Structural Breaks and Predictive Regression Models of Aggregate U.S. Stock Returns

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Abstract

In this paper, we examine the structural stability of predictive regression models of U.S. quarterly aggregate real stock returns over the postwar era. We consider predictive regressions models of S&P 500 and CRSP equal-weighted real stock returns based on eight financial variables that display predictive ability in the extant literature. We test for structural stability using the popular Andrews (1993) *SupF* statistic and the Bai (1997) subsample procedure in conjunction with the Hansen (2000) heteroskedastic fixed-regressor bootstrap. We also test for structural stability using the recently developed methodologies of Elliott and Müller (2003) and Bai and Perron (1998, 2003a, 2004). We find strong evidence of structural breaks in five of eight bivariate predictive regression models of S&P 500 returns and some evidence of structural breaks in the three other models. There is less evidence of structural instability in bivariate predictive regression models of CRSP equal-weighted returns, with four of eight models displaying some evidence of structural breaks. We also obtain evidence of structural instability in a multivariate predictive regression model of S&P 500 returns When we estimate the predictive regression models over the different regimes defined by structural breaks, we find that the predictive ability of financial variables can vary markedly over time.

JEL classifications: C22, C52, C53, G12

Key words: Predictive regression model; Real stock returns; Structural breaks

1. Introduction

A large literature has identified a number of financial variables that are useful for predicting future stock returns. These include the dividend-price ratio (Rozeff, 1984; Campbell and Shiller, 1988a; Fama and French, 1988b; Hodrick, 1992), price-earnings ratio (Campbell and Shiller, 1988b, 1998), market value-to-net worth ratio or "Fed q" (Smithers and Wright, 2000; Robertson and Wright, 2002), payout (dividends-earnings) ratio (Lamont, 1998), term and default spreads on bonds (Campbell, 1987; Fama and French, 1989), short-term interest rate (Campbell, 1987; Hodrick, 1992; Ang and Bekaert, 2001), and consumption-wealth ratio (Lettau and Ludvigson, 2001). Despite a number of econometric difficulties associated with predictive regression models (Mankiw and Shapiro, 1986; Richardson and Stock, 1989; Stambaugh, 1986, 1999; Nelson and Kim, 1993; Kirby, 1997), the consensus appears to be that stock returns contain a significant predictable component (Campbell, 2000).

Given the popularity of predictive regression models in the extant literature—along with the fact that predictive regression models are typically estimated using relatively long spans of data—an important research topic is the structural stability of the parameters in predictive regression models of stock returns. Structural breaks in the parameters that relate stock returns to state variables can occur for a number of reasons. For example, Pesaran and Timmerman (2002) cite major changes in market sentiment, speculative bubbles, regime changes in monetary policy, changes in debt management policies, and learning by investors as possible sources of instability in predictive regression models. It is quite possible that these types of changes have occurred in the U.S. economy, especially over a period as long as, say, the postwar era.[1] However, the structural stability of predictive regression models of stock returns has received limited attention in the extant literature. Instead of formal tests, structural change is typically addressed by estimating predictive regression models for various subsamples, and some of this informal

[1] See Stock and Watson (1996) for extensive evidence that numerous macroeconomic relationships are unstable over the postwar era.

analysis suggests that the pattern of predictability varies over time.[2] The present paper contributes to the existing literature on stock return predictability by formally testing for structural breaks in a large number of predictive regression models of aggregate U.S. stock returns based on many of the financial variables appearing in the extant literature. More specifically, we use the Andrews (1993) *SupF* statistic in concert with the Hansen (2000) heteroskedastic fixed-regressor bootstrap, as well as the recently developed $\hat{J}$ statistic of Elliott and Müller (2003), to test for a structural break at an unknown date in the parameters of 16 bivariate predictive regression models of aggregate U.S. stock returns for 1953:3-2000:4. We use the eight financial variables listed in the opening paragraph (in turn) as explanatory variables in bivariate predictive regressions models of S&P 500 and CRSP equal-weighted real stock returns. We also use the subsample procedure of Bai (1997) and the recently developed methodology of Bai and Perron (1998, 2003a, 2004) to test for multiple structural breaks at unknown dates in the bivariate predictive regression models. In addition to the bivariate models, we test for structural breaks in multivariate predictive regression models of S&P 500 and CRSP equal-weighted real stock returns, where we select the variables to include in the multivariate models using the Akaike information criterion (AIC) and the Schwarz information criterion (SIC). In our applications, we address a number of econometric issues that are relevant when making inferences concerning structural breaks in predictive regression models of stock returns.[3]

Previewing our results, we find extensive evidence of structural breaks in bivariate predictive

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[2] See, for example, Schwert (2003) and Goyal and Welch (2003). Viceira (1997) and Neely and Weller (2000) are two papers that formally test for structural breaks in predictive regression models of stock returns. Viceira (1997) tests for structural change in a predictive regression model of stock returns based on the dividend-price ratio for the 1926-1995 period, while Neely and Weller (2000) test the structural stability of three VAR models used to predict international equity and foreign exchange market returns over the 1981-1996 period in a re-examination of Bekaert and Hodrick (1992). Viceira (1997) is primarily concerned with deriving theoretical distributions for statistics used to test for structural stability, while Neely and Weller (2000) are primarily concerned with out-of-sample tests of predictability.

[3] In recent independent research, Paye and Timmermann (2005) test for structural breaks in predictive regression models of stock returns for a number of international portfolios. Their predictive regression models are based on four financial variables (dividend-price ratio, short-term interest rate, term spread, and default spread) from the extant literature. In contrast to Paye and Timmermann (2005), we focus on the returns to two broad U.S. market indices and consider a larger number of financial variables from the extant literature, including the price-earnings ratio, Fed q, payout ratio, and consumption-wealth ratio.

regression models of stock returns over the postwar era, especially models of S&P 500 real stock returns. Of the eight bivariate predictive regression models of S&P 500 returns we consider, there is strong evidence of structural instability in five models (based on the dividend-price ratio, Fed q, payout ratio, consumption-wealth ratio, and default spread). By "strong" evidence we mean that the Elliott and Müller (2003) test and either one or both of the Bai (1997) subsampling and Bai and Perron (1998, 2003a, 2004) procedures produce significant evidence of structural instability. There is some evidence of structural breaks in three more predictive regression models of S&P 500 returns (based on the price-earnings ratio, default spread, and nominal interest rate). In these cases, either one or both of the Bai (1997) subsampling and Bai and Perron (1998, 2003a, 2004) procedures generate significant evidence of a structural break, but the Elliott and Müller (2003) test fails to reject the null hypothesis of structural stability. A number of the models appear to have multiple structural breaks, and when we estimate the bivariate predictive regression models over the different regimes defined by the structural breaks, we find that the predictive ability of financial variables can vary markedly over time. For bivariate predictive regression models of CRSP equal-weighted returns, we find less evidence of structural instability, with three (based on the dividend-price ratio, Fed q, and default spread) of the eight models we consider displaying some evidence of a structural break. Again, we find that the predictive power of financial variables can vary markedly over time in the predictive regression models that display some evidence of structural breaks. Overall, our results indicate that structural change is prevalent in bivariate predictive regression models of aggregate stock returns, especially S&P 500 returns.[4] We also obtain evidence of structural instability in a multivariate predictive regression models of S&P 500 returns, where the regressors are selected using the AIC.

The rest of the paper is organized as follows. Section 2 describes the econometric procedures we use to test for structural breaks in predictive regression models of aggregate stock returns and discusses important issues relating to the time-series properties of the regressors appearing in predictive regression

[4] Paye and Timmermann (2005) also find evidence of structural change in predictive regression models of stock returns, thereby providing some corroboration for our results.

models of stock returns. Section 3 describes the data and reports the results of the tests for structural breaks in bivariate and multivariate predictive regression models of S&P 500 and CRSP equal-weighted real returns. Section 4 concludes by summarizing our main findings and suggesting avenues for future research.

2. Econometric Methodology

The bivariate predictive regression model takes the form,

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

where r_t is the log real stock return from period $t-1$ to period t, z_t is a candidate predictor, ε_t is a disturbance term with mean zero and variance σ^2,[5] and $t = 1, \ldots, T$. Using array notation, the predictive regression model can be expressed as

$$r_t = x_{t-1}' \beta + \varepsilon_t , \tag{2}$$

where $x_{t-1} = (1, z_{t-1})'$ and $\beta = (\beta_0, \beta_1)'$. We are interested in testing the structural stability of the regression parameters β_0 and β_1. We consider breaks in both the intercept and slope coefficients of the predictive regression model, as the intercept and slope coefficients both affect the conditional expected stock return, $E(r_t \mid z_{t-1})$. Suppose there is a structural break in the predictive regression model at period k, so that

$$r_t = x_{t-1}' \beta^0 + \varepsilon_t , \; t = 1, \ldots, k , \tag{3}$$

$$r_t = x_{t-1}' (\beta^0 + \delta) + \varepsilon_t , \; t = k+1, \ldots, T , \tag{4}$$

where $\beta^0 = (\beta_0^0, \beta_1^0)'$ and $\delta = (\delta_0, \delta_1)'$. Writing the model with a structural break in matrix notation, we have

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

[5] We assume homoskedasticity in this portion of the paper for ease of exposition. All of the econometric procedures we employ account for potential heteroskedasticity.

where $r = (r_1,..., r_T)'$, $X = (x_0,..., x_{T-1})'$, $X_{0k} = (0,...,0, x_k,..., x_{T-1})'$, and $\varepsilon = (\varepsilon_1,..., \varepsilon_T)'$. If the breakpoint k is known *a priori*, we can use the familiar Chow (1960) procedure to test the null hypothesis of no structural change ($H_0 : \delta = 0$) against the alternative hypothesis of a structural break at period k ($H_1 : \delta \neq 0$). The Chow (1960) test is based on the Wald statistic,

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

where $\hat{\sigma}_k^2 = (\hat{\varepsilon}_k ' \hat{\varepsilon}_k)/(T-4)$, $\hat{\sigma}_R^2 = (\hat{\varepsilon}_R ' \hat{\varepsilon}_R)/(T-2)$, $\hat{\varepsilon}_k$ is the vector of least-squares residuals from equation (5), and $\hat{\varepsilon}_R$ is the vector of least squares residuals from equation (5) with the restriction $\delta = 0$ imposed. Intuitively, we reject the null hypothesis of no structural break if the sum of squared residuals corresponding to the model with no breaks is significantly greater than the sum of squared residuals corresponding to the model with a break at period k.

The key drawback to the Chow (1960) test is that it is not operational if the breakpoint k is unknown, as is likely to be the case in many instances. Indeed, in our applications, we do not necessarily have strong prior beliefs concerning the exact timing of possible breakpoints in predictive regression models of stock returns. Building on Quandt (1960), Andrews (1993) makes the Chow (1960) test operational for the case of an unknown breakpoint. He derives the limiting distribution of the supremum of the F_k statistics over the interval $[\pi T, (1-\pi)T]$, or the test statistic,

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

where π is a trimming parameter (required for the asymptotic distribution theory) that is typically set equal to 0.05, 0.10, or 0.15. Andrews (1993) shows that the limiting distribution of the *SupF* statistic is nonstandard and depends on the trimming parameter π. For a given value of the trimming parameter, the null hypothesis of no structural break can be tested using the asymptotic critical values in Andrews (1993).[6] If the null hypothesis is rejected, the breakpoint can be consistently estimated as

[6] Andrews and Ploberger (1994) develop two variants of the *SupF* statistic—the *AveF* and *ExpF* statistics—that can also be used to test for a structural break at an unknown breakpoint in a regression model. While we focus on the

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

Given the formula for F_k in equation (6), $\hat{k}$ will coincide with the value of k corresponding to the *SupF* statistic in equation (7) (Bai, 1997). In Section 3 below, we use the *SupF* statistic to test the structural stability of sixteen bivariate predictive regression models of real stock returns. Following the recommendation of Andrews (1993), we set the trimming parameter π equal to 0.15.

Nonstationarities in the regressors are a potential problem when testing for structural breaks in regression models using the Andrews (1993) *SupF* statistic. Hansen (2000) shows that the limiting distribution derived by Andrews (1993) for the *SupF* statistic does not apply in the presence of a variety of nonstationarities in the regressors, including mean and variance breaks and unit roots. As observed by Hansen (2000), this means that the *SupF* statistic and the asymptotic distribution in Andrews (1993) cannot distinguish between structural breaks in the conditional distribution of the regressand—the parameters of the regression model—and the marginal distribution of the regressors. This is important, as researchers are typically interested in breaks in the former distribution, as we are in the present paper. The problem identified by Hansen (200) is relevant for predictive regression models of stock returns, as nonstationarities may characterize the financial variables appearing as regressors in predictive regression models of stock returns; for example, valuation ratios appear to be quite persistent, so that they may have a unit root.[7] Hansen (2000) develops a heteroskedastic fixed-regressor bootstrap procedure that delivers the correct asymptotic distribution for the *SupF* statistic in the presence of general nonstationarities in the regressors, including mean and variance breaks and unit roots.[8] He finds that this bootstrap procedure has good size properties in finite samples in Monte Carlo simulations, and we rely on the Hansen (2000)

SupF statistic, results obtained using these other statistics are generally similar to those reported for the *SupF* statistic in Section 3 below.

[7] Focusing on persistent regressors, Wright (1996) and Viceira (1997) show that the asymptotic distribution of the *SupF* statistic differs from the asymptotic distribution in Andrews (1993) when a regressor is nearly integrated, which they model by assuming that the regressor has a root that is local-to-unity (Elliott and Stock, 1994; Cavanaugh, Elliott, and Stock, 1995). Also see Valkanov (2003) and Torous, Valkanov, and Yan (2004) on predictive regression tests in the presence of nearly integrated regressors.

[8] The Hansen (2000) heteroskedastic fixed-regressor bootstrap allows for heteroskedasticity in the disturbance term of the predictive regression model.

heteroskedastioc fixed-regressor bootstrap procedure to make inferences for the *SupF* statistic in Section 3 below. This allows us to test for breaks in the parameters of the predictive regression model, even in the presence of nonstationarities in the marginal distribution of the regressors.[9]

While the Andrews test is primarily designed to test for a single structural break, multiple breaks may exist. Bai (1997) develops a subsample procedure utilizing the *SupF* statistic that is designed to detect and locate multiple structural breaks in a regression model. The Bai (1997) subsample methodology, which we augment with the Hansen (2000) heteroskedastic fixed-regressor bootstrap, proceeds as follows. First, we test for a structural break using the *SupF* statistic and the fixed-regressor bootstrap for the full sample of data. If there is significant evidence of a structural break over the full sample according to the *SupF* statistic and the fixed-regressor bootstrap, we then calculate the *SupF* statistic for each of the two subsamples defined by the full-sample breakpoint. If we fail to find evidence of a structural break using the *SupF* statistic and fixed-regressor bootstrap for each of the two subsamples, we conclude that there is a single break. If there is significant evidence of a structural break in either of the two subsamples, we compute the *SupF* statistic for each of the new subsamples defined by the new breakpoint. We proceed in this manner until all of the subsamples defined by any significant breakpoint have insignificant *SupF* statistics.[10] When the subsample procedure identifies multiple structural breaks, the breakpoints can be re-estimated using the refinement in Bai (1997). Under the refinement, a breakpoint should be re-estimated if it was originally estimated using a sample with more than one significant break; see Bai (1997, p. 557) for details.

While Andrews (1993) shows that the *SupF* statistic is consistent against the alternative hypothesis of multiple structural breaks, Bai (1997) observes that the *SupF* statistic can have low power in the presence of multiple breaks in finite samples, and this is confirmed by Bai and Perron (2004) in extensive Monte Carlo simulations. Low power can result because $\hat{\sigma}_k^2$ underestimates σ_k^2 in equation (6)

[9] We implement the heteroskedastic fixed-regressor bootstrap using the GAUSS program available from Bruce E. Hansen's web page at http://www.ssc.wisc.edu/~bhansen/.

[10] In our applications of the Bai (1997) subsample procedure in Section 3 below, we impose the restriction that the minimum length of any regime is 15% of the full sample. This makes our applications of the Bai (1997) subsample procedure consistent with our applications of the Bai and Perron (1998, 2003a, 2004) methodology described below.

when there are multiple breaks, thereby inducing a downward bias in the *SupF* statistic. In order to address this, Bai (1997) proposes applying the *SupF* statistic to the two subsamples defined by the estimated breakpoint using the full sample, even if the *SupF* statistic cannot reject the null hypothesis of no structural break for the full sample. If there are multiple breaks, they are more likely to be apparent in the subsample analysis, and the breakpoint estimated for the full sample often turns out to be significant for a subsequent subsample. If the *SupF* statistics for the full sample and the first two subsamples are all insignificant based on the fixed-regressor bootstrap, we take this as evidence against any structural breaks.

We also use the recently developed methodology of Bai and Perron (1998, 2003a, 2004; hereafter, BP) to test for multiple structural breaks in the predictive regression models. BP (1998) develop a methodology explicitly designed for estimating and testing regression models with multiple structural breaks. Consider the predictive regression model with *m* breaks ($m+1$ regimes),

$$r_t = z_{t-1}^{'}\beta^j + \varepsilon_t\,,\; t = T_{j-1}+1,\ldots,T_j\,, \tag{9}$$

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

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

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

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

where the set of admissable *m*-partitions is subject to a set of restrictions given below. From equation

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

BP (1998) consider testing procedures aimed at identifying the number of structural breaks (*m*) in equation (9). They begin by testing the null hypothesis of no structural breaks against the alternative of $m = b$ breaks. Let $(T_1,...,T_b)$ be a partition such that $T_i = [T\lambda_i]$ ($i = 1,...,b$). Also define R such that $(R\beta)' = (\beta^{1'} - \beta^{2'},...,\beta^{b'} - \beta^{b+1'})$. BP (1998) specify the following statistic:

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

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

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

where $\hat{\lambda}_1,...,\hat{\lambda}_b$ minimize the global sum of squared residuals, $S_T(T\lambda_1,...,T\lambda_b)$, under the restriction that $(\hat{\lambda}_1,...,\hat{\lambda}_b) \in \Lambda_\pi$, where $\Lambda_\pi = \{(\lambda_1,...,\lambda_b); |\lambda_{i+1} - \lambda_i| \geq \pi, \lambda_1 \geq \pi, \lambda_b \leq 1-\pi\}$ for some arbitrary positive number π (the trimming parameter). BP (1998) develop two statistics, what they call the "double maximum" statistics, for testing the null hypothesis of no structural breaks against the alternative hypothesis of an unknown number of breaks given an upper bound *M*. The first double maximum statistic is given by

$$UDmax = \max_{1 \leq m \leq M} SupF_T(m)\,. \tag{14}$$

The second double maximum statistic, *WDmax*, applies different weights to the individual $SupF_T(m)$ statistics so that the marginal *p*-values are equal across values of *m*; see BP (1998, p. 59) for details.

Finally, BP (1998) develop what they label the $SupF_T(l+1|l)$ statistic to test the null hypothesis of *l* breaks against the alternative hypothesis of $l+1$ breaks. It begins with the global minimized sum of squared residuals for a model with *l* breaks. Each of the intervals defined by the *l* breaks is then analyzed for an additional structural break. From all of the intervals, the partition allowing for an additional break that results in the largest reduction in the sum of squared residuals is treated as the model with $l+1$ breaks. The $SupF_T(l+1|l)$ statistic is used to test whether the additional break leads to a significant reduction in the sum of squared residuals. BP (1998, 2003b) derive asymptotic distributions for the double maximum and $SupF_T(l+1|l)$ statistics and provide critical values for various values of π and *M*.

A nice feature of the BP methodology is that it allows for quite general specifications when computing test statistics and confidence intervals for the break dates and regression coefficients. These specifications include autocorrelation in the regression model residuals, heteroskedasticity in the residuals, and different moment matrices for the regressors in the different regimes. The latter two specifications are potentially important for our applications, and we allow for heteroskedasticity in the residuals and different moment matrices for the regressors in our applications. Serial correlation in the residuals is less relevant for our applications, as our quarterly real stock return data exhibit little serial correlation (see Section 3 below). Using the notation of BP (2004), we set *cor_u* = 0, *het_u* = 1, and *het_z* = 1 in our applications of the BP methodology in Section 3 below.[11]

BP (1998) discuss sequential application of the $SupF_T(l+1|l)$ statistics—a specific-to-general modeling strategy—as a way to determine the number of structural breaks. We call this the BP sequential procedure. The first step is to examine the $SupF_T(1|0)$ statistic. If this statistic is insignificant, we conclude that there are no structural breaks. If the $SupF_T(1|0)$ statistic is significant, we then examine the $SupF_T(2|1)$ statistic. If the $SupF_T(2|1)$ statistic is insignificant, we conclude that there is a single structural break. If the $SupF_T(2|1)$ statistic is significant, we proceed to examine the $SupF_T(3|2)$ statistic and

[11] We implement the BP methodology using the GAUSS program available from Pierre Perron's web page at http://econ.bu.edu/perron/.

continue in a similar manner. In extensive Monte Carlo simulations, BP (2004) find that this procedure performs well in a number of circumstances. We consider the BP sequential procedure in our applications in Section 3 below.

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

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

$$x_t = \alpha_0 + \alpha_1 x_{t-1} + u_t \,. \tag{15}$$

They find that the *UDmax* statistic, as well as the *SupF* statistics based on the fixed-regressor bootstrap, can exhibit considerable size distortions in situations where x_t is highly persistent (α near unity) and the disturbance terms in equations (1) and (15) (ε_t and u_t) are strongly correlated. This is likely to be the case when x_t is a valuation ratio such as the dividend-price or price-earnings ratio. Paye and Timmermann (2005) find that a recently developed statistic by Elliott and Müller (2003) has relatively good size properties when x_t is highly persistent and the disturbance terms in equations (1) and (15) are strongly correlated. Elliott and Müller (2003) use what they term the $\hat{J}$ statistic to test the null hypothesis that $\beta_t = 0 \forall t$, where $\beta = (\bar{\beta} + \beta_t)$ in equation (2), against the alternative hypothesis that $\beta_t \neq 0$ for some $t > 1$. Details on the computation of the $\hat{J}$ statistic are given in Steps 1-6 of Elliott and Müller (2003, p. 12), and they provide asymptotic critical values in their Table 1. We include the Elliott and Müller (2003) $\hat{J}$ statistic in our analysis as a robustness check that guards against potential size distortions in our other tests, especially when x_t in equation (1) is the dividend-price or price-earnings ratio. Paye and Timmermann (2005) show that the $\hat{J}$ statistic tends to be less powerful than the other statistics we consider. This presents a challenge in situations where we reject the null hypothesis of no structural breaks using the *UDmax* or *SupF* statistic but fail to reject the null hypothesis using the $\hat{J}$ statistic, as we cannot be sure whether this is due to the spurious detection of breaks by the *UDmax* or *SupF* statistic or a lack of power on the part of the $\hat{J}$ statistic.

3. Empirical Results

Our data contain quarterly observations for 1953:2-2000:4. We have two measures of real stock returns that we use as the dependent variable in equation (1): log real returns on the S&P 500 index and log real returns on the CRSP equal-weighted index. The financial variables we use as explanatory variables in equation (1) all appear in the extant literature and have been found to have predictive power for stock returns. They are the dividend-price ratio,[12] price-earnings ratio for the S&P 500 index, market value-to-net worth ratio (Fed q),[13] payout ratio, consumption-wealth ratio (denoted by *cay*),[14] term spread, default spread, and

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[12] We use two dividend-price ratios, one corresponding to S&P 500 returns and the other to CRSP equal-weighted returns. For CRSP equal-weighted returns, price and dividend series are derived from CRSP equal-weighted returns with and without dividends.

[13] The Fed q data are described in Smithers and Wright (2000) and Robertson and Wright (2002). The quarterly data we use are available at http://www.valuingwallstreet.com/updates.html. We thank Eric Zivot for making us aware of the Fed q.

[14] The *cay* data are available from Martin Lettau's web page at http://www.stern.nyu.edu/~mlettau/index.htm.

short-term interest rate (short rate). Following most of the extant literature, we use the natural logarithm of the dividend-price ratio, price-earnings ratio, Fed q, and payout ratio. The consumption-wealth ratio is from Lettau and Ludvigson (2001, 2004) and is calculated as $cay = c - 0.2985a - 0.597y$, where c is real per-capita consumption of nondurables and services, a is financial wealth, and y is labor income, all measured in natural logarithms. The coefficients are based on the estimated cointegrating vector in Lettau and Ludvigson (2004).[15] The term spread is the difference between the interest rate on a 10-year Treasury bond and a 3-month Treasury bill. The default spread is the difference between Moody's seasoned Baa and Aaa corporate bond yields. The short rate is the 3-month Treasury bill rate. The two returns and the financial variables are plotted in Figure 1.

Table 1 reports descriptive statistics for all variables, including the mean, standard deviation, and first- through fourth-order autocorrelations. It is clear from Table 1 that S&P 500 and CRSP equal-weighted log real returns are highly volatile. They also appear very close to being serially independent processes, as any persistent component in returns is dominated by the short-term volatility in returns.[16] In contrast, the valuation ratios we consider (dividend-price ratio, price-earnings ratio, and Fed q) all display considerable persistence, with the autocorrelations decaying more slowly over time. A similar pattern holds for the payout ratio and short rate. The other financial variables we consider (*cay*, term spread, and default spread) appear to be intermediate cases. According to the autocorrelation functions, they exhibit more persistence than the two real stock return series, but they are typically less persistent than the valuation ratios, payout ratio, and short rate.

3.1. S&P 500 Log Real Returns

Estimation results for equation (1) with S&P 500 log real returns serving as the regressand are

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[15] We do not account for the estimation uncertainty regarding the cointegrating vector due to the super-consistency of the cointegrating vector estimate.

[16] The autocorrelations are insignificant using standard tests. Fama and French (1988a) find evidence of some persistence in monthly real stock returns.

reported in Table 2. Each of the eight financial variables appear in turn as the explanatory variable.[17] After allowing for the lagged regressor, the sample period is 1953:3-2000:4, resulting in a sample of 190 usable observations. The coefficient estimates and their standard errors are reported in columns (2) and (3) of Table 2. The slope coefficients in column (3) all have their hypothesized sign, as the price-earnings ratio, Fed q, and short rate have a negative sign, while the dividend-price ratio, payout ratio, *cay*, term spread, and default spread have a positive sign. Using one-sided tests and the 10% significance level, the slope coefficient is significant for the Fed q, *cay*, term spread, default spread, and short rate.[18] As is common in the literature, the R^2 statistics in column (4) show that even when a financial variable has a significant effect on future stock returns, the predictable component in stock returns tends to be relatively small. Nevertheless, as shown by, for example, Kandel and Stambaugh (1996), even a small predictable component in stock returns can have important implications for asset-allocation decisions. We next proceed to test for structural breaks in these predictive regression models.

Andrews (1993) *SupF* statistics for testing the null hypothesis of no structural change are reported in column (5). As indicated in Section 2 above, we use 15% trimming and generate *p*-values using the Hansen (2000) heteroskedastic fixed-regressor bootstrap. There is no evidence of structural change at conventional significance levels (that is, the 10% level or less) in the bivariate predictive regression models based on the price-earnings ratio, Fed q, and default spread. In contrast, the null hypothesis of no structural change is rejected when the dividend-price ratio, payout ratio, *cay*, term spread, and short rate are used as predictors. The endogenously selected breakpoints are reported in column (6). For the dividend-price ratio, the breakpoint occurs relatively late in the sample (1990:3), while the breakpoints for the payout ratio, *cay*, term

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

[18] Given that the observations for the regressand are not overlapping, as well as the small autocorrelations for both real stock returns in Table 1, serial correlation is not relevant when computing standard errors. Using standard errors that are robust to heteroskedasticity has little effect on inferences in column (2). (Also note that there is no evidence of conditional heteroskedasticity in the residuals of the predictive regressions models.) In order to control for the finite-sample biases pointed out by Mankiw and Shapiro (1986) and Stambaugh (1986, 1999) in predictive regression models, we also computed *p*-values for the slope coefficients using a bootstrap procedure similar to those in Mark (1995), Kilian (1999), and Stambaugh (1999). Inferences are similar to those discussed in the text.

spread, and short rate all occur in the mid-1970s. Column (7) of Table 2 reports the Elliott and Müller (2003) $\hat{J}$ statistics, and we are able to reject the null hypothesis of structural stability in five of the eight predictive regression models (dividend-price ratio, Fed q, payout ratio, *cay*, and default spread). In Table 2, both the *SupF* and $\hat{J}$ statistics provide evidence of structural breaks in the three predictive regression models based on the dividend-price ratio, payout ratio, and *cay*. There is evidence of structural breaks according to the *SupF*, but not the $\hat{J}$ statistic, in predictive regression models based on the term spread and short rate, while there is evidence of breaks according to the $\hat{J}$ statistic, but not the *SupF* statistic, for predictive regression models based on the dividend-price ratio and default spread.[19] Finally, we report the Rossi (2005) QLR_T^* statistic for each bivariate predictive regression model in column (8) of Table 2. This statistic is designed to be optimal for testing the joint null hypothesis that β_0 and β_1 are constant over time and equal to zero in equation (1), so that it is a test of no predictability over the entire sample. The null hypothesis is easily rejected for all of the predictive regression models.

In order to test for multiple structural breaks in the predictive regression models, we first employ the Bai (1997) subsample procedure, and the results are reported in Table 3. The Bai (1997) subsample procedure indicates a single significant break for the dividend-price ratio, *cay*, and term spread, so that there are no breaks in addition to those reported in Table 2 for these variables. For both the payout ratio and short rate, the Bai (1997) subsample procedure in Table 3 detects a significant break in 1962:3, in addition to the significant break in 1974:3 reported in Table 2. While there is no evidence of a structural break for the price-earnings ratio, Fed q, and default spread in Table 2, there is evidence of multiple breaks for these variables in Table 3 according to the Bai (1997) subsample procedure. As discussed above, this is likely due to the potentially low power of the *SupF* statistic when applied to the full sample in the presence of multiple breaks. The Bai (1997) subsample procedure indicates two breaks for the price-earnings ratio (1972:4 and 1982:2), three breaks for

[19] We also calculated *p*-values for the *SupF* statistic using a bootstrap procedure similar to those in Mark (1995), Kilian (1999), and Stambaugh (1999). The bootstrap procedure does not impose the restriction that the slope coefficient equals zero in equation (1) for the data-generating process, as in Mark (1995), Kilian (1999), and Stambaught (1999), but only that the slope coefficient is constant, in line with our null hypothesis. These bootstrap *p*-values generally deliver the same inferences as those for the fixed-regressor bootstrap.

the Fed q (1962:3, 1973:3, and 1984:2), and two breaks for the default spread (1968:2 and 1975:2).

We next employ the BP methodology in order to test for multiple structural breaks, and the results are reported in Table 4. Using the $SupF_T(l+1|l)$ statistics and the BP sequential procedure, there is evidence of a single structural break for the dividend-price ratio, payout ratio, term spread, and short rate, as the $SupF_T(1|0)$ statistic is significant, while the $SupF_T(2|1)$ statistic is insignificant, for these four variables. The $SupF_T(1|0)$ is insignificant for the other four variables, indicating no structural breaks according to the BP sequential procedure. Given that the sequential procedure can have low power in the presence of multiple breaks, we also consider the BP double maximum procedure, following the recommendation of BP (2004). In agreement with the BP sequential procedure results, neither the *UDmax* nor any of the *WDmax* statistics is significant for *cay*, indicating no breaks. For the dividend-price ratio, payout ratio, term spread, and short rate, the *UDmax* statistic and at least two of the *WDmax* statistics are significant, while the only significant $SupF_T(l+1|l)$ statistic is $SupF_T(1|0)$, indicating a single structural break and again confirming the BP sequential procedure results. While the BP sequential procedure indicates no structural breaks for the price-earnings ratio, Fed q, and default spread, the *UDmax* and/or at least one of the *WDmax* statistics are significant. For each of these three variables, the $SupF_T(2|1)$ statistic is significant, indicating two structural breaks. Note that the Bai (1997) subsample and BP double maximum procedures both indicate a single break for the dividend-price ratio and term spread and two breaks for the price-earnings ratio and default spread. In some cases, the Bai (1997) subsample procedure detects one more break than the BP double maximum procedure: one break versus zero breaks for *cay*; two breaks versus one break for the payout ratio and short rate; and three breaks versus two breaks for the Fed q.[20]

Summarizing the results in Tables 2-4, we have strong evidence of structural breaks in bivariate predictive regression models of S&P 500 returns based on the dividend-price ratio, Fed q, payout ratio, *cay*,

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[20] We also used the BP methodology to test for parameter instability in the slope coefficient alone in equation (1). We tend to find the same number of breaks as when we allow for structural breaks in both the intercept and slope coefficients. This indicates that breaks in the slope coefficients are important. The complete results are available at http://pages.slu.edu/faculty/rapachde/Research.htm.

and default spread. For these predictors, the $\hat{J}$ statistic is significant, and the Bai (1997) subsampling and/or BP double maximum procedures also provide significant evidence of one or more breaks. There is more limited evidence of structural breaks in bivariate predictive regression models based on the price-earnings ratio, term spread, and short rate, with the Bai (1997) subsampling and BP double maximum procedures, but not the $\hat{J}$ statistic, offering significant evidence of one or more breaks. There is at least some evidence of structural breaks in all eight bivariate predictive regression models of S&P 500 returns.

Table 5 reports multiple regime bivariate predictive regression model estimation results for models based on each of the eight predictors. With the exception of *cay*, the number of breaks is selected according to the BP double maximum procedure, and the breakpoints correspond to the global minimizers in equation (11).[21] For the dividend-price ratio, the slope coefficient is almost three times smaller as we move from the first regime, which ends in 1990:3, to the second regime, so that the predictive power of the dividend-price ratio is substantially reduced over the last decade of the full sample. The 1990:3 break date corresponds to the first Gulf War and an increase in oil prices, as well the beginning of a recession in the U.S. Turning to the price-earnings ratio, it is interesting to note that the slope coefficient is significant in each of the three regimes, while it is insignificant over the full sample. The first regime ends in 1972:4, and the slope coefficient grows (in absolute value) as we move from the first to the second regime, but becomes smaller in the last regime that begins in 1982:3. The upper limit of the 90% confidence interval for the first break is 1973:4, so this break may correspond to the OPEC oil price shock, and the second break in 1982:3 occurs near the end of the Fed's period of monetary targeting. For the Fed q, the slope coefficient is significant in each regime and again grows (in absolute value) as we move from the first to the second regime, which begins in 1972:4, and decreases as we move from the second to third regime, which begins in 1990:3. It is interesting to note that for both the price-earnings ratio and Fed q, the second regime (which begins in 1973:1 for both variables and is near the OPEC oil price shock) has the highest R^2 statistic, indicating that these middle regimes were times of

[21] For *cay*, we allow for the single break selected by the Bai (1997) subsample procedure (the $\hat{J}$ statistic is also significant), even though the BP double maximum procedure detects no significant break.

relatively strong predictive ability for these variables. The second break date for the Fed q in 1990:3 matches the break date for the dividend-price ratio and corresponds to the first Gulf War and start of a U.S. recession.

With respect to the payout ratio, its predictive power is quite different in each of the two regimes defined by the single break. In the first regime, the payout ratio has a slope coefficient of 23.93 and an R^2 statistic of 0.16, indicating a fairly sizable degree of predictive ability for the payout ratio with respect to S&P 500 returns over the first regime. However, the slope coefficient decreases to 0.05 in the second regime, which begins in 1974:3 and corresponds to the OPEC oil price shock, and the R^2 statistic falls to essentially zero, so that the predictive ability of the payout ratio essentially disappears during the second regime. A similar pattern holds for *cay*, the term spread, and short rate: there is considerable predictive ability over the first regime, which ends in the mid-1970s around the time of the OPEC oil price shock, but a marked decrease in predictive ability during the second regime. Finally, the default spread exhibits some predictive ability during the first regime ending in 1967:3 and strong predictive ability during the second regime ending in 1975:2, and any predictive ability essentially disappears during the third regime. The second break date in 1975:2 is close to breaks occurring in the mid-1970s for the price-earnings ratio, Fed q, payout ratio, *cay*, term spread, and short rate.[22]

Overall, the estimation results in Table 5 show that the predictive ability of many financial variables from the extant literature varies considerably over time, indicating that failure to account for structural breaks in predictive regression models of S&P 500 returns can lead one to substantially overestimate or underestimate predictive ability during certain periods. Note that a number of variables exhibit structural breaks during the mid-1970s. This is not too surprising, as this was a volatile period for the U.S. economy marked by the OPEC oil price shock. It is also interesting to observe that the mid-1970s signals the start of a regime with relatively strong predictive ability for the price-earnings ratio and Fed q; however, the mid-1970s

[22] Recall that the evidence of a structural break for *cay* is somewhat limited, as neither of the BP procedures indicates a break. This is reinforced by the 90% confidence interval for the endpoint of the first regime in Table 5, which is very wide (just under 20 years). Also note that the confidence intervals for the break dates occurring in the mid-1970s are quite wide for the payout ratio and term spread, with the confidence intervals spanning more than a decade. There is thus substantial uncertainty surrounding the exact timing of some breaks in Table 5.

marks the beginning of a period with very weak predictive ability for the payout ratio, *cay*, term spread, default spread, and short rate.

3.2. Multivariate Models of S&P 500 Log Real Returns

In this section, we investigate the stability of multivariate predictive regression models of S&P 500 log real returns. A difficulty with multivariate predictive regression models of stock returns is selecting the predictors to include in the model. We specify multivariate predictive regression models using the AIC and SIC, with all eight of the individual financial variables analyzed in the previous section considered as potential predictors.[23] The AIC selects six variables—dividend-price ratio, price-earnings ratio, Fed q, *cay*, default spread, and short rate—to include in the multivariate predictive regression model, and the estimation results for this model and the full sample are reported in Panel A of Table 6. Each of the six financial variables enters significantly in the multivariate predictive regression model, and the R^2 statistic is a fairly sizable 0.18. While the *SupF* statistic based on the heteroskedastic fixed-regressor bootstrap is not significant, the $\hat{J}$ statistic is significant at the 10% level, indicating structural instability in the multivariate model selected by the AIC. Not surprisingly, the SIC selects a more parsimonious model that includes *cay*, the default spread, and short rate. From Panel B of Table 6, we see that each of these financial variables enters the model significantly, and the R^2 statistic is 0.15. Neither the *SupF* nor $\hat{J}$ statistic is significant, so there is no evidence in Table 6 of a structural break in the multivariate model selected by the SIC.[24]

Bai (1997) subsample analysis results designed to test for multiple structural breaks in the multivariate models selected by the AIC and SIC are reported in Table 7, and there is no significant evidence of structural breaks. Test results based on the BP methodology are reported in Table 8. Using the

[23] We obtain similar results when we use the general-to-specific procedure studied by Clark (2004), which is similar to the procedures analyzed in Hoover and Perez (1999), to select the financial variables to include in the multivariate predictive regression model. It would be interesting in future research to consider Bayesian model selection methods, as in Avramov (2002). These could be combined with Bayesian methods for analyzing structural breaks like those used in Wang and Zivot (2000).

[24] Both of the QLR_T^* statistics are significant at the 1% level in Table 6.

$SupF_T(l+1|l)$ statistics and the BP sequential procedure, we find evidence of a single structural break for the model selected by the AIC, as the $SupF_T(1|0)$ statistic is significant, while the $SupF_T(2|1)$ statistic is insignificant. The BP sequential procedure does not detect any breaks for the model selected by the SIC. Similar to the BP sequential procedure, the BP double maximum procedure indicates a single break for the model selected by the AIC, as the *UDmax* and all three *WDmax* statistics are significant, and the $SupF_T(1|0)$ is the only significant $SupF_T(l+1|l)$ statistic. The *UDmax* and all of the *WDmax* and statistics are insignificant for the model selected by the SIC. Overall, there is strong evidence of a single structural break in the multivariate model selected by the AIC, with the $\hat{J}$ statistic and BP procedures providing significant evidence of a structural instability. We find no evidence of a structural break in the multivariate model selected by the SIC. Table 9 presents estimation results for the multivariate regression model selected by the AIC over the two regimes defined by the structural break dated by the BP global minimizer in equation (11). The breakpoint occurs in 1988:4, and, interestingly, the R^2 statistics for two regimes (0.27 and 0.31 in the first and second regime, respectively) are higher than the R^2 statistic for the single regime model reported in Table 6. The coefficients on all of the included variables increase (in absolute value) as we move from the first to the second regime, with the exception of *cay*.

3.3. CRSP Equal-Weighted Log Real Returns

Table 10 reports full-sample bivariate predictive regression model estimation results and structural break test results with CRSP equal-weighted log real returns serving as the regressand in equation (1). The sample is again 1953:3-2000:4. The slope coefficients all have their hypothesized signs, and using one-sided tests and the 10% significance level, seven of the eight predictors are significant in equation (1); the exception is the payout ratio. As in Table 2, the R^2 statistics reported in column (4) of Table 10 indicate that the predictable component in stock returns is limited for each variable, with *cay* having the highest R^2 value of 0.07. From column (5) of Table 10, we see that there is only evidence of structural instability for the short rate according to the full-sample *SupF* statistics. The $\hat{J}$ statistics reported in column (7) are all insignificant at conventional levels.[25]

The multiple structural break test results for the Bai (1997) subsample procedure are reported in Table 11. For five variables, the Bai (1997) subsample procedure gives no indication of any structural breaks. The exceptions are the Fed q, default spread, and short rate. For the short rate, there is evidence of a single break. For the Fed q and default spread, there is significant evidence of two structural breaks, with the first breakpoint occurring in 1968:4 for each variable. The second break occurs in 1990:4 for the Fed q and 1976:1 for the default spread. Further test results for multiple breaks based on the BP methodology are reported in Table 12. According to the BP sequential procedure, there is evidence of a single structural break for the dividend-price ratio and short rate. Using the BP double maximum procedure, there is also evidence of a single structural break for the dividend-price ratio and short rate, as the *UDmax* and is significant at the 5% level, two *WDmax* statistics are significant (at the 10% and 5% levels), and the $SupF_T(1|0)$ statistic is significant at the 5% level. This matches the inference from the BP sequential procedure. There is also some evidence of structural breaks for the two interest rate spreads, with the *UDmax* and *WDmax* statistics being significant at the 10% level for the term spread, and the *WDmax* statistic being significant at the 10% level for the default spread. However, none of the $SupF_T(l+1|l)$ statistics are significant for either variable, so it is difficult to decide on the number of breaks for the two spreads. Recall that the Bai (1997) subsample procedure indicates two structural breaks for the default spread. For the Fed q, the $SupF_T(2|1)$ statistic is significant, but neither of the double maximum statistics is significant. Overall, there is some evidence in Tables 10-12 for structural instability for the dividend-price ratio, Fed q, default spread, and short rate and only very weak evidence for the term spread.

Table 13 reports multiple regime predictive regression model estimation results using the BP methodology for the dividend-price ratio, Fed q, default spread, and short rate. For the dividend-price ratio, the first regime ends in 1990:4. Note that this is very near the endpoint (1990:3) of the first regime for the

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[25] The QLR_T^* statistics are all significant at the 1% level in Table 10.

dividend-price ratio and S&P 500 returns reported in Table 5. In Table 13, the slope coefficient for the dividend-price ratio is significant in the first regime and becomes almost four times larger in the second regime. The R^2 statistic also increases from 0.05 to 0.15 as we move from the first to the second regime. This is in contrast to the slope coefficient estimate and R^2 statistic in the second regime for the dividend-price ratio and S&P 500 returns in Table 5. There, the slope coefficient becomes much smaller and the R^2 statistic falls as we move from the first to the second regime. Returning to Table 13, the Fed q exhibits no predictive ability during the first regime, which ends in 1968:4. In the second regime, which ends in 1990:4, the Fed q demonstrates strong predictive ability, while it shows significant—but reduced—predictive ability in the third regime. The break in 1990:4 for the Fed q occurs at the same time as the single break for the dividend-price ratio. With respect to the default spread, there is significant evidence of predictive ability during the first regime, which ends in 1968:4. Predictive ability increases dramatically as we move from the first to the second regime, which ends in 1976:1, with the R^2 statistic increasing from 0.04 to 0.29. In the third regime, predictive ability is markedly reduced. The predictive ability of the short rate decreases considerably as we move from the first regime, which ends in 1976:1, to the second regime, as the R^2 statistic falls from 0.14 to 0.01. Note that breaks occur at similar times for the different variables in Table 13. The single break for the dividend-price ratio and the second break for Fed q both occur in 1990:4, corresponding to the first Gulf War and start of a U.S. recession. In addition, the first break for the Fed q and default spread both occur in 1968:4. Finally, the single break for the short rate and the second break for the default spread both occur in the mid-1970s (1974:4 and 1976:1, respectively), around the time of the OPEC oil price shock.[26]

Overall, there is less evidence of structural breaks in Tables 10-12 for bivariate predictive regression models of CRSP equal-weighted returns than in Tables 2-4 for models of S&P 500 returns. This suggests that large-cap stock returns are more susceptible to changes in economic structure. In general, when estimating predictive regression models using relatively long samples, one appears to be on firmer statistical ground with

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[26] The confidence intervals are quite wide for the breaks occurring in 1968:4 and 1974:4 for the Fed q and short rate, respectively. It is thus difficult to precisely date the first break for the Fed q and short rate.

CRSP equal-weighted returns. Nevertheless, as indicated in Table 13, the predictive power of some variables with respect to CRSP equal-weighted returns—such as the dividend-price ratio, Fed q, default spread, and short rate—can vary substantially over time.

3.4. Multivariate Models of CRSP Equal-Weighted Log Real Returns

We next consider multivariate models of CRSP equal-weighted log real returns. As in Section 3.2 above, we use the AIC and SIC in turn to select the variables to include in the multivariate predictive regression model, and the results are reported in Table 14. The AIC selects four predictors (*cay*, term spread, default spread, and short rate), while the SIC selects three predictors (*cay*, default spread, and short rate). Neither the *SupF* nor $\hat{J}$ statistic is significant for either model, so that there is no significant evidence of a structural break in either model in Table 14.[27] From Table 14, we see that the Bai (1997) subsample analysis provides no significant evidence of a structural break for the model selected by the AIC, while there is some evidence of a single break for the model selected by the SIC. In Table 15, the BP sequential procedure does not indicate a structural break for either model. There is also only weak evidence for a structural break in either model according to the BP double maximum procedure (see Table 16). The *UDmax* statistic is significant at the 10% level, and the *WDmax* is significant at the 10% and 5% levels, for the model selected by the AIC, but none of the $SupF_T(l+1|l)$ statistics is significant. For the model selected by the SIC, while the $SupF_T(2|1)$ statistic is significant at the 10% level, none of the *UDmax* or *WDmax* statistics is significant. Overall, there is very limited evidence of structural breaks in the multivariate predictive regression models for CSRP equal-weighted returns in Tables 14-16

4. Conclusion

In this paper, we test for structural breaks over the postwar era in a large number of predictive regression models of aggregate U.S. stock returns. We test for structural breaks using procedures

[27] Both of the QLR_T^* statistics are significant at the 1% level in Table 14.

developed by Andrews (1993), Bai (1997), BP (1998, 2001, 2003), Hansen (2000), and Elliott and Müller (2003). We find strong evidence of structural breaks in bivariate predictive regression models of S&P 500 real stock returns based on the dividend-price ratio, Fed q, payout ratio, *cay*, and default spread and some evidence of structural breaks in models based on the price-earnings ratio, term spread, and default spread. The evidence points to a single structural break in bivariate models of S&P 500 real stock returns based on the dividend-price ratio, payout ratio, *cay*, term spread, and short rate and two structural breaks in models based on the price-earning ratio, Fed q, and default spread. We also find some evidence of a structural break in a multivariate predictive regression model of S&P 500 real stock returns, with the predictors selected using the AIC. There is less evidence of structural instability in predictive regression models of CRSP equal-weighted returns, but four of eight bivariate predictive regression models of CRSP equal-weighted returns (based on the dividend-price ratio, Fed q, default spread, and short rate) still display some evidence of structural breaks. For the predictive regression models for which we find significant evidence of structural breaks, we find that the degree of predictability of stock returns can differ widely across the regimes defined by the structural breaks. The main conclusion of the present paper is that structural breaks appear prevalent in predictive regression models aggregate U.S. stock returns, especially S&P 500 returns. This highlights the importance of recent research by Pesaran and Timmermann (2002) and Pesaran, Timmermann, and Pettenuzzo (2005), who develop out-of-sample forecasting schemes that take explicit account of potential structural breaks in predictive regression models. Given the extensive evidence of structural breaks in predictive regression models of aggregate U.S. stock returns in the present paper, such strategies may prove quite useful to investors when taking asset-allocation decisions.[28]

[28] See Guidolin and Timmermann (2005) for recent research in this direction.

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Table 1: Descriptive statistics, 1953:2-2000:4

(1) Variable	(2) Mean	(3) Standard deviation	(4) AC(1)	(5) AC(2)	(6) AC(3)	(7) AC(4)
Log(real return, S&P 500)	7.82	31.43	0.11	-0.07	0.00	0.00
Log(real return, CRSP EW)	8.78	45.21	0.02	-0.06	-0.08	0.06
Log(dividend-price ratio, S&P 500)	-3.41	0.35	0.95	0.89	0.83	0.77
Log(dividend-price ratio, CRSP EW)	-3.74	0.38	0.94	0.89	0.83	0.80
Log(price-earnings ratio)	2.71	0.36	0.96	0.89	0.83	0.77
Log(Fed q)	-0.27	0.39	0.96	0.91	0.87	0.82
Log(payout ratio)	-0.70	0.17	0.96	0.87	0.77	0.67
cay	0.61	0.01	0.83	0.68	0.55	0.45
Term spread	1.29	1.12	0.87	0.70	0.59	0.47
Default spread	0.94	0.43	0.93	0.84	0.77	0.70
Short rate	5.45	2.76	0.96	0.90	0.86	0.81

Notes: Columns (2) and (3) report the mean and standard deviation of the variable in column (1). The first- through fourth-order autocorrelations are reported in columns (4)-(7).

Table 2: Bivariate predictive regression model and structural change test results, S&P 500 returns, 1953:3-2000:4

(1) Predictor	(2) $\hat{\beta}_0$	(3) $\hat{\beta}_1$	(4) R^2	(5) *SupF*	(6) Breakpoint	(7) $\hat{J}$	(8) QLR_T^*
Log(dividend-price ratio)	32.17 (22.55)	2.52 (2.33)	0.01	9.72† [0.05]	1990:3	-16.97*	37.88**
Log(price-earnings ratio)	18.67 (17.62)	-1.41 (2.30)	0.00	6.52 [0.33]	1982:2	-11.09	44.82**
Log(Fed q)	5.64 (2.79)	-3.30 (2.30)	0.01	7.46 [0.17]	1990:3	-17.34*	38.34**
Log(payout ratio)	16.43 (9.61)	2.11 (2.32)	0.00	16.27* [0.01]	1974:3	-14.13†	25.58**
cay	-467.29 (111.59)	9.34 (2.19)	0.09	9.18† [0.08]	1976:1	-16.45*	63.37**
Term spread	0.67 (3.45)	6.27 (2.26)	0.04	12.47* [0.04]	1974:3	-10.82	76.81**
Default spread	0.79 (5.51)	3.25 (2.28)	0.01	4.71 [0.63]	1967:3	-14.85*	22.79**
Short rate	16.43 (5.02)	-4.30 (2.27)	0.02	22.43** [0.00]	1974:3	-10.59	98.54**

Notes: $\hat{\beta}_0$ in column (2) and $\hat{\beta}_1$ in column (3) are the least-squares estimates of β_0 and β_1, respectively, in the bivariate predictive regression model,

$$r_t = \beta_0 + \beta_1 x_{t-1} + \varepsilon_t ,$$

where r_t is the log real return for the S&P 500 index, x_t is the predictor given in column (1), and ε_t is a disturbance term (all at time *t*); standard errors are given in parentheses. The R^2 statistic for the predictive regression model is reported in column (4). The *SupF* statistic in column (5) is used to test the null hypothesis of no structural change against the one-sided (upper-tail) alternative hypothesis of a structural break; 15% trimming is used; *p*-values generated using the Hansen (2000) heteroskedastic fixed-regressor bootstrap are given in brackets; 0.00 indicates <0.005; †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The estimated date for the breakpoint is reported in column (6). The $\hat{J}$ statistic in column (7) is used to test the null hypothesis of parameter stability against the one-sided (lower-tail) alternative hypothesis of parameter instability using the critical values in Elliott and Müller (2003). The QLR_T^* statistic in column (8) is used to test the null hypothesis that β_0 and β_1 have constant values of zero against the one-sided (upper-tail) alternative hypothesis of nonzero β_0 and β_1 values for at least part of the sample using the critical values in Rossi (2005).

Table 3: Bai (1997) subsample analysis, bivariate predictive regression models, S&P 500 returns, 1953:3-2000:4

(1) Predictor	(2) Sample	(3) *SupF*	(4) Breakpoint
Log(dividend-price ratio)	1953:3-2000:4	9.72† [0.05]	1990:3
	1953:3-1990:3	6.30 [0.32]	-
Log(price-earnings ratio)	1953:3-2000:4	6.52 [0.33]	1982:2
	1953:3-1982:2	14.81** [0.01]	1972:4
	1973:1-2000:4	16.22** [0.00]	1982:2
	1953:3-1972:4	3.02 [0.56]	-
	1982:3-2000:4	7.29 [0.19]	-
Log(Fed q)	1953:3-2000:4	7.46 [0.17]	1990:3
	1953:3-1990:3	12.99* [0.04]	1972:4
	1973:1-2000:4	18.15** [0.00]	1984:2
	1953:3-1972:4	8.26† [0.05]	1962:3
	1984:3-2000:4	6.09† [0.08]	1991:3
(Refinement for 1972:4)	1962:4-1984:2	27.16** [0.01]	1973:3
(Refinement for 1984:2)	1973:4-1991:3	13.42** [0.00]	1984:2
Log(payout ratio)	1953:3-2000:4	16.27* [0.01]	1974:3
	1953:3-1974:3	8.03† [0.09]	1962:3
	1974:4-2000:4	3.95 [0.60]	-
(Refinement for 1974:3)	1962:4-2000:4	24.13** [0.00]	1974:3
cay	1953:3-2000:4	9.18† [0.08]	1976:1
	1953:3-1976:1	0.95 [0.96]	-
	1976:2-2000:4	3.85 [0.50]	-
Term spread	1953:3-2000:4	12.47* [0.04]	1974:3
	1953:3-1974:3	6.83 [0.11]	-
	1974:4-2000:3	1.80 [0.88]	-
Default spread	1953:3-2000:4	4.71 [0.61]	1967:3
	1953:3-1967:3	0.69 [0.76]	-
	1967:4-2000:4	14.22* [0.03]	1975:2
	1953:3-1975:2	20.28** [0.00]	1968:2
	1975:3-2000:4	7.56 [0.12]	-
Short rate	1953:3-2000:4	22.43** [0.00]	1974:3
	1953:3-1974:3	9.33* [0.03]	1962:3
	1974:4-2000:4	3.04 [0.71]	-
(Refinement for 1974:3)	1962:4-2000:4	19.47** [0.00]	1974:3

Notes: The *SupF* statistic reported in column (3) is used to test the null hypothesis of no structural change over the sample against the one-sided (upper-tail) alternative hypothesis of a structural break; *p*-values generated using the Hansen (2000) heteroskedastic fixed-regressor bootstrap are given in parentheses; †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The estimated date for the breakpoint is reported in column (4). The minimum length of any regime is required to be 15% of the full sample.

Table 4: Bai and Perron (1998) statistics for tests of multiple structural breaks in the bivariate predictive regression models, S&P 500 returns, 1953:3-2000:4

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Predictor	*UDmax*[a]	*WDmax*(10%)[b]	*WDmax*(5%)[c]	*WDmax*(1%)[d]	$SupF_T(1\|0)$[e]	$SupF_T(2\|1)$[f]	$SupF_T(3\|2)$[g]	$SupF_T(4\|3)$[h]	$SupF_T(5\|4)$[i]
Log(dividend-price ratio)	12.26*	15.96†	16.83*	18.35**	10.74†	6.32	6.72	2.52	-
Log(price-earnings ratio)	9.91	12.98†	13.68*	15.32	6.97	13.19*	6.76	6.33	1.27
Log(Fed q)	13.27*	17.33†	18.26*	20.45**	9.09	12.07†	9.33	9.34	-
Log(payout ratio)	16.77**	16.77†	16.85*	18.12**	16.77**	7.66	3.89	-	-
cay	9.16	9.16	9.16	9.50	9.16	4.11	1.69	1.61	0.46
Term spread	12.88*	13.85†	14.61*	15.93	12.88*	5.91	6.38	1.82	-
Default spread	9.31	11.73†	12.35	13.83	5.51	12.29†	7.86	5.02	0.76
Short rate	24.08**	24.08†	24.08*	24.08**	24.08**	10.01	3.02	1.71	-

Notes: †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively, according to the critical values in Bai and Perron (2003b); the minimal length of any regime is required to be 15% of the full sample; - indicates that there was no more place to insert an additional break given the minimal length requirement.

[a]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.

[b]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.

[c]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.

[d]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.

[e]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of 1 break.

[f]One-sided (upper-tail) test of the null hypothesis of 1 break against the alternative hypothesis of 2 breaks.

[g]One-sided (upper-tail) test of the null hypothesis of 2 breaks against the alternative hypothesis of 3 breaks.

[h]One-sided (upper-tail) test of the null hypothesis of 3 breaks against the alternative hypothesis of 4 breaks.

[i]One-sided (upper-tail) test of the null hypothesis of 4 breaks against the alternative hypothesis of 5 breaks.

Table 5: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results, S&P 500 returns, 1953:3-2000:4

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Regime 1				Regime 2				Regime 3			
Predictor	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	Endpoint	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	Endpoint	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	Endpoint
Log(dividend-price ratio)	117.52	11.98	0.05	1990:3	57.62	4.03	0.03	2000:4				
	(40.24)	(4.33)		[1988:4,2000:3]	(38.99)	(3.57)						
Log(price-earnings ratio)	109.57	-12.90	0.06	1972:4	102.79	-17.00	0.09	1982:2	68.59	-6.90	0.05	2000:4
	(43.99)	(5.64)		[1970:1,1973:4]	(54.48)	(8.56)		[1981:2.1985:1]	(28.03)	(3.46)		
Log(Fed q)	2.46	-12.83	0.10	1972:4	-28.66	-20.86	0.12	1990:3	16.35	-6.40	0.04	2000:4
	(3.82)	(4.48)		[1965:4,1974:3]	(10.98)	(6.67)		[1989:4,1994:4]	(4.22)	(4.89)		
Log(payout ratio)	89.38	23.93	0.16	1974:3	10.51	0.05	0.00	2000:4				
	(20.88)	(5.86)		[1972:4,1983:1]	(12.65)	(2.78)						
cay	-842.16	16.75	0.23	1976:1	-167.04	3.45	0.01	2000:4				
	(167.67)	(3.25)		[1967:3,1986:3]	(150.00)	(2.93)						
Term spread	-12.01	22.48	0.19	1974:3	7.49	1.89	0.00	2000:4				
	(4.93)	(5.01)		[1971:2,1983:2]	(4.96)	(2.67)						
Default spread	-7.92	13.36	0.04	1967:3	-73.21	31.95	0.29	1975:2	5.54	1.36	0.00	2000:4
	(13.43)	(8.81)		[1964:1,1968:3]	(20.92)	(9.08)		[1973:3,1979:3]	(7.74)	(2.73)		
Short rate	38.90	-24.62	0.24	1974:3	15.50	-2.11	0.00	2000:4				
	(7.57)	(4.98)		[1973:1,1980:1]	(7.88)	(2.98)						

Notes: $\hat{\beta}_0$ in columns (2), (6), and (10) and $\hat{\beta}_1$ in columns (3), (7), and (11) are the least-squares estimates of β_0 and β_1, respectively, in the bivariate predictive regression model,

$$r_t = \beta_0 + \beta_1 x_{t-1} + \varepsilon_t ,$$

for the different regimes, where r_t is the log real return for the S&P 500 index, x_t is the predictor given is column (1), and ε_t is a disturbance term (all at time *t*); standard errors are given in parentheses. The R^2 statistics for the regimes are reported in columns (4), (8), and (12). The endpoints of the regimes are reported in columns (5), (9), and (13); 90% confidence intervals for the endpoints are given in brackets. Regime 1 begins in 1953:3.

Table 6: Multivariate predictive regression model and structural change test results, S&P 500 returns, 1953:3-2000:4

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predictor	$\hat{\beta}_0$	$\hat{\beta}_i$	R^2	*SupF*	Breakpoint	$\hat{J}$	QLR_T^*
A. Model selected by AIC	-1.05 (0.02)		0.18	25.23 [0.56]	1988:4	-40.37†	65,904.15**
Log(dividend-price ratio)		-393.14 (190.35)					
Log(price-earnings ratio)		-395.82 (191.65)					
Log(payout ratio)		193.95 (93.91)					
cay		0.02 (0.01)					
Default spread		0.03 (0.01)					
Short rate		-0.03 (0.01)					
B. Model selected by SIC	-0.99 (0.28)		0.15	10.74 [0.40]	1991:1	-18.49	172.65**
cay		0.02 (0.01)					
Default spread		0.02 (0.01)					
Short rate		-0.02 (0.01)					

Notes: $\hat{\beta}_0$ in column (2) and $\hat{\beta}_i$ in column (3) are the least-squares estimates of β_0 and β_i ($i = 1, \ldots, n$), respectively, in the multivariate predictive regression model,

$$r_t = \beta_0 + \sum_{i=1}^{n} \beta_i x_{i,t-1} + \varepsilon_t \,,$$

where r_t is the log real return for the S&P 500 index, $x_{i,t}$ is the predictor given in column (1), and ε_t is a disturbance term (all at time *t*); standard errors are given in parentheses. The R^2 statistic for the predictive regression model is reported in column (4). The *SupF* statistic in column (5) is used to test the null hypothesis of no structural change against the one-sided (upper-tail) alternative hypothesis of a structural break; 15% trimming is used; *p*-values generated using the Hansen (2000) heteroskedastic fixed-regressor bootstrap are given in brackets; 0.00 indicates <0.005; †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The estimated date for the breakpoint is reported in column (6). The $\hat{J}$ statistic in column (7) is used to test the null hypothesis of parameter stability against the one-sided (lower-tail) alternative hypothesis of parameter instability using the critical values in Elliott and Müller (2003). The QLR_T^* statistic in column (8) is used to test the null hypothesis that β_0 and β_i ($i = 1, \ldots, n$) have constant values of zero against the one-sided (upper-tail) alternative hypothesis that β_0 and β_i ($i = 1, \ldots, n$) have nonzero values for at least part of the sample using the critical values in Rossi (2005).

Table 7: Bai (1997) subsample analysis, multivariate predictive regression model, S&P 500 returns, 1953:3-2000:4

(1) Predictor	(2) Sample	(3) *SupF*	(4) Breakpoint
Model selected by AIC	1953:3-2000:4	25.23 [0.97]	1988:4
	1964:1-1988:4	13.75 [0.96]	-
Model selected by SIC	1953:3-2000:4	10.74 [0.40]	1991:1
	1953:3-1991:1	9.26 [0.56]	-

Notes: The *SupF* statistic reported in column (3) is used to test the null hypothesis of no structural change over the sample against the one-sided (upper-tail) alternative hypothesis of a structural break; *p*-values generated using the Hansen (2000) heteroskedastic fixed-regressor bootstrap are given in parentheses; †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The estimated date for the breakpoint is reported in column (4). The minimum length of any regime is required to be 15% of the full sample.

Table 8: Bai and Perron (1998) statistics for tests of multiple structural breaks in the multivariate predictive regression model, S&P 500 returns, 1953:3-2000:4

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Predictor	*UDmax*[a]	*WDmax*(10%)[b]	*WDmax*(5%)[c]	*WDmax*(1%)[d]	$SupF_T(1\|0)$[e]	$SupF_T(2\|1)$[f]	$SupF_T(3\|2)$[g]	$SupF_T(4\|3)$[h]	$SupF_T(5\|4)$[i]
Model selected by AIC	26.81**	29.33†	30.31*	32.85**	26.81**	16.24	15.25	23.87	-
Model selected by SIC	14.07	15.04	15.78	17.13	14.07	7.86	10.24	10.24	-

Notes: †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively, according to the critical values in Bai and Perron (2003b); the minimal length of any regime is required to be 15% of the full sample; - indicates that there was no more place to insert an additional break given the minimal length requirement.
[a]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.
[b]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.
[c]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.
[d]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.
[e]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of 1 break.
[f]One-sided (upper-tail) test of the null hypothesis of 1 break against the alternative hypothesis of 2 breaks.
[g]One-sided (upper-tail) test of the null hypothesis of 2 breaks against the alternative hypothesis of 3 breaks.
[h]One-sided (upper-tail) test of the null hypothesis of 3 breaks against the alternative hypothesis of 4 breaks.
[i]One-sided (upper-tail) test of the null hypothesis of 4 breaks against the alternative hypothesis of 5 breaks.

Table 9: Bai and Perron (1998, 2003a, 2004) multiple regime multivariate predictive regression model estimation results, S&P 500 returns, 1953:3-2000:4

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Regime 1				Regime 2			
Predictor	$\hat{\beta}_0$	$\hat{\beta}_i$	R^2	Endpoint	$\hat{\beta}_0$	$\hat{\beta}_i$	R^2	Endpoint
Model selected by AIC	-0.37 (0.49)		0.27	1988:4 [1988:1,1989:4]	1.08 (1.16)		0.31	2000:4
Log(dividend-price ratio)		-75.14 (282.89)				-716.33 (216.66)		
Log(price-earnings ratio)		-75.69 (284.82)				-721.25 (216.66)		
Log(payout ratio)		37.11 (139.57)				353.38 (106.89)		
cay		0.02 (0.01)				-0.01 (0.02)		
Default spread		0.02 (0.01)				0.04 (0.03)		
Short rate		-0.03 (0.01)				-0.06 (0.04)		

Notes: $\hat{\beta}_0$ in columns (2) and (6) and $\hat{\beta}_i$ in columns (3) and (7) are the least-squares estimates of β_0 and β_i $i = 1,\ldots,n$, respectively, in the multivariate predictive regression model,

$$r_t = \beta_0 + \sum_{i=1}^{n} \beta_i x_{i,t-1} + \varepsilon_t ,$$

for the different regimes, where r_t is the log real return for the S&P 500 index, x_t is the predictor given is column (1), and ε_t is a disturbance term (all at time *t*); standard errors are given in parentheses. The R^2 statistics for the regimes are reported in column (4) and (8). The endpoints of the regimes are reported in columns (5) and (9); 90% confidence intervals for the endpoints are given in brackets. Regime 1 begins in 1953:3.

Table 10: Bivariate predictive regression model and structural change test results, CRSP equal-weighted returns, 1953:3-2000:4

(1) Predictor	(2) $\hat{\beta}_0$	(3) $\hat{\beta}_1$	(4) R^2	(5) *SupF*	(6) Breakpoint	(7) $\hat{J}$	(8) QLR_T^*
Log(dividend-price ratio)	75.22 (32.43)	6.69 (3.26)	0.02	8.95 [0.15]	1990:4	-8.57	27.43**
Log(price-earnings ratio)	42.17 (25.26)	-4.38 (3.30)	0.01	3.42 [0.77]	1990:4	-4.86	18.35**
Log(Fed q)	4.56 (3.99)	-6.27 (3.29)	0.02	5.39 [0.43]	1990:4	-7.66	21.99**
Log(payout ratio)	22.41 (13.82)	3.35 (3.34)	0.01	9.31 [0.13]	1974:4	-4.79	21.02**
cay	-605.71 (162.03)	12.08 (3.18)	0.07	4.80 [0.49]	1983:2	-9.26	42.67**
Term spread	0.69 (5.00)	7.12 (3.27)	0.03	4.47 [0.66]	1971:1	-6.25	49.79**
Default spread	-5.35 (7.89)	6.49 (3.26)	0.02	8.10 [0.32]	1968:4	-9.77	25.81**
Short rate	18.85 (7.24)	-5.01 (3.27)	0.01	11.85† [0.09]	1974:4	-5.60	56.67**

Notes: $\hat{\beta}_0$ in column (2) and $\hat{\beta}_1$ in column (3) are the least-squares estimates of β_0 and β_1, respectively, in the bivariate predictive regression model,

$$r_t = \beta_0 + \beta_1 x_{t-1} + \varepsilon_t ,$$

where r_t is the log real return for the CRSP equal-weighted index, x_t is the predictor given in column (1), and ε_t is a disturbance term (all at time *t*); standard errors are given in parentheses. The R^2 statistic for the predictive regression model is reported in column (4). The *SupF* statistic in column (5) is used to test the null hypothesis of no structural change against the one-sided (upper-tail) alternative hypothesis of a structural break; 15% trimming is used; *p*-values generated using the Hansen (2000) heteroskedastic fixed-regressor bootstrap are given in brackets; 0.00 indicates <0.005; †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The estimated date for the breakpoint is reported in column (6). The $\hat{J}$ statistic in column (7) is used to test the null hypothesis of parameter stability against the one-sided (lower-tail) alternative hypothesis of parameter instability using the critical values in Elliott and Müller (2003). The QLR_T^* statistic in column (8) is used to test the null hypothesis that β_0 and β_1 have constant values of zero against the one-sided (upper-tail) alternative hypothesis of nonzero β_0 and β_1 values for at least part of the sample using the critical values in Rossi (2005).

Table 11: Bai (1997) subsample analysis, bivariate predictive regression models, CRSP equal-weighted returns, 1953:3-2000:4

(1) Predictor	(2) Sample	(3) *SupF*	(4) Breakpoint
Log(dividend-price ratio)	1953:3-2000:4	8.95 [0.15]	1990:4
	1953:3-1990:4	5.79 [0.43]	-
Log (price-earnings ratio)	1953:3-2000:4	3.42 [0.77]	1990:4
	1953:3-1990:4	8.98 [0.18]	-
Log(Fed q)	1953:3-2000:4	5.39 [0.43]	1990:4
	1953:3-1990:4	15.01* [0.01]	1968:4
	1953:3-1968:4	1.01 [0.73]	-
	1969:1-2000:4	15.84* [0.05]	1990:4
	1969:1-1990:4	2.71 [0.69]	-
Log(payout ratio)	1953:3-2000:4	9.31 [0.13]	1974:4
	1953:3-1974:4	6.04 [0.17]	-
	1975:1-2000:4	6.19 [0.29]	-
cay	1953:1-2000:4	4.80 [0.49]	1983:2
	1953:1-1983:2	3.91 [0.66]	-
	1983:3-2000:4	2.96 [0.60]	-
Term spread	1953:1-2000:4	4.47 [0.63]	1971:1
	1953:1-1971:1	4.34 [0.25]	-
	1971:2-2000:4	1.86 [0.94]	-
Default spread	1953:3-2000:4	8.10 [0.32]	1968:4
	1953:3-1968:4	0.55 [0.89]	-
	1969:1-2000:4	14.39* [0.04]	1976:1
	1953:3-1976:1	23.92** [0.00]	1968:4
	1976:2-2000:4	5.11 [0.41]	-
Short rate	1953:3-2000:4	$11.85^{\dagger}$ [0.09]	1974:4
	1953:3-1974:4	5.28 [0.23]	-
	1975:1-2000:4	6.67 [0.21]	

Notes: The *SupF* statistic reported in column (3) is used to test the null hypothesis of no structural change over the sample against the one-sided (upper-tail) alternative hypothesis of a structural break; *p*-values generated using the Hansen (2000) heteroskedastic fixed-regressor bootstrap are given in parentheses; †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The estimated date for the breakpoint is reported in column (4). The minimum length of any regime is required to be 15% of the full sample.

Table 12: Bai and Perron (1998) statistics for tests of multiple structural breaks in the bivariate predictive regression models, CRSP equal-weighted returns, 1953:3-2000:4

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Predictor	*UDmax*[a]	*WDmax*(10%)[b]	*WDmax*(5%)[c]	*WDmax*(1%)[d]	$SupF_T(1\|0)$[e]	$SupF_T(2\|1)$[f]	$SupF_T(3\|2)$[g]	$SupF_T(4\|3)$[h]	$SupF_T(5\|4)$[i]
Log(dividend-price ratio)	11.96*	13.89†	14.63*	16.38	11.96*	5.66	5.75	1.40	-
Log(price-earnings ratio)	5.69	6.65	7.01	7.85	4.09	9.16	3.13	2.20	2.20
Log(Fed q)	9.34	10.62	10.99	11.82	6.53	14.97*	2.50	1.40	-
Log(payout ratio)	9.74	9.74	9.77	10.94	9.74	5.60	5.60	5.03	5.03
cay	5.04	5.74	5.94	6.61	4.88	3.44	1.29	1.25	1.75
Term spread	10.34†	11.76†	12.17	13.08	5.27	3.39	2.69	3.82	3.03
Default spread	9.78	11.66†	12.34	13.74	9.78	10.13	5.58	2.81	0.48
Short rate	12.58*	12.58†	12.58*	12.81	12.58*	6.27	6.27	1.43	-

Notes: †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively, according to the critical values in Bai and Perron (2003b); the minimal length of any regime is required to be 15% of the full sample; - indicates that there was no more place to insert an additional break given the minimal length requirement.
[a]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.
[b]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.
[c]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.
[d]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.
[e]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of 1 break.
[f]One-sided (upper-tail) test of the null hypothesis of 1 break against the alternative hypothesis of 2 breaks.
[g]One-sided (upper-tail) test of the null hypothesis of 2 breaks against the alternative hypothesis of 3 breaks.
[h]One-sided (upper-tail) test of the null hypothesis of 3 breaks against the alternative hypothesis of 4 breaks.
[i]One-sided (upper-tail) test of the null hypothesis of 4 breaks against the alternative hypothesis of 5 breaks.

Table 13: Bai and Perron (1998, 2003a, 2004) multiple regime bivariate predictive regression model estimation results, CRSP equal-weighted returns, 1953:3-2000:4

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
	Regime 1				Regime 2				Regime 3			
Predictor	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	Endpoint	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	Endpoint	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	Endpoint
Log(dividend-price ratio)	118.78	11.58	0.05	1990:4	487.44	42.74	0.15	2000:4				
	(41.29)	(4.29)		[1987:1,1991:2]	(169.44)	(15.27)						
Log(Fed q)	15.01	-0.86	0.00	1968:4	-29.84	-25.37	0.14	1990:4	19.94	-14.95	0.08	2000:4
	(5.81)	(6.17)		[1959:3,1970:3]	(9.94)	(6.66)		[1989:3,1994:3]	(6.84)	(8.01)		
Default spread	-10.80	17.69	0.04	1968:4	-113.35	42.52	0.29	1976:1	-3.53	5.17	0.02	2000:4
	(16.68)	(10.83)		[1965:2,1969:2]	(32.53)	(12.42)		[1974:1,1981:2]	(10.92)	(3.92)		
Short rate	40.56	-25.35	0.14	1974:4	20.19	-3.32	0.01	2000:4				
	(10.58)	(6.85)		[1972:1,1985:1]	(12.04)	(4.56)						

Notes: $\hat{\beta}_0$ in columns (2), (6), and (10) and $\hat{\beta}_1$ in columns (3), (7), and (11) are the least-squares estimates of β_0 and β_1, respectively, in the bivariate predictive regression model,

$$r_t = \beta_0 + \beta_1 x_{t-1} + \varepsilon_t ,$$

for the different regimes, where r_t is the log real return for the CRSP equal-weighted index, x_t is the predictor given is column (1), and ε_t is a disturbance term (all at time t); standard errors are given in parentheses. The R^2 statistics for the regimes are reported in columns (4), (8), and (12). The endpoints of the regimes are reported in columns (5), (9), and (13); 90% confidence intervals for the endpoints are given in brackets. Regime 1 begins in 1953:3.

Table 14: Multivariate predictive regression model and structural change test results, CRSP equal-weighted returns, 1953:3-2000:4

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Predictor	$\hat{\beta}_0$	$\hat{\beta}_i$	R^2	*SupF*	Breakpoint	$\hat{J}$	QLR_T^*
A. Model selected by AIC	-575.84 (166.76)		0.15	6.61 [0.97]	1963:04	-14.43	157.58**
cay		11.51 (3.30)					
Term spread		-6.14 (4.01)					
Default spread		18.91 (4.88)					
Short rate		-17.98 (4.81)					
B. Model selected by SIC	-497.72 (159.31)		0.14	4.25 [0.99]	1968:4	-12.09	144.68**
cay		9.86 (3.13)					
Default spread		14.90 (4.13)					
Short rate		-14.15 (4.12)					

Notes: $\hat{\beta}_0$ in column (2) and $\hat{\beta}_i$ in column (3) are the least-squares estimates of β_0 and β_i ($i = 1, \ldots, n$), respectively, in the multivariate predictive regression model,

$$r_t = \beta_0 + \sum_{i=1}^{n} \beta_i x_{i,t-1} + \varepsilon_t ,$$

where r_t is the log real return for the CRSP equal-weighted index, $x_{i,t}$ is the predictor given in column (1), and ε_t is a disturbance term (all at time *t*); standard errors are given in parentheses. The R^2 statistic for the predictive regression model is reported in column (4). The *SupF* statistic in column (5) is used to test the null hypothesis of no structural change against the one-sided (upper-tail) alternative hypothesis of a structural break; 15% trimming is used; *p*-values generated using the Hansen (2000) heteroskedastic fixed-regressor bootstrap are given in brackets; 0.00 indicates <0.005; †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The estimated date for the breakpoint is reported in column (6). The $\hat{J}$ statistic in column (7) is used to test the null hypothesis of parameter stability against the one-sided (lower-tail) alternative hypothesis of parameter instability using the critical values in Elliott and Müller (2003). The QLR_T^* statistic in column (8) is used to test the null hypothesis that β_0 and β_i ($i = 1, \ldots, n$) have constant values of zero against the one-sided (upper-tail) alternative hypothesis that β_0 and β_i ($i = 1, \ldots, n$) have nonzero values for at least part of the sample using the critical values in Rossi (2005).

Table 15: Bai (1997) subsample analysis, multivariate predictive regression model, CRSP equal-weighted returns, 1953:3-2000:4

(1) Predictor	(2) Sample	(3) *SupF*	(4) Breakpoint
Model selected by AIC	1953:3-2000:4	6.61 [0.97]	1963:4
	1964:1-1990:3	10.16 [0.78]	-
Model selected by SIC	1953:3-2000:4	4.25 [0.99]	1968:4
	1953:3-1968:4	13.61* [0.03]	1961:1
	1961:2-2000:4	9.13 [0.70]	-

Notes: The *SupF* statistic reported in column (3) is used to test the null hypothesis of no structural change over the sample against the one-sided (upper-tail) alternative hypothesis of a structural break; *p*-values generated using the Hansen (2000) heteroskedastic fixed-regressor bootstrap are given in parentheses; †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively. The estimated date for the breakpoint is reported in column (4). The minimum length of any regime is required to be 15% of the full sample.

Table 16: Bai and Perron (1998) statistics for tests of multiple structural breaks in the multivariate predictive regression model, CRSP equal-weighted returns, 1953:3-2000:4

(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Predictor	*UDmax*[a]	*WDmax*(10%)[b]	*WDmax*(5%)[c]	*WDmax*(1%)[d]	$SupF_T(1\|0)$[e]	$SupF_T(2\|1)$[f]	$SupF_T(3\|2)$[g]	$SupF_T(4\|3)$[h]	$SupF_T(5\|4)$[i]
Model selected by AIC	19.33†	21.71†	22.56*	23.57	12.40	8.04	5.85	3.53	-
Model selected by SIC	9.19	10.77	11.26	12.10	5.62	16.24†	7.68	4.74	-

Notes: †,*,** indicate significance at the 10%, 5%, and 1% levels, respectively, according to the critical values in Bai and Perron (2003b); the minimal length of any regime is required to be 15% of the full sample; - indicates that there was no more place to insert an additional break given the minimal length requirement.

[a]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.

[b]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.

[c]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.

[d]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks given an upper bound of 5.

[e]One-sided (upper-tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of 1 break.

[f]One-sided (upper-tail) test of the null hypothesis of 1 break against the alternative hypothesis of 2 breaks.

[g]One-sided (upper-tail) test of the null hypothesis of 2 breaks against the alternative hypothesis of 3 breaks.

[h]One-sided (upper-tail) test of the null hypothesis of 3 breaks against the alternative hypothesis of 4 breaks.

[i]One-sided (upper-tail) test of the null hypothesis of 4 breaks against the alternative hypothesis of 5 breaks.

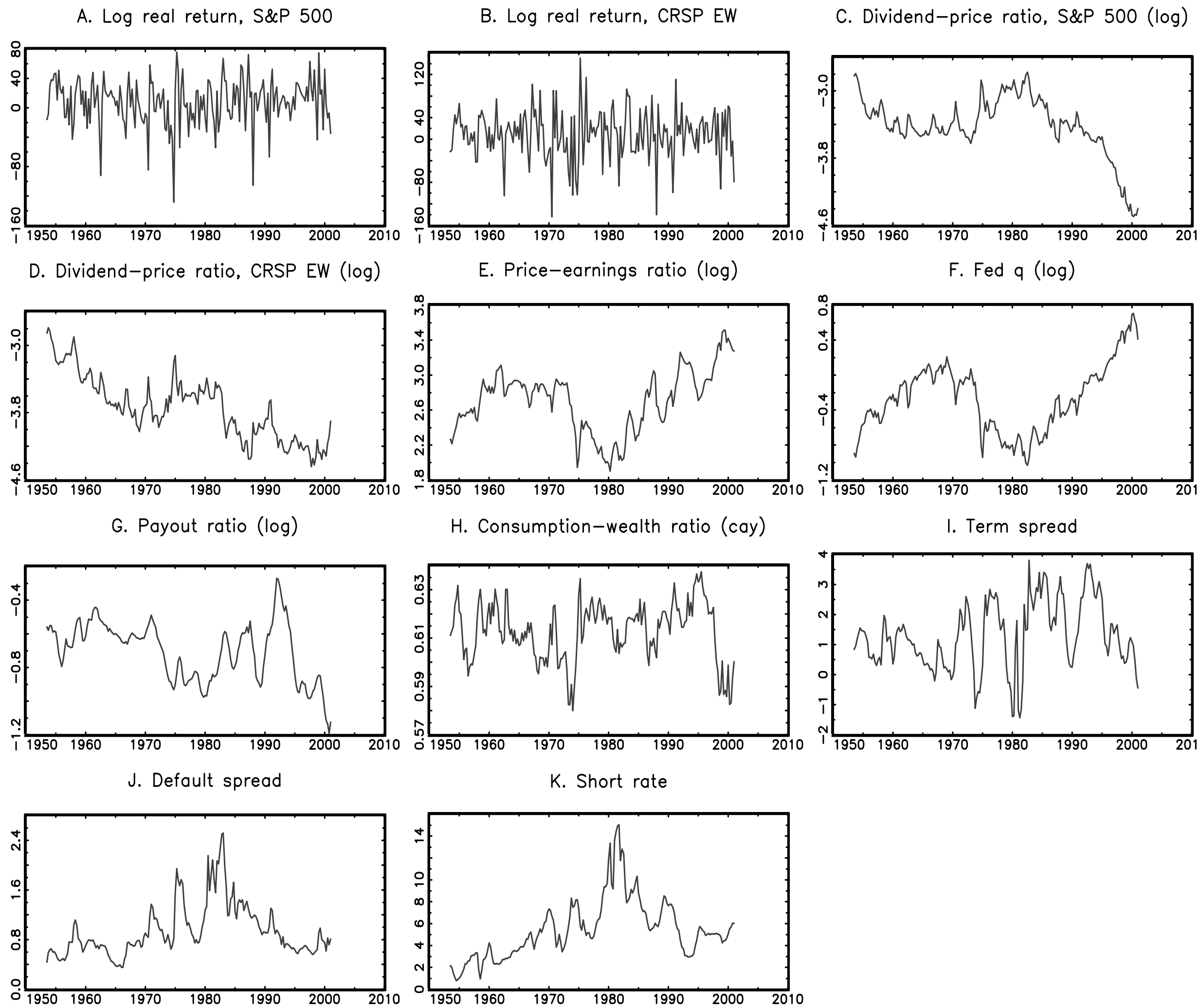

Figure 1. Time-series plots, quarterly data, 1953:2-2000:4