favoured by Burns, who shows that the beta estimates resulting from this model are qualitatively similar to the beta predictions generated from the GARCH model favoured by MPW, i.e. that their GARCH model does not provide any new insights about the time-varying properties of betas.[46]

Indeed, we believe the rolling-window OLS approach may potentially provide the most suitable method for analysing time-varying properties of betas in the regulatory context, as it offers the best trade-off between various regulatory objectives. It i) is easy to implement and well understood, ii) incorporates time-varying betas, and iii) minimizes the scope for regulatory discretion/arbitrariness.

The advantage of a RW OLS model highlighted in the last point relates to the vast array of models from which the regulator has to choose when employing a GARCH model. MPW choose one particular variant, the so-called BEKK-MGARCH(1,1), although several alternatives would have also been possible. The authors do not discuss their modelling choice. Any beta estimation relying on GARCH-models should consider several alternatives tested against each other using appropriate statistical selection criteria to justify the eventual use of one particular model.[47] This is especially relevant as the family of GARCH models includes so many different variants, each possibly leading to different beta estimates.

In fact, as Burns points out, Wright, Mason, and Miles (MMW) considered this as an argument against the use of GARCH models in a regulatory setting in their earlier 2003 report.[48] MMW (2003) argued that there are many different ways to model time variation

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44 Hollstein, F. and Prokopczuk, M. (2016), Estimating Beta, Journal of Financial and Quantitative Analysis, vol. 51(4), pp. 1437-1466.

45 Hollstein, F. and Prokopczuk, M. (2016), op. cit., p. 1464.

46 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., Figure F.12, p. F-136.

47 In our analysis underlying this report we focus on the model suggested by MPW and therefore do not further discuss model selection.

48 Wright, S., Mason, R., & Miles, D. (2003), A Study into Certain Aspects of the Cost of Capital for Regulated Utilities in the UK. London: Smithers & Co Ltd report to the UK Regulators and the Office for Fair Trading.

and that it *"would be a problem of getting a beta estimated with a time*-*varying technique to be widely accepted as a standard estimate"*.[49]

In contrast, the rolling-window OLS model applied to the CAPM leaves far less discretion to the regulator and therefore makes the replication of any beta estimate more straightforward for stakeholders.

However, as noted by Burns,[50] irrespective of the model chosen to estimate betas (OLS, GARCH, KF), regulators would still be faced with the question over what time period the estimated time-varying betas should be averaged for the purpose of setting the allowed cost of equity at future reviews (as discussed in section 3).

49 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. F-137.

50 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), op. cit., p. F-136.

Appendix A. Our implementation of the GARCH model proposed by MPW

GARCH models are computationally much more demanding than OLS. Whereas the latter may be implemented in Excel, GARCH models require the use of specialised statistical software. MPW published a technical appendix of four pages together with the UKRN report that aims to explain their implementation of the GARCH approach.

We were unable to implement the model suggested by MPW in Stata, one of the most widely used commercial statistical packages, because the necessary optimisation did not converge. We resolved the issues of implementing the GARCH-approach proposed by MPW in two ways.

- Firstly, we implemented the model as suggested by MPW using the statistical programming language R and a library specifically written to estimate the subcategory of MGARCH models MPW propose.[51] We consider this implementation as our benchmark model. Figures presented in this report are generated from this implementation, unless stated otherwise.
- Secondly, we implemented slightly different, yet similar types of GARCH models in Stata, for which we could achieve convergence.[52]

We note that for both of these implementations we achieved similar, yet not identical, figures as reported by MPW.[53]

We note that GARCH models do not produce one beta estimate for the entire period on which they are estimated (as is the case in OLS), but provide for an “instantaneous” beta estimate at each point in time. To aggregate the many instantaneous betas into one single figure based on which the cost of equity may be set, MPW propose three different methods which they denote (i) short-run beta, (ii) average beta and (iii) long-run beta. We adopt this nomenclature in our report. It should be noted that all three methods take into account the entire time period over which the GARCH model is estimated.

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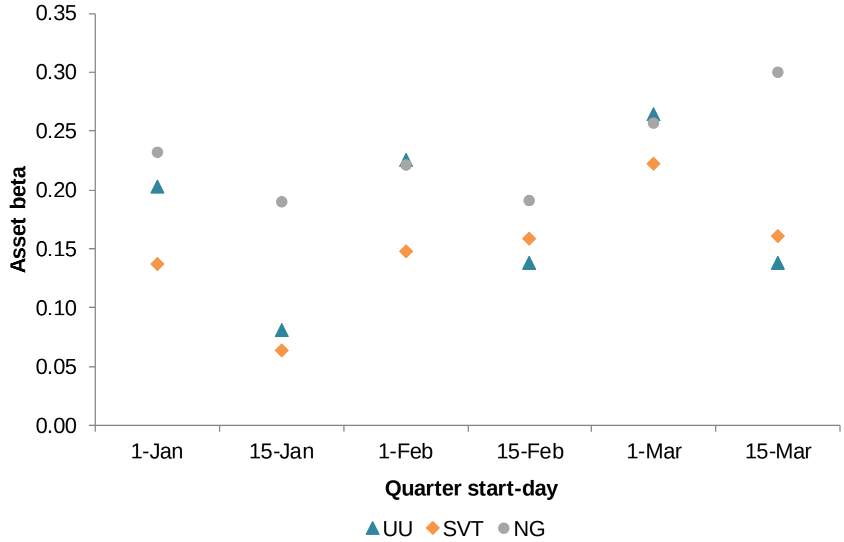
51 The library *mgarchBEKK* is provided by courtesy of Harald Schmidbauer, Angi Rösch, and Vehbi Sinan Tunalioglu. Source: https://cran.rstudio.com/web/packages/mgarchBEKK/index.html

52 Wright et al. suggest a bivariate GARCH(1,1) model of the so called BEKK specification. We implement this in R as our benchmark model. In Stata, we implement a linear regression model of the firm’s stock return on the market return allowing for the error term to have a univariate GARCH structure to achieve convergence.

53 Wright, S, Burns, P, Mason, R, and Pickford, D (2018), Estimating the cost of capital for implementation of price controls by UK Regulators, An update of Mason, Miles and Wright (2003)., Table 1, p. G-148.

Appendix B. Sensitivity of MGARCH estimates to aggregation method for quarterly returns

Figure B.1
GARCH-based asset betas for UU, SVT and NG plc show similar sensitivity to quarter definition as OLS betas



Source: Bloomberg, NERA calculations
Note: The figure shows asset betas for UU, SVT and NG plc when the start date of the first quarter is the one given on the horizontal axis. Figures are obtained from an OLS regression with an univariate GARCH structure of the error term. We use quarterly returns and a time period of 2000Q1-2017Q3.

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