Structural Breaks and Predictive Regressions Models of South African Equity Premium*

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Abstract

In this paper, we test for the structural stability of both bivariate and multivariate predictive regression models for equity premium in South Africa over the period of 1990:01 to 2010:12, based on 23 financial and macroeconomic variables. We employ a wide range of methodologies, namely, the popular Andrews (1993) *SupF* statistic and the Bai (1997) subsample procedure in conjunction with the Hansen (2000) heteroskedastic fixed-regressor bootstrap. We also used the Elliott and Müller (2003) $\hat{J}$ statistic and Bai and Perron (1998, 2003a, 2004) methodologies. We find strong evidence of at least two structural breaks in 22 of 23 bivariate predictive regression models. We also obtain evidence of structural instability in the multivariate predictive regression models of equity premium. Our results also show that the predictive ability of the 23 variables can vary widely across different regimes.

Keywords: Predictive regression model, equity premium, structural breaks, South Africa
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1 – Introduction

Recently, major global economies experience economic slowdown. The likelihood that the global economy may experience a double-dip recession stresses the need for predicting the behaviour of leading indicators such as stock returns and equity premium. An understanding of market behaviour helps in guiding both policy and trading decisions. The main objective of this study is to examine the predictive role of financial and other economic variables for South Africa's equity premium while recognizing potential structural breaks. The equity premium is the expected excess return on a stock market portfolio over the risk-free interest rate. Equity prices capture expected firms' profitability, which is linked to the future rate of growth of the economy [Pástor and Stambaugh (2001), Kim et al. (2005)]. The popularity of predictive regression models, and the fact that these models are usually estimated using relatively long span of data, necessitates the need to test for the structural stability of the parameters in these models. Numerous macroeconomic and financial variables are unstable over time (Stock and Watson; 1996; Rapach and Wohar, 2006). Ignoring structural changes have statistical inference as well as investment allocation implications. From statistical inference perspective, it is shown that ignoring structural breaks in financial or economic time series can have persistence or long memory effects [Mikosch and Stărică (2004), Hillebrand (2005)] and can have implications about the existence of higher order unconditional moments such as kurtosis or tail index in financial time series [Mikosch and Stărică (2004), Andreou and Ghysels (2005)] as well as forecasting [Pesaran and Timmermann (2004)]. Therefore, ignoring structural breaks in econometric modelling can lead to model misspecification and spurious estimation results of model parameters. From an economic perspective, structural breaks can affect fundamental financial indicators such as, financial returns and volatility, the tail of the distribution and risk management measures, the shape of the option implied volatility smile, the equity premium, credit risk models and default measures. [Pástor and Stambaugh (2001), Andreou and Ghysels (2005, 2006, 2009), Horváth et al. (2006)]. More importantly, structural breaks affects optimal asset allocation decisions since these rely on forecasts of future returns, often at long horizons. For instance, Pettenuzzo and Timmermann (2005) find empirically that model instability can have a larger effect on the asset allocation than sources of risk such as parameter estimation uncertainty and can lead to a steep negative slope in the relationship between the investment horizon and the proportion of wealth that a buy-and-hold investor allocates to stocks. Various economic events can lead to structural changes detected in a large number of financial series, such as major changes in market sentiment, speculative bubbles, regime changes in monetary policy, changes in debt management policies, and learning by investors, financial liberalization of emerging markets, integration of world equity markets, collapse of exchange rate systems among others [Pesaran and Timmermann (2002), Andreou and Ghysels (2009)]. The precise estimation of a change point helps to uncover the source of a structural change by spotting special events around the break dates and can also be used to evaluate the impact of an event or a new policy by estimating the response time of the economy to the shocks [Liao (2008)]. Similar events as listed above may have occurred in South Africa especially within the last two decades. As we do not have strong prior beliefs concerning the exact timing of possible breakpoints in predictive regression models of equity premium, the role of statistical tests in contrast to simple assumption in detecting the exact change point cannot be overstressed as this gives a better and more scientific judgement.

A number of studies have predicted the behaviour of equity premium using financial and other macroeconomic variables. Nelson (1976) and Fama and Schwert (1977) found predictive ability for the inflation rate. Rozeff (1984), Fama and French (1988), Campbell and Shiller (1988a, 1988b) and Bekaert and Hodrick, (1992) presented evidence that valuation ratios, such as the dividend yield, predict the equity premium. Similarly, Keim and Stambaugh (1986), Campbell (1987), Breen, *et al.* (1989), and Fama and French (1989) found that nominal interest rates and interest rate spreads, such as the default and term spreads, predict the equity premium. More recent studies continue to support equity premium predictability using valuation ratios [Cochrane (2008), Pástor and Stambaugh (2009)], interest rates [Ang and Bekaert (2007)], and inflation [Campbell and Vuolteenaho (2004)]. Other studies identified additional financial and macroeconomic variables with predictive power, including financial share prices; money supply, corporate bond yields, industrial production, world oil production, oil price and employment rates [Baker and Wurgler (2000), Lettau and Ludvigson (2001), Guo (2006), Boudoukh, *et al*. (2007), Campbell and Thompson (2008), Goyal and Welch (2003, 2008), Allen and Bujang (2009), Jiang *et al*. (2009), Kellard *et al*. (2010), Nelly *et al.* (2010, 2011), Rapach *et al*. (2010), Rapach *et al.* (2011), Gupta *et al.* (2011)]. Majority of these studies are conducted for US and other advanced countries. Findings may often differ depending on the specific country or methodology. Moreover, none of these studies formally examined structural breaks in predictive (bivariate or multivariate) models of equity premium.[1] Therefore, the current study formally tests for structural breaks in the predictive regression model of South Africa's equity premium based on the 23 financial and macroeconomic variables that appear popularly in the literature of in-sample equity premium prediction. To the best of our knowledge, the structural stability of predictive regression models of South Africa's equity premium has not been previously investigated.

To test for structural break, we use the methodology described in Rapach and Wohar (2006). However, instead of testing structural stability of predictive stock returns as in Rapach and Wohar (2006), we test for structural stability of equity premium. Specifically, the Andrews (1993) $SupF$ statistic in concert with the Hansen (2000) heteroskedastic fixed-regressor bootstrap, as well as the recently developed $\hat{J}$ statistic of Elliott and Müller (2003) were used to test for a structural break at an unknown date in the parameters of 23 bivariate predictive regression models of South Africa's equity premium for 1990:01–2010:12 periods. The sample period covers events including a move to democratic rule in 1994 in South Africa, the Asian financial crisis, South Africa's decision to move to an inflation targeting regime in 2000, the currency crisis in late 2001, and the global financial crisis since late 2007. We use the 23 financial variables listed in the data section below as explanatory variables in the bivariate predictive regression models of South Africa's equity premium. We also use the subsample procedure of Bai (1997) and the Bai and Perron (1998, 2003a, 2004) methodologies to explicitly test for multiple structural breaks at unknown dates in the bivariate predictive regression models. In addition to the bivariate models, we also test for structural breaks in multivariate predictive regression models of equity premium.

The rest of the paper is organized as follows. Section 2 describes the econometric procedures. Section 3 describes the data and reports the results of the tests for structural breaks in bivariate and multivariate predictive regression models of equity premium. Section 4 concludes.

2 – Econometric methodology

The standard bivariate predictive regression model is specified as

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[1] Pástor and Stambaugh, 2001; Fama and French, 2002; Chang-Jin et al. 2005; Kim et al., 2005 examined structural breaks in equity premium in a univariate framework.

$$r_t = \beta_0 + \beta_1 z_{t-1} + \varepsilon_t \tag{1}$$

where r_t is the equity premium from period $t-1$ to period t, z_{t-1} is a candidate predictor lagged one time, ε_t is the disturbance term and $t = 1,...,T$. Using array notation, the predictive regression model can be expressed as

$$r_t = x'_{t-1}\beta + \varepsilon_t \tag{2}$$

where $x_{t-1} = (1, z_{t-1})'$, $\beta = (\beta_0, \beta_1)'$. The structural stability of the regression parameters β_0 and β_1 are tested. Breaks in both the intercept and slope coefficients of the predictive regression model are considered as both these affect the conditional expected equity premium, $E(r_t / z_{t-1})$. Suppose there is a structural break in the predictive regression model at period k, so that

$$r_t = x'_{t-1}\beta^0 + \varepsilon_t,\ t = 1,...,k \tag{3}$$

$$r_t = x'_{t-1}(\beta^0 + \delta) + \varepsilon_t,\ t = k+1,...,T \tag{4}$$

where $\beta^0 = (\beta_0^0, \beta_1^0)'$ and $\delta = (\delta_0, \delta_1)'.$ The model with a structural break could be written in matrix notation as

$$r = X\beta^0 + X_{0k}\delta + \varepsilon \tag{5}$$

where $r = (r_1,...,r_T)'$, $X = (x_0,...,x_{T-1})'$, $X_{0k} = (0,...,0.x_k,...,x_{T-1})'$ and $\varepsilon = (\varepsilon_1,...,\varepsilon_T)'$.

If the breakpoint k is known a priori, the familiar Chow (1960) procedure can be used to test the null hypothesis of no structural change $(H_0 : \delta = 0)$ against the alternative hypothesis of a structural break at period k $(H_1 : \delta \neq 0)$. The Chow (1960) test is based on the Wald statistic,

$$F_k = [(T-2)\hat{\sigma}_R^2 - (T-4)\hat{\sigma}_k^2] / \hat{\sigma}_k^2 \tag{6}$$

where $\hat{\sigma}_k^2 = (\hat{\varepsilon}_k{}' \hat{\varepsilon}_k)/(T-4)$, $\hat{\sigma}_R^2 = (\hat{\varepsilon}_R{}' \hat{\varepsilon}_R)/(T-2)$, $\hat{\varepsilon}_k$ is the vector of least-squares residuals from Equation (5), and $\hat{\varepsilon}_R$ is the vector of least-squares residuals from Equation (5) with the restriction $\delta = 0$ imposed. The null hypothesis of no structural break is rejected if the calculated F-statistics is greater than the critical value (the rejection-acceptance limit) at a pre-specified significance level.

The key weakness of the Chow (1960) test is that it is not operational if the breakpoint k is unknown, as is likely to be the case in many instances (Rapach and Wohar, 2006). In our case, we are not certain of the exact timing of possible breakpoints in predictive regression models of South Africa's equity premium. Building on Quandt (1960), Andrews (1993) makes the Chow (1960) test operational for the case of an unknown breakpoint. Chow (1960) derives the limiting distribution of the supremum of the F_k statistics over the interval $[\pi T, (1-\pi)T]$, or the test statistic,

$$SupF = \sup_{k \in [\pi T, (1-\pi)T]} F_k \tag{7}$$

where π is a trimming parameter (required for the asymptotic distribution theory) that is typically set equal to 0.05, 0.10, or 0.15. Andrews (1993) shows that the limiting distribution of the $SupF$ statistic is non-standard and depends on the trimming parameter π. For a given value of the trimming parameter, the null hypothesis of no structural break can be tested using the asymptotic critical values in Andrews (1993). If the null hypothesis is rejected, the breakpoint can be consistently estimated as

$$\hat{k} = \arg\min_{k \in [\pi T, (1-\pi)T]} (\hat{\varepsilon}_k{}' \hat{\varepsilon}_k) \tag{8}$$

Bai (1997) notes that given the formula for F_k in Equation (6), $\hat{k}$ will coincide with the value of k corresponding to the $SupF$ statistic in Equation (7). In Section 3, the $SupF$ statistic is used to test the structural stability of 23 bivariate predictive regression models of equity premium. Following the recommendation of Andrews (1993), the trimming parameter π is set equal to 0.15.

To guard against possible nonstationarities in the marginal distribution of the regressors, we follow Rapach and Wohar (2006) and rely on the Hensen (2000) heteroskedasticity fixed regressor bootstrap procedure to make inferences for the SupF statistic in Section 3 below.

Multiple structural breaks are likely to exist in the predictive regressions for South Africa's equity premium because of changes in the regimes and external shocks that may have changed the structure of the data during the period under review. As a result, we follow Rapach and Wohar (2006) and test for multiple structural breaks using the Bai (1997) procedure – augmented with the Hansen (2000) heteroskedastic fixed-regressor bootstrap.[2]

In addition to Bai (1997), we used the recently developed methodology of Bai and Perron (1998, 2003a, 2004) to test for multiple structural breaks in the predictive regression models. Their methodology is explicitly designed for estimating and testing regression models with multiple structural breaks. Consider the predictive regression model with m breaks ($m+1$ regimes),

$$r_t = z'_{t-1}\beta^j + \varepsilon_t, \ \ t = T_{j-1} + 1, \dots, T \tag{9}$$

for $j = 1,\dots,m+1,$ where β^j is the vector of regression coefficients in the jth regime. The m-partition $(T_1,\dots,T_m)$ represents the breakpoints for the different regimes (by convention, $T_0 = 0$ and $T_{m+1} = T$). Bai and Perron explicitly treat the breakpoints as unknown. Equation (9) is estimated using least squares. For each m-partition $(T_1,\dots,T_m)$, the least-squares estimates of β^j are generated by minimizing the sum of squared residuals,

$$S_T(T_1,\dots,T_m) = \sum_{i=1}^{m+1} \sum_{t=T_{i-1}+1}^{T_i} (r_t - z'_{t-1}\beta^j)^2 \tag{10}$$

Let the regression coefficient estimates based on a given m-partition ($T_1,\dots,T_m$) be denoted by $\hat{\beta}(\{T_1,\dots,T_m\})$, where $\beta = (\beta^{1'},\dots,\beta^{m+1'})'$. Substituting these into Equation (10), the estimated breakpoints are given by

$$(\hat{T}_1,\dots,\hat{T}_m) = \arg\min_{T_1,\dots,T_m} S_T(T_1,\dots,T_m) \tag{11}$$

where the set of admissible m-partitions is subject to a set of restrictions given below. From Equation (11), it is clear that the breakpoint estimators

[2] For further details on how the Bai (1997) procedure is constructed, the reader is referred to Rapach and Wohar (2006).

correspond to the global minimum of the sum of squared residuals objective function. With the breakpoint estimates in hand, it is straightforward to calculate the corresponding least-squares regression parameter estimates as $\hat{\beta} = \hat{\beta}\left(\{\hat{T}_1,...,\hat{T}_m\}\right)$. Bai and Perron (2003a) described an efficient algorithm for the minimization problem in Equation (11) based on the principle of dynamic programming.

A special testing procedure aimed at identifying the number of structural breaks (m) in Equation (9) was developed by Bai and Perron (1998). They begin by testing the null hypothesis of no structural breaks against the alternative of $m = b$ breaks. Let $(T_1,...,T_b)$ be a partition such that $T_i = [T\lambda_i](i = 1,...,b)$. Also define R such that $(R\beta)' = \left(\beta^{1'} - \beta^{2'},...,\beta^{b'} - \beta^{b+1''}\right)$. Bai and Perron (1998) specify the following statistic:

$$F_T(\lambda_1,...,\lambda_b) = \frac{1}{T}\left(\frac{T-(b+1)2}{2b}\right)\hat{\beta}'R'\left[R\hat{V}\left(\hat{\beta}R'\right)\right]^{-1}R\hat{\beta} \qquad (12)$$

where $\beta = \left(\beta^{1'},...,\beta^{b+1''}\right)'$ is the vector of regression coefficient estimates and $\hat{V}\left(\hat{B}\right)$ is an estimate of the variance-covariance matrix for $\hat{\beta}$ that is robust to heteroskedasticity and serial correlation. Bai and Perron (1998) then consider a type of maximum F-statistic corresponding to Equation (12),

$$SupF_T(b) = F_T\left(\hat{\lambda}_1,...,\hat{\lambda}_b\right) \qquad (13)$$

where $\hat{\lambda}_1,...,\hat{\lambda}_b$ minimize the global sum of squared residuals, $S_T\left(T\lambda_1,...,T\lambda_b\right)$, under the restriction that $\left(\hat{\lambda}_1,...,\hat{\lambda}_b\right) \in \Lambda_\pi$, where $\Lambda_\pi = \left\{(\lambda_1,...,\lambda_b); |\lambda_{i+1} - \lambda_i| \geq \pi, \lambda_1 \geq \pi, \lambda_b \leq 1-\pi\right\}$ for some arbitrary positive number π (the trimming parameter). Bai and Perron (1998) develop two statistics, called the ‘‘double maximum’’ statistics, for testing the null hypothesis of no structural breaks against the alternative hypothesis of an unknown number of breaks given an upper bound M. The first double maximum statistic is given by

$$UD\max = \max_{1 \leq m \leq M} SupF_T(m) \qquad (14)$$

The second double maximum statistic, $WD\max,$ applies different weights to the individual $UD\max$ statistics so that the marginal p-values are equal across values of $m;$ see Bai and Perron (1998:59) for details.

Bai and Perron (1998) also developed the $SupF_T(l+1|l)$ statistic which is used to test the null hypothesis of l breaks against the alternative hypothesis of $l+1$ breaks. This test is further useful in that it is used to test whether the additional break leads to a significant decrease in the sum of squared residuals. Bai and Perron (1998, 2003b) derive asymptotic distributions for the double maximum and $SupF_T(l+1|l)$ statistics and provide critical values for various values of π and M .

One of the advantages of the Bai and Perron methodology is that it allows for general specifications when computing test statistics and confidence intervals for the break dates and regression coefficients. These specifications include autocorrelation in the regression model residuals, heteroskedasticity in the residuals, and different moment matrices for the regressors in the different regimes. The latter two specifications are potentially important for our applications, and we allow for heteroskedasticity in the residuals and different moment matrices for the regressors in our applications. Using the notation of Bai and Perron (2004), we set $cor\_u=0$, $het\_u=1$, and $het\_z=1$ in our applications of the Bai and Perron methodology in Section 3.

We consider the sequential application of the $SupF_T(l+1|l)$ statistics – a specific to general modelling strategy – discussed by Bai and Perron (1998) as a way of determining the number of structural breaks as this procedure was found to perform well in a number of circumstances (Bai and Perron, 2004).

While Bai and Perron (2004) find that the Bai and Perron sequential procedure performs well in a number of settings, its performance can be improved upon when multiple breaks are present, as the $SupF_T(1|0)$ statistic, which is essentially the Andrews (1993) test, can have low power in the presence of multiple breaks (as discussed above). With multiple breaks, Bai and Perron (2004) find that the double maximum statistics are much more powerful. Based on their Monte Carlo simulations, Bai and Perron (2004) recommended the following strategy. First, examine the double maximum statistics to determine if any structural breaks are present. If the double maximum statistics are significant, then examine the $SupF_T\left(l+1|l\right)$ statistics to decide on the number of breaks, choosing the $SupF_T\left(l+1|l\right)$ statistic that rejects for the largest value of l. We also use this strategy – referred to as the Bai and Perron double maximum procedure – in our applications in Section 3 below. Finally, Bai and Perron (2004) recommend using a trimming parameter π of at least 0.15 (corresponding to $M=5$) when allowing for heteroskedasticity, and we follow this recommendation.

Monte Carlo simulations in Paye and Timmermann (2005) have potential implications for the testing procedures we employ. Paye and Timmermann (2005) consider processes where returns are generated by Equation (1), and the predictor z_t in Equation (1) is governed by a first-order autoregressive process,

$$z_t = \alpha_0 + \alpha_1 z_{t-1} + u_t \tag{15}$$

They find that the $UD\max$ statistic, as well as the $SupF$ statistic based on the fixed-regressor bootstrap, can exhibit considerable size distortions in situations where z_t is highly persistent (α near unity) and the disturbance terms in Equations (1) and (15) (ε_t and u_t) are strongly correlated. This is likely to be the case when z_t is a valuation ratio such as the dividend-price or price-earnings ratio. Paye and Timmermann (2005) find that a recently developed statistic by Elliott and Müller (2003) has relatively good size properties when z_t is highly persistent and the disturbance terms in Equations (1) and (15) are strongly correlated. Elliott and Müller (2003) use the $\hat{J}$ statistic to test the null hypothesis that $\beta_t = 0 \;\; \forall t$, where $\beta = \left(\overline{\beta} + \beta_t\right)$ in Equation (2), against the alternative hypothesis that $\beta_t \neq 0$ for some $t > 1$. Details on the computation of the $\hat{J}$ statistic are given in steps 1–6 of Elliott and Müller (2003:12), and they provide asymptotic critical values in their Table 1. Following Rapach and Wohar (2006), we include the Elliott and Müller (2003) $\hat{J}$ statistic in our analysis as a robustness check that guards against potential size distortions in our other tests.

3 – Results

The results obtained from the various tests for structural break in the predictive regression models of South Africa's equity premium are discussed in this section and reported in Tables 1 to 4. We begin by discussing the data used in the analysis.

3.1 – Data

We use monthly data from 1990:01 to 2010:12 for the equity premium and the 23 predictors. The variables are discussed below:

Equity premium: Nominal return on a stock market index (All-share index) in excess of the risk-free interest rate (the Treasury bill rate);

Financials share prices: Real stock returns for the financial sector in South Africa, computed as the first difference in the log-levels of real Financial Stock Index;

Industrial share prices: Real stock returns for the industries in South Africa, computed as the first difference in the log-levels of real Industrial Stock Index;

Price-dividend ratio (log-level): One-year moving sum of the ratio of nominal dividend to nominal stock prices;

Price-earnings ratio (log-level): One-year moving sum of the ratio of nominal earnings to nominal stock prices;

Payout ratio (log-level): The ratio of price-earnings to price-dividend;

Relative long-term bond yield: Difference between the long-term government bond yield and a 12-month backward-looking moving average;

Relative 90 days Treasury bill rate: Difference between the 90-day Treasury bill rate and a 12-month backward-looking moving average;

Term spread: Difference between long-term government bond yield and the 90-day Treasury bill rate;

Relative money market rate: Difference between the prime rate and the 12-month backward-looking moving average;

DAX (log-level): The real stock returns for Germany, computed as the first difference of the real DAX (Deutscher Aktien-Index) – a blue chip stock market index consisting of the 30 major German companies trading on the Frankfurt Stock Exchange;

CAC (log-level): The real stock returns for France, computed as the first difference of the real CAC 40 (the benchmark French stock market index);

S&P 500 (log-level): The real stock returns for the US, computed as the first difference of the real S&P 500, which is the free-float capitalisation-weighted index of the prices of 500 large-cap common stocks;
FTSE 100 (log-level): The real stock returns for the United Kingdom, computed as the first difference of the real FTSE 100 all-share index, which is a capitalisation-weighted index of around 100 companies traded on the London Stock Exchange;
NIKKEI (log-level): The real stock returns for Japan, computed as the first difference of the real Nikkei 225 stock index for the Tokyo Stock Exchange;
Hang-Seng (log-level): The real stock returns for Hong Kong, computed as the first difference of the real Hang Seng Index, which is a free float-adjusted market capitalisation-weighted stock market index;
Real effective exchange rate: First difference in log-levels of real effective exchange rate index;
Broad money supply growth rate: First difference in the log-levels of real broadly defined money stock;
Narrow money supply growth rate: First difference in the log-levels of real narrowly defined money stock;
The inflation rate: First difference in the log-levels of the consumer price index;
Industrial production growth rate: First difference in the log-levels of industrial production;
Employment growth rate: First difference in the log-levels of employment;
World oil production growth rate: First difference in the log-levels of the world oil production; and
Crude oil price growth rate: Refiner acquisition cost of imported crude oil growth rate in real terms. To obtain the rand denominated price, we use the rand/dollar exchange rate, and then deflate the nominal value using the consumer price index to obtain the real crude oil price.

The monthly data is obtained from the South African Reserve Bank, Statistics South Africa, Bloomberg and the US Energy Information Administration[3]. Following Rapach *et al.* (2005), we measure interest rate

[3] The mean (standard deviation) for the variables is as follows: Allshare: 1.309 (21.675), Financials share prices: 0.006 (0.039): Industrial share prices: 0.006 (0.039), Price-dividend ratio: 0.377 (0.084), Price-earnings ratio: 0.146 (0.031), Payout ratio: 0.388 (0.037), Long term bond: 0.185 (0.908), Treasury bill rate: 0.246 (1.366), Term-spread: 0.858 (1.932), Money market rate: 0.236 (1.418), DAX: 0.002 (0.028), CAC 40: 0.001 (0.025), S&P 500: 0.001 (0.019), FTSE 100: 0.001 (0.019), NIKKEI: -0.002 (0.028), Hang Seng: 0.003 (0.033), REER: 0.000 (0.013), Broad money supply: 0.005 (0.006), Narrow money supply: 0.005 (0.017),

variables as deviations from a backward-moving average. This is because, if real interest rates play a crucial role in determining stock returns, then measuring the interest rate as deviations from a backward-looking moving average tends to make the nominal interest rate effectively a real interest rate. That is, the behaviour of expected inflation is such that most of the fluctuations in the relative nominal interest rate reflect movements in the relative real component. All the variables were tested for unit roots. Based on standard tests, only inflation rate was nonstationary, hence the first difference was used in the analysis[4].

3.2 – Structural breaks for bivariate and multivariate models of South Africa's equity premium

Table 1 presents the estimation results for Equation (1) based on the 23 explanatory variables for the bivariate predictive regressions as well as the results for the multivariate regressions.[5] The reported results in Table 1 are for the SupF, $\hat{J}$, QLR_T, WDmax and the SupFT test statistics.[6] For the bivariate regressions, the coefficients for all variables are positive with the exception of financial share prices, industrial share prices, payout ratio, long term bond, real effective exchange rate and inflation which have negative signs. Using the t-test statistic and the 10% significance level, the slope coefficient is significant for all variables except financial share price, industrial share price, payout ratio, long term bond, Treasury bill rate, US S&P 500, real effective exchange rate, broad money supply, inflation and world oil production. As is common in the literature, the R^2 statistics show that even when a variable has a significant effect on future equity premium, the predictable component in equity premium tends to be relatively small. Nevertheless, even a small predictable component in equity premium can have important implications for asset-allocation decisions (Kandel and Stambaugh, 1996). Andrews (1993) *SupF* statistics for testing the null hypothesis of no structural change are reported in column (2) while the

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Inflation: 0.003 (0.002), Industrial production: 0.000 (0.012), World oil production: 0.000 (0.004), Oil price: 10.109 (38.477), and Employment rate: -0.001 (0.002).

[4] The unit root tests are available from the authors upon request.

[5] To facilitate comparisons across variables, we divide the explanatory variable by its standard deviation before it enters Equation (1).

[6] The results for the coefficient, R2, WDmax (10% and 5%) and SupF (2|1, 3|2 and 4|3) are available from the authors upon request.

corresponding p-values are reported in column (3) of Table 1. As indicated in Section 2 above, we use 15% trimming and generate p-values using the Hansen (2000) heteroskedastic fixed regressor bootstrap. The null hypothesis of no structural change is rejected at 1% significant level in all 23 bivariate predictive regression models. The endogenously selected breakpoints are reported in column (4). The break points for price earnings ratio, price dividend ratio, payout ratio and employment rate occur in 1999:06, 2001:09, 2002:10 and 2005:06 respectively. For the money market and Treasury bill rate, the breakpoint occurs in 2004:03. The breakpoints for the rest of the variables occur in either 2003:11 or 2003:12. Column (5) of Table 1 reports the Elliott and Müller (2003) $\hat{J}$ statistics. Again, we are able to reject the null hypothesis of structural stability in all the 23 predictive regression models. We report the Rossi (2005) QLR_T statistic for each bivariate predictive regression model in column (6) of Table 1. This statistic is designed to be optimal for testing the joint null hypothesis that β_0 and β_1 are constant over time and equal to zero in Equation (1), meaning, a test of no predictability over the entire sample. The null hypothesis is rejected for all of the bivariate predictive regression models.

Next, we employ the Bai and Perron methodology in order to test for multiple structural breaks, and the results are reported in Table 1. Using the $SupF_T(l+1|l)$ statistics and the Bai and Perron sequential procedure, there is evidence of a single structural break for all the variables, as the $SupF_T(1|0)$ statistics are significant. The $SupF_T(2|1)$ statistics are also significant for all variables except employment, suggesting two structural breaks for the other models. Out of the 23 predictive regressions, 8 show at least 5 structural breaks (see Table 1, column 10). Given that the sequential procedure can have low power in the presence of multiple breaks, we also consider the Bai and Perron double maximum procedure, following the recommendation of Bai and Perron (2004). The results are reported in columns 7 and 8 of Table 1. The entire statistics are significant for each of the 23 predictors.

We further investigate the stability of multivariate predictive regression models of equity premium. A difficulty with multivariate predictive regression models of equity premium is selecting the predictors to include in the model. Following Rapach and Wohar (2006), we specify multivariate predictive regression models using the AIC and SIC, with all 23 of the individual variables analyzed in the previous section considered as potential predictors. These results are presented lower panel of Table 1. The

AIC selects five variables – price-earnings ratio, term spread, money market rate, Hang Seng and employment rate – to include in the multivariate predictive regression model, while the SIC selects three predictors – price-earnings ratio, money market and employment rates Each of the selected variables enters significantly with R^2 statistics of 0.56 and 0.58 for the model selected by AIC and SIC respectively. This indicates a high predictive power of the multivariate models. The $SupF$ statistic based on the heteroskedastic fixed-regressor bootstrap, as well as the $\hat{J}$ statistics are significant at the 1% level, indicating structural instability in the multivariate models selected by both the AIC and SIC. Also, the null hypothesis of no predictability over the entire sample is rejected as the QLR_T statistic is significant for both models. For the two multivariate models, there is strong and significant evidence of structural breaks in both cases. Using the $SupF_T\left(l+1|l\right)$ statistics and the Bai and Perron sequential procedure, we find strong evidence of structural breaks for the models selected by both the AIC and the SIC – four breaks are detected for each model. Similar to the Bai and Perron sequential procedure, the Bai and Perron double maximum procedure indicates multiple breaks for the two multivariate models, as the $UD\max$ and the $WD\max$ statistics are significant.

The results for the Bai (1997) subsample procedure for both bivariate and multivariate predictive regressions are reported in Table 2. The Bai (1997) subsample procedure for the bivariate regressions indicates a single significant break for the employment rate, so that there are no breaks in addition to the one reported in Table 1 for this variable. For Financial share price, S&P 500, FTSE 100, NIKKEI, Hang Seng, M3, and inflation, the Bai (1997) subsample procedure in Table 2 detects two significant structural breaks. Four significant breaks were detected for payout ratio, money market rate, DAX, CAC 40 and narrow money supply. For the remaining 10 variables, there is evidence of three significant breaks according to the Bai (1997) subsample procedure in Table 2. The break points occur mostly in 1993, 1994, 1996, 1999, 2003, 2004 and 2007 at different months. There is also strong and significant evidence of structural breaks in the multivariate regressions.

The observed structural breaks so far can now be explained based on certain events that took place in South Africa at different times. The first structural break (in 1993/1994) marks the change to the first democratic government. This period was viewed as a crisis mainly because the closing years of the apartheid government proved extraordinarily expensive and economically crippling [Rustomjee (2006)]. The outgoing administration left escalating fiscal deficits, considerably high levels of domestic indebtedness by the private sector and high levels of debt service costs. The increasingly poor quality of expenditure and an inability to reduce the structural inflationary pressures intensified the crisis. The installation of the democratic administration was coupled with significant outflows, affecting the financial sector negatively [Rustomjee (2006)].

The second year that exhibits a structural break for a number of predictive regression models is 1996. Structural breaks in 1996 may have been caused by the introduction of the democratic government's economic strategy – GEAR (Growth, Employment and Redistribution). This was the basic macroeconomic policy of the South African government. Both global and domestic investors were very critical of the new policy introduces by the government resulting in large capital outflows and as a result, excessive volatility in the economy. The main criticisms included the focus being on macroeconomic variables instead of microeconomic reforms and the lack of consultation preceding its tabling in parliament [Naidoo *et al*. (2008)].

Not surprising, the late 1990s and the early 2000s exhibit structural breaks because of a number of events in the country. Firstly, because of its sophisticated financial markets and substantial private capital flows, South Africa was fully exposed to contagion from the world financial crisis. The weakening of investor confidence in May 1998 and the ensuing downward pressure on the rand was exacerbated by the monetary authorities' large-scale intervention in the foreign exchange market and the uneven stance of monetary policy [Harris (1991)]. Secondly, the political situation also brought uncertainty for South Africa as 1999 was a year when Thabo Mbeki took over Nelson Mandela and the government also announced that Tito Mboweni will take over would take over the then governor of the South African Reserve Bank, Chris Stals. Thirdly, the government announced that South Africa will be adopting an inflation targeting in 2000. Fourthly, the crisis that began in Argentina flooded to other emerging economies with developed financial markets, and South Africa was not immune to it. Prior to the 2001 currency crisis, South Africa was experiencing large short-term capital flows which increased its vulnerability. When investors globally started taking out their money from riskier financial markets – emerging markets mainly – the rand depreciated significantly as this caused panic for South African investors resulting in a currency crisis.

The year 2003 is broadly seen as a start of the global boom that ended in 2007. The US finally recovered from the IT bubble experienced in prior years and economic growth was increasing around potential growth, while the Japanese authorities nationalised a major bank in response to the earlier financial crisis. The global market for securitized assets grew rapidly and investors began demanding more emerging market equities. Asian countries were growing fast, especially China. South Africa was also growing noticeably, with inflation rate moderating to single digits and macro stability maintained. Growth was mainly driven by household consumption, investment, financial and business services, construction, and trade. The budget deficit and the current account were also under control. The 2005 break dictated for employment could be as a result of the redefinition of the measure of employment by Statistics South Africa during this period. The current financial crisis – which started in the US housing market – is a result of the structural breaks for 2007.

Table 3 reports multiple regime bivariate predictive regression model estimation results for models based on each of the 23 predictors . The number of breaks is selected according to the Bai and Perron double maximum procedure, and the breakpoints correspond to the global minimizers in Equation (11). For the financial shares prices, the absolute value of the slope coefficient increased significantly as we move from the first regime, which ends in 1993:5, to the third regime which ends in 1999:10 but declined in the fourth and fifth regimes and slightly increased in the last regime. The slope coefficient was only significant in regime 3. The R^2 recorded for this model is relatively low – the highest R^2 is recorded for the third regime (0.04) – suggesting that financial share prices have weak predictive power. A similar trend is also observed for industrial share prices. We note that the end period for regime 5 which corresponds to the beginning point for regime 6 occur in 2007:10 and this period corresponds to global financial and economic crisis. Therefore, the observed decline in the slope coefficients of financials and industrial share price is not surprising. Even for the industrial share prices, the R^2 values for the different regimes are low, suggesting weak predictive power for the variable. Turning to the price-dividend ratio, it is interesting to note that the slope coefficient is significant in each of the five regimes. The first regime ends in 1994:10, and the slope coefficient grows as we move from the first to the third regime, declined to 22.6 in regime 4 which begins in 2001:08 and to 18.3 in the 5^{th} regime. The 1994 break date corresponds to a period of change to democratic government in South Africa. The 2001 break date corresponds to the currency crisis in 2001. This trend is also seen in the behaviour of the R^2 values for the different regimes. For the first regime, the R^2 value is 0.78, and then declines to 0.4 in the third regime. The R^2 value for the fourth regime rises to 0.78 (the highest R^2 value for the regime in our analysis). The R^2 values show that the price-dividend ratio has a very strong predictive power for the different regimes. For the price-earnings ratio, the slope coefficient is significant in each regime and again grows as we move from the first to the last regime, which begins in 2006:09. There is a slight decline in the second regime which ends in 1999:06. The R^2 values for the price-earnings ratio are the highest for the first regime (0.72), second regime (0.62) and the third regime (0.64), while it remains high for the fourth regime (0.67). In general, our results highlight the importance of valuation ratios as predictors of the behaviour of equity premium in South Africa.

With respect to the payout ratio, the slope coefficient (in absolute value) was 9.53 in regime 1. This increased to 17.5 in regime 2, declined to 7.26 in regime 3, increased to 9.74 and 17.8 in regime 4 and 5 respectively. The slope coefficient was significant in all the regimes. The payout ratio shows a relative strong predictive power only during the third and fourth regimes – with the R^2 values of 0.34 for both regimes. A similar trend holds for long term bond, Treasury bill rate and term spread with the exception that their coefficients were insignificant in one or two of the regimes. For the money market rate, the absolute value of the coefficient was 6.1 in the first regime which ends in 1993:06. By the end of regime 2 in 1996:10, it increased to 22.1. The value declined afterwards until it was 1.17 in the last regime which began in 2007:10. The slope coefficients were significant except for the last regime. Although the predictive power is not as strong as for the valuation ratios, most interest rate variables have some predictive power in some regime. The R^2 values are particularly large in the second and third regimes and, to some extent, the fourth regime. The highest R^2 values are associated with the money market interest rates (0.48) and the term spread (0.46) in the second regime.

The same pattern holds for inflation rate except that inflation's slope coefficient was insignificant in the first and last regimes. For the real effective exchange rate, the slope coefficient declined in absolute value for five regimes except in regime 4 which begins in 2003:12 and ends in 2007:10. For employment rate, the slope coefficient increases from 7.7 in regime 1 which ends in 2005:06 to 20.1 in regime two which begins in the same period. All our results indicate 2005:06 as a break point for employment rate. This could be as a result of the redefinition of the measure of employment by Statistics South Africa. The interpretation for the rest of other variables in the predictive regression models of equity premium follows in similar fashion. The R^2 values for most of these variables are low, suggesting weak predictive power.

In general, the estimation results in Table 3 show that most of the variables exhibit structural breaks in 1993/94 at the end of the first regime and in 2007 at the beginning of the last regime. This is not surprising as the 1993/94 break period marks the beginning of democratic rule in South Africa, while the 2007 break period marks the beginning of global financial crisis. Further, the results show that the predictive ability of many variables varies considerably over time, indicating that failure to account for structural breaks in predictive regression models of equity premium can lead one to substantially overestimate or underestimate predictive ability during certain periods.

Table 4 presents estimation results for the multivariate regression model selected by the AIC over the four regimes defined by the structural break dated by the Bai and Perron global minimizer in Equation (11). The breakpoints occur in 1994:10, 1999:6, 2007:10. The R^2 values for the model are significantly high for the different regimes (0.87, 0.80, and 0.78, respectively) – showing significant predictive power. Five regimes were defined by the structural breaks for the model selected by SIC. The breakpoints occur in 1994:10, 1996:6, 2002:10 and 2007:10 – with R^2 values of 0.84, 0.78, 0.46, 0.85 and 0.74, respectively. The multivariate regression models selected by AIC and SIC have significant predictive power compared to most bivariate regression models in our analysis.

Overall, there is strong evidence of a multiple structural breaks in the bivariate and multivariate regressions models, with the structural break formal tests providing significant evidence of structural instability. Also, the R^2 results show that the predictive ability of many variables varies considerably over time, indicating that failure to account for structural breaks in predictive regression models of equity premium can lead one to substantially overestimate or underestimate predictive ability during certain periods.

4 – Conclusion

In this paper, we test for structural breaks over 1990:01-2010:12 using a large number of predictive regression models for South Africa's equity premium. We test for structural breaks using procedures developed by Andrews (1993), Bai (1997), Bai and Perron (1998, 2003a, 2004), Hansen (2000), and Elliott and Müller (2003). We find strong evidence of structural breaks in bivariate predictive regression models of equity premium based on all 23 financial and macroeconomic variables included. The evidence points to a single structural break in bivariate models of equity premium based on the employment rate. For the remaining 22 variables, there is a minimum of two significant structural breaks. We also find strong evidence of structural breaks in a multivariate predictive regression model of equity premium. Our findings show that that the degree of predictability of equity premium can differ widely across the regimes defined by the structural breaks. The main conclusion of this study is that structural breaks appear prevalent in predictive regression models of South Africa's equity premium. The extensive evidence of structural breaks in the predictive regression models of equity premium in South Africa indicates the need for out-of-sample forecasting schemes that take explicit account of potential structural breaks in predictive regression models as this may improve asset allocation decisions by investors.

Table 1: Structural Break results for different tests for both bivariate and multivariate predictive regressions

Predictor	SupF	Breakpoint	$\hat{J}$		QLR_T^*	
Financials share prices	24.55	Nov-03	-41.19	***	23.88	***
Industrial share prices	24.66	Nov-03	-41.49	***	26.33	***
Price-dividend ratio	37.49	Sep-01	-94.48	***	22.83	***
Price-earnings ratio	54.71	Jun-99	-95.73	***	25.66	***
Payout ratio	37.87	Oct-02	-68.12	***	24.04	***
Long term bond	24.05	Nov-03	-51.29	***	21.81	***
Treasury bill rate	38.30	Mar-04	-57.41	***	22.60	***
Term-spread	46.59	Dec-03	-65.88	***	25.11	***
Money market rate	39.07	Apr-04	-56.40	***	21.64	***
DAX	32.66	Dec-03	-44.36	***	24.98	***
CAC 40	36.23	Dec-03	-46.49	***	48.76	***
S&P 500	35.24	Dec-03	-48.15	***	28.18	***
FTSE 100	32.08	Dec-03	-44.30	***	21.45	***
NIKKEI	27.42	Nov-03	-39.80	***	26.91	***
Hang Seng	27.01	Dec-03	-41.24	***	31.46	***
REER	24.70	Nov-03	-40.46	***	24.15	***
Broad money supply	32.07	Nov-03	-42.27	***	23.81	***
Narrow money supply	25.52	Nov-03	-40.76	***	25.70	***
Inflation	27.31	Nov-03	-43.10	***	22.10	***
Industrial production	27.37	Nov-03	-43.57	***	22.58	***

World oil production	24.99	Nov-03	-40.28	***	25.83	***
Oil price	27.20	Nov-03	-53.34	***	30.41	***
Employment rate	31.28	Jun-05	-42.03	***	33.59	***
Multivariate Model						
AIC Model	65.566	Jun-95	-166.1	***	33.59	**
SIC Model	47.128	Dec-93	-149.3	***	28.32	***

***, **, * represents 1%, 5% and 10% confidence intervals

Table 1: Structural Break results for different tests for bivariate and multivariate predictive regressions, contd

Predictor	UDmax[1]	Wdmax (1%)[1]	SupFT (1|0)[1]	SupFT (5|4)	
Financials share prices	105.17	142.93	20.46	14.91	**
Industrial share prices	105.33	143.29	20.52	13.69	**
Price-dividend ratio	156.36	255.12	37.59	-	
Price-earnings ratio	122.78	162.57	54.85	-	
Payout ratio	131.57	180.65	31.16	-	
Long term bond	108.50	167.69	20.01	28.36	***
Treasury bill rate	114.51	175.70	30.46	14.57	**
Term-spread	149.28	188.84	35.45	12.54	**
Money market rate	119.01	180.52	30.42	12.26	*
DAX	104.43	140.67	27.56	10.74	
CAC 40	105.47	142.33	30.75	11.28	
S&P 500	108.30	143.17	29.71	10.85	
FTSE 100	106.25	141.15	27.06	10.69	
NIKKEI	100.25	133.44	23.36	10.31	
Hang Seng	104.59	139.24	22.43	10.35	
REER	105.45	142.34	20.55	10.52	
Broad money supply	101.57	136.47	27.54	9.83	
Narrow money supply	105.78	141.91	21.22	10.46	
Inflation	101.74	139.75	23.66	22.38	***
Industrial production	107.55	141.25	23.16	10.56	
World oil production	111.22	149.65	20.78	11.86	*
Oil price	106.94	165.75	23.48	8.83	
Employment rate	65.17	82.44	29.25	3.90	
Multivariate					
AIC model	151.54	237.19	70.24	14.40	
SIC model	124.16	151.75	103.40	-	

***, **, * represents 1%, 5% and 10% confidence intervals; 1 means significant at 1%

Table 2: Bai (1997) subsample analysis, bivariate and multivariate predictive regression models

Predictor	Sample	*SupF*	p-values	Breakpoint
Bivariate				
Financials share prices	1990:01 - 2010:12	24.55	0.00	Nov-03
	1990:01 - 2003:11	8.79	0.11	Sep-96
	2003:11 - 2010:12	64.48	0.00	Sep-07
Industrial share prices	1990:01 - 2010:12	24.66	0.00	Nov-03
	1990:01 - 2003:11	9.78	0.09	Sep-96
	2003:11 - 2010:12	64.04	0.00	Sep-07
Price-dividend ratio	1990:01 - 2010:12	37.49	0.00	Sep-01
	1990:01 - 2001:09	102.81	0.00	Oct-94
	2001:10 - 2010:12	71.63	0.00	Nov-06
Price-earnings ratio	1990:01 - 2010:12	54.71	0.00	Jun-99
	1990:01 - 1999:06	152.13	0.00	Oct-94
	1999:07 - 2010:12	56.43	0.00	Oct-06
Payout ratio	1990:01 - 2010:12	37.87	0.00	Oct-02
	1990:01 - 2002:10	26.55	0.00	Jun-99
	2002:11 - 2010:12	58.02	0.00	Jun-07
	1990:01 - 1999:06	71.24	0.00	May-93
Long term bond	1990:01 - 2010:12	24.05	0.00	Nov-03
	1990:01 - 2003:11	20.63	0.00	Dec-94
	2003:12 - 2010:12	75.42	0.00	Oct-07
Treasury bill rate	1990:01 - 2010:12	38.30	0.00	Mar-04
	1990:01 - 2004:04	28.53	0.00	Nov-94
	2004:05 - 2010:12	54.79	0.00	Oct-07
Term-spread	1990:01 - 2010:12	46.59	0.00	Dec-03
	1990:01 - 2003:12	19.83	0.00	May-93
	2004:01 - 2010:12	85.42	0.00	Oct-07
Money market rate	1990:01 - 2010:12	39.07	0.00	Apr-04
	1990:01 - 2004:04	15.37	0.01	Oct-96
	2004:05 - 2010:12	54.22	0.00	Oct-07

	1990:01 - 1996:10	74.83	0.00	Jun-93
DAX	1990:01 - 2010:12	32.66	0.00	Dec-03
	1990:01 - 2003:12	9.40	0.08	Sep-96
	2004:01 - 2010:12	60.22	0.00	Jun-07
	1990:01 - 1996:09	28.64	0.00	May-93
CAC 40	1990:01 - 2010:12	36.23	0.00	Dec-03
	1990:01 - 2003:12	8.63	0.11	Oct-96
	2004:01 - 2010:12	57.54	0.00	Oct-07
	1990:01 - 1996:10	29.69	0.00	May-93
S&P 500	1990:01 - 2010:12	35.24	0.00	Dec-03
	1990:01 - 2003:12	8.30	0.12	Oct-96
	2004:01 - 2010:12	65.38	0.00	Oct-07
FTSE 100	1990:01 - 2010:12	32.08	0.00	Dec-03
	1990:01 - 2003:12	8.16	0.14	Oct-96
	2004:01 - 2010:12	63.76	0.00	Oct-07
NIKKEI	1990:01 - 2010:12	27.42	0.00	Nov-03
	1990:01 - 2003:11	8.68	0.11	Oct-96
	2003:11 - 2010:12	57.53	0.00	Oct-07
Hang Seng	1990:01 - 2010:12	27.01	0.00	Dec-03
	1990:01 - 2003:12	7.97	0.18	Sep-96
	2004:01 - 2010:12	63.36	0.00	Oct-07
REER	1990:01 - 2010:12	24.70	0.00	Nov-03
	1990:01 - 2003:11	9.18	0.10	Oct-96
	2003:11 - 2010:12	64.09	0.00	Oct-07
	1990:01 - 1996:10	27.60	0.00	May-93
M3	1990:01 - 2010:12	32.07	0.00	Nov-03
	1990:01 - 2003:11	8.87	0.11	Sep-96
	2003:11 - 2010:12	52.50	0.00	Oct-07
M1A	1990:01 - 2010:12	25.52	0.00	Nov-03
	1990:01 - 2003:11	9.03	0.09	Oct-96
	2003:11 - 2010:12	62.93	0.00	Oct-07
	1990:01 - 1996:10	30.82	0.00	May-93
Inflation	1990:01 - 2010:12	27.31	0.00	Nov-03

	1990:01 - 2003:11	8.27	0.14	Apr-93
	2003:11 - 2010:12	61.65	0.00	Oct-07
Industrial production	1990:01 - 2010:12	27.37	0.00	Nov-03
	1990:01 - 2003:11	9.08	0.10	Sep-96
	2003:11 - 2010:12	75.81	0.00	Oct-07
	1990:01 - 1996:09	28.84	0.00	May-93
World oil production	1990:01 - 2010:12	24.99	0.00	Nov-03
	1990:01 - 2003:11	8.66	0.10	Sep-96
	2003:11 - 2010:12	74.52	0.00	Oct-07
Oil price	1990:01 - 2010:12	27.20	0.00	Nov-03
	1990:01 - 2003:11	43.45	0.00	Nov-94
	2003:11 - 2010:12	69.03	0.00	Oct-07
Employment rate	1990:01 - 2010:12	31.28	0.00	Jun-05
	1990:01 - 2005:06	5.71	0.37	May-93
Multivariate				
Model selected by AIC	1990:01 - 2010:12	47.13	0.00	Dec-93
	1990:01 - 1995:06	49.99	0.00	Oct-94
	1994:01 - 2010:12	54.60	0.00	Jul-99
	1999:07 - 2010:12	43.30	0.00	Oct-07
Model selected by SIC	1990:01 - 2010:12	65.57	0.00	Jun-95
	1990:01 - 1995:07	68.37	0.00	Oct-94
	1995:08 - 2010:12	55.73	0.00	Jul-99
	1999:07 - 2010:12	30.19	0.00	Oct-07

Table 3: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results

	Regime 1					
	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point
Financials share prices	-8.47	2.23	-0.12	2.60	0.00	May-93[Sep-92, Sep-93]
Industrial share prices	-8.09	2.24	-1.82	2.61	0.01	May-93[Sep-92, Sep-93]
Price-dividend ratio	-64.13	5.49	17.75	1.43	0.72	Oct-94[Aug-94, Nov-94]
Price-earnings ratio	-61.53	5.24	14.78	1.18	0.72	Oct-94[Aug-94, Dec-94]
Payout ratio	99.64	40.38	-9.54	3.56	0.16	May-93[Jan-93, Jul-93]
Long term bond	-6.25	2.16	-7.10	2.61	0.15	May-93[Aug-92, Sep-93]
Treasury bill rate	-4.33	2.74	-7.41	3.24	0.11	May-93[Jan-93, Jun-93]
Term-spread	-8.59	2.20	0.61	2.31	0.00	May-93[Aug-92, Jun-94]
Money market rate	-6.06	2.51	-6.00	4.04	0.06	Jun-93[Feb-93, Aug-93]
DAX	-8.49	2.10	3.72	2.25	0.06	Jun-93[Sep-92, Sep-93]
CAC 40	-8.51	2.12	3.11	2.07	0.05	May-93[Sep-92, Sep-93]
S&P 500	-8.62	2.17	1.59	2.39	0.01	May-93[Oct-92, Sep-93]
FTSE 100	-8.53	2.17	0.59	1.91	0.00	May-93[Sep-92, Sep-93]
NIKKEI	-8.36	2.22	0.50	1.67	0.00	May-93[Sep-92, Oct-93]
Hang Seng	-9.02	2.20	3.15	2.92	0.03	May-93[Sep-92, Sep-93]
REER	-8.26	2.18	-4.93	6.94	0.01	May-93[Sep-92, Sep-93]
M3	-8.09	2.46	-0.70	2.04	0.00	May-93[Sep-92, Sep-93]
M1A	-7.70	2.18	-2.70	1.83	0.05	May-93[Sep-92, Sep-93]
Inflation	-14.84	5.20	3.13	2.34	0.05	May-93[Dec-92, Jul-93]
Industrial production	-8.52	2.17	-0.53	2.01	0.00	May-93[Sep-92, Sep-93]
World oil production	-8.54	2.17	-0.64	1.42	0.01	May-93[Sep-92, Sep-93]
Oil price	-0.78	2.63	-12.69	4.49	0.13	Nov-94[Jul-94, Sep-95]
Employment rate	2.92	1.43	7.70	1.26	0.15	Jun-05[Apr-04, Jul-06]

90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 3: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results, contd

	Regime 2					
	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point
Financials share prices	11.12	2.72	-2.92	2.74	0.04	Sep-96[May-96, Jan-97]
Industrial share prices	11.09	2.71	-2.83	2.70	0.03	Sep-96[May-96, Jan-97]
PD ratio	-132.35	17.83	23.95	3.39	0.54	Jul-98[Sep-97, Aug-98]
Price-earnings ratio	-80.86	7.83	13.60	1.50	0.62	Jun-99[May-99, Jul-99]
Payout ratio	-180.35	20.16	17.26	1.95	0.12	Jun-99[Mar-99, Oct-99]
Long term bond	9.93	2.62	-1.29	1.76	0.01	Oct-96[Apr-96, Feb-97]
Treasury bill rate	16.75	2.25	18.25	3.14	0.40	Sep-96[Jul-96, Nov-96]
Term-spread	-9.35	1.44	12.11	1.14	0.46	Dec-03[Oct-03, Feb-04]
Money market rate	16.01	2.12	21.22	3.36	0.48	Oct-96[Jul-96, Dec-96]
DAX	10.24	2.71	1.47	3.84	0.02	Sep-96[Dec-95, Apr-97]
CAC 40	10.10	2.63	0.32	3.23	0.00	Oct-96[Dec-95, May-97]
S&P 500	11.32	2.63	-8.16	4.61	0.07	Oct-96[Feb-96, May-97]
FTSE 100	10.24	2.65	-1.28	3.36	0.00	Oct-96[Dec-95, Jun-97]
NIKKEI	10.06	2.62	1.25	2.68	0.00	Oct-96[Dec-95, Jun-97]
Hang Seng	10.28	2.67	1.67	2.52	0.01	Oct-96[Dec-95, Apr-97]
REER	10.06	2.66	-0.38	4.05	0.00	Oct-96[Dec-95, Jun-97]
M3	9.26	3.93	1.25	3.11	0.01	Oct-96[Nov-95, Apr-97]
M1A	9.58	2.81	1.24	2.48	0.01	Oct-96[Dec-95, Jun-97]
Inflation	-4.51	5.61	11.95	4.05	0.19	Sep-96[May-96, Dec-96]
Industrial production	10.42	2.69	0.01	2.88	0.00	Sep-96[Dec-95, May-97]
World oil production	10.28	2.75	0.86	4.04	0.00	Sep-96[Dec-95, Apr-97]
Oil price	-9.59	1.45	7.76	1.17	0.29	Nov-03[Sep-03, Jan-03]
Employment	14.26	2.38	20.11	2.29	0.53	Dec-10

90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 3: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results, contd

	Regime 3					
	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point
Financials share prices	-14.28	2.52	4.44	2.68	0.04	Oct-99[Aug-98, Jul-00]
Industrial share prices	-14.02	2.48	4.91	2.62	0.06	Oct-99[Jun-98, Aug-00]
PD ratio	-132.90	23.54	27.36	4.96	0.39	Aug-01[Jun-01, Nov-01]
Price-earnings ratio	-94.07	8.14	23.19	1.81	0.64	Sep-06[Mar-06, Jan-07]
Payout ratio	71.41	13.70	-7.27	1.36	0.34	Nov-03[Sep-03, Jan-04]
Long term bond	-10.40	2.13	9.00	1.79	0.30	Jul-01[Mar-01, Oct-01]
Treasury bill rate	-15.54	1.89	6.39	1.09	0.42	Oct-99[Apr-98, May-00]
Term-spread	27.22	1.78	-4.22	2.54	0.10	Oct-07[Jun-07, Nov-07]
Money market rate	-8.86	1.72	6.21	1.24	0.22	Dec-03[Oct-03, Feb-04]
DAX	-7.23	1.90	0.80	1.49	0.00	Dec-03[Oct-03, Mar-04]
CAC 40	-7.32	1.93	0.91	1.62	0.00	Dec-03[Oct-03, Mar-04]
S&P 500	-7.18	1.93	-0.74	1.64	0.00	Dec-03[Oct-03, Mar-04]
FTSE 100	-7.23	1.93	0.27	1.80	0.00	Dec-03[Oct-03, Mar-04]
NIKKEI	-6.94	1.93	2.59	2.13	0.02	Dec-03[Oct-03, Mar-04]
Hang Seng	-7.26	1.89	2.20	1.59	0.02	Dec-03[Oct-03, Mar-04]
REER	-7.24	1.93	-0.21	1.68	0.00	Dec-03[Oct-03, Mar-04]
M3	-7.49	2.34	0.38	1.72	0.00	Dec-03[Oct-03, Mar-04]
M1A	-7.69	1.98	1.58	1.76	0.01	Dec-03[Oct-03, Mar-04]
Inflation	-6.65	3.51	-7.33	2.67	0.14	Oct-99[Dec-98, Apr-00]
Industrial production	-7.13	1.89	2.51	1.84	0.02	Dec-03[Oct-03, Mar-04]
World oil production	-7.37	1.92	1.22	1.79	0.00	Dec-03[Oct-03, Mar-04]
Oil price	20.88	1.80	9.04	2.55	0.26	Oct-07[Apr-07, Nov-07]
Employment					-	

90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 3: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results, contd

	Regime 4					
	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point
Financials share prices	-1.91	2.45	-3.93	2.71	0.04	Dec-03[Oct-03, Apr-04]
Industrial share prices	-2.03	2.49	-2.24	2.57	0.01	Dec-03[Oct-03, Apr-04]
PD ratio	-84.25	6.24	22.61	1.46	0.78	Oct-06[May-06, Dec-06]
PE ratio	-92.92	9.58	19.09	1.91	0.67	Dec-10
Payout ratio	127.95	23.36	-9.75	2.21	0.34	Sep-07[Apr-07, Oct-07]
Long term bond	2.77	2.33	-16.12	2.73	0.45	Aug-04[Jun-04, Oct-04]
Treasury bill rate	-3.88	2.40	6.33	2.35	0.14	Dec-03[Oct-03, Mar-04]
Term-spread	-10.10	3.28	14.98	3.34	0.30	Dec-10
Money market rate	25.68	1.46	-3.59	2.19	0.12	Oct-07[Apr-07, Nov-07]
DAX	24.78	1.62	3.29	3.01	0.00	Oct-07[Apr-07, Nov-07]
CAC 40	24.96	1.58	3.26	3.20	0.00	Oct-07[Apr-07, Nov-07]
S&P 500	25.48	1.53	0.36	3.09	0.00	Oct-07[May-07, Nov-07]
FTSE 100	25.30	1.54	1.64	3.12	0.00	Oct-07[Apr-07, Nov-07]
NIKKEI	25.14	1.52	2.53	2.48	0.01	Oct-07[Apr-07, Nov-07]
Hang Seng	25.09	1.59	2.40	3.15	0.00	Oct-07[Apr-07, Nov-07]
REER	25.51	1.49	-0.44	1.40	0.00	Oct-07[Apr-07, Nov-07]
M3	21.38	2.30	3.56	1.56	0.12	Oct-07[Mar-07, Nov-07]
M1A	25.31	1.58	0.72	1.75	0.00	Oct-07[Apr-07, Nov-07]
Inflation	-7.51	3.42	5.56	2.62	0.08	Dec-03[Oct-03, Mar-04]
Industrial production	25.73	1.53	-0.27	1.72	0.00	Sep-07[Apr-07, Oct-07]
World oil production	25.68	1.46	-3.38	2.19	0.08	Oct-07[Apr-07, Nov-07]
Oil price	-10.28	3.83	7.58	3.03	0.14	Dec-10
Employment					-	

90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 3: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results, contd

	Regime 5					
	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point
Financials share prices	25.55	1.50	-0.43	1.37	0.00	Oct-07[Apr-07, Nov-07]
Industrial share prices	25.56	1.50	-0.30	1.34	0.00	Oct-07[Apr-07, Nov-07]
PD	-86.65	9.82	18.31	2.02	-	
PE ratio					-	
Payout ratio	178.22	73.36	-17.78	7.01	-	
Long term bond	28.33	1.67	-2.45	2.54	0.00	Oct-07[May-07, Nov-07]
Treasury bill rate	25.65	1.47	-2.99	2.45	0.09	Oct-07[Apr-07, Nov-07]
Term-spread					-	
Money market rate	-7.78	4.32	-1.17	4.27	-	
DAX	-7.51	3.88	6.79	3.68	-	
CAC 40	-6.72	3.91	6.80	3.42	-	
S&P 500	-7.10	3.84	5.87	2.70	-	
FTSE 100	-7.43	3.86	5.90	2.96	-	
NIKKEI	-7.27	4.04	4.01	3.35	-	
Hang Seng	-8.01	3.97	4.08	3.41	-	
REER	-8.21	4.04	0.15	3.08	-	
M3	-8.02	5.01	-0.34	5.72	-	
M1A	-8.78	4.19	3.36	6.67	-	
Inflation	24.74	2.49	0.97	2.49	0.01	Oct-07[Apr-07, Nov-07]
Industrial production	-7.32	3.67	9.31	3.54	-	
World oil production	-8.35	3.92	8.48	5.70	-	
Oil price					-	
Employment rate					-	

90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 3: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results, contd

	Regime 6					
	$\hat{\beta}_0$	S.E	$\hat{\beta}_1$	S.E	R^2	End point
Financials share prices	-8.03	4.05	-1.36	3.25	0.01	Dec-10
Industrial share prices	-8.26	4.11	0.25	3.57	0.00	Dec-10
PD ratio					-	
PE ratio					-	
Payout ratio					-	
Long term bond	-8.82	3.87	-10.51	5.60	0.45	Dec-10
Treasury bill rate	-7.10	4.26	-3.69	4.81	0.02	Dec-10
Term-spread					-	
Money market rate					-	
DAX					-	
CAC 40					-	
S&P 500					-	
FTSE 100					-	
NIKKEI					-	
Hang Seng					-	
REER					-	
M3					-	
M1A					-	
Inflation	-6.15	5.14	-1.84	2.86	0.01	Dec-10
Industrial production					-	Dec-10
World oil production					-	Dec-10
Oil price					-	
Employment rate					-	

90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 4: Bai and Perron (1998, 2003a, 2004) multiple regime multivariate predictive regression model estimation results

	Regime 1						Regime 2					
	$\hat{\beta}_0$	SE	$\hat{\beta}_1$	SE	R^2	End point	$\hat{\beta}_0$	SE		SE		$\hat{\beta}_1$ End point
AIC Model	-0.24	0.02			0.87	Oct-94 [Aug-94, Nov-94]	-0.23	0.02			0.80	Jun-99 [Apr-99, Jul-99]
PE ratio			0.06	0.01					0.04	0.01		
Term spread			-0.03	0.01					0.00	0.00		
Money market rate			0.00	0.00					0.00	0.00		
Hang Seng			0.00	0.00					0.00	0.00		
Employment			0.00	0.00					-0.01	0.00		
SIC Model	-0.15	0.01			0.84	Oct-94 [Aug-94, Nov-94]	-0.24	0.02			0.78	Jun-99 [Apr-99, Aug-99]
PE ratio			0.04	0.00					0.04	0.00		
Money market rate			-0.03	0.01					0.01	0.00		
Employment			0.00	0.01					-0.01	0.00		

Standard errors are given in parenthesis; 90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

Table 4: Bai and Perron (1998, 2003a, 2004) multiple regime multivariate predictive regression model estimation results, contd

	Regime 3						Regime 4					
AIC Model	-0.18	-0.02			0.78	Oct-07 [Feb-07, Mar-08]	-0.05	0.04				
PE ratio			0.04	0.00					0.01	0.01		
Term spread			0.02	0.00					0.03	0.01		
Money market rate			0.00	0.00					0.00	0.01		
Hang Seng			0.00	0.00					0.01	0.01		
Employment			0.01	0.00					0.03	0.01		
SIC Model	-0.06	-0.05			0.46	Oct-02 [Jun-02, May-03]	-0.26	0.02			0.85	Oct-07 [Feb-07, Dec-07]
PE ratio			0.02	0.01					0.06	0.00		
Money market rate			0.02	0.01					0.02	0.00		
Employment			0.02	0.01					0.01	0.00		

Standard errors are given in parenthesis; 90% confidence intervals for the endpoints are given in square brackets. Regime 1 begins in 1990:01.

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