Parameter Uncertainty, Financial Turbulence and Aggregate Stock Returns*†

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Abstract

We develop a novel, intuitive and objective measure of time-varying parameter uncertainty (PU) based on a simple statistical test. Plugging this measure into the model of portfolio selection with parameter uncertainty of Garlappi et al. (2007), it outperforms all other predictors of the equity premium, including the strongest known predictor(s) to date. A simple trading strategy based on PU generates an annual certainty equivalent return of 6.44% in the 1990-2015 period. Additionally, PU is the only predictor to fulfill all the criteria of Welch and Goyal (2008). Our results are robust to a large variety of different specifications.

Keywords: parameter uncertainty; aggregate investor behavior; equity risk premium; predictive regression; out-of-sample predictability; asset allocation; financial turbulence

JEL classification: G12, G14, G17

1 Introduction

A considerable amount of papers is concerned with the difficulty of estimating parameters for the implementation of optimal portfolio rules. Due to the very short available timeseries of returns in relation to the number of assets[1] the literature often finds that it is better not to estimate (all) parameters and invest using heuristic portfolios rules, such as an equal weighting of assets.[2] And even if one reliably estimates such parameters, "financial markets often change their behavior abruptly" which might change "the mean, volatility, and correlation patterns in stock returns [...] dramatically" (Ang and Timmermann, 2012).

In this paper we will not deal with the question whether and how to reliably estimate parameters, but to judge how well estimated parameters fit to current market conditions. To this point, we suggest a novel, intuitive and objective measure to capture such "*uncertainty* of *parameter* estimates" (PU) based on a multivariate extension of a simple t-test applied to a variety of market cross-sections (Fama-French-portfolios). The measure implies that parameter uncertainty will increase (decrease) when recent returns within the portfolios deviate more (less) from their estimated means given their estimated covariances.[3] As this measure perfectly fits to the model of portfolio selection under parameter uncertainty of Garlappi, Uppal, and Wang (2007) (henceforth GUW), we employ their model in a second step to capture the possible reaction of investors with aversion to parameter uncertainty. It implies that such investors reduce their allocation to risky assets given elevated levels of PU.[4] We verify this behavior by showing that the combination of model and PU creates the best predictor of aggregate stock returns within a large set of commonly employed predictors in a very competitive setting. This holds true in-sample as well as out-of-sample, for economic applications as well as a large variety of robustness checks.

Our measure PU is related to, but extends the measure of financial turbulence of Kritzman and Li (2010)[5] by taking into account a larger number of recent returns and being based on cross-sectional partitions of the entire market rather than a variety of (heuristically selected) asset class indices. We first demonstrate that PU has a strong

[1] De Miguel and Nogales (2009) give many examples for the necessary time dimension using different estimators, portfolio constraints and optimization rules

[2] The $1/n$ portfolio rule was advocated by (De Miguel et al., 2009b). Other, more sophisticated models deal with the uncertainty of parameters by arguing for adapted portfolio rules that take this uncertainty into account (e.g., Kan and Zhou, 2007; De Miguel et al., 2009a).

[3] The goodness of fit of currently observed returns to (historical) parameter estimates is evaluated using a Hotelling (1931) T-test. Such fitting tests are used in quality and process control (for an overview of methods, see Makis, 2008), portfolio monitoring (e.g., Bodnar, 2009) and for the surveillance of portfolio input parameters (e.g., Bodnar, 2007; Bodnar and Schmid, 2007; Bodnar et al., 2009).

[4] This result is not available in the published version of their paper but can be found in Kan and Zhou (2007, eq. 56).

[5] Which has been shown to indicate periods of high risk, illiquidity and devalued risky assets

negative correlation with future aggregate returns, making it an ideal candidate for the prediction of the equity premium. Second, we show that in combination with the model of GUW a rise in PU predicts a strong decline in aggregate stock returns very well in-sample ($R^2_{IS} = 2.29$) and out-of-sample ($R^2_{OS} = 2.30$) on a monthly horizon. It outperforms a large set of popular and less popular predictors, including the short interest index of Rapach et al. (aka "the strongest known predictor" to date 2016) ($R^2_{IS} = 1.47$ and $R^2_{OS} = 1.45$) and the financial uncertainty index of Ludvigson et al. (2017) ($R^2_{IS} = 1.79$ and $R^2_{OS} = 2.14$), and performs very well for horizons up to one year. It is also robust to the market partition (the particular selection of Fama-French portfolios), the estimation time horizon, the number of recent returns employed and economically outperforms all other tested variables with annual certainty-equivalent return (CER) gains of 6.44% for a mean-variance investor with a risk-aversion coefficient of three. We additionally show that no other predictor encompasses PU on short predictive horizons. Finally, we highlight that PU produces a predictor of the equity premium that uniquely fulfills all of Welch and Goyal's criteria, as is typically expected of a predictor of the equity premium. We use a dataset similar to that employed by Rapach et al. (2016) to help us relate our results to the "strongest known predictor of aggregate stock returns" and avoid data snooping.

To the best of our knowledge, this is the first paper to develop a measure of time-varying parameter uncertainty and to subsequently employ it - by using the portfolio selection framework of GUW - to predict aggregate stock returns.[6] Our results can therefore be seen as evidence that their model very well describes the aggregate behavior of investors with an aversion to parameter uncertainty. Our work also allows for an endogenous determination of the 'level of confidence'- parameter in the GUW model, a crucial input on which (to the best of our knowledge) the literature[7] has not (yet) given any guidance.

We additionally contribute to the literature in several ways: First, as will be shown in Section 2.2, our measure closely relates to the literature on time-varying risk aversion (cf. Guiso et al., 2013), which according to Li (2007) similarly has a countercyclical relationship with the equity risk premium but does not predict future stock market returns at all (Henkel et al., 2011). A corresponding stream of papers uses time-varying ambiguity aversion (Miao et al., 2012) to explain the variance risk premium (VRP) of Bollerslev et al. (2009), which is also well known to predict aggregate stock returns. While GUW use the terms "ambiguity" and "parameter uncertainty" interchangeably, PU is uncorrelated with the VRP. To relate the predictive power of PU to the VRP, we additionally conduct our experiments for a shorter time horizon.

[6] Dangl and Weissensteiner (2017) employ their model to investigate the impact of predictability on the long-term asset allocation of investors who are averse to parameter uncertainty (ambiguity).
[7] As of May 2018, their paper has 528 citations according to Google scholar.

Second, as we capture the impact of time-varying PU on the stock market through the behavior of investors with an aversion to PU, our work also relates to behavioral factors that produce and predict predict movements in the stock markets. These are, for example, measures of investor sentiment as developed by Baker and Wurgler (2006) and return over-extrapolation as described by Greenwood and Shleifer (2014). Regarding the index of investor sentiment, we only find a very low correlation with PU, and including it in our predictive regression framework yields only weak predictability according to the findings of Stambaugh et al. (2014). The link to investors that overweigh recent returns in the estimation of expected returns is given through the nature of our measure, but essentially PU is very different from the idea of over-extrapolation. Nonetheless, We include a measure of return over-extrapolation[8] into our framework, but only find a very weak correlation with PU and an almost nonexistent predictive ability.

Third, as PU is essentially a measure derived from a cross-section of stock returns, it also relates to other cross-sectional measures that are known to predict stock returns, such as cross-sectional moments (Maio, 2016; Stöckl and Kaiser, 2016). In fact, Maio's measure of cross-sectional volatility (CSV) correlates with PU at 0.69, which is why we include it in a more thorough analysis below. We find competitive predictive power for CSV only at longer horizons.

Fourth, due to the construction of PU in relating recent returns to longer horizon estimates, our work also connects to the literature on stock market predictability using technical indicators (Neely et al., 2014). In this sense, their best-performing indicator – which relates two- to 12-month moving averages ($MA_{2,12}$) – is related to PU, which relates recent returns to their (long-term) historical means. We also find an above-average correlation with PU and confirm its (only weak) predictive ability in our detailed analysis below.

Finally, PU relates to other measures of macroeconomic, real and financial uncertainty such as those recently developed by Jurado et al. (2015) and Ludvigson et al. (2017).[9] Specifically, their measure of financial uncertainty is (partly) based on the same cross-section of equity portfolio returns and correlates highly with PU. Therefore, we also include it in our more detailed analysis below. We find some competitive predictive power at shorter horizons.

[8] A monthly exponentially weighted moving average (EWMA), where, to determine appropriate parameters, we conduct a numerical experiment in which we relate the EWMA given the values of Cassella and Gulen (2017, annual $\mu = 0.06$, $\sigma = 0.16$ and $\lambda = 0.51$) for 60 quarterly returns to 120 monthly returns (to better match our data) and subsequently employ a value of $\lambda_{\text{monthly}} \approx 0.80$.

[9] Bali et al. (2017) show that stocks with low exposure to economic uncertainty significantly outperform stocks with positive uncertainty exposure.

In the following Section 2, we will first motivate our measure of PU, contextualize it in the literature, explain the model of Garlappi et al. (2007) and then link the two. In Section 3 we describe the data and variables in detail. Next, in Section 4, we will use the framework of Welch and Goyal (2008) in the setting of Rapach et al. (2016) to research the in- and out-of-sample predictive performance of all variables and conduct a variety of robustness checks. Finally, in Section 5, we will present the results documenting the economic significance of our findings, before we conclude the paper in Section 6.

2 Theory

In this section, we first motivate our measure of parameter uncertainty (PU) and discuss its properties. We then describe the model of portfolio choice under parameter uncertainty developed by Garlappi et al. (2007) and link it to our measure of PU.

2.1 Measuring Parameter Uncertainty

We follow the idea mentioned in the introduction and assume that confidence in parameter estimates (parameter uncertainty) depends on their goodness of fit to more recent average returns. Given the N-vector of average current returns $\bar{\mathbf{r}}_t = \frac{1}{T_c}\sum_{s=0}^{T_c-1}\mathbf{r}_{t-s}$ and parameter estimates for expected returns $\hat{\boldsymbol{\mu}} = \frac{1}{T}\sum_{s=0}^{T-1}\mathbf{r}_{t-s}$ (with $T \gg T_c$) and their covariance matrix $\frac{1}{T-1}\sum_{s=0}^{T-1}\left(\mathbf{r}_{t-s}-\hat{\boldsymbol{\mu}}\right)\left(\mathbf{r}_{t-s}-\hat{\boldsymbol{\mu}}\right)'$, the fit of $\bar{\mathbf{r}}_t$ to parameters $\hat{\boldsymbol{\mu}}, \hat{\boldsymbol{\Sigma}}$[10] can be judged by Hotelling's T^2-statistic:

$$\mathrm{PU}_t = \frac{1}{N}\left(\bar{\mathbf{r}}_t-\hat{\boldsymbol{\mu}}\right)'\hat{\boldsymbol{\Sigma}}^{-1}\left(\bar{\mathbf{r}}_t-\hat{\boldsymbol{\mu}}\right). \tag{1}$$

The possible distributions of this statistic depend on T_c and whether the T_c recent returns are part of the larger sample T[11] and are given in Table 1.

[Place Table 1 about here.]

For $N = 1$, there is an obvious similarity to univariate two-sample t-tests with unequal sample sizes, where the exact distributions are given in the literature on analysis of the mean (ANOM, see Nelson et al., 2005). Such statistics are usually applied in quality control (Bersimis et al., 2007), where the quality of one or several goods is controlled by statistically testing several (dependent) features against those of a

[10]Here, we assume that returns are independently generated by a multivariate normal distribution $N(\boldsymbol{\mu}, \boldsymbol{\Sigma})$). However, our results are also asymptotically valid for other distributions.
[11]See Johnson, Wichern, et al. (2002) and Montgomery (2012).

control group. Frequently, when control parameters also have to be estimated and are therefore subject to estimation errors (outliers), robust moments are used to determine $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$.[12]

A measure similar to (1) (for $T_c = 1$) is suggested by Chow et al. (1999) and Kritzman and Li (2010) to separate good from bad regimes and named "financial turbulence" (FT):

$$\mathrm{FT}_t = \frac{1}{N} \left(\mathbf{r}_t - \hat{\boldsymbol{\mu}}\right)' \hat{\boldsymbol{\Sigma}}^{-1} \left(\mathbf{r}_t - \hat{\boldsymbol{\mu}}\right). \tag{2}$$

Kritzman and Li (2010) calculate their measures of financial turbulence for a variety of asset classes and markets, such as world equities, US sectors and currencies, and find the following: "Financial turbulence often coincides with excessive risk aversion, illiquidity, and devaluation of risky assets". Further, FT is known to recognize periods of financial market turmoil (e.g., Duarte and Eisenbach, 2013; Nystrup et al., 2015) and is therefore often used to construct indicators of financial market stress and systemic risk (e.g., Bisias et al., 2012; Berger and Pukthuanthong, 2016; Stöckl et al., 2017). In a very recent application, Giglio et al. (2016) show that turbulence in the cross-section of the 20 largest financial institutions in the US (as a measure of systemic risk) has excellent predictive power for macroeconomic shocks as measured by the Chicago Fed National Activity Index (CFNAI). Our measure PU can be seen as an extension of FT that nests all of its features but also provides a more realistic background for inclusion in a model of investor reaction based on the uncertainty of input parameters. In a next step, we define the model of portfolio selection with parameter uncertainty of Garlappi et al. (2007) and employ our measure of parameter uncertainty (PU).

2.2 Portfolio choice of ambiguity-averse investors

The well-known model of optimal portfolio choice under parameter uncertainty for ambiguity-averse mean-variance investors of Garlappi et al. (2007) employs a multi-prior Bayesian framework. Therein, an investor solves the following optimization problem:

$$\max_{\mathbf{w}} \min_{\boldsymbol{\mu}} \mathbf{w}'\boldsymbol{\mu} - \frac{\gamma}{2}\mathbf{w}'\boldsymbol{\Sigma}\mathbf{w}', \tag{3}$$

$$\text{s.t.} \quad \left(\hat{\boldsymbol{\mu}} - \boldsymbol{\mu}\right)' \boldsymbol{\Sigma}^{-1} \left(\hat{\boldsymbol{\mu}} - \boldsymbol{\mu}\right) \leq \varepsilon, \tag{4}$$

where $\boldsymbol{\mu}$ is the N-vector of true excess returns (assuming the existence of a risk-free asset), $\boldsymbol{\Sigma}$ is the true $N \times N$-covariance matrix, γ is the scalar risk aversion coefficient, and ε is a scalar that combines aversion to PU with the level of PU in the market. The minimization over $\boldsymbol{\mu}$ in (3) takes the most conservative $\boldsymbol{\mu}$ that lies in

[12] For robust controls see, e.g., Chenouri et al. (2009).

the confidence region defined by (4) to arrive at an optimal portfolio that is robust to uncertainty (and, therefore, changes) in $\hat{\boldsymbol{\mu}}$ (based on the minimax rule of Gilboa and Schmeidler, 1989). The parameter ε is crucial in this setting, as it determines the level of investor confidence in parameters across all N assets. In a geometrical sense, ε can be interpreted as a confidence interval around $\hat{\boldsymbol{\mu}}$ that takes the form of a hyper-ellipsoid (e.g., Meucci, 2009):

$$P\left[\frac{T(T-N)}{(T-1)N}\left(\hat{\boldsymbol{\mu}}-\boldsymbol{\mu}\right)'\boldsymbol{\Sigma}^{-1}\left(\hat{\boldsymbol{\mu}}-\boldsymbol{\mu}\right)\leq\epsilon\right]=1-p,\quad \varepsilon=\epsilon\cdot\frac{(T-1)N}{T(T-N)} \tag{5}$$

where $\frac{T(T-N)}{(T-1)N}\left(\hat{\boldsymbol{\mu}}-\boldsymbol{\mu}\right)'\boldsymbol{\Sigma}^{-1}\left(\hat{\boldsymbol{\mu}}-\boldsymbol{\mu}\right)$ is χ^2 distributed with N degrees of freedom,[13] and p is the investor's confidence in parameters $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$.

In the presence of a risk-free asset, the closed-form solution of the above optimization problem is given by Kan and Zhou (2007, eq. 56) as

$$w^*=\frac{c_{\text{PU}}}{\gamma}\hat{\boldsymbol{\Sigma}}^{-1}\hat{\boldsymbol{\mu}},\quad c_{\text{PU}}=\begin{cases}1-\left(\frac{\varepsilon}{\hat{\theta}^2}\right)^{\frac{1}{2}} & \text{if } \hat{\theta}^2>\varepsilon\\ 0 & \text{if } \hat{\theta}^2\leq\varepsilon.\end{cases} \tag{6}$$

Relative to the case in which the investor is completely confident in his parameter estimates ($p=1\Rightarrow\varepsilon=0\Rightarrow c_{PU}=1$), an investor with less confidence reduces his investment in the risky assets by a factor that is determined from the relationship between ε and $\hat{\theta}^2$ (the squared sample Sharpe ratio as an estimate of the true Sharpe ratio θ).

Equation (6) allows for several interpretations: First, a lower confidence in parameters – similar to an increase in risk aversion – leads to reduced investment in the optimal risky portfolio with respect to the risk-free rate (cf. Dangl and Weissensteiner, 2017). Second, it can be interpreted as a downward adjustment of the average past returns that are used as estimates of expected returns. Similarly, it can be interpreted as an inflation (by $\frac{1}{c_{PU}}$) of the covariance matrix. The latter two effects are substitutes in the sense that the reduction in expected returns leads to the same portfolio as does an increase in risk.

2.3 Assembling the model

Instead of allowing each investor to individually choose his confidence in parameters p, we now employ our measure of PU as an objective measure of parameter uncertainty. Assuming that we employ (1) for $T_c>1$ and let the recent returns in $\bar{r}_t$ be a subset

[13] If $\boldsymbol{\Sigma}$ is estimated by $\hat{\boldsymbol{\Sigma}}$, the distribution becomes an F distribution with N and $T-N$ degrees of freedom.

of the larger sample that determines $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$, Table 1 tells us that the time-varying probability of parameter misfit is given by

$$1 - p_t = F^{-1}\left(\frac{T_c(T - T/T_c - N + 1)}{(T/T_c - 1)(T_c - 1)}\,\mathrm{PU}_t; N; T - T/T_c - N + 1\right). \tag{7}$$

According to (5) and Garlappi et al. (2007), we similarly derive

$$1 - p = P\left[\frac{T(T-N)}{(T-1)N}\left(\hat{\boldsymbol{\mu}} - \boldsymbol{\mu}\right)' \hat{\boldsymbol{\Sigma}}^{-1}\left(\hat{\boldsymbol{\mu}} - \boldsymbol{\mu}\right) \leq \epsilon\right] = F^{-1}\left(\epsilon; N; T - N\right). \tag{8}$$

As T is large relative to the cross-section N and the lookback window for the recent returns is small (e.g. $T_c = 12$), we can safely assume that $F(x; N; T) \approx F(x; N; T - T/T_c - N + 1)$[14] and obtain

$$\varepsilon_t = \epsilon_t \frac{(T-1)N}{T(T-N)} = \frac{T_c(T - T/T_c - N + 1)}{(T/T_c - 1)(T_c - 1)}\,\mathrm{PU}_t\,\frac{(T-1)N}{T(T-N)} := \lambda\,\mathrm{PU}_t\,. \tag{9}$$

Applying this to (6) yields

$$c_{\mathrm{PU},t} = \begin{cases} 1 - \left(\frac{\lambda\,\mathrm{PU}_t}{\hat{\theta}_t^2}\right)^{\frac{1}{2}} & \text{if } \hat{\theta}_t^2 > \lambda\,\mathrm{PU}_t \\ 0 & \text{if } \hat{\theta}_t^2 \leq \lambda\,\mathrm{PU}_t\,. \end{cases} \tag{10}$$

Due to its properties as an objective measure of parameter uncertainty (PU), the model of Garlappi et al. (2007) directly provides a measure of how much investors with aversion to PU are willing to invest relative to the optimal Markowitz (1952) portfolio. Regarding the second interpretation of the term c_{PU} above, it also tells us the (robust) expected return that such investors use in their mean-variance optimization. For this reason, we expect c_{PU} to perform well as a predictor of aggregate stock returns.

In the next section, we describe our data and derive and describe our measures of PU and c_{PU} before we conduct the empirical analysis in Section 4.

3 Data and Variables

To evaluate the predictive power of different specifications of c_{PU}, we employ a slight extension of the framework of Rapach et al. (2016) to benchmark our results against the "strongest known predictor of aggregate stock returns". Our analysis begins in January 1973 and ends in December 2014 but could be extended to the full timespan

[14] Numerically, for 50 years of data and 25 assets, we find a cumulative difference of $\int_{-\infty}^{\infty}\left(F(x; N; T - N) - F(x; N; T - T/T_c - N + 1)\right)dx = 0.00032$ between the two distribution functions.

covered by the datasets available on Kenneth French's website. From his website, we also take the value-weighted market excess return[15] and calculate monthly log excess returns. For the out-of-sample evaluation, we reserve an initial estimation period of 204 observations (1973:01-1989:12), which leaves 300 monthly observations (1990:01-2014:12) for the out-of-sample evaluation.

3.1 Parameter Uncertainty

We calculate the main version of PU from the value-weighted log returns of 25 portfolios sorted according to size and value (P25SV) available on Kenneth French's website.[16] We do this for two reasons: First the number of assets or portfolios cannot be too large, as we need relatively accurate estimates of $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$, and we know from De Miguel et al. (2009b) that even for 25 assets, one would need 3,000 observations to obtain estimates that are good enough to outperform the $1/n$ investment strategy. Second, these research portfolios partition the market that we want to predict according to well-researched characteristics and are often used as the basis for calculating cross-sectional predictive measures (Stivers and Sun, 2010; Maio, 2016; Stöckl and Kaiser, 2016).

For our predictive analysis to begin in 1973:01, we therefore need additional observations to calculate the initial moments $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ and therefore extend our sample by 120 observations to 1963:01. We then reestimate $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ every period based on a recursively growing window.[17] Furthermore, following the literature (see, for example, Bloom, 2009; Rapach et al., 2016), we calculate a version of PU for the in-sample analysis that uses the full data sample (1963:01-2014:12) for the estimation of $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$. Additionally, we assume the lookback period for the recent average returns $\bar{\mathbf{r}}_t$ to be $T_c = 12$ months.[18]

To relate our results to the voluminous literature, we use the 15 monthly predictors – including the short interest index (SII) – from Welch and Goyal (2008) and Rapach et al. (2016):[19] log dividend-price ratio (logDP), log dividend yield (logDY), log earnings-price ratio (logEP), log dividend-payout ratio (logDE), excess stock return

[15] As robustness checks, we also use the S&P500 value-weighted market excess returns, which we retrieve from Datastream.

[16] For robustness checks on sorts for different (combinations of) characteristics and different numbers of portfolios, see Section 4.3.2.

[17] We conduct robustness checks with initial estimation windows starting in January 1953 and August 1926 and rolling windows in Section 4.3.3.

[18] This assumption will also be tested for robustness in Section 4.3.4.

[19] All variables are available from Dave Rapach `http://sites.slu.edu/rapachde/home/research`, and some of them were originally retrieved from Amit Goyal's webpage at `http://www.hec.unil.ch/agoyal/`.

volatility (RVOL),[20] book-to-market ratio (BM), net equity expansion (NTIS), T-bill rate (TBL), long-term yield (LTY), term spread (TMS), default yield spread (DFY), default return spread (DFR) and inflation (INFL). As mentioned in the introduction, we also include cross-sectional volatility[21] (CSV) calculated on the same dataset (P25SV), the 2-month versus 12-month moving average rule ($\text{MA}_{2,12}$) of Neely et al. (2014), a sentiment index (SENT, the version according to eq. 2 in Baker and Wurgler, 2006, due to its better predictive performance),[22] a 12-month EWMA (WMA) to highlight return extrapolation (Greenwood and Shleifer, 2014; Cassella and Gulen, 2017), the VRP of Bollerslev et al. (2009)[23] and the one-month ahead predictors of macro $UNC_{M,1}$, real $UNC_{R,1}$ and financial uncertainty $UNC_{F,1}$ indices of Jurado et al. (2015) and Ludvigson et al. (2017)[24].

3.2 Sample properties

In Figure 1, we plot time series for the aggregate monthly log excess returns, its within-month volatility σ_e, $\text{MA}_{2,12}$, WMA, CSV, SII, VRP, SENT, $UNC_{F,1}$, PU and c_{PU}. NBER recessions are depicted in gray. We observe that PU (and, consequently, c_{PU}) nearly always increases (decreases) before cumulative market returns drop and enter a recession. Within recessions, the two measures show the opposite behavior and track the stock market growth that generally signals an end to recession periods. Interestingly, in some periods, its behavior is most closely mirrored by $\text{MA}_{2,12}$, which due to its binary scheme cannot cover the specific movements of the aggregate excess return. We also observe that c_{PU} captures specific movements of several of the other predictors (CSV, SII, WMA and $\text{MA}_{2,12}$). The sentiment index clearly signals the arrival of the dot.com bubble but does not react before the arrival of the global financial crisis. In contrast, the (well-documented) predictive power of VRP seems to derive entirely from the huge decline during the 2008-2009 financial crisis. The financial uncertainty index is the most related to PU, but it appears to react sluggishly and often spikes when there is no apparent reaction from PU.

[Place Figure 1 about here.]

Table 2 contains summary statistics for the 25 variables plus the equity premium and its volatility for the sample period 1973:01-2014:12.[25] PU has a mean of 0.09 and a

[20] Due to outliers in SVAR, this variable is calculated from a 12-month moving standard deviation estimator (cf. Mele, 2007; Rapach et al., 2016).

[21] Following Maio (2016), we calculate a 3-month moving average to obtain the best performance.

[22] Available from Jeffrey Wurgler's website at `http://people.stern.nyu.edu/jwurgler/`.

[23] From Hao Zhou's website at `http://sites.google.com/site/haozhoususpersonalhomepage/`.

[24] Provided by Sydney Ludvigson on her website at `https://www.sydneyludvigson.com/data-and-appendixes/`.

[25] Except for VRP, which only starts in 1990:01.

standard deviation of 0.07. More interesting is the mean of c_{PU}, which indicates that the average investor with aversion to parameter uncertainty reduces his investment in risky assets by 48%, with a standard deviation of 12%. For all forecasting variables except LTR and DFR, we find very high persistence, with autocorrelation coefficients close to one. Panel A of Table 3 displays correlation coefficients for all variables. A closer examination of PU (and c_{PU}) in Panel C indicates that both have relatively low correlation with most predictor variables, especially with SII and WMA. Their highest correlation (in magnitude) is with CSV, $UNC_{F,1}$, $UNC_{M,1}$, σ_e, logEP and RVOL. We conclude that PU (c_{PU}) contains significantly different information from other predictor variables. An additional examination of the cross-correlations at different lags ($k = -1, \ldots, 11$) between c_{PU} , the market excess returns and their volatility in Panel B of Table 3 reveals a highly positive (negative) correlation with future returns (volatilities). This can be interpreted as indicative evidence for the predictive power of c_{PU} for the equity premium and its volatility (not tested in this paper).

[Place Table 2 about here.]

[Place Table 3 about here.]

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

4.1 In-sample tests

To test whether c_{PU} actually predicts an increase in aggregate excess returns, we employ predictive regressions (Welch and Goyal, 2008; Rapach et al., 2016):

$$r_{t+1,t+k} = \alpha_k + \beta_k x_t + \varepsilon_{t+1,t+k} \tag{11}$$

where $r_{t+1,t+k} = (1/k)\,(r_{t+1} + \cdots + r_{t+k})$ is the average Fama-French log equity premium[26] over the next k periods, and x_t is the predictor variable used for forecasting at time t. Following our research question and the motivation for PU, we concentrate on forecasting the (very) short horizons of $k = 1, 3, 6, 9$ and 12 months. All predictor variables are normalized to have zero mean and unit standard deviation. Furthermore, we change the signs of those variables that suggest a negative relationship between the predictor variable and the equity premium (NTIS, TBL, LTY, INFL, WMA, SENT,

[26] We use average instead of aggregate returns to obtain regression coefficients that are comparable across forecasting horizons (cf. Rapach et al., 2016).

$UNC_{M,1}$, $UNC_{R,1}$, $UNC_{F,1}$, CSV and SII). This leads to positive regression slopes $\hat{\beta}$, where we can test the one-sided hypothesis $H_0 : \beta = 0$ against $H_A : \beta > 0$ (Inoue and Kilian, 2005). To account for the autocorrelation and heteroskedasticity of the predictor variable, as well as the Stambaugh (1999) bias and the use of overlapping observations for $k > 1$ (e.g., Hodrick, 1992), we employ Newey and West (1987; 1994) t-statistics with lag lengths suggested by (Clark and McCracken, 2015, 0 if $h = 1$ and $1.5 \cdot h$ otherwise) and determine one-sided significance levels from a wild bootstrap experiment (cf. Gonçalves and Kilian, 2004; Jiang and Kang, 2012; Rapach et al., 2016).

[Place Table 4 about here.]

Table 4 presents the OLS results (estimate and t-statistics and R^2 in %, with significance levels from a wild bootstrap) of the predictive regressions (11). The results for the 23 variables and SII are similar to those presented in Rapach et al. (2016). For CSV, we confirm the results of Maio (2016) in showing that CSV outperforms all traditional variables for horizons $k = 6, 9, 12$. Relating our results to Neely et al. (2014), we cannot confirm the predictive power of $\text{MA}_{2,12}$ for the one-month-ahead equity premium.[27] Similarly, WMA does not show any predictive power at all tested horizons. For SII, we actually improve on the results of Rapach et al. (2016) in showing that short interest is the strongest existing predictor at all forecasting horizons relative to all of the aforementioned variables. On the monthly horizon, however, c_{PU} improves the forecasting power of SII by over 55% in terms of R^2. This value is significant at the 1% level according to the wild bootstrap experiment, and its β estimate is economically and statistically significant: A one-standard-deviation increase leads to a 71 basis-point increase in the equity premium for the upcoming month. For forecasting horizons of $k = 1, 3$ and 6 months, the predictive ability of c_{PU} exceeds all other Welch and Goyal (2008) predictors and is only surpassed by SII (for $k = 3$ and 6). Clearly, c_{PU} shows its best predictive ability at the very short monthly horizon, where an in-sample R^2 of 2.29% represents approximately 4.6 times the level suggested by Campbell and Thompson (2008) to be economically significant. Interestingly, we additionally find the financial uncertainty predictor $UNC_{F,1}$ of Ludvigson et al. (2017) to perform rather well relative to the traditional predictors and SII but that it nevertheless underperforms with respect to c_{PU}.

Adding to that evidence, we follow Ludvigson and Ng (2007) and Rapach et al. (2016) and incorporate the first three principal components (PCA_i) over all 14 Welch and

[27] We can verify the correctness of the calculation and estimation through the program and data made available by Neely et al. on Dave Rapach's website http://sites.slu.edu/rapachde/home/research. Our $\text{MA}_{2,12}$ measure (for FF excess returns) corresponds at 96% to theirs (for S&P500 excess returns).

Goyal (2008) predictors plus $\text{MA}_{2,12}$, WMA, SENT, $UNC_{M,1}$, $UNC_{R,1}$, $UNC_{F,1}$, CSV and SII in a predictive regression of the form

$$r_{t+1,t+k} = \alpha_k + \beta_{k,c_{\text{PU}}} c_{\text{PU},t} + \sum_{i=1}^{3} \beta_{t,PCA_i} PCA_{t,i} + \varepsilon_{t+1,t+k}. \tag{12}$$

Incorporating principal components as aggregators of the predictive power of other variables helps to highlight the additional role of c_{PU}.[28] The results in the last row (labeled c_{PU} (-) | PC) of Table 4 report β and the corresponding t-statistic and partial R^2 of Equation (12). After controlling for the other variables, the additional predictive ability of c_{PU} is shown, with significant monthly beta (0.58) and partial $R^2 = 0.66\%$, thus highlighting the additional predictive power of c_{PU} even in the presence of the aggregate power of all other predictors.[29]

In summary, we find very strong evidence that c_{PU} predicts aggregate future stock returns at all horizons but shows its most promising results at the monthly horizon, where it outperforms all other predictors, and even shows additional predictive power when incorporating principal components of the other predictors. These results make a very strong case for the descriptive power of the Garlappi et al. (2007) model in combination with our measure of parameter uncertainty. In the next section, we find even stronger evidence in the – more important – case of out-of-sample predictability.

4.2 Out-of-sample tests

To support the in-sample evidence of the predictive power of c_{PU} for the equity premium, we conduct single-variable out-of-sample analyses, where we forecast $r_{t+1,t+k}$ as

$$\hat{r}_{t+1,t+k} = \hat{\alpha}_t + \hat{\beta}_t x_t \tag{13}$$

using estimates $\hat{\alpha}_t$ and $\hat{\beta}_t$ from in-sample regressions (11) up to (and including) month t. To be true out-of-sample forecasts, SII and c_{PU} (through PU) are calculated by only relying on information that was available up to time t. The out-of-sample evaluation period is 1990:01-2014:12 ($T_{OS} = 300$), leaving 204 monthly observations for the initial estimation of $\hat{\alpha}$ and $\hat{\beta}$.

To quantify the out-of-sample predictive performance, we employ a restricted model and assume that the average historical equity premium is a better predictor of the

[28]This strategy is also used by Rapach et al. (2016) to demonstrate the additional predictive ability of SII with respect to the other variables.

[29]These results remain robust even to the incorporation of up to ten principal components (in which case, at the monthly horizon, we obtain a partial R^2 of 0.61 and a significant $\beta = 0.52$).

future equity premium (the null therefore assumes that $\beta_t = 0$) than the (unrestricted) model of Equation (11) (the alternative).

$$\begin{aligned} H_0 &: r_{t+1,t+k} = \alpha_k + \varepsilon_{t+1,t+k} \\ H_A &: r_{t+1,t+k} = \alpha_k + \beta_k x_t + \varepsilon_{t+1,t+k} \end{aligned} \tag{14}$$

[Place Table 5 about here.]

The first part of Table 5 (columns 2 - 6) reports out-of-sample R^2_{OS} (in %) that measures the reduction in *mean-squared* forecast *error* (MSE) of the restricted (MSE_R) against the unrestricted model (MSE_U)[30] (cf. Campbell and Thompson, 2008)

$$R^2_{OS} = 1 - \frac{MSE_U}{MSE_R}, \tag{15}$$

where a positive value signals higher out-of-sample forecasting power of the unrestricted model relative to the restricted model. To ascertain the statistical significance of the out-of-sample R^2_{OS}, we report significance levels of the Clark and West (2007) statistic with the R^2_{OS} testing $H_0 : R^2_{OS} \leq 0$ against $H_A : R^2_{OS} > 0$.[31] Additionally, we report the McCracken (2007) F-statistic with significance levels in columns 7-11. While the former test relies on an approximation that is normally distributed, the latter test statistic is exact but based on a non-standard distribution tabulated in their 2007 paper.[32] For the monthly forecast horizon, column 2 of Table 5 shows that all 14 Welch and Goyal (2008) predictors, WMA and SENT have negative R^2_{OS}. While we confirm the results of Rapach et al. (2016) with SII having a large and significant R^2_{OS} of 1.45, we find the R^2_{OS} of c_{PU} to be almost 60% larger (2.30) and highly significant for all considered test statistics. For longer forecast horizons, we find c_{PU} and CSV to have increasing R^2_{OS} that is clearly surpassed by the predictive performance of SII for horizons $k \geq 6$. This largely confirms that c_{PU} documents the immediate reaction of investors with aversion to parameter uncertainty to an increase in PU, which cannot surpass the predictive performance of a macroeconomic variable such as SII at longer horizons and can only partially be explained by the the predictor of financial uncertainty ($UNC_{F,1}$) that also outperforms all other variables in the dataset with the exception of c_{PU}. To confirm this hypothesis, we report test statistics and significance for the Harvey et al. (1998) and Clark and McCracken (2001) $ENC - NEW$

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

[31] Following Rapach et al. (2016), we account for overlapping observations by using Newey and West (1987)-corrected statistics with lag length equal to the forecast-horizon h.

[32] It is calculated as $MSEF = (T_{OS} - k + 1) \frac{MSE_R - MSE_U}{MSE_U}$, and its 1%, 5% and 10% critical values are – based on the recursive regression scheme and the fact that the ratio of observations for the initial estimation to the number of forecasts is approximately 1.4 – 3.589, 1.623 and 0.698, respectively (cf. McCracken, 2007).

encompassing test, which (using a bivariate predictive regression of the tested variable and c_{PU}) tests whether the respective variable encompasses c_{PU}.[33] We can reject this hypothesis for all tested variables except $UNC_{F,1}$ at a horizon of $k = 1$ months and for all statistics at horizons of $k = 3$ and 6 months, which means that c_{PU} contains information about future aggregate stock returns that is different from all other tested variables with respect to out-of-sample forecasting. For longer horizons, we cannot reject the that CSV encompasses c_{PU}. With regard to $UNC_{F,1}$, note that Jurado et al. use 147 different Fama-French-Portfolios and very advanced statistics to extract their forward-looking measure of financial uncertainty, whereas we only use 25 Fama-French portfolios and a simple T^2-statistic to outperform the predictive ability of $UNC_{F,1}$.

[Place Figure 2 about here.]

Figure 2 follows Welch and Goyal (2008) and analyzes the predictive performance of the four best-performing predictors of Table 5, SII, $\text{MA}_{2,12}$, CSV, $UNC_{F,1}$ and c_{PU}, over time. For in-sample (dashed black line) and out-of-sample (red line) performance it calculates cumulative differences in squared prediction errors between the restricted model (the prevailing mean) and (minus) the unrestricted model. According to Welch and Goyal (2008), both lines should be constantly upward sloping and not (only) driven by positive drifts during unique market conditions. As can be seen in Figure 2, most of the out-of-sample performance of SII is generated since the beginning of the global financial crisis in 2008. However, it performs negatively in the growth period 2001-2008. A similar picture is drawn by $\text{MA}_{2,12}$, where the only predictive performance was generated during the 2008-2009 crisis and almost entirely lost thereafter. CSV does not really show any predictive performance at all in relation to the prevailing mean. $UNC_{F,1}$ does show its strong in-and out-of-sample predictive performance but also highlights the fact that most of this performance is driven by the financial crisis. Finally, the picture drawn by c_{PU} is almost entirely as requested by Welch and Goyal: (i) reasonable (in- and out-of-sample) performance over the entire sample period,[34] (ii) a general upward drift that (iii) does not only occur in short/unusual periods and (iv) a positive drift that remains positive for the most recent decades. In short, c_{PU} is an almost perfect example of these conditions. To the best of our knowledge, it is also the only predictor that simultaneously fulfills all of these conditions.

This section confirms our in-sample results and offers further evidence that c_{PU} is the strongest existing predictor at the monthly horizon, thereby confirming our research

[33] Clark and McCracken (2001) and others show that the $ENC - NEW$ statistic is the most powerful with respect to test size and power but is also based on an asymptotic distribution tabulated by the authors in their 2001 paper. The $ENC - NEW$ statistic is calculated as $ENC = \frac{T_{OS}-k+1}{T_{OS}} \frac{\sum_{t=1}^{T_{OS}} (\hat{\varepsilon}_{Rt}^2 - \hat{\varepsilon}_{Rt}\hat{\varepsilon}_{Ut})}{MSE_U}$, and its critical 5% and 10% values are 2.085 and 1.28, respectively.

[34] This is tested by the Clark and West (2007) and the older (here unused) Giacomini and White (2006) tests.

hypothesis (ii). In the following section, we conduct a variety of robustness checks that confirm the main findings.

4.3 Robustness

Our results remain robust under a variety of different specifications. In the following sections, we discuss alternative forecasting frameworks and robustness checks, as well as different specifications for the calculation of PU (and, therefore, c_{PU}).

4.3.1 Dependent variables

First, our results are robust to alternative specifications of value-weighted aggregate market excess returns, namely when we use the CRSP and S&P500 value-weighted market returns. Value-weighted market returns seem to be the natural choice in the context of the Garlappi et al. (2007) model, where investment in the tangency portfolio and – given market equilibrium – therefore, investment in the value-weighted market portfolio is reduced by our factor c_{PU}. As we also use value-weighted portfolio returns to calculate PU from different partitions of the market, the value-weighted market return is a natural choice for the dependent variable. Indeed, we find the predictive power of c_{PU} for the CRSP and S&P500 value-weighted market excess returns to be as good (and sometimes better) as that of the Fama-French one, in- and out-of-sample. For the case of equally weighted returns, we do not find in- or out-of-sample predictive power for CRSP or S&P500 excess returns.

[Place Table 6 about here.]

4.3.2 Market partition and characteristic portfolios

In a second step, we show that the choice of portfolios for the calculation of PU has little impact on the predictive performance of c_{PU}. We calculate alternative versions of PU based on a variety of portfolios derived from Kenneth French's data library, namely 25 portfolios sorted on size and value (the base case P25SV), size and operating profitability (P25SOp), size and investment (P25SInv), size and accruals (P25SAC), size and net share issues (P25SNI), size and variance (P25SVar), size and residual variance (P25SResVar), size and beta (P25SBeta), value and operating profitability (P25VOp), and value and investment (P25VInv), as well as 10 portfolios sorted on size (P10S) and value (P10V) and 100 portfolios sorted on size and value (P100SV).

We observe an interesting interplay between the different characteristics: Univariate sorts (unfortunately, we only have 10 portfolios and therefore cannot account for the role of dimension) show that both *Size* and *Value* play a role in predictive performance and when combined into 25 portfolios deliver the best performance of all tested characteristics. Individually combining *Size* and *Value* with other characteristics (*Op* and *Inv*), we find that these also boost performance but only to levels below those of combining *Size* and *Value*. From the other characteristics that we combine with *Size* (*AC*, *NI*, *Var*, *ResVar* and *Beta*), we find that *Beta* and *NI* increase the performance of *Size* the most. In terms of out-of-sample performance (albeit not significant), we find that *SOp* and *SNI* deliver the best performance across all forecast horizons.

Finally, we find that increasing the partition size to 100 portfolios sorted on *Size* and *Value* does not lead to increased predictive performance, probably due to a larger error when estimating $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ as discussed in Section 2.1. One remaining task is therefore to find the optimal partition size (dependent on individual and combined characteristics) to calculate PU and forecast aggregate excess stock returns with the subsequently determined c_{PU}.

[Place Table 7 about here.]

4.3.3 Initial estimation windows

Third, to reduce (potential) estimation error for $\boldsymbol{\mu}$ and $\boldsymbol{\Sigma}$ in the case of a larger partition size, we employ larger initial estimation windows, starting in 1953:01 and 1926:08, respectively. As we are also aware that the economy might have changed entirely sometime in the past (Ang and Timmermann, 2012), which might bias the parameter estimates $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$ as reference points for the calculation of PU, we also employ rolling windows rather than growing windows for their estimation.

In Table 8, we find that larger initial estimation periods lead to a slight decrease in the in-sample performance but to substantial increases in the out-of-sample performance of c_{PU} across all forecasting horizons ($R^2_{OS} = 2.57$ for an estimation period starting in 1953:01 and $R^2_{OS} = 2.42$ for a period starting in 1926:01). As only the out-of-sample predictions use measures of c_{PU} that are based on the level of information that investors would have had at this point in time, the increase in out-of-sample forecasting performance is another indication that investors that are subject to PU relate recent returns to long-term estimates to determine how well these estimates fit the current market situation and invest accordingly. For the case of rolling windows, we find an overall decrease in in- and out-of-sample predictive performance for PU and c_{PU}, probably due to the lower quality of the moment estimates $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$.

[Place Table 8 about here.]

4.3.4 Lookback periods T_c

Fourth, the measurement of PU is determined based on the average returns from the last 12 months $\bar{\mathbf{r}}_t$ relative to their long-term means $\hat{\boldsymbol{\mu}}$ given their covariance matrix $\hat{\boldsymbol{\Sigma}}$. The reason for this is twofold: First, a larger T_c increases statistical significance, and second, investors – from their perspective – will probably check more than just the most recent return when determining their confidence in parameters. As the assumption of $T_c = 12$ months seems natural but is nevertheless arbitrary, our last robustness check is on the length of the lookback window for recent returns. Therefore, we calculate PU (and c_{PU}) for $T_c = 1, 3, 6, 9$ and 12 months and depict the results in Table 9.

Most interesting, we observe that the lookback period that delivers the best in- and out-of-sample performance for growing forecast horizons k is decreasing in T_c. While c_{PU} for $T_c = 12$ performs best (significant $R^2_{OS} = 2.30$) on the monthly horizon but loses significance for longer horizons, c_{PU} for $T_c = 9$ at horizons of $k = 3, 6$ months delivers the best (significant) out-of-sample performance, followed by $T_c = 6$ for $k = 9$ and $T_c = 1$ for $k = 12$ months. We conclude from this observation that the further investors look into the future, the less they look into the past to determine parameter uncertainty. Given these patterns, we also find that the different c_{PU}s outperform all other tested variables (except CSV and SII) based on (significant) out-of-sample performance.

[Place Table 9 about here.]

4.3.5 Alternative timeframe

As mentioned above, we also want to test the predictive performance of c_{PU} for an alternative timeframe. This allows us to research the predictive performance of all variables for a shorter in- and out-of sample horizon, which might be important for variables whose predictive power derives primarily from earlier periods (such as TMS as documented by Stöckl and Kaiser (2016)). Furthermore, it allows us to include additional variables that are only available for shorter horizons, such as the VRP of Bollerslev et al. (2009), which has demonstrated very good short-horizon predictability (Faias et al., 2017). As VRP is only available as of 1990:01, we limit our in-sample analysis to the period 1990:01-2014:12 and reserve 60 initial months for the initial estimation window in the out-of-sample analysis. Furthermore, we recalculate SII and PU (c_{PU}) with an additional 120 observations, starting as of 1980:01.

[Place Table 10 about here.]

[Place Figure 3 about here.]

The results in Table 10 demonstrate the superior short-horizon predictive power of VRP. Among all the variables, c_{PU} again has the highest predictive power on a monthly horizon, surpassed only by SII (for $k = 3$) and SENT (for $k = 6$) in terms of out-of-sample R^2. For longer horizons, the predictive power of c_{PU} diminishes relative to several popular predictor variables. When we assess the extraordinary predictive power of VRP in Figure 3, we find that most of this power comes from large jumps during the financial crisis and in 2012, when the predictive power of the other variables declines sharply. However, especially in the subsequent period, the out-of-sample predictive ability of VRP shows a decreasing trend. We conclude, that – while VRP overall shows substantial predictive power in- and out-of-sample – its performance does not satisfy criteria (iii) and (iv) of Welch and Goyal (2008). In contrast, the predictive performance of c_{PU} again satisfies their criteria (i)-(iv) despite showing lower overall performance.

To conclude this section, all in- and out-of sample results, including the robustness checks, statistically confirm our research hypothesis by showing that c_{PU} (the combination of our measure PU with the model of Garlappi et al. (2007)) not only shows predictive power across all forecasting horizons that outperforms (most of) the other tested variables but also satisfies all criteria of Welch and Goyal (2008) that a predictor should have to be successful in the future. What remains is to demonstrate the economic significance of our results.

5 Economic Significance

This section analyzes the economic significance of c_{PU}'s predictive ability. Following Campbell and Thompson (2008), Rapach et al. (2010), Ferreira and Santa-Clara (2011), and Rapach et al. (2016), we consider a mean-variance investor (without aversion to parameter uncertainty) who invests in equities and the risk-free rate using weights

$$w_t = \frac{1}{\gamma} \frac{\hat{r}_{t+1}}{\hat{\sigma}^2_{t+1}}, \tag{16}$$

where γ is the coefficient of relative risk aversion, and $\hat{r}_{t+1}$ is the one-period-ahead forecast of the expected excess stock return.[35] The variance forecast $\hat{\sigma}^2_{t+1}$ is calculated from a 10-year rolling window (cf. Campbell and Thompson, 2008; Rapach et al., 2016). We also restrict the weights w_t of the strategy to lie between –0.5 and 1.5 to avoid extreme outliers and produce better-behaved portfolios that are closer to reality.

[35] Here, simple excess returns are forecasted instead of the log excess return.

All asset allocations are evaluated against the prevailing mean forecast and two buy-and-hold strategies, where the investor holds 100% (150%) of the market portfolio. Table 11 shows annualized Sharpe ratios and the annualized CER gain in percentage terms against the prevailing mean strategy for an investor with a relative risk aversion coefficient of $\gamma = 3$ (cf. Campbell and Thompson, 2008; Maio, 2016; Rapach et al., 2016)

$$CER = \bar{r}_P - \frac{\gamma}{2}\sigma_P^2. \tag{17}$$

The CER is the risk-free return that an investor would accept for giving up the risky investment. We also depict turnover and annualized return loss (in %, cf. De Miguel et al., 2009b)[36].

[Place Table 11 about here.]

[Place Figure 4 about here.]

Table 11 shows that the strategy based on c_{PU} yields substantially higher Sharpe ratios of 0.83 relative to all other strategies at all investment horizons, except for $UNC_{F,1}$ at horizon $k = 1$ and SII and CSV at investment horizons of $k = 6$ and 12. In terms of CER gains relative to the prevailing mean strategy, we find that c_{PU} outperforms all other variables at horizons of $k = 1$ and 3 months. We show that an investor with a risk-aversion coefficient of $\gamma = 3$ would exchange a monthly investment based on c_{PU} for a riskless annual return of 6.44%, which is more than 80% more than for the SII-based monthly investment strategy. If we additionally include transaction costs (50BP) to account for the slightly lower turnover of the SII-based strategy, we find that an investor could still have a 2.76% lower return in the monthly strategy based on c_{PU} before reaching the same Sharpe ratio as for SII (i.e., return loss of -5.01 for c_{PU} over -2.25 for SII).[37]

Figure 4 sheds further light on the predictive power of c_{PU} at the monthly horizon, where we find the investment strategy based on c_{PU} to almost perfectly time the market. It goes short whenever markets drop and goes fully long whenever markets gain, leading to almost constant positive performance (Panel B), which largely outperforms the strategies based on the prevailing mean and SII, as well as the buy-and-hold portfolio. The low weight fluctuation (Panel A) also helps to explain the low turnover and subsequent dominance in terms of return loss for the strategy based on c_{PU}. These results clearly show that investors strongly react to parameter uncertainty (measured

[36] The return loss depicts the necessary additional return of the respective strategy, given volatility, to beat the benchmark buy-and-hold Sharpe ratio after accounting for a transaction/rebalancing cost of 50BP.

[37] Note that return loss measures the additional return necessary (left) to increase (decrease) the after-transaction-cost Sharpe ratio

by PU) in the market (decreasing their investment by factor c_{PU}), making markets quite predictable and subsequently helping an investor who is aware of this behavior to time the market very well and achieve substantially higher returns with less portfolio volatility.

[Place Table 12 about here.]

As a robustness check, we also include calculations for the alternative timeframe (1990:01-2014:12) in Table 12. In contrast to its superior out-of-sample performance above, VRP cannot compete with the outcomes of the asset allocation exercise in terms of the Sharpe ratio, or CER gain and return loss. All other results remain strongly in favor of c_{PU}, with an even higher CER gain of an annual 9.58% for the monthly strategy.

The results in this section clearly highlight the substantial economic value that can be generated by the combination of our measure of parameter uncertainty with the portfolio selection model of Garlappi et al. (2007). It also adds strong economic evidence in favor of our research hypothesis. In the next section, we conclude on these results.

6 Conclusion

In this paper, we develop a novel measure of time-varying parameter uncertainty based on simple statistical tests. We also show that this measure of parameter uncertainty in combination with the model of portfolio selection under parameter uncertainty of Garlappi et al. (2007) has substantial statistical and economical power to forecast the equity premium in- and out-of-sample. We thereby indirectly demonstrate the value of their model and its accuracy in describing the behavior of investors averse to parameter uncertainty. Additionally, their model, in combination with our measure of parameter uncertainty, yields a predictor of the equity premium that fulfills all of the four criteria developed by Welch and Goyal (2008). To the best of our knowledge, it is the only predictor to date that can achieve this.

We also show that c_{PU} does not proxy for any of the other popular macroeconomic, technical and behavioral predictors and that it substantially outperforms all of these measures (statistically and economically) at the monthly horizon, except for the variance risk premium, the predictive power of which stems almost entirely from two brief periods during and after the financial crisis. In contrast to most other measures, our measure's predictive performance is not only limited to periods of recession but also performs well in periods of expansion.

References

Ang, A. and Timmermann, A. (2012). Regime Changes and Financial Markets. *Annual Review of Financial Economics* 4 (1), 313–337.

Baker, M. and Wurgler, J. (2006). Investor Sentiment and the Cross-Section of Stock Returns. *The Journal of Finance* 61 (4), 1645–1680.

Bali, T. G., Brown, S. J., and Tang, Y. (2017). Is Economic Uncertainty Priced in the Cross-Section of Stock Returns? *Journal of Financial Economics.*

Berger, D. and Pukthuanthong, K. (Jan. 2016). Fragility, Stress, and Market Returns. *Journal of Banking & Finance* 62, 152–163.

Bersimis, S., Psarakis, S., and Panaretos, J. (Aug. 1, 2007). Multivariate Statistical Process Control Charts: An Overview. *Quality and Reliability Engineering International* 23 (5), 517–543.

Bisias, D., Flood, M. D., Lo, A. W., and Valavanis, S. (2012). A Survey of Systemic Risk Analytics. *Annual Review of Financial Economics* 4 (1), 255–296.

Bloom, N. (2009). The Impact of Uncertainty Shocks. *Econometrica* 77 (3), 623–685.

Bodnar, O. (2007). Sequential Procedures for Monitoring Covariances of Asset Returns. *Advances in Risk Management*, 241–264.

Bodnar, O. (2009). Sequential Surveillance of the Tangency Portfolio Weights. *International Journal of Theoretical and Applied Finance* 12 (6), 797–810.

Bodnar, O., Bodnar, T., and Okhrin, Y. (July 1, 2009). Surveillance of the Covariance Matrix Based on the Properties of the Singular Wishart Distribution. *Computational Statistics & Data Analysis* 53 (9), 3372–3385.

Bodnar, O. and Schmid, W. (2007). Surveillance of the Mean Behavior of Multivariate Time Series. *Statistica Neerlandica* 61 (4), 383–406.

Bollerslev, T., Tauchen, G., and Zhou, H. (Feb. 12, 2009). Expected Stock Returns and Variance Risk Premia. *Review of Financial Studies* 22 (11), 4463–4492.

Campbell, J. Y. and Thompson, S. B. (July 1, 2008). Predicting Excess Stock Returns Out of Sample: Can Anything Beat the Historical Average? *Review of Financial Studies* 21 (4), 1509–1531.

Cassella, S. and Gulen, H. (Apr. 8, 2017). Extrapolation Bias and the Predictability of Stock Returns by Price-Scaled Variables. SSRN Scholarly Paper ID 2676860.

Chenouri, S., Steiner, S. H., and Variyath, A. M. (July 2009). A Multivariate Robust Control Chart for Individual Observations. *Journal of Quality Technology; Milwaukee* 41 (3), 259–271.

Chow, G., Jacquier, E., Kritzman, M., and Lowry, K. (1999). Optimal Portfolios in Good Times and Bad. *Financial Analysts Journal* 55 (3), 65–73.

Clark, T. E. and McCracken, M. W. (Nov. 2001). Tests of Equal Forecast Accuracy and Encompassing for Nested Models. *Journal of Econometrics* 105 (1), 85–110.

Clark, T. E. and McCracken, M. W. (2015). Nested forecast model comparisons: a new approach to testing equal accuracy. *Journal of Econometrics* 186 (1), 160–177.

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

Dangl, T. and Weissensteiner, A. (Jan. 13, 2017). Long-Term Asset Allocation under Time-Varying Investment Opportunities: Optimal Portfolios with Parameter and Model Uncertainty. SSRN Scholarly Paper ID 2883768.

De Miguel, V., Garlappi, L., Nogales, F. J., and Uppal, R. (2009a). A Generalized Approach to Portfolio Optimization: Improving Performance by Constraining Portfolio Norms. *Management Science* 55 (5), 798–812.

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

De Miguel, V. and Nogales, F. J. (2009). Portfolio Selection with Robust Estimation. *Operations Research* 57 (3), 560–577.

Duarte, F. and Eisenbach, T. M. (2013). Fire-Sale Spillovers and Systemic Risk. 645. Federal Reserve Bank of New York.

Faias, J. A., Zambrano, A., and Juan (Mar. 1, 2017). Equity Premium Predictability from Cross-Sectoral Downturns. SSRN Scholarly Paper ID 2617242. Rochester, NY: Social Science Research Network.

Ferreira, M. A. and Santa-Clara, P. (June 2011). Forecasting Stock Market Returns: The Sum of the Parts is More than the Whole. *Journal of Financial Economics* 100 (3), 514–537.

Garlappi, L., Uppal, R., and Wang, T. (Jan. 1, 2007). Portfolio Selection with Parameter and Model Uncertainty: A Multi-Prior Approach. *Review of Financial Studies* 20 (1), 41–81.

Giacomini, R. and White, H. (2006). Tests of Conditional Predictive Ability. *Econometrica* 74 (6), 1545–1578.

Giglio, S., Kelly, B., and Pruitt, S. (2016). Systemic Risk and the Macroeconomy: An Empirical Evaluation. *Journal of Financial Economics* 119 (3), 457–471.

Gilboa, I. and Schmeidler, D. (1989). Max-Min Expected Utility with Non-Unique Prior. *Journal of Mathematical Economics* 18 (2), 141–153.

Gonçalves, S. and Kilian, L. (2004). Bootstrapping Autoregressions with Conditional Heteroskedasticity of Unknown Form. *Journal of Econometrics* 123 (1), 89–120.

Greenwood, R. and Shleifer, A. (Mar. 1, 2014). Expectations of Returns and Expected Returns. *The Review of Financial Studies* 27 (3), 714–746.

Guiso, L., Sapienza, P., and Zingales, L. (Aug. 2013). Time Varying Risk Aversion. Working Paper 19284. National Bureau of Economic Research.

Harvey, D. I., Leybourne, S. J., and Newbold, P. (Apr. 1, 1998). Tests for Forecast Encompassing. *Journal of Business & Economic Statistics* 16 (2), 254–259.

Henkel, S. J., Martin, J. S., and Nardari, F. (2011). Time-Varying Short-Horizon Predictability. *Journal of Financial Economics* 99 (3), 560–580.

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.

Hotelling, H. (Aug. 1931). The Generalization of Student's Ratio. *The Annals of Mathematical Statistics* 2 (3), 360–378.

Inoue, A. and Kilian, L. (2005). In-Sample or Out-of-Sample Tests of Predictability: Which One Should We Use? *Econometric Reviews* 23 (4), 371–402.

Jiang, X. and Kang, Q. (2012). Cross-Sectional PEG Ratios, Market Equity Premium, and Macroeconomic Activity.

Johnson, R. A., Wichern, D. W., et al. (2002). Applied Multivariate Statistical Analysis. Vol. 5. 8. Upper Saddle River, NJ: Prentice Hall.

Jurado, K., Ludvigson, S. C., and Ng, S. (2015). Measuring Uncertainty. *The American Economic Review* 105 (3), 1177–1216.

Kan, R. and Zhou, G. (Sept. 1, 2007). Optimal Portfolio Choice with Parameter Uncertainty. *The Journal of Financial and Quantitative Analysis* 42 (3), 621–656.

Kritzman, M. and Li, Y. (2010). Skulls, Financial Turbulence, and Risk Management. *Financial Analysts Journal* 66 (5), 30–41.

Li, G. (Jan. 1, 2007). Time-Varying Risk Aversion and Asset Prices. *Journal of Banking & Finance* 31 (1), 243–257.

Ludvigson, S. C., Ma, S., and Ng, S. (2017). Uncertainty and Business Cycles: Exogenous Impulse or Endogenous Response? National Bureau of Economic Research.

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

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

Makis, V. (Mar. 1, 2008). Multivariate Bayesian Control Chart. *Operations Research* 56 (2), 487–496.

Markowitz, H. (1952). Portfolio Selection. *The Journal of Finance* 7 (1), 77–91.

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

Mele, A. (2007). Asymmetric Stock Market Volatility and the Cyclical Behavior of Expected Returns. *Journal of Financial Economics* 86 (2), 446–478.

Meucci, A. (2009). Risk and Asset Allocation. 1st ed. New York, USA: Springer.

Miao, J., Wei, B., and Zhou, H. (2012). Ambiguity Aversion and Variance Premium.

Montgomery, D. C. (Aug. 7, 2012). Statistical Quality Control. 7th ed. Hoboken, NJ: John Wiley & Sons. 768 pp.

Neely, C. J., Rapach, D. E., Tu, J., and Zhou, G. (2014). Forecasting the Equity Risk Premium: The Role of Technical Indicators. *Management Science* 60 (7), 1772–1791.

Nelson, P., Wludyka, P., and Copeland, K. (Jan. 1, 2005). The Analysis of Means. ASA-SIAM Series on Statistics and Applied Mathematics. Society for Industrial and Applied Mathematics. 252 pp.

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.

Nystrup, P., Hansen, B. W., Madsen, H., and Lindström, E. (2015). Regime-Based versus Static Asset Allocation: Letting the Data Speak. *The Journal of Portfolio Management* 42 (1), 103–109.

Rapach, D. E., Ringgenberg, M. C., and Zhou, G. (July 2016). Short Interest and Aggregate Stock Returns. *Journal of Financial Economics* 121 (1), 46–65.

Rapach, D. E., Strauss, J. K., and Zhou, G. (2010). Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy. *The Review of Financial Studies* 23 (2), 821–862.

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

Stambaugh, R. F., Yu, J., and Yuan, Y. (2014). The Long of It: Odds That Investor Sentiment Spuriously Predicts Anomaly Returns. *Journal of Financial Economics* 114 (3), 613–619.

Stivers, C. and Sun, L. (Aug. 2010). Cross-Sectional Return Dispersion and Time Variation in Value and Momentum Premiums. *Journal of Financial and Quantitative Analysis* 45 (4), 987–1014.

Stöckl, S., Hanke, M., and Angerer, M. (2017). PRIX - A Risk Index for Global Private Investors. *The Journal of Risk Finance* 18 (2), 214–231.

Stöckl, S. and Kaiser, L. (Mar. 14, 2016). Higher Moments Matter! Cross-Sectional (Higher) Moments and the Predictability of Stock Returns. SSRN Scholarly Paper 2747627.

Tracy, N. D., Young, J. C., and Mason, R. L. (1992). Multivariate Control Charts for Individual Observations. *Journal of Quality Technology* 24 (2), 88–95.

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.

Figures

Figure 1: Time series plots of the equity premium r_e, its within-month volatility, $\text{MA}_{2,12}$, WMA, CSV, SII, VRP, SENT, $UNC_{F,1}$, PU and c_{PU}.
This figure plots the monthly cumulated log equity premium, its volatility (calculated from daily returns within each month), $\text{MA}_{2,12}$, WMA, SII, VRP, SENT, $UNC_{F,1}$, CSV, PU and c_{PU} (the latter three calculated from 25 portfolios sorted according to size and value). The sample period is 1973:01-2014:12 (except for VRP that starts in 1990:01). Gray bars depict NBER recessions.

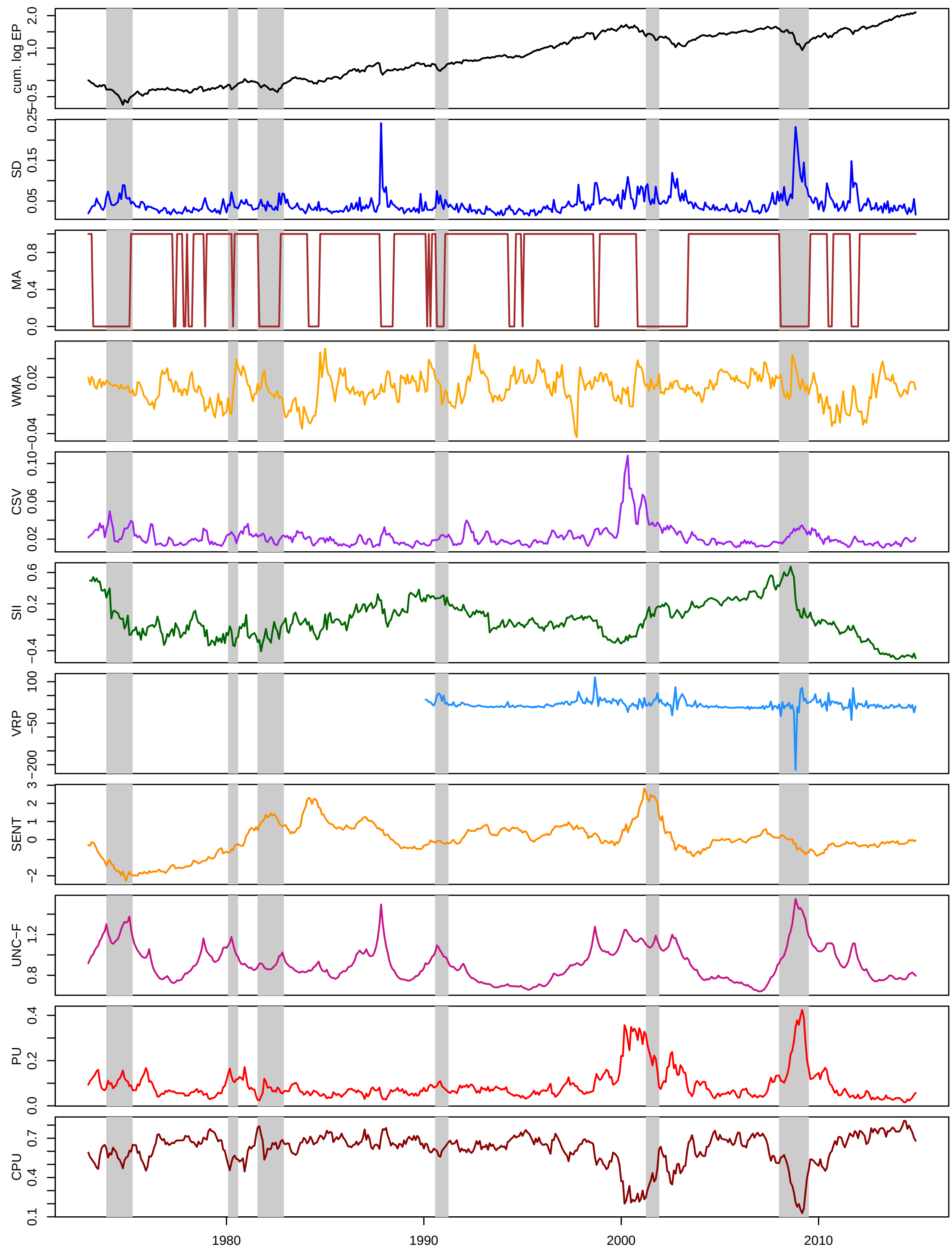


Figure 2: Relative performance of SII, $MA_{2,12}$, CSV, $UNC_{F,1}$ and c_{PU} for monthly forecasts of the equity premium (1973:01-2014:12).
This figure examines the relative in-sample (IS) and out-of-sample (OOS) performance for each predictive variable against the prevailing mean over time (see Welch and Goyal, 2008). It is calculated as the cumulative squared prediction errors of the restricted model (the null) minus the unrestricted model (the alternative) to evaluate the estimated equity premium against the full period (IS) and prevailing (OOS) mean equity premium. Therefore, an increase in any of the lines signals better performance of the unrestricted model relative to the prevailing mean. The relative performance of the IS prediction is depicted in black and is dashed and (usually above) the OOS prediction, which is depicted in red. The first graph shows the predictive performance of SII, whereas the next four graphs delineate the predictive performance of $MA_{2,12}$, CSV, $UNC_{F,1}$ and c_{PU} (the best-performing predictors in Table 5). The sample period is 1973:01-2014:12, with the OOS analysis beginning in 1990:01. As a visual reference across plots, a level of 0.05 is highlighted in both plots (dark red and dotted). A second axis on the right side shows the OOS performance since its worst point, which is additionally marked by a blue dashed line.

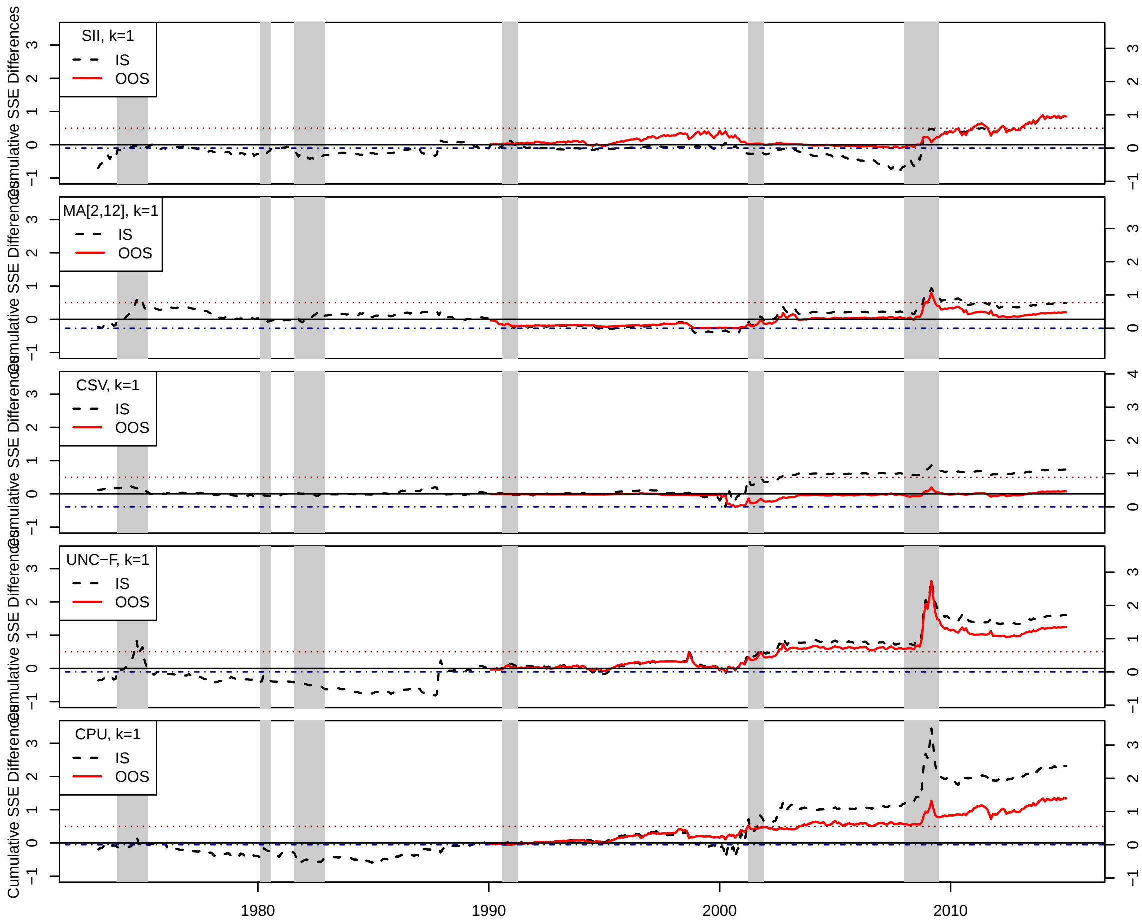


Figure 3: Relative performance of SII, VRP, SENT and c_{PU} for monthly forecasts of the equity premium (alternative timeframe, 1990:01-2014:12).
This figure examines the relative in-sample (IS) and out-of-sample (OOS) performance for each predictive variable against the prevailing mean over time (see Welch and Goyal, 2008).It is calculated as the cumulative squared prediction errors of the restricted model (the null) minus the unrestricted model (the alternative) to evaluate the estimated equity premium against the full period (IS) and prevailing (OOS) mean equity premium. Therefore, an increase in any of the lines signals better performance of the unrestricted model relative to the prevailing mean. The relative performance of the IS prediction is depicted in black and is dashed and (usually above) the OOS prediction, which is depicted in red. The first graph shows the predictive performance of SII, whereas the next three graphs delineate the predictive performance of VRP, SENT and c_{PU}. The sample period is 1990:01-2014:12, with the OOS analysis beginning in 2000:01. As a visual reference across plots, a level of 0.05 is highlighted in both plots (dark red and dotted). A second axis on the right side shows the OOS performance since its worst point, which is additionally marked by a blue dashed line.

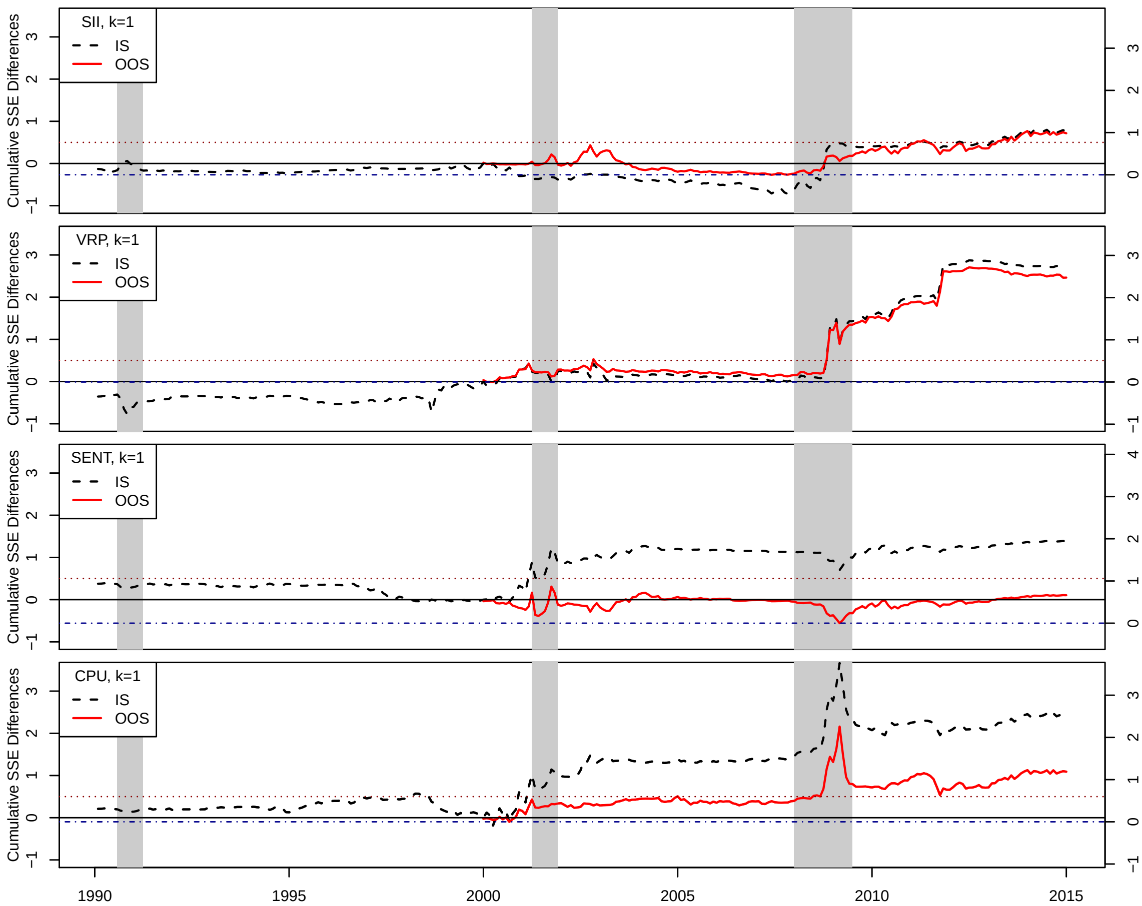
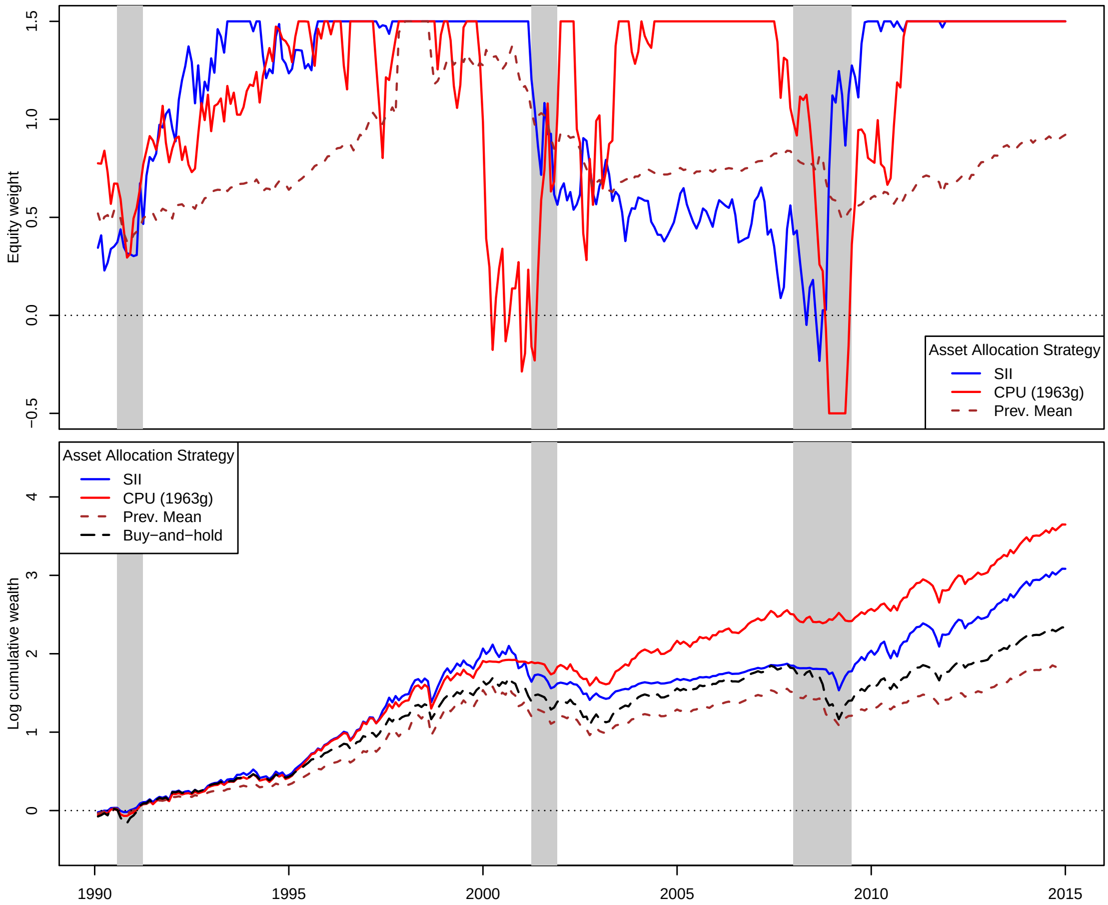


Figure 4: Asset Allocation: Equity weights and log cumulative wealth (1990:01-2014:12). This figure shows equity weights and the log cumulative return of monthly asset allocation strategies based on predictions of the expected excess return and expected volatility. The weights are derived for a mean-variance investor with relative risk aversion of $\gamma = 4$ and constrained to lie between -0.5 and 1.5. The strategies depicted are based on forecasts using the prevailing mean, short interest (SII) and financial turbulence (FT). Gray bars depict NBER recessions.



Tables

Table 1: Distribution of Hotelling-T^2 for combinations of assumptions (1) and (2).
Future returns relates to returns that are not part of (and are therefore independent of) the parameter estimates, whereas *subsample* relates to recent returns being a subsample of the returns used for calculating $\hat{\boldsymbol{\mu}}$ and $\hat{\boldsymbol{\Sigma}}$. In the case of $T_c > 1$, the full sample would have to be divided into T/T_c equally sized subsamples, with a covariance estimate that is pooled from subsample covariances. The case of $T_c = 1$ for single observations out of the full sample is given by Tracy et al. (1992).

		Distribution
future returns	$T_c = 1$	$\frac{(T+1)(T-1)N}{T(T-N)} F\left(N, T-N\right)$
	$T_c > 1$	$\frac{(T/T_c+1)(T_c-1)N}{T_c(T-T/T_c-N+1)} F\left(N, T-T/T_c-N+1\right)$
subsample	$T_c = 1$	$\frac{(T-1)^2}{T} B\left(\frac{N}{2}, \frac{T-N-1}{2}\right)$
	$T_c > 1$	$\frac{(T/T_c-1)(T_c-1)N}{T_c(T-T/T_c-N+1)} F\left(N, T-T/T_c-N+1\right)$

Table 2: Descriptive statistics for the equity premium, its volatility and 21 predictor variables (1973:01-2014:12).

This table reports descriptive statistics for the annual log equity premium r_e in percentage terms, its annualized (within-month) volatility σ_e and all predictor variables. These variables are log dividend-price ratio (logDP), log dividend yield (logDY), log earnings-price ratio (logEP), log dividend-payout ratio (logDE), excess stock return volatility (RVOL, calculated from a 12-month moving standard deviation estimator replacing SVAR (cf. Mele, 2007; Rapach et al., 2016)), book-to-market ratio (BM), net equity expansion (NTIS), T-bill rate (TBL), long-term yield (LTY), term spread (TMS), default yield spread (DFY), default return spread (DFR), inflation (INFL), a moving average technical indicator ($MA_{2,12}$; see Neely et al., 2014), a weighted moving average (WMA; see Greenwood and Shleifer, 2014), the variance risk premium (VRP, only available as of 1990:01, therefore only used for robustness checks), a sentiment index (the non-orthogonalized version according to eq. 2 of Baker and Wurgler, 2006), the three indices of aggregate (macro, real and financial) uncertainty (the one month ahead version; see Jurado et al., 2015; Ludvigson et al., 2017), short interest (SII, standardized to have mean zero and standard deviation one; see Rapach et al., 2016), cross-sectional volatility (CSV, calculated as a three-month moving average from 25 portfolios sorted according to size and value, cf. Maio, 2016), parameter uncertainty (PU calculated from 25 portfolios sorted according to size and value, estimation of sample moments starting in 1963:01, see Equation (2)) and the model-implied factor of parameter uncertainty c_{PU} from Equation (6). ρ represents the first-order autocorrelation coefficient (persistence). LTR, DFR, INFL and VRP (RVOL, TBL, LTY, TMS and DFY) are measured in percentage terms (annual percent).

Name	**Mean**	**StDev.**	**Min.**	**Max.**	**Skew.**	**Kurt.**	ρ
r_e (%, Ann.)	5.00	16.17	−317.38	179.14	−0.83	2.88	0.08
σ_e (%, Ann.)	14.51	8.58	4.84	83.79	3.46	19.07	0.65
logDP	−3.62	0.44	−4.52	−2.75	−0.04	−1.12	0.994
logDY	−3.61	0.44	−4.53	−2.75	−0.04	−1.10	0.994
logEP	−2.82	0.49	−4.84	−1.90	−0.75	1.88	0.990
logDE	−0.80	0.34	−1.24	1.38	3.10	14.85	0.985
RVOL (Ann.)	0.15	0.05	0.06	0.32	0.70	0.42	0.960
BM	0.49	0.29	0.12	1.21	0.80	−0.68	0.994
NTIS	0.01	0.02	−0.06	0.05	−0.72	0.57	0.976
TBL (%, Ann.)	5.05	3.44	0.01	16.30	0.51	0.30	0.988
LTY (%, Ann.)	7.16	2.73	2.06	14.82	0.47	−0.17	0.989
LTR (%)	0.73	3.13	−11.24	15.23	0.37	2.41	0.051
TMS (%, Ann.)	2.11	1.51	−3.65	4.55	−0.73	0.33	0.949
DFY (%, Ann.)	1.10	0.47	0.55	3.38	1.69	3.53	0.963
DFR (%)	0.00	1.48	−9.75	7.37	−0.48	7.89	−0.040
INFL (%)	0.34	0.34	−1.77	1.81	0.14	4.02	0.636
$MA_{2,12}$	0.74	0.44	0.00	1.00	−1.08	−0.83	0.804
WMA	0.01	0.02	−0.04	0.05	−0.33	0.41	0.807
VRP (%)	24.85	18.72	−218.56	115.85	−4.16	56.22	0.438
SENT	−0.01	0.91	−2.27	2.84	0.08	0.44	0.988
$UNC_{M,1}$	0.67	0.09	0.55	1.02	1.39	1.69	0.989
$UNC_{R,1}$	0.64	0.06	0.54	0.91	1.38	2.03	0.971
$UNC_{F,1}$	0.92	0.17	0.64	1.55	0.74	0.22	0.980
SII	0.00	1.00	−2.27	2.92	0.23	−0.07	0.950
CSV	0.02	0.01	0.01	0.11	3.45	18.02	0.917
PU	0.09	0.07	0.02	0.42	2.47	6.79	0.952
c_{PU}	0.62	0.12	0.13	0.83	−1.55	2.77	0.950

Table 3: Correlations of dependent and predictor variables (1973:01-2014:12)

In Panel A, this table reports Pearson correlation coefficients for the log equity premium r^e, its volatility σ^e and all predictor variables according to Table 2. In Panel B, it reports cross-correlations for 11 positive and negative lags between the log equity premium, its volatility and c_{PU}. In Panel C, we report an extended set of correlations with PU and c_{PU}.

Panel A: Correlations

	r^e	σ^e	logDP	logDY	logEP	logDE	RVOL	BM	NTIS	TBL	LTY	LTR	TMS	DFY	DFR	INFL	$MA_{2,12}$	WMA	VRP	SII	CSV	PU	c_{PU}
r_e	1	−0.3	−0.0	0.0	−0.0	0.0	0.0	−0.0	−0.0	−0.0	−0.0	0.1	0.0	0.0	0.2	−0.0	0.2	−0.0	−0.0	−0.1	−0.0	−0.1	0.17
σ_e		1	−0.1	−0.1	−0.3	0.2	0.4	−0.1	−0.2	−0.1	−0.1	0.1	0.0	0.3	−0.1	−0.1	−0.4	0.0	−0.1	0.1	0.3	0.5	−0.55
logDP			1	0.9	0.7	0.2	0.0	0.9	0.0	0.6	0.7	0.0	−0.1	0.4	0.0	0.4	−0.0	−0.1	0.3	−0.1	−0.2	−0.2	0.26
logDY				1	0.7	0.2	0.0	0.9	0.0	0.6	0.7	0.0	−0.1	0.4	0.0	0.4	−0.0	−0.1	0.3	−0.1	−0.2	−0.3	0.28
logEP					1	−0.4	−0.2	0.8	0.1	0.6	0.6	0.0	−0.3	0.1	−0.0	0.5	0.0	−0.1	0.2	−0.2	−0.2	−0.4	0.46
logDE						1	0.3	0.0	−0.0	−0.0	0.1	0.0	0.3	0.4	0.1	−0.1	−0.2	0.0	0.1	0.1	0.0	0.3	−0.32
RVOL							1	0.0	−0.1	−0.0	0.0	0.0	0.1	0.4	0.1	−0.0	−0.2	−0.2	0.2	−0.1	0.3	0.3	−0.39
BM								1	0.1	0.6	0.7	0.0	−0.2	0.4	0.0	0.5	−0.1	−0.1	0.4	−0.2	−0.1	−0.2	0.20
NTIS									1	0.0	0.1	−0.0	0.0	−0.3	0.0	0.1	0.0	−0.0	0.1	−0.2	0.1	−0.1	0.08
TBL										1	0.9	0.0	−0.6	0.2	−0.0	0.5	−0.0	−0.0	0.4	−0.0	0.0	−0.1	0.07
LTY											1	−0.0	−0.2	0.3	0.0	0.4	−0.0	−0.0	0.4	−0.0	−0.0	−0.1	0.12
LTR												1	−0.0	0.1	−0.4	−0.0	−0.0	0.0	0.0	−0.0	0.0	0.0	−0.02
TMS													1	0.0	0.1	−0.4	0.0	−0.0	−0.1	−0.0	−0.1	−0.0	0.05
DFY														1	0.1	0.0	−0.2	−0.1	0.1	−0.0	0.0	0.2	−0.24
DFR															1	−0.0	0.0	−0.0	0.0	−0.0	−0.0	−0.0	0.06
INFL																1	−0.0	−0.0	0.2	−0.0	0.0	−0.1	0.05
MA																	1	−0.0	−0.1	−0.1	−0.2	−0.3	0.35
WMA																		1	−0.1	0.2	−0.0	0.0	−0.04
VRP																			1	−0.0	0.0	−0.0	0.01
SII																				1	−0.0	0.1	−0.17
CSV																					1	0.6	−0.67
PU																						1	−0.98
c_{PU}																							1

Panel B: Cross-Correlations

	k=-11	k=-10	k=-9	k=-8	k=-7	k=-6	k=-5	k=-4	k=-3	k=-2	k=-1	k=0	k=1	k=2	k=3	k=4	k=5	k=6	k=7	k=8	k=9	k=10	k=11
r^e_{t+k}	0.07	0.10	0.09	0.08	0.10	0.11	0.12	0.12	0.14	0.15	0.18	0.17	0.15	0.12	0.12	0.08	0.07	0.04	0.03	0.04	0.03	0.04	0.07
σ^e_{t+k}	−0.29	−0.30	−0.31	−0.33	−0.35	−0.39	−0.43	−0.45	−0.46	−0.49	−0.51	−0.55	−0.57	−0.53	−0.50	−0.46	−0.41	−0.37	−0.32	−0.29	−0.28	−0.26	−0.26

Panel C: Extended Data-Set of Correlations

	$\boldsymbol{r^e}$	$\boldsymbol{\sigma^e}$	**logDP**	**logDY**	**logEP**	**logDE**	**RVOL**	**BM**	**NTIS**	**TBL**	**LTY**	**LTR**	**TMS**	**DFY**	**DFR**	**INFL**	**MA**	**WMA**	**VRP**	**SENT**	$\boldsymbol{UNC_{M,1}}$	$\boldsymbol{UNC_{R,1}}$	$\boldsymbol{UNC_{F,1}}$
PU	−0.18	0.57	−0.28	−0.30	−0.47	0.31	0.37	−0.22	−0.13	−0.11	−0.16	0.03	−0.04	0.25	−0.07	−0.10	−0.34	0.06	−0.06	0.11	0.43	0.30	0.64
c_{PU}	0.17	−0.55	0.26	0.28	0.46	−0.32	−0.39	0.20	0.08	0.07	0.12	−0.02	0.05	−0.24	0.06	0.05	0.35	−0.04	0.01	−0.08	−0.44	−0.31	−0.65

	SII	**CSV**
PU	0.12	0.69
c_{PU}	−0.17	−0.67

Table 4: In-sample predictive regression results (1973:01-2014:12)

This table reports the results of univariate predictive regressions (cf. Equation (11)) on log market excess returns (Fama-French value-weighted), averaged over forecasting horizons of $k = 1, 3, 6, 9$ and 12 months. The forecasting variables are according to Table 2. Each predictor variable is standardized to have zero mean and unit standard deviation; variables followed by *(-)* have been multiplied by (-1) to obtain positive betas and allow for one-sided significance testing. For each forecasting horizon, the table shows the regression coefficient (β), autocorrelation- and heteroskedasticity-robust one-sided Newey-West t-statistics (lag-number equal to 0 for $k = 1$ and $1.5 \cdot k$ otherwise, cf. Clark and McCracken, 2015) in parentheses and R^2 in percentage terms. Statistical significance at the 10%, 5% and 1% level is indicated by *, ** and *** based on wild bootstrapped p-values (cf. Gonçalves and Kilian, 2004) with the t-statistics and the R^2s. The last two lines $\ldots/PC$ report results based on the multiple regression (12) of log market returns on PU (c_{PU}) and the first three principal components of the other 18 predictors. This includes the partial R^2 in percentage terms (without significance indication).

	K = 1			**K = 3**			**K = 6**			**K = 9**			**K = 12**		
Predictor	β	t-stat	$R^2_{IS}(\%)$	β	t-stat	$R^2_{IS}(\%)$	β	t-stat	$R^2_{IS}(\%)$	β	t-stat	$R^2_{IS}(\%)$	β	t-stat	$R^2_{IS}(\%)$
logDP	0.19	[0.86]	0.17	0.21	[0.79]	0.57*	0.23	[0.82]*	1.29**	0.24	[0.81]**	1.99***	0.24	[0.76]**	2.71***
logDY	0.22	[1.01]	0.23	0.22	[0.83]	0.63*	0.24	[0.82]*	1.35***	0.24	[0.81]**	2.02***	0.24	[0.79]**	2.81***
logEP	0.12	[0.40]	0.06	0.09	[0.23]	0.11	0.08	[0.19]	0.17	0.10	[0.24]	0.34	0.10	[0.25]	0.50
logDE	0.08	[0.25]	0.03	0.14	[0.40]	0.25	0.18	[0.62]*	0.75*	0.16	[0.77]**	0.97**	0.16	[0.92]**	1.23**
RVOL	0.39	[1.91]**	0.69*	0.36	[1.54]***	1.62***	0.30	[1.64]***	2.19***	0.23	[1.36]***	1.94***	0.21	[1.19]***	2.17***
BM	0.04	[0.15]	0.01	0.06	[0.21]	0.05	0.10	[0.31]	0.23	0.11	[0.34]	0.40	0.10	[0.30]	0.50
NTIS (-)	0.07	[0.23]	0.03	0.00	[0.00]	0.00	-0.01	[-0.02]	0.00	0.00	[-0.01]	0.00	0.01	[0.02]	0.00
TBL (-)	0.29	[1.28]	0.38	0.24	[0.85]*	0.69*	0.20	[0.60]*	0.94**	0.19	[0.55]**	1.23**	0.18	[0.59]**	1.52***
LTY (-)	0.15	[0.66]	0.10	0.10	[0.36]	0.13	0.07	[0.19]	0.12	0.02	[0.05]	0.02	0.00	[0.01]	0.00
LTR	0.41	[2.18]**	0.76*	0.17	[1.08]*	0.38	0.27	[2.72]***	1.71***	0.19	[2.57]***	1.25**	0.16	[3.10]***	1.22**
TMS	0.38	[1.71]**	0.66*	0.34	[1.34]***	1.51***	0.32	[1.21]***	2.44***	0.37	[1.50]***	5.09***	0.39	[1.90]***	7.36***
DFY	0.22	[0.67]	0.23	0.23	[0.56]*	0.68*	0.29	[0.91]***	2.09***	0.26	[0.90]***	2.36***	0.23	[0.95]***	2.56***
DFR	0.48	[1.40]*	1.05	0.22	[1.17]	0.63	0.15	[1.21]	0.51	0.09	[1.14]	0.32	0.06	[0.73]	0.15
INFL (-)	0.08	[0.28]	0.03	0.17	[0.77]	0.38	0.24	[1.17]***	1.41**	0.28	[1.57]***	2.91***	0.24	[1.70]***	2.81***
$\text{MA}_{2,12}$	0.37	[1.42]**	0.64*	0.22	[0.62]**	0.64*	0.22	[0.61]**	1.14***	0.19	[0.62]***	1.36***	0.09	[0.33]*	0.40
WMA	-0.16	[-0.68]	0.11	-0.16	[-0.72]	0.31	-0.08	[-0.54]	0.14	-0.09	[-0.79]	0.30	-0.04	[-0.44]	0.10
SENT (-)	0.15	[0.59]	0.10	0.14	[0.45]	0.24	0.15	[0.52]	0.54	0.15	[0.53]*	0.80**	0.13	[0.47]*	0.87**
$UNC_{M,1}$	0.45	[1.33]*	0.92**	0.34	[0.66]**	1.48***	0.28	[0.59]**	1.85***	0.26	[0.58]**	2.39***	0.23	[0.55]***	2.57***
$UNC_{R,1}$	0.32	[0.94]	0.46	0.18	[0.36]*	0.41	0.15	[0.39]*	0.52	0.14	[0.46]**	0.70*	0.10	[0.38]*	0.48
$UNC_{F,1}$	0.63	[1.83]**	1.79***	0.41	[0.94]***	2.15***	0.26	[0.66]**	1.57***	0.22	[0.68]**	1.80***	0.20	[0.64]***	1.87***
CSV (-)	0.35	[1.73]*	0.56*	0.33	[1.77]***	1.40***	0.39	[2.38]***	3.63***	0.46	[3.47]***	7.84***	0.44	[3.64]***	9.23***
SII (-)	0.57	[2.51]***	1.47***	0.62	[2.06]***	4.81***	0.62	[2.02]***	8.80***	0.60	[1.86]***	12.03***	0.57	[1.94]***	14.06***
c_{PU}	0.71	[2.28]***	2.29***	0.61	[1.52]***	4.69***	0.45	[1.27]***	4.94***	0.36	[1.12]***	4.53***	0.34	[1.07]***	5.54***
c_{PU} |PC	0.58	[1.63]**	0.66	0.61	[2.03]***	2.05	0.38	[1.59]***	1.63	0.16	[0.67]*	0.43	0.20	[0.92]**	0.91

Table 5: Out-of-sample test results (1990:01-2014:12)

This table reports the out-of-sample test results from Equation (13) of log market excess returns (Fama-French value-weighted), averaged over forecasting horizons of $k = 1, 3, 6, 9$ and 12 months. The forecasting variables are according to Table 2. The initial estimation interval is 1973:01-1989:12 (204 observations); subsequent forecasts for the period 1990:01-2014:12 are made based on recursively growing estimation windows. Columns two through six report out-of-sample R^2 in percentage terms with significance levels based on the Clark and West (2007) statistic for testing that the prevailing mean delivers a better forecast (smaller MSE) than the respective predictor variable. Columns 7 through 11 report the $MSEF$ McCracken (2007) F-statistic and significance levels based on McCracken (2007). Finally, columns 11 through 16 report the ENC-statistic proposed by Clark and McCracken (2001) and Harvey et al. (1998), testing the null that the respective predictive variable encompasses the forecast of c_{PU}. 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).

	$R^2_{OS}(\%)$					$MSEF$					ENC				
Predictor	**K = 1**	**K = 3**	**K = 6**	**K = 9**	**K = 12**	**K = 1**	**K = 3**	**K = 6**	**K = 9**	**K = 12**	**K = 1**	**K = 3**	**K = 6**	**K = 9**	**K = 12**
logDP	-2.74	-5.90	-8.94	-11.56	-13.61	-8.00	-16.50	-23.81	-29.44	-33.30	8.72***	19.94***	24.14***	25.16***	32.47***
logDY	-3.02	-5.78	-8.95	-10.68	-13.00	-8.78	-16.18	-23.82	-27.40	-31.98	8.86***	20.00***	23.83***	25.05***	32.43***
logEP	-1.56	-3.38	-5.85	-8.01	-10.33	-4.62	-9.68	-16.03	-21.06	-26.02	7.32***	15.78***	17.53***	17.77***	23.08***
logDE	-1.90	-1.40	-0.05	0.75	1.39	-5.60	-4.10	-0.14	2.14**	3.92***	7.21***	16.42***	19.43***	18.93***	24.60***
RVOL	-0.73	-1.14	-0.90	-0.65	-1.25	-2.19	-3.34	-2.59	-1.84	-3.43	12.10***	26.47***	29.63***	26.82***	33.03***
BM	-0.81	-1.71	-2.79	-3.80	-5.27	-2.42	-4.97	-7.86	-10.41	-13.91	8.39***	19.65***	24.20***	25.27***	32.13***
NTIS	-2.92**	-5.58	-10.39*	-13.43*	-13.93*	-8.52	-15.64	-27.29	-33.63	-33.98	6.20***	12.70***	11.62***	8.92***	12.66***
TBL	-0.24	0.38	1.03	1.64	2.21	-0.73	1.13*	3.01**	4.74***	6.28***	4.13**	10.06***	10.74***	9.54***	13.55***
LTY	-0.33	-0.59	-1.32	-3.53	-5.26	-0.98	-1.73	-3.78	-9.69	-13.89	5.86***	14.15***	16.24***	18.01***	24.46***
LTR	-0.59	-1.72	-1.13	-0.15	-1.31	-1.76	-5.01	-3.24	-0.44	-3.61	6.50***	13.63***	14.98***	14.31***	18.55***
TMS	-0.52	-0.61	0.39	2.19	5.35	-1.54	-1.78	1.13*	6.36***	15.73***	4.21**	8.96***	8.73***	5.59***	7.88***
DFY	-3.24	-5.78	-6.83	-5.13	-3.70	-9.42	-16.17	-18.55	-13.86	-9.91	11.95***	26.84***	36.87***	37.75***	47.13***
DFR	-1.72	-0.60	-0.78	-0.48	-0.60	-5.08	-1.77	-2.24	-1.35	-1.65	5.73***	13.07***	14.21***	13.61***	18.07***
INFL	-0.59	0.13	1.82*	3.58*	3.83*	-1.77	0.38	5.38***	10.56***	11.09***	6.30***	12.30***	11.04***	7.83***	12.25***
$MA_{2,12}$	0.36	0.22	1.41	1.75	0.16	1.09*	0.66	4.15***	5.06***	0.44	4.39**	11.02***	11.05***	10.17***	16.63***
WMA (-)	-0.18	0.21	-0.11	-0.43	-0.92	-0.53	0.62	-0.33	-1.23	-2.53	6.61***	14.49***	15.34***	14.78***	18.66***
SENT	-0.05	0.16	0.60	0.80	0.44	-0.16	0.47	1.76**	2.30**	1.24*	6.52***	14.22***	15.73***	15.10***	19.67***
$UNC_{M,1}$	1.27	2.19	2.78	3.69	3.89	3.87***	6.61***	8.29***	10.89***	11.25***	2.90**	8.43***	8.15***	4.97**	8.26***
$UNC_{R,1}$	0.45	-0.17	0.25	1.00	0.63	1.36*	-0.50	0.73*	2.88**	1.76**	4.44**	13.81***	14.52***	11.54***	18.21***
$UNC_{F,1}$	2.14	3.14	2.19	2.39	2.36	6.55***	9.59***	6.49***	6.95***	6.72***	1.02	5.39***	7.62***	6.03***	8.91***
CSV	0.13	1.99	4.15	6.96	8.91	0.40	6.01***	12.55***	21.26***	27.18***	3.69**	7.64***	4.24**	-0.76	0.46
SII	1.45***	5.94**	11.42**	15.04**	14.43*	4.43***	18.68***	37.40***	50.26***	46.88***	3.29**	6.72***	6.78***	5.97***	8.27***
c_{PU}	2.30***	5.34**	5.92	5.60	6.96	7.05***	16.71***	18.25***	16.86***	20.80***					

Table 6: Robustness checks: Aggregate market excess returns (1973:01-2014:12)

This table reports in-sample and out-of-sample results from predictive regressions on different versions of the equity premium, namely the CRSP and S&P500 value- and equally weighted log excess market returns. c_{PU} is always standardized to have zero mean and unit standard deviation. For each forecasting horizon, the table shows the regression coefficient (β) and in-sample R^2_{IS} in percentage terms with statistical significance at the 10%, 5% and 1% level indicated by *, ** and *** based on wild bootstrapped p-values (cf. Gonçalves and Kilian, 2004). Every third column reports out-of-sample R^2_{OS} (1990:01-2014:12) with corresponding statistical significance based on the the Clark and West (2007) test.

		K = 1			**K = 3**			**K = 6**			**K = 9**			**K = 12**		
Predictor	Market return	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$
c_{PU} (P25SV)	FF VW	0.71***	2.29***	2.30***	0.61***	4.69***	5.34***	0.45***	4.94***	5.92***	0.36***	4.53***	5.60***	0.34***	5.54***	6.96***
c_{PU} (P25SV)	CRSP VW	0.69***	2.19***	2.18***	0.59***	4.36***	4.96***	0.43***	4.42***	5.42***	0.34***	3.97***	5.14***	0.33***	4.96***	6.56***
c_{PU} (P25SV)	CRSP EW	0.43*	0.57*	0.16	0.30*	0.65*	0.24*	0.09	0.11	-0.63	-0.05	0.06	-1.51	-0.08	0.18	-1.90
c_{PU} (P25SV)	S&P500 VW	0.67***	2.23***	2.33***	0.58***	4.80***	5.64***	0.45***	5.24***	6.42***	0.36***	4.99***	6.30***	0.35***	6.21***	7.79***
c_{PU} (P25SV)	S&P500 EW	0.46**	0.78**	0.65**	0.33**	1.09**	1.01**	0.15	0.44	-0.03	0.04	0.06	-1.01	0.05	0.10	-1.01

Table 7: Robustness checks: Different portfolio cross-sections (1973:01-2014:12)

This table reports in-sample and out-of-sample results from predictive regressions of c_{PU} calculated for different partitions of the cross-section of stock returns: 25 portfolios sorted on size and value (the base case P25SV), size and beta (P25SBeta), size and investment (P25SInv), size and operating profitability (P25SOp), size and accruals (P25SAC), size and net share issues (P25SNI), size and variance (P25SVar), size and residual variance (P25SResVar), value and investment (P25VInv), and value and operating profitability (P25VOp), 10 portfolios sorted on size (P10S) and value (P10V) and 100 portfolios sorted on size and value (P100SV). c_{PU} is always standardized to have zero mean and unit standard deviation. For each forecasting horizon, the table shows the regression coefficient (β) and in-sample R^2_{IS} in percentage terms with statistical significance at the 10%, 5% and 1% level indicated by *, ** and *** based on wild bootstrapped p-values (cf. Gonçalves and Kilian, 2004). Every third column reports out-of-sample R^2_{OS} (1990:01-2014:12) with corresponding statistical significance based on the the Clark and West (2007) test.

	K = 1			**K = 3**			**K = 6**			**K = 9**			**K = 12**		
Predictor	β	R^2_{IS}(%)	R^2_{OS}(%)	β	R^2_{IS}(%)	R^2_{OS}(%)	β	R^2_{IS}(%)	R^2_{OS}(%)	β	R^2_{IS}(%)	R^2_{OS}(%)	β	R^2_{IS}(%)	R^2_{OS}(%)
c_{PU} (P100SV)	0.67***	2.03***	-1.24	0.59***	4.37***	-1.49	0.47***	5.22***	-2.85	0.37***	4.92***	-3.79	0.34***	5.51***	-3.10
c_{PU} (P25SV)	0.71***	2.29***	2.30***	0.61***	4.69***	5.34**	0.45***	4.94***	5.92	0.36***	4.53***	5.60	0.34***	5.54***	6.96
c_{PU} (P25SOp)	0.59***	1.59***	2.09*	0.58***	4.21***	6.42	0.49***	5.78***	10.27	0.44***	7.02***	11.98*	0.41***	8.17***	14.05
c_{PU} (P25SInv)	0.60***	1.68***	1.33**	0.57***	4.05***	3.79**	0.43***	4.46***	5.92*	0.42***	6.20***	8.10	0.43***	8.65***	11.52
c_{PU} (P25SAC)	0.63***	1.85***	2.16***	0.56***	4.02***	4.95*	0.48***	5.68***	7.23*	0.48***	8.46***	9.32	0.46***	10.34***	10.07
c_{PU} (P25SNI)	0.59***	1.62***	2.58	0.54***	3.70***	7.29	0.43***	4.42***	10.64	0.37***	5.03***	13.45	0.37***	6.51***	17.22
c_{PU} (P25SVar)	0.32	0.47	0.41	0.27**	0.91**	1.29	0.23**	1.24**	3.16	0.20**	1.47**	4.64	0.19***	1.77***	6.90
c_{PU} (P25SResVar)	0.26	0.31	-0.28	0.16	0.34	0.08	0.14	0.44	1.78	0.16**	0.90**	4.42	0.20***	1.92***	7.78
c_{PU} (P25SBeta)	0.69***	2.15***	2.21**	0.50***	3.15***	4.14	0.25**	1.43**	4.04	0.19**	1.24**	4.56	0.21***	2.04***	6.60
c_{PU} (P25VOp)	0.54***	1.32***	0.43	0.50***	3.17***	3.13	0.39***	3.55***	4.89	0.35***	4.26***	5.84	0.31***	4.46***	6.27
c_{PU} (P25VInv)	0.70***	2.27***	1.78*	0.62***	4.90***	4.09	0.48***	5.43***	3.62	0.40***	5.60***	3.35	0.35***	5.86***	3.48
c_{PU} (P10Mom)	0.33	0.49	0.20	0.33***	1.39***	1.32	0.31***	2.31***	2.64	0.29***	2.92***	3.48	0.26***	3.24***	3.92
c_{PU} (P10S)	0.48**	1.08**	1.52*	0.39***	1.97***	2.50	0.29***	2.07***	2.60	0.27***	2.67***	2.61	0.30***	4.31***	4.01
c_{PU} (P10STR)	0.34	0.53	0.26	0.23*	0.68*	0.96	0.16*	0.64*	1.39	0.14*	0.67*	1.68	0.09	0.38	1.21
c_{PU} (P10V)	0.65***	1.94***	1.10	0.56***	3.92***	2.63	0.38***	3.37***	1.52	0.31***	3.40***	-0.63	0.26***	3.02***	-0.28

Table 8: Robustness checks: Initial estimation windows (1973:01-2014:12)
This table reports in-sample and out-of-sample results from predictive regressions of c_{PU} calculated for different methods and time windows used to estimate the moments necessary for the calculation of c_{PU}. We estimate recursively (g) starting in 1953:01, 1963:01 or 1926:08 or based on rolling windows of 60 and 120 months (r60, r120). c_{PU} is always standardized to have zero mean and unit standard deviation. For each forecasting horizon, the table shows the regression coefficient (β) and in-sample R^2_{IS} in percentage terms with statistical significance at the 10%, 5% and 1% level indicated by *, ** and *** based on wild bootstrapped p-values (cf. Gonçalves and Kilian, 2004). Every third column reports out-of-sample R^2_{OS} (1990:01-2014:12) with corresponding statistical significance based on the the Clark and West (2007) test.

	K = 1			**K = 3**			**K = 6**			**K = 9**			**K = 12**		
Predictor	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$
c_{PU} (1963, r60)	0.35*	0.57*	0.75	0.32***	1.27***	2.06	0.29***	2.08***	3.49	0.27***	2.61***	4.36	0.27***	3.55***	5.81
c_{PU} (1963, r120)	0.38*	0.65*	0.93	0.36***	1.62***	2.68	0.30***	2.25***	3.76	0.24***	2.11***	3.42	0.24***	2.67***	4.34
c_{PU} (1953, g)	0.68***	2.13***	2.57*	0.59***	4.41***	6.24	0.45***	4.84***	7.20	0.36***	4.58***	7.03	0.34***	5.56***	8.77
c_{PU} (1963, g)	0.71***	2.29***	2.30***	0.61***	4.69***	5.34**	0.45***	4.94***	5.92	0.36***	4.53***	5.60	0.34***	5.54***	6.96
c_{PU} (1926, g)	0.65***	1.91***	2.42*	0.55***	3.86***	5.96	0.43***	4.43***	7.63	0.38***	5.10***	9.44	0.38***	6.83***	12.44

Table 9: Robustness checks: Length of lookback window T_c (1973:01-2014:12)
This table reports in-sample and out-of-sample results from predictive regressions of c_{PU} calculated for different lookback windows of $T_c = 1, 3, 6, 9$ and 12 months for the calculation of c_{PU}. c_{PU} is always standardized to have zero mean and unit standard deviation. For each forecasting horizon, the table shows the regression coefficient (β) and in-sample R^2_{IS} in percentage terms with statistical significance at the 10%, 5% and 1% level indicated by *, ** and *** based on wild bootstrapped p-values (cf. Gonçalves and Kilian, 2004). Every third column reports out-of-sample R^2_{OS} (1990:01-2014:12) with corresponding statistical significance based on the the Clark and West (2007) test.

	K = 1			**K = 3**			**K = 6**			**K = 9**			**K = 12**		
Predictor	β	R^2_{IS}(%)	R^2_{OS}(%)	β	R^2_{IS}(%)	R^2_{OS}(%)	β	R^2_{IS}(%)	R^2_{OS}(%)	β	R^2_{IS}(%)	R^2_{OS}(%)	β	R^2_{IS}(%)	R^2_{OS}(%)
c_{PU} ($T_c = 1$)	0.38*	0.65*	0.65*	0.46***	2.70***	3.59***	0.37***	3.22***	4.40***	0.39***	5.54***	6.49**	0.37***	6.42***	7.42**
c_{PU} ($T_c = 3$)	0.36	0.58	0.54	0.57***	4.10***	4.52**	0.40***	3.95***	4.67*	0.39***	5.53***	6.11**	0.34***	5.57***	6.21
c_{PU} ($T_c = 6$)	0.57**	1.47**	1.37**	0.58***	4.28***	4.79*	0.45***	4.90***	5.85*	0.39***	5.40***	6.67*	0.34***	5.55***	7.23
c_{PU} ($T_c = 9$)	0.56***	1.45***	1.47**	0.62***	4.90***	5.52**	0.48***	5.58***	6.60*	0.39***	5.51***	7.04	0.33***	5.29***	6.93
c_{PU} ($T_c = 12$)	0.71***	2.29***	2.30***	0.61***	4.69***	5.34**	0.45***	4.94***	5.92	0.36***	4.53***	5.60	0.34***	5.54***	6.96

Table 10: Robustness checks: Alternative Time Frame (1990:01-2014:12)

This table reports in-sample and out-of-sample results from predictive regressions with forecasting variables according to Table 2 including VRP. Each predictor variable is standardized to have zero mean and unit standard deviation; variables followed by *(-)* have been multiplied by (-1) to obtain positive betas and allow for one-sided significance testing. For each forecasting horizon, the table shows the regression coefficient (β) and in-sample R^2_{IS} in percentage terms with statistical significance at the 10%, 5% and 1% level indicated by *, ** and *** based on wild bootstrapped p-values (cf. Gonçalves and Kilian, 2004). Every third column reports out-of-sample R^2_{OS} (2000:01-2014:12) with corresponding statistical significance based on the the Clark and West (2007) test.

	K = 1			**K = 3**			**K = 6**			**K = 9**			**K = 12**		
Predictor	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$	β	$R^2_{IS}(\%)$	$R^2_{OS}(\%)$
logDP	0.39	0.78	0.40	0.45	2.83***	3.16	0.48	6.11***	6.51	0.50	9.48***	9.91	0.53	14.20***	15.12
logDY	0.44	0.98*	0.67	0.48	3.19***	3.63	0.49	6.32***	6.56	0.51	9.94***	10.38	0.54	14.92***	15.90
logEP	0.24	0.29	-1.77	0.17	0.41	-2.14	0.13	0.41	-2.05	0.14	0.80	-1.47	0.17	1.39**	-1.18
logDE	0.06	0.02	-2.88	0.16	0.34	-3.21	0.22	1.24*	-2.42	0.21	1.70**	-1.57	0.22	2.33***	-0.70
RVOL	0.21	0.23	-0.74	0.21	0.61	-0.32	0.19	0.97*	0.06	0.16	0.96*	0.18	0.13	0.90	0.31
BM	0.28	0.40	0.01	0.39	2.12**	2.26	0.48	6.02***	6.29**	0.50	9.69***	10.07***	0.51	12.80***	13.42***
NTIS (-)	-0.41	0.86	-0.05	-0.45	2.84***	2.38	-0.49	6.16***	6.09	-0.44	7.59***	7.31	-0.38	7.31***	6.62
TBL (-)	0.19	0.19	-1.20	0.16	0.36	-0.91	0.19	0.87	-0.32	0.21	1.54**	0.36	0.22	2.17**	0.74
LTY (-)	0.18	0.17	-1.33	0.14	0.28	-1.21	0.13	0.43	-0.86	0.09	0.30	-0.88	0.05	0.11	-1.04
LTR	0.17	0.15	-0.80	-0.06	0.06	-1.26	0.10	0.27	-0.84	0.11	0.45	-0.53	0.04	0.09	-0.76
TMS	0.10	0.05	-0.65	0.10	0.13	-0.88	0.15	0.59	-0.43	0.23	2.02**	1.19	0.29	4.27***	3.18
DFY	-0.20	0.20	-2.87	-0.08	0.10	-3.59	0.07	0.14	-5.66	0.13	0.62	-5.15	0.17	1.41**	-2.47
DFR	0.30	0.47	-4.02	0.20	0.55	-3.19	0.13	0.43	-3.83	0.10	0.40	-2.56	0.12	0.70	-1.81
INFL (-)	-0.19	0.19	-1.37	0.10	0.14	-1.46	0.25	1.57**	0.79*	0.28	3.02***	2.58	0.25	3.05***	2.57
$MA_{2,12}$	0.38	0.76	-1.73	0.21	0.61	-4.68	0.30	2.31***	0.60	0.27	2.76***	0.84	0.18	1.71**	-0.26
WMA	-0.35	0.62	0.25	-0.29	1.20*	0.93	-0.15	0.57	-0.14	-0.07	0.20	-0.30	0.00	0.00	-1.22
CSV (-)	0.50	1.27*	-0.66	0.45	2.80***	1.77	0.44	5.15***	4.23	0.50	9.55***	8.55	0.48	11.62***	11.50
SII (-)	0.58	1.70**	1.82**	0.66	5.83***	8.55*	0.69	11.39***	16.25	0.63	13.54***	19.60	0.55	12.68***	19.23
SENT	-0.56	1.61**	0.27	-0.54	4.11***	4.04	-0.57	8.34***	9.15	-0.59	13.17***	13.50	-0.59	17.63***	18.28
VRP	0.98	4.94***	6.25*	0.83	9.65***	9.16**	0.49	6.32***	3.16**	0.27	2.80***	-0.53**	0.21	2.31***	-1.13*
$UNC_{M,1}$	0.77	3.04***	1.36	0.62	5.32***	4.20	0.47	5.62***	2.42	0.37	5.17***	0.84	0.31	4.67***	0.19
$UNC_{R,1}$	0.73	2.78***	1.64	0.52	3.82***	2.86	0.35	3.21***	0.70	0.20	1.60**	-1.32	0.10	0.51	-1.69
$UNC_{F,1}$	0.72	2.68***	2.45	0.54	4.00***	4.04	0.35	3.24***	2.17	0.28	2.90***	1.71	0.23	2.66***	1.54
c_{PU}	0.86	3.82***	2.77**	0.78	8.44***	7.18**	0.60	9.32***	7.22	0.49	9.03***	6.17	0.47	10.53***	5.89
c_{PU} |PC	0.86**	4.53		0.78*	10.90		0.60	8.49		0.49	4.75		0.47	5.55	

Table 11: Economic application: Asset allocation based on out-of-sample predictions of the equity premium (1990:01-2014:12).
This table reports the results for mean-variance asset allocation strategies based on predictions of the expected excess return and expected volatility (cf. Equation (16)). The forecasting variables are according to Table 2. Columns two through five show annualized Sharpe ratios, followed by annualized CER gains in percentage terms (cf. Equation (17)) with respect to the strategy based on the prevailing mean in columns six to nine. Columns ten to 14 show the turnovers of the respective strategies, while columns 15 to 17 depict the return loss (assuming rebalancing costs of 50BP) against the prevailing mean strategy according to De Miguel et al. (2009b). Weights are calculated based on predictive regressions for the excess return and a rolling estimate of the standard deviation (120 months) and are constrained to lie between -0.5 and 1.5. 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 strategy based on the prevailing mean.

	Sharpe Ratio (ann.)				**CER gain ($\gamma = 3$, ann. %)**				**Turnover**				**Retun-Loss (ann. %)**			
Predictor	**K = 1**	**K = 3**	**K = 6**	**K=12**	**K = 1**	**K = 3**	**K = 6**	**K = 12**	**K = 1**	**K = 3**	**K = 6**	**K = 12**	**K = 1**	**K = 3**	**K = 6**	**K = 12**
Prevailing Mean	0.41	0.37	0.45	0.43					12.07	7.75	6.29	6.06				
logDP	-0.05	0.13	0.11	0.26	-4.46	-2.21	-3.45	-1.66	34.63	19.44	16.34	13.90	3.72	1.28	2.13	0.88
logDY	-0.04	0.14	0.13	0.29	-4.26	-2.14	-3.26	-1.35	46.16	20.68	17.60	14.23	3.59	1.24	1.90	0.56
logEP	0.31	0.35	0.41	0.34	-1.20	-0.09	-0.77	-1.09	30.04	20.47	18.47	15.50	0.85	-0.32	-0.09	0.99
logDE	0.34	0.39	0.40	0.44	-0.90	0.26	-0.69	0.08	40.23	26.74	19.09	12.13	1.61	0.17	1.30	0.04
RVOL	0.29	0.28	0.33	0.43	-2.07	-2.18	-1.68	0.18	63.78	34.49	23.95	12.40	3.67	2.94	2.34	-0.20
BM	0.28	0.28	0.39	0.39	-1.70	-1.14	-0.92	-0.42	21.45	12.03	8.95	8.93	1.80	1.15	0.25	0.19
NTIS	0.20	0.23	0.27	0.25	-2.96	-2.02	-2.43	-3.76	50.17	28.93	23.99	16.94	3.96	2.45	3.03	3.93
TBL	0.46	0.42	0.48	0.44	0.55	0.43	0.51	0.14	28.50	15.16	10.43	7.15	0.58	-0.05	0.02	-0.10
LTY	0.39	0.35	0.46	0.36	-0.31	-0.23	-0.14	-0.70	24.09	13.26	11.14	12.11	0.80	0.31	-0.42	0.32
LTR	0.34	0.40	0.43	0.48	-1.09	0.36	-0.31	1.05	371.61	83.12	41.26	18.05	8.81	1.28	1.14	-0.83
TMS	0.46	0.45	0.51	0.50	0.74	1.15	0.89	1.27	63.81	33.49	22.64	18.50	0.77	-0.45	-0.06	-0.98
DFY	0.00	0.10	0.14	0.36	-4.99	-3.40	-3.87	-0.80	50.02	29.24	25.28	13.59	5.42	3.51	4.05	0.80
DFR	0.44	0.40	0.49	0.47	0.42	0.42	0.47	0.68	378.72	48.10	16.12	6.65	7.22	0.48	-0.20	-0.67
INFL	0.38	0.35	0.53	0.49	-0.55	-0.53	1.20	1.07	98.12	27.71	15.27	12.86	2.82	1.14	-0.73	-0.94
$MA_{2,12}$	0.53	0.40	0.52	0.42	1.52	0.53	0.65	-0.35	56.26	20.88	14.59	8.75	-0.69	-0.43	-0.74	0.39
WMA	0.39	0.36	0.46	0.43	-0.33	-0.14	0.09	0.01	49.05	26.48	10.24	8.29	1.19	0.56	0.02	0.02
CSV	0.56	0.58	0.76	0.56	1.92	2.92	3.42	2.23	59.18	35.76	26.95	16.61	-1.10	-2.54	-3.30	-2.03
SII	0.62	0.59	0.73	0.60	3.53	3.78	4.60	3.46	40.45	21.04	15.52	11.29	-2.25	-3.28	-3.76	-3.31
SENT (-)	0.40	0.37	0.49	0.43	-0.10	-0.05	0.53	-0.18	18.89	10.71	7.35	6.72	0.48	0.21	-0.37	0.22
$UNC_{M,1}$	0.56	0.46	0.55	0.42	2.11	1.32	1.14	-0.22	28.23	17.71	12.54	12.23	-1.62	-1.09	-1.21	0.39
$UNC_{R,1}$	0.46	0.36	0.43	0.40	0.63	-0.08	-0.28	-0.67	29.89	16.62	11.23	7.92	-0.26	0.16	0.27	0.73
$UNC_{F,1}$	0.91	0.65	0.62	0.45	5.45	3.45	1.85	0.15	55.18	27.46	15.66	14.38	-5.09	-3.46	-1.99	0.07
c_{PU}	0.83	0.70	0.72	0.46	6.44	5.31	3.82	0.35	59.69	32.63	19.54	17.48	-5.01	-4.63	-3.21	-0.05
Buy-and-Hold (100%)	0.50	0.46	0.51	0.45	1.29	1.41	1.02	0.43								
Buy-and-Hold (150%)	0.50	0.46	0.51	0.45	0.78	-0.01	0.74	-1.97								

Table 12: Economic application: Asset allocation based on out-of-sample predictions of the equity premium, alternative timeframe (2000:01-2014:12).
This table reports the results for mean-variance asset allocation strategies based on predictions of the expected excess return and expected volatility (cf. Equation (16)). The forecasting variables are according to Table 2 including VRP. Columns two through five show annualized Sharpe ratios, followed by annualized CER gains in percentage terms (cf. Equation (17)) with respect to the strategy based on the prevailing mean in columns six to nine. Columns ten to 14 show the turnovers of the respective strategies, while columns 15 to 17 depict the return loss (assuming rebalancing costs of 50BP) against the prevailing mean strategy according to De Miguel et al. (2009b). Weights are calculated based on predictive regressions for the excess return and a rolling estimate of the standard deviation (120 months) and are constrained to lie between -0.5 and 1.5. 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 strategy based on the prevailing mean.

	Sharpe Ratio (ann.)				**CER gain (γ = 3, ann. %)**				**Turnover**				**Retun-Loss (ann. %)**			
Predictor	**K = 1**	**K = 3**	**K = 6**	**K=12**	**K = 1**	**K = 3**	**K = 6**	**K = 12**	**K = 1**	**K = 3**	**K = 6**	**K = 12**	**K = 1**	**K = 3**	**K = 6**	**K = 12**
Prevailing Mean	0.11	0.11	0.08	0.09					11.04	5.32	4.35	3.63				
logDP	0.16	0.21	0.23	0.28	0.83	0.79	2.03	3.30	17.11	12.90	8.78	8.37	-0.59	-1.15	-1.83	-3.04
logDY	0.21	0.20	0.23	0.33	1.61	0.85	2.00	4.26	29.69	14.78	10.13	8.43	-0.89	-1.03	-1.80	-3.71
logEP	0.49	0.38	0.34	0.07	5.77	4.16	3.44	-0.64	24.21	17.77	16.26	15.40	-4.97	-3.36	-2.64	0.83
logDE	0.13	0.10	0.06	0.08	0.57	-0.16	-0.75	-0.14	25.87	17.18	12.58	5.74	0.07	0.57	0.74	0.24
RVOL	0.10	0.13	0.15	0.13	-0.27	0.27	0.65	1.06	30.91	16.72	11.21	7.75	0.86	0.10	-0.57	-0.62
BM	0.17	0.30	0.35	0.30	0.75	2.37	3.55	3.47	16.11	13.91	9.56	9.98	-0.71	-2.76	-3.40	-3.41
NTIS	0.08	0.11	0.12	0.13	0.01	0.39	1.25	1.68	33.56	19.48	16.89	10.42	1.01	0.34	-0.42	-0.70
TBL	0.05	0.10	0.16	0.08	-0.97	0.24	1.28	-0.21	31.67	18.02	14.78	9.46	1.60	0.50	-0.76	0.32
LTY	0.04	0.07	0.12	-0.01	-0.44	0.18	1.30	0.41	34.96	18.92	12.64	10.28	1.60	0.78	-0.58	0.77
LTR	0.03	0.07	0.20	0.08	-1.68	-1.57	1.64	-0.74	72.27	24.21	19.56	4.42	3.42	1.63	-1.04	0.28
TMS	0.07	0.10	0.10	0.20	-0.66	-0.22	-0.04	2.10	24.74	11.53	7.70	6.93	1.03	0.43	-0.04	-1.83
DFY	0.13	0.22	0.38	-0.06	0.58	2.09	3.93	-2.08	30.28	18.37	16.35	11.53	0.29	-1.24	-3.17	2.48
DFR	0.01	0.15	0.07	-0.04	-1.86	0.38	-0.96	-1.81	146.46	54.21	25.83	7.73	6.13	1.17	1.17	2.10
INFL	0.05	0.12	0.05	0.13	-1.06	0.18	-0.58	0.04	112.31	14.69	17.30	6.48	4.29	0.16	0.95	-0.48
$MA_{2,12}$	0.23	0.13	0.33	0.03	1.92	0.67	3.44	-0.79	40.83	17.85	16.79	9.82	-0.83	0.08	-2.70	1.09
WMA	0.22	0.23	0.12	0.07	1.23	1.55	0.28	-0.73	60.55	22.44	7.44	4.85	-0.04	-1.24	-0.36	0.51
CSV	0.34	0.30	0.30	0.24	3.53	2.81	2.76	1.74	51.56	27.75	12.03	12.31	-2.16	-2.11	-2.76	-2.27
SII	0.38	0.55	0.64	0.36	4.18	6.97	7.86	4.47	40.04	17.81	15.43	8.25	-3.48	-7.23	-7.54	-4.72
SENT (-)	0.36	0.37	0.40	0.51	2.94	2.81	3.58	7.00	44.70	24.37	15.81	10.85	-3.46	-4.30	-5.00	-7.54
VRP	0.44	0.27	0.02	0.09	5.00	1.92	-0.04	1.01	184.38	46.03	19.59	4.60	0.47	-1.29	0.87	-0.36
$UNC_{M,1}$	0.53	0.39	0.57	0.45	6.07	4.43	5.58	5.71	43.47	29.55	22.20	16.50	-4.24	-3.19	-4.52	-4.33
$UNC_{R,1}$	0.31	0.23	0.30	0.06	3.32	1.91	3.09	0.22	57.18	30.49	21.36	14.59	-1.43	-0.97	-2.26	0.59
$UNC_{F,1}$	0.54	0.42	0.45	0.17	6.38	4.85	4.54	1.64	35.93	25.82	15.11	13.46	-5.11	-3.94	-3.78	-1.00
c_{PU}	0.73	0.65	0.58	0.31	9.58	8.42	6.64	3.14	52.89	28.79	22.30	18.38	-8.20	-7.68	-5.97	-3.22
Buy-and-Hold (100%)	0.28	0.27	0.29	0.26	2.59	1.89	2.45	2.35								
Buy-and-Hold (150%)	0.28	0.27	0.29	0.26	0.12	-1.68	0.22	-1.57								