REPORT TO THE AER

REVIEW OF REGIME SWITCHING FRAMEWORK AND CRITIQUE OF SURVEY EVIDENCE

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REPORT DATED SEPTEMBER 7, 2012.

Expert Witness Compliance Declaration

We have read the Guidelines for Expert Witnesses in proceedings in the Federal Court of Australia and this report has been prepared in accordance with those guidelines. As required by the guidelines we have made all the inquiries that we believe are desirable and appropriate and that no matters of significance that we regard as relevant have, to our knowledge, been withheld from the Court.

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Michael McKenzie Graham Partington

Preamble

With reference to the NERA report titled 'Prevailing conditions and the market risk premium' (March 2012) and the SFG report titled 'Review of NERA regime-switching framework' (29 March 2012), and drawing on material in the background documents and any other relevant material as required, we have been asked to provide advice in the following areas:

1. NERA's regime-switching framework to estimate the MRP. In particular:

    a. Critically evaluate the methodologies and assumptions in NERA's regime switching model

    b. Critically evaluate SFG's review of NERA regime-switching framework.

    c. Advise on whether NERA's regime switching framework provides good estimates of the MRP in the context of the AER's WACC framework.

    d. Advise on whether the use of NERA's regime switching framework (which is based in part on Merton (1973)) to estimate the MRP is consistent with the use of Sharpe-Lintner CAPM to estimate the cost of equity.

    e. Advise on whether NERA's regime switching model provides better estimates of the MRP than long run averages of historical excess returns or other measures of the MRP

2. Critically assess NERA's critique of the AER's use of survey evidence as a measure of the MRP

    a. Your answer should take into account the AER's discussion of survey evidence in both the Aurora draft decision and Aurora final decision.

3. Advise on the extent that survey evidence can be relied on to estimate the MRP in the context of the AER's WACC framework. Provide a point estimate for the MRP which is supported by survey evidence in the context of the AER's WACC framework.

In addressing these issues, we have engaged with the relevant academic literature and other research as well as the key documents provided, including the following papers that address historical volatility and regime switching frameworks:

- NERA, *Prevailing conditions and the market risk premium*, March 2012, pp.17-31, 42.
- SFG, *Review of NERA regime-switching framework*, March 2012.

- AER, *Aurora Energy—Final distribution determination—Appendices*, pp.24-25

as well as the following papers on survey evidence:

- NERA, *Prevailing conditions and the market risk premium*, March 2012, pp.43-52.
- AER, *Aurora Energy—Draft distribution determination*, November 2011, pp.229-230.
- AER, *Aurora Energy—Final distribution determination—Attachments*, pp.146-148
- AER, *Aurora Energy—Final distribution determination—Appendices*, pp.25-29
- Professor McKenzie and Associate Professor Partington, *Equity market risk premium*, 21 December 2011
- Professor McKenzie and Associate Professor Partington, *Supplementary report on the market risk premium*, 22 February 2012

Summary

It is well known that the use of long histories of stock market index data to estimate the market risk premium (MRP) has a number of problems. As such, the use of alternative methods to estimate the MRP is well worth considering. Merton (1973, 1980) provides one such framework in which he derives a theoretical link between the Market Risk Premium (MRP) and market volatility in the context of his multi-period I-CAPM model. Merton (1980) however, does concede that there are many problems to be overcome in implementing his suggested method for estimating the market risk premium. As such, its use for this purpose should be considered as exploratory.

In an attempt to estimate the MRP for the Australian market, NERA (2012) build on the research of Merton (1973, 1980). NERA (2012) study the volatility of the Australian stock market over the period 1883 to 2011 and observe that the data exhibits a low and a high volatility regime. They propose a Markov regime switching specification to model this feature of the data and proceed to forecast the MRP using the derived volatility estimates and Merton's theoretical relationship.

This paper critically evaluates NERA's (2012) regime switching approach to estimating the MRP. Our main issue is the lack of consideration that NERA (2012) give to establishing the validity of their estimated model. To provide some insights, we take the same dataset as provided by Handley (2012) and fit a simple constant return model, an unrestricted Markov regime switching model, a restricted Markov regime switching model in which the mean returns is assumed to be equal across periods, and a NERA (2012) type restricted Markov regime switching model. We evaluate each model by applying a series of tests to the residuals of the model as well as considering the plausibility of the volatility forecasts. We also consider the relative merits of each model and find that the restricted switching model is the best fit of the data in a relative sense, although it must be said that none of the models fit the data particularly well. In particular, the volatility forecasts produced by the regime switching models are implausible and a simple comparison to the well known U.S. VIX volatility index highlights the issue. In short, the NERA (2012) model does not provide a good model of volatility.

To provide a basis for further comparison, we also fit a more commonly used EGARCH model to the data and find that the volatility estimates are more consistent with events in the equity markets.

We should emphasise that the analysis of this report should not be interpreted as finding in favour of EGARCH models over regime switching models, or arguing the superiority of conditional over unconditional models. Our analysis It was simply designed to highlight the point that if we take the data as given, the NERA model does not perform well relative to a simple GARCH specification in terms of both model fit and plausibility of the volatility estimates.

The analysis presented in this paper clearly highlights the misspecification of NERA's model and the unreliable nature of the volatility estimates provided. As such, we are of the view that zero weight should be given to these NERA regime switching MRP estimates.

This paper also reviews the use of survey evidence in light of NERA's (2012) comments. We do not regard these criticisms as unique to the surveys cited by the AER. Rather, the problems cited by NERA (2012) are common to all surveys, as discussed by McKenzie and Partington (2011, p. 19 – 22). As such, we retain our view that despite the potential problems, we give significant weight to the survey evidence because there is the possibility of triangulation of the survey evidence across various sources. We do argue in favour of weighting these sources however, in which case, some surveys may be given a lesser weight. One such survey is provided by Asher (2011), which NERA (2012) argues may be biased. We view the highlighted concerns as trivial relatively to the more important issues that relate to the framing of the questions, the accuracy of the answers, the representativeness of the respondents, and how the data was interpreted by the researcher. Thus, we remain in favour of the use of surveys to provide evidence that may usefully be weighed in the balance with estimates of the MRP from other methods.

1. An Evaluation of NERA's regime-switching framework to estimate the MRP

a. Critically evaluate the methodologies and assumptions in NERA's regime switching model

It is well known that the use of long histories of stock market index data to estimate the market risk premium (MRP) has a number of problems. As such, the use of alternative methods to estimate the MRP is well worth considering.

One such approach would be to link stock market risk to the MRP as intuitively, such a relationship must exist.[1] Merton (1980, p. 329, equation 2.6) shows that in the context of the Merton (1973) Intertemporal or I-CAPM model, the excess return on the market can be reasonably approximated by:

$$\alpha(t) - r(t) = Y_1 \sigma^2(t) \tag{1}$$

where $\alpha(t)$ denotes the expected rate of return at time t, $r(t)$ is the riskless interest rate at time t, $\sigma^2(t)$ is the variance of the market return at time t and Y_1 is a measure of investor risk aversion. Thus, a theoretical foundation is provided for a proportional link between the volatility of the share market and the market risk premia. NERA (2012, equation 17) present this relationship as:

$$MRP = \theta \sigma_m^2$$

[1] SFG (2011, March) provide an alternative that is based on levels of variables that are known to be related to the MRP.

where:

- θ is a measure of the representative investors aversion to risk, and
- σ_m^2 is the risk of the return to the market portfolio (proxied by its variance).

NERA (2012) examine the long history of annual stock market data provided by Brailsford, Handley and Mahareshwan (2012) and observe that:

> "the data appear to behave as if there are two regimes: a low volatility regime and a high volatility regime." (p. 18)

Based on this observation, NERA (2012) argue that the volatility of the market (and so the MRP) changes through time, in which case NERA (2012, equation 17) would be more appropriately specified as:

$$MRP_t = \theta\sigma_{m,t}^2 \tag{2}$$

NERA (2012) propose the use of a standard Markov specification regime switching model to capture the time varying nature of the risk of the market (we discuss the details of this model in a later section).[2] As pointed out by SFG (2012), this type of model has been used extensively in the academic finance literature (see Guidolin, 2011,a,b for a survey of switching models in finance).

Using this model, NERA (2012, p. 18) estimate that:

> "the expected *not* continuously compounded return to the market portfolio is on average over the five years from the end of 2011 to the end of 2016 12.43 per cent per annum.
>
> It follows that with a 10-year bond yield of 3.99 per cent per annum, an estimate of the *MRP* for the next five years derived from the regime-switching model, relative to the yield, will be 8.44 per cent per annum."

Critique of the NERA (2012) regime switching approach

NERA's (2012) observations on volatility regimes in the Australian market lead them to specify the *MRP* in the current period as conditional on the contemporaneous volatility regime. Equation (2) however, assumes that the representative investors aversion to risk (θ) is a constant. This may not necessarily be the case however, as evidence exists to suggest that investors risk preferences are time-varying (see *inter alia* Smith and Whitelaw, 2009), in which case an appropriate specification is:

[2] A related literature exists that has focused on the regime switching nature of beta in the CAPM (see Galagedera, 2007, p. 825)

$$MRP_t = \theta_t \sigma^2_{m,t} \quad (3)$$

where not only does market volatility exhibit regimes, but investor risk preferences may also vary across time.[3] In this case, the link between volatility and the MRP is more complex and the nature of the evolution of θ_t would need to be modelled.

The discussion of the preceding paragraph serves to highlight our main issue with the NERA (2012) analysis. Good econometric practice dictates that any estimated model should be subject to a range of diagnostic tests in order to establish how well the model fits the data. NERA (2012) do not provide any discussion on whether their model is appropriately specified.[4] Valid inferences can only be made from a valid model and any estimated model should be subjected to a range of diagnostic tests to consider whether this is the case.

To address this issue and provide insights into the performance of the NERA (2012) model, we use the accumulated stock return data sampled annually over the period 1883-2011 as presented in Handley (2012). Further, the bond and bill data from 1883-2010 were sourced from Brailsford, Handley and Maheswaran (2012) and updated for 2011 using data sourced from the RBA website. We measure equity returns, r_t, over the entire sample period as the return in excess of the annual yield to rolling over three-month Treasury Bills.

We should emphasise that in the analysis that follows, we take this data as given and estimate and interpret a number of different models of returns, including the NERA (2012) regime switching model. The purpose of this analysis is simply to establish how well each model fits this data and critically examine the volatility estimate provided by each. The results of our analysis should not be interpreted as finding in favour of one class of model over another, nor to argue for the superiority of conditional over unconditional models in a more general context.

We begin our analysis of the data by considering the simplest possible unconditional model of returns in which only a constant term is specified, ie.:

[3] Of course, both equations (2) and (3) assume that Merton's model holds in the presence of regime shifts, which may not be the case. To the best of the authors knowledge, this issue has not been addressed.

[4] In addition to diagnostic tests, one may also consider the size of the standard errors relative to its empirical estimate. For example, in NERA (2012) Table 3.1, the investor risk aversion coefficient is 2.059 with a standard error of 0.651 (note: this is actually an estimate of θ - 0.5 for reasons discussed on p. 23). NERA (2012, p. 25) use the estimated coefficients from the regime switching model, including this estimate of risk aversion, to provide a MRP estimate of 2.059 x 0.043 = 8.852 (2.059 x 0.010 = 2.146) per cent in state 1 (2). The standard error of the risk aversion parameter is relatively large however, which means that we are unable to statistically distinguish between a risk aversion estimate of 2.059 and 2.059 $\pm$ 2(0.651) at the 95% level of significance. This variation in the estimate of the coefficient of risk aversion will have a large impact on the *MRP* estimate obtained. We can re-estimate the MRP using a risk aversion coefficient of 2.059 - 2(0.651) = 0.757. In this case, the MRP estimate becomes 0.757 x 0.043 = 3.25 (0.757 x 0.010 = 0.75) per cent in state 1 (2). Thus, accounting for the error in the risk aversion parameter introduces a significant source of variation to the *MRP* estimate.

$$r_t = \mu + \varepsilon_t \quad (4)$$

Table 1 presents the OLS estimates of equation (4) as well as residual diagnostics for ε_t. Most importantly, we note that the residuals of this model are clearly non-normal: a Ljung-Box test for serial correlation of up to the 5th order was marginally significant at the 5% level and there is very strong evidence of higher order serial correlation[5] (the marginal significance level of the 10th order *Q*-statistic was 0.0002). The data also appears to display conditional heteroscedasticity, as tests for serial correlation in the squared residuals (denoted as Q^2 in table 1) had marginal significance levels of [0.0000].

Table 1
OLS Estimates of (1) and Diagnostic Statistics

$\hat{\mu}$	*Log L*	*Q(5)*	*Q(10)*	$Q^2(5)$	$Q^2(10)$	*Normality*
0.0629	47.4032	11.289	33.839	27.429	58.897	10.5212
(0.0148)		[0.0459]	[0.0002]	[0.0000]	[0.0000]	[0.0052]

Note: LogL is the value of the maximised log-likelihood function. Standard errors displayed as (.). Marginal significance levels displayed as [.]. *Q*(p) is a Ljung-box test for p th order serial correlation in the residuals while Q^2(p) is a Ljung-box test for p th order serial correlation in the squared residuals.

Any credible model of excess returns should be free from misspecification error. The previous discussion of the diagnostic tests for the residuals of equation (4) clearly shows that this model is misspecified. As such, any inference based on this model is likely to be misleading.

An Unrestricted Markov Switching Model

The specification of a regime switching model of returns was motivated by the apparent change in the underlying data as described in Kearns and Pagan (1993) and NERA (2011). To understand this class of model, we define S_t as a variable taking the value $S_t = 0$ when the excess return is drawn from an $N(\mu_0, \sigma_0^2)$ distribution. On the other hand, $S_t = 1$ when the data are drawn from an $N(\mu_1, \sigma_1^2)$ distribution.

That is to say, when $S_t = 0$, the trend in prices is equivalent to the average return in state 0, ie. it is μ_0. When $S_t = 1$ however, the average return is μ_1. In practice S_t , the variable that identifies the regime is unobserved.

[5] Serial correlation in the errors refers to the existence of a relationship between the current error term and lagged error terms. The number of lags is referred to as the order.

The model presented below is a special case of the Hamilton (1989) model with two states, no autoregressive dynamics and regime dependent heteroscedasticity. More formally, we may write this unrestricted Markov switching model as:

$$\begin{aligned} r_t &\sim N\left(\mu_0, \sigma_0^2\right) \text{ if } S_t = 0 \\ r_t &\sim N\left(\mu_1, \sigma_1^2\right) \text{ if } S_t = 1 \end{aligned} \tag{5}$$

Engel and Hamilton (1991) use a Markov rule to describe S_t, where:

$$\begin{aligned} p\left(S_t = 0 \middle| S_{t-1} = 0\right) &= p_{00} \\ p\left(S_t = 1 \middle| S_{t-1} = 0\right) &= 1 - p_{00} \\ p\left(S_t = 0 \middle| S_{t-1} = 1\right) &= 1 - p_{11} \\ p\left(S_t = 1 \middle| S_{t-1} = 1\right) &= p_{11} \end{aligned} \tag{6}$$

Implicitly S_t depends on past realisations of *r* and *S* only through S_{t-1}.

Table 2 presents maximum likelihood estimates of this unrestricted Markov switching model obtained using Hamilton's (1989) approach. Note that due to the inherent non-normality of the data, quasi-maximum likelihood estimation is more appropriate. All reported standard errors are constructed as the period-by-period average of the inverse of the Hessian and the outer product of the gradient. Failure to use appropriately constructed standard errors may lead to invalid inference in the face of non-normality in the underlying data.[6]

We can test whether this unrestricted regime switching specification in equation (5) is an improvement over the simple linear model presented in equation (4). More formally, testing the null of linearity in equation (5) involves a test of the null hypothesis $H_0 : \mu_0 = \mu_1; \sigma_0 = \sigma_1$. While a likelihood ratio test may be employed for this purpose, the distribution of the test statistic is non-standard as the transition probabilities are unidentified under the null. As such, we draw on Garcia (1998, Table 6A), which provides the appropriate critical values obtained by simulation. The estimated test statistic of 36.9156 (calculated using the Log Likelihood values in tables 1 and 2) is far in excess of the critical value of 14.11, assuming a level of confidence of 5%. Thus, the linear model in equation (4) may be rejected in favour of this unrestricted Markov switching model. Figure 1 displays the smoothed probability of being in the low variance regime (ie. regime 0).

[6] Note that given the size of the standard errors, the difference between μ_0 and μ_1 is unlikely to be meaningful. We consider this point more fully in the next section where we estimate a restricted Markov switching model, which assumes of $\mu_0 = \mu_1$ and compare it to the unrestricted model.

Table 2
Estimates of the Unrestricted Markov Regime Switching Model

$\hat{\mu}_0$	0.0753 (0.0112)	$\hat{\mu}_1$	0.0505 (0.0301)	$\hat{p}_{00}$	0.9134 (0.0526)
$\hat{\sigma}_0$	0.07329 (0.0088)	$\hat{\sigma}_1$	0.2251 (0.0296)	$1-\hat{p}_{11}$	0.0797 (0.0564)

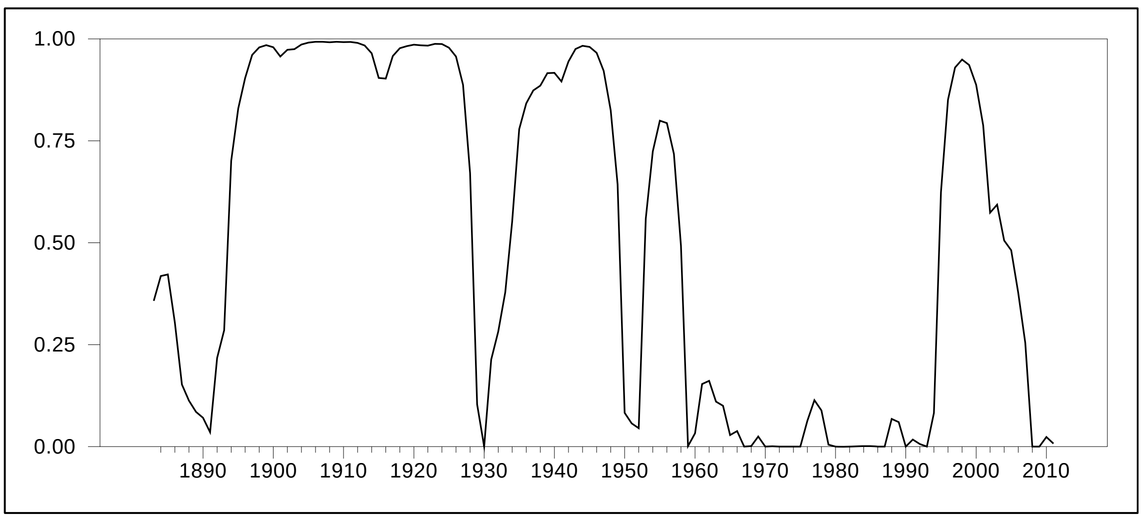
Matrix of Markov Transition Probabilities

$$\begin{bmatrix} 0.9314 & 0.0797 \\ 0.0686 & 0.9203 \end{bmatrix}$$

Log L	*Q(5)*	*Q(10)*	*Q^2(5)*	*Q^2(10)*	*Normality*
65.8610	7.758	25.567	3.080	8.477	32.4598
	[0.1701]	[0.0044]	[0.6877]	[0.5823]	[0.0000]

Note: LogL is the value of the maximised log-likelihood function. Quasi-maximum likelihood standard errors displayed as (.). Marginal significance levels displayed as [.]. *Q*(p) is a Ljung-box test for pth order serial correlation in the standardised residuals while Q^2(p) is a Ljung-box test for pth order serial correlation in the squared standardised residuals.

Figure 1
p_{00} **from the Unrestricted Markov Regime Switching Model**



The residual diagnostic tests presented in Table 2, suggests that the unrestricted two-regime Markov switching model provides a reasonable conditional characterisation of the data. The only caveats are that there is some evidence of 10th order serial correlation in the standardised residuals. There is also clear evidence that the distribution of the standardised residuals deviates from normality in a statistically significant fashion.

Panel A of Figure 2 displays the conditional standard deviation of stock returns implied by the unrestricted Markov switching model.[7] We note that the stochastic behaviour of σ_t implied by the model is not consistent with actual events in the market.[8] To understand this point, Panel B of Figure 2 presents annual estimates of the U.S. VIX Volatility Index (measured as the average VIX estimate in December each year) over the period 1986 to 2011.[9] The VIX is a well known and highly regarded volatility index and while it is a U.S. volatility measure, it provides a good indication of the type of behaviour we would expect to observe in a volatility measure.[10] From Panel B of Figure 2, the 1987 crash is clearly visible in the early part of the sample. Further, peaks in volatility are also observed at the time of the 1990 recession and Gulf War, the 1997 currency crisis, the 2000 dot.com boom, the 2002 invasion of Iraq and of course the 2008 financial crisis.

The regime switching model implies that there are two regimes: a low volatility and a high volatility regime. We note that for this unrestricted model, the estimate of the mean in regime 0, $\hat{\mu}_0$, lies within the 95% confidence interval for $\hat{\mu}_1$. This implies that the hypothesis $H_0 : \mu_0 = \mu_1$ should be satisfied for the data under consideration. A Wald test of the null hypothesis $H_0^1 : \mu_0 = \mu_1$, distributed as $\chi^2(1)$, may be constructed as:

$$\frac{(\hat{\mu}_0 - \hat{\mu}_1)}{[\text{var}(\hat{\mu}_0) + \text{var}(\hat{\mu}_1) - 2Cov(\hat{\mu}_0, \hat{\mu}_1)]} \tag{7}$$

As expected, the test statistic is 0.5394 with p-value 0.4626, implying that the restriction is satisfied for the data. A Wald test for null of equality of variances alone was strongly rejected with a test statistic of 29.7235 with marginal significance Level 0.0000.

[7] Note that our analysis is based on the standard deviation. NERA (2012) however, focus on the variance of the residual. We do not believe this difference in our analysis will have any impact on the basic tenor of our results or our conclusions.

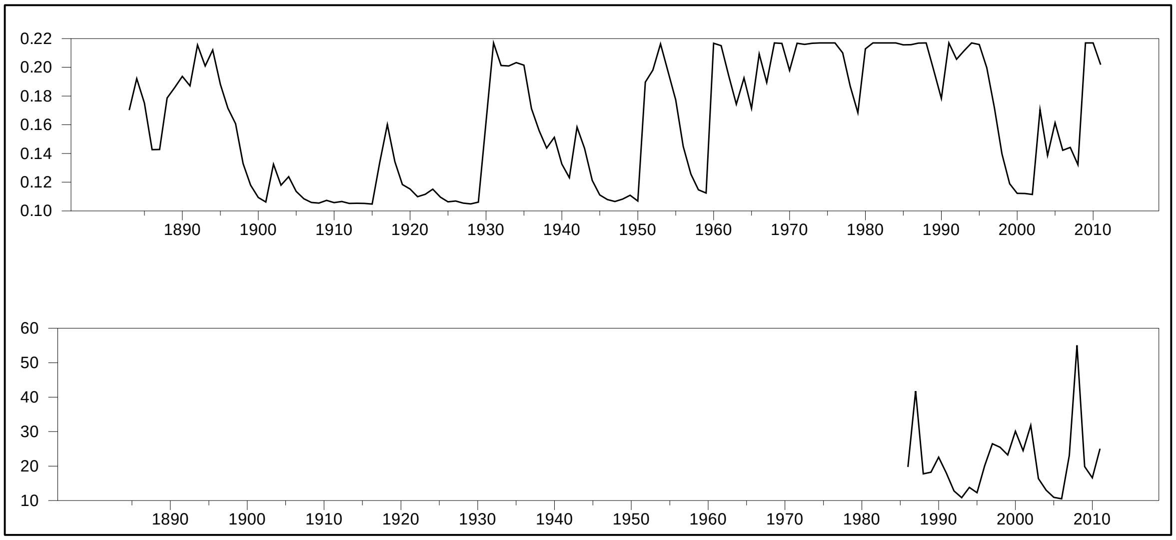
[8] The academic finance literature (see inter alia Cont, 2001, and Tseng and Li, 2011) suggests that there are three important stylized facts about daily equity returns: first, the distribution of equity returns is not normal; second, there is no correlation between equity returns across different days; and third there is positive dependence between the squared returns on nearby days, and likewise for absolute returns. All these stylized facts can be explained by assuming that volatility follows a stochastic process in which today's volatility is positively correlated with the volatility on any future day. While these observations are based on an extensive literature that has studied daily data, it is not clear whether these characteristics may also apply to annual data. Where clustering is argued to be a feature of annual data, then the observed volatility estimates of the regime switching model do not exhibit this stylised characteristic of volatility.

[9] The longest period for which the data is available. For details of the VIX index, refer to www.cboe.com/micro/vix/historical.aspx

[10] We note that Kearns and Pagan (1993) observe differences between the risk of the US and Australian market. The significant features of the US index we mention would be reflected in a comparable Australian volatility index. See the Appendix for further details.

Figure 2

Panel A: Conditional Standard Deviation of r_t from the Unrestricted Markov Regime Switching Model. Panel B: Annual VIX Index (1986 – 2011)



Note: The data presented in Panel B are the average of the daily closing value for the VIX volatility index in December each year.

A Restricted Markov Switching Model

It is possible to modify the unrestricted Markov regime switching model discussed in the previous section and impose a restriction of the equality of means across regimes. This restricted version of the model takes the form:

$$
\begin{aligned}
r_t &\sim N\left(\mu, \sigma_0^2\right) \text{ if } S_t = 0 \\
r_t &\sim N\left(\mu, \sigma_1^2\right) \text{ if } S_t = 1
\end{aligned}
\tag{8}
$$

where the Markov rule is again used to describe S_t. Table 3 reports quasi-maximum likelihood estimates of the restricted Markov switching model defined by equations (8) and (6). We note that this restricted model appears to be a reasonable conditional characterisation of the data, despite some evidence of 10th order serial correlation in the standardised residuals. As was also the case with the unrestricted model, the quasi-maximum likelihood estimation underlying the construction of the standard errors means that any inference is robust to the non-normality observed in the standardised residuals. Figure 3 displays the smoothed probability of being in the low variance regime (ie. regime 0).

Table 3
Estimates of the Restricted Markov Regime Switching Model

$\hat{\mu}$	0.0712			$\hat{p}_{00}$	0.9149
	(0.0099)				(0.0526)
$\hat{\sigma}_0$	0.0734	$\hat{\sigma}_1$	0.2252	$1-\hat{p}_{11}$	0.0766
	(0.0086)		(0.0299)		(0.0541)

Matrix of Markov Transition Probabilities

$$\begin{bmatrix} 0.9149 & 0.0766 \\ 0.0581 & 0.9234 \end{bmatrix}$$

Log L	*Q(5)*	*Q(10)*	*Q^2(5)*	*Q^2(10)*	*Normality*
65.5701	7.469	25.347	3.029	8.814	28.3656
	[0.1880]	[0.0047]	[0.6955]	[0.5499]	[0.0000]

Note: LogL is the value of the maximised log-likelihood function. Quasi-maximum likelihood standard errors displayed as (.). Marginal significance levels displayed as [.]. *Q*(p) is a Ljung-box test for pth order serial correlation in the standardised residuals while *Q^2*(p) is a Ljung-box test for pth order serial correlation in the squared standardised residuals.

Figure 3
p_{00} from the Restricted Markov Regime Switching Model

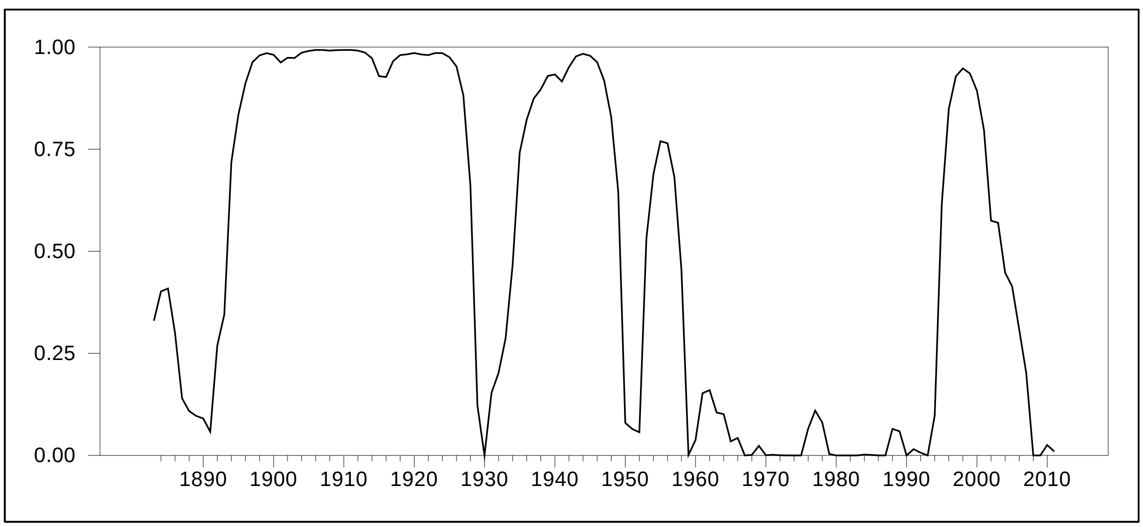
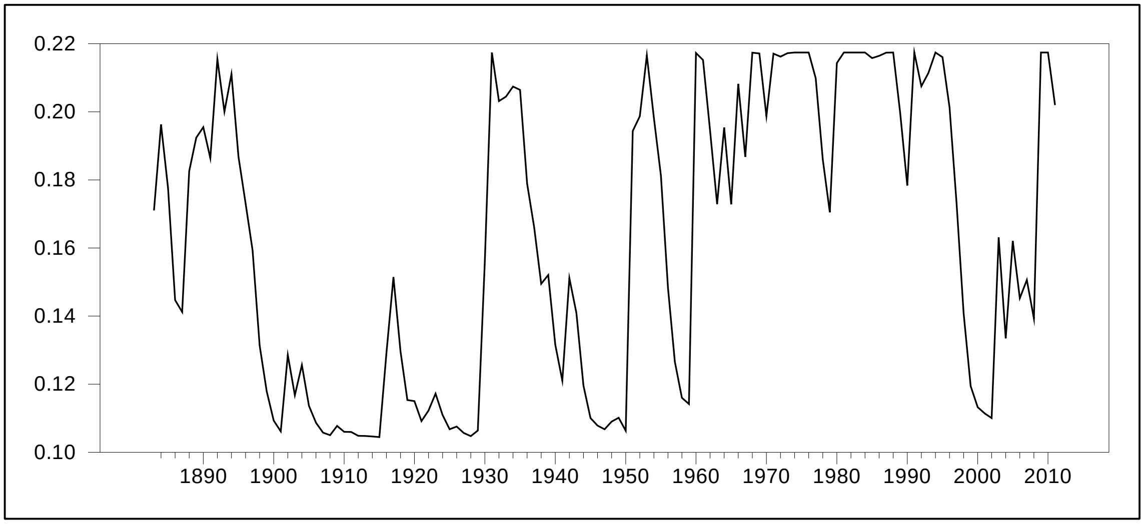


Figure 4 displays the conditional standard deviation of stock returns implied by this restricted Markov switching model. We again note that the estimated conditional standard deviation of the excess stock returns are implausible.

Figure 4
Conditional Standard Deviation of r_t from the Restricted Markov Regime Switching Model



The NERA (2012) Restricted Markov Switching Model

NERA (2012) estimate a restricted version of the Markov regime switching model in which the returns are again modelled as:

$$\begin{aligned} r_t &\sim N\left(\mu_0, \sigma_0^2\right) \text{ if } S_t = 0 \\ r_t &\sim N\left(\mu_1, \sigma_1^2\right) \text{ if } S_t = 1 \end{aligned} \tag{9}$$

however, taking the predictions of Merton (1980) into account, NERA (2012) impose the restriction that $\mu_j = (\theta - 0.5)\sigma_j^2$, *j* = 0,1 when estimating their model.

Table 4 presents quasi-maximum likelihood estimates of the NERA (2012) model. We should point out that although we are estimating the same model as NERA (2012, Table 3.1) using what we believe to be the same data, the parameter estimates are not directly comparable for the following reasons: first, our model estimates the standard deviation of the residual, while NERA (2012) estimate the variance of the residual; second, we do not know what estimation algorithm NERA (2012) use; and third, we do not know if the NERA (2012) model has achieved global convergence or even if it is at the same maximum as our model.

The residual tests applied to our model show clear evidence of 10th order serial correlation in the standardised and squared standardised residuals. Figure 5 displays the probability of being in regime 0 implied by the Markov Switching Model defined by (9) and (6). Figure 6 displays the conditional standard deviation of excess stock returns implied the NERA Markov switching model and we again note that the stochastic behaviour of σ_t is implausible.

Table 4
Estimates of the NERA Markov Regime Switching Model

$\hat{\theta}$	2.8791 (0.5478)			$\hat{p}_{00}$	0.9669 (0.0296)
$\hat{\sigma}_0$	0.1150 (0.0132)	$\hat{\sigma}_1$	0.2193 (0.0302)	$1-\hat{p}_{11}$	0.0497 (0.0650)

Matrix of Markov Transition Probabilities

$$\begin{bmatrix} 0.9699 & 0.0497 \\ 0.0301 & 0.9503 \end{bmatrix}$$

Log L	*Q(5)*	*Q(10)*	*Q^2(5)*	*Q^2(10)*	*Normality*
56.8373	5.930	24.724	7.439	22.228	15.8747
	[0.3131]	[0.0059]	[0.1900]	[0.0140]	[0.0003]

Note: LogL is the value of the maximised log-likelihood function. Quasi-maximum likelihood standard errors displayed as (.). Marginal significance levels displayed as [.]. *Q*(p) is a Ljung-box test for pth order serial correlation in the standardised residuals while *Q^2*(p) is a Ljung-box test for pth order serial correlation in the squared standardised residuals.

Figure 5
p_{00} from the NERA Markov Regime Switching Model

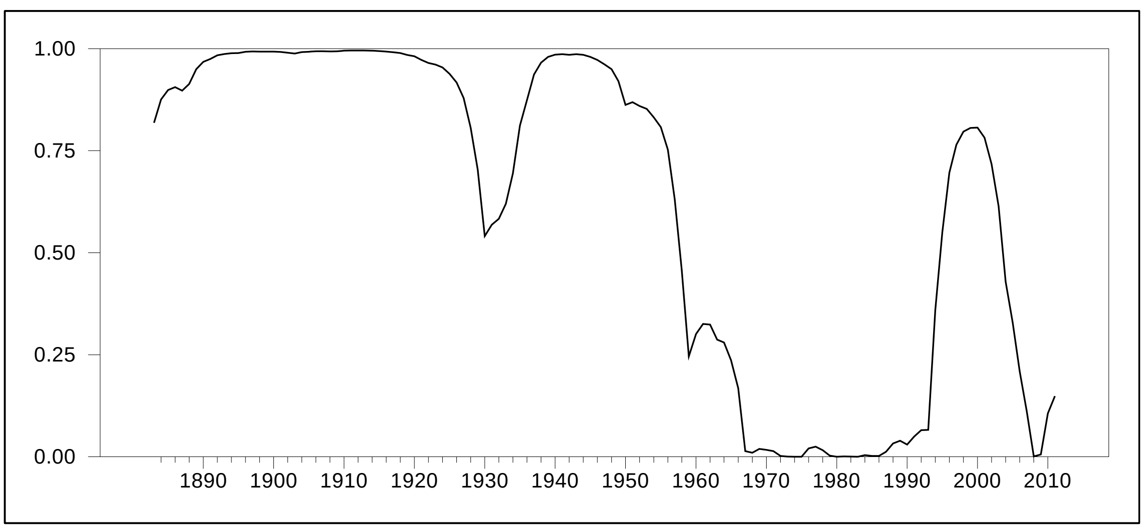
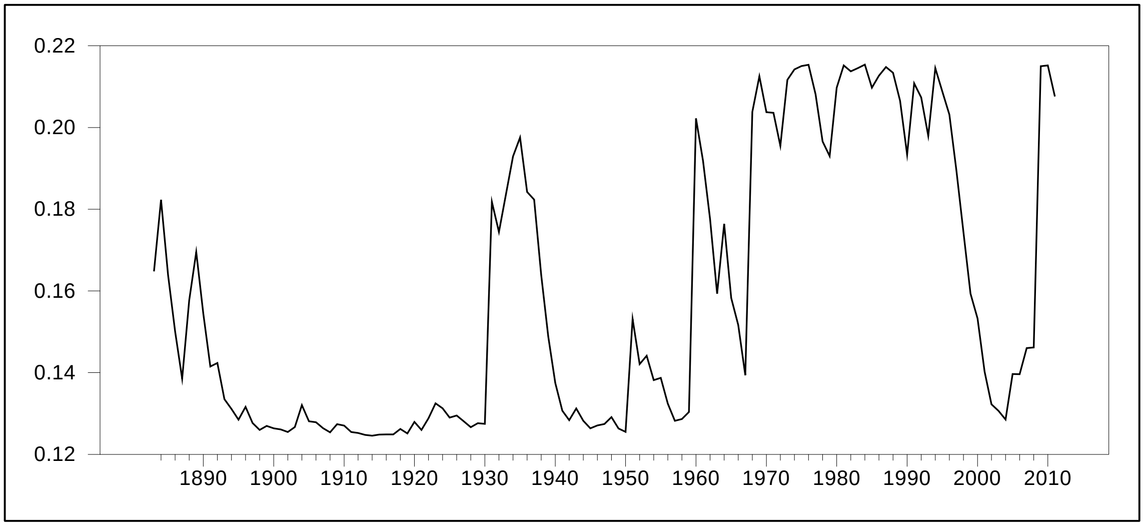


Figure 6
Conditional Standard Deviation of r_t from the NERA Markov Regime Switching Model



On balance, we find that the restricted Markov switching model defined by equation (8) provides a superior conditional characterisation of the data compared to both the unrestricted version of the model and the NERA version of the model. Moreover, any inference NERA make based on the model estimated under $\mu_j = (\theta - \gamma)\sigma_j^2$ is likely to be misleading due to the misspecification of the functional form.

The main implication of the evidence displayed in Figures 2, 4 and 6 is that the Markov switching model is a very poor estimator of the conditional variance of equity return. A more commonly used model of equity volatility is the Exponential-GARCH (EGARCH) model of Nelson (1990). The EGARCH model takes the following form:

$$r_t = \mu_t + h_t^{1/2} z_t, \ z_t \sim i.i.d..N(0,1)$$
$$\log(h_t) = \mu_{\log(h)} + \beta \log\left(h_{t-1} - \mu_{\log(h)}\right) + g(z_{t-1})$$

(10)

Here $g(z_{t-1}) = \vartheta z_{t-1} + \gamma\left(|z_{t-1}| - \sqrt{2/\pi}\right)$ and the four variance parameters are the mean $\mu_{\log(h)}$ of the process $\log(h_t)$, the autoregressive parameter, β, and the two parameters ϑ and γ, that appear in the function *g*(z_{t-1}). The terms function *g*(z_{t-1}) have zero expectation when the standardised residuals z_{t-1} are assumed to be Gaussian because $E\left[|z_{t-1}|\right] = \sqrt{2/\pi}$. The terms in *g*(z_{t-1}) are also i.i.d. since the variables in *g*(z_{t-1}) share this property. The process defined in (10) is stationary when $-1 < \beta < 1$.

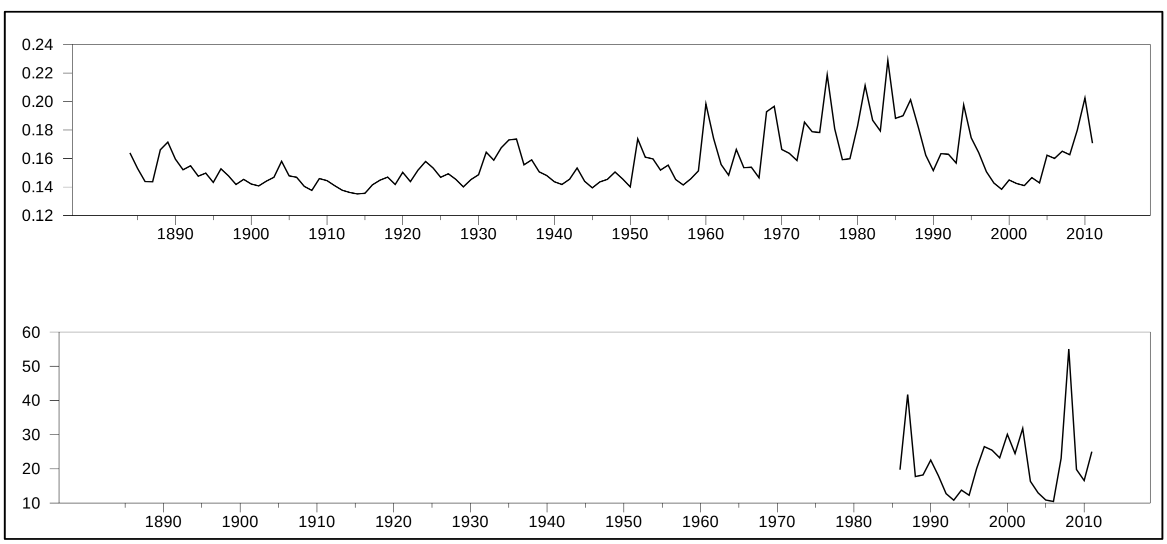
Quasi-maximum likelihood estimates of an EGARCH(1,1) equation are presented in Table 5 along with residual diagnostics for the model. The estimated parameters suggest that volatility is subject to persistence and clustering. Moreover, the estimates in table 5 suggest that the volatility of excess returns responds asymmetrically to positive and negative shocks. These important features of the data are not captured by the Markov switching model. The diagnostics show that there is some evidence of serial correlation and neglected ARCH in the standardised residuals, which suggests that the model may be misspecified to a degree.

Table 5
EGARCH Quasi-Maximum Likelihood Estimates

μ	$\mu_{\log(h)}$	β	ϑ	γ
0.0667	-1.7393	0.5702	0.2018	0.0947
(0.0134)	(0.0462)	(0.0045)	(0.0038)	(0.0025)
Q(5)	*Q(10)*	*$Q^2(5)$*	*$Q^2(10)$*	*Normality*
7.960	29.771	9.439	25.433	10.1331
[0.1580]	[0.000934]	[0.0928]	[0.0046]	[0.0063]

Panel A of Figure 7 presents a time series plot of the estimated conditional standard deviation from the EGARCH model (ie. v_t), while Panel B presents the annual VIX index. We note that the EGARCH conditional volatility plot is far more plausible and exhibits many of the features we would expect of a volatility measure including peaks in 1987 and the early 1990's. The figure also highlights the increased volatility observed in the post-2007 period.

Figure 7
Panel A: Estimated Conditional Standard Deviation from the EGARCH Model.
Panel B: Annual VIX Index (1986 – 2011)



Note: The data presented in Panel B are the average of the daily closing value for the VIX volatility index in December each year.

To conclude, in this section of our report we consider a Markov switching model of the annual return to the Australian equity market in excess of the return to rolling over Treasury Bills. The parameterisation suggested by NERA (2012) was rejected on the grounds of misspecification of the functional form of the model. We note however, that none of the Markov switching models considered provides plausible estimates of the volatility of excess equity returns as the models are all misspecified to some degree. The volatility estimates from an EGARCH(1,1) model are far more consistent with events in the equity markets.

Long History Data, Index Construction and Volatility Regimes

The analysis of the preceding section should not be interpreted as finding in favour of GARCH models over regime switching models, or arguing the superiority of conditional over unconditional models. It was simply designed to highlight the point that if we take the data as given, the NERA model does not perform well relative to a simple GARCH specification once we perform some fairly standard model diagnostic tests.

In any study of this type, the data is always problematic both in terms of the sample size (which is typically small[11]) and its quality. In terms of the latter, Brailsford, Handley and Maheswaran (2008) note that the early part of their data series has problems with data quality including survival bias and other sources of return overstatement. NERA (2012, p. 17) make the more general observation that:

> "(t)he longer the series of returns one uses ... the greater the danger that:
>
> - one will be forced to rely in part on low quality data; and that
> - the characteristics of the market portfolio will have changed over the sample."

The implication is that any inference made from such data (including estimates of the *MRP*, volatility and so on) should be interpreted with caution. By way of example, NERA (2012, p. 17) plot their updated Brailsford, Handley and Maheswaran (2012) dataset and note that:

> "...the Australian market portfolio was substantially less risky in the later part of the 19th century and the earlier part of the 20th century than in the later part of the 20th century and the early part of the 21st century" (a similar observation is made on p. 20).

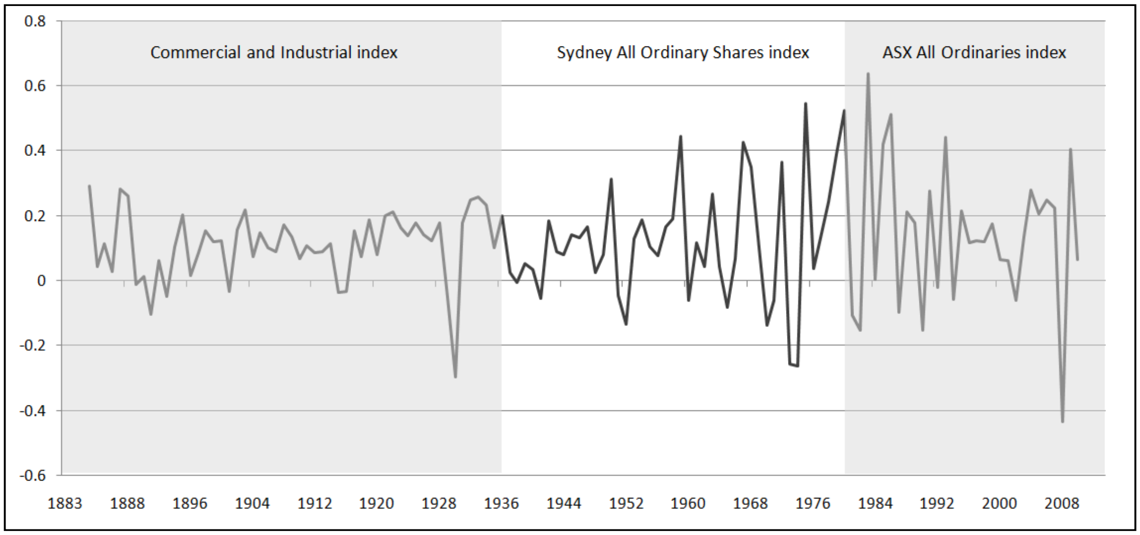
Similar observations have previously been made by Kearns and Pagan (1993). NERA (2012, p. 18) use their observations about the volatility regimes present in the data to justify their model specification (and as the discussion in the previous section shows, this model does not fit the data particularly well).

[11] For example, McClain, Humphreys and Boscan (1996) suggest that at least 300 observations are required to estimate a reliable ARCH model.

We note that the Brailsford, Handley and Mahareshwan (2012) data is constructed using the Commercial and Industrial index from 1882 to 1936, the Sydney All Ordinary Shares index from 1936 to 1979 and the Australian Stock Exchange (ASX) All Ordinaries index from 1980 to 2010. Recall the basic volatility regimes NERA attributed to these data. It is interesting to note that the underlying index changes roughly coincide with the time the volatility shifts are observed. That is, the low volatility regime ended in the "earlier part of the 20th century", which was around the same time the Sydney All Ordinary Shares index was used in place of the Commercial and Industrial index, ie. 1936. Further, the high volatility regime begins in the latter part of the 20th century, which is the time when the All Ordinaries index was used in preference to the Sydney All Ordinary Shares index. Given the differences between these indices in terms of coverage and construction (see Brailsford, Handley and Mahareshwan, 2008 and references therein for details), it is possible that the volatility regimes are, at least in part, a reflection of the underlying index. To aid the reader in understanding the issue, Figure 8 presents the stock accumulation index data from Appendix 1 of Brailsford, Handley and Mahareshwan (2012) overlayed with shaded areas that highlight the different periods over which each index was referenced.

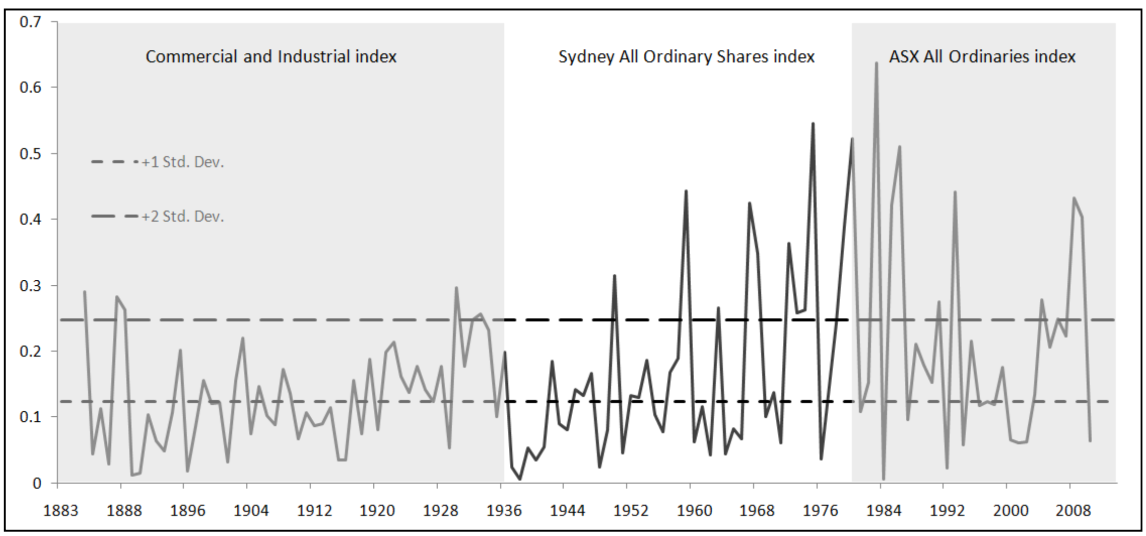
Figure 9 presents the absolute values of these returns data, which is a basic volatility proxy, again with the periods shaded to highlight the different indices used. Figure 9 also features two horizontal dashed lines that represent one and two standard deviations of this data (σ = 0.1249). These standard deviation based reference points serve to highlight the arbitrary nature of the two regime approach NERA (2012) take to modelling volatility. One could just as easily argue that rather than two regimes (high and low), a three regime approach is more sensible with a low, average and high volatility regime classified using these standard deviation based reference points. In fact, an n-regime approach is possible, where n is > 1, with no compelling argument to be made for any one approach. The two regime model is certainly easier to estimate, however, ease of estimation is not a particularly valid justification for model choice.

Figure 8
Accumulation Index Data with Different Source Indices Highlighted



Source: Data Appendix to Brailsford, Handley and Mahareshwan (2012).

Figure 9
Absolute Returns to the Accumulation Index with Different Source Indices Highlighted



Source: Data Appendix to Brailsford, Handley and Mahareshwan (2012).

b. Critically evaluate SFG's review of NERA regime-switching framework.

SFG (2012) provide a review of the NERA (2012) regime switching approach to estimating the *MRP*. In this report, SFG (2012) provide a basic description of regime switching models and the Merton (1973) model of the relationship between stock market volatility and the MRP. SFG also summarise the findings of the NERA (2012) report and come to the conclusion that, "the regime-switching approach ... is an appropriate method for obtaining an estimate of the market risk premium that is commensurate with the prevailing conditions in the market for funds" (p. 6). While we disagree with their conclusions, the SFG (2012) report does not present any further insights or information that necessitate review or comment beyond that provided for the NERA (2012) report in the previous section.

c. Advise on whether NERA's regime switching framework provides good estimates of the MRP in the context of the AER's WACC framework.

Under the AER's approach, a nominal vanilla Weighted Average Cost of Capital (WACC) formula is used:

$$WACC = r_e \frac{E}{D+E} + r_d \frac{D}{D+E}$$

where r_e is the cost of equity, r_d is the cost of debt, E is the market value of the firm's equity and D is the market value of the firm's debt. The cost of equity, r_e, is determined using the standard Sharpe-Lintner Capital Asset Pricing Model (CAPM):

$$r_e = r_f + \beta_e \times MRP$$

where r_f is the risk free rate, β_e is the equity beta and MRP is the Market Risk Premium. The MRP captures the reward to investors for holding risk, ie. it is the market price of risk, and it is the expected return to the market in excess of the risk free rate.

The question raised is whether the NERA approach provides a 'good' estimate of the *MRP* for use in this context. Based on the discussion of the previous sections, we conclude that the NERA regime switching model is not a good fit of the data and does not provide sensible volatility estimates.

Thus, we argue that a regime switching MRP is unlikely to provide a good estimate of the MRP in this context.

d. Advise on whether the use of NERA's regime switching framework (which is based in part on Merton (1973)) to estimate the MRP is consistent with the use of Sharpe-Lintner CAPM to estimate the cost of equity.

The Sharpe-Lintner CAPM is a 'single-period' *ex ante* equilibrium asset pricing model and it is derived under a number of critical assumptions. Specifically, if risk-averse investors:

- choose between portfolios on the basis of the mean and variance of each portfolio's return measured over a single period;
- share the same investment horizon and beliefs about the distribution of returns;
- face no taxes (or the same rate of tax on all forms of income) and there are no transaction costs; and
- can borrow or lend freely at a single risk-free rate,

then the market portfolio of risky assets must be mean-variance efficient (NERA, 2012, p.3).

In essence, given these simplifying assumptions, the CAPM model predicts that the expected return from holding a stock is a function of that stocks risk and the reward for bearing risk. Risk in this context specifically refers to 'market risk', while the reward for bearing risk is the market risk premium, ie. the market return in excess of the risk free rate of return.

The Sharpe-Lintner CAPM is commonly represented as:

$$E(R_i) = R_f + \beta_{i,M}[E(R_M) - R_f)]$$

where $E(R_i)$ is the expected return on asset *i*, $E(R_M)$ is the expected return on the market, $\beta_{i,M}$ is the market beta of asset *i*, and R_f is the risk free rate.

This version of the CAPM model assumes a 'single-period' insomuch as investors establish their portfolios, hold it for the duration of the investment period and then consume their entire wealth at the end of the period. The implicit assumption is that investors only care about the wealth their portfolio produces at the end of the current period.

The lack of time sub subscripts in this equation provides the clearest answer to the question asked, in that time is not considered in this model. As such, there are no volatility regimes (or otherwise) as there is only one period in which the given risk free rate and the market risk premium prevail.

The standard CAPM framework has been modified to establish what happens when some of these assumptions are violated. For example, the Black CAPM assumes no risk free asset (it is replaced by the zero beta portfolio)

Most relevant in the current context is the Intertemporal-CAPM (also known as the I-CAPM or the Merton CAPM), which relaxes the one period assumption and allows multiple investment periods. The I-CAPM model concludes that in addition to market risk, reinvestment risk is also important (thus a low beta risk stock may be high risk if it has low reinvestment opportunities). The I-CAPM is the most relevant here as it shows that in multiple period settings, investors care not only about market risk, but also reinvestment opportunities. The main problem with this model is in capturing/quantifying these reinvestment opportunities.

In addition to market risk, Fama and French (2004) found that book-to-market (BTM) and size (SMB) are also important for explaining the cross-sectional distribution of returns. The resulting three-factor model has generated a great deal of literature and much of it has focused on explaining what these two additional risk factors are capturing. Most relevant in the current context is the contributions of Berk, Green and Naik (1999) and Brennan, Wang and Xia (2004), who have argued that the book-to-market and size factors may be interpreted as proxies for a stock's exposure to reinvestment.

Berk, Green and Naik (1999) and Brennan, Wang and Xia (2004), however, provide just one of many interpretations of these Fama and French risk factors. For example, Campbell and Vuolteenaho (2004), explain the size and book-to-market factors using a two-beta model, which capture information about cash flows and discount rates. Chung et al. (2006, p. 923-4), provide a good summary of the literature:

> "Fama and French suggest that book-to-market and size are proxies for firm distress. Lakonishok, Shleifer and Vishny (1994) argue that book-to-market proxies for investor bias in earnings-growth extrapolation. Daniel and Titman (1997) find that SMB and HML pick up the comovements of stocks with similar characteristics, so it is the characteristics, not the comovements, that explain cross-sectional return variation. Rolph (2003) and Ferguson and Shockley (2003) argue that the Fama-French factors proxy for leverage effects. Berk (1995), Kothari, Shanken and Sloan (1995), and Ferson, Sarkissian and Simin (1999) argue that the explanatory power of SMB and HML are spurious."

This issue is further complicated when we take into account the evidence of Chung et al. (2006), who observed that the two Fama and French factors are no longer relevant when higher order systematic co-moments are accounted for (ie the nonnormality of asset prices means that in addition to covariance, coskewness and cokurtosis are important to pricing). Finally, Goyal (2012, p. 6) notes that, "CAPM is a single-period model and, for testing purposes, so is ICAPM with deterministic investment opportunity sets."

e. Advise on whether NERA's regime switching model provides better estimates of the MRP than long run averages of historical excess returns or other measures of the MRP

Our view on MRP estimates from long run historical data is best summarised by this quote from our earlier work:

> "While the required equity market risk premium is a forward looking (ie. ex-ante) concept, by far the most common technique used to generate estimates of this premium is an examination of past data and some form of historical averaging, resulting in a backward looking (ie. ex-post) realised estimate. An advantage of using averages from historic data, particularly in a regulatory context, is that it is relatively transparent. The choices that can be made (most of which are discussed below) are generally well defined and most of their consequences can be readily investigated. Historical estimates have also been extensively studied and as a consequence are quite well understood. There is also plenty of international evidence which allows a cross check on the reasonableness of Australian estimates. The historical approach also has support as the benchmark method for estimating the risk premium in Australia (see Hathaway, 2005, and Officer and Bishop, 2008).

> Despite its widespread use and popular appeal, a significant number of estimation issues confront the researcher when attempting to estimate the equity market risk premium using historical data. These problems are by no means trivial, and Goetzmann (in Welch, 2000) goes so far as to argue that the estimation of a 'pure' estimate of the historical equity premium may be impossible." McKenzie and Partington (2011, p. 5 - 6)

While the use of long dated share market data has some definite appeal, caution must nonetheless be exercised. As we stated in McKenzie and Partington (2011, p. 17):

> "... attempting to estimate an equity market risk premium from a long series of data, risks using poor quality data and crossing structural breaks. One alternative is to estimate a equity risk premium which is conditioned on the current state of information."

McKenzie and Partington (2011) provides an extensive summary of the alternative methods that can be used to estimate the MRP, such as forward looking models (including the Gordon Growth model and various extensions to this approach) and adjustments to global MRP to account for country risk, credit spread and other options based estimates of the MRP and so on. We find significant problems with each and caution against their use to estimate the MRP.

To our minds, the discussion and evidence presented in this paper only serves to reinforce this previously stated view of these alternative techniques. The NERA regime switching approach is yet another method that can be used to generate a conditional estimate the MRP. The analysis presented in this paper clearly highlights the misspecification of NERA's model and the unreliable nature of the volatility estimates provided. As such, we are of the view that zero weight should be given to these NERA regime switching MRP estimates.

To sum up, we believe it worthwhile to reiterate our previously held view, that while there are some arguments in favour of a conditional estimate

> "... there are some compelling reasons to avoid the use of conditional equity market risk premium estimates." McKenzie and Partington (2011, p. 17)

> "For regulatory purposes, it seems undesirable to have conditional estimates of the market risk premium varying, sometimes sharply from period to period. The general view seems to be that a stable long run MRP (approximating the unconditional mean) should be used for regulation." McKenzie and Partington (2011, p. 18)

This remains our preferred view.

2. Critically assess NERA's critique of the AER's use of survey evidence as a measure of the MRP

NERA (2012, p. 43) cite a number of concerns over the use of survey based estimates of the MRP cited by the AER. We do not regard these criticisms as unique to the surveys cited by the AER. Rather, the problems cited by NERA (2012) are common to all surveys as discussed by McKenzie and Partington (2011, p. 19 – 22).

More specifically, In response to each point raised by NERA, we offer the following observations:

a) the surveys that the AER cites typically do not explain how those surveyed were chosen;

   We presume this criticism is a reflection of a more general concern over sample bias. Ideally, the respondents to a survey would be a broad and representative cross section of all investors. Most surveys however, tend to focus on a particular group and fund managers, financial analysts, corporate financial managers, finance academics and individual investors have all been questioned in MRP surveys. Typically, there are good reasons for selecting a particular group. For example if we are to determine the cost of capital for use in valuing companies and projects, then it is appropriate to collect survey data on the MRP that managers actually use for this purpose.

   Survey risk premiums are known to be sample dependent - for example, surveys of individual investors tend to provide higher market risk premium estimates compared to surveys of academics, managers and analysts. Thus, without knowing how the survey group were selected, it would be difficult to discount the possibility that the survey group exhibit some form of bias. Thus, many questionnaire studies make a point of clearly describing the selection of the sample surveyed. Indeed, academic papers would not get published unless there was a clear explanation of how the sample of respondents was chosen.

b) a majority of those surveyed in the surveys that the AER cites did not respond;

   Low response rates are a common problem with the survey method in general, and even where the number of people surveyed is high, small samples may result. For example, Graham and Harvey's (2010) survey generated a very low (5-8%) response rate, which is not unusual. The authors closely examine this issue and conclude the small sample did not seriously compromise the integrity of their results.

   Whether or not low response rates are an issue comes down to whether any systematic reason exists for non-respondents to systematically favour a higher or lower MRP than the respondents to the survey. We can think of no reason why this might be the case, but we cannot rule it out. Since by definition we do not know the responses of the non-respondents, checking for response bias is difficult. One technique, as used by Graham and Harvey (2010), is to compare response of early and late respondents. The idea is that late respondents, relative to early respondents, are more likely to be like non-respondents.

Thus, our view is that as long as the respondents are a representative sample of the target population and are in a position to make informed judgements about the MRP, we argue that low response rates do not necessarily invalidate the results of the survey.

c) it is unclear what incentives were provided to individuals contacted by the surveys that the AER cites to ensure that respondents would provide accurate responses;

The quality of any survey will clearly reflect the accuracy of the answers provided, as well as the representativeness of the respondents, the framing of the questions and how the data is interpreted by the researcher. Confidence in respect to these issues can be enhanced when the work is published in a refereed academic journal as it has been subject to peer review.

With respect to ensuring accurate responses, it is standard practice to review the questionnaires received for internally inconsistent responses, for careless completion of the questionnaire, and for responses that are inconsistent with externally verifiable data. When the survey is repeated, a stable set of questions allows comparisons of response through time, which can also contribute to identifying inaccurate responses. In our experience of surveying CFOs and their equivalent we have found the responses to be internally and externally consistent.

d) it is unclear whether respondents are supplying estimates of the MRP that use continuously compounded returns or not continuously compounded returns;

It is true that few surveys clearly distinguish between whether the MRP survey response reflects an arithmetic (rebalanced portfolio) or geometric (buy and hold) average risk premium. Welch (2000a) makes a correction for this ambiguity in the first of his surveys. It is also clear that the Graham and Harvey (2010) survey is for buy and hold returns.

e) it is often unclear what value respondents place on imputation credits;

There is a great deal of uncertainty about whether or not survey respondents allow for the value of imputation credits in their estimate of the MRP.

On the one hand, the survey evidence suggests that imputation credits are not typically allowed for in project evaluation or expert valuations, so it would seem unlikely that they would typically be added to the market risk premium. On the other hand, as Truong, Partington and Peat (2008) show, there are several reasons why respondents do not adjust for imputation, including a belief that it is already taken into account in the cost of capital estimate.

The respondents to surveys may use their understanding of long run historic average returns in forming their MRP estimates. Consistent with this, a majority of the responses in Truong, Partington and Peat (2008) indicated that they used traditional standards in setting the MRP, which seem likely to be based the historic MRP. If the historic MRP is used an adjustment for imputation credits is only required if respondents attach significant weight to the post imputation period and if the estimate of average returns for that period is lower due to the effect of imputation credits. Given that we don't really know whether survey responses do, or do not, allow for imputation credits and given that any adjustment for imputation would likely lie within the margin of measurement error, it seems best to take the survey evidence at face value, but tempered by the uncertainty about whether an imputation adjustment is needed.

f) it unclear what risk-free rate respondents use;

This is probably true for some studies, but it is not true in general. For example, Truong, Partington and Peat (2008), show that the overwhelming majority of respondents use the Treasury bond rate.

g) it is unclear how relevant some of the surveys that the AER cites are because of changes in market conditions since the time at which the surveys were conducted.

It is quite possible to find estimates from up to date surveys and in our previous MRP report we provided such estimates. The most current survey we are aware of is For the USA and dated June 2012. The premium we report from this survey is based on 391 equally weighted responses from senior finance executives. With a benchmark for the risk premium as at May 2012, the MRP estimate is a 3.4 percent based on the expected buy and hold return (see www.cfosurvey.org).

NERA (2012, p. 44) specifically comment on the Asher (2011) survey and argue its findings should be dismissed due to possible bias. To recap, in May 2010, Asher stated in a seminar in front of individuals whom he later surveyed that, "the implied equity premium is more or less equal to the dividend yield which is probably at this stage somewhere between 3 and 4 per cent". Further, he also stated to this same group that he intended to conduct surveys on a regular basis and publish the results.

NERA (2012, p. 44) argue that:

> "This public statement about the surveyor's view of what would be a correct response to the primary question he plans to ask in a survey he plans to conduct raises the possibility that the results of the survey will merely mirror his own views."

To the best of our knowledge, it is not known how many of the 49 respondents to the survey were in that audience and further, it is also unknown whether those people present were influenced by the commentary (over and above any other form of information they may have come across prior to the survey period). Given the problems with the survey method (as discussed above), these concerns are trivial and the far bigger issues relate to the framing of the questions, the accuracy of the answers, the representativeness of the respondents, and how the data was interpreted by the researcher.

To summarise, we see nothing new in NERA's (2012) critique of the AER's use of survey evidence as a measure of the MRP. The issues mentioned are common to any survey and we considered each in our previous report. As such, we retain our view that despite the potential problems, we give significant weight to the survey evidence because there is the possibility of triangulation of the survey evidence across various sources. We do argue in favour of weighting these sources however, in which case, the Asher (2011) survey may be given a lesser weight. We note that even if it were down-weighted to zero it would not change our recommendation of a six percent MRP.

3. Advise on the extent that survey evidence can be relied on to estimate the MRP in the context of the AER's WACC framework. Provide a point estimate for the MRP which is supported by survey evidence in the context of the AER's WACC framework.

In McKenzie and Partington (2011, p. 22) we concluded:

> "that survey evidence cannot be used as a sole arbiter of the market risk premium. However, the triangulation of results across surveys in Australia and the U.S. provides a consistent picture. In summary the evidence suggests that 6% is an appropriate risk premium for Australia, although a case could be made for a slightly lower value. ... We argue that surveys do provide evidence that may usefully be weighed in the balance with estimates of the MRP from other methods. Some surveys are more reliable than others, so surveys should not all receive equal weight."

In our view, this conclusion is still valid.

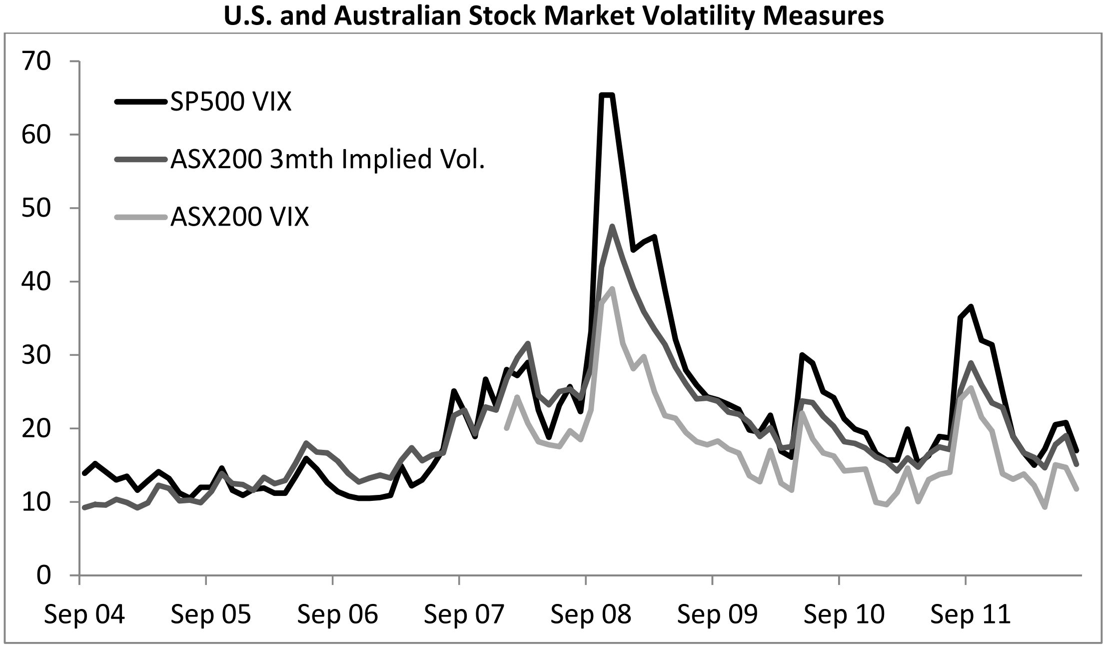
Appendix

In this paper, we benchmarked the volatility estimates of our models estimated using annual Australian data from 1883 – 2011 against implied volatility estimates from index options data. Ideally, we would like to have used Australia data, but no series is available over a long enough period to provide a sufficient number of observations for comparison. As such, we chose to benchmark our models against the VIX index, which is based on options prices of contracts written against the S&P500 index. The U.S. VIX is available from January 1986, whereas comparable Australian data is only available for a much shorter period.

While the VIX does provide a larger sample of data, it does raise the question as to how well this U.S. volatility data captures events on the Australian market. To provide some insights into this issue, we can compare the U.S. VIX data against comparable Australian market data in the form of the S&P ASX200 VIX index, which is available from Reuters beginning January, 2008. An alternative would be to use the equally weighted implied volatility estimates from 3 month put and call options contracts for the S&P ASX200 contract, which are available from Bloomberg from September, 2004.

Figure 10 plots these volatility index measures at a monthly frequency and they are clearly closely related - the correlation between the US and both of the Australian data is around 0.95. Thus, we believe that our use of the U.S. VIX data provides a reasonable benchmark for comparison against the Australian volatility estimates provided by our models.

Figure 10
U.S. and Australian Stock Market Volatility Measures



Note: The annual VIX data used in the main body of our analysis is the average of the daily closing value for the VIX volatility index in December each year. This figure plots the monthly volatility index value, where each months observation is the average daily index value in that month.

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