Studies in Economics and Finance

Industry based equity premium forecasts

Journal:	*Studies in Economics and Finance*
Manuscript ID	SEF-10-2016-0256.R4
Manuscript Type:	Research Paper
Keywords:	Equity premium prediction, Combination of forecasts, Particle filter, Industries

Industry based equity premium forecasts

Nuno Silva

Coimbra University, School of Economics and CeBER

E-mail: nmbgs2@hotmail.com

Phone number: +351 966655019

Adress: Faculdade de Economia da Universidade de Coimbra

Av. Dias da Silva, 165

3004-512 Coimbra, Portugal

1. Introduction

The efficient markets hypothesis, characterized by Fama (1965), states that prices fully reflect all the available information. Later, Grossman and Stiglitz (1980) prove that, if the process of information gathering is costly, prices can not incorporate all the available information. They argue that prices only partially reveal the information because, otherwise, informed investors could not obtain a return that would justify paying the cost of acquiring information. The fact that information is costly and that investors have limited time and resources is closely related to the limited attention hypothesis, according to which investors must choose to analyze only a subset of the available information because they can not process it all. The hypothesis that investors have limited ability to process new information led Hong et al. (2007) to build a model which shows that new information flows slowly across industries. Therefore, there is a positive cross-industry momentum. These authors also perform an empirical analysis that tests if industries predict the broad market index.

Their results show that the number of industries that have significant predictive ability in-sample is higher than the number that would be expected by mere chance.

We extend the work of Hong et al. (2007) in several directions. First, unlike these authors, we analyze the out-of-sample performance of the predictions. Second, we consider predictive regressions with both drifting parameters and stochastic volatility. Finally, we combine the individual forecasts, based on their past performance. Our method generates forecasts that show significant predictive ability, both at the statistical and economic level, which is coherent with the cross-industry momentum hypothesis. Note that, even tough predictability is consistent with the limited attention hypothesis, it may also be due to time-varying risk premia (Bekaert and Hodrick (1992), Narayan et al. (2016) and Aboura and Wagner (2016)) or non-synchronous trading (Camilleri and Green (2014)).

Several authors report that predictive regressions are not stable over time. Pettenuzzo and Timmermann (2011) search for breaks in predictive regressions, based on the dividend yield and the short rate, in the US. They conclude that there is strong evidence of breaks and that they may have a substantial impact on the optimal asset allocation. Paye and Timmermann (2006) also test for the presence of breaks in several developed countries and reached similar results. Henkel et al. (2011) use a regime-shifting model to predict the equity premia in the G7 countries. They show that parameter estimates are different in the two regimes, and that predictability is substantially higher during recessions than during expansionary periods. Dangl and Halling (2012) use a dynamic linear model, which implies gradual coefficients changes, in order to forecast the equity premium in the US. Liu et al. (2015) also use a dynamic linear model and show that their approach generates more accurate forecasts than constant parameter models. They show that the model's predictions generate substantial utility gains for an investor with CRRA preferences. Johannes et al. (2014) propose a model to estimate the relation between the net payout ratio and the equity premium, in the US, that featured both drifting coefficients and time-varying volatility. They conclude that their model delivers statistically and economically significant out-of-sample utility gains, for a power utility investor, unlike traditional predictive models, with constant parameters and volatility, that generate no benefit for the investor. Rapach et al. (2010) argue that model uncertainty and instability limits the ability of individual predictive models. In order to overcome this problem, they combine the predictions of univariate regressions and conclude that the resulting forecasts are smoother and generate both statistical and economic out-of-sample gains. Pettenuzzo and Ravazzolo (2016) apply a new method to combine forecasts. Their results reveal that the combined predictions are more accurate that the ones based on univariate models.

In this paper, we estimate equity premium predictive regressions, based on 32 US industries. We consider models with i) constant coefficients and constant volatility, ii) drifting coefficients and constant volatility, iii) constant coefficients and stochastic volatility and iv) drifting coefficients and stochastic volatility. We combine the forecasts of the industries' predictive regressions, for each model type, according to their past performance. The combined forecasts deliver both statistical and economic gains, relative to the predictions based on the historical mean. The simpler models with constant volatility outperform stochastic volatility models at the statistical level, but stochastic volatility models generate slightly higher economic gains.

The rest of this paper is organized as follows. Section 2 describes the methodology used in the estimation of the predictive regressions and the out-of-sample evaluation measures. Section 3 presents the dataset. Section 4 displays our results, and section 5 presents the main conclusions.

2. Methodology

2.1 The model

It is a well-known fact that stock returns exhibit conditional stochastic volatility. Besides, past research provides extensive evidence that the relation between the equity premium and a set of commonly used predictive variables is not stable over time. Therefore, we choose the following model that contemplates both these features

$$R_{t+1} = \alpha + \beta_0 I_t + \beta_{t+1} I_t + exp(V_{t+1}/2)\varepsilon_{t+1}^R \qquad (1)$$

$$I_{t+1} = \alpha_I + \beta_I I_t + exp(W_{t+1}/2)\varepsilon_{t+1}^I \qquad (2)$$

where R_{t+1} is the equity premium from the end of month t to the end of month t+1, I_{t+1} is the excess return of the industry over the riskless interest rate, V_{t+1} and W_{t+1} are stochastic conditional volatilities for the equity premium and industry equations, respectively, $\varepsilon_{t+1}^R$and ε_{t+1}^I are standard normal errors with correlation ρ.

Traditional models that attempt to predict the equity premium assume volatility is constant, which implies that all observations have the same weight in the estimation. Stochastic volatility models, underweight observations that correspond to high volatility periods, whose information content is presumably lower. We choose a log-stochastic volatility specification (Jacquier et al. (2005)), because of its simplicity and its ability to incorporate volatility clusters

$$V_{t+1} = \alpha_v + \beta_v V_t + \sigma_v \eta_{t+1}^{v} \quad (3)$$

$$W_{t+1} = \alpha_w + \beta_w W_t + \sigma_w \eta_{t+1}^{w} \quad (4)$$

where η_{t+1}^{v} and η_{t+1}^{w} are standard normal independent errors.

We model the time-varying nature of predictability assuming that β_{t+1}, in equation (1), follows an AR(1) process, as in Johannes et al. (2004)

$$\beta_{t+1} = \beta_\beta \beta_t + \sigma_\beta \varepsilon_{t+1}^{\beta} \quad (5)$$

where $\varepsilon_{t+1}^{\beta}$ is a standard normal independent error.

Equations (1) to (5) characterize the general model, which features both drifting coefficients and stochastic volatility (DC-SV model). We also consider other restricted versions of this model, namely:

- Constant coefficients and stochastic volatility (CC-SV model)- β_{t+1} equals zero;

- Drifting coefficients and constant volatility (DC-CV model)- V_{t+1} and W_{t+1} are constant;

- Constant coefficients and constant volatility (CC-CV model)- V_{t+1} and W_{t+1} are constant and β_{t+1} equals zero.

2.2 Particle filter

Particle filters are a class of sequential Monte Carlo methods which are particularly suitable for problems that involve sequential parameter and state learning. They approximate a continuous probability distribution by a discrete distribution of weighted draws named particles. Historically, particle filters were used to estimate sequentially an unknown set of state variables, assuming that the parameters were known[1] (for example, the bootstrap filter, and the auxiliary particle filter). Later, new methods were developed that can be used to estimate both the state variables and the parameters, such as the Storvik (2002) filter and particle learning (Carvalho et al. (2010)), which we use to estimate equations (1) to (5).

The particle learning algorithm requires the computation a set of sufficient statistics, that are deterministically updated, in order to represent the posterior parameter vector. This algorithm can be described as follows

i) Resample $\left\{\tilde{z}_t^{(i)}\right\}_{i=1}^{N}$ from $z_t^{(i)} = (x_t, s_t, \theta)^{(i)}$ with weights $w_t \propto p\left(y_{t+1}|z_t^{(i)}\right)$

ii) Propagate $\tilde{x}_t^{(i)}$ to $x_{t+1}^{(i)}$ via $p\left(x_{t+1}|\tilde{z}_t^{(i)}, y_{t+1}\right)$

iii) Propagate sufficient statistics $s_{t+1}^{(i)} = S\left(\tilde{s}_t^{(i)}, x_{t+1}^{(i)}, y_{t+1}\right)$

iv) Sample $\theta^{(i)}$ from $p\left(\theta|s_{t+1}^{(i)}\right)$

where x_t is the state vector, s_t is the sufficient statistics vector, y_t is the data vector, and θ is the parameter vector. For further details about the estimation procedure for equation (1) to (5), see the internet appendix to Johannes et al. (2014).

In order to implement the algorithm described above, we had to define the prior parameter and state values. We followed Johannes et al. (2014) and we used the three initial years as a training sample.

2.3 Combination of forecasts

Equity premium forecasts, based on a single predictive variable, are known to be unstable and volatile (Goyal and Welch (2003)), which compromises their out-of-sample performance. Rapach et al. (2010) proposed a new approach that combines predictions from univariate models according to their past performance. They show

[1] Lopes and Tsay (2011) provide an excellent review of particle filters in financial econometrics.

that this method generates smoother forecasts, that outperform the predictions based on the historical mean. We draw on their approach and combine the equity premium forecasts from the various industries, in order to generate better performing predictions.

Hong et al. (2007) show that not all industries incorporate useful information for predicting the equity premium. Therefore, unlike Rapach et al. (2010), we choose to restrict the set of industries included in the weighted forecasts, based on their mean-squared prediction error (MSPE).

The procedure we used to generate weighted forecasts is the following

1- We compute the mean-squared prediction errors for industry i, from t_1 until the end of the sample

$$MSPE_t^i = \sum_{s=t_1}^{t-1} \left(R_{s+1} - \hat{R}_{s+1}^i\right)^2 \qquad (6)$$

where $\hat{R}_{s+1}^i$ is the equity premium prediction from industry i, for period $s+1$. The MSPE computation starts at t_1, 120 periods (10 years) after the estimation begins, in order to obtain sufficiently reliable parameter estimates.

2- For each period, from t_2 (t_2=t_1+120 periods) until the end of the sample, we sort the individual predictions according to the reciprocal of their MSPE. Then, we compute the individual predictions' weights, based on the N-best industries (N=1 to 32). When industry i is amongst that N with lowest MSPE at time t, its weight in the combined forecast is

$$w_t^i = \frac{\frac{1}{MSPE_t^i}}{\sum_{n=1}^{N}\left(\frac{1}{MSPE_t^n}\right)} \qquad (7)$$

3- We generate combined predictions. The equity premium combined forecast for t+1, based on the best N industries is

$$\hat{R}_{t+1}^{N} = \sum_{i=1}^{N} w_t^i \, \hat{R}_{t+1}^{i} \tag{8}$$

2.4 Performance evaluation

We use several measures, that complement each other, in order to evaluate the forecasts. We follow Campbell and Thompson (2008) who measure the predictions' performance based on the pseudo-R^2 out-of-sample, which reveals whether the predictions are close to the realized equity premia, in a mean-square sense. The statistical significance of the pseudo-R-squared out-of-sample is tested using the MSPE-adjusted statistic. We also compute the utility gain for an investor that uses the equity premia predictions based on the model, relative to an investor that based his asset allocation decisions on the historical mean (see, for example, Rapach et al. (2010) and Zhu and Zhu (2013)).

The pseudo-R^2 is

$$R_{OOS}^2 = 1 - \frac{MSPE^{mod}}{MSPE^{mean}} \tag{9}$$

where $MSPE^{mod}$ is the mean-squared prediction error from the model and $MSPE^{mean}$ represents the mean-squared prediction error from the historical mean. Note that the pseudo-R^2 out-of-sample are positive whenever the model predictions outperform the forecasts based on the historical mean.

The MSPE-adjusted statistic, proposed by Clark and West (2007), is an approximately normal modified version of McCraken (2007) MSE-F-statistic, which is used to test the null hypothesis that the unrestricted model MSPE is equal to the restricted model MSPE, against the one-sided alternative hypothesis that the former MSPE is lower than the later. The most convenient way to implement this test is to compute

$$\hat{f}_t = \left(R_t - \hat{R}_t^{mean}\right)^2 - \left[\left(R_t - \hat{R}_t^{mod}\right)^2 - \left(\hat{R}_t^{mean} - \hat{R}_t^{mod}\right)^2\right] \qquad (10)$$

where $\hat{R}_t^{mod}$ is the equity premium prediction at month t, based on the model, and $\hat{R}_t^{mean}$ is the equity premium prediction at month t, based on the historical mean. The MSPE-adjusted statistic is calculated by regressing $\hat{f}_t$ on a constant and using the resulting t-statistic for a zero coefficient. The null hypothesis of equal predictive ability is rejected, at the 5% confidence level, if the t-statistic exceeds 1.645 (one-sided test).

The previous performance evaluation measures are statistical in nature and do not necessarily bear a direct relation to the benefits of forecasting the equity premium for an investor. In order to assess the economic value of the predictions, we evaluate the utility gains for a mean-variance investor, who incorporates the models' predictions in his investment decisions. We assume that the investor can choose between two types of investments, the stock market and the riskless asset and, as in Campbell and Thompson (2008), we assume that the fraction of wealth invested in equities can neither exceed 150% nor fall below 0% (no short-selling). The technique that we use to measure these gains is based on commonly used forecasting evaluation procedure for out-of-sample predictions (see e.g. Marquering and Verbeek (2004), Rapach et al. (2010) or Zhu and Zhu (2013)).

A mean-variance investor with coefficient of relative risk aversion γ, who forecasts the equity premium using the historical average, will invest a fraction w_t^{mean} of his wealth in equities, at each month t

$$w_t^{mean} = \frac{1}{\gamma}\frac{\hat{R}_{t+1}^{mean}}{\hat{\sigma}_{t+1}^2} \tag{11}$$

where $\hat{\sigma}_{t+1}$ is an estimate of standard deviation of stock returns based on historical data. Over the out-of-sample period, an investor that follows this strategy obtains an average utility

$$\hat{v}^{mean} = \hat{\mu}_{mean} - \frac{1}{2}\gamma\hat{\sigma}_{mean}^2 \tag{12}$$

where $\hat{\mu}_{mean}$ and $\hat{\sigma}_{mean}^2$ represent the sample average and variance, respectively, over the out-of-sample period, for the portfolio formed using only information about the historical mean.

The optimal portfolio weights for an investor that bases his investment decisions on the predictive model are

$$w_t^{mod} = \frac{1}{\gamma}\frac{\hat{R}_{t+1}^{mod}}{\hat{\sigma}_{N,t+1}^2} \tag{13}$$

where $\hat{\sigma}_{N,t+1}$ is the combination of the standard deviation estimates, for period t+1, from the N-best models, with weights given by equation (7). This investor obtains an average utility, over the out-of-sample period given by

$$\hat{v}^{mod} = \hat{\mu}_{mod} - \frac{1}{2}\gamma\hat{\sigma}_{mod}^2 \tag{14}$$

where $\hat{\mu}_{mod}$ and $\hat{\sigma}_{mod}^2$ are the sample average and variance, respectively, over the out-of-sample period, for the portfolio formed using the predictive model.

The net average benefit per month for an investor who uses the predictive model is

$$\Delta U = \hat{v}^{mod} - \hat{v}^{mean} \qquad (15)$$

and can be interpreted as the average monthly fee that an investor would be willing to pay to have access to the model's forecasts.

3. Data

We obtained monthly returns to the 38 value-weighted industries, from the Kenneth French website, for the period between July 1927 and December 2013. We had to exclude six industries due to missing data, namely, agriculture, forestry and fishing, sanitary services, steam supply, irrigation systems, public administration and other. We also extracted from this website the one-month treasury bill rate (risk-free rate) and the excess return, over the risk-free rate, on the market value-weighted return of all CRSP firms incorporated in the US and listed on the NYSE, AMEX, or NASDAQ (equity premium).

Table 1 presents descriptive statistics for the equity premium and for the excess return, over the risk-free rate, for all the industries. The average monthly equity premium is 0.64%, and the average excess returns for the industries ranges between 0.53% (phone) and 0.94% (oil). The equity premium standard deviation is 5.42%, and it is higher for most industries, reaching 10.11% for chair. The last two columns show that monthly excess returns are widely dispersed, as was expected, given that our sample includes the great depression. The highest monthly excess return across all the industries is 100.37% for rubber, and the lowest reaches -46.51% (chair).

4. Results

We present the main results in three separate subsections. In the first one, we consider the full sample results. In the second subsection, we analyze the results in three subsamples of approximately equal length. Finally, in the last subsection, we compare the predictors' performance in expansion and recession periods.

We do not show the results from all the forecast combinations in order to save space, and because we expect the predictions based on a small number of industries to outperform the forecasts based on a large number of industries [2] (Hong et al. (2007) show that only a small subset of industries presents predictive ability).

4.1 Full sample

Table 2 exhibits the pseudo-R-squared out-of-sample for combinations of forecasts, based on four different models (CC-CV, DC-CV, CC-SV, and DC-SV). All the models considered have a statistically significant predictive ability, with pseudo-R-squared often higher than 1%. The best result overall is obtained for the combination of the two best industries, based on the model with constant coefficients and constant volatility. It is noticeable that forecasts based on the weighted average of a small number of industries (four or less) outperform predictions that use many industries. In particular, predictions that combine all the industries underperform the best forecast by more than 1%.

Rows 9 to 11 of table 2 display the average, maximum and minimum pseudo-R-squared out-of-sample for the individual industries. It is clear that combinations of forecasts, based on a small number of industries, outperform the

[2] The full result are available from the author upon request.

predictions from a single industry. This result is coherent with Rapach et al. (2010) who show that combined predictions are smoother and more reliable.

It is also noticeable that the forecast based on the best industry, according to its past performance, exhibits pseudo-R-squared that exceeds 1% for all models. This fact indicates that industries' predictive ability is persistent, that is, industries that generated good forecasts in the past tend to provide good predictions in the future.

In the bottom of the table, we present the t-value of a test for the difference in means of the out-of-sample R-squared between the models, as in Kinateder et al. (2016). We chose to conduct the test using forecast combinations with up to 5 industries[3]. The test results reveal that models with constant volatility outperform stochastic volatility ones, but there is no significant difference between constant and drifting coefficients models.

Table 3 presents the average net annualized utility gains, for an investor with a coefficient of relative risk aversion equal to 3. All the models generate sizable utility gains, as high as 5%. Generally, weighted forecasts based on only a few industries provide higher utility gains than predictions based on a large number of industries. Stochastic volatility models also tend to deliver higher utility gains than constant volatility models, due to the fact that the former are able to time market volatility and reduce the fraction of wealth invested in stocks during high volatility periods.

[3] We have not considered forecast combinations with more than 5 industries because, as we stressed before, we expect these predictions to outperform the forecasts based on a larger number of industries. The test results based on all the forecasts are similar.

Figure 1 aims to illustrate this phenomenon. The top panel exhibits the difference between the fraction of wealth invested in stocks according to the constant coefficients and stochastic volatility model and the constant coefficients and constant volatility models, for combined predictions based on the 5 best industries, during the last 20 years. The bottom panel shows the squared monthly equity premium. It is clear that the investment strategy, driven by the stochastic volatility model, allocates a smaller fraction of wealth to the stock market during the turbulent periods comprised between 1999 and 2002, and after the recent financial crisis. In the remaining low volatility periods, the investment in the stock market is higher for the stochastic volatility model.

4.2 Subsamples

In this subsection, we analyze the results in three different subsamples. The first subsample ranges from 9/1950 and 12/1953, the second one is comprised between 1/1974 and 12/1993, and the final one covers the period between 1/1994 and 12/2013.

Table 4 exhibits the pseudo-R-squared out-of-sample for the three subsamples. All the R-squared are positive, which indicates that the models outperform predictions based on the historical mean. The evidence of predictive ability is stronger in subsamples one and two than in the last one but, even in the last 20 years, there is some evidence of predictability at the 10% level. Even though the results are similar for the different models, the model that features constant coefficients and volatility presents the best overall performance.

The bottom part of the table reveals that the models DC-CC and CC-SV are dominant in the first subsample, and constant volatility models outperform stochastic volatility ones in the second subsample. In the most recent subsample the simplest model and the most general one, with drifting coefficients and stochastic volatility exhibit the best performance.

Table 5 shows the annualized utility gains for each subsample. Almost all the models deliver positive gains, except the SV-CC model, for the 4 best industries. The economic benefits generated by the constant volatility models are higher during the middle subsample, and the gains for the stochastic volatility models are higher in the first part of the sample. Overall, stochastic volatility models tend to outperform constant volatility ones.

4.3 Expansions and recessions

Rapach et al. (2010), Neely et al. (2014) and Aboura and Wagner (2016) among others, have shown that equity premium predictability, based on a wide set of traditional predictive variables, is strong during recessions and absent in expansions. In this subsection, we tested if our industry based equity premium forecasts present the same pattern. We split the sample into recession and expansion periods, according to NBER data. Tables 6 and 7 present the pseudo-R-squared out-of-sample and the annualized utility gains, respectively, for each subsample.

Predictability is strong in recessions for all the models, with R-squared values often exceeding 5%. In contrast, there is no evidence that any of the models considered is able to forecast the equity premium during expansionary periods. These results are consistent with the ones obtained by the aforementioned authors.

The bottom part of the table shows that the model with constant coefficients and volatility outperforms the remaining models during recessions, but all the models present a similar performance during expansionary periods.

Table 7 reveals that the combined forecast generates positive utility gains, both in recessions and expansions. However, the economic benefit of the predictions is clearly superior in recessions, with gains as high as 9.57%. Stochastic volatility models deliver higher gains in both subsamples relative to constant volatility models.

5. Concluding remarks

In this paper, we show that industries can be used to predict the equity premium. Our equity premium forecasts present an out-of-sample performance that is comparable, or even better, than the predictions from previous studies that use macroeconomic and financial forecasting variables. Furthermore, unlike other studies that report that predictive ability tends to disappear in the most recent years, in ours, it remains significant even in the most recent subsample.

We found that predictability is a persistent phenomenon: industries that perform well in the past tend to provide good equity premium forecasts. Moreover, the combinations of forecasts based on the past performance of the individual industries' predictions deliver considerable utility gains, for a mean-variance investor. Predictability is lower during the last subsample, which was expected, given that the cost of acquiring information has decreased. Grossman and Stiglitz (1980) argue that when the cost of acquiring information decreases, the fraction of investors who decide to be informed is higher, and prices become more informative.

We also found that predictability is strong during recessions, and absent during expansion. This predictability pattern, that has also been reported in previous studies, deserves further research.

References

- Aboura, Sofiana and Wagner, Niklas (2016). Extreme asymmetric volatility: Stress and aggregate asset prices. Journal of International Financial Markets, Institutions & Money, 41, 47-59.

- Bekaert, Geert and Hodrick, Robert J. (1992). Characterizing Predictable Components in Excess Returns on Equity and Foreign Exchange Markets. Journal of Finance, 47 (2), 467-509.

- Camilleri, Silvio John and Green, Christopher J. (2014). Stock market predictability: Non-synchronous trading or inefficient markets? Evidence from the national stock exchange of India. Studies in Economics and Finance, 31 (4), 354-370.

- Campbell, J. Y. and Thompson, S. B. (2008). Predicting the equity premium out of sample: Can anything beat the historical average? Review of Financial Studies, 21 (4), 1509-31.

- Carvalho, Carlos M., Johannes, Michael S., Lopes, Hedibert F. and Polson, Nicholas G. (2010). Particle Learning and Smoothing. Statistical Science, 25 (1), 88-106.

- Clark, T. E. and West, K. D. (2007). Approximately normal tests for equal predictive accuracy in nested models. Journal of Econometrics, 138 (1), 291-311.

- Dangl, T. and Halling, M. (2012). Predictive regressions with time-varying coefficients. Journal of Financial Economics, 106 (1), 157-181.

- Fama, Eugene (1965). The Behavior of Stock Market Prices. Journal of Business, 38, 34-105.

- Goyal, A. and Welch, I. (2008). A comprehensive look at the empirical performance of equity premium prediction. Review of Financial Studies, 21 (4), 1455-1508.

- Grossman, Sanford J. and Stiglitz Joseph E. (1980). On the Impossibility of Informationally Efficient Markets. American Economic Review, 70 (3), 393-408.

- Henkel, S. J., Martin, S. J. and Nardiri, F. (2001). Time-varying short-horizon predictability. Journal of Financial Economics, 99 (3), 560-580.

- Hong, Harrison, Torous, Walter and Valkanov, Rossen (2007). Do Industries lead stock markets? Journal of Financial Economics, 83, 367-396.

- Jacquier, E., Polson, N. G. and Rossi, P (2005). Bayesian analysis of correlated stochastic volatility models. Journal of Econometrics, 122, 185-212.

- Johannes, Michael, Korteweg, Arthur and Polson, Nicholas (2014). Sequential Learning, Predictability, and Optimal Portfolio Returns. Journal of Finance, 69 (2), 611-644.

- Kinateder, H., Hofstetter, B. and N. Wagner (2016). Do liquidity variables improve out-of-sample prediction of sovereign spreads during crisis periods? Finance Research Letters, forthcoming.

- Liu, Li, Ma, Feng and Wang, Yudong (2015). Forecasting excess stock returns with crude oil market data. Energy Economics, 48, 316-324.

- Lopes, Hedibert F. and Tsay, Ruey S. (2011). Particle Filters and Bayesian Inference in Financial Econometrics. Journal of Forecasting, 30, 168-209.

- Marquering, W. and Verbeek M. (2004). The economic value of predicting stock index returns and volatility. Journal of Financial and Quantitative Analysis, 39, 407–429.

- McCracken, M. W. (2007). Asymptotics for the out-of-sample test of Granger causality. Journal of Econometrics, 140 (2), 719-752.

- Narayan, Paresh Kumar, Kannan, Thuraisamy S. and Wagner, Niklas F. (2016). How do bond, equity and commodity cycles interact? Finance Research Letters, forthcoming.

- Neely, Christopher J, Rapach, David E., Tu, Jun and Zhou, Goufu (2014). Forecasting the Equity Risk Premium: The Role of Technical indicators. Management Science, 60 (7), 1772-1791.

- Paye, B. S. and Timmermann, A. (2006). Instability of return prediction models. Journal of Empirical Finance, 13 (3), 274-315.

- Pettenuzzo, D. and Ravazzolo, F. (2016). Optimal portfolio choice under decision-based model combinations. Journal of Applied Econometrics, 31 (12), 1312-1332.

- Pettenuzzo, D. and Timmermann, A. (2011). Predictability of stock returns and asset allocation under structural breaks. Journal of Econometrics, 164 (1), 60-78.

-Rapach, David E., Strauss, Jack K. and Zhou, Guofu (2010). Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy. Review of Financial Studies, 23 (2), 821-862.

- Storvik, G. (2002). Particle filters for state-space models with the presence of unknown static parameters. IEEE Transactions on Signal Processing, 50, 281-289.

- Zhu, X. and J. Zhu (2013). Predicting stock returns: A regime-switching combination approach and economic links. Journal of Banking and Finance 37, 4120–4133.

Figure 1

The top panel exhibits the difference between the fraction of wealth invested in stocks according to the constant coefficients and stochastic volatility model and the constant coefficients and constant volatility models, for combined predictions based on the 5 best industries, during the last 20 years. The bottom panel shows the squared monthly equity premium

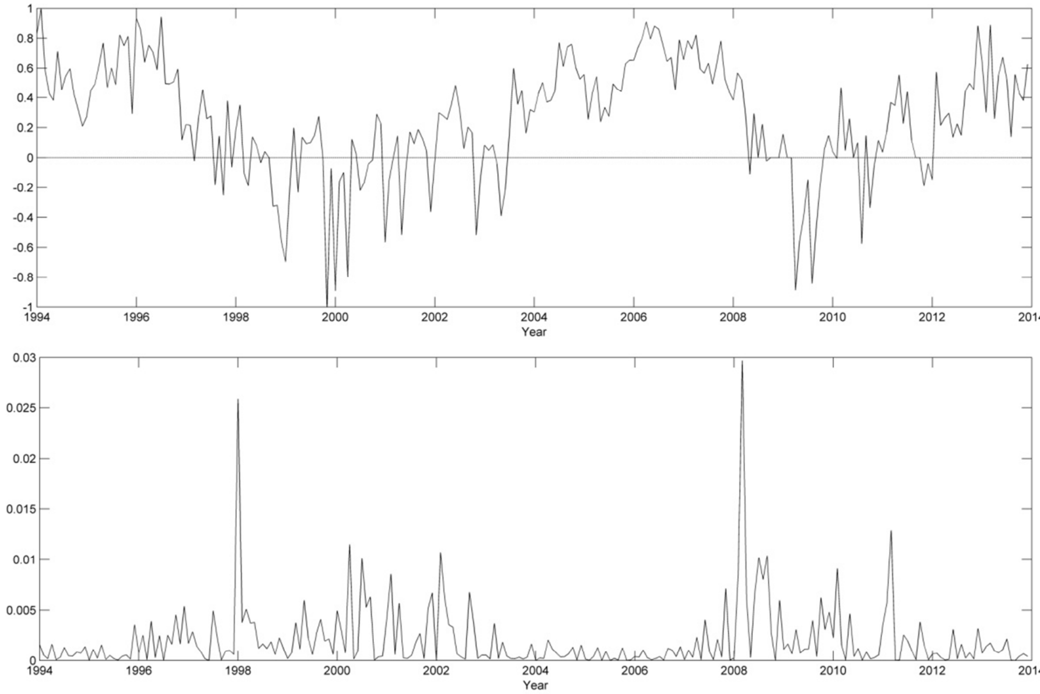

Table 1

Descriptive statistics for the 32 industries' monthly returns and for the equity premium (EP), in %.

	Average	Std.	Max	Min
Mines	0.66	7.49	33.48	-34.32
Oil	0.94	7.82	41.05	-27.57
Stone	0.83	7.94	55.23	-35.22
Cnstr	0.79	9.55	67.27	-38
Food	0.72	4.84	32.43	-27.94
Smoke	0.86	5.83	33.33	-25.32
Txtls	0.70	7.76	59.03	-33.19
Apprl	0.74	8.43	90.01	-33.16
Wood	0.85	7.71	42.73	-34.38
Chair	0.87	10.11	91.68	-46.51
Paper	0.79	7.07	70.37	-31.5
Print	0.63	7.09	53.4	-30.36
Chems	0.76	5.66	47.79	-31.31
Ptrlm	0.83	5.99	39.02	-29.95
Rubbr	0.93	8.78	100.37	-35.7
Lethr	0.70	6.70	41.34	-29.82
Glass	0.71	7.43	50.36	-31.83
Metal	0.65	8.53	80.7	-33.1
MtlPr	0.70	6.24	39.97	-28.48
Machn	0.81	7.25	50.2	-33.73
Elctr	0.79	8.01	59.38	-34.65
Cars	0.82	7.35	71.63	-34.23
Instr	0.72	5.82	27.81	-30.79
Manuf	0.64	7.67	60.14	-35.26
Trans	0.63	7.20	65.35	-34.52
Phone	0.53	4.77	30.79	-21.59
TV	0.98	7.27	29.62	-29.58
Utils	0.60	5.59	42.82	-32.88
Whlsl	0.63	7.31	59.17	-44.63
Rtail	0.74	6.02	42.21	-30.32
Money	0.73	6.89	59.75	-39.62
Srvc	0.78	7.85	51.95	-39.29
EP	0.64	5.42	37.93	-29.07

Table 2

Pseudo R-squared out-of-sample for the models with constant coefficients and constant volatility (CC-CV), drifting coefficients and constant volatility (DC-CV), constant coefficients and stochastic volatility (CC-SV) and drifting coefficients and stochastic volatility (DC-SV), based on the best industry (1), combinations of 2, 3, 4, 5, 10, 15 best industries, and all the industries (All), in %. The rows labeled "Average", "Maximum" and "Minimum" display the average, maximum and minimum pseudo R-squared out-of-sample for the predictions based on the individual industries, respectively (in %). The bottom part of the table exhibits the t-value of a mean difference test between the mean out-of sample R-squared of the model indicated in the column and the mean out-of-sample R-squared of the model indicated in the row, using up to five industries.

a- significant at 1%, b- significant at 5% c- significant at 10%

	CC-CV	**DC-CV**	**CC-SV**	**DC-SV**
1	1.8[a]	1.78[a]	1.52[a]	1.36[a]
2	1.98[a]	1.74[a]	1.79[a]	1.79[a]
3	1.75[a]	1.9[a]	1.49[a]	1.27[a]
4	1.6[a]	1.78[a]	1.49[a]	1.60[a]
5	1.65[a]	1.8[a]	1.24[a]	1.5[a]
10	1.44[a]	1.34[a]	1.02[b]	1.21[a]
15	1.2[a]	1.13[b]	0.83[b]	1.01[a]
All	0.52[c]	0.5[c]	0.49[c]	0.51[b]
Average	0.1	0.01	-1.55	-0.29
Maximum	1.23	1.22	1.30	1.45
Minimum	-1.87	-1.65	-10.8	-2.82
$t_{DC\text{-}CV}$	-0.57			
$t_{CC\text{-}SV}$	5[a]	2.89[b]		
$t_{DC\text{-}SV}$	2.79[b]	2.61[c]	0.03	

Table 3

Annualized utility gains for the models with constant coefficients and constant volatility (CC-CV), drifting coefficients and constant volatility (DC-CV), constant coefficients and stochastic volatility (CC-SV) and drifting coefficients and stochastic volatility (DC-SV), based on the best industry (1), combinations of 2, 3, 4, 5, 10, 15 best industries, and all the industries (All), in %.

	CC-CV	DC-CV	CC-SV	DC-SV
1	2.78	2.78	3.68	2.35
2	2.54	2.35	4.78	3.77
3	2.40	2.40	4.70	3.36
4	2.30	2.32	1.02	3.93
5	2.23	2.39	4.11	3.47
10	1.97	1.90	3.18	3.38
15	1.7	1.67	2.66	3.41
All	1.1	0.98	1.02	2.38

Table 4

Pseudo R-squared out-of-sample for the models with constant coefficients and constant volatility (CC-CV), drifting coefficients and constant volatility (DC-CV), constant coefficients and stochastic volatility (CC-SV) and drifting coefficients and stochastic volatility (DC-SV), based on the best industry (1), combinations of 2, 3, 4, 5, 10, 15 best industries, and all the industries (All), in %. The bottom part of the table exhibits the t-value of a mean difference test between the mean out-of sample R-squared of the model indicated in the column and the mean out-of-sample R-squared of the model indicated in the row, using up to five industries. In each cell, the first value corresponds to the period from 9/1950 to 12/1973, the second value corresponds to the period from 1/1974 to 12/1993, and the last values corresponds to the period from 1/1994 to 12/2013.

a- significant at 1%, b- significant at 5% c- significant at 10%

	CC-CV	**DC-CV**	**CC-SV**	**DC-SV**
1	1.46^{b}/2.23^{b}/1.50^{c}	3.01^{a}/1.83^{b}/0.84	2.19^{b}/1.50^{b}/1.05^{c}	0.21/1.59/1.83^{c}
2	2.01^{b}/2.30^{b}/1.54^{c}	2.10^{b}/2.11^{b}/1.00	2.80^{b}/2.03^{b}/0.76	1.50^{b}/2.33^{b}/1.32^{c}
3	1.81^{b}/2.10^{b}/1.24^{c}	2.47^{b}/2.26^{b}/1.04	2.19^{b}/1.44^{c}/1.00	1.18^{c}/1.74^{b}/0.76
4	1.69^{b}/1.91^{b}/1.13^{c}	2.27^{b}/2.11^{b}/1.00	1.94^{b}/1.52^{c}/1.09	1.48^{b}/1.84^{b}/1.36^{c}
5	1.69^{b}/1.94^{b}/1.24^{c}	2.13^{b}/2.10^{b}/1.19^{c}	1.26^{b}/1.36^{c}/1.06	2.01^{b}/1.32^{c}/1.33^{c}
10	1.87^{b}/1.57^{c}/0.93	1.61^{b}/1.44^{c}/0.99	1.21^{c}/1.11^{c}/0.74	1.63^{b}/1.07^{b}/1.04^{b}
15	1.51^{b}/1.20^{c}/0.94	1.48^{b}/1.11^{c}/0.86	0.94^{c}/0.98^{c}/0.95	1.31^{b}/0.87^{c}/0.93^{c}
All	0.89^{c}/0.40/0.37	0.75/0.45/0.35	0.13/0.87/0.27	0.71/0.51/0.35
t_{DC-CV}	-2.76^{c}/0.13/2.68^{c}			
t_{CC-SV}	-1.57/6.22^{a}/2.63^{c}	1.13/3.73^{a}/0.21		
t_{DC-SV}	1.78/2.44^{c}/0.09	2.44^{c}/1.92/-1.49	1.75^{c}/-2.7^{c}/-1.88	

Table 5

Annualized utility gains for the models with constant coefficients and constant volatility (CC-CV), drifting coefficients and constant volatility (DC-CV), constant coefficients and stochastic volatility (CC-SV) and drifting coefficients and stochastic volatility (DC-SV), based on the best industry (1), combinations of 2, 3, 4, 5, 10, 15 best industries, and all the industries (All), in %. In each cell, the first value corresponds to the period from 9/1950 to 12/1973, the second value corresponds to the period from 1/1974 to 12/1993, and the last values corresponds to the period from 1/1994 to 12/2013.

	CC-CV	**DC-CV**	**CC-SV**	**DC-SV**
1	2.02/3.65/2.67	2.60/3.89/1.86	5.11/2.38/3.54	2.75/1.41/2.87
2	1.98/3.71/1.95	1.84/3.53/1.69	7.08/3.46/3.77	5.45/2.68/3.14
3	1.79/3.18/2.24	1.97/3.28/1.93	7.50/2.71/3.85	5.48/2.13/2.42
4	1.64/3.15/2.12	1.84/3.19/1.93	4.05/-2.35/1.30	2.83/2.73/3.18
5	1.52/2.99/2.18	1.80/3.15/1.93	6.43/1.95/3.90	5.69/1.69/2.97
10	1.52/2.73/1.68	1.39/2.45/1.85	5.23/1.76/2.52	6.02/1.61/2.53
15	1.34/2.13/1.62	1.26/2.07/1.70	4.54/1.42/2.00	5.95/1.40/2.84
All	0.91/1.27/1.11	0.76/1.15/1.02	2.15/0.44/0.46	4.94/0.33/1.82

Table 6

Pseudo R-squared out-of-sample for the models with constant coefficients and constant volatility (CC-CV), drifting coefficients and constant volatility (DC-CV), constant coefficients and stochastic volatility (CC-SV) and drifting coefficients and stochastic volatility (DC-SV), based on the best industry (1), combinations of 2, 3, 4, 5, 10, 15 best industries, and all the industries (All), in %. The bottom part of the table exhibits the t-value of a mean difference test between the mean out-of sample R-squared of the model indicated in the column and the mean out-of-sample R-squared of the model indicated in the row, using up to five industries. In each cell, the first value corresponds to expansions and the second one to recessions.

a- significant at 1%, b- significant at 5% c- significant at 10%

	CC-CV	**DC-CV**	**CC-SV**	**DC-SV**
1	0.01/5.80[a]	-0.43/6.69[a]	-0.66/6.36[a]	-0.99/6.58[a]
2	-0.26/6.96[a]	-0.65/7.08[a]	-0.20/6.23[a]	-0.47/6.84[a]
3	-0.53/6.83[a]	-0.47/7.19[a]	-0.35/5.59[a]	-0.55/5.35[a]
4	-0.58/6.46[a]	-0.51/6.90[a]	-0.18/5.20[a]	-0.13/5.45[a]
5	-0.37/6.32[a]	-0.34/6.60[a]	-0.36/4.81[a]	-0.04/4.93[a]
10	-0.37/5.47[a]	-0.53/5.52[a]	-0.40/4.18[a]	-0.15/4.24[a]
15	-0.57/5.15[a]	-0.66/5.11[a]	-0.54/3.90[a]	-0.16/3.62[a]
All	-0.97/3.86[a]	-0.89/3.60[a]	-1.04/3.89[a]	-0.35/2.44[a]
$t_{DC\text{-}CV}$	1.01/-3.24[a]			
$t_{CC\text{-}SV}$	-0.05/2.26[c]	-1.07/4.42[a]		
$t_{DC\text{-}SV}$	0.3/1.5	-0.26/2.9[b]	0.71/-1.4	

Table 7

Annualized utility gains for the models with constant coefficients and constant volatility (CC-CV), drifting coefficients and constant volatility (DC-CV), constant coefficients and stochastic volatility (CC-SV) and drifting coefficients and stochastic volatility (DC-SV), based on the best industry (1), combinations of 2, 3, 4, 5, 10, 15 best industries, and all the industries (All), in %. In each cell, the first value corresponds to expansions and the second one to recessions.

	CC-CV	DC-CV	CC-SV	DC-SV
1	1.8/7.45	1.64/8.33	2.48/9.57	0.95/9.29
2	1.47/7.75	1.22/7.91	3.88/9.07	2.64/9.25
3	1.31/7.73	1.22/8.13	3.94/8.21	2.3/8.45
4	1.19/7.73	1.18/7.92	0.20/4.88	2.96/8.57
5	1.15/7.49	1.29/7.76	3.54/6.63	2.67/7.22
10	0.97/6.79	0.83/7.07	2.57/5.93	2.87/5.55
15	0.73/6.37	0.67/6.53	2.10/5.16	3.09/4.62
All	0.3/4.89	0.22/4.53	0.35/4.10	2.33/2.15