Empirical essays on stock return predictability using macroeconomic variables and technical indicators

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Kurzfassung

Die Frage, ob Risikoprämien am Aktienmarkt prognostizierbar sind oder nicht, scheint bis heute aufgrund konträrer Ergebnisse unbeantwortet. Eine Vielzahl von empirischen Studien stützt sich bei der Beantwortung dieser Frage auf makroökonomische Informationen als relevante Prognosevariablen. Während die Prognoseeigenschaft dieser Variablen lange Zeit als validiert angesehen wurde, zeigen neuere Studien (z.B. Goyal und Welch, 2008), dass ein solcher Zusammenhang lediglich partiell bestätigt werden kann. Insbesondere weisen eine Vielzahl von makroökonomischen Variablen strukturelle Instabilitäten auf, welche erheblichen Einfluss auf die Prognosegüte der letzten Jahrzehnte ausüben. Diese Arbeit trägt zur existierenden Literatur bei, indem zum einen die Prognosegüte alternativer Prognosevariablen (Indikatoren der Technischen Analyse) und zum anderen jüngst in der Literatur entwickelte Ansätze Anwendung finden.

Kapitel 1 beschäftigt sich mit der Fragestellung, ob und in welchem Umfang makroökonomische Variablen und Indikatoren der Technischen Analyse Instabilitäten hinsichtlich der Prognose von Aktienmarktrenditen aufweisen. Empirische Befunde dieser Studie zeigen, dass lediglich Indikatoren der Technischen Analyse über zeitkonstante Prognosegüte verfügen und einen ökonomischen Nutzen stiften. Kapitel 2 greift die empirischen Befunde von Neely et al. (2014) auf, welche zeigen, dass makroökonomische Variablen und Indikatoren der Technischen Analyse allgemein komplementäre Prognoseeigenschaften am Aktienmarkt aufweisen. Hierzu wird unter Verwendung des Summe-der-Komponenten-Ansatzes von Ferreira und Santa-Clara (2011) untersucht, welche Renditekomponente durch makroökonomische Variablen und/oder durch Indikatoren der Technischen Analyse vorhergesagt werden können. Unsere Ergebnisse bestätigen einen komplementären Informationsgehalt, da beide Informationsarten unterschiedliche Komponenten der Marktrisikoprämie prognostizieren können. Kapitel 3 beschäftigt sich primär mit der Fragestellung, ob eine häufig verwendete Vorauswahl an makroökonomischen Variablen für die aufgezeigte Instabilität verantwortlich ist. In diesem Zusammenhang wird die komplexe Beziehung zwischen Aktienmarktrenditen und makroökonomischen Informationen mit Hilfe neuerer Verfahren, die es ermöglichen eine Vielzahl von potentiell relevanten Informationen zu verwenden, analysiert.

Schlagwörter: Marktrisikoprämien, Prognose, Technische Analyse, Makroökonomische Variablen

Short summary

The question whether stock market risk premia are predictable or not seems to be still unanswered due to contrary findings in the literature. In reply to this question, a large bulk of empirical studies makes use of macroeconomic information as relevant predictor variables. Although the predictive performance of these variables have been seen as validated for a long time, more recent studies (e.g. Goyal and Welch, 2008) show that this relationship can solely partially be confirmed. In particular, macroeconomic variables exhibit some structural instability having a strong influence on the forecast performance, especially in more recent years. This thesis contributes to the existing literature by applying alternative predictor variables (technical indicators) as well as different forecasting approaches, which have been developed in the latest finance literature.

Chapter 1 pays attention to the question whether, and if so to which extent, the forecast performance of macroeconomic variables and technical indicators is affected by potential instability issues. Empirical results show that solely technical indicators can predict the equity premium quite stable over time and indicate persistent economic value. Chapter 2 incorporates findings proposed by Neely et al. (2014) who show that macroeconomic variables and technical indicators provide complementary information for equity risk premium prediction. Here, we use of the sum-of-parts approach, developed by Ferreira and Santa-Clara (2011), to verify which equity premium component can be predicted by macroeconomic and/or technical indicators. Results confirm that both predictor groups contain complementary information by forecasting different components of the equity premium. The primary objective of Chapter 3 is to verify whether a preselection of macroeconomic information (commonly done in the literature) is responsible for the lack of time-consistent predictability. In this context, the complexity between stock market risk premia and macroeconomic variables is analyzed by evaluating recently developed forecasting approaches which enable forecasters to consider a large amount of potentially relevant information.

Keywords: Equity risk premium, forecasting, technical indicators, macroeconomic variables

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Preface

Since many years, stock markets have been one of the most commonly used investment opportunities for institutional and private investors. Every day, media agencies inform on recent developments of stock markets and, therefore, provide information about stock markets' performance, business cycle outlooks and/or alternative investment strategies. Although it is generally accepted that expected stock returns are crucial variables for academic researchers and practitioners alike, comparatively little is known about the underlying data-generating process surrounding stock returns. Unfortunately, expected stock returns are unobservable. As a consequence, investors face the challenge of precise estimates of future stock price movements. Knowledge about future evolvements is of general interest for practitioners because stock market return forecasts are related to real-time asset allocation decisions and, hence, may affect investments' performance. On the other side, since a long time academics have tried to explore the key driving forces of stock prices for a better understanding why and how equity prices move.

One of the most crucial challenges seems to be the construction of forecasting models, including prediction model selection without knowing the true data-generating process for returns. From a general point of view, one should expect that the equity premium, i.e. the difference between stock market index returns and returns on a risk-free bill, is predictable given its relation with economic conditions. Empirical studies show that the equity premium moves countercyclical, i.e. being high during recessions and low at business cycle peaks. Hence, Fama and French (1989), Campbell and Cochrane (1999), and Cochrane (2007) mention that suitable predictors for excess returns should be correlated with economic conditions. Over the last decades this was the conventional wisdom in academic research by making use of macroeconomic variables as predictors. More recently, there is increasing evidence that stock returns are not predictable at all (Bossaerts and Hillion, 1999; Goyal and Welch, 2003, Timmermann, 2008) or at least partially (Goyal and Welch, 2008). Whenever forecasts are conducted, numerous problems arise including model uncertainty, unstable forecasting relationships and, most crucially, poor out-of-sample performance.

In this thesis, I consider the general question whether U.S. stock returns are predictable and provide new insights into central questions regarding equity premium prediction models. In particular, **Chapter 1** examines the forecast stability of economic and technical indicators. In a seminal work, Goyal and Welch (2008) show that most commonly used economic variables provide highly unstable forecast, and that the prediction performance of nearly all predictors vanish after the 1970s. This result offers the opportunity that other variables might be better suited to predict future stock returns. Most recently, Neely et al. (2014) highlight that technical indicators, which are commonly used by practitioners, provide forecasting gains exceeding the performance of macroeconomic variables. In addition, combining both predictor groups significantly improves equity premium forecasts by supplying complementary information. This chapter contributes to existing studies by analysing the structural stability of forecasting models based on macroeconomic variables, technical indicators, and both predictor groups. In detail, it examines whether the predictive ability is affected by an empirical relationship concentrated in the distant past and their possible disappearance thereafter. Applying conventional approaches support the view of structural instability, but not in a consistent way. Therefore, this chapter extends previous analysis by using a rolling-recursive estimation approach which combines the advantages from rolling and expanding window estimation models and evaluates the prediction performance over hundreds of overlapping sub-periods. Findings show that technical indicators deliver stable economic value in predicting the U.S. equity premium over the out-of-sample period from 1966 to 2014. Results tentatively improve over time and beat alternatives over a large continuum of sub-periods. By contrast, economic indicators work well only until the 1970s, but thereafter they lose predictive power. Translating the predictive power of technical indicators into a standard investment strategy delivers an annualized average Sharpe ratio of 0.55 p.a. (after transaction costs) for investors who entered the market at any point in time.

Chapter 2 extends preceding analysis by proposing a refined way of forecasting the equity premium. Following Ferreira and Santa-Clara (2011), this chapter makes use of the sum-of-parts (SOP) approach. This method firstly decomposes the equity premium into its four components: growth rates of the price-earnings ratio, the growth in earnings, the dividend-price ratio, and the return of the risk-free rate. Secondly, Ferreira and Santa-Clara (2011) highlight that separating predictions of the components of the equity premium can provide advantageous results – compared to the conventional approach of predicting the equity premium as a whole – by adopting statistical and economic constraints. Obviously, this decomposition also supplies the opportunity to better understand drivers of the equity premium. Taking this consideration into account, this chapter examines whether macroeconomic and technical indicators capture different information on total stock market excess returns and provides some further indication about their complementary information content. Results reveal that economic and technical indicators catch different information on the equity premium. While the overall predictive performance of economic variables is largely determined by the predictability of the price-earnings growth rate, technical indicators have statistically significant predictive ability for the earnings growth rate. By exploiting these insights, this chapter introduces into the extended-SOP (ESOP) approach predicting equity premium components by those indicators which seem to be mostly related to each component. Applying this allocation strategy exhibits statistically and economically significant superior predictive power than previously used forecasting strategies. Moreover, this chapter provides some indication that macroeconomic variables and technical indicators inform on different aspects of the business cycle emphasizing their complementary character for equity premium forecasts.

Chapter 3 expands the traditional consideration of equity premium predictability by returns to a size portfolio (SMB), a value portfolio (HML), and a momentum portfolio (MOM) as further risk factors (Fama and French, 1993, Carhart, 1997). Given the conventional wisdom that stock market risk premia are determined to a great extend by their exposure to macroeconomic risks, a variety of studies casts doubt on the view that stock returns are predictable by economic variables (see, e.g., Goyal and Welch, 2003, 2008; among others). Earlier empirical evidence shows that most prediction models suffer from a loss of information, model uncertainty, and structural instability by relying on low-dimensional information sets. Obviously, the relation between the macroeconomic situation and the stock market is difficult to grasp by relying on low-dimensional forecasting models. Nowadays, numerous variables are available for model specification leaving the question unanswered which variables are the most relevant ones for stock return predictability. This chapter addresses the inherent complexity to this relation and evaluates the predictive ability of various recently refined pooling strategies which handle these issues by incorporating information from many potential predictor variables simultaneously. In detail, this chapter investigates whether pooling strategies that (i) combine information; (ii) combine individual forecasts are useful to predict U.S. stock returns, i.e. market excess return, size, value, and momentum premium. Results show that methods combining information have remarkable in-sample predictive ability. However, the out-of-sample performance suffers from highly volatile forecast errors. Forecast combinations face a better bias-efficiency trade-off yielding a consistently superior forecast performance for the market excess return and the size premium even after the 1970s.

References for Preface

Bossaerts, P., and P. Hillion (1999), Implementing statistical criteria to select return forecasting models: What do we learn? *Review of Financial Studies* 12 (2), 405-428.

Campbell, J.Y., and J.H. Cochrane (1999), By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107 (2), 205-251.

Carhart, M. M., (1997), On persistence in mutual fund performance, *Journal of Finance* 52 (1), 57-82.

Cochrane, J.H. (2007), Financial markets and the real economy, in R. Mehra, eds.: *Handbook of Equity Premium*, Elsevier, Amsterdam.

Fama, E.F., and K.R. French (1989), Business conditions and expected returns on stocks and bonds, *Journal of Financial Economics* 25 (1), 23-49.

Fama, E. F., and K. R. French (1993), Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33 (1), 3-56

Ferreira, M. A., and P. Santa-Clara (2011), Forecasting stock market returns: The sum of the parts is more than the whole, *Journal of Financial Economics* 100 (3), 514-537.

Goyal, A., and I. Welch (2003), Predicting the equity premium with dividend ratios, *Management Science* 49 (5), 639-654.

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

Neely, C.J., D. Rapach, J. Tu, and G. Zhou (2014), Forecasting the equity risk premium: The role of technical indicators, *Management Science* 60 (7), 1772-1791.

Timmermann, A. (2008), Elusive return predictability, *International Journal of Forecasting*, 24 (1), 1-18.

Chapter 1

Equity premium prediction: Are economic and technical indicators unstable?

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Chapter 2

Predicting the equity premium via its components

Joint work with

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2.1 Introduction to Chapter 2

Academics and practitioners alike are highly interested in predicting the equity premium. While the consensus wisdom seems mixed whether the equity premium is predictable at all (see Spiegel, 2008), forecasters continuously search for models to improve predictability. From a general point of view, academics are motivated by the fact that successful prediction models offer a deeper insight into the empirical risk-return trade-off and stock market efficiency. Practitioners, in some contrast, face the challenge of finding beneficial investment strategies which strongly depends on their ability to predict future return movements. In any case, the degree of predictability that has been reached by applying commonly used macroeconomic indicators is very limited (see Rapach and Zhou, 2013, for an overview), and also the stability of predictions has been questioned (Goyal and Welch, 2008).

Therefore, we prefer a different route from most literature and follow the recent innovative approach of Ferreira and Santa-Clara (2011). They show in their sum-of-parts (SOP)-approach that separate predictions of the components of the equity premium can provide advantageous results compared to the conventional approach of predicting the equity premium as a whole. This decomposition also provides the opportunity to better understand drivers of the equity premium. When it comes to predicting these components, Ferreira and Santa-Clara (2011) use one reasonable procedure for each component, i.e. basically relying on either macroeconomic indicators or a time-series process. Obviously, this leaves the opportunity open that other predictors may work even better. In particular, the universe of technical indicators has not been applied by them, whereas some studies indicate that these indicators may provide value (Brock et al., 1992; Lo et al., 2000; Zhu and Zhou, 2009; among others).

Combining these two ingredients, i.e. decomposing the equity premium and applying a wider range of forecasting variables, we create a new extended SOP (i.e. the ESOP)-strategy with a promising result: predictability improves beyond the results of earlier comparable work. For example, the average annualized Sharpe ratio of the ESOP-strategies over our full out-of-sample period from 1966 to 2014 is 0.49, and thus clearly better than the historical average with 0.20, the original SOP-strategy with 0.25 and the conventional pooling across indicators with 0.35. Moreover, we get a first intuition why this procedure may work better than common approaches, i.e. because components are predicted differently: earnings growth is predicted by technical indicators, and the price-earnings multiple is predicted by macro indicators.

Furthermore, we analyze whether the predictive content of macroeconomic and technical indicators can be related to different macroeconomic fundamentals underlying stock return movements. We find indeed specific predictive ability supporting the importance of our ESOP-strategy: While technical indicators provide statistically significant out-of-sample forecast performance for industrial production (see Cochrane, 2007), macroeconomic indicators are also informative for inflation forecasts (see Feldstein, 1980).

Our study is conventional by purpose regarding its data and procedures. That means we use standard data provided by Goyal and Welch (2008) for calculations based on the S&P 500. Moreover, we use the standard predictive regression framework. As inputs we rely on the macroeconomic indicators as used by Goyal and Welch (2008) and many others, and regarding the technical indicators we strictly use the rules of Neely et al. (2014). Finally, the formation of pooling strategies and the calculation of economic values of strategies are all widely used in the literature. Consequently, we can reproduce earlier results in the literature and thus isolate where our new result comes from: It is due to the complementary information content of economic and technical indicators with respect to different stock market return components.

Our research belongs to a large literature which aims for explaining and predicting the equity premium, or relatedly the stock market return. Recent studies document that model uncertainty and parameter instability have a large impact on the forecasting performance as highlighted by Goyal and Welch (2008). To account for these problems, we follow studies which use forecast combinations (Rapach et al., 2010), economically motivated restrictions (Campbell and Thompson, 2008; Ferreira and Santa-Clara, 2011) or diffusion models, such as relying on a principal components (Ludvigson and Ng, 2007; Kelly and Pruitt, 2013).

This chapter continues with seven sections: Section 2.2 describes the methodology applied and Section 2.3 provides data and descriptive statistics. Summary results on forecasting performance of various indicators, informing also about their use in predicting the components of the sum-of-parts (SOP)-approach, are shown in Section 2.4. Based on this, we introduce extended SOP-forecasting strategies (ESOP-strategies) in Section 2.5. Section 2.6 shows extended results on the ESOP-strategy, Section 2.7 contains robustness tests and Section 2.8 concludes.

2.2 Methodology

We first follow the line of Ferreira and Santa-Clara (2011) by describing the decomposition of the equity premium (Section 2.2.1). Then, we briefly outline our standard forecasting approach (Section 2.2.2).

2.2.1 Equity premium decomposition

Analyzing whether a specific variable or a set of variables have predictive ability for the equity premium is typically determined by the following predictive regression

$$r_{t+1} = \alpha + \beta x_t + \varepsilon_{t+1} \tag{2.1}$$

where r_{t+1} is the return on a stock market index in excess of the risk-free rate, x_t characterizes the predictor variable being observable at time *t* and ε_{t+1} is the corresponding unexplained return innovation. Following this regression setting, recent research focuses on the overall prediction performance of specific variables, or more general, advanced forecasting strategies. From this point of view, little can be said about the predictability of underlying stock return components which jointly determine the constantly evolving data-generating process for stock returns.

To account for this missing fact, we follow Ferreira and Santa-Clara (2011) and decompose the total market return into three components. In detail, the total stock market return (including dividends) is determined by the sum of capital gains and the dividend yield.

$$1 + R_{t+1} = 1 + CG_{t+1} + DY_{t+1} = \frac{P_{t+1}}{P_t} + \frac{D_{t+1}}{P_t} \tag{2.2}$$

R_{t+1} is the total stock market return from the end of month *t* to the end of month *t+1*. Capital gains and the dividend yield are defined by CG_{t+1} and DY_{t+1}, respectively. While the capital gain component equals the percentage change in the stock price index, the dividend yield is defined as dividend payments per share over a one-month holding period.

By making use of conventional stock valuation methods, price changes of stock indices can be related to changes in stock price multiples and the growth of the corresponding fundamental. To maintain comparability with Ferreira and Santa-Clara (2011) we further decompose the capital gain component into the price-earnings multiple growth rate and the earnings growth rate.

$$CG_{t+1} = \frac{P_{t+1}}{P_t} = \frac{P_{t+1}/E_{t+1}}{P_t/E_t}\frac{E_{t+1}}{E_t} = \frac{M_{t+1}}{M_t}\frac{E_{t+1}}{E_t} = (1 + GM_{t+1})(1 + GE_{t+1}) \quad (2.3)$$

E_{t+1} denotes the stock index fundamental, i.e. earnings per share and M_{t+1} is the price-earnings multiple. Then, total stock market capital gains are equal to the price-earnings multiple growth rate (GM_{t+1}) and the earnings growth rate (GE_{t+1}).

For the dividend yield component we make use of the following notation

$$DY_{t+1} = \frac{D_{t+1}}{P_t} = \frac{D_{t+1}}{P_{t+1}}\frac{P_{t+1}}{P_t} = DP_{t+1}(1 + GM_{t+1})(1 + GE_{t+1}), \quad (2.4)$$

where DP_{t+1} is the dividend-price ratio. If we sum up both expressions, we end up with the following stock return decomposition, where the total stock market return is the product of the growth rates of the price-earnings ratio, the growth in earnings and the dividend-price ratio.

$$1 + R_{t+1} = (1 + GM_{t+1})(1 + GE_{t+1})(1 + DP_{t+1}) \quad (2.5)$$

Using logs and taking the (log) return on the risk-free rate into consideration, we receive our final expression which completely disaggregates the equity premium into its four components.

$$r_{t+1} = gm_{t+1} + ge_{t+1} + dp_{t+1} - rf_{t+1} \quad (2.6)$$

2.2.2 Forecasting approach

As previously mentioned, our primary objective is not the determination of the equity premium prediction performance per se, our research is based on the identification of different diving forces for individual equity premium components, according to equation (2.6). In this context, we make use of five different predictive specifications. For comparison purposes, we start with commonly used predictive regressions according to equation (2.1), where the equity premium is regressed on one-month lagged predictive variables. Additionally, recalling equation (2.6), obtained predictions for the equity premium are equal to the sum of individual component forecasts. Thus, a natural way to analyze whether different predictors capture different information of total stock market excess returns is to forecast each component separately.

$$\begin{aligned} gm_{t+1} &= \alpha_{gm} + \beta_{gm} x_t + \varepsilon_{gm_{t+1}} \\ ge_{t+1} &= \alpha_{ge} + \beta_{ge} x_t + \varepsilon_{ge_{t+1}} \\ dp_{t+1} &= \alpha_{dp} + \beta_{dp} x_t + \varepsilon_{dp_{t+1}} \\ rf_{t+1} &= \alpha_{rf} + \beta_{rf} x_t + \varepsilon_{rf_{t+1}} \end{aligned} \tag{2.7}$$

Based on this regression setup, we will employ various specifications to determine where the forecasting ability of various predictor variables comes from.

Moreover, we use six recently refined pooling strategies which are able to incorporate information from many predictive variables simultaneously (see Rapach and Zhou, 2013, and Huang and Lee, 2010, for an overview and discussion) and which are less affected by model uncertainty and parameter instability (Pesaran and Timmermann, 1995; Hendry and Clements, 2004; Timmermann, 2006). In this study, we look at the prediction performance of forecast combination strategies, successfully employed by Rapach et al. (2010).

We consider six pooling strategies, i.e. (i) mean, (ii) median and (iii) trimmed-mean combinations. Additionally, we construct forecast combination weights based on individual variables' past forecast performance, yielding a discounted MSFE (mean square forecast error) combination forecast. For this purpose we follow Rapach et al. (2010) and use DMSFE combination weights based on a discount factor of 1 (strategy iv) and 0.9 (strategy v), respectively. A discount factor of 1 equally weights the entire history of forecast errors, while a discount factor of 0.9 assigns higher weights to the most recent forecast performance. As a final pooling strategy (vi) we follow Stock and Watson (2002), Ludvigson and Ng (2007, 2009) and use principal components. The identification of latent common components is another appropriate approach when dealing with large datasets of possible predictor variables.

2.3 Data and descriptive statistics

Equity premium: In our empirical application, we use the data provided by Goyal and Welch (2008) and define the monthly (log) equity premium as the continuously compounded stock return of the S&P 500 (including dividends) minus the log return on a risk-free bill. Regarding the equity premium decomposition, our dataset also covers monthly averages of dividends and earnings paid on the S&P 500 over the previous 12 months to compute individual stock return components. Table 2.1 reports corresponding summary statistics over the sample period from December 1950 through December 2014.

Table 2.1: Summary statistics: Equity premium and excess return components

Return component	Mean	Std.	Skew.	Kurt.	JB p-val.	AC(1)	AC(2)	AC(3)
Panel A: Univariate statistics								
gm	0.15	6.09	-1.34	40.86	0.00	0.36	0.25	0.23
ge	0.47	4.80	1.99	96.76	0.00	0.75	0.60	0.48
dp	0.27	0.11	0.56	2.93	0.00	0.99	0.97	0.96
rf	0.37	0.25	0.87	4.18	0.00	0.99	0.97	0.96
r	0.52	4.20	-0.67	5.42	0.00	0.06	-0.03	0.04
Panel B: Correlations								
	gm	*ge*	*dp*	*rf*	*r*			
gm	1							
ge	-0.73	1						
dp	0.03	-0.08	1					
rf	0.00	-0.04	0.38	1				
r	0.62	0.09	-0.04	-0.09	1			

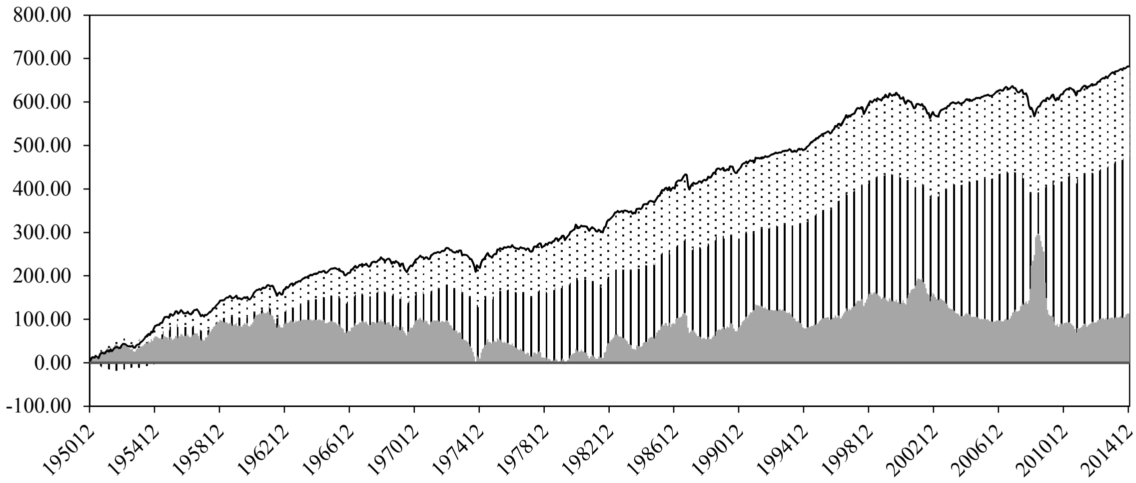
Notes: The table shows summary statistics of the (log) equity premium (*r*) defined as the S&P 500 return including dividends in excess of the risk-free rate (*rf*) and corresponding stock market return components (defined in Eq. 6), covering the growth in price-earnings ratio (*gm*), the growth in earnings (*ge*), and the dividend-price ratio (*dp*). Reported statistics in Panels A include the mean, standard deviation (Std.), skewness (Skew.), kurtosis (Kurt.), p-values for the Jarque-Bera test for normality (JB p-val), and first (AC(1)) to third (AC(3)) order autocorrelation coefficients over the sample period 1950:12 – 2014:12. Panel B shows the correlation structure between the equity premium and corresponding excess return components.

In a nutshell, Table 2.1 shows that the average monthly equity premium is about 0.52% with a monthly standard deviation of 4.20. Individual return components are related in the following way. The stock market return is predominantly driven by earnings growth and the dividend-price ratio; taken both factors together accounts for approximately 85% of the level of the total average stock return. The return of the risk-free bill is 0.37% per month, yielding an excess return which is on average 140% in relation to the risk-free rate.

However, excess return volatility is mainly driven by the growth rate in the price-earnings ratio and the growth rate of earnings. Thus it seems that the dividend-price ratio and the risk-free rate only play a minor role in explaining time-variations of stock market returns. First to third-order autocorrelation coefficients confirm these findings.[1]

Besides full sample statistics, Figure 2.1 gives insight into the equity premium constitution over time. For simplicity, we solely focus on stock market return components, i.e. neglecting the risk-free rate.

Figure 2.1: Cumulative stock return over time



Notes: This figure shows the relative contribution of stock return components to the total stock market return (S&P 500 in log returns) over time. The black line represents the pathway of the cumulative stock market return over the full sample 1950:12-2014:12. The grey shaded area corresponds to the realized price-earnings growth rate (*gm*), the black dashed area represents the earnings-growth component (*ge*), and, finally, the dotted area represents the dividend-price ratio.

At a first glance, Figure 2.1 confirms previously described statistics; however, the equity premium constitution exhibits large variation over time. While earnings growth and the dividend-price ratio reveal consistent growth over time, the growth rate of the price-earnings ratio indicates a more constant behavior with a sharp decline in the 1970s. In relation to the pathway of the cumulative equity premium, Figure 2.1 shows that the price-earnings multiple especially determines total stock market returns at the beginning of the sample but their contribution declines throughout time.

Predictor variables: In a recent study, Neely et al. (2014) contribute to the literature on equity premium prediction by analyzing the predictive ability of technical indicators in addition to commonly used macroeconomic variables. They find that technical trading rules deliver statistically and economically significant forecasting gains. We follow this consideration to specify our dataset of potential predictor variables. In detail, we make use of 14 macroeconomic and 14 technical indicators which have been used earlier in the equi-

[1] As mentioned by Ferreira and Santa-Clara (2011), the growth rate of earnings indicates persistent behavior which is strongly related to a substantial overlap of data to measure monthly earnings.

ty premium forecasting literature (e.g. Goyal and Welch, 2008; Rapach and Zhou, 2013; Neely et al., 2014). Their exact definitions are available in these references and are repeated for convenience in the Data appendix to Chapter 2. Summary statistics for individual predictors are reported in Appendix I.b (Table A.2.1).

Economic variables have been used extensively in the related literature because stock returns are closely linked to state variables of the real economy. In this respect, our set of 14 macroeconomic indicators covers: indicators informing about stock characteristics like the dividend-price ratio; dividend yield; earnings-price ratio; dividend-payout ratio; equity risk premium volatility; book-to-market ratio; net equity expansion, and interest related variables like the treasury bill rate; long-term yield; long-term return; term spread; default yield spread; default return spread and the inflation rate.

Technical trading rules on the other side are commonly used by practitioners. However, relatively few studies evaluate the profitability of technical indicators, including Brock et al. (1992), Brown et al. (1998), Lo et al. (2000), and more recently Zhu and Zhou (2009), Fang et al. (2014) and Neely et al. (2014). In order to avoid any data mining concerns we follow Neely et al. (2014) and apply 14 technical indicators based on three popular trading strategies, i.e. moving-average rules, momentum rules and volume-based rules. All have in common, that each month these indicators generate a buy ($S_{i,t} = 1$) or a sell ($S_{i,t} = 0$) signal depending on recent stock price movements.

2.4 Forecasting the equity premium and its components

In this section, we present first results. These show that the in-sample and out-of-sample predictability of the equity premium in our relatively recent sample period fits into the literature and thus provides a useful benchmark for the later forecasting examinations (Section 2.4.1). Moreover, we find an interesting pattern when predicting the equity premium components with macroeconomic and technical indicators (Section 2.4.2).

2.4.1 In-sample and out-of-sample predictability of the equity premium

To make our results directly comparable to previous studies, we first determine the in-sample and the out-of-sample predictive ability of above described pooling strategies (see Inoue and Kilian, 2004, and Cochrane, 2008).[2] We use an expanding estimation window with an initial estimation period of 15 years for parameter identification (Hansen and Timmermann, 2012). These parameter estimates are then used to conduct out-of-sample forecasts over the evaluation period from 1966:1 through 2014:12. Statistical forecast evaluation metrics are based on in-sample and out-of-sample R-squares to compare the prediction performance of previously described pooling strategies with the forecast performance of the historical average which serves as the benchmark model (assuming β=0). Like the in-sample R-square, the out-of-sample accuracy of predictive regression forecasts is determined by the proportional reduction in MSFE for the pooling strategies relative to the benchmark model (following Campbell and Thompson, 2008).

$$R^2_{OS} = 1 - \frac{\sum_{t=s}^{T}(r_t - \hat{r}_t)^2}{\sum_{t=s}^{T}(r_t - \bar{r}_t)^2} \tag{2.8}$$

where $\{\bar{r}_t\}_{t=s}^{T}$ corresponds to historical average forecast and $\{\hat{r}_t\}_{t=s}^{T}$ represents forecasts using pooling strategies over the out-of-sample evaluation period [s:T]. To test whether improvements in the forecast performance are statistically significant ($H_0: R^2 \leq 0$ against $H_A: R^2 > 0$), we evaluate in-sample predictability by the F-statistic and out-of-sample forecastability by the MSFE-adjusted test statistic proposed by Clark and West (2007). The MSFE-adjusted test statistic assesses significance by a one-sided (upper-tail) t-test obtained by regressing $\{d_t\}_{t=s}^{T}$ on a constant:

$$d_t = (r_t - \bar{r}_t)^2 - \left[\left(r_t - \hat{r}_{t,i}\right)^2 - \left(\bar{r}_t - \hat{r}_{t,i}\right)^2\right] \quad for\ t = s, \dots, T \tag{2.9}$$

Results presented in Table 2.2 are very well in line with previous findings, highlighting that the equity premium is hard to predict.[3] Panel A describes results for the macroeconomic indicators with in-sample R-squares in the range of 0.00% to 0.63%. Only four R-squares are statistically significant at least at the 5% level. Pooling strategies based on technical indicators perform clearly better on average (see Panel B) with R-square values between 0.84% and 1.08%. Three pooling strategies outperform a constant expected return at the 1% and three at the 5% significance level.

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[2] In the following, results for principal component predictive regressions are based on the first common factor which is selected by the Schwarz information criterion (SIC) using full sample information.

[3] Ross (2005) and Zhou (2010) confirm the view of low levels of predictability by identifying on upper bound of predictive regressions R-squares. However, small or even negative R-squares can provide utility gains for risk-averse investors (see Kandel and Stambaugh, 1996; Xu, 2004; Campbell and Thompson, 2008; Cenesizoglu and Timmermann, 2012).

Table 2.2: Equity premium forecasting results

Pooling strategy	In-sample R-square	Out-of-sample R-square		
		Full sample	Expansion	Recession
Panel A: Predictive regression forecasts; macroeconomic indicators				
Mean	0.63%**	1.15%***	0.75%***	2.00%**
	(4.88)	(3.16)	(2.35)	(2.16)
Median	0.34%	0.69%***	0.61%**	0.85%**
	(2.58)	(2.86)	(2.23)	(1.80)
Trimmed mean	0.51%**	1.06%***	0.73%***	1.76%**
	(3.91)	(3.24)	(2.40)	(2.22)
DMSFE (1.0)	0.63%**	1.18%***	0.79%***	1.99%**
	(4.88)	(3.08)	(2.37)	(2.04)
DMSFE (0.9)	0.63%**	1.19%***	0.73%**	2.18%**
	(4.89)	(2.78)	(2.24)	(1.83)
PC	0.00%	1.30%***	0.36%*	3.30%***
	(0.02)	(3.01)	(1.53)	(2.99)
Panel B: Predictive regression forecasts; technical indicators				
Mean	0.85%**	0.56%*	-0.18%	2.16%**
	(6.53)	(1.47)	(0.14)	(1.77)
Median	1.08%***	0.73%**	-0.01%	2.31%**
	(8.33)	(1.77)	(0.50)	(1.89)
Trimmed mean	0.92%***	0.62%*	-0.11%	2.17%**
	(7.13)	(1.57)	(0.30)	(1.78)
DMSFE (1.0)	0.84%**	0.57%*	-0.18%	2.16%**
	(6.53)	(1.47)	(0.14)	(1.77)
DMSFE (0.9)	0.84%**	0.57%*	-0.18%	2.17%**
	(6.51)	(1.48)	(0.14)	(1.78)
PC	0.87%***	0.69%*	-0.32%	2.85%**
	(6.76)	(1.56)	(0.24)	(1.80)

Notes: This table reports in-sample and out-of-sample results for equity premium forecast using pooling strategies based on macroeconomic (Panel A) and technical indicators (Panel B). Pooling strategies encompass forecast combinations (following Rapach et al., 2010) and principal component predictive regressions using on the entire set of 14 macroeconomic variables (technical indicators). Empirical evidence is determined by the in-sample R-square over the full sample period and by the out-of-sample R-square (following Campbell and Thompson, 2008) over the sample period from 1966:01 through 2014:12. Stars refer to significance levels of 10% (*), 5% (**), and 1% (***) of the in-sample F-statistic (reported in parenthesis) and of the out-of-sample *MSFE-adjusted* statistic of Clark and West (2007). The *MSFE-adjusted* statistic tests the null hypothesis $R_{OS}^2 \leq 0$ against the one-sided alternative $R_{OS}^2 > 0$. Corresponding t-values are reported in parenthesis. Out-of-sample evidence is also reported separately for NBER-dated expansion and recession periods.

In some contrast to the conventional wisdom that the out-of-sample prediction performance lags behind their in-sample counterparts (see e.g. Bossaerts and Hillion, 1999; Goyal and Welch, 2008, among others), pooling strategies deliver significant out-of-sample gains for macroeconomic variables (see Panel A). Technical indicators, however, slightly lose predictive power in an out-of-sample approach. All prediction models have in common that the out-of-sample forecast performance is predominantly located during recession periods which is in line with the literature (see Henkel et al., 2011).

2.4.2 Marginal predictive performance for equity premium components

In extending the literature, we subsequently analyze the marginal predictive performance for individual equity premium components. We note that previously obtained equity premium forecasts are equal to the sum of forecasts obtained from each return component separately. This setup allows us to determine the marginal predictability, measured by the loss (gain) in the overall predictive performance if we impose zero beta restrictions for individual excess return components. For example, to specify the marginal forecast contribution for the earnings growth rate (ge), we first construct a new equity premium forecast by imposing the single restriction β_{ge}=0 in the forecasting system according to equation (2.7).[4] The marginal loss (gain) is then obtained by looking at the differences between the in-sample (out-of-sample) R-square estimated under the restricted regression setting with the R-square reported in Table 2.2 (unrestricted model). If the difference is negative, this would indicate that the predictive variable has superior forecasting ability for the equity premium component under analysis, in the case above for the earnings growth rate. We conduct this procedure for all equity premium components to determine where the overall equity premium predictive performance comes from.

For comparability purposes we use the same forecast combination weights obtained from equity premium predictive regressions (with the exception of median combinations weights). We assess statistical significance by a one-sided t-test based on the two series of resulting squared forecasting errors according to the MSFE test proposed by Diebold and Mariano (1995).

Results reported in Table 2.3 reveal that economic and technical indicators capture different information of the equity premium. In line with findings presented by Ferreira and Santa-Clara (2011), empirical evidence supports the view that the overall predictive performance of economic variables is largely determined by the predictability of the price-earnings growth rate (gm). Thus, imposing the restriction β_{gm}=0 substantially shrinks the equity premium predictive performance of pooling strategies based on economic information. The marginal contribution of the remaining return components is less strong in magnitude. In addition, findings can be confirmed in-sample as well as out-of-sample.

[4] Imposing zero beta restrictions on individual components yields equity premium forecasts which are partially equal to the benchmark specification, recalling that the historical average benchmark assumes ($\beta_{gm} = \beta_{ge} = \beta_{dp} = \beta_{rf} = 0$).

Table 2.3: Marginal forecast contribution for equity premium components

Pooling strategy	Δ In-sample *R*-square (in%)				Δ Out-of-sample *R*-square (in%)			
	(β_{gm}=0)	(β_{ge}=0)	(β_{dp}=0)	(β_{rf}=0)	(β_{gm}=0)	(β_{ge}=0)	(β_{dp}=0)	(β_{rf}=0)
Panel A: Marginal forecast contribution; macroeconomic indicators								
Mean	-0.79**	-0.03	-0.04	-0.11	-1.93***	0.48	-0.11*	-0.16
	(-1.94)	(-0.10)	(-0.63)	(-0.88)	(-2.63)	(0.85)	(-1.53)	(-1.10)
Median	-0.57**	-0.05	-0.13	-0.10	-0.91**	0.54	0.41	0.43
	(-1.86)	(-0.30)	(-0.80)	(-0.96)	(-2.14)	(2.26)	(2.67)	(2.67)
Trimmed mean	-0.74**	0.04	-0.04	-0.10	-1.89***	0.52	-0.11**	-0.12
	(-1.81)	(0.12)	(-0.81)	(-0.88)	(-2.58)	(0.91)	(-1.78)	(-1.01)
DMSFE (1.0)	-0.79**	-0.04	-0.04	-0.11	-1.95***	0.48	-0.11*	-0.16
	(-1.94)	(-0.11)	(-0.63)	(-0.89)	(-2.60)	(0.85)	(-1.56)	(-1.11)
DMSFE (0.9)	-0.79**	-0.03	-0.04	-0.11	-1.98***	0.50	-0.11*	-0.16
	(-1.98)	(-0.08)	(-0.65)	(-0.88)	(-2.54)	(0.90)	(-1.64)	(-1.05)
PC	-0.66	-0.29	-0.05	-0.20	-2.60***	0.07	-0.19	-0.32
	(-0.99)	(-0.66)	(-0.27)	(-0.54)	(-2.57)	(0.14)	(-1.10)	(-0.81)
Panel B: Marginal forecast contribution; technical indicators								
Mean	-0.44	-3.41***	0.02	-0.03	0.05	-0.79*	0.02	-0.07
	(-0.55)	(-2.47)	(0.57)	(-0.70)	(0.15)	(-1.29)	(0.98)	(-0.92)
Median	-0.54	-4.35***	0.01	-0.04	0.07	-0.95*	0.07	-0.04
	(-0.60)	(-2.93)	(0.16)	(-0.64)	(0.17)	(-1.50)	(0.88)	(-0.43)
Trimmed mean	-0.39	-3.72***	0.02	-0.04	0.04	-0.86*	0.03	-0.08
	(-0.47)	(-2.64)	(0.68)	(-0.80)	(0.12)	(-1.37)	(1.07)	(-1.06)
DMSFE (1.0)	-0.44	-3.41***	0.02	-0.03	0.05	-0.79*	0.02	-0.07
	(-0.55)	(-2.47)	(0.57)	(-0.70)	(0.14)	(-1.29)	(0.98)	(-0.92)
DMSFE (0.9)	-0.45	-3.40***	0.02	-0.03	0.05	-0.79*	0.02	-0.07
	(-0.56)	(-2.47)	(0.56)	(-0.69)	(0.13)	(-1.29)	(0.97)	(-0.92)
PC	-1.73*	-4.93***	-0.00	-0.01	-0.06	-1.02	0.02	-0.06
	(-1.54)	(-2.58)	(-0.05)	(-0.09)	(-0.12)	(-1.20)	(0.51)	(-0.61)

Notes: This table reports the marginal gain (loss) in the equity premium prediction performance if we impose zero beta restrictions on individual equity premium components (named in the headings). The marginal contribution of equity premium components is determined by the difference between the in-sample (out-of-sample) *R*-squares obtained under the restricted (β_j=0) predictive regression setting and the unrestricted forecasts. Statistical significance corresponds to a one-sided t-test based on the resulting prediction errors of the restricted and the unrestricted forecasting approach. Asterisks denote significance of the t-statistic (denoted in parenthesis) with significance levels of 10%, 5%, 1% characterized by *, **, ***. Panel A reports results for pooling strategies based on economic information, while panel B presents results for forecasting strategies incorporating technical indicators.

Considering the marginal contribution of technical indicators shows a completely different behavior. Regarding in-sample evidence, Table 2.3 shows that technical indicators have statistically significant predictive ability for the earnings growth rate (*ge*) at the 1% level. Out-of-sample evidence is significant at the 10% level which is comparable to the overall forecast performance. If we solely focus on the magnitude of the change in the predictive performance, we find a substantial loss in the predictive performance if we assume no predictive ability for the earnings growth rate. Finally and in line with previous findings, out-of-sample evidence is primarily located during economic downswings.[5]

2.5 SOP-forecast performance with an extended set of variables

In this section, we make use of the insight gained in Section 2.4.2, i.e. we predict the components of the equity premium by those indicators which seem to be most related to each component. By this decision the SOP-approach of Ferreira and Santa-Clara (2011) is enriched and gains forecasting power. We then compare the predictive performance of this extended SOP (ESOP)-strategy to alternative forecasting strategies.

Benchmark results: We have shown that economic variables mainly predict the price-earnings growth rate (*gm*), whereas technical indicators better predict the earnings growth rate (*ge*). Thus we construct equity premium forecasts where price-earnings growth rate forecasts are obtained by using pooling strategies solely based on economic variables. Expectations for the earnings growth component are estimated by incorporating information from technical indicators. Given the fact that the forecast contributions of the remaining excess return components are less important, we impose the following restrictions: For the dividend-price ratio we assume a random-walk process as suggested by Campbell (2008) and Ferreira and Santa-Clara (2011). Thus, forecasts are defined by the current level of the dividend-price ratio ($\widehat{dp}_{t+1} = dp_t$). For the risk-free rate we do not impose further restrictions but forecasts are obtained by incorporating information from the full set of 28 predictors.[6]

Table 2.4 Panel A reports forecasting results for the ESOP-approach which delivers highly statistically significant forecasting gains in-sample and especially out-of-sample. In detail, forecast combinations provide an in-sample *R*-square in the range of 1.23% up to 1.47% which is statistically significant from zero at the 1% level. The forecast performance further increases if we conduct an out-of-sample exercise. All ESOP-strategies produce high R^2_{OS} with values of up to 2.79% and deliver MSFEs which are significantly low-

[5] Results are confirmed by bivariate predictive regressions (see Section 2.7.1) and when we only look at recession periods (Table A.2.2).

[6] We also investigate whether imposed restrictions on the dividend-price ratio and the risk-free rate are binding in the sense that the overall forecast performance might change under different assumptions regarding the underlying set of predictor variables. In a nutshell, findings remain nearly unchanged under different specifications. Results are reported in Section 2.7.2.

er than the historical average benchmark at the 1% level. While the forecast performance is better during recession periods, ESOP forecasts also deliver forecasting gains during expansions. The performance of principal component regressions slightly lags behind combination strategies, which is especially true for in-sample analysis.

Table 2.4: Forecast results based on (un-)restricted predictive regression settings

Pooling strategy	In-sample R-square	Out-of-sample R-square		
		Full sample	Expansion	Recession
Panel A: Forecasting performance; extended sum-of-parts approach				
Mean	1.44%***	2.37%***	0.85%**	5.61%***
	(11.20)	(3.80)	(1.90)	(3.98)
Median	1.26%***	2.24%***	0.87%**	5.16%***
	(9.74)	(3.69)	(1.82)	(4.01)
Trimmed mean	1.47%***	2.19%***	0.66%**	5.46%***
	(11.42)	(3.66)	(1.68)	(4.21)
DMSFE (1.0)	1.37%***	2.79%***	1.30%***	5.96%***
	(10.67)	(3.93)	(2.55)	(3.09)
DMSFE (0.9)	1.23%***	2.76%***	1.23%***	6.02%***
	(9.53)	(3.72)	(2.49)	(2.82)
PC	-0.26%	1.92%***	-0.77%*	7.66%***
	(-2.00)	(3.09)	(1.33)	(3.48)
Panel B: Forecasting performance; pooling strategies based on 28 predictors				
Mean	0.86%***	0.96%***	0.40%*	2.16%**
	(6.68)	(2.67)	(1.56)	(2.21)
Median	1.14%***	0.92%**	0.30%	2.22%**
	(8.81)	(2.26)	(1.11)	(2.02)
Trimmed mean	0.84%**	0.91%***	0.37%*	2.05%**
	(6.45)	(2.63)	(1.47)	(2.22)
DMSFE (1.0)	0.86%***	1.01%***	0.47%**	2.16%**
	(6.67)	(2.73)	(1.73)	(2.15)
DMSFE (0.9)	0.86%**	1.02%***	0.43%*	2.27%**
	(6.64)	(2.53)	(1.58)	(2.02)
PC	0.92%**	1.60%***	-0.48%	6.04%***
	(3.57)	(2.67)	(1.00)	(2.94)
Panel C: Forecasting performance; standard sum-of-parts approach				
SOP	----	0.92%***	0.44%*	1.95%**
		(2.37)	(1.53)	(1.90)

Notes: This table reports in-sample and out-of-sample results for equity premium forecast based on our extended sum-of-parts method (Panel A), conventional pooling strategies based on the full set of 28 predictors (Panel B), and results using the standard sum-of-parts approach (Panel C). Polling strategies encompass forecast combinations (following Rapach et al., 2010) and principal component predictive regressions. Empirical evidence is determined by the in-sample R-square over the full sample period and by the out-of-sample R-square (following Campbell and Thompson, 2008) over the sample period from 1966:01 through 2014:12. Stars refer to significance levels of 10% (*), 5% (**), and 1% (***) of the in-sample F-statistic (reported in parenthesis) and of the out-of-sample *MSFE-adjusted* statistic of Clark and West (2007). The *MSFE-adjusted* statistic tests the null hypothesis $R_{OS}^2 \leq 0$ against the one-sided alternative $R_{OS}^2 > 0$. Corresponding t-values are reported in parenthesis. Out-of-sample evidence is also reported separately for NBER-dated expansion and recession periods.

Unconditional pooling strategies: We also compute forecasts using pooling strategies based on the full set of 28 predictive variables. Thus, we closely follow the approach proposed by Neely et al. (2014) who show that incorporating information from economic and technical indicators substantially improves the forecast performance. The pooled information from the entire set of 28 predictors provide R^2_{OS} of about 1.00% using forecast combinations and 1.60% based on principal component predictive regressions (Table 2.4, Panel B).[7]

Standard SOP-approach: For further comparison purposes, we also evaluate forecasts obtained by the standard SOP-approach proposed by Ferreira and Santa-Clara (2011). They conduct out-of-sample forecasts based on the following restrictions. Given the highly persistent behavior of the price-earnings multiple and the dividend-price ratio, forecasts are either set to zero ($\widehat{gm}_{t+1} = 0$) or dp_t ($\widehat{dp}_{t+1} = dp_t$), respectively. Additionally, the standard SOP approach strictly relies on the presumption that the earnings-growth component is nearly unpredictable (following Campbell and Shiller, 1988; Fama and French, 2002; Cochrane, 2008) with the exception of a low-frequency component (see Binsbergen and Koijen, 2010). Therefore, we form expectations by using a 15-years moving average of log earnings growth rates based on past realizations up to the point in time where forecasts are made.[8] Thus equity premium forecasts are given by

$$\hat{r}_{t+1} = \overline{ge}_t^{15} + dp_t - rf_{t+1}. \tag{2.10}$$

While Ferreira and Santa-Clara (2001) highlight the outperformance of SOP forecasts for stock market returns, we extend their approach by computing equity premium forecasts to ensure a direct comparison. In the following, we treat the (log) risk-free rate as given (see Rapach and Zhou, 2013) so that the performance of SOP forecasts is unrelated to prediction errors regarding the risk-free rate component. Still, the forecasting performance of the standard SOP-approach is obviously not as good as that of the ESOP-approach with an R-square of 0.92% (see Table 2.4, Panel C).

Comparing ESOP performance to alternative strategies: Furthermore, to test whether differences between the employed strategies documented in Table 2.4 are statistically significant, we apply the MSFE-adjusted test statistic described in Section 2.4.1 and

[7] Results reported for principal component predictive regressions take into account the first common factor of both predictor groups which ensures that information from macroeconomic and technical indicators is comprised at each point in time.

[8] For consistency purposes we use 15 years of data instead 20 years which has been considered by Ferreira and Santa-Clara (2011).

replace the historical average benchmark with conventional forecasting strategies reported in Table 2.4. Overall, we find that the ESOP-approach performs always statistically significant better than conventional strategies in term of MSFEs. Results are reported in Table A.2.3.

2.6 Extended results

In this section we extend the above results (Section 2.5) by looking at the dynamic forecasting performance (Section 2.6.1), and by complementing the so far statistical performance measures by measures of economic value (Section 2.6.2). Moreover, we relate our disaggregated analysis of the equity premium to driving forces of the stock market, i.e. industrial production and sentiment (Section 2.6.3).

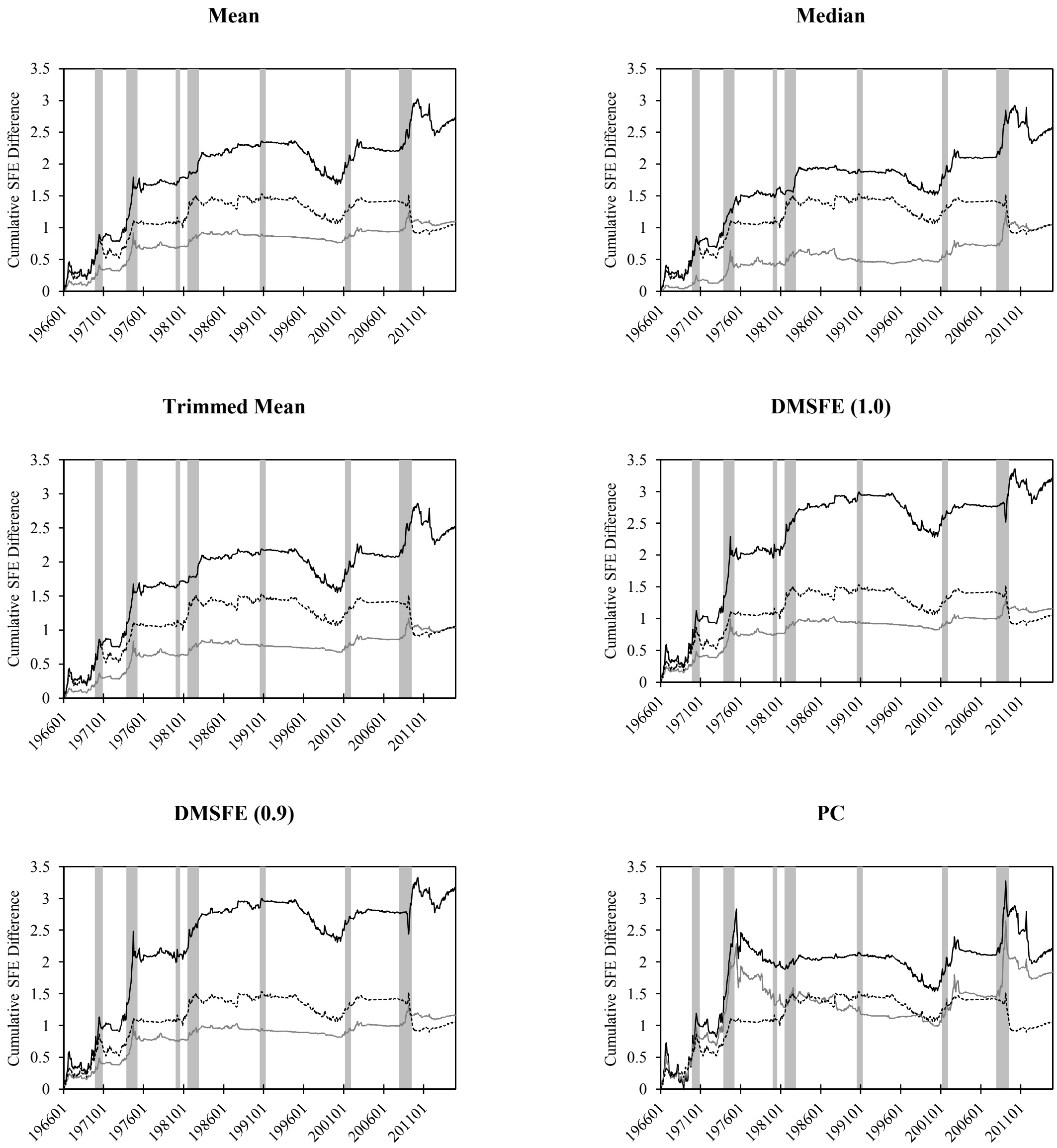
2.6.1 Dynamic out-of-sample forecast performance

To account for the fact that the composition of the equity premium is time-varying (Figure 2.1), we also investigate the dynamics of the prediction performance at each point in time over the entire out-of-sample evaluation period. We follow Goyal and Welch (2003, 2008) in this respect and check for structural stability based on the cumulative difference in the squared forecast errors of the historical average benchmark model and the prediction errors obtained by using alternative forecasting models instead:

$$CDSFE(t,m) = \sum_{t=s}^{T}((r_t - \bar{r}_t)^2 - (r_t - \hat{r}_{t,m})^2) \qquad (2.11)$$

where $(r_t - \bar{r}_t)$ is the out-of-sample prediction error of historical average forecasts (benchmark), and $(r_t - \hat{r}_{t,m})$ denotes the error using the forecasting model of interest (m) instead. In general, a positive slope indicates that the prediction model yields lower prediction errors than the benchmark model at a particular period of time. If the *CDSFE*-function is consistently greater than zero, the overall performance is consistently better than the historical average benchmark.

Figure 2.2: Dynamic out-of-sample forecast performance



Notes: The figures plots the dynamic out-of-sample predictive performance of forecasts obtained from forecast combinations and principal component predictive regressions. The black solid line represents the dynamic predictive performance of the extended sum-of-parts method. The grey line signals the forecast performance of conventional pooling strategies based on the full set of 28 predictors and the black dotted line corresponds to the conventional sum-of-parts approach, according to Ferreira and Santa-Clara (2011). Following Goyal and Welch (2003, 2008), the graphs show the cumulative sum of differences in the squared prediction errors using historical average forecasts and the squared prediction errors based on the prediction model of interest (named in the headings): $CDSFE(t,m) = \sum_{t=s}^{T}((r_t - \bar{r}_t)^2 - (r_t - \hat{r}_{t,m})^2)$. Shaded areas respond to NBER dated recessions. Overall, upward sloping curves characterize a reduction in mean squared forecast errors for the pooling strategy to the historical average at a specific point in time. The forecast evaluation period is from 1966:01 through 2014:12.

The *CDSFE*-plots show that conventional pooling strategies based on 28 predictors and SOP forecasts have an overall good performance over time compared to the historical average forecast. However, if we compare their dynamic performance through time with ESOP-forecasts, we find further evidence in favor of ESOP-strategies.

Nevertheless, all graphs confirm the findings by Goyal and Welch (2008) and Timmermann (2008) of time-varying predictability with periods of underperformance. Although ESOP-forecast combinations outperform previously used forecast models consistently over time, the lines show deterioration in predictive performance in the mid-1990s; however, the performance recovers afterwards.[9] In line with previous findings, out-of-sample gains are extremely concentrated during recessions, especially for principal component predictive regressions.

2.6.2 Economic value of prediction models

Statistical measures to determine the value of prediction models, such as the out-of-sample *R*-square, do not necessarily also imply economic value regarding asset allocation decisions (Cenesizoglu and Timmermann, 2012). Therefore, we examine whether the ESOP-strategy also provides additional economic value for investors (see e.g. Marquering and Verbeek, 2004; Rapach et al., 2010; Ferreira and Santa-Clara, 2011; Rapach and Zhou, 2013; Neely et al., 2014). The economic added value of equity premium forecasts is analyzed by considering a risk-averse investor who composes his portfolio by investing into a risky and/or a risk-free asset:

$$R_{p,t} = w_{t-1}R_t + Rf_t \quad \text{for } t = s, \dots, T \tag{2.12}$$

where $R_{p,t}$ corresponds to the portfolio return at time *t* which depends on the return of the risky asset R_t multiplied by the portfolio weight w_{t-1}, and Rf_t is the return of the risk-free asset. For simplicity reasons, log equity premium forecasts are reverted to simple returns to conduct the profitability of equity premium forecasts using utility-based metrics.[10] At the end of each month, a mean-variance investor faces the following optimization problem:

$$\max_{w_{t-1}} U(R_{p,t}) = E_{t-1}(R_{p,t}) - \frac{1}{2}\gamma Var_{t-1}(R_{p,t}) \quad \text{for } t = s, \dots, T. \tag{2.13}$$

Solving equation (2.13) yields the optimal investment share that a mean-variance investor should select for an investment in the risky asset in period *t*:

[9] A clear identification of the source of the underperformance in the 1990's is unclear, because both technical indicators and economic variables are influenced by structural changes around that point in time (see Park and Irwin, 2007; Rapach and Wohar, 2006; Paye and Timmermann, 2006).

[10] For convenience reasons, simple equity premium forecasts are proxied by the following transformation: $\hat{R}_t = \exp(\hat{r}_t) - 1$.

$$w_{t-1} = \left(\frac{1}{\gamma}\right)\left(\frac{E_{t-1}(r_t)}{Var_{t-1}(r_t)}\right) \quad \text{for } t = s, \dots, T \tag{2.14}$$

Each month, the investor determines the optimal portfolio weight depending on her relative risk aversion (γ), the expected equity premium $E_{t-1}(r_t)$, and forecasts regarding the risk inherent in stock returns $Var_{t-1}(r_t)$. We follow Campbell and Thompson (2008), among others, by making use of a five-year moving window of historical returns as a proxy for the conditional variance. Thus, differences in portfolio allocation are independent of volatility estimates. We further restrict investors' portfolio weight of the risky asset (w_{s-1}) to be positive (short-sale constrained) and less than 150% (taking leverage of no more than 50%).

To assess whether equity premium forecasts are beneficial in an economic sense, we evaluate utility gains by the annualized certainty equivalent return (CER) which is defined in levels. According to equation (2.12), the average utility realized by model m is determined by $\widehat{U}(m) = \hat{\mu}_p(m) - 0.5\gamma\hat{\sigma}_p^2(m)$, where $\hat{\mu}_p$ ($\hat{\sigma}_p^2$) is the sample mean (variance) of portfolio returns over the forecast evaluation period. Differences between models (ΔCER) can thus be understood as a percentage management fee that an investor would be willing to pay to have access to information in the predictive regression forecast. In addition, we also evaluate the economic value by the annualized Sharpe ratio.

Results reported in Table 2.5 show that the portfolio performance of ESOP-strategies (Panel A) largely confirms previous findings (measured by the R_{OS}^2) by producing the comparatively highest portfolio gain with and without transaction costs. In detail, while historical average return forecasts provide a certainty equivalent return of 409 basis points (bp) p.a. and an annualized Sharpe ratio of 0.21 (Panel C), all forecasting strategies provide gains, however, to very different degrees. The standard SOP-approach proposed by Ferreira and Santa-Clara (2011) provides utility gains of 164 bp compared to the historical average forecast. More sizeable portfolio gains are delivered by conventional pooling strategies based on 28 predictor variables (Panel B), with Sharpe ratios between 0.35 and 0.51. The highest utility gains are obtained for ESOP-strategies which outperform the historical average by 390 bp, standard SOP forecasts by 225 bp and conventional pooling strategies by 150 bp. These findings are fully confirmed by reported Sharpe ratios.

Table 2.5: Portfolio performance evaluation

Pooling strategy	CER (ann., in %)	Sharpe ratio (ann.)	Relative avg. turnover	CER (ann., in %) costs=50bp	Sharpe ratio (ann.) costs=50bp
Panel A: Performance results; extended sum-of-parts					
Mean	8.16	0.58	5.32	7.51	0.50
Median	8.73	0.64	5.74	8.03	0.56
Trimmed mean	8.37	0.61	5.19	7.74	0.53
DMSFE (1.0)	7.30	0.47	4.81	6.71	0.41
DMSFE (0.9)	7.09	0.45	5.06	6.47	0.38
PC	8.20	0.59	2.87	7.85	0.55
Panel B: Performance results; pooling strategies based on 28 predictors					
Mean	6.14	0.36	3.15	5.75	0.32
Median	6.34	0.39	2.84	5.98	0.36
Trimmed mean	6.03	0.35	3.03	5.66	0.31
DMSFE (1.0)	6.27	0.37	3.35	5.86	0.33
DMSFE (0.9)	6.31	0.37	3.49	5.88	0.33
PC	7.64	0.51	4.08	7.13	0.46
Panel C: Performance results; further benchmark strategies					
SOP	5.73	0.28	1.59	5.54	0.25
HA	4.09	0.21	2.00	3.96	0.20

Notes: This table reports portfolio performance measures for an investor with mean-variance preferences and relative risk aversion coefficient of five using our extended SOP approach (Panel A), conventional pooling strategies (Panel B) and further benchmark strategies covering the standard SOP method proposed by Ferreira and Santa-Clara (2011) and historical average forecasts. In detail, CER describes the annualized percentage certainty equivalent return, i.e. the realized portfolio utility for each model. Sharpe ratios are defined as the average portfolio return in excess of the risk-free rate divided by its variance and the relative average turnover is the average portfolio turnover for each prediction model divided by the average turnover based on the historical average forecast.

All pooling strategies (with the exception of SOP) indicate a monthly turnover which is two up to six times higher compared to the historical average portfolio. Nevertheless, accounting for proportional transaction costs of 50 bp per transaction still leaves earlier results qualitatively unchanged: for example, EOSP-strategies still provide CER gains of 135 bp in comparison to conventional pooling strategies and a surplus of 185 (343) bp relative to the standard SOP approach (historical average return). Again, results are qualitatively confirmed by Sharpe ratios.

2.6.3 Linkages to driving forces of stock returns

From a theoretical point of view, stock returns and state variables of the real economy are both closely linked to business-cycle fluctuations. Thus, variables which correspond to future business cycle movements should also be appropriate to predict stock returns (Campbell and Cochrane, 1999; Cochrane, 2007; Møller and Rangvid, 2015). However, empirical evidence shows that most economic variables do not seem to be suitable to predict economic growth (e.g. Stock and Watson, 2003).

Decomposing the equity premium allows a more nuanced view on economic driving forces of components in stock returns. According to our ESOP-approach technical indicators predict earnings growth, and thus may be able to predict a driver of earnings growth, i.e. industrial production, too (Chauvet and Potter, 2000). In addition, macroeconomic indicators predict growth in the price-earnings multiple, and thus may be able to predict a driver of investors' willingness to pay for earnings, i.e. inflation, too: when expected inflation rises, the price-earnings ratio declines and vice versa (see Feldstein, 1980, Campbell and Vuolteenaho, 2004).[11]

For the forecasting tests, we use because of comparability reasons the same evaluation period as for equity premium prediction models from 1966:01-2014:12. We follow Stock and Watson (2003), Rapach et al. (2010), among others and consider the following regression specification.

$$y_{t+1} = \alpha + \beta y_t + \gamma x_t + \varepsilon_{t+1} \tag{2.15}$$

where y_{t+1} either represents monthly growth rates of industrial production or growth rates of the producer price index. To account for autocorrelation properties, we include a lagged y_t term. We evaluate the predictive power of previously described combination methods based on macroeconomic or technical indicators which are denoted by x_t. To differentiate between short and medium-term importance, we also regard quarterly growth rates according to equation (2.16).

$$y_{t+1:t+3} = \alpha + \beta y_{t-2:t} + \gamma x_t + \varepsilon_{t+1:t+3}. \tag{2.16}$$

The results of out-of-sample forecasting industrial production and inflation are reported in Table 2.6. Whereas this table only provides forecast for mean combinations, full

[11] Industrial production and producer price index data are obtained from the Federal Reserve Bank of St. Louis.

results also providing forecasts for other combination strategies referred to before in this chapter can be found as Table A.2.4 and Table A.2.5, respectively. Table 2.6 shows that macroeconomic indicators significantly forecast industrial production but that technical do this even much better.[12] Concerning predictive ability regarding inflation, we find that macroeconomic indicators again perform significantly well, whereas technical indicators fail.

Table 2.6: Forecasting industrial production and inflation

Dependent variable	Monthly growth rates			Quarterly growth rates
	R^2_{OS}	$R^2_{OS,Exp.}$	$R^2_{OS,Rec.}$	R^2_{OS}
Panel A: Forecast based on macroeconomic indicators				
Industrial production	2.11%***	-0.62%	6.70%***	5.39%***
	(3.07)	(0.45)	(3.75)	(3.97)
Inflation	2.21%***	2.57%***	1.59%**	1.66%***
	(4.09)	(3.80)	(1.89)	(3.85)
Panel B: Forecast based on technical indicators				
Industrial production	5.20%***	-1.02%***	15.66%***	13.12%***
	(5.37)	(2.75)	(5.30)	(7.50)
Inflation	-0.28%	-0.34%	-0.17%	-0.79%
	(-0.53)	(-0.82)	(-0.09)	(-3.89)

Notes: This table reports out-of-sample R^2_{OS} statistic (in percent) proposed by Campbell and Thompson (2008) of industrial production and inflation predictability by comparing the forecast performance of mean combination strategies based on macroeconomic variables (Panel A) or technical indicators (Panel B) to the AR(1) benchmark model over the sample period 1966:01 to 2014:12. Statistical significance is assessed by the out-of-sample MSFE-adjusted statistic proposed by Clark and West (2007). The MSFE-adjusted statistic tests the null hypothesis $R^2_{OS} \leq 0$ against the one-sided alternative $R^2_{OS} > 0$. Corresponding t-values are reported in parenthesis with stars referring to significance levels of 10% (*), 5% (**), and 1% (***).

With regard to our ESOP-approach, results show that the differentiated use of technical and economic indicators for individual stock market return components can be motivated by their impact on different economic drivers of stock returns: technical indicators predict earnings growth and – related to it – industrial production, while macroeconomic indicators predict growth of the price-earnings multiple and – related to it – inflation.

[12] Aside from business cycle movements recent literature shows that also sentiment provides forecasting power for the equity premium by a cash flow cannel explanation (Huang et al., 2015; see earlier Baker and Wurgler, 2006, Schmeling, 2009, among others). Similarly, Sibley et al. (2016) provide evidence that the predictive power of sentiment is mainly driven by its informational content to business cycle related variables (see also, Neely et al., 2014).

2.7 Robustness checks

In this section, we report three kinds of robustness tests: first, we also report for completeness major examinations with single indicators and pooling strategies which are solely based on one predictor group (Section 2.7.1). Then, we test for binding restrictions regarding the dividend-price ratio and the risk free rate (Section 2.7.2). Finally, we report findings for more recent forecasting periods in order to address concerns of periods with disappearing forecasting ability (Section 2.7.3).

2.7.1 Forecast performance of single indicators

Earlier results presented in the main text of this chapter rely on pooled information. As argued above, pooling strategies are well-established and there are good reasons to rely on them instead of bivariate regressions only. Nevertheless, in order to demonstrate that pooled results are not driven by potentially strange single indicator results, we show here the full underlying results for main steps of our analysis.

First, we document – in line with earlier Table 2.2 for pooling strategies – in-sample and out-of-sample forecasting performance for single indicators in Table A.2.6. Regarding macroeconomic indicators, many of them can significantly forecast the equity premium in-sample although with considerable variation in performance across indicators. The out-of-sample performance is clearly worse and driven by some predictability in recessions. This pattern also holds for technical indicators, however, at a more advantageous level of predictability. In sum, the use of pooling strategies is especially crucial for the forecasting performance of economic variables.

Table A.2.7 reports results on marginal forecast contributions analogous to Table 2.3 in the main text. The allocation of predictability can also be recognized at the level of bivariate regressions: macroeconomic indicators are more important for predicting growth rates in the price-earnings ratio, while technical indicators are more important for predicting the earnings growth component. This pattern is particularly visible during recessions (see Table A.2.8).

Finally, Table A.2.9 reports portfolio performance evaluation (analogous to Table 2.5). Again pooling strategies usually provide better results than single indicators (see Pesaran and Timmermann, 1995).

2.7.2 Forecast performance under different restrictions imposed on *dp* and *rf*

Up to now, we investigate the forecast performance of ESOP-strategies which are partially based on the assumption that we suppose a random-walk process for the dividend-price ratio and predict the risk-free rate component by using the entire set of 28 variables. In this section, we explore whether results also hold under different restrictions. In detail, referring to Section 2.4.2, we investigate the in-sample and out-of-sample forecasting performance of pooling strategies by assuming predictive ability of economic variables, technical indicators or all predictors for the dividend-price ratio, the risk-free rate, or both components. Results are reported in Table A.2.10. In a nutshell, our main results (see Section 2.5) only slightly change.

2.7.3 Subsample analysis

Finally, we address the concern that our results for equity premium prediction may be driven by the distant past, as argued, for example, by Goyal and Welch (2008) for their setting. As first argument we refer to our Figure 2.2 introduced above which demonstrates that pooling methods within our ESOP-strategy are able to generate predictability also during more recent times, although one can recognize – in line with Goyal and Welch (2008) – the strong predictability during the mid 1970s.

As second analysis we present performance statistics for more recent sub-periods. In order to avoid concerns about an ex post selection of such periods we strictly follow the starting points for the analysis as suggested by Rapach et al. (2010). Results of the two periods, starting in 1976 and 2000, respectively, are provided in Table A.2.11.

Like Goyal and Welch (2008), we find lower predictive performance in the first subsample, however, ESOP-strategies (with the exception of principal component predictive regressions) deliver out-of-sample R-squares in the range of 1.07% up to 1.39% which are statistically significant at conventional levels of 5% and 1%. In comparison with conventional pooling strategies and the standard SOP approach, ESOP-based forecasts provide the highest outperformance even over the subsample beginning in 1976. CER gains are positive and mostly better than conventional forecasting strategies. Results for the sample period beginning in 2000 indicate that nearly all pooling strategies yield sizeable outperformance over the recent years. Nevertheless, we confirm previously mentioned findings that the differentiated use of macroeconomic variables and technical indicators for individual equity premium components increases the overall forecast performance considerably. In detail, over the most recent years, ESOP-strategies outperform the historical average benchmark with R_{OS}^2 of up to 2.88%. Even utility gains are sizeable and higher than gains achieved by conventional pooling strategies in nearly all cases.

2.8 Conclusions of Chapter 2

The prediction of the equity premium is of great interest for academics and practitioners alike, but recent literature documents that predictability is small if existent at all. We closely follow the procedures of this literature (such as Ang and Bekaert, 2007; Campbell and Thomson, 2008; Goyal and Welch, 2008; Timmermann, 2008; Rapach et al., 2010; among others) in order to isolate the effect from our innovation and being able to show its relevance. We newly bring two elements together: we first use the decomposition of the equity premium as suggested by Ferreira and Santa-Clara (2011) with their sum-of-parts (SOP)-strategy, and, second, we extend the set of predictors considered by also looking at technical indicators as suggested by Neely et al. (2014).

For a short sketch of predictive power of the ESOP-strategy we just report outcomes for mean values as pooling method. For the out-of-sample period of 1966-2014 and considering transaction costs, the Sharpe ratio of the ESOP-strategy is 0.49. The Sharpe ratio of the typical benchmark in this literature, the historical average, is 0.20. The Sharpe ratio for the original SOP-strategy is 0.25, for conventional strategies pooling across the full set of 28 predictors the Sharpe ratio is 0.35.

We conclude that the ESOP-strategy is superior to these alternative strategies and that two elements are necessary for its success, i.e. relying on the SOP-approach and on macroeconomic as well as technical indicators. This finding does not depend on the selection of the pooling method, is robust concerning various performance measures and is corroborated by linkages to general economic forces driving stock price movements. We also note that in line with other forecasting strategies, predictability mainly comes from recession periods. Finally, the ESOP-strategy uses the allocation of either macroeconomic or technical indicators to different components of the equity premium. This indicates complementary contributions of both kinds of indicators. Thus, our result provides some intuition why practitioners may use both, fundamental and technical forecasting indicators.

References for Chapter 2

Andrews, D.W.K. (1991), Heteroskedasticity and autocorrelation consistent covariance matrix estimation, *Econometrica* 59 (3), 817-858.

Ang, A., and G. Bekaert (2007), Stock return predictability: Is it there?, *Review of Financial Studies* 20 (3), 651-707.

Baker, M., and J. Wurgler (2006), Investor sentiment and the cross-section of stock returns, *Journal of Finance* 61 (4), 1645-1680.

van Binsbergen, J.H., and R.S.J. Koijen (2010), Predictive regressions: A present-value approach, *Journal of Finance* 65 (4), 1439-1471.

Bossaerts, P., and P. Hillion (1999), Implementing statistical criteria to select return forecasting models: What Do We Learn? *Review of Financial Studies* 12 (2), 405-428.

Brock, W., J. Lakonishok, and B. LeBaron (1992), Simple technical trading rules and the stochastic properties of stock returns, *Journal of Finance* 47 (5), 1731-1764.

Brown, S.J., W.N. Goetzmann, and A. Kumar (1998), The Dow Theory: William Peter Hamilton's track record reconsidered, *Journal of Finance* 53 (4), 1311-1333.

Campbell, J.Y. (2008), Estimating the equity premium, *Canadian Journal of Economics* 41 (1), 1-21.

Campbell, J.Y., and J.H. Cochrane (1999), By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* 107 (2), 205-251.

Campbell, J.Y., and R.J. Shiller (1988), Stock prices, earnings, and expected dividends, *Journal of Finance* 43 (3), 661-676.

Campbell, J.Y., and S.B. Thompson (2008), Predicting excess stock returns out-of-sample: Can anything beat the historical average, *Review of Financial Studies* 21 (4), 1509-1531.

Campbell, J.Y., and T. Vuolteenaho (2004), Inflation illusion and stock prices, *American Economic Review* 94 (2), 19-23.

Cenesizoglu, T., and A. Timmermann (2012), Do return prediction models add economic value? *Journal of Banking and Finance* 36 (11), 2974-2987.

Chauvet, M., and S. Potter (2000), Coincident and leading indicators of the stock market, *Journal of Empirical Finance* 7 (1), 87-111.

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

Cochrane, J.H. (2007), Financial markets and the real economy, in R. Mehra, ed.: *Handbook of the Equity Premium*, Elsevier, Amsterdam.

Cochrane, J.H. (2008), The dog that did not bark: A defense of return predictability, *Review of Financial Studies* 21 (4), 1533-1575.

Diebold, F.X., and R.S. Mariano (1995), Comparing predictive accuracy, *Journal of Business and Economic Statistics* 13 (3), 253-263.

Fama, E.F., and K.R. French (2002), The equity premium, *Journal of Finance* 57 (2), 637-659.

Fang, J., B. Jacobsen, and Y. Qin (2014), Predictability of the simple technical trading rules: An out-of-sample test, *Review of Financial Economics* 23 (1), 30-45.

Feldstein, M. (1980), Inflation and the stock market, *American Economic Review* 70 (5), 839-847.

Ferreira, M. A., and P. Santa-Clara (2011), Forecasting stock market returns: The sum of the parts is more than the whole, *Journal of Financial Economics* 100 (3), 514-537.

Goyal, A., and I. Welch (2003), Predicting the equity premium with dividend ratios, *Management Science* 49 (5), 639-654.

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

Granville, J. (1963), *Granville's New Key to Stock Market Profits*, Prentice-Hall, New-York.

Hansen, P.R., and A. Timmermann (2012), Choice of sample split in out-of-sample forecast evaluation, European University Institute Working Paper ECO 2012/10.

Hendry, D.F., and M.P. Clements (2004), Pooling of forecasts, *The Econometrics Journal* 7 (1), 1-31.

Henkel, S.J., J.S. Martin, and F. Nardari (2011), Time-varying short-horizon predictability, *Journal of Financial Economics* 99 (3), 560-580.

Huang, D., F. Jiang, J. Tu, and G. Zhou (2015), Investor sentiment aligned: A powerful predictor of stock returns, *Review of Financial Studies* 28 (3), 791-837.

Huang, H., and T.H. Lee (2010), To combine forecasts or to combine information? *Econometric Reviews* 29 (5-6), 534-570.

Inoue, A., and L. Kilian (2004), In-sample and out-of-sample tests of predictability: Which one should we use? *Econometric Reviews* 23 (4), 371-402.

Kandel, S., and R.F. Stambaugh (1996), On the predictability of stock returns: An asset-allocation perspective, *Journal of Finance* 51 (2), 385-424.

Kelly, B., and S. Pruitt (2013), Market expectations in the cross-section of present values, *Journal of Finance* 68 (5), 1721-1756.

Lo, A.W., H. Mamaysky, and J. Wang (2000), Foundations of technical analysis: Computational algorithms, statistical inference, and empirical implementation, *Journal of Finance* 55 (4), 1705-1765.

Ludvigson, S.C., and S. Ng (2007), The empirical risk-return relation: A Factor Analysis Approach, *Journal of Financial Economics* 83 (1), 171-222.

Ludvigson, S.C., and S. Ng (2009), Macro factors in bond risk premia, *Review of Financial Studies* 22 (12), 5027-5067.

Marquering, W., and M. Verbeek (2004), The economic value of predicting stock index returns and volatility, *Journal of Financial and Quantitative Analysis* 39 (2), 407-429.

Mele, A. (2007), Asymmetric stock market volatility and the cyclical behavior of expected returns, *Journal of Financial Economics* 86 (2), 446-478.

Møller, S.V., and J. Rangvid (2015), End-of-the-year economic growth and time-varying expected returns, *Journal of Financial Econometrics* 115 (1), 136-154.

Neely, C.J., D. Rapach, J. Tu, and G. Zhou (2014), Forecasting the equity risk premium: The role of technical indicators, *Management Science* 60 (7), 1772-1791.

Park, C.H., and S.H. Irwin (2007), What do we know about the profitability of technical analysis? *Journal of Economic Surveys* 21 (4), 786-826.

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

Pesaran, M.H., and A. Timmermann (1995), Predictability of stock returns: Robustness and economic significance, *Journal of Finance* 50 (4), 1201-1228.

Rapach, D.E., J.K. Strauss, and G. Zhou (2010), Out-of-sample equity premium prediction: Combination forecasts and links to the real economy, *Review of Financial Studies* 23 (2), 821-862.

Rapach, D.E., and M.E. Wohar (2006), Structural breaks and predictive regression models of aggregate U.S. stock returns, *Journal of Financial Econometrics* 4 (2), 238-274.

Rapach, D.E., and G. Zhou (2013), Forecasting stock returns, in G. Elliot and A. Timmermann, eds.: *Handbook of Economic Forecasting*, Volume 2, Elsevier, Amsterdam.

Ross, S.A. (2005), *Neoclassical Finance*, Princeton University Press, Princeton, N.J.

Schmeling, M. (2009), Investor sentiment and stock returns: Some international evidence, *Journal of Empirical Finance* 16 (3), 394-408.

Sibley, S.E., Y. Wang, Y. Xing, and X. Zhang (2016), The information content of the sentiment index, *Journal of Banking and Finance* 62, 164-179.

Spiegel, M. (2008), Forecasting the equity premium: Where we stand today, *Review of Financial Studies* 21 (4), 1453-1454.

Stock, J.H., and M.W. Watson (2002), Forecasting using principal components from a large number of predictors, *Journal of the American Statistical Association* 97 (460), 1167-1179.

Stock, J.H., and M.W. Watson (2003), Forecasting output and inflation: The role of asset prices, *Journal of Economic Literature* 41 (3), 788-829.

Timmermann, A. (2006), Forecast combinations, in G. Elliot and A. Timmermann, eds.: *Handbook of Economic Forecasting*, Volume 1, Elsevier, Amsterdam.

Timmermann, A. (2008), Elusive return predictability, *International Journal of Forecasting*, 24 (1), 1-18.

Xu, Y. (2004), Small levels of predictability and large economic gains, *Journal of Empirical Finance* 11 (2), 247-275.

Zhou, G. (2010), How much stock return predictability can we expect from an asset pricing model? *Economics Letters* 108 (2), 184-186.

Zhu, Y., and G. Zhou (2009), Technical analysis: An asset allocation perspective on the use of moving averages, *Journal of Financial Economics* 92 (3), 519-544.

I Appendix to Chapter 2

I.a Data appendix

Technical indicators:

1. Moving Average Rules (MA(s,l)): Defined as the difference between short-term (*s*) and long-term (*l*) moving averages based on the level of the S&P 500 stock price index

$$S_{i,t} = \begin{cases} 1 \; if \; MA_{s,t} \geq MA_{l,t} \\ 0 \; otherwise \end{cases} \quad s=(1,2,3);\ l=(9,12)$$

where

$$MA_{j,t} = \left(\frac{1}{j}\right) \sum_{i=0}^{j-1} P_{t-i} \qquad for\ j = s, l$$

P_t is the level of the S&P 500 stock price index.

2. Defined as the difference between the current level of the S&P 500 stock price index and the price index *m* months ago.

$$S_{i,t} = \begin{cases} 1 \; if \; P_t \geq P_{t-m} \\ 0 \; otherwise \end{cases} \quad m=(9,12)$$

3. Defined as the difference between short-term (*s*) and long-term (*l*) moving averages based on "on-balance" volume data (OBV), following Granville (1963).

$$OBV_t = \sum_{k=1}^{t} VOL_k D_k$$

where D_k is a dummy variable which takes a value of 1 if $P_k - P_{k-1} \geq 0$ and 0 otherwise, and VOL_k is the monthly trading volume on the S&P 500 index.[13] Buy (sell) recommendations are then obtained by

$$S_{i,t} = \begin{cases} 1 \; if \; MA_{s,t}^{OBV} \geq MA_{l,t}^{OBV} \\ 0 \; otherwise \end{cases}$$

with

$$MA_{j,t}^{OBV} = \left(\frac{1}{j}\right) \sum_{i=0}^{j-1} OBV_{t-i} \qquad \text{for } j = s,\ l.$$

[13] Volume data on the S&P 500 index is obtained from http://de.finance.yahoo.com

Economic variables:

1. Dividend Price Ratio (d/p): Defined as the difference between the log of a twelve-month moving sum of dividends paid on the S&P 500 index and the log of stock prices.
2. Dividend Yield (d/y): Defined as the difference between the log of a twelve-month moving sum of dividends paid on the S&P 500 index and the log of lagged stock prices.
3. Earnings Price Ratio (e/p): Defined as the difference between the log of a twelve-month moving sum of earnings on the S&P 500 index and the log of stock prices.
4. Dividend Payout Ratio (d/e): Defined as the difference between the log of a twelve-month moving sum of dividends paid on the S&P 500 and the log of a twelve-month moving sum of earnings on the S&P 500.
5. Equity Risk Premium Volatility (rvol): Following Neely et al. (2014) and Mele (2007) we make use of a volatility measure that avoids for 'outlying' observations. Equity risk premium volatility is defined as

$$\hat{\sigma}_t = \frac{1}{12}\sum_{i=1}^{12}|r_{t+1-i}|$$

$$\widehat{rvol}_t \equiv \sqrt{\frac{\pi}{2}}\sqrt{12}\hat{\sigma}_t.$$

6. Book-to-Market Ratio (b/m): Defined as the ratio of book value to market value for the Dow Jones Industrial Average.
7. Net Equity Expansion (ntis): Defined as the ratio of a twelve-month moving sum of net equity issued by NYSE-listed stocks divided by the total end-of-year market capitalization of NYSE stocks.
8. Treasury Bill Rate (tbl): Defined as the 3-month Treasury bill rate (secondary market)
9. Long-term Yield (lty): Defined as the long-term government bond yield.
10. Long-term Return (ltr): Defined as the return on long-term government bonds.
11. Term Spread (tms): Defined as the difference between the long-term yield and the 3-month Treasury bill rate.
12. Default Yield Spread (dfy): Defined as the difference between Moody's BAA- and AAA- rated corporate bond yields.
13. Default Return Spread (dfr): Defined as the difference between the return on long-term corporate bonds and returns on long-term government bonds.

14. Inflation (infl): Calculated from the Consumer Price Index (CPI, All Urban Consumers). To account for a delay in CPI releases, we use the 1-month lagged inflation in the predictive regression.

I.b Further results

Table A.2.1: Summary statistics; individual macroeconomic and technical indicators

Variable	Mean	Std.	Skew.	Kurt.	AC(1)	AC(2)	AC(3)
<u>Macroeconomic indicators</u>							
DP	-3.51	0.42	-0.31	2.47	0.99	0.98	0.97
DY	-3.50	0.42	-0.31	2.49	0.99	0.98	0.97
EP	-2.78	0.43	-0.85	6.09	0.99	0.97	0.94
DE	-0.73	0.30	2.54	18.06	0.99	0.95	0.90
RVOL	0.14	0.05	0.81	3.88	0.96	0.92	0.88
BM	0.53	0.25	0.52	2.60	0.99	0.99	0.98
NTIS	0.01	0.02	-1.08	4.46	0.98	0.95	0.92
TBL	4.46	3.05	0.88	4.20	0.99	0.97	0.95
LTY	6.15	2.72	0.83	3.22	0.99	0.98	0.98
LTR	0.55	2.75	0.51	6.33	0.05	-0.07	-0.02
TMS	1.69	1.42	-0.11	2.81	0.96	0.91	0.86
DFY	0.96	0.45	1.81	7.54	0.97	0.92	0.88
DFR	0.02	1.38	-0.34	10.00	-0.09	-0.06	-0.02
INFL	0.30	0.33	0.55	7.29	0.61	0.47	0.38
<u>Technical indicators</u>							
MA (1,9)	0.69	0.46	-0.82	1.68	0.70	0.55	0.43
MA (1,12)	0.72	0.45	-0.96	1.92	0.78	0.65	0.53
MA (2,9)	0.70	0.46	-0.85	1.72	0.77	0.60	0.47
MA (2,12)	0.72	0.45	-0.95	1.91	0.83	0.69	0.56
MA (3,9)	0.70	0.46	-0.88	1.77	0.80	0.62	0.48
MA (3,12)	0.72	0.45	-0.98	1.95	0.83	0.68	0.57
MOM (9)	0.71	0.45	-0.95	1.90	0.76	0.69	0.58
MOM (12)	0.73	0.44	-1.05	2.10	0.81	0.72	0.64
VOL (1,9)	0.68	0.47	-0.77	1.60	0.61	0.54	0.42
VOL (1,12)	0.71	0.46	-0.90	1.82	0.71	0.64	0.50
VOL (2,9)	0.68	0.47	-0.75	1.57	0.76	0.56	0.46
VOL (2,12)	0.70	0.46	-0.88	1.77	0.82	0.65	0.56
VOL (3,9)	0.69	0.46	-0.84	1.70	0.76	0.58	0.45
VOL (3,12)	0.70	0.46	-0.88	1.78	0.83	0.70	0.58

Notes: The table reports summary statistics, including mean, standard deviation (Std.), Skewness (Skew.) and Kurtosis (Kurt.) of predictor variables stemming from macroeconomic and technical indicators. We also report the first to third-order autocorrelation coefficient AC(.). The sample period is December 1950 to December 2014.

Table A.2.2: Marginal out-of-sample forecast contribution during recession periods

Pooling strategy	**Δ Out-of-sample *R*-square (in %)**			
	(β_{gm}=0)	(β_{ge}=0)	(β_{dp}=0)	(β_{rf}=0)
Panel A: Marginal forecast contribution; macroeconomic indicators				
Mean	-3.25**	0.75	-0.26**	-0.15
	(-1.75)	(0.46)	(-2.26)	(-0.44)
Median	-1.38*	1.13	0.71	0.96
	(-1.56)	(1.89)	(1.83)	(2.27)
Trimmed mean	-3.13*	0.74	-0.25**	-0.08
	(-1.63)	(0.45)	(-2.34)	(-0.28)
DMSFE (1.0)	-3.24**	0.75	-0.26**	-0.15
	(-1.72)	(0.47)	(-2.29)	(-0.43)
DMSFE (0.9)	-3.50**	0.88	-0.27***	-0.15
	(-1.75)	(0.55)	(-2.44)	(-0.43)
PC	-5.19***	1.91	-0.71**	0.18
	(-3.60)	(3.07)	(-2.31)	(0.22)
Panel B: Marginal forecast contribution; technical indicators				
Mean	0.05	-2.04*	0.08	-0.27*
	(0.08)	(-1.51)	(1.64)	(-1.56)
Median	0.12	-1.99*	0.28	-0.12
	(0.17)	(-1.54)	(1.81)	(-0.68)
Trimmed mean	0.06	-2.06*	0.09	-0.28*
	(0.09)	(-1.52)	(1.63)	(-1.60)
DMSFE (1.0)	0.05	-2.04*	0.08	-0.27*
	(0.07)	(-1.51)	(1.64)	(-1.56)
DMSFE (0.9)	0.03	-2.03*	0.08	-0.27*
	(0.05)	(-1.51)	(1.63)	(-1.56)
PC	0.11	-2.74*	0.10	-0.34*
	(0.12)	(-1.47)	(1.39)	(-1.40)

Notes: This table reports the marginal gain (loss) in the out-of-sample equity premium prediction performance during NBER dated recession periods. The marginal contribution of equity premium components (named in the headings) is determined by the difference between the out-of-sample R-squares obtained under the restricted (βj=0) predictive regression setting and the unrestricted forecasts. Statistical significance corresponds to a one-sided t-test based on the resulting prediction errors of the restricted and the unrestricted forecasting approach. Asterisks denote significance of the t-statistic (denoted in parenthesis) with significance levels of 10%, 5%, 1% characterized by *, **, ***. Panel A reports results for pooling strategies based on economic information, while panel B presents results for forecasting strategies incorporating technical indicators.

Table A.2.3: Testing for equal predictive ability between restricted and unrestricted forecasts

Pooling strategy	**Out-of-sample *R*-square**		
	Full sample	Expansion	Recession
Panel A: Forecasting comparison; pooling strategies based on 28 predictors			
Mean	1.43%***	0.41%*	3.53%***
	(2.94)	(1.29)	(3.21)
Median	1.34%***	0.54%*	3.01%***
	(2.73)	(1.44)	(2.58)
Trimmed mean	1.30%***	0.25%	3.49%***
	(2.85)	(1.09)	(3.61)
DMSFE (1.0)	1.79%***	0.78%**	3.88%***
	(3.13)	(1.90)	(2.47)
DMSFE (0.9)	1.75%***	0.76%**	3.84%**
	(2.99)	(1.88)	(2.27)
PC	0.32%	-0.32%	1.72%**
	(1.27)	(0.41)	(1.67)
Panel B: Forecasting comparison; standard sum-of-parts approach			
Mean	1.47%***	0.38%*	3.73%***
	(2.69)	(1.40)	(2.56)
Median	1.33%***	0.42%*	3.28%***
	(2.60)	(1.37)	(2.67)
Trimmed mean	1.29%***	0.20%	3.59%***
	(2.55)	(1.19)	(2.71)
DMSFE (1.0)	1.88%***	0.83%**	4.09%**
	(3.01)	(1.91)	(2.29)
DMSFE (0.9)	1.85%***	0.76%**	4.15%**
	(2.83)	(1.85)	(2.09)
PC	1.01%**	-1.25%	5.83%***
	(2.31)	(0.70)	(3.30)

Notes: This table compares the out-of-sample forecast performance of extended sum-of-parts forecasts against conventional pooling strategies which incorporate information from the entire set of macroeconomic and technical indicators and against conventional sum-of-parts forecasts. Polling strategies encompass forecast combinations (following Rapach et al., 2010) and principal component predictive regressions. The empirical evidence is determined by the out-of-sample R-square (following Campbell and Thompson, 2008) over the sample period from 1966:01 through 2014:12. Stars refer to significance levels of 10% (*), 5% (**), and 1% (***) of the out-of-sample MSFE-adjusted statistic proposed by Clark and West (2007). The MSFE-adjusted statistic tests the null hypothesis $R^2_{OS} \leq 0$ against the one-sided alternative $R^2_{OS} > 0$. Corresponding t-values are reported in parenthesis. Out-of-sample evidence is also reported separately for NBER-dated expansion and recession periods.

Table A.2.4: Forecasting industrial production

Pooling strategy	Monthly growth rates			Quarterly growth rates
	R^2_{OS}	$R^2_{OS,Exp.}$	$R^2_{OS,Rec.}$	R^2_{OS}
Panel A: Forecast based on macroeconomic indicators				
Median	1.49%***	-0.63%	5.06%***	3.93%***
	(2.45)	(0.25)	(2.98)	(3.35)
Trimmed mean	1.85%***	-0.73%	6.20%***	4.70%***
	(2.86)	(0.33)	(3.52)	(3.62)
DMSFE (1.0)	2.12%***	-0.67%	6.82%***	5.67%***
	(3.07)	(0.45)	(3.74)	(3.93)
DMSFE (0.9)	2.28%***	-0.86%	7.56%***	8.91%***
	(3.11)	(0.20)	(3.92)	(4.76)
PC	-4.94%	-9.19%	2.22%*	-18.16%
	(1.03)	(0.04)	(1.55)	(0.96)
Panel B: Forecast based on technical indicators				
Median	3.14%***	-2.75%**	13.06%***	8.61%***
	(4.53)	(2.28)	(4.50)	(6.92)
Trimmed mean	5.03%***	-1.29%***	15.68%***	12.49%***
	(5.33)	(2.73)	(5.27)	(7.47)
DMSFE (1.0)	5.18%***	-1.04%***	15.64%***	13.40%***
	(5.36)	(2.74)	(5.29)	(7.50)
DMSFE (0.9)	5.14%***	-1.16%***	15.74%***	13.86%***
	(5.34)	(2.69)	(5.31)	(7.58)
PC	2.70%***	-6.85%***	18.77%***	5.92%***
	(5.31)	(2.72)	(5.25)	(7.49)

Notes: This table reports out-of-sample R^2_{OS} statistic (in percent) proposed by Campbell and Thompson (2008) of industrial production predictability by comparing the forecast performance of prediction models given in the row headings to the AR(1) benchmark model over the sample period 1966:01 to 2014:12. Statistical significance is assessed by the out-of-sample MSFE-adjusted statistic proposed by Clark and West (2007). The MSFE-adjusted statistic tests the null hypothesis $R^2_{OS} \leq 0$ against the one-sided alternative $R^2_{OS} > 0$. Corresponding t-values are reported in parenthesis with stars referring to significance levels of 10% (*), 5% (**), and 1% (***).

Table A.2.5: Forecasting inflation

Pooling strategy	**Monthly growth rates**			**Quarterly growth rates**
	R^2_{OS}	$R^2_{OS,Exp.}$	$R^2_{OS,Rec.}$	R^2_{OS}
Panel A: Forecast based on macroeconomic indicators				
Median	0.89%***	1.18%***	0.39%	0.74%***
	(2.78)	(2.59)	(1.11)	(2.99)
Trimmed mean	1.90%***	2.20%***	1.39%**	1.42%***
	(3.98)	(3.59)	(1.91)	(3.87)
DMSFE (1.0)	2.32%***	2.69%***	1.68%**	1.97%***
	(4.15)	(3.87)	(1.92)	(4.20)
DMSFE (0.9)	2.78%***	3.11%***	2.21%**	3.02%***
	(4.59)	(4.27)	(2.16)	(5.18)
PC	0.48%***	1.76%***	-1.71%	1.26%***
	(3.18)	(3.07)	(1.11)	(3.69)
Panel B: Forecast based on technical indicators				
Median	-0.33%	-0.43%	-0.18%	-0.82%
	(-0.55)	(-0.87)	(-0.06)	(-3.82)
Trimmed mean	-0.29%	-0.38%	-0.13%	-0.79%
	(-0.50)	(-0.86)	(-0.02)	(-3.76)
DMSFE (1.0)	-0.28%	-0.34%	-0.17%	-0.79%
	(-0.53)	(-0.82)	(-0.09)	(-3.89)
DMSFE (0.9)	-0.28%	-0.34%	-0.16%	-0.78%
	(-0.52)	(-0.81)	(-0.08)	(-3.84)
PC	-0.44%	-0.55%	-0.24%	-1.11%
	(-0.50)	(-0.83)	(-0.04)	(-3.69)

Notes: This table reports out-of-sample R^2_{OS} statistic (in percent) proposed by Campbell and Thompson (2008) of inflation predictability by comparing the forecast performance of prediction models given in the row headings to the AR(1) benchmark model over the sample period 1966:01 to 2014:12. Statistical significance is assessed by the out-of-sample MSFE-adjusted statistic proposed by Clark and West (2007). The MSFE-adjusted statistic tests the null hypothesis $R^2_{OS} \leq 0$ against the one-sided alternative $R^2_{OS} > 0$. Corresponding t-values are reported in parenthesis with stars referring to significance levels of 10% (*), 5% (**), and 1% (***).

Table A.2.6: Equity premium forecasting results; bivariate predictive regressions

Predictor	In-sample *R*-square	Out-of-sample *R*-square			Predictor	In-sample *R*-square	Out-of-sample *R*-square		
		Full sample	Exp.	Rec.			Full sample	Exp.	Rec.
DP	0.40%*	-0.22%	-1.06%	1.55%*	MA (1,9)	0.60%**	0.30%	-0.67%	2.39%**
	(3.11)	(1.08)	(0.43)	(1.30)		(4.59)	(1.12)	(-0.42)	(1.94)
DY	0.48%*	-0.17%	-1.37%	2.39%**	MA (1,12)	0.92%***	0.70%*	-0.52%	3.30%**
	(3.66)	(1.22)	(0.28)	(1.88)		(7.15)	(1.63)	(0.16)	(2.07)
EP	0.19%	-0.58%	-0.30%	-1.17%	MA (2,9)	0.65%**	0.39%*	-0.61%	2.53%**
	(1.43)	(0.01)	(0.32)	(-0.21)		(5.01)	(1.28)	(-0.12)	(1.89)
DE	0.07%	-0.88%	-1.72%	0.89%	MA (2,12)	1.09%***	0.85%**	-0.41%	3.53%**
	(0.56)	(0.67)	(-0.04)	(0.77)		(8.42)	(1.81)	(0.38)	(2.14)
RVOL	0.62%**	0.06%*	-0.16%	0.53%	MA (3,9)	0.75%**	0.48%*	-0.67%	2.94%**
	(4.81)	(1.48)	(1.25)	(0.79)		(5.80)	(1.51)	(0.23)	(1.87)
BM	0.05%	-1.26%	-0.31%	-3.30%	MA (3,12)	0.35%	0.09%	-0.43%	1.19%
	(0.37)	(-1.37)	(0.27)	(-2.21)		(2.67)	(0.67)	(-0.31)	(1.11)
NTIS	0.01%	-0.91%	-0.12%*	-2.61%	MOM (9)	0.36%*	0.12%	-0.45%	1.34%*
	(0.11)	(0.40)	(1.34)	(-1.32)		(2.74)	(0.66)	(-0.57)	(1.29)
TBL	0.77%**	-0.84%**	-1.90%**	1.43%*	MOM (12)	0.38%*	0.16%	-0.41%	1.39%*
	(5.97)	(2.18)	(1.74)	(1.43)		(2.88)	(0.72)	(-0.59)	(1.32)
LTY	0.36%*	-0.77%**	-1.58%	0.98%	VOL (1,9)	0.63%**	0.48%*	-0.53%	2.61%**
	(2.79)	(1.65)	(1.17)	(1.20)		(4.84)	(1.41)	(-0.23)	(2.22)
LTR	0.73%**	0.26%**	-1.92%	4.90%***	VOL (1,12)	0.93%***	0.80%**	-0.20%	2.94%**
	(5.61)	(2.01)	(0.28)	(2.74)		(7.21)	(1.81)	(0.47)	(2.01)
TMS	0.54%**	-0.84%**	-3.14%	4.06%**	VOL (2,9)	0.69%**	0.47%*	0.04%	1.37%*
	(4.18)	(2.17)	(1.19)	(2.19)		(5.34)	(1.45)	(0.63)	(1.47)
DFY	0.03%	-0.63%	-0.54%	-0.83%	VOL (2,12)	0.66%**	0.35%	0.19%	0.69%
	(0.21)	(-0.35)	(-0.06)	(-0.60)		(5.11)	(1.19)	(0.88)	(0.81)
DFR	0.28%	-0.42%	0.35%*	-2.07%	VOL (3,9)	0.29%	0.03%	-0.37%	0.89%
	(2.14)	(0.11)	(1.31)	(-0.82)		(2.25)	(0.52)	(-0.40)	(1.03)
INFL	0.11%	-0.27%	0.16%	-1.19%	VOL (3,12)	0.82%**	0.68%**	0.10%	1.91%*
	(0.83)	(0.43)	(1.21)	(-0.04)		(6.36)	(1.68)	(0.83)	(1.51)

Notes: This table reports in-sample and out-of-sample results for equity premium forecast using economic variables and technical indicators in bivariate predictive regressions. Empirical evidence is determined by the in-sample *R*-square over the full sample period and by the out-of-sample *R*-square (following Campbell and Thompson, 2008) over the sample period from 1966:01 through 2014:12. Stars refer to significance levels of 10% (*), 5% (**), and 1% (***) of the in-sample *F*-statistic (reported in parenthesis) and of the out-of-sample *MSFE-adjusted* statistic of Clark and West (2007). The *MSFE-adjusted* statistic tests the null hypothesis $R_{OS}^2 \leq 0$ against the one-sided alternative $R_{OS}^2 > 0$. Corresponding t-values are reported in parenthesis. Out-of-sample evidence is also reported separately for NBER-dated expansion and recession periods.

Table A.2.7: Marginal forecast contribution of equity premium components

Predictor	Δ In-sample *R*-square				Δ Out-of-sample *R*-square			
	(β_{gm}=0)	(β_{ge}=0)	(β_{dp}=0)	(β_{rf}=0)	(β_{gm}=0)	(β_{ge}=0)	(β_{dp}=0)	(β_{rf}=0)
Panel A: Marginal forecast contribution; macroeconomic indicators								
DP	-1.76**	-0.50	-0.06	-0.05	-0.54	-2.06***	0.18	-0.29**
	(-1.74)	(-0.94)	(-0.32)	(-0.30)	(-0.35)	(-2.53)	(0.71)	(-2.06)
DY	-1.40*	-0.27	-0.06	-0.05	-0.62	-2.10***	0.18	-0.28**
	(-1.57)	(-0.69)	(-0.32)	(-0.29)	(-0.39)	(-2.55)	(0.72)	(-2.05)
EP	-1.56*	-0.53	-0.04	-0.08	-1.28*	0.66	0.08	-0.22
	(-1.42)	(-0.79)	(-0.22)	(-0.31)	(-1.30)	(0.68)	(0.30)	(-0.72)
DE	-0.00	-0.00	-0.00	-0.01	-7.32**	-3.34*	-0.09	0.51
	(-0.07)	(-0.06)	(-0.07)	(-0.11)	(-1.68)	(-1.48)	(-0.92)	(1.29)
RVOL	-0.09	-0.24	-0.00	-0.00	-2.50*	-1.24*	0.01	-0.07
	(-0.43)	(-0.70)	(-0.00)	(-0.01)	(-1.39)	(-1.48)	(0.21)	(-1.22)
BM	-0.62	-0.22	-0.05	-0.10	0.89	-1.10**	0.10	-0.26
	(-0.95)	(-0.58)	(-0.27)	(-0.39)	(0.84)	(-1.77)	(0.46)	(-0.86)
NTIS	-6.49***	-5.56***	-0.00	-0.00	-1.28	-2.20*	-0.11**	-0.36**
	(-3.03)	(-2.58)	(-0.06)	(-0.02)	(-0.63)	(-1.41)	(-1.78)	(-1.96)
TBL	-0.00	-0.17	-0.01	-0.36	0.99	-0.76**	0.05	1.15
	(-0.05)	(-0.55)	(-0.13)	(-0.79)	(0.48)	(-1.74)	(0.52)	(2.05)
LTY	-0.03	-0.00	-0.01	-0.28	0.46	-0.61*	0.06	0.86
	(-0.23)	(-0.04)	(-0.10)	(-0.71)	(0.25)	(-1.31)	(0.47)	(1.64)
LTR	-2.71**	-0.59	-0.00	-0.00	-1.38	-0.67	-0.01	-0.04*
	(-1.96)	(-0.92)	(-0.01)	(-0.02)	(-0.73)	(-1.05)	(-0.99)	(-1.42)
TMS	-0.17	-0.90	-0.00	-0.07	1.10	0.56	-0.02	0.42
	(-0.56)	(-1.27)	(-0.09)	(-0.36)	(0.78)	(1.55)	(-0.67)	(1.95)
DFY	-7.73***	-6.02***	-0.00	-0.04	-4.98**	-2.49	0.03	-0.45
	(-3.00)	(-2.57)	(-0.05)	(-0.22)	(-1.80)	(-1.17)	(0.53)	(-1.22)
DFR	-0.80	-1.95	-0.00	-0.00	-0.30	-0.01	-0.00	-0.04*
	(-0.82)	(-1.20)	(-0.00)	(-0.02)	(-0.40)	(-0.01)	(-0.02)	(-1.60)
INFL	-2.00*	-1.72*	-0.01	-0.09	0.97	-1.04*	-0.07	0.24
	(-1.63)	(-1.39)	(-0.08)	(-0.34)	(0.99)	(-1.55)	(-1.23)	(0.87)
Panel B: Marginal forecast contribution; technical indicators								
MA(1,9)	-1.59*	-3.94***	-0.00	-0.01	0.53	-1.16**	0.01	-0.01
	(-1.54)	(-2.43)	(-0.04)	(-0.10)	(1.17)	(-1.67)	(0.22)	(-0.12)
MA(1,12)	-0.81	-3.35**	-0.00	-0.00	-0.35	-0.30	0.01	-0.04
	(-1.08)	(-2.19)	(-0.04)	(-0.08)	(-0.73)	(-0.45)	(0.21)	(-0.47)
MA(2,9)	-1.33*	-3.68***	-0.00	-0.01	0.01	-0.55	-0.00	-0.01
	(-1.42)	(-2.36)	(-0.04)	(-0.09)	(0.03)	(-0.86)	(-0.11)	(-0.15)
MA(2,12)	-0.69	-3.43**	-0.00	-0.00	-0.42	-0.36	0.01	-0.05
	(-1.00)	(-2.23)	(-0.04)	(-0.07)	(-0.96)	(-0.50)	(0.41)	(-0.58)
MA(3,9)	-1.21*	-3.72***	-0.00	-0.01	0.15	-0.58	-0.01	0.01
	(-1.36)	(-2.38)	(-0.05)	(-0.10)	(0.26)	(-0.90)	(-0.58)	(0.11)
MA(3,12)	-1.82*	-3.69**	-0.00	-0.00	-0.17	-0.39	-0.00	-0.03
	(-1.63)	(-2.32)	(-0.04)	(-0.06)	(-0.41)	(-0.52)	(-0.13)	(-0.33)
MOM(9)	-1.70*	-3.56**	-0.00	-0.00	-0.51	-0.14	0.01	-0.04
	(-1.58)	(-2.28)	(-0.05)	(-0.07)	(-1.24)	(-0.19)	(0.43)	(-0.52)
MOM(12)	-0.47	-1.71*	-0.00	-0.00	0.03	-0.74	0.01	-0.03
	(-0.83)	(-1.58)	(-0.04)	(-0.03)	(0.07)	(-0.97)	(0.60)	(-0.44)
VOL(1,9)	-1.17*	-3.38**	-0.00	-0.01	-0.08	-0.63	0.02	-0.04
	(-1.35)	(-2.29)	(-0.05)	(-0.09)	(-0.19)	(-1.05)	(0.50)	(-0.56)
VOL(1,12)	-1.27*	-4.28***	-0.00	-0.00	0.09	-1.17*	0.03	-0.04
	(-1.37)	(-2.51)	(-0.05)	(-0.08)	(0.19)	(-1.56)	(0.87)	(-0.51)
VOL(2,9)	-1.08*	-3.41**	-0.00	-0.00	0.35	-1.19**	0.04	-0.11*
	(-1.30)	(-2.30)	(-0.05)	(-0.08)	(0.77)	(-1.92)	(1.24)	(-1.46)
VOL(2,12)	-1.38*	-3.88***	-0.00	-0.00	0.62	-1.52**	0.08	-0.08
	(-1.43)	(-2.40)	(-0.06)	(-0.08)	(1.31)	(-2.25)	(1.67)	(-1.19)
VOL(3,9)	-2.08**	-3.86***	-0.00	-0.00	0.28	-0.94*	0.02	-0.03
	(-1.77)	(-2.41)	(-0.05)	(-0.07)	(0.55)	(-1.36)	(0.57)	(-0.46)
VOL(3,12)	-1.41*	-4.29***	-0.00	-0.00	0.18	-1.21*	0.03	-0.04
	(-1.47)	(-2.55)	(-0.05)	(-0.08)	(0.46)	(-1.63)	(0.77)	(-0.55)

Notes: This table reports the marginal gain (loss) in the equity premium prediction performance if we impose zero beta restrictions on individual equity premium components (named in the headings). The marginal contribution of equity premium components is determined by the difference between the in-sample (out-of-sample) R-squares obtained under the restricted ($\beta j=0$) predictive regression setting and the unrestricted forecasts. Statistical significance corresponds to a one-sided t-test based on the resulting prediction errors of the restricted and the unrestricted forecasting approach. Asterisks denote significance of the t-statistic (denoted in parenthesis) with significance levels of 10%, 5%, 1% characterized by *, **, ***.^

Table A.2.8: Marginal out-of-sample forecast contribution during recessions

Predictor	**Δ Out-of-sample *R*-square**				**Predictor**	**Δ Out-of-sample *R*-square**			
	(β_{gm}=0)	(β_{ge}=0)	(β_{dp}=0)	(β_{rf}=0)		(β_{gm}=0)	(β_{ge}=0)	(β_{dp}=0)	(β_{rf}=0)
Macroeconomic indicators					**Technical indictors**				
DP	-2.48	0.30	-0.41	0.13	MA(1,9)	-0.07	-2.02*	0.07	-0.39**
	(-1.04)	(0.27)	(-1.16)	(0.63)		(-0.09)	(-1.55)	(1.68)	(-1.80)
DY	-3.53*	0.58	-0.54*	0.15	MA(1,12)	-1.05	-1.74*	0.06	-0.33*
	(-1.55)	(0.57)	(-1.58)	(0.82)		(-1.13)	(-1.30)	(1.29)	(-1.50)
EP	-1.95	1.51	0.06	0.06	MA(2,9)	-0.57	-1.59*	0.04	-0.31*
	(-0.93)	(0.58)	(0.10)	(0.09)		(-0.69)	(-1.30)	(1.00)	(-1.50)
DE	-19.47*	-6.15	-0.06	-0.31	MA(2,12)	-0.87	-2.17*	0.07	-0.30*
	(-1.56)	(-0.90)	(-0.21)	(-0.35)		(-1.06)	(-1.46)	(1.31)	(-1.49)
RVOL	-3.63	-0.07	-0.02	0.10	MA(3,9)	-0.82	-1.59	0.02	-0.28
	(-1.03)	(-0.04)	(-0.28)	(1.10)		(-0.70)	(-1.27)	(0.52)	(-1.22)
BM	2.95	-1.30	-0.03	0.51	MA(3,12)	0.73	-1.99	0.02	-0.18
	(1.38)	(-0.92)	(-0.06)	(0.90)		(0.98)	(-1.25)	(0.50)	(-0.86)
NTIS	4.28	-7.88**	-0.30**	-0.56*	MOM(9)	0.65	-2.11*	0.05	-0.23
	(0.83)	(-1.75)	(-2.12)	(-1.51)		(0.98)	(-1.38)	(1.00)	(-1.19)
TBL	-1.67	-0.07	-0.21	1.37	MOM(12)	1.20	-3.01**	0.06	-0.18
	(-0.32)	(-0.07)	(-0.95)	(1.07)		(1.40)	(-1.68)	(1.20)	(-1.24)
LTY	-1.40	-0.15	-0.17	0.99	VOL(1,9)	-0.53	-1.84**	0.14	-0.33**
	(-0.29)	(-0.13)	(-0.63)	(0.84)		(-0.77)	(-1.76)	(2.18)	(-2.01)
LTR	-7.13**	0.48	-0.02*	0.00	VOL(1,12)	-0.35	-2.39*	0.15	-0.28*
	(-1.72)	(0.29)	(-1.43)	(0.01)		(-0.41)	(-1.62)	(1.89)	(-1.51)
TMS	-3.65**	0.67	-0.10*	-0.27	VOL(2,9)	0.69	-1.98**	0.12	-0.33**
	(-1.74)	(1.31)	(-1.60)	(-0.63)		(0.99)	(-1.75)	(2.14)	(-2.08)
DFY	-8.04	-5.94	0.11	-0.81	VOL(2,12)	1.21	-2.13*	0.17	-0.18
	(-1.06)	(-0.95)	(0.69)	(-0.81)		(1.45)	(-1.58)	(1.83)	(-1.25)
DFR	-0.60	2.22	-0.01	-0.07	VOL(3,9)	0.74	-1.77*	0.09	-0.18
	(-0.35)	(1.25)	(-0.29)	(-1.02)		(0.88)	(-1.33)	(1.28)	(-1.09)
INFL	3.32	-2.98*	-0.26*	0.90	VOL(3,12)	0.15	-2.05*	0.10	-0.15
	(1.16)	(-1.54)	(-1.53)	(1.17)		(0.20)	(-1.36)	(1.26)	(-0.92)

Notes: This table reports the marginal gain (loss) in the out-of-sample equity premium prediction performance during NBER dated recession periods. The marginal contribution of equity premium components (named in the headings) is determined by the difference between the out-of-sample *R*-squares obtained under the restricted (β_j=0) predictive regression setting and the unrestricted forecasts. Statistical significance corresponds to a one-sided t-test based on the resulting prediction errors of the restricted and the unrestricted forecasting approach. Asterisks denote significance of the t-statistic (denoted in parenthesis) with significance levels of 10%, 5%, 1% characterized by *, **, ***.

Table A.2.9: Portfolio performance evaluation; individual predictors

Variable	CER (ann., in %)	Sharpe ratio (ann.)	Relative avg. turnover	CER (ann., in %) costs=50bp	Sharpe ratio (ann.) costs=50bp	Variable	CER (ann., in %)	Sharpe ratio (ann.)	Relative avg. turnover	CER (ann., in %) costs=50bp	Sharpe ratio (ann.) costs=50bp
<u>Macroeconomic indicators</u>						<u>Technical indicators</u>					
DP	3.80	0.13	2.06	3.57	0.10	MA(1,9)	6.03	0.35	4.68	5.42	0.30
DY	4.21	0.15	2.89	3.86	0.12	MA(1,12)	6.87	0.44	3.97	6.35	0.39
EP	4.54	0.20	1.65	4.34	0.18	MA(2,9)	6.27	0.38	4.65	5.68	0.33
DE	3.52	0.12	2.12	3.25	0.09	MA(2,12)	7.09	0.46	3.63	6.63	0.42
RVOL	3.87	0.28	4.33	3.36	0.25	MA(3,9)	6.68	0.43	4.57	6.10	0.38
BM	2.90	0.12	2.52	2.59	0.10	MA(3,12)	5.61	0.32	2.79	5.26	0.29
NTIS	4.22	0.28	3.37	3.80	0.25	MOM(9)	5.57	0.32	2.76	5.22	0.28
TBL	5.73	0.33	1.50	5.54	0.31	MOM(12)	5.48	0.31	2.47	5.17	0.28
LTY	5.55	0.29	1.11	5.41	0.27	VOL(1,9)	5.90	0.35	5.42	5.20	0.29
LTR	5.08	0.35	24.94	2.03	0.13	VOL(1,12)	6.67	0.42	4.63	6.08	0.37
TMS	5.88	0.43	4.58	5.32	0.39	VOL(2,9)	5.73	0.34	3.12	5.34	0.31
DFY	3.23	0.18	2.69	2.90	0.16	VOL(2,12)	5.56	0.32	2.59	5.23	0.30
DFR	4.31	0.22	11.35	2.92	0.10	VOL(3,9)	5.02	0.27	2.70	4.68	0.24
INFL	4.78	0.27	7.57	3.85	0.19	VOL(3,12)	6.31	0.39	2.85	5.94	0.36
Mean	5.86	0.32	4.19	5.35	0.27	Mean	6.14	0.37	3.13	5.75	0.34
Median	4.90	0.25	3.86	4.43	0.21	Median	6.34	0.39	2.91	5.97	0.36
Trimmed Mean	5.63	0.30	4.07	5.13	0.25	Trimmed Mean	6.23	0.38	3.08	5.84	0.34
DMSFE(1.0)	5.95	0.33	4.32	5.42	0.28	DMSFE(1.0)	6.14	0.37	3.14	5.75	0.34
DMSFE(0.9)	6.00	0.34	4.53	5.45	0.28	DMSFE(0.9)	6.15	0.37	3.14	5.75	0.34
PC	6.26	0.37	2.04	6.00	0.34	PC	6.50	0.41	3.65	6.03	0.37

Notes: This table reports portfolio performance measures for an investor with mean-variance preferences and relative risk aversion coefficient of five using macroeconomic variables and technical indicators as predictors, Additionally, we report results for pooling strategies, using forecast combinations (following Rapach et al, 2010) and principal component predictive regressions based on the set of 14 macroeconomic variables (technical indicators). CER describes the annualized percentage certainty equivalent return, i.e. the realized portfolio utility for each model. Sharpe ratios are defined as the average portfolio return in excess of the risk-free rate divided by its variance and the relative average turnover is the average portfolio turnover for each prediction model divided by the average turnover based on the historical average forecast.

Table A.2.10: Forecast performance under alternative restrictions for *dp* and *rf*

Pooling strategy	Macroeconomic variables				Technical indicators				Macroeconomic and technical indicators			
	R^2_{IS}	R^2_{OS}	$R^2_{OS;Exp.}$	$R^2_{OS;Rec.}$	R^2_{IS}	R^2_{OS}	$R^2_{OS;Exp.}$	$R^2_{OS;Rec.}$	R^2_{IS}	R^2_{OS}	$R^2_{OS;Exp.}$	$R^2_{OS;Rec.}$
Panel A: Restrictions imposed on *dp*												
Mean	1.18***	2.30***	0.92**	5.24***	1.17***	2.18***	0.90**	4.90***	1.17***	2.24***	0.91**	5.07***
Median	0.93***	2.11***	0.90**	4.71***	0.99***	2.05***	0.88**	4.54***	0.98***	2.07***	0.89**	4.59***
Trimmed Mean	1.21***	2.13***	0.74**	5.09***	1.21***	2.01***	0.72**	4.78***	1.20***	2.07***	0.73**	4.93***
DMSFE (1.0)	1.22***	2.74***	1.30***	5.81***	1.02***	2.47***	1.23***	5.13***	1.81***	2.68***	1.29***	5.64***
DMSFE (0.9)	1.08***	2.72***	1.23***	5.91***	0.87***	2.43***	1.14***	5.19***	1.63***	2.69***	1.23***	5.82***
PC	-0.58	1.86***	-0.85*	7.64***	-0.46	1.89***	-0.54*	7.00***	-0.57	1.85***	-0.85*	7.60***
Panel B: Restrictions imposed on *rf*												
Mean	1.52***	2.40***	0.94**	5.52***	1.35***	2.32***	0.75**	5.68***	---	---	---	---
Median	1.33***	2.18***	0.95**	4.80***	1.24***	2.25***	0.83**	5.28***	---	---	---	---
Trimmed Mean	1.56***	2.21***	0.74**	5.32***	1.43***	2.18***	0.59*	5.58***	---	---	---	---
DMSFE (1.0)	2.15***	2.79***	1.30***	5.96***	1.34***	2.35***	0.78**	5.68***	---	---	---	---
DMSFE (0.9)	1.97***	2.76***	1.23***	6.02***	1.15***	2.33***	0.70**	5.79***	---	---	---	---
PC	-0.28	1.94***	-0.67*	7.50***	-0.76	1.50***	-1.48	7.85***	---	---	---	---
Panel C: Restrictions imposed on *dp* and *rf*												
Mean	1.24***	2.32***	0.99**	5.14***	1.10***	2.15***	0.82**	5.00***	---	---	---	---
Median	0.99***	2.03***	0.96**	4.33***	0.97***	2.07***	0.85**	4.66***	---	---	---	---
Trimmed Mean	1.27***	2.13***	0.81**	4.94***	1.19***	2.02***	0.66**	4.92***	---	---	---	---
DMSFE (1.0)	2.00***	2.74***	1.30***	5.81***	1.10***	2.18***	0.86**	4.99***	---	---	---	---
DMSFE (0.9)	1.84***	2.72***	1.23***	5.91***	0.90***	2.15***	0.77**	5.10***	---	---	---	---
PC	-0.60	1.88***	-0.74*	7.49***	-0.78	1.61***	-1.06	7.30***	---	---	---	---

Notes: This table reports in-sample and out-of-sample results for equity premium forecast based on alternative restrictions imposed on the dividend-price ratio and the risk-free rate according to results presented in Table 5. Panel A (Panel B) shows the forecast performance of restricted polling strategies under the assumption that solely macroeconomic variables, technical indicators or both predictor groups have predictive ability for the dividend-price ratio (risk-free rate). Panel C impose simultaneous restriction on *dp* and *rf*. Polling strategies encompass principal component predictive regressions and forecast combinations (following Rapach et al., 2010). Empirical evidence is determined by the in-sample R-square over the full sample period and by the out-of-sample R-square (following Campbell and Thompson, 2008) over the sample period from 1966:01 through 2014:12. Stars refer to significance levels of 10% (*), 5% (**), and 1% (***) of the in-sample F-statistic and of the out-of-sample *MSFE-adjusted* statistic of Clark and West (2007). The *MSFE-adjusted* statistic tests the null hypothesis $R^2_{OS} \leq 0$ against the one-sided alternative $R^2_{OS} > 0$. Out-of-sample evidence is also reported separately for NBER-dated expansion and recession periods.

Table A.2.11: Forecast performance: subsamples

Pooling strategy	Evaluation period: 1976-2014			Evaluation period: 2000-2014		
	R^2_{OS}	ΔCER (ann., in %)	ΔCER (ann., in %) costs=50bp	R^2_{OS}	ΔCER (ann., in %)	ΔCER (ann., in %) costs=50bp
Panel A: Forecasting performance; extended sum-of-parts approach						
Mean	1.25%**	2.21	1.78	2.84%**	6.44	5.97
	(2.30)			(2.22)		
Median	1.29%**	3.16	2.73	2.88%**	8.26	7.91
	(2.18)			(2.03)		
Trimmed mean	1.07%**	2.50	2.10	2.64%**	7.35	6.90
	(2.07)			(2.07)		
DMSFE (1.0)	1.39%***	1.18	0.80	2.51%**	3.75	3.33
	(2.48)			(2.20)		
DMSFE (0.9)	1.27%***	0.97	0.56	2.30%**	2.96	2.53
	(2.36)			(2.05)		
PC	0.04%	2.02	1.78	1.83%*	7.50	7.26
	(0.91)			(1.32)		
Panel B: Forecasting performance; pooling strategies based on 28 predictors						
Mean	0.49%**	1.22	1.00	0.89%*	2.84	2.68
	(1.72)			(1.55)		
Median	0.74%**	1.99	1.77	1.59%**	4.93	4.73
	(1.83)			(1.81)		
Trimmed mean	0.48%**	1.23	1.01	0.97%*	3.01	2.85
	(1.71)			(1.63)		
DMSFE (1.0)	0.48%**	1.23	1.00	0.90%*	2.86	2.69
	(1.70)			(1.54)		
DMSFE (0.9)	0.45%*	1.22	0.98	0.92%*	2.98	2.81
	(1.55)			(1.53)		
PC	0.17%	1.54	1.17	2.26%*	5.97	5.74
	(0.96)			(1.42)		
Panel C: Forecasting performance; standard sum-of-parts approach						
SOP	-0.04%	-0.08	-0.14	-0.04%	0.66	0.59
	(0.56)			(0.25)		

Notes: This table reports out-of-sample R-squares (following Rapach et al., 2010) comparing equity premium forecasting models named in the row to the historical average benchmark. Forecasts are based on our extended sum-of-parts method (Panel A), conventional pooling strategies based on the full set of 28 predictors (Panel B), and based the standard sum-of-parts approach (Panel C). Polling strategies encompass forecast combinations (following Rapach et al., 2010) and principal component predictive regressions. Statistical significance is assessed by the *MSFE-adjusted* statistic of Clark and West (2007), testing the null hypothesis $R^2_{OS} \leq 0$ against the one-sided alternative $R^2_{OS} > 0$. Stars refer to significance levels of 10% (*), 5% (**), and 1% (***). ΔCER denotes annualized percentage gains in the certainty equivalent return for a risk-averse investor who makes use of the forecasting models instead of the historical average forecast.

Chapter 3

Does a lot help a lot? Forecasting stock returns with pooling strategies in a data-rich environment

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