



UNIVERSITY OF ANTWERP

Faculty of Applied Economic Sciences

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The Aligned Economic Index & The State Switching model

A powerful predictor of stock returns across all market regimes

A thesis submitted in partial fulfilment

Ilias Aarab

for the degree of

Business Engineering

Promotor: Gertjan Verdickt



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Abstract

Recent findings show that stock return predictability is solely concentrated around recessions while being non-existent during expansions. I examine stock return predictability of the U.S. market across different economic regimes and document significant evidence of time-varying expected returns across all market states, expansions and recessions. I contribute to current literature in two ways. First, I introduce a state switching model in which the current market state is defined by the slope of the yield curve. The state switching model increases both the in-sample and out-of-sample R^2 of the 14 popular predictors used in Welch & Goyal (2008) on average by 1.15% resulting in statistical and economical, out-of-sample, significance of 11 predictors. Second, I introduce a new U.S. aggregate stock market predictor, the aligned economic index. The aligned economic index under the state switching model exhibits statistically and economically significant in-sample ($R^2 = 5.9\%$) and out-of-sample ($R_{oos}^2 = 4.12\%$) predictive power across both recessions and expansions while outperforming a range of well-known predictors in current literature. I compute economic gains for a mean-variance investor and find substantial added benefit of using the new index under the state switching model across all market states. The aligned economic index can thus be implemented on a consistent real-time basis. These findings are crucial for both academics and investors as expansions are much longer-lived than recessions.

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Introduction

There is a large body of work that tries to uncover stock return predictability [e.g, Fama & French (1988), Campbell and Shiller (1989), Kandel and Stambaugh (1996), Guo (2002), Lewellen (2004), and Polk, Thompson and Vuolteenaho (2006)]. However, Welch & Goyal (2008) extensively show that time-varying models are unable to aid an investor to profitably time the market by using solely ex-ante information. Model uncertainty, where one does not know a priori the right model specification, and parameter instability, where parameter estimation is highly dependent on the sample period, lead to poor out-of-sample performance of all predictors.

However, during the last decennia a great number of papers have introduced models, taking model uncertainty and parameter instability into account by incorporating the following adjustments:

- (I) economically motivated model restrictions [e.g. Campbell and Thompson (2008), Ferreira and Santa-Clara (2011), Pettenuzzo and Timmermann (2014), and Pan, Pettenuzzo and Wang (2018)]
- (II) combining multiple predictors [e.g. Rapach and Strauss (2010), Neely, Rapach, Tu and Zhou (2014), Kelly and Pruitt (2013), and Huang, Jiang, Tu and Zhou (2015)]
- (III) introducing regime-shifts [e.g. Henkel et al (2011), Hammerschmid and Lohre (2018), and Sander (2018)]
- (IV) introducing new predictors [e.g. Rapach, Ringgenberg, Zhou, Drive and Louis (2016) and Jiang, Lee, Martin and Zhou (2019)]

These papers, among many others, provide evidence of significant return predictability both in sample and out of sample. Nonetheless, the particular models fail to predict stock returns across all states of the economy, with most forecasting performance being concentrated across recessions. Henkel, Martin, and Nardari (2011) and Dangl and Halling (2012) condition on the business cycle and find further evidence that return predictability only exist during recessionary periods, while being non-existing during expansionary periods. Cujean and Hasler (2017) build an equilibrium model showing that investors use different forecasting models and react to different types of news depending on the current state, which helps explain why stock returns are only predictable during certain states. Devpura, Kumar, and Sunila (2018) formally test for time-varying return predictability and find that return predictability is indeed time-varying and even predictor dependent. Thus, although stock return predictability is becoming a stylized fact, more research is in place to uncover predictability across different market states.

In this paper, I propose a simple state dependent model with predictor coefficients that are free to change depending on the current state. By introducing state-dependent coefficients, my model can significantly predict stock returns, both in sample and out-of-sample, across all market states, during expansionary and recessionary periods. In contrary to most existing models which only benefits investors during recessionary periods that are typically short lived, my state switching model adds more practical value to investors as it significantly outperforms naïve models (e.g. the historical average or a simple buy and hold strategy) across all market states and thus can be used on a consistent basis.

In line with the findings of Boyd, Hu and Jagannathan (2005) and more recently Huang et al. (2017), I show that traditional one-state regression models are misspecified. For example, when using the popular net equity expansion predictor in the state switching model, its slope changes sign from negative in good periods to positive in bad periods. Other predictors (e.g. the equity risk premium volatility) forecast the market significantly during good periods but fail to do so during bad periods, while some predictors (e.g. the default yield spread) are the counterimage, predicting the market in bad periods but fail to do so during good periods.

I estimate the current state in two ways. Markov hidden models are a natural way of departure to capture state-dependence in returns. The great advantage of using Markov hidden models is that they do not dependent on exogenous information, and instead estimate unobservable realizations of a Markov chain directly linked to the return distribution [e.g. B. Y. J. D. Hamilton (2019) and J. D. Hamilton (2005)].

On the other hand, Markov hidden models are nonlinear and utilize numerical estimation procedures to infer the hidden states of a distribution. Although great in sample performance can be obtained, the added complexity might lead to poor estimations in out-of-sample forecasting (Sander, 2018). I therefore consider a less complicated alternative where I use a dummy indicator to condition on the current state. Since the NBER-dated recession indicator is determined ex-post it can't be utilized in a real-time setting. Sander (2018) shows that estimating such a recession indicator in real time is a hit or miss approach, where wrong estimated turning points lead to substantial losses. For this reason, I construct an ex-ante dummy indicator based on the yield curve, which equals one whenever the yield curve is inverted or flat (indicating a down state) and is zero otherwise (indicating an up state).

The slope of the Treasury yield curve has often been cited as a leading economic indicator and a barometer of economic sentiment, with inversion of the curve being thought of as a precursor of a recession. For example, on July 17, 2006, the 10-year U.S. treasury bill yielded 5.07%, while the 3-month note yielded 5.12% indicating that bad times were ahead. The yield curve stayed inverted in the months afterwards and went back and forth between an inverted and flat curve during the summer of 2007. The Fed became concerned in September 2007 and lowered the fed funds rate and continued to do so until it reached zero by the end of 2008. The yield curve was no longer inverted, but it was too late: the U.S. economy had entered the worst recession since the Great Depression.

I combine the state dependent model with a new powerful predictor: an aligned economic index of the 14 popular economic predictors of Welch and Goyal (2008) supplemented by the bond and equity premium. The aligned index is formed by employing the partial least squares (PLS) method introduced by Wold (1975) and refined by Kelly and Pruitt (2013,

2015). Neely et al. (2014) shows that the 14 popular predictors contain complementary information and that using principal component analysis (PCA) enhances the forecasting powers of the predictors. However, the PCA predictor still fails to predict the stock market during expansionary periods.

In this paper, I exploit the information of the 14 fundamental variables in a more efficient manner, resulting in a new aligned index with the goal of explaining excess returns. When using the aligned economic index under the state switching model I find significant return predictability across all market states. More so, using the aligned economic index under the state switching model significantly outperforms the historical average forecast (and the buy and hold strategy) across all market states.

2 Data

The aggregate stock market return is computed as the excess return, which is the continuously compounded log return on the S&P 500 index (including dividends) minus the risk-free rate (proxied by the three-month Treasury-bill). By focusing on excess returns, I net out inflation and the level of interest rates, thus focusing directly on predictability of the real risk premia.

I use updated data of Welch and Goyal (2008) consisting of 14 popular fundamental variables spanning January 1950 to December 2017¹. The reason of using a post-war sample period is twofold. First, from an investor's added value perspective, it makes intuitively sense to examine stock return predictability in the most recent years. Analysis of the most recent decades can help shed light on whether a model is still likely to perform well nowadays. As argued by Welch and Goyal (2008) a predictive model would inspire confidence in a potential investor if it consistently outperforms, in an out-of-sample setting, the historical forecast over the most recent several decades, irrespective of its past performance—otherwise, even a reader taking the long view would have to be concerned

¹ The data can be retrieved from Amit Goyal's web page at <http://www.hec.unil.ch/agoyal/> and a detailed description can be found in Welch and Goyal (2008).

with the possibility that the underlying model has drifted. Secondly, from a statistical perspective, Lewellen (2004) recommends to estimate predictive models only with data after World War II. The properties of stock prices were much different prior to 1945: Returns were extremely volatile in the 1930s, and this volatility is reflected in both the variance and persistence of multiple predictors (e.g. the dividend yield). More so, Chen (2009) documents a dramatic reversal of predictability in the 134 years during 1872-2005: stock returns are largely unpredictable in the first seven decades, but become predictable in the postwar period; while dividend growth is strongly predictable in the prewar years though this predictability disappears in the postwar era. More recently, Golez and Koudijs (2018) examine the equity markets of the last four centuries and find that dividend yields are stationary and consistently forecast returns. However, when looking at subsamples they find weak stock return predictability during the period 1871-1945, but significant and robust return stock return predictability during 1945-2015. Furthermore, I exclude the 1945-1949 period as dividend policies during the war era were quite volatile which might affect the predictive capabilities of some of the considered predictors (George M. Frankfurter, 1997). Lastly, due to some initial analysis using the first 10 years of data, the final sample period used throughout the paper is January 1960 to December 2017, covering 696 months.

The variables used throughout the paper to predict excess stock returns are:

1. Dividend-price ratio (log), DP, is the log of a 12-month moving sum of dividends paid on the S&P 500 index minus the log of stock prices (i.e. the S&P 500 index value)
2. Dividend yield (log), DY, is the log of a 12-month moving sum of dividends minus the log of 1 month-lagged stock prices
3. Earnings-price ratio (log), EP, is the log of a 12-month moving sum of earnings on the S&P 500 index minus the log of stock prices
4. Dividend-payout ratio (log), DE, is the log of a 12-month moving sum of dividends minus the log of a 12-month moving sum of earnings

5. Equity risk premium volatility, RVOL: calculated based on a 12-month moving standard deviation estimator (Mele, 2007)
6. Book-to-market ratio, BM, of the Dow Jones Industrial Average
7. Net equity expansion, NTIS, is the ratio of a 12-month moving sum of net equity issues by NYSE listed stocks to the total end-of-year market capitalization of NYSE stocks
8. Treasury bill rate, TBL, is the interest rate on a 3-month treasury bill from the secondary market
9. Long-term yield, LTY, on long-term government bonds
10. Long-term return, LTR, on long-term government bonds
11. Term spread, TMS, is the difference between the long-term government bond yield and the treasury bill rate
12. Default yield spread, DFY, is the difference between Moody's BAA- and AAA-rated corporate bond yields
13. Default return spread, DFR, is the difference between the returns on a long-term corporate bond and a long-term government bond
14. Inflation, INFL, is calculated from the Consumer Price Index (CPI) for all urban consumers. The inflation rates are lagged one month to account for the delay in CPI releases.

Guidolin and Timmermann (2005) show that both the bond premium and equity premium exhibit return predictability when regressed on first-order lags of each other. I thus add two new predictors to the list, the first one being the one-month lag of the equity premium, and the second one being the risk premium on long term corporate bonds.

15. Lagged equity premium, LEP, the lagged one-month excess returns on the S&P 500 index
16. Corporate bond premium, CBP, the continuously compounded log return on long-term corporate bond returns minus the three-month Treasury-bill

All data are in monthly frequency, and the analysis of the paper focuses on the one-month forecasting horizon. There are two main reasons of doing so. First and foremost, the main goal of the paper is to analyze stock return predictability across different regimes (e.g. expansions and recessions). The state indicators covered in this paper (like the NBER-dated recession indicator²) identify states with a duration ranging from 5 to 15 months, thus using longer horizon regressions would include random combinations of different states which might affect the importance of the market states. Second, Cochrane (2011) shows that return predictability with a short horizon is usually magnified at longer horizons, with further evidence provided from multiple papers [e.g. Huang et al. (2015) and Rapach et al. (2016)].

Table 1 reports the summary statistics of the data. The monthly excess market return has a mean of 0.43% and a standard deviation of 4.24%, implying a monthly Sharpe ratio of 0.10. Even though the excess market return has little autocorrelation, most of the other variables are quite persistent, with first-order autocorrelation coefficients between 0.96 and 0.99 for most predictors. These results indicate that the well-known Stambaugh (1999) small sample bias might be a concern. I therefore take the first difference of the persistent variables before estimating the predictive models. In sum, the summary statistics are generally consistent with the literature.

² The data can be retrieved from the database of the Federal Reserve Bank of St. Louis, and is composed of dummy variables that represent periods of expansions and recessions based on US Business Cycle Expansions and Contractions data provided by The National Bureau of Economic Research (NBER).

Table 1 Summary statistics

	Mean	Std	Skew	Kurt	Min	Max	$\rho(1)$	SR
R^m (%)	0.43	4.24	-0.68	5.59	-24.82	14.92	0.06	0.10
R^f (%)	0.38	0.26	0.67	3.80	0.00	1.35	0.99	
DP	-3.59	0.39	-0.19	2.28	-4.52	-2.75	0.99	
DY	-3.59	0.39	-0.20	2.31	-4.53	-2.75	0.99	
EP	-2.85	0.43	-0.66	6.00	-4.84	-1.90	0.99	
DE	-0.75	0.31	2.74	18.25	-1.24	1.38	0.99	
RVOL(%)	0.21	0.43	10.35	141.80	0.01	7.09	0.47	
BM	0.50	0.26	0.77	2.74	0.12	1.21	0.99	
NTIS	0.01	0.02	-0.73	3.43	-0.06	0.05	0.98	
TBL (%)	4.62	3.18	0.68	3.82	0.01	16.30	0.99	
LTY (%)	6.45	2.70	0.72	3.17	1.75	14.82	0.99	
LTR (%)	0.61	2.90	0.43	5.77	-11.24	15.23	0.04	
TMS (%)	1.82	1.45	-0.33	2.87	-3.65	4.55	0.96	
DFY (%)	1.01	0.45	1.76	7.33	0.32	3.38	0.97	
DFR (%)	0.02	1.45	-0.41	9.65	-9.75	7.37	-0.08	
INFL (%)	0.31	0.36	0.03	6.10	-1.92	1.81	0.57	

This table provides summary statistics for the excess market return (R^m , the log return on the S&P 500 index in excess of the risk-free rate), risk-free rate (R^f), log dividend-price ratio (DP), log dividend yield (DY), log earnings-price ratio (EP), log dividend-payout ratio (DE), Equity risk premium volatility (RVOL), book-to-market-ratio (BM), net equity expansion (NTIS), Treasury bill rate (TBL), long-term bond yield (LTY), long-term bond return (LTR), term spread (TMS), default yield spread (DFY), default return spread (DFR), inflation rate (INFL), Corporate bond premium (CBP). For each variable, the time-series average (Mean), standard deviation (Std), skewness (Skew), kurtosis (Kurt), minimum (Min), maximum (Max), and first-order autocorrelation ($\rho(1)$) are reported. The monthly Sharpe ratio (SR) is the mean excess market return divided by its standard deviation. The sample period is over January 1960 to December 2017.

3 Return predictability and switching between states

I estimate the current state in two ways. Markov hidden models are a natural way of departure to capture state-dependence in returns. The great advantage of using Markov hidden models is that they do not depend on exogenous information, and instead estimate unobservable realizations of a Markov chain directly linked to the return distribution [e.g. B. Y. J. D. Hamilton (2019) and J. D. Hamilton (2005)]. On the other hand, Markov hidden models are nonlinear and utilize numerical estimation procedures to infer the hidden states of a distribution. Although great in sample performance can be obtained, the added complexity might lead to poor estimations in out-of-sample forecasting (Sander, 2018). I therefore also consider a less complicated alternative where I use a dummy indicator to condition on the current state. Since the NBER-dated recession indicator is determined ex-post it can't be utilized in a real-time setting. Sander (2018) shows that estimating such a recession indicator in real time is a hit or miss approach, where wrong

estimated turning points lead to substantial losses. For this reason, I construct an ex-ante dummy indicator based on the yield curve, which equals one whenever the yield curve is inverted or flat (indicating a down state) and is zero otherwise (indicating an up state).

The main results of the paper are based on the newly introduced yield curve state indicator, while the appendix resorts to the Markov model results.

3.1 Regime shifts and the inversion of the yield curve

Under the expectation hypothesis, the term spread measures the difference between the current short-term interest rate and the average of expected short-term interest rates over a longer future horizon. Higher long-term rates thus reflect expectations that economic growth will continue, but when the term spread shrinks it's a signal that investors are less certain of future conditions and require a higher risk premium to accommodate for the added uncertainty. The yield curve captures exactly this investor sentiment (Wright, 2006).

The market state at month t is defined as a down state if the yield curve was inverted or flat in one of the preceding τ months, more formally,

$$S_t = \begin{cases} 1 & \text{if } tms_{t-i} \leq 0 \text{ for } i = 1, \dots, \tau \\ 0 & \text{otherwise} \end{cases} \quad (1)$$

with S_t denoting the current market state and tms_{t-i} (i.e. the term spread) defined as the difference between the long-term yield on government bonds and the Treasury-bill [See, e.g., Fama and French (1989) and Welch and Goyal (2008)]. The yield curve only acts as a turning point of the current state and thus a lag τ needs to be introduced to define the duration of the new state. I use a constant length of $\tau = 9$ months for the following two reasons³. First, from a statistical point of view, one might be induced to find an optimal duration of the market states (e.g. $i = 1, \dots, \tau$ with τ the duration that optimizes the in-sample performance) to yield maximum performance of the state switching model. However, to stray away from potential data snooping issues as noted by Welch and Goyal (2008) I simply choose to use a constant duration that is less than the average historical

³ Using a duration of anything between 3 and 12 months does not change the main results of the paper.

recession duration before the start of my sample period. The reason for choosing a lag length less than the historical average accounts for the fact that recessions tend to be shorter lived as we move further into the future. Secondly, parameter optimization tends to increase in sample performance, but might lead to worse out-of-sample performance as noted by Xia (2001). Thus, as an ex-ante dummy indicator, the market state of next month is simply determined by the slope of the yield curve during the past nine months.

Table 2 reports summary statistics of stock returns across different states. During an up state (i.e. $S_t = 0$), the average return is high with a relatively low standard deviation leading to a high Sharpe ratio. The kurtosis is relatively low, and skewness is highly negative. In contrast, during a down state (i.e. $S_t = 1$), the average return is negative with a high standard deviation resulting in a negative Sharpe ratio which indicates that the risk-return trade-off is much less attractive compared to an upstate. More so, although skewness is roughly the same across states, kurtosis is twice the amount compared to an up state. The excess kurtosis in addition to the negative skewness suggests that the market tends to experience more severe crashes during a down state. In addition, the first-order autocorrelation is low and constant throughout the states, indicating the non-persistence of the return series across the states. Overall, the state indicator differentiates the return distributions of stocks in an up state with positive and relative stable returns (similar to a bull market or expansionary period), and a down state characterized by negative and volatile average returns (similar to a bear market or recessionary period).

The state indicator signals a downstate in the months leading up to a recession eight of the nine times over the sample period. The only false negative is during the Recession of 1960-1961, which starts three months after the start of the sample period, thus disabling the full potential of the state indicator. This result is quite significant as the state indicator only uses ex-ante information to predict a recession while the NBER recession dummy is determined ex-post and revised multiple times throughout history. Furthermore, the state indicator produces a false positive during the sample period, predicting a down state while no actual recession followed. However, the false positive occurred at the start of 1966 where subsequently the monthly stock returns were negative from February up to September. Thus, even though the state indicator does not exactly match the NBER

recession dummy, it can predict recessions at a remarkable rate and even identify low points of the stock market that the NBER dummy oversees.

Lastly, the state indicator classifies about 22% of the months as a down state, which is 33% more than the number of months indicated as a recession by the NBER dummy. This is not necessarily a problem, as these numbers are consistent with the fact that the state indicator is able to detect low market points which the NBER dummy cannot and, more interestingly, in line with the earlier findings of Henkel et al. (2011) and Huang et al. (2017) who respectively identify 30% and 32% as recessionary periods using Bayesian learning algorithms and economic intuition.

Table 2 Summary statistics across market states

	Mean (%)	Std (%)	Skew	Kurt	$\rho(1)$	SR	N	rec. (NBER)
Panel A: Overall market	0.43	4.24	-0.68	5.59	0.06	0.10	694	101
Panel B: Two-state market								
Up state	0.53	3.63	-0.84	8.38	0.05	0.14	534	46
Down state	-0.09	2.18	-0.80	15.47	0.06	-0.04	151	55

This table reports the summary statistics of the monthly market return (the log return on the S&P 500 index in excess of the risk-free rate) with one or two market states over the sample period January 1960 to December 2017. One state means that the market always stays in one state (no structural breaks), whereas two states mean that the market moves between two states, up states and down states. Month $t + 1$ is in a downstate if the state indicator, S_t , equals one when the slope of the yield curve was inverted or flat in the preceding nine months and in an upstate otherwise. The statistics include the time-series average (Mean), standard deviation (Std), skewness (Skew), kurtosis (Kurt), the first-order autocorrelation ($\rho(1)$), and the monthly Sharpe ratio (SR), which is defined as the average market return divided by its standard deviation. N is the number of time periods. Rec. (NBER) represents the number of NBER-dated economic recessions.

3.1 Regime shifts and the Markov process

Financial time series and markets are not only characterized by a long-term trend and cyclical variations, but more often than not display structural breaks that change their statistical behavior abruptly. More so, the transitioning process between different regimes is an intrinsic property of the true data-generating process underlying financial time series and thus unobservable (J. D. Hamilton, 2016). More specifically, stock returns tend to be characterized by a high return-low volatility state and a shorter lived low return-high volatile state associated with respectively bull and bear markets as shown extensively by

Ang and Bekaert (2004). Lettau and Van Nieuwerburgh (2008) find that when including regime shifts in predictive regression models that utilize financial ratios, their predictive performance becomes statistically significant and stable over time. In real time, however, changes in the steady state make the in-sample return predictability hard to exploit in an out-of-sample setting due to uncertainty of estimating the size of the steady-state shifts. Markov regime switching models on the other hand estimate both the probability and size of a future regime shift by extraction of unobserved information from the underlying switching process, but again might lead to poor out-of-sample performance due to overparameterization as documented by Guidolin and Timmermann (2005).

In contrast, Hammerschmid and Lohre (2018) consider a simple two-stage regression approach. A Markov switching model is used to extract information that governs the underlying economic dynamics driving the security returns, and in particular to identify different macroeconomic states. In the second step, the regime information is transformed into a regime indicator that acts as a predictor in a traditional univariate regression model which makes it possible to include structural and intrinsic changes in the return predictability and asset allocation process. Next, Hammerschmid and Lohre (2018) combine information of the derived regime indicators and fundamental variables [i.e. the well-known predictors examined in Welch and Goyal (2008)] in a multivariate regression model to predict the stock market which leads to significant in sample and out-of-sample performance. However, the forecasting performance is once again concentrated during recessionary periods.

I follow Hammerschmid and Lohre (2018) closely and use a similar, but not identical, two-step approach to predict stock returns. In particular, there are two distinct differences between my approach and the one of Hammerschmid and Lohre (2018). First, I estimate regime indicators by extracting information directly underlying the data-generating process of stock returns instead of looking at macro-economic indicators (Hammerschmid and Lohre (2018) use Inflation, GNP, Unemployment, Consumption, Production and Money stock indicators). Rapach, Wohar and Rangvid (2005) examine the predictability of stock returns using macro-economic variables in 12 industrialized countries and find limited evidence of predictability in most countries, especially with regard to industrial production

and the unemployment rate. In contrast, Guidolin and Timmermann (2005) derive a Markov switching model, using solely information of stock and bond return distributions, to successfully identify persistent 'bull' and 'bear' regimes in UK stock and bond markets. Secondly, instead of combining the derived regime indicator with fundamental variables in a simple multivariate regression framework, I utilize the regime indicator to let the slope coefficients of the fundamental variables switch across the different states to better capture the dynamics between the predictors and the different market states.

3.1.1 The hidden Markov model

Consider the following simple process:

$$R_t = \mu_{S_t} + \sigma_{S_t} \varepsilon_t, \quad (2)$$

With R_t the realized return at month t , μ_{S_t} and σ_{S_t} respectively the regime-dependent mean and volatility of realized returns in month t , $S_t \in \{1, \dots, k\}$ a discrete random variable that takes integer values between 1 and k , with k the number of latent states underlying the return series and $\varepsilon_t \sim i. i. d. \mathcal{N}(0,1)$.

Thus, both μ_{S_t} and σ_{S_t} switch between states given an indicator variable S_t . With $S_t \in \{1, \dots, k\}$ there are k possible states underlying the return series, hence μ_{S_t} and σ_{S_t} can take on k different values. Note that in the special case of $k = 1$, there is only one latent state and Equation (2) reduces to a simple linear regression model of the shape $R_t = \mu_t + \varepsilon_t$ with $\varepsilon_t \sim i. i. d. \mathcal{N}(0, \sigma_\varepsilon^2)$.

I follow Hammerschmid and Lohre (2018) and assume that the observed return series is derived either from a recessionary or from an expansionary distribution, that is I set $k = 2$ which reduces Equation (2) to:

$$R_t = \begin{cases} \mu_1 + \sigma_1 \varepsilon_t & \text{if } S_t = 1 \\ \mu_2 + \sigma_2 \varepsilon_t & \text{if } S_t = 2 \end{cases} \quad (3)$$

Equation (3) clearly shows that R_t can be described by two different processes. When the state of the market at month t is $S_t = 1$ ($S_t = 2$) the expected value of R_t is μ_1 (μ_2), and the

volatility of the disturbance term is σ_1 (σ_2). Furthermore, I assume that the switching process (i.e. going from one state to another) is governed by a first-order homogeneous Markov chain with transition probability matrix P,

$$P = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{bmatrix}, \quad (4)$$

With $p_{ij} = P(S_t = j | S_{t-1} = i)$ $i, j = 1, 2$ the conditional probability of going from state i to state j in month t .

I follow Hammerschmid and Lohre (2018) and use the expectation-maximization (EM) algorithm of maximizing the associated likelihood of observing the underlying data in order to estimate the regime switching parameters.

Table 3 shows the results of the two-state Markov regime switching model, fitted to the excess stock return series. Note how the regimes are clearly identified by the first two moments of the return series, with positive-stable returns in one state, and negative-volatile returns in the other state. The value of $\mu_1 = 0.97\%$ can be seen as the expected excess return of the market index during an expansionary period ($S_t = 1$), which implies a positive trend of the market. The negative value $\mu_2 = -0.17\%$ can be read as the expected excess return during a recessionary period ($S_t = 2$), which then implies a negative trend in prices. The different volatilities (σ_1 and σ_2) in each state represent the higher uncertainty regarding the predictive power of the model in each state of the world. With σ_2 being much higher than σ_1 , the identified recessionary regime is accompanied with a higher volatility which means that prices go down faster than they go up. These findings are similar to the ones of Hammerschmid and Lohre (2018) who fit a two-state Markov regime switching model on macro-economic timeseries and find a state where returns are positive and stable, and a state characterized by negative, unstable returns. Judging by the transition probabilities, both regimes are highly persistent with the recessionary state having a slightly higher conditional transition probability.

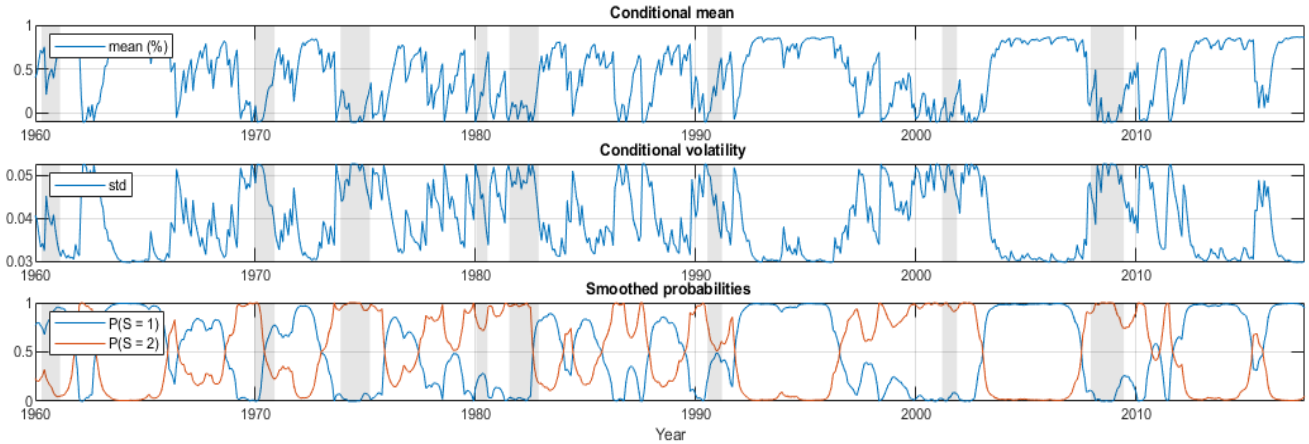
Table 3 hidden Markov model switching parameters

	Return parameters		Transition probabilities	
	Mean (%)	Std (%)	State 1	State 2
State 1	0.97	2.71	0.95	0.05
State 2	-0.17	5.42	0.06	0.94
Overall	0.43	4.24		

This table summarizes results of the Markov regime switching model estimated according to Equation (3) and fitted to the time series of the excess market return for the sample period January 1960 to December 2017. Column two and three give the estimated mean and standard deviation of the monthly S&P 500 excess returns conditional on the two states. The last two columns give the conditional transition probability of going from one state to the other as defined by Equation (4).

It is of interest to see how well the estimated latent states of the Markov model match with the expansionary and recessionary states indicated by the NBER recession dummy. Figure 1 plots the conditional mean, conditional standard deviation, and the smoothed state probabilities derived from the two-state Markov model. Note how the conditional mean becomes negative during all recessions indicated by the NBER dummy (except for the first recession at the very start of the sample period), while the conditional volatility tends to be highest during the recessionary periods. Furthermore, when looking at the smoothed probabilities the Markov model's indicated recessionary periods (i.e. when the smoothed probability of being in State 2 is higher than 50%) tend to line up nicely with the NBER indicated recessions, with all of the NBER recessions overlapping the Markov model's indicated recessionary periods (except again for the first recession at the very start of the sample period). Thus, the Markov model is able to identify the NBER indicated recessions at a considerable rate using only the first two moments of the return series. However, note how the Markov model, just like the state indicator of the yield curve, identifies more recessionary periods than indicated by the NBER dummy. Again, this is not an issue as these numbers are consistent with the fact that the Markov model is able to detect low market points which the NBER dummy cannot (e.g. the Markov model, just like the yield curve, indicated the year 1966 as a recessionary period, in which realized returns were negative for 8 of the 12 months.).

Figure 1. estimated regime shifts of the hidden Markov model



This figure shows the in-sample regime profiles of the Markov regime switching model estimated according to Equation (3) and fitted to the time series of the excess market return for the sample period January 1960 to December 2017. The upper panel depicts the estimates conditional mean (in %) of the excess return series, the middle panel plots the estimated conditional volatility, the bottom panel shows the estimated conditional transition probabilities of going from state 1 to 2 (orange) and from state 2 to 1 (blue). The vertical bars correspond to NBER-dated recessions.

3.1.2 The Markov regime indicator

After estimating the Markov model, I construct the following regime indicator,

$$S_t^* = \begin{cases} 1 & \text{if } \hat{P}_t^*(S_t = 2) \geq 0.50 \\ 0 & \text{if } \hat{P}_t^*(S_t = 1) \geq 0.50 \end{cases}, \quad (5)$$

with $\hat{P}_t^*(S_t = 2)$ [$\hat{P}_t^*(S_t = 1)$] the estimated smoothed probability of being in the identified recessionary period (expansionary period).

As noted by Hammerschmid and Lohre (2018), out-of-sample evaluation calls for a properly constructed regime indicator that does not suffer from forward looking biases. I therefore proceed as follows in the construction of an out-of-sample variant of the Markov regime indicator. First, I estimate the hidden Markov model of Equation (3) with data up until the current month t . Secondly, I estimate the current regime in month t using Equation (5). In particular, the regime indicator, S_t^* , equals 1 when the smoothed probability $\hat{P}_t^*(S_t = 2)$ is greater than 0.5 and zero otherwise. Lastly, I reiterate the process using an expanding window for the entire out-of-sample period. Note that during the

iteration process the previous regime indicator is not being updated using the new estimated smoothed probabilities obtained in the current month, ensuring that the iterative regime indicator is free from any forward-looking bias.

3.2 The state switching model

I extend the traditional ordinary least squares (OLS) regression model to allow the coefficient of the predictor to change freely across states, as in Boyd et al (2005) and Sander (2018),

$$R_{t+1} = (\beta_0 + \delta_0 S_t) + \beta_1 S_t x_t + \gamma_1 (1 - S_t) x_t + \varepsilon_{t+1}, \quad (6)$$

with R_{t+1} the excess return on the S&P 500 index, S_t the state indicator defined in either Equation (1) (the yield curve state indicator) or Equation (5) (the Markov regime state indicator), x_t a lagged predictor at month t (i.e. one of the predictors discussed in section 2) and $\varepsilon_{t+1} \sim \mathcal{N}(0, \sigma_\varepsilon^2)$ the regression's disturbance. Note that equation (6) reduces to the traditional OLS regression when the predictor makes the same forecast irrespective of the current market state (i.e. when $\beta_1 = \gamma_1$).

Apart from looking at the in-sample performance of the state switching model, I also evaluate its out-of-sample capabilities by running the following recursive regression,

$$\hat{r}_{t+1|t} = (\hat{b}_0 + \hat{\delta}_0 S_t) + \hat{b}_1 S_t x_t + \hat{\gamma}_1 (1 - S_t) x_t, \quad (7)$$

with \hat{b}_0 , $\hat{\delta}_0$, \hat{b}_1 and $\hat{\gamma}_1$ the OLS estimates of respectively β_0 , δ_0 , β_1 and γ_1 from (6) and $\hat{r}_{t+1|t}$ the out-of-sample forecast in month t+1 made in month t. The estimates at month t are obtained by regressing $\{R_{t+1}\}_{t=1}^{\tau-1}$ on $\{(\beta_0 + \delta_0 S_t) + \beta_1 S_t x_t + \gamma_1 (1 - S_t) x_t\}_{t=1}^{\tau-1}$ in a recursive manner for $\tau = M, \dots, T - 1$ with M the start of the out-of-sample period and T-1 the penultimate observation of the sample period, thus ensuring no look-ahead bias is introduced in the out-of-sample regressions.

Next, following common practice in the literature on return predictability [e.g. Pettenuzzo and Timmermann (2014), Rapach et al. (2016) and Pan et al. (2018)], I use Campbell and

Thompson (2008) out-of-sample R^2 statistic to evaluate the state switching model's performance⁴,

$$R_{OOS}^2 = 1 - \frac{\sum_{t=M}^T (R_{t+1} - \hat{r}_{t+1|t})^2}{\sum_{t=M}^T (R_{t+1} - \bar{r}_{t+1|t})^2}, \quad (8)$$

where $\hat{r}_{t+1|t}$ is the excess return forecast and $\bar{r}_{t+1|t}$ is the historical mean, both of which are estimated using data up to month t . R_{t+1} the realized return in month $t+1$. If the mean-squared forecast error (MSFE) of the state switching model is smaller than the MSFE of the historical mean, R_{OOS}^2 will be greater than 0, indicating outperformance of the naïve benchmark model.

In general, both in-sample and out-of-sample tests have relative strengths. In-sample tests are more suited to detect the overall existence of return predictability. They use the whole sample set and thus have more power and reduce estimation errors compared to out-of-sample tests that utilize only a part of the sample set (Ludvigson & Ng, 2010). In contrast, out-of-sample tests are able to detect overfitting issues and guard partially against datamining concerns, thus making them the more relevant factor for investors (Tu & Wang, 2013). The R_{OOS}^2 statistic shows how the alternative model would have benefited investors if they used the model in real time over the out-of-sample period.

Note that equation (7) reduces to the benchmark model in the special case where $\hat{\delta}_0 = 0$, $\hat{b}_1 = 0$ and $\hat{\gamma}_1 = 0$, thus the constant expected excess return model is nested within the more general model of (7). Clark and McCracken (2001) show that the t-statistic to test for significant R_{OOS}^2 performance has a non-standard asymptotic distribution when comparing forecasts from nested models. Therefore, Clark and West (2007) developed a MSFE-adjusted statistic for comparing nested model forecasts, which has an asymptotic distribution well approximated by the standard normal. Clark and West (2007) goes on to

⁴ A more traditional forecast evaluation statistic is the Theil's U statistic, defined as $\frac{SSE_1}{SSE_0}$ with SSE_1 and SSE_0 respectively the sum of squared errors of the predictive model and the historical forecast. The U-statistic evaluates the relative performance of the predictive model, where a value of less than 1 indicates outperformance of the historical forecast. Overall, the same qualitative results are obtained when replacing the out-of-sample R^2 statistic of Campbell and Thompson (2008) with the U-static.

show that the adjusted statistic performs well in finite-sample simulations. Intuitively, under the null hypothesis of constant expected returns, the predictive model generates noisier forecasts than the benchmark model due to the estimation of regression slopes with zero population values. Thus, one expects the MSFE of the predictive model to be larger than of the historical average model under the null. The adjusted statistic takes this expected difference into account, leading to possible rejection of the null even when R_{00S}^2 is negative.

I utilize the Clark and West (2007) MSFE-adjusted statistic to test the null hypothesis $R_{00S}^2 \leq 0$ against the alternative hypothesis $R_{00S}^2 > 0$. Define,

$$f_{t+1} = (R_{t+1} - \bar{r}_{t+1|t})^2 - \left\{ (R_{t+1} - \hat{r}_{t+1|t})^2 - (\bar{r}_{t+1|t} - \hat{r}_{t+1|t})^2 \right\}^2, \quad (9)$$

the MSFE-adjusted statistic is then simply the t-statistic obtained from the regression of f_{t+1} on a constant and its statistical significance can then be computed using a one-sided upper-tail t-test. Campbell and Thompson (2008) show that a monthly $R_{00S}^2 > 0.5\%$ can yield substantial economic value for a mean-variance investor.

The focus of this paper is to show that combining predictor information yields significant forecasting power across all states of the market when letting slope coefficients change freely across states. To do so, I separately compute the in-sample adjusted R^2 and out-of-sample R_{00S}^2 during an up state and a down state, by following Huang et al. (2015) and many others and compute,

$$R_S^2 = 1 - \frac{\sum_{t=1 \text{ or } M}^T I_{S,t} (r_t - \hat{r}_t)^2}{\sum_{t=1 \text{ or } M}^T I_{S,t} (r_t - \bar{r}_t)^2}, \quad S = \text{up, down}, \quad (10)$$

With $I_{S,t} = I_{up,t} (I_{down,t})$ an indicator that takes the value of one when month t is classified as an up state (down state) and zero otherwise, \bar{r}_t is the return mean of the entire sample when calculating the in-sample statistics and is the return mean with data up to month t - 1 when calculating the out-of-sample statistics, M is the starting point of the out-of-sample period when calculating the out-of-sample statistics. Note that unlike the traditional in-sample R^2 , R_S^2 can be both positive and negative. I also estimate (10) for expansions (exp) and recessions (rec) using the NBER recession indicator.

3.3 forecasting with the state switching model

This section presents the results of the empirical analysis of predicting the one-month ahead excess market return by using the state switching model defined in Equation (6) combined with the predictors laid out in section 2.

3.3.1 switching with the yield curve state indicator

This section compares the forecasting results of the state switching model with the traditional one-state OLS regression. Table 4 shows the regression results of the 14 popular economic variables used in Welch and Goyal (2008) and many other papers [e.g. Campbell and Thompson (2008), Hammerschmid & Lohre (2018), Johnson (2017), Neely et al. (2014), Rapach et al. (2016)] on the equity premium. I take the first difference of the predictors and use Newey-West t-statistics controlling for heteroskedasticity and autocorrelation with a lag of 12 throughout the paper.

The left side of Table 4 shows the regression results of the traditional one-state model. Among the 16 predictors, seven show significant forecasting abilities at the 10% level, while five are even significant at the 5% level or stronger; including the dividend-earnings ratio, stock variance, T-bill rate, long-term yield, and the newly introduced corporate bond premium. The in-sample adjusted R^2 ranges from 0.47% for the dividend-earnings ratio to 2.02% for the equity risk premium volatility. Albeit the significant t-statistics of multiple predictors, only the stock variance and the T-bill rate (although barely) are able to produce adjusted R^2 values exceeding 1%. Column 5 depicts the R^2_{oos} results. I use the first 20 years (239 observations) of the dataset for in-sample training and the remaining 38 years (455 observations) for out-of-sample forecasting⁵. I use an expanding window to recursively estimate the expected return. The last training day is 1980:01, and the out-of-sample

⁵ Hansen and timmermann (2012) extensively show that very large size distortions can occur for conventional tests of predictive accuracy. Spurious rejections are most likely to occur with a short evaluation sample, while conversely the power of forecast evaluation tests is strongest with long out-of-sample periods.

period begins on 1980:02⁶ and ends in 2017:12. Out of the 16 predictors, 10 yield a negative R_{oos}^2 while only two display significant positive R_{oos}^2 at the 5% level or stronger. More intriguing, none of the 16 predictors exceeds the economic threshold of 0.50%, confirming the earlier findings of Welch and Goyal (2008) and many others that most economic variables fail to predict the market return using a traditional one-state model.

The right side of Table 4 reports the same statistics for the state switching model. There are several noteworthy observations. First, the coefficient of the state indicator is significant at the 1% level, independent of which predictor is utilized in the state switching model, indicating that none of the other predictors contain similar information as the indicator in predicting excess returns. Second, eight of the 16 predictors can significantly predict the market return, either in an up state or down state, at the 10% level or stronger with the T-bill rate showing forecasting powers in both states. All the significant predictors (except for the book-to-market ratio) of the one-state regression remain significant within the state switching model. More so, from the remaining insignificant predictors the default return spread turns significant with the new model suggesting that the one-state regression fails to efficiently extract predictive information underlying the predictors.

Lastly, in great contrast with the one-state model, the state switching version produces adjusted R^2 values exceeding the 1% level for all but one predictor (the earnings price ratio, which has an adjusted R^2 of 0.99%). For the eight significant predictors, the adjusted R^2 values range from 1.41% for the dividend-earnings ratio up to a remarkable 3.07% for the equity risk premium volatility (although the R_{oos}^2 is highly negative). Looking at the out-of-sample performance, 11 of the 16 predictors yield a positive R_{oos}^2 value exceeding the 1% level while being significant at the 5% level or stronger. The last two columns of Table 4 show the difference in performance of the two models. The state switching model increases both the in-sample adjusted R^2 and the R_{oos}^2 of the predictors, on average, with 1.16% and none of the predictors is better off with the one-state model. For example, the highest R_{oos}^2 value using the state switching model is 2.72% for the net equity expansion, in contrast with the one-state regression where the book-to-market ratio yields the highest

⁶ Using a starting period five years earlier, or five years later yields the same qualitative results.

R^2_{oos} of 0.49%. In short, the state switching model significantly improves the forecasting potential of the fundamental variables, both in-sample and out-of-sample.

Note that the predictive capabilities of the predictors are asymmetrical. Most of the predictors within the state switching model have a far greater significance level within a specific market state. For example, the equity risk premium volatility shows strong predictive significance during an upstate but produces a small t-statistic during a down state while the default yield spread exhibits strong significance during a down state but becomes insignificant during an up state. The same pattern can be found back for several predictors, confirming the earlier findings of Devpura et al. (2018) that time-varying predictability is not a general phenomenon, but rather predictor dependent.

To further investigate the asymmetrical behavior of the predictors, Table 5 presents the out-of-sample performance of the 16 predictors across different market states using Equation (10). The left panel shows results for the one-state regression, while the right panel presents results for the state switching model.

The one-state regression models do a poor job of predicting the equity premium both during up states and down states. Only the lagged equity premium is able to predict the next month equity premium during up states with an $R^2_{oos,up}$ of 1.86%, while solely the dividend-earnings ratio predicts excess returns during down states with an $R^2_{oos,up}$ of 0.43%. Next, when evaluating performance across expansions and recessions, it is clear that none of the predictors is able to outperform the historical forecast during expansions, while, in contrast, five of the 16 predictors significantly predict the market during recessions. The significant $R^2_{oos,rec}$ values range from 1.2% (long-term return) up to 6.75% (long-term yield). Overall, these findings are in line with the conclusions of Henkel et al. (2011) whom document that stock return predictability is solely concentrated during recessionary periods.

These findings however do not hold for the state switching model. First, when looking across up and down states, note how some predictors are able to significantly forecast the equity premium during up states but fail to do so during down states, while others outperform the historical forecast during down states but are unsuccessful in doing so

during up states. More precise, five out of the 16 predictors can significantly (at the 5% level) outperform the historical forecast during up states, with $R_{oos,up}^2$ values ranging from 0.78% (long-term yield) up to 2.38% (net-equity expansion). On the other hand, 11 of the 16 predictors produce significant $R_{oos,down}^2$ statistics during down states ranging from 2.43% (T-bill rate) up to 10.64% (default yield spread). More interestingly, eight of the 11 significant down state predictors fail to predict the equity premium during up states, whereas two of the five up states predictors fail to do so during down states. This illustrates the asymmetrical behavior of the predictors, where some predictors contain information to predict excess returns during an upstate whereas others have predicting information during down states. The same pattern is visible across expansions and recessions as can be seen on the last two columns of Table 5. Six of the 16 predictors show significant outperformance during recessions with $R_{oos,rec}^2$ values ranging from 1.07% (T-bill rate) up to 8.62% (long-term yield). During expansions eight predictors significantly outperform the historical forecast with $R_{oos,exp}^2$ ranging from 0.89% (book-to-market ratio) up to 1.89% (net-equity expansion). Similar to the up and down states, there are several predictors that can only forecast the equity premium during a specific state. More specifically, five of the eight significant expansion predictors fail to outperform the historical forecast during recessions, while four of the six recession predictors fail to do during expansions.

Combining the complementary information of the predictors can thus lead to optimal performance across both market states. However, as shown by Welch and Goyal (2008), a multivariate regression (i.e. a 'kitchen sink' regression) will surely lead to poor out-of-sample performance due to parameter instability and overfitting issues. In the next section I extract the information of the 16 predictors in a more efficient manner, producing an aligned economic index that can forecast the market return across all states.

The economic intuition is as follows. Investors are likely to pay extra attention to certain stock return fundamentals and macroeconomic indicators during certain market states. Indeed, Barber, Odean, and Zhu (2009) and Da, Engelberg and Gao (2011) show that investor's attention change over time in a way that tends to influence future stock returns.

Table 4 Forecasting the market excess return with the state switching model

Predictor	One-state model				State switching model								Difference	
	β_1	t-stat	\bar{R}^2	R_{oos}^2	δ_0	t-stat	β_1	t-stat	γ_1	t-stat	\bar{R}^2	R_{oos}^2	\bar{R}^2	R_{oos}^2
DP	-0.06	-1.26	0.18	-0.01	-1.14***	-2.46	-0.05	-0.78	-0.05	-0.79	1.12	1.12***	0.94	1.13
DY	0.04	1.04	-0.02	-0.13	-1.22***	-2.46	0.07	1.13	0.03	0.87	1.11	1.06**	1.13	1.19
EP	0.02	0.67	-0.08	-0.82	-1.18***	-2.55	-0.02	-0.30	0.02	0.81	0.99	0.42*	1.07	1.24
DE	-0.07***	-2.35	0.47	-0.67	-1.05***	-2.19	-0.15	-0.87	-0.05*	-1.83	1.41	-0.95*	0.94	-0.28
RVOL	-1.41***	-4.10	2.03	-2.71	-1.18***	-2.52	-0.81	-0.28	-1.42***	-4.05	3.07	-1.78*	1.04	0.93
BM	-0.10*	-1.77	0.32	0.49	-1.14***	-2.49	-0.09	-1.01	-0.09	-1.15	1.25	1.68***	0.93	1.19
NTIS	-0.77*	-1.67	0.34	0.24	-1.14***	-2.45	1.26	1.51	-1.41***	-3.19	2.46	2.72***	2.12	2.48
TBL	-1.09***	-2.95	1.07	0.09**	-1.20***	-2.56	-0.89**	-2.11	-1.72***	-2.68	2.31	1.21***	1.24	1.12
LTY	-1.47***	-2.71	0.91	0.10**	-1.10***	-2.32	-1.39*	-1.66	-1.31*	-1.87	1.77	0.94***	0.86	0.84
LTR	0.05	1.00	0.08	-1.47	-1.18***	-2.49	0.07	1.00	0.04	0.64	1.11	-0.37	1.03	1.10
TMS	0.39	1.04	0.01	-0.37	-1.23***	-2.62	0.71	1.52	0.15	0.25	1.20	0.94***	1.19	1.31
DFY	0.59	0.32	-0.12	-0.52	-1.31***	-2.70	5.05***	2.90	-1.21	-0.53	1.63	1.39***	1.75	1.91
DFR	0.11	1.30	0.17	-0.49	-1.18***	-2.51	0.03	0.23	0.15	1.38	1.29	0.36*	1.12	0.85
INFL	0.67	1.27	0.12	-0.02	-1.18***	-2.50	0.16	0.14	0.84	1.39	1.21	1.30***	1.09	1.32
CBP	0.11**	2.08	0.71	0.03	-1.18***	-2.50	0.10	1.47	0.12*	1.65	1.75	1.13***	1.04	1.10
LEP	0.05	1.42	0.29	0.18	-1.17***	-2.50	0.06	1.43	0.04	1.01	1.32	1.29***	1.03	1.11
Average													1.16	1.16

This table reports the results of forecasting the market excess return with popular economic variables by using the standard one-state predictive regression or the state switching model of Equation (6). the state indicator, S_t , equals one when the slope of the yield curve was inverted or flat in the preceding nine months and is zero otherwise. \bar{R}^2 is the in-sample adjusted R-square over the period January 1960 to December 2017. R_{oos}^2 is the Campbell and Thompson (2008) out-of-sample R-square with the first 20 years as the initial training period and with January 1980 to December 2017 as the evaluation period. All t-statistics are the Newey-West t-statistics controlling for heteroskedasticity and autocorrelation. Statistical significance for R_{oos}^2 is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R_{oos}^2 \leq 0$ against $H_A : R_{oos}^2 \geq 0$. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5 Forecasting the market excess return across different states

Predictor	One-state model				State switching model			
	Up/Down states		Expansions/recessions		Up/Down states		Expansions/recessions	
	$R^2_{oos,up}$	$R^2_{oos,down}$	$R^2_{oos,exp}$	$R^2_{oos,rec}$	$R^2_{oos,up}$	$R^2_{oos,down}$	$R^2_{oos,exp}$	$R^2_{oos,rec}$
DP	0.13	-0.03	-1.03	2.83***	0.47*	5.11**	0.18	3.76***
DY	1.26*	-0.36	-0.16	-0.05	0.28	5.83***	1.14**	0.84
EP	-1.28	-0.75	-1.06	-0.15	-0.14	3.85**	0.16	1.16
DE	-7.40	0.43**	-0.26	-1.81	-0.41	-4.26	0.14**	-3.97
RVOL	0.13	-3.18	-4.37	1.88	-2.49	2.60	-3.09	1.86
BM	0.40	0.51	-0.21	2.44**	0.97**	5.97***	0.89**	3.85***
NTIS	-0.74	0.39	0.33	-0.04	2.38***	4.81**	1.89***	5.00*
TBL	-4.04	0.76	0.00	0.33**	1.01**	2.43**	1.26***	1.07**
LTY	-2.8	0.58	-2.29	6.75***	0.78**	1.94*	-1.82	8.62***
LTR	-5.52	-0.81	-2.44	1.20*	-0.64	1.30*	-1.65	3.19*
TMS	-0.20	-0.40	-0.09	-1.16	0.16	5.72*	1.00**	0.78
DFY	2.88*	-1.08	-0.22	-1.36	-0.12	10.64***	1.26***	1.77
DFR	-1.17	-0.38	-0.22	-1.26	-0.33	4.60**	0.94**	-1.25
INFL	-1.08	0.16	0.00	-0.08	1.00**	3.18*	1.19**	1.61
CBP	-2.17	0.39	-1.81	5.15***	0.77*	3.38**	-0.78	6.46***
LEP	1.86**	-0.10	-0.82	2.95***	0.42*	6.62***	0.40*	3.75***

This table reports the results of forecasting the market excess return across different market states with popular economic variables by using the standard one-state predictive regression or the state switching model of Equation (6). Month $t+1$ is defined as a downstate if the state indicator, S_t , equals one when the slope of the yield curve was inverted or flat in the preceding nine months and is defined as an upstate otherwise. Month $t+1$ is defined as a recession if the NBER recession indicator equals one and is defined as an expansion otherwise. $R^2_{oos,up}$; $R^2_{oos,down}$; $R^2_{oos,exp}$ and $R^2_{oos,rec}$ are respectively the Campbell and Thompson (2008) out-of-sample R-square statistic across up states, down states, expansions and recessions. The first 20 years act as the initial training period, where after the out-of-sample period begins with January 1980 to December 2017 as the evaluation period. Statistical significance for the different Campbell and Thompson (2008) out-of-sample R-squares are based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R^2_{oos} \leq 0$ against $H_A : R^2_{oos} \geq 0$. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

3.3.2 switching with the hidden Markov model

Table A.1 shows the same statistics as Table 4 but uses the hidden Markov regime indicator discussed in section 3.1, in the state switching model defined in Equation (6). Most findings of the yield curve indicator seem to spill over. First, the Markov model state indicator is significant at the 1% level, independent of which predictor is utilized in the state switching model, indicating that none of the other predictors contains similar information as the indicator in predicting excess returns. Second, using the Markov model enhances overall return predictability, with 10 of the 16 predictors having adjusted R^2 values exceeding the 1% level. When looking at out-of-sample performance, eight of the 16 predictors yield a positive R^2_{oos} value exceeding the 0.50% level while being significant at the 5% level or stronger. Overall, the Markov state switching model increases respectively the in-sample adjusted R^2 and the out-of-sample R^2_{oos} of the predictors, on average, with 0.95% and 0.45% with most of the predictors (14 of the 16) being better off with the Markov model. Thus, although the results are overall weaker compared to the yield curve model, switching across states seems to induce better predictability independent of the switching model used.

Next, Table A.2 replicates the statistics of Table 5 when using the Markov model. Whereas the yield curve indicator showed asymmetrical behavior across predictors, the Markov model exhibits the same behavior as the one-state regression model. When looking at the Markov indicated regimes (MC up/down states), all the predictors significantly forecast the equity premium during down states while none do so during up states. The same pattern is found back across NBER indicated recessions and expansions. Only the default return spread can forecast the market during expansions with a positive R^2_{oos} value of 0.72%, while seven of the 16 predictors outperform the historical forecast during recessions with R^2_{oos} values between 3.13% and 9.79%. Thus, the asymmetrical relationship of the predictors, where some predictors forecast the market solely during expansions (up states) while others solely do so during recessions (down states), seems to be specific to the yield curve switching model. This helps explain why Sander (2018) finds no added benefit when letting slope coefficients switch between states.

4 The aligned economic index

In this section, I first lay out the econometric method to construct the aligned economic index. Following Huang et al. (2015), I utilize the three stage least squares regression approach of Kelly and Pruitt (2015). Next, I briefly analyze the new index and compare it with other combination methods. Finally, I thoroughly examine its in-sample and out-of-sample performance, both statistically and economically.

4.1 Construction of the aligned economic index E^{PLS}

If the fundamental variables provide complementary information regarding the time-varying true underlying factor that ultimately drives market returns, then combining these predictors may enhance the overall forecasting abilities of the predictors. However, utilizing a single multivariate regression will almost surely lead to poor out-of-sample results as it suffers from overfitting issues. An alternative is to first try to extract the underlying hidden factor and then use the extracted factor in a parsimonious univariate regression.

From an econometric point of view, one can use principal component analysis (PCA) to identify the key co-movements between the entire set of predictors, the dimension reduction thereby avoids in-sample overfitting. However, the predictors are mere proxies for the true hidden latent factor that ultimately drives returns and thus contain a substantial amount of idiosyncratic components, and these noise components are part of the predictor's variation. More so, in case the noise components of the different proxies exhibit some co-movement, the PCA factors will be contaminated with these common noise components, leading to model instability and failing to predict the risk premium even when the true latent factor is a strong predictor of the risk premium. In contrast, the partial least squares method (PLS) can effectively filter out the noise components that are irrelevant for forecasting, by looking at the common covariance of the predictors with future stock returns rather than utilizing the total common variation between the predictors. More formally, assume that the risk premium can be decomposed in a conditional expectation component and an unpredictable innovation component:

$$R_{t+1} = E_t\{R_{t+1}\} + \xi_{t+1}, \quad (11)$$

where the expected risk premium $E_t\{R_{t+1}\}$ is driven by the true but unobservable (latent) factor F_t , assuming a linear relationship between the latent factor F_t and $E_t\{R_{t+1}\}$ we get:

$$E_t\{R_{t+1}\} = \alpha_0 + \alpha_1 F_t, \quad (12)$$

Replacing $E_t\{R_{t+1}\}$ in (11) by (12) we get,

$$R_{t+1} = \alpha_0 + \alpha_1 F_t + \xi_{t+1}, \quad (13)$$

The realized risk premium is thus equal to a linear combination of the latent factor and an innovation component that is unforecastable and uncorrelated with F_t . Further, assume that the set of economic predictors follow a linear factor structure,

$$x_{i,t} = \delta_{i,0} + \delta_{i,1} F_t + \delta_{i,2} Y_t + \eta_{i,t}, \quad i = 1, \dots, N, \quad (14)$$

with $x_{i,t}$ one of the N proxies of the aforementioned latent factor F_t , Y_t the common noise component underlying the N proxies, and $\eta_{i,t}$ the idiosyncratic noise component related specifically to proxy i . PCA optimally determines the linear combination of $x_{i,t}$ that explains the total variation in the proxies which includes the common noise component Y_t , resulting in an factor extraction that is unable to forecast the risk premium. In contrast, PLS extracts the latent factor F_t , while at the same time filtering out the common noise component Y_t by using a two-stage regression method.

More specifically, in the first step, I run N time series regressions for each lagged proxy $x_{i,t-1}$ on the realized risk premium R_t which acts as an instrument for the true latent factor F_t :

$$x_{i,t-1} = \phi_{i,0} + \phi_{i,1} R_t + v_{i,t}, \quad t = 1, \dots, T, \quad (15)$$

With $v_{i,t}$ the disturbance term of proxy $x_{i,t-1}$. Taking conditional expectations from both sides gives,

$$E_t\{x_{i,t-1}\} = \phi_{i,0} + \phi_{i,1} E_t\{R_t\}, \quad t = 1, \dots, T, \quad (16)$$

Noting that $E_t\{x_{i,t-1}\} = x_{i,t-1}$, and replacing $E_t\{R_t\}$ by (12) yields,

$$x_{i,t-1} = \phi_{i,0} + \phi_{i,1}\{\alpha_0 + \alpha_1 F_{t-1}\} \quad t = 1, \dots, T, \quad (17)$$

Therefore, the coefficient $\phi_{i,1}$ in (15) describes how $x_{i,t-1}$ depends on a unique but unknown rotation of the true latent factor F_{t-1} , without being correlated with the unpredictable innovation component ξ_{t+1} .

In the second step, I run cross-sectional regressions for each time period $t = 1, \dots, T$ of $\{x_{i,t}\}_{i=1}^{i=N}$ on the extracted factor loadings $\{\hat{\phi}_{i,t}\}_{i=1}^{i=N}$, more formally I run the following regression T times,

$$x_{i,t} = \phi_{0,t} + F_t \hat{\phi}_i + \varphi_{i,t}, \quad i = 1, \dots, N, \quad (18)$$

With $\{\hat{\phi}_{i,t}\}_{i=1}^{i=N}$ the estimated factor loadings of (15) whom act as independent variables in the second stage regressions. Estimating (18) yields,

$$E\{x_{i,t}\} = \hat{\phi}_{0,t} + E_t^{PLS} \hat{\phi}_i + \varphi_{i,t}, \quad i = 1, \dots, N, \quad (19)$$

With $E_t^{PLS} = \hat{F}_t$ the aligned economic index at month t . I then carry forward the estimated E_t^{PLS} to the third stage regression which contains the state switching model,

$$R_{t+1} = (\beta_0 + \delta_0 S_t) + \beta_1 S_t E_t^{PLS} + \gamma_1 (1 - S_t) E_t^{PLS} + \varepsilon_{t+1}, \quad (20)$$

The estimated slope of (19) thus becomes the independent variable in the state switching model. Based on the theoretical results of Kelly and Pruitt (2015), the estimated second-stage coefficient is a consistent estimator that converges to the true latent factor F_t .

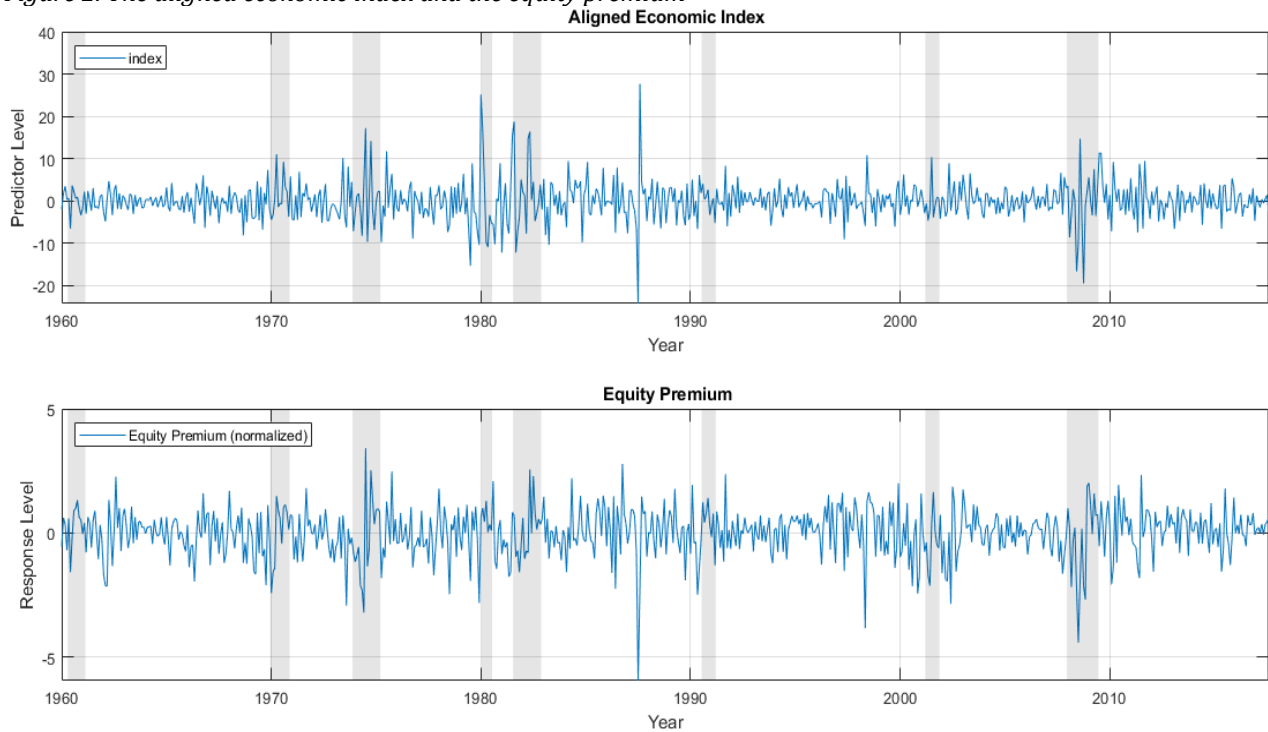
4.2 preliminary results

Figure 2 plots the timeseries of the aligned economic index (upper graph) and the normalized equity premium (lower graph) throughout the sample period January 1960 to December 2017. The grey bars denote recessions indicated by the NBER recession indicator. If the aligned index has forecasting powers, we would expect that the two timeseries tend to rise and fall together.

Figure 2 clearly shows that this is the case. Both the equity premium and the aligned index drop drastically in the beginning of the sample period during the first recession, they both

increase significantly during the middle of the third recession, they both hit their all-time lows at the end of 1987 during the Black Monday occurrence, and both increase right after the sixth recession, both decrease at the start of the subprime crisis at the end of 2007, and rise back up in 2009. The time series are more volatile during recessions than expansions. Lastly, note the non-persistence of the aligned economic index which indicates that the small-sample bias of Stambaugh (1999) is not an issue here.

Figure 2. The aligned economic index and the equity premium



The upper panel depicts the aligned economic index E^{PLS} extracted from the 14 popular fundamental variables of Welch & Goyal (2008) supplemented by the bond and (lagged) equity premium by applying the partial least squares method. The lower panel depicts the normalized equity premium. The estimated aligned economic index is standardized to have zero mean and unit variance. The sample period starts in January 1960 and ends in December 2017. The vertical bars correspond to NBER-dated recessions.

4.2 forecasting with E^{PLS}

In this section I show that the aligned economic index, E^{PLS} , combined with the state switching model can successfully forecast the equity premium at all times, during expansionary and recessionary periods.

Table 6 reports the results of predicting the market return with the aligned economic index. Panel A shows results of regressing E^{PLS} on the one-month ahead risk premium using the conventional one-state univariate model, while panel B reports findings using the state switching model described in section 3.2. For comparison, I also consider two alternative methods of combining information of multiple predictors.

The first one being the PCA method discussed above⁷, and the second one being the forecast combination (FC) approach introduced by Rapach et al. (2010). Rapach et al. (2010) show that a combination forecast of the quarterly risk premium using economic and fundamental variables delivers significant and robust out-of-sample performance. I use the following procedure to set up the FC method: In the first step, I regress N out-of-sample predictive regressions on each individual predictor,

$$\hat{r}_{i,t+1|t} = (\hat{b}_0 + \hat{\delta}_0 S_t) + \hat{b}_1 S_t x_{i,t} + \hat{\gamma}_1 (1 - S_t) x_{i,t}, \quad i = 1, \dots, N, \quad (21)$$

With $\hat{r}_{i,t+1|t}$ the one-month ahead forecast of the risk premium at month t using predictor x_i , and N the total number of predictors considered. The N individual forecasts are then combined to compute the combination forecast,

$$\hat{r}_{t+1|t}^{FC} = \sum_{i=1}^N \omega_i \hat{r}_{i,t+1|t}, \quad (22)$$

With $\{\omega_i\}_{i=1}^N$ the combining weights of the individual forecast. Lin, Wang and Wu (2014) show that a simple weighing scheme generally outperforms more complex variants, I therefore consider an equal weight approach with $\omega_i = \frac{1}{N}$ for $i=1, \dots, N$. Note that the

⁷ I only utilize the first factor extracted with the PCA-method. Unreported results show that using more than one factor consistently reduces the out-of-sample performance of both the one-state and switching state model.

forecast combination approach combined with the state switching model results in a special case of the traditional FC approach,

$$\hat{r}_{t+1}^{FC} = \begin{cases} \hat{r}_{t+1}^{FC,Down} & \text{if } S_t = 1 \\ \hat{r}_{t+1}^{FC,Up} & \text{if } S_t = 0 \end{cases}, \quad (23)$$

with $\hat{r}_{t+1}^{FC,Down}$ and $\hat{r}_{t+1}^{FC,Up}$ the forecast combination during respectively a downstate and upstate. As long as $\hat{b}_1 \neq \hat{\gamma}_1$ In Equation (21), the forecast combination during a downstate will be different than during upstate. Thus, in contrast to the traditional FC approach, where the panel of predictors give the same input independent of the current market state, the new FC approach allows the predictors to adapt their input depending on the current state which allows for more flexibility during the forecast procedure.

In the case of in-sample regressions, the Forecast Combination method reduces to,

$$R_{t+1} = (\beta_0 + \delta_0 S_t) + \beta_1 S_t \sum_{i=1}^N \omega_i x_{i,t} + \gamma_1 (1 - S_t) \sum_{i=1}^N \omega_i x_{i,t} + \varepsilon_{t+1}, \quad (24)$$

where $\sum_{i=1}^N \omega_i x_{i,t}$ is the average of the N predictors $x_{i,t}$ at month t. If time-varying return predictability is indeed predictor dependent, as mentioned by Devpura et al. (2018), and even state-dependent as shown in section 3.3, one would expect that the different combination methods would substantially improve within the state switching model relative to the one-state regression model.

Panel A shows that both the aligned economic index E^{PLS} and the extracted PCA factor E^{PCA} can significantly predict the risk premium in-sample at the 1% level or stronger. However, the Newey-West t-statistic for E^{PLS} is far greater than for the PCA factor indicating that E^{PLS} is able to explain more of the one-month ahead variation of the equity premium. This is further confirmed by the adjusted \bar{R}^2 which is equal to 4.65% for the aligned index and 0.61% for the PCA factor. The forecast combination E^{FC} generates a small t-statistic 0.84 and an adjusted \bar{R}^2 that is even negative. However, different results are obtained when looking at the out-of-sample performance. E^{PCA} produces a positive R_{oos}^2 of 0.31%, and thus outperforms the historical average. However, the R_{oos}^2 is statistically insignificant

according to the Clark & West (2007) t-statistic, and does not reach the economic threshold of 0.50% implied by Campbell & Thompson (2008).

In contrast the forecast combination method E^{FC} can further enhance the forecasting performance to 1.18% and is statistically significant at the 1% level⁸, consistent with the earlier findings of Rapach et al. (2010). Lastly, the aligned economic index E^{PLS} exhibits much stronger out-of-sample performance. Its R_{oos}^2 is 2.60%, exceeding the two other forecasting approaches substantially and is significant at the 1% level. In short, combining multiple predictors in an efficient way enhances the overall performance of the one-state regression, with E^{PLS} able to generate the highest in-sample and out-of-sample performance. However, as will be explained shortly, the forecasting abilities are still concentrated around certain states, and the one-state model still fails to generate substantial gains across all market states.

Panel B of Table 6 moves on to the state switching model, where the current state is dictated by the slope of the yield curve. Several findings are noteworthy. First, the state indicator is highly significant with a Newey-West t-statistic of around 2.5, independent of which predictor is used in the model. Confirming the earlier findings of Table 4 that none of the other predictors contain similar information as the indicator in predicting excess market returns. Second, both the in-sample adjusted R^2 and the out-of-sample R_{oos}^2 increase substantially when compared to the one-state model for all three predictor combination methods. This confirms the earlier findings that the switching model consistently enhances the performance of all predictors, even when considering more advanced forecasting methods.

Two of the three models, E^{PLS} and E^{PCA} , have a significant in-sample adjusted R^2 , and all three models (E^{PLS} , E^{PCA} and E^{FC}) produce significant R_{oos}^2 values at the 1% level or stronger and all exceed substantially the Campbell & Thompson (2008) economic

⁸ Note that the in-sample and out-of-sample regressions of E^{FC} are obtained through different methods and thus not directly comparable with each other. The in-sample regressions use a naïve cross-sectional predictor mean to predict the equity premium (which leads to a negative adjusted \bar{R}^2), while the out-of-sample regressions make use of the more sophisticated forecasting combination approach (which leads to a significant R_{oos}^2)

threshold of 0.50%⁹. Even though all three combination methods perform rather well under the state switching model, the aligned economic index E^{PLS} considerably outperforms the other two methods and the 16 individual predictors of Table 4, both in-sample and out-of-sample. E^{PLS} has an adjusted R^2 of 5.9% and a out-of-sample R_{oos}^2 of 4.12% which is significant at the 1% level using the Clark & West (2007) t-statistic. E^{PLS} is not only able to outperform the predictors considered in this paper, but also numerous new predictors introduced in recent literature, such as the aligned investor sentiment of Huang et al. (2015), short interest of Rapach et al. (2016) and the news implied volatility of Manela & Moreira (2017).

Lastly, Panel C presents the results using the Markov model combined with E^{PLS} (named $E^{PLS,MC}$ hereafter). The in-sample performance of $E^{PLS,MC}$ outperforms all previous considered models with an adjusted R^2 of 6.23%. The out-of-sample performance however, although still relatively high, fails to outperform E^{PLS} with an R_{oos}^2 of 3.2%. More interestingly, whereas E^{PLS} has significant slope coefficients across both induced states, $E^{PLS,MC}$ only has a significant slope coefficient during MC down periods. This is in line with the findings of section 3.3, where none of the individual predictors under the Markov switching model was able to predict the equity premium during MC up periods.

⁹ Note again, the in-sample and out-of-sample regressions of E^{FC} are based on different methods, hence the different results.

Table 6 Forecasting the market excess return with predictor combination methods

Panel A: One-state model									
Predictor	β_1	t-stat	\bar{R}^2	R_{oos}^2					
E^{PLS}	0.05***	4.38	4.65	2.6***					
E^{PCA}	0.2**	1.96	0.61	0.31					
E^{FC}	0.13	0.84	-0.08	1.18*					
Panel B: State switching model									
Predictor	δ_0	t-stat	β_1	t-stat	γ_1	t-stat	\bar{R}^2	R_{oos}^2	
E^{PLS}	-0.27***	-2.51	0.03***	3.46	0.06***	3.68	5.9	4.12***	
E^{PCA}	-0.01***	-2.54	0.17	1.27	0.25**	1.97	1.65	1.58***	
E^{FC}	-1.22***	-2.43	0.24	0.85	0.15	0.81	1.02	2.64***	
Panel C: Markov switching model									
Predictor	δ_0	t-stat	β_1	t-stat	γ_1	t-stat	\bar{R}^2	R_{oos}^2	
$E^{PLS,MC}$	0.21***	2.82	0.24	0.93	1.36***	4.57	6.23	3.2***	

This table reports the results of forecasting the market excess return with either E^{PLS} , E^{PCA} , E^{FC} or $E^{PLS,MC}$ by using the standard one-state predictive regression (Panel A), the state switching model of Equation (6) (Panel B) or the Markov switching model of Equation (3) (Panel C). The state indicator in Panel B, S_t , equals one when the slope of the yield curve was inverted or flat in the preceding nine months and is zero otherwise. The state indicator in Panel C, S_t , equals one when the estimated smoothed probability of being in the identified recessionary period is greater than 50% and is zero otherwise.

E^{PLS} , E^{PCA} , E^{FC} are $E^{PLS,MC}$ respectively the aligned economic index constructed with the PLS-method, the predictor index based on the PCA-method, the predictor based on the forecast combination approach and the aligned economic index under the Markov switching model. \bar{R}^2 is the in-sample adjusted R-square over the period January 1960 to December 2017. R_{oos}^2 is the Campbell and Thompson (2008) out-of-sample R-square with the first 20 years as the initial training period and with January 1980 to December 2017 as the evaluation period. All t-statistics are the Newey-West t-statistics controlling for heteroskedasticity and autocorrelation. Statistical significance for R_{oos}^2 is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R_{oos}^2 \leq 0$ against $H_A : R_{oos}^2 \geq 0$. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Although E^{PLS} is a strong predictor of excess monthly returns when looking at the entire sample period, it is interesting to further evaluate its performance during certain market states. Table 7 reports the results. Panel A shows the forecasting performance using the conventional one-state univariate model, while panel B reports findings using the state switching model.

The left part of Panel A of table 7 shows the in-sample and out-of-sample performance of the one-state model across expansions and recessions. Both E^{PLS} and E^{PCA} can forecast, in-sample, the equity premium during recessions, however only E^{PLS} is able to generate a positive adjusted R^2 during expansions. Looking at the out-of-sample performance, both E^{PCA} and E^{FC} produce significant positive R_{oos}^2 values during recessions, but fail to do so

during expansions, with E^{PCA} even failing to outperform the benchmark model of the historical mean. These findings are in line with the conclusions of Henkel et al. (2011) and Dangl & Halling (2012): return predictability only exist during recessionary periods.

In contrast, the newly formed aligned economic index can significantly predict the equity premium during recessions and expansions. E^{PLS} has a $R_{OOS,rec}^2$ of 5.99% during recessions and a $R_{OOS,exp}^2$ of 1.45% during expansions, both significant at the 5% level or stronger.

This confirms that using combined information of the predictors in an efficient way leads to improvement across different states.

The right part of panel A shows the same statistics across up and down states as defined by the state indicator based on the inversion of the yield curve. All three models produce positive in-sample R^2 across both states, with E^{PLS} outperforming the models substantially across both states. The out-of-sample results are less clear. First, E^{PCA} fails to significantly outperform the benchmark model during an upstate and during a downstate. Thus, E^{PCA} is only able to capture predictability during parts of the recessionary periods that do not overlap with the downstate periods. Second, both E^{PLS} and E^{FC} outperform, significantly on the 5% level or stronger, the naïve benchmark model during an upstate but fail to do so during a downstate with E^{PLS} even generating a negative $R_{OOS,down}^2$ of -7.86%. As mentioned in section 3.1, a downstate is initiated whenever the yield curve inverts, which generally happens right before the start of a recession. Thus, within the one-state model E^{PLS} fails to predict the equity premium right before the start of a recession. These findings are in line with Sander (2018) who shows that estimating the start of a recession inaccurately can lead to large economic consequences. In short, even though E^{PLS} outperforms the other two combination methods across different states, it still fails to outperform the naïve benchmark model around the start of a recession.

Moving on to the state switching model in panel B of table 7, we see substantial performance gains across different states. First the in-sample performance of all three combination methods are further enhanced within the state switching model, however in line with panel A only E^{PLS} is able to generate performance gains exceeding 1% across all states. More noteworthy, the out-of-sample performance is substantially affected by the

state switching model. E^{PCA} is able to significantly forecast the equity premium during recessions, up states and down states. During expansions however both E^{PCA} and the benchmark model predict, on average, the equity premium with the same capacity producing an R_{00S}^2 of zero. In contrast, both E^{PLS} and E^{FC} can significantly, on the 5% level or stronger, predict the equity premium during expansions, recessions, up states and down states. E^{PLS} generates R_{00S}^2 values of respectively 1.71% and 1.68% during expansions and down states, while producing R_{00S}^2 values of respectively 11.21% and 4.51% during recessions and up states. All of the values thus exceed the economic threshold of 0.50% of Campbell & Thompson (2008) meaning that an investor using the state switching model with E^{PLS} would make consistent substantial gains across the different market states.

The main difference with the one-state model is the fact that E^{PLS} is now able to predict the equity premium during the recessionary turning points as well, with the inversion of the yield curve (i.e. a down state) helping to time the right moment to change slope coefficients. Interestingly, the forecast combination method E^{FC} exhibits the same overall behavior as E^{PLS} . E^{FC} generates R_{00S}^2 values of respectively 2.19% and 6.36% during expansions and down states, while producing R_{00S}^2 values of respectively 3.95% and 2.03% during recessions and up states. Thus both E^{PLS} and E^{FC} are able to consistently outperform the naïve benchmark model across all market states, with E^{PLS} yielding the overall greatest performance. In the next section I further analyze the relationship between E^{PLS} and E^{FC} .

Lastly panel C displays results for $E^{PLS,MC}$, as expected the Markov switching model out-of-sample performance is concentrated across specific market states. More precise, $E^{PLS,MC}$ outperforms the historical average during NBER indicated recessions ($R_{00S}^2 = 10.24\%$) and MC down states ($R_{00S}^2 = 4.87\%$), but fails to do so during NBER expansions ($R_{00S}^2 = -1.74\%$) and MC up states ($R_{00S}^2 = -1.53\%$). These findings are in line with the results presented in section 3.3.2 where almost none of the individual predictors under the Markov switching model was able to forecast the equity premium during NBER expansions and MC up states.

Table 7 Forecasting the market excess return with predictor combination methods across different states

Panel A: One-state model								
Predictor	Expansions/Recessions				Up/Down states			
	\bar{R}_{exp}^2	\bar{R}_{rec}^2	$R_{oos,exp}^2$	$R_{oos,rec}^2$	\bar{R}_{up}^2	\bar{R}_{down}^2	$R_{oos,up}^2$	$R_{oos,down}^2$
E^{PLS}	0.57	14.49	1.45**	5.99***	5.51	2.83	4.31***	-7.86
E^{PCA}	-0.70	4.26	-1.36	5.24***	0.57	1.27	0.05	1.88
E^{FC}	0.03	0.14	0.77	2.38***	0.06	0.07	1.24**	0.80

Panel B: State switching model								
Predictor	Expansions/Recessions				Up/Down states			
	\bar{R}_{exp}^2	\bar{R}_{rec}^2	$R_{oos,exp}^2$	$R_{oos,rec}^2$	\bar{R}_{up}^2	\bar{R}_{down}^2	$R_{oos,up}^2$	$R_{oos,down}^2$
E^{PLS}	1.01	19.13	1.71**	11.21***	6.06	6.98	4.51***	1.68**
E^{PCA}	-0.60	8.50	0.00	6.23***	0.92	5.18	0.67**	7.12***
E^{FC}	0.02	4.92	2.19***	3.95***	0.40	4.29	2.03***	6.36***

Panel C: Markov switching model								
Predictor	Expansions/Recessions				MC Up/Down states			
	\bar{R}_{exp}^2	\bar{R}_{rec}^2	$R_{oos,exp}^2$	$R_{oos,rec}^2$	\bar{R}_{up}^2	\bar{R}_{down}^2	$R_{oos,up}^2$	$R_{oos,down}^2$
$E^{PLS,MC}$	1.00	13.92	-1.74	10.24***	-1.92	6.59	-1.53	4.87***

This table reports the results of forecasting the market excess return across different market states with either E^{PLS} , E^{PCA} , E^{FC} or $E^{PLS,MC}$ by using the standard one-state predictive regression (Panel A), the state switching model of Equation (6) (Panel B) or the Markov switching model of Equation (3) (Panel C). The state indicator in Panel B, S_t , equals one when the slope of the yield curve was inverted or flat in the preceding nine months and is zero otherwise. The state indicator in Panel C, S_t , equals one when the estimated smoothed probability of being in the identified recessionary period is greater than 50% and is zero otherwise. E^{PLS} , E^{PCA} , E^{FC} are $E^{PLS,MC}$ respectively the aligned economic index constructed with the PLS-method, the predictor index based on the PCA-method, the predictor based on the forecast combination approach and the aligned economic index under the Markov switching model. \bar{R}_{exp}^2 ; \bar{R}_{rec}^2 ; \bar{R}_{up}^2 and \bar{R}_{down}^2 are respectively the in-sample adjusted R-square across expansions, recessions, up states and down states as defined by the slope of the yield curve (Panel B), up states and down states as defined by the smoothed transition probabilities of the Markov hidden model (Panel C) over the period January 1960 to December 2017. $R_{oos,exp}^2$; $R_{oos,rec}^2$; $R_{oos,up}^2$ and $R_{oos,down}^2$ are respectively the Campbell and Thompson (2008) out-of-sample R-square across the same defined states as for the in-sample adjusted R-square with the first 20 years as the initial training period and with January 1980 to December 2017 as the evaluation period. All t-statistics are the Newey-West t-statistics controlling for heteroskedasticity and autocorrelation. Statistical significance for R_{oos}^2 is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R_{oos}^2 \leq 0$ against $H_A : R_{oos}^2 \geq 0$. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

4.3 E^{PLS} versus E^{FC}

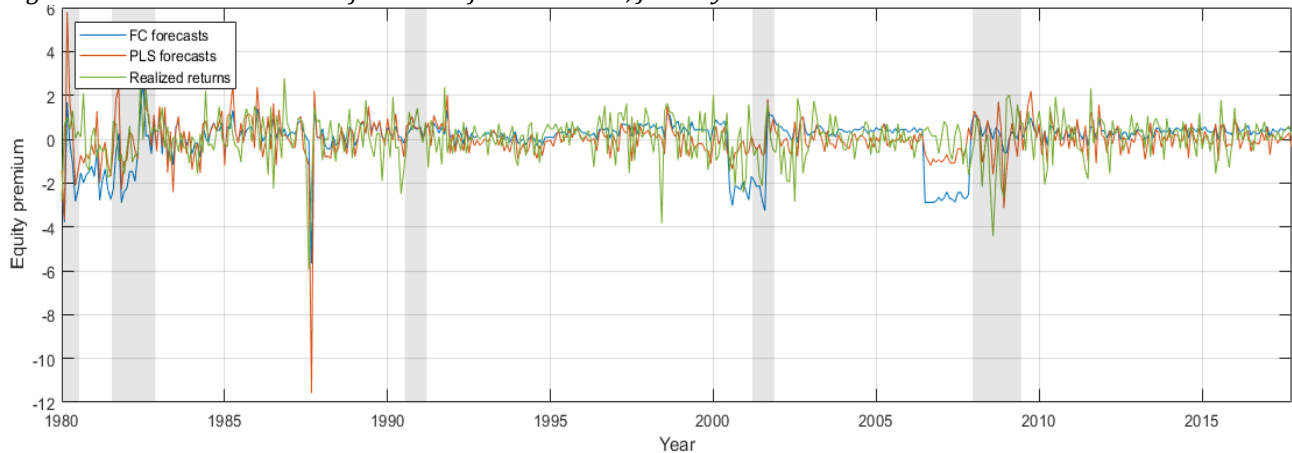
A simple analysis correlation shows a correlation of 65% over the entire out-of-sample period between the forecasts produced by the aligned economic index E^{PLS} and the forecasts of the forecast combination approach E^{FC} , the correlation rises to 83% during a downstate and is respectively 67% and 69% during a recession and expansion. This suggests that both predictors, under the state switching model, are able to capture partially similar variations of the latent factor driving the equity premium. The increase in

correlation during a downstate stems likely from the fact that both predictors use the state indicator in the same manner to change slopes when a downstate occurs.

To further analyse the relationship between the two predictors, Figure 3 depicts the forecasts of the equity premium as well as the realized premium for the January 1980 through December 2017 out-of-sample period. Notice how the E^{PLS} forecasts are much more volatile compared to the E^{FC} based forecasts, while the realized premium has the highest volatility. The fact that the E^{PLS} forecasts are more volatile than the E^{FC} forecasts makes intuitively sense, E^{PLS} is based on a predictor centered approach where PLS is used to extract information of underlying proxies according to the covariance with the forecast target (i.e. the equity premium) which in this case is highly volatile. In contrast, the E^{FC} is simply based on an equal weighing scheme resulting in more stable forecasts and substantially reduces the volatility of the individual forecasts (Rapach et al., 2010). This helps explain why E^{PLS} overall outperforms E^{FC} , as E^{PLS} adapts to the changing market dynamics more timely.

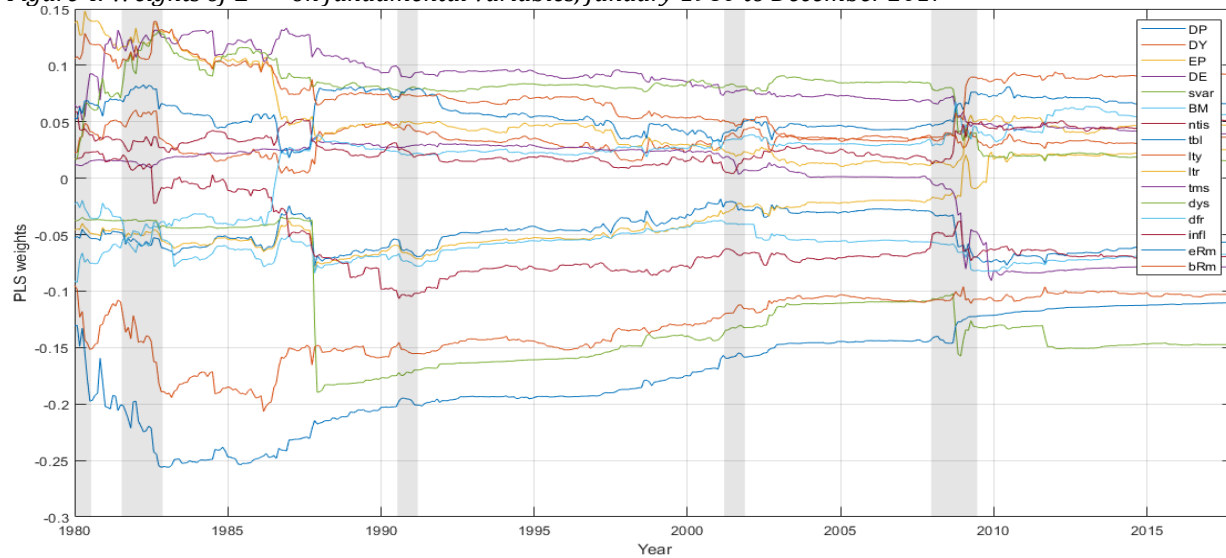
To further understand the difference between the aligned economic index and the forecast combination approach, Figure 4 plots the weights of E^{PLS} on the 16 fundamental proxies over the entire out-of-sample period. Figure 4 shows that the E^{PLS} weights vary over time with the equity risk premium volatility, treasury bills rate and long-term government bond yield having the highest average weights. The fact that the E^{PLS} weights are more volatile than the E^{FC} weights (where each predictor has an equal constant weight of 6.25%) explains the volatile forecasts seen in Figure 3, and is in line with the earlier findings of Devpura et al. (2018) whom find strong evidence of time-varying return predictability of the fundamental variables. Additionally, note how the weights act more volatile when going from one state to the other, providing additional evidence that return predictability is not only time-varying but also state dependent as argued in section 3.

Figure 3. Excess market return forecasts of E^{PLS} and E^{FC} , January 1980 to December 2017



The orange line depicts the out-of-sample predictive regression forecast for the excess market return based on the recursively constructed aligned economic index E^{PLS} . The blue line depicts the out-of-sample excess market return forecast based on forecast combination approach E^{FC} . The green line depicts the excess market return. The economic indices and excess market return forecasts are estimated recursively based on information up to the period of forecast formation period t alone. The vertical bars correspond to NBER-dated recessions.

Figure 4. Weights of E^{PLS} on fundamental variables, January 1980 to December 2017



The figure depicts the weights of the 16 fundamental variables for the recursively constructed aligned economic sentiment index E^{PLS} . The index weights are estimated recursively based on information up to the forecast formation period t alone, based on the PLS method. The 16 fundamental variables are the Dividend-price ratio (log), DP; Dividend yield (log), DY; Earnings-price ratio (log), EP; Dividend-payout ratio (log), DE; Equity risk premium volatility, SVAR; Book-to-market ratio, BM; Net equity expansion, NTIS; Treasury bill rate, TBL; Long-term yield, LTY; Long-term return, LTR; Term spread, TMS; Default yield spread, DFY; Default return spread, DFR; Inflation, INFL; Lagged equity premium, eRm and the Corporate bond premium, eBm. The vertical bars correspond to NBER-dated recessions.

4.4 Forecast encompassing

I conduct a forecasting encompassing test, to further compare the information content of the different models. Harvey, Leybourne and Newbold (1998) develop a statistic to test the null hypothesis of whether a given forecast contains all of the relevant information found in a competing forecast (i.e., the given forecast encompasses the competitor) against the alternative that the competing forecast contains relevant information beyond that in the given forecast. The test statistic is based on the possibility of forming a combined forecast as a weighted average of the individual ones and estimating the weights that should be optimally attached to each forecast. If the entire weight should optimally be associated with one forecast, that forecast is said to encompass the other (Harvey et al., 1998). More specifically the test statistic is based on the linear regression,

$$r_{t+1}^{optimal} = r_{t+1}^i(1 - \lambda) + r_{t+1}^j\lambda, \quad i, j = E^{PLS}, E^{PCA}, E^{FC}, \quad (25)$$

with $0 \leq \lambda \leq 1$ the optimal weight, r_{t+1}^i and r_{t+1}^j the forecasts of the equity premium in month t+1 generated by one of the previously considered models and $r_{t+1}^{optimal}$ the optimal forecast combination. If $\lambda \geq 0$, then the optimal combination forecast of (25) indicates that r_{t+1}^j incorporates relevant information that is beyond that in the information package of r_{t+1}^i for forecasting excess returns. Alternatively, if $\lambda = 0$, then Equation (25) reduces to $r_{t+1}^{optimal} = r_{t+1}^i$, indicating that i is the preferred predictive model as it contains all the information present in the predictive model that generates forecast r_{t+1}^j . The Harvey, Leybourne and Newbold (1998) test evaluates the null of $\lambda = 0$ against $\lambda \geq 0$.

Table 8 presents the results. The statistic corresponds to the estimated weight of Equation (25) and to a one-sided (upper-tail) test of the null hypothesis that the predictive regression forecast for the monthly excess market return based on one of the predictors given in the rows encompasses the forecast based on one of the predictors given in the columns, against the alternative hypothesis that the forecast given in the rows do not encompass the forecast given in the columns. I summarize the results with three main

observations. First, in accordance with the positive R_{OOS}^2 statistics in Table 6, all of the predictive models significantly (on the 5% level or stronger) encompass the forecasts of the historical forecast with relatively high weights ranging from 0.75 (E^{PLS}) up to 1 (E^{PCA} and E^{FC}). Secondly, none of the one-state regression models encompasses their respective state switching model, thus rejecting the null that the predictive regression forecast based on the one-state regressions encompasses those based on the switching state model, thus providing additional evidence of the superior informational content of the switching state models relative to the one state models as earlier seen with the out-of-sample performance. Lastly, E^{PLS} under the state switching model is the only model to encompass all of the competing models, both the one-state regression models as well as the other two switching state models, on the 1% level or stronger. Therefore, suggesting that E^{PLS} is the most efficient index that incorporates all of the relevant forecasting information, which helps in understanding the overall superior forecasting performance as reported in Table 6.

Table 8 Forecast encompassing tests

	HC	One-state model			State switching model		
		E^{PLS}	E^{PCA}	E^{FC}	E^{PLS}	E^{PCA}	E^{FC}
HC		0.75*** (0.01)	1.00** (0.03)	1.00** (0.03)	0.75*** (0.00)	1.00** (0.02)	1.00** (0.02)
One-state model							
E^{PLS}	0.26 (0.12)		0.29* (0.10)	0.29 (0.11)	1.00*** (0.00)	0.30* (0.09)	0.29* (0.09)
E^{PCA}	0.00 (0.89)	0.71*** (0.01)		0.00 (0.56)	0.74*** (0.00)	1.00** (0.04)	1.00* (0.08)
E^{FC}	0.00 (0.89)	0.71*** (0.01)	1.00** (0.04)		0.74*** (0.00)	1.00* (0.06)	1.00*** (0.01)
State switching model							
E^{PLS}	0.25 (0.13)	0.00 (0.58)	0.25* (0.08)	0.26* (0.08)		0.26* (0.08)	0.25* (0.08)
E^{PCA}	0.00 (0.91)	0.70*** (0.01)	0.00 (0.96)	0.00 (0.93)	0.74*** (0.00)		1.00** (0.04)
E^{FC}	0.00 (0.92)	0.70*** (0.01)	0.00 (0.90)	0.00 (0.99)	0.74*** (0.00)	0.00 (0.58)	

This table reports the estimated weight of Equation (25) on the predictive regression forecast based on one of predictor combination methods. Corresponding p -values for the Harvey, Leybourne, and Newbold (1998) statistic are depicted in brackets. The statistic corresponds to a one-sided (upper-tail) test of the null hypothesis that the predictive regression forecast for the monthly excess market return based on one of the predictors given in rows encompasses the forecast based on one of the predictors given in the columns, against the alternative hypothesis that the forecast given in the rows does not encompass the forecast given in the columns. The predictors are the historical forecast (HC), aligned economic index constructed with the PLS-method E^{PLS} , the predictor index based on the PCA-method E^{PCA} and the predictor based on the forecast combination approach E^{FC} . The sample period is over January 1960 to December 2017, with January 1980 to December 2017 the out-of-sample evaluation period.

4.5 Subsample analysis

One might be concerned that the out-of-sample performance of the aligned economic index is an artefact of specific moments in time (e.g. during the subprime crisis) rather than consistent performance over the entire out-of-sample period. The fact that E^{PLS} produces significant R_{OOS}^2 values across different market states is a first indication that the index consistently outperforms the naïve benchmark model. To further analyze the out-of-sample behavior of E^{PLS} I follow Welch & Goyal (2008) and Huang et al. (2015), and plot the time-series of the difference between the cumulative squared forecast error (CSFE) of the historical average model and the CSFE of the aligned economic index over the entire out-of-sample period. Welch & Goyal (2008) show that the time-series plot can be used to further

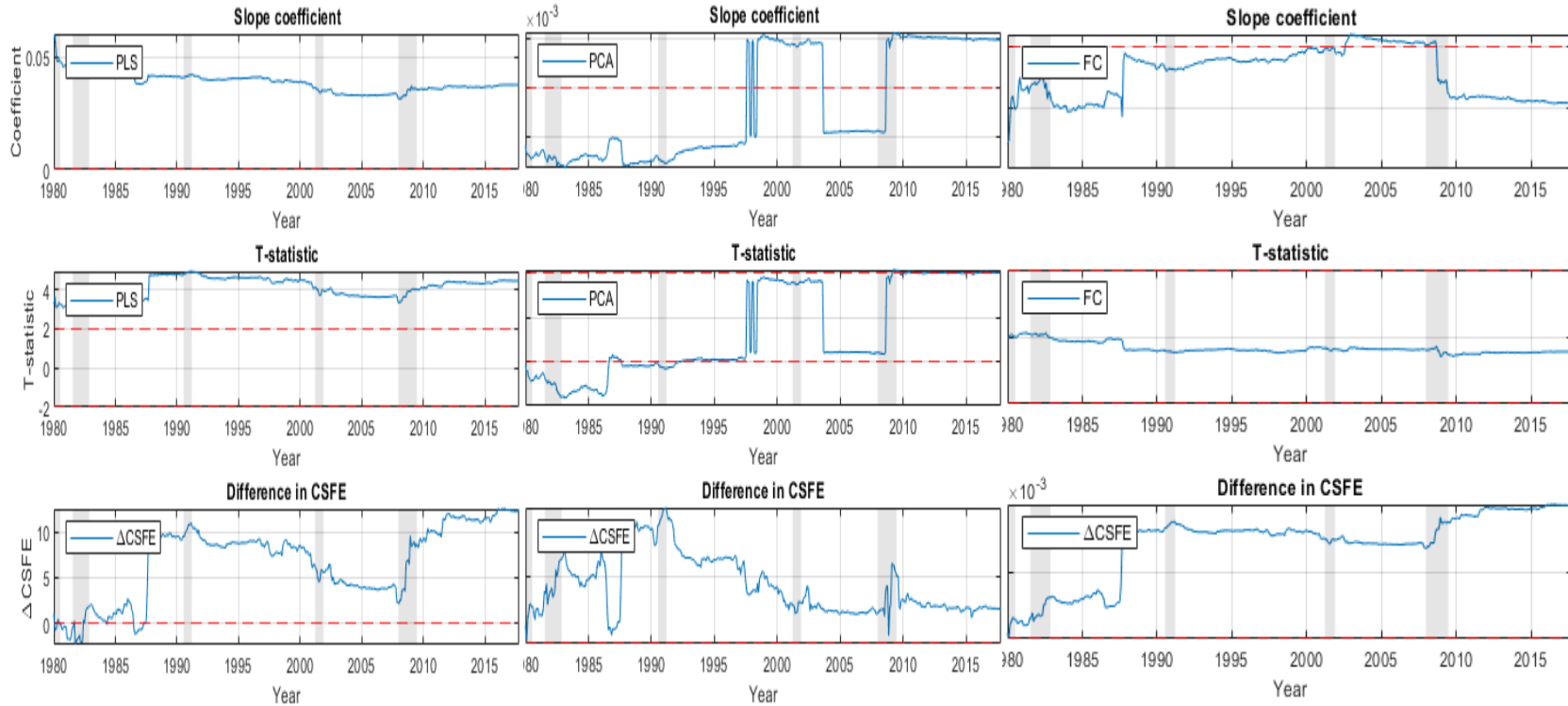
analyze the consistency of out-of-sample forecasting performance over time, and strongly suggest that future articles proposing equity premium predictive models include similar plots. Whenever the slope of the time-series is positive (i.e. when the difference in CSFE increases) the E^{PLS} forecast outperforms the historical average, whenever the slope is decreasing the opposite holds and the historical average performs better than the aligned economic index. Thus, the great advantage of the graph lies in the fact that one can easily see whether a certain predictive model can outperform the historical average for any particular out-of-sample period. The units in the graphs are not intuitive, but the timeseries pattern allows diagnosis of months with good or bad performance, with the final $\Delta CSFE$ being sign-identical with the R_{OoS}^2 statistics in Table 6.

To further reduce the concern that the outperformance of E^{PLS} is driven by certain occasional periods, I supplement the $\Delta CSFE$ graph with two additional intuitive time-series. The first one being the regression slopes of the switching model using E^{PLS} over the out-of-sample period, and the second time-series being the accompanying t-statistics. If E^{PLS} consistently outperforms the historical average by having more predictive information over the historical average, one would expect regression slopes that are significantly different from zero across the entire out-of-sample period. In contrast, when the performance of E^{PLS} is attributed to certain events, one would expect to find non-significant regression slopes close to zero over prolonged periods in time.

Figure 5 plots the timeseries of the three one-state regression models. The left panel shows results of E^{PLS} . As can be seen, E^{PLS} has a highly significant positive slope across the entire out-of-sample period of around 0.05, though looking at the $\Delta CSFE$ graph it is clear that the predictor cannot consistently outperform the historical average. E^{PLS} displays quite a volatile performance rate during the first part of the sample period, with a sudden increase in performance in 1988, afterwards the historical average consistently outperforms E^{PLS} up to 2007, where subsequently E^{PLS} begins to display consistent performance till the end of the sample period. The middle panel showcases the performance of E^{PCA} . E^{PCA} exhibits a quite volatile slope coefficient with values ranging between -0.2 (at the start of the sample period) up to 0.2 (at the end of the sample period), with an accompanying t-statistic that is only significant at the start and end of the sample period. The $\Delta CSFE$ graph is highly

volatile with most of the performance accumulated during recessionary periods, during expansions E^{PCA} clearly fails to outperform the historical average. Lastly, the right panel of Figure 4 shows the results of E^{FC} . Note, that the timeseries of the slope coefficient and t-statistic in this case are simply computed as the average value of the predictor's individual slope coefficients and t-statistics. Although, the slope coefficients of the individual predictors are, on average, not significantly different from zero, the forecast combination of the individual forecasts do exhibit stable performance over time when looking at the $\Delta CSFE$ graph.

Figure 5. One-state models, The difference in cumulative squared forecast error (CSFE), January 1980 to December 2017



The upper panel depicts the regression slopes of the one-state regression models E^{PLS} (left), E^{PCA} (middle) and E^{FC} (right) during the out-of-sample period, the red dotted line is the horizontal line $y = 0$. The middle panel shows the corresponding t-statistics, with the red dotted lines corresponding to significance thresholds of $y = 2$ or $y = -2$. The bottom panel depicts the difference between the cumulative squared forecast error (CSFE) for the historical average benchmark and the CSFE for the out-of-sample predictive regression forecast based on the recursively constructed E^{PLS} (left), E^{PCA} (middle) and E^{FC} (right) indices. The indices and regression coefficients are estimated recursively based on information up to the period of forecast formation period t alone. The vertical bars correspond to NBER-dated recessions.

Figure 6 plots the timeseries of the state switching model. The left panel shows once again results of E^{PLS} . First, note how the slope coefficients of both states are significantly positive across the sample period indicating that the use of switching coefficients adds consistent value in predicting returns. Further evidence of the added value of switching can be seen by how the slope coefficient diverge more across recessionary periods with the downstate coefficient implying a higher effect of the aligned economic index on excess returns. Second, in contrast to the one-state regression, the $\Delta CSFE$ graph is much less volatile and increases consistently throughout the sample period (with the exception of the start of the sample period where the graph is still quite volatile).

The middle panel showcases the performance of E^{PCA} . In line with the one-state model, E^{PCA} exhibits a quite volatile slope coefficients which tend to move together across different states implying that switching does not add much value. The accompanying t-statistics are, once again, only significant at the start and end of the sample period. When looking at the $\Delta CSFE$ graph one can clearly see a significant improvement, with an overall increasing $\Delta CSFE$ over the sample period. However, the graph is still quite volatile and shows numerous occasions where the historical forecast model outperforms E^{PCA} . For example, the historical forecast dominates E^{PCA} across the expansionary period from 1990 up to 2000, and continuous do so during the subprime crisis of 2007-08.

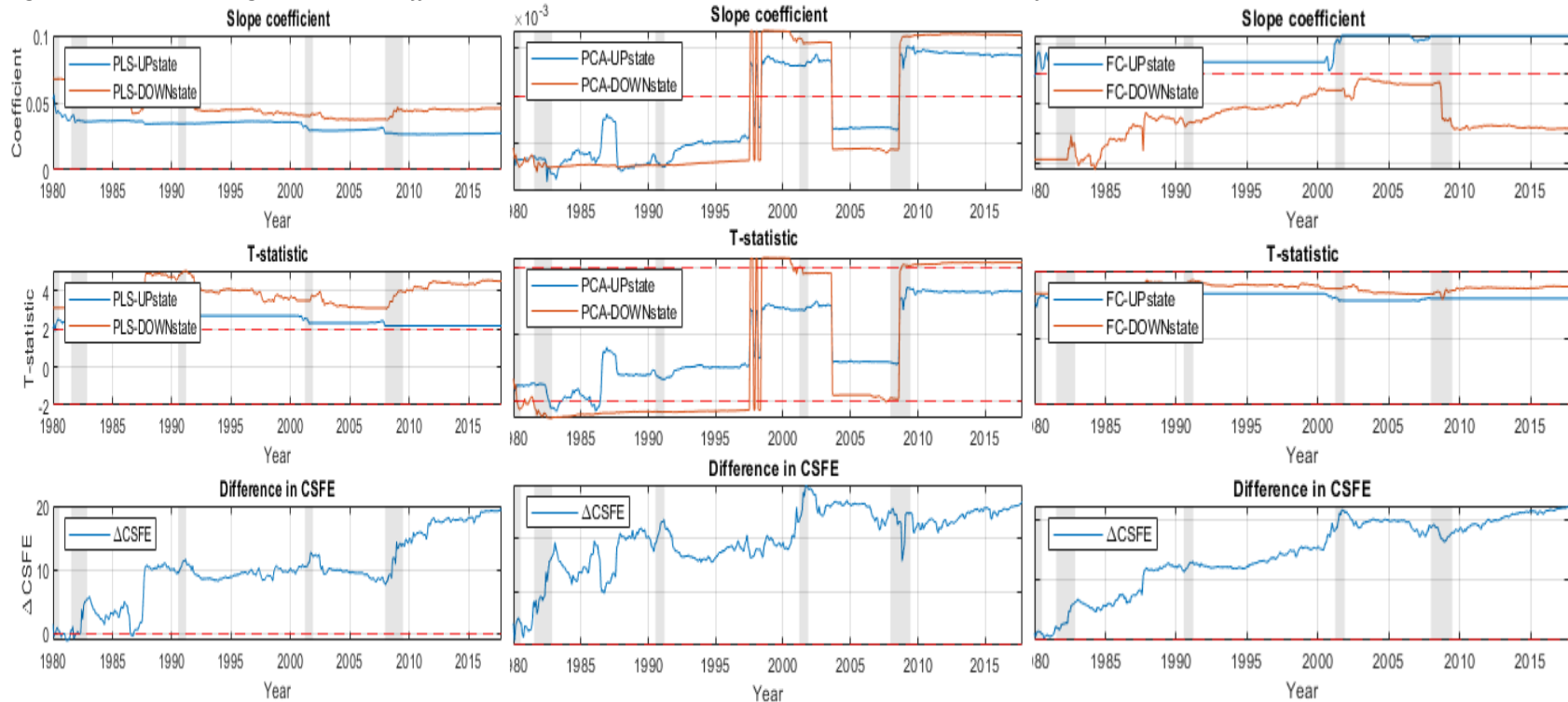
Third, the right panel of Figure 6 shows the results of E^{FC} . As earlier, the timeseries of the slope coefficients and t-statistics in this case are simply computed as the average value of the predictor's individual slope coefficients and t-statistics. Notice how the average slope coefficients are quite time-dependent with values ranging from -0.6 up to 0 (downstate coefficient) and from 0 up to 0.26 (upstate coefficient). The corresponding average (absolute) t-statistics are quite stable and hover under the significance threshold of 2 across the sample period. Unreported results show that multiple individual t-statistics actually exceed the threshold significance threshold of 2 during certain periods but are 'countered' by non-significant t-statistics leading to non-significant average values. These findings are highly compelling as they provide further evidence of time-varying return predictability and predictor-dependent predictability as found by Devpura et al. (2018). The $\Delta CSFE$ graph shows how E^{FC} continuously outperforms the historical average across

the entire sample period. In contrast to the other models, the $\Delta CSFE$ graph of E^{FC} displays no abrupt shocks or spikes with a highly stable slope that stays positive for almost the entire duration of the sample period.

Lastly, note how the $\Delta CSFE$ graph of E^{FC} displays an overall smoother pattern than of E^{PLS} . The smoother pattern is attributed to the more conservative forecasts of E^{FC} compared to the ones of E^{PLS} , as seen earlier in Figure 3. The volatile forecasts of E^{PLS} , which are caused by the volatility of the weights as seen in Figure 4, result in a more erratic $\Delta CSFE$ graph, although still relatively stable.

In conclusion, the analysis of the timeseries plots of Figure 5 and 6 are consistent with the earlier out-of-sample results obtained. The one-state models, although outperforming the naïve forecast overall, fail to deliver consistent performance across the entire sample period while the switching state models of E^{PLS} and E^{FC} are able to provide superior performance in a consistent manner. The analysis also confirms the findings of Devpura et al. (2018): return predictability is time-varying and predictor dependent.

Figure 6. State switching models, The difference in cumulative squared forecast error (CSFE), January 1980 to December 2017



The upper panel depicts the regression slopes of the state switching models E^{PLS} (left), E^{PCA} (middle) and E^{FC} (right) during the out-of-sample period, the red dotted line is the horizontal line $y = 0$. The state indicator, S_t , equals one when the slope of the yield curve was inverted or flat in the preceding nine months and is zero otherwise. The middle panel shows the corresponding t-statistics, with the red dotted lines corresponding to significance thresholds of $y = 2$ or $y = -2$. The bottom panel depicts the difference between the cumulative squared forecast error (CSFE) for the historical average benchmark and the CSFE for the out-of-sample predictive regression forecast based on the recursively constructed E^{PLS} (left), E^{PCA} (middle) and E^{FC} (right) indices. The indices and regression coefficients are estimated recursively based on information up to the period of forecast formation period t alone. The vertical bars correspond to NBER-dated recessions.

5 Asset allocation exercise

The previous section analyzed the forecasting performance of the aligned economic index from a statistical perspective, while implicitly looking at the economic performance of the index. In this section however, I explicitly analyze the economic value of the aligned index when used by a mean-variance investor to provide a more direct measure of the forecasting value of the new index to economic agents. The question of interest is whether the newly developed predictive model is better at guiding investment decisions than a preexisting baseline model.

5.1 Asset allocation optimization

Consider an economic agent with an investment horizon of one month that wishes to maximize expected utility of terminal wealth W_{t+1} conditional on information up to time t . I follow Campbell & Thompson (2008), Neely et al. (2014), Rapach et al. (2016), Sander (2018) and many others and assume a mean-variance investor as defined by Markowitz (1952). The investor can choose to either allocate its wealth in the S&P 500 index, in U.S. treasury bills, or a combination of both. The utility function of the investor is

$$U_t(R_{t+1}^p) = E_t(R_{t+1}^p) - \frac{\gamma}{2}\sigma_t^2(R_{t+1}^p), \quad (26)$$

with R_{t+1}^p the simple¹⁰ return at month $t+1$ of the portfolio consisting of the S&P 500 index and U.S treasury bills, $E_t(R_{t+1}^p)$ and $\sigma^2(R_{t+1}^p)$ are respectively the conditional mean and variance of the portfolio return at month $t+1$ and γ is the investor's coefficient of risk aversion.

Next, let R_{t+1}^r and R_{t+1}^f be respectively the return on the S&P 500 index at time $t+1$ (i.e. the return on the risky asset) and the return on the treasury bills at time $t+1$ (i.e. the return on

¹⁰ Note that I forecast the simple excess return—and not the log excess return—for the asset allocation analysis.

the risk-free asset). Let ω_t denote the portion of the investment allocated to the risky asset. The investor's portfolio return at the end of each month is then simply,

$$R_{t+1}^p = \omega_t R_{t+1}^r + (1 - \omega_t) R_{t+1}^f, \quad (27)$$

Expanding the brackets and rearranging terms gives,

$$R_{t+1}^p = \omega_t R_{t+1}^e + R_{t+1}^f, \quad (28)$$

With $R_{t+1}^e = (R_{t+1}^r - R_{t+1}^f)$, the excess return on the risky asset.

Thus, the investor wishing to maximize expected utility is faced with the following objective function,

$$\max_{\omega_t} U_t(R_{t+1}^p) = E_t(\omega_t R_{t+1}^e + R_{t+1}^f) - \frac{\gamma}{2} \sigma_t^2(\omega_t R_{t+1}^e + R_{t+1}^f), \quad (29)$$

I follow Johnson (2017) and many others and assume that the next period's risk-free rate R_{t+1}^f is observable to the investor at the end of current month t , meaning the conditional first and second moment of the portfolio R_{t+1}^p satisfy:

$$E_t(R_{t+1}^p) = \omega_t E_t(R_{t+1}^e) + R_{t+1}^f, \quad (29.2)$$

$$\sigma^2(R_{t+1}^p) = \omega_t^2 \sigma^2(R_{t+1}^e), \quad (29.3)$$

Setting the first derivative of the objective function (29) equal to zero and solving for ω_t gives then,

$$\omega_t^* = \frac{1}{\gamma} \frac{E(R_{t+1}^e)}{\sigma^2(R_{t+1}^e)}, \quad (30)$$

the optimal ex-ante weight that maximizes (29) is thus a function of the unknown conditional mean and variance of the portfolio return at month $t+1$ and hence needs to be estimated. I estimate $E(R_{t+1}^e)$ based on the forecasts of the aligned economic index, that is

$$E(R_{t+1}^e) = \hat{r}_{t+1|t}, \quad (31)$$

with $\hat{r}_{t+1|t}$ the forecast made by the state switching model that uses the aligned economic index as the predictor based on a recursive window. To allow for a time-varying variance, I

follow Campbell & Thompson (2008) and estimate $\sigma^2(R_{t+1}^e)$ using the sample variance computed from a five-year rolling window of historical returns:

$$\hat{\sigma}^2(R_{t+1}^e) = s^2(R_{t+1}^e) = \frac{1}{N} \sum_{i=t-N+1}^t (R_i^e)^2 - \left(\frac{1}{N} \sum_{i=t-N+1}^t (R_i^e) \right)^2, \quad (32)$$

With $N = 12 * 5 = 60$ months. As follows, the investor decides at month t to allocate the following share of her portfolio to the risky asset during month $t+1$:

$$\hat{\omega}_t^* = \frac{1}{\gamma} \frac{\hat{r}_{t+1|t}}{s^2(R_{t+1}^e)}, \quad (33)$$

Using Equation (33) I compute the time series of portfolio returns these weights imply,

$$R_{t+1}^p = \hat{\omega}_t^* R_{t+1}^e + R_{t+1}^f, \quad (34)$$

From these returns, I compute the Certainty Equivalent Return (CER) of the investor (i.e. the risk-free rate of return that a risk-averse investor is willing to accept instead of holding the given risky equity portfolio),

$$CER = E(\hat{\omega}_t^* R_{t+1}^e + R_{t+1}^f) - \frac{\gamma}{2} \sigma^2(\hat{\omega}_t^* R_{t+1}^e + R_{t+1}^f), \quad (35)$$

I estimate CER using the unconditional moments of the full sample of realized portfolio returns, instead of computing the average of the month-to-month conditional CER the investor expects when making her portfolio choice. The use of unconditional moments is more conservative because it requires the out-of-sample conditional moments to match the subsequent return distributions (Johnson, 2017).

Next, I redo the same exercise but assume that the investor uses the one-state historical forecast model rather than the state switching model to estimate the optimal weight (30) of the objective function,

$$\hat{\omega}_{t,0}^* = \frac{1}{\gamma} \frac{\bar{r}_{t+1|t}}{s^2(R_{t+1}^e)}, \quad (36)$$

With $\bar{r}_{t+1|t}$ the sample mean up to month t and $s^2(R_{t+1}^e)$ once again the sample variance computed from a five-year rolling window of historical returns¹¹.

The Certainty Equivalent Return (CER) of the investor becomes then,

$$CER_0 = E(\hat{\omega}_{t,0}^* R_{t+1}^e + R_{t+1}^f) - \frac{\gamma}{2} \sigma^2(\hat{\omega}_{t,0}^* R_{t+1}^e + R_{t+1}^f), \quad (37)$$

Finally, I compute the difference between the CER's of the two investors,

$$\Delta CER = CER - CER_0. \quad (38)$$

Equation (38) represents the utility gain accumulated by using the predictive regression forecast of the equity premium in place of the historical average forecast in the asset allocation decision. This utility gain, or certainty equivalent return, can be interpreted as the portfolio management fee that an investor would be willing to pay to have access to the information in the predictive regression forecast relative to the information in the historical average forecast alone (Rapach et al., 2016).

5.2 Empirical results

For each predictor combination method mentioned in section 4 of the paper (i.e. PLS, PCA and FC), I compute the out-of-sample certainty equivalent return (CER). Following the same approach I use in Section 3 and 4, I estimate out-of-sample forecasts in a monthly sample from 1980:01 up to 2017:12 starting after an 20-year training period. For each month I compute the first two conditional moments of the portfolio return series. Based on these estimated moments, I compute optimal portfolio weights using Equation (30). To examine the effect of risk aversion I follow Huang et al. (2015) and consider portfolio rules based on risk aversion coefficients 3 and 5. Following Johnson (2017), I impose leverage

¹¹ Using the same variance estimates as the main model ensures that any differences between the CER gains are due to the expected return estimates.

restrictions on the investor up to 50% and don't allow for any short selling, which imposes realistic portfolio constraints¹².

In addition, the investor is not allowed to more than double (or half) its investment in the risky asset from one month to the other in order to produce better-behaved portfolio weights, given the well-known sensitivity of mean-variance optimal weights to return forecasts (Barbara J, 2015). Next, I compute the difference in CER gains between an investor using one of the forecasting models and an investor (with the same utility function) who uses the benchmark model of the historical mean. I multiply the difference by 1,200 so that it can be interpreted as the annual percentage portfolio management fee that an investor would be willing to pay to have access to the predictive regression forecast instead of the historical average forecast. I also consider the scenario where the investor needs to pay transaction costs for rebalancing her portfolio, by assuming a proportional cost of 50 basis points (bps) per transaction. To further benchmark my results, I consider an investor who simply buys the market at the start of the out-of-sample period and holds the market without rebalancing till the end of the sample period (named the buy and hold strategy hereafter). Both the aligned economic index E^{PLS} and the forecast combination E^{FC} can significantly outperform the naïve benchmark model across all market states when looking at out-of-sample R_{OOS}^2 results as shown in section 4, it is of interest to see how well these results spill over in a mean-variance investor context. I therefore compute ΔCER gains for all forecasting models considered across different market states in the same manner as I did in section 4 for the R_{OOS}^2 results.

Furthermore, I examine the statistical significance of the ΔCER gains by evaluating the null $H_0: \Delta CER \leq 0$ against the alternative $H_a: \Delta CER > 0$. McCracken and Valente (2018) show thoroughly that when $\Delta CER = 0$, ΔCER is asymptotically normal with zero mean.

However, ΔCER has an asymptotic variance that is affected by estimation error due to the fact that the forecasting models must be estimated prior to their use in the asset allocation exercise. Estimating the asymptotic variance can thus (although still possible) be quite complicated. McCracken and Valente (2018) therefore provide an alternative way to

¹² Short selling was banned by many countries after the global financial crisis of 2008 (Bensoussan, Wong, Yam, & Yung, 2014).

evaluate the null $H_0: \Delta CER \leq 0$, based on a percentile-bootstrap approach which is much easier to implement. McCracken and Valente (2018) goes on to show through simulations that, while the two approaches may yield different results, the bootstrap approach yields comparable size and power properties. I therefore implement the same bootstrap procedure of McCracken and Valente (2018) to infer statistical significance of ΔCER . More concrete I use the following procedure:

Step 1: I draw a random number L from an exponential distribution with mean $T^{0.6}$ to determine the block length of a block of the stationary bootstrapped timeseries. With T equal to the number of observations in the out-of-sample period.

Step 2: I draw a random observation, with replacement, from the empirical distribution which becomes the first observation within the block of the bootstrapped timeseries and fill the remainder of the block in with L consecutive observations after the drawn observation. I wrap the observations of the empirical distribution around in a circle so that the last observation is followed by the first observation in case the end of the empirical sample is reached while filling a block.

Step 3: I repeat *Step 2* until the bootstrapped timeseries contains the same number of observations as the empirical distribution.

Step 4: I repeat step 2-3 to generate bootstrapped timeseries from the return series, predictor series and from state indicator series.

Step 5: I repeat steps 1-4 B times to generate B bootstrapped timeseries.

Step 6: I use the bootstrapped data to construct the bootstrapped performance fee measure ΔCER_b^* for $b = 1, \dots, B$.

Step 7: I recenter ΔCER^* to reflect the null hypothesis: $\overline{\Delta CER_b^*} = \Delta CER_b^* - \sum_{b=1}^B \Delta CER_b^*$ for $b=1, \dots, B$.

Step 8: I estimate critical values based on the bootstrapped distribution of $\overline{\Delta CER_b^*}$.

I follow McCracken and Valente (2018) and set $B = 999$.

5.2.1 The one-state regression model

Panel A of table 9 shows the results assuming a risk aversion coefficient of 3. The upper part of panel A displays results for the one-state regression models while the lower part depicts results when using the state switching model¹³. The second column presents the difference in CER gains (ΔCER) without transaction costs, while column five reports the difference in CER gains net of transaction costs. I also include some additional portfolio performance measures, column 3 shows the monthly Sharpe ratio computed as the mean portfolio return in excess of the risk-free rate divided by the standard deviation of the excess portfolio return. The fourth column reports relative average monthly turnover, with monthly turnover defined as the percentage of wealth being rebalanced at the end of the month. The relative average monthly turnover is then simply the average monthly turnover divided by the average monthly turnover of the investor that uses the historical average forecast. Panel B shows the same results assuming a risk aversion coefficient of 5.

There are several noteworthy observations. First, the CER for the portfolio based on the historical average forecast is 7.56% for January 1980 to December 2017. the ΔCER of all three combination methods are positive under the one state regression model, however only E^{PLS} has a ΔCER that is significantly different from zero at the 10% level or stronger. In line with the positive certainty equivalent gains, the Sharpe ratios of the forecasting models are all greater than that of the historical average (which has a ratio of 0.13), with E^{PLS} and E^{FC} yielding the highest ratio of 0.16. The average turnover is 2.09% for the historical average. Portfolios based on the forecasting models turn over approximately three to four times more often than the historical average portfolio. Thus, after accounting for transactions costs, the relatively high turnovers reduce the ΔCER gains from positive to negative values for E^{PCA} and E^{FC} and none of the forecasting models produce significant ΔCER gains different from zero.

¹³ I exclude the aligned economic index under the Markov switching model ($E^{PLS,MC}$) from the asset allocation exercise due to the weak out-of-sample performance during certain market states as shown in previous section, and due to the computational stress of the iteration process of the EM algorithm within McCracken and Valente (2018) bootstrap procedure.

When looking across different states, the historical average model produces substantial CER gains during expansions and up states of respectively 13% and 10.74% but yield negative gains across recessions and down states of respectively -17.46% and -1.08%. As expected, the historical average model is unable to quickly adapt to the drops in equity returns during recessions and down states.

The forecasting models exhibit the same underlying behavior across different states. All three models fail to generate significant ΔCER gains during expansions, with E^{PCA} and E^{FC} even failing to outperform the benchmark model, in contrast during recessions all three models significantly produce ΔCER values at the 5% level or stronger, with E^{PCA} yielding the highest gains of 5.82%. Across up states the results are similar to expansions: none of the three models are able to significantly outperform the benchmark model, with E^{FC} even producing negative values. The results are more mixed across down states, both E^{FC} and E^{PCA} significantly outperform the benchmark model, with E^{PCA} generating a substantial value of 4.28%, in contrast E^{PLS} produces a negative value of -2% meaning that an investor that utilizes the simple historical average model would generate 2% more risk-adjusted return relative to an investor using the E^{PLS} model across down states. Note that in great contrast to the three forecasting models, the simple buy and hold strategy yields significant ΔCER gains of 1.51% when looking at the entire sample period.

More so, the buy and hold strategy yields positive ΔCER values across expansions (although not significantly), recessions and up states. During down states however, the buy and hold strategy loses to the historical average model and produces ΔCER gains of -3.9%. In conclusion, none of the forecasting models can significantly outperform the naïve historical benchmark model when investors are faced with transaction costs with all the positive ΔCER gains concentrated around recessions. More surprising, of all the models considered the simple buy and hold strategy yields the highest ΔCER value and is the only one to outperform the historical average forecast, but still fails to do so across all market states. These results echo the earlier findings of Henkel et al. (2011): the short-horizon

performance of aggregate return predictors such as the dividend yield and the short rate appears non-existent during business cycle expansions but sizable during contractions.

5.2.2 The switching state model

These results however, change drastically when looking at the state switching models. First note that the ΔCER of all three combination methods are significantly positive and highly substantial under the state switching model, with E^{FC} yielding the highest performance of 6.09%. In line with the high ΔCER gains, the state switching models generate considerably higher monthly Sharpe ratios than that of the historical average (with a Sharpe ratio of 0.13), with E^{PLS} generating the highest ratio of 0.25 which is almost double the Sharpe ratio of the benchmark model. The state switching models turn over approximately two to three times more often than the historical average portfolio, which is considerably lower than the turnover rate of the one-state models. With the lower turnover rate, the state switching models are less affected by transaction costs. After netting transaction costs of 50bp per transaction, all three models still produce large certainty equivalent return gains in excess of the benchmark model and all are significantly different from zero at the 5% level or stronger. More specific, E^{PLS} still yields the highest performance gains after netting transaction costs with a ΔCER value of 5.54% meaning that a mean-variance investor would be willing to pay an annual management fee of up to 5.54% to have access to the forecasts made by the aligned state switching economic index instead of using the naïve historical average. E^{FC} produces the second highest performance gains of a hefty 4.15% while E^{PCA} generates gains of 3.58% under the state switching model.

The improvement from the one-state regression models to the state switching models is clearly substantial. The average Sharpe ratio increases from 0.15 when using the one-state model to a hefty average of 0.23 under the state switching model. More so, while none of the predictors can significantly outperform the benchmark model under the one-state model, all three predictors (E^{PLS} , E^{PCA} and E^{FC}) display significant outperformance of the benchmark when introducing the state switching model. The average net-of-transactions-costs ΔCER gains increase from -0.03% under the one-state model to an average of 4.42%

under the state switching model, confirming the earlier findings that combining the complementary information of the predictors leads to optimal performance when letting the regression coefficient change across states. Most noticeably perhaps is the fact that the simple buy and hold strategy outperforms the myopic predictors under the one-state model but fails to do so when introducing the state switching model. All three state switching models produce ΔCER gains far exceeding the gains of the buy and hold strategy, with E^{PLS} generating gains that are almost four times greater than of the buy and hold strategy.

The improvement when using the state switching models is also noticeable when looking at the performance across different states. First, in line with the one-state regression models, all three state switching models can significantly outperform the historical average during recessions. Second, where the one-state models fail to outperform the benchmark during expansions the state switching models all exhibit positive ΔCER gains, with both E^{PLS} and E^{FC} (generating ΔCER values of respectively 0.89% and 1.26%) significantly outperforming the historical average at the 5% level or stronger.

The same results are seen when looking at performance during up states, all three models generate positive gains with once again E^{PLS} and E^{FC} being significant at the 5% level or stronger, E^{FC} produces the highest ΔCER gains of 2.02% while E^{PLS} generates a substantial 1.5% ΔCER value. This, in great contrast with the one-state regression models who all fail to significantly outperform the historical average during up states.

Looking across down states, all three models outperform the historical average, with ΔCER gains ranging from 7.09% (E^{PCA}) up to 9.59% (E^{FC}). Note how both E^{PLS} and E^{FC} under the state switching model are able to consistently outperform the historical average across all different market states. In contrast, not even the robust buy and hold strategy can significantly outperform the historical average during expansions and generates a negative value of -3.9% during down states (i.e. when the yield curve inverts which coincides most often right before the start of a recession). Notice how these findings are a mirror image of the out-of-sample R_{0oS}^2 results discussed in section 4: Under the state switching model both

E^{PLS} and E^{FC} are able to consistently outperform the naïve benchmark model across all market states, with E^{PLS} yielding the overall greatest performance.

These results are overall robust to changes in the risk aversion coefficient (RRA). Panel B of table 9 shows the same statistics as panel A but assumes a risk aversion coefficient of 5 rather than 3. First note the general decrease of ΔCER gains. The net-of-transaction cost average ΔCER of the one-state models decrease from 0.35% to 0% when going from an RRA of 3 to 5, while the average performance of the state switching models decrease from 3.7% to 2.86%. However, despite the general decrease the same qualitative results are shown as before: the one-state models are unable to outperform the benchmark model, while the simple Buy and hold strategy can do so with a significant ΔCER value of 0.96%. When introducing the switching state model, all three predictors (E^{PLS} , E^{PCA} and E^{FC}) significantly outperform both the naïve benchmark and the buy and hold strategy, with E^{PLS} yielding the overall highest performance of 4.19% (which is four times as large as the ΔCER gains generated by the buy and hold strategy). More so, E^{PLS} is still able to produce significant positive gains across all market states.

Table 9 Asset allocation results

Panel A: risk aversion $\gamma = 3$								
Predictor	Overall				Across states			
	ΔCER	SR	Relative average turnover	ΔCER cost = 50bps	ΔCER_{exp} cost = 50bps	ΔCER_{rec} cost = 50bps	ΔCER_{up} cost = 50bps	ΔCER_{down} cost = 50bps
HA	7.65	0.13	2.47	7.5	13.00	-17.46	10.74	-1.08
Buy & hold	1.35**	0.16	0.00	1.51**	1.10	4.09**	2.39**	-3.90
One-state model								
E^{PLS}	1.17*	0.16	5.42	0.52	0.30	5.58***	0.93	-2.00
E^{PCA}	0.54	0.14	8.65	-0.59	-1.17	5.82***	0.38	1.46**
E^{FC}	1.16	0.16	8.93	-0.03	-0.89	2.44**	-0.02	4.28**
Switching state model								
E^{PLS}	6.09***	0.25	4.76	5.54**	0.89**	18.66***	2.02**	9.27***
E^{PCA}	4.45**	0.22	6.82	3.58**	0.20	23.81***	0.46	7.09***
E^{FC}	4.71***	0.22	4.70	4.15***	1.26**	2.92***	1.50**	9.59***
Panel B: risk aversion $\gamma = 5$								
Predictor	Overall				Across states			
	ΔCER	SR	Relative average turnover	ΔCER cost = 50bps	ΔCER_{exp} cost = 50bps	ΔCER_{rec} cost = 50bps	ΔCER_{up} cost = 50bps	ΔCER_{down} cost = 50bps
HA	5.99	0.12	2.04	5.85	10.54	-11.49	8.70	1.24
Buy & hold	0.82**	0.16	0.00	0.96**	1.72**	-6.26	2.28***	-8.51
One-state model								
E^{PLS}	0.71	0.14	5.05	0.22	-0.07	3.48*	0.44	-1.15
E^{PCA}	-0.08	0.12	7.88	-0.92	-0.60	-1.45	-0.28	1.12**
E^{FC}	0.69	0.14	8.78	-0.25	-0.25	-2.50	0.01	2.57**
Switching state model								
E^{PLS}	4.66***	0.24	4.77	4.19**	0.67*	14.28***	0.63**	6.77***
E^{PCA}	3.54**	0.22	7.36	2.76**	0.12	17.63***	-0.11	4.81***
E^{FC}	4.03***	0.22	5.01	3.54**	1.13**	-1.58	0.99**	7.25***

This table reports portfolio performance measures for an investor with mean-variance preferences and relative risk-aversion coefficient of three (Panel A) or five (Panel B) who monthly allocates between equities and risk-free bills using either an historical average (HA) or predictive regression equity risk premium forecast. The predictors are the aligned economic index constructed with the PLS-method E^{PLS} , the predictor index based on the PCA-method E^{PCA} and the predictor based on the forecast combination approach E^{FC} under either the traditional one-state regression model or the state switching model of Equation (6). The ΔCER statistic is the annualized certainty equivalent return gain for an investor who uses the predictive regression forecast instead of the historical average forecast; for the historical average forecast, the table reports the CER level; ΔCER statistics are also reported separately across different states. ΔCER_{exp} ; ΔCER_{rec} ; ΔCER_{up} ; ΔCER_{down} are respectively the CER return gains across expansions, recessions, up states and down states. Relative average turnover is the average turnover for the portfolio based on the predictive regression forecast divided by the average turnover for the portfolio based on the historical average forecast; for the historical average forecast, the table reports the average turnover level. The ΔCER cost = 50bps statistic is the CER gain assuming a proportional transactions cost of 50 basis points per transaction.

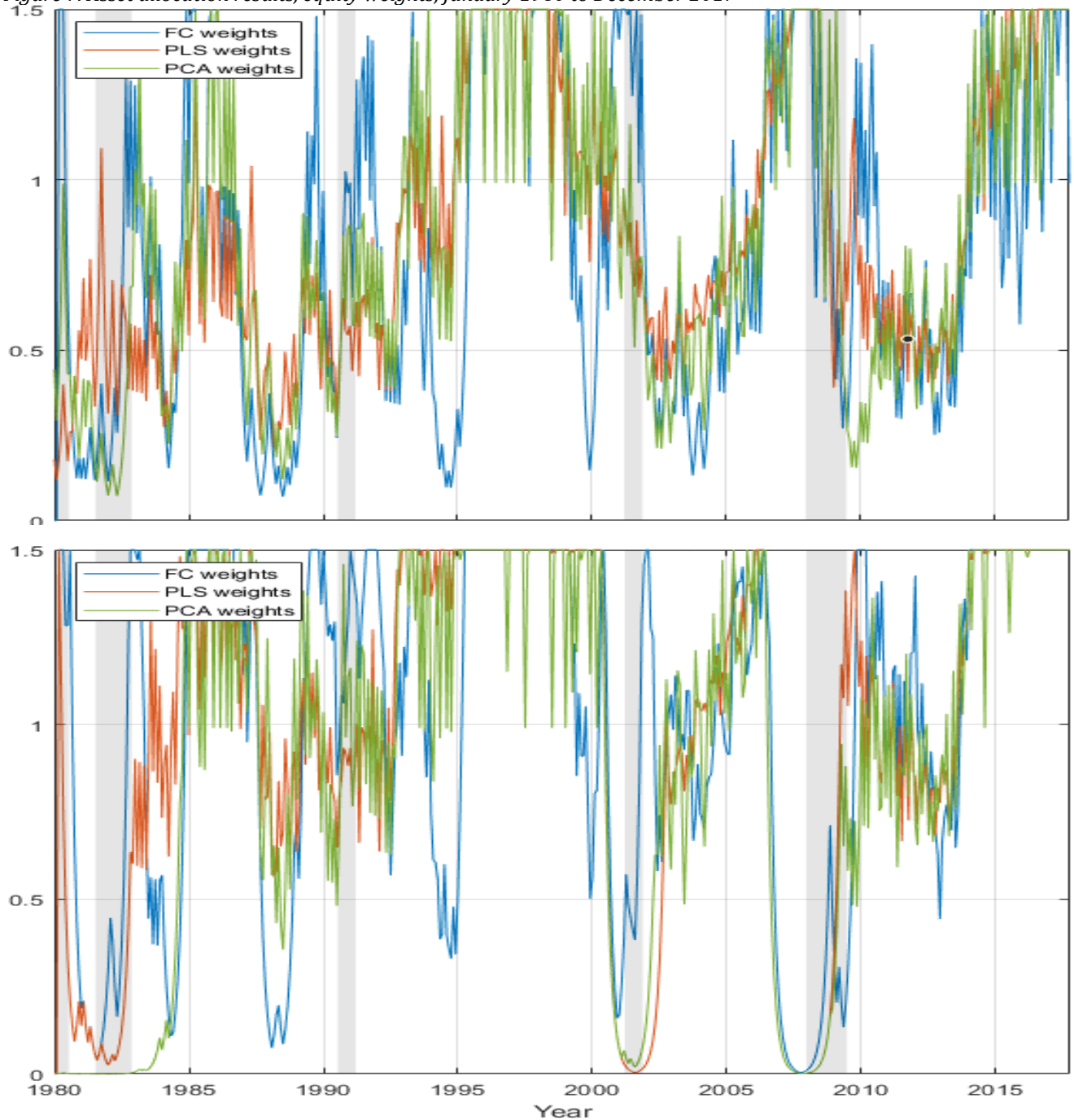
5.2.3 Equity weights and cumulative wealth exercise

To further investigate the behavior of the monthly portfolio based on the different models, the upper part of Figure 7 depicts the equity weights throughout the sample period of the one state models, assuming a risk aversion coefficient of three. First note how the equity weights of the one-state models are quite volatile, with E^{PCA} and E^{FC} having the highest volatility, which is in line with the high turnover rates previously shown in table 8. More importantly, notice how all three predictors (E^{PLS} , E^{PCA} and E^{FC}) fail to disinvest in the equity part of the portfolio right before the start of a recession. For example, at the start of the subprime crisis all three models are fully invested in the equity market with weights of 150%, afterwards during the recession the models start disinvesting in the risky asset in quite a volatile manner while reaching their lowest weights at the end of the recession with weights of respectively 39% (E^{PLS}), 27% (E^{FC}), 16% (E^{PCA}). Thus all of the models fail to adjust in a timely manner for the turning point of a recession, and keep invested in the risky asset throughout the recessionary period leading to poor performance in terms of certainty equivalent returns. These findings are in line with the conclusions of Sander (2018): wrongly estimating the turning points from a expansionary to a recessionary period leads to substantial losses.

The lower part of Figure 7 displays the weights of the state switching models (again assuming a risk aversion coefficient of three). In contrast with the one-state regression models, the switching state models exhibit a much smoother pattern across recessions. More so, note how all three models start disinvesting before a recession occurs, hit their lowest weights at the start of the recession and increase their weights again at the end of the recession. For example, before the start of the subprime crisis all three models start slowly disinvesting in the equity market, with weights decreasing from 150% at the end of 2006 to 0% by the end of 2007. After the start of the recessionary period all three models gently start to increase their investment in the risky asset again, with local highs of approximately 130% (E^{PLS}), 80% (E^{PCA}) and 70% (E^{FC}) at the end of the recession. Across expansions, the state switching models tend to behave more volatile than the one-state

regression models and invest more heavily into the risky asset. This in line with the earlier findings of section 4, where the coefficients of E^{PLS} and E^{PCA} are greater during up states compared to down states which leads to a more flexible investment process across different states. In contrast, the one-state regression models need to estimate one average regression slope across up and down states leading to a more overall conservative investment process.

Figure 7. Asset allocation results, equity weights, January 1980 to December 2017



The upper panel delineates the equity weight for a mean-variance investor with relative risk aversion coefficient of three who optimally allocates across equities and the risk-free asset using a predictive regression excess return forecast based on the one-state regression model of the aligned economic index constructed with the PLS-method E^{PLS} (red), the predictor index based on the PCA-method E^{PCA} (green) or the predictor based on the forecast combination approach E^{FC} (blue). The bottom panel corresponds to the same statistics but assumes return forecast based on the state switching model. The indices, regression coefficients and equity weights are estimated recursively based on information up to the period of forecast formation period t alone. The vertical bars correspond to NBER-dated recessions.

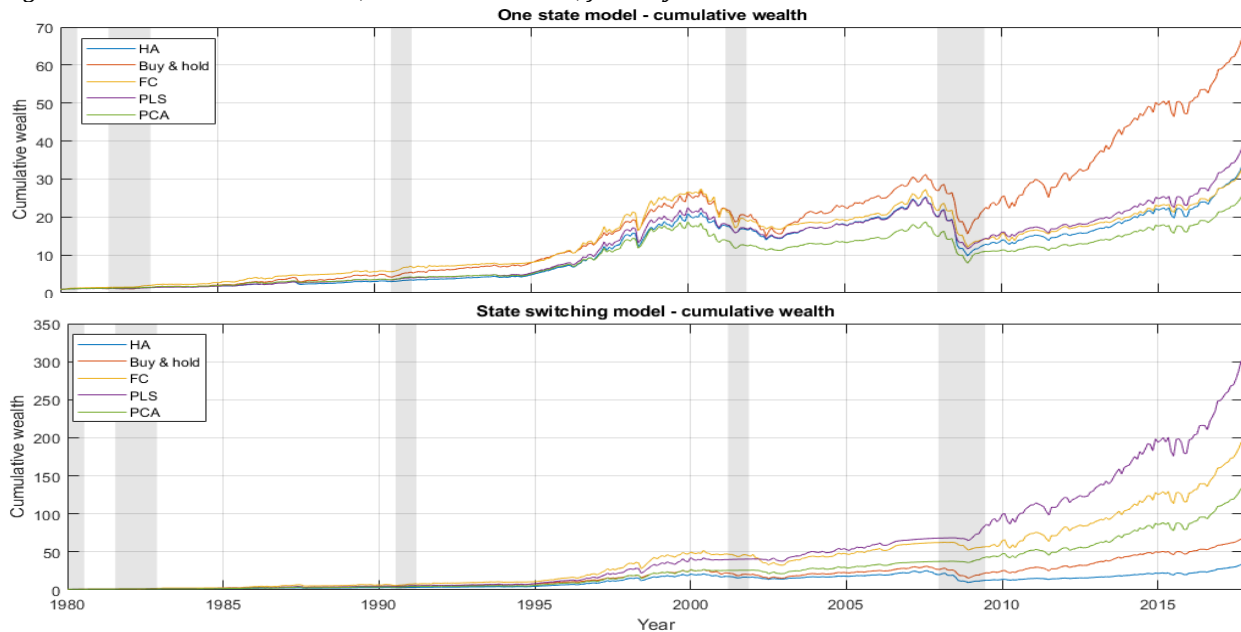
Lastly, to show the potential gains a mean-variance investor can make using the aligned economic index under the state switching model, I consider the following intuitive and simple simulation. First, I examine eight mean-variance investors, with the same utility function, who all have 1\$ to invest in a portfolio consisting of T-bills, the market index or some combination of both. All the investors choose one of the previously analyzed models (that is, the historical average benchmark model, the buy and hold strategy, E^{PLS} +one-state model, E^{PCA} + one-state model, E^{FC} + one-state model, E^{PLS} + switching state model, E^{PCA} + switching state model, E^{FC} + switching state model). Next, the investors start investing in the risky portfolio on January 1980 up to December 2017 using the optimal weights determined by the different models considered. All proceeds are fully reinvested during the investment period. Furthermore, I assume that all eight investors have a risk aversion coefficient of three.

Figure 8 plots the cumulative wealth of the investors across the investment horizon. The upper panel shows the one-state models. First note that, in line with the findings of Figure 7, all investors make substantial losses during the start of the different recessions as they do not disinvest soon enough in the market index. Second, the investor following the simple buy and hold strategy consistently outperforms the other models during expansionary periods yielding a terminal wealth of 68\$ at the end of December 2017. In contrast, the three investors utilizing the one-state forecasting models obtain a terminal wealth of around 35\$, which is about the same as the investor that utilizes the historical average model (34\$). These findings are completely in line with the results of Table 9: Of all the models considered the simple buy and hold strategy yields the highest performance and is the only one to significantly outperform the historical average forecast.

Next, the lower panel of Figure 8 displays the cumulative wealth of the investors exploiting the state switching models. First note how all three switching models are much more resilient against the recessionary turning points with barely any losses being made across recessions. Second, note how all three investors using the switching state models gain drastically more wealth than the investors using the historical average model or the simple buy and hold strategy. More concrete, the investors using the state switching models

accrue a terminal wealth of respectively a remarkable 305\$ (E^{PLS}), 197\$ (E^{FC}) and 135\$ (E^{PCA}) which substantially exceed the gains of the buy and hold investor (68\$) and the historical average investor (34\$). Lastly, note the outperformance of the E^{PLS} investor during expansionary periods, for example, after the last recession of 2008 the E^{PLS} investor increases its wealth from 91\$ to 305\$ (an increase of 235%) while the buy and hold investor increases its wealth from 23\$ to 68\$ (an increase of 195%) which shows the added value of using the aligned economic index under the state switching model even during expansionary periods.

Figure 8. Asset allocation results, cumulative wealth, January 1980 to December 2017



The upper panel delineates the cumulative wealth for a mean-variance investor with relative risk aversion coefficient of three who optimally allocates across equities and the risk-free asset using a predictive regression excess return forecast based on the one-state regression model of the aligned economic index constructed with the PLS-method E^{PLS} (red), the predictor index based on the PCA-method E^{PCA} (green) or the predictor based on the forecast combination approach E^{FC} (blue). The bottom panel corresponds to the same statistics but assumes return forecast based on the switching state model. The indices, regression coefficients and equity weights are estimated recursively based on information up to the period of forecast formation period t alone. The vertical bars correspond to NBER-dated recessions.

6 Concluding remarks

In this paper, I use a regime-switching model with a new aligned economic index to predict excess stock returns. First, I document that the predictive abilities of many predictors are understated due to the use of the traditional one-state regression model, which is likely misspecified for most predictors. In my proposed ex-ante state switching model, which is based on the slope of the yield curve, the predictability of all existing predictors is generally improved, both in-sample and out-of-sample. Next, I propose a new aligned economic index (E^{PLS}) constructed by incorporating 14 well-known fundamental variables from Welch and Goyal (2008), and supplemented by the bond and equity premium, using the PLS method. I find that the E^{PLS} index under the state switching model is a statistically and economically significant predictor of the aggregate stock market over January 1960 through December 2017. In-sample results show that the E^{PLS} index exhibits stronger predictive power than the E^{PCA} index, the E^{FC} index and 16 individual fundamental variables; and that its predictability is both statistically and economically significant. In out-of-sample tests, a predictive regression forecast based on E^{PLS} outperforms the prevailing average benchmark in terms of MSFE by a statistically and economically significant margin. The information contained in the E^{PLS} -based forecast under the state switching model encompasses the information found in forecasts based on the one-state regression model of E^{PLS} , as well as the forecasts based on the E^{PCA} and E^{FC} index under both the one-state and switching state model. Utilizing the E^{PLS} index in a real-time setting adds consistent statistically and economically value to a mean-variance investor across all market states as expressed by the added CER gains and outperforms all of the considered models including the robust buy-and-hold strategy. These findings are not to be underestimated as, in contrary to most existing models which only benefits investors during recessionary periods which are typically short lived, my state switching model adds more practical value to investors as it can be used on a consistent basis.

My work complements early studies by Neely et al. (2014) and many others, who find that fundamental variables play an important role in equity risk premium predictability. Furthermore, there are a number of subjects that are of interest for future research. First, one might try to answer the question of why the aligned economic index predicts future market returns. One can do so by exploring the economic driving force of the predictability of E^{PLS} by implementing stock return decomposition in a similar fashion as Campbell and Shiller (1988) and decompose stock returns in the expected return component, the cash flow news component and the discount rate news component by applying a VAR framework and analyze the relationship of the different components with the aligned index. Second, it will be valuable to extend the analysis of this paper in a cross-sectional setting by testing the predictive capabilities of E^{PLS} on sorted (e.g. by size, Book-to-market, momentum and industry) portfolios to further enhance our understanding of the economic sources of equity risk premium predictability. Lastly, both the state switching model and the aligned economic index E^{PLS} can easily be implemented (individually or together) in other financial markets, such as the bond and futures market, to see whether the same improvements can be documented as in the stock market.

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Appendices

Tables

Table A. 1 Forecasting the excess market return with the hidden Markov model

Predictor	One-state model				Markov switching model								Difference	
	β_1	t-stat	\bar{R}^2	R_{oos}^2	δ_0	t-stat	β_1	t-stat	γ_1	t-stat	\bar{R}^2	R_{oos}^2	\bar{R}^2	R_{oos}^2
DP	-0.06	-1.26	0.18	-0.01	0.87***	2.88	0.07	1.56	-0.08	-1.55	1.22	0.94**	1.04	0.95
DY	0.04	1.04	-0.02	-0.13	0.90***	2.63	0.03	0.54	0.05	1.15	0.83	0.36*	0.85	0.49
EP	0.02	0.67	-0.08	-0.82	0.88***	2.69	0.06	1.36	0.01	0.44	0.73	-0.34	0.81	0.48
DE	-0.07***	-2.35	0.47	-0.67	0.85***	2.73	-0.01	-0.17	-0.06***	-2.64	1.17	-0.82*	0.70	-0.15
RVOL	-1.41***	-4.10	2.03	-2.71	0.87***	2.72	0.23	0.15	-1.43***	-4.16	2.82	-4.84	0.79	-2.13
BM	-0.10*	-1.77	0.32	0.49	0.85***	2.76	0.02	0.23	-0.12*	-1.79	1.13	1.05**	0.81	0.56
NTIS	-0.77*	-1.67	0.34	0.24	0.86***	2.60	-0.44	-0.97	-0.89	-1.44	1.10	0.40*	0.76	0.16
TBL	-1.09***	-2.95	1.07	0.09**	0.93***	2.88	-1.97***	-3.18	-1.02***	-2.46	2.07	1.12***	1.00	1.03
LTY	-1.47***	-2.71	0.91	0.10**	0.86***	2.68	-1.25**	-2.14	-1.55**	-2.06	1.67	0.66**	0.76	0.56
LTR	0.05	1.00	0.08	-1.47	0.87***	2.67	0.04	0.82	0.06	0.77	0.84	-1.16	0.76	0.31
TMS	0.39	1.04	0.01	-0.37	0.89***	2.76	0.37	0.73	0.47	1.05	0.82	0.25**	0.81	0.62
DFY	0.59	0.32	-0.12	-0.52	0.89***	2.64	-0.47	-0.22	1.48	0.62	0.74	-0.22	0.86	0.30
DFR	0.11	1.30	0.17	-0.49	0.87***	2.69	-0.22***	-2.39	0.25**	2.26	2.11	1.10**	1.94	1.59
INFL	0.67	1.27	0.12	-0.02	0.86***	2.67	0.00	-0.01	1.21	1.41	1.09	0.66**	0.97	0.68
CBP	0.11**	2.08	0.71	0.03	0.87***	2.67	-0.02	-0.36	0.19***	2.57	2.10	0.99**	1.39	0.96
LEP	0.05	1.42	0.29	0.18	0.87***	2.70	-0.02	-0.59	0.07	1.60	1.31	1.00**	1.02	0.82
Average	-0.06	-1.26	0.18	-0.01									0.95	0.45

This table reports the results of forecasting the market excess return with popular economic variables by using the standard one-state predictive regression or the Markov switching model of Equation (3). The state indicator, S_t , equals one when the estimated smoothed probability of being in the identified recessionary period is greater than 50% and is zero otherwise. \bar{R}^2 is the in-sample adjusted R-square over the period January 1960 to December 2017. R_{oos}^2 is the Campbell and Thompson (2008) out-of-sample R-square with the first 20 years as the initial training period and with January 1980 to December 2017 as the evaluation period. All t-statistics are the Newey-West t-statistics controlling for heteroskedasticity and autocorrelation. Statistical significance for R_{oos}^2 is based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R_{oos}^2 \leq 0$ against $H_A : R_{oos}^2 \geq 0$. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A. 2 Forecasting across different states and the hidden Markov model

Predictor	One-state model				State switching model			
	MC Up/Down states		Expansions/recessions		MC Up/down states		Expansions/recessions	
	$R_{oos,up}^2$	$R_{oos,down}^2$	$R_{oos,exp}^2$	$R_{oos,rec}^2$	$R_{oos,up}^2$	$R_{oos,down}^2$	$R_{oos,exp}^2$	$R_{oos,rec}^2$
DP	0.13	-0.03	-1.03	2.83***	-0.13	5.69**	-0.57	5.38***
DY	1.26*	-0.36	-0.16	-0.05	-0.66	4.92*	-0.43	2.68*
EP	-1.28	-0.75	-1.06	-0.15	-1.59	5.26**	-0.93	1.4
DE	-7.40	0.43**	-0.26	-1.81	-1.95	4.23***	-0.23	-2.55
RVOL	0.13	-3.18	-4.37	1.88	-6.86	4.24*	-8.19	5.04*
BM	0.40	0.51	-0.21	2.44**	0.26	4.62**	-0.26	4.92***
NTIS	-0.74	0.39	0.33	-0.04	-0.59	4.83*	-0.05	1.73
TBL	-4.04	0.76	0.00	0.33**	0.08*	5.78	0.42**	3.18***
LTY	-2.8	0.58	-2.29	6.75***	-0.14	4.26**	-1.78	7.88***
LTR	-5.52	-0.81	-2.44	1.20*	-1.9	2.16**	-2.62	3.13***
TMS	-0.20	-0.40	-0.09	-1.16	-0.59	4.00*	-0.19	1.53*
DFY	2.88*	-1.08	-0.22	-1.36	-1.29	4.58*	-0.86	1.66
DFR	-1.17	-0.38	-0.22	-1.26	0.48	3.89**	0.72**	2.24
INFL	-1.08	0.16	0.00	-0.08	-0.23	4.65**	-0.03	2.69
CBP	-2.17	0.39	-1.81	5.15***	0.05	5.23*	-1.99	9.79***
LEP	1.86**	-0.10	-0.82	2.95***	0.12	4.95**	-0.67	5.94***

This table reports the results of forecasting the market excess return across different market states with popular economic variables by using the standard one-state predictive regression or the Markov switching model of Equation (3). Month $t + 1$ is defined as a MC downstate if the state indicator, S_t , equals one when the estimated smoothed probability of being in the identified recessionary period is greater than 50% and is defined as an MC upstate otherwise. Month $t + 1$ is defined as a recession if the NBER recession indicator equals one and is defined as an expansion otherwise. $R_{oos,up}^2$; $R_{oos,down}^2$; $R_{oos,exp}^2$ and $R_{oos,rec}^2$ are respectively the Campbell and Thompson (2008) out-of-sample R-square across MC up states, MC down states, expansions and recessions. The first 20 years act as the initial training period, where after the out-of-sample period begins with January 1980 to December 2017 as the evaluation period. Statistical significance for the different Campbell and Thompson (2008) out-of-sample R-squares are based on the p-value of the Clark and West (2007) MSFE-adjusted statistic for testing $H_0 : R_{oos}^2 \leq 0$ against $H_A : R_{oos}^2 \geq 0$. ***, ** and * indicate significance at the 1%, 5%, and 10% levels, respectively.