Economics Bulletin

Volume 30, Issue 2

An examination of the stability of short-run Canadian stock predictability

Ryan Compton
University of Manitoba

Syeed Khan
University of Manitoba

Abstract

Using monthly data from 1975-2001, we consider the stability of bivariate and multivariate models for short run in-sample predictability of Canadian stock returns. We test for model stability using a range of tests including the Andrews SupF statistic, Bai subsample procedure, and Bai and Perron sequential SupF procedure. We find evidence of instability in two of our nine bivariate cases considered as well as our preferred multivariate model. When estimated to account for these breaks, we find the degree and direction of predictability can change markedly.

We would like to thank James Morley and Mark Wohar for kindly reading an earlier draft of this paper. The usual disclaimer applies.
Citation: Ryan Compton and Syeed Khan, (2010) "An examination of the stability of short-run Canadian stock predictability ", *Economics Bulletin*, Vol. 30 no.2 pp. 1293-1306.
Submitted: Jan 12 2010. **Published:** May 11, 2010.

I. Introduction

The issue of stock return predictability is an area which has been heavily studied, but remains an open and active research area due to mixed findings in the ability of macroeconomic and financial variables to predict returns (see for example, Chen, Ross and Roll, 1986; Fama and French, 1989; Durham, 2001; Goyal and Welch, 2004; Rapach, Wohar and Rangvid, 2005; and Campbell and Thompson, 2008). While some studies find certain variables are useful for predicting stock returns, others find these same variables are not (see Rapach, Wohar and Rangvid, 2005 for a good overview). Similarly while some variables perform well in terms of in-sample predictability, these same variables may perform poorly out-of-sample. A possible explanation for these mixed findings is that of model instability. A variable might perform well in certain samples but poorly in other samples due to the fact the model is unstable (for example, a variable may have predictive power largely in the 1970s, and so for a sample which includes this period we may find predictability, while for a sample which does not, we may fail to find predictability). Further, a variable may predict well in-sample, but perform poorly out-of-sample because again the predictability itself has changed with the changing sample. For instance, Pesaran and Timmerman (2002) list reasons such as speculative bubbles, investor's market sentiment, and regime change in monetary policy as possible sources of structural instability in regression models.[1]

Empirical work investigating breaks in predictive regression models of stock returns has largely been US focused and provides clear evidence that there exist breaks in the predictive ability of a number of macroeconomic and financial variables (see Pesaran and Timmerman, 2002; Rapach and Wohar, 2006; and Giannetti, 2007). Work on stock predictability for countries outside the US generally has been limited (Rapach, Wohar, and Rangvid, 2005 is a notable exception), and work on structural breaks in non-US predictability even more so. As a result, the goal of our paper is to consider the stability of Canadian stock predictability over a very short horizon (1 month) in order to extend this literature beyond the U.S. and to highlight the need to consider model instability for stock return prediction more broadly.[2]

We consider the ability of nine variables used recently by Rapach, Wohar and Rangvid (2005) to predict in-sample 1-month ahead stock returns in bivariate and multivariate models, and apply a range of structural break tests to explicitly test the stability of these regression models. We find our bivariate predictive models to be rather stable with evidence of structural breaks in only two of the nine bivariate models as well as our preferred multivariate model. We find estimating the regimes for those models with breaks though does have important implications for the degree and direction of predictability.

[1] Another possible reason for differences in performance in-sample versus out-of-sample is due to the power of in-sample tests of predictability relative to out-of-sample tests. Inoue and Kilian (2004) investigate why in-sample tests of predictability tend to reject the null of no predictability more often than out-of-sample tests, and argue that systematically higher power of in-sample tests (rather than data mining, or spurious results, as is sometimes posited in the literature) is the reason. Interested readers are encouraged to read their paper for more.

[2] We are aware of only a few studies that examine Canadian stock predictability. Adjaoud and Rahman (1996), and Rapach, Wohar and Rangvid (2005) examine Canadian stock predictability explicitly, while Huang and Yang (2004) include Canadian data as part of a panel looking at return predictability. We are aware of no studies which consider breaks in the prediction model for Canadian stock returns.

The remainder of the paper proceeds as follows. Section II details the data and empirical methodology employed in this study, section III provides the results of our structural break tests and model estimation, while section IV concludes.

II. Data and Empirical Approach

The data used in this study is drawn from the Canadian variables in the Rapach, Wohar and Rangvid (2005) dataset. This data consists of monthly observations over the 1975.12 – 2001.12 period and includes nine variables as possible predictors: relative money market rate (RMM), relative treasury bill rate (RTB), relative long-term government bond yield (RGB), term spread (TSP), inflation rate (INF), industrial production growth (IPG), narrow money growth (NMG), broad money growth (BMG), and the change in the unemployment rate (DUN). For stock returns, we use real stock returns as our measure. These variables are all fairly standard in the stock prediction literature. Further information on their construction and summary statistics can be found in Table 1.

In terms of our empirical approach, as a first step we use the full sample to estimate the following bivariate predictive regression with each of our nine variables considered in turn:

$$r_t = \beta_0 + \beta_1 z_{t-1} + \varepsilon_t \qquad (1)$$

where r_t is the log real return from period $t-1$ to t (in our case 1-month), z_{t-1} is our possible predictor at time $t-1$ and ε_t is our error term with mean 0 and variance σ^2.[3] In testing for model stability we are interested in the stability of the model parameters β_0 and β_1. Therefore we consider the following model with m possible breaks ($m+1$ possible regimes):

$$r_t = \beta_0^j + \beta_1^j z_{t-1} + \varepsilon_t,\ t=T_{j-1}+1, \ldots, T_j \qquad (2)$$

for $j=1,\ldots,m+1$, where β_0^j and β_1^j are the regression coefficients for the jth regime. We want to treat these break dates as unknown rather than impose them a priori. In order to endogenously test for any unknown breaks we rely on a number of procedures including the Andrews (1993) *SupF* test, Bai (1997) subsample procedure, and Bai and Perron's sequential *SupF* procedure along with the double max statistics (*UDmax* and *WDmax*) developed by Bai and Perron (1998). Once any breaks have been identified, the resulting regimes are then estimated, and any differences in coefficients and R^2 are reported.[4]

Following up on these bivariate results, we also consider the ability of our variables to predict returns in a multivariate model. While all 9 potential predictors are considered as possible predictors for the multivariate prediction model, for specification purposes we follow Rapach

[3] Note that throughout this paper we standardize the regressors based on their standard deviation. Further, testing for autocorrelation in our stock returns measure, we find little evidence of autocorrelation, and so do not account for this in our standard errors.

[4] We would like to sincerely thank David Rapach and Mark Wohar for making publicly available, their programs underlying Rapach and Wohar (2006), as well as Pierre Perron and Jushan Bai for the public availability of their Bai and Perron (2003) code. These programs were used in implementing the procedures for our paper. For more on these procedures, please see Rapach and Wohar (2006) and Bai and Perron (2003).

and Wohar (2006) and determine which of these variables to include based on the AIC and BIC. Again, the stability of the selected multivariate model is then examined using the above procedures, and the resulting regimes estimated taking into account any identified structural breaks.

III. Results

Table 2 provides the fixed coefficient results for our bivariate models over the entire sample. Our results are similar to the 1-month Canadian results of Rapach, Wohar, and Rangvid (2005), and we find using two-sided t-tests that only relative government bond yield (RGB) possesses statistically significant predictive power for 1 month ahead stock returns.[5]

Table 2 also provides the fixed coefficient results for our multivariate model. With all nine variables considered as possible predictors, the AIC selects 3 variables- relative money market rate, relative government bond yield, and industrial production growth- to include in the multivariate model, while the SIC selects only 1 variable, relative government bond yield.[6] As a result, only the model selected using AIC is reported in the multivariate regression section of Table 2. Interestingly, based on the full sample results, relative money market rate and industrial production growth, which do not prove to be significant predictors in the bivariate regressions, enter along with relative government bond yield as significant predictors in the multivariate regression.

To investigate the stability of these results, Tables 3 and 4 provide results for a range of possible structural break tests. Table 3 provides results from standard procedures used in the literature to test for structural breaks; these are the *SupF* statistic from Andrews (1993), the "double maximum" statistics (*UDmax* and *WDmax*) developed by Bai and Perron (1998), as well as Bai and Perron (1998)'s sequential procedure. While the *SupF* statistic is used to test for a single structural break in each of our bivariate predictive models, the double maximum statistics allow us to test the null of no structural breaks against the alternative of an unknown number of breaks subject to an upper bound (in our case 5 breaks), while Bai and Perron's sequential procedure using the $SupF_T(l+1|l)$ statistic allows us to test the null of l structural breaks against the alternative of $l+1$ breaks (so for instance we can test 0 versus 1 break, 1 versus 2 breaks, up to 4 versus 5 breaks in our application). Further, Table 4 provides results based on the Bai (1997) subsample procedure which tests for multiple breaks using the *SupF* statistic.[7]

---

[5] This of course is not surprising as we are using the same data as Rapach, Wohar and Rangvid (2005). Our regressions differ from theirs however as RWR include lagged returns in each of their prediction regressions while we do not as we are concerned only with structural breaks in the constant or coefficient for the variable of interest rather than any breaks occurring due to a break in lagged returns. Further, RWR employ a bootstrap procedure for determining their standard errors, which we do not, which likely accounts for why they find industrial production growth to be significant. Lastly we note that the use of robust standard errors does not fundamentally change our Table 1 results in terms of significance.

[6] We also considered the variables to include based on Clark (2004)'s general-to-specific procedure and found support for the inclusion of only relative money market rate and relative government bond yield. The break using this model corresponds with the break for the model selected using AIC, and the change in coefficients for RMM and RGB are similar as well.

[7] Rapach and Wohar (2006) provide a nice discussion of the strengths and weaknesses of each approach.

What we see from Table 3 is that our statistics generally are in agreement. Testing for a single structural break, the *SupF* statistic is able to detect a single significant break (rejecting the null of no structural breaks against the alternative of a single structural break) only for our relative government bond yield variable, while the *UDmax* and *WDmax* statistics are able to reject the null of no structural breaks against the alternative of as many as 5 structural breaks again for the relative government bond yield measure and inflation measure. Finally, testing for the presence of multiple structural breaks, using Bai and Perron's sequential procedure we are able to reject the null of no structural breaks relative to the alternative of 1 structural break for relative government bond yield and inflation, but unable to reject the null for further structural breaks, indicating that for these two variables there are at most 1 structural break present. For our multivariate model, the statistics similarly all point towards at least one structural break, with the sequential procedure suggesting the number of structural breaks is at most 1.[8]

Table 4 provides results based on the Bai (1997) procedure. Using the *SupF* statistic we test for a structural break using the full sample, and based on the break date identified (even if not significant by standard measures) split the sample and test for breaks in these subsamples (where sufficient sample size allows) and any further subsamples should a given earlier subsample be found to have a structural break.[9] Thus if the *SupF* statistic finds significant evidence of a structural break in the full sample but no evidence of a structural break in the subsamples, we can conclude there is 1 structural break. Also if the *SupF* statistic finds no evidence of a structural break for the entire sample and none for the resulting subsamples, we can conclude there are no structural breaks. From the Bai (1997) subsample procedure, we can see that a single break exists for our relative government bond yield predictor as well as our multivariate model, but not for our remaining bivariate predictors. Noteworthy none-the-less is that for a number of our predictors, while not significant, breaks are often identified among the first seven months of 1980.

In summary, from Tables 3 and 4 we see for our bivariate models, that there is no significant evidence of a break in the sample for 7 of our 9 predictors, while for the relative government bond yield and inflation we do find fairly consistent support across the statistics for a single break. Further, in the case of our multivariate model, we again find consistent support for a single structural break.

---

[8] The results of this study are based on a 15% sample trimming for our Bai and Perron tests. For robustness we also considered trimming of 10%, 20%, and 25%. Those bivariate models which are stable using the 15% trimming are also stable using the alternative trimming parameters. In the case of the model with inflation as the predictor, the single structural break continues to be identified across the 10%-25% ranges, while for the model with real government bond yield as the predictor, the identified structural break using the 10% trimming matches that of the 15% trimming, though once we move to 20% and 25% trimming no structural break is identified (this is largely due to the fact the identified break in the 10% and 15% trimming is early in the sample and so the 20% and 25% trimming doesn't allow for a break that early in the sample. In the case of our multivariate model again we see the indentified break using the 10% trimming matches that using 15%, but with 20% and 25% trimming no break is indentified (again because the break occurs early in the sample and a 20% or 25% trimming parameter doesn't allow for such an early break).

[9] The reason to consider subsamples even if the initial full sample fails to reject the null of no structural breaks arises from the fact the *SupF* statistic is known to have low power for finite samples with multiple structural breaks. Thus while we may fail to find evidence of a structural break in the full sample, when subsamples are considered, there is evidence of multiple structural breaks. See Bai (1997) for more.

In Table 5, we provide the results for estimates of the bivariate predictive model using relative government bond yield and then inflation as the predictor, as well as our multivariate model. The break point for each model is identified and the resulting model estimated for each sub-sample or regime.

What we see in Table 5 is that when our predictors are considered in each regime, the degree and direction of predictability can change markedly. For instance consider first the bivariate results for relative government bond yield. Recall in the full sample results in Table 1, the coefficient is negative and significant with an R^2 of 0.05. In Table 5, we see evidence of a break in 1980.3 which coincides with the second oil price shock of 1979-1980. Further, we see the estimate based on the first regime is positive and significant, while for the second regime, the coefficient continues to be significant but now mirrors the full sample results in having a negative coefficient. Interestingly, allowing for this break provides increased predictability as measured by the R^2 (0.14 and 0.09) relative to the full sample result (0.05).

Turning to the inflation measure, the selected break is 1988.12, which coincides with the Bank of Canada's move towards price stability as its primary focus in 1988, and the eventual movement from a rather high inflation environment to a low inflation environment based on the explicit adoption of inflation targeting in 1991. Again accounting for the structural break we see the implications for predictability can be sizeable. Recall in Table 1 based on the full sample results, inflation does not prove to be a significant predictor of stock returns over the monthly horizon with statistical insignificance of the coefficient and an R^2 of 0.00. With the break, we see in Table 5 that the R^2 in both regimes increase to 0.03 and the inflation variable takes on significance, with a positive coefficient in the first regime and similarly sized negative coefficient in the second regime.

Finally in the case of the multivariate model, recall from Table 2 in the full sample results, all variables entered significantly and with an overall R^2 of 0.07. In Table 4, the structural break corresponds to 1980.3, and we see in the first regime, the R^2 is much higher at 0.14, with relative government bond yield being the only significant predictor among the three. In the second regime, the R^2again remains very high at 0.13 and now all three predictors are significant. Of particular interest is that mirroring its bivariate results, the relative government bond yield measure again flips signs and become negative in the second regime.[10]

VI. Conclusion

This article considers the stability of a range of macroeconomic and financial predictors of Canadian stock returns over the very short-run (1 month). It represents to our knowledge, the first paper to do this in a Canadian context. What we find is that accounting for structural breaks in the prediction model can have significant ramifications for the degree of a variable's

[10] At times it has been pointed out that the R^2 found in many prediction studies (including this one) may appear rather small. This argument is sometimes used to dismiss the economic or financial relevance of these findings (beyond the statistical significance of the coefficient). We would point readers concerned with "low R^2" to consider Campbell and Thompson (2008) who show that even rather small R^2 are relevant for investors in terms of improving their portfolio performance.

predictive power as well as the direction of the prediction, though most of our bivariate prediction models are stable. Of our 9 bivariate regressions, only 2 were found to possess structural breaks, as did our multivariate model.

While a priori, the finding of structural breaks in only 2 of the 9 bivariate models may seem few, we don't consider this as evidence that structural breaks are only a minor nuisance, but rather given the changes seen when estimating these regressions with the breaks, feel this is strong evidence of the need to consider structural breaks for future work on Canadian stock predictability. Further, we believe, with the extension of the sample to dates prior to 1975 (such as Rapach and Wohar (2006) have done in the US case), perhaps more of these bivariate models would also exhibit structural breaks. Further, the consideration of other possible predictors such as the price-earnings ratio and price-dividend ratio could also yield important information on structural breaks in the predictability of Canadian stock returns. We consider these areas of further research.

There is also the issue of the in-sample approach used in this paper. We want to make it clear that the results of this paper, while in-sample, have important ramifications for the out-of-sample literature as well. We believe the changing predictability seen when estimating models across regimes goes part of the way in explaining why some variables have had mixed success out-of-sample despite in-sample success.

Lastly, there is the issue of what studying Canadian returns brings to the general literature. Beyond the fact that there is a lack of research on Canadian stock predictability, and so our findings help fill a hole in this regard, these findings also have relevance for the general stock predictability literature as well. Examination of non-US predictability informs us on the stability of predictors not only over time, but also across countries (i.e. do results for the US hold for other countries as well). Further, while studies of structural breaks in predictability are generally explained using country-specific explanations (as to be fair, has ours), as the number of studies which consider breaks in predictability grow, we may begin to see that breaks in certain variables occur at the same time across countries, allowing us to consider broader more systemic (rather than country specific) explanations of these breaks. In fact, while comparing our results with other US and non-US studies may yield insights on common break downs in predictability, future researchers may want to even consider an approach such as Rapach, Wohar, and Rangvid (2005) which studies a large group of countries in a single study. While Rapach, Wohar and Rangvid have considered the ability of variables to predict returns for a number of countries and horizons, the next step may be to examine breaks in predictability found for this group of countries and examine whether these breaks coincide and why.

References

Adjaoud, F. and Rahman, A. (1996) A note on the temporal variability of Canadian financial services stock returns, *Journal of Banking and Finance,* **20**, 165-77.

Andrews, D. W. K. (1993) Tests for parameter instability and structural change with unknown change point, *Econometrica,* **61**, 821-56.

Bai, J. (1997) Estimation of a change point in multiple regimes, *Review of Economics and Statistics*, **79**, 551-563.

Bai, J. and Perron, P. (1998) Estimating and testing linear models with multiple structural changes, *Econometrica*, **66**, 47-78.

Bai, J. and Perron, P. (2003) Computation and analysis of multiple structural change models, *Journal of Applied Econometrics,* **18**, 1-22.

Campbell, J.Y. and Thompson, S.B. (2008) Predicting excess stock returns out-of-sample: can anything beat the historical average?, *Review of Financial Studies* **21**, 1509-1531.

Chan, L. K. C., Karceski, J. and Lakonishok, J. (1998) Risk and return from factors, *Journal of Financial and Quantitative analysis,* **33**, 159-88.

Chen, N., Roll, R. and Ross, S. A. (1986) Economic forces and the stock market, *Journal of Business,* **59**, 383-403.

Clark, T.E. (2004) Can out-of-sample forecast comparisons help prevent over-fitting? *Journal of Forecasting*, **23**, 115-139.

Durham, J. B. (2001) The effects of monetary policy on monthly and quarterly stock market returns: cross-country evidence and sensitivity analyses, *Federal Reserve Board of Governors, Finance and Economics Discussion Series,* Paper#2001-42.

Fama, E. F. and French, K. R. (1989) Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics,* **25**, 23-49.

Flannery, M. J. and Protopapadakis, A. A. (2002) Macroeconomic factors do influence aggregate stock returns, *Review of Financial Studies,* **15**, 751-82.

Giannetti, A. (2007) The short term predictive ability of earnings-price ratios: the recent evidence (1994-2003), *Quarterly Review of Economics and Finance,* **47**, 26-39.

Goyal, A. and Welch, I. (2004) A comprehensive look at the empirical performance of equity premium prediction, *NBER Working Paper,* WP#10483.

Hansen, B.E. (2000) Testing for structural change in conditional models, *Journal of Econometrics*, **97**, 93-115.

Huang, B. and Yang, C. (2004) Industrial output and stock price revisited: an application of the multivariate indirect causality model, *The Manchester School*, **72**, 347-62.

Inoue, A. and Kilian, L. (2004) In-sample or out-of-sample tests of predictability: which one should we use? *Econometric Reviews*, **23**, 371-402.

Newey, W. and West, K. J. (1987) A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica*, **55**, 703-08.

Pesaran, M. H. and Timmerman, A. (2002) Market timing and return prediction under model instability, *Journal of Empirical Finance,* **9**, 495-510.

Rapach, D. E. and Wohar, M. E. (2006) Structural breaks and predictive regression models of aggregate U.S. returns, *Journal of Financial Econometrics*, 4, 238-74.

Rapach, D. E., Wohar, M. E. and Rangvid, J. (2005) Macro variables and international stock return predictability, *International Journal of Forecasting*, **21**, 137-66.

Tables

Table 1: Data Description

Variable Name	Acronym	Description	Mean	Standard Deviation
Relative money market rate	RMM	Difference between the money market interest rate and a 12-month backward-looking moving average	-0.07	1.64
Relative 3-month Treasury bill rate	RTB	Difference between the 3-month Treasury bill rate and a 12-month backward-looking moving average	-0.08	1.44
Relative long-term government bond yield	RGB	Difference between the long-term government bond yield and a 12-month backward-looking moving average	-0.06	0.77
Term spread	TSP	difference between the long-term government bond yield and the 3-month Treasury bill rate	0.95	1.76
Inflation rate	INF	First difference in the log-levels of the consumer price index	6.81	20.56
Industrial production growth	IPG	First difference in the log-levels of the industrial production index	2.30	15.03
Narrow money growth	NMG	First difference in the log levels of the narrowly defined money stock	7.46	17.50
broad money growth	BMG	First difference in the log levels of the broadly defined money stock	8.37	6.07
Change in the unemployment rate	DUN	Change in the unemployment rate	0.003	0.23
Real Stock Return (Dependant Variable)	RSR	Morgan Stanley Capital International stock price index deflated by the consumer price index	1.55	63.64

Table 2: Full Sample Estimates

Bivariate Models			
Predictor	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2
RMM	1.37	0.48	0.00
	(3.61)	(3.62)	
RTB	1.13	-4.15	0.00
	(3.61)	(3.61)	
RGB	0.27	-13.58	0.05
	(3.54)	(3.53)	
TSP	0.96	0.72	0.00
	(4.09)	(3.62)	
INF	0.55	2.40	0.00
	(3.80)	(3.61)	
IPG	0.50	5.49	0.01
	(3.64)	(3.60)	
NMG	1.07	0.65	0.00
	(3.92)	(3.61)	
BMG	4.72	-2.44	0.00
	(6.14)	(3.61)	
DUN	1.37	-4.58	0.01
	(3.60)	(3.62)	
Multivariate Model			0.07
Constant	-0.62		
	(3.54)		
RMM		9.38	
		(3.98)	
RGB		-17.90	
		(3.96)	
IPG		6.04	
		(3.51)	
Notes:	Standard errors in parentheses.		

Table 3 : Testing for Structural Breaks

Predictor	*SupF*[a]	*UDmax*[b]	*WDmax*[b] *(10%)*	*WDmax*[b] *(5%)*	*WDmax*[b] *(1%)*	$SupF_T(1\|0)$[c]	$SupF_T(2\|1)$[d]	$SupF_T(3\|2)$[e]	$SupF_T(4\|3)$[f]	$SupF_T(5\|4)$[g]
RMM	2.37	3.41	5.14	5.44	6.06	2.07	3.68	1.79	5.26	__
RTB	7.23	7.94	7.95	8.42	9.39	7.93	4.04	1.47	6.91	__
RGB	19.11*	21.00***	21.00***	21.00***	21.00***	21.00***	3.19	1.63	2.09	__
TSP	5.16	5.68	5.76	6.06	6.79	5.68	3.04	4.01	3.24	__
INF	9.73	10.24*	11.64*	12.05	12.96	10.01*	4.91	2.01	2.21	__
IPG	5.97	5.05	5.79	6.11	6.66	5.05	3.44	5.11	1.44	__
NMG	3.42	3.58	5.40	5.72	6.37	2.65	2.35	1.70	4.39	__
BMG	3.10	3.27	5.61	5.90	6.61	3.01	2.09	5.18	1.93	__
DUN	7.34	6.18	6.18	6.18	6.39	6.18	2.63	2.13	__	__
Multivariate Model	22.88*	24.41***	24.41***	24.41***	24.41***	24.41***	5.48	2.06	4.10	__

Notes: *,**,*** indicates 10%, 5%, and 1% significance levels.
Minimum length of a given regime is 15% of the full sample; __ indicates no ability to insert a further break given the trimming requirement.
a SupF statistic tests the null of no structural break against the one-sided alternative hypothesis of a structural break. Hansen (2000) heteroskedastic fixed-regressor bootstrap used.
b One-sided (upper tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of an unknown number of breaks (5 upper bound)
c One-sided (upper tail) test of the null hypothesis of 0 breaks against the alternative hypothesis of 1 break.
d One-sided (upper tail) test of the null hypothesis of 1 break against the alternative hypothesis of 2 breaks.
e One-sided (upper tail) test of the null hypothesis of 2 breaks against the alternative hypothesis of 3 breaks.
f One-sided (upper tail) test of the null hypothesis of 3 breaks against the alternative hypothesis of 4 breaks.
g One-sided (upper tail) test of the null hypothesis of 4 breaks against the alternative hypothesis of 5 breaks.

Table 4: Bai (1997) Subsample Analysis

Predictor	Sample	SupF	Break
RMM	1976:1-2001:12	2.37	1980:7
	1980:8-2001:12	4.50	—
RTB	1976:1-2001:12	7.23	1980:3
	1980:4-2001:12	5.19	—
RGB	1976:1-2001:12	19.11*	1980:3
	1980:4-2001:12	5.05	—
TSP	1976:1-2001:12	5.16	1980:3
	1980:4-2001:12	3.95	—
INF	1976:1-2001:12	9.73	1988:12
	1976:1-1988:12	1.83	—
	1989:1-2001:12	5.10	—
IPG	1976:1-2001:12	5.97	1980:7
	1980:8-2001:12	3.73	—
NMG	1976:1-2001:12	3.42	1997:8
	1976:1-1997:8	2.15	—
BMG	1976:1-2001:12	3.10	1994:12
	1976:1-1994:12	2.32	—
DUN	1976:1-2001:12	7.34	1982:7
	1982:8-2001:12	2.85	—
Multivariate Model	1976:1-2001:12	22.89*	1980:3
	1980:4-2001:12	8.72	

Notes: *,**,*** indicates 10%, 5%, and 1% significance levels.
Minimum length of a given regime is 15% of the full sample.
SupF tests the null of no structural break over the sample against the one-sided (upper tail) alternative hypothesis of a structural break. Hansen (2000) heteroskedastic fixed-regressor bootstrap used.

Table 5: Bai and Perron Multiple Regime Estimates

Bivariate Models

	Regime 1				Regime 2		
Predictor	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2	Endpoint	$\hat{\beta}_0$	$\hat{\beta}_1$	R^2
RGB	-0.10	34.94	0.14	1980:3	-3.03	-18.48	0.09
	(8.62)	(12.01)		[1979:4, 1981:7]	(3.81)	(3.63)	
INF	-6.00	11.36	0.03	1988:12	5.43	-11.24	0.03
	(5.87)	(4.90)		[1984:4, 1993:11]	(4.70)	(5.31)	
Multivariate Model			0.14	1980:3			0.13
				[1979:5-1981:5]			
Constant	0.93				-3.81		
	(9.06)				(3.79)		
RMM		-2.14				11.85	
		(9.76)				(4.16)	
RGB		35.37				-23.76	
		(12.58)				(4.04)	
IPG		-2.54				8.11	
		(9.11)				(3.67)	

Notes: Standard errors in parentheses.
Reported regime endpoints include 90% confidence intervals in brackets.
Regime 1 begins in 1976.1