Higher moments matter! Cross-sectional (higher) moments and the predictability of stock returns*

Sebastian Stöckl†, Lars Kaiser‡

First version: December, 2015
This version: November, 2016

Abstract

In this paper we investigate the predictive power of cross-sectional volatility, skewness and kurtosis for future stock returns. Adding to the work of Maio (2016), who finds cross-sectional volatility to forecast a decline in the equity premium with high predictive power in-sample as well as out-of-sample, we highlight the additional role of cross-sectional skewness and cross-sectional kurtosis. Applying a principal component approach, we show that cross-sectional higher moments add to the predictive quality of cross-sectional volatility by stabilizing the predictive performance and yielding a positive trend in in-sample and out-of-sample predictive quality since the burst of the dot-com bubble. In particular, we observe cross-sectional skewness to span the predictive quality of cross-sectional volatility over short-forecasting horizons, whereas cross-sectional kurtosis significantly contributes to long-horizon forecasting of 12 months and above. Results are both statistically and economically significant.

Keywords: cross-sectional volatility; cross-sectional skewness; cross-sectional kurtosis; principal components; return dispersion; predictability of stock returns; out-of-sample predictability; equity premium

JEL classification: G12, G14, G17

*We are grateful to Kenneth French, Amit Goyal, Robert Shiller, Robert Stambaugh as well as Dave Rapach for providing research data on their webpages.

†Chair in Finance, University of Liechtenstein, sebastian.stoeckl@uni.li

‡Chair in Business Administration, Banking and Financial Management, University of Liechtenstein, lars.kaiser@uni.li

Electronic copy available at: https://ssrn.com/abstract=2747627

1 Introduction

Forecasting the equity premium is a crucial task and subject to endless empirical analysis in financial economics. However, the fact that equity premium realizations are very noisy makes the task of accurate forecasting all the more difficult. As return prediction is essential for the benefit of portfolio management, the community was once more rudely awakened when DeMiguel et al. (2009) showed that estimation errors are too large for any optimization-based portfolio model to outperform a naive 1/N strategy in the long run. In fact, one would require 500 years of data for a 50 asset portfolio to generate estimates accurate enough to beat the equally-weighted Goliath. Previously contributing to this debate, Welch and Goyal (2008) provide a comprehensive study on the empirical performance of various state variables for predicting the equity premium and report sobering evidence. According to their findings, the majority of forecasting models yield unstable or even spurious results. Whilst the majority of prediction factors are of a time-series nature, they also consider the cross-sectional beta premium proposed by Polk et al. (2006).

Polk et al. (2006) are arguably the first to analyze the predictive power of a cross-sectional measure for the equity premium, whilst earlier studies have largely provided evidence on the predictive power of cross-sectional averages of time-series factors based on firm characteristics (such as dividends and earnings). Based on the CAPM, they argue that the pricing of risk should be consistent for both the time-series and cross-sectional setting. Furthermore, Campbell et al. (2013) show that cross-sectional patterns matter when forecasting the equity premium and that cross-sectional asset pricing models can improve predictive quality, as they are not fully accounted for by pure time-series approaches.

Motivated by earlier studies on the relation between cross-sectional volatility (CSV) and future stock market volatility, Maio (2016) examines whether CSV entails information about future asset returns and reports statistically significant evidence for short- and long term predictions. Replicating the results by Maio (2016) and plotting the in- (IS) and out-of-sample (OOS) predictive quality of CSV in Figure 1, we observe that the positive predictive quality is dominantly driven by the post-2001 period. Building on the observed predictive quality of cross-sectional volatility – in particular during the 2001-2003 period – and taking into account the explicit structural break in the post-2001 period, we seek to extend existing empirical evidence by examining the potential of higher cross-sectional moments to improve and stabilize the quality of existing models for the prediction of the equity premium.

In this study we investigate the role of cross-sectional higher moments – namely cross-sectional skewness (CSS) and cross-sectional kurtosis (CSK) – in predicting the eq-

Electronic copy available at: https://ssrn.com/abstract=2747627

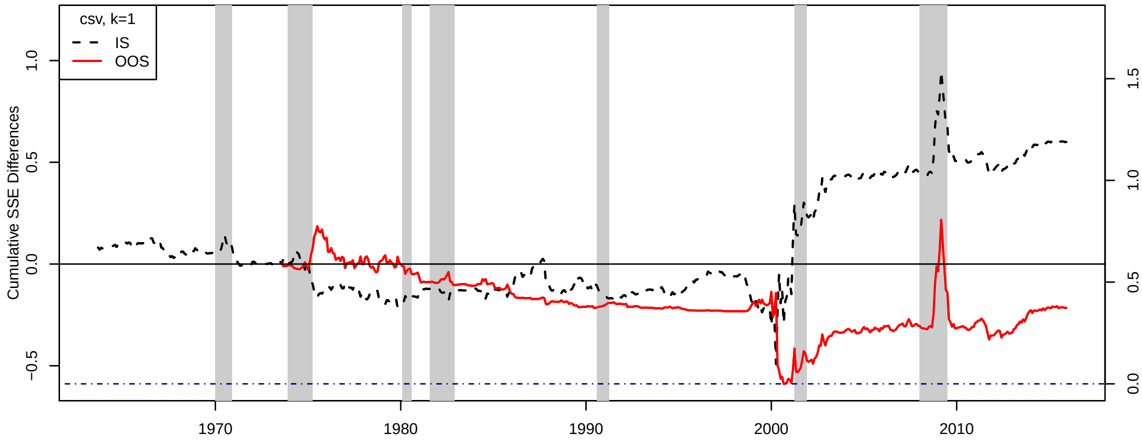


Figure 1: In this figure we plot the in-sample (IS) and out-of-sample (OOS) forecasting power of Cross-Sectional Volatility (CSV) for 1-month ahead predictive regressions according to Welch and Goyal (2008).[1]

uity premium in the short- and long-run. We pay particular attention to issues raised by Welch and Goyal (2008) and consider multiple robustness checks. In line with Maio (2016); Stivers and Sun (2010) we rely on cross-sectional measures derived from portfolios rather than single stocks, as the aggregation of single stocks into portfolios reduces extreme outliers and thereon yields more robust variables for predicting the equity premium. In particular, we make use of an updated sample of the one considered by Maio (2016), in order to provide a comparable basis for analysis, and thus rely on the cross-section of 100 Fama-French portfolios between 1963 and 2015.

To better understand the contribution of cross-sectional higher moments with respect to portfolio management, we test for economic significance by implementing market timing strategies based on predictions of the equity premium according to different combinations of cross-sectional moments. We do so for the benefits brought forward by Cenesizoglu and Timmermann (2012). Their results indicate that many models – and variables in that respect – underperform from a statistical perspective and provide no additional value compared to a constant mean benchmark in terms of out-of-sample predictability, however they may still result in superior economic performance once embedded in the investment decision process.

Furthermore, we predict excess market returns disaggregated with respect to size and value for up to 12 months ahead. We show that accounting for cross-sectional skewness and kurtosis in our predictive model spans forecasting accuracy from predominantly large-caps and growth stocks over 6+ month ahead predictions to additionally improve forecastability of small-caps and value stocks. As such, the inclusion of higher cross-sectional moments adds to the predictive power of CSV by responding more strongly

[1] For a more detailed explanation, see Figure 3.

Electronic copy available at: https://ssrn.com/abstract=2747627

to alternative portfolio characteristics and thereby increasing the predictive quality across the spectrum of considered equity returns.

The remainder of this paper is as follows: In section 2 we review the literature on higher cross-sectional moments and asset pricing as well as return predictability using higher cross-sectional moments. In section 3 we describe cross-sectional moments and our main dataset. In section 4 we run long-horizon regressions for single variables as well as (principal components of) combinations on the excess market return and conduct in-sample and out-of-sample statistical inference. In section 5 we test the economic significance of higher cross-sectional moments in market timing strategies and in section 6 we perform an out-of-sample analysis for the predictive power of cross-sectional moments on excess returns of different decile portfolios. In section 7 we conclude. All figures and tables can be found at the end of the paper.

2 Literature Review

Already from the very beginning of modern portfolio theory, the role of deriving accurate estimates of future expected returns has played a central role. Markowitz (1952) clearly separates the process of portfolio selection into two distinct stages. First, the task of formulating accurate expectations on the future return and risk of assets and, secondly applying these expectations in a portfolio formation process. Whilst his initial work has focused on the latter, a vast amount of literature has emerged for the specification of expected moments of returns and identifying relevant factors in that respect.

Literature on stock market predictability is extensive and both fundamental and economic factors have been reported as entailing forecasting power. Current literature commonly discusses single and multi-factor models relying on various factors for predicting asset returns and equity returns in particular. Just to mention a few popular variables from influential studies: Dividend-price ratio, price-earnings ratio, book-to-market ratio, short-term interest rates, credit spread, yield spreads or stock momentum. Along these line, Welch and Goyal (2008) account for the majority of previously mentioned variables and show that the gain in out-of-sample predictive quality relative to a simple empirical mean is not provided.

More recently, there has been a shift towards cross-sectional variables (beginning with Polk et al., 2006) and the question on how assets co-move at a certain point in time. Maio (2016) provides an extensive study on the power of return dispersion for the benefit of in- and out-of-sample predictability of the equity premium. In his study, he shows that return dispersion is significantly negatively related to future equity

Electronic copy available at: https://ssrn.com/abstract=2747627

returns and results in a higher predictive power compared to classical predictors, both over the short- and long-term. Other studies document that return dispersion bears a significant positive price of risk (Jiang, 2010) and has an impact on future stock market volatility (Bekaert and Harvey, 1997, 2000; Stivers, 2003). Adding to these findings, Jiang (2013) reports that CSV measures aggregate overpricing resulting from investor overconfidence and is negatively related to future aggregate returns. He documents, that (consistent with theory) dispersion measures relate positively to aggregate valuations, trading volume, idiosyncratic volatility, past market returns and current and future sentiment indices. A simple forecasting model based on CSV outperforms the historical mean equity premium, especially in market downturns. Additionally, cross-sectional volatility (returns dispersion) is often used as proxy for aggregate idiosyncratic volatility (formally proven by Garcia et al., 2014) and average stock market correlation (Solnik and Roulet, 2000, see also Pollet and Wilson (2010)). Besides, Grant and Satchell (2016) break up expected cross-sectional volatility into dispersion of alpha, beta and cross-sectional correlation. They show that predicted dispersion explains about 80% of realized dispersion.

As a natural extension to cross-sectional volatility one can calculate cross-sectional skewness and kurtosis. Garcia et al. (2014) also proof that cross-sectional skewness proxies aggregate idiosyncratic skewness[2] and use cross-sectional skewness to explain some observed asymmetry in the cross-sectional distribution of stock returns.[3] In the context of our paper, Jondeau and Zhang (2015) show, that average idiosyncratic skewness (they also use cross-sectional skewness for a robustness check) in conjunction with the current market return performs well at predicting future aggregate returns. Their paper refers to earlier work by Kapadia (2006), who makes use of cross-sectional skewness to explain why stocks with high idiosyncratic volatility have low subsequent returns (see Ang et al., 2006). Similarly, Colacito et al. (2015) document strong evidence for the cross-sectional skewness of analyst forecasts on GDP growth to predict the equity premium. The predictive power of different measures of aggregate skewness is supported by the fact that it is a positively priced risk factor (first determined by Adrian and Rosenberg, 2008). More recently, Chang et al. (2013), who consider option implied volatility, skewness and kurtosis to explain the cross-section of US stock returns, find a significant skewness risk premium that cannot be explained by other well-known asset pricing factors[4].

One of the reasons for the performance of cross-sectional moments in asset pricing applications is, that cross-sectional moments proxy the business cycle. This is shown

[2] Which is available from these authors upon request.
[3] That is supposedly similar to the leverage effect put forward by Black (1976).
[4] Other authors who use option implied moments for this purpose are Conrad et al. (2013); Xing et al. (2010).

Electronic copy available at: https://ssrn.com/abstract=2747627

by Higson et al. (2002), who examine the cross-sectional skewness of growth rates of firms and observe that cross-sectional volatility and skewness are strongly related to the business cycle. Also, Bachmann et al. (2014) calculates cross-sectional volatility, skewness and kurtosis on a panel of firm-level innovations to determine their relation with the business cycle and observes, that the cross-sectional skewness and kurtosis of investment innovations are largely acyclical. Other papers referring to cross-sectional moments are Zhang (2005), who demonstrates that the cross-sectional skewness of similar firms (as defined by industry, size or book-to-market) predicts future total skewness of individual stocks even better than by using the stocks' own history.[5]

This paper, based on the above literature review, contributes to the literature in three ways: First, it extends the literature on the attributes of higher cross-sectional moments by analyzing their (additional) contribution in predicting the equity premium. Second, it contributes to the literature on stock return predictability, where mainly the predictive performance of cross-sectional volatility is documented, so far. Third, in a more general sense, it contributes to the asset pricing literature, where the pricing of risk due to higher moments is only documented for option-implied moments.

3 Data and Variables

In this sections, we briefly explain cross-sectional (higher) moments and our main dataset, before we move on to our analysis, describe our results and conduct some robustness tests. For a detailed description of the underlying methodology we refer the interested reader to Welch and Goyal (2008) and Maio (2016).

We define cross-sectional volatility as

$$csv_t = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(r_{i,t} - \bar{r}_t)^2} \tag{1}$$

[5]Other use of cross-sectional skewness in the finance and economics literature can be found in Krüger and Nolte (2015); Guo et al. (2014); Boyer and Vorkink (2014).

Electronic copy available at: https://ssrn.com/abstract=2747627

where N denotes the number of portfolios, $r_{t,i}$ the return of portfolio i at time t and $\bar{r}_t = \frac{1}{N}\sum_{i=1}^{N} r_{i,t}$ the cross-sectional mean.[6] Furthermore, we calculate cross-sectional skewness as[7]

$$css_t = \frac{\frac{1}{N}\sum_{i=1}^{N}(r_{i,t} - \bar{r}_t)^3}{csv_t^3} \tag{2}$$

and cross-sectional kurtosis as

$$csk_t = \frac{\frac{1}{N}\sum_{i=1}^{N}(r_{i,t} - \bar{r}_t)^4}{csv_t^4}. \tag{3}$$

In a second step we calculate principal components from possible combinations of all three cross-sectional moments, as to capture the benefits of accounting for cross-sectional higher moments. Ludvigson and Ng (2007, 2009) show that the application of principal components based on a large set of potential predictor variables yields significant predictability for aggregated stock market returns. Furthermore, Rapach et al. (2016) also consider principal components as a parsimonious way to evaluate the additional contribution to predictive power of one (new) variables within the large space of existing predictors. We code these variables as $PC\ldots$, where for example the second principal component between CSV and CSK is depicted as $PCvk2$ or the third principal component between CSV, CSS and CSK as $PCvsk3$.[8] As such we pool the information from CSV, CSS and CSK in different combinations, which allows us the identify periods and stock characteristics for which cross-sectional higher moments play a significant role. In contrast to Rapach et al. (2016) we do not turn the predictive model into a multi-variate setting by simultaneously considering the first three principal components together, but show that the inclusion of a single principal component is enough to significantly span the predictive power of CSV in a univariate setting.

All moments and their principal components are calculated based on 100 portfolios sorted on size and value ($P100SV$, retrieved from Kenneth French's data library), instead of using the full cross-section of stock returns. This methodology has been advocated by a number of authors (Stivers and Sun, 2010; Maio, 2016) to reduce idiosyncrasies in the data, and to avoid extreme outliers. While Maio (2016) also uses alternative portfolio cross-sections, we emphasize that skewness and kurtosis are statistical measures that live from a certain amount of statistical outliers to be significant, which can more easily be found in larger cross-sections. If in fact, we check

[6] Garcia et al. (2014) also suggest using a value weighted dispersion measure, however, they find that the equally weighted cross-sectional volatility in general has higher forecasting power than the value weighted one.

[7] Garcia et al. (2014) robustify their measure of cross-sectional skewness to protect against the impact of outliers, which in our case is already taken care of by the use of data on portfolio- rather than on firm-level.

[8] The numbering of the principal components is arbitrary and depends on the software package used.

Electronic copy available at: https://ssrn.com/abstract=2747627

for the number of significant skewnesses and kurtoses within our sample, we find over 2.7 and 3.5 times more significant cross-sectional skewness and cross-sectional kurtosis within the cross-section of 100 portfolios as opposed to 25 portfolios sorted on size and value.[9]

Our observation period is August 1963 to December 2015. Due to missing observations we exclude $P100SV_{1,3}$, $P100SV_{7,10}$, $P100SV_{10,8}$, $P100SV_{10,9}$ and $P100SV_{10,10}$ (cf. Maio, 2016). The value-weighted market return and the risk-free interest rate are also taken from Kenneth French's website. To avoid the impact of outliers, we apply a three month moving average of all state variables for our predictive regressions (Stivers and Sun, 2010).

Maio (2016) relates the forecasting power of cross-sectional volatility to six other popular measures from the literature. We will extend his approach and follow Rapach et al. (2016) in taking 14 predictor variables from Welch and Goyal (2008)[10] as benchmark for our approach and thereby provide a more comprehensive basis for comparison.

[Place Table 1 about here.]

First of all, we provide descriptive statistics for the log equity premium r^e, it's volatility as well as for all predictive variables in Table 1. As can be seen in the last column of Table 1, we find all explanatory variables to be stable over time with varying degrees of persistence. The inclusion of all common predictors, CSV and our factors of cross-sectional higher moments allows for a direct comparison to the existing literature. With respect to our PC factors we observe zero means, as implied by way of construction, as well as covering the full spectrum of positive and negative values, whereas CSV and CSS on there own are restricted to positive values only. We expect this property to positively influence the predictive quality of the equity premium, which can also take on negative values.

[Place Table 2 about here.]

Table 2 reports the correlations between log equity premium, its volatility and a selected number of predictor variables from the literature, as well as all our state variables. For our three cross-sectional measure we observe a negative correlation between r^e and CSV, as is well documented in literature, and a positive connection towards CSS and CSK, although lower for the latter. The highest absolute correlation of CSS towards r^e is also reflected in our principal components, as all combinations

[9] According to the D'Agostino (1970) and Anscombe and Glynn (1983) tests, we find 31% (25%) of all cross-sectional skewnesses (kurtoses) to be significant at the 5%-level for $P100SV$.

[10] Available from Amit Goyal's webpage at `http://www.hec.unil.ch/agoyal/`.

Electronic copy available at: https://ssrn.com/abstract=2747627

including CSS also show positive correlations to r^e that are also the highest in absolute terms.

[Place Figure 2 about here.]

In a next step we provide a graphical description of the three major state variables CSV, CSS and CSK, as well as their three principal components and the cumulated log equity premium in Figure 2. We observe CSV, CSS and CSK to have quite distinct shapes. CSV has its highest levels around 2000-2003, which is almost twice as high as the levels observable during the financial crisis between 2007-2009. In contrast, CSS has its highest positive peak around 2010, immediately followed by an all-time low in 2011. Finally, CSK has its highest peaks around 1979, 2003 and 2010. Adding all of this up, we find all three variables together to contribute to periods of large losses and gains of the equity premium, depicted in the topmost panel of Figure 2. This provides a first indication, that cross-sectional higher moments potentially capture additional components of the equity premium. In the next section we will first depict our in-sample and out-of-sample analysis framework, before we examine the empirical results.

4 In-Sample and Out-of-Sample Predictions of the Equity Premium

In this section, we will first give a brief overview about our in- and out-of-sample prediction framework, and the evaluation measures applied, before highlighting our results, conducting some robustness checks and providing a brief discussion on the theoretical underpinnings of the empirical results observed.

4.1 In-sample and out-of-sample predictability

To evaluate the in-sample predictability, we apply univariate predictive regressions of the form

$$r^e_{t+1,t+k} = \alpha_k + \beta'_k x_t + \varepsilon_{t+1,t+k} \tag{4}$$

where $r^e_{t+1,t+k}$ is the continuously compounded equity premium over the next k periods and x_t are respective cross-sectional moments or their combinational principal components used for forecasting at time t. The applied forecasting horizons are $k = 1, 3, 6, 9, 12, 24, 36$ and 48 months. All predictor variables are normalized to have zero mean and unit standard deviation. To account for the autocorrelation and heteroskedasticity of the predictor variable, the Stambaugh (1999) bias as well as the use

Electronic copy available at: https://ssrn.com/abstract=2747627

of overlapping observations for $k > 1$ (e.g., Hodrick, 1992), we employ Newey and West (1987, 1994) t-statistics and determine significance-levels for regression coefficients as well as R^2 from a structured bootstrap experiment (cf. Mark, 1995; Kilian, 1999; Welch and Goyal, 2008; Maio, 2016).

To add to the in-sample results, we conduct a single variable out-of-sample analyses, where we forecast $r^e_{t+1,t+k}$ as

$$\hat{r^e}_{t+1,t+k} = \hat{\alpha}_t + \hat{\beta}_t x_t \tag{5}$$

using estimates $\hat{\alpha}_t$ and $\hat{\beta}_t$ from recursive in-sample regressions (4) up to (and including) month t. To be true out-of-sample forecasts, the principal components are calculated by only relying on information that was available up to time t.[11] The out-of-sample evaluation period is 1973:08-2015:12, leaving 120 monthly observations for the initial estimation of $\hat{\alpha}$ and $\hat{\beta}$.

To quantify the out-of-sample predictability we make use of a restricted model assuming that the average historical equity premium is a better predictor for the future equity premium (the null therefore assumes $\beta_t = 0$) than the (unrestricted) model of (4) (the alternative).

$$\begin{aligned} H_0 &: r_{t+1,t+k} = \alpha_k + \varepsilon_{t+1,t+k} \\ H_A &: r_{t+1,t+k} = \alpha_k + \beta_k x_t + \varepsilon_{t+1,t+k} \end{aligned} \tag{6}$$

As measure of out-of-sample predictive performance, we employ out-of-sample R^2_{OOS}s (in %) that report the reduction in mean-squared forecast error of the restricted (MSE_R) against the unrestricted model (MSE_U)[12] (cf. Campbell and Thompson, 2008; Welch and Goyal, 2008)

$$R^2_{OOS} = 1 - \frac{MSE_U}{MSE_R}, \tag{7}$$

where a positive value signals higher out-of-sample forecasting power of the unrestricted model in relation to the restricted model. To ascertain the statistical significance of the out-of-sample R^2_{OOS} we use the exact McCracken (2007) F-statistic instead of relying on the approximation of Clark and West (2007).[13] The McCracken

[11] We re-orient the eigenvectors in the principal component analysis to always point in the same direction and rescale the input variables to a constant (and predetermined) level. This does not change the results, but keeps the weights and combination directions of the input variables within each principal component constant.

[12] Calculated as $MSE = \frac{1}{T_{OOS}} \sum_{t=1}^{T_{OOS}} \hat{\varepsilon}_t^2$

[13] For nested models, the F-statistic of McCracken (2007) has a nonstandard distribution, while the approximation of Clark and West (2007) is approximately normal. It is calculated as $MSE-F = (T_{OOS} - k + 1)\frac{MSE_R - MSE_U}{MSE_U}$, and its' 1%, 5% and 10% critical values based on the recursive

Electronic copy available at: https://ssrn.com/abstract=2747627

(2007) F-statistic is used to test the null $H_0 : MSE_U \leq MSE_R$ against the alternative $H_A : MSE_U > MSE_F$ (corresponding to $H_0 : R^2_{OOS} \leq 0$ against $H_A : R^2_{OOS} > 0$).

In Table 3 we depict univariate in-sample regression results for all predictor variables. The top panel reports the results for well-known predictors extensively covered in the literature, whereas the bottom Panel focuses on cross-sectional measures for return prediction. As this paper can be understood as an extension of the cross-sectional volatility focused paper by Maio (2016), we relate all measures to CSV and indicate superior IS predictive quality in bold. Starting with well-known predictor variables we find term spread (TMS) to outperform CSV across all horizons and in particular so for long-horizon forecasts of 24–48 months. Besides, CSP is also outperforming CSV for long-horizon IS predictions. Alternative variables also show significant IS predictability, however are not able to beat CSV based forecasts.

[Place Table 3 about here.]

Next, we move to the in-sample predictive quality of cross-sectional higher moments and combinations thereof, as presented in the bottom Panel of Table 3. Results indicate that neither CSS nor CSK are able to outperform the in-sample predictions by CSV on a standalone basis, which should not come as a surprise given we are considering higher moments as an add-on to cross-sectional volatility and do not expect them to perform better without accounting for the variation in the cross-sectional mean. Thereon, we test for the additional contribution of higher moments by constructing principal components as alternative combinations of the three cross-sectional measures. Whilst the first PC of any combination of either two or three cross-sectional measures does not significantly span the predictive quality of CSV, we do observe strong improvements with respect to second principal components. We show compelling enhancement in terms of alternative cross-sectional measures increasing the predictive quality of CSV with respect to both CSS and CSK for time horizons of up to 12 months, whereafter only CSK can actively contribute to the quality of in-sample forecasts.

Besides, we observe a positive impact for noisy one-month ahead forecasts, for which Campbell and Thompson (2008) argue that in-sample R^2 values above 0.5 can already be viewed as an economically relevant degree of predictability. Consequently, we present economically significant predictability of cross-sectional measures for $PCvs2$, $PCvk2$ and $PCvsk2$ of 0.57, 0.61 and 0.59, respectively. In contrast, CSV is not statistically nor economically significant with an in-sample R^2 of 0.43 for one-month predictions.

regression scheme and the fact that the relation of observations for the initial estimation to the number of forecasts is larger than 2 are 3.951, 1.518 and 0.616, respectively (cf. McCracken, 2007).

Electronic copy available at: https://ssrn.com/abstract=2747627

In addition, we confirm previous observations on CSS and CSK spanning the dimensions of CSV, rather than showing high predictive quality by themselfs, is confirmed when considering the combination of the two ($PCsk2$), which – without accounting for variations in the cross-sectional mean – does not yield statistically significant IS predictability. Furthermore, we observe that the combination of all three cross-sectional measures ($PCvsk2$) cannot further enhance the predictability above what we observe for $PCvk1$, which indicates that combining both CSS and CSK leads to effects that compete against each other and, therefore slightly reduce the in-sample predictive power.

[Place Table 4 about here.]

In a second step, we analyze the out-of-sample predictability of all variables and present our results in Table 4. Consistent with our IS findings, we observe that both CSS and CSK positively contribute to the OOS predictive quality of CSV across all forecasting horizons, with the exception of 1-month predictions for which none of the traditional or cross-sectional measures can generate statistically significant forecast. We contribute this fact to higher levels of noise with respect to very short horizon forecasts, which has also been documented by Rapach et al. (2016). Especially, for long-term forecasts above 12 months, do cross-sectional higher moments show their full potential with R^2_{OOS} of up to 15.66 for $PCvsk3$ compared to 2.08 for CSV in the case of 48-month forecasts.

More specifically, we document highest OOS predictability for the second principal component combing both CSV and CSK across the full spectrum and a higher relevance of cross-sectional skewness for predictions of up to 12 months. Results display a humped-shaped pattern for CSS with it peak around the 12-month forecasting horizon and a monotonically increasing pattern for $PCvk2$. In fact the only other two variables which yield a monotonically increasing pattern are CSP and TMS, however predictive quality for CSP is always below that of cross-sectional measures. With respect to TMS, which generates the highest IS and OOS predictive quality across all factors, we find its positive predictive performance to be driven by crises in the past and performing poorly in the last two decades as revealed by Figure 3.

[Place Figure 3 about here.]

Figure 3 depicts the relative performance of TMS, CSV and selected principal components of CSV, CSS and CSK for the 3-month horizon. As mentioned, the good results for TMS can be traced back to the oil crisis in the mid-70s and the US recession period of the early 1980s. On the other hand, the predictive quality of TMS has been stagnating from the mid-80s until the burst of the IT bubble and declining thereafter. Thereon, we question todays relevance of the documented predictive quality of TMS

Electronic copy available at: https://ssrn.com/abstract=2747627

reported across our sample period from 08/1963–12/2015. Furthermore, we observe two sharp drops in the forecasting quality of TMS, namely the period during and after the burst of the IT bubble and the financial crisis of 2007-08. Interestingly these drops correspond to significant increases in CSV and CSK as presented in Figure 2, which implies that common factors – taking TMS as a representative example – suffer when expected returns are more disperse. This observation, with respect to the predictive power of factors and CSV, was previously touched upon by Senechal (2004), who shows that the explanatory power of Barra's US Equity Model decreases and CSV is increasing due to a decrease in the proportion of predicted variance stemming from common factors. Consequently, cross-sectional measures can be understood as a valuable complement to traditional forecasting variables.

Finally, we look at the contribution of cross-sectional higher moments as a supplement to CSV from a graphical perspective. Plots 2-4 from Figure 3 present the relative performance of CSV and combinations with CSS and CSK in excess of the prevailing mean model. We make four main observations. First of all, none of the cross-sectional variables yield significant IS and OOS predictive quality before the 21^{st} century, which corresponds to the burst of the IT bubble, and is the period where TMS has generated the best performance. Secondly, all cross-sectional factors have picked up explanatory power since the dot-com bubble, the same period when the decline of TMS begins. Third, the outperformance of cross-sectional volatility over the prevailing mean was generated around the IT bubble and the financial crisis, when CSV was highest, but moved sideways otherwise. Fourth, combining CSV with both CSS and CSK leads to a monotonic increase in relative performance and reduces the drop in single CSV performance in aftermath of the financial crisis in 2007-08. This is a crucial property, as discussed by Welch and Goyal (2008): both lines should be constantly upward sloping and not driven by positive drifts during unique market conditions.

Overall, the results of the IS and OOS analysis reveal two major findings: Adding cross-sectional kurtosis to the predictive equation significantly enhances the predictive performance of CSV, both in the long-run as well as in the short run. Adding cross-sectional skewness to the equation also leads to a significant increase of predictive performance, but only for horizons smaller than 12 month. Additionally, the plot of the relative predictive performances (Figure 3 shows, that the performance of CSV in the short run is mainly driven by rather short periods surrounding the years 2000-2003 and 2010. Accounting for CSS and CSK does consistently add to the predictive performance after the year 2000. In the long run, we find CSS and CSK to add significant explanatory power to the predictive performance of CSV, especially regarding the losses before and after the financial crisis. These results are less robust for the alternative predictors.

Electronic copy available at: https://ssrn.com/abstract=2747627

4.2 Discussion

The negative relation between cross-sectional volatility and future market returns is frequently explained (Jiang, 2013; Maio, 2016) in a behavioral framework (see Daniel et al., 2001; Scheinkman and Xiong, 2003; Hong et al., 2006), where CSV is used as an indicator of investor overreaction and market mispricing. Either high aggregate overconfidence in markets, or the existence of short-selling constraints in markets with heterogeneous beliefs (where only some agents show overconfidence) lead to market prices that are too high today and therefore exhibit lower subsequent returns.

We additionally conjecture, that the distribution of overconfidence among investors has an influence on prices today. If one follows along the line of argument in Hong and Stein (2003) (cf. Bohl and Klein, 2012), that in markets with overconfidence and short-selling constraints, pessimists fail to impound their beliefs into prices and subsequent returns (when markets decline) will be even more negative (leading to a pronounced negative market skewness). So, the larger the size of the group of pessimists that cannot impound their beliefs into prices in relation to the optimists (positive CSS), the larger will be the subsequent negative returns. Furthermore, the more extreme the positions between optimists and pessimists in terms of CSK, the higher should be the negative return given short-sale constraints for the pessimists.

5 Economic Significance

In this section, we test the impact of higher cross-sectional moments on the economic significance of market timing strategies, based on out-of-sample predictions of the monthly (simply compounded) equity premium (r^e). We therefore implement the following regressions:

$$r_s^e = \alpha + \beta' x_{s-1} + \varepsilon_s, \tag{8}$$

where we predict the equity premium $\hat{r}_{t+1}^e = \hat{\alpha} + \hat{\beta}' x_t$ for every period. If positive, we allocate 150% of our wealth to the market portfolio, shorting the risk-free rate $r_{f,t+1}$. In case of a negative forecast on the market excess return, we allocate 150% of our wealth to the risk-free asset and go 50% in the market portfolio (r^s denotes the simple market return)

$$r_{t+1} = \begin{cases} 1.5 r_{t+1}^s - 0.5 r_{f,t+1} & \hat{r}_{t+1}^e \geq 0 \\ -0.5 r_{t+1}^s + 1.5 r_{f,t+1} & \hat{r}_{t+1}^e < 0 \end{cases} \tag{9}$$

We evaluate the results of these strategies against a buy-and-hold strategy, where we continuously allocate 150% of our wealth to the market portfolio ($r_{t+1}^M = 1.5 r_{t+1} - 0.5 r_{f,t+1}$). We depict annualized means, standard deviations and Sharpe-Ratios, as

Electronic copy available at: https://ssrn.com/abstract=2747627

well as the certainty-equivalent gain for an investor with a mean-variance utility function and risk aversion of $\gamma = 3$ (cf. Campbell and Thompson, 2008; Maio, 2016):

$$CER = \left(E\left[r_{t+1}\right] - E\left[r_{t+1}^{M}\right]\right) + \frac{\gamma}{2}\left(Var\left[r_{t+1}^{M}\right] - Var\left[r_{t+1}\right]\right) \tag{10}$$

The CE gain is then the difference between the CER for the investor when she uses the predictive regression forecast to guide asset allocation and the CER when she uses the prevailing mean benchmark forecast. We annualize the CE gain so that it can be interpreted as the annual portfolio management fee that the investor would be willing to pay to have access to the predictive regression forecast in place of the prevailing mean forecast. In this way, we measure the direct economic value of return predictability. The last part shows turnovers for each strategy and investment horizon.

[Place Table 5 about here.]

Table 5 presents annualized measures of Sharpe ratio, certainty-equivalent gain and turnover. We begin by putting results in perspective with existing studies, as to show the impact of the observation period on the relative performance of predictors. Rapach et al. (2016) state full-sample Sharpe ratios for the prevailing mean benchmark of 0.31–0.39 and for a buy-and-hold strategy of 0.48–0.52 across forecasting horizons of 1–12 months, whereas our sample yields Sharpe ratios varying between 0.39–0.46 for the prevailing mean and 0.39–0.42 for a buy-and-hold strategy for identical forecasting horizons. This shows that underlying market characteristics have a strong outcome on the ranking strategies. In contrast, Maio (2016) only compares his results relative to a buy-and-hold strategy, but disregards the prevailing mean as a benchmark.

Turning to the economic significance of predictors for the observation period we report results in-line with Rapach et al. (2016), as the 14 predictors from the literature rarely outperform the prevailing mean. This is especially true for short 1-month forecasts where only a quarter of classical predictors yields equal or higher Sharpe ratios whilst all show higher turnover. This is also true with respect to CSV, which only slightly outperforms both the prevailing mean and the buy-and-hold benchmark for 12-months forecasts. Along these lines standalone variables of cross-sectional higher moments also underperform against either benchmark and yield lower risk-adjusted return compared to CSV.

In contrast, the proposed extension of CSV to account for higher moments by means of principal component factors once more yields favorable results. Focusing on previously discussed $PCvs2$ and $PCvk2$ factors, we observe both combinations to outperform CSV. Again, skewness is predominantly contributing over the short-horizon, whereas kurtosis is picking up momentum for longer forecasting horizons. Also in terms of CE gain, does the combination of CSV and CSS outperform CSV on its own for up to and

Electronic copy available at: https://ssrn.com/abstract=2747627

including 6-month forecast, after which CSK is again outperforming. Furthermore, the previously mentioned stabilizing effect of accounting for cross-sectional higher moments as an add on to CSV is reflected in a lower turnover in $3/4$ of the cases.

6 The Predictability of Equity Portfolio Returns

In this section we predict disaggregated excess market returns with respect to size and value portfolios[14] at forecasting horizons of $k = 1, 3, 6, 9$ and 12 months in order to shed light on the the benefits of accounting for higher cross-sectional moments in terms of enhancing the forecasting accuracy of CSV. Table 6 documents CSV to yield best result over forecasting horizons larger than 6 months with respect to large-cap and growth stocks,which is in line with Maio (2016). Adding to this observation, we find significant OOS predictive quality of up to 8.24 for the largest size portfolio (D10) and 9.38 for the extreme growth portfolio (D1), both for a 12-month forecasting horizon.

[Place Table 6 about here.]

Next, we examine the combined forecasting power of cross-sectional volatility and cross-sectional skewness ($PCvs2$) as well as cross-sectional volatility and cross-sectional kurtosis ($PCvk2$) for excess returns of size and value portfolios. Results are presented in Table 7 and Table 8. We make three major observations. First of all, both enhancements of CSV with respect to CSS and CSK improve the IS and OOS predictive power for forecasting horizons larger than three months across the full set of size-ranked decile portfolios. Second, when looking at decile portfolios sorted from growth to value stocks, we find that $PCvs2$ strongly adds to the predictive quality of value stocks expanding in the cross-section of decile portfolios alongside an increase in the forecasting horizon. Thirdly, $PCvk2$ shows a similar pattern with respect to an increasing forecasting horizon, but with a strong improvement in predictability for growth stocks.

[Place Table 7 about here.]

[Place Table 8 about here.]

[14] Available from Kenneth French's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Electronic copy available at: https://ssrn.com/abstract=2747627

7 Conclusion

In this paper we investigate the impact of accounting for cross-sectional higher moments alongside the classical measure of return dispersion for predictions of the equity premium. We do so across forecasting horizons varying between 1 and 48 months and with respect to statistical and economic significance. Our result present that the inclusion of cross-sectional skewness adds significantly to the forecasting power of cross-sectional volatility in the short run (forecasting horizons of 1 up to 12 months), while the addition of cross-sectional kurtosis adds even more to the predictive power in the long run (12 to 48 months).

Further analysis with regard to the source of the predictive power – applying a graphical analysis according to Welch and Goyal (2008) – shows that the high predictive power of cross-sectional volatility has stagnated and moved horizontally with a short positive peak during the financial crisis, but back to normal – low levels of predictive power– thereafter. We document that accounting for cross-sectional higher moments enhances pure CSV-based forecasts by yielding a positive and more stable trend in in- and out-of-sample forecastability since the burst of the dot-com bubble.

In particular, accounting for cross-sectional skewness leads to a significant and constant rise in out-of-sample predictability in the post-2011 period. At the 36 month horizon we observe cross-sectional kurtosis to be the variable that contributes most significantly to the performance of cross-sectional volatility, especially with regard to recovering from a sharp drop in predictive power after 2007/08. Besides, we document a clear benefit of including higher moments when disaggregating excess returns along the value and size dimension. In this case, both cross-sectional skewness and cross-sectional kurtosis achieve a spanning of predictive quality decile portfolios ranked according to size and book-to-market.

Overall, the addition of higher order cross-sectional moments significantly improves and stabilizes the predictive performance of cross-sectional volatility, a variable that is already regarded as having high predictive power with respect to the equity premium. In a broader context, the identification of new predictors for the benefit of forecasting the equity premium is of increasing relevance given the decline in forecasting power of traditional, well-know forecasting variables as shown for the example of term spread. We related this decline in predictive power of extensively studied forecasting variables to Cochrane (2008) and what he refers to as a catch-22: *"if there is a substantial number of agents who, on net, should take the advice, the phenomenon will disappear"*.

Electronic copy available at: https://ssrn.com/abstract=2747627

References

Adrian, T. and Rosenberg, J. (2008). Stock Returns and Volatility: Pricing the Short-Run and Long-Run Components of Market Risk. *The Journal of Finance*, 63(6):2997–3030.

Ang, A., Hodrick, R. J., Xing, Y., and Zhang, X. (2006). The Cross-Section of Volatility and Expected Returns. *The Journal of Finance*, 61(1):259–299.

Anscombe, F. J. and Glynn, W. J. (1983). Distribution of the Kurtosis Statistic B2 for Normal Samples. *Biometrika*, 70(1):227–234.

Bachmann, R., Elstner, S., and Hristov, A. (2014). Surprise, Surprise-Measuring Firm-level Investment Innovations.

Bekaert, G. and Harvey, C. R. (1997). Emerging Equity Market Volatility. *Journal of Financial Economics*, 43(1):29–77.

Bekaert, G. and Harvey, C. R. (2000). Foreign Speculators and Emerging Equity Markets. *The Journal of Finance*, 55(2):565–613.

Black, F. (1976). The Pricing of Commodity Contracts. *Journal of Financial Economics*, 3(1):167–179.

Bohl, M. T. and Klein, A. C. (2012). Short Sale Constraints and the Likelihood of Crashes and Bubbles. SSRN Scholarly Paper ID 1947145.

Boyer, B. H. and Vorkink, K. (2014). Stock Options as Lotteries. *The Journal of Finance*, 69(4):1485–1527.

Campbell, J. Y., Giglio, S., and Polk, C. (2013). Hard Times. *Review of Asset Pricing Studies*, 3(1):95–132.

Campbell, J. Y. and Thompson, S. B. (2008). Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average? *Review of Financial Studies*, 21(4):1509–1531.

Cenesizoglu, T. and Timmermann, A. (2012). Do Return Prediction Models Add Economic Value? *Journal of Banking & Finance*, 36(11):2974–2987.

Chang, B. Y., Christoffersen, P., and Jacobs, K. (2013). Market Skewness Risk and the Cross Section of Stock Returns. *Journal of Financial Economics*, 107(1):46–68.

Clark, T. E. and West, K. D. (2007). Approximately Normal Tests for Equal Predictive Accuracy in Nested Models. *Journal of Econometrics*, 138(1):291–311.

Electronic copy available at: https://ssrn.com/abstract=2747627

Cochrane, J. H. (2008). The Dog That Did Not Bark: A Defense of Return Predictability. *The Review of Financial Studies*, 21(4):1533–1575.

Colacito, R., Ghysels, E., Meng, J., and Siwasarit, W. (2015). Skewness in Expected Macro Fundamentals and the Predictability of Equity Returns: Evidence and Theory. SSRN Scholarly Paper ID 2185659, Rochester, NY.

Conrad, J., Dittmar, R. F., and Ghysels, E. (2013). Ex Ante Skewness and Expected Stock Returns. *The Journal of Finance*, 68(1):85–124.

D'Agostino, R. B. (1970). Transformation to Normality of the Null Distribution of G1. *Biometrika*, pages 679–681.

Daniel, K. D., Hirshleifer, D., and Subrahmanyam, A. (2001). Overconfidence, Arbitrage, and Equilibrium Asset Pricing. *The Journal of Finance*, 56(3):921–965.

DeMiguel, V., Garlappi, L., and Uppal, R. (2009). Optimal versus Naive Diversification: How Inefficient Is the 1/N Portfolio Strategy? *The Review of Financial Studies*, 22(5):1915–1953.

Garcia, R., Mantilla-García, D., and Martellini, L. (2014). A Model-Free Measure of Aggregate Idiosyncratic Volatility and the Prediction of Market Returns. *Journal of Financial and Quantitative Analysis*, 49(5-6):1133–1165.

Grant, A. and Satchell, S. (2016). Theoretical Decompositions of the Cross-Sectional Dispersion of Stock Returns. *Quantitative Finance*, 16(2):169–180.

Guo, H., Kassa, H., and Ferguson, M. F. (2014). On the Relation Between EGARCH Idiosyncratic Volatility and Expected Stock Returns. *Journal of Financial and Quantitative Analysis*, 49(01):271–296.

Higson, C., Holly, S., and Kattuman, P. (2002). The Cross-Sectional Dynamics of the US Business Cycle: 1950–1999. *Journal of Economic Dynamics and Control*, 26(9):1539–1555.

Hodrick, R. J. (1992). Dividend Yields and Expected Stock Returns: Alternative Procedures for Inference and Measurement. *The Review of Financial Studies*, 5(3):357–386.

Hong, H., Scheinkman, J., and Xiong, W. (2006). Asset Float and Speculative Bubbles. *The Journal of Finance*, 61(3):1073–1117.

Hong, H. and Stein, J. C. (2003). Differences of Opinion, Short-Sales Constraints, and Market Crashes. *The Review of Financial Studies*, 16(2):487–525.

Electronic copy available at: https://ssrn.com/abstract=2747627

Jiang, D. (2013). The Second Moment Matters! Cross-Sectional Dispersion of Firm Valuations and Expected Returns. *Journal of Banking & Finance*, 37(10):3974–3992.

Jiang, X. (2010). Return Dispersion and Expected Returns. *Financial Markets and Portfolio Management*, 24(2):107–135.

Jondeau, E. and Zhang, Q. (2015). Average Skewness Matters! *Swiss Finance Institute Research Paper*, (15-47).

Kapadia, N. (2006). The Next Microsoft? Skewness, Idiosyncratic Volatility, and Expected Returns. SSRN Scholarly Paper ID 970120.

Kilian, L. (1999). Exchange Rates and Monetary Fundamentals: What Do We Learn from Long-Horizon Regressions? *Journal of Applied Econometrics*, 14(5):491–510.

Krüger, F. and Nolte, I. (2015). Disagreement Versus Uncertainty: Evidence from Distribution Forecasts. *Journal of Banking & Finance*, forthcoming.

Ludvigson, S. C. and Ng, S. (2007). The Empirical Risk–Return Relation: A Factor Analysis Approach. *Journal of Financial Economics*, 83(1):171–222.

Ludvigson, S. C. and Ng, S. (2009). Macro Factors in Bond Risk Premia. *The Review of Financial Studies*, 22(12):5027–5067.

Maio, P. (2016). Cross-Sectional Return Dispersion and the Equity Premium. *Journal of Financial Markets*, 29:87–109.

Mark, N. C. (1995). Exchange Rates and Fundamentals: Evidence on Long-Horizon Predictability. *The American Economic Review*, 85(1):201–218.

McCracken, M. W. (2007). Asymptotics for Out of Sample Tests of Granger Causality. *Journal of Econometrics*, 140(2):719–752.

Newey, W. K. and West, K. D. (1987). A Simple, Positive Semi-Definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Econometrica*, 55(3):703–708.

Newey, W. K. and West, K. D. (1994). Automatic Lag Selection in Covariance Matrix Estimation. *The Review of Economic Studies*, 61(4):631–653.

Polk, C., Thompson, S., and Vuolteenaho, T. (2006). Cross-Sectional Forecasts of the Equity Premium. *Journal of Financial Economics*, 81(1):101–141.

Pollet, J. M. and Wilson, M. (2010). Average Correlation and Stock Market Returns. *Journal of Financial Economics*, 96(3):364–380.

Electronic copy available at: https://ssrn.com/abstract=2747627

Rapach, D. E., Ringgenberg, M. C., and Zhou, G. (2016). Short interest and aggregate stock returns. *Journal of Financial Economics*, 121(1):46–65.

Rapach, D. E. and Zhou, G. (2013). Forecasting Stock Returns. *Handbook of Economic Forecasting*, 2(Part A):328–383.

Scheinkman, J. A. and Xiong, W. (2003). Overconfidence and Speculative Bubbles. *Journal of Political Economy*, 111(6):1183–1220. 01303.

Senechal, E. (2004). The Challenges of Declining Cross-Sectional Volatility. *BARRA Insight*, pages 2–10.

Solnik, B. and Roulet, J. (2000). Dispersion as Cross-Sectional Correlation. *Financial Analysts Journal*, 56(1):54–61.

Stambaugh, R. F. (1999). Predictive Regressions. *Journal of Financial Economics*, 54(3):375–421.

Stivers, C. and Sun, L. (2010). Cross-Sectional Return Dispersion and Time Variation in Value and Momentum Premiums. *Journal of Financial and Quantitative Analysis*, 45(04):987–1014.

Stivers, C. T. (2003). Firm-Level Return Dispersion and the Future Volatility of Aggregate Stock Market Returns. *Journal of Financial Markets*, 6(3):389–411.

Welch, I. and Goyal, A. (2008). A Comprehensive Look at the Empirical Performance of Equity Premium Prediction. *The Review of Financial Studies*, 21(4):1455–1508.

Xing, Y., Zhang, X., and Zhao, R. (2010). What Does the Individual Option Volatility Smirk Tell Us About Future Equity Returns? *Journal of Financial and Quantitative Analysis*, 45(03):641–662.

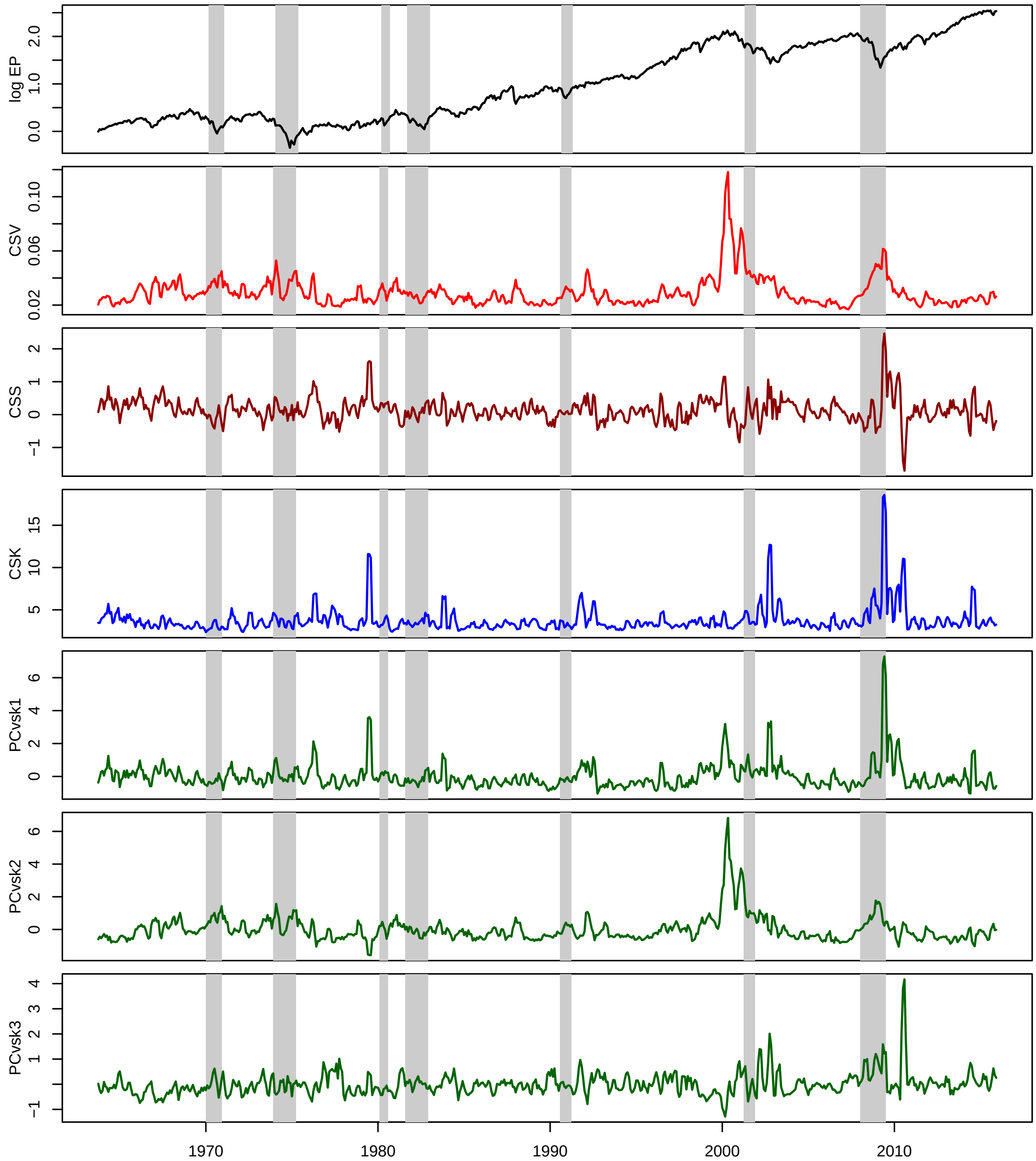
Zhang, Y. (2005). Individual Skewness and the Cross-Section of Average Stock Returns. *Unpublished working paper. Yale University.*

Electronic copy available at: https://ssrn.com/abstract=2747627

A Figures and Tables

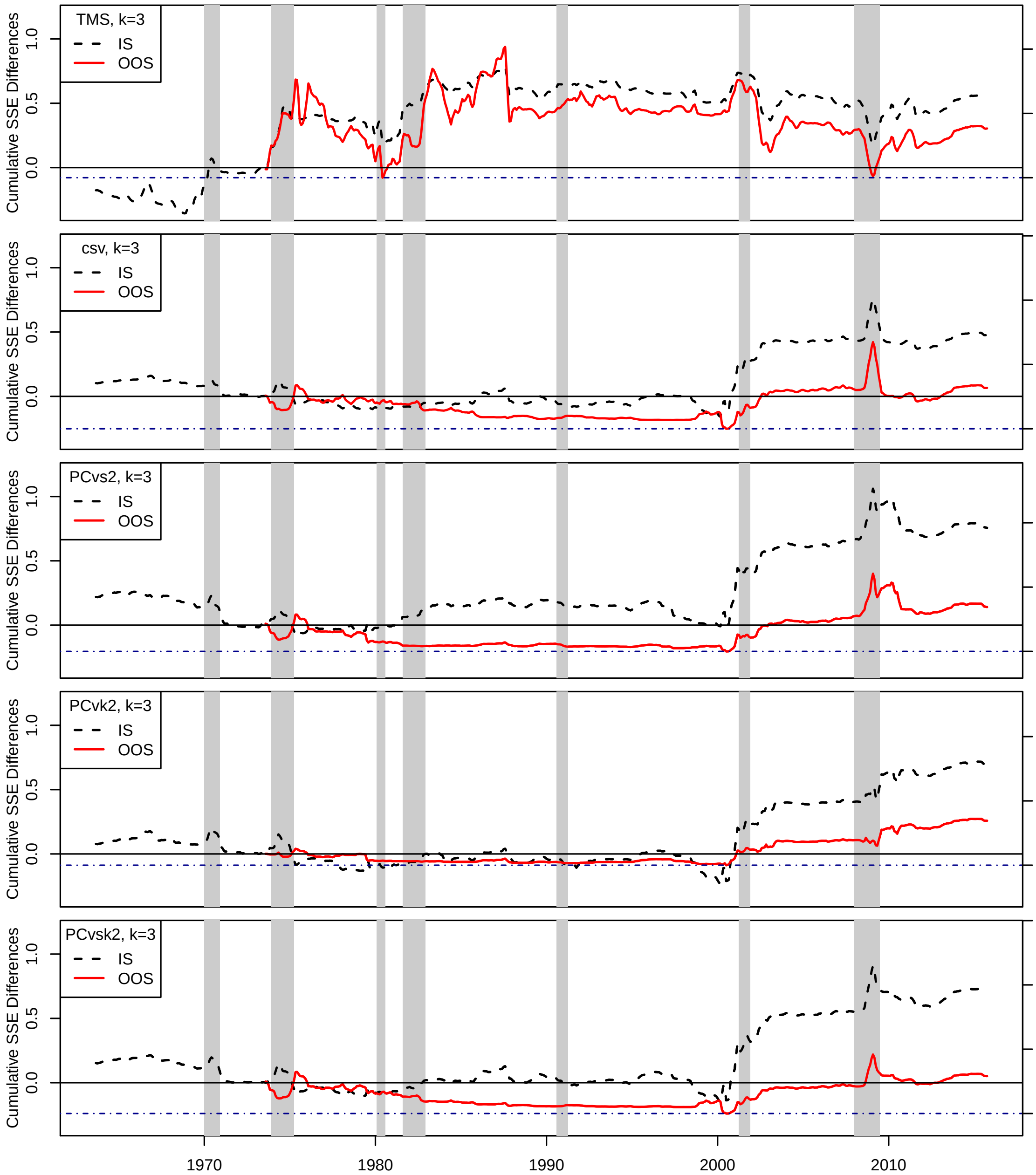
A.1 Figures

Figure 2: Time series plots of the equity premium r^e, CSV, CSS and CSK.
In this figure we plot a 12 month moving average of the market excess return and 3-month moving averages of time series of cross-sectional volatility (CSV), cross-sectional skewness (CSS) and cross-sectional kurtosis (CSK), as well as their three principal components. The sample period is 1963:08-2015:12. Gray bars depict NBER-recessions.



Electronic copy available at: https://ssrn.com/abstract=2747627

Figure 3: Relative performance of TMS, CSV, $PCvs2$, $PCvk2$ and $PCvsk2$ for 3-month forecasts of the equity premium.
This figure examines the relative IS and OS performance for each predictive variable against the prevailing mean across time (see Welch and Goyal, 2008). It is calculated from the cumulative squared prediction errors of the unrestricted and the restricted model, to evaluate the estimated equity premium against the full period (IS) and prevailing (OS) mean equity premium. The relative performance of the in-sample prediction is depicted in black and dashed and (usually above) the out-of-sample prediction depicted in red. The first graph shows the predictive performance of TMS (as benchmark of the alternative predictors), whereas the second to fifth graph delineate the predictive performance of CSV, $PCvs2$, $PCvk2$ and $PCvsk2$, respectively. The sample period is 1963:08-2015:12, with the out-of-sample analysis beginning in 1973:08. A second axis on the right side is supposed to show the performance after the changes in the early 2000s, so it is set to zero (IS) in 2000:01 and additionally marked by a blue and dashed line. Gray bars depict NBER-recessions.



Electronic copy available at: https://ssrn.com/abstract=2747627

A.2 Tables

A.2.1 Descriptive Statistics

Table 1: Descriptive statistics for the equity premium, its volatility, 14 classical and our predictor variables (1963:07-2015:12)

This table reports descriptive statistics for the log equity premium r_e, its volatility σ_e and possible predictor variables. These are the 14 variables from Welch and Goyal (2008) and Rapach and Zhou (2013), where we replace SVAR by RVOL (following Rapach et al., 2016), as well as cross-sectional volatility (Maio, 2016) and higher cross-sectional moments and the principal components extracted from all possible combinations of the cross-sectional moments (all of them calculated as 3-month moving average from 100 portfolios sorted according to size and value). ρ represents the first-order autocorrelation coefficient (persistence).

Name	**Mean**	**StDev.**	**Min.**	**Max.**	**Skew.**	**Kurt.**	ρ
r_e (%, Ann.)	4.83	15.57	−317.38	179.14	−0.79	2.79	0.08
σ_e (%, Ann.)	13.47	8.25	2.79	83.79	3.40	19.61	0.67
logDP	−3.59	0.41	−4.52	−2.75	−0.19	−0.80	0.994
logDY	−3.59	0.41	−4.53	−2.75	−0.20	−0.78	0.994
logEP	−2.83	0.44	−4.84	−1.90	−0.75	2.84	0.989
logDE	−0.77	0.32	−1.24	1.38	2.89	15.43	0.986
RVOL	0.14	0.05	0.05	0.32	0.78	0.58	0.964
CSP (%)	−0.17	0.18	−0.42	0.37	0.38	−0.35	0.985
BM (Ann.)	0.50	0.27	0.12	1.21	0.74	−0.43	0.994
NTIS	0.01	0.02	−0.06	0.05	−0.75	0.74	0.977
TBL	0.05	0.03	0.00	0.16	0.58	0.79	0.988
LTY (%, Ann.)	6.76	2.64	2.04	14.82	0.68	0.18	0.990
LTR (%, Ann.)	0.63	3.00	−11.24	15.23	0.42	2.50	0.030
TMS (%)	1.85	1.51	−3.65	4.55	−0.36	−0.32	0.956
DFY (%, Ann.)	1.04	0.46	0.32	3.38	1.65	3.85	0.966
DFR (%, Ann.)	0.00	1.47	−9.75	7.37	−0.41	6.73	−0.078
INFL (%)	0.33	0.32	−1.77	1.81	0.18	4.44	0.626
CSV	0.03	0.01	0.02	0.12	3.43	18.69	0.928
CSS	0.14	0.36	−1.71	2.47	1.01	6.94	0.706
CSK	3.78	1.63	2.36	18.58	4.84	31.70	0.728
$PCvs1$	0.00	0.79	−2.19	5.27	2.49	11.10	0.851
$PCvk1$	0.00	0.81	−0.95	5.83	3.22	15.08	0.861
$PCsk1$	0.00	0.75	−1.25	6.84	4.13	26.66	0.711
$PCvsk1$	0.00	0.81	−1.04	7.29	3.93	24.85	0.754
$PCvs2$	0.00	0.69	−5.33	2.02	−2.45	11.98	0.853
$PCvk2$	0.00	0.68	−2.38	5.21	1.92	13.49	0.849
$PCsk2$	0.00	0.45	−4.18	0.99	−3.06	20.30	0.734
$PCvsk2$	0.00	0.79	−1.57	6.82	3.46	19.77	0.914
$PCvsk3$	0.00	0.45	−1.29	4.17	2.91	19.96	0.734

Electronic copy available at: https://ssrn.com/abstract=2747627

Table 2: Correlations of dependent and predictor variables (1963:07-2015:12)
This table reports correlations for the log equity premium r_e, its volatility σ_e and a selected number of alternative predictor variables, as well as all our predictor variables according to Table 1.

	r_e	σ_e	logDP	logDY	logDE	CSP	TMS	DFY	CSV	CSS	CSK	$PCvs1$	$PCvk1$	$PCsk1$	$PCvsk1$	$PCvs2$	$PCvk2$	$PCsk2$	$PCvsk2$	$PCvsk3$
r_e	1.00	−0.33	−0.06	0.04	0.00	0.03	0.09	0.04	−0.06	0.15	0.01	0.03	−0.04	0.09	0.06	0.15	−0.06	0.13	−0.09	−0.13
σ_e		1.00	−0.16	−0.20	0.17	−0.25	0.13	0.38	0.44	−0.06	0.24	0.30	0.46	0.11	0.24	−0.42	0.23	−0.30	0.42	0.26
logDP			1.00	0.99	0.27	0.33	−0.20	0.40	−0.25	0.03	−0.04	−0.17	−0.20	−0.01	−0.09	0.23	−0.19	0.06	−0.25	−0.04
logDY				1.00	0.27	0.34	−0.19	0.40	−0.25	0.04	−0.04	−0.17	−0.21	0.00	−0.09	0.25	−0.20	0.08	−0.26	−0.05
logDE					1.00	0.14	0.22	0.34	0.20	0.24	0.36	0.28	0.35	0.35	0.38	−0.03	−0.06	−0.13	0.10	0.12
CSP						1.00	−0.42	−0.12	0.22	0.04	−0.21	0.19	0.05	−0.10	−0.02	−0.17	0.34	0.25	0.25	−0.27
TMS							1.00	0.21	−0.08	0.02	0.22	−0.05	0.06	0.14	0.10	0.08	−0.22	−0.20	−0.12	0.21
DFY								1.00	0.14	0.00	0.21	0.11	0.22	0.13	0.16	−0.12	−0.01	−0.20	0.11	0.19
CSV									1.00	0.15	0.19	0.84	0.84	0.20	0.51	−0.78	0.76	−0.05	0.95	−0.05
CSS										1.00	0.47	0.66	0.37	0.85	0.79	0.50	−0.18	0.49	−0.13	−0.49
CSK											1.00	0.40	0.69	0.86	0.82	0.13	−0.49	−0.54	−0.06	0.54
$PCvs1$												1.00	0.84	0.62	0.82	−0.32	0.48	0.23	0.65	−0.31
$PCvk1$													1.00	0.62	0.83	−0.51	0.29	−0.33	0.67	0.26
$PCsk1$														1.00	0.94	0.36	−0.40	−0.04	−0.11	0.04
$PCvsk1$															1.00	0.06	−0.09	−0.05	0.23	0.02
$PCvs2$																1.00	−0.78	0.35	−0.91	−0.26
$PCvk2$																	1.00	0.32	0.88	−0.40
$PCsk2$																		1.00	−0.07	−0.99
$PCvsk2$																			1.00	−0.03
$PCvsk3$																				1.00

Electronic copy available at: https://ssrn.com/abstract=2747627

A.2.2 Equity premium predictions

Table 3: In-sample predictability of the equity premium (1963:08-2015:12)
This table reports the results for univariate long-horizon regressions on log market excess returns (Fama-French value-weighted), averaged over forecasting horizons of $k = 1, 3, 6, 9, 12, 24, 36$ and 48 months. The forecasting variables are according to Table 1 (cross-sectional moments and their combinational principal components are calculated as 3-month moving average from 100 portfolios sorted according to size and value). Each predictor variable is standardized to have zero mean and unit standard deviation. For each forecasting horizon, the table shows in-sample R^2 in %. Statistical significance at the 10%, 5% and 1% level is indicated by *, ** and *** based on bootstrapped p-values to account for the Stambaugh (1999) bias.

	K = 1	**K = 3**	**K = 6**	**K = 9**	**K = 12**	**K = 24**	**K = 36**	**K = 48**
logDP	0.17	0.57*	1.24***	1.83***	2.38***	4.03***	4.68***	**5.92*** **
logDY	0.23	0.62**	1.31***	1.85***	2.45***	3.87***	4.49***	**5.68*** **
logEP	0.07	0.13	0.22	0.41	0.58*	0.38	0.63*	0.19
logDE	0.03	0.21	0.58*	0.69**	0.81**	2.84***	2.66***	6.18***
RVOL	0.60*	**1.61*** **	**2.43*** **	2.51***	3.09***	3.26***	1.13***	0.80**
CSP	0.08	0.34	1.56***	3.17***	4.55***	**9.52*** **	**11.86*** **	**10.94*** **
BM	0.01	0.07	0.25	0.39	0.44*	0.16	0.01	0.07
NTIS	0.06	0.04	0.09	0.23	0.38	0.48*	0.58*	1.54***
TBL	0.42	0.73**	1.00**	1.26***	1.52***	1.50***	1.41***	0.73**
LTY	0.10	0.10	0.07	0.00	0.01	0.31	1.30***	3.79***
LTR	**1.06*** **	0.51*	1.99***	1.49***	1.27***	0.48*	0.73**	0.69**
TMS	**0.64** **	**1.55*** **	**2.63*** **	**5.08*** **	**7.20*** **	**11.60*** **	**17.86*** **	**22.47*** **
DFY	0.26	0.79**	2.07***	2.29***	2.63***	2.70***	3.62***	**6.44*** **
DFR	0.40	0.55*	0.36	0.26	0.10	0.04	0.05	0.06
INFL	0.09	0.58*	1.53***	2.67***	2.62***	1.17***	0.72**	0.92**
CSV	0.43	0.83**	2.14***	4.28***	5.31***	6.39***	7.97***	4.93***
CSS	0.09	0.22	0.53*	0.56*	0.71**	0.01	1.48***	0.15
CSK	0.09	0.30	0.40	1.05**	1.33***	1.91***	1.70***	**6.40*** **
$PCvs1$	0.11	0.19	0.51*	1.36***	1.68***	3.54***	7.90***	3.62***
$PCvk1$	0.10	0.14	0.54*	0.92**	1.13***	1.24***	1.87***	0.06
$PCsk1$	0.12	0.35	0.63**	1.08***	1.36***	0.77**	0.01	1.67***
$PCvsk1$	0.01	0.05	0.04	0.05	0.06	0.01	0.76**	0.15
$PCvs2$	**0.57* **	**1.18*** **	**3.02*** **	**5.21*** **	**6.48*** **	5.21***	2.97***	2.92***
$PCvk2$	**0.61* **	**1.36*** **	**2.93*** **	**6.28*** **	**7.84*** **	**10.01*** **	**11.35*** **	**13.26*** **
$PCsk2$	0.00	0.01	0.00	0.09	0.12	1.61***	5.87***	**8.09*** **
$PCvsk2$	**0.59* **	**1.20*** **	**2.98*** **	**5.77*** **	**7.17*** **	**7.78*** **	7.90***	**6.52*** **
$PCvsk3$	0.01	0.04	0.01	0.28	0.36	2.38***	7.36***	**9.55*** **

Electronic copy available at: https://ssrn.com/abstract=2747627

Table 4: Out-of-sample predictability of the equity premium (1963:08-2015:12)
This table reports the results for long-horizon regressions on log market excess returns (Fama-French value-weighted), averaged over forecasting horizons of $k = 1, 3, 6, 9, 12, 24, 36$ and 48 months. The forecasting variables are according to Table 1 (cross-sectional moments and their combinational principal components are calculated as 3-month moving average from 100 portfolios sorted according to size and value). The initial estimation interval is 1963:08-1973:08 (120 observations), subsequent forecasts for the period 1973:09-2015:12 are made based on recursively growing estimation windows. We report out-of-sample R^2 in % with significance levels based on the McCracken (2007) $MSE - F$ statistic, testing that the prevailing mean delivers a better forecast (smaller MSE) than the respective predictor variable. Statistical significance at the 10%, 5% and 1% level is indicated by *, ** and *** (critical values - where available - were taken from the respective papers, based on the most conservative assumptions).

	K = 1	**K = 3**	**K = 6**	**K = 9**	**K = 12**	**K = 24**	**K = 36**	**K = 48**
logDP	-1.80	-1.66	-2.23	-2.84	-3.16	-8.66	1.89***	**5.46*****
logDY	-1.76	-1.69	-2.64	-3.06	-3.27	-8.63	2.22***	**5.14*****
logEP	-1.98	-1.92	-2.79	-2.77	-1.97	-4.93	-1.91	-0.95
logDE	-2.09	-2.43	-3.24	-4.67	-6.20	-6.30	1.84***	**6.13*****
RVOL	0.01	**0.96*****	1.53***	1.20***	1.10***	-0.22	0.93***	-1.55
CSP	-0.36	-0.04	0.99***	2.52***	4.00***	6.96***	7.79***	**8.47*****
BM	-1.61	-1.32	-1.59	-1.27	-0.76	-0.49	-1.97	-3.90
NTIS	-0.97	-1.49	-2.49	-3.29	-3.58	-0.74	0.23*	-0.82
TBL	-1.31	-1.44	-1.40	-1.11	-0.59	1.37***	0.80**	-0.65
LTY	-1.31	-1.47	-1.68	-1.91	-2.00	-1.96	-0.93	-1.17
LTR	-0.13	-0.34	1.01***	0.55**	0.70**	0.10	0.51**	0.27*
TMS	0.00	**0.77****	**2.03*****	**5.04*****	**7.70*****	**12.01*****	**13.53*****	**22.65*****
DFY	-0.49	-0.08	1.59***	2.12***	2.49***	2.41***	-0.98	0.60**
DFR	-0.80	-0.01	-0.28	-0.26	-0.51	-0.55	-0.44	-0.34
INFL	-1.36	-1.20	-0.42	1.05***	0.89***	0.27*	0.37**	-0.71
CSV	-0.19	0.17*	1.70***	4.01***	5.27***	7.40***	8.59***	2.08***
CSS	-0.41	-0.27	0.12	-0.01	0.36**	-0.50	1.12***	-0.88
CSK	-0.60	-0.44	-1.07	0.20*	0.82***	2.05***	1.42***	**5.19*****
$PCvs1$	-0.44	-0.38	-0.10	0.77**	1.20***	4.15***	**10.33*****	**4.82*****
$PCvk1$	-0.58	-1.16	-1.94	-1.58	-1.13	0.22*	1.73***	-0.68
$PCsk1$	-0.32	-0.02	0.20*	0.79**	1.20***	0.58**	-0.46	0.77**
$PCvsk1$	-0.36	-0.14	-0.30	-0.04	0.08	-0.32	-0.51	-0.05
$PCvs2$	-0.04	**0.36****	**2.37*****	**4.57*****	**6.38*****	5.98***	3.74***	**2.42*****
$PCvk2$	0.01	**0.65****	**2.13*****	**5.61*****	**7.67*****	**11.46*****	**13.64*****	**15.16*****
$PCsk2$	-0.60	-0.96	-2.08	-1.69	-0.89	2.08***	7.05***	**10.37*****
$PCvsk2$	-0.12	0.13*	1.65***	3.97***	**5.79*****	**8.60*****	**10.60*****	**6.43*****
$PCvsk3$	-0.48	-0.51	-1.08	0.11	0.98***	5.55***	**13.02*****	**15.66*****

Electronic copy available at: https://ssrn.com/abstract=2747627

A.2.3 Asset Allocation

Table 5: Economic application: Asset allocation strategy based on out-of-sample predictability of the equity premium and it's volatility (1973:08-2015:12).
This table reports the results for of simple in- and out portfolio strategies based on predictions of the expected excess return. The forecasting variables are according to Table 1. We show annualized Sharpe ratios, certainty equivalent gains (in %) with respect to the prevailing mean for an investor with the same risk aversion level and the turnover of every strategy. Forecasting horizons and rebalancing frequency are given by k ($\in 1, 3, 6, 12$). *Buy and hold* corresponds to an investment in the market portfolio and *Prevailing Mean* is the same strategy based on the prevailing mean.

	Sharpe Ratio (ann.)				**CER gain ($\gamma = 3$, %)**				**Turnover**			
	k=1	**k=3**	**k=6**	**k=12**	**k=1**	**k=3**	**k=6**	**k=12**	**k=1**	**k=3**	**k=6**	**k=12**
buy & hold	0.42	0.39	0.41	0.41					0	0	0	0
prevailing mean	0.43	0.40	0.46	0.39					36	27	22	20
logDP	0.36	0.42	0.36	0.31	-0.79	0.87	-2.20	-1.50	143	96	60	42
logDY	0.23	0.39	0.32	0.35	-3.40	0.22	-2.96	-0.30	182	81	68	38
logEP	0.41	0.49	0.45	0.35	0.05	2.64	-0.07	-1.22	81	64	52	50
logDE	0.38	0.40	0.43	0.41	-0.34	0.58	-0.25	0.78	53	29	18	16
RVOL	0.30	0.34	0.42	0.44	-2.84	-2.04	-1.10	1.75	150	78	50	39
CSP	0.28	0.40	0.41	0.41	-2.12	0.00	-1.52	0.64	165	27	15	12
BM	0.40	0.48	0.45	0.30	-0.44	2.15	0.06	-2.21	66	58	45	35
NTIS	0.40	0.40	0.47	0.49	-0.51	-0.42	0.17	2.82	79	54	50	39
TBL	0.47	0.43	0.45	0.50	1.50	1.21	0.40	3.03	69	53	33	32
LTY	0.43	0.39	0.42	0.43	0.68	0.15	-0.18	1.35	45	37	33	16
LTR	0.46	0.44	0.52	0.39	1.23	1.09	1.64	0.00	684	160	46	20
TMS	0.48	0.49	0.46	0.45	1.47	2.38	0.27	1.54	94	54	38	35
DFY	0.40	0.35	0.41	0.39	-0.50	-1.53	-1.40	0.00	123	75	29	20
DFR	0.39	0.40	0.36	0.41	-0.61	0.40	-1.91	0.64	152	65	29	12
INFL	0.45	0.34	0.42	0.42	0.88	-1.05	-0.62	1.13	141	78	42	24
CSV	0.37	0.34	0.35	0.44	-0.83	-1.33	-2.33	1.42	97	96	36	27
CSS	0.36	0.33	0.28	0.32	-1.44	-1.98	-4.16	-1.77	155	**66**	37	35
CSK	0.32	0.34	**0.37**	0.39	-2.49	-1.84	**-2.05**	0.00	114	**27**	**26**	**20**
*PCvs*1	0.36	0.31	0.31	**0.49**	-1.27	-2.58	-3.43	**3.02**	130	**73**	**29**	**27**
*PCvk*1	0.34	**0.40**	**0.41**	0.41	-1.50	**0.49**	**-1.38**	0.78	184	112	37	34
*PCsk*1	**0.38**	**0.40**	**0.46**	0.39	-1.10	**-0.06**	**0.00**	0.00	**91**	**35**	**22**	**20**
*PCvsk*1	**0.40**	**0.42**	**0.46**	0.39	**-0.68**	**0.33**	**0.00**	0.00	**84**	**35**	**22**	**20**
*PCvs*2	**0.42**	**0.42**	**0.39**	0.39	**0.05**	**0.39**	**-1.82**	0.20	98	**89**	68	35
*PCvk*2	**0.37**	**0.40**	**0.35**	**0.47**	-1.13	**-0.16**	-2.52	**2.35**	**91**	**50**	**22**	**20**
*PCsk*2	0.34	**0.35**	0.26	0.41	-1.94	**-1.32**	-4.56	0.64	**83**	**58**	52	**12**
*PCvsk*2	0.36	**0.43**	**0.42**	**0.44**	-1.22	**0.86**	**-1.27**	**1.70**	**90**	**73**	**29**	**27**
*PCvsk*3	**0.40**	**0.38**	**0.39**	0.41	**-0.66**	**-0.80**	**-1.52**	0.64	**52**	**35**	**29**	**12**

Electronic copy available at: https://ssrn.com/abstract=2747627

A.2.4 Portfolio predictions

Table 6: Univariate in- and out-of-sample predictability for excess portfolio returns sorted on size & value, given monthly CSV

In this table we report the in- and out-of-sample results of univariate predictive regressions on monthly log portfolio excess returns, at forecasting horizons of $k = 1, 3, 6, 9$ and 12 months. The forecasting variable is the 3-month moving average of cross-sectional volatility (CSV). The sample is 1963:08-2015:12 and the initial estimation horizon for the out-of-sample analysis contains 120 observations for 1963:08-1973:07. For each regression, in line 1 we report the R^2 in % for the in sample analysis together with significance levels based on an F-test. Line 2 reports the R^2 in % for the out-of-sample analysis (see (7)) together with significance levels based on the $MSE-F$-test of McCracken (2007). We depict statistical significance at the 10%, 5% and 1% level as *, ** and ***. D1 (D10) denotes the first (last) decile of each portfolio group.

		D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
Size (CSV)						**K = 1**					
	$\bar{R}^2_{IS}(\%)$	0.01	0.01	0.10	0.08	0.14	0.13	0.10	0.02	0.10	0.54*
	$\bar{R}^2_{OOS}(\%)$	-2.22	-1.53	-1.07	-0.80	-0.69	-0.48	-0.66	-0.78	-0.51	-0.16
						K = 3					
	$\bar{R}^2_{IS}(\%)$	0.00	0.02	0.08	0.07	0.17	0.21	0.16	0.01	0.20	1.26***
	$\bar{R}^2_{OOS}(\%)$	-2.46	-1.95	-1.69	-1.24	-0.88	-0.78	-0.96	-1.06	-0.54	0.82***
						K = 6					
	$\bar{R}^2_{IS}(\%)$	0.00	0.00	0.24	0.34	0.54*	0.80**	0.52*	0.18	0.66**	3.21***
	$\bar{R}^2_{OOS}(\%)$	-1.50	-1.59	-1.04	-0.70	-0.35	-0.05	-0.45	-0.76	0.00	2.96***
						K = 9					
	$\bar{R}^2_{IS}(\%)$	0.01	0.01	0.41	0.70**	1.11***	1.66***	0.96**	0.57*	1.42***	6.20***
	$\bar{R}^2_{OOS}(\%)$	-1.46	-1.91	-0.94	-0.38	0.22*	1.03***	0.01	-0.41	0.80***	6.21***
						K = 12					
	$\bar{R}^2_{IS}(\%)$	0.09	0.05	0.15	0.42	0.90**	1.66***	0.77**	0.52*	1.71***	8.00***
	$\bar{R}^2_{OOS}(\%)$	-1.29	-1.88	-1.21	-0.73	0.05	1.30***	-0.15	-0.21	1.36***	8.24***
		D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
Value (CSV)						**K = 1**					
	$\bar{R}^2_{IS}(\%)$	0.60*	0.18	0.11	0.03	0.00	0.08	0.00	0.02	0.02	0.00
	$\bar{R}^2_{OOS}(\%)$	-0.05	-0.36	-0.42	-0.66	-0.56	-0.43	-0.69	-0.59	-0.58	-0.49
						K = 3					
	$\bar{R}^2_{IS}(\%)$	1.05**	0.32	0.36	0.04	0.00	0.25	0.00	0.08	0.04	0.00
	$\bar{R}^2_{OOS}(\%)$	0.70**	-0.40	-0.66	-0.77	-0.50	-0.26	-0.84	-0.64	-1.11	-0.48
						K = 6					
	$\bar{R}^2_{IS}(\%)$	3.03***	0.83**	1.16***	0.03	0.01	0.57*	0.00	0.11	0.18	0.03
	$\bar{R}^2_{OOS}(\%)$	2.93***	0.03	0.00	-1.06	-0.67	0.15*	-0.86	-0.69	-1.16	-0.36
						K = 9					
	$\bar{R}^2_{IS}(\%)$	6.39***	1.61***	2.04***	0.05	0.02	1.04**	0.00	0.09	0.33	0.06
	$\bar{R}^2_{OOS}(\%)$	6.86***	0.75**	0.44**	-1.32	-0.86	0.72**	-1.01	-0.86	-1.51	-0.37
						K = 12					
	$\bar{R}^2_{IS}(\%)$	8.57***	2.29***	2.06***	0.05	0.00	0.84**	0.00	0.27	0.18	0.01
	$\bar{R}^2_{OOS}(\%)$	9.38***	1.44***	0.43**	-1.30	-0.80	0.56**	-0.70	-0.54	-1.50	-0.38

Electronic copy available at: https://ssrn.com/abstract=2747627

Table 7: Univariate in- and out-of-sample predictability for excess portfolio returns sorted on size & value, given monthly $PCvs2$

In this table we report the in- and out-of-sample results of univariate predictive regressions on monthly log portfolio excess returns, at forecasting horizons of $k = 1, 3, 6, 9$ and 12 months. The forecasting variable is the 3-month moving average of the second principal component of CSV and CSS ($PCvs2$). The sample is 1963:08-2015:12 and the initial estimation horizon for the out-of-sample analysis contains 120 observations for 1963:08-1973:07. For each regression, in line 1 we report the R^2 in % for the in sample analysis together with significance levels based on an F-test. Line 2 reports the R^2 in % for the out-of-sample analysis (see (7)) together with significance levels based on the $MSE-F$-test of McCracken (2007) . We depict statistical significance at the 10%, 5% and 1% level as *, ** and ***. D1 (D10) denotes the first (last) decile of each portfolio group.

		D1	D2	D3	D4	D5	D6	D7	D8	D9	D10
Size ($PCvs2$)						**K = 1**					
	$\bar{R}^2_{IS}(\%)$	0.33	0.12	0.21	0.20	0.24	0.20	0.30	0.10	0.19	**0.62****
	$\bar{R}^2_{OOS}(\%)$	-0.68	-0.66	-0.47	-0.27	-0.27	-0.27	-0.25	-0.47	-0.32	-0.02
						K = 3					
	$\bar{R}^2_{IS}(\%)$	0.08	0.00	0.11	0.16	0.31	0.33	0.43	0.12	0.37	**1.70*****
	$\bar{R}^2_{OOS}(\%)$	-0.94	-0.92	-0.88	-0.53	-0.43	-0.43	-0.40	-0.72	-0.30	**0.91*****
						K = 6					
	$\bar{R}^2_{IS}(\%)$	0.28	0.12	**0.51***	**0.74****	**1.09*****	**1.34*****	**1.28*****	**0.83****	**1.32*****	**4.02*****
	$\bar{R}^2_{OOS}(\%)$	-0.12	-0.44	-0.10	**0.32****	**0.50****	**0.78****	**0.59****	-0.07	**0.61****	**3.40*****
						K = 9					
	$\bar{R}^2_{IS}(\%)$	**0.55***	0.41	**1.01****	**1.41*****	**2.07*****	**2.46*****	**2.01*****	**1.68*****	**2.55*****	**6.57*****
	$\bar{R}^2_{OOS}(\%)$	**0.33****	-0.19	**0.47****	**1.08*****	**1.55*****	**2.07*****	**1.28*****	**0.48****	**1.79*****	5.98***
						K = 12					
	$\bar{R}^2_{IS}(\%)$	0.35	0.35	**1.09*****	**1.43*****	**2.41*****	**3.03*****	**2.24*****	**2.12*****	**3.29*****	**8.09*****
	$\bar{R}^2_{OOS}(\%)$	**0.22***	-0.01	**0.95*****	**1.37*****	**2.43*****	**3.27*****	**1.92*****	**1.49*****	**3.08*****	7.90***
		D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
Value ($PCvs2$)						**K = 1**					
	$\bar{R}^2_{IS}(\%)$	0.33	0.12	0.21	0.20	0.24	0.20	0.30	0.10	0.19	**0.62****
	$\bar{R}^2_{OOS}(\%)$	-0.68	-0.66	-0.47	-0.27	-0.27	-0.27	-0.25	-0.47	-0.32	-0.02
						K = 3					
	$\bar{R}^2_{IS}(\%)$	0.08	0.00	0.11	0.16	0.31	0.33	0.43	0.12	0.37	**1.70*****
	$\bar{R}^2_{OOS}(\%)$	-0.94	-0.92	-0.88	-0.53	-0.43	-0.43	-0.40	-0.72	-0.30	**0.91*****
						K = 6					
	$\bar{R}^2_{IS}(\%)$	0.28	0.12	0.51*	**0.74****	**1.09*****	**1.34*****	**1.28*****	**0.83****	**1.32*****	**4.02*****
	$\bar{R}^2_{OOS}(\%)$	-0.12	-0.44	-0.10	**0.32****	**0.50****	**0.78****	**0.59****	-0.07	**0.61****	**3.40*****
						K = 9					
	$\bar{R}^2_{IS}(\%)$	0.55*	0.41	1.01**	**1.41*****	**2.07*****	**2.46*****	**2.01*****	**1.68*****	**2.55*****	**6.57*****
	$\bar{R}^2_{OOS}(\%)$	0.33**	-0.19	**0.47****	**1.08*****	**1.55*****	**2.07*****	**1.28*****	**0.48****	**1.79*****	**5.98*****
						K = 12					
	$\bar{R}^2_{IS}(\%)$	0.35	0.35	1.09***	**1.43*****	**2.41*****	**3.03*****	**2.24*****	**2.12*****	**3.29*****	**8.09*****
	$\bar{R}^2_{OOS}(\%)$	0.22*	-0.01	**0.95*****	**1.37*****	**2.43*****	**3.27*****	**1.92*****	**1.49*****	**3.08*****	**7.90*****

Electronic copy available at: https://ssrn.com/abstract=2747627

Table 8: Univariate in- and out-of-sample predictability for excess portfolio returns sorted on size & value, given monthly $PCvk2$

In this table we report the in- and out-of-sample results of univariate predictive regressions on monthly log portfolio excess returns, at forecasting horizons of $k = 1, 3, 6, 9$ and 12 months. The forecasting variable is the 3-month moving average of the second principal component of CSV and CSK ($PCvk2$). The sample is 1963:08-2015:12 and the initial estimation horizon for the out-of-sample analysis contains 120 observations for 1963:08-1973:07. For each regression, in line 1 we report the R^2 in % for the in sample analysis together with significance levels based on an F-test. Line 2 reports the R^2 in % for the out-of-sample analysis (see (7)) together with significance levels based on the $MSE-F$-test of McCracken (2007). We depict statistical significance at the 10%, 5% and 1% level as *, ** and ***. D1 (D10) denotes the first (last) decile of each portfolio group.

		D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
Size ($PCvk2$)						**K = 1**					
	$\bar{R}^2_{IS}(\%)$	0.13	0.07	0.22	0.19	0.26	0.24	0.24	0.14	0.26	**0.69****
	$\bar{R}^2_{OOS}(\%)$	-0.92	-0.70	-0.46	-0.32	-0.25	-0.21	-0.31	-0.38	-0.22	0.06
						K = 3					
	$\bar{R}^2_{IS}(\%)$	0.27	0.10	**0.44***	**0.46***	**0.64****	**0.68****	**0.54***	0.35	**0.62****	**1.65*****
	$\bar{R}^2_{OOS}(\%)$	-0.53	-0.60	-0.20	0.00	**0.16***	**0.19***	-0.07	-0.18	0.08	**0.86*****
						K = 6					
	$\bar{R}^2_{IS}(\%)$	**0.54***	0.20	**0.79****	**0.99****	**1.33*****	**1.71*****	**1.18*****	**0.87****	**1.41*****	**3.61*****
	$\bar{R}^2_{OOS}(\%)$	**0.34****	-0.07	**0.48****	**0.69****	**0.96*****	**1.32*****	**0.73****	**0.32****	**0.86*****	2.54***
						K = 9					
	$\bar{R}^2_{IS}(\%)$	**1.38*****	**0.95****	**2.06*****	**2.54*****	**3.27*****	**4.19*****	**2.73*****	**2.55*****	**3.33*****	**7.35*****
	$\bar{R}^2_{OOS}(\%)$	**1.73*****	**0.92*****	**2.16*****	**2.86*****	**3.34*****	**4.41*****	**2.58*****	**2.05*****	**2.92*****	**6.25*****
						K = 12					
	$\bar{R}^2_{IS}(\%)$	**1.01****	**0.81****	**2.05*****	**2.78*****	**3.84*****	**5.40*****	**3.21*****	**3.31*****	**4.33*****	**8.94*****
	$\bar{R}^2_{OOS}(\%)$	**1.63*****	**1.09*****	**2.66*****	**3.78*****	**4.63*****	**6.56*****	**3.59*****	**3.28*****	**4.43*****	8.11***

		D1	**D2**	**D3**	**D4**	**D5**	**D6**	**D7**	**D8**	**D9**	**D10**
Value ($PCvk2$)						**K = 1**					
	$\bar{R}^2_{IS}(\%)$	**0.80****	0.39	0.26	0.10	0.10	0.16	0.03	0.00	0.05	0.00
	$\bar{R}^2_{OOS}(\%)$	**0.15***	-0.04	-0.22	-0.33	-0.29	-0.21	-0.40	-0.36	-0.39	-0.30
						K = 3					
	$\bar{R}^2_{IS}(\%)$	**1.53*****	**0.83****	**1.02****	0.26	0.23	**0.59***	0.11	0.01	0.32	0.09
	$\bar{R}^2_{OOS}(\%)$	0.79***	**0.39****	**0.33****	-0.11	-0.12	**0.19***	-0.26	-0.25	-0.22	-0.23
						K = 6					
	$\bar{R}^2_{IS}(\%)$	**4.07*****	**1.54*****	**2.11*****	0.23	0.20	**0.99****	0.04	0.04	0.25	0.18
	$\bar{R}^2_{OOS}(\%)$	**2.94*****	**1.17*****	**1.44*****	-0.15	-0.25	**0.45****	-0.32	-0.19	-0.13	-0.34
						K = 9					
	$\bar{R}^2_{IS}(\%)$	**7.80*****	**3.07*****	**4.02*****	**0.86****	**0.91****	**2.67*****	0.37	0.02	**1.08*****	**0.87****
	$\bar{R}^2_{OOS}(\%)$	6.73***	**2.90*****	**3.14*****	**0.54****	**0.72****	**2.54*****	**0.13***	-0.30	**0.72****	**0.64****
						K = 12					
	$\bar{R}^2_{IS}(\%)$	**10.35*****	**4.10*****	**4.29*****	**1.02****	**0.92****	**2.87*****	**0.44***	0.02	**0.97****	**0.56***
	$\bar{R}^2_{OOS}(\%)$	**9.67*****	**4.22*****	**3.67*****	**0.80****	**0.90*****	**3.02*****	**0.30***	-0.27	**0.70****	**0.42****

Electronic copy available at: https://ssrn.com/abstract=2747627