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Abstract

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Keywords: Active factor models, model averaging and selection, computational finance, quantitative equity investing, stock selection strategies, return-based factor models.

JEL Classification: C11, C52, G11, G15, G17, F37.

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1. Introduction

This paper proposes a novel approach to construct tailored equity portfolios. We employ a highly flexible and robust dynamic model combination (or averaging) approach to compute return forecasts of individual equities from a factor based regressor set for stocks contained in a broad cross-section of international equity indices. We then rank the individual equities based on their forecast performance relative to a simple random walk (or historic average) benchmark forecast from ‘best’ to ‘worst’, and take the top 25% of equities in each constituent index to form equally weighted long only portfolios. Transaction (or portfolio) re-balancing costs are explicitly accounted for through a simple mark-up price.

Our motivation for employing a dynamic model averaging (DMA) approach for the prediction of individual stock returns is due to the following. First, as the recent study by Linnainmaa and Roberts (2018) shows, the importance, and thereby the predictive content, of various pricing factors has substantially changed over time. Classic factor models, which implicitly rely on static factor loadings, are often only able to capture return relations over short sample periods. Moreover, a point forcefully made by Linnainmaa and Roberts (2018) is that many of the ‘significant’ factors are merely due to p -hacking and fail to remain ‘significant’ when evaluated over a larger sample period that does not contain the original sample over which the factor was discovered (see also Harvey *et al.* (2015) and Hou *et al.* (2017)).

Second, and perhaps more importantly, the way we implement DMA is purposefully designed to prevent p -hacking or data snooping. There are only two ‘free’ parameters that need to be specified in the model. These are the two ‘forgetting factors’ that, respectively, determine the degree of equally weighted model averaging and the rate of smoothing over time.¹ Since the literature on model averaging prescribes what values to consider for monthly data (see Raftery *et al.* (2010) and Koop and Korobilis (2012)), there is very little room to fine-tune these param-

¹In fact, there is one more parameter that needs to be set in the specification of the exponentially weighted moving average (EWMA) process for the time varying volatilities. Nevertheless, since there are direct guidelines from RiskMetrics (1996) (see Table 5.9 on page 100) to use a decay factor of 0.94 for daily data and 0.97 for monthly data, it is impossible to tune these values without the reader noticing that they are not aligned with the RiskMetrics (1996) recommendation.

eters to obtain a better fit of the model. Furthermore, to minimize the risk of data snooping, we use the same *'forgetting factors'* for all 895 individual equity returns that are predicted in the cross-section and do not adjust these separately for each stock.

Averaging across a large number of models, as devised in the seminal work of Bates and Granger (1969) and implemented in the frequentist and Bayesian model averaging literature, allows one to explicitly mitigate *'model risk'*, that is, the idea of relying on one *'true'* data generating process for the empirical series of interest. Moreover, West and Harrison (1997) have argued that allowing for time varying parameters can proxy for omitted variable bias and possible *'local'* non-linearities in the relationship between the dependent variable and its predictors. In the finance literature, several authors have advocated the use of model averaging for return forecasting. For instance, Pastor and Stambaugh (2000) use Bayesian model averaging and shrinkage for return and covariance forecasting. Similarly, Garlappi *et al.* (2007) offer a comprehensive overview of the use of model averaging approaches in portfolio management. Dynamic model averaging has the extra advantage of detecting changes in the underlying time-series dynamics of the processes in real time.

Our paper is related to a broader literature on return predictability. It is related to the time series predictability literature (see Rapach *et al.* (2010), Moskowitz *et al.* (2012), Neely *et al.* (2014), Rapach *et al.* (2016), Buncic and Tischhauser (2017), Goyal and Jegadeesh (2018), and others) as it uses the time series dimension to construct forecasts of individual equity returns from a set of value, momentum and quality factors. But it is also related to the cross-sectional return predictability literature because we employ a cross-sectional sort of the individual stocks to obtain a ranking.² Nevertheless, contrary to the existing cross-sectional return predictability literature which relies upon current or lagged observed characteristics such as value, momentum or any of the other factors that have been proposed, we create a forward looking ranking based on the stocks expected or predictive performance. This fundamentally distinguishes our approach

²The literature on cross-sectional return predictability is large. A comprehensive review of the various pricing factors that have been proposed and their performance for cross-sectional return predictability is offered in Harvey *et al.* (2015) and Linnainmaa and Roberts (2018).

from existing cross-sectional return predictability studies.

Using individual equity returns from a large cross-section of stocks contained in the SP500, FTS100, DAX30, CAC40 and SPX30 headline indices with value, momentum, and quality factors as predictor variables, we show that our proposed dynamic model generates accurate out-of-sample forecasts. More specifically, for the considered out-of-sample forecast evaluation and portfolio construction period from 2011:06 to 2015:07, statistically significant point forecasts for 173 (281) individual equities at the 1% (5%) level are obtained from a total of 895 stocks. We show further that these statistical gains in the forecasts of the individual stocks translate into considerable economic gains, producing out-of-sample R^2 values above 5% (10%) for 283 (166) of the 895 individual stocks. A trading strategy that constructs long only portfolios for the best 25% forecasts in each headline index can generate sizable returns in excess of a passive investment strategy in that index itself, even when transaction costs and risk taking are accounted for.

The remainder of the paper is organized as follows. In [Section 2](#) we describe our proposed dynamic model averaging framework to be used for the prediction of the individual stocks. The data that is used in the analysis and the statistical forecast evaluation are presented in [Section 3](#) and [Section 4](#), respectively. In [Section 5](#) we outline how we construct the portfolios and how transaction costs are accounted for in the trading strategy. The trading strategy is evaluated in [Section 6](#). [Section 7](#) concludes the study.

2. Modelling approach

Our dynamic model averaging and selection framework is implemented as follows. For simplicity, we outline the modelling approach for a single equity i to avoid confusion and needing to introduce extra notation to describe the model. We therefore do not use an additional subscript i to index each individual equity that is modelled in the description of the model that follows below.

Let r_t denote the return series (of some equity i) to be predicted at time period t . Also, let \mathbf{x}_{t-1} be a $(1 \times K)$ vector that contains the full set of k predictors plus an intercept term ($K = k + 1$), and let $m = 1, \dots, M$ denote the model index, where $M = 2^k$ is the total number of possible (linear) model combinations, given k regressors. The set of predictors contained in the m^{th} model is denoted by $\mathbf{x}_{t-1}^{(m)}$, with the dimension of $\mathbf{x}_{t-1}^{(m)}$ being $(1 \times K_m)$. The two equations that make up the dynamic modelling framework (for a single model m) are:

$$\text{Measurement : } r_t = \mathbf{x}_{t-1}^{(m)} \boldsymbol{\beta}_t^{(m)} + u_t^{(m)} \quad (1a)$$

$$\text{State : } \boldsymbol{\beta}_t^{(m)} = \boldsymbol{\beta}_{t-1}^{(m)} + \boldsymbol{\epsilon}_t^{(m)}, \quad (1b)$$

where (1a) and (1b) are measurement and state equations, respectively. The two disturbance terms $u_t^{(m)}$ and $\boldsymbol{\epsilon}_t^{(m)}$ in (1) are jointly Multivariate Normal (MN) distributed, uncorrelated with each other and over time, that is:

$$\begin{bmatrix} u_t^{(m)} \\ \boldsymbol{\epsilon}_t^{(m)} \end{bmatrix} \sim \text{MN} \left(\begin{bmatrix} 0 \\ \mathbf{0} \end{bmatrix}, \begin{bmatrix} H_t^{(m)} & \mathbf{0} \\ \mathbf{0} & \mathbf{Q}_t^{(m)} \end{bmatrix} \right), \quad (2)$$

where $H_t^{(m)}$ and $\mathbf{Q}_t^{(m)}$ are the variance and covariance matrix of the measurement and state equations, respectively.

Given $H_t^{(m)}$ and $\mathbf{Q}_t^{(m)}$ (and one specific model m), the system in (1) takes the form of a standard state-space model, so that we can extract or ‘filter’ the time varying parameters $\boldsymbol{\beta}_t^{(m)}$ as ‘latent states’ using standard Kalman Filter recursions. One-step ahead forecasts and forecast errors are available as a by product of the Kalman Filter. The Kalman Filter recursions are:

$$\begin{aligned} \text{Prediction : } \hat{\boldsymbol{\beta}}_{t|t-1}^{(m)} &= \hat{\boldsymbol{\beta}}_{t-1|t-1}^{(m)} \\ \mathbf{P}_{t|t-1}^{(m)} &= \mathbf{P}_{t-1|t-1}^{(m)} + \mathbf{Q}_t^{(m)} \end{aligned} \quad (3a)$$

$$\hat{r}_{t|t-1}^{(m)} = \mathbf{x}_{t-1}^{(m)} \hat{\boldsymbol{\beta}}_{t|t-1}^{(m)} \quad (3b)$$

$$\text{Prediction errors : } \hat{u}_t^{(m)} = (r_t - \hat{r}_{t|t-1}^{(m)})$$

$$\text{MSE of prediction errors : } F_t^{(m)} = \mathbf{x}_{t-1}^{(m)} \mathbf{P}_{t|t-1}^{(m)} \mathbf{x}_{t-1}^{\top(m)} + H_t^{(m)} \quad (3c)$$

$$\text{Kalman Gain : } \mathbf{G}_t^{(m)} = \mathbf{P}_{t|t-1}^{(m)} \mathbf{x}_{t-1}^{\top(m)} / F_t^{(m)}$$

$$\text{Updating : } \hat{\boldsymbol{\beta}}_{t|t}^{(m)} = \hat{\boldsymbol{\beta}}_{t|t-1}^{(m)} + \mathbf{G}_t^{(m)} (r_t - \hat{r}_{t|t-1}^{(m)}) \quad (3d)$$

$$\mathbf{P}_{t|t}^{(m)} = \mathbf{P}_{t-1|t-1}^{(m)} - \mathbf{G}_t^{(m)} \mathbf{x}_{t-1}^{(m)} \mathbf{P}_{t-1|t-1}^{(m)}$$

where $\hat{\boldsymbol{\beta}}_{t|t-1}^{(m)} = \mathbb{E}_{\mathcal{I}_{t-1}}(\boldsymbol{\beta}_t^{(m)})$, $\mathbb{E}_{\mathcal{I}_{t-1}}(\cdot)$ is the expectation taken with respect to a time $t - 1$ information set denoted by \mathcal{I}_{t-1} , and $\mathbf{P}_{t|t-1}^{(m)}$ is the mean square error (MSE) of $\hat{\boldsymbol{\beta}}_{t|t-1}^{(m)}$. Model m forecasts given \mathcal{I}_{t-1} are denoted by $\hat{r}_{t|t-1}^{(m)}$. One-step ahead forecast errors are $\hat{u}_t^{(m)}$. The associated MSE is denoted by $F_t^{(m)}$. The terms $\hat{\boldsymbol{\beta}}_{t|t}^{(m)}$ and $\mathbf{P}_{t|t}^{(m)}$ are updated (or time t) estimates of the latent states $\boldsymbol{\beta}_t^{(m)}$ and their corresponding MSEs.

As is evident from above, the Kalman Filter recursions in (3) are conditional on $H_t^{(m)}$ and $\mathbf{Q}_t^{(m)}$ (and model m). Rather than estimate $H_t^{(m)}$ and $\mathbf{Q}_t^{(m)}$, we follow the literature and make two simplifying assumptions. The first is to replace $\mathbf{P}_{t|t-1}^{(m)}$ in (3a) by

$$\mathbf{P}_{t|t-1}^{(m)} = \frac{1}{\lambda} \mathbf{P}_{t-1|t-1}^{(m)} \quad (4)$$

where $\lambda \in [0, 1]$. This approximation implies that $\mathbf{Q}_t^{(m)} = (\lambda^{-1} - 1) \mathbf{P}_{t-1|t-1}^{(m)}$. The λ parameter is commonly referred to as a ‘*forgetting factor*’, since it captures how many observations are effectively used for estimation. The second simplifying assumption is to use an exponentially weighted moving average (EWMA) estimate for the volatility term $H_t^{(m)}$, taking the form:

$$H_t^{(m)} = \kappa H_{t-1}^{(m)} + (1 - \kappa) \hat{u}_{t-1}^{2(m)}, \quad (5)$$

where $\kappa \in [0, 1]$ is the EWMA smoothing parameter. Note here that an EWMA model is a restricted integrated GARCH(1, 1). The restriction is that the intercept term is fixed at 0, rather than estimated.³

³GARCH models are known to be difficult to beat benchmarks in forecasting evaluations. One alternative model that does seem to produce consistently superior forecasts to a GARCH benchmark model is the Heterogeneous AutoRegressive (HAR) model of Corsi (2009), in particular, augmented versions of it (see for instance, Corsi *et al.*

2.1. Model weighting, averaging, and selection

The Kalman Filter relations in (3) are for the single model case (that is, model m). Model averaging is implemented by weighting the forecasts by their respective predictive model probabilities. To clarify this, define $\pi_{t|t-1}^{(m)}$ as the probability of model m given information up to time $t - 1$, which we write as:

$$\pi_{t|t-1}^{(m)} = \Pr(\mathcal{M}_t = m | \mathcal{I}_{t-1}), \quad (6)$$

where \mathcal{M}_t denotes the model set at time t . The DMA forecast of r_t , given information up to time $t - 1$, written as $E(r_t | \mathcal{I}_{t-1})$, is then computed as:

$$\hat{r}_{t|t-1}^{(\text{DMA})} = \sum_{m=1}^M \hat{r}_{t|t-1}^{(m)} \pi_{t|t-1}^{(m)}, \quad (7)$$

that is, as the weighted average of the forecasts from all possible models, $\{\hat{r}_{t|t-1}^{(m)}\}_{m=1}^M$, with the averaging weights being the predictive probabilities $\{\pi_{t|t-1}^{(m)}\}_{m=1}^M$.

To make the construction of the DMA forecasts in (7) feasible, we need prediction and updating recursions for the model probability π . Following Raftery *et al.* (2010) and Koop and Korobilis (2012), these prediction and updating equations are constructed as:

$$\text{Model Probability Prediction : } \pi_{t|t-1}^{(m)} = \frac{\pi_{t-1|t-1}^{\alpha(m)}}{\sum_{j=1}^M \pi_{t-1|t-1}^{\alpha(j)}} \quad (8a)$$

$$\text{Model Probability Updating : } \pi_{t|t}^{(m)} = \frac{\pi_{t|t-1}^{(m)} f_{\mathbb{N}}^{(m)}(r_t | \mathcal{I}_{t-1})}{\sum_{j=1}^M \pi_{t|t-1}^{(j)} f_{\mathbb{N}}^{(j)}(r_t | \mathcal{I}_{t-1})}, \quad (8b)$$

where $f_{\mathbb{N}}^{(m)}(r_t | \mathcal{I}_{t-1})$ is the predictive density of r_t , given model m and information up to time $t - 1$, and $\pi_{0|0}^{(m)}$ is an initial or prior model probability needed to start the recursions. The relation in (8a) is used as an approximation to the model probability prediction to avoid having to specify an $M \times M$ dimensional model probability transition matrix, which would make model (2010, 2012), Corsi and Renó (2012) and Buncic and Gisler (2016, 2017) for recent empirical evidence).

prediction computationally infeasible when M is large. The α parameter in (8a) is also defined over the $[0, 1]$ interval and interpreted as a ‘forgetting factor’, however, now in the model space.

As a byproduct to the (dynamic) model averaged forecasts, we also form forecasts of r_t based on the best performing model at time $t - 1$. This dynamic model selection forecast (abbreviated as DMS henceforth) is obtained by selecting the model m with the highest predicted probability, i.e., $\max_{\pi} \{\pi_{t|t-1}^{(m)}\}_{m=1}^M$. The DMS forecasts are denoted by $\hat{r}_{t|t-1}^{(\text{DMS})}$.

2.2. Priors and calibrated parameters

The DMA/DMS modelling approach requires the specification of priors for the time varying parameter vector $\hat{\beta}_{0|0}^{(m)}$ and model probabilities $\pi_{0|0}^{(m)}$ for the Kalman Filter to be initialised. We set a shrinkage prior for the parameters, that is, we set $\hat{\beta}_{0|0}^{(m)}$ equal to the $(K_m \times 1)$ dimensional zero vector and $\mathbf{P}_{0|0}^{(m)}$ to a $(K_m \times K_m)$ dimensional identity matrix scaled by $1/\lambda$. For the model probabilities $\pi_{0|0}^{(m)}$ we use an uninformative prior such that all models have equally likely probabilities of being included, viz, $\pi_{0|0}^m = \frac{1}{M}, \forall m = 1, \dots, M$. We further need to set the forgetting factors α and λ , as well as the EWMA smoothing parameter κ . We follow the recommendation of Raftery *et al.* (2010) and specify $\alpha = 0.95$ and $\lambda = 0.99$, which offers a balance between parameter stability and model flexibility. The EWMA smoothing parameter κ is set to 0.97, inline with the recommendation by RiskMetrics (1996) for monthly data. These parameter calibrations are *intentionally* kept the same across all individual equities that are modelled and are not ‘fine-tuned’ to improve the fits.⁴

2.3. Forecasts based on alternative models

To complement our DMA/DMS modelling and forecasting framework, we include two additional approaches in our analysis. As pointed out by Raftery *et al.* (2010), the first one of these turns out to be a special case of DMA/DMS and is obtained by setting the forgetting factors α and λ to unity. Following Raftery *et al.* (2010), we will refer to these models simply as Bayesian

⁴See also Raftery *et al.* (2010), Koop and Korobilis (2012), Buncic and Moretto (2015), Buncic and Piras (2016), among others, on the choice of forgetting factors and their influence on model fit.

Model Averaging and Selection methods, which are abbreviated as BMA and BMS, respectively. Model Averaging has a long history in the statistics literature, going back to the seminal work of Leamer (1974) and Hoeting *et al.* (1999). In this context, BMA can be thought of as a precursor to DMA. The second alternative model that we employ is a recursively estimated ‘*kitchen sink*’ model, which includes all x_{t-1} regressors as control variables in the prediction model. Due to its simple structure, this model is estimated by ordinary least squares (OLS) and updated at each time period as new information becomes available.

There exist other stock selection models which use similar factors, but different modelling frameworks. For instance, Bloch *et al.* (1993) and Guerard *et al.* (2015) use robust regression techniques such as weighted latent roots models to select stocks, while Beaton and Tukey (1974) use a bi-square criterion. Despite these alternative approaches, we will restrict our evaluation analysis to the ones listed above.

3. Data

We apply our forecast rank tailored portfolio construction methodology to equities from five major stock price indices for which sufficiently detailed accounting data are available. These are: *i*) Deutscher Aktienindex (DAX), *ii*) Cotation Assistée en Continu (CAC), *iii*) Financial Times Stock Exchange 100 Index (FTSE), *iv*) Swiss Market Index (SMI), *v*) Standard & Poor’s 500 (SPX). Our selection of equity indices is driven by the reliability of detailed corporate accounting data, consistent use of accounting standards, and availability of data. All corporate accounting and equity price data are obtained from Bloomberg.⁵ The corporate accounting data were retrieved at a monthly frequency, while the equity price data are converted from daily Bloomberg prices (PXLAST) to end-of-month data, using the last trading day of the month for the monthly series. The time frame of our empirical analysis is from 2009:06 to 2015:07.

We follow standard practice in the literature and use a 1/3 in-sample and 2/3 out-of-sample

⁵For simplicity and due to limited information on revisions in corporate accounting data, we disregard possible revisions in these data, and use the latest published data as of July 2015.

split. We require at least 25 time series observations of the corporate accounting data for a stock to be included in the analysis. For the investment strategy, we consider all stocks that are a component of the respective equity index at the date the investment decision is made. In the section below we describe and motivate our predictor variables upon which the forecasts will be based.

3.1. Predictor variables

Factor models, as popularised by Ross (1976), assume that the expected return of any security is a linear combination of a systematic and an idiosyncratic factor. For instance, the capital asset pricing model (CAPM) of Sharpe (1964) is an asset pricing model with only one factor, the beta of the stock, which measures the stocks' systematic sensitivity to the market. The CAPM was modified by Fama and French (1992) in the size and value dimension, while the four factor model of Carhart (1997) allows for momentum as another additional factor to be included.

We use three different groups of factors as predictor variables to obtain information about the driving force behind a stock's price movements. These three factor groups are: *i*) a value factor group, *ii*) a quality factor group, and *iii*) a momentum factor group.

The value factor group consists of the Price to Earnings (PE) ratio, the Cash-Flow to Price (CFP) ratio, and the Sales to Price (SP) ratio. The PE ratio has a long history as a value factor, going back to fundamental valuations as outlined in Graham (1934). The study by Easton *et al.* (1992) found a strong correlation between earnings and stock returns, especially when considering longer term horizons. Bloch *et al.* (1993), Haugen and Baker (2010) and Guerard *et al.* (2013) show that the use of value ratios such as the Cash-Flow to Price or the Sales to Price ratio have predictive power for stock returns in their cross-sectional analysis.

The momentum factor group consists of three relative momentum factors, that is, relative to a 36 month moving average to capture possible local trend effects. These are the relative strength of: Price to Earnings (RPE), Cash-Flow to Price (RCFP) and Sales to Price (RSP). Notice here that we follow the factor pricing literature and focus on momentum in earnings, cash-

flow, and sales (deflated by prices), rather than on price momentum (see, for instance, Hou *et al.* (2017) for a range of different momentum factors that are used in this literature). We take a moving average of the ratios to construct a local trend with the intention of removing the effect of local low frequency movements from the momentum series.

The quality factor group consists of three variables constructed by Bloomberg that show analyst’s consensus one year-ahead price targets. More specifically, the first quality variable is the one year-ahead target price (TP). The second is the analysts’ revision to the one year-ahead target price from the previous period (TPR), expressed as a percentage of the initial target price from the previous period. The third quality factor is defined as a negative rating revision (RRN), which is a binary variable that is equal to 1 if the consensus rating outlook is negative (downward revision), and 0 otherwise.

In [Table 1](#), we list all three groups of factor variables that we use as predictors, with short names listed in column one, a longer description in column two, and their exact calculation is shown in column three. For the remainder of the analysis, we combine these three groups of factor variables to form the predictor variable $\mathbf{x}_t^{(i)}$ at time t , for stock i . That is, $\mathbf{x}_t^{(i)}$ is defined as:

$$\mathbf{x}_t^{(i)} = \left[\text{PE}_t^{(i)}, \text{CFP}_t^{(i)}, \text{SP}_t^{(i)}, \text{RPE}_t^{(i)}, \text{RCFP}_t^{(i)}, \text{RSP}_t^{(i)}, \text{TP}_t^{(i)}, \text{TPR}_t^{(i)}, \text{RRN}_t^{(i)} \right]. \quad (9)$$

To alleviate problems with extreme outliers in the accounting data, we Winsorize the data at the $[\cdot 01, \cdot 99]$ interval. Also, the value factors (ie., the PE, CFP, and SP variables) are transformed by using the monotonic and continuous log-modulus transformation of [John and Draper \(1980\)](#).⁶ The log-modulus is, in contrast to a standard log transformation, continuous around zero and applicable to values below zero. It is thus useful for series with possibly negative values. As with a standard log-transform, the log-modulus transform increases normality, and mitigates (any remaining) outliers in the data.

In [Figure 1](#) and [Table 2](#) we provide histograms and summary statistics of the predictor vari-

← [Table 1](#)
about here

⁶That is, the log-modulus transform on variable \mathbb{N} is defined as: $\log\text{-mod}(\mathbb{N}) = \text{sign}(\mathbb{N}) \times \log(|\mathbb{N} + 1|)$.

ables. Our intention here is to give the reader a brief visual description of the data, without discussing the series in any greater detail to conserve space. These histograms and statistics are provided jointly across all companies and over the entire sample period that we consider. Note here, that although we analyse the data for every company separately and not cross-sectionally, the information of the combined data may seem of limited value. However, the histograms in [Figure 1](#) provide a quick overview of the predictor variables' distributions in terms of location, scale and outlying observations.

[← Figure 1
about here](#)

In [Table 2](#), we report means, medians, and standard deviations, as well as information coefficients (ICs) for each predictor variable. The IC is defined as the Spearman correlation coefficient between a factor at time t and next period's equity return (see, for instance, [Grinold and Kahn \(2000\)](#) for more details and its use in finance). The IC is commonly used as a preliminary indicator of the forecasting ability of a factor ([Hua and Qian, 2004](#)). From the results reported in [Table 2](#), we can see that the magnitude of the ICs are in line with other studies. For instance, [Guerard *et al.* \(2015\)](#) report an IC of 0.037 for the Earnings-to-Price ratio, and for the combined consensus analyst forecast an IC value of 0.04, which is consistent with our findings of -0.02 for the PE (note the inverse definition here) and our range of -0.01 to 0.04 for the analyst forecast variables (RRN, TP, TPR), respectively. The signs of the ICs are also according to our expectations from a valuation perspective.

[← Table 2
about here](#)

4. Forecast evaluation

Our dataset spans the sample period from 2009:05 to 2015:07. We use a standard 1/3 in-sample and 2/3 out-of-sample split in our model evaluation. This leaves us with 24 in-sample date points and 50 out-of-sample (OOS) data points over which the models can be evaluated. Note here that we intentionally allow for a larger out-of-sample evaluation period, as our objective is out-of-sample forecasting and portfolio construction. Also, recall that both, DMA/DMS and BMA/BMS, do not contain any parameters to be estimated. All '*forgetting factors*' as well as

the EWMA smoothing parameter are calibrated following recommendations in earlier studies. The choice of a shorter in-sample period should therefore not affect our forecasting results in a negative way. Note here again that we do not tailor the ‘*forgetting factor*’ parameters to the individual equities of interest, but keep them the same across all 896 stocks that are forecasted. This leaves no room to fine-tune these parameters to improve our out-of-sample results.

4.1. Evaluation setting and criteria

We assess the out-of-sample forecast performance of our proposed modelling approach by following the mainstream finance literature. That is, we employ the methods used by Rapach *et al.* (2013), Neely *et al.* (2014), Buncic and Piras (2016), Buncic and Tischhauser (2017) and many others and evaluate the forecasts in terms of the Campbell and Thompson (2008) out-of-sample R^2 (denoted by R_{OOS}^2 henceforth) and the Clark and West (2007) Mean Squared Forecast Error (MSFE) adjusted t -statistic, which we denote by CW – statistic henceforth. In line with recent practices (see Campbell and Thompson (2008), Goyal and Welch (2008) and others), we use the recursively estimated historic average (HA) as the benchmark model for each equity return.

To formalise the notation used below, let $\hat{e}_{t+1|t}^{(\ell^*)}$ denote the (one-step ahead) forecast errors from prediction model ℓ^* , where $\ell^* = \{\text{HA}, \ell\}$ and $\ell = \{\text{DMA}, \text{DMS}, \text{BMA}, \text{BMS}, \text{OLS}\}$.⁷ These forecast errors are computed as:

$$\hat{e}_{t+1|t}^{(\ell^*)} = (r_{t+1} - \hat{r}_{t+1|t}^{(\ell^*)}), \quad (10)$$

with corresponding MSFEs being

$$\text{MSFE}^{(\ell^*)} = \frac{1}{T_{OOS}} \sum_{t=T_{IS}}^T \hat{e}_{t+1|t}^{2(\ell^*)}, \quad (11)$$

where T_{OOS} and T_{IS} denote, respectively, the number of out-of-sample and in-sample observa-

⁷This applies again to each equity i , but for matters of convenience in notation, we do not index over the individual equities that are included.

tions. The Campbell and Thompson (2008) $R_{OOS}^{2(\ell)}$ for model ℓ , relative to the HA forecast is then computed as:

$$R_{OOS}^{2(\ell)} = 1 - \frac{\text{MSFE}^{(\ell)}}{\text{MSFE}^{(\text{HA})}}. \quad (12)$$

Intuitively, the $R_{OOS}^{2(\ell)}$ statistic in (12) measures the reduction in the MSFE of the proposed model relative to the HA benchmark model, with $R_{OOS}^2 > 0$ ($R_{OOS}^2 < 0$) being an indication that the proposed model performs better (worse) than the benchmark model.

The Clark and West (2007) t -statistic is computed (again relative to the HA model) as:

$$\text{CW} - \text{statistic}^{(\ell)} = \frac{\overline{cw}^{(\ell)}}{\sqrt{\text{Var}(\overline{cw}^{(\ell)})}}, \quad (13)$$

where $\overline{cw}^{(\ell)} = T_{OOS}^{-1} \sum_{t=T_{IS}}^T cw_{t+1}^{(\ell)}$ and $\text{Var}(\overline{cw}^{(\ell)})$ is the variance of the sample mean, which is obtained as the heteroskedasticity and autocorrelation (HAC) robust t -statistic on the intercept term from a regression of $cw_{t+1}^{(\ell)}$ on a constant. The $cw_{t+1}^{(\ell)}$ sequence is constructed as:

$$cw_{t+1}^{(\ell)} = \left[\hat{e}_{t+1|t}^{2(\text{HA})} - \hat{e}_{t+1|t}^{2(\ell)} \right] + \left[\hat{r}_{t+1|t}^{(\text{HA})} - \hat{r}_{t+1|t}^{(\ell)} \right]^2. \quad (14)$$

The CW – statistic implements a test of the null hypothesis that the MSFE of the benchmark HA model is equal to the MSFE of the forecasts from model ℓ , against the one sided alternative that the benchmark’s MSFE is greater than that of model ℓ . A rejection of the null hypothesis hence suggests that forecasts from model ℓ are (on average) significantly better than the historic average.⁸

In addition to the out-of-sample R^2 and the CW – statistic, we also compute and plot the cumulative difference of the squared forecast errors from the HA and ℓ models’ forecasts over the out-of-sample period. This cumulative difference (denoted by cumSFE) is commonly used in the equity premium forecasting literature as a tool to highlight the predictive performance of

⁸It should be highlighted here that the CW – statistic is particularly suitable in the given context, as it is designed for a comparison of *nested* (forecasting) models. Our benchmark model is the HA model, which can be obtained from any of the proposed models by just including a constant term in the prediction model.

the proposed model relative to a benchmark over time (see Goyal and Welch (2008) and Rapach *et al.* (2013), among many others). In our setting, this difference is computed as:

$$\text{cumSFE}_{t+1}^{(\ell)} = \sum_{t=T_{IS}}^{T_{OOS}} \left(\hat{e}_{t+1|t}^{2(\text{HA})} - \hat{e}_{t+1|t}^{2(\ell)} \right), \quad (15)$$

where a value of $\text{cumSFE}_{t+1}^{(\ell)}$ above zero suggests that the forecasts of the HA benchmark are worse than those of model ℓ .

4.2. Forecast evaluation results

Aggregate out-of-sample R^2 values of Campbell and Thompson (2008) $\left(R_{OOS}^{2(\ell)} \right)$ for all 5 models $\ell = \{\text{DMA, DMS, BMA, BMS, OLS}\}$ over the evaluation period from 2011:06 to 2015:07 are presented in Table 3. The first column of Table 3 shows the indices of interest, together with the number of individual stocks included in each index (N). Columns two to six provide the average $R_{OOS}^{2(\ell)}$ values for the 5 forecasting methods employed. Note that these $R_{OOS}^{2(\ell)}$ values are relative to the historic average (HA) benchmark, as defined in (12), so that a positive value suggests an improvement of the considered model over the HA benchmark. The averages that are provided here are simple, equally weighted arithmetic means, and are provided as a summary measure only. They do not take account of the market capitalisation of the individual stocks in the indices.

[← Table 3
about here](#)

Looking over the results presented in Table 3, one can initially notice how poorly the OLS based ‘*kitchen sink*’ model, which is based on all regressors and an expanding estimation window, performs. All R_{OOS}^2 values, whether they are averaged over the 896 stocks that are available, or when aggregated to the individual index level, are decisively negative, suggesting a substantially worse performance than the historic average. The four model averaging/selection based approaches, whether dynamic or static, vastly outperform the ‘*kitchen sink*’ model. Overall, model averaging appears to perform slightly better than model selection, with the static approach (BMA/BMS), where the forgetting factors are set to unity, producing marginally larger

improvements. These aggregate results can be confirmed at the individual company level from [Table 4](#).

In [Table 4](#), we present MSFEs for each individual equity that is included in the five indices. In columns one and two of [Table 4](#), we list the index of interest as well as the Bloomberg Ticker name of the individual firm that is analysed. In columns three to seven, the MSFEs of the 5 different forecasting models are reported, showing also the levels of statistical significance of the improvement in the MSFEs based on the Clark and West (2007) t -statistics (CW – statistics), which are annotated using standard asterisk notation.⁹ From the disaggregate results in [Table 4](#) it is evident that the predictive improvements are fairly evenly spread over the 5 different indices, that they are sizeable, with most MSFE reductions in the 7% to 17% range, and that they are significant (mainly) at the 1% and 5% level. Note here also that, from the DMA results, there are 336, 281, and 173 individual equities that have significantly smaller MSFEs than the benchmark HA model at the 10%, 5%, and 1% levels, respectively. With 896 stocks to test and a nominal test size of 1%, one would normally expect about 9 false positives on average, i.e., rejections of the null hypothesis when it is true. The improvements that we present here are thus unlikely to be due to chance or p -hacking, that is, due to the large number of tests that are performed. Note here again that we do not modify the model parameters, the ‘*forgetting factors*’, in the DMA framework, but keep these fixed for all individual equities that are predicted.

Overall, our results suggest that the DMA forecasting approach performs favourably across the 896 stocks, with improvements similar in magnitude to the principal component and reduced rank forecasting models employed by Deistler and Hamann (2005). Deistler and Hamann (2005) focus on a set of 7 banking stocks listed on the EURO STOXX50 exchange, using a daily frequency. They report out-of-sample R^2 values of up to 3.2% for the best performing principal component model, and up to 10% for the best reduced rank model, with averages of 1% and 8.29%, respectively. Compared to our sample of 896 stocks, we can see that the DMA approach provides forecast improvements in line with those attained with the PCA model by Deistler

⁹We follow the convention in the empirical finance literature and use {*, **, ***} to denote significance at the 10%, 5%, and 1%, respectively, using one sided (upper tail) t -tests.

and Hamann (2005), but performs noticeably worse than their preferred reduced rank model. It should be pointed out here though that we have a much broader and more heterogeneous set of firms included in the 5 equity indices that we analyze. Having only 7 banking stocks makes it possible to choose the predictor variables included in x_t to be highly relevant for banks specifically, rather than relying on a small set of more broadly relevant financial ratios for valuation.

Before we discuss how the equity portfolios are constructed with our framework, we provide a final visual impression of the out-of-sample forecast performance of the proposed modelling approach of the individual stocks by showing plots of the empirical distributions (histograms) of the R_{OOS}^2 values of all 896 equities that are analyzed in [Figure 2](#). As can be seen from [Figure 2](#), all four subplots show highly positively skewed R_{OOS}^2 values, suggesting that the presented models and predictor variables (factors) produce particularly good forecasts for some equities. For instance, from the DMA results, 283, 166 and 81 forecasts produce R_{OOS}^2 values above 5%, 10% and 15%, respectively. Thus, for nearly 10% of the stocks, that is, for 81 equities, the R_{OOS}^2 values are above 15 percentage points. This is a substantial improvement. It highlights that, at the cross-sectional level, large gains in forecast accuracy can be obtained for some equities when a flexible prediction model is utilized.

5. Portfolio construction

We now describe how the predictions from our proposed forecasting models can be used to build a trading strategy based on combining and weighting the factors. Our main intention here is to assess empirically what economic gains one can achieve from using our forecast rank tailored portfolio construction methodology. There exists a wide variety of methods to evaluate the performance of factors, with some of these relying on portfolio sorts, factor models, or factor portfolios in more general (see [Fabozzi et al. \(2010\)](#) for an extensive discussion of selection criteria).

Many approaches apply naive portfolio sorts, where factor weighting is static. Stocks are

grouped into quintiles or deciles, in which the constructed factor portfolio replicates the respective factor influence. By examining the return behavior of the portfolio, the return performance across time and in the cross-section can be used to gain information on the excess return attached to each factor. Although such approaches are intuitive and widely employed, they fail to account for the time varying relative performance of the factors and the cross-correlation of these factors. As discussed earlier, Linnainmaa and Roberts (2018) have recently raised the point that many well known factors fail to produce consistent excess returns when different time periods are employed in the evaluation windows.¹⁰

To test our proposed forecast ranked portfolio construction framework’s economic significance, we implement a long only equity strategy based on the forecasts from our proposed models, and follow the three step portfolio construction procedure outlined in Grinold and Kahn (2000).¹¹ That is, we initially predict the returns, then we construct the portfolio, and last we evaluate the performance out-of-sample. Note here that the forecasts presented in Section 4 form the basis of our ranking mechanism.

5.1. Timing, ranking and trading strategy

The portfolio evaluation period is chosen to be in line with the statistical forecast evaluation period used in Section 4, that is, from 2011:06 to 2015:07. We compute the portfolio values from end-of-month closing prices. For each time period in the evaluation, we rank the individual equities of each index according to their projected values at time t , that is, we sort along the predicted returns $\hat{r}_{t+1|t}$ from highest to lowest. We then construct a portfolio of the stocks with the highest predicted return $\hat{r}_{t+1|t}$. For each index we invest equally in the top 25% of the

¹⁰In Bloch *et al.* (1993), a comparison of different regression methods for cross sectional factor weighting is provided, which discusses multi-collinearity concerns and the effect of outlier distortion on portfolio evaluation results. Bloch *et al.* (1993) compare ordinary least squares (OLS) and robust regression techniques with Beaton and Tukey’s (1974) bi-square criterion, latent roots and weighted latent roots (WLRR) models. Using the predicted values for a mean-variance portfolio optimization problem, they show that WLRR based portfolios are able to outperform OLS based ones by generating higher Sharpe ratios.

¹¹We present results for DMA/DMS only, although the results from the BMA/BMS approach yield similar portfolio performance, much in line with what we found from the statistical evaluation. To avoid repetition, we only present the results from the DMA/DMS frameworks.

forecast-ranked constituents. This means that in each equity index portfolio we hold 10 stocks in the CAC, 7 stocks in the DAX and the SMI, 125 stocks in the SPX, and 25 stocks in the FTSE.

In our simplified, synthetic trading model, all trades are executed at the beginning of the month before markets open, using the previous month's closing prices as given. The portfolio is initially created on June 1, 2011 and then re-balanced every first day of the month over the portfolio evaluation period. We assume that any dividends or earnings that are distributed are re-invested at the current price at the beginning of each month when the portfolio is re-balanced.

5.2. Transaction costs

Portfolio turnover involved in active management can produce large transaction costs that could render re-balancing inefficient by nullifying any gains that the statistical superiority of our stock selection framework generates. To account for portfolio re-balancing costs in our trading strategy, we include a general measure of transaction costs in the evaluation of the constructed portfolios, following an approach similar to that of [Guerard *et al.* \(2015\)](#). Explicit costs such as commissions, market fees, clearing and settlement costs, are combined with implicit costs such as compensation for inventory, liquidity and other costs into one '*cost factor*'. Estimates of this one '*cost factor*' are provided by [Elkins and McSherry \(2016\)](#) in a subscription based database, which is also used in other studies. For instance, [Pollin and Heintz \(2011\)](#) compute average two-way (buy-sell) transaction costs of 47.3 basis points (bps) for U.S. stocks, and 57.2 bps for U.K stocks over the period from January 2009 to December 2011 using the [Elkins and McSherry \(2016\)](#) database. For the SPX, [Brandes *et al.* \(2012\)](#) find transaction costs of 40 bps to be appropriate. In international dimensions, [Domowitz *et al.* \(2001\)](#) compare transaction costs in 1998 to 2000 across global markets and report a global mean of 60 bps.

Although some of these figures seem outdated, they indicate that international trading costs are approximately between 40 to 60 bps. Based on these studies, we use a simple trading cost model that assumes a fixed price of 50 bps per trade, thereby disregarding any variation across

international markets, and the possible influence of scale effects on the cost of a trade. At any time t , the cost of executing a trade of value δ (ie., the quantity times the price, irrespective of whether it is a buy or sell order) is computed as 50 bps times the value of the trade, that is, $0.005 \times \delta$. Initial investment costs are assumed to be the same for the passive benchmark index investment strategy and the active portfolio strategy based on the forecasts from the DMA/DMS models. Conceptually, our approach to tackle transaction costs is different from Focardi *et al.* (2016), who calculate a break-even transaction costs given a simulated trading result, whereas we assume a fixed fee linked to each transaction. They find for the long-only strategy break-even transaction cost to be between 15 and 46 basis points, which is somewhat smaller than our more conservatively chosen transaction cost of 50 bps.

5.3. Trading strategy evaluation

We evaluate the performance of the trading strategy by reporting a set of summary results for each forecasting model's constructed portfolio and the respective benchmark index. That is, we compute the annualized mean return, the annualized standard deviation, the maximum drawdown, the portfolio's benchmark Alpha, and the information ratio. In the notation that follows, we use $\iota = \{\text{DAX, SPX, FTSE, CAC, SMI}\}$ to denote the index of interest, and $\mathcal{S} = \{\text{DMA, DMS}\}$ for the forecasting model or portfolio construction strategy. The maximum drawdown (MDD) is defined as the peak monthly loss in each reported year of the out-of-sample period, that is:

$$\text{MDD}(\mathcal{S}, \iota) = \max_{\tau \in (T_0, \mathcal{T}_T)} \left[\max_{t \in (\mathcal{T}_0, \tau)} \{\mathcal{V}_t(\mathcal{S}, \iota) - \mathcal{V}_\tau(\mathcal{S}, \iota)\} \right], \quad (16)$$

where \mathcal{T} indices the period of interest, and $\mathcal{V}_t(\mathcal{S}, \iota)$ is the value of the portfolio at time t , of strategy \mathcal{S} and index of interest ι . MDD thus measures the downside risk of the portfolio strategy, and can be compared to the MDD of the respective benchmark index.

The (ex-post) benchmark Alpha is obtained by regressing the return of strategy \mathcal{S} and index

of interest ι on the return of the corresponding benchmark index ι . More specifically, we have the relations:

$$r_t(\mathcal{S}, \iota) = \alpha(\mathcal{S}, \iota) + \beta r_t(\iota) + \epsilon_t. \quad (17)$$

The term $\alpha(\mathcal{S}, \iota)$ in (17) captures the extra return one obtains from following the portfolio construction strategy \mathcal{S} , which is in excess of the return of the (passive) benchmark investment in index ι .

The information ratio (IR) is constructed as:

$$\text{IR}(\mathcal{S}, \iota) = \frac{\alpha(\mathcal{S}, \iota)}{\sigma(\mathcal{S}, \iota)}, \quad (18)$$

where $\sigma(\mathcal{S}, \iota)$ denotes the annualized standard deviation of the excess return of strategy \mathcal{S} (in excess of the investment benchmark index, also known as the *'tracking error'*), and $\alpha(\mathcal{S}, \iota)$ is the benchmark Alpha from (17). The IR summarizes the risk-adjusted performance of the active management strategy. It can be perceived as an indicator of the *'value added'* of the active strategy \mathcal{S} . The use of IR is widespread in the portfolio management literature. For instance, Sharpe (1994) recommends the IR over the Sharpe ratio to evaluate the performance of an active portfolio. Grinold and Kahn (2000) view the maximization of IR as the main objective of active portfolio management. All values that we report in the tables below are annualized values over the out-of-sample values from 2011:06 to 2015:07.

6. Trading Strategy Results

We now present the portfolio evaluation results. In Panels (a) and (b) of [Figure 3](#) we plot the relative performance of our DMA, respectively, DMS based strategy against a passive investment in the index. That is, the performance of the forecast ranked portfolios is benchmarked against the passive indices $\iota = \{\text{DAX, SPX, FTSE, CAC, SMI}\}$, with all plots in [Figure 3](#) showing the cumulative return (or total value) of the portfolios over the out-of-sample period from 2011:06

to 2015:07 in excess of their respective passive indices. The value of the portfolio is normalized to unity in 2011:06. Transaction costs are explicitly accounted for, following the procedure described in [Section 5.2](#).

[← Figure 3
about here](#)

As can be seen from the plots in [Figure 3](#), our forecast based strategies, irrespective of whether DMA or DMS is used as the framework that generates the predictions and hence rankings of the models, can outperform the passive benchmark indices of the FTSE, SPX and, at times, of the CAC. Our active strategy performs particularly well for the portfolio of the FTSE index, yielding a cumulative gain factor of approximately 1.4 and 1.3 for DMA and DMS based forecast ranks, respectively. For the SPX, cumulative returns are positive only from the second half of 2013 onwards, but remain positive until the end of the out-of-sample period in 2015:07. The performance relative to the index is thus noticeably weaker. For the CAC, the models perform well for most of the out-of-sample period, in particular for the first few years following 2011, but drop off towards the end of the sample, with some noticeable drawdown visible in the DMA ranked portfolio from the end of 2013 onwards. The DMS ranked portfolio seem to perform best (relative to DMA) for stocks of the CAC index.

The overall performance of our tailored portfolios for the SMI and the DAX are disappointing. Both active strategies are not able to outperform a passive investment in these respective benchmark indices. Although we do not report the results here, this is also true even when transaction costs are reduced. We have investigated whether adjusting the size of the transaction costs would alter this conclusion substantially, that is, by dropping transaction costs to 25 bps, 10 bps, and finally 0 bps. However, the results do not change markedly enough to generate gains in the order of magnitude observed for the other three indices.¹² Evidently, the SMI and the DAX are the two indices with the smallest number of constituent stocks, while the CAC is the third smallest. As outlined earlier, using the top 25% ranked forecasts from the DMA/DMS prediction models results in 7 stocks to be included in the SMI and DAX tailored portfolios, and 10 stocks in the CAC. It could thus be the case that the relatively poor performance is

¹²To conserve space, we do not report these results here, but make them available upon request.

due to the stock selection being already extremely concentrated in these indices, offering less variability overall. One should also note that the DAX and the SMI indices have rebounded much stronger than any of the other 3 indices since the end of the financial crisis, with global equity prices bottoming out in March 2009. As such, these two indices present a difficult to beat benchmark.

The choice of the prediction model when constructing the portfolios, that is, being based on either model averaging or model selection, appears to be of less importance for the overall performance of the portfolios that are constructed. Particular for the FTSE and the SPX, the overall co-movement and direction in the DMA and DMS based portfolios are largely aligned for much of the out-of-sample period. For the DAX and SMI, the DMS based strategy seems to perform marginally worse overall, nevertheless yielding somewhat higher returns than the DMA based strategy at the beginning of the sample, while ending in the same negative range at the end of the five year period. A noticeable difference in the performance of DMS relative to DMA is only visible for the CAC, where the DMS based strategy outperforms its DMA counterpart. DMS based cumulative returns are nearly uniformly above those from DMA over the entire out-of-sample period, where a decisively higher portfolio value of about 1.2 as opposed to 1.1 at the end of the evaluation period is reached.

6.1. Detailed results at the index level

In [Table 5](#) we offer a more detailed overview of the performance of the DMA/DMS based portfolio ranking strategies. The table is arranged in the following column blocks. Under column 1 and 2, the index of interest and the time period (Year) that is analysed are shown. The time period column is aggregated in rows to a total value over the entire out-of-sample period marked by 'All' in the table, as well as annual aggregates for each year from 2011 to 2015. Column blocks (3–5), (6–8), and (9–11) list, respectively, the annualized return, the annualized standard deviation, and the maximum drawdown as defined in (16) for the indices of interest $\iota = \{\text{DAX, SPX, FTSE, CAC, SMI}\}$, as well as the corresponding DMA/DMS forecast

ranked portfolios on those indices. The last two column blocks under the headings ‘Alpha’ and ‘Info. Ratio’ report the respective benchmark Alpha and the information ratio (IR) as defined in (17) and (18), which are computed relative to the index of interest ι . These are reported only over the full sample period, with corresponding robust t -statistics in parenthesis.

[← Table 5
about here](#)

Recall that the benchmark ‘Alpha’ gives the excess return relative to a passive investment index benchmark, but does not adjust the excess return for the risk associated with the portfolio. The information ratio (IR) corrects for this risk by deflating by the tracking error. The tracking error computed as the annualized standard deviation of the excess return of the portfolio measures this risk. Given that the tracking error cannot become negative, a positive IR implies that the tailored portfolio outperforms its passive underlying benchmark index, which means that a risk averse investor receives greater utility from the forecast based stock selection.

Focusing initially on the IRs, we can see that the active portfolio selection strategies based on DMA/DMS forecasts add economic value, with the only obvious exception being the strategies on the CAC. On average, these are zero (or even negative) over the out-of-sample period, as is evident from the ‘All’ row. This result is interesting and in stark contrast to the finding from [Figure 3](#), where the active DMS based strategy was found to outperform the passive index. Examining the corresponding ‘Alpha’ values, it seems that the relative performance has to be due to the ‘Beta’ of the portfolio, that is, its co-movement with the market. For the SMI, the magnitude of the economic value added is almost zero, where an ‘Alpha’ of 1% for the DMA/DMS based active strategies is attained. For the DAX, SPX, and FTSE, the Alpha’s are 7%, 4%, and up to 11% when a DMA based portfolio ranking strategy is used for all three indices.

Interestingly, the standard deviations of the actively managed strategies have a range of values that are more or less in line with those from the passive benchmark indices, with average differences being of an order of magnitude of less than one percentage point. In some years, for instance, in 2015 the standard deviations of the DMA/DMS based portfolios are less than the passive benchmark indices for SPX and FTSE, but yield a higher return. For the DAX and CAC, the standard deviation of the active strategies are equal to those from the benchmark, with

returns again higher over the full out-of-sample period. This illustrates some of the attractive features that can be obtained with our forecast ranked tailored portfolios. Not only can risk be contained, but it can be done with a minimal loss in (expected) return, with returns in some years even outperforming the benchmark.

Utilizing a comparable factor set, albeit with a static rather than a dynamic forecasting approach, but with a more complex mean-variance optimizing portfolio mechanism, *Guerard et al. (2015)* are able to achieve IRs of a similar (or slightly higher) magnitude for the SPX. For their main model which lies on the efficient frontier during the 1999 to 2011 period, they report IRs between 0.44 and 0.78, depending on the chosen calibration of one of the tuning parameters. Given this result, it may be possible to further extend our naive equal-weighting based portfolio sorting by implementing a more advanced portfolio optimization framework. Nevertheless, we leave this avenue for potential future work.

7. Conclusion

This paper introduces a novel approach to construct equity portfolios. We employ the highly flexible and robust dynamic model averaging (DMA) framework of *Raftery et al. (2010)* and *Koop and Korobilis (2012)* to construct return forecasts of a large cross-section of individual stocks contained in the SP500, FTSE100, DAX30, CAC40 and SPX30 headline indices using value, momentum, and quality factors as predictor variables. Given the individual forecasts, we rank the equities from best performing to least — relative to a historic average benchmark — and then take the top quartile of the best stocks for each index to construct an equally weighted long only portfolio. Based on this ranking and weighting, we form our so called forecast ranked tailed equity portfolios, and evaluate the performance of these portfolio relative to its own passive benchmark index.

We find that, using a given set of fixed forgetting factors in the DMA prediction framework, highly significant return forecasts relative to the historic average benchmark are obtained for

173 (281) stocks at the 1% (5%) level for a one-month ahead forecast horizon. These statistical improvements in forecast accuracy are furthermore economically meaningful, producing out-of-sample R^2 values above 5% (10%) for 283 (166) of the 895 individual stocks. Constructing equally weighted long portfolios from the top 25% ranked stocks of the forecasts in each headline index generates sizable returns in excess of a passive investment strategy for some indices. These results hold even when transaction costs are accounted for, and when we adjust the excess returns for the embedded risks of that strategy.

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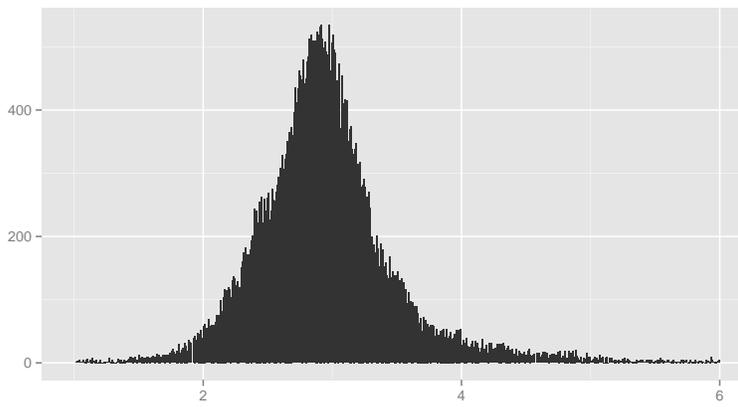
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Figures and Tables

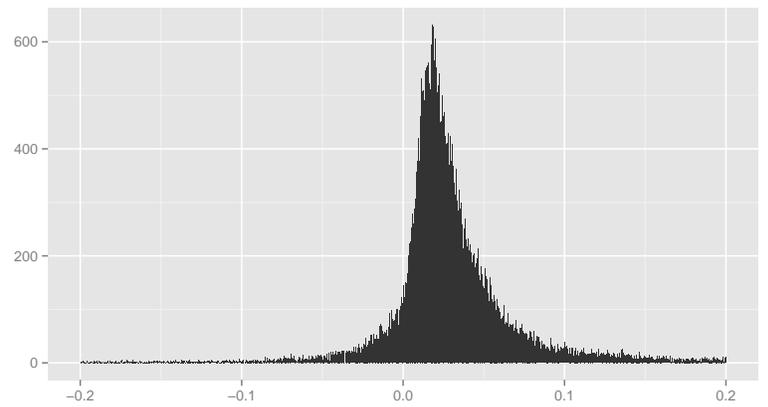
Table 1: Description and calculation of predictor variables

Short name	Full name	Calculation
Value		
PE	Price to earnings	Price (end-of-month) relative to annualized earnings per share trailing twelve-month as stated in the most recent quarterly report.
CFP	Cash flow to price	Cash-Flow as stated in the most recent quarterly report (if not available, earnings plus depreciation) relative to Price (end-of-month).
SP	Sales to price	Sales per share (most recent quarter) relative to Price (end-of-month).
Momentum		
RPE	Relative Price to Earnings	PE relative to the 36-month moving average of PE.
RCFP	Relative Cash-Flow to Price	CFP relative to the 36-month moving mean of CFP.
RSP	Relative Sales to Price	SP relative to the 36-month moving mean of SP.
Quality		
TP	One year ahead Target Price	One year forward consensus target price of analysts, as calculated by Bloomberg relative to current price in period t .
TPR	One year ahead TP revision	Revision (relative) to target price of previous period, computed as: $TP_t/TP_{t-1} - 1$.
RRN	Negative rating revision	Binary variable which is equal to 1 if a downward (consensus) analyst rating revision in period $t - 1$ occurs, 0 otherwise.

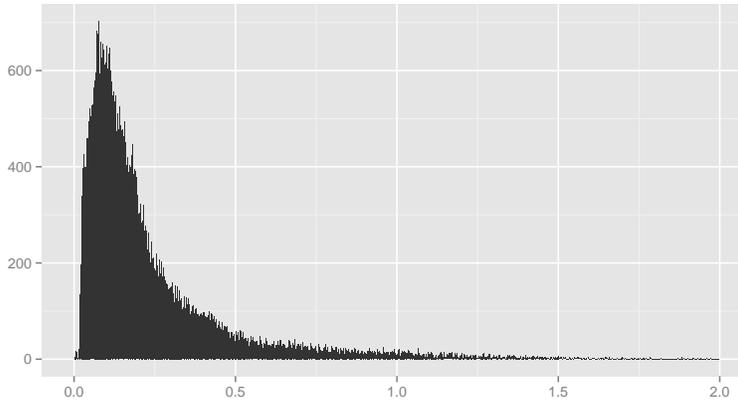
Notes: This table shows the predictor variables that are used in the forecasting models. The first column shows the short names of the predictor variables, followed by the long names in column two, and a detailed descriptions of the construction of the predictors in column three.



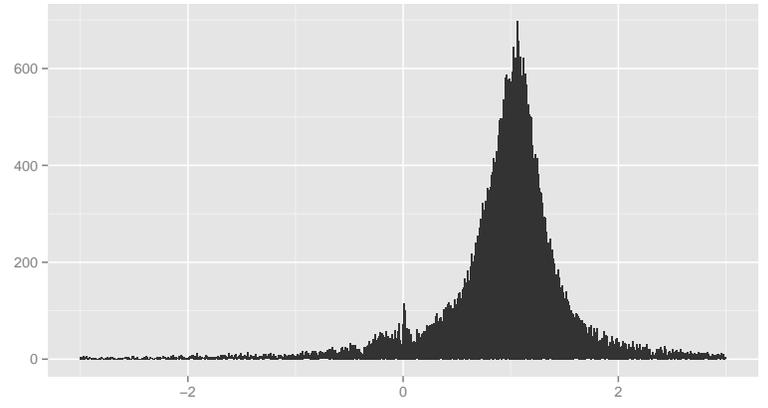
(a) PE



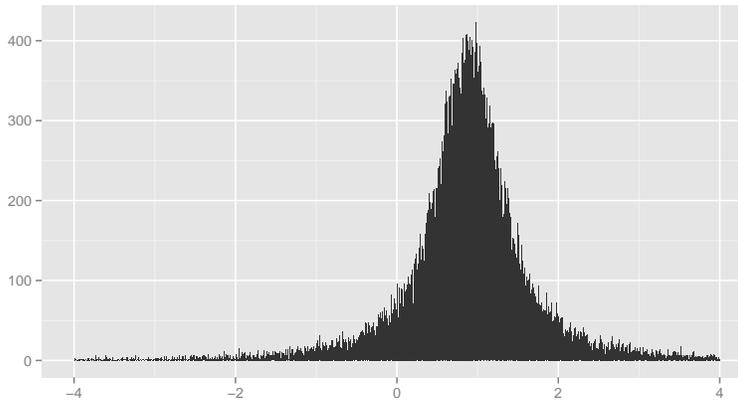
(b) CFP



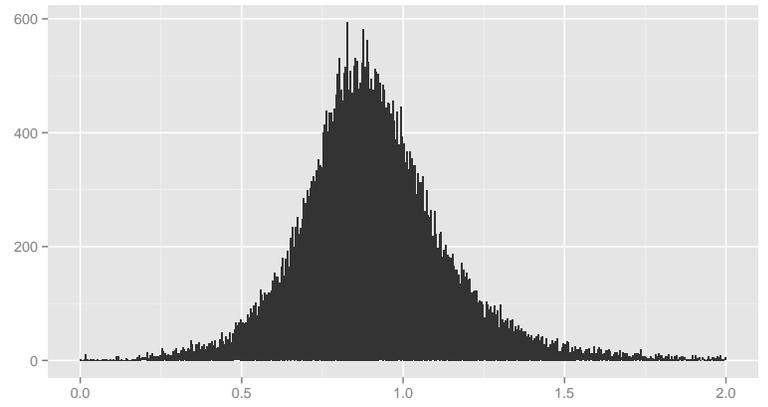
(c) SP



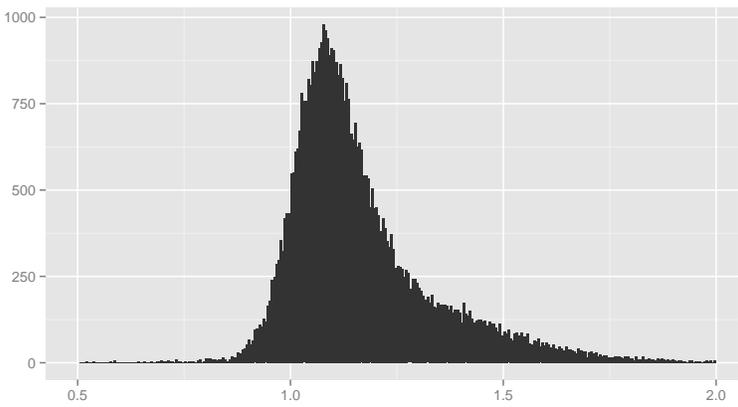
(d) RPE



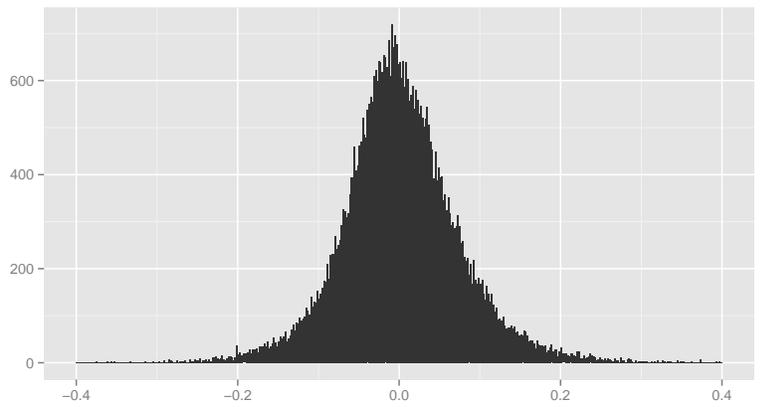
(e) RCFP



(f) RSP



(g) TP



(h) TPR

Figure 1: Aggregate distributions of predictor across all companies over the entire sample period

Table 2: Summary statistics of the predictor variables

Variable	Mean	Median	Std.dev	IC
PE	2.87	2.90	0.96	-0.0209
CFP	0.03	0.02	0.12	0.0639
SP	0.25	0.16	0.30	0.0151
RPE	0.94	1.01	0.85	-0.0133
RCFP	0.90	0.89	0.94	0.0740
RSP	0.91	0.89	0.43	0.0365
TP	1.18	1.12	0.57	0.0336
TPR	0.01	-0.01	0.08	0.0448
RRN	-	-	-	-0.0103

Notes: This table shows common summary statistics of the predictor variables of interest. These are shown in aggregated form across all $N = 896$ companies over the entire sample period from 2009:06 to 2015:07. Note that RRN, that is, negative rating revision, is a binary variable. Due to this, we do not report measures of central tendency or its standard deviation, but only its information coefficient (IC). The IC measures the Spearman correlation between the current value of the predictor variable with next periods equity return.

Table 3: Average out-of-sample R^2 values

Equity Index	DMA	DMS	BMA	BMS	OLS
All ($N = 896$)	2.37%	1.78%	3.41%	3.32%	-117.27%
CAC ($N = 52$)	-0.69%	-0.55%	0.79%	0.33%	-143.68%
DAX ($N = 34$)	3.92%	3.73%	3.62%	3.62%	-196.37%
SMI ($N = 27$)	-0.77%	0.43%	1.49%	1.52%	-210.16%
SPX ($N = 643$)	2.75%	1.96%	3.66%	3.59%	-100.97%
FTSE ($N = 140$)	2.03%	1.62%	3.57%	3.43%	-145.42%

Notes: This table reports the out-of-sample R^2 values (R^2_{OOS}) of Campbell and Thompson (2008) for all models $\ell = \{DMA, DMS, BMA, BMS, OLS\}$ that are considered, relative to the forecasts of the historic average (HA) benchmark. The out-of-sample evaluation period is from 2011:06 to 2015:07. The first column shows the equities belonging to a particular index that is analyzed, together with the number of individual equities included in the index. Columns two to six report the (average) R^2_{OOS} of the 5 different forecasting models, relative to the HA benchmark.

Table 4: Detailed CW – statistic results for every stock that is analysed in each equity index

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
French CAC	AC_FP_Equity	1.0041	1.0061	1.0077	1.0076	2.1133
	AL_FP_Equity	0.9073***	0.9310***	0.8894***	0.9182***	2.0709
	AF_FP_Equity	1.0590	0.9950	0.9956	0.9953	2.0320
	AIR_FP_Equity	0.9810*	1.0036	1.0205	1.0204	1.4643
	ALU_FP_Equity	1.0832	1.0539	1.0315	1.0314	2.1990
	ALO_FP_Equity	1.1869	1.3019	1.0569	1.2471	10.2000
	BN_FP_Equity	0.9434**	0.9360**	0.9362**	0.9362**	1.1717
	BNP_FP_Equity	1.0204	1.0095	1.0103	1.0102	3.2788
	CA_FP_Equity	1.0391	1.0295	1.0308	1.0307	5.3177
	CAP_FP_Equity	1.0449	1.0412	1.0416	1.0413	1.3002
	CS_FP_Equity	1.1765	1.1546	1.1324	1.1324	4.3993
	CO_FP_Equity	0.8998**	0.9321**	0.9310**	0.9310**	2.6617
	DG_FP_Equity	1.0089	1.0174	1.0178	1.0179	1.8942
	DEXB_BB_Equity	1.0884	1.0480	1.0255	1.0504	11.2376
	EDF_FP_Equity	1.0590	1.0293	1.0307	1.0307	1.2077
	EI_FP_Equity	0.9606*	0.9891	0.9827	0.9826	1.1114
	EN_FP_Equity	0.9903	1.0317	1.0307	1.0318	2.4021
	DSY_FP_Equity	1.0678	1.0139	1.0141	1.0141	1.7008
	ENGL_FP_Equity	0.9948	0.9699	0.9701	0.9696	2.0754
	FP_FP_Equity	1.0676	1.0231	1.0245	1.0245	1.4725
	HO_FP_Equity	0.9809	0.9852	0.9872	0.9872	1.5540
	GTO_FP_Equity	1.0385	1.0376	1.0339	1.0339	2.6115
	GTO_NA_Equity	1.0487	1.0335	1.0336	1.0336	1.9111
	FR_FP_Equity	1.0442	0.9959	0.9960	0.9958	2.5196
	KER_FP_Equity	0.9236**	0.9163**	0.9336**	0.9336**	2.2830
	KN_FP_Equity	1.0119	1.1119	1.0012	1.0019	1.4290
	MC_FP_Equity	0.9210***	0.9322**	0.9321**	0.9321**	1.7953
	LR_FP_Equity	0.9471**	0.9341**	0.9288**	0.9286**	1.2838
	ML_FP_Equity	0.9622*	0.9906	0.9940	0.9952	1.2127
	MT_NA_Equity	0.9838	0.9223**	0.9248**	0.9237**	5.1265
	MMB_FP_Equity	1.0280	1.0270	1.0279	1.0279	1.3866
	OR_FP_Equity	1.0381	1.0387	1.0163	1.0163	1.4285
	ORA_FP_Equity	1.0916	1.0946	1.0306	1.0291	1.8984
	PUB_FP_Equity	0.9852	1.0231	1.0051	1.0051	1.2396
	RI_FP_Equity	1.0326	1.0081	1.0088	1.0088	1.5836
	RNO_FP_Equity	1.0358	1.0316	1.0323	1.0322	1.4442
	SAN_FP_Equity	1.0401	1.0402	1.0460	1.0460	1.6556
	SAF_FP_Equity	0.8555***	0.8976***	0.8338***	0.8338***	1.2353
	SGO_FP_Equity	0.9720*	0.9589*	0.9504*	0.9479*	1.8876
	STM_FP_Equity	1.0359	1.0276	0.9968	0.9961	1.7477
SEV_FP_Equity	0.8345***	0.8121***	0.8052***	0.8049***	3.8019	
SU_FP_Equity	0.8916***	0.8925***	0.8919***	0.8919***	5.2471	
SW_FP_Equity	1.0040	1.0160	1.0166	1.0166	1.5358	
SOLB_BB_Equity	0.9997	1.0188	1.0195	1.0194	1.4783	
UG_FP_Equity	1.0253	1.0091	1.0099	1.0099	1.8445	
TEC_FP_Equity	0.8633***	0.8226***	0.8225***	0.8217***	2.2858	
TFL_FP_Equity	1.0257	1.0375	1.0098	1.0098	1.4891	
UL_FP_Equity	1.0185	1.0222	1.0118	1.0118	1.9034	
VIE_FP_Equity	0.9984	1.0613	1.0368	1.0368	1.5626	
UL_NA_Equity	1.0815	1.0119	1.0087	1.0086	2.0808	
VIV_FP_Equity	1.0520	1.0361	1.0364	1.0364	2.9684	
VK_FP_Equity	1.0055	1.0218	1.0282	1.0258	1.9716	
German DAX	ADS_GY_Equity	0.9729	0.9698	0.9724	0.9724	1.4767
	ALV_GY_Equity	1.0360	1.0130	1.0011	1.0135	7.0482
	BAS_GY_Equity	0.8483***	0.8675***	0.8692***	0.8691***	1.2973
	BAYN_GY_Equity	1.0319	1.0456	1.0459	1.0458	2.2099
	BMW_GY_Equity	0.9484**	0.9512**	0.9530**	0.9522**	1.5847
	BEL_GY_Equity	1.0245	1.0177	1.0184	1.0184	1.7693
	DAL_GY_Equity	1.0090	0.9985	0.9996	0.9988	2.7875
	CON_GY_Equity	0.9198**	0.9203**	0.9250**	0.9252**	1.1976
	DBK_GY_Equity	1.0301	1.0028	1.0035	1.0033	4.0074
	DB1_GY_Equity	1.0458	1.0462	1.0420	1.0420	1.5788
	DPW_GY_Equity	1.0598	1.0715	1.0522	1.0522	2.9374
	DTE_GY_Equity	1.0450	1.0271	1.0283	1.0283	1.3287
	EOAN_GY_Equity	1.0381	1.0279	1.0298	1.0298	15.1766
	FME_GY_Equity	0.9489**	0.9191***	0.9187***	0.9187***	1.7047

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Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	HEN3.GY_Equity	0.9184**	0.9247**	0.9251**	0.9251**	1.4861
	FRE.GY_Equity	0.9341**	1.0347	0.9521**	0.9371**	1.4343
	HEL.GY_Equity	1.0064	1.0047	1.0054	1.0054	1.2898
	IFX.GY_Equity	0.7685***	0.7676***	0.7427***	0.7426***	12.0243
	HNR1.GY_Equity	1.0483	1.0241	1.0259	1.0258	1.1875
	LHA.GY_Equity	0.9742*	0.9700	0.9699	0.9699	1.4487
	LIN.GY_Equity	0.9020***	0.8797***	0.8794***	0.8794***	1.7764
	MAN.GY_Equity	0.8940***	0.8867***	0.8966***	0.8960***	2.1135
	MEO.GY_Equity	0.9202**	0.9321**	0.9321**	0.9321**	7.1304
	MRK.GY_Equity	0.9208**	0.9720	0.9720	0.9720	1.2511
	LXS.GY_Equity	0.7942***	0.7929***	0.7867***	0.7829***	2.1213
	MUV2.GY_Equity	1.0285	1.0266	1.0272	1.0272	1.8273
	RWE.GY_Equity	1.0469	1.0349	1.0363	1.0363	2.2335
	SAP.GY_Equity	0.9939	1.0132	1.0138	1.0138	1.4834
	SDF.GY_Equity	0.9945	1.0178	1.0181	1.0180	1.4396
	SIE.GY_Equity	0.8655***	0.8601***	0.8599***	0.8598***	1.2829
	TKA.GY_Equity	0.9615*	0.9420**	0.9425**	0.9424**	2.9409
	SZG.GY_Equity	0.9945	1.0180	1.0183	1.0183	3.3287
	VOW.GY_Equity	0.8855***	0.8541***	1.0055	1.0144	3.2400
	VOW3.GY_Equity	0.8556***	0.8972***	0.9011***	0.9011***	3.6218
Swiss SMI	ABBN.VX_Equity	0.9391**	0.9481*	0.9485*	0.9484*	1.3506
	ADEN.VX_Equity	1.0200	1.0193	1.0304	1.0303	2.0219
	BALN.VX_Equity	1.0293	1.0372	1.0393	1.0377	15.5434
	ATLN.VX_Equity	1.0560	1.0076	0.9990	0.9988	10.6252
	CFR.VX_Equity	0.8754***	0.8647***	0.8469***	0.8468***	1.4986
	CLN.VX_Equity	0.8896***	1.0120	0.8983***	0.8982***	1.5422
	LHN.VX_Equity	1.0061	0.9797	0.9807	0.9807	2.5284
	GIVN.VX_Equity	1.0708	1.0510	1.0527	1.0527	1.7708
	GEBN.VX_Equity	0.9654*	0.9682*	0.9632*	0.9624*	1.6025
	LONN.VX_Equity	1.0032	1.0031	0.9965	0.9964	1.5449
	KUD.SW_Equity	1.0579	1.0331	1.0405	1.0405	1.8137
	NESN.VX_Equity	0.9368**	0.9194**	0.9198**	0.9198**	1.5011
	NOBN.SW_Equity	1.0291	1.0298	1.0329	1.0329	1.4361
	NOVN.VX_Equity	1.0668	1.0358	1.0369	1.0368	1.7942
	ROG.VX_Equity	1.0079	0.9919	0.9902	0.9901	1.7955
	SCMN.VX_Equity	1.0367	1.0137	1.0144	1.0144	4.2240
	SGSN.VX_Equity	1.0418	0.9898	0.9905	0.9904	1.4151
	OERL.SW_Equity	1.1409	1.1982	1.0554	1.0552	2.0519
	SLHN.VX_Equity	1.0185	1.0011	1.0021	1.0021	3.5110
	SREN.VX_Equity	1.1987	1.0255	1.0306	1.0271	5.0436
	SYNN.VX_Equity	0.9569	1.0111	1.0110	1.0110	1.6802
	SYST.VX_Equity	1.0499	1.0321	1.0358	1.0355	4.3681
	UBSN.SW_Equity	1.0512	1.0349	1.0323	1.0321	4.2835
	UBSG.VX_Equity	1.0430	1.0399	1.0327	1.0321	4.9011
	UHR.VX_Equity	0.8636***	0.8281***	0.8089***	0.8086***	1.2752
	ZURN.VX_Equity	1.0608	1.0356	1.0363	1.0363	1.4482
	SUN.SW_Equity	0.7915***	0.7739***	0.7720***	0.7714***	1.1734
U.S. SPX	X011145D.UN_Equity	0.8032	0.6152***	0.6197***	0.6128***	0.9658
	X0848680D.UN_Equity	1.0338	1.0357	1.0377	1.0370	1.7901
	X125459D.UW_Equity	1.1896	1.3339	1.0291	1.0290	1.3563
	X1284849D.UN_Equity	1.0563	1.0270	1.0274	1.0274	1.5218
	A.UN_Equity	0.7962***	0.7914***	0.8018***	0.8018***	1.2608
	X0961514D.UN_Equity	1.0496	1.0496	1.0518	1.0518	2.4972
	X1086832D.UN_Equity	1.0692	1.0692	1.0692	1.0692	1.2140
	AA.UN_Equity	1.0181	1.0291	1.0322	1.0322	4.9620
	X9876544D.UN_Equity	1.1031	1.1258	1.0199	1.0198	1.4901
	AAPL.UW_Equity	0.9769*	0.9371**	0.9380**	0.9380**	1.3912
	ABC.UN_Equity	0.9482**	0.9388**	0.9393**	0.9393**	1.5305
	ABT.UN_Equity	1.0381	1.0689	1.0412	1.0412	2.7340
	ACE.UN_Equity	0.9771	0.9991	1.0071	1.0071	1.9730
	X0948669D.UN_Equity	0.9138***	1.2436	0.7782***	0.8042***	2.1929
	ACN.UN_Equity	0.9192***	0.9794*	0.9435**	0.9439**	1.6723
	ADBE.UW_Equity	1.1152	1.0405	1.0451	1.0396	2.5031
	ADP.UW_Equity	1.0201	1.0287	1.0302	1.0302	2.4792
	ADS.UN_Equity	0.9966	0.9691*	0.9774	0.9774	1.5836
	ADSK.UW_Equity	0.9833	0.9441**	0.9448**	0.9443**	1.6561
	ADI.UN_Equity	0.9882	0.9856	0.9869	0.9871	1.0627
	AEE.UN_Equity	1.0093	1.0310	1.0179	1.0179	1.5170

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Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	AEP.UN_Equity	1.0045	1.0348	1.0046	1.0045	1.6034
	AES.UN_Equity	0.8959**	0.9099**	0.9150**	0.9151**	4.4606
	ACAS.UW_Equity	0.9440**	0.9557	0.9646	0.9656	1.9152
	AET.UN_Equity	1.0627	1.0864	1.0173	1.0176	1.5764
	AFL.UN_Equity	0.9192**	0.9051**	0.8960**	0.8960**	4.3281
	AGN.UN_Equity	1.0779	1.0273	1.0275	1.0275	3.1773
	AIV.UN_Equity	0.6039***	0.6276***	0.5917***	0.6317***	2.5288
	AIZ.UN_Equity	1.0190	1.0442	1.0057	1.0057	1.5349
	AKAM.UW_Equity	1.0604	1.0506	1.0585	1.0585	1.1930
	ALL.UN_Equity	1.0502	1.0525	1.0528	1.0528	2.4758
	ALTR.UW_Equity	0.8747***	0.8386***	0.8389***	0.8389***	1.0483
	ALXN.UW_Equity	0.9842	1.0050	0.9879	0.9879	1.2516
	AMAT.UW_Equity	1.0285	1.0469	1.0249	1.0240	1.6489
	AKS.UN_Equity	1.0049	1.0120	0.9909	0.9907	1.7842
	AME.UN_Equity	0.9526**	0.9620*	0.9625*	0.9624*	1.2706
	AMG.UN_Equity	0.9880	0.9627*	0.9650	0.9649	3.1085
	AMGN.UW_Equity	0.9868	1.0255	0.9995	0.9995	1.2164
	AMP.UN_Equity	0.9317**	0.9257**	0.9246**	0.9246**	10.9721
	AMZN.UW_Equity	0.9979	0.9637*	0.9682	0.9619*	2.8285
	AN.UN_Equity	0.9532*	1.0277	0.9973	0.9967	0.9713
	ANF.UN_Equity	0.8571***	0.8732***	0.8341***	0.8352***	1.7329
	ANTM.UN_Equity	1.0402	1.0127	1.0145	1.0144	1.5530
	AAPL.UQ_Equity	0.9769*	0.9371**	0.9380**	0.9380**	1.3912
	ANRZQ.UN_Equity	0.9381**	0.7568***	0.7592***	0.7563***	4.2809
	AON.UN_Equity	1.0291	1.0195	1.0211	1.0211	1.7470
	APA.UN_Equity	1.0758	0.9942	0.9950	0.9950	2.3153
	APC.UN_Equity	1.0322	1.0324	0.9467*	0.9467*	3.6867
	APD.UN_Equity	0.9956	1.0049	1.0057	1.0056	1.1796
	APH.UN_Equity	1.0282	1.0440	1.0194	1.0194	2.6970
	ADBE.UQ_Equity	1.1152	1.0405	1.0451	1.0396	2.5031
	ARG.UN_Equity	1.0083	0.9864	1.0234	1.0231	2.6244
	ALTR.UQ_Equity	0.8747***	0.8386***	0.8389***	0.8389***	1.0483
	APOL.UW_Equity	0.9859	1.0252	1.0253	1.0254	1.7027
	ATL.UN_Equity	0.9739***	0.9030***	0.9040***	0.9026***	4.1861
	AVB.UN_Equity	0.8767***	0.8279***	0.8475***	0.8470***	2.1797
	AVGO.UW_Equity	1.0324	1.0312	1.0247	1.0247	3.8095
	AVP.UN_Equity	1.0985	1.0580	1.1204	1.2175	2.0716
	AVY.UN_Equity	0.9251**	0.9093**	0.9117**	0.9118**	1.7907
	ADSK.UQ_Equity	0.9833	0.9441**	0.9448**	0.9443**	1.6561
	AXP.UN_Equity	0.8450***	0.8665**	0.8986***	0.8992***	1.7049
	AZO.UN_Equity	1.0772	1.0536	1.0531	1.0527	1.4217
	BA.UN_Equity	0.9383**	0.9348**	0.9352**	0.9352**	1.3770
	BAC.UN_Equity	1.0673	1.0492	1.0558	1.0555	1.4930
	BAX.UN_Equity	1.0136	0.9987	1.0001	1.0001	1.6297
	BBBY.UW_Equity	0.9607*	0.9208**	0.9224**	0.9224**	1.7449
	BBT.UN_Equity	1.0793	1.2000	1.0419	1.0418	1.8276
	ASH.UN_Equity	0.8329***	0.8243***	0.8127***	0.8125***	3.9110
	BBY.UN_Equity	1.0577	1.0519	1.0238	1.0221	2.7569
	BCR.UN_Equity	1.0284	1.0226	1.0253	1.0234	1.9059
	BDX.UN_Equity	1.0677	1.0541	1.0211	1.0163	1.6831
	BEN.UN_Equity	0.8718***	0.8701***	0.8718***	0.8716***	1.3632
	AMAT.UQ_Equity	1.0285	1.0469	1.0249	1.0240	1.6489
	BEAM.UN_Equity	1.0099	1.0100	1.0151	1.0151	1.4316
	BF.B.UN_Equity	1.0544	1.0299	1.0300	1.0300	1.5795
	BHI.UN_Equity	0.9183***	0.8960***	0.8960***	0.8960***	1.6757
	AMGN.UQ_Equity	0.9868	1.0255	0.9995	0.9995	1.2164
	BIIB.UW_Equity	1.0548	1.0316	1.0323	1.0323	2.2464
	AMCC.UQ_Equity	0.9715*	0.9911	0.9870	0.9870	1.4889
	BK.UN_Equity	1.1095	1.0765	1.0773	1.0762	2.6928
	AMZN.UQ_Equity	0.9979	0.9637*	0.9682	0.9619*	2.8285
	BLK.UN_Equity	1.0578	1.2165	1.0598	1.0652	1.3028
	ABX.UN_Equity	0.9196**	0.9104**	0.9105**	0.9104**	1.3739
	BIG.UN_Equity	1.0922	1.1714	1.0145	1.0174	1.7160
	BLL.UN_Equity	0.9447**	0.9336**	0.9368**	0.9368**	1.3957
	BMJ.UN_Equity	1.0319	1.0279	1.0287	1.0287	1.6110
	BMS.UN_Equity	1.0388	1.0463	1.0246	1.0244	1.7091
	BRCM.UW_Equity	1.0679	0.9939	1.0065	1.0066	1.4929
	BMC.UW_Equity	1.0122	1.0002	1.0022	1.0021	2.6149
	BSX.UN_Equity	0.9881	0.9971	0.9912	0.9911	1.6402

(Continues on next page)

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	BWA.UN.Equity	0.9076***	0.9122***	0.9153***	0.9153***	1.6306
	APOL.UQ.Equity	0.9859	1.0252	1.0253	1.0254	1.7027
	BTU.UN.Equity	0.7944***	0.7609***	0.7849***	0.7826***	1.4170
	BXP.UN.Equity	0.7867***	0.7716***	0.7862***	0.7862***	1.1888
	C.UN.Equity	1.0572	1.0255	1.0265	1.0257	1.6061
	CA.UW.Equity	0.9996	0.9789	0.9796	0.9795	2.4267
	BC.UN.Equity	1.0846	0.9962	1.0369	1.0326	2.3861
	CAG.UN.Equity	1.0484	1.0230	1.0239	1.0239	1.8129
	CAH.UN.Equity	0.9918*	0.9726*	0.9728*	0.9728*	2.1671
	ALTR.UA.Equity	1.0644	1.0659	1.0697	1.0697	1.3265
	CAM.UN.Equity	1.0487	1.1259	0.9196**	0.9196**	2.1438
	CAT.UN.Equity	0.7547***	0.7534***	0.7509***	0.7509***	1.7386
	CB.UN.Equity	0.9240**	0.9675*	0.9352**	0.9352**	0.9715
	CBG.UN.Equity	0.8508***	0.8524***	0.8541***	0.8541***	3.1455
	CBS.UN.Equity	0.8541***	0.8346***	0.8347***	0.8342***	1.5518
	CBEY.UN.Equity	0.9733*	0.9381**	0.9467**	0.9460**	7.7527
	BBBY.UQ.Equity	0.9607*	0.9208**	0.9224**	0.9224**	1.7449
	CCL.UN.Equity	1.0622	1.0186	0.9928	0.9928	1.9258
	CELG.UW.Equity	1.0293	1.0217	1.0203	1.0203	1.4678
	CBE.UN.Equity	0.9948	0.9938	0.9938	0.9938	4.1634
	CERN.UW.Equity	0.9431**	0.9664*	0.9629*	0.9629*	2.2970
	CF.UN.Equity	1.0121	1.1433	1.0075	1.0075	1.7703
	CHK.UN.Equity	0.8966***	0.9160**	0.9157**	0.9157**	1.6153
	CFN.UN.Equity	0.8267***	0.8264***	0.8510***	0.8510***	6.6283
	CHRW.UW.Equity	0.9254**	0.9146**	0.9174**	0.9174**	1.8355
	CI.UN.Equity	1.0066	0.9902	0.9907	0.9906	1.3850
	CINF.UW.Equity	1.0329	1.0289	1.0302	1.0301	1.1901
	CEG.UN.Equity	1.0933	0.8317*	0.8291*	0.8303*	1.9258
	CL.UN.Equity	0.9773*	1.0263	0.9946	0.9931	1.4745
	CLX.UN.Equity	1.0460	1.0230	1.0248	1.0248	1.6029
	CMA.UN.Equity	1.0736	1.0584	1.0595	1.0594	1.8133
	CMCSA.UW.Equity	0.9944	0.9705	1.0185	1.0185	1.9715
	BIIB.UQ.Equity	1.0548	1.0316	1.0323	1.0323	2.2464
	CME.UW.Equity	1.0085	1.0017	0.9875	0.9875	1.9111
	CLF.UN.Equity	0.7678***	0.7879***	0.7738***	0.7738***	1.3949
	CMG.UN.Equity	0.8776***	0.9119***	0.9128***	0.9128***	1.8946
	ARB.UN.Equity	1.0238	1.0174	1.0203	1.0182	1.8274
	CMI.UN.Equity	0.7751***	0.8103***	0.8305***	0.8305***	1.3307
	CMS.UN.Equity	0.9711	0.9683*	0.9673*	0.9673*	1.3978
	CNP.UN.Equity	0.8492***	0.8513***	0.8456***	0.8456***	1.4112
	CNX.UN.Equity	0.8855***	0.8819***	0.8817***	0.8817***	1.7931
	COF.UN.Equity	1.0374	1.0228	1.0241	1.0240	1.7087
	COG.UN.Equity	1.0589	1.0176	1.0194	1.0180	1.6996
	CIEN.UW.Equity	0.9100**	0.9395*	0.9417*	0.9497*	16.8298
	COH.UN.Equity	0.8527***	0.8554***	0.8539***	0.8539***	1.0920
	COL.UN.Equity	0.9331**	0.9707*	0.9542*	0.9552*	1.6336
	BRCM.UQ.Equity	1.0679	0.9939	1.0065	1.0066	1.4929
	COP.UN.Equity	0.9045**	0.8565***	0.8555***	0.8554***	4.0718
	COST.UW.Equity	0.9604**	0.9611*	0.9605*	0.9605*	1.1746
	CPB.UN.Equity	1.0043	1.0173	1.0184	1.0184	1.3561
	CRM.UN.Equity	0.9552*	1.1001	0.9280**	0.9267**	9.3821
	COV.UN.Equity	0.9302*	0.9222**	0.9206**	0.9206**	2.2838
	CSCO.UW.Equity	1.0231	1.0334	1.0343	1.0343	1.6344
	CSX.UN.Equity	0.7986***	0.7785***	0.7780***	0.7780***	1.1533
	CTAS.UW.Equity	1.0460	0.9883	0.9884	0.9884	1.6088
	CTL.UN.Equity	0.9528**	0.9313**	0.9308**	0.9304**	1.5015
	CTSH.UW.Equity	0.7976***	0.8443***	0.8384***	0.8383***	0.9241
	CTXS.UW.Equity	0.8900***	0.9368**	0.8979***	0.8979***	1.4381
	CVC.UN.Equity	0.9376**	0.9263**	0.9196**	0.9195**	1.6419
	CVS.UN.Equity	1.0132	0.9601*	0.9612*	0.9611*	2.0014
	CVX.UN.Equity	0.8386***	0.9584**	0.8737***	0.8737***	1.0971
	CPWR.UW.Equity	0.9932	0.9897	0.9902	0.9901	1.8936
	D.UN.Equity	0.9432**	0.9437**	0.9364**	0.9364**	1.5019
	DAL.UN.Equity	0.9843*	0.9732	0.9348**	0.9320**	1.4684
	BGG.UN.Equity	0.8784***	0.9450**	0.9456**	0.9455**	2.0363
	DD.UN.Equity	0.9153**	0.9134**	0.9138**	0.9136**	1.5336
	DE.UN.Equity	0.8538***	0.8341***	0.8324***	0.8324***	1.5809
	DFS.UN.Equity	0.9209**	0.9485*	0.9479*	0.9478*	1.7643
	DG.UN.Equity	1.0429	1.0430	1.0393	1.0393	1.4973

(Continues on next page)

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	DGX.UN.Equity	1.0467	1.0307	1.0312	1.0312	1.4590
	CIEN.UQ.Equity	0.9100**	0.9395*	0.9417*	0.9497*	16.8298
	CVH.UN.Equity	1.0186	0.9977	0.9991	0.9986	2.4747
	DHL.UN.Equity	1.0172	1.1745	1.0598	1.2168	2.4254
	BMC.UQ.Equity	1.0122	1.0002	1.0022	1.0021	2.6149
	CINF.UQ.Equity	1.0329	1.0289	1.0302	1.0301	1.1901
	DHR.UN.Equity	0.9106***	0.9182**	0.9180**	0.9180**	1.4013
	DIS.UN.Equity	1.0249	1.0150	1.0162	1.0162	2.1144
	DELL.UW.Equity	1.0034	0.9988	0.9989	0.9989	1.6779
	DISCA.UW.Equity	0.9640	0.9575	0.9626	0.9626	1.5845
	CVG.UN.Equity	1.1012	1.0726	1.0368	1.0350	3.9194
	DISCK.UW.Equity	0.9675	0.9847	0.9738	0.9738	1.6681
	CMCSA.UQ.Equity	0.9944	0.9705	1.0185	1.0185	1.9715
	DLTR.UW.Equity	1.0280	1.0030	1.0033	1.0033	1.1937
	DNB.UN.Equity	1.0354	1.0152	1.0161	1.0161	1.5314
	DO.UN.Equity	1.0173	1.1135	0.9769	0.9769	2.2971
	DOV.UN.Equity	0.8881***	0.8991***	0.8973***	0.8973***	1.3389
	DNR.UN.Equity	1.0187	0.9724	0.9725	0.9725	1.6825
	DOW.UN.Equity	0.9583*	0.9438*	0.9463*	0.9462*	2.7549
	DPS.UN.Equity	1.0076	1.0075	1.0084	1.0084	1.7692
	DRI.UN.Equity	1.0355	1.0431	1.0374	1.0374	2.0131
	DDR.UN.Equity	1.0305	1.2048	1.0541	1.0994	8.8731
	DTE.UN.Equity	0.9299**	0.9438**	0.9174**	0.9173**	1.0375
	DTV.UW.Equity	1.0660	1.0759	1.0763	1.0763	1.8363
	DUK.UN.Equity	0.9970	1.0145	0.9956	0.9956	1.4158
	DVA.UN.Equity	0.9762	0.9819	0.9830	0.9829	2.1278
	COST.UQ.Equity	0.9604**	0.9611*	0.9605*	0.9605*	1.1746
	DVN.UN.Equity	0.9125**	0.9013***	0.9016***	0.9016***	2.3793
	DDS.UN.Equity	0.7518***	0.7842***	0.7803***	0.7802***	3.7063
	CPWR.UQ.Equity	0.9932	0.9897	0.9902	0.9901	1.8936
	ECL.UN.Equity	1.0300	1.0274	1.0347	1.0347	1.4387
	CSCO.UQ.Equity	1.0231	1.0334	1.0343	1.0343	1.6344
	ED.UN.Equity	0.9400**	0.9420**	0.9611*	0.9611*	1.2062
	CCK.UN.Equity	0.9406***	1.0196	0.9744	0.9745	1.8712
	EFX.UN.Equity	1.0310	1.0049	1.0063	1.0061	1.6687
	CMCSK.UQ.Equity	1.0202	0.9988	1.0259	1.0246	2.1317
	CTAS.UQ.Equity	1.0460	0.9883	0.9884	0.9884	1.6088
	EIX.UN.Equity	1.0196	1.0451	1.0119	1.0119	1.2432
	CTB.UN.Equity	0.9209**	0.8840***	0.8891**	0.8831***	2.3876
	EL.UN.Equity	0.7601***	0.8808***	0.7995***	0.8380***	1.1922
	EMC.UN.Equity	0.8807***	0.8707***	0.8720***	0.8719***	1.0858
	CTXS.UQ.Equity	0.8900***	0.9368**	0.8979***	0.8979***	1.4381
	DV.UN.Equity	1.0222	0.9935	0.9944	0.9944	1.9036
	EMN.UN.Equity	0.8761***	0.8609***	0.8966**	0.8966**	1.1444
	EMR.UN.Equity	0.8776***	0.8932***	0.8931***	0.8931***	1.5137
	ENDP.UW.Equity	1.0652	0.9560*	0.9590*	0.9590*	2.1688
	CR.UN.Equity	0.8811***	0.9199***	0.9223***	0.9223***	1.3647
	EOG.UN.Equity	1.0337	1.0107	1.0061	1.0061	1.6939
	EQIX.UW.Equity	1.0359	1.0359	1.0366	1.0364	2.0986
	DYNIQ.UN.Equity	0.8366*	0.8222**	0.8188**	0.8186**	1.3108
	EQR.UN.Equity	0.7823***	0.7932***	0.7913***	0.7913***	3.1112
	EQT.UN.Equity	1.0192	1.0069	1.0078	1.0078	1.6225
	ES.UN.Equity	0.9253**	0.9240***	0.9147**	0.9147**	1.3723
	ESRX.UW.Equity	0.9979	0.9968	0.9977	0.9977	3.0563
	DELL.UQ.Equity	1.0034	0.9988	0.9989	0.9989	1.6779
	ESS.UN.Equity	0.9081***	0.9152***	0.9252**	0.9257**	1.7815
	ESS.UN.Equity	0.8852*	0.9684	0.8504***	0.8503***	1.3637
	ETFC.UW.Equity	1.0596	1.0401	1.0382	1.0378	2.4840
	ETN.UN.Equity	0.8591***	0.8945***	0.8646***	0.8648***	1.1515
	ETR.UN.Equity	0.9839	1.0296	1.0308	1.0308	1.6038
	EW.UN.Equity	0.9686**	1.0158	0.9543**	0.9544**	1.5372
	EP.UN.Equity	1.0421	1.0418	1.0427	1.0427	1.7987
	EXC.UN.Equity	1.0752	1.0267	1.0268	1.0268	1.7441
	EXPD.UW.Equity	0.9419**	0.9532**	0.9596*	0.9596*	1.3684
	EXPE.UW.Equity	1.0784	1.0423	1.0427	1.0423	1.9096
	F.UN.Equity	0.8200***	0.8326***	0.8197***	0.8198***	2.0882
	FAST.UW.Equity	0.9744*	0.9943	0.9781	0.9782	1.4229
	FCX.UN.Equity	0.8657***	0.9447**	0.8458***	0.8458***	1.3057
	FDO.UN.Equity	1.0247	1.0097	1.0072	1.0072	1.4599

(Continues on next page)

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	FDX.UN_Equity	1.0806	1.2252	1.0132	1.0049	1.4342
	FE.UN_Equity	1.0413	1.1030	1.0257	1.0253	1.6464
	DLX.UN_Equity	1.0361	1.0534	1.0232	1.0232	2.2531
	FFIV.UW_Equity	0.8977***	0.8793***	0.8792***	0.8788***	1.7051
	FIS.UN_Equity	0.9932	0.9867	0.9873	0.9873	1.4762
	FISV.UW_Equity	1.0498	1.0403	1.0402	1.0402	1.5644
	FITB.UW_Equity	1.0441	1.0572	1.0445	1.0444	1.8837
	FLIR.UW_Equity	0.9568**	0.9984	0.9590*	0.9591*	1.4282
	FLR.UN_Equity	0.8796***	0.9530**	0.9070**	0.9066**	1.2424
	FHN.UN_Equity	1.0757	1.0426	1.0441	1.0427	3.2333
	FLS.UN_Equity	0.9735	0.9618	0.9659	0.9658	1.2979
	FMC.UN_Equity	0.9674	0.9382**	0.9380**	0.9381**	1.8749
	FIL.UN_Equity	1.0571	1.0391	1.0403	1.0399	1.6479
	FOSL.UW_Equity	0.8841***	0.8955***	0.8466***	0.8460***	1.3066
	FOXA.UW_Equity	1.0134	1.0227	1.0252	1.0252	1.7520
	FSLR.UW_Equity	1.0269	1.0583	1.0493	1.0493	4.6335
	FTL.UN_Equity	0.8617***	0.8204***	0.8205***	0.8205***	1.4651
	GAS.UN_Equity	0.9920	0.9794	0.9800	0.9800	1.4333
	ESRX.UQ_Equity	0.9979	0.9968	0.9977	0.9977	3.0563
	GD.UN_Equity	1.1045	1.2233	1.0263	1.0275	2.7521
	GGP.UN_Equity	1.1189	1.1136	1.0855	1.0851	3.3878
	GILD.UW_Equity	0.8528***	0.8337***	0.8304***	0.8292***	1.2702
	GIS.UN_Equity	0.9616**	0.9382**	0.9397**	0.9396**	1.3645
	GHC.UN_Equity	1.0235	0.9884	0.9763	0.9746	2.0776
	GLW.UN_Equity	0.9751	0.9857	0.9885	0.9885	1.5389
	FTR.UN_Equity	0.9744	0.9744	0.9707	0.9707	0.5072
	GM.UN_Equity	0.9390	0.8042	0.8079	0.8038	3.5883
	GMC.R.UW_Equity	0.9447*	0.9711	0.9722	0.9722	1.0880
	GME.UN_Equity	1.0242	0.9990	1.0020	0.9995	2.7012
	GNW.UN_Equity	0.9887**	1.5417	0.7957***	0.8002***	2.3371
	GOOGL.UW_Equity	1.0732	1.0401	1.0424	1.0424	1.2411
	GPC.UN_Equity	1.0226	1.0032	1.0050	1.0049	1.1328
	FISV.UQ_Equity	1.0498	1.0403	1.0402	1.0402	1.5644
	GPS.UN_Equity	1.0449	1.0236	1.0260	1.0260	1.7305
	FITB.UQ_Equity	1.0441	1.0572	1.0445	1.0444	1.8837
	GRMN.UW_Equity	1.0758	0.9941	0.9957	0.9957	1.8312
	GS.UN_Equity	1.0704	1.0573	1.0585	1.0584	1.5452
	GWV.UN_Equity	0.9451**	0.9407**	0.9427**	0.9427**	1.4893
	HAL.UN_Equity	0.8827***	0.8800***	0.8879***	0.8812***	1.8815
	GR.UN_Equity	1.0160	1.0218	1.0235	1.0239	2.0780
	HAR.UN_Equity	0.9625	0.9800	0.9839	0.9830	1.6485
	HAS.UW_Equity	0.8466***	0.8448***	0.8274***	0.8271***	6.3094
	GT.UN_Equity	1.0340	0.9708	0.9724	0.9711	1.2587
	HBAN.UW_Equity	1.0898	1.1507	1.0878	1.0935	1.7121
	HBL.UN_Equity	0.7868***	0.7796***	0.7791***	0.7791***	1.3643
	HCBK.UW_Equity	1.0096	1.0180	1.0239	1.0235	3.1773
	HCN.UN_Equity	1.0257	1.0291	1.0299	1.0299	1.7596
	HAS.US_Equity	1.0278	1.0027	1.0029	1.0029	2.1104
	HCP.UN_Equity	0.8296***	0.8234***	0.8527***	0.8528***	1.7076
	HD.UN_Equity	1.0523	1.0164	1.0171	1.0171	1.4111
	GILD.UQ_Equity	0.8527***	0.8337***	0.8304***	0.8292***	1.2683
	HES.UN_Equity	1.0205	0.9718	0.9724	0.9723	2.2847
	HIG.UN_Equity	0.8994***	0.8809***	0.8612***	0.8587***	3.6072
	HOG.UN_Equity	0.9765**	1.0021	0.9517**	0.9517**	1.3814
	HON.UN_Equity	0.9102**	0.9178**	0.9174**	0.9174**	1.7875
	GOOGL.UQ_Equity	1.0732	1.0401	1.0424	1.0424	1.2411
	HOT.UN_Equity	0.8015***	0.8124***	0.8410***	0.8410***	1.0679
	HNZ.UN_Equity	0.9722	0.9954	0.9972	0.9973	2.0976
	HP.UN_Equity	0.9603*	0.9651*	0.9653*	0.9653*	2.4257
	HPQ.UN_Equity	1.0527	1.0277	1.0316	1.0316	2.2705
	HRB.UN_Equity	1.0527	1.0396	1.0401	1.0401	1.7281
	HRL.UN_Equity	0.9659*	0.9774	0.9715	0.9715	1.0826
	HRS.UN_Equity	0.9698**	1.0601	0.9805	0.9820	1.5676
	HSP.UN_Equity	1.0328	1.0283	1.0382	1.0308	6.9019
	HST.UN_Equity	0.8693***	0.8569***	0.8565***	0.8559***	2.0024
	HSIC.UW_Equity	0.9705*	0.9748	0.9765	0.9765	1.2460
	FWLT.US_Equity	1.0092	0.9991	0.9918	0.9918	1.9990
	HSY.UN_Equity	0.9277**	0.9395**	0.9800	0.9827	1.5207
	HUM.UN_Equity	0.9956	0.9792	0.9787	0.9787	1.3105

(Continues on next page)

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	IBM.UN_Equity	0.8856**	0.8674***	0.8678***	0.8678***	1.3227
	HBAN.UQ_Equity	1.0898	1.1507	1.0878	1.0935	1.7121
	HSB.UN_Equity	0.9972	0.9884	0.9892	0.9892	2.4453
	ICE.UN_Equity	1.0180	1.0586	1.0377	1.0352	1.3360
	HMA.UN_Equity	1.0294	0.9872	0.9876	0.9873	2.7568
	IFF.UN_Equity	0.9136***	0.9239**	0.9236**	0.9236**	1.1266
	INTC.UW_Equity	1.0258	0.9957	0.9965	0.9965	1.3077
	INTU.UW_Equity	0.8413***	0.8329***	0.8358***	0.8358***	1.3151
	IP.UN_Equity	0.8307***	0.8138***	0.8339***	0.8339***	1.4126
	IPG.UN_Equity	1.0211	0.9723	0.9807	0.9795	2.4014
	IACLUW_Equity	0.9930	0.9649*	0.9653*	0.9653*	1.2444
	IR.UN_Equity	0.9494**	0.9456*	0.9462*	0.9461*	1.7668
	IRM.UN_Equity	1.0155	1.0229	1.0257	1.0257	1.5449
	GRA.UN_Equity	0.6714***	0.6969***	0.7035***	0.7035***	2.8123
	HBAN.UA_Equity	1.0019	1.0067	0.9959	0.9960	1.9732
	ISRG.UW_Equity	0.8638***	0.8678***	0.8679***	0.8679***	1.3729
	ITW.UN_Equity	0.9603*	0.9501*	0.9520*	0.9520*	2.3051
	IVZ.UN_Equity	1.2040	1.2081	1.1099	1.1099	2.2473
	HLS.UN_Equity	1.0211	1.0245	1.0252	1.0252	2.5885
	JBL.UN_Equity	1.0481	0.9953	1.0160	1.0150	1.7823
	JCL.UN_Equity	0.8881***	0.9152**	0.9139**	0.9143**	1.3396
	JCP.UN_Equity	1.0439	1.1063	0.9734	0.9731	2.3895
	JEC.UN_Equity	1.0182	1.0635	0.9940	0.9940	0.9263
	JBHT.UW_Equity	0.9822	1.0010	1.0087	1.0087	1.4640
	ITT.UN_Equity	1.0469	1.0418	1.0415	1.0415	3.2170
	JNJ.UN_Equity	1.0305	1.0250	1.0256	1.0256	1.5478
	JNPR.UN_Equity	1.0966	1.0979	1.0986	1.0986	2.3916
	JPM.UN_Equity	1.0484	1.0450	1.0452	1.0452	1.7221
	JWN.UN_Equity	0.8822***	0.9859***	0.8573***	0.8574***	1.5716
	K.UN_Equity	0.9658*	0.9875	0.9732*	0.9732*	1.1935
	INTC.UQ_Equity	1.0258	0.9957	0.9965	0.9965	1.3077
	KEY.UN_Equity	1.0687	1.0713	1.0388	1.0388	1.5958
	INTU.UQ_Equity	0.8413***	0.8329***	0.8358***	0.8358***	1.3151
	KIM.UN_Equity	1.0293	1.0269	1.0273	1.0273	1.8359
	KLAC.UW_Equity	0.9926	0.9889	0.9889	0.9889	2.0670
	JNS.UN_Equity	0.8586***	0.8335***	0.8345***	0.8344***	1.4812
	KMB.UN_Equity	1.0168	1.0263	1.0269	1.0269	1.6659
	JNY.UN_Equity	1.0016	1.0082	1.0100	1.0099	1.2439
	KMX.UN_Equity	0.9290**	0.9492*	0.9485*	0.9483*	3.4278
	JOY.UW_Equity	1.0460	1.0076	1.0010	0.9994	2.5214
	KO.UN_Equity	0.9259**	0.9236**	0.9237**	0.9237**	1.1541
	KR.UN_Equity	0.9802	0.9485**	0.9494**	0.9493**	1.4572
	KBH.UN_Equity	1.0135	1.0413	1.0033	1.0050	1.8796
	KSS.UN_Equity	1.0036	1.1320	1.0272	1.0272	0.9677
	KSU.UN_Equity	0.7068***	0.7056***	0.7324***	0.7368***	1.1123
	L.UN_Equity	0.7649***	0.7765***	0.7679***	0.7679***	0.9498
	LB.UN_Equity	0.8206***	0.8966***	0.7733***	0.7764***	0.9513
	LEG.UN_Equity	0.9765**	0.9912**	0.9707*	0.9706*	1.5856
	LDOS.UN_Equity	1.0566	1.0195	1.0022	1.0005	4.7448
	LEN.UN_Equity	0.9974	1.0629	1.0117	1.0159	3.7442
	LH.UN_Equity	1.0045	0.9881	0.9890	0.9890	1.3362
	LLL.UN_Equity	1.0585	1.0304	1.0308	1.0308	1.7209
	LLTC.UW_Equity	0.9684*	0.9665	0.9670	0.9670	1.8858
	LLY.UN_Equity	0.9766	0.9604*	0.9608*	0.9608*	1.4826
	LM.UN_Equity	1.0217	1.0118	1.0101	1.0084	2.1247
	LMT.UN_Equity	0.9379**	0.9459**	0.9166***	0.9077***	1.6905
	KLAC.UQ_Equity	0.9926	0.9889	0.9889	0.9889	2.0670
	LNC.UN_Equity	0.9729**	0.9516**	0.9494**	0.9494**	1.3684
	LO.UN_Equity	0.9534	0.9600	0.9624	0.9628	2.1162
	LOW.UN_Equity	1.0136	1.0154	1.0163	1.0162	1.5192
	LRCX.UW_Equity	0.9797	0.9768	0.9777	0.9777	1.4741
	LUV.UN_Equity	0.9523*	0.9918	1.0252	1.0252	1.8074
	LSI.UN_Equity	1.0122	0.9944	0.9975	0.9958	1.6641
	M.UN_Equity	1.0063	1.2122	1.0237	1.0252	1.2499
	MA.UN_Equity	1.0059	1.0423	1.0290	1.0289	1.2785
	LXK.UN_Equity	1.0955	1.0906	1.0488	1.0486	1.2930
	MAC.UN_Equity	0.7164***	0.8458***	0.8655***	0.8823***	2.0892
	MAR.UN_Equity	1.0370	1.0286	1.0269	1.0267	1.6484
	MAS.UN_Equity	0.8581***	0.8579***	0.8717***	0.8715***	1.9255

(Continues on next page)

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	MAT.UN.Equity	0.7986*	0.6937**	0.8393**	0.8964*	1.2941
	LLTC.UQ.Equity	0.9684*	0.9665	0.9670	0.9670	1.8858
	MCD.UN.Equity	0.9105***	0.9187***	0.9144***	0.9143***	1.1667
	MCHP.UW.Equity	0.8841***	0.8618***	0.9349**	0.9349**	1.2394
	LPX.UN.Equity	0.9737*	1.0985	0.9848	1.0086	2.6528
	MCK.UN.Equity	0.9459**	0.9380**	0.9388**	0.9388**	1.3332
	MCO.UN.Equity	1.0744	1.0374	1.0357	1.0351	2.5244
	MBI.UN.Equity	0.8849**	0.9441*	0.8751***	0.8751***	1.4129
	MDT.UN.Equity	1.0625	1.0337	1.0352	1.0350	2.0505
	MDLZ.UN.Equity	1.0396	1.0392	1.0407	1.0407	4.0393
	MET.UN.Equity	1.0188	1.0087	1.0093	1.0091	1.5013
	MDP.UN.Equity	1.0194	1.0357	1.0365	1.0364	1.7694
	MHFL.UN.Equity	1.0118	1.0557	1.0353	1.0367	2.2207
	MJN.UN.Equity	1.0811	1.0767	1.0589	1.0589	2.6459
	MHK.UN.Equity	0.9660*	1.0203	1.0291	1.0290	2.0876
	MKC.UN.Equity	0.9661*	0.9648*	0.9660*	0.9660*	1.3438
	MMC.UN.Equity	0.9974	1.0443	1.0435	1.0435	1.7533
	MMM.UN.Equity	0.9543*	0.9747*	0.9771	0.9776	1.5825
	MLM.UN.Equity	1.0411	1.1045	1.0341	1.0341	1.1970
	MO.UN.Equity	1.0060	0.9980	0.9997	0.9997	1.6047
	MHS.UN.Equity	1.0484	1.0417	1.0432	1.0430	1.3844
	MOLX.UW.Equity	1.0211	1.0162	1.0167	1.0167	1.5945
	MON.UN.Equity	0.9946**	1.0468	1.0045	1.0046	1.4290
	MOS.UN.Equity	0.9111***	0.8993***	0.8996***	0.8995***	2.1287
	MNST.UW.Equity	1.0834	1.0152	1.0157	1.0156	1.3722
	MRK.UN.Equity	0.9975	0.9972	0.9979	0.9979	1.5811
	MRO.UN.Equity	0.9759	0.9423**	0.9447**	0.9447**	1.4781
	MS.UN.Equity	0.8860***	0.8831***	0.8806***	0.8806***	1.3322
	MSFT.UW.Equity	1.0700	1.0986	1.0519	1.0519	1.1066
	MSI.UN.Equity	1.1289	2.4973	0.8079***	0.8069***	1.6769
	MTB.UN.Equity	0.9467*	0.9436**	0.9425**	0.9424**	1.5558
	MDR.UN.Equity	0.9314***	1.1186	0.8692***	0.8693***	2.8299
	MU.UW.Equity	0.9627*	0.9616	0.9803	0.9801	1.2460
	MUR.UN.Equity	0.9263**	0.9269**	0.9278**	0.9278**	1.3526
	MWV.UN.Equity	0.9275**	0.9048***	0.9037***	0.9037***	1.6343
	MYL.UW.Equity	0.9649	0.9621	0.9616	0.9616	1.1164
	NBL.UN.Equity	0.9489*	0.9404**	0.9416**	0.9416**	1.4849
	NBR.UN.Equity	0.9586*	0.9461*	0.9671	0.9672	3.0251
	NDAQ.UW.Equity	1.0495	1.0235	1.0236	1.0236	1.7380
	MTW.UN.Equity	0.9879*	1.0518	1.0225	1.0227	1.1122
	NE.UN.Equity	0.9480*	0.8994**	0.9001**	0.9001**	1.6479
	NEE.UN.Equity	1.0286	1.0018	0.9988	0.9988	1.4054
	MOLX.UQ.Equity	1.0211	1.0162	1.0167	1.0167	1.5945
	MTG.UN.Equity	1.0606	1.0552	0.9819**	1.0082	14.0578
	NEM.UN.Equity	0.9379*	0.9613*	0.9352**	0.9361**	1.5580
	NFLX.UW.Equity	1.1568	1.3833	1.1867	1.1912	2.5890
	NFX.UN.Equity	0.9103***	0.8953***	0.8953***	0.8953***	1.4166
	NI.UN.Equity	0.9552*	0.9890	0.9905	0.9905	1.1331
	NKE.UN.Equity	1.0575	1.0349	1.0352	1.0352	1.8815
	MSFT.UQ.Equity	1.0700	1.0986	1.0519	1.0519	1.1066
	NOC.UN.Equity	1.0382	1.0254	1.0273	1.0270	1.5343
	NOV.UN.Equity	0.8450***	0.8097***	0.8105***	0.8101***	1.8206
	MXIM.UW.Equity	0.8732***	0.8782***	0.8550***	0.8550***	1.1489
	NRG.UN.Equity	1.0271	0.9954	0.9969	0.9959	2.6253
	NSC.UN.Equity	0.8391***	0.8691***	0.8850***	0.8849***	1.5667
	NTAP.UW.Equity	0.8164***	0.7988***	0.7971***	0.7968***	1.1477
	NTRS.UW.Equity	1.0009	1.0243	1.0175	1.0175	1.8920
	NAV.UN.Equity	0.9832	0.9908	0.9598*	0.9558*	1.5042
	NCR.UN.Equity	1.0553	1.1144	0.9974	0.9711*	1.5354
	NUE.UN.Equity	0.9833	0.9652*	0.9651	0.9649	2.1720
	NVDA.UW.Equity	0.9738	0.9704*	1.0688	1.0689	1.5151
	MXIM.UQ.Equity	0.8732***	0.8782***	0.8550***	0.8550***	1.1489
	NWL.UN.Equity	1.0450	1.0270	1.0274	1.0272	2.3109
	NYX.UN.Equity	1.0011	0.9928	0.9950	0.9950	1.4677
	OL.UN.Equity	1.0300	1.0177	1.0149	1.0148	1.7196
	NC.UN.Equity	0.9748	1.0124	1.0189	1.0174	1.7391
	NYT.UN.Equity	1.0609	1.0436	1.0439	1.0437	2.0713
	OKE.UN.Equity	0.8579***	0.8219***	0.8218***	0.8211***	1.3025
	OMC.UN.Equity	0.9748	0.9849	0.9867	0.9866	1.9626

(Continues on next page)

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	O.UN_Equity	0.9392**	0.9690	0.9813	0.9812	1.3659
	ORLY.UW_Equity	0.9895	1.0125	1.0019	1.0019	1.1983
	ORCL.UW_Equity	0.9495	0.9505	0.9512	0.9512	1.7952
	OXY.UN_Equity	0.8700***	0.8495***	0.8503***	0.8502***	1.4065
	PAYX.UW_Equity	1.0523	1.0316	1.0322	1.0322	1.5599
	PBCT.UW_Equity	1.0042	1.0159	1.0132	1.0132	2.3684
	PBI.UN_Equity	1.0469	1.0271	1.0283	1.0282	2.5303
	PCAR.UW_Equity	0.9375**	1.0307	1.0375	1.0375	1.3584
	PCG.UN_Equity	1.0033	1.0090	1.0061	1.0061	1.7362
	PCL.UN_Equity	1.0161	1.0432	1.0060	1.0064	2.0997
	OMX.UN_Equity	1.0628	1.0454	1.0457	1.0455	2.5854
	PCLN.UW_Equity	0.7477***	0.7390***	0.7501***	0.7501***	1.0984
	NTAP.UQ_Equity	0.8164***	0.7988***	0.7971***	0.7963***	1.1477
	PCP.UN_Equity	0.8876**	0.9973*	0.8373***	0.8300***	1.6305
	NTRS.UQ_Equity	1.0009	1.0243	1.0175	1.0175	1.8920
	PDCO.UW_Equity	0.9005**	0.8986**	0.8995**	0.8995**	1.3164
	PEG.UN_Equity	1.0327	1.0551	1.0265	1.0264	1.4044
	NVDA.UQ_Equity	0.9738	0.9704*	1.0688	1.0689	1.5151
	PEP.UN_Equity	0.9914	0.9794	0.9811	0.9810	1.3916
	PETM.UW_Equity	1.0300	1.0149	1.0158	1.0158	1.3688
	NVDA.UA_Equity	1.0275	1.0969	1.0266	1.0266	1.5229
	PFE.UN_Equity	0.9772	0.9834	0.9847	0.9846	1.3168
	CFG.UN_Equity	0.9089**	0.9092**	0.8970***	0.8968***	4.0193
	PG.UN_Equity	0.9850	1.0088	0.9860	0.9860	1.4176
	PGR.UN_Equity	1.0107	1.0002	1.0007	1.0007	1.2131
	ORCL.UQ_Equity	0.9495	0.9505	0.9512	0.9512	1.7952
	PH.UN_Equity	0.9692*	0.9352**	0.9385**	0.9339**	1.7702
	PHM.UN_Equity	0.7053***	0.8447***	0.7643***	0.7986***	1.9281
	PAYX.UQ_Equity	1.0523	1.0316	1.0322	1.0322	1.5599
	PLL.UN_Equity	0.9397**	0.9396**	0.9788	0.9788	1.3697
	PCAR.UQ_Equity	0.9375**	1.0307	1.0375	1.0375	1.3584
	PNM.UN_Equity	0.7689***	0.8294***	0.8140***	0.8140***	0.8858
	PNC.UN_Equity	1.0263	0.9824	0.9796	0.9796	1.8772
	PNW.UN_Equity	0.9401**	0.9546*	0.9446**	0.9445**	1.1904
	PDCO.UQ_Equity	0.9005**	0.8986**	0.8995**	0.8995**	1.3164
	POM.UN_Equity	0.8517***	0.8397***	0.8384***	0.8384***	1.2668
	PBY.UN_Equity	0.9599**	0.9850	0.9938	0.9937	1.4607
	PPG.UN_Equity	0.9948	0.9909	0.9915	0.9915	1.7182
	PPL.UN_Equity	1.0548	1.0201	1.0188	1.0187	1.3606
	PMCS.UW_Equity	1.0262	1.0309	1.0311	1.0311	2.2310
	PRU.UN_Equity	0.9087***	0.9044**	0.9046**	0.9046**	2.0017
	PRGO.UW_Equity	0.8398**	0.8616***	0.8430***	0.8430***	2.0997
	PSA.UN_Equity	0.9119***	0.9922	0.9705	0.9705	1.0557
	PWR.UN_Equity	1.1146	1.0381	1.0271	1.0271	2.8584
	PVH.UN_Equity	1.1117	0.9728	0.9371**	0.9680*	1.6879
	PX.UN_Equity	0.8870***	1.0020	0.9405**	0.9441**	1.6404
	PXD.UN_Equity	0.9345**	0.9502**	0.9503**	0.9503**	1.4499
	QCOM.UW_Equity	0.9635*	1.0099	0.9861	0.9861	1.4925
	QLGC.UW_Equity	0.9459**	1.0091	1.0127	1.0125	1.8708
	PMCS.UQ_Equity	1.0262	1.0309	1.0311	1.0311	2.2310
	R.UN_Equity	0.9497***	1.0307	0.9773	0.9789	1.5829
	QEP.UN_Equity	1.0184	1.0235	1.0244	1.0249	4.0792
	PTC.UW_Equity	0.9728*	0.9813*	0.9732	0.9753	1.4084
	RAI.UN_Equity	0.9421**	0.9475**	0.9534**	0.9533**	1.3902
	RDC.UN_Equity	0.7476***	0.8068***	0.7357***	0.7354***	0.9864
	RHI.UN_Equity	1.0560	1.0853	1.0317	1.0315	2.4892
	REGN.UW_Equity	1.0132	1.0112	1.0024	1.0023	1.8908
	RCL.UN_Equity	0.9885**	0.9317**	0.9347**	0.9340**	4.4927
	RIG.UN_Equity	1.0313	0.9556	0.9485*	0.9485*	1.7294
	RHT.UN_Equity	0.9053**	0.9326**	0.9133**	0.9164**	1.6457
	PTC.UQ_Equity	0.9728*	0.9813*	0.9732	0.9753	1.4084
	RL.UN_Equity	0.8263***	0.8515***	0.8362***	0.8362***	1.1228
	ROK.UN_Equity	0.8625***	0.8541***	0.8542***	0.8542***	1.5530
	ROP.UN_Equity	0.9680	0.9677	0.9699	0.9698	1.3812
	PWER.UQ_Equity	0.7596***	0.9016***	1.0801	1.1610	2.0253
	RRC.UN_Equity	1.0614	0.9956	0.9962	0.9962	1.2223
	ROST.UW_Equity	1.0288	1.0345	1.0108	1.0112	1.3786
	QCOM.UQ_Equity	0.9635*	1.0099	0.9861	0.9861	1.4925
	RRD.UW_Equity	1.1211	1.1235	1.1238	1.1241	3.0239

(Continues on next page)

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	QLGC.UQ_Equity	0.9459**	1.0091	1.0127	1.0125	1.8708
	RTN.UN_Equity	1.0015	0.9988	1.0005	1.0005	1.4673
	RSG.UN_Equity	0.9515**	0.9308**	0.9317**	0.9317**	1.6040
	SBUX.UW_Equity	0.9887**	0.9579*	0.9581*	0.9581*	3.8363
	RAD.UN_Equity	1.0901	1.1845	1.0177	1.0175	2.7023
	SANM.UW_Equity	0.9734**	0.9706**	0.9438**	0.9438**	1.4517
	SE.UN_Equity	1.0177	0.9990	0.9989	0.9989	1.7644
	SCG.UN_Equity	0.9911	0.9761	0.9767	0.9767	1.4333
	SEE.UN_Equity	1.0631	1.0322	1.0337	1.0337	5.3094
	SCHW.UN_Equity	0.9171***	0.9022***	0.8978***	0.8978***	1.7515
	SHLD.UW_Equity	0.9202**	0.9096**	1.0434	1.0263	14.1374
	SHW.UN_Equity	1.0185	1.0024	1.0042	1.0037	2.2915
	SIAL.UW_Equity	1.0226	0.9742	0.9774	0.9774	2.1350
	SLB.UN_Equity	1.0005	0.9430**	0.9313**	0.9313**	3.4997
	SJM.UN_Equity	0.8651***	0.8893***	0.8895***	0.8894***	1.2695
	SANM.UQ_Equity	0.9734**	0.9706**	0.9438**	0.9438**	1.4517
	SNA.UN_Equity	1.0754	1.0802	1.0397	1.0388	1.5295
	SBUX.UQ_Equity	0.9887**	0.9579*	0.9581*	0.9581*	3.8363
	SNDK.UW_Equity	0.9202***	0.9201***	0.8941***	0.8942***	1.4768
	SLG.UN_Equity	0.7313***	0.7529***	0.6712***	0.6692***	5.0845
	SNV.UN_Equity	1.1323	1.0639	1.0894	1.0743	8.4839
	SO.UN_Equity	0.9672*	0.9701*	0.9704*	0.9703*	1.3091
	SNL.UN_Equity	1.0513	1.0514	1.0573	1.0574	0.9497
	SAPE.UQ_Equity	0.9480*	0.9972	0.9726	0.9735	1.2380
	SHLD.UQ_Equity	0.9202**	0.9096**	1.0434	1.0263	14.1374
	SPG.UN_Equity	0.8033***	0.8354***	0.8370***	0.8370***	1.5916
	SPLS.UW_Equity	1.2883	1.2240	1.0897	1.0234	3.4213
	SIAL.UQ_Equity	1.0226	0.9742	0.9774	0.9774	2.1350
	SRE.UN_Equity	1.0490	1.0285	1.0282	1.0282	1.9897
	SRCL.UW_Equity	0.8132***	0.8970***	0.8707***	0.8710***	0.9118
	SCI.UN_Equity	0.8173***	0.7822***	0.8149***	0.8149***	1.7421
	SSP.UN_Equity	1.0069	1.0825	1.0331	1.0334	1.3914
	STL.UN_Equity	1.0509	1.0176	1.0170	1.0170	2.2641
	STJ.UN_Equity	1.0257	1.0032	1.0043	1.0043	1.4214
	SNDK.UQ_Equity	0.9202***	0.9201***	0.8941***	0.8942***	1.4768
	STR.UN_Equity	0.8556***	0.8682***	0.8430***	0.8430***	1.0758
	STT.UN_Equity	1.0819	1.0773	1.0649	1.0648	2.7357
	STZ.UN_Equity	1.0538	1.0561	1.0376	1.0372	1.2844
	SUNE.UN_Equity	1.0199	1.0316	1.0278	1.0278	2.3058
	SVU.UN_Equity	1.0430	1.0244	1.0246	1.0245	1.7750
	SWK.UN_Equity	0.9870**	0.9600*	0.9603*	0.9603*	1.2792
	SWN.UN_Equity	1.0163	0.9851	0.9855	0.9853	1.6511
	SPLS.UQ_Equity	1.2883	1.2240	1.0897	1.0234	3.4213
	SWY.UN_Equity	1.0496	1.0264	1.0277	1.0276	1.4358
	SWKS.UW_Equity	0.9953*	0.9753*	0.9755*	0.9755*	2.9398
	SPLS.UA_Equity	0.9849	0.9751	0.9802	0.9749	1.5761
	SYK.UN_Equity	1.0317	0.9998	0.9993	0.9993	1.4123
	SYMC.UW_Equity	1.0014	1.1579	1.0231	1.0254	1.2715
	SYU.UN_Equity	0.9890	1.0073	1.0132	1.0132	2.0510
	T.UN_Equity	1.0086	1.0390	1.0155	1.0154	1.4429
	TAP.UN_Equity	1.0493	1.0348	1.0346	1.0345	1.4759
	TDC.UN_Equity	0.8061***	0.8231***	0.8191***	0.8191***	1.5245
	TE.UN_Equity	0.7698***	0.7809***	0.7793***	0.7792***	1.0675
	TEG.UN_Equity	0.8662**	0.9462***	0.8736***	0.8736***	1.0850
	TEL.UN_Equity	1.0420	1.0402	1.0423	1.0422	1.5976
	SYMC.UQ_Equity	1.0014	1.1579	1.0231	1.0254	1.2715
	TER.UN_Equity	0.8689***	0.8611***	0.8612***	0.8612***	1.0829
	TGT.UN_Equity	1.0612	1.0240	1.0300	1.0300	1.3221
	TEX.UN_Equity	1.1476	1.0222	1.0221	1.0224	1.5322
	THC.UN_Equity	0.9222***	0.8919***	0.8638***	0.8602***	1.3818
	TIE.UN_Equity	0.9617	0.9535	0.9501	0.9497	2.4641
	TIF.UN_Equity	0.9196**	0.9235**	0.9215**	0.9237**	1.7619
	TJX.UN_Equity	0.9974	0.9851	0.9858	0.9858	1.5249
	TMK.UN_Equity	0.8780***	0.9025**	0.9029**	0.9028**	1.2235
	TMO.UN_Equity	0.9917	1.0052	0.9959	0.9957	1.5335
	TIN.UN_Equity	1.0626	1.0597	1.0614	1.0612	2.1024
	TLAB.UW_Equity	1.0225	0.9920	0.9947	0.9942	4.6413
	TROW.UW_Equity	0.9279**	0.9127**	0.9136**	0.9135**	1.5424
	TRV.UN_Equity	0.9602	1.0081	1.0079	1.0079	1.7425

(Continues on next page)

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	TKR.UN_Equity	0.8188***	0.8270***	0.8270***	0.8270***	1.4560
	TSN.UN_Equity	1.0523	1.0418	1.0413	1.0413	1.5908
	TSCO.UW_Equity	0.9168***	0.9188**	0.9224**	0.9224**	1.2617
	TLAB.UQ_Equity	1.0225	0.9920	0.9947	0.9942	4.6413
	TSO.UN_Equity	1.0129	1.0257	1.0261	1.0260	1.1122
	TSS.UN_Equity	1.0753	1.1897	1.0428	1.0428	1.4988
	TWC.UN_Equity	0.9985	1.0305	1.0308	1.0308	1.0696
	TNB.UN_Equity	1.0353	1.0346	1.0376	1.0376	1.3763
	TWX.UN_Equity	1.0370	1.0145	1.0152	1.0152	3.0163
	TXT.UN_Equity	1.0154	1.1685	1.0423	1.0577	1.8119
	TROW.UQ_Equity	0.9279**	0.9127**	0.9136**	0.9135**	1.5424
	TYC.UN_Equity	0.8954***	0.8706***	0.8724***	0.8710***	2.0678
	TXN.UN_Equity	0.8976	0.8975	0.9039	0.9039	1.6848
	UNH.UN_Equity	1.0220	0.9796	0.9801	0.9801	1.9142
	UA.UN_Equity	1.0278	1.0237	1.0241	1.0241	1.5542
	TUP.UN_Equity	0.8111***	0.8051***	0.8055***	0.8055***	1.1959
	UNP.UN_Equity	0.8898**	0.9162**	0.9176**	0.9175**	1.3537
	UHS.UN_Equity	1.0447	1.0105	1.0109	1.0109	1.5655
	UPS.UN_Equity	0.9964	0.9921	0.9905	0.9923	1.3574
	URBN.UW_Equity	0.9608*	0.9851	0.9852	0.9852	2.1501
	UIS.UN_Equity	1.0153	1.0186	0.9538**	0.9537**	2.2892
	USB.UN_Equity	1.1282	1.4814	1.0173	1.0173	1.9989
	UTX.UN_Equity	0.8607***	0.8812***	0.8810***	0.8810***	0.8575
	V.UN_Equity	0.9716	0.9722	0.9730	0.9729	1.5849
	VAR.UN_Equity	0.8106***	0.9500***	0.8630***	0.8765***	1.1895
	URL.UN_Equity	0.7831***	0.7576***	0.7579***	0.7578***	1.1562
	VFC.UN_Equity	1.0173	0.9899	1.0311	1.0308	1.3811
	VIAV.UW_Equity	0.6952***	0.7251***	0.7480***	0.7480***	1.2003
	VIAB.UN_Equity	0.9789	0.9789	0.9781	0.9781	1.7582
	VLO.UN_Equity	0.9487*	1.0365	0.9905	0.9910	1.3742
	VMC.UN_Equity	0.9758	0.9520**	0.9509**	0.9503**	2.2653
	VNO.UN_Equity	1.0200	1.0375	1.0373	1.0376	3.6746
	VRSN.UW_Equity	0.9664*	0.9761	1.0048	1.0049	1.8034
	VTR.UN_Equity	0.8925***	0.8712***	0.8719***	0.8713***	1.7227
	VIAV.UQ_Equity	0.6952***	0.7251***	0.7480***	0.7480***	1.2003
	VZ.UN_Equity	0.9983	1.0020	1.0042	1.0042	1.5998
	WAT.UN_Equity	0.8106***	0.9634***	0.8401***	0.8398***	0.6987
	WBA.UN_Equity	1.0482	1.0239	1.0248	1.0248	1.7872
	VRSN.UQ_Equity	0.9664*	0.9761	1.0048	1.0049	1.8034
	WEC.UN_Equity	0.9667	0.9696*	0.9695*	0.9695*	1.0851
	WDC.UN_Equity	1.0032	0.9985	0.9989	0.9993	2.8866
	WFC.UN_Equity	1.1264	1.2204	1.0210	1.0210	2.1713
	WFM.UW_Equity	0.8210***	0.8185***	0.7909***	0.8046***	1.2142
	WFT.UN_Equity	0.9780	0.9997	0.9911	0.9947	1.6255
	WHR.UN_Equity	1.0141	1.0140	1.0143	1.0143	1.4857
	WIN.UW_Equity	1.0020	1.0015	1.0123	1.0123	3.7023
	WM.UN_Equity	0.9730*	0.9677*	0.9676*	0.9676*	1.7406
	WFM.UQ_Equity	0.8210***	0.8185***	0.7909***	0.8046***	1.2142
	WMB.UN_Equity	1.0094	0.9670*	0.9679*	0.9679*	1.7414
	WMT.UN_Equity	0.9885	1.0285	1.0293	1.0293	1.1591
	WU.UN_Equity	1.0122	1.0293	1.0283	1.0283	3.3790
	WY.UN_Equity	1.0110	0.9830	1.0053	1.0012	3.9521
	WYN.UN_Equity	0.9889	1.0691	0.9781	0.9781	1.5464
	WOR.UN_Equity	0.9887	1.1152	1.0084	1.0142	1.1014
	WYNN.UW_Equity	0.6770***	0.6737***	0.7218***	0.7219***	0.7444
	X.UN_Equity	0.8967***	0.9146**	0.9015***	0.9015***	2.1373
	XEL.UN_Equity	1.0089	1.0066	1.0071	1.0070	1.4245
	XEC.UN_Equity	0.8349***	0.8230***	0.8230***	0.8229***	1.3143
	XL.UN_Equity	0.7226***	0.7522***	0.7339***	0.7339***	1.7902
	XLNX.UW_Equity	0.9884	0.9805	0.9820	0.9820	1.3624
	XOM.UN_Equity	0.9308**	0.9526*	0.9560*	0.9560*	1.7158
	XLNX.UQ_Equity	0.9884	0.9805	0.9820	0.9820	1.3624
	XRAY.UW_Equity	1.0121	1.0094	1.0112	1.0112	1.4703
	XRX.UN_Equity	0.9607**	0.9481*	0.9470*	0.9456*	1.3749
	YHOO.UW_Equity	1.0355	1.0196	1.0211	1.0211	3.9435
	YHOO.UQ_Equity	1.0355	1.0196	1.0211	1.0211	3.9435
	YUM.UN_Equity	1.0531	1.0198	1.0204	1.0204	1.5143
	ZBH.UN_Equity	1.0170	1.0094	1.0098	1.0098	1.6807
	ZION.UW_Equity	1.0921	1.0514	1.0402	1.0387	2.4751

(Continues on next page)

Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	ZION.UQ.Equity	1.0921	1.0514	1.0402	1.0387	2.4751
U.K. FTSE	AAL.LN.Equity	0.8101***	0.7813***	0.7742***	0.7742***	1.8310
	ABF.LN.Equity	0.9825	0.9657*	1.0121	1.0126	1.2500
	ADM.LN.Equity	0.9142**	0.9198**	0.9209**	0.9208**	1.7587
	AMFW.LN.Equity	0.8535***	0.8718***	0.8695***	0.8695***	0.9660
	AGK.LN.Equity	0.7285***	0.7275***	0.7218***	0.7218***	1.7612
	ADN.LN.Equity	0.9895	1.0111	1.0144	1.0143	1.2071
	ANTO.LN.Equity	0.8499***	0.9448**	0.8376***	0.8368***	1.0237
	AHT.LN.Equity	0.9710	1.2062	1.0452	1.1684	2.7505
	AV.LN.Equity	0.9984	1.0013	1.0041	1.0041	5.1135
	AZN.LN.Equity	1.0113	1.0333	1.0146	1.0147	1.4965
	AU.LN.Equity	0.9751	0.9845	0.9906	0.9908	1.3879
	ARM.LN.Equity	0.7492***	0.8190***	0.8171***	0.8171***	0.8990
	BA.LN.Equity	1.0044	0.9983	0.9990	0.9990	1.4355
	ASHM.LN.Equity	0.9056**	1.0884	1.0044	1.0044	1.2773
	BATS.LN.Equity	0.9548*	0.9478*	0.9482*	0.9482*	1.8979
	BDEV.LN.Equity	0.8866***	0.9753**	0.9188***	0.9234***	2.0142
	BAB.LN.Equity	1.0094	1.0115	1.0113	1.0113	2.5781
	BG.LN.Equity	0.9924	0.9454**	0.9462**	0.9461**	1.3040
	BBY.LN.Equity	1.0549	1.0334	1.0340	1.0342	4.3296
	BLT.LN.Equity	0.8870***	0.8536***	0.8532***	0.8532***	1.2769
	BP.LN.Equity	1.1487	1.0239	1.0267	1.0267	2.6687
	BNZL.LN.Equity	1.1293	1.0730	1.0342	1.0809	2.7177
	BT.A.LN.Equity	0.9777*	0.9703*	0.9715*	0.9715*	1.4255
	BRBY.LN.Equity	0.9419**	1.0897	0.9259**	0.9120***	1.2444
	CCL.LN.Equity	1.0570	1.0178	1.0185	1.0185	1.3356
	CNA.LN.Equity	1.1468	0.9538*	0.9528*	0.9528*	1.8424
	CNE.LN.Equity	0.9039***	1.0795	0.8675***	1.0442	1.1561
	CPG.LN.Equity	0.9184**	0.9602*	0.9474**	0.9476**	1.6068
	CPI.LN.Equity	1.0189	1.0250	1.0258	1.0258	1.5981
	CWC.LN.Equity	1.0249	0.9897	0.9963	0.9921	5.1511
	DGE.LN.Equity	0.9875	0.9795	0.9802	0.9801	1.3749
	COB.LN.Equity	1.1027	0.9949	0.9931	0.9931	1.6753
	DMGT.LN.Equity	1.0043	0.9925	0.9928	0.9928	1.8638
	DRX.LN.Equity	1.1019	1.0432	1.0078	1.0076	1.9875
	EMG.LN.Equity	0.9982	0.9998	1.0149	1.0144	2.1104
	CRH.LN.Equity	1.0548	1.0119	1.0124	1.0125	1.9134
	CRDA.LN.Equity	0.7299***	0.7813***	0.7467***	0.7466***	1.1365
	DXNS.LN.Equity	0.9488**	0.9404***	0.9336***	0.9336***	1.8972
	ENRC.LN.Equity	1.0363	1.0317	1.0326	1.0324	9.7485
	ETI.LN.Equity	1.0381	1.0233	1.0233	1.0233	3.1487
	EXPN.LN.Equity	0.9761	0.9646*	0.9630*	0.9633*	1.5229
	FLG.LN.Equity	0.9639	0.9600	0.9648	0.9647	0.9962
	COLT.LN.Equity	0.9360	0.9352	0.9358	0.9358	1.6660
	FGP.LN.Equity	1.0112	1.0029	1.0019	1.0019	2.6461
	FRES.LN.Equity	1.0483	1.0465	1.0469	1.0467	2.1715
	EZJ.LN.Equity	0.9439**	0.9451*	0.9591*	0.9591*	1.4019
	GSK.LN.Equity	0.9372*	0.9827	0.9774	0.9753	1.5512
	GFS.LN.Equity	1.0316	1.1069	0.9726*	0.9648*	3.6387
	GKN.LN.Equity	0.8534***	0.8522***	0.8520***	0.8520***	1.6597
	HIBU.LN.Equity	1.2716	1.0207	1.0748	1.0206	2.1951
	ECM.LN.Equity	0.8770***	0.9716*	0.9471**	0.9498**	1.7160
	HMSO.LN.Equity	0.9755**	0.9459**	0.9492**	0.9478**	2.9722
	HL.LN.Equity	1.0315	1.1687	1.0259	1.0259	1.1145
	HOME.LN.Equity	1.0402	1.0370	1.0369	1.0368	1.5375
	FXPO.LN.Equity	1.1139	1.0091	1.0060	1.0060	1.9876
	HAS.LN.Equity	1.0508	1.0247	1.0257	1.0257	1.9488
	HIK.LN.Equity	0.9570*	1.0566	1.0108	1.0114	1.3960
	IAP.LN.Equity	1.0271	1.0091	1.0095	1.0095	1.5144
	IHG.LN.Equity	0.9541*	0.9486**	0.9481**	0.9481**	1.5533
	III.LN.Equity	0.9332**	0.9326**	0.9322**	0.9322**	1.9655
	IMI.LN.Equity	0.7596***	0.7967***	0.7868***	0.7868***	2.1295
	IMT.LN.Equity	1.0454	1.0112	1.0119	1.0118	1.4536
	INTU.LN.Equity	1.0150	1.1024	0.9680*	0.9557**	3.9653
	INVP.LN.Equity	1.0365	1.0029	1.0029	1.0029	1.5429
	ITRK.LN.Equity	0.9096**	0.8866***	0.8823***	0.8823***	1.3875
	ITV.LN.Equity	1.1049	0.9970	1.0053	0.9971	1.9361
	ISAT.LN.Equity	1.0847	1.0443	1.0461	1.0461	1.6848
	ISYS.LN.Equity	1.0728	1.0026	1.0023	1.0029	9.5217

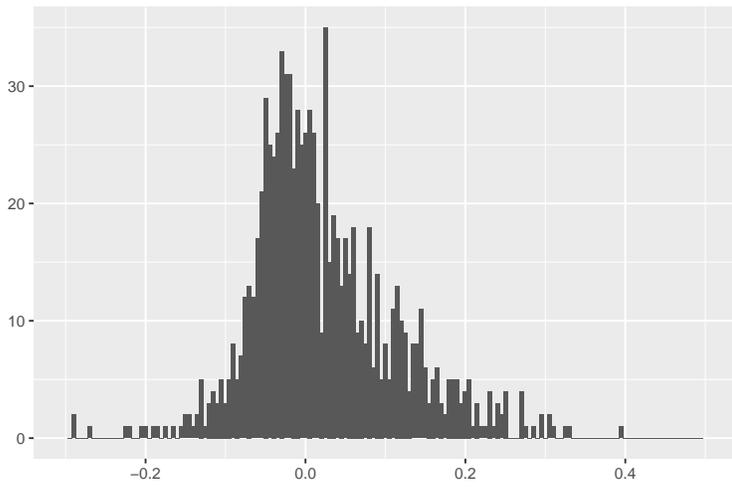
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Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	JMAT.LN.Equity	0.9934	0.9874	0.9879	0.9879	1.7822
	KGF.LN.Equity	1.0229	0.9991	0.9996	0.9996	1.9193
	KAZ.LN.Equity	0.8912**	0.8444***	0.8451***	0.8443***	2.0044
	LAND.LN.Equity	1.0250	1.0224	1.0229	1.0228	4.6767
	LSE.LN.Equity	0.9402**	0.9378**	0.9350**	0.9350**	1.6430
	LAD.LN.Equity	1.0487	1.0186	1.0196	1.0196	1.4821
	MGGT.LN.Equity	0.8923***	0.8972***	0.8959***	0.8959***	1.3837
	LMI.LN.Equity	1.0024	1.0337	0.9783	0.9774	15.7393
	MKS.LN.Equity	1.0408	1.0252	1.0259	1.0259	1.2731
	MAB.LN.Equity	1.1031	1.0302	1.0318	1.0311	2.6103
	MRO.LN.Equity	0.6888***	0.6982***	0.6887***	0.6887***	15.0548
	MNDI.LN.Equity	1.0350	1.0304	1.0306	1.0304	1.6577
	MRW.LN.Equity	0.9516	0.9485*	0.9489*	0.9490*	2.7551
	NG.LN.Equity	0.9568	1.0243	1.0248	1.0248	1.5096
	NXT.LN.Equity	1.0411	1.0005	1.0012	1.0011	2.1356
	OML.LN.Equity	0.8993**	0.9091**	0.9204**	0.9205**	1.6212
	LOG.LN.Equity	1.0012	1.0009	1.0013	1.0013	7.1671
	PFC.LN.Equity	0.8133***	0.7870***	0.7819***	0.7818***	1.6968
	PRU.LN.Equity	0.9666	0.9791	0.9790	0.9790	4.6151
	PNN.LN.Equity	1.0272	0.9790	0.9791	0.9791	11.8315
	PSN.LN.Equity	0.9398**	0.9632*	0.9545*	0.9589*	1.6396
	PSON.LN.Equity	0.9922	0.9381**	0.9387**	0.9376**	1.3985
	MSY.LN.Equity	1.0424	1.0368	1.0163	1.0154	2.2560
	RB.LN.Equity	1.0594	1.0278	1.0291	1.0291	1.6347
	PFG.LN.Equity	1.0071	0.9865	0.9867	0.9867	1.2147
	PUB.LN.Equity	1.1290	1.0951	1.0637	1.0291	4.1433
	RBS.LN.Equity	0.8809**	0.9485**	1.0195	1.0280	1.3602
	RDSA.LN.Equity	0.8812***	0.8965***	0.8600***	0.8597***	1.0689
	RDSB.LN.Equity	0.8355***	0.9137***	0.8654***	0.8654***	1.1708
	REL.LN.Equity	0.9884	1.0011	0.9870	0.9870	1.5640
	REX.LN.Equity	0.9991	0.9883	1.0064	1.0065	1.5114
	RIO.LN.Equity	1.0401	1.0365	1.0365	1.0368	2.8700
	RR.LN.Equity	0.9459*	0.9319**	0.9311**	0.9309**	1.5923
	RRS.LN.Equity	1.0182	0.9899	0.9866	0.9866	2.3049
	RSA.LN.Equity	1.0680	1.5355	1.0096	1.0097	6.7081
	RTO.LN.Equity	0.9871	0.9669*	0.9680*	0.9679*	1.9008
	SAB.LN.Equity	0.8626***	0.8668***	0.8661***	0.8665***	1.2813
	SBRY.LN.Equity	1.0425	1.0313	1.0139	1.0139	2.1089
	SDR.LN.Equity	1.0358	1.0083	1.0095	1.0089	2.3162
	SGE.LN.Equity	1.0460	1.0281	1.0173	1.0172	2.7110
	SDRC.LN.Equity	1.0473	1.0518	1.0521	1.0521	1.6974
	SHP.LN.Equity	0.9908	1.0069	0.9951	0.9950	1.1068
	SGC.LN.Equity	0.9509**	0.9456**	0.9432**	0.9432**	1.7897
	SKY.LN.Equity	0.9835***	1.1103	0.9487**	0.9487**	6.1554
	SL.LN.Equity	0.9982	1.0127	1.0136	1.0135	1.3004
	SGRO.LN.Equity	1.0547	1.0298	1.0300	1.0298	2.1317
	SMIN.LN.Equity	0.8349***	0.8801***	0.8323***	0.8323***	1.3430
	SN.LN.Equity	1.0654	1.0131	1.0130	1.0130	1.6523
	SRP.LN.Equity	0.8477***	0.8668**	0.8329***	0.8329***	1.2035
	SSE.LN.Equity	1.0159	1.0138	1.0169	1.0168	1.4398
	SPD.LN.Equity	0.9936	1.0029	1.0125	1.0125	1.7200
	SVT.LN.Equity	1.0117	0.9960	0.9966	0.9966	3.0775
	TATE.LN.Equity	0.7286***	0.7570***	0.7577***	0.7577***	1.3761
	TLW.LN.Equity	0.8735***	0.8999**	0.8222***	0.8222***	1.4784
	STJ.LN.Equity	0.9985*	0.9987	0.9989	0.9989	1.6121
	TPK.LN.Equity	1.0112	0.9821	0.9920	0.9919	3.1002
	SPT.LN.Equity	0.8284***	0.9071***	0.7893***	0.7875***	2.4432
	TSCO.LN.Equity	0.9855	0.9503	0.9491*	0.9482*	1.7836
	TT.LN.Equity	1.2246	1.1464	1.2154	1.1469	2.5005
	ULVR.LN.Equity	0.9764	0.9683*	0.9687*	0.9687*	1.5964
	UU.LN.Equity	1.0304	1.0296	1.0294	1.0294	1.3906
	TW.LN.Equity	1.1662	1.1914	1.0352	1.0213	4.9087
	VED.LN.Equity	0.9379*	0.9391*	0.9142**	0.9135**	2.4347
	VOD.LN.Equity	1.0149	0.9886	0.9891	0.9890	1.7648
	UBM.LN.Equity	1.0378	1.0246	1.0250	1.0250	2.7535
	WEIR.LN.Equity	0.7545***	0.8246***	0.7639***	0.7638***	1.9144
	WG.LN.Equity	0.8621***	0.8454***	0.8452***	0.8452***	1.7529
	WOS.LN.Equity	1.0724	1.2028	1.0293	1.0913	4.6376
	WMH.LN.Equity	0.9688	0.9853	0.9860	0.9860	1.3986

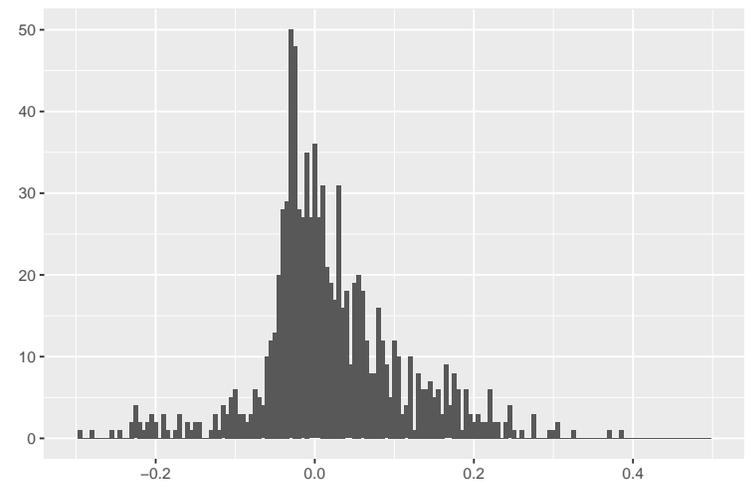
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Index	Bloomberg Ticker	DMA	DMS	BMA	BMS	OLS
	WPP.LN_Equity	1.0155	1.0068	1.0021	1.0017	2.3956
	WTB.LN_Equity	1.0518	1.0282	1.0292	1.0292	1.9651
	XTA.LN_Equity	0.9242*	0.9208*	0.9206*	0.9206*	2.5115

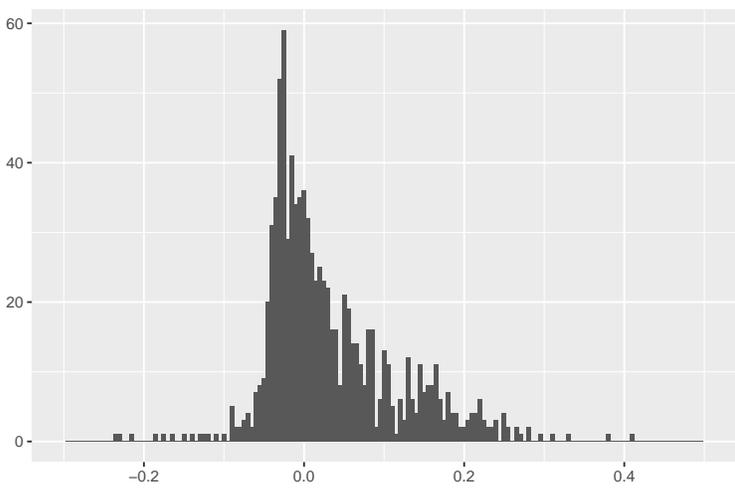
(Table 4 Continued from previous page) This table shows detailed test results of the CW – statistic for all equities that are analysed in each equity index of interest for all models $\ell = \{\text{DMA, DMS, BMA, BMS, OLS}\}$ that we consider, relative to the forecasts of the historic average (HA) benchmark. The out-of-sample evaluation period is from 2011:06 to 2015:07. We use $\{*, **, ***\}$ to denote significance at the 10%, 5%, and 1%, respectively, using one sided (upper tail) t -tests.



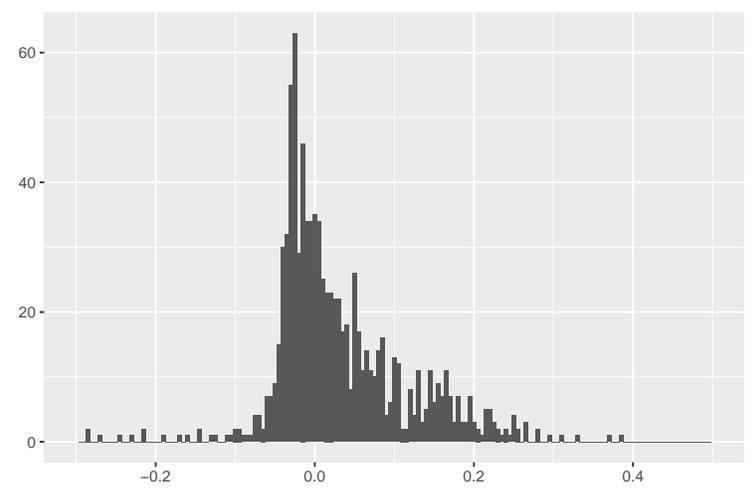
(a) DMA



(b) DMS

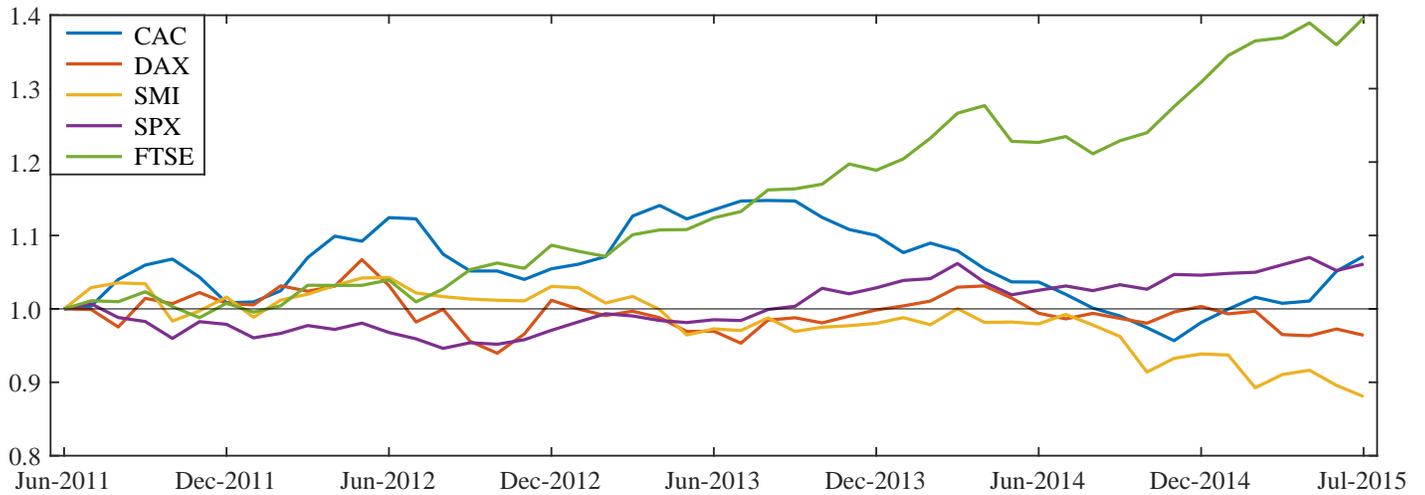


(c) BMA

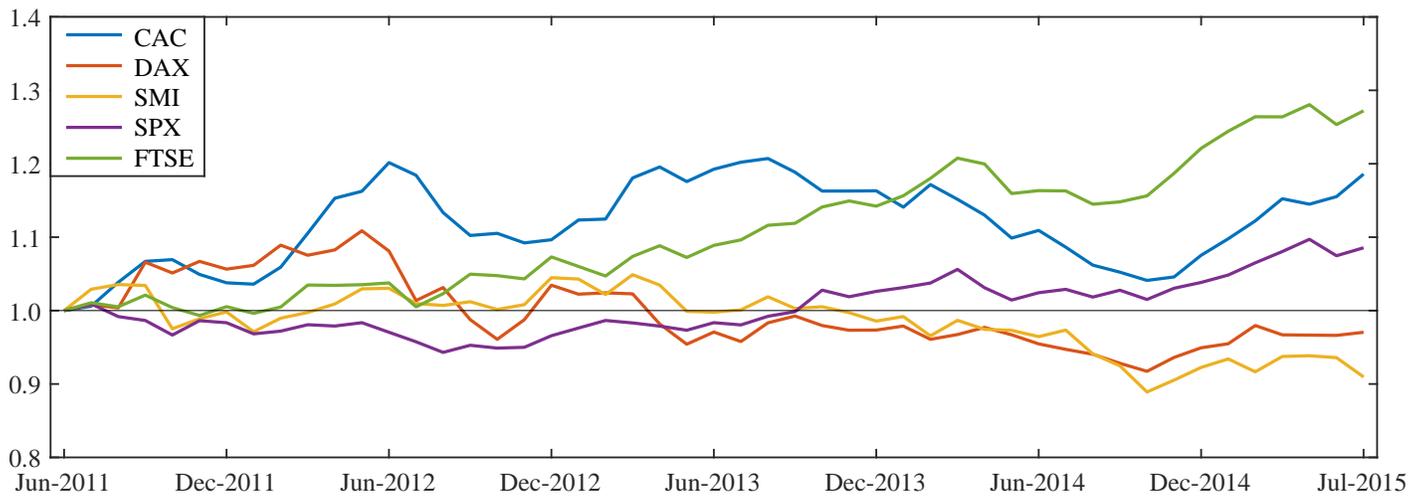


(d) BMS

Figure 2: Empirical distributions (histograms) of the out-of-sample R^2 values for All ($N = 896$) equities.



(a) DMA



(b) DMS

Figure 3: Portfolio value of DMA/DMS forecast based long strategy for each index in excess of the respective benchmark indices and accounting for trading costs. The value of the first period is normalized to 1. The out-of-sample period of the portfolio is from 2011:06 to 2016:07.

Table 5: Results of the portfolio trading model with transaction costs

Index Name	Year	Return			Standard Deviation			Max. Drawdown			Alpha		Info. Ratio	
		Index	DMA	DMS	Index	DMA	DMS	Index	DMA	DMS	DMA	DMS	DMA	DMS
CAC	All	22.61%	34.04%	44.24%	15.29%	15.55%	15.60%	25.58%	20.61%	20.42%	1.85%	4.60%	0.26	0.62
	2011	-16.50%	-36.90%	-32.62%	20.35%	19.03%	18.83%	27.45%	20.61%	20.42%	1.08%	4.16%	0.04	0.15
	2012	15.19%	20.41%	23.47%	14.12%	15.67%	14.79%	12.61%	9.86%	8.17%	5.87%	9.72%	0.70	1.00
	2013	17.24%	18.71%	18.86%	11.33%	11.13%	11.84%	5.31%	4.31%	4.55%	1.75%	1.84%	0.25	0.27
	2014	0.05%	-7.14%	-3.68%	11.34%	13.14%	12.44%	6.34%	14.86%	12.79%	-7.11%	-3.76%	-1.26	-0.54
	2015	10.19%	56.62%	59.09%	20.87%	11.90%	17.02%	12.34%	0.00%	0.00%	26.62%	29.81%	4.15	5.75
DAX	All	47.08%	48.21%	48.84%	17.50%	18.72%	18.78%	25.41%	24.82%	22.21%	-1.02%	-0.84%	-0.15	-0.11
	2011	-12.54%	-30.97%	-22.29%	25.83%	30.37%	28.91%	26.78%	24.82%	22.21%	0.64%	7.50%	0.02	0.22
	2012	26.79%	27.02%	23.73%	14.81%	19.85%	19.82%	9.82%	12.66%	13.53%	-0.72%	-4.77%	-0.06	-0.41
	2013	23.49%	24.22%	19.42%	11.25%	13.86%	14.26%	4.67%	6.28%	5.94%	0.54%	-5.34%	0.11	-0.81
	2014	3.18%	2.17%	0.87%	11.09%	11.95%	12.89%	6.20%	6.93%	8.45%	-1.11%	-2.53%	-0.26	-0.57
	2015	11.70%	30.87%	42.76%	23.65%	17.53%	21.09%	19.27%	4.54%	4.31%	-9.91%	5.74%	-1.69	1.07
SMI	All	31.87%	24.92%	28.10%	11.28%	12.90%	12.82%	15.66%	17.01%	17.70%	-3.41%	-2.55%	-0.52	-0.37
	2011	-7.26%	-17.93%	-20.91%	13.07%	14.32%	14.51%	16.37%	17.01%	17.70%	-1.65%	-4.13%	-0.07	-0.18
	2012	14.37%	18.43%	21.68%	9.03%	9.31%	9.91%	6.18%	5.18%	4.19%	4.67%	8.50%	1.11	1.60
	2013	19.02%	14.98%	14.00%	10.04%	10.47%	10.74%	3.32%	4.47%	4.88%	-4.76%	-5.89%	-0.85	-0.99
	2014	9.34%	4.25%	3.62%	6.92%	9.87%	10.85%	3.05%	4.97%	6.11%	-5.64%	-6.38%	-0.80	-0.86
	2015	-0.53%	-5.45%	2.37%	17.07%	26.13%	22.81%	9.70%	11.11%	8.41%	-14.85%	-6.62%	-1.66	-0.95
SPX	All	45.58%	54.87%	57.08%	11.49%	13.97%	13.78%	15.89%	19.28%	18.70%	1.67%	2.32%	0.40	0.53
	2011	1.15%	-15.73%	-14.50%	15.97%	25.00%	24.32%	17.03%	19.28%	18.70%	-5.95%	-4.79%	-0.20	-0.16
	2012	13.16%	15.56%	14.12%	10.56%	11.67%	11.75%	6.97%	7.49%	7.77%	2.58%	0.93%	0.74	0.25
	2013	26.54%	32.37%	32.28%	8.56%	9.92%	9.93%	3.13%	2.70%	2.51%	7.44%	7.32%	2.18	1.93
	2014	11.14%	12.31%	13.05%	8.11%	11.02%	11.15%	3.56%	3.33%	2.98%	1.03%	1.84%	0.23	0.39
	2015	0.11%	9.13%	14.61%	13.66%	12.65%	12.25%	8.89%	2.96%	1.56%	3.10%	9.22%	0.78	1.70
FTSE	All	11.28%	57.73%	51.03%	11.77%	12.50%	12.34%	14.38%	14.20%	14.06%	10.65%	8.79%	1.84	1.59
	2011	-4.88%	-10.36%	-10.49%	13.39%	15.84%	15.92%	15.51%	14.20%	14.06%	0.79%	0.67%	0.04	0.03
	2012	6.18%	16.09%	15.60%	10.26%	11.58%	11.93%	9.38%	8.16%	8.29%	10.78%	10.17%	1.78	1.57
	2013	14.24%	27.14%	25.21%	12.26%	14.27%	13.36%	5.58%	4.70%	4.69%	15.19%	12.89%	3.63	2.90
	2014	-2.36%	10.10%	7.08%	9.20%	10.86%	11.04%	4.35%	5.04%	5.80%	12.71%	9.45%	1.75	1.44
	2015	-4.23%	25.06%	22.23%	13.27%	7.64%	7.47%	13.21%	1.00%	1.13%	11.89%	8.39%	1.85	1.52

Notes: This table provides summary results of the DMA/DMS forecast ranked tailored portfolios. Entries under column one and two show the index of interest and the time period (Year) that is analysed. Column blocks (3–5), (6–8), and (9–11) report, respectively, the annualized return, the annualized standard deviation, and the maximum drawdown as defined in (16) for the indices of interest $\iota = \{DAX, SPX, FTSE, CAC, SMI\}$ as well as the respective DMA/DMS forecast ranked portfolios on those indices. The last two column blocks under the headings Alpha and Info. Ratio give the benchmark Alpha and the information ratio (IR) as defined in (17) and (18), respectively, which are computed relative to the index of interest ι . The out-of-sample evaluation period is from 2011:06 to 2015:07.