Time-Varying Short-Horizon Predictability

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ABSTRACT

In a sample of seven developed countries across three continents, the short-horizon informativeness of aggregate return predictors such as the dividend and short rate diminish greatly during business cycle expansions. We examine this phenomenon in light of its theoretical and empirical links to identifiable economic dynamics: the smoothing of dividends by firms and the adjustment of rates by central banks. Short-term conditional predictability is not driven by the market volatility of returns, but instead by the additional informativeness of less-smoothed predictor variables during recessions. Corroborative tests confirm that the disparity in predictability between good and bad times is not spuriously driven by persistence bias, nor by the prediction of negative expected returns in bad times. As a practical matter, because statistical return predictability is concentrated during periods of higher volatility, its overall economic value for mean-variance investors will tend to be overstated by common methods of analysis which ignore the state-varying nature of predictability.

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JEL Codes: E32, E44, G11, G12

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ABSTRACT

In a sample of seven developed countries across three continents, the short-horizon informativeness of aggregate return predictors such as the dividend and short rate diminish greatly during business cycle expansions. We examine this phenomenon in light of its theoretical and empirical links to identifiable economic dynamics: the smoothing of dividends by firms and the adjustment of rates by central banks. Short-term conditional predictability is not driven by the market volatility of returns, but instead by the additional informativeness of less-smoothed predictor variables during recessions. Corroborative tests confirm that the disparity in predictability between good and bad times is not spuriously driven by persistence bias, nor by the prediction of negative expected returns in bad times. As a practical matter, because statistical return predictability is concentrated during periods of higher volatility, its overall economic value for mean-variance investors will tend to be overstated by common methods of analysis which ignore the state-varying nature of predictability.

1. Introduction

A number of studies document a disappearance of stock return predictability from US markets. Some researchers point to parameter instability or structural breaks and identify the date of disappearance circa 1991 (Pesaran and Timmermann, 2002; Lettau and Van Nieuwerburgh, 2007). A related hypothesis is that predictability gets arbitraged away once discovered, in a scenario similar to attenuation of the January effect (Neely and Weller, 2000). Still others take a Galbraithian view, contending it was never actually there (Bossaerts and Hillion, 1999; Goyal and Welch, 2003).[1] Recently, Ang and Bekaert (2007) find that predictability is primarily a short horizon phenomenon. In this study, we cast predictability as a phenomenon whose strength is distinctively time-varying.

The predictive relation is the byproduct of potentially complicated dynamics of the predictors as well as those of expected returns. In particular, we are interested in the potential interactions of predictor variables and the behavior of firms and central banks. These agents at times pursue actions that may tend to smooth aggregate economic indicators such as the dividend yield and the short term interest rate. Reduced-form expressions of Taylor rules and dividend smoothing functions lead us to re-examine predictability using a regime-switching vector autoregression (RSVAR) framework capable of matching the dynamics of predictors to the dynamics of expected returns.[2]

Our approach can be considered an extension of Campbell (1996) that allows for modeling of term structure variables in line with Gray (1996), Ang and Bekaert (2002b) and Bansal and Zhou (2002).[3] The RSVAR specification permits both faster transition dynamics and more parameter estimation discipline than traditional rolling regressions, but we also show that our results are still robust to using simpler OLS regressions with NBER regime dates.

The regime shifting analytical framework is compatible with more than one potential economic storyline. For instance, based upon theoretical contributions by Lintner (1956), Kumar (1988), Fudenberg and Tirole (1995) and Davig and Leeper (2007) and the empirical work of Mankiw and Miron (1986) and Gray (1996), short-horizon return predictability might vary inversely with agents' ability to manipulate the dividend and

[1] John Kenneth Galbraith is widely reported to have said, "There are two types of forecasters: those who don't know and those who don't know they don't know."
[2] See Taylor (1993), Davig and Leeper (2007) and Timmermann (1994).
[3] While our approach is reduced-form, several other papers consider dividend yield predictability within a general equilibrium framework. In a seminal paper, Menzly, Santos, and Veronesi (2004) find time-varying dividend yield predictability relating to confounding effects of dividend growth in the present value relation. With a different present value construction, Engstrom (2003) considers changes in risk attributes over the business cycle as the driver of time-varying dividend yield predictability. In these models, changes in risk attributes, rather than changes in the behavior of managers and central banks, drive changes in predictability.

term structure indicator variables. Alternatively, it could be the case that news in bad times diffuses slowly, as in Hong, Lim, and Stein (2000), and the slow incorporation permits observation of predictability that would be invisible in the good times.

Our study adds to the existing literature along three main dimensions. First, it explores a more structured link between the predictability and persistent, observable macro- and microeconomic behavior patterns, a link also applicable in other international markets. Second, it extends our understanding of the relation between (excess) market volatility and predictability. Third, it complements and adds robustness to previous findings by rationalizing the history of research findings on predictability.

When predictability is present, the dividend yield and commonly used term structure variables such as the short rate and the term spread are effective predictors primarily during recessions. For instance, in the US over the 1953–2005 period, the adjusted R^2 ($\overline{R}^2$) of the monthly predictability multiple regression is about 16% during recessions yet less than 2% in expansions. The same pattern holds for six of the G7 countries, with Germany as the lone exception.[4]

Further, in the US, other plausible partitions of the data besides those of the NBER and RSVAR partitions provide considerably less explanatory power. Disparities in persistence bias, conditioning bias, sample sizes and the negative skewness of returns across regimes do not explain the eroding explanatory power. Thus, observed parameter stability is not random or rare as in, for instance, Pesaran and Timmermann (2002), Paye and Timmermann (2005) and Lettau and Van Nieuwerburgh (2007), but related to cyclical economic conditions.[5]

Crucially, countercyclical predictability is not induced by the phenomenon of excess market volatility. Predictive regression coefficients can be decomposed simply into two parts, raw informativeness and a volatility multiplier. We define raw informativeness as the (conditional) correlation between today's regressor and tomorrow's realized market risk premium. The remaining explanatory power comes from the volatility multiplier, which we define as the ratio of the (conditional) standard deviation of tomorrow's market return over the (conditional) standard deviation of today's predictor. The volatility multiplier, or volatility ratio, magnifies the basic underlying link given by the raw informativeness. Measurement of both effects strongly suggests that the driver is the informativeness, which from recessions to expansions erodes by 64% (dividend yield) to 90% (short rate). In contrast, the multiplier sometimes decreases in recessions because the dynamics of

[4] The point estimates are an order of magnitude different for Italy, but their difference is only marginally significant.

[5] In fact, our results are quite consistent with the findings in these other papers - the long booms of the post 1970's ought to imply a structural break in the data as found. The main difference is that structural breaks imply that following a break, all past information is useless, while regime-switching suggests past information is conditionally useful.

the predictors change more than those of expected returns. These predictors tend to be less smoothed (less persistent, more volatile) and better correlated with next period returns during recessions. Further, these correlations appear to be stable in very small samples from recession to recession.

Combining our results with the benefit of hindsight, we illustrate how prior predictability research findings are a product of their contemporaneous economic history. Figure 1 shows the cumulative proportion of NBER recession months to all months in CRSP since its inception in 1963. Overlayed are indicative initial, not comprehensive, citations of early research on predictability for each variable we consider. Several features stand out: (1) the random walk model of stock prices prevailed in the 1970's, based upon CRSP data from the long 1960's era expansion, (2) predictability emerged in research of the mid-1980's, following several recessions and (3) predictability was subsequently doubted in the 1990's following the long booms of the 1980's and 1990's. Therefore, our results are consistent with the time series of research findings about predictability.

Our results have possible practical implications as well. For instance, investors following a commonly used OLS predictive benchmark model without consideration of state-varying return predictability would have incorrectly predicted Treasury Bills to outpace the market throughout the boom years of the late 1960's and 1990's. Potential exploitability, however, is not our intended focus.

Taken as a whole, our findings enrich the extant literature by exploring whether predictability depends on the differential dynamics of predictor variables arising from the behavior, in good versus bad times, of central banks and firms. Our results also give rise to the out-of-sample testable hypothesis that stronger return predictability will follow future recessions. More specifically, stronger dividend yield predictability will follow from the cash-constrained segment of firms and that aggregate predictability will be more apparent when more firms in the economy are constrained.[6]

The remainder of the paper proceeds as follows. We lay the foundations of our work in Section 2. Section 3 expands on our empirical approach and is followed by a brief description of the data in Section 4. Section 5 discusses our main results and shows that they are robust to common biases related to the econometric methodology. Section 6 concludes.

[6] We thank Duane Seppi for pointing this out.

2. Background and Theoretical Motivation

2.1. Existing Literature

Going back as far as Dow (1920), evidence has amassed in a great debate on whether aggregate stock returns are predictable, and if so, which predictors work and why. Much research focuses on the predictive power of macroeconomic variables such as the dividend yield (Rozeff, 1984), the short rate (Fama and Schwert, 1977; Fama, 1981), the slope of the term structure (Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1989), and the default premium (Fama and Bliss, 1987; Campbell, 1987; Fama and French, 1989).

On the whole, however, these papers abstract from the actions of managers and central bankers that induce the macro behavior of the predictors involved. On this front, our paper also has ties to the literature on information feedbacks (Dow and Gorton, 1997; Bernanke and Woodford, 1997). Whereas this literature considers the inferential problems of managers and central banks learning from the information impounded in stock prices, we acknowledge the reverse: investors' inferential problem of learning about expected returns from indicators controlled by managers and central banks. Central banks manage common market-wide prices, most notably and directly short-term interest rates. Managers also manage earnings and smooth dividends. While aggregate stock index prices are unlikely to be manipulated, interest rates and dividends are, in comparison, more subject to influence.[7]

The interplay amongst market participants, managers and central banks is unobserved by the econometrician. As such, simple econometric approaches may not uncover predictability even if it exists. Fortunately, however, noticeable and persistent patterns in the behavior of central banks and managers over monetary policy regimes and over the business cycle identify one dimension of this interaction, the smoothing of signals, as documented by Mankiw and Miron (1986), Gray (1996), Lintner (1956), Kumar (1988), and Fudenberg and Tirole (1995). For example, Davig and Leeper (2007, p. 20) theorize that the regime-switching behavior of interest rates is consistent with a generalized Taylor rule which allows the central bank to focus either on price stability (fighting inflation) or on financial stability and job creation.

As an econometric expression of the inferential problems discussed, a growing body of empirical evidence documents persistence, instabilities, and nonlinearities in the time-series properties of economic variables typically used in predictive regressions. Chan, Karolyi, Longstaff, and Sanders (1992), Gray (1996), and Ang and Bekaert (2002a), among others, focus on the short-term interest rate (***SR*** henceforth). Chan et al. (1992)

[7] The scope and direction of influence are a matter of continued inquiry. Chang, Kumar, and Sivaramakrishnan (2007) report that firms use dividends to signal future returns most successfully in good economic times.

find that only non-stationary models of the short-rate are not rejected by the data. They search for a single structural break, but fail to find one. Subsequent research by Gray (1996), building upon Hamilton (1989)'s regime-switching structure, finds not one structural break, but many. Gray (1996) models the evolution of the short rate as drawn from a mixture of two normal distributions. In the low mean, low volatility regime the short rate behaves like a random-walk process, and in the high mean, high volatility regime it displays a significant amount of mean reversion.[8] While the mean-reverting regimes are highly correlated with recessions and with the Fed experiment period of 1979-1982, the more frequent episodes of random-walk behavior are associated with periods in which the Fed targeted rates. Applying a similar regime-switching framework and obtaining comparable findings, Ang and Bekaert (2002b, p. 166) say "In expansions, the interest rate persistence may arise from the smoothing efforts of the monetary authorities." In related work, Mankiw and Miron (1986) examine the relation between Fed targeting and the (univariate) predictability of interest rates. As Hardouvelis (1988, p. 340) summarizes, "In their view, the Fed's targeting of interest rates makes interest rate changes unpredictable."

Although no study we know of focuses exclusively on instabilities in the dynamics of the term spread ($TERM$), the evidence previously cited on short rate coupled with the findings by Ang and Bekaert (2002b), Bansal and Zhou (2002), Bansal, Tauchen, and Zhou (2004), and Boudoukh, Richardson, Smith, and Whitelaw (1999) suggest that the inclusion of term spread information improves the ability to forecast the short rate itself and partially resolves puzzles relating to the expectations hypothesis, indicating that the term spread may plausibly be characterized by a similar switching-type structure. Similar considerations apply to corporate bond yields and, thus, the default spread (DEF), defined as the difference in yields between high-grade and low-grade corporate bonds.

Dividend dynamics are also known to be potentially complicated. For instance, the existence of a unit-root in the dividend yield (DY) process is hard to reject empirically (see, e.g., Torous, Valkanov, and Yan (2004)). Even more so than interest rates, dividend payouts are known to be the subject of explicit policy decisions at the corporate level that persist even today (Lintner, 1956; Brav, Graham, Harvey, and Michaely, 2005). Marsh and Merton (1987) model aggregate dividend dynamics based on managerial smoothing, but do not consider return predictability. Engstrom (2003) finds that modeling time-varying predictability coefficients by an AR(1) process is insufficient to account for their variation and resorts to a modification to risk preferences more extreme than habit-formation called "moody investors."

[8] Regime switching is not the only alternative. Through a non-linear specification for the short rate drift, Aït-Sahalïa (1996) finds mean reversion only for relatively high and low short rate levels. In the middle, the short rate follows a random walk.

While this discussion has focused on the dynamics of predictors, sudden declines in the equity premium are also considered a cause of diminished predictability in Lettau and Van Nieuwerburgh (2007). Our expected return model picks up this decline in the equity premium (from ∼1.5% per month in 1953 to ∼0.5% per month in 2005), but countercyclical variation in the premium appears to have a substantially larger impact than the overall decline. Although market return volatility is 44% higher in recessions, our expected return model suggests a proportionally larger cyclical change in the equity premium during these periods.

Although our approach shares some outward similarities in cross-sectional results, our focus and our findings differ from Perez-Quiros and Timmermann (2000). Because our focus falls directly on the issue of eroding return predictability, we control for conditioning bias, persistence bias, and consider small sample biases and non-negativity constraints on expected returns. In addition, our findings are notably different. Perez-Quiros and Timmermann (2000) report substantial predictability in expansions, but we find almost no predictability. Along this dimension, our results also go farther than Goyal and Welch (2003, 2007): whereas they show a lack of "out-of-sample" predictability, we show a lack of even in-sample predictability during expansions. This reduction of in-sample predictability in good times is consistent with the smoothing hypothesis.

3. Research Design

3.1. Choice of Horizon

All of our predictability analysis is at the one-month interval. Substantial evidence shows return predictability is consistent with a short-horizon phenomenon that is magnified at longer horizons (for examples, see Campbell, Lo, and MacKinlay (1997, p. 271) and Cochrane (2001, p. 393)). In a sample of four developed countries, Ang and Bekaert (2007) show, by an exact Gordon growth formulation and proper annualization of returns, that return predictability is concentrated at the short horizon.[9]

In addition to allowing easy comparisons with the literature, our choice of frequency conveniently abstracts away from the econometric issues associated with long-horizon regressions and overlapping observations (Hodrick, 1992). For example, Boudoukh, Richardson, and Whitelaw (2007) provide simulation evidence that long horizon predictability may result from highly correlated sampling errors. However, more important than the circumvention of these econometric challenges, predictability regressions at annual horizons or longer would be

[9] The nature of the long horizon cointegrating relationship between expected returns, expected dividend growth and the dividend yield is also an open issue, as best articulated by Cochrane (2006) and Bansal and Yaron (2006). Cochrane (2006) argues that all of the variation in dividend yields is due to variation in expected returns, but Bansal and Yaron (2006) argue that up to 50% of the variation in dividend yields is due to variation in expected dividend growth once fully accounting for share issuances and repurchases. However, our analysis here cannot directly address this important and emerging controversy.

unlikely to detect the results we report. The estimated transition probability matrices of our monthly RSVAR converge in less than nine months. Thus, as the state of the economy evolves through time, long-horizon predictions would tend to converge to an average state, with any differences between predictability estimates in expansions and recessions hopelessly blurred.

3.2. Choice of Predictive Variables

Following the discussion in Section 2, our set of predictive variables includes SR, $TERM$, DEF and DY. These are precisely measured, high-frequency, market-traded ex ante quantities, as opposed to quarterly, lagged or often-revised government statistics. Moreover, except for the default spread which is available only for the US, these quantities are readily comparable across countries. Following the approach of Chordia and Shivakumar (2002), Avramov and Chordia (2006) and Petkova (2006), among others, we do not impose additional filters on the raw data, such as separating the short rate into real and inflationary components, or taking a stand on expected versus unexpected inflation.

In addition to the above ex ante state variables, we need an indicator of expansions and recessions. The most obvious candidate for the US is the NBER business cycle measure. However, the NBER determines business cycles by looking at many time series and then selecting dates ex post by committee.[10] The unobservable and ex post nature of the determination process makes the measure objectively unknowable and contemporaneously unavailable to either the agent or the econometrician. Still, we perform some analyses using the NBER dates as they (1) provide convenient economic intuition, (2) allow our results a connection to the larger macroeconomic literature and (3) provide a hedge against the risk of data mining. After all, the degree of return predictability is a highly unlikely metric for the NBER to use in classifying business cycles.

As for international data, NBER-type indicators are either unavailable or not commonly used. We draw from the business cycle research of Hamilton (1989, 1994) and let the data determine the state of the indicator based on a Regime-Switching Vector Autoregression (RSVAR).[11] Unlike the RSVARs typically applied in the macroeconomic literature, we do not use government statistics such as GDP, consumption, investment

[10] Typical announcements have occurred between six and 18 months after the fact. Another unexplored issue is that the NBER dating methodology may evolve over time and across administrations. We collect business cycle peaks and troughs from the NBER web page, http://www.nber.org/cycles.

[11] RSVARs have become increasingly popular in other finance applications as well, and particularly for asset allocation problems and for risk analysis in the cross-section of returns. Ang and Bekaert (2002a) is the seminal paper on international asset allocation with regime switching. Guidolin and Timmermann (2007) provides a useful extension, with switching dynamics between stock and bond returns. Regarding the cross-section of returns, Stivers and Sun (2004) look at momentum and regimes. Gu (2005) uses Bayesian MCMC methods to allow the switching to be simultaneously determined by 25 size and book-to-market portfolios and the market. Besides the applications already discussed, regime-switching has been used directly to forecast business cycles using GDP or the index of coincident and leading indicators (CLI).

or labor income for the same reasons already given. Instead, we only use the RSVAR system to determine the state probabilities. The RSVAR is capable of determining time t latent state probabilities in three ways. Ex ante probabilities use information up to $t-1$, filtered probabilities include information up through t, and finally, smoothed probabilities use all of the information up to the final observation, T. Overall, the US results determined by the RSVAR and by the NBER dates are qualitatively comparable, so we report them nearly interchangeably.

3.3. Empirical Framework

In RSVAR, z_t (a vector of observable variables) is assumed to be drawn from one of k different distributions at each time t. As a consequence, autoregressive coefficients and the residuals' variance are allowed to jump between k values. The RSVAR takes the form

$$z_t = c(s_t) + A(s_t)z_{t-1} + \varepsilon(s_t), \tag{1}$$

where $z_t = (R^e_{m,t},\ SR_t,\ TERM_t,\ DEF_t,\ DY_t)'$, $c(s_t)$ and $A(s_t)$ are the constant vector and the coefficient matrix in state $s_t \in [0,1]$ and $\varepsilon(s_t) \sim N(0,\Sigma(s_t))$ is an error vector of zero mean with a generalized (i.e., non-diagonal) state-dependent error covariance matrix.[12] The states s_t follow a Markov chain where the transition probabilities between one regime at time t and the contiguous regime at time $t+1$ are fixed and contained in a transition matrix P. The two-state RSVAR applied here may be seen as an approximation of a more complex, as yet unknown, model of return predictability. The shocks to the system, ε_t are assumed to be normally distributed, but this is not an especially restrictive choice. Because many distributions can be approximated by a mixture of normal distributions, the regime switching approach has had wide appeal in fitting non-normalities, non linearity, volatility clustering, and higher distributional moments of returns. Although we might err on the side of a simpler specification, incorporation of richer multivariate GARCH dynamics should only improve the identification of regimes. On the other hand, the analysis in Hamilton and Susmel (1994) shows that GARCH effects in aggregate stock returns disappear at the monthly horizon once the variance is allowed to follow a Markov switching process. Unlike prior studies, we include the dividend yield as part of the switching model

[12] Regarding the number of parameters in the RSVAR, there are two states, one lag and five variables, so the system has 112 parameters to be estimated. Although 112 parameters may not seem especially parsimonious, we jointly fit five time series with 645 observations each, or 3,225 total degrees of freedom. In the international setting, we typically have 419 observations per series and only four variables, or 74 parameters to be estimated and 1676 degrees of freedom.

so as to pick up business cycle variation in return predictability. Finally, we note that this specification nests those of Campbell (1996) and Petkova (2006).

Our RSVAR most closely resembles that of Guidolin and Timmermann (2007), but we use bond yields rather than bond returns. This subtle difference can lead to large differences in results since bond yields are persistent but bond returns are not. This difference can be seen in the weak role that bond returns play in Chen, Roll, and Ross (1986) and Fama and French (1993) compared to the much stronger role bond yields play in Keim and Stambaugh (1986) and Campbell (1996). As such, Guidolin and Timmermann (2007) is about asset allocation with state-varying return comovement between stocks and bonds.

Our RSVAR approach is also related to Perez-Quiros and Timmermann (2000), but bears substantive technical and qualitative distinctions. First, we model a complete dynamic system of market returns and predictors in a VAR, rather than a switching regression for market returns only. Portfolio returns are a prime driver of the regimes in Perez-Quiros and Timmermann (2000), since these portfolio returns are the only distinguishing variable across their size portfolios. Obviously, the economy-wide variables are common to all portfolios. Second, we also allow the predictive relation with the dividend yield to switch across states. Third, we incorporate inferences about future expected returns through the term spread. Fourth, we rely exclusively on high-precision market-measured real-time quantities. Finally, we rely on a different estimation and inference methodology: while Guidolin and Timmermann (2007) and Perez-Quiros and Timmermann (2000) rely on a Maximum Likelihood framework implemented through the EM algorithm, we adopt a Bayesian approach, as detailed below.

3.3.1. Bayesian Estimation: Motivations

We employ Bayesian Markov chain Monte Carlo (MCMC) methods to analyze the RSVAR. Our Bayesian MCMC analysis builds on techniques developed in Kim and Nelson (1999) and, especially, in Krolzig (1998). The Bayesian framework possesses several attractive features for our analysis. First, models with latent variables (regimes and their respective probabilities, in this case) are especially amenable to estimation using MCMC methods. Using the Bayesian approach, the parameter space is augmented with the state probabilities and the Gibbs sampler algorithm effectively "integrates out" these nuisance parameters. The model parameters and latent variables are estimated simultaneously by drawing them from their joint distribution, so posterior densities implicitly incorporate estimation error (i.e., parameter uncertainty). In contrast, in a standard maximum likelihood approach based on, say, the commonly adopted EM algorithm, inference on the unobserved state vector is made conditional on the parameter estimates. Second, the distribution of test statistics in a frequentist framework relies on asymptotic arguments and on approximations such as the delta-method. In our context, we aim to investigate the properties of recessionary periods, which are expected to be relatively short, fostering concerns about the small sample validity of frequentist inference. In addition, we are interested in quantities, such as the RSVAR's R-squared, which are non-linear functions of the model parameters: again, their small sample distribution may need to be extensively explored. On the other hand, the Bayesian framework delivers finite-sample posterior densities for both parameters and features of interests. Third, frequentist estimation of VAR predictive regressions is problematic in its own rights. Employing lagged endogenous regressors, especially highly autocorrelated ones such as the dividend yield, can induce finite-sample biases.[13] This is because return innovations are correlated with innovations in the predictive regressors. Stambaugh (1999) derives the finite-sample properties of the OLS estimator in this case and proposes a correction for the bias. However, the validity of the correction depends critically on the assumed stationarity of the predictive variable (Lewellen, 2004; Torous, Valkanov, and Yan, 2004) and on the linearity of the model. If the predictive variable's order of integration is uncertain, as it tends to be in the case of many well-known predictive variables, then the asymptotic distribution of the MLE estimator is of non-standard form and traditional inferential tools (e.g., t-tests and p-values) are invalid (Campbell and Yogo, 2006; Torous, Valkanov, and Yan, 2004). The RSVAR we consider is non-linear: the combined effect of persistent lagged endogenous regressors and a non-linear predictive model on the distributional properties of test statistics is, to date, unexplored. In the Bayesian approach to estimating predictive regressions, inferences made from posterior densities are valid even if the predictive regressor is nearly-integrated or exhibits a unit root (Sims, 1988; Sims and Uhlig, 1991) and whether or not the model is linear. The Appendix contains an outline of the Gibbs sampling schem we follow.

3.3.2. Assessing Regime Fit

As a measure of the fit of the regimes, we adopt the RCM measure used by Ang and Bekaert (2002b).

$$RCM(M) \quad = \quad 1 - M^M T^{-1} \sum_{t=1}^{T} \left(\prod_{m=1}^{M} p(s_t = m | S_{t-1}) \right), \tag{2}$$

where M is the number of regimes and $p(s_t = m|S_{t-1})$ is the probability that the process is in state m conditional on the information set S at time $t-1$. If the algorithm cannot distinguish two regimes from the data, then

[13] See Mankiw and Shapiro (1986), Kim and Nelson (1993), and Stambaugh (1999) for detailed discussions.

$p(s_t = 1|S_{t-1}) = p(s_t = 2|S_{t-1}) = 0.5 \ \forall\, t \in \{1, 2, \ldots, T\}$ and $RCM(2) = 0$. If the segmentation is perfectly distinguishable (i.e., $p(s_t = 1|S_{t-1}) = 1$ or $p(s_t = 2|S_{t-1}) = 1 \ \forall\, t \in \{1, 2, \ldots, T\}$), then $RCM(2) = 1$. Therefore, the RCM statistic is a measure of the fit of the regimes, similar in spirit to the R^2.

4. Data

4.1. International Data Sample

The international sample (Canada, France, Germany, Italy, Japan and the UK) includes country index returns, short bond yields, term spreads and market dividend yields from 1973 to 2007. Panel A of Table ?? shows the span of data available for each of the G7 countries, ranging from 34 to 54 years. Overall, the span is long enough to pick up several business cycles.

The country index returns are from Thompson Financial's Datastream ($TOTMK$) series in local currencies. As a check, we compare these total market returns to local value-weighted returns from Kenneth French's website.[14] The respective total return series are at least 95% correlated between the two sources. We stick with the Datastream return series because it has better coverage. We form excess returns by subtracting the appropriately de-annualized short-term interest rate. The market dividend yield is the MSCI dividend yield, available through Datastream. The correlation between the US dividend yield from CRSP and the US dividend yield from Datastream are 96% correlated.

The term structure data come from Global Financial Database.[15] We take monthly short rate measures as the 3 month Treasury Bill. The term spread is the difference in yields between the 10-year government bonds and the short rate. For Japan, the 3-month Treasury Bill series from the Global Financial Database series exhibits strange behavior (a series of flat plateaus) in the 1973 to 1985 period. Therefore, we draw the same series from Global Insight which exhibits more expected patterns. The two series are virtually the same from 1985 onward.

4.2. US Data Sample

The US data span April, 1953 to December, 2006, again at monthly frequency. The data series are limited to 646 periods (645 net observations) because yields are not available prior to April, 1953. Even if such data

[14] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[15] In an earlier draft, we use term structure data exclusively from Global Insight with similar results. With the exception of Japan, we switch to Global Financial Data to increase coverage to the 1960s for the UK and into the 1970s for the other international countries.

were available, the 1951 Treasury Accord imposes a structural break often considered the advent of the modern macroeconomic era.[16]

Excess monthly returns are from Ken French's website. As in Campbell and Shiller (1988), we construct the dividend yield, DY, as the sum of dividends on the CRSP value-weighted market portfolio smoothed over the past 12 months and scaled by the price level of the index. The dividends are calculated as the difference between the total returns with dividends ($VWRETD$) and the capital gains ($VWRETX$). To account for share repurchases, we follow the procedure of Bansal, Dittmar, and Lundblad (2005). Net share repurchases can be calculated using changes in the number of shares outstanding along with the CRSP split factor.

The term structure variables are from $FRED$, the web-based economic data source made available by the Federal Reserve Bank in St. Louis.[17] The Treasury Bill yield, SR, is the 30-day constant maturity yield. The term spread, $TERM$, is the difference between the 10-year Treasury Bond and the 1-year constant maturity Treasury Bill. We use the 10-year Treasury bond because the 20-year series has several years of missing data and the 30-year bond has been discontinued.[18] The default spread, DEF, is the difference between Moody's BAA and AAA bond yields.

5. Results

In this section we first report the conditional return predictability results for our international sample. Next, we focus on the US sample to investigate more closely the state-varying features of return predictability and to show that this regularity is not econometrically spurious. Last, we briefly consider the economic significance of state-dependent return predictability.

5.1. International Sample

For each of the G7 countries, we estimate the regime indicators using the RSVAR specification from equation (1) of Section 3.3. We run the Gibbs sampler outlined in the Appendix and summarize the posterior distributions of interest by their posterior mean and by the 95% Highest Posterior Density (HPD) interval, which in the tables is reported in square brackets below the posterior mean.[19] Panel A of Table 1 displays the

[16] The Accord officially ended the artificial pegging of long-term nominal interest rates, and effectively concentrated control of monetary policy in the Federal Reserve as opposed to the Treasury Department.

[17] The Fed St. Louis web site is http://research.stlouisfed.org/fred2.

[18] The 20-year Treasury constant maturity series was discontinued December 31st, 1986. The 30-year constant maturity series was discontinued February 18th, 2002, but has been recently reintroduced starting February 9th, 2006.

[19] Heuristically, a Bayesian HPD interval may be seen as similar to a frequentist confidence interval. Formally, though, the two are quite different.

regime characteristics. The recession regime, identified by lower market returns and higher market volatility, represents about 14% of the sample for Canada but almost 39% of the sample for Germany. It is 30% for the US.

Panel B shows that the regime probabilities vary considerably across countries. The relatively short HPD intervals indicate that the estimates are quite precise. Across all countries, the probability of going from expansion state to expansion state, denoted by $\hat{\pi}_{E,E}$ in Panel B, is high for Canada, Japan and the US with $\hat{\pi}_{E,E}$ between 91 and 94%. This probability is quite a bit lower for Germany and France at 74%. As expected, the probability of persisting in the recession regime, denoted by $\hat{\pi}_{R,R}$, is much lower, ranging from 57 to 91%. The expected duration of an expansion averages 8.3 months compared to roughly half that, or 4.2 months, for recessions. A common feature across countries is the reduced persistence and volatility of the predictors from the high market volatility regime ("recession") to the low market volatility regime ("expansion").

Despite the variation in the evolution of the state variables across countries, the RCM statistic shows that regimes can be easily distinguished. The RCM statistic is the highest for Japan (94%), followed by the US and Canada (89%) and the lowest for Germany (79%) and France (78%). Even an RCM of 78% suggests relative certainty about the state of the process: it corresponds to an average state probability that is within 0.1 of absolute certainty, either 0 or 1.

Table 2 reports the overall $\overline{R}^2$ of a full sample VAR of the market return, the short rate, the term spread and the dividend yield (with a constant included), followed by the $\overline{R}^2$'s for the regressions conditional on the state. The seven-country average full sample $\overline{R}^2$ is 2.3%. However, we find large differences in predictive power between regimes. The $\overline{R}^2$ in expansions is 2.0% compared to 14.0% in periods flagged as recessions by the RSVAR. More importantly, for the "expansion" regime the 95% Highest Posterior Density (HPD) intervals for the estimated $\overline{R}^2$'s include zero with no exception. As a result, very little confidence can be placed on the existence of any predictability at all in such regime. On the other hand, the $\overline{R}^2$'s in the recession regime are much larger in six out of seven countries, with Germany being the exception: they range from 7.7% for France to over 28% for the UK. In all six cases, 95% of the posterior distribution does not include zero. The posterior distributions of the differences in $\overline{R}^2$s between regimes also indicate the high degree of confidence one can place on the existence of such differences: with the exception of Italy and Germany, the HPD for the difference in $\overline{R}^2$s never includes zero. The stark differences in predictive power between regimes found in several countries is our baseline result.

After assessing the overall predictive power of the RSVAR, it is important to analyze the sources of differences between regimes. Looking at the posterior estimates of the predictive coefficients reported in Table 3, two features are especially relevant for our study. First, it is never the case that a predictor displays a posterior density which is 95% away from zero in expansions but not in recessions. In other words, no predictor in any country appears to be more important in good times than in bad times. Second, in five out of seven countries (Italy and Germany excepted), most of the differences in predictive coefficients between regimes are comfortably distributed away from zero. This is true for all predictors in the UK and France, for the short rate and for the default spread in the US, for the Dividend Yield in Canada and Japan. Again, when there are differences in predictive power, the larger predictive power occurs in "bad times".

5.2. Looking more closely: the US data sample

When we apply the RSVAR to US data, an ***RCM*** of 89% suggests the regimes are quite distinct — 89% corresponds to an average state probability within 3 hundredths (0.03) of absolute certainty, either state 0 or 1. The estimated transition probability matrix is $\hat{\pi}_{E,E} = 0.92$ and $\hat{\pi}_{R,R} = 0.83$. Of the 645 observations, 192 observations are flagged as recessions and 453 as expansions, compared to 102 and 543 for NBER recessions and expansions, respectively. Figure 2 shows a 76% agreement (490 of 645 observations) in the state identification by RSVAR and NBER regimes (shaded in gray).[20] As part of its learning process, the RSVAR misses the first NBER recession in 1953-1954.

The RSVAR picks up the Fed experiment from 1979-1982 as part of a "recession" regime, but the NBER does not. At the start of this Volcker era, the Federal Reserve allowed the short rate to float freely and instead used non-borrowed reserves and M1 as the primary instruments of policy (Mankiw and Miron, 1986; Hardouvelis, 1988). This period was, like previous recessions, a time of unsmoothed and, consequently, informative short rates. Given the "stagflationary" business climate and the extreme interest rates, it is also likely that firms were less able to effectively smooth dividends. Because our hypothesis is about the smoothing of predictive variables by central banks and firms rather than specifically about the business cycle, that the RSVAR identifies this change in monetary policy as "recession" is a positive sign for our empirical approach.

Compared to the NBER cycle dates, we find more frequent and shorter instances of recessions via the RSVAR, which is consistent with either expected, but unrealized, recessions not observed by the NBER or with recessions of shorter duration than would be considered by the NBER. The more frequent recession

[20] We follow the common practice of assigning any probability less than 0.5 to indicate the expansion state and any probability greater than or equal to 0.5 to indicate the recession state. However, our regression results are stronger when we use the actual continuous state probabilities, $p(s_t = R|S_{t-1}) \in [0,1]$, as a conditioning variable instead of binary recession indicators.

indications from the RSVAR are also consistent with Paul Samuelson's observation that "the stock market has predicted twelve of the last eight recessions."

Table 4 shows the simple regression statistics for the full sample and samples conditional on NBER business cycle dates. The results cleanly reaffirm the stylized facts we document using the RSVAR approach and the international sample. The signs of the coefficients match those expected, although during recessions they are larger in magnitude (by at least a factor of 3) and in statistical significance. Full-sample return predictability is driven predominantly by NBER recession periods, in which the $\overline{R}^2$'s rises from less than 1.5% during expansions to as high as 19.0% during recessions. If predictability exists, it does so primarily in recessions.

In the following analyses, we examine possible alternative hypotheses for explaining these new findings about the disappearance of predictability in expansions. These observed facts are interesting in their own right, even if the smoothing hypothesis should prove not to be the cause. We first consider changes in market volatility and conditioning biases in section 5.3. The stability of predictive correlations is examined in section 5.4. Finally, section 5.5 addresses the possibility that the disparity in state-dependent R^2's come from the downside of return predictability: recessions may have more severe negative skewness of returns, or alternatively, proportionally more negative realized returns that are erroneously considered "predictable." None of these alternatives can explain the increased correlations, betas and explanatory power of predictive macroeconomic variables in recessions.

5.3. Correlations, Volatility and Conditioning Bias

To assess whether our results could be driven by changes in market volatility and possibly suffer from conditioning bias, we consider the following basic decomposition of the predictive coefficients

$$\beta_x = \rho_{R^e_{m,t},x_{t-1}} \frac{\sigma_{R^e_{m,t}}}{\sigma_{x,t-1}}. \tag{3}$$

We refer to the ratio of market return volatility to predictor volatility, $\sigma_{R^e_{m,t}}/\sigma_{x,t-1}$, as volatility multiplier. We loosely refer to the cross-serial correlation, $\rho_{R^e_{m,t},x_{t-1}}$, as the informativeness of the predictive relation, irrespective of excess volatility. Equation (3) suggests that changes in excess volatility across regimes may generate conditioning bias: assuming $\rho_{R^e_{m,t},x_{t-1}}$ and $\sigma_{x_{t-1}}$ were constant, increased market volatility mechanically induces increased magnitude (and possibly statistical significance) of the simple regression coefficient β_x. If the increased predictability shown in Tables 2 and 4 occurs simply because market volatility is higher, which is the case in recessions, then our main results would be the uninteresting by-product of conditioning bias.[21]

What is the potential conditioning bias in our application? Notice, first, that the (unadjusted) R^2 of the simple regressions in Table 4 are the squares of the correlation coefficients in (3). It follows that the increase in $\overline{R}^2$'s suggests that informativeness rather than excess market volatility is largely responsible for the substantial increases in the predictive coefficients from expansions to recessions. Corroborating such intuition, Table 5 shows that both the magnitude of betas and conditional correlations rise in recessions while the changes in the volatility multiplier are not extreme. Conditional market volatility increases 46% from expansions to recessions, but with the exception of the term spread, the conditional volatilities of the predictors also rise. More importantly, conditional correlations are larger in recessions by a factor of between 3 and 10. As seen in Panel B, the largest increase in the volatility multiplier is for the term spread, where excess volatility of the market return to the term spread is 51.2% larger in recessions than in expansions. This increase, however, cannot explain either the nearly 10-fold increase in the correlation or the 16-fold increase in the term spread's β. For the short rate and the default spread, excess volatilities actually drop in recessions, indicating the increased informativeness of these predictors is larger than their β's suggest when taking conditioning bias into account.

Since Table 5 shows that the conditional volatility differential does not vary across states nearly as much as does the conditional correlation, short horizon return predictability seems due to time- or state-varying correlations rather than to changes in the volatility of the market relative to predictors.

Although not shown in Table 5, the contemporaneous correlations of the predictive variables do not appreciably change across regimes, save one exception. The correlation between the short rate and the dividend yield drops from 41% in expansions to just 10% in recessions. Neither the overall stability of the contemporaneous correlations, nor the de-linkage in correlation between the short rate and the dividend yield in bad times, would fit an extreme correlation or a conditioning bias explanation.[22]

[21] For a very similar intuition applied to cross-market contemporaneous correlations and further details on conditioning bias, see Forbes and Rigobon (2002).

[22] This analysis refers to the extreme correlation literature in international finance, in which contemporaneous correlations across assets are higher in bad times. In this context, if one were to presume constant betas in the International CAPM regression,

$$\begin{aligned} R^e_{c,t} &= \alpha + \beta R^e_{wm,t} + error \\ \overline{\beta} &= \rho \frac{\sigma_{c,t}}{\sigma_{wm,t}}, \end{aligned}$$

then maintenance of the simple econometric equality requires that any increase in the (world) market return volatility, $\sigma_{wm,t}$ relative to the (country) asset return volatility, $\sigma_{c,t}$ must be offset by increase in the correlation, ρ. However, our application is not an extreme correlation story because (1) the relation under study is predictive, not contemporaneous, (2) it does not involve the conditional correlation of assets, but the conditional correlation of possible risk factors to aggregate expected excess returns,

5.4. Did Predictability Disappear in the 1990's?

Like the January effect, which vanished after its discovery, perhaps short-term predictability was arbitraged away after its discovery in the 1980's and 1990's. If so, our results would be spuriously driven by the concurrence of comparatively more recessions during the period before the discovery of predictable returns.[23] Further, arbitrageable return predictability would be unrelated to risk, undermining the theoretical basis of the ICAPM methodology of Campbell (1996). Besides the evidence presented in the immediately preceding subsection using pre-1982 and pre-1991 indicators, we now look at the stability of informativeness in the period following Fama and Schwert (1977), as have Neely and Weller (2000).

The small sample correlations in Table 6 also addresses an alternative to the smoothing hypothesis and the arbitrage hypothesis: changes in predictability result from random structural breaks, rather than business cycles. Pesaran and Timmermann (2002) identify 1991 as the period of the most recent structural break, after which there have been one or two NBER recessions (1991.07-1991.03 and 2001.03-2001.11). Under different assumptions, Lettau and Van Nieuwerburgh (2007) also pinpoint a structural break for the equity premium/dividend yield relation also around 1991.

Table 6 shows the small sample correlations for expansions and recessions following Fama and Schwert (1977). We break these out each by expansion and recession to convey a better sense of parameter stability. Because of the very limited sample sizes given the very few incidences of recessions in the post predictability discovery period, the results are only suggestive and not rooted in formal statistical inference.

Panel A gives the dates of NBER expansions and recessions for four business cycles, labeled Cycles 1-4. If predictability disappeared in the post-1980's or post-1990's period, the correlations in the NBER expansions column should horizontally match that of the recessions column, rather than vertically within its own column. If the parameters were unstable from recession to recession, we might also expect these small sample correlations to change signs. The recession correlations do vary in magnitude, and are weakest in the most recent 2001 recession, but none of the 20 recession period correlations switch signs. Again, we would not want to overemphasize the correlations from the most recent 1991 and 2001 recessions, but they provide some counter evidence to offset the random structural break hypothesis as well as the evidence that finds disappearing predictability circa 1991 (Bossaerts and Hillion, 1999; Pesaran and Timmermann, 2002).

and (3) whereas the market proxies for risk factors in the International CAPM setting, it is the asset class of interest in our setting.

[23] The criticism would not apply to the dividend yield, which has been a focus of practitioners since at least Dow (1920).

We also note that the low sub-sample correlations for the dividend yield in the most recent recession are challenges not only for us, but for any predictability model. One explanation is that if the 2001 recession was a comparatively brief or shallow one, then the budget constraints of firms as expressed by aggregate dividends may not have been as severely affected nor as information-revealing as prior recessions.

Finally, the expansion era correlations do exhibit anomalously high levels during the business cycle "2" expansion. However, this anomaly is fairly consistent with our story when we look at the Fed activity of the time, as discussed in section 5.2. Overall, it seems that neither the arbitrage hypothesis nor random structural break hypothesis can adequately explain the business cycle patterns in the small sample correlations of Table 6. Further, although parameter stability could be a problem, Table 6 displays considerable stability in the sign of informativeness within regimes.

5.5. Does Predictability Come from Predicting Negative Returns?

Thus far we have followed the literature and allowed for the possibility of negative expected returns in our specifications. This possibility has been investigated by Boudoukh, Richardson, and Smith (1993), who find empirical evidence that the market could earn a discount rather than a premium when its conditional covariance with the intertemporal marginal rate of substitution is positive. Alternatively, Campbell and Thompson (2007) find that out-of-sample predictability can be improved by ruling out negative expected returns. Pástor and Stambaugh (2007) use the information contained in negative realized returns along with the economic belief that expected and unexpected returns are negatively correlated to improve predictive estimates. Regardless, if return predictability, which we argue is largely recession specific, arises from predicting negative expected returns, then our finding may either be expected, given the well-known negative skewness of realized returns, or spurious if expected returns are, in fact, always positive.

To address this, we compute the explanatory power separately for positive and negative returns. We first fix the parameters estimated in the unconditional full sample model and the models conditional on regimes from a regression of $R^e_{m,t}$ on SR_{t-1}, $TERM_{t-1}$, DEF_{t-1} and DY_{t-1} and a constant. We then compute the conditional explanatory power as

$$R^2_{|R^e_{m,t}>0} = 1 - \frac{SSE_{|R^e_{m,t}>0}}{SST_{|R^e_{m,t}>0}} \tag{4}$$

where $SSE_{|R^e_{m,t}>0}$ is the sum of squared errors and SST is the sum of total squared variation, each summed only over observations where $R^e_{m,t} > 0$. Similar computations are done for $R^e_{m,t} < 0$.

Table 7 shows that explanatory power is higher for negative realized returns as expected, but this bias is dwarfed by the increased explanatory power during recessions, both for positive and negative realized returns. The small bias toward negative returns also shows up in the unconditional model that attempts to fit the negative skewness of returns. Indeed, the evidence is more damning for the unconditional model when looking only at positive realized returns. Here, the full period in-sample $R^2_{|R^e_{m,t}>0}$ is less than half, only 2.2% instead of 5.1%. Conditional on NBER and RSVAR expansions, $R^2_{|R^e_{m,t}>0} = 0.6\%$ and 0.8%, respectively. For these positive market moves, recession periods also experience drop offs to 22.9% and 17.6% in explanatory power for the NBER and RSVAR, respectively. The difference in explanatory power between expansion and recessions periods is still more than 17%, however, when considering only positive market returns. Therefore, the contribution to return predictability of negative returns, or the negative skewness in returns, is small.

5.6. Economic Significance

We now turn to quantifying the economic significance of state-dependent return predictability. Because the predictability we document comes at times of high volatility, statistical predictability may be of limited economic use to a prototypical mean-variance utility investor. The economic significance is attenuated both by the infrequency of predictable periods and by the large volatility of returns that accompany them, which the mean-variance investor eschews.

The goal here is not to address the exploitability, or the possibility of out-of-sample gains, but to identify in economic terms how much of the gains come from brief periods of large predictability and how much from the gains are due to the recognition of absent predictability in the large bulk of the sample.[24] Against this backdrop, we consider (1) a null model that assumes no predictability, (2) a benchmark model based on in-sample OLS estimates, (3) a regime-switching model and (4) a hybrid model that follows the null model most of the time, but follows the conditional estimates of the regime-switching model when the RSVAR flags a recession. Each model uses the full period parameter estimates. We abstract from transaction costs, as these are expected to be small for broad stock indices and do not vary appreciably over the business cycle.

[24] To fully address the possibility of exploitability, one would have to incorporate learning about model and parameter uncertainty. See, e.g., managers earn abnormal returns only in recession regimes.

The mean-variance investor attempts to maximize her utility given her level of risk aversion, γ, and her information about the first two moments of returns. ω is the weight of the portfolio the investor invests in the market return and R is the return on that portfolio. The investor's problem is then

$$max\, U[E_{t-1}(R_t),\, Var_{t-1}(R_t)], \tag{5}$$

where R is the return on a portfolio of the risky asset, R_m, which is the market return, and the risk-free asset, R_f, which is the return on a 30-day Treasury Bill (both from Ken French's website). As such,

$$R_t = R_{f,t} + \omega_t(R_{m,t} - R_{f,t}) \tag{6}$$

Maximizing the utility function with respect to ω gives the standard results

$$U(.) = E_{t-1}(R_t) - \frac{1}{2}\gamma \cdot Var_{t-1}(R_t) \tag{7}$$

with ω given by

$$\omega_t = E_{t-1}\left(\frac{R_t - R_{f,t}}{\gamma \cdot Var_{t-1}(R_t)}\right). \tag{8}$$

We further require that $\omega \in [0,1]$. This precludes borrowing at the risk-free rate or exploiting the predictability of expected negative excess returns.

Clearly, predicting the variance is as important as predicting the mean. Further, ample evidence shows that the variance is more persistent and, therefore, more predictable.[25] While the null model and the benchmark assume unconditional volatility, the regime-switching model and the hybrid model allow regime-switching, but otherwise constant, volatilities. At first consideration, it may seem we are rigging the results in favor of the regime-switching model since the model may partially exploit changes in volatility. However, since the predictability we document is in the high volatility state, accounting for this volatility attenuates the impact of the superior regime-switching model's mean prediction in the investor's allocation problem.[26]

All three predictability models dominate the null model. Figure 4 shows the ex post realized utility for our investor with risk aversion ranging from 0 to 5 and for models 2-4 net of the null model. As expected, the economic value of predictability falls as the investor becomes more sensitive to risk. For all levels of risk

[25] For more on modeling the economic significance of time-varying volatility, see Fleming, Kirby, and Ostdiek (2001).

[26] For completeness, we consider an additional hybrid model, (5), which uses the OLS predictability estimates but also uses the regime-switching volatility estimates to net out the impact of volatility. However, the results with this model are not qualitatively better than model (2).

aversion, the regime-switching model (3) gives at least 41% higher realized utility compared to OLS model (2). The hybrid model (4) is only about 14% better than the OLS model. This suggests that the marginal predictability during low volatility times night be important to the mean-variance investor. Mainly, the hybrid model uses an unconditional mean of 0.88% equity premium in expansions, but this fails to pick up the long term decline of the equity premium that the RSVAR picks up and seen in Figure 3. This drop is substantial, falling from about 1.5% in the 1950's to less than 0.5% in recent years. This long term decline turns out to be empirically important in this investor allocation problem. Further, Kandel and Stambaugh (1996) argue that in such a setting with Bayesian learning, even marginal predictability can have a significant influence on investor allocations. Overall, this particular analysis hints at a potential disconnection between the sources of statistical and economic valuable return predictability.

6. Conclusion

We hypothesize that the time-varying effectiveness of aggregate predictors should be reconcilable with the behavior of agents in the economy. One possibility is that predictors will be at their informative zenith when agents in the economy are least able to smooth away the information contained in these signals. We find a strong link between the dynamics of aggregate return predictability and the dynamics of the information content of predictor variables throughout the business cycle. In six of the G7 countries, short horizon predictive regressions have substantially higher estimates of $\overline{R}^2$ in the sample of recession months than in the sample of expansion months. Predictability appears during recessions but is absent during expansions.

Further analysis of the US data reveals that the dynamics of correlation between predictor and market risk premium are responsible for the link. The dynamics of the ratio of their volatilities, the phenomenon we call the volatility multiplier, is ruled out as the cause. Moreover, the results are not driven by persistence bias, small recession samples nor by the negative skewness of returns in bad times.

Our results indicate that the goodness of fit for unconditional predictive regressions should be increasing in the fraction of recession months in the available data. As this fraction changes over time, so do the discoveries and inferences made about predictability. We go beyond a pure structural break (or parameter instability) approach to assign economic reasons for the time varying strength of predictive regressions. Predictability's apparent disappearing act is in the end no conjurer's trick, but an economically rationalizable phenomenon.

In both the US and international data, a key avenue of future investigation will be the interplay between time-varying firm-specific predictors which ultimately give rise to the information revealed through aggregate macroeconomic predictors. Our results lead to the prediction that financially constrained firms will tend to be the largest contributors to aggregate predictability.

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A Appendix: MCMC Analysis

Bayesian estimation requires three elements: the data, a likelihood function dictated by the model, and prior densities for the model's parameters. For illustration of the general principle, let D denote the data, $p(D|\theta)$ denote the likelihood function, and $\pi(\theta)$ denote the prior density for the parameter set θ. In Bayesian analysis, the object of interest is the joint posterior density of the parameters given the data, $\pi(\theta|D)$. Following Bayes rule, the joint posterior density for the parameters is proportional to the product of the likelihood function and the prior density on the parameters:

$$\pi(\theta|D) \propto p(D|\theta)\pi(\theta).$$

Bayesian inference is accomplished by analyzing the joint posterior density of the model's parameters, or other functions of interest.

1.1 Likelihood Functions

For notational convenience, let $\mathbf{z} = \{z_1, \ldots, z_T\}$ denote the dependent variables of the k-dimensional RSVAR system. Let θ denote the vector of model parameters The likelihood function (i.e., sampling density) for the RSVAR model in equation (1) is

$$p(\mathbf{z};\theta) \quad = \quad \prod_{t=1}^{T}\sum_{i=1}^{2} f(z_t|\mathscr{I}_{t-1}, s_t = i;\theta)p(s_t = 1|\mathscr{I}_{t-1};\theta)$$

where $\mathscr{I}_{t-1}$ denotes information available at tiime $t-1$ and $\mathscr{N}_k$ a k-variate Normal density.

1.2 Priors

In Bayesian econometrics, prior densities summarize the researcher's prior beliefs about the model's parameters. It is possible to model prior beliefs on the parameters by adopting virtually any reasonable distributional form. The choice is by nature subjective. In our empirical applications we aim to minimize the impact of the priors on the estimates. Denote with A_i the matrix $A(s_t = i), i = 0,1$, with B_i the matrix containing the vector of constants, $c_t = i, i = 0,1$ in the first column and the matrix $A_i, i = 0,1$ in the remaining columns and with b_i the vector stacking the columns of B_i. We assume that the parameters are mutually independent within and across regimes and, thus, can be factored as

$$\pi(\theta) = \pi(b_0)\pi(b_1)\pi(\Sigma_0)\pi(\Sigma_1)\pi(vec(P)) \tag{9}$$

We choose

$$\pi(b_i) = \mathscr{N}_{k(k+1)}(\boldsymbol{\gamma}_{\mathbf{0}}, \blacksquare_{\mathbf{0}}) \quad i = 1,2$$

$$\pi(\Sigma_i^{-1}) = \mathscr{W}(S_0, s_0) \quad i = 1,2$$

$$\pi(p_{ii}) = \mathscr{B}(p_0, \nu_0), \quad i = 1,2$$

for $i = 0,1$, where $\mathscr{N}_k$ a k-variate Normal density, $\mathscr{W}$ denotes the Wishart density and $\mathscr{B}$ denotes the Beta density. These are fairly standard choices in the analysis of vector autoregression models.

As for the prior parameters we set

$$\boldsymbol{\gamma}_{\mathbf{0}} = \mathbf{0} \quad \Gamma_0 = I_{k(k=1)} * 10^9$$

$$s_0 = 8 \quad S_0 = I_k * 10^{-9}$$

$$p_0 = 2.7 \quad \nu_0 = 0.3$$

The hyperparameters on the diagonal elements of the P matrix imply a prior mean of 0.9 and a prior standard deviation of 0.15, Although fairly diffused, they reflect the expected persistence in economic regimes. The priors about the bs' and the Σs reflect extremely diffuse beliefs. It follows that the posterior densities will be largely determined by the sample data. As an aside, when the priors are completely uninformative(improper), the posterior means from the Gibbs sampler will equal the Maximum Likelihood point estimates.

1.3 Prior-Posterior Analysis

Combining the likelihood function and the priors via Bayes rule, one obtains the joint posterior density of the model's parameters given the data. Given the form of the likelihood functions in (9) and given the priors described above, the joint posterior cannot be estimated (i.e., sampled) directly. Fortunately, the Gibbs sampling method bypasses the computation of the likelihood function and computation of the joint posterior density. Rather, the Gibbs sampler algorithm generates draws from the conditional distribution of each block of parameters (i.e., the distribution of each block given the data, the prior and the other blocks of parameters). The draws from these conditional densities eventually converge to draws from the joint posterior density. Inference is based on summary statistics (e.g., mean, standard deviation, etc.) describing the distribution of the sample draws of the model's parameters, and of functions thereof.

In our applications, the Gibbs sampler consists of four blocks. Namely, the sampling proceeds with the following structure:

1. Initialize A_i, Σ_i and p_{ii}, $i = 1,2$.
2. Draw the state probabilities $p_{ii} = Prob(s_t = i), i = 1, \ldots, T$ using the multi-move filtering/smoothing algorithm first proposed by Carter and Kohn (1994)
3. Draw the elements of the transition matrix, P, from a beta variate

4. Draw the elements of the matrix B_i, i=1,2 from a multivariate normal variate
5. Draw the elements of the matrix $Sigma_i$, i=1,2 from an Inverse Wishart variate
6. Go to step 2 and repeat

Our implementation of the Bayesian MCMC approach follows closely the scheme proposed by Krolzig (1998, Chapters 8 and 9). As the steps are now standard in Bayesian analysis we refer the reader to that book treatment for details.

Table 1

Sample and Regime Characteristics

This table shows that the span and regime characteristics for the G7 sample of countries across expansions and recessions. To determine the expansion and recession states, we use a Regime-switching Vector Autoregression (RSVAR) which takes the following form, $z_t = A(s_t)z_{t-1} + \Sigma(s_t)$ where $z_t = (R^e_{m,t},\ SR_t,\ TERM_t,\ DY_t)'$, $A(s_t)$ is the state-dependent companion matrix with $s_t \in [0,1]$. $\Sigma(s_t)$ is a state-dependent error covariance matrix. For the US sample, $z_t = (R^e_{m,t},\ SR_t,\ TERM_t,\ DEF_t,\ DY_t)'$ Panel A. shows the span of monthly country index returns, short rate yields, term spreads and dividend yields taken from Datastream and Global Financial Database. *Recession* is the number of total months flagged by the RSVAR as a recession state, a state with lower average mean returns, higher volatility and lower persistence. Panel B. shows the persistence of expansion and recession states, $\hat{\pi}_{E,E} = Prob(s_t = Expansion|s_{t-1} = Expansion)$ and $\hat{\pi}_{R,R} = Prob(s_t = Recession|s_{t-1} = Recession)$, respectively. Panel B also shows summary statistics regarding the fits of the RSVAR. $RCM \in [0,1]$ measures the ability of the algorithm to distinguish between expansion and recession states, $RCM(2) = 1 - 4 \cdot T^{-1} \sum_{t=0}^{T} [p(s_t = E|S_{t-1}) p(s_t = R|S_{t-1})]$. The RSVAR was estimated using Markov chain Monte Carlo (MCMC) techniques. The posterior mean and the 95% Highest Posterior Density intervals (in square brackets) are based on 50,000 Gibbs sampler iterations from a suitably constructed Markov chain.

Panel A. Sample Characteristics

Country	*Start*	*End*	*Periods*	*Recession*
Canada	1973.01	2007.12	420	59
France	1973.01	2007.12	420	156
Germany	1973.01	2007.12	420	162
Italy	1973.01	2007.12	420	122
Japan	1973.06	2007.08	412	155
United Kingdom	1965.01	2007.12	516	123
United States	1953.03	2006.12	646	192

Panel B. Regime Characteristics

Country	$\hat{\pi}_{EE}$	$\hat{\pi}_{RR}$	*RCM*
Canada	0.91	0.57	0.89
	[0.87,0.94]	[0.43,0.71]	[0.86,0.92]
France	0.74	0.63	0.78
	[0.68,0.80]	[0.55,0.71]	[0.76,0.81]
Germany	0.74	0.64	0.79
	[0.67,0.80]	[0.54,0.72]	[0.77,0.81]
Italy	0.78	0.58	0.85
	[0.72,0.84]	[0.49,0.67]	[0.83,0.87]
Japan	0.94	0.91	0.94
	[0.89,0.97]	[0.85,0.96]	[0.88,0.97]
United Kingdom	0.82	0.57	0.84
	[0.77,0.86]	[0.48,0.66]	[0.81,0.87]
United States	0.92	0.83	0.89
	[0.88,0.94]	[0.76,0.88]	[0.87,0.91]

Table 2

Predictive Explanatory Power Across Economic Conditions - International

This table shows that the explanatory power of return predictability for the G7 sample of countries across expansions and recessions. To determine the expansion and recession states, we use a Regime-switching Vector Autoregression (RSVAR) which takes the following form, $z_t = A(s_t)z_{t-1} + \Sigma(s_t)$ where $z_t = (R^e_{m,t},\ SR_t,\ TERM_t,\ DY_t)'$, $A(s_t)$ is the state-dependent companion matrix with $s_t \in [0,1]$. $\Sigma(s_t)$ is a state-dependent error covariance matrix. For the US sample, $z_t = (R^e_{m,t},\ SR_t,\ TERM_t,\ DEF_t,\ DY_t)'$ The table reports the (average) adjusted R^2's from predictive regressions of next month's country-level return on this month's short rate yield, term spread and dividend yield. The adjusted R^2's are first for the full sample and then shown for the expansion and recession periods. The RSVAR was estimated using Markov chain Monte Carlo (MCMC) techniques. The posterior mean and the 95% Highest Posterior Density intervals (in square brackets) are based on 50,000 Gibbs sampler iterations from a suitably constructed Markov chain.

Predictive Explanatory Power by Regime (Adjusted R^2's)

Country	*Full Sample*	*Expansion*	*Recession*	*Difference*
Canada	0.026	0.012	0.105	0.093
	[0.001,0.052]	[-0.008,0.047]	[-0.026,0.287]	[0.042,0.278]
France	0.039	0.032	0.077	0.045
	[0.003,0.070]	[-0.005,0.089]	[0.004,0.171]	[0.048,0.148]
Germany	0.015	0.034	0.031	-0.002
	[-0.003,0.040]	[-0.007,0.096]	[-0.016,0.108]	[-0.084,0.088]
Italy	0.011	0.009	0.086	0.077
	[-0.005,0.034]	[-0.011,0.047]	[-0.001,0.201]	[-0.018,0.195]
Japan	0.019	0.023	0.236	0.213
	[-0.001,0.046]	[-0.010,0.075]	[0.105,0.352]	[0.069,0.335]
United Kingdom	0.052	0.011	0.285	0.274
	[0.023,0.086]	[-0.008,0.044]	[0.137,0.421]	[0.122,0.412]
United States	0.064	0.020	0.163	0.143
	[0.035,0.097]	[-0.004,0.054]	[0.073,0.261]	[0.046,0.245]

Table 3

Comparison of RSVAR Coefficients

This table shows the mean coefficients from the expected return equation of RSVARs for the G7 sample of countries across expansions and recessions and the difference between the two. To determine the expansion and recession states, we use a Regime-switching Vector Autoregression (RSVAR) which takes the following form, $z_t = A(s_t)z_{t-1} + \Sigma(s_t)$ where $z_t = (R^e_{m,t},\ SR_t,\ TERM_t,\ DY_t)'$, $A(s_t)$ is the state-dependent companion matrix with $s_t \in [0,1]$. $\Sigma(s_t)$ is a state-dependent error covariance matrix. For the US sample, $z_t = (R^e_{m,t},\ SR_t,\ TERM_t,\ DEF_t,\ DY_t)'$. The RSVAR was estimated using Markov chain Monte Carlo (MCMC) techniques. The posterior mean and the 95% Highest Posterior Density intervals (in square brackets) are based on 50,000 Gibbs sampler iterations from a suitably constructed Markov chain.

Canada	Expansion	Recession	Difference
SR_{t-1}	-0.182	-0.850	-0.668
	[-0.414 , 0.044]	[-1.801 , -0.076]	[-1.664 , -0.009]
$TERM_{t-1}$	-0.033	-0.566	-0.533
	[-0.396 , 0.333]	[-2.197 , 1.049]	[-2.204 , 1.150]
DY_{t-1}	0.915	9.999	9.084
	[-0.601 , 2.463]	[1.986 , 18.726]	[0.760 , 18.064]

France	Expansion	Recession	Difference
SR_{t-1}	-0.178	-0.784	-0.606
	[-0.482 , 0.120]	[-1.376 , -0.186]	[-1.305 , -0.044]
$TERM_{t-1}$	0.385	-1.240	-1.625
	[-0.430 , 1.234]	[-2.518 , 0.078]	[-3.265 , -0.063]
DY_{t-1}	1.813	9.467	7.654
	[-1.063 , 4.978]	[3.472 , 15.384]	[0.664 , 14.487]

Germany	Expansion	Recession	Difference
SR_{t-1}	-0.295	-0.195	0.100
	[-0.725 , 0.119]	[-0.968 , 0.580]	[-0.854 , 1.066]
$TERM_{t-1}$	0.122	0.043	-0.079
	[-0.514 , 0.758]	[-1.216 , 1.296]	[-1.556 , 1.406]
DY_{t-1}	0.454	2.121	1.667
	[-1.028 , 2.168]	[-1.604 , 5.951]	[-2.728 , 6.082]

Italy	Expansion	Recession	Difference
SR_{t-1}	0.021	0.058	0.038
	[-0.155 , 0.193]	[-0.269 , 0.391]	[-0.353 , 0.443]
$TERM_{t-1}$	0.422	-0.021	-0.442
	[-0.185 , 1.028]	[-1.178 , 1.126]	[-1.782 , 0.909]
DY_{t-1}	0.594	2.906	2.312
	[-1.220 , 2.749]	[-1.616 , 7.355]	[-2.941 , 7.364]

Japan	Expansion	Recession	Difference
SR_{t-1}	-0.482	-0.906	-0.425
	[-0.907 , -0.063]	[-1.525 , -0.267]	[-1.164 , 0.361]
$TERM_{t-1}$	-0.726	0.700	1.426
	[-1.701 , 0.246]	[-0.731 , 2.223]	[-0.318 , 3.246]
DY_{t-1}	1.587	6.011	4.424
	[-0.104 , 3.396]	[3.152 , 9.730]	[0.963 , 8.462]

United Kingdom	Expansion	Recession	Difference
SR_{t-1}	-0.147	-1.837	-1.690
	[-0.367 , 0.067]	[-2.715 , -0.832]	[-2.605 , -0.646]
$TERM_{t-1}$	-0.177	-2.045	-1.868
	[-0.657 , 0.272]	[-3.338 , -0.663]	[-3.279 , -0.362]
DY_{t-1}	1.568	28.209	26.641
	[-0.544 , 3.868]	[16.075 , 38.387]	[13.873 , 37.204]

United States	Expansion	Recession	Difference
SR_{t-1}	-0.159	-0.678	-0.520
	[-0.375 , 0.057]	[-1.151 , -0.218]	[-1.052 , -0.001]
$TERM_{t-1}$	-0.169	-0.087	0.083
	[-0.632 , 0.289]	[-1.176 , 0.996]	[-1.127 , 1.290]
DEF_{t-1}	-0.074	3.888	3.962
	[-1.956 , 1.818]	[1.512 , 6.279]	[0.892 , 7.047]
DY_{t-1}	2.153	4.746	2.593
	[0.418 , 3.889]	[0.182 , 9.732]	[-2.749 , 7.978]

Table 4

Simple Regression Statistics for the US

Coefficients from the simple regression

$$R^e_{m,t} = \alpha + \beta x_{t-1} + \eta_{1,t}$$

are shown. Panel A represents the full sample from 1953.04 to 2006.12, Panels B and C condition on NBER expansions and recessions, respectively. The dependent variable, $R^e_{m,t}$, is the excess total return on the value-weighted CRSP index in month t. SR, $TERM$ and DEF are the short rate, term spread and default spread, respectively, from the FRED database. DY is the Dividend Yield as constructed as the 12-month smoothed difference between CRSP total returns ($VWRETD$) and CRSP capital gains ($VWRETX$) and adjusted for share repurchases as in Bansal, Dittmar, and Lundblad (2005). The standard errors are corrected for heteroskedasticity using White (1980). *, ** and *** represent statistical significance at the 10, 5 and 1% levels, respectively.

Panel A. Full Sample

	$\hat{\beta}^{OLS}$	$s.e.(\hat{\beta}^{OLS})$	$\overline{R}^2$
SR	-0.180***	(0.062)	0.013
$TERM$	0.531***	(0.178)	0.015
DEF	0.717*	(0.439)	0.003
DY	0.587***	(0.182)	0.014

Panel B. NBER Expansions

	$\hat{\beta}^{OLS}$	$s.e.(\hat{\beta}^{OLS})$	$\overline{R}^2$
SR	-0.091	(0.067)	0.002
$TERM$	0.153	(0.170)	-0.000
DEF	0.364	(0.491)	-0.001
DY	0.438**	(0.195)	0.008

Panel C. NBER Recessions

	$\hat{\beta}^{OLS}$	$s.e.(\hat{\beta}^{OLS})$	$\overline{R}^2$
SR	-0.342***	(0.143)	0.044
$TERM$	2.538***	(0.515)	0.190
DEF	2.163**	(0.962)	0.039
DY	1.394***	(0.547)	0.052

Table 5

A Simple Decomposition of Return Predictability

Higher explanatory power of predictive regressions during recessions not primarily due to conditioning bias. Here, we show that increased informativeness dominate changes in the volatility ratio as the source of increased explanatory power. Panel A part 1 shows the full sample correlations, volatility, volatility ratio and computed β. ρ is the correlation between $R^e_{m,t}$ and x_{t-1} where $x \in \{SR, TERM, DEF, DY\}$. σ is the time series (conditional) volatility and $\sigma^{ex} = \sigma_{R^e_{m,t}}/\sigma_{x_{t-1}}$ is the excess ratio of the market relative to the predictor. Panel A parts 2 and 3 show the same quantities conditional on NBER state. Panel B. shows the percent difference in volatility ratios across NBER regimes $\in \{E,R\}$ for each predictor,

$$(\%\Delta)\sigma^{ex} = \frac{\sigma^{ex}_{|s_t=R} - \sigma^{ex}_{|s_t=E}}{\sigma^{ex}_{|s_t=E}}.$$

Panel A. Decomposition of Conditional βs

Full Sample	ρ	σ	σ^{ex}	*Computed* β
R^e_m	1.000	4.253	1.000	1.000
SR	-0.118	2.842	1.496	-0.180
TERM	0.130	1.042	4.082	0.531
DEF	0.069	0.412	10.323	0.717
DY	0.126	0.913	4.658	0.587
NBER Expansions	$\rho_{\vert s_t=E}$	$\sigma_{\vert s_t=E}$	$\sigma^{ex}_{\vert s_t=E}$	*Computed* $\beta_{\vert s_t=E}$
R^e_m	1.000	3.916	1.000	1.000
SR	-0.058	2.517	1.556	-0.091
TERM	0.040	1.038	3.773	0.153
DEF	0.033	0.353	11.093	0.364
DY	0.099	0.889	4.405	0.438
NBER Recessions	$\rho_{\vert s_t=R}$	$\sigma_{\vert s_t=R}$	$\sigma^{ex}_{\vert s_t=R}$	*Computed* $\beta_{\vert s_t=R}$
R^e_m	1.000	5.704	1.000	1.000
SR	-0.232	3.873	1.473	-0.342
TERM	0.445	1.000	5.704	2.538
DEF	0.219	0.579	9.851	2.162
DY	0.247	1.010	5.648	1.394

Panel B. Percent Changes Across Regimes

	SR	*TERM*	*DEF*	*DY*
$(\%\Delta)\sigma^{ex}$	-5.4	51.2	-11.2	28.2
$(\%\Delta)\rho$	300.0	1012.5	563.6	149.5
$(\%\Delta)\beta$	278.6	1582.0	490.6	219.7

Table 6

Did Predictability Disappear in the 1990's? Small Sample Correlations

Because there are more recessions in the predictability pre-discovery period (before Fama and Schwert (1977), for example), recession-centric predictability could arise spuriously due to the correlation between recession and pre-discovery periods. This table shows the correlation between this month's predictor and next month's market return in the post-discovery period, by regime. Panel A shows the time periods for four NBER business cycles from 1975 to 2001. Panels B-E show the cross-serial correlations for each expansion and recession for the short rate, term spread, default spread and dividend yield, respectively. $R^e_{m,t}$ is the excess total return on the value-weighted CRSP index. SR, $TERM$, and DEF are the short rate, the term spread, and default spread, respectively, from the FRED database. DY is the Dividend Yield as constructed as the 12-month smoothed difference between CRSP total returns ($VWRETD$) and CRSP capital gains ($VWRETX$) and adjusted for share repurchases as in Bansal, Dittmar, and Lundblad (2005).

Panel A. NBER Business Cycle Dates

Business Cycle	NBER Expansions	NBER Recessions
Cycle 1	1975.04 - 1979.12	1980.01 - 1980.07
Cycle 2	1980.08 - 1981.06	1981.07 - 1982.11
Cycle 3	1982.12 - 1990.06	1990.07 - 1991.03
Cycle 4	1991.04 - 2001.02	2001.03 - 2001.11

Panel B. The Short Rate

Business Cycle	NBER Expansions	NBER Recessions
Cycle 1	-0.04	-0.68
Cycle 2	-0.36	-0.70
Cycle 3	-0.02	-0.72
Cycle 4	-0.03	-0.31

Panel C. The Term Spread

Business Cycle	NBER Expansions	NBER Recessions
Cycle 1	0.07	0.69
Cycle 2	0.26	0.67
Cycle 3	-0.07	0.49
Cycle 4	-0.00	0.37

Panel D. The Default Spread

Business Cycle	NBER Expansions	NBER Recessions
Cycle 1	0.17	0.34
Cycle 2	-0.47	0.63
Cycle 3	0.13	0.74
Cycle 4	-0.00	0.33

Panel E. The Dividend Yield

Business Cycle	NBER Expansions	NBER Recessions
Cycle 1	0.09	0.35
Cycle 2	0.37	0.56
Cycle 3	0.12	0.59
Cycle 4	0.04	0.09

Table 7

Does Explanatory Power Come From Predicting Negative Returns?

Because recessions have proportionally more frequent and larger in magnitude negative returns, increased explanatory power in recessions may come from fitting negative and negatively skewed realized returns. Here we show the explanatory power is higher for negative realized returns, but this does not explain the increased explanatory power during recessions.

To calculate R^2's conditional on positive and negative returns, we first fix the parameters estimated from a multiple regression of $R^e_{m,t}$ on SR_{t-1}, $TERM_{t-1}$, DEF_{t-1} and DY_{t-1} for the unconditional full sample model and the models conditional on regimes. We then compute the explanatory power for positive and negative returns from the squared variation in excess returns and squared prediction errors as

$$R^2_{|R^e_{m,t}>0} = 1 - \frac{SSE_{|R^e_{m,t}>0}}{SST_{|R^e_{m,t}>0}}$$

where $SSE_{|R^e_{m,t}>0}$ is the squared errors summed only over observations where $R^e_{m,t} > 0$. Likewise, SST, the total squared variation, is summed only over observations where $R^e_{m,t} > 0$. The computations similar for $R^e_{m,t} < 0$.

Panel A. Number of Observations

	N	$N_{\|R^e_{m,t}>0}$	$N_{\|R^e_{m,t}<0}$
Full Sample	633	377	252
NBER Expansion	531	325	202
NBER Recession	102	52	50
RSVAR Expansion	464	292	169
RSVAR Recession	169	85	83

Panel B. RSVAR Restricted Parameters

	R^2	$R^2_{\|R^e_{m,t}>0}$	$R^2_{\|R^e_{m,t}<0}$
Full Sample	0.051	0.022	0.075
NBER Expansion	0.014	0.008	0.018
NBER Recession	0.296	0.229	0.360
RSVAR Expansion	0.008	0.006	0.011
RSVAR Recession	0.197	0.176	0.215

Figure 1. The Time Series of Predictability Research

The literature on stock return predictability follows closely the availability of recession data as a cumulative proportion of the total data in CRSP which originally started in 1962. Shown are the percentages of recession data as a percentage of the available data at a given date, as measured by NBER and RSVAR dates. Both the NBER and RSVAR samples show similar profiles, although RSVAR recession probabilities represent a much larger proportion of the data. Ironically, many seminal, and first, papers on return predictability were published just after the peaking of the proportion of recession data to total available data in 1985 and are followed by a decline in the proportion of recession data thereafter. The citations are intended to be indicative of initial research, not a comprehensive literature survey.

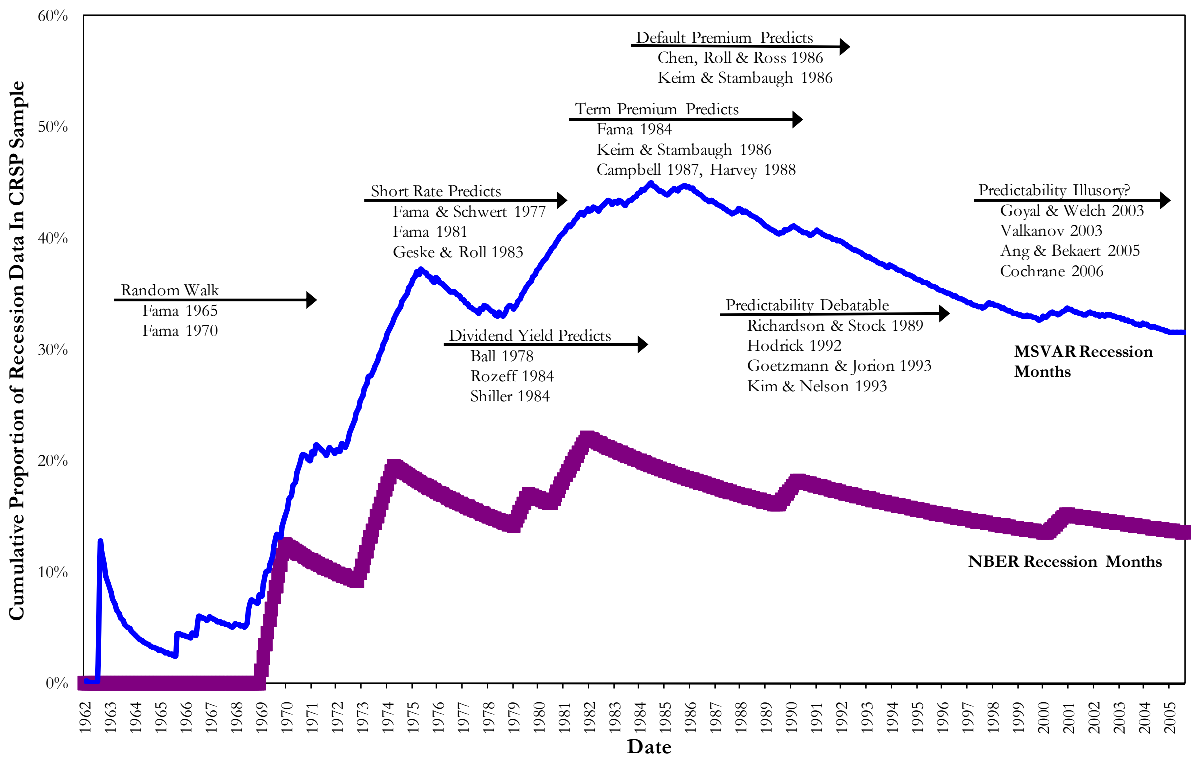
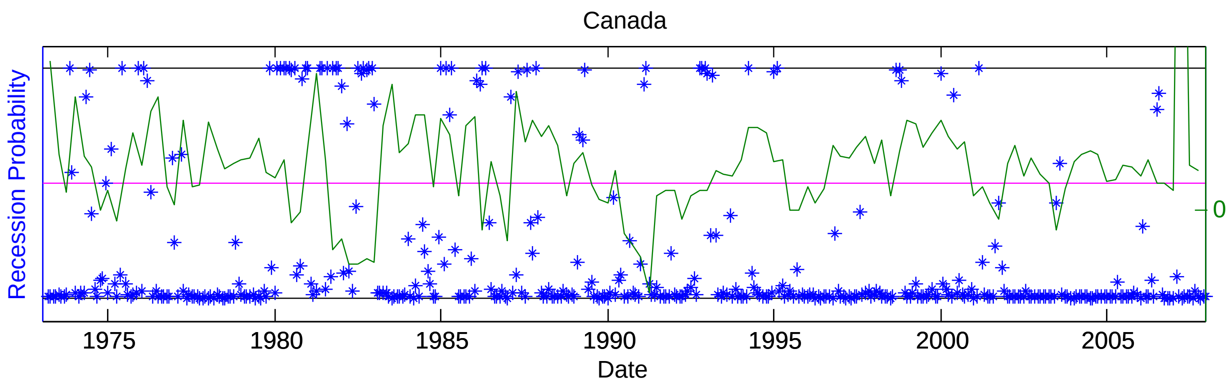


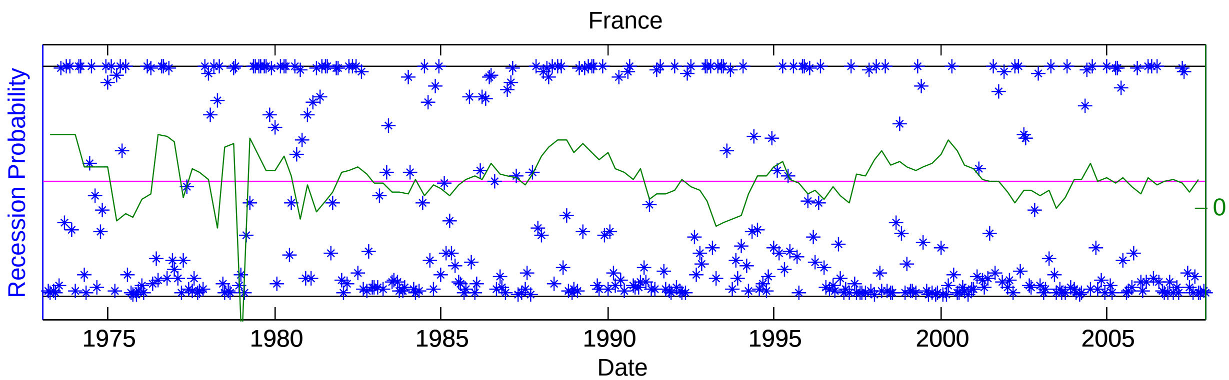
Figure 2. RSVAR Estimates of Regimes

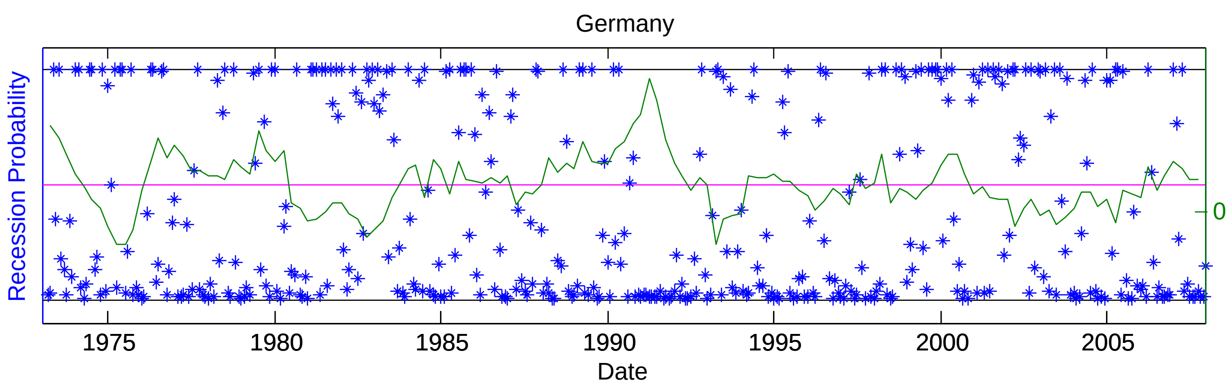
Consistent with the literature that stock returns and term structure variables forecast recessions, a Regime-switching VAR (RSVAR) based on such a system detects the latent state probabilities of recession and correlates well with the ex post measure of recessions by the NBER (35%, compared to 31% for the large portfolio of Perez-Quiros and Timmermann (2000, p. 1245) and 11% for the regime-switching term structure model of Bansal, Tauchen, and Zhou (2004, p. 13)). Unlike NBER dates, which require ex post examination of many series and ultimately decided by committee, recession states in the RSVAR exploit the forward-looking nature of market-traded financial instruments. The US data span 1953.04 to 2006.12 and are limited by data availability and by the current monetary regime, starting in 1951 with the Treasury Accord. The international G7 data span at least from 1973.06 to 2007.08 (Japan). Overall, the regime fit is high (between 0.78 to 0.94) where

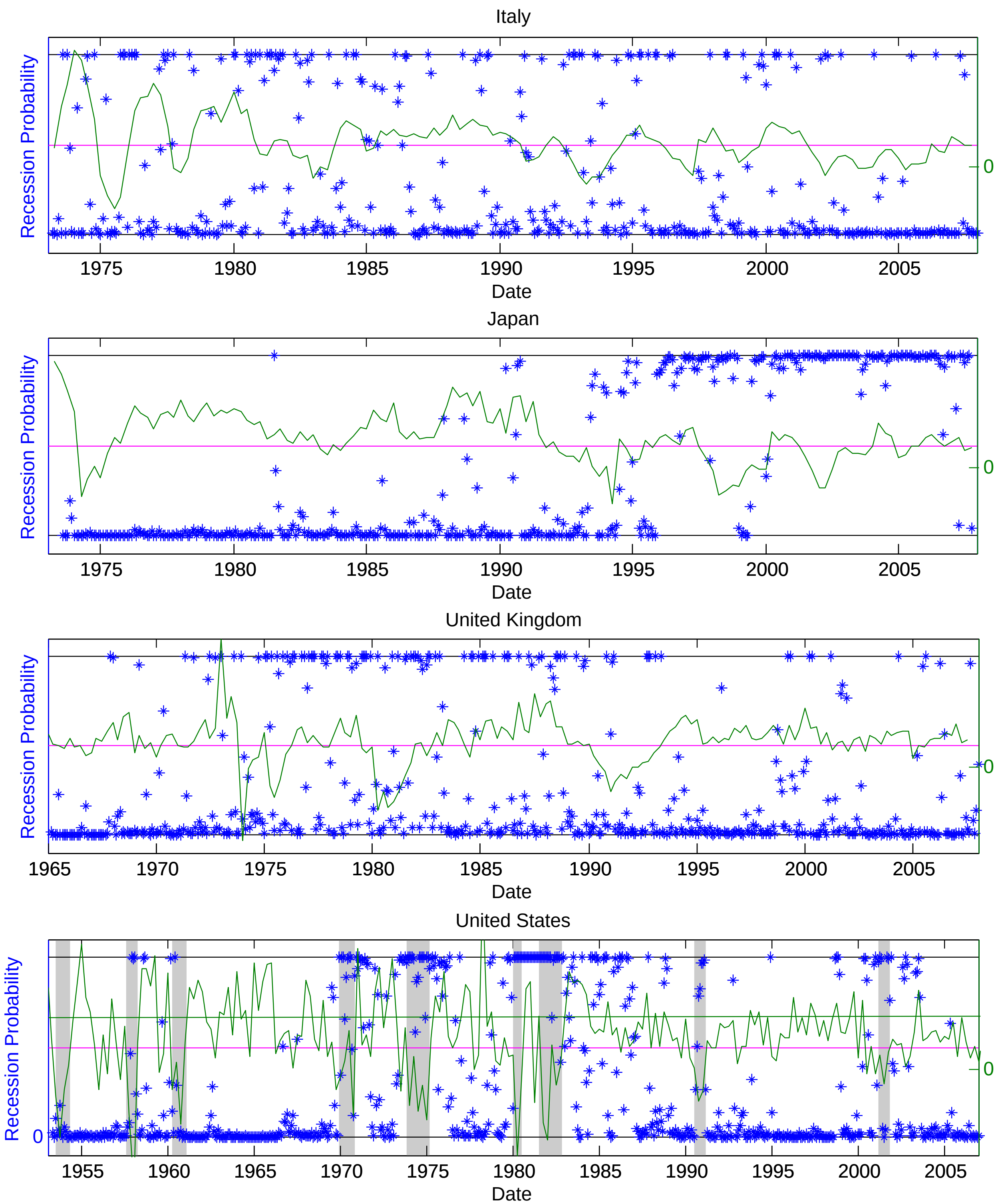
$$RCM(2) = 1 - 4 \cdot T^{-1} \sum_{t=0}^{T} [p(s_t = 0|S_{t-1}) p(s_t = 1|S_{t-1})].$$

The recession states, characterized by lower persistence, lower realized returns and higher volatility, are more prevalent and shorter-lived than NBER recessions, possibly because the market forecasts recessions that are not realized or are of shorter duration than the NBER considers. The RSVAR was estimated using Markov chain Monte Carlo (MCMC) techniques. The estimate of the posterior distributions are based on 50,000 Gibbs sampler iterations from a suitably constructed Markov chain.








Italy
Recession Probability
1975
1980
1985
1990
1995
2000
2005
Date
0
Japan
Recession Probability
1975
1980
1985
1990
1995
2000
2005
Date
0
United Kingdom
Recession Probability
1965
1970
1975
1980
1985
1990
1995
2000
2005
Date
0
United States
Recession Probability
0
1955
1960
1965
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1975
1980
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1995
2000
2005
Date
0

Figure 3. Economic Significance

The figure shows the excess economic significance (realized utility net of the null model with no predictability) of the portfolio strategies implied by the OLS estimates (long dashes, red), the regime-switching model (solid line, blue) and the hybrid model (short dashes, green) that follows the null model in good times and the regime-switching estimates in bad times. Risk Aversion ranges from 0 to 5 on the x-axis.