# How stable are Financial Prediction Models? Evidence from US and International Stock Market Data

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**Abstract**

This study examines evidence of structural breaks in models of predictable components in stock returns related to state variables such as the lagged dividend yield, Treasury bill rate, term spread and default premium. We examine a large set of size- and industry-sorted portfolios of US stocks as well as 18 international stock market portfolios and find systematic evidence of breaks in the vast majority of portfolios. The breakpoints most frequently identified in the US data are 1966, 1974, 1983 and 1990. The 1966 and 1974 breaks appear to have been driven by the T-bill rate and the default premium coefficients, while the 1983 break reflects changes in the coefficient on the T-bill rate and the term spread and the 1990 break was driven by the dividend yield and default premium coefficients. Our evidence also suggests that, while the size of the predictable component in stock returns has come down after the most recent break, many predictors continue to be significant. Although in-sample predictability of returns was lower in the 1990s than in some previous decades, it does not seem to have disappeared.

## I. Introduction

Evidence of predictability in stock returns is well documented in empirical finance.[1] Variables commonly used to predict stock returns in US and international data include the dividend yield, the short term interest rate, and term and default premia. Most studies assume a stable prediction model in which the coefficients on the state variables do not change over time.

Recent empirical studies cast doubt upon the assumed stability in return forecasting models. In a forecasting model based on the dividend yield and earnings yield, Lettau and Ludvigson (2001) find some evidence of instability in the second half of the 1990s. Likewise, Goyal and Welch (2002) uncover instability in return models based on the dividend yield when data from the 1990s is added to the sample. Ang and Bekaert (2001) find that "the predictability patterns formerly found in US data appear not to be robust to the addition of the last few years of the 1990s". While these papers thus identify a shift that appears to have occurred some time during the 1990s, they do not determine the exact time of the break, nor do they consider the possibility of earlier breaks or the time of their occurrence. However, if financial prediction models are subject to structural breaks, the economic significance of return predictability can only be assessed provided we determine how widespread breaks are both over time and across portfolios and the extent to which such breaks affect the predictability of stock returns.

In this study we provide a systematic analysis of the stability of forecasting models using a large data set of monthly stock returns, including both size-sorted and industry-sorted portfolios of US stocks as well as 18 international portfolios. We test for the presence of structural breaks in stock returns and characterize the timing and nature of the breaks. We find evidence of breaks in the vast majority of these portfolios. Further, our results indicate that the relationship between particular state variables and stock returns may change substantially following a break.

Our empirical experiments examine the predictive strength of models with and

[1] An incomplete list includes Ait-Sahalia and Brandt (2001), Bekaert and Hodrick (1992), Brandt (1999), Campbell (1987), Campbell and Shiller (1988), Cochrane (1991), Fama and Schwert (1977), Fama and French (1988), Ferson and Harvey (1991), French, Schwert and Stambaugh (1987), Harvey (1989), Keim and Stambaugh (1986), Lamont (1998), Lettau and Ludvigson (2001), Lewellen (2001), Pesaran and Timmermann (1995), Whitelaw (1994).

without breaks over different sub-samples. In general, our findings suggest that predictability is very much a time-varying phenomenon. Empirical evidence of predictability is not uniform over time and appears to be concentrated in certain periods. The predictability suggested by $R^2$-values based on long samples of returns should be viewed as an historical average for predictability. In particular, we find that (*ex post)* predictability was relatively high in the 1970s and 1980s and relatively low in the 1960s and 1990s.

Although the evidence of breaks varies across the size- and industry-sorted portfolios and across countries, we also find strong common components in the US breaks. For the US portfolios, most breaks cluster around four periods, namely 1966, 1974, 1983 and 1990. Addressing each regressor separately yields additional insights into the nature of the breaks identified in the full regression model and suggests that the 1966 and 1974 breaks were driven by the T-bill rate and default premium, while the 1983 break was driven by the T-bill rate and the term spread and the 1990 break was driven by the dividend yield and default premium. There does not appear to be the same commonality in the breaks identified in the international data, suggesting perhaps that the breaks occur in a local return factor.

Breaks or jumps in the parameters that relate security returns to state variables could arise from a number of factors, such as major changes in market sentiments or regime switches in monetary policies (e.g., from money supply targeting to inflation targeting). Institutional changes or large macroeconomic shocks that give rise to changes in economic growth or affect risk premia may also cause a break in the financial return models. Similarly, if predictability of returns partly reflects market inefficiencies and not just time-varying risk premia, then such predictive relationships should disappear once discovered provided that sufficient capital is allocated towards exploiting them. For example, Dimson and Marsh (1999) argue that the small-cap premium disappeared in the UK stock market after it became publicly known. These possibilities are important both because they introduce new sources of risk and because they fundamentally affect the extent to which returns are predictable.

Structural breaks, particularly when studied across a large set of portfolios, therefore offer important clues to the sources of predictability in stock returns. Several explanations have been proposed for this predictability, including inefficient markets (Cutler, Poterba and Summers (1990)), time-varying risk premia (Kandel and Stambaugh (1990), Campbell and Cochrane (1999)), data-snooping (Lo and MacKinlay (1990)), small sample biases (Ang and Bekaert (2001), Goetzmann and Jorion (1993), Hodrick (1992), Nelson and Kim (1993)) and incomplete learning (Timmermann (1993)).

Predictability, though weaker during the 1990s, does not seem to have disappeared and many predictors remain statistically significant even after the most recent break. This suggests that data-snooping or inefficient markets are unlikely to fully explain predictability. In addition our evidence on the size and frequency of breaks is sufficiently systematic to rule out small-sample noise as the explanation. Given the empirical results, we address the concern of whether our tests are likely to detect spurious breaks by conducting a simulation experiment using data generating processes that exhibit time-varying conditional variance, persistent regressors and relatively noisy errors. We find that the tests do not necessarily result in over-sized tests and poor model selection even in the presence of time-varying volatility and with highly persistent regressors. In contrast, time-varying risk premium models do not appear to be ruled out by our findings. If a break affects the ability of the state-variables to predict the conditional covariance between investors' intertemporal marginal rate of substitution and stock returns, then the coefficients in a linear regression model for returns should also exhibit a break. Likewise, incomplete learning stories are not ruled out by our findings since large shifts in the parameters of the fundamentals process would require investors to reestimate their return forecasting models and could lead to breaks in the forecasting model.

The remainder of the paper is organized as follows. Section II introduces the breakpoint methodology applied in this study. Section III describes the US returns data and presents empirical results of tests for breakpoints and structural stability in size-sorted and industry-sorted portfolios of US stocks. Section IV describes the international returns data and presents results of tests for breakpoints and structural stability in international data. Section V addresses the question of variation in the predictive relationships documented in the literature and Section VI presents the results of a Monte Carlo simulation experiment designed to investigate the statistical properties of our tests for structural instability. Section VII summarizes our findings and outlines opportunities for additional study in this area.

## II. Breaks in Financial Prediction Models

In the context of linear regression models many empirical studies have documented the ability of a variety of economic variables to predict returns, at least within sample.[2] For examples, see the references in footnote 1. To apply models of this type in practice, parameters must be estimated using historic data of returns and predictor variables. Besides determining which variables to include, a key decision when estimating return forecasting models is how much data to use.

Determining the sample size for the return prediction model can be very important if the coefficients are not constant over time and including pre-break data will lead to biased forecasts. For example, Brandt (1999, p. 1611) points out the importance of stability in the relation between state variables and stock returns: "Returns and forecasting variables must have a time-invariant Markov structure. If the relation between returns and forecasting variables is time-varying... conditional expectations cannot be estimated with conditional sample averages." There are good empirical and theoretical reasons for suspecting instability. In a very thorough study of a large set of financial and macroeconomic time series, Stock and Watson (1996) find breaks in the regression models for the majority of the variables they consider.

### *A. Methodology*

Some recent studies have considered breaks in the equity premium. Using a Bayesian framework, Pastor and Stambaugh (2001) examine a long history of annual returns on US stocks and find evidence of structural breaks in the equity premium in the form of high posterior probabilities that breaks occurred during certain months of the sample. As pointed out by Pastor and Stambaugh, detection of breaks in the mean of stock returns is made extremely difficult by the very noisy nature of stock market returns. Without conditioning (state) variables, tests for structural breaks are therefore unlikely to have sufficient power to identify breaks in the equity premium of an economically interesting size even if they truly oc-

[2]Brandt (1999) uses non-parametric kernel estimation methods to deal with functional form misspecification in the context of return forecasting models. The sensitivity of these methods to the presence of instability in the relation between state variables and stock returns has not yet been studied.

curred. Pastor and Stambaugh deal with this problem in an ingenious way by assuming that there is a concurrent relationship between the level of volatility and the equity premium. Since it is easier to identify shifts in the volatility of returns, this provides an instrument to identify the timing of the breaks. While the combination of a Bayesian setup and this identifying assumption provides a way to identify breaks, the drawback is of course that the number and timing of breaks in the equity premium may be sensitive to the nature of prior beliefs.[3]

The approach and focus in this paper are very different from those in earlier studies. First, as we are interested in breaks in the return forecasting models that are now so widely used throughout finance, we test for breaks in the conditional equity premium as a function of a set of commonly used state variables. Furthermore, we use the estimation framework for linear models with multiple structural breaks developed by Bai and Perron (1998).[4] This allows us to determine the number of breaks, confidence intervals for the time of their occurrence as well as the value of the coefficients around the time of the breaks. By considering instruments whose correlation with the equity premium is sufficiently strong to identify breaks we therefore do not need to impose any identifying restrictions on our model. Of course, this approach is also not without disadvantages and some of our results will be quite noisy given the low predictive power typical of return prediction models.

Early breakpoint tests such as Chow (1960) proceeded under the assumption that the time of the break was known and did not consider the possibility of multiple breaks. Tests were obtained under fairly strict assumptions such as independent regressors and normally distributed and homoskedastic regression errors. In the context of a model for stock returns these assumptions are very restrictive. Predictor variables such as the lagged interest rate and dividend yield are highly persistent. The regressors may themselves exhibit structural change over the historical period examined and this may lead to false inference regarding a change in the coefficients of the linear regression. The error terms of the regression may not

[3]Kim, Morley and Nelson (2000) also apply a Bayesian framework and test for a structural break in a model of excess returns in which the equity premium responds to recurrent changes in volatility. They find evidence of a structural break in the Markov switching variance process in the early 1940s, but do not find evidence of breaks in the equity premium given the level of volatility.

[4]Computations in this paper related to the Bai and Perron (1998, 2000) methodology were carried out using Gauss programs made available by Pierre Perron.

be independent of the predictors, and it is well known that returns data exhibit time-varying conditional variance.

Fortunately, recent advances in methods for estimating and testing models with multiple structural breaks permit sufficiently flexible assumptions for our purpose.[5] Suppose that (excess) returns at time $t+1$, $Ret_{t+1}$, depend linearly on a set of state variables, $\mathbf{x}_t$, but that the model is subject to $K$ breaks occurring at times $(T_1, T_2, ..., T_K)$. This gives the model

$$Ret_{t+1} = \begin{cases} \boldsymbol{\beta}_1'\mathbf{x}_t + \varepsilon_{t+1}, & t = 1, ..., T_1 \\ \boldsymbol{\beta}_2'\mathbf{x}_t + \varepsilon_{t+1}, & t = T_1 + 1, ..., T_2 \\ \vdots & \vdots \\ \boldsymbol{\beta}_K'\mathbf{x}_t + \varepsilon_{t+1}, & t = T_{K-1} + 1, ..., T_K \\ \boldsymbol{\beta}_{K+1}'\mathbf{x}_t + \varepsilon_{t+1}, & t = T_K + 1, ..., T \end{cases} \tag{1}$$

In many respects this is a simplified representation of the return generating model and breaks may well occur over more than one period. Nevertheless, it can be viewed as a useful approximation to more complicated representations of time-variation in the parameters linking the state variables to stock returns. In fact, some of the potential sources of breaks such as shifts in economic policy regimes, large macroeconomic shocks or publication of predictable patterns are likely to lead to rather sudden shifts in the parameters of the return forecasting model.

The key question is of course to determine the number of breaks, $K$, the time of their occurrence, $(T_1, T_2, ..., T_K)$, as well as estimating the parameters around the time of the breaks, $(\boldsymbol{\beta}_1', \boldsymbol{\beta}_2', ..., \boldsymbol{\beta}_{K+1}')'$.[6]

Bai and Perron (1998) provide a least-squares method for optimally determining the unknown breakpoints as well as the resulting size of shifts in the parameter values. The basic principle involves searching over the possible $K$-partitions

[5] Andrews (1993) derives the distributions for tests of a single break with unknown timing. These tests apply to a wide class of nonlinear models and permit temporally dependent data. Andrews and Ploberger (1994) derive asymptotically optimal tests that apply to tests of a one-time structural break in linear models as well as to tests of multiple breaks. Bai (1997a,b) develops the asymptotic theory for a linear model with a single change point. The model allows for lagged dependent variables and trending regressors and the regression errors may be dependent and heteroskedastic.

[6] We adopt the convention that $T_0 = 1$ and $T_{K+1} = T$, where $T$ is the total number of available observations.

$(T_1, T_2, ..., T_K)$ of the data to compute the minimizer of the sum of squared residuals. For a set of $K$ breakpoints, $(T_1, T_2, ..., T_K) = \{T_j\}$, the coefficient estimates $\hat{\boldsymbol{\beta}}_{k,\{T_j\}}$ are chosen to minimize the sum of squared residuals

$$S_T(\{T_j\}) = \sum_{k=1}^{K+1} \sum_{t=T_{k-1}+1}^{T_k} \left( Ret_t - \hat{\boldsymbol{\beta}}'_{k,\{T_j\}} \mathbf{x}_{t-1} \right)^2 . \tag{2}$$

The estimated break dates $\left(\hat{T}_1, \hat{T}_2, ..., \hat{T}_K\right)$ are selected so as to satisfy

$$\left(\hat{T}_1, \hat{T}_2, ..., \hat{T}_K\right) = \arg \min_{T_1, T_2, ..., T_K} S_T(T_1, ..., T_K), \tag{3}$$

where the minimization is over all partitions such that $T_k - T_{k-1} \geq \pi T$. The trimming percentage parameter $\pi$ imposes a minimum length for the time between breaks, $\pi T$. Choosing $\pi$ in practice involves a trade-off between the ability to detect regimes of relatively short length and the desire to avoid overfitting the data and simply identifying 'outliers'. While $\pi T$ in principle may take any value greater than or equal to the number of regressors, in practice it is best to use values significantly larger than this.[7] Given the estimated break dates $\{\hat{T}_j\}$, the estimated regression coefficients $\hat{\boldsymbol{\beta}}_k$ are the least squares coefficients associated with the partition comprised of the estimated break dates, i.e., $\hat{\boldsymbol{\beta}}_k = \hat{\boldsymbol{\beta}}_{k,\{\hat{T}_j\}}$.

*B. Determining the number of breaks*

Several types of hypothesis tests may be of interest when multiple breaks are considered. For the purposes of establishing whether breaks are present, we are interested in testing the hypothesis of no breaks versus an alternative of $K$ breaks, where $K$ could be any number greater than or equal to one. Once the presence of breaks has been established, we are furthermore interested in establishing the exact number of breaks. We consider both types of tests. For the first case Bai and Perron (1998) propose a so-called sup $F$ test that considers the null hypothesis of no breaks versus the alternative hypothesis that there are $K$ breaks. To determine the number of breaks we adopt the sequential $SupF(k+1|k)$ test procedure proposed by Bai and Perron which selects a model based on sequential tests of the null hypothesis of $k$ breaks versus the alternative of $k+1$ breaks.

[7] Bai and Perron (2000) discuss computational and practical aspects of determining these design parameters.

*C. Breaks in the regressors*

Hansen (2000) derives the large sample distributions of several test statistics for structural breaks allowing for structural change in the marginal distribution of the regressors. Hansen suggests a 'fixed regressor bootstrap' for determining the critical values under the null hypothesis. This test therefore permits the most general assumptions regarding the regressors and the distribution of the regression errors. However, it does not permit multiple structural breaks in the regression coefficients.[8]

The Bai and Perron (1998) methodology permits multiple breaks, and allows quite general assumptions regarding the regressors and error terms. However, this method does not permit arbitrary structural change in the regressors. Since we wish to entertain the possibility of multiple breaks, we adopt the following methodology in this study. We apply the method of Bai and Perron (1998) to determine the number of breaks and their timing. We then apply the Hansen (2000) tests for a single break as a robustness check on the results obtained using the Bai and Perron (1998) method.[9]

In a recent paper that also tests for breaks in US stock returns, Rapach and Wohar (2002) use the Hansen (2000) method sequentially to identify breaks, i.e. they first test for a single break and then, if a break is identified, test for additional breaks in the sub-samples identified by the first break. There are several differences between this study and ours. Most importantly, we focus on documenting evidence of breaks across a large set of size-, industry- and international portfolios, while Rapach and Wohar's study is limited to the S&P500 and the equal-weighted CRSP portfolios. Furthermore, they use quarterly data while we use monthly data and also focus on a very different set of regressors. These differences could be important since relatively large data sets are required to identify breaks in financial return predictions. Even so, consistent with our findings, Rapach and Wohar find evidence of breaks in their return regressions.

[8] Computations related to the Hansen (2000) methodology were carried out using Gauss programs made available by Bruce Hansen.

[9] We find that results regarding the presence of at least one structural break are quite robust. That is, in cases where a break is identified by the method of Hansen (2000) we tend to find at least one break when the method of Bai and Perron (1998) is applied.

## III. Breaks in US Stock Returns

We first consider returns on a variety of US stock market portfolios, focusing on small and large firms as well as firms in different industries. Firms divided by size and industry are likely to have different exposures to the sources that generate breaks (e.g. large oil price shocks affecting economic growth or shifts in monetary policy). A more complete picture of the frequency and sources of breaks can therefore be obtained by considering a large cross-section of stock market portfolios.

### *A. Data*

Monthly value-weighted index returns for size-sorted decile portfolios of US equities were obtained from the Center for Research in Security Prices (CRSP). Returns are inclusive of dividends. Size-sorted decile portfolios are formed based on an annual ranking of all New York Stock Exchange (NYSE) companies by market capitalization. The decile portfolios are in increasing order of capitalization, so that Decile 1 represents the smallest-cap stocks and Decile 10 the largest. The study also examines value-weighted and equal-weighted index returns on the entire CRSP universe. Monthly equal-weighted returns for 12 industry-sorted portfolios were obtained from Kenneth French's Data Library.[10] The industry portfolios are rebalanced annually based on primary SIC code classification. All returns are calculated in excess of a one-month risk-free rate taken from the CRSP Risk Free Rates File and based on average prices.

We focus on four predictor variables that are prevalent in the empirical literature on predictability of returns. These variables are the lagged dividend yield (used, e.g., by Campbell and Shiller (1988), Fama and French (1988), Ferson and Harvey (1991)); nominal interest rate (Fama and French (1988), Fama and Schwert (1977), Ferson and Harvey (1991)); term spread (Campbell (1987), Fama and French (1988), Ferson and Harvey (1991)) and default spread (Fama and French (1988), Ferson and Harvey (1991), Keim and Stambaugh (1986)).

The first instrument considered is the lagged dividend yield for the CRSP value-

[10] Available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. We use equal-weighted industry portfolio returns in order not to replicate the size effects from the decile portfolios. However, the breakpoint results are robust to using value-weighted industry portfolios instead.

weighted index calculated as dividends paid over the preceding 12-month period scaled by the current value of the stock price index. As our second instrument we use the lagged one-month Treasury bill rate. The third instrument is the difference between the yield on a five-year discount bond and the yield on the one-month Treasury bill. Five-year discount bond yields were obtained from the CRSP Fama-Bliss Discount Bond Yield file. The final instrument considered is the default premium or quality spread, defined as the difference in yields between Moody's Baa and Aaa rated bonds. The data sample ranges from July, 1952 through December, 1999, for a total of 570 observations.

Table 1 presents summary statistics for excess returns on US size-sorted and industry-sorted portfolios as well as summary statistics for the instruments included in the model. Small cap stocks and the telecommunications, business equipment and healthcare industries had the highest mean excess returns in the sample.

To confirm that our data displays properties similar to those found in earlier studies on return predictability, Table 2 reports full sample coefficient estimates. A constant is always included in the regressions but is not reported to preserve space. In the 'all' model that includes all four regressors the dividend yield and the term spread are almost never statistically significant, while conversely the T-bill rate and default premium have significant coefficients for all portfolios. Interpretation of the statistical significance and even the sign of individual coefficients is of course made difficult in these regressions by the correlation between regressors. To deal with this we also report single-variable regression results. These suggest that the full-sample evidence of predictability from the dividend yield is rather weak and that only a third of the portfolios generate significant coefficients on the default premium. Interestingly, the term spread is now significant for the vast majority of portfolios and the T-bill rate continues to be significant for most portfolios.

### *B. Model with All Instruments*

In our implementation we allow all coefficients to change at each break since there is no strong reason to believe that the coefficient on any of the regressors should be immune from shifts. The model is therefore

$$
\begin{aligned}
Ret_t &= \beta_{0k} + \beta_{1k} Div_{t-1} + \beta_{2k} Tbill_{t-1} + \beta_{3k} Spread_{t-1} + \beta_{4k} Def_{t-1} + \varepsilon_t \\
t &= T_{k-1}+1, ..., T_k;\ k = 1, ..., K+1, \qquad (4)
\end{aligned}
$$

where $Ret_t$ represents the return on the portfolio in question during month $t$, $Div_{t-1}$ is the lagged dividend yield , $Tbill_{t-1}$ is the lagged one month Treasury Bill rate, $Spread_{t-1}$ is the lagged term spread and $Def_{t-1}$ is the lagged default premium.

Table 3 presents results of tests for the number of structural breaks when all instruments are included in the basic model set forth in equation (4). These results set the trimming percentage, $\pi$, to 15 percent of the total sample. This corresponds to a minimum window of 85 months (7 years and one month) between breaks. There is strong overall evidence of structural breaks in the models for US returns. The $SupF(k)$ tests reject the null hypothesis in nearly every case for $k = 1, 2, 3$.[11] Exceptions include the value-weighted CRSP portfolio, decile 9, and the utility and shops industries. The sequential test statistics tend to be significant for at least the $SupF(2|1)$ and $SupF(3|2)$ tests and the sequential method selects a model with two or three breaks in many cases and at least one break in all but the above-mentioned four portfolios. For these four portfolios, the $SupF(2|1)$ test favors two breaks over one except for the utilities industry. These results suggest that for those portfolios where there is not strong evidence of a single break, there is some evidence of two breaks, with a structure that perhaps makes a single break difficult to detect.[12] Finally, the Hansen (2000) tests, robust to arbitrary structural change in the marginal distribution of the regressors, identify a break in nearly all of the portfolios.

For each portfolio the estimated break dates and 90 percent confidence intervals are shown in Figure 1. The most commonly identified break dates in the 'all' model occur during the years 1962, 1966, 1974, and 1990 respectively. The confidence intervals for the break dates are often very tight, particularly for the break occurring

[11] Here and in the following discussion, rejection of null hypotheses is considered at the 10 percent significance level unless otherwise indicated. This critical level, rather than the more customary 5%, is appropriate here given the weak power of tests for structural breaks.

[12] For intuition on this case, consider a regression with only a constant as a regressor and suppose that the sample is divided into three equally long parts. If the mean of the variable changes in the second sample but is the same in the first and third sample, a model with a single break may not pick up the change, whereas a model allowing for two breaks would identify it.

in 1962 or 1966. The industry portfolio results suggest that some breaks occur fairly broadly across sectors (the 1962/66 break) while others appear to be concentrated in specific industries (the 1974 and 1990 breaks). Interestingly, the 1966 break shows up nearly uniformly in the decile portfolios but does not appear for a single industry. Decile 10 is the only cap-based portfolio to exhibit a break in 1962, a year in which many of the industry-based portfolios show a break. While this may seem to suggest that the industry-based portfolios are dominated by large firms, the industry-based portfolios are in fact equal-weighted.

Table 4 presents coefficient estimates for the models selected by the sequential method. The standard errors that we report are corrected for heteroskedasticity and serial correlation using the method suggested by Newey and West (1987). There are several interesting results. The dividend yield is only significant after the most recent break for 8 of the 20 portfolios that experience at least one break. Interestingly, the coefficient on the T-bill rate after the most recent break is insignificant for many size-sorted portfolios but significant at standard levels for most of the industry sorted portfolios. Overall, the T-bill rate generates a significant coefficient after the most recent break for 11 out of 20 portfolios. The term spread variable is significant for only 5 out of 20 portfolios following the most recent break. Finally, the coefficient on the default premium is statistically significant for nearly all of the portfolios (16 out of 20) following the most recent break.

With four coefficients (and a constant) in each interval, characterizing the evolution in the coefficients is more difficult than in models with a single instrument. To facilitate further interpretation of the results, we therefore next examine univariate regressions on each instrument separately. That is, we restrict the model of equation (4) so that the coefficients on all instruments, save the instrument of interest, are set equal to zero. A constant term is included in each model. This is done in turn for all instruments.

For each of these restricted models, we investigate the existence and timing of structural breaks using the sequential method. Further, we examine whether the existence and timing of breaks appears to vary significantly according to cap size or industry. While these univariate models are probably of limited interest to investors given their extremely low $R^2$-values, we find that examining the univariate case provides interesting insights into the source of the breaks identified for the full model. They are also likely to have better power to detect breaks in the event of a partial break occurring only in a subset of the regressors in the 'all' model.

### *C. Dividend Yield*

Breakpoint dates for the return prediction model based on the dividend yield are presented in Figure 2. Of the 24 cap and industry based portfolios examined, at least one break was selected for 8 portfolios. For those portfolios that exhibit breaks, Figure 2 shows that 1990 is identified as a break point in almost every case. For four of the portfolios an additional change point is identified. Cap size appears to be important in considering structural change in the returns model. The three cap-based portfolios that exhibit a break are the portfolios with the largest stocks. Thus, any changepoint identified in the relationship between the dividend yield and returns appears to be limited to large cap stocks.

The estimated coefficients and standard errors for the dividend yield instrument are presented in Table 5. As always, caution should be exercised when interpreting the coefficient estimates on the dividend yield because of lagged endogenous variable bias, see, e.g., Ang and Bekaert (2001), Stambaugh (1999).[13] Typically, the coefficient is positive and statistically significant prior to 1990. For those portfolios exhibiting a break in 1990, the coefficient tends to become insignificant over the subsequent decade and only one of the post-break coefficients is statistically significant. In the energy industry, however, the coefficient on the dividend yield becomes negative although this estimate is not significant at the 5% significance level.[14] For seven out of eight portfolios with a break in the dividend yield coefficient, the $R^2$ declines after the most recent break.[15] Although the evidence of predictability from the dividend yield is rather weak at the monthly horizon, it is interesting to note that allowing for breaks does uncover some cases of predictability that were concealed by the full-sample results in Table 2. For example, our results suggest that the dividend yield was statistically significant prior to 1990 for the portfolios

[13] Ang and Bekaert (2001) find strong size distortions on the dividend yield coefficient for long return horizons while the distortions are relatively small at a short horizon of 1 month such as the one used in our paper.

[14] This represents the clearest example of a break in the dividend yield regressions. Of course, it is also consistent with a situation in which returns in these sectors were unrelated to the fundamentals as reflected in dividends.

[15] To conserve space, we do not report separately these $R^2$ values but merely summarize the number of cases where the value declines after the most recent break.

dominated by large firms (deciles 8-10 and the value-weighted portfolio), but that predictability from this regressor has broken down subsequently.

*D. Treasury Bill rate*

There is very strong evidence of one or two breaks in the univariate returns model based on the T-bill rate. Figure 3 shows that the sequential method identifies a break around 1974-1975 in nearly all of the cap-sorted portfolios and for many of these portfolios an additional break is identified around 1983. Breaks are identified for over half of the industry portfolios. The break points for this model are reasonably precisely estimated and most confidence intervals are quite narrow.

Table 6 shows that the estimated coefficients for the T-bill rate model are nearly always negative and significant at the 5% level as previous findings suggest. The energy industry again exhibits unusual behavior since for this industry the estimated coefficient for the T-bill rate is positive, but this estimate is not significantly different from zero. For portfolios dominated by large stocks (decile 10 and the value-weighted CRSP portfolio) the Treasury bill rate becomes insignificant at the 10 percent level following the break in 1974. In 18 of 19 regressions with a break in the T-bill coefficient the $R^2$ declines after the most recent break. Even so, 11 of 19 coefficients remain statistically significant at the five percent critical level.[16] Once again, the evidence varies across firm size. The statistical significance of the T-bill rate disappears post-1974 for the large cap portfolios (D6-D10), while it continues for the small cap portfolios (D1-D5) and for a number of industry portfolios.

*E. Term Spread*

Sequential tests for breaks based on the term spread identify a single break for most of the decile portfolios and half of the industry portfolios, c.f. Figure 4. In no case is more than one break selected. The break dates are rather imprecisely estimated as evidenced by the wide confidence intervals. These confidence intervals tend to center around 1983, but the 90 percent confidence interval often spans over 10 years, suggesting that the time of the break is ill-defined even though its presence is

[16] This is consistent with the finding in Ang and Bekaert (2001) that the coefficient on the T-bill rate is statistically significant across a range of sample periods.

statistically significant. Interestingly, the confidence interval includes the period of the change in monetary policy (1981) which may well have affected the relationship between the term premium and stock returns. Evidence of breaks appears to be concentrated in the small to mid-cap portfolios. Deciles 8 and 9, which are composed of relatively large stocks, do not exhibit a break over the sample period examined. Decile 10, composed of the largest stocks, is an important exception to this observation as this portfolio exhibits a break in 1983.

Coefficient estimates for each sub-period as well as standard errors for these estimates are presented in Table 7. Prior to 1983, the coefficient on the term spread tends to be positive and highly significant. Following the estimated break in 1983, the coefficient tends to fall in value and in some cases becomes negative. In nearly every case, the coefficient after 1983 is no longer significantly different from zero even at a 5 percent confidence level and in 14 of 15 cases the $R^2$ value declines after the most recent break.

### *F. Default Premium*

The returns model with the default premium regressor exhibits the most frequent breaks among the models with a single instrument. Figure 5 plots the estimated break dates along with confidence intervals for these estimates. The breaks are quite precisely estimated and the most commonly identified break dates occur during the years 1968, 1976 and 1990. These results are consistent with the findings for the 'all' model since 90% confidence intervals for the breaks centered on 1968 mostly included 1966 and the confidence intervals centered on 1976 included 1974. Evidence of breaks is distinctly concentrated among very small and very large stocks. In fact, while deciles 1 to 4 (the smallest stocks) and decile 10 (the largest stocks) exhibit two breaks, deciles 5-9 exhibit no breaks at all. The value-weighted portfolio exhibits 2 breaks, while no breaks are found for the equal-weighted portfolio. Most of the industry portfolios (9 of 12) exhibit at least one break and often more. The tests only fail to detect breaks in the manufacturing, chemicals and healthcare industries.

The estimated coefficients for the default premium and their standard errors are presented in Table 8. As expected, nearly all of the estimated coefficients for the default premium are positive.[17] Prior to 1968, the coefficients on the default

[17] Again, the energy industry is an exception, as the estimated coefficient on the default premium

premium tend to be insignificant or barely significant at the 10 percent level. For those portfolios with an estimated break in 1968, the coefficient tends to become highly significant during the next sub-period, which typically lasts until 1976. For many of these portfolios (particularly the small cap portfolios), the period following 1976 is quite similar to the period before 1968, with estimates that are only borderline significant. Finally, for those portfolios that exhibit a break in 1990, the coefficient once again becomes highly significant. Thus, the default premium, more than the other individual regressor considered in this study, appears to remain significant in the 1990s. Nevertheless, in 11 of 15 models with a break the $R^2$ value declines after the most recent break.

## IV. International Evidence

When exploring patterns of predictability in stock market returns it is important to consider international data. The US data has been extensively researched and hence earlier evidence of predictability could be a result of data mining. Though still a factor, this is likely to be less of a concern for the international return data. Another advantage of considering international returns is that these are not directly affected by some of the institutional shifts observed in the US such as the change in monetary policy during 1979-1981. This is helpful when identifying the sources of breaks.

We therefore considered international returns on stock indices from 18 countries, including the US. Table 9 provides a list of the countries examined in the study. Monthly value-weighted returns were obtained from Morgan Stanley Capital International (MSCI). Returns include dividends and assume reinvestment of gross dividends. All returns are denominated in local currencies.

The predictors considered were a local dividend yield, a short term local interest rate, a local term spread measure, and the US default premium. Local country dividend yields were obtained from MSCI. The MSCI dividend yields for country portfolios are value-weighted averages of the dividend yields for the equities underlying the index.

Local country short term interest rates were collected from the International Financial Statistics (IFS) database. The particular instrument varies over the

is less than zero during the second interval and this estimate is significant at the 5% level.

countries considered. The instrument is typically either a local country Treasury Bill rate or a money market rate. If a longer term interest rate, such as a yield on government bonds, was available, then this was used along with the short term rate to construct a measure of the term spread.[18]

The final instrument considered was the US default premium. US data were used for all countries since comparable local country data were typically unavailable.[19] The US default premium may be thought of as a proxy for the US business cycle. The earliest available MSCI monthly returns and dividend yield data is from December, 1969. The exact sample period for the data varies by country. Typically over 350 months of data are available but for some countries the sample period is significantly shorter. Table 9 presents the sample period by country as well as a range of summary statistics for each of the 18 countries considered.

Once again we start by reporting full-sample regression results which serve as a benchmark for our breakpoint regressions (see Table 10). The $R^2$-values tend to be somewhat lower than those found in the US regressions, ranging as they do from 0.00 to 0.08 with most countries generating values of 0.03 or below. The weakness of predictability in these international return regressions is confirmed by the statistical insignificance of most of the regression coefficients. The dividend yield is only significant in a couple of countries and the T-bill rate, term spread and default premium regressors are never significant for more than 8 of the 18 countries in the 'all' model or for more than 3 of 18 countries in the univariate regression models.

### *A. Existence and Characterization of Breaks*

Table 11 summarizes the results of various tests for breakpoints in the regression of international returns on the full set of predictor variables, namely the local dividend yield, short interest rate, term spread, and the US default premium. To preserve space we do not report results from univariate regressions on the individual state variables. For certain countries not all variables were included due to a lack

[18]The variable definitions are available from the authors on request.

[19]But see also Ang and Bekaert (2001) who find that US instruments have strong predictive power over foreign equity returns.

of available data.[20] Qualitatively, the results in Table 11 are similar to those reported for US returns in Table 3. The $SupF(k)$ tests reject the null hypothesis in many cases for $k = 1, 2, 3$. The models selected by the sequential method for the international data tend to exhibit fewer breaks across portfolios, but this is in part due to the shorter sample size for the international data. The sequential method identifies at least one break for 13 of the 18 international indices examined. The exceptions include Austria, Hong Kong, Japan, Switzerland and the UK. Two or more breaks are identified for Italy and Sweden. The Hansen (2000) tests again tend to corroborate the results obtained using the method of Bai and Perron (1998).

Figure 6 shows the timing of breaks for the models selected by the sequential method. The most common break dates occur during the 1976-1978 period, and during the 1991-1992 period. The break dates are in general precisely estimated although the confidence intervals tend to be wider than those observed in the US data. There is no general clustering in the estimated times of the breaks across countries. Perhaps this suggests that the source of the identified breaks is more likely to be country-specific than global.

Table 12 presents the estimated coefficients for the selected models. The coefficients on the dividend yield are typically positive and are not statistically significant at the 10 percent level for those cases with a negative point estimate. The coefficients on the Treasury bill instrument tend to be negative and are often highly significant for at least one of the sub-intervals.

The behavior of the coefficient on the term spread varies the most among the four instruments. The coefficient on the term spread generally tends to be negative, especially when the estimate is significant at the 10 percent level. An exception to this general observation is Italy, which has a positive and significant coefficient on the term spread during the first interval. All other positive estimates are not significant at the 10 percent level. Finally, the coefficient on the default premium tends to be positive and is never significant in cases where the estimate is negative. In a number of countries (Australia, Belgium, Denmark, Italy, Norway, Spain) the coefficient on the default premium is never significantly different from zero.

Two factors are likely to explain the relatively weaker evidence of breaks in the international data as compared to the US data. First, the power to detect multiple

[20] Specifically, the term spread is missing in the regression for Denmark and Sweden, and both the term spread and T-bill rate are missing for the Hong Kong regression.

breaks, even if they exist, is likely to be weaker in the international data since some of the instruments we use rely on US data rather than local data and since the predictive $R^2-$values tend to be somewhat lower in the international data. Secondly, the shorter sample means that it is more difficult to detect breaks in the international data. It is very difficult to detect breaks at the beginning or at the end of the sample period. When we set the 'trimming' distance required between breaks (as a proportion of the total sample) to 0.15 rather than 0.20, a break was identified in 1974 in many of the international regressions. With a trimming percentage of 0.20, this break point could not be identified because of the minimum window length requirement.[21] While this may suggest that 0.15 is preferable, we found that with the shorter international data sets trimming percentages lower than 0.20 sometimes resulted in fitting outliers, particularly for the countries with the shortest span of sample data.

Even though it is generally more difficult to detect breaks in the international data, it is interesting to note that for those countries where a break is identified, the statistical significance of the regressors tends to be stronger for at least some subsamples than in the full sample. For example, the dividend yield is significant in all countries with a break in the 'all' regression model in at least one subsample, while it is only significant for two countries in the full sample.

## V. How much does in-sample Predictability vary over Time?

Breaks in the regression coefficients of our prediction models do not provide a direct measure of the economic significance of breaks. To assess the extent to which in-sample predictability varies over time and across portfolios, we compared the in-sample $R^2-$values of the returns regression over each calendar decade in the sample.[22] For the $i$th calendar decade the $R^2$ is given by

[21] Many of the international samples start in 1970 and comprise 30 years of data. A trimming percentage of 20 therefore means that the earliest detectable breakpoint is 1976.

[22] Although it seems natural to study the $R^2-$values corresponding to the segments between breaks, we elected not to do this for the following reasons. Even for a given portfolio the length of a break segment $(T_k - T_{k-1})$ varies substantially so the $R^2$ values are not directly comparable across segments as they are not estimated with the same precision. Some of the break segments are quite short and their $R^2$-values will be estimated with considerable uncertainty. Furthermore, as the break segments vary across portfolios, they cannot be compared cross-sectionally.

$$R_i^2 = 1 - \frac{\sum_{j=N_{i-1}+1}^{N_i} (\varepsilon_j - \bar{\varepsilon}_i)^2}{\sum_{j=N_{i-1}+1}^{N_i} (y_j - \bar{y}_i)^2}, \tag{5}$$

where $i$ indexes each decade beginning with the 1950's and $N_i$ indicates the final observation for the $i$th decade. We note that the US results reported for the 1950's include only data from 1952:7 to 1959:12. The reason that $\bar{\varepsilon}_i$ appears in equation (5) is that over any particular decade we cannot expect that $\bar{\varepsilon}_i = 0$. Of course, over the full sample $\bar{\varepsilon} = 0$ and the familiar analogue of equation (5) may be applied.

It should be noted that there is a sense in which the issue of variation in predictive $R^2-$values is quite separate from the question of breaks. Even in the absence of breaks, the $R^2$ will vary if the variance of the regressors changes over time relative to the variance of the residual term, $\varepsilon$. For example, if the 1-month T-bill rate is the only predictor and its variance goes down while the variance of the residual term remains unchanged, then the $R^2$ would decline. Conversely breaks, if present, will lead to changes in $R^2-$values even if the variance of the regressors and residuals never change.

To establish a benchmark for predictability, first consider the full sample $R^2$ values. For the US data Table 2 shows that the $R^2$-values for the model with all instruments and no breaks vary in size across the portfolios from a minimum value of 0.03 (energy) to a maximum of 0.09 (nondurables). The average $R^2$-value over the 22 portfolios is 0.064. These $R^2$- values accord with earlier studies in the literature. Single variable models do not have strong predictive power over the full sample. The range of full-sample $R^2$-values lies between 0.001 and 0.016 for the dividend yield model, between 0.003 and 0.018 for the T-bill model, between 0.000 and 0.023 for the spread model and between 0.001 and 0.026 for the default premium model.[23]

Turning next to the subsample results, Figure 7 shows systematic variation in the $R^2$-measure over the calendar decades. When interpreting these figures, it should be recalled that even with 120 monthly observations for each decade, there is bound to be some unrealistically large in-sample $R^2-$values as a reflection of

[23]These results are not reported separately in the tables to conserve space.

random sampling variation across a large number of portfolio-decades. Furthermore, since the reported $R^2-$values are based on minimizing the sum of squared residuals in-sample, they are by construction higher than what can be achieved in an out-of-sample experiment. Bearing this in mind, the return forecasting model produces relatively high $R^2-$values in the 1950s, 1970s and 1980s and relatively low values in the 1960s and 1990s. Interestingly, the sorting of decades into periods with high and low return predictability is robust to whether or not breaks are allowed (see Figure 7 Panel B). In the 1980s the average in-sample $R^2$ is 17.2% without a break versus 19.8% when breaks are included. This compares with $R^2$-values of 6.0% in the 1990s without breaks versus 7.4% when breaks are included. Our findings suggest that although predictability certainly seems much lower in the 1990s compared to the 1980s, viewed from a longer perspective there has been no uniform decline in the predictability of stock returns.

Turning next to the international data, since the samples are not the same for each country (c.f. Table 9) we elected to split the total sample for each market two ways, into thirds and into halves. Figure 8 shows $R^2$-values calculated for various sub-samples for each of the international market indices. In Panel A of Figure 8 no breaks are included in the model while in Panel B breaks are permitted. The results are similar in spirit to those obtained for US portfolios. Typically the $R^2$-values for the latter portion of the sample are significantly lower than the corresponding values over the full sample. There are some exceptions to this general observation, notably Italy, Japan, Singapore and Switzerland, where the $R^2$ is higher in the second half of the sample relative to the first half. Denmark exhibits the most notable decline in $R^2$ over the sample, falling from 9.9% to 1.4% when the sample is split into thirds. Although not reported separately in the tables and figures, we also computed $R^2$-values over the same sample fractions for the model with breaks. For 7 of the 13 countries where at least one break was detected, the $R^2$ goes down after the most recent break. An examination of the statistical significance of the individual regression coefficients in Table 12 shows that some predictability nevertheless remains after the most recent break: 11 of 13 dividend yield coefficients, 7 of 13 T-bill rate coefficients, 5 of 11 spread coefficients and 4 of 13 default premium coefficients remain significant at the 5% level after the most recent break. Furthermore, in the breakpoint model the average $R^2$-value remains at 7.6% in the last third or 6.4% in the last half of the sample. This figure is very similar to the average $R^2-$values found in the US data during the 1990s.

## VI. Robustness of Results: Monte Carlo Simulations

In applying the method of Bai and Perron (1998) to our setting, a primary concern is the potential of 'over-fitting', i.e. spuriously finding breaks when truly none exist. The results underlying the test statistics discussed above rely on asymptotic theory. For any specific data generating process, the adequacy of the tests in small samples must be assessed via Monte Carlo simulation experiments. Given the evidence presented above of structural instability in predictive regressions for (excess) returns, our concern is primarily with the size properties of the tests for breaks. Bai and Perron (2001) perform a series of simulation experiments and assess the size and power of the various tests for breaks under a variety of data generating processes. These range from an independent Gaussian noise process to linear processes subject to two breaks where both the regressor and the error term are distributed heterogeneously across regimes. Also considered are cases with serially dependent errors, although in these cases only intercept shifts are included.

Bai and Perron (2001) find that serial correlation and/or heterogeneity in the data or errors across segments can induce significant size distortions when low values of the trimming value $\pi$ are used. Thus, if these features are present in the data, $\pi$ values of 15% or higher are recommended, depending on the sample size and the particular features of the data. Bai and Perron find that the sequential procedure performs better than statistical information criteria, particularly if heterogeneity across segments is present. For the processes considered by Bai and Perron (2001), the tests have reasonable power and corrections for heterogeneity and serial correlation in the residuals (when these truly exist) improve power.

While these results provide support for application of the tests in our setting, the data considered in this study exhibit characteristics that differ significantly from all of the data generating mechanisms considered by Bai and Perron (2001). Specifically, returns are inherently very noisy, and the instruments we consider explain only a small fraction of the variation in returns. Furthermore, heteroskedasticity and time varying conditional variance are the rule rather than the exception for returns data. Finally, at least two of the regressors in our study, the dividend yield and the one month T-bill rate, are known to be highly persistent. The first of these features may dilute the power of tests to detect breaks while the latter two features may lead to spurious rejections. Since we find ample evidence of breaks in our analysis, we focus on potential size distortions and conduct a Monte Carlo experiment with data generating processes that capture some of the important features of our data.

### *A. Design of the Simulation Experiment*

If the tests are over-sized, then a true null hypothesis of no breaks will be rejected more frequently than the asymptotic theory suggests. In examining the finite-sample size properties of the breakpoint tests, we consider several different types of data generating processes, as follows:

1. $y_t = \gamma x_t + \varepsilon_t$; $\varepsilon_t \sim N(0,1)$
   $x_t = \varphi x_{t-1} + \upsilon_t$; $\upsilon_t \sim N(0,1)$ with $\rho(\varepsilon_t, \upsilon_t) = 0$;
2. $y_t = \gamma x_t + \varepsilon_t$; $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$
   $x_t = \varphi x_{t-1} + \upsilon_t$; $\upsilon_t \sim N(0, \sigma_\nu^2)$ with $\rho(\varepsilon_t, \upsilon_t) \neq 0$;
3. $y_t = \varepsilon_t$; where $\varepsilon_t \sim N(0, h_t^2)$, where $h_t^2 = \omega + \beta h_{t-1}^2 + \alpha \varepsilon_{t-1}^2$

Our first experiment generates $y_t$ as a linear function of $x_t$ with a Gaussian white noise error term added. The variable $x_t$ follows a first order autoregressive process with $\varphi$ governing the persistency of the process. We simulate data under four different values for the parameter $\varphi$, including $\varphi = 0$ (which corresponds to the case of a Gaussian white noise process for $x_t$), $\varphi = 0.3$, $\varphi = 0.9$, and finally $\varphi = 0.98$.[24] Given the value of the persistency parameter $\varphi$, the parameter $\gamma$ on the regressor is tuned so that the population $R^2$ for the process is 0.07, which is roughly consistent with the $R^2$-values typically encountered in regressions of returns on predictor variables.

An important consideration in predictive regressions such as those considered here is the potential of bias toward finding predictability. It is well known that the OLS coefficients on lagged endogenous regressors are biased. When financial ratios such as the dividend yield or functions of interest rates are used to predict returns the resulting least squares coefficients are biased although asymptotically consistent. Many recent studies examine inference in this setting and the extent to which returns are truly predictable is still an ongoing debate. Ang and Bekaert

[24] The assumptions of Bai and Perron (1998) do not permit unit root regressors so we only consider highly persistent processes and not an actual unit root process.

(2001), however, consider a model that includes both the dividend and earnings yields as well as the short interest rate and find that the only statistically significant regressor is the short rate and its significance is limited to short horizons.[25] Our model includes both the lagged dividend yield and short rate, as well as lagged term and default premia.

Our second experiment accounts for these concerns by relaxing the assumption that the regressor is strictly exogenous. Specifically, the innovations in the equations for $y_t$ and $x_t$ are assumed to have a correlation of $-0.93$. The parameter choices for the system are based on in-sample estimates obtained by regressing returns for the equal-weighted CRSP portfolio on a constant and the lagged dividend yield and separately regressing the dividend yield on a constant and its own lagged value over the sample period 1952:7 to 1999:12. The sample correlation between the two sets of regression errors was $-0.93$, the value chosen for the correlation of the regression innovations.

Lastly, we conduct simulations where $y_t$ follows a GARCH(1,1) process. This process, of course, features the time varying conditional volatility observed in stock returns. The specific parameters for the process were selected based on the results obtained by fitting GARCH(1,1) models to excess returns for several of the CRSP portfolios analyzed in this study. As is commonly the case for GARCH(1,1) models of stock returns, the sum of the parameters $\alpha+\beta$ is close to one. We consider sample sizes of 100 and 200 and the following combinations of values for the trimming percentage $\pi$ and the maximum number of breaks $K$: $\pi = 15\%$ and $K = 5$, $\pi = 20\%$ and $K = 3$, $\pi = 25\%$ and $K = 2$. Each experiment consists of $1,000$ simulations. Finally, we allow for serial correlation in the errors and for heterogeneity in the errors across breaks.

### *B. Summary of Simulation Results*

Table 13 (Panels A-C) summarizes the results of the simulation experiments. All tests are evaluated at the ten percent significance level, and Table 13 reports the percentage of cases in which the null hypothesis of no breaks is rejected when there is in fact no break in the process. We evaluate the size distortions of the tests

[25] Examples of other studies that examine small sample inference with lagged endogenous regressors in the context of predicting returns include Goetzmann and Jorion (1993), Hodrick (1992), Nelson and Kim (1993), Lamont (1998), Stambaugh (1999) and Lewellen (2001).

and the adequacy of model selection techniques by comparing the results in Table 13 with those predicted by the asymptotic theory. For instance, the $SupF(1)$ test applied at a 10 percent significance level rejects the null of no breaks 10 percent of the time asymptotically. We can compare this theoretical value to that obtained in the simulation analysis. Values substantially higher than 10 percent suggest that the test is over-sized and values substantially lower than 10 percent suggest that the test is under-sized.

For the process with a strictly exogenous, serially uncorrelated Gaussian regressor (the columns of Panel A with the persistence parameter set at 0), the tests appear to be mildly over-sized when the sample size is 100 and the trimming percentage is 15 since the rejection frequency is between 13 and 18 percent rather than ten percent as suggested by the asymptotic theory. The size distortion for the $SupF(k)$ tests appears to be increasing in $k$. The size distortion becomes milder when the trimming percentage is increased and nearly disappears when the sample size is increased to 200. For the strictly exogenous regressor in Panel A, adding persistency appears to actually reduce the size distortion relative to the serially uncorrelated Gaussian case. In fact, for a sample size of 200 and the case of a highly persistent regressor ($\varphi = 0.98$) the tests appear to be slightly under-sized.

When we consider the system with correlated disturbances (Panel B of Table 13) the distortions are much larger. The $SupF(k)$ tests are clearly over-sized and the size distortion increases with $k$. Fortunately, while the $SupF(4)$ and $SupF(5)$ tests have very poor size properties with rejection rates of over 35 percent, the sequential method for selecting the number of breaks still performs relatively well and selects the correct model 84.5 percent of the time. The reason is of course that the sequential method begins by considering the $SupF(1)$ test, which is only slightly over-sized. Increasing the sample size from 100 to 200 drastically reduces the size distortion, as does increasing the trimming percentage from 15 to 25. With a sample size of 200 and a trimming percentage of 15 the sequential method correctly selects a model of no breaks 90.8% of the time, almost exactly as the asymptotic theory suggests.

Panel C reports results for the GARCH(1,1) process. The results obtained here are roughly similar to those obtained for the Gaussian white noise process. If anything, the size distortion appears slightly less than in the benchmark white noise case. Of course, the simulation uses only one particular set of parameters for the process, but these parameters are consistent with the features of our data.

While these experiments are limited in scope, they suggest that the presence of features of financial return models such as persistent regressors, low $R^2-$values and time-varying conditional volatility do not lead to spurious findings of breaks in sample sizes comparable to ours.

## VII. Conclusion

This study presents systematic empirical evidence of structural breaks in models of predictable components in stock returns based on the lagged dividend yield, Treasury bill rate, term spread and default premium. We find evidence of breaks in most of the size and industry-sorted portfolios of US stocks examined. The break points most frequently identified are 1966, 1974, 1983 and 1990. Turning to data from 18 international markets, we find additional evidence of breaks in regressions of returns on predictor variables, although there does not seem to be a similar clustering in the timing of breaks across countries.

The 1974 breaks in many US return forecasting models is likely related to the large macroeconomic shocks reflecting large oil price increases and the resulting break in the trend of US GDP found to have occurred around this time by Perron (1989). Perhaps this suggests that breaks in the underlying fundamentals can explain breaks in financial return models. There is no reason to expect financial return models to be immune to breaks in economic growth since these are likely to affect investors' intertemporal marginal rates of substitution and hence the process driving risk premia. The break around 1983 in the coefficients on the T-bill rate and the term spread could well be related to the earlier change in monetary policy regime which occurred in 1981. Indeed, this period is included in many of the confidence intervals for the 1983 breakpoint. Alternatively, the break could be related to the low inflation regime that followed 1983. We think it is reasonable to expect that the relationship between stock returns and nominal interest rates could well differ across low and high inflation states. This may also have bearing on the break identified for 1966. This was the start of a period with higher inflation following the early stages of the Vietnam war.

It is perhaps less easy to explain the factors driving the break around 1990, but certainly the ability of the dividend yield to act as a 'fundamentals' proxy appears to have broken down after 1990 as witnessed by the simultaneously high stock returns and low dividend yield that occurred in this decade.

Accounting for breaks in the prediction models does not necessarily weaken the evidence of predictability. In many cases we found individual coefficients that were insignificant in the full sample but were significant in sub-samples. Considering only full sample results may thus in some cases conceal predictability.

To be sure, predictability in the US stock market appears to have declined in the 1990s. However, in-sample predictability does not seem to have disappeared. In the US data the T-bill rate and particularly the term premium remain significant after the most recent break. Of the 20 US portfolios for which we identified a break in the 'all' model, only two did not have at least one coefficient that remained statistically significant at the 5% level after the most recent break. In the international data we found that the dividend yield and T-bill rate continue to be statistically significant after the most recent break.

We therefore think that data-snooping and inefficient markets are unlikely to fully explain the findings of predictability of stock returns. Predictor variables such as the nominal interest rate and the dividend yield were known by the early eighties and continued to have predictive power after this period.

Ang and Bekaert (2001) suggest that "it is conceivable that the lack of predictive power is simply a small sample phenomenon, due to the very special nature of the last decade for the US stock market data." Similarly, Lettau and Ludvigson (2001) write that "It is clear, for example, that the last five years have been marked by highly unusual stock market behavior..." Our study suggests that the weaker evidence of predictability in the 1990s is not unique and is similar to what was found for the 1960s. There were earlier breaks in the return forecasting model and the ability of various regressors to predict stock returns appears to vary significantly over time.

While this paper concentrated on examining in-sample evidence of breaks in standard return forecasting models, there are several questions that need to be addressed in future research. Our results suggest that past data must be used judiciously in forecasting future returns, since the return process may have undergone several breaks over the historical period examined. This point is partially addressed by Pesaran and Timmermann (2002) who consider forecasting the returns on an equal-weighted portfolio of US stocks that is subject to breaks. They consider using data after the most recent break to forecast future stock returns. Their results indicate that out-of-sample predictability can be improved by accounting for breaks.

Another direction for future research is to study the impact of breaks on optimal asset allocation. In recent contributions, Barberis (2000), Brandt (1999), Campbell and Viceira (1998) and Kandel and Stambaugh (1996) examine the asset allocation decision when returns are predictable. Our findings suggest that there was evidence of two or three breaks in most of the US portfolios considered over a 45 year period. While structural breaks therefore may not matter much to short-term asset allocation it has the potential to affect long-term asset allocation decisions. Accounting for such breaks requires putting forth a model for the frequency and size of the breaks. While doing this extends beyond the present paper, our empirical results is a first step in this direction.

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## Table 1: Summary Statistics for US Stock Returns and Instrumental Variables

This table reports summary statistics for the US excess returns data and predictive instruments. The value-weighted, equal-weighted and decile portfolios (sorted by market capitalization) were obtained from CRSP while the industry portfolios were obtained from Kenneth French's website. The sample kurtosis is reported in excess of three, the value for the normal distribution. The sample period is 1952:7 - 1999:12 and returns are observed monthly and computed in excess of a 1-month T-bill rate. The dividend yield is the dividend over the previous 12 months divided by the current stock price. The T-bill rate is for 30-day instruments, the term spread is the difference between the yield on a 5-year Government bond and the yield on a 1-month Treasury bill and the default premium is the difference between Moody's AAA and BAA rates.

### Equity Returns

| ***Portfolio*** | ***Mean*** | ***Std. Dev.*** | ***Skew*** | ***Kurtosis*** |
|---|---|---|---|---|
| Value-weghted | 0.6685 | 4.2550 | -0.4993 | 2.1270 |
| Equal-weighted | 0.8187 | 5.2885 | -0.2598 | 3.4947 |
| Decile 1 (Smallest Cap) | 1.2623 | 7.1561 | 0.8334 | 4.4947 |
| Decile 2 | 0.9400 | 6.3874 | 0.2174 | 3.3140 |
| Decile 3 | 0.8579 | 6.1173 | -0.0172 | 3.3132 |
| Decile 4 | 0.8034 | 5.8394 | -0.0390 | 3.9319 |
| Decile 5 | 0.7643 | 5.6821 | -0.3167 | 3.7745 |
| Decile 6 | 0.7449 | 5.5257 | -0.3630 | 3.4268 |
| Decile 7 | 0.7327 | 5.3215 | -0.5209 | 3.6471 |
| Decile 8 | 0.7546 | 5.0998 | -0.5639 | 3.2605 |
| Decile 9 | 0.7381 | 4.7899 | -0.5789 | 3.3440 |
| Decile 10 (Largest Cap) | 0.6408 | 4.1706 | -0.3748 | 1.8309 |
| Nondurables | 0.6617 | 4.9826 | -0.2238 | 4.2058 |
| Durables | 0.7392 | 6.0258 | -0.0560 | 3.9032 |
| Manufacturing | 0.8287 | 5.5362 | -0.2808 | 3.0868 |
| Energy | 0.8092 | 6.3887 | -0.0976 | 1.8775 |
| Chemicals | 0.8058 | 5.2181 | -0.5005 | 3.4196 |
| Business Equipment | 1.0647 | 7.4897 | 0.1131 | 1.9601 |
| Telecommunications | 1.3141 | 6.2499 | 0.0074 | 2.2342 |
| Utility | 0.6406 | 3.3784 | 0.2805 | 3.0230 |
| Shops | 0.7067 | 5.5861 | -0.2507 | 3.8306 |
| Healthcare | 1.0782 | 6.3710 | -0.2702 | 2.3883 |
| Money | 0.8049 | 4.9864 | 0.0331 | 3.4540 |
| Other | 0.8188 | 5.8652 | -0.2339 | 2.9062 |

### Instrumental Variables

| ***Instrument*** | ***Mean*** | ***Std. Dev.*** | ***Skew*** | ***Kurtosis*** |
|---|---|---|---|---|
| US Dividend Yield | 3.4458 | 3.5752 | -1.7868 | -0.4006 |
| US T-Bill Rate | 0.4896 | 0.5445 | -1.3789 | -0.8998 |
| US Spread | 0.0441 | 0.0771 | -0.5064 | -1.0183 |
| US Default Premium | 0.0782 | 0.0860 | -1.3923 | -0.8060 |

### Table 2: US Full Sample Predictability Regressions (No Breaks)

This table presents the results of least squares regressions of portfolio returns upon the full set of predictor variables and upon each predictor variable separately. Results are presented for returns in excess of the one-month T-bill rate for size and industry-sorted portfolios of US stocks. The instruments include a constant, the lagged dividend yield (YLD), T-bill rate (TBL), term spread (SPD) and default premium (DEF). Coefficients on the constant term are suppressed to conserve space. The dividend yield is the dividend over the previous 12 months divided by the current price. The T-bill rate is for 30-day instruments, the term spread is the difference between the yield on a 5-year Government bond and the yield on a 1-month Treasury bill and the default premium is the difference between Moody's AAA and BAA rates. Heteroskedasticity and autocorrelation consistent standard errors for coefficient estimates based on the method suggested by Newey and West (1987) are also provided. The sample period is monthly 1952:7 - 1999:12. Bold face type indicates statistical significance at the 5% level.

| | Model With All Regressors | | | | | Univariate Models | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $R^2$ | YLD | TBL | SPD | DEF | YLD | TBL | SPD | DEF |
| **VW** | 0.05 | 0.12 | **-4.85** | 0.20 | **28.13** | 0.22 | **-1.92** | **8.04** | 8.00 |
| | | *0.20* | *1.17* | *3.10* | *8.25* | *0.20* | *0.73* | *2.86* | *6.02* |
| **EW** | 0.07 | 0.17 | **-7.59** | -2.51 | **47.70** | 0.40 | **-2.44** | **10.19** | 15.08 |
| | | *0.27* | *1.56* | *4.12* | *11.59* | *0.25* | *0.90* | *3.91* | *8.23* |
| **D1** | 0.06 | -0.23 | **-10.36** | -8.30 | **71.47** | 0.23 | **-2.77** | 10.55 | 20.87 |
| | | *0.37* | *2.15* | *6.07* | *16.98* | *0.35* | *1.24* | *5.61* | *11.58* |
| **D2** | 0.07 | -0.05 | **-9.62** | -5.98 | **60.34** | 0.27 | **-3.15** | **10.62** | 15.46 |
| | | *0.36* | *1.91* | *5.27* | *15.07* | *0.32* | *1.09* | *5.01* | *10.53* |
| **D3** | 0.06 | 0.01 | **-8.92** | -6.46 | **56.21** | 0.32 | **-2.77** | 8.84 | 14.92 |
| | | *0.33* | *1.82* | *4.86* | *13.70* | *0.29* | *1.07* | *4.71* | *9.42* |
| **D4** | 0.07 | 0.14 | **-8.60** | -4.76 | **52.39** | 0.40 | **-2.83** | **9.54** | 14.39 |
| | | *0.31* | *1.73* | *4.65* | *13.10* | *0.29* | *0.98* | *4.43* | *9.18* |
| **D5** | 0.07 | 0.22 | **-7.90** | -2.62 | **47.62** | 0.44 | **-2.69** | **10.29** | 14.17 |
| | | *0.30* | *1.69* | *4.54* | *12.56* | *0.28* | *0.94* | *4.12* | *8.79* |
| **D6** | 0.06 | 0.28 | **-7.49** | -2.59 | **46.03** | 0.50 | **-2.38** | **9.60** | 15.01 |
| | | *0.29* | *1.62* | *4.24* | *12.05* | *0.27* | *0.92* | *4.00* | *8.26* |
| **D7** | 0.06 | 0.27 | **-6.96** | -2.26 | **42.91** | 0.48 | **-2.19** | **9.05** | 14.29 |
| | | *0.26* | *1.52* | *3.96* | *11.20* | *0.24* | *0.88* | *3.77* | *7.64* |
| **D8** | 0.06 | 0.29 | **-6.47** | -1.10 | **41.36** | 0.49 | **-1.94** | **9.49** | **15.38** |
| | | *0.26* | *1.45* | *3.81* | *10.73* | *0.25* | *0.88* | *3.60* | *7.48* |
| **D9** | 0.06 | 0.24 | **-6.15** | -1.16 | **38.53** | 0.43 | **-1.94** | **8.89** | 13.50 |
| | | *0.24* | *1.32* | *3.41* | *9.68* | *0.23* | *0.82* | *3.25* | *6.98* |
| **D10** | 0.04 | 0.10 | **-4.31** | 0.88 | **24.34** | 0.17 | **-1.83** | **7.81** | 6.58 |
| | | *0.20* | *1.13* | *3.06* | *7.88* | *0.19* | *0.71* | *2.73* | *5.75* |
| **Nondur.** | 0.09 | 0.31 | **-7.52** | -3.28 | **49.36** | **0.63** | **-2.13** | **10.89** | **22.04** |
| | | *0.24* | *1.40* | *3.96* | *9.76* | *0.22* | *0.82* | *3.69* | *7.08* |
| **Durab.** | 0.08 | 0.11 | **-9.16** | -2.83 | **55.00** | 0.40 | **-3.48** | **14.49** | **19.24** |
| | | *0.28* | *1.75* | *4.95* | *11.91* | *0.26* | *1.03* | *4.36* | *8.78* |
| **Manuf.** | 0.07 | 0.30 | **-7.48** | -1.39 | **39.83** | 0.46 | **-3.21** | **11.82** | 13.11 |
| | | *0.28* | *1.61* | *4.47* | *11.12* | *0.26* | *0.95* | *3.96* | *8.43* |
| **Energy** | 0.03 | 0.29 | **-6.62** | -8.69 | 19.73 | 0.27 | **-3.57** | 1.40 | -5.93 |
| | | *0.42* | *2.00* | *6.51* | *14.51* | *0.40* | *1.63* | *5.93* | *11.01* |
| **Chem.** | 0.06 | 0.27 | **-6.74** | -2.83 | **41.26** | **0.51** | **-2.22** | **9.61** | **16.69** |
| | | *0.25* | *1.46* | *4.06* | *10.00* | *0.23* | *0.87* | *3.58* | *7.63* |
| **Bus. Equip.** | 0.06 | -0.06 | **-10.91** | -10.66 | **65.10** | 0.35 | **-3.64** | 10.29 | 18.40 |
| | | *0.45* | *2.32* | *6.52* | *16.94* | *0.41* | *1.26* | *5.56* | *11.86* |
| **Telecom** | 0.06 | 0.07 | **-8.58** | -5.49 | **50.01** | 0.35 | **-3.14** | **10.63** | 15.40 |
| | | *0.39* | *1.99* | *6.18* | *13.66* | *0.36* | *1.07* | *4.66* | *8.67* |
| **Utility** | 0.05 | **0.36** | **-3.08** | 1.17 | **18.06** | **0.43** | -1.10 | **6.31** | **9.97** |
| | | *0.16* | *0.93* | *2.72* | *5.87* | *0.15* | *0.58* | *2.35* | *3.86* |
| **Shops** | 0.08 | 0.15 | **-8.78** | -6.51 | **56.93** | **0.53** | **-2.50** | **10.40** | **22.05** |
| | | *0.27* | *1.65* | *4.79* | *11.48* | *0.26* | *0.95* | *4.16* | *8.26* |
| **Healthcare** | 0.07 | 0.38 | **-9.23** | -10.24 | **55.29** | **0.74** | **-2.52** | 6.66 | **19.80** |
| | | *0.33* | *1.97* | *6.03* | *13.80* | *0.31* | *1.15* | *4.95* | *9.75* |
| **Money** | 0.07 | 0.25 | **-6.24** | 0.66 | **35.58** | 0.41 | **-2.62** | **11.89** | 13.89 |
| | | *0.27* | *1.53* | *4.61* | *10.39* | *0.24* | *0.88* | *3.73* | *6.97* |
| **Other** | 0.07 | 0.19 | **-8.78** | -5.92 | **50.71** | 0.47 | **-3.12** | **10.29** | 16.40 |
| | | *0.30* | *1.81* | *5.20* | *12.62* | *0.28* | *1.07* | *4.43* | *9.61* |

## Table 3: Selection of the Number of Breaks: U.S. Data

The table presents the statistics (except for the Hansen test, for which p-values are available) for various hypothesis tests regarding the occurrence and number of breaks in the regression model for size and industry-sorted portfolios of U.S. stocks. For each portfolio, the regression model is excess returns on a constant and the lagged dividend yield, Treasury bill rate, term spread and default premium. Critical values for the test statistics appear at the bottom of the table. The trimming percentage for the *Sup F* tests is set at 15. Bold-faced numbers indicate statistical significance at the 10% critical level.

| | Null of Zero Breaks Versus Alternative of k Breaks | | | Sequential Tests of *k* versus k+*1* breaks | | | | Null of Zero Breaks Versus Alternative of One Break (Columns Contain P-values) | | | Number of Breaks by Sequential Method | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | ***Sup F(k)*** | | | ***Sup F(k+1/k)*** | | | | ***Hansen*** | | | ***Seq. Method*** | |
| *Portfolio* | *1* | 2 | 3 | *2 vs 1* | *3 vs 2* | *4 vs 3* | *5 vs 4* | *Sup F* | *Exp F* | *Ave F* | *10%* | 5% |
| Value-weighted | 13.59 | **21.02** | **24.69** | **28.29** | **21.77** | 18.02 | 0.00 | 0.10 | **0.08** | **0.02** | 0 | 0 |
| Equal-weighted | **19.54** | **25.70** | **23.93** | **22.87** | **20.03** | 13.42 | 13.67 | **0.02** | **0.03** | **0.00** | 3 | 3 |
| Decile 1 | **31.54** | **24.84** | **26.24** | **26.56** | **25.05** | 12.22 | 2.57 | **0.04** | **0.03** | **0.01** | 3 | 3 |
| Decile 2 | **20.73** | **24.94** | **21.83** | **23.20** | 15.63 | 8.89 | 8.89 | **0.03** | **0.03** | **0.02** | 2 | 2 |
| Decile 3 | **22.35** | **26.87** | **23.44** | **25.10** | 13.09 | 7.66 | 7.96 | **0.02** | **0.03** | **0.01** | 2 | 2 |
| Decile 4 | **20.40** | **24.74** | **23.12** | **24.33** | **20.56** | 10.37 | 9.43 | **0.02** | **0.03** | **0.01** | 3 | 3 |
| Decile 5 | **17.01** | **22.81** | **23.72** | **25.77** | **20.19** | 10.22 | 10.22 | **0.04** | **0.05** | **0.01** | 3 | 0 |
| Decile 6 | **18.45** | **26.50** | **25.02** | **22.41** | **19.37** | 11.25 | 11.25 | **0.03** | **0.05** | **0.01** | 3 | 3 |
| Decile 7 | **16.51** | **21.63** | **31.98** | **21.68** | 16.18 | 19.23 | 14.75 | **0.05** | **0.07** | **0.01** | 3 | 0 |
| Decile 8 | **17.48** | **22.04** | **32.94** | **29.21** | 17.25 | **20.15** | 16.36 | **0.08** | **0.08** | **0.02** | 4 | 0 |
| Decile 9 | 13.73 | **23.27** | **31.54** | **26.94** | **23.34** | 13.45 | 0.00 | 0.13 | 0.13 | **0.02** | 0 | 0 |
| Decile 10 | **22.40** | **20.21** | **25.53** | **27.07** | **21.51** | 16.57 | 0.00 | 0.10 | **0.04** | **0.01** | 3 | 3 |
| Nondurables | **16.77** | **20.96** | **25.56** | **21.99** | 16.08 | **21.14** | **21.14** | 0.13 | 0.13 | **0.05** | 2 | 0 |
| Durables | **26.03** | **16.79** | **21.96** | 13.10 | 13.93 | 13.93 | 13.93 | **0.09** | **0.08** | **0.05** | 1 | 1 |
| Manufacturing | **34.27** | **25.33** | **25.59** | 13.90 | 8.38 | 12.54 | 0.00 | **0.02** | **0.02** | **0.01** | 1 | 1 |
| Energy | **18.05** | **32.45** | **25.29** | **40.19** | 14.07 | 6.26 | 0.00 | **0.01** | **0.01** | **0.00** | 2 | 0 |
| Chemicals | **32.77** | **24.30** | **20.67** | **44.42** | **27.93** | **34.28** | 0.00 | **0.05** | **0.05** | **0.02** | 2 | 2 |
| Business Equip. | **24.30** | **26.30** | **21.90** | **26.95** | 14.00 | 5.95 | 0.00 | **0.01** | **0.01** | **0.00** | 2 | 2 |
| Telecomm. | **21.81** | **27.12** | **24.76** | **37.38** | 9.69 | 4.95 | 0.00 | **0.01** | **0.00** | **0.00** | 2 | 2 |
| Utility | 14.70 | **22.79** | **18.49** | 17.31 | 10.37 | 10.37 | 0.00 | **0.08** | **0.06** | **0.01** | 0 | 0 |
| Shops | 15.76 | **20.87** | **28.11** | **21.83** | 17.55 | 10.47 | 15.32 | 0.14 | 0.14 | **0.03** | 0 | 0 |
| Healthcare | **45.66** | **37.73** | **34.64** | **36.54** | 8.74 | 19.23 | 0.00 | **0.00** | **0.00** | **0.01** | 2 | 2 |
| Money | **17.67** | **20.12** | **20.04** | **24.22** | 17.13 | 7.35 | 0.00 | **0.08** | **0.07** | **0.01** | 2 | 0 |
| Other | **39.79** | **30.61** | **30.47** | **19.04** | 10.99 | 13.20 | 0.00 | **0.01** | **0.01** | **0.01** | 2 | 1 |
| ***Critical Values-10%*** | ***16.14*** | ***14.37*** | ***12.90*** | ***18.14*** | ***19.10*** | ***19.84*** | ***20.50*** | | | | | |
| ***Critical Values-5%*** | ***18.23*** | ***15.62*** | ***13.93*** | ***19.91*** | ***20.99*** | ***21.71*** | ***22.37*** | | | | | |

# Table 4: Coefficient Estimates from Breakpoint Regressions (All Regressors)

This table presents the estimated coefficients and standard error for the dividend yield, Treasury bill, term spread and default premium during each subinterval identified using the sequential breakpoint method of Bai and Perron (1998). Confidence intervals for the break dates for this model may be found in Figure 1. The following portfolios are omitted since no breaks were identified: Value-weighted CRSP, decile 9, utility and shops. Standard errors are heteroskedasticity and autocorrelation consistent.

| | *Interval 1* | | *Interval 2* | | *Interval 3* | | *Interval 4* | |
|---|---|---|---|---|---|---|---|---|
| ***Portfolio*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** |
| **Equal-weighted CRSP** | | | | | | | | |
| Div. Yield | **-1.347** | 0.541 | **3.027** | 1.444 | **3.788** | 0.925 | 1.915 | 1.327 |
| T-Bill Rate | **-25.440** | 8.477 | **-46.566** | 9.899 | **-14.564** | 3.203 | -9.820 | 6.419 |
| Spread | -31.490 | 22.682 | **-52.217** | 24.957 | -5.576 | 6.464 | -25.843 | 13.583 |
| Def. Prem. | 19.793 | 23.731 | 48.550 | 67.025 | **38.787** | 13.439 | **97.404** | 34.034 |
| **Decile 1** | | | | | | | | |
| Div. Yield | **-1.484** | 0.723 | **3.194** | 1.401 | **3.699** | 1.051 | 2.125 | 1.816 |
| T-Bill Rate | **-38.763** | 12.032 | **-55.508** | 9.682 | **-19.253** | 4.193 | **-17.479** | 8.654 |
| Spread | -48.401 | 32.583 | **-66.332** | 20.560 | -14.037 | 8.131 | -35.985 | 19.508 |
| Def. Prem. | 88.697 | 47.157 | **125.546** | 33.372 | **61.632** | 19.936 | **197.172** | 45.473 |
| **Decile 2** | | | | | | | | |
| Div. Yield | **-1.809** | 0.643 | **3.350** | 1.552 | **1.498** | 0.670 | | |
| T-Bill Rate | **-28.934** | 10.764 | **-61.477** | 12.756 | **-18.228** | 3.724 | | |
| Spread | -37.694 | 28.509 | **-72.947** | 29.227 | **-18.749** | 7.038 | | |
| Def. Prem. | 15.662 | 33.274 | 52.202 | 83.735 | **56.804** | 16.374 | | |
| **Decile 3** | | | | | | | | |
| Div. Yield | **-1.630** | 0.605 | **3.315** | 1.481 | **1.438** | 0.616 | | |
| T-Bill Rate | **-27.085** | 9.342 | **-56.942** | 11.271 | **-17.073** | 3.477 | | |
| Spread | -28.997 | 25.306 | **-67.740** | 28.126 | **-20.464** | 6.658 | | |
| Def. Prem. | 21.750 | 28.323 | 56.288 | 78.089 | **50.442** | 14.790 | | |
| **Decile 4** | | | | | | | | |
| Div. Yield | **-1.431** | 0.553 | **3.112** | 1.383 | **4.303** | 1.034 | 1.519 | 1.835 |
| T-Bill Rate | **-24.877** | 8.752 | **-51.543** | 10.204 | **-16.369** | 3.657 | -6.956 | 8.342 |
| Spread | -26.830 | 23.312 | **-61.211** | 25.278 | -7.400 | 7.648 | -23.091 | 18.212 |
| Def. Prem. | 16.483 | 25.636 | 53.949 | 67.709 | **43.283** | 15.200 | **104.963** | 41.110 |
| **Decile 5** | | | | | | | | |
| Div. Yield | -1.150 | 0.640 | **3.549** | 1.472 | **4.329** | 0.990 | 1.569 | 1.626 |
| T-Bill Rate | **-23.004** | 10.091 | **-51.507** | 10.449 | **-15.248** | 3.389 | -4.894 | 7.503 |
| Spread | -23.039 | 27.060 | **-63.682** | 25.861 | -4.221 | 7.425 | -20.756 | 16.141 |
| Def. Prem. | 11.064 | 31.509 | 59.672 | 67.729 | **39.606** | 14.257 | **96.535** | 40.048 |
| **Decile 6** | | | | | | | | |
| Div. Yield | **-1.316** | 0.588 | **3.282** | 1.521 | **4.367** | 0.941 | 1.723 | 1.612 |
| T-Bill Rate | **-25.725** | 9.361 | **-47.623** | 9.861 | **-14.348** | 3.251 | -7.508 | 7.516 |
| Spread | -32.617 | 25.761 | **-56.447** | 26.137 | -3.348 | 6.756 | -24.495 | 15.393 |
| Def. Prem. | 24.842 | 29.138 | 55.987 | 68.033 | **34.986** | 13.648 | **92.066** | 41.463 |
| **Decile 7** | | | | | | | | |
| Div. Yield | **-1.225** | 0.505 | 2.929 | 1.487 | **3.978** | 0.961 | 1.880 | 1.344 |
| T-Bill Rate | **-24.837** | 7.798 | **-42.574** | 9.167 | **-12.795** | 3.241 | -8.648 | 7.441 |
| Spread | -34.084 | 20.961 | -47.854 | 24.655 | -1.676 | 6.812 | **-27.444** | 13.572 |
| Def. Prem. | 28.317 | 19.786 | 54.548 | 64.509 | **32.212** | 13.519 | 54.022 | 38.241 |
| **Decile 8*** | | | | | | | | |
| Div. Yield | -0.570 | 0.565 | 2.764 | 1.770 | **7.710** | 1.691 | **6.851** | 2.433 |
| T-Bill Rate | **-20.784** | 8.788 | **-40.135** | 6.963 | -4.506 | 5.763 | **-24.707** | 6.658 |
| Spread | -13.880 | 21.995 | **-58.478** | 19.816 | 24.244 | 14.464 | -0.152 | 9.064 |
| Def. Prem. | **53.070** | 24.991 | **130.015** | 31.789 | 43.577 | 25.282 | 1.254 | 23.958 |
| **Decile 10** | | | | | | | | |
| Div. Yield | -0.657 | 0.567 | **1.648** | 0.667 | **2.632** | 0.792 | 2.165 | 1.259 |
| T-Bill Rate | **-22.525** | 8.600 | **-21.518** | 3.760 | **-10.535** | 2.901 | 1.639 | 6.166 |
| Spread | -22.516 | 22.185 | **-23.365** | 8.416 | 0.061 | 5.660 | -25.947 | 13.116 |
| Def. Prem. | 32.631 | 22.694 | **53.479** | 17.237 | 17.004 | 11.440 | 84.930 | 51.215 |

## Table 4 (Continued)

| Portfolio | Interval 1 Beta | Interval 1 S.E. | Interval 2 Beta | Interval 2 S.E. | Interval 3 Beta | Interval 3 S.E. |
|---|---|---|---|---|---|---|
| **Nondurables** | | | | | | |
| Div. Yield | **-0.820** | *0.389* | 1.229 | *1.213* | **1.219** | *0.403* |
| T-Bill Rate | **-36.306** | *9.771* | **-28.812** | *8.034* | **-11.822** | *2.627* |
| Spread | -41.599 | *21.827* | -40.639 | *21.647* | -11.306 | *5.656* |
| Def. Prem. | **73.843** | *26.454* | 75.251 | *42.056* | **41.807** | *10.535* |
| **Durables** | | | | | | |
| Div. Yield | **-1.311** | *0.528* | **1.128** | *0.471* | | |
| T-Bill Rate | **-43.257** | *11.840* | **-14.742** | *2.413* | | |
| Spread | -39.795 | *28.163* | -9.280 | *5.393* | | |
| Def. Prem. | 50.863 | *39.785* | **53.418** | *12.309* | | |
| **Manufacturing** | | | | | | |
| Div. Yield | -0.741 | *0.528* | **1.165** | *0.466* | | |
| T-Bill Rate | **-44.101** | *11.104* | **-12.910** | *2.139* | | |
| Spread | -38.951 | *27.057* | -8.307 | *4.761* | | |
| Def. Prem. | 33.662 | *41.633* | **40.236** | *11.478* | | |
| **Energy** | | | | | | |
| Div. Yield | -1.059 | *0.545* | **3.369** | *0.938* | 0.659 | *1.038* |
| T-Bill Rate | **-41.553** | *11.344* | **-22.549** | *7.259* | **-10.542** | *3.560* |
| Spread | -32.960 | *25.453* | **-46.445** | *16.064* | -6.106 | *9.625* |
| Def. Prem. | 23.025 | *23.405* | **70.821** | *26.719* | -0.247 | *21.048* |
| **Chemicals** | | | | | | |
| Div. Yield | **-1.090** | *0.522* | **2.350** | *0.559* | **2.483** | *1.050* |
| T-Bill Rate | **-47.382** | *11.873* | **-13.395** | *2.182* | -6.767 | *6.914* |
| Spread | **-53.910** | *26.412* | -11.724 | *6.106* | -23.752 | *13.567* |
| Def. Prem. | 59.396 | *33.688* | **38.991** | *11.937* | **73.478** | *28.531* |
| **Business Equipment** | | | | | | |
| Div. Yield | -0.731 | *0.514* | **4.932** | *1.168* | 1.201 | *2.364* |
| T-Bill Rate | **-19.295** | *6.562* | **-20.130** | *3.813* | -18.129 | *11.900* |
| Spread | -29.155 | *22.751* | **-18.903** | *9.322* | -43.652 | *23.141* |
| Def. Prem. | 54.168 | *34.339* | **49.361** | *18.362* | **184.326** | *64.882* |
| **Telecommunications** | | | | | | |
| Div. Yield | -0.737 | *0.508* | **3.408** | *0.674* | -1.595 | *1.850* |
| T-Bill Rate | **-53.032** | *13.624* | **-15.003** | *2.865* | **-33.261** | *14.501* |
| Spread | **-68.454** | *28.887* | -10.416 | *7.378* | -29.632 | *20.576* |
| Def. Prem. | **84.201** | *27.910* | **33.356** | *14.180* | **164.549** | *50.065* |
| **Healthcare** | | | | | | |
| Div. Yield | -0.781 | *0.467* | **3.372** | *0.640* | **4.875** | *1.764* |
| T-Bill Rate | **-43.345** | *13.060* | **-17.231** | *2.776* | -10.337 | *10.697* |
| Spread | **-65.595** | *29.223* | **-18.144** | *7.545* | **-60.750** | *21.207* |
| Def. Prem. | **90.620** | *27.063* | **46.430** | *15.210* | **152.247** | *51.258* |
| **Money** | | | | | | |
| Div. Yield | -0.657 | *0.414* | 0.855 | *1.289* | **0.993** | *0.410* |
| T-Bill Rate | **-44.638** | *11.031* | **-35.924** | *8.969* | **-9.377** | *2.692* |
| Spread | **-56.052** | *23.099* | **-66.528** | *24.870* | -5.771 | *5.881* |
| Def. Prem. | **68.704** | *21.386* | **116.931** | *43.236* | **23.320** | *11.287* |
| **Other** | | | | | | |
| Div. Yield | -0.738 | *0.549* | **4.283** | *0.843* | 0.598 | *0.719* |
| T-Bill Rate | **-41.194** | *11.352* | **-33.600** | *6.370* | **-14.693** | *2.738* |
| Spread | -26.165 | *26.848* | **-44.013** | *15.425* | **-18.249** | *7.924* |
| Def. Prem. | 47.830 | *44.001* | **59.342** | *24.780* | **59.753** | *15.602* |

* A fourth break was identified for decile 8. For the final (fifth) subinterval, the coefficients (standard errors in parentheses) were as follows:
Div. Yield: 1.448 (1.544); T-bill Rate: -4.354 (7.681); Spread -19.094 (14.768); Def. Prem. 69.110 (39.107)

# Table 5: Breakpoint Coefficient Estimates (Dividend Yield Regressor)

This table presents the estimated coefficients and associated heteroskedasticity and autocorrelation consistent standard error from a regression of excess stock returns on a constant and the lagged dividend yield during each subinterval identified using the sequential breakpoints method of Bai and Perron (1998). We only display results for the portfolios where at least one breakpoint was identified. Confidence intervals for the estimated break dates for this model may be found in Figure 2.

| | ***Interval 1*** | | ***Interval 2*** | | ***Interval 3*** | |
|---|---|---|---|---|---|---|
| ***Portfolio*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** |
| Value-weighted | **0.772** | *0.266* | 0.280 | *0.624* | - | - |
| Decile 8 | **1.077** | *0.339* | 0.964 | *0.941* | - | - |
| Decile 9 | **1.002** | *0.313* | 0.817 | *0.891* | - | - |
| Decile 10 | **0.727** | *0.256* | 0.169 | *0.593* | - | - |
| Energy | -0.228 | *0.374* | **3.076** | *0.809* | -1.022 | *0.535* |
| Business Equipment | **1.371** | *0.501* | 0.306 | *1.632* | - | - |
| Utility | **0.673** | *0.226* | **2.333** | *0.596* | 0.390 | *0.411* |
| Money | 0.217 | *0.417* | **1.920** | *0.523* | **1.700** | *0.840* |

## Table 6: Breakpoint Coefficient Estimates (Treasury Bill Regressor)

This table presents the estimated coefficients and associated heteroskedasticity and autocorrelation consistent standard error from a regression of excess stock returns on a constant and the lagged T-bill rate during each subinterval identified using the sequential breakpoints method of Bai and Perron (1998). We only display results for the portfolios where at least one breakpoint was identified. Confidence intervals for the estimated break dates for this model may be found in Figure 3.

| | ***Interval 1*** | | ***Interval 2*** | | ***Interval 3*** | | ***Interval 4*** | |
|---|---|---|---|---|---|---|---|---|
| ***Portfolio*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** |
| Value-weighted | **-10.854** | *2.147* | **-17.082** | *4.174* | -1.879 | *1.175* | **-** | - |
| Equal-weighted | **-8.406** | *1.980* | **-2.873** | *1.229* | - | - | - | - |
| | | | | | | | | |
| Decile 1 | **-16.819** | *3.726* | **-25.313** | *5.223* | **-7.392** | *3.128* | **-8.971** | *2.519* |
| Decile 3 | **-9.384** | *2.158* | **-7.020** | *2.871* | **-6.460** | *2.106* | **-** | - |
| Decile 4 | **-9.004** | *2.014* | **-7.085** | *2.851* | **-6.027** | *1.897* | **-** | - |
| Decile 5 | **-8.812** | *2.064* | **-3.084** | *1.291* | **-** | - | **-** | - |
| Decile 6 | **-8.777** | *2.102* | -2.530 | *1.308* | - | - | **-** | - |
| Decile 7 | **-8.605** | *2.007* | -2.165 | *1.299* | - | - | **-** | - |
| Decile 8 | **-8.432** | *2.056* | -1.945 | *1.334* | **-** | - | **-** | - |
| Decile 9 | **-8.048** | *2.012* | -1.972 | *1.282* | **-** | - | **-** | - |
| Decile 10 | **-11.203** | *2.345* | **-15.994** | *3.974* | -1.805 | *1.130* | - | - |
| | | | | | | | | |
| Nondurables | **-8.391** | *2.030* | **-5.872** | *1.949* | -4.548 | *3.794* | - | - |
| Manufacturing | **-27.095** | *4.694* | **-4.217** | *1.174* | - | - | - | - |
| Energy | 1.910 | *2.727* | **-7.513** | *1.465* | - | - | - | - |
| Business Equipmer | **-10.659** | *3.067* | **-8.841** | *3.157* | **-11.171** | *2.981* | - | - |
| Telecommunication | **-26.063** | *5.392* | **-15.977** | *3.695* | **-4.177** | *1.578* | - | - |
| Utility | **-6.580** | *1.526* | -0.489 | *0.966* | - | - | - | - |
| Money | **-8.904** | *2.199* | **-2.851** | *0.994* | - | - | **-** | - |
| Other | **-28.961** | *5.187* | **-16.728** | *3.927* | **-7.091** | *2.213* | **-6.361** | *2.274* |

## Table 7: Breakpoint Coefficient Estimates (Term Spread Regressor)

This table presents the estimated coefficients and associated heteroskedasticity and autocorrelation consistent standard error from a regression of excess stock returns on a constant and the lagged term spread during each subinterval identified using the sequential breakpoints method of Bai and Perron (1998). We only display results for the portfolios where at least one breakpoint was identified. Confidence intervals for the estimated break dates for this model may be found in Figure 4.

| | ***Interval 1*** | | ***Interval 2*** | |
|---|---|---|---|---|
| ***Portfolio*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** |
| Value-weighted | **15.777** | *3.984* | -5.775 | *4.846* |
| Equal-weighted | **20.684** | *5.263* | 0.846 | *6.417* |
| | | | | |
| Decile 2 | **24.236** | *6.842* | 1.380 | *8.240* |
| Decile 3 | **22.900** | *6.378* | -5.379 | *7.745* |
| Decile 4 | **21.769** | *6.070* | 0.320 | *7.238* |
| Decile 5 | **21.211** | *5.621* | 1.367 | *7.170* |
| Decile 6 | **20.247** | *5.586* | 0.401 | *6.705* |
| Decile 7 | **19.430** | *5.208* | -1.967 | *6.260* |
| Decile 10 | **15.027** | *4.169* | -6.637 | *4.739* |
| | | | | |
| Nondurables | **21.332** | *5.059* | 4.258 | *6.076* |
| Durables | **26.955** | *5.894* | 7.067 | *7.214* |
| Energy | 2.339 | *9.055* | 13.421 | *6.714* |
| Shops | **22.470** | *5.574* | 1.507 | *7.360* |
| Healthcare | **20.559** | *5.693* | -8.250 | *9.310* |
| Other | **23.165** | *5.891* | 0.396 | *7.082* |

## Table 8: Breakpoint Coefficient Estimates (Default Premium Regressor)

This table presents the estimated coefficients and associated heteroskedasticity and autocorrelation consistent standard error from a regression of excess stock returns on a constant and the lagged default premium during each subinterval identified using the sequential breakpoints method of Bai and Perron (1998). We only display results for the portfolios where at least one breakpoint was identified. Confidence intervals for the estimated break dates for this model may be found in Figure 5.

| | *Interval 1* | | *Interval 2* | | *Interval 3* | | *Interval 4* | |
|---|---|---|---|---|---|---|---|---|
| ***Portfolio*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** | ***Beta*** | ***S.E.*** |
| Value-weighted | 24.691 | *13.646* | **26.462** | *8.531* | 37.177 | *20.158* | **-** | - |
| | | | | | | | | |
| Decile 1 | 34.722 | *34.335* | **54.730** | *16.132* | **188.562** | *46.287* | **-** | - |
| Decile 2 | 36.494 | *27.567* | **121.198** | *32.704* | 11.621 | *14.189* | **-** | - |
| Decile 3 | 43.904 | *24.059* | **115.452** | *30.092* | 9.226 | *12.746* | **-** | - |
| Decile 4 | 34.422 | *22.987* | **111.230** | *30.252* | 10.222 | *12.330* | **-** | - |
| Decile 10 | 20.680 | *13.908* | **23.444** | *7.880* | 30.508 | *19.010* | - | - |
| | | | | | | | | |
| Nondurables | **54.768** | *18.075* | **115.710** | *24.991* | **19.594** | *8.627* | **-** | - |
| Durables | 28.221 | *27.990* | **123.540** | *31.315* | 28.925 | *14.525* | **125.957** | *34.651* |
| Energy | **37.855** | *12.883* | **-26.930** | *12.925* | **-** | - | **-** | - |
| Business Equipment | 28.288 | *28.251* | **52.854** | *17.138* | **148.182** | *50.061* | - | - |
| Telecommunications | **47.603** | *22.260* | **40.454** | *12.316* | **272.500** | *88.743* | **-** | - |
| Utility | **40.801** | *13.644* | **13.162** | *4.321* | **-** | - | **-** | - |
| Shops | **50.690** | *19.603* | **122.460** | *27.247* | 19.567 | *10.600* | **-** | - |
| Money | **70.398** | *19.335* | **89.006** | *26.702* | 7.923 | *9.672* | **-** | - |
| Other | 24.599 | *26.438* | **109.170** | *27.831* | 15.663 | *12.420* | - | - |

## Table 9: Summary Statistics for MSCI International Stock Returns

This table reports summary statistics for the MSCI international returns data and the endpoints of the sample range for each country. The sample kurtosis is reported in excess of three, the value for the normal distribution. Returns are observed monthly and are denominated in the local currency. The dividend yield is the dividend over the previous 12 months divided by the current stock price. The T-bill rate is on a short term debt instrument from the local country. The specific choice of instrument varies by country. The term spread is the difference between the yields on a Government bond and the yield on a Government T-bill. The default premium is the US default premium defined as the difference between Moody's AAA and BAA rates.

| Equity Returns | | | | | Sample Range | |
|---|---|---|---|---|---|---|
| *Country* | *Mean* | *Std. Dev.* | *Skew* | *Kurtosis* | *Start* | *End* |
| Australia | 0.862 | 6.422 | -1.692 | 13.607 | 1970:1 | 2000:6 |
| Austria | 0.614 | 5.599 | 0.059 | 4.840 | 1971:1 | 1998:12 |
| Belgium | 1.111 | 4.920 | -0.232 | 3.791 | 1970:1 | 2000:6 |
| Canada | 0.987 | 5.099 | -0.719 | 2.792 | 1970:1 | 2000:6 |
| Denmark | 1.237 | 5.220 | -0.140 | 0.121 | 1972:1 | 2000:5 |
| France | 0.542 | 6.616 | -0.379 | 1.642 | 1970:1 | 2000:5 |
| Germany | 0.828 | 5.415 | -0.608 | 2.294 | 1970:1 | 2000:6 |
| Hong Kong | 1.120 | 10.938 | -0.711 | 5.444 | 1973:1 | 2000:9 |
| Italy | 1.050 | 7.219 | 0.197 | 0.478 | 1971:1 | 2000:6 |
| Japan | 0.746 | 5.447 | -0.306 | 1.274 | 1970:1 | 2000:5 |
| Netherlands | 1.125 | 5.105 | -0.475 | 2.383 | 1970:1 | 1998:12 |
| Norway | 0.850 | 7.607 | -0.571 | 1.922 | 1971:8 | 2000:4 |
| Singapore | 0.778 | 7.805 | -1.476 | 8.912 | 1978:1 | 2000:5 |
| Spain | 1.556 | 6.517 | -0.516 | 2.459 | 1978:3 | 2000:5 |
| Sweden | 1.530 | 6.458 | -0.066 | 1.492 | 1970:1 | 2000:6 |
| Switzerland | 1.131 | 5.114 | -1.168 | 3.996 | 1980:1 | 2000:6 |
| United Kingdom | 1.154 | 6.124 | 0.281 | 7.787 | 1970:1 | 2000:6 |
| United States | 1.025 | 4.540 | -0.580 | 2.423 | 1970:1 | 2000:6 |

## Table 10: International Full Sample Predictability Regressions (No Breaks)

This table presents the results of least squares regressions of international portfolio returns upon the full set of predictor variables and upon each of the predictor variables separately. Results are presented for monthly returns on MSCI international portfolio for 18 countries. The instruments include a constant, the lagged (local) dividend yield, (local) T-bill rate, (local) term spread and (US) default premium. Coefficients on the constant term are suppressed to conserve space. The dividend yield is the dividend over the previous 12 months divided by the current price. Heteroskedasticity and autocorrelation consistent standard errors for coefficient estimates based on the method suggested by Newey and West (1987) are also provided. The sample period varies from country to country and is shown explicitly in Table 9. Bold face type indicates statistical significance at the 5% level. The symbol '-' indicates that the corresponding regressor was not available for that particular country.

| | Model With All Regressors | | | | | Univariate Models | | | |
|---|---|---|---|---|---|---|---|---|---|
| | $R^2$ | YLD | TBL | SPD | DEF | YLD | TBL | SPD | DEF |
| **Australia** | 0.02 | 0.91 | -1.62 | -2.63 | 10.36 | **0.88** | 1.22 | -1.66 | 13.23 |
| | | *0.49* | *2.14* | *3.62* | *10.12* | *0.36* | *0.88* | *1.97* | *8.24* |
| **Austria** | 0.02 | 0.63 | -7.54 | **-10.44** | 8.67 | 0.12 | -0.83 | -1.13 | 0.56 |
| | | *0.47* | *4.27* | *5.13* | *6.69* | *0.35* | *1.75* | *2.45* | *6.32* |
| **Belgium** | 0.02 | 0.14 | **-5.16** | -4.38 | **20.84** | 0.07 | 0.01 | 0.07 | 11.17 |
| | | *0.11* | *2.38* | *3.43* | *9.33* | *0.08* | *1.26* | *2.50* | *7.72* |
| **Canada** | 0.03 | 0.14 | **-6.39** | -6.89 | **27.80** | -0.01 | -1.31 | 1.28 | 7.04 |
| | | *0.39* | *2.07* | *3.50* | *10.25* | *0.35* | *0.99* | *1.87* | *9.05* |
| **Denmark** | 0.03 | 0.17 | **-2.19** | - | **19.46** | 0.11 | -0.86 | - | 13.09 |
| | | *0.21* | *0.90* | *-* | *8.27* | *0.18* | *0.84* | *-* | *7.48* |
| **France** | 0.02 | 0.42 | -4.94 | -1.75 | 18.40 | 0.13 | -1.21 | 4.71 | 7.92 |
| | | *0.37* | *3.44* | *5.79* | *13.79* | *0.20* | *1.12* | *3.03* | *8.08* |
| **Germany** | 0.02 | 0.25 | **-5.83** | -3.85 | 13.91 | 0.04 | -2.43 | 2.78 | 9.25 |
| | | *0.34* | *2.41* | *2.91* | *8.42* | *0.22* | *1.31* | *1.94* | *6.74* |
| **Hong Kong** | 0.03 | **1.41** | - | - | 8.28 | **1.50** | - | - | 23.68 |
| | | *0.65* | *-* | *-* | *20.27* | *0.62* | *-* | *-* | *18.63* |
| **Italy** | 0.00 | 0.28 | -0.29 | -1.84 | 5.23 | 0.26 | 0.53 | -1.62 | 5.47 |
| | | *0.53* | *1.51* | *3.03* | *14.47* | *0.50* | *1.10* | *2.73* | *11.70* |
| **Japan** | 0.05 | 0.64 | -1.50 | 6.09 | **30.01** | 0.42 | -0.29 | 2.92 | **18.75** |
| | | *0.34* | *2.71* | *5.12* | *9.32* | *0.30* | *1.06* | *2.45* | *6.60* |
| **Netherlands** | 0.05 | 0.47 | **-11.66** | **-11.31** | **23.86** | 0.12 | -1.88 | 1.86 | **15.11** |
| | | *0.25* | *3.02* | *3.55* | *8.57* | *0.20* | *1.04* | *1.22* | *7.05* |
| **Norway** | 0.01 | 0.46 | 0.82 | 0.04 | -10.70 | 0.35 | 0.82 | -1.06 | 1.90 |
| | | *0.42* | *2.27* | *3.28* | *13.55* | *0.33* | *1.24* | *1.97* | *10.59* |
| **Singapore** | 0.03 | 2.18 | -5.68 | 1.12 | 19.11 | 1.66 | -1.44 | 5.02 | 10.18 |
| | | *1.30* | *5.12* | *7.56* | *19.13* | *0.97* | *2.51* | *4.39* | *12.47* |
| **Spain** | 0.02 | 0.21 | -2.94 | -0.70 | 5.59 | 0.05 | -1.38 | **2.18** | 5.84 |
| | | *0.18* | *2.25* | *2.13* | *14.26* | *0.09* | *0.69* | *0.59* | *9.98* |
| **Sweden** | 0.03 | -0.37 | -1.09 | - | **33.95** | -0.02 | 0.72 | - | 22.89 |
| | | *0.27* | *1.48* | *-* | *15.21* | *0.22* | *1.41* | *-* | *11.97* |
| **Switzerland** | 0.01 | 1.44 | -3.67 | 0.35 | -17.53 | -0.06 | -1.97 | 3.44 | -2.81 |
| | | *0.93* | *6.81* | *9.75* | *12.73* | *0.49* | *1.74* | *2.58* | *6.96* |
| **United Kingdom** | 0.08 | **2.18** | **-12.61** | **-10.96** | **32.11** | 0.75 | 0.85 | 0.61 | **25.89** |
| | | *0.99* | *4.55* | *3.81* | *13.71* | *0.50* | *1.02* | *2.14* | *8.60* |
| **United States** | 0.03 | 0.09 | **-3.68** | -1.50 | **23.03** | 0.07 | -0.81 | 2.38 | 12.74 |
| | | *0.29* | *1.76* | *2.81* | *7.22* | *0.17* | *0.73* | *2.16* | *6.44* |

## Table 11: Selection of the Number of Breaks: International Data

The table presents the statistics (except for the Hansen test, for which p-values are available) for various hypothesis tests regarding the occurrence and number of breaks in the regression model for stock indices from 18 international countries. For each portfolio, the regression model is excess returns on a constant and the lagged (local) dividend yield, (local) T-bill rate, (local) term spread and (US) default premium. Critical values for the test statistics appear at the bottom of the table. The trimming percentage for the *Sup F* tests is set at 20. Bold-faced numbers indicate statistical significance at the 10% critical level.

| | Null of Zero Breaks Versus Alternative of k Breaks | | | Sequential Tests of *k* versus k+*1* Breaks | | Null of Zero Breaks Versus Alternative of One Break (Columns Contain P-values) | | | Number of Breaks by Sequential Method | |
|---|---|---|---|---|---|---|---|---|---|---|
| | ***Sup F(k)*** | | | ***Sup F(k+1/k)*** | | ***Hansen*** | | | ***Seq. Method*** | |
| *Portfolio* | *1* | 2 | 3 | *2 vs 1* | *3 vs 2* | *Sup* F | *Exp* F | *Ave* F | *10%* | 5% |
| AustraIia | **23.90** | **18.27** | **19.78** | 10.25 | 6.01 | 0.13 | **0.09** | **0.05** | 1 | 1 |
| Austria | 9.33 | 10.77 | 10.61 | 15.39 | 9.32 | 0.11 | 0.13 | 0.15 | 0 | 0 |
| Belgium | **34.37** | **27.85** | **21.37** | 10.71 | 8.80 | **0.00** | **0.00** | **0.00** | 1 | 1 |
| Canada | **26.58** | **20.17** | **15.43** | 8.75 | 0.00 | **0.08** | **0.07** | 0.19 | 1 | 1 |
| Denmark* | **16.91** | 10.50 | 10.34 | 7.10 | 12.02 | 0.19 | 0.25 | 0.36 | 1 | 1 |
| France | **35.84** | **23.57** | **17.06** | 8.98 | 5.73 | **0.01** | **0.00** | **0.01** | 1 | 1 |
| Germany | **23.62** | **17.71** | **20.39** | 13.72 | 13.40 | **0.09** | **0.08** | **0.03** | 1 | 1 |
| Hong Kong* | 11.35 | 8.41 | 5.89 | 4.75 | 2.17 | 0.23 | 0.28 | 0.39 | 0 | 0 |
| Italy | **24.09** | **19.39** | **20.79** | **21.85** | **19.32** | 0.12 | 0.11 | **0.06** | 2 | 2 |
| Japan | 15.17 | **16.38** | **13.40** | 6.01 | 5.38 | **0.09** | **0.09** | 0.15 | 0 | 0 |
| Netherlands | **56.10** | **38.71** | **31.68** | 15.97 | 14.84 | **0.00** | **0.01** | **0.00** | 1 | 1 |
| Norway | **19.37** | **17.45** | **14.55** | 13.23 | 1.40 | **0.07** | **0.08** | 0.43 | 1 | 1 |
| Singapore | **20.90** | **19.76** | **13.37** | 8.19 | 8.15 | **0.07** | 0.11 | **0.10** | 1 | 1 |
| Spain | **17.08** | **19.02** | **23.22** | 15.98 | 0.00 | **0.03** | **0.03** | **0.02** | 1 | 0 |
| Sweden* | 14.91 | **21.83** | **23.75** | **29.42** | **22.73** | **0.02** | **0.03** | **0.02** | 3 | 0 |
| Switzerland | 9.66 | **17.17** | **26.46** | 10.41 | **19.79** | 0.69 | 0.68 | 0.55 | 0 | 0 |
| United Kingdom | 14.42 | 10.96 | 10.01 | 6.40 | 9.29 | 0.12 | 0.17 | 0.74 | 0 | 0 |
| United States | **47.38** | **24.63** | **19.62** | 15.74 | 14.94 | 0.13 | **0.08** | **0.00** | 1 | 1 |
| ***Critical Values-10%*** | ***16.14*** | ***14.37*** | ***12.90*** | ***18.14*** | ***19.10*** | | | | | |
| ***Critical Values-5%*** | ***18.23*** | ***15.62*** | ***13.93*** | ***19.91*** | ***20.99*** | | | | | |

* For these countries, not all regressors were available and the critical values above do not apply. For all other countries, significance may be assessed by reference to the critical values in the table.

## Table 12: Coefficient Estimates from Breakpoint Regressions (International Data, All Regressors)

This table presents the estimated coefficients and standard error for all regressors during each subinterval identified using the sequential breakpoint method of Bai and Perron (1998). The model is estimated for returns on MSCI index portfolios from 18 countries. Confidence intervals for the break dates for this model may be found in Figure 6. No Breaks were found for Austria, Hong Kong, Japan, Switzerland and the United Kingdom.

| | Interval 1 | | Interval 2 | | Interval 3 | |
|---|---|---|---|---|---|---|
| **Portfolio** | **Beta** | **S.E.** | **Beta** | **S.E.** | **Beta** | **S.E.** |
| **Australia** | | | | | | |
| Div. Yield | **4.105** | *1.326* | 0.996 | *0.785* | | |
| T-Bill Rate | **-38.127** | *11.758* | -4.340 | *3.238* | | |
| Spread | 10.113 | *12.170* | -7.240 | *4.315* | | |
| Def. Prem. | -8.520 | *33.600* | 16.862 | *13.879* | | |
| **Belgium** | | | | | | |
| Div. Yield | **0.951** | *0.283* | **1.533** | *0.375* | | |
| T-Bill Rate | **-21.717** | *6.225* | **-16.631** | *4.067* | | |
| Spread | 9.187 | *12.971* | **-21.543** | *4.909* | | |
| Def. Prem. | 12.176 | *14.446* | -28.924 | *18.910* | | |
| **Canada** | | | | | | |
| Div. Yield | 2.207 | *1.212* | **2.036** | *0.641* | | |
| T-Bill Rate | -22.736 | *13.468* | **-14.134** | *3.625* | | |
| Spread | -15.211 | *19.825* | **-13.373** | *4.217* | | |
| Def. Prem. | **37.983** | *18.270* | **31.891** | *11.295* | | |
| **Denmark** | | | | | | |
| Div. Yield | 0.684 | *0.508* | **1.192** | *0.377* | | |
| T-Bill Rate | **-3.895** | *1.238* | -1.241 | *1.349* | | |
| Spread | - | - | - | - | | |
| Def. Prem. | 4.775 | *12.582* | -6.859 | *13.597* | | |
| **France** | | | | | | |
| Div. Yield | **1.985** | *0.564* | **2.756** | *1.038* | | |
| T-Bill Rate | **-13.712** | *4.556* | **-15.521** | *6.221* | | |
| Spread | -12.684 | *8.071* | -13.974 | *8.663* | | |
| Def. Prem. | 28.177 | *15.753* | **55.407** | *23.846* | | |
| **Germany** | | | | | | |
| Div. Yield | 0.496 | *0.395* | **4.935** | *1.508* | | |
| T-Bill Rate | -2.504 | *2.656* | **-22.822** | *7.132* | | |
| Spread | 2.270 | *3.769* | -10.364 | *7.715* | | |
| Def. Prem. | **21.690** | *8.149* | 0.451 | *37.853* | | |
| **Italy** | | | | | | |
| Div. Yield | -1.217 | *0.937* | 1.930 | *1.013* | **4.302** | *1.785* |
| T-Bill Rate | **5.531** | *2.453* | 1.654 | *3.112* | -2.948 | *3.186* |
| Spread | **11.595** | *4.247* | **-17.572** | *5.212* | -12.251 | *8.132* |
| Def. Prem. | 16.796 | *19.336* | 33.504 | *27.128* | 15.819 | *76.944* |
| **Netherlands** | | | | | | |
| Div. Yield | **1.174** | *0.355* | **4.098** | *1.469* | | |
| T-Bill Rate | **-15.585** | *3.786* | **-33.246** | *8.531* | | |
| Spread | **-15.469** | *4.310* | **-20.545** | *8.751* | | |
| Def. Prem. | **31.936** | *8.892* | **123.916** | *23.345* | | |
| **Norway** | | | | | | |
| Div. Yield | 1.921 | *1.004* | **1.344** | *0.550* | | |
| T-Bill Rate | **-85.532** | *28.101* | -0.694 | *3.095* | | |
| Spread | **-94.467** | *29.747* | -3.780 | *3.600* | | |
| Def. Prem. | 41.551 | *27.433* | -27.739 | *20.281* | | |
| **Singapore** | | | | | | |
| Div. Yield | **5.024** | *1.950* | **7.209** | *2.736* | | |
| T-Bill Rate | 9.770 | *8.315* | **-30.344** | *10.888* | | |
| Spread | 1.855 | *10.041* | -18.172 | *12.181* | | |
| Def. Prem. | 2.554 | *21.930* | 56.059 | *43.363* | | |
| **Spain** | | | | | | |
| Div. Yield | 0.262 | *0.318* | **3.142** | *0.927* | | |
| T-Bill Rate | 2.091 | *4.839* | **-15.034** | *4.058* | | |
| Spread | 4.415 | *4.559* | **-15.305** | *5.673* | | |
| Def. Prem. | -13.882 | *15.823* | 50.163 | *27.764* | | |
| **Sweden*** | | | | | | |
| Div. Yield | **8.293** | *1.726* | 1.049 | *0.640* | 1.546 | *1.405* |
| T-Bill Rate | **-16.175** | *3.502* | **8.088** | *3.328* | -3.644 | *5.006* |
| Spread | - | - | - | - | - | - |
| Def. Prem. | 3.615 | *18.081* | -12.657 | *17.261* | **78.920** | *20.192* |
| **United States** | | | | | | |
| Div. Yield | **1.040** | *0.502* | **1.435** | *0.658* | | |
| T-Bill Rate | **-5.495** | *2.233* | 0.029 | *5.168* | | |
| Spread | -0.519 | *3.215* | **-15.043** | *7.330* | | |
| Def. Prem. | **26.195** | *8.739* | 11.525 | *17.288* | | |

* A third break was identified for Sweden. For the final subinterval, the coefficients (standard errors in parentheses) were as follows:
Div. Yield: 3.809 (2.267); T-Bill Rate: -0.156 (3.999); Def. Prem. 92.840 (84.387)

**Table 13: Size of Breakpoint Tests - Monte Carlo Simulations**

This table reports the results of 1,000 simulation experiments. The table reports the percentage of cases in which the null hypothesis of no break is rejected at the ten percent significance level when there is no break in the data generating process. To generate random samples in Panel A, we first generated an AR(1) process 'the regressor' and the sample values were then computed as the lagged value of the regressor plus a normally distributed error term. We obtain results for AR coefficients ranging from 0 to 0.98. Given the AR coefficient, the other parameters were chosen so that the $R^2$ is 7%. The disturbance innovations are uncorrelated in Panel A and consequently the regressor is strictly exogenous. We drop this assumption in Panel B and consider a process similar to that in Panel A except that the innovations are now correlated. Parameters for the process were determined based on the estimation of a system where both returns on the equal-weighted CRSP portfolio and the dividend yield are linear functions of the lagged dividend yield. The in-sample correlation of the errors is -0.93.
In Panel C the process is a Garch (1,1) where the parameter values are tuned to accord with in-sample values for returns on the equal-weighted CRSP portfolio over the sample period 1952:7 - 1999:12. We obtain results for trimming percentage values of 15, 20 and 25 and we allow for serial correlation in the residuals and heteroskedasticity of error terms across breaks (see Bai and Perron (1998)). Results for sample sizes of 100 and 200 are reported in each case. The symbol '-' indicates that the test is not applicable because the trimming percentage times the hypothesized number of breaks exceeds the sample size.

**Panel A: Regressor follows AR(1) process with Uncorrelated Disturbances**

**Sample Size = 100**

| **Persistence** | **0** | **0** | **0** | **0.3** | **0.3** | **0.3** | **0.9** | **0.9** | **0.9** | **0.98** | **0.98** | **0.98** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Trimming Percentage** | **15** | **20** | **25** | **15** | **20** | **25** | **15** | **20** | **25** | **15** | **20** | **25** |
| SupF(1) | 13.4 | 12.8 | 11.1 | 13.2 | 9.7 | 9.9 | 9.1 | 11.4 | 10.2 | 9.7 | 9.6 | 8.0 |
| SupF(2) | 13.9 | 14.4 | 12.5 | 13.8 | 10.0 | 9.8 | 11.5 | 12.9 | 12.8 | 10.5 | 11.0 | 8.7 |
| SupF(3) | 16.0 | 14.8 | - | 16.3 | 10.8 | - | 15.5 | 13.6 | - | 11.4 | 11.0 | - |
| SupF(4) | 17.8 | - | - | 17.3 | - | - | 15.2 | - | - | 12.7 | - | - |
| SupF(5) | 17.9 | - | - | 17.0 | - | - | 14.8 | - | - | 12.6 | - | - |
| Seq(2\|1) | 6.2 | 4.4 | 2.2 | 5.3 | 2.9 | 2.1 | 5.2 | 4.7 | 3.1 | 2.8 | 2.8 | 1.8 |
| Seq(3\|2) | 0.7 | 0.3 | - | 1.2 | 0.0 | - | 1.2 | 0.5 | - | 0.4 | 0.2 | - |
| Seq(4\|3) | 0.2 | - | - | 0.2 | - | - | 0.1 | - | - | 0.0 | - | - |
| Seq(5\|4) | 0.0 | - | - | 0.1 | - | - | 0.0 | - | - | 0.0 | - | - |
| P(SQM = 0) | 86.6 | 87.2 | 88.9 | 86.8 | 90.3 | 90.1 | 90.9 | 88.6 | 89.8 | 90.3 | 90.4 | 92.0 |
| P(SQM = 1) | 12.2 | 12.1 | 10.9 | 12.3 | 9.3 | 9.6 | 9.0 | 10.6 | 9.7 | 9.7 | 9.4 | 7.6 |
| P(SQM = 2) | 1.1 | 0.7 | 0.2 | 0.8 | 0.4 | 0.3 | 0.1 | 0.8 | 0.5 | 0.0 | 0.2 | 0.4 |

**Sample Size = 200**

| **Persistence** | **0** | **0** | **0** | **0.3** | **0.3** | **0.3** | **0.9** | **0.9** | **0.9** | **0.98** | **0.98** | **0.98** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Trimming Percentage** | **15** | **20** | **25** | **15** | **20** | **25** | **15** | **20** | **25** | **15** | **20** | **25** |
| SupF(1) | 11.0 | 11.6 | 10.0 | 11.7 | 10.3 | 8.5 | 10.0 | 7.3 | 7.1 | 8.4 | 8.0 | 7.7 |
| SupF(2) | 10.4 | 12.5 | 9.6 | 11.9 | 10.3 | 10.0 | 10.2 | 7.9 | 8.4 | 8.1 | 8.2 | 7.9 |
| SupF(3) | 11.1 | 12.7 | - | 14.5 | 9.9 | - | 11.5 | 9.6 | - | 7.8 | 9.0 | - |
| SupF(4) | 12.1 | - | - | 13.8 | - | - | 11.3 | - | - | 8.1 | - | - |
| SupF(5) | 11.1 | - | - | 14.3 | - | - | 10.9 | - | - | 8.9 | - | - |
| Seq(2\|1) | 3.2 | 3.3 | 1.7 | 3.3 | 2.5 | 1.8 | 5.1 | 1.9 | 2.0 | 2.4 | 2.0 | 1.1 |
| Seq(3\|2) | 0.2 | 0.3 | - | 0.4 | 0.3 | - | 0.3 | 0.1 | - | 0.6 | 0.1 | - |
| Seq(4\|3) | 0.0 | - | - | 0.0 | - | - | 0.0 | - | - | 0.0 | - | - |
| Seq(5\|4) | 0.0 | - | - | 0.0 | - | - | 0.0 | - | - | 0.0 | - | - |
| P(SQM = 0) | 89.0 | 88.4 | 90.0 | 88.3 | 89.7 | 91.5 | 90.0 | 92.7 | 92.9 | 91.6 | 92.0 | 92.3 |
| P(SQM = 1) | 10.5 | 11.2 | 9.7 | 10.9 | 10.1 | 8.1 | 9.4 | 7.0 | 6.8 | 8.2 | 7.6 | 7.6 |
| P(SQM = 2) | 0.5 | 0.4 | 0.3 | 0.8 | 0.2 | 0.4 | 0.6 | 0.3 | 0.3 | 0.1 | 0.4 | 0.1 |

| | **Panel B: AR(1) with Correlated Disturbances** | | | | | | **Panel C: Garch(1,1) Process** | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Sample Size** | **100** | | | **200** | | | **100** | | | **200** | | |
| **Trimming Percentage** | **15** | **20** | **25** | **15** | **20** | **25** | **15** | **20** | **25** | **15** | **20** | **25** |
| SupF(1) | 15.5 | 15.5 | 12.6 | 9.2 | 7.5 | 10.0 | 10.9 | 13.4 | 11.5 | 11.7 | 10.3 | 11.3 |
| SupF(2) | 23.9 | 21.5 | 16.4 | 12.5 | 10.9 | 10.7 | 11.7 | 13.8 | 12.9 | 12.9 | 11.6 | 11.2 |
| SupF(3) | 29.7 | 27.6 | - | 14.9 | 14.2 | - | 14.6 | 13.8 | - | 13.6 | 10.1 | - |
| SupF(4) | 36.2 | - | - | 20.1 | - | - | 13.8 | - | - | 12.9 | - | - |
| SupF(5) | 43.0 | - | - | 24.8 | - | - | 11.7 | - | - | 11.4 | - | - |
| Seq(2\|1) | 10.1 | 6.3 | 1.9 | 4.0 | 2.4 | 1.6 | 5.8 | 3.0 | 2.2 | 6.5 | 3.7 | 1.9 |
| Seq(3\|2) | 3.5 | 0.9 | - | 1.4 | 0.4 | - | 0.9 | 0.0 | - | 0.7 | 0.2 | - |
| Seq(4\|3) | 0.9 | - | - | 0.6 | - | - | 0.1 | - | - | 0.3 | - | - |
| Seq(5\|4) | 0.2 | - | - | 0.0 | - | - | 0.0 | - | - | 0.2 | - | - |
| P(SQM = 0) | 84.5 | 84.5 | 87.4 | 90.8 | 92.5 | 90.0 | 89.1 | 86.6 | 88.5 | 88.3 | 89.7 | 88.7 |
| P(SQM = 1) | 14.9 | 15.1 | 12.5 | 9.0 | 7.1 | 10.0 | 10.1 | 13.0 | 11.0 | 10.5 | 9.7 | 10.9 |
| P(SQM = 2) | 0.6 | 0.4 | 0.1 | 0.2 | 0.3 | 0.0 | 0.8 | 0.4 | 0.5 | 1.2 | 0.6 | 0.4 |

## Figure 1: Breakpoint Dates - All Regressors

This figure presents the estimated breakpoints (marked by an 'X') and 90% confidence intervals using the sequential breakpoint method of Bai and Perron (1998). The model is estimated for excess returns on value-weighted (VW) and equal-weighted (EW) CRSP portfolios and for cap-based (D1-D10) and industry-based portfolios. The instruments are a constant, the US dividend yield, the Treasury Bill rate, the term spread and the default premium lagged one month. The sample is monthly 1952:7 through 1999:12. Panel A presents results for size-sorted portfolios and Panel B presents results for industry-sorted portfolios.

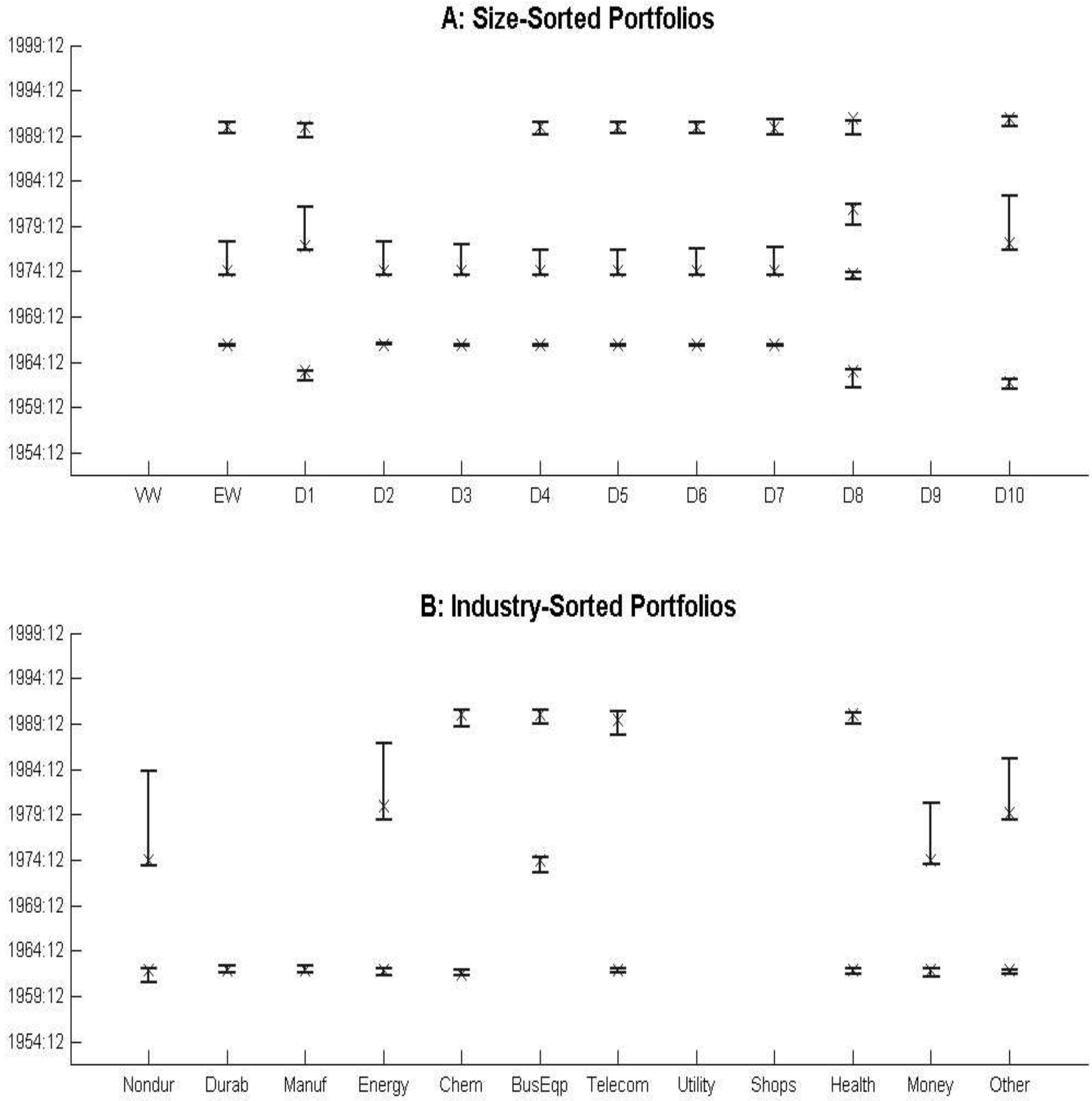


**Figure 2: Breakpoint Dates – Dividend Yield Regressor**

This figure presents the estimated breakpoints (marked by an 'X') and 90% confidence intervals using the sequential breakpoint method of Bai and Perron (1998). The model is estimated for excess returns on value-weighted (VW) and equal-weighted (EW) CRSP portfolios and for cap-based (D1-D10) and industry-based portfolios. The instruments are a constant and the US dividend yield. The sample is monthly 1952:7 through 1999:12. Panel A presents results for size-sorted portfolios and Panel B presents results for industry-sorted portfolios.

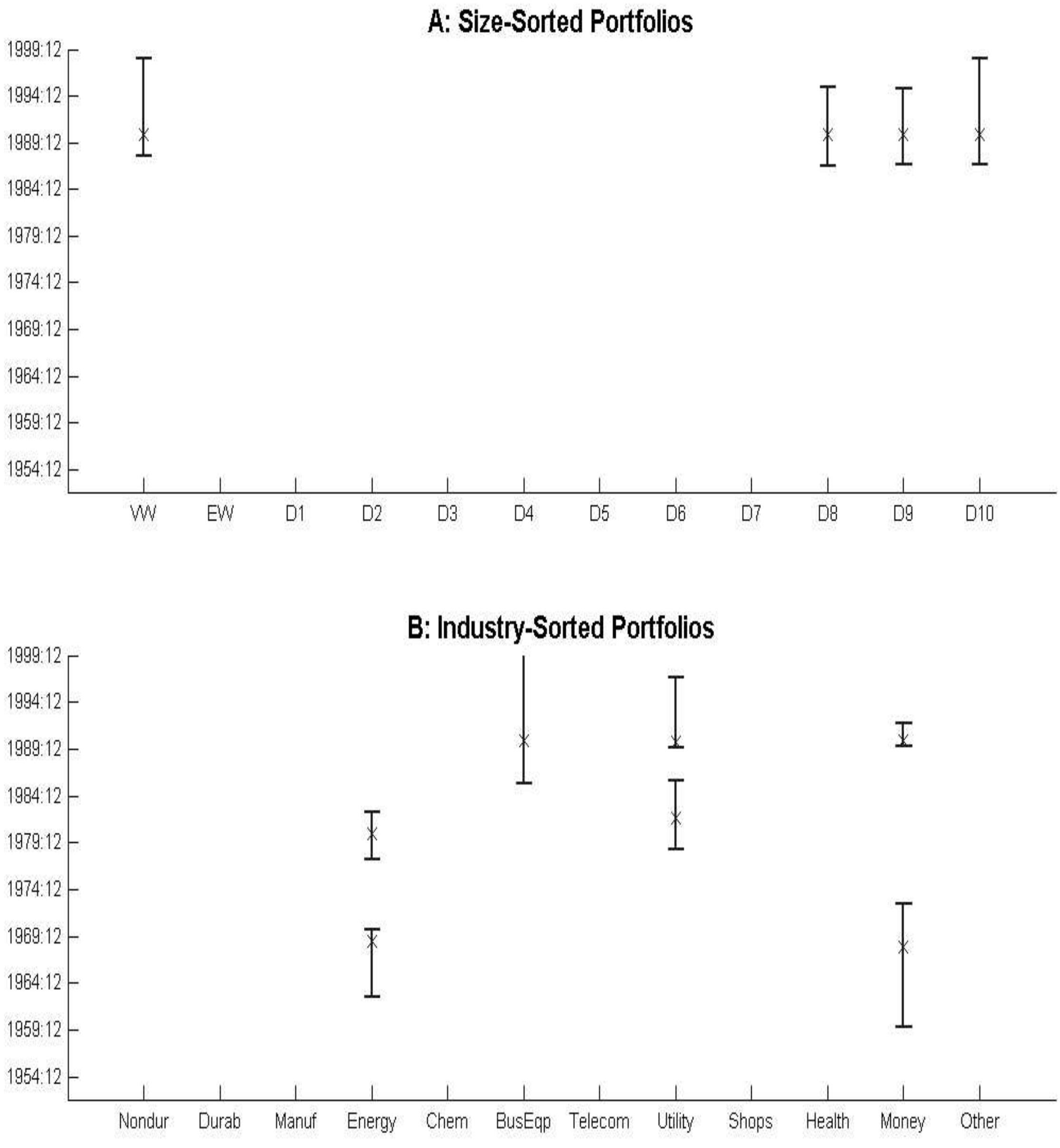
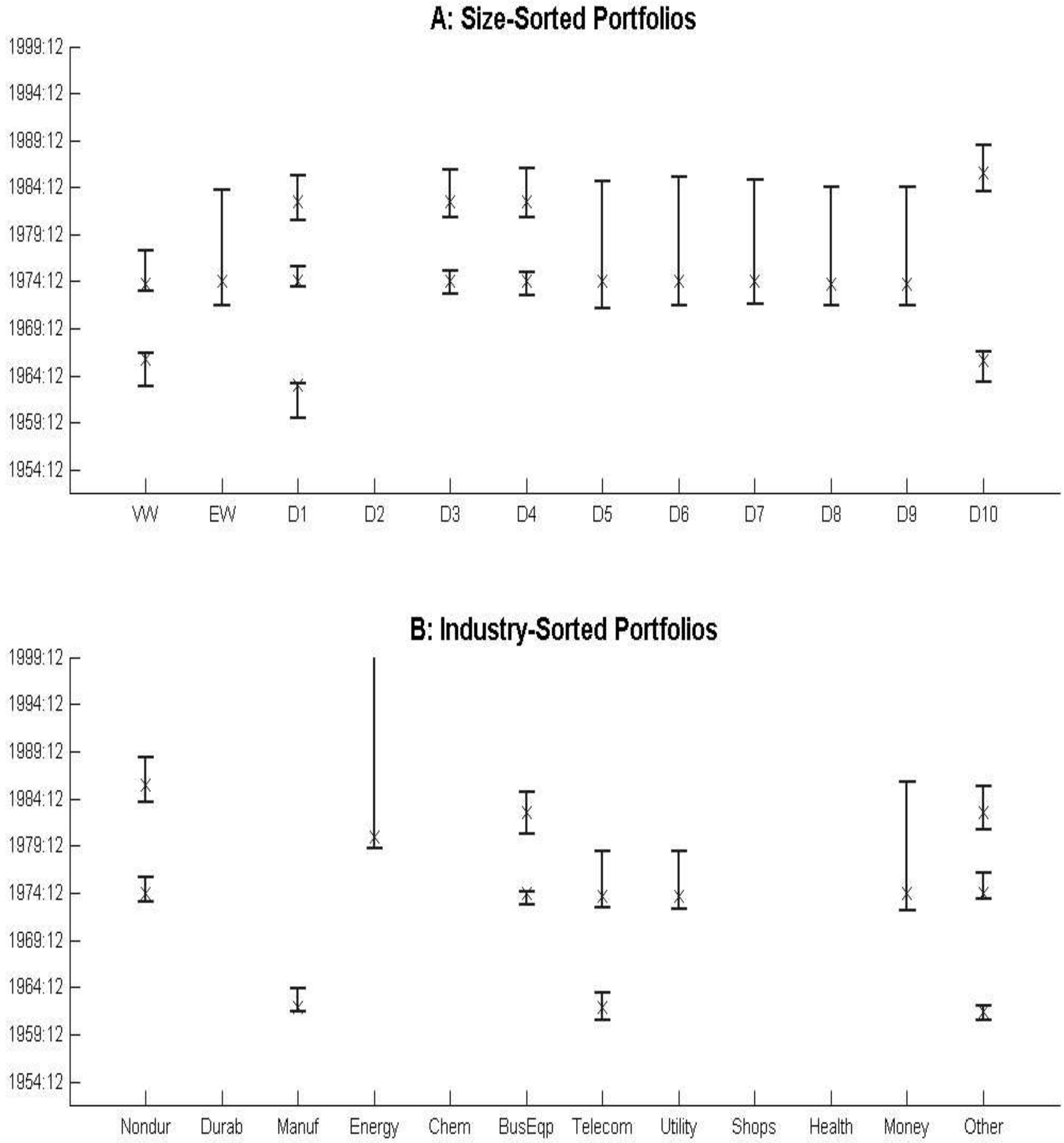


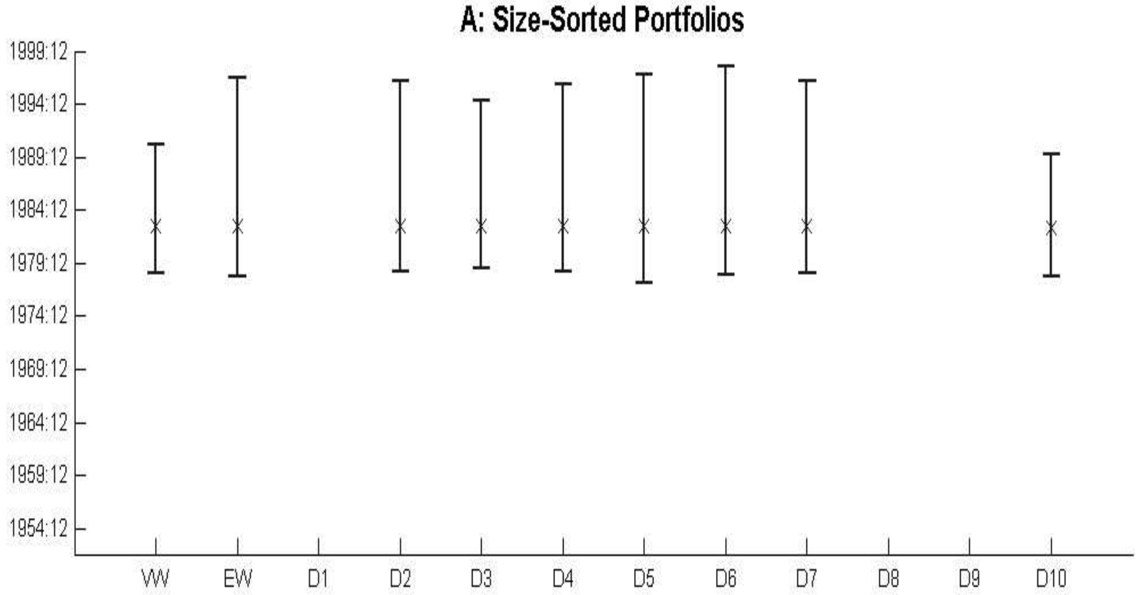
**Figure 3: Breakpoint – Treasury Bill Regressor**

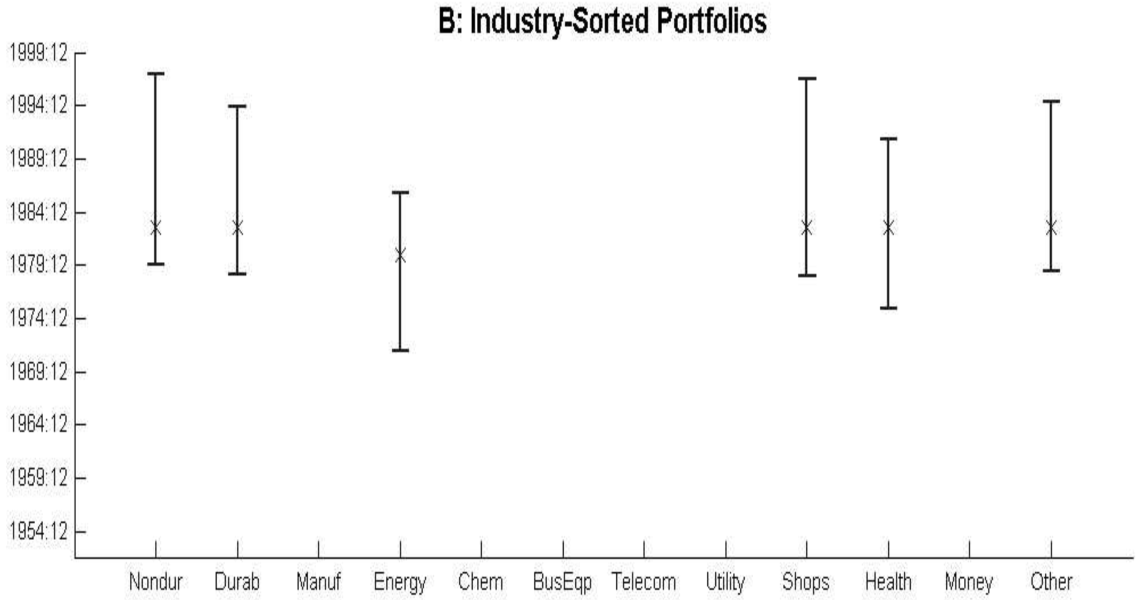
This figure presents the estimated breakpoints (marked by an 'X') and 90% confidence intervals using the sequential breakpoint method of Bai and Perron (1998). The model is estimated for excess returns on value-weighted (VW) and equal-weighted (EW) CRSP portfolios and for cap-based (D1-D10) and industry-based portfolios. The instruments are a constant and the US Treasury Bill rate. The sample is monthly 1952:7 through 1999:12. Panel A presents results for size-sorted portfolios and Panel B presents results for industry-sorted portfolios.



## Figure 4: Breakpoint Dates – Term Spread Regressor

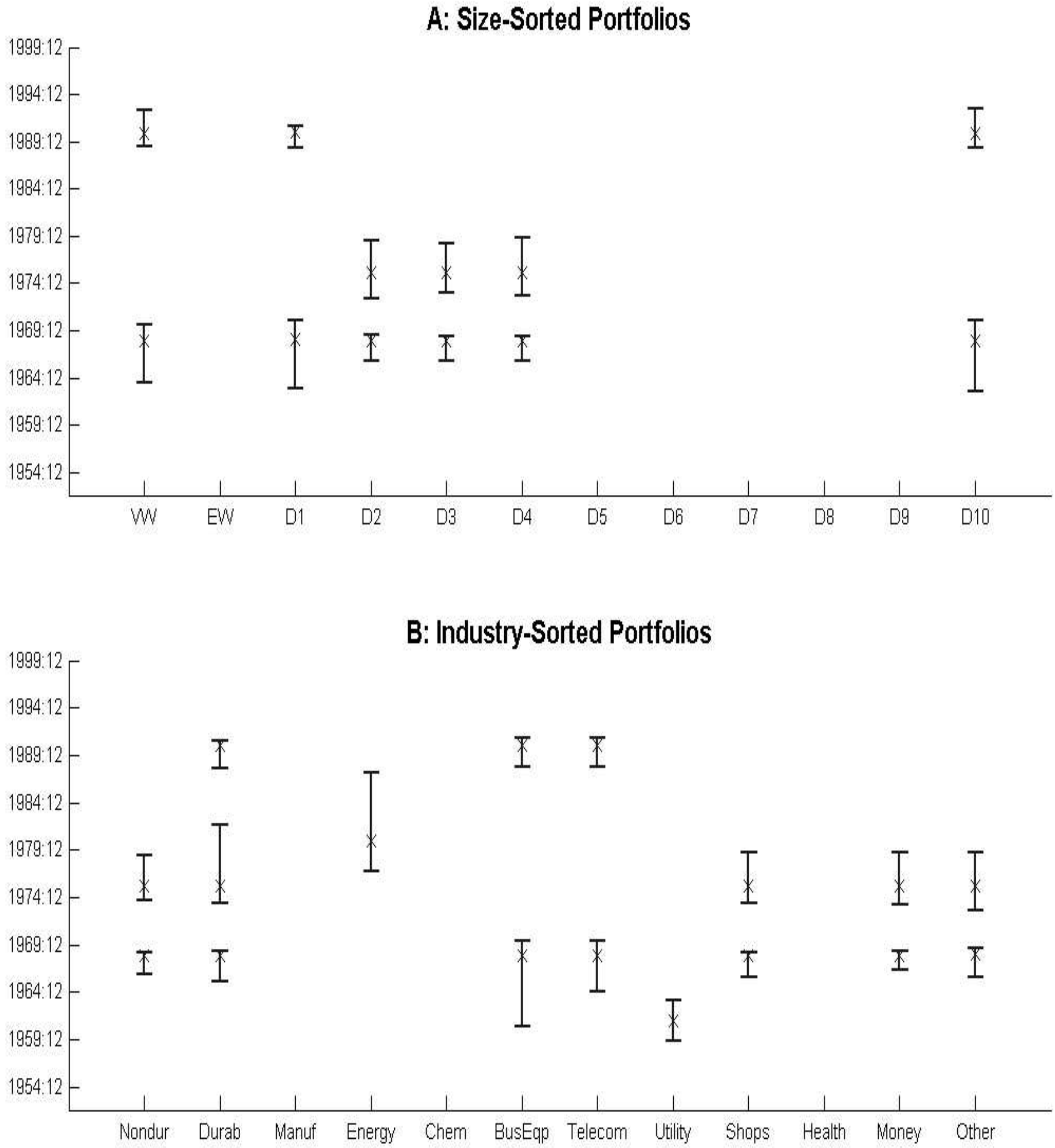
This figure presents the estimated breakpoints (marked by an 'X') and 90% confidence intervals using the sequential breakpoint method of Bai and Perron (1998). The model is estimated for excess returns on value-weighted (VW) and equal-weighted (EW) CRSP portfolios and for cap-based (D1-D10) and industry-based portfolios. The instruments are a constant and the US term spread. The sample is monthly 1952:7 through 1999:12. Panel A presents results for size-sorted portfolios and Panel B presents results for industry-sorted portfolios.



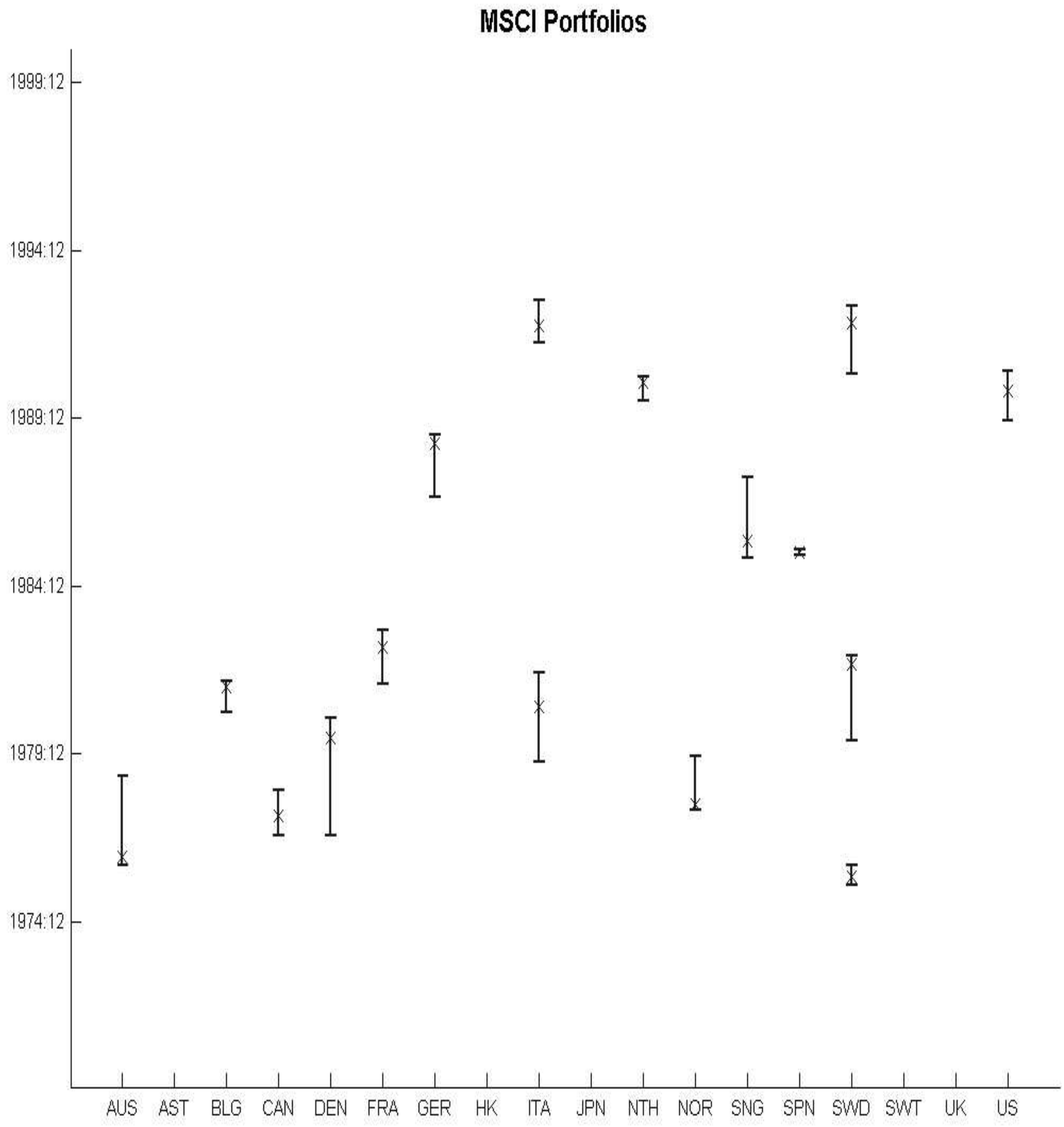
## Figure 5: Breakpoint Dates– Default Premium Regressor

This figure presents the estimated breakpoints (marked by an 'X') and 90% confidence intervals using the sequential breakpoint method of Bai and Perron (1998). The model is estimated for excess returns on value-weighted (VW) and equal-weighted (EW) CRSP portfolios and for cap-based (D1-D10) and industry-based portfolios. The instruments are a constant and the US default premium. The sample is monthly 1952:7 through 1999:12. Panel A presents results for size-sorted portfolios and Panel B presents results for industry-sorted portfolios.



## Figure 6: Breakpoint Dates – International Portfolios (All Regressors)

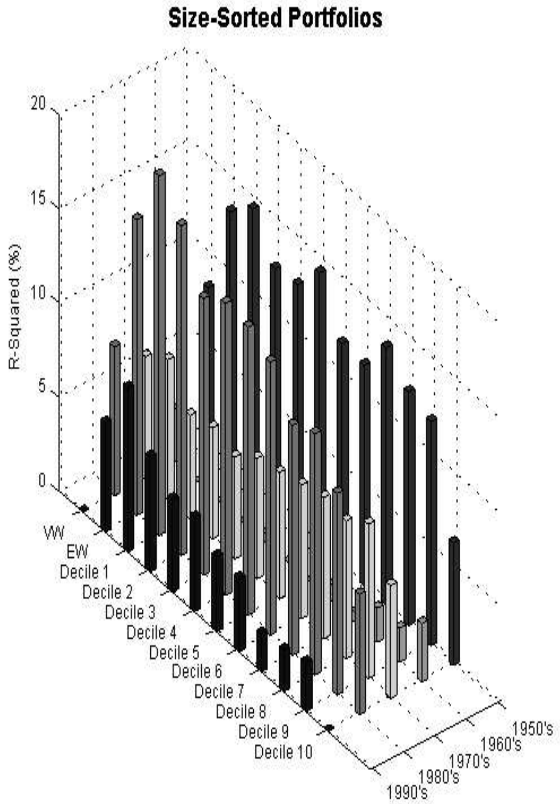
This figure presents the estimated breakpoints (marked with an 'X') and 90% confidence intervals applying the sequential breakpoint method of Bai and Perron (1998) to MSCI portfolios for 18 countries. The model is estimated for returns on the MSCI index for the country and the instruments are a constant, the local dividend yield, a local short term interest rate, the local term spread and the US default premium, all lagged one period. Neither the term spread nor the short term interest rate was available for Hong Kong. The term spread was unavailable for Denmark and Sweden.

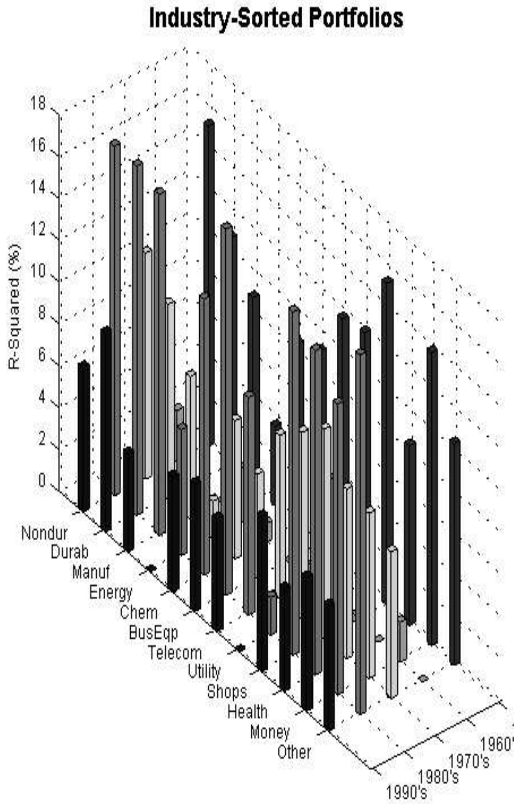


## Figure 7: $R^2$ values by Decade for US Portfolios

### Panel A: Model without Breaks

This figure presents $R^2$ values over each decade from the 1950's to the 1990's based on regressions of US portfolio returns on the full set of predictor variables. The US portfolios include the value-weighted (VW) and equal-weighted (EW) CRSP portfolios as well as size-sorted (D1-D10) and industry-sorted portfolios. See Table 2 for the estimated (full-sample) regression coefficients for each portfolio. The left side of the figure presents these values for US size-sorted portfolios while the right side of the figure presents results for US industry-sorted portfolios. Data for the 1950's begins in 1952:7.



## Figure 7: $R^2$ values by Decade for US Portfolios

## Panel B: Model with Breaks

This figure presents $R^2$ values over each decade from the 1950's to the 1990's for US portfolio returns based on the model selected by the sequential method of Bai and Perron (1998). The US portfolios include the value-weighted (VW) and equal-weighted (EW) CRSP portfolios as well as size-sorted (D1-D10) and industry-sorted portfolios. The estimated breakpoints and confidence interval for each portfolio are presented in Figure 2. The left side of the figure presents these values for US size-sorted portfolios while the right side of the figure presents results for US industry-sorted portfolios. Data for the 1950's begins in 1952:7.

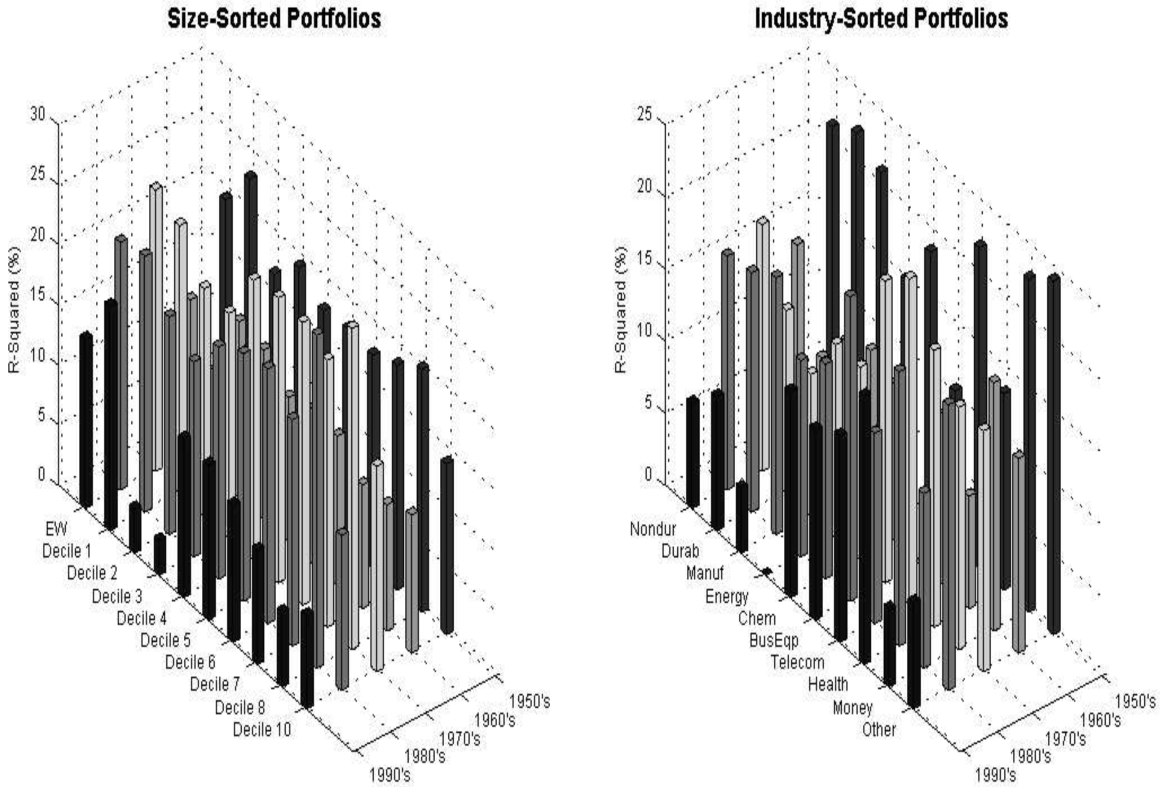
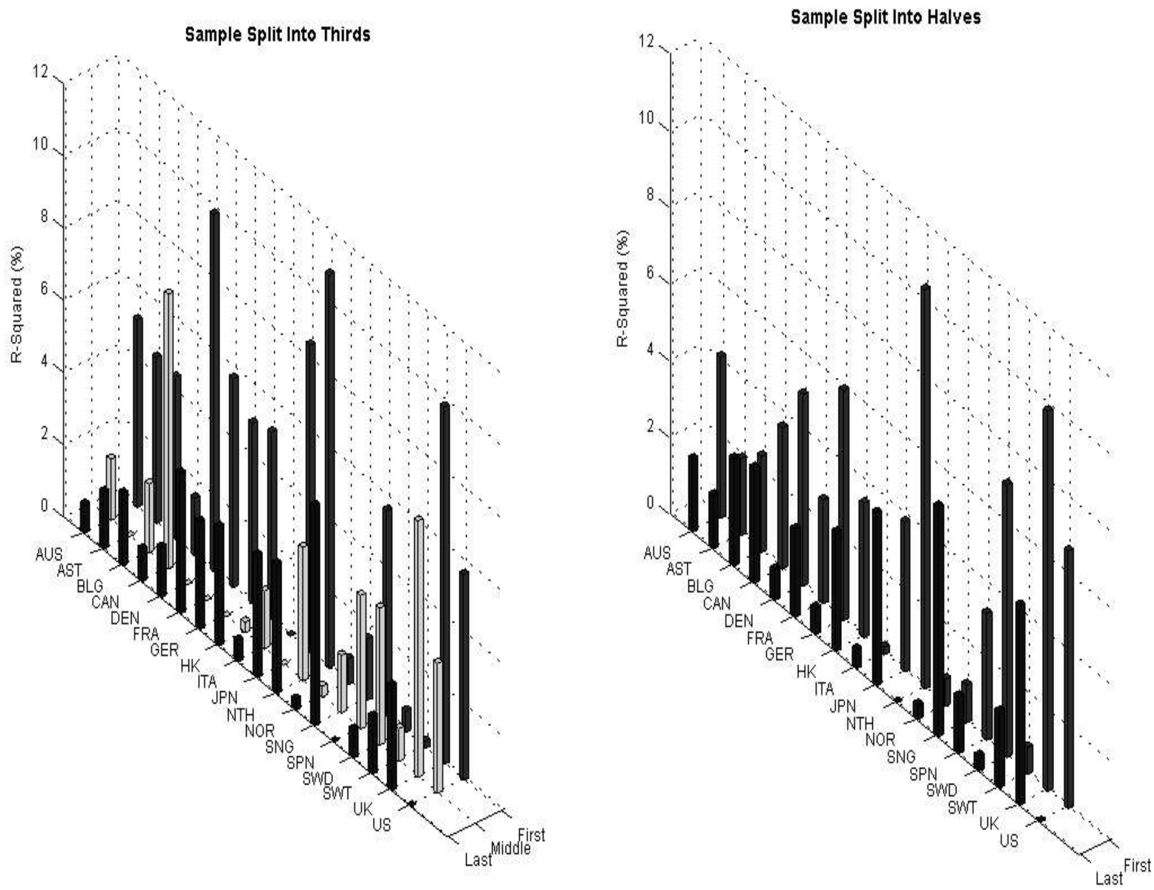


**Figure 8: $R^2$ values by Sample Period for International Portfolios**

**Panel A: Model without Breaks**

This figure presents $R^2$ values over various sub-intervals based on a regression of international portfolio returns on the full set of predictor variables. See Table 10 for the estimated regression coefficients for each country. The left side of the figure divides the total sample period into thirds. The 'last' third represents the most recent third of data for each country, while 'first' represents the earliest third of data. Note that these periods are country-specific in the sense that the sample period varies slightly over the different countries (see Table 9). The right side of the figure breaks the total sample period into halves.



## Figure 8: $R^2$ values by Sample Period for International Portfolios

## Panel B: Model with Breaks

This figure presents $R^2$ values for international portfolios based on the model selected by the sequential method of Bai and Perron (1998). The estimated breakpoints and confidence interval for each country are presented in Figure 6. The left side of the figure divides the total sample period into thirds. The 'last' third represents the most recent third of data for each country, while 'first' represents the earliest third of data. Note that these periods are country-specific in the sense that the sample period varies slightly over the different countries (see Table 9). The right side of the figure breaks the total sample period into halves.