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Equity Premium Predictions with Adaptive Macro Indexes

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Abstract

Fundamental economic conditions are crucial determinants of equity premia. However, commonly used predictors do not adequately capture the changing nature of economic conditions and hence have limited power in forecasting equity returns. To address the inadequacy, this paper constructs macro indexes from large data sets and adaptively chooses optimal indexes to predict stock returns. I find that adaptive macro indexes explain a substantial fraction of the short-term variation in future stock returns and have more forecasting power than both the historical average of stock returns and commonly used predictors. The forecasting power exhibits a strong cyclical pattern, implying the ability of adaptive macro indexes to capture time-varying economic conditions. This finding highlights the importance of using dynamically measured economic conditions to investigate empirical linkages between the equity premium and macroeconomic fundamentals.

Key words: adaptive macro index, forecasting

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1 INTRODUCTION

Empirical studies increasingly cast doubt on the forecasting power of price-based predictors of equity returns. The literature in this area has documented numerous problems,[1] including small-sample bias with highly persistent predictors,[2] poor out-of-sample performance,[3] and unstable forecasting relationships.[4] One potential reason for their weak performance is that fixed financial predictors fail to capture time-varying economic conditions suffciently. Nevertheless, fundamental economic forces are crucial determinants of equity premia in the financial markets.[5] The challenge thus far has been to find a way to capture changing fundamental conditions that affect equity returns.

This paper answers the challenge in two ways. First, I construct macro indices from a large number of economic series as quantitative descriptions of economic conditions. Second, I design an adaptive procedure to choose optimal indices for equity premium predictions. Using this procedure, I find that adaptively selected macro indices are able to predict equity premia. Trading strategies based on these indices significantly and consistently outperform a buy-and-hold strategy benchmark under varying assumptions of transaction costs and risk tolerance. Furthermore, I connect these indices to economic sectors, comparing ex ante and ex post forecasting. The results provide new evidence that four sectors—interest rates, price indices, housing, and employment—are particular relevant in predicting the equity premium.

Given the deficiency of financial predictors, previous papers (for example, Lettau and Ludvigson (2001) [41], Piazzesi, Schneider and Tuzel (2007) [52] and Gomes, Kogan and Yogo (2007) [35]) have attempted to explore alternative predictors involving macroeconomic series.[6] Common to all these papers is a focus on a small set of predictors based on theoretical models. From an academic viewpoint, the use of model-based predictors facilitates an understanding of specific aspects of the

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[1] Campbell and Thompson (2007) [15] and Cochrane (2007a) [25] provide excellent surveys of this literature.

[2] Examples are Nelson and Kim (1993) [48], Stambaugh (1999) [57], Ang and Bekaert (2007) [1], Ferson, Sarkissian and Simin (2003) [33], and Valkanov (2003) [63]. A number of recent papers discuss alternative econometric methods for conducting valid inference, such as Cavanagh, Elliott and Stock (1995) [20], Polk, Thompson and Vuolteenaho (2006) [54], Lewellen (2004) [44], Torous, Valkanov and Yan (2004) [62], Campbell and Yogo (2006) [18], and Eliasz (2005) [29].

[3] Goyal and Welch (2007) [36] have systematically investigated most predictors used in the literature and concludes that, except for equity-issuing activity, current predictors hardly have meaningful and robust predictive power on the equity premium. Additional contributions include Bossaerts and Hillion (1999) [12], and Butler, Grullon and Weston (2005) [14]. See also Campbell and Thompson (2007) [15], and Cochrane (2007b) [26] for different interpretations of the out-of-sample evidence.

[4] Viceira (1996) [64] and Paye and Timmermann (2006) [50] report evidence that counters the hypothesis of constant coefficient in the forecasting regression. Lettau and Nieuwerburgh (2007) [43] analyze structural shifts in the mean of the dividend-price ratio. Pastor and Stambaugh (2001) [49] use Bayesian methods to estimate structural breaks in the equity premium.

[5] Equity risk premia are closely related to economic conditions. Equity returns seem to be high at business cycle troughs and low at peaks. In line with the pioneering work by Ferson and Merrick (1987) [32], Fama and French (1989) [31], researchers suggest that predictors of excess returns should be correlated with economic conditions. Lettau and Ludvigson (2005) [41] summarize the literature and point out that we should expect to "find evidence from predictive regressions of excess returns on macroeconomic variables over business cycle horizons."

[6] Lettau and Ludvigson (2001) [41] use "cay", a measure of the consumption-wealth ratio; Piazzesi, Schneider and Tuzel (2007) [52] employ the housing-expenditure ratio; Gomes, Kogan and Yogo (2007) [35] use the ratio of durables to nondurables consumption.

economic mechanism. From an investor's viewpoint, however, these predetermined variables may not be enough to capture all information required in decision making.

Taking an investor's position, this paper examines broad economic conditions by constructing macro indices from a large number of economic series, which is in line with the dynamic factor method by Stock and Watson (2002a, 2002b) [59, 60]. These macro indices distinguish themselves for the ability to synthesize multidimensional information inherent in economic conditions. As noted in Ludvigson and Ng (2007a) [46], the use of macro indices "eliminates the arbitrary reliance on a small number of exogenous predictors." Indeed, anecdotal evidence suggests that investors monitor and analyze literally hundreds of data series. Since macro indices can consistently cover a broad range of economic conditions, they are more likely to span an investor's unobservable information set. Applications of macro indices abound in the macroeconomic literature,[7] but are rarely found in the empirical finance literature. The only exceptions, as far as I know, are Ludvigson and Ng (2007a, 2007b) [45, 46] and Emanuel (2006) [30].[8] This paper contributes to the literature with a new application in real-time equity premium predictions.

Also attempting to address the deficiency of financial predictors, Lettau and Nieuwerburgh (2007) [43] allow for dynamic shifts in the mean of financial ratios (for example, dividend-price ratios) and show that adjusted predictors reconcile some of the controversy regarding return predictability. Their adjustment, however, is impossible in real-time prediction since investors cannot observe future data. This paper instead designs an adaptive prediction process based on macro indices for the real-time equity premium prediction. Adaptability is important since a fixed set of predictors, even using information from a large number of sources, may not accurately reflect investors' learning processes.

In related work, Pesaran and Timmermann (1995) [51] develop a recursive method to select optimal predictors over time according to a predetermined criterion. This paper incorporates their idea of dynamic modeling with two important modifications. First, I use an out-of-sample criterion for model selection and show that such a criterion increases the likelihood of a successful forecast than in-sample criteria. Second, I extend their base set from a few predictors to high-dimensional economic variables. In doing so, the adaptive prediction procedure captures time-varying economic conditions and allows for a time-varying forecasting relationship between equity returns and macro indices.

Applying this procedure to the CRSP value-weighted index over the one-month Treasury bill, I find that adaptively selected macro indices explain a substantial fraction of the short-term variation in future excess returns. Adaptive forecasts conditional on macro indices generate smaller prediction errors than both unconditional forecasts using the historical average[9] and the conditional forecasts based on many popular predictors (such as financial ratios, traditional business cycle proxies and

[7]Growing empirical evidence suggests that a large set of macroeconomic variables may in fact be crucial to properly capture the economy's dynamics. For example, Stock and Watson (1999, 2002a) [58, 59] and Forni, Hallin, Lippi and Reichlin (2000) [34] find that macro indices lead to considerable improvements over small scale vector autoregressive models. Bernanke and Boivin (2003) [9], Bernanke, Boivin and Eliasz (2005) [10], and Giannone, Reichlin and Sala (2004) show that the large information set appears to matter empirically to model monetary policy. Boivin and Giannoni (2006) [11] incorporate the dynamic factor approach to estimate dynamic stochastic general equilibrium models.

[8]Ludvigson and Ng (2007) [45, 46] use the dynamic factor method to analyze the empirical risk-return relationship. Ludvigson and Ng (2006) [46] adopt the same method to examine the bond risk premia. Emanuel (2006) [30] applies the factor method to forecast the bond yield curve.

[9]The unconditional forecast is equal to the regression of excess returns on a constant.

other individual macroeconomic series).[10] The superior predictive power of adaptive macro indices have persisted over the past three decades, even in the late 1990s when stock return predictability becomes particularly challenging. Moreover, the accuracy of forecasts both in magnitude and in sign exhibits a strong cyclical pattern: the predictive power of indices (measured by the difference of prediction errors from the benchmark, the prevailing mean) decreases before recessions and lately rebounds during recessions. Timing ability (measured by the percentage of correct forecasting signs) shares the same pattern.

Finally, to test the real-world economic significance of these adaptive predictions, I examine the protability of trading portfolios under two investment strategies: 100% stock/bond allocation and a utility-based dynamic portfolio allocation. In both cases, investment strategies exploiting the adaptive forecasts yield greater profits when compared with a buy-and-hold strategy in the market portfolio. The 100% stock/bond switching portfolios earn significantly higher returns over various subperiods with moderate transaction costs. The utility-based portfolios exhibits poor performance due to frequent trading and they make profits only under zero transaction costs and a high tolerance of risk.

The approach in this paper uses time-varying combinations of a large number of variables. It is therefore not immediately clear what specific economic forces contribute to the predictability of returns over time. To overcome this obstacle, I compare several types of forecasts using different information sets. In ex post forecasting, I construct indices using the entire sample, and study the performance of each index with fixed weights. The second principal component (F2) stands out with both a relatively good in-sample and simulated out-of-sample performance.[11] In semi *ex post* forecasting, I recursively construct indices using only the historical information available for each month, and I consistently choose the "same" index (principal components with the same order) and study the performance of each index with dynamic loadings. F2 and F5 outperform all other indices. In *ex ante* forecasting, I recursively construct indices using only the historical information available for each month, I sequentially choose indices (principal components with different orders) and I study the performance of adaptive macro indices. Again, F2 and F5 remain the most frequently selected predictors in the adaptive forecasting. Decomposing these indices and projecting them onto each economic sector, I show that the economic fundamentals that contribute most to equity premium prediction are interest rates, price indices, housing and employment.

The paper proceeds as follows. The next section sets up the adaptive prediction process, introduces the special model selection criterion and presents empirical predictability results. Section 3 assesses the economic significance of real-time forecasting. I then move on to explore the connection between ex ante and ex post forecasting in Section 4. A robustness check follows in Section 5 and I discuss directions for future research in Section 6.

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[10]Fama and French (1989) [31] show how dividend-price ratios, term spreads and default spreads forecast stock and bond returns. Since this seminal paper, these three variables have become representatives of business cycle proxies in empirical finance literature. The individual macroeconomic series include the growth rate of industrial production and the consumer price index.

[11] Here I use the same criteria advocated by Goyal and Welch (2007) [36]. A good predictor should satisfy three rules: 1) both a significant in-sample and a reasonably good out-of-sample performance over the entire sample period; 2) it should have a general upward trend in the graph of ΔSSE, the difference in cumulative prediction errors from the benchmark of historical average; and 3) an upward drift that remains positive over the past several decades.

2 FORECASTS OF EQUITY RETURNS

2.1 The Adaptive Prediction Process

In this paper I consider an agnostic investor who has no strong beliefs in any particular model, but who trusts in the time-varying inference drawn from her information set. The evolution of forecasting models over time may reflect an investor's learning process or the changing nature of the underlying economic conditions. The use of an adaptive prediction procedure explicitly accounts for the continuous uncertainty an investor faces in real time. The advantage of adaptive prediction is that all possible models are constantly re-estimated and re-evaluated in order to reflect an investor's search for the optimal predictive relation based solely on the historical information.

In related work, Pesaran and Timmermann (1995) [51] develop a recursive method to select optimal predictors over time according to a predetermined in-sample criterion. This paper incorporates their idea of dynamic modeling with two important modifications. First, I separate the model selection period from the in-sample estimation period and select an optimal model based on its out-of-sample performance. In Section 5, I show that such an out-of-sample criterion increase the likelihood of a successful forecast than in-sample criteria. Second, I extend their base set from a few predictors to high-dimensional economic variables. In doing so, the adaptive prediction procedure captures time-varying economic conditions and allows for a time-varying forecasting relationship between equity returns and macro indices.

Suppose that at time $t = N - m$, an investor constructs an information set including an array of K macroeconomic variables with $N - m$ time-series observations. As with Stock and Watson (2002b) [60], the investor uses principal component analysis and decomposes the information set into K factors,

$$X_t = \Lambda Z_t = \lambda_1 z_{1,t} + \lambda_2 z_{2,t} + \cdots + \lambda_K z_{K,t}, \tag{1}$$

where X_t is the panel of economic variables assumed to cover the investor's information set, $z_{i,t}$ ($i = 1, \ldots, K$) are principal components of the panel data ordered by their ranks in explaining the variance,[12] and λ_i is the loadings on the individual series.

The investor then defines a universe of parsimonious models based on in-sample estimations,[13]

$$r_t = a_i + b_i z_{i,t-1} + \epsilon_t, \tag{2}$$

and chooses the optimal model according to a predefined selection criterion. In other words, the investor treats all models under consideration as equally likely. Choosing a particular model at time t does not necessary restrict the model choice at subsequent periods. Such a treatment is different from

[12] z_1 explains the most of the variance and it has the biggest eigenvalue.

[13] Since factors zi are mutually orthogonal by construction, it is sufficient for an investor to consider only univariate predictive regression. A regression with multiple factors has the same explanatory power as the sum of each individual factor. The explanatory power from different factors does not overlap.

Two stage estimation usually involves the error-in-variable problem. But Bai and Ng (2005) [4] show that the pre-estimation of the factors z_t does not affect the consistency of the second-stage parameter estimates. Moreover they prove that the least squares estimates from factor-augmented forecasting regressions are $\sqrt{T}$ consistent and asymptotically normal. Stock and Watson (2002b) [60] provide both theoretical arguments and empirical evidence that factors using estimated principal components are consistent even in the face of temporal instability in the individual time series used to construct the factors. The reason is that such instability may "average out" in the construction of common factors if the instability is sufficiently dissimilar from one to the next.

typical dynamic factor models proposed by Stock and Watson (2002a, 2002b) [59, 60], in the sense that this procedure does not restrict the base set of predictors to be the first few principal components. Instead, the investor seek an optimal predictor from all principal components.

Whereas most studies use in-sample model selection criteria based on the predictive regression (2), I introduce an out-of-sample criterion: the predictive least squares principle, which is based on a predictor's forecasting performance in a simulated out-of-sample period. The model selection period is a moving window with a length of m-months. In this period, the investor records prediction errors for all macro indices by comparing their forecasts with realized returns.

At the end of the training period $t = N$, the investor choose an index with the smallest cumulative prediction errors in previous m-months and use it to predict the one-month-ahead excess market return at the first point of the trading period, $t = N + 1$. Meanwhile, the investor transforms the predicting result into trading strategies that bring profits or losses, depending on the realization of the true market return (Section 3 presents investment strategies).

All stages of the adaptive prediction process re-occur on a monthly basis via a rolling window framework. Macro indices are also reconstructed each month via a recursive window starting from the beginning of the sample. For example, the first investment decision made at $t = N$, is based on an estimation during the in-sample period of $[1, N - m]$ and a model selection in the training period of $[N - m + 1, N]$. For the second investment decision, the corresponding estimation period is $[1, N - m + 1]$; the training period is $[N - m + 2, N + 1]$.

2.2 Model Selection Criterion

A key step in the adaptive prediction process is to choose the optimal predictor according to a pre-defined selection criterion. Conventional measures such as R^2, Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are calculated only from the in- sample information. Thus they have limitations as guides for finding an optimal indicator in forecasting future excess returns. Bossaerts and Hillion (1999) [12] show that the use of these in-sample criteria fails to find sufficient out-of-sample predictability. In this paper I introduce an out-of-sample model selection criterion, predictive least squares (PLS), advocated by Rissanen (1986) and Wei (1992). The PLS principle selects the optimal forecasting model Mi which minimizes the cumulative squared prediction errors in the training period:

$$M_i : \quad \mathrm{PLS}(z_i) = \sum_{t=N-m}^{N} \left[r_t - (\hat{a}_{i,t-1} + \hat{b}_{i;t-1}) z_{i,t-1}) \right]^2 , \qquad i = 1, \ldots, K \tag{3}$$

where $(\hat{a}_{i,t-1}; \hat{b}_{i,t-1})$ is estimated from the predictive regression using only historical information up to time $t - 1$. The PLS principle is consistent with the main purpose of real-time forecasting: finding a predictor with the least prediction errors. Models selected in this way intuitively tend to have a good performance in the second out-of-sample trading period.

Another potential benefit of PLS is its natural link to the information-based criteria. Define $\epsilon_t(N) = r_t - (\hat{a}_{i,t-1} + \hat{b}_{i,t-1} + z_{i,t-1})$ and $e_t = r_t - (\hat{a}_{i,t-1} + b_{i,t-1} + z_{i,t-1})$, we can decompose PLS into two terms:

$$\sum_{t=N-m}^{N} e_t^2 = \underbrace{\sum_{t=1}^{N} \epsilon_t^2(N) \sum_{t=1}^{N-m} \epsilon_t^2(N-m)} + \underbrace{\sum_{t=N-m}^{N} a'_{i,t} \Sigma_{z_i} a_{i,t} e_t^e} \ . \tag{4}$$

Recall that the in-sample period is from $t = 1$ to $N - m$ and the training period is from $N - m + 1$ until N. The estimation of b_N uses only information in the in-sample period and $\epsilon t(N)$ is the fitting error of the predictive regression. As with the information-based criteria, the first two terms in the formula (4) can be viewed as the measure of the goodness of fit; the third one as a penalty that reflects the complexity of the model.

2.3 Data and Empirical Implementation

The equity premium is measured by the end-of-month return of the CRSP value-weighted index in excess of the one-month Treasury Bill rate. All variables in this paper are at a monthly frequency covering the period from January 1960 to November 2006, for a total of 563 observations.

The base set of forecasting variables comprises 100 macroeconomic variables. Following Stock and Watson (2002a, 2005) [59, 61], I chose this panel to represent broad sectors of U.S. economic conditions: real output, unemployment and employment, wages, housing, foreign exchange rates, money and credit aggregates, interest rates, inventories and orders, price indices, consumption, and consumer expectation.[14] The series are transformed so as to insure stationarity. In addition, the transformed data are standardized prior to index construction and estimation. All economic series are from the Global Insights Basic Economics Database. A detailed description of the data and its transformation is given in Appendix A.1.

To facilitate the comparison, I adopted ten monthly variables in Goyal and Welch (2007) [36] as the control predictors, including price-dividend ratios, price-earnings ratios, dividend pay- out, book-to-market ratios, long term government bond returns, information measured by Consumer Price Index (all urban consumers), net issuing activity, term spread, default spread and default payout. Their explicit definitions are given in Appendix A.2. The contrast set of forecasting variables does not include cay, the consumption wealth ratios proposed by Lettau and Ludvigson (2001), because the construction of cay uses forward-looking information, which is impossible in real-time forecasting. The base set also excludes the investment to capital ratios proposed by Cochrane (1991) [22], since this variable is not available at the monthly frequency.

With constructed indices, investors can easily implement the adaptive prediction procedure: estimate the linear prediction models, select the optimal model using the PLS principle and then compute a one-month-ahead forecast. The first in-sample estimation is based on monthly observations over the period 1960:1 to 1974:12. Other estimations occur recursively with the same start. The year 1960 was chosen as the start of the estimation sample since reliable monthly measures for most macroeconomic time series were not available until the late 1950s.[15] Also, a number of studies have suggested the possibility that stock returns may have varied systematically over the business cycles in the early 1960s. The year 1975 was chosen as the start of the out of sample since the oil shock of 1973-1975 probably improved the significance of predictability for many models, as pointed out by Goyal and

[14]Strictly speaking, variables in the interest rate sector (bond yields) are not pure macroeconomic variables. But interest rates are important indicators of monetary policy and hence are included here to capture specific information of economic conditions. For a robustness check, I also construct macro indices and redo the experiment without using interest rate variables. I find that the resulting macro indices still have significant predictive power. Detailed results are available from the author on request.

[15]Many macroeconoomic series became available after World War II. But the data immediately after the war were volatile due to the unusually intensive re-construction. To obtain reliable macro data, I take a rather conservative stand and commence with the estimation at the beginning of 1960.

Welch (2007) [36]. Excluding the oil shock recession from the out-of-sample period increases the credibility of a predictive model.

The length of the training period is an ad hoc choice. There is a tradeoff between the length and the quality of the model selection. A long rolling window has more statistical power. But a short rolling window easily captures the dynamic changes of economic conditions and hence an optimal predictor selected under a short window tends to reect the most recent information. Motivated by real-time forecasting, this paper adopts a 24-month rolling window under which an investor may switch more frequently from one model to another in response to newly obtained information. For a robustness check, I also conduct the same experiment by choosing an optimal predictor according to their performance in previous 12, 18, 30, 36, 42, 7 and 48 months. The results are not significantly different.[16]

2.4 Empirical Results

A. Real-time Out-of-Sample Performance

Similar to Goyal and Welch (2007) [36], the performance is measured by the difference in the cumulative squared prediction errors between the benchmark (a forecast equal to the historical average excess return measured at each time-point) and the prediction model (a forecast based on a single predictor with the smallest cumulative prediction errors in the previous 24 months). Panel A displays the results using adaptive macro indices; Panel B displays the results using the same adaptive procedure with the application to ten commonly used predictors, summarized in Goyal and Welch (2007) [36].

The graph of cumulative prediction error difference (ΔSSE) offers special advantages in displaying forecasting performance. First, it provides a continuous evaluation of forecasting performance over the whole out-of-sample period. Its complete records avoid biased judgement based on only single time-point evaluation. In contrast, common practice in the literature conducts out-of-sample tests based solely on the ending point estimate for a fixed sample period, though a good ending cannot guarantee the goodness of the whole process. Second, the time-series pattern of the graph allows for recognizing months with a good, or a bad, performance. An increase in a line indicates better performance of the testing prediction model, whereas a decrease in a line suggests better performance of the benchmark. A good month means that the ΔSSE at that month is included in an upward trend along the line. Finally, the graph is invariant to the choice of the out-of-sample period (though it does affect the in-sample estimation results).

The first impression on the graph in Panel A is a positive ΔSSE line over the entire out-of-sample period, which means that the macro index prediction model generates smaller cumulative prediction errors and hence is superior to the benchmark for the period of January 1977 to December 2005. In addition, the ΔSSE line tends to increase in general, suggesting an increasing difference in prediction errors between the benchmark and the prediction model. The ΔSSE line edges upward from the beginning of 1977, increases substantially in the early 1980s, but then starts to shake up and down until the early 1990s. During the 1990 recession, the predictive power of the macro indices, as measured by ΔSSE, jumps by approximately 70% and then grows steadily until 1998. After the tumultuous period of 1998-1999, the ΔSSE line rebounds to a new peak and remains stable until the end of 2005.

[16]Detailed results are available from the author on request.

TABLE 1

Real-time Out-of-Sample Performance: 1977:01 – 2005:12

	Panel A: Macro Indices			Panel B: GW Predictors		
Period	R^2_{oos}	ΔRMSE	MSE-F	R^2_{oos}	ΔRMSE	MSE-F
1977:1 – 2005:12	2.70	0.0604	**9.66**	−2.26	−.0500	−12.94
1980:1 – 1989:12	1.73	0.0425	**2.11**	−0.42	−0.0083	−0.51
1990:1 – 1999:12	1.10	0.0214	1.33	−3.86	−0.0892	−3.01
2001:1 – 2005:12	4.15	0.0924	**3.51**	−2.26	−0.0500	−8.24

This table presents the statistical results of real-time out-of-sample performance for the monthly predictive regressions. During each out-of-sample month, investors choose a predictor from the base set which generates the smallest cumulative prediction errors in previous 24 months. There are two base sets: A: Macro Indices constructed from a panel of 100 economic variables using principal component analysis; and B: the ten monthly Predictors in Goyal and Welch (2007) [36] (GW Predictors). The performance uses three measures: the out-of-sample R-square (R^2_{oos}), the difference of the root-mean-squared prediction error (ΔRMSE) and the MSE-F statistics (McCracken (2004) [47]) to test for the equal forecast accuracy. The benchmark is the unconditional forecast equal to the historical average. The alternative is the conditional forecast using adaptively selected predictors. One-sided critical values of MSE-F are obtained empirically from bootstrapped distributions. The boldface numbers indicate that the alternative model is superior to the benchmark with at least 90% statistical significance. The formulas for the three statistics are:

$$R^2_{oos} = 1 - \sum \hat{u}^2_{A,\tau} \Big/ \sum \hat{u}^2_{B,\tau}$$

$$\Delta\text{RMSE} = \sqrt{\sum \hat{u}^2_{B,\tau}} - \sqrt{\sum \hat{u}^2_{A,\tau}}$$

$$\text{MSE-F} = R \cdot \left(\frac{\sum_r \hat{u}^2_{A,\tau} - \sum_r \hat{u}^2_{B,\tau}}{\sum_r \hat{u}^2_{B,\tau}} \right)$$

where $u_{B,\tau}$ is the forecasting error from the benchmark and $u_{A,\tau}$ is the forecasting error from the alternative adaptive prediction model. R is the number of out-of-sample observations.

Another striking pattern of the out-of-sample performance is its tight correlation with the business cycles. The predictive power of macro indices decreases before the recessions but rebounds quickly during them. As evidenced in the graph, the ΔSSE line has three sharp downward drifts in the period 1986:02 - 1986:10 (before the 1987 stock market crash), the period 1989:07 - 1990:02 (before the 1990-91 recession) and the period 1998:02 - 1998:09 (before the "bubble period" of 1999-2001). With each decline, a corresponding upward drift is observed during the recession or market downturns. This phenomenon in turn indicates that macro indices are suitable predictors for excess stock returns since macro indices suffciently describe economic conditions.

Important information of the real-time forecasting performance is also provided in Table 1, which displays the statistical results using three measures: the out-of-sample R-square statistics (R^2_{oos}), the difference of the root-mean-squared-error statistics (ΔRMSE), and the F-statistics for the test of equal forecast accuracy (MSE-F).[17] The benchmark is the unconditional forecast equal to the historical average. The alternative is the conditional forecast using adaptively selected predictors: macro indices in Panel A and financial predictors in Panel B. During each out-of-sample month, investors choose a predictor from the macroeconomic or financial base set, which has the smallest cumulative prediction errors in previous 24-months. All calculations are based on the adaptive prediction process described in Section 2.1.

As shown in Panel A of Table 1, adaptive macro indices robustly predict excess stock returns for the whole sample of 1977:1 to 2005:12, with a 2:7% out-of-sample R^2 and a 9.66 MSE-F value which is 99% statistically significant. For both subperiods of 1980–1989 and 2001–2005, the F statistics are both significant above the 90% level: 2.11 for the 1980s and 3.51 for the 2000s. These numbers confirm that the conditional forecasts based on adaptive macro indices have smaller prediction errors and hence are superior to the unconditional forecasts based on the historical average.

The subperiod 1990–1999 has a R^2 value of 1.10, but the F-statistic (1.33) is not statistically significant, suggesting that adaptive macro indices have a seemingly unimproved forecasting power. However, these numbers only reveal the predictability information at a single point, that is December 1999; it hides the time-series pattern of predictability over the course of the 1990s. As shown in the ΔSSE graph, the low ΔRMSE number at 1999:12 is due to the sharp drop of predictability during the bubble period 1998-1999. Macro indices do have steadily increasing predictive power from the beginning of 1990 to the beginning of 1998. This example demonstrates that it is important to use the cumulative-prediction-error-difference graph to evaluate out-of-sample performance.

In sharp contrast, the adaptive forecasts of excess returns based on financial/accounting ratios (Panel B) have much higher prediction errors than the benchmark. For either the full out-of-sample period or for three subperiods, the R^2_{oos} are all negative as are the F-statistics. These results are consistent with the findings in Goyal and Welch (2007) [36], who show that commonly used predictors in the current literature have a poor out-of-sample performance. Note that a striking difference of this paper from Goyal and Welch (2007) [36] lies in that they examine the forecasting power of fixed predictors using the whole sample infomration, whereas I study the real-time forecasting using only historical information available up to each prediction time. Supplementing Goyal and Welch's ex post results, this paper further shows that those popular predictors also have poor ex ante forecasting power even when carefully selected over time.

B. The Sign of Excess Returns Forecasts

The predictive least squares criterion chooses optimal predictors according to the magnitude of their forecasting errors. Investors, however, probably consider the sign of forecasting to be equally important. Leitch and Tanner (1991) [40] found that traditional measures like R^2 fail to pick up predictors that generate equal profits from a trading strategy as a measure of the "sign" criterion. Given investors' concerns regarding the sign of forecasting, I now examine whether the PLS criterion can choose predictors that also correctly predict the sign of excess returns.

Figure 1 presents the accuracy rate of timing the stock market under the PLS principle, which is measured by the percentage of correct signs of the excess returns predicted by macro indices. On

[17]The out-of-sample R^2 statistic is computed as it is in Campbell and Thompson (2007) [15] . MSE-F reports the F-statistics defined by McCracken (2004) [47]. A rejection of the benchmark hypothesis suggests the superiority of the alternative model, rather than the benchmark in the sense that the alternative model generates smaller prediction errors.

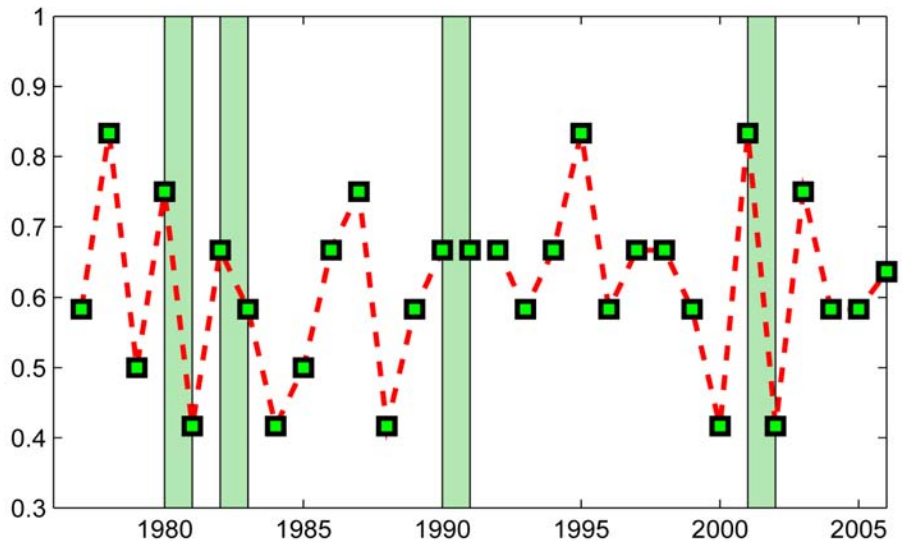

FIGURE 1. Accuracy Rate of Excess Return Forecasts, measured by the proportion of correct signs predicted by macro indices in each year of the trading period: 1977:1 - 2006:11. For example, an 83% accuracy rate means that excess return forecasts get the same sign as the realized returns for ten months within a year. Shading denotes years of recessions identified by NBER.

average, the adaptive predictions get the same sign as the realized excess returns for 62 percent of all months in the trading period 1977:01 to 2006:12. Two interesting findings are worth noting. First, predictability from macro indices seems particularly high during the years of recessions and market downturns. In four recent recessions, the forecasting accuracy is locally high with respect to the years before and after recessions; the year of 2001 shows the correct predictions for 10 months with an accuracy rate of 83%, 67% for the year of 1991, 75% for 1980 and 67% for 1982. Three other spikes with the highest accurate forecasting rates occur in 1978 (83%), 1987 (75%) and 1995 (83%). Second, the degree to which the stock returns are predictable seems quite low before each recession.

The accuracy of forecasts both in magnitude and in sign exhibits a strong cyclical pattern. One possible explanation is that the predictability of stock returns may be particularly pro- nounced in periods of economic "regime switches" where the markets are relatively unsettled and investors are particularly uncertain of which forecasting model to use for trading (Pesearan and Timmermann (1995) [51]). Another possible explanation of the cyclical pattern is the difficulty investors have in identifying the turning points of business cycles when macro indices carry more noise.

In solving this dynamic programming problem,[18] the optimal portfolio allocation in the risky asset is

$$\alpha_t = \frac{1}{\gamma} \frac{\mu_t - r_f}{\sigma_t^2} \tag{5}$$

where γ is the local coecient of relative risk aversion.The proportion invested in the risky asset depends on the investor's risk aversion γ and the conditional distribution of the expected stock returns (μ_t, σ_t).

[18]Cochrane (2007c) [27] provides details for solving this dynamic programming problem.

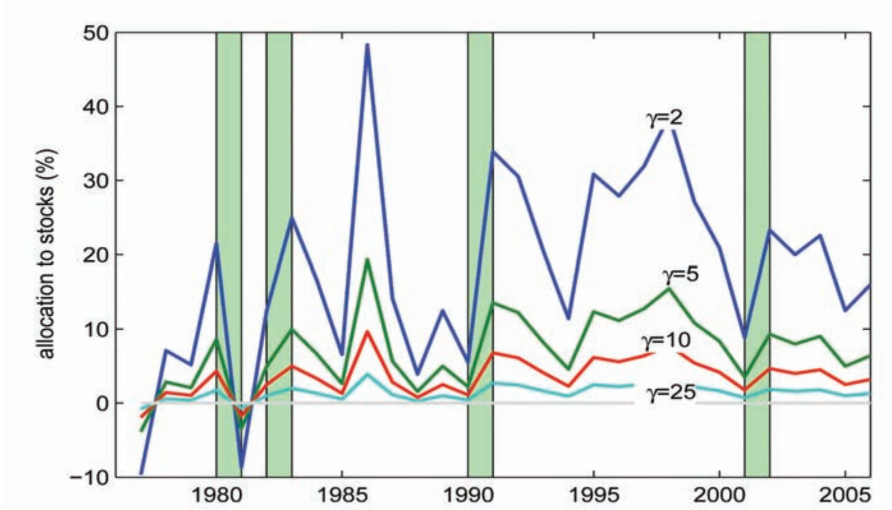

FIGURE 2. Optimal Portfolio Allocation Over Time. The allocation to risky stocks is $\alpha_t = \frac{1}{\gamma}\frac{E_t(r^e)}{\sigma_t^3}$. Expected excess returns come from the adaptive forecasts based on macro indices, $r^e_{t+1} = \hat{a}_i + \hat{b}_i z_{i,t}$. The variance of excess returns is estimated by the variance of predictive regression residuals. γ is the coeffcient of risk aversion. This figure shows the annual allocation, which is calculated as the average of monthly allocations. The sample period is from January 1977 to November 2006. Shading denotes recessions identified by NBER.

In practice, an investor adaptively forecasts the conditional mean and the conditional variance based on the predictive regression. The allocation to the risky asset may rise or fall over time, determined by the investor's ability to hedge the changes in economic conditions signaled by the optimal macro index, the "market timing" ability.

Figure 2 shows the optimal allocation to risky stocks over time, based on sequentially selected macro indices which reflect the changes of economic conditions over time. A common feature for both the allocation and the predictability is a strong cyclical pattern: reduced investment in risky stocks at the beginning of recession and increased investment at the end of recession. A strong position in stocks coincides with high stock market returns. A weak position in stocks accompanies relatively low stock market returns. The optimal allocation to stocks varies mildly, from -10 to 50 percent.

3 ECONOMIC SIGNIFICANCE OF PREDICTABILITY

The ability to predict stock returns ahead of time is the backbone of investment strategies, but predictability, in itself, does not guarantee that an investor can earn profits from a trading strategy that is based on such forecasts.[19]

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[19]Some authors report significant profits using *ex ante* model calibration, see Balduzzi and Lynch (1999, 2000) [5, 6], and Kandel and Stambaugh (1996) [39]. Other studies of real-time investment performance, however, document that the use of predictability fails to earn excess profits over the market. Carhart (1997) [19] and Wermers (2000) [66] find that the failure to mutual finds; Barber and Odean (2000) [7] find it in individual investors, Christopherson, Ferson, and Glassman

Table 2 presents the trading results. For each panel, I report the mean and the standard deviation of excess returns, and their Sharpe ratio. I also list the percentage of the total months when trading portfolios have negative returns and I show the final amount of wealth obtained from trading portfolios, assuming that investors start off with $100 at the beginning of 1977 and reinvest portfolio income every month until the end of 2005. In the case of a buy-and- hold market portfolio, only the dividends are reinvested on a monthly basis. In contrast, the switching portfolios may reallocate funds between stocks and bonds, depending on whether a change in the sign of the excess return is predicted. The utility-based portfolios always have positions in both stocks and bonds but they adjust optimal allocations according to the forecasts of adaptive macro indices. A transaction cost is incurred only when investors switch or adjust positions.

Taxes also erode trading profits but are diffult to deal with, partly because they are investor- and investment-specific, and will therefore not be considered in this paper. For trading costs, I make a simplifying assumption that they are constant through time and symmetric with respect to whether the investor is buying or selling assets. I further assume that trading costs are simply proportional to the value of the trade, letting c^1 and c^2 be the percentage trading costs on stock shares and bonds, respectively.[20] Besides zero trading costs, I consider two additions scenarios: "Low" transaction costs with 25 basis points on trading in one unit share of stock ($c^1 = 0 : 0025$) and 5 basis points in one unit of bond ($c^2 = 0 : 0005$), and "High" transaction costs with 50 basis points on trading in one unit share of stock ($c^1 = 0 : 005$) and 5 basis points in one unit of bond ($c^2 = 0 : 0005$). The buy-and-hold strategy is a relatively passive investment strategy and it hence incurs low transaction costs. Compared with this benchmark, an investment strategy based on adaptive predictions is likely to incur considerably higher transaction costs.

First I consider the results for switching portfolios. Under all three transaction cost scenarios, the switching portfolios based on conditional forecasts by adaptively selected macro indices perform better than a buy-and-hold market portfolio: they have higher mean returns, As Vanguard founder Jack Bogle said, the strength of indexing (buy-and-hold strategy) stems primarily from its inherent cost advantage.

4 FORECASTING: *Ex Post* VS *Ex Ante*

The approach in this paper uses time-varying combinations of a large number of variables. It is therefore not immediately clear what specic economic forces contribute to the predictability of returns over time. To overcome this obstacle, I compare several types of forecasts using different information sets. Beginning with ex post forecasting, I construct indices using the entire sample and examine the performance of each index with fixed weights. Then I recursively construct indices using only the historical information available for each month. In this semi ex post forecasting, I consistently choose the "same" index (principal components with the same order in explaining the variation of the panel data) and study the performance of each index with dynamic loadings. Finally, I revisit ex ante forecasting adopted in this paper, where I sequentially choose indices (principal components with different orders) rather than use the fixed index as in ex post forecasting. If there exists a consistent

(1998) [21] confirm that for pension funds; and Pirinsky (2001) [53] documents the failure in banks, investment advisors, and insurance companies.

[20]This paper doesn't consider other types of trading costs like commission fees and bid-ask spreads.

TABLE 2

Pseudo Out-of-Sample Performance: 1977:1 - 2005:12

Predictor	$R^2_{in}(\%)$	$R^2_{oos}(\%)$	ΔRMSE	MSE-F
Panel A: Significant Macro Indices				
F2	4.97	2.58	0.0581	9.58
F5	0.20	1.73	0.0380	6.54
Panel B: Selected Insignificant Macro Indices				
F1	0.90	$-.07$	-0.0015	-0.25
F3	0.82	-0.29	-0.0060	-1.09
Panel C: Other Insignificant Predictors				
Dividend-Price Ratio	0.26	-0.87	-0.0194	-3.20
Earnings-Price Ratio	0.24	-1.31	-0.0293	-4.82
Book-to-Market Ratio	0.03	-1.36	-0.0304	-4.99
Net Issuing Activity	0.69	0.43	0.0096	1.60
Term Spread	0.87	-0.37	-0.0082	-1.36
Default Spread	0.72	0.16	0.0035	0.59
Default Return	0.05	-0.37	-0.0083	-1.37
Long-term Bond Return	1,02	-0.63	-0.0141	-2.33

This table presents pseudo out-of-sample performance of selected predictors. The performance uses four measures: in-sample and out-of-sample R-square (R^2_{in} and R^2_{oos}), the difference of the root-mean-squared prediction error (ΔRMSE) and the MSE-F statistic (McCracken, 2004) [47] to test equal forecast accuracy. The benchmark is the unconditional forecast equal to the historical average of excess market returns. The alternative is the conditional forecast using selected predictors listed in the first column. See Table 1 for formulas of the statistics. Macro indices are recursively constructed at each month of the trading period. Other financial predictors are from Goyal and Welch (2007) [36], including dividend-price ratios, earnings-price ratios, book-to-market ratios, net issuing activity, term spread, default spread, default return and long-term bond return.

connection from ex post to ex ante forecasting, we may understand the important economic forces that contribute to equity premium predictions.

4.1 Summary

The increasing predictive power of indices comes at the cost of diminishing clarity in economic identity. Real-time prediction using adaptively selected macro indices has strong and robust performance, but obscure economic interpretations. The ex post prediction using fixed weight indices has a relatively poor performance but a sharp economic identity. Between them lies the ex post prediction using indices with dynamic loadings. The more adaptable the procedure is, the more predictive power it has. By decomposing indices, I find that the economic fundamentals link to the financial market combining the effect of interest rates, price indices, housing and employment.

5 ROBUSTNESS CHECK

5.1 Other Model Selection Criteria

A special feature of this adaptive prediction procedure is the use of an out-of-sample criterion for model selection: predictive least squares (PLS). In this subsection, I compare the real-time forecasting performance using the out-of-sample PLS and other model selection criteria: the in-sample R-square (R^2_{in}), Bayesian Information Criterion (BIC) and the in-sample $A.m = 24$ PLS. The difference between the in-sample and the out-of-sample PLS lies in the information set used to construct macro indices. The in-sample PLS is calculated as the cumulative square fitting errors where macro indices are estimated using both historical information and information of the model selection period. The out-of-sample PLS is the cumulative square prediction errors where macro indices are estimated using only historical information.

6 CONCLUDING REMARKS

By recursively choosing the optimal index under the conditional forecasts outperform both the unconditional forecasts (historical average) and forecasts conditional on prominent variables from the literature. It is robust—the ex ante forecasting performs well over the past three decades. More importantly, investment strategies exploiting real-time forecasts are able to earn excess profits over the market portfolio with moderate transaction costs.

There are several promising directions for future research. Macro indices explored in this paper provide a fresh opportunity to investigate the determinants of asset risk. The findings on the time-series behavior of excess returns can be linked to the large body of literature on cross-sectional asset pricing. According to the ICAPM of Merton (1973), innovations in state variables—only those state variables that are capable of predicting the expected returns over time—are likely to describe stochastic investment opportunities and hence command risk premia. Macro indices F2 and F5 are the most frequently selected optimal predictors in real-time forecasting; thus, innovations to them could be potential risk factors that explain the cross-sectional pattern of expected returns. No matter what these macro indices turn out to be, whether priced factors or merely good conditioning variables, the cross-sectional investigation takes us one step closer to understanding the main challenge of financial markets: what are the fundamental macroeconomic forces that drive risk premia in the stock market?

An alternative direction involves exploring the connection between structural breaks in financial ratios and time-varying macroeconomic conditions. Lettau and Nieuwerburgh (2007) [41] suggest that the inconsistent results for in-sample and out-of-sample regressions based on financial ratios can be reconciled once we adjust for shifts in the conditional mean. Since detecting a structural break is impossible for investors in real-time forecasting, it is more meaningful to ask why there are structural breaks in the conditional mean (or volatility) of financial ratios, and to seek what is the source of such instability. As quantitative descriptions of economic conditions, macro indices may play a key role in uncovering the real mechanism of financial ratios' nonstationarity.

APPENDIX

A DATA DESCRIPTION

A.1 Macroeconomic Series

Following Stock and Watson (2002, 2005) [59, 60], I choose series to capture broad U.S. economic conditions. This panel data comprises 100 economic series, a subset of Stock and Watson's 132 dataset excluding stock market data and various author-calculated spreads of interest rates. I also extends the panel to include the most recent available observations, a sample period from 1960:01 to 2006:11. The format is: series number, short name of each series, its mnemonic (the series label used in the source database), the transformation applied to the series, and a brief data description. All series come from the Global Insights Basic Economics Database.

In the transformation column, ln denotes logarithm, Mln and M2 ln denote the first and second differences of the logarithm, Δ ln denotes the level of the series, and Δ^2 ln the difference of the level.

A.2 Predictors in Goyal and Welch (2007)

In the monthly prediction, Goyal and Welch (2007), [**?**], uses the following predictors: the dividend ration, the earnings price ratio, the dividend-earnings ratio, the book-to-market ratio, the long-term government bond return, net equity expansion, inflation measured by the first difference of the logarithm in Consumer Price Index (All Urban Consumers), the term spread, the default yield spread, and the default return spread. For a detailed description and data sources, please see the original paper. In this paper, I use these data for a sample period of January 1960 to December 2005.

[The blue numbers following some references link to the page or pages where the citation to this reference appeared. You can click on the number to go to that page.]

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