Are Short Term Stock Asset Returns Predictable? An Extended Empirical Analysis

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Abstract

In this paper, the question is addressed, whether or not short term stock asset returns are predictable from the knowledge of the past return series. Several methods like *Hodrick-Prescott*-filtering, *Kalman*-filtering, GARCH-M, EWMA and non-parametric regression are benchmarked against naive mean predictions. The extended empirical analysis includes data of several hundred stocks and indexes over the last ten years. The root mean square error of the concerning prediction methods is calculated for several rolling windows of different length, in order to assess whether or not local model fit is favorable.

Keywords: *Hodrick-Prescot*-Filter; *Kalman*-Filter; GARCH-Model; Non-Parametric Regression; Maximum-Likelihood Estimation; *Nadaraya-Watson*-Estimator.

1. Introduction

The question whether or not stock asset returns are predictable is a most active and controversially discussed issue since the influential works of Fama and French (1988a,b), Campbell and Shiller (1988) and Poterba and Summers (1988). Subsequent research has focused on middle- and long-term predictability. Additional variables, beyond the stock asset price and its dividend, were used to enhance predictive power. An incomplete list includes changes in interest rates and yield spreads between short- and long-term interest rates (Keim and Stambaugh, 1986; Campbell, 1987, 1991), book-to-market ratios (Kothari and Shanken, 1997; Pontiff and Schall, 1998), price-earnings ratios (Lamont, 1998), consumption-wealth ratios (Lettau and Ludvigson, 2001) and stock market volatility (Goyal and Santa-Clara, 2003). A comparative survey of aggregated stock prediction with financial ratios is provided in Lewellen (2004). An excellent review is given in Rey (2003).

Unfortunately, short-term returns are exceedingly difficult to predict for different reasons. First, the signal-to-noise ratio is extremely unfavorable for short-term returns or log-returns, respectively. Second, additional variables, like those

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mentioned in the previous paragraph, usually contribute to the trend of a stock asset over an extended period. Thus, in case of daily returns, their influence is not detectable and one relies solely on statistical instruments and the information contained in the observation history. Nonetheless, predicting short-term returns of stock assets is of great importance for example in risk-management and related fields.

This paper contributes to the existing literature in that an extended empirical analysis of short-term (daily) log-returns of stock assets and indexes is conducted to answer the question, whether or not they are predictable to a certain degree. For this purpose, more than 360 stocks are analyzed over the last 10 years. Several statistical prediction methods are applied and benchmarked against each other by assessing their root mean square errors.

The remainder of the paper is organized as follows: Section 2 introduces the statistical instruments used in this survey. Section 3 provides a detailed analysis of eight influential stock indexes. Based on the results, an optimized study design is established for the analysis of the 355 stock assets contained in the indexes. In section 4 the procedure is exercised on thirty DAX stocks. The results are summarized in table form. Additional results from the remaining stock assets are provided in appendix B. Section 5 summarizes the findings and discusses the implications.

2. Prediction Methods

In this section the prediction methods used in this survey are introduced. Prior to this it is necessary to distinguish between local and global methods. In what follows, local methods are understood as prediction methods, which incorporate only a limited amount of past information. A typical information horizon reaches 40 or 100 days into the past. Global methods are prediction methods that rely on the complete information available; in this case log-return data from 01-January-2000 to 31-January-2010. On the one hand, local methods often experience large variability in their parameter estimates because of the small sample size. On the other hand, structural shifts due to environmental influences can cause the model parameters themselves to vary over time. Local methods can better adjust to such structural changes than global ones.

2.1. Mean Prediction

Log-returns, when analyzed with time series methods, generally turn out to be white noise processes. Therefore, the mean is the optimal linear predictor. It is although the most simple predictor to compute and hence serves as benchmark in this survey, both locally and globally.

Let $x_t = \log S_t$ be the logarithmic stock asset price at time t. Let further $\nabla = 1 - B$ be the difference operator and B the usual backward shift operator, then the log-return is $\nabla x_t = x_t - x_{t-1}$ and its linear local predictor is

$$\widehat{\nabla x}_{t+1} = \frac{1}{K} \sum_{k=0}^{K-1} \nabla x_{t-k} = \frac{x_t - x_{t-K}}{K}. \tag{1}$$

K defines the size of the window for the rolling mean calculation. The global predictor is calculated analogously, but the telescoping series yields $x_T - x_1$.

Remark: Notice that in case of global prediction future information is involved in the prediction at time $t < T$. This is not a problem if the log-return process is ergodic. In this case the distribution of the predictor is identical to the distribution of another predictor, using the same amount of information but shifted back into the past by $T - t$ days. Thus, equation (1) applies for the global predictor as well with $K = T - 1$.

2.2. *Hodrick-Prescott*-Filter

The *Hodrick-Prescott*-Filter (Hodrick and Prescott, 1997) basically divides a time series into its trend and cyclical component. Let

$$x_t = g_t + c_t, \tag{2}$$

again with $x_t = \log S_t$, g_t the growth component, c_t the cyclical (noise) component and $t = 1, \dots, K$. Then the HP-Filter is determined by solving the optimization problem

$$\min_{\{g_t\}_{t=1}^{K}} \left[\sum_{t=1}^{K} (x_t - g_t)^2 + \lambda \sum_{t=2}^{K-1} (\nabla^2 g_{t+1})^2 \right]. \tag{3}$$

Because of the logarithmic transformation the trend of x_t can be expected to be linear. If changes in the trend are only due to random fluctuations, one can formulate a random walk model for the growth rate $\nabla g_t = \nabla g_{t-1} + \nabla^2 g_t$. It can be shown (for example Reeves et al., 2000) that for $\nabla^2 g_t \sim N(0, \sigma_g^2)$, $c_t \sim N(0, \sigma_c^2)$, $\nabla^2 g_t$ and c_t independent and $\lambda = \sigma_c^2/\sigma_g^2$, minimizing (3) yields the Maximum-Likelihood estimator for $\mathbf{g} = (g_1, \dots, g_K)'$

$$\hat{\mathbf{g}}(\lambda) = (\mathbf{I} + \lambda \mathbf{F}'\mathbf{F})^{-1}\mathbf{x}, \tag{4a}$$

with

$$\mathbf{F} = \begin{pmatrix} 1 & -2 & 1 & 0 & \cdots & 0 \\ 0 & 1 & -2 & 1 & \cdots & 0 \\ \vdots & & \ddots & \ddots & \ddots & \vdots \\ 0 & \cdots & 0 & 1 & -2 & 1 \end{pmatrix}. \tag{4b}$$

In most cases the variances σ_c^2 and σ_g^2, and hence λ, will not be known (they may even not be constant in time, see section 2.4). Remarkably, Schlicht (2005) was able to derive the log-likelihood function for λ

$$l(\lambda; \mathbf{x}) = -\log\det\big[\mathbf{I} + \lambda \mathbf{F}'\mathbf{F}\big] - K \log\big[\mathbf{x}'\mathbf{x} - \mathbf{x}'\hat{\mathbf{g}}(\lambda)\big] + (K-2)\log\lambda. \tag{5}$$

Equation (5) has to be maximized numerically with *Newton-Raphson* or a similar algorithm (for an excellent treatment on this subject see Dennis and Schnabel, 1983). The first and second derivative with respect to λ is derived analytically in appendix A.1.

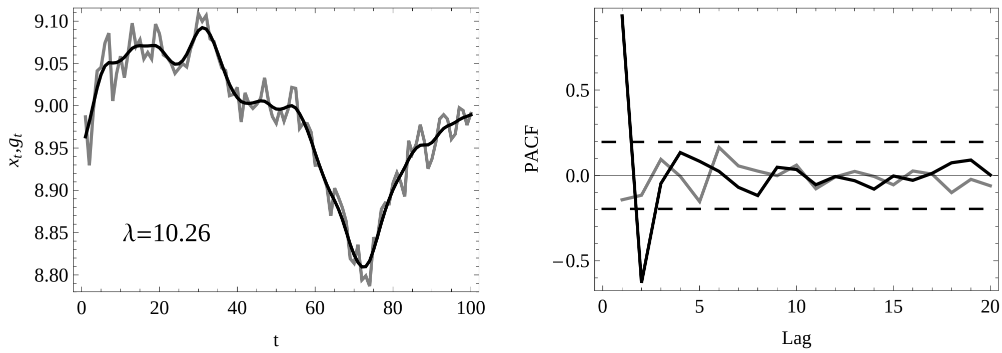

Figure 1: Original and HP-Filtered Logarithmic DJI (left) – Partial Sample Autocorrelation Function for Log-Returns (right)

In figure 1 (left) a portion of the Dow Jones Industrial Average index is shown in logarithmic scale (gray) and HP-Filtered (black). The estimated variance ratio is $\lambda = 10.263$. Obviously, the filtered log-return series has partial autocorrelations at lag one and two (figure 1 right), whereas the original log-returns are white noise. The dashed lines indicate the 95% confidence band under the white noise hypothesis. The correlation structure of ∇g_t is used to fit an AR(p) model, where the model order is selected with BIC (Schwarz, 1978). In this case a AR(2)-model is identified with $\phi_1 = 1.522$ and $\phi_2 = -0.629$.

The general prediction formula under *Hodrick-Prescott*-filtering is thus

$$\widehat{\nabla x}_{t+1} = \mu + \sum_{k=1}^{p} (\phi_k \nabla g_{t-k+1} - \mu), \tag{6a}$$

with

$$\mu = \frac{g_t - g_{t-K}}{K}. \tag{6b}$$

The HP-prediction is clearly a local method because it involves a $(K+1)\times(K+1)$ matrix inversion and the predictor cannot be updated recursively.

2.3. *Kalman*-Filter

The *Kalman*-Filter (Kalman, 1960) is a sophisticated estimator for a partially or completely unobservable system state, conditioned on an information set provided by a corresponding measurement process. If both, system and measurement process, are linear with *Gauss*ian noise, the *Kalman*-Filter is the optimal estimator. For nonlinear processes, it is still the best linear estimator.

Because the *Kalman*-Filter is used as local predictor, the variance of the log-return process is assumed locally constant[1]. Thus, a basic structural state-space

[1]Prediction methods allowing for time varying variance, even locally, are introduced in sections 2.4 and 2.5.

model called local linear trend model can be formulated

$$\begin{pmatrix} y_t \\ \mu_t \end{pmatrix} = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \begin{pmatrix} y_{t-1} \\ \mu_{t-1} \end{pmatrix} + \begin{pmatrix} \epsilon_t \\ \eta_t \end{pmatrix} \tag{7a}$$

$$x_t = \begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} y_t \\ \mu_t \end{pmatrix}. \tag{7b}$$

The noise vector is assumed identically and independently $N(\mathbf{0}, \mathbf{Q})$-distributed. The variance of ϵ_t can be estimated by the sample variance of ∇x_t, $\text{Var}[\epsilon_t] = E[(\nabla x_t - \hat{\mu})^2] = \hat{\sigma}^2$. To determine the variance of η_t is a little more involved, because the mean process is unobserved. Because η_t represents the variability of the estimated mean, its variance can be estimated by cross validation of $\hat{\mu}$. Let $\hat{\mu}_{-k}$ be the estimated mean, omitting the k-th log-return. Then the cross validated mean estimator is

$$\tilde{\mu} = \frac{1}{K} \sum_{k=1}^{K} \hat{\mu}_{-k} = \frac{1}{K(K-1)} \sum_{k=0}^{K-1} \sum_{j \neq k} \nabla x_{t-j}. \tag{8}$$

It is easy to see that $\tilde{\mu}$ is unbiased, because $E[\tilde{\mu}] = E[\hat{\mu}]$, and its sample variance is $\text{Var}[\tilde{\mu}] = \hat{\sigma}^2 / K(K-1)$, which is an estimator for the variance of η_t. Because y_t and μ_t are assumed mutually independent, the off-diagonal entries of $\mathbf{Q}$ vanish and one obtains

$$\mathbf{Q} = \begin{pmatrix} \hat{\sigma}^2 & 0 \\ 0 & \frac{\hat{\sigma}^2}{K(K-1)} \end{pmatrix}. \tag{9}$$

The rekursive *Kalman*-scheme provides an optimal estimator for the unobserved system state. It is convenient to write (7a) and (7b) in vector/matrix-form as $\mathbf{y}_t = \mathbf{A}\mathbf{y}_{t-1} + \boldsymbol{\epsilon}_t$ and $x_t = \mathbf{H}\mathbf{y}_t$, respectively. Let further $\hat{\mathbf{y}}_t$ be the system state expectation at time t and $\mathbf{P}_t$ the state error covariance. Then the optimal filter is provided by the *Kalman*-recursions

$$\begin{aligned} \hat{\mathbf{y}}_{t+1|t} &= \mathbf{A}\hat{\mathbf{y}}_{t|t} \\ \mathbf{P}_{t+1|t} &= \mathbf{A}\mathbf{P}_{t|t}\mathbf{A}' + \mathbf{Q} \end{aligned} \tag{10a}$$

$$\begin{aligned} \mathbf{K}_t &= \mathbf{P}_{t|t-1}\mathbf{H}'(\mathbf{H}\mathbf{P}_{t|t-1}\mathbf{H}')^{-1} \\ \hat{\mathbf{y}}_{t|t} &= \hat{\mathbf{y}}_{t|t-1} + \mathbf{K}_t(x_t - \mathbf{H}\hat{\mathbf{y}}_{t|t-1}) \\ \mathbf{P}_{t|t} &= (\mathbf{I} - \mathbf{K}_t\mathbf{H})\mathbf{P}_{t|t-1}. \end{aligned} \tag{10b}$$

Finally, the *Kalman*-Filter has to be initialized with prior state expectation and error covariance. It is assumed that $\mu_0 = \hat{\mu}$ and $y_0 = x_1 - \hat{\mu}$ and therefore, $\text{Var}[\mu_0] = \text{Var}[y_0] = \hat{\sigma}^2/K$. Then the initial prior moments are

$$\hat{\mathbf{y}}_{1|0} = \begin{pmatrix} x_1 \\ \hat{\mu} \end{pmatrix} \quad \text{and} \quad \mathbf{P}_{1|0} = \frac{\hat{\sigma}^2}{K} \begin{pmatrix} K+2 & 1 \\ 1 & \frac{K}{K-1} \end{pmatrix}. \tag{11}$$

Figure 2 illustrates the filtered mean process and log-predictions for the "Deutscher Aktien Index" (DAX) from November-2009 until January-2010.

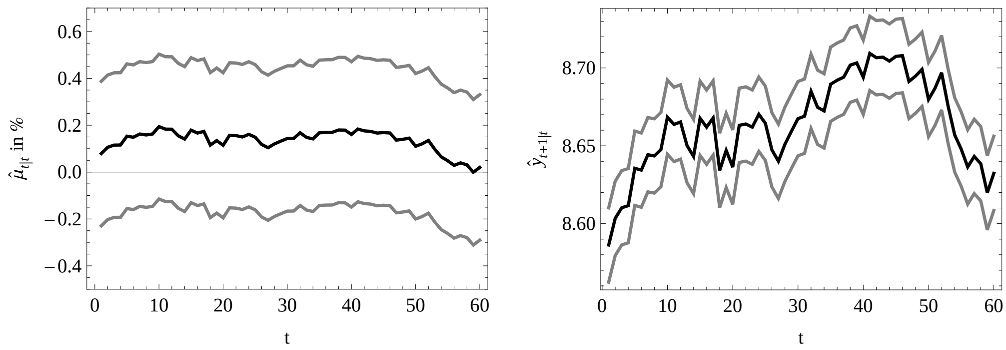

Figure 2: Filtered Mean Process and 95% HPD-Band for DAX (left) – Predicted Logarithmic DAX and 95% HPD-Band (right)

The *Kalman*-predicted log-return takes the particularly simple form

$$\widehat{\nabla x}_{t+1} = \hat{y}_{t+1|t} - x_t. \tag{12}$$

The *Kalman*-Filter is clearly a local instrument because the variance is assumed constant. In the next two subsections methods are introduced that do not suffer from this restriction.

2.4. GARCH-in-Mean

In this subsection the GARCH-in-Mean-model is introduced. ARCH- and GARCH-models (Engle, 1982; Bollerslev, 1986) are extraordinary successful in econometrics and finance because they account for heteroscedasticity and other stylized facts of financial time series (e.g. volatility clustering). This is accomplished by conditioning the variance on former variances and squared errors. The ARCH-in-Mean model (Engle et al., 1987) involves an additional point of great importance. It relates the expected return to the level of present volatility. This is significant from an economic point of view, because in arbitrage pricing theory it is assumed that an agent has to be compensated for the risk he is taking in form of a risk premium. Thus, GARCH-in-Mean models are the starting point for GARCH-based option valuation methods (e.g. Duan, 1995; Duan et al., 1999, 2004; Heston and Nandi, 1997, 2000; Mazzoni, 2008). Recent research challenges the calibration of option valuation models under the physical probability measure (Christoffersen and Jacobs, 2004). Therefore, the results of this survey may provide some insights on this topic.

For the empirical analysis a standard GARCH(1,1)-model has been chosen and the risk premium is modeled linearly regarding volatility. The model equations are

$$\nabla x_t = \mu + \lambda \sigma_t + \epsilon_t \tag{13a}$$
$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{13b}$$

with $\epsilon_t = \sigma_t z_t$ and $z_t \sim N(0,1)$. The parameters have to be estimated with Maximum-Likelihood. This can cause problems because on the one hand, ML is only asymptotically optimal. In small samples ML-estimates can be seriously biased and the distribution of the estimates can suffer from large deviations from normality. On the other hand, in small samples the likelihood-surface might be nearly flat, which causes problems in numerical maximization routines. Therefore the model parameters are estimated using the full time series, which makes the prediction a global one. Under GARCH-in-Mean, the prediction formula is

$$\widehat{\nabla x}_{t+1} = \mu + \lambda\sqrt{\omega + \alpha\epsilon_t^2 + \beta\sigma_t^2}. \tag{14}$$

2.5. EWMA

Exponentially Weighted Moving Average (EWMA, McNeil et al., 2005, sect. 4.4) is an easy to calculate alternative to ARCH/GARCH specification. It is also able to track changing volatility, but its theoretical rational is not as strong as for the heteroscedastic models of section 2.4. The variance equation (13b) is replaced by a simpler version

$$\sigma_t^2 = \gamma\sigma_{t-1}^2 + (1-\gamma)(\nabla x_{t-1})^2, \tag{15}$$

where γ is a persistence parameter, yet to be determined. If it is known, and the initial value σ_{t-K}^2 is approximated, for example by the sample variance, the whole series $\sigma_{t-K}^2, \ldots, \sigma_{t+1}^2$ can be calculated. Thus, the parameters in (13a) can be estimated directly with Generalized Least-Squares (GLS). Let $\boldsymbol{\theta} = (\mu, \lambda)'$ then

$$\hat{\boldsymbol{\theta}} = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\boldsymbol{\nabla}\mathbf{x}, \tag{16a}$$

with

$$\mathbf{X} = \begin{pmatrix} 1 & \sigma_t \\ \vdots & \vdots \\ 1 & \sigma_{t-K} \end{pmatrix} \quad \text{and} \quad \mathbf{W} = \begin{pmatrix} \sigma_t^2 & & 0 \\ & \ddots & \\ 0 & & \sigma_{t-K}^2 \end{pmatrix}. \tag{16b}$$

The volatility persistence γ can either be obtained by external estimation or be fixed at $\gamma = 0.9$, which is a practitioners setting. Figure 3 shows log-returns of the FTSE 100 index of the last ten years. A GARCH-in-Mean model was fitted and the local volatility σ_t was calculated. The upper limit of the 95% confidence area in figure 3 is calculated from these GARCH-volatilities. The lower limit is calculated from an EWMA-model with volatility persistence $\gamma = 0.9$. Both limits are virtually symmetric, but the GARCH-estimation is much more demanding. Furthermore, the EWMA-method can be used as local predictor and the corresponding prediction formula is

$$\widehat{\nabla x}_{t+1} = \mu + \lambda\sqrt{\gamma\sigma_t^2 + (1-\gamma)(\nabla x_t)^2}. \tag{17}$$

2.6. Non-Parametric Regression

The general idea of the non-parametric regression method is to establish a non-linear function for the conditional expectation $m(x) = E[\nabla x_t | \nabla x_{t-1} = x]$ and

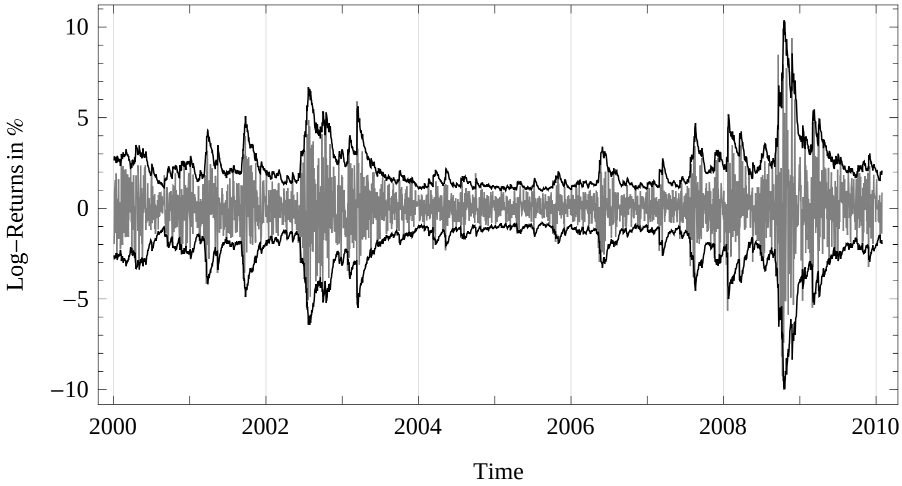

Figure 3: FTSE 100 Log-Returns and Confidence Band – GARCH-in-Mean (upper) and EWMA (lower)

estimate this function from the data under the model

$$\nabla x_t = m(\nabla x_{t-1}) + \epsilon_t, \tag{18}$$

(cf. Franke et al., 2001, sect. 13.1). The non-linear function $m(x)$ can be approximated by *Taylor*-series expansion in the neighborhood of an arbitrary observation ∇x_t

$$m(\nabla x_t) \approx \sum_{j=0}^{p} \frac{m^{(j)}(x)}{j!}(\nabla x_t - x)^j \tag{19}$$

and hence, one can formulate a Least-Squares problem of the kind

$$\sum_{k=0}^{K-1} \epsilon_{t-k}^2 = \sum_{k=0}^{K-1} \left(\nabla x_{t-k} - \sum_{j=0}^{p} \theta_j (\nabla x_{t-k-1} - x)^j \right)^2, \tag{20}$$

with the coefficients $\theta_j = m^{(j)}(x)/j!$. Notice that (20) is only a local approximation. Thus, the observations have to be weighted according to their distance to x. This is usually done by using kernel-functions.

Kernel-functions are mainly used in non-parametric density estimation[2]. Certain characteristics are required by a kernel function, which are already satisfied, if a valid probability density function is used as kernel function. In this application, the standard normal density function is used as kernel function, because it is sufficiently efficient compared to the optimal kernel (Silverman, 1986, tab. 3.1 on p. 43) and it has smooth derivatives of arbitrary order

$$K_h(x) = \frac{1}{h} \phi \left(\frac{x}{h} \right). \tag{21}$$

[2]For an excellent treatment on this subject see Silverman (1986).

The parameter h is the bandwidth or smoothing parameter of the kernel function; its determination has a strong impact on the results of the nonparametric regression. Now the coefficient vector $\boldsymbol{\theta}(x)$ can be estimated by solving the optimization problem

$$\hat{\boldsymbol{\theta}} = \arg\min_{\theta} \sum_{k=1}^{K} \Big(\nabla x_{t-k+1} - \sum_{j=0}^{p} \theta_j (\nabla x_{t-k} - x)^j \Big)^2 K_h(\nabla x_{t-k} - x). \tag{22}$$

This optimization problem can be solved by GLS, if the bandwidth of the kernel function is determined prior to the estimation procedure. This is usually done by cross validation (e.g. Bhar and Hamori, 2005, sect. 4.5). But if the distribution of the log-returns is assumed locally normal, the optimal bandwidth can be calculated analytically (Silverman, 1986, sect. 3.4.2)

$$h_{opt} = \sqrt[5]{\frac{4}{3K}}\sigma. \tag{23}$$

Estimating σ and inserting the resulting optimal bandwidth in (22), the optimization problem has the solution

$$\hat{\boldsymbol{\theta}} = (\mathbf{X}'\mathbf{W}\mathbf{X})^{-1}\mathbf{X}'\mathbf{W}\boldsymbol{\nabla}\mathbf{x}, \tag{24a}$$

with

$$\mathbf{X} = \begin{pmatrix} 1 & \nabla x_{t-1} - x & \dots & (\nabla x_{t-1} - x)^p \\ \vdots & \vdots & \ddots & \vdots \\ 1 & \nabla x_{t-K} - x & \dots & (\nabla x_{t-K} - x)^p \end{pmatrix}, \quad \boldsymbol{\nabla}\mathbf{x} = \begin{pmatrix} \nabla x_t \\ \vdots \\ \nabla x_{t-K+1} \end{pmatrix}$$
$$\text{and} \quad \mathbf{W} = \begin{pmatrix} K_h(\nabla x_{t-1} - x) & & 0 \\ & \ddots & \\ 0 & & K_h(\nabla x_{t-K} - x) \end{pmatrix}. \tag{24b}$$

The desired non-parametric estimator for the conditional expectation is given by

$$\hat{m}(x) = \hat{\theta}_0(x). \tag{25}$$

Notice: for $p = 0$ the optimization problem, and hence the non-parametric estimator (24a) and (24b), reduces to the ordinary *Nadaraya-Watson*-estimator (Nadaraya, 1964; Watson, 1964).

In figure 4 non-parametric regression estimates of orders $p = 0$ (solid black), $p = 1$ (dashed) and $p = 2$ (gray) are given. Observe that higher order polynomial fits tend to diverge for peripheral values. This is the case for $p = 2$ in figure 4 left. Divergent behavior of the approximation can be counteracted to a certain degree by increasing the bandwidth of the kernel function, see figure 4 right. Obviously, the non-parametric regression yields a roughly parabolic structure, which could explain the absence of linear correlation.

Non-parametric regression is clearly a local method and the log-return predictor is

$$\widehat{\nabla x}_{t+1} = m(\nabla x_t). \tag{26}$$

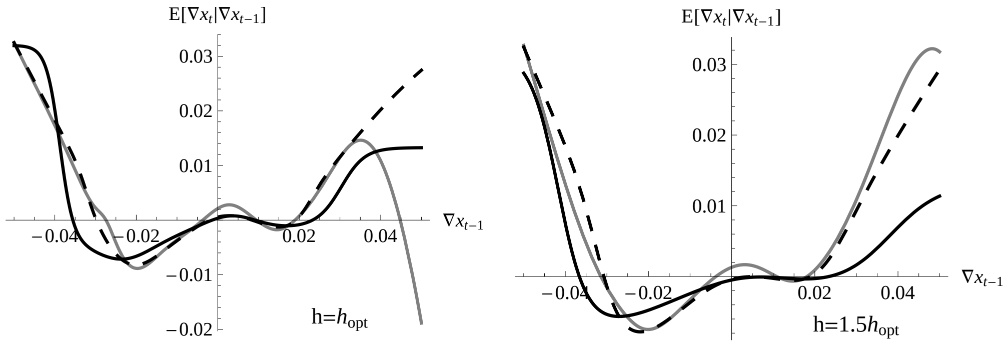

Figure 4: Non-Parametric Regression of Hang Seng Index

3. Empirical Analysis of Index Returns

In this section, the log-returns of eight representative stock indexes are analyzed. The stock assets contained in each index are analyzed in detail in the next section. The indexes are Deutscher Aktienindex (DAX), Dow Jones Euro Stoxx 50 (STOXX50E), Dow Jones Industrial Average Index (DJI), Financial Times Stock Exchange 100 Index (FTSE), Hang Seng Index (HSI), Nasdaq Canada (CND), Nasdaq Technology Index (NDXT) and TecDAX (TECDAX). The analyzed log-return data ranges from 01-January-2000 to 31-January-2010, if available[3].

Table 1 gives the root mean square error of the applied prediction method in %. The table is organized as follows:

- Index indicates the analyzed stock index. All abbreviations refer to Wolfram's financial and economic database.
- K gives the window size, used in local prediction methods.
- Mean indicates the overall mean value (global) and the ordinary rolling mean (local), respectively.
- The abbreviation HP indicates prediction with the *Hodrick-Prescott*-Filter. HP(λ) means that the filter was applied with the fixed smoothing parameter λ. This is computationally more convenient because numerical maximization routines are no longer required.
- KF indicates prediction with the *Kalman*-Filter.
- EW(γ) indicates prediction with the EWMA method. Volatility persistence γ is given in %.
- NR(p) means non-parametric regression. The parameter p indicates the order of polynomial approximation. For $p = 0$ the method results in the ordinary *Nadaraya-Watson*-estimator.
- GARCH indicates the prediction with a globally fitted GARCH-in-Mean model.

[3]The TecDAX index gained approval to the Prime Standard of Deutsche Börse AG at 24-March-2003. It replaced the Nemax50 index.

Index	K	Local RMSE Mean	HP	HP(6)	HP(10)	HP(20)	KF	EW(80)	EW(90)	EW(95)	NR(0)	NR(1)	NR(2)	Global RMSE Mean	GARCH
DAX	40	1.6884	1.8102	1.8168	1.8026	1.7858	1.6901	1.7540	1.7629	1.7613	1.7335	1.8769	7.7156	**1.6670**	1.6695
STOXX50E	40	1.5758	1.6984	1.7109	1.6975	1.6790	1.5785	1.6319	1.6407	1.6378	1.6089	1.7167	23.3640	**1.5560**	1.5584
DJI	40	1.3305	1.4279	1.4379	1.4240	1.4070	1.3321	1.3809	1.3821	1.3818	1.3605	1.6544	11.7722	**1.3115**	1.3129
FTSE	40	1.3548	1.4632	1.4704	1.4572	1.4396	1.3570	1.4128	1.4156	1.4132	1.3948	1.5477	5.0607	**1.3365**	1.3375
HSI	40	1.7137	1.8475	1.8392	1.8279	1.8118	1.7149	1.8263	1.8290	1.8164	1.7815	2.5769	16.9932	**1.6928**	1.6938
CND	40	2.2914	2.4423	2.4331	2.4190	2.4030	2.2899	2.4074	2.3952	2.3795	2.3462	3.1807	52.0094	2.2709	**2.2705**
NDXT	40	2.1137	2.2806	2.2971	2.2716	2.2399	2.1172	2.2145	2.2180	2.2206	2.1524	2.4040	6.0588	**2.0938**	2.0981
TECDAX	40	1.7523	1.863	1.8652	1.8591	1.8508	1.7527	1.8195	1.814	1.8133	1.8183	2.0185	6.8387	**1.7327**	1.7337
DAX	100	1.6733	1.8163	1.8228	1.8070	1.7872	1.6743	1.7128	1.7167	1.7208	1.7118	1.8093	4.4208	**1.6668**	1.6691
STOXX50E	100	1.4818	1.6162	1.6266	1.6101	1.5918	1.4832	1.5228	1.5269	1.5328	1.5146	2.0347	24.1967	**1.4765**	1.4783
DJI	100	1.3056	1.4189	1.4320	1.4157	1.3970	1.3068	1.3354	1.3400	1.3444	1.3224	1.5263	9.7191	**1.3003**	1.3020
FTSE	100	1.3392	1.4643	1.4729	1.4583	1.4396	1.3407	1.3767	1.3769	1.3801	1.3700	1.6050	6.8907	**1.3342**	1.3354
HSI	100	1.6836	1.8284	1.8288	1.8140	1.7961	1.6841	1.7555	1.7437	1.7387	1.7572	4.6404	53.0186	**1.6763**	1.6768
CND	100	2.2862	2.4517	2.4498	2.4333	2.4139	2.2853	2.3258	2.3248	2.3293	2.3222	3.2307	37.2829	2.2795	**2.2791**
NDXT	100	2.1649	2.3602	2.3799	2.3503	2.3141	2.1658	2.2219	2.2268	2.2335	2.1876	2.3724	3.2032	**2.1584**	2.1629
TECDAX	100	1.7402	1.8659	1.8706	1.8646	1.8554	1.7407	1.7844	1.7841	1.7851	1.7808	2.0986	12.6642	**1.7346**	1.7359
DAX	250	1.6909	1.8517	1.8530	1.8357	1.8138	1.6909	1.7173	1.7176	1.7163	1.7214	2.1478	7.8891	**1.6874**	1.6896
STOXX50E	250	1.4021	1.5388	1.5427	1.5257	1.5062	1.4019	1.4362	1.4328	1.4328	1.4202	1.6333	1.6621	**1.3986**	1.4005
DJI	250	1.3168	1.4373	1.4486	1.4321	1.4125	1.3169	1.3422	1.3411	1.3416	1.3356	1.5753	1.8065	**1.3137**	1.3154
FTSE	250	1.3561	1.4941	1.4996	1.4831	1.4624	1.3564	1.3874	1.3825	1.3826	1.3725	1.4975	2.2697	**1.3534**	1.3545
HSI	250	1.6747	1.8312	1.8328	1.8156	1.7955	1.6745	1.7212	1.7069	1.6980	1.7241	6.3393	86.4545	**1.6708**	1.6715
CND	250	2.3212	2.4910	2.4947	2.4773	2.4557	2.3201	2.3572	2.3631	2.3625	2.3729	3.1625	12.6406	2.3131	**2.3121**
NDXT	250	2.3515	2.5684	2.5897	2.5562	2.5164	2.3512	2.3882	2.3910	2.3966	2.3733	2.5462	6.3705	**2.3453**	2.3507
TECDAX	250	1.7688	1.9034	1.9104	1.9019	1.8904	1.7682	1.7931	1.7945	1.7954	1.8203	2.6563	79.7466	**1.7632**	1.7649

Table 1: Root Mean Square Error in % of Index Log-Return Prediction

The minimum root mean square error in % over all prediction methods is indicated in boldface.

In particular, each prediction is generated by considering the last K values $x_t, \ldots, x_{t-K}$ and then calculating the one step log-return prediction $\widehat{\nabla x}_{t+1}$. This is also done for the global predictors, even if their parameter estimates do not depend on the rolling window position or size.

Obviously, the global mean provides the best predictor for log-returns in almost all cases. Its RMSE differs only slightly from the RMSE of the GARCH-in-Mean prediction. Because all root mean square errors are in %, the difference is roughly $\mathcal{O}(10^{-5})$. Hence, the first surprising result is that using local methods does not seem to enhance prediction quality. Among all local predictors, rolling mean and *Kalman*-Filter provide the most precise forecasts. Observe further that the RMSE for the *Hodrick-Prescott*-predictor nearly coincides with the HP-Filter prediction with fixed smoothing parameter $\lambda = 10$. Thus, in further computations HP(10) is used to speed up calculations. All EWMA predictions provide very similar results. Therefore, only EW(90) will be used in further analysis, because it provides a good average. The non-parametric regression method clearly indicates that higher order *Taylor*-series expansion is ineffective in this situation. Only NR(0), which coincides with the *Nadaraya-Watson*-estimator, generates reasonable RMSEs. Thus, higher order NR-predictors are abandoned in further analysis.

From this first survey it can be concluded that the benefit of local prediction is questionable. Furthermore, it seems that the global mean value is the simplest and most efficient predictor.

4. Empirical Analysis of Stock Asset Returns

In this section the stock assets contained in the "Deutscher Aktien Index" (DAX) are analyzed in detail. A similar analysis was conducted for the stocks contained in the other indexes of section 3. The results are summarized in appendix B, and will be discussed comprehensively in section 5. The results of local and global log-return predictions of DAX stocks are summarized in table 2. The organization of the data is analogous to table 1, with two exceptions. First, smoothing- or persistence-parameters are fixed as indicated in the previous section and therefore no longer listed, and second, the abbreviation NW now indicates the *Nadaraya-Watson*-prediction method.

Again, the mean prediction is the dominant method. But despite the results for indexes, a smaller RMSE can be achieved by local prediction in roughly one half of the cases. For some stock assets, the most efficient prediction is accomplished by the *Kalman*-Filter, which virtually tracks the changes in the log-return expectation. Furthermore, in those cases, where the GARCH-in-Mean method appears superior, GARCH-prediction RMSEs are barely smaller than the corresponding global mean RMSEs.

Some preliminary conclusions can be drawn from this observation. First, obviously market portfolios, or indexes as their proxies, are unaffected by local trends in the expected log-returns, whereas stock assets may be. Second,

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
ADS.DE	**3.7735**	3.9933	3.7764	3.8518	3.8086	3.7738	4.0138	3.7759	3.8049	3.8035	3.9075	4.1602	3.9083	3.9361	3.9366	3.8997	3.9466
ALV.DE	2.6845	2.8746	2.6880	2.8269	2.7880	**2.6455**	2.8566	2.6467	2.7142	2.7380	2.6912	2.9219	2.6910	2.7368	2.7880	2.6854	2.6886
BAS.DE	2.3546	2.5275	2.3599	2.5527	2.3725	2.3423	2.5428	2.3451	2.4623	**2.3173**	2.3310	2.5455	2.3316	2.3853	2.3585	2.3254	2.3320
BAYN.DE	2.6902	2.8828	2.6960	2.8976	2.8113	2.6873	2.9089	2.6890	2.8537	2.6674	2.6155	2.8589	2.6160	2.6632	2.6253	**2.6091**	2.6330
BEI.DE	3.0727	3.2356	3.0739	3.1150	3.1101	**3.0703**	3.2450	3.0705	3.0781	3.0969	3.1591	3.3457	3.1594	3.1645	3.1656	3.1542	4.0011
BMW.DE	2.1269	2.2777	2.1305	2.1934	2.2330	2.0551	2.2285	2.0569	2.0867	2.1205	2.0585	2.2382	2.0589	2.0767	2.1322	**2.0540**	2.0543
CBK.DE	3.2402	3.4465	3.2438	3.3841	3.3113	3.1955	3.4321	**3.1951**	3.2719	3.2455	3.2358	3.4849	3.2334	3.2887	3.2906	3.2246	3.4090
DAI.DE	2.3475	2.4922	2.3479	2.4751	2.4163	**2.3008**	2.4751	2.3031	2.3669	2.3478	2.3334	2.5148	2.3330	2.3796	2.3734	2.3276	2.3304
DB1.DE	5.6528	5.9800	5.6569	5.7368	5.6800	2.8094	2.9837	2.8054	2.9097	2.8400	2.8157	3.0342	2.8136	2.8679	2.8356	**2.8038**	2.9608
DBK.DE	2.7007	2.8958	2.7037	2.8189	2.8080	2.6744	2.8868	**2.6741**	2.7476	2.7655	2.7293	2.9574	2.7284	2.7789	2.8702	2.7208	2.7224
DPW.DE	2.4675	2.6191	2.4694	2.7354	2.5444	2.2589	2.4346	2.2614	2.3734	2.3590	2.1819	2.3612	2.1819	2.2352	2.3186	**2.1769**	2.1775
DTE.DE	2.5324	2.7233	2.5364	2.6314	2.5900	2.4383	2.6519	2.4405	2.4951	2.4957	2.3659	2.5917	2.3669	2.4001	2.4000	**2.3621**	2.3626
EOAN.DE	2.5767	2.7669	2.5837	2.8690	2.7113	2.5640	2.7824	2.5670	2.8354	2.7138	2.5441	2.7807	2.5451	2.6046	2.6600	**2.5387**	2.6286
FME.DE	3.0104	3.1915	3.0138	3.0669	3.0326	**2.9965**	3.1833	2.9979	3.0188	3.0063	3.0767	3.2754	3.0775	3.0839	3.0925	3.0699	3.0724
FRE3.DE	3.2477	3.4341	3.2499	3.3138	3.2847	**3.2377**	3.4311	3.2387	3.2665	3.2639	3.3315	3.5392	3.3315	3.3416	3.3525	3.3234	3.4660
HEN3.DE	3.1154	3.2858	3.1157	3.1674	3.1991	**3.1105**	3.2927	3.1111	3.1280	3.1259	3.2174	3.4150	3.2178	3.2228	3.2289	3.2105	3.7094
IFX.DE	4.0161	4.1975	4.0122	4.1376	4.1019	4.0061	4.2248	**4.0014**	4.0544	4.0851	4.0268	4.2626	4.0254	4.0697	4.0752	4.0181	4.1817
LHA.DE	2.0820	2.2221	2.0841	2.1818	2.1396	1.9863	2.1474	1.9883	2.0128	1.9899	1.9051	2.0595	1.9046	1.9291	1.9238	1.8997	**1.8996**
LIN.DE	1.9550	2.0973	1.9581	2.0051	1.9757	1.8774	2.0386	1.8789	1.9189	1.8965	1.8186	1.9808	1.8187	1.8540	1.8419	1.8137	**1.8133**
MAN.DE	2.9191	3.1218	2.9236	3.1359	2.9635	2.8709	3.1078	2.8734	3.1494	2.9340	2.5208	2.7356	2.5200	2.5395	2.5768	**2.5149**	2.5151
MEO.DE	2.1569	2.3137	2.1583	2.3072	2.2152	2.0645	2.2377	2.0667	2.1576	2.1448	2.0407	2.2128	2.0407	2.1249	2.1529	**2.0360**	2.0382
MRK.DE	1.9590	2.0925	1.9605	2.0312	1.9911	1.8947	2.0574	1.8965	1.9219	1.9216	1.8262	1.9953	1.8267	1.8397	1.8698	1.8227	**1.8207**
MUV2.DE	2.0257	2.1634	2.0279	2.1330	2.0633	1.8117	1.9602	1.8131	1.8852	1.8601	1.7226	1.8778	1.7233	1.7739	1.8029	1.7187	**1.7186**
RWE.DE	1.8070	1.9346	1.8092	2.0040	1.9080	1.6653	1.7990	1.6660	1.7606	1.7906	1.6582	1.8038	1.6588	1.7068	1.7697	**1.6560**	1.6582
SAP.DE	1.9209	2.0391	1.9226	1.9641	1.9643	1.8371	1.9732	1.8378	1.8788	1.8753	1.7193	1.8599	1.7199	1.7559	1.7475	**1.7151**	1.7650
SDF.DE	2.4995	2.6578	2.5016	2.5890	2.5795	**2.4735**	2.6578	2.4737	2.5177	2.5365	2.5189	2.7231	2.5192	2.5509	2.5795	2.5137	2.5144
SIE.DE	2.1927	2.3413	2.1940	2.2982	2.2636	**2.1478**	2.3258	2.1492	2.2123	2.2068	2.1757	2.3646	2.1756	2.2095	2.2424	2.1686	2.2493
SZG.DE	2.9912	3.2117	2.9955	3.1138	3.0947	**2.9904**	3.2442	2.9921	3.0832	3.0422	3.0753	3.3561	3.0760	3.1272	3.1570	3.0738	3.0760
TKA.DE	3.0377	3.2372	3.0425	3.3715	3.0946	**2.9912**	3.2186	2.9934	3.4251	3.0302	3.0366	3.2870	3.0369	3.5320	3.0912	3.0291	3.0547
VOW3.DE	2.5967	2.7513	2.5948	2.7760	2.7069	2.5704	2.7460	**2.5680**	2.6758	2.6936	2.5947	2.7843	2.5936	2.6878	2.7431	2.5874	2.5838

Table 2: Root Mean Square Error in % of Log-Return Prediction for Deutscher Aktien Index (DAX) Stocks

there seems to be very little exploitable systematic information to infer from the knowledge of previous log-returns to future log-returns. The GARCH-in-Mean prediction, which associates information about the current volatility with the desired risk-premium, generates barely more efficient forecasts than the corresponding mean prediction, and only for a few stock assets. Only for BASF the incorporation of nonlinear information results in more precise forecasts. Thus, for most stocks the log-return process seems to be a noise process.

5. Summary and Conclusions

Daily log-returns of 355 stock assets and 8 indexes were analyzed over more than ten years. Several non trivial methods were used to calculate a one-step-ahead prediction. The efficiency of the predictions was assessed by the root mean square error criterium.

In roughly half the cases, the global mean prediction generated the smallest RMSE. The GARCH-in-Mean prediction achieved RMSEs of similar magnitudes in some cases. Especially indexes seem to be dominated by global parameters, whereas stock assets occasionally are better predicted by local methods. Among all local prediction methods the rolling mean is superior in almost all cases. In a small number of occasions the *Kalman*-Filter method generates the best predictions. The *Nadaraya-Watson*-estimator only prevails on very rare exceptions. Other prediction methods seem to be inferior.

What conclusions can be drawn from this analysis? First, short-term stock asset log-returns are modeled adequately by noise processes. The same is true of indexes. Nonlinear dependencies, if they exist, are obviously of minor importance. As a consequence, knowledge of the past is not instrumental in predicting the next value of the log-return process. Second, the parameters of those noise models have not necessarily to be invariant in time. It is common knowledge that volatilities are not constant. One possible way to account for this fact mathematically are GARCH-models. But the results of the current analysis suggest that expectation values might be subject to local trends as well. This can be inferred from the fact that local prediction methods are successful in roughly half the cases. Third, one would have expected the GARCH-in-Mean prediction to be superior, because it involves well established economic assumptions about risk premia. This is not the case, which is problematic for the arbitrage pricing theory. GARCH-in-Mean models are used for option valuation (Duan, 1995; Heston and Nandi, 2000; Mazzoni, 2008) in that they are estimated under a physical probability measure $\mathcal{P}$ and subsequently translated into an equivalent model with risk-neutral measure $\mathcal{Q}$, under which the option is valuated. This might explain why recent approaches to calibrate the model directly under the risk-neutral measure $\mathcal{Q}$ are partially more successful (Christoffersen and Jacobs, 2004).

The current investigation clearly indicates that daily log-return processes are not predictable, at least not beyond their mean value. Therefore, they are not suited for profit-oriented investment strategies. This clearly classifies financial markets as risk transfer markets, at least in short term.

A. Mathematical Appendix

A.1. Log-Likelihood Derivatives

Let $\mathbf{M}(\lambda) = (\mathbf{I} + \lambda \mathbf{F}'\mathbf{F})^{-1}$. For notational convenience, functional arguments are omitted in what follows. Then the log-likelihood function (5) can be written

$$l = -\log\det\mathbf{M}^{-1} - K\log\big[\mathbf{x}'(\mathbf{I}-\mathbf{M})\mathbf{x}\big] + (K-2)\log\lambda. \qquad (27)$$

The differential of the determinant of an arbitrary quadratic and invertible matrix $\mathbf{A}$ is $d\det\mathbf{A} = \det\mathbf{A}\cdot\operatorname{tr}\big[\mathbf{A}^{-1}d\mathbf{A}\big]$ (cf. Magnus and Neudecker, 2007, sect. 8.3). In particular, $d\log\det\mathbf{A} = \operatorname{tr}\big[\mathbf{A}^{-1}d\mathbf{A}\big]$ holds. Further, the differential of the inverse is $d\mathbf{A}^{-1} = -\mathbf{A}^{-1}(d\mathbf{A})\mathbf{A}^{-1}$ (Magnus and Neudecker, 2007, sect. 8.4). Observe that $\mathbf{M}$ can be expanded into a *Taylor*-series $\mathbf{M} = \mathbf{I} - \lambda\mathbf{F}'\mathbf{F} + (\lambda\mathbf{F}'\mathbf{F})^2 - \ldots$ and hence, $\mathbf{M}$ and $\mathbf{F}'\mathbf{F}$ commute. Therefore, the derivative of $\mathbf{M}$ with respect to λ is $-\mathbf{M}^2\mathbf{F}'\mathbf{F}$. Now the derivative of (27) can be calculated and one obtains

$$\frac{dl}{d\lambda} = -\operatorname{tr}\big[\mathbf{M}\mathbf{F}'\mathbf{F}\big] - K\frac{\mathbf{x}'\mathbf{M}^2\mathbf{F}'\mathbf{F}\mathbf{x}}{\mathbf{x}'(\mathbf{I}-\mathbf{M})\mathbf{x}} + \frac{K-2}{\lambda}. \qquad (28)$$

Because $d\operatorname{tr}\mathbf{A} = \operatorname{tr}d\mathbf{A}$ (Magnus and Neudecker, 2007, p. 148), the calculation of the second derivative is straight forward

$$\frac{d^2 l}{d\lambda^2} = \operatorname{tr}\big[(\mathbf{M}\mathbf{F}'\mathbf{F})^2\big] + K\left(\frac{\mathbf{x}'\mathbf{M}^2\mathbf{F}'\mathbf{F}\mathbf{x}}{\mathbf{x}'(\mathbf{I}-\mathbf{M})\mathbf{x}}\right)^2 + 2K\frac{\mathbf{x}'\mathbf{M}^3(\mathbf{F}'\mathbf{F})^2\mathbf{x}}{\mathbf{x}'(\mathbf{I}-\mathbf{M})\mathbf{x}} - \frac{K-2}{\lambda^2}. \qquad (29)$$

B. Tables

B.1. RMSE of Dow Jones Euro Stoxx 50 Index (STOXX50E) Stocks

	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
Stock	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
ABI.BR	**5.7713**	6.1225	5.7724	5.9143	5.9220	5.8001	6.1791	5.7991	5.9630	6.0225	5.9648	6.3620	5.9641	7.1517	6.2110	5.9518	6.7439
ACA.PA	2.6277	2.8167	2.6312	2.7293	2.7077	2.6271	2.8534	2.6295	2.6778	2.6947	2.5515	2.7811	2.5516	2.5737	2.6068	**2.5449**	2.5452
AGN.AS	3.4509	3.6843	3.4548	3.5978	3.5550	**3.2917**	3.5527	3.2957	3.3650	3.4038	3.3260	3.5935	3.3265	3.3755	3.4430	3.3172	3.4623
AI.PA	**3.3125**	3.5281	3.3219	3.8965	3.7945	3.3147	3.5538	3.3187	4.1444	3.7617	3.4294	3.6848	3.4309	4.2989	3.8959	3.4223	5.3999
ALO.PA	**2.9533**	3.1702	2.9578	3.0579	3.0253	2.9651	3.2152	2.9676	3.0135	3.0453	2.9926	3.2724	2.9934	3.0325	3.0398	2.9880	2.9877
ALV.DE	2.6845	2.8746	2.6880	2.8269	2.7880	**2.6455**	2.8566	2.6467	2.7142	2.7380	2.6912	2.9219	2.6910	2.7368	2.7880	2.6854	2.6886
BAS.DE	2.3546	2.5275	2.3599	2.5527	2.3725	2.3423	2.5428	2.3451	2.4623	**2.3173**	2.3310	2.5455	2.3316	2.3853	2.3585	2.3254	2.3320
BAYN.DE	2.6902	2.8828	2.6960	2.8976	2.8113	2.6873	2.9089	2.6890	2.8537	2.6674	2.6155	2.8589	2.6160	2.6632	2.6253	**2.6091**	2.6330
BBVA.MC	1.9364	2.0548	1.9361	2.0110	1.9784	**1.8775**	2.0144	1.8788	1.9213	1.8951	1.9080	2.0495	1.9077	1.9338	1.9073	1.9031	1.9069
BN.PA	2.3207	2.4707	2.3220	2.4041	2.3537	**2.3036**	2.4756	2.3056	2.3455	2.3328	2.3825	2.5668	2.3835	2.4112	2.4016	2.3791	2.3964
BNP.PA	2.4473	2.6121	2.4512	2.5483	2.5281	**2.4165**	2.5967	2.4166	2.4499	2.4685	2.4718	2.6747	2.4722	2.4927	2.4958	2.4658	2.4832
CA.PA	1.7783	1.8981	1.7806	1.8476	1.8354	**1.6975**	1.8312	1.6986	1.7532	1.7552	1.7101	1.8529	1.7106	1.7417	1.7732	1.7072	1.7074
CRG.IR	2.2364	2.4119	2.2406	2.3228	2.3118	**2.2284**	2.4326	2.2309	2.2570	2.2766	2.2760	2.5010	2.2773	2.2975	2.3159	2.2731	2.2736
CS.PA	5.2962	5.6475	5.3146	6.4790	5.3263	**5.2718**	5.6654	5.2809	7.1877	5.3041	5.4736	5.8946	5.4769	7.5498	5.5002	5.4622	6.0403
DAI.DE	2.3475	2.4922	2.3479	2.4751	2.4163	**2.3008**	2.4751	2.3031	2.3669	2.3478	2.3334	2.5148	2.3330	2.3796	2.3734	2.3276	2.3304
DB1.DE	5.6528	5.9800	5.6569	5.7368	5.6800	2.8094	2.9837	2.8054	2.9097	2.8400	2.8157	3.0342	2.8136	2.8679	2.8356	**2.8038**	2.9608
DBK.DE	2.7007	2.8958	2.7037	2.8189	2.8080	2.6744	2.8868	**2.6741**	2.7476	2.7655	2.7293	2.9574	2.7284	2.7789	2.8702	2.7208	2.7224
DG.PA	**3.1277**	3.3200	3.1295	3.2093	3.1654	3.1345	3.3548	3.1365	3.1804	3.1603	3.2405	3.4740	3.2409	3.2686	3.2737	3.2344	3.4804
DTE.DE	2.5324	2.7233	2.5364	2.6314	2.5900	2.4383	2.6519	2.4405	2.4951	2.4957	2.3659	2.5917	2.3669	2.4001	2.4000	**2.3621**	2.3626
ENEL.MI	1.5414	1.6477	1.5432	1.6769	1.6430	**1.5278**	1.6530	1.5292	1.6190	1.6178	1.5665	1.7029	1.5671	1.6348	1.6958	1.5654	1.5689
ENI.MI	1.7244	1.8477	1.7270	1.8145	1.7373	**1.7024**	1.8458	1.7037	1.7628	1.7208	1.7446	1.9020	1.7456	1.7834	1.7540	1.7422	1.7431
EOAN.DE	2.5767	2.7669	2.5837	2.8690	2.7113	2.5640	2.7824	2.5670	2.8354	2.7138	2.5441	2.7807	2.5451	2.6046	2.6600	**2.5387**	2.6286
FP.PA	**3.8330**	4.0643	3.8382	3.8932	3.8571	3.8403	4.0843	3.8419	3.8830	3.8402	3.9848	4.2485	3.9858	4.0010	3.9960	3.9772	4.3575
FTE.PA	1.7132	1.8539	1.7168	1.8053	1.7724	1.5668	1.7061	1.5680	1.6019	1.5996	1.5431	1.6939	1.5435	1.5546	1.5674	**1.5394**	1.5396
GLE.PA	2.5801	2.7429	2.5819	2.7151	2.6845	**2.5415**	2.7372	2.5437	2.5932	2.5820	2.6106	2.8183	2.6107	2.6529	2.6363	2.6057	2.6089
G.MI	1.6760	1.7734	1.6761	1.7494	1.7429	**1.6579**	1.7743	1.6589	1.7049	1.7082	1.6728	1.7973	1.6728	1.6950	1.7154	1.6687	1.6695
IBE.MC	**3.8166**	4.0322	3.8174	3.9388	3.8630	3.8452	4.0772	3.8460	3.8767	3.8784	3.9917	4.2375	3.9914	3.9937	4.0220	3.9799	4.3596

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
INGA.AS	3.4984	3.7022	3.4966	3.7399	3.5918	**3.3746**	3.6180	3.3775	3.5001	3.4772	3.4808	3.7337	3.4798	3.5674	3.5585	3.4694	3.9115
ISP.MI	2.5033	2.6791	2.5045	2.6310	2.5651	**2.4246**	2.6243	2.4257	2.4786	2.4660	2.4571	2.6714	2.4570	2.4983	2.4958	2.4504	2.4539
MC.PA	1.8439	1.9715	1.8464	1.9066	1.8954	**1.7925**	1.9410	1.7939	1.8376	1.8295	1.8193	1.9809	1.8196	1.8442	1.8507	1.8152	1.8206
MUV2.DE	2.0257	2.1634	2.0279	2.1330	2.0633	1.8117	1.9602	1.8131	1.8852	1.8601	1.7226	1.8778	1.7233	1.7739	1.8029	1.7187	**1.7186**
OR.PA	1.6337	1.7525	1.6360	1.7041	1.6606	**1.5579**	1.6935	1.5596	1.6144	1.5915	1.5711	1.7138	1.5713	1.5919	1.5733	1.5675	1.5670
PHIA.AS	2.7297	2.9183	2.7331	2.8332	2.7925	2.6511	2.8693	2.6532	2.6894	2.6766	2.5629	2.7853	2.5630	2.5804	2.6027	**2.5565**	2.5570
REP.MC	1.7069	1.8225	1.7079	1.7920	1.7570	**1.6858**	1.8201	1.6870	1.7362	1.7442	1.7419	1.8870	1.7420	1.7681	1.7555	1.7375	1.7374
RWE.DE	1.8070	1.9346	1.8092	2.0040	1.9080	1.6653	1.7990	1.6660	1.7606	1.7906	1.6582	1.8038	1.6588	1.7068	1.7697	**1.6560**	1.6582
SAN.MC	2.1723	2.2934	2.1726	2.2672	2.2188	2.1265	2.2640	2.1266	2.1770	2.1766	2.0873	2.2330	2.0864	2.1092	2.1135	**2.0800**	2.2472
SAN.PA	1.7148	1.8422	1.7181	1.7757	1.7605	**1.6507**	1.7917	1.6524	1.6880	1.6778	1.6582	1.8136	1.6588	1.6816	1.6673	1.6544	1.6546
SAP.DE	1.9209	2.0391	1.9226	1.9641	1.9643	1.8371	1.9732	1.8378	1.8788	1.8753	1.7193	1.8599	1.7199	1.7559	1.7475	**1.7151**	1.7650
SGO.PA	2.4859	2.6431	2.4860	2.5978	2.5452	**2.4172**	2.6160	2.4211	2.4897	2.4412	2.4642	2.6661	2.4646	2.5070	2.5044	2.4598	2.4632
SIE.DE	2.1927	2.3413	2.1940	2.2982	2.2636	**2.1478**	2.3258	2.1492	2.2123	2.2068	2.1757	2.3646	2.1756	2.2095	2.2424	2.1686	2.2493
SU.PA	2.1059	2.2594	2.1086	2.1985	2.1748	**2.0751**	2.2587	2.0773	2.1369	2.1031	2.1289	2.3291	2.1294	2.1686	2.1477	2.1244	2.1254
TEF.MC	1.9318	2.0666	1.9338	2.0168	1.9836	1.8886	2.0403	1.8894	1.9257	1.9400	1.7937	1.9550	1.7942	1.8159	1.8355	**1.7905**	1.7910
TIT.MI	5.8648	6.3562	5.8833	6.2027	5.8856	5.3006	5.7710	5.3068	5.3838	5.7531	4.1179	4.6287	4.1200	4.1145	4.3072	**4.1072**	4.4009
UCG.MI	2.3855	2.5315	2.3862	2.5191	2.4508	**2.3451**	2.5157	2.3468	2.4162	2.3812	2.3920	2.5718	2.3915	2.4487	2.4353	2.3857	2.4655
UL.PA	**1.7791**	1.9116	1.7822	1.8470	1.8325	1.7825	1.9338	1.7835	1.8048	1.8250	1.8353	2.0021	1.8355	1.8437	1.8591	1.8318	1.8309
UNA.AS	**1.7665**	1.9037	1.7698	1.8734	1.7991	1.7891	1.9477	1.7909	1.8437	1.8346	1.9088	2.0905	1.9092	1.9457	1.9398	1.9043	1.9059
VIV.PA	1.7543	1.8911	1.7568	1.8278	1.8053	1.6169	1.7550	1.6181	1.6533	1.6508	1.5668	1.7069	1.5672	1.5887	1.5894	**1.5628**	1.5636

B.2. RMSE of Dow Jones Industrial Average Index (DJI) Stocks

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
AA	3.0149	3.2228	3.0178	3.1141	3.1188	2.9891	3.2319	2.9912	3.0558	3.0886	2.9598	3.2077	2.9587	3.0249	3.0676	**2.9501**	2.9506
AXP	2.7836	2.9831	2.7868	2.9014	2.8219	2.7500	2.9842	2.7519	2.7937	2.7716	2.7500	2.9917	2.7501	2.7872	2.7829	**2.7433**	2.8644

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
BA	2.1733	2.3042	2.1739	2.2501	2.2182	2.1334	2.2872	2.1341	2.1793	2.1636	2.1047	2.2621	2.1046	2.1329	2.1315	2.1003	**2.0996**
BAC	3.5313	3.7723	3.5355	3.6699	3.6907	**3.5222**	3.8047	3.5235	3.5684	3.6685	3.5516	3.8622	3.5522	3.6286	3.7406	3.5436	3.8402
CAT	2.2914	2.4275	2.2902	2.3671	2.3610	2.2436	2.4132	2.2454	2.2741	2.2791	2.2250	2.3969	2.2245	2.2434	2.2384	**2.2182**	2.2190
CSCO	3.0387	3.2574	3.0436	3.1379	3.1051	2.9708	3.2188	2.9727	3.0088	3.0031	2.8531	3.1062	2.8535	2.8700	2.8963	**2.8478**	2.8496
CVX	1.8139	1.9436	1.8168	1.9291	1.8322	1.7819	1.9327	1.7837	1.8595	**1.7719**	1.7863	1.9486	1.7873	1.8495	1.7933	1.7837	1.7842
DD	2.0274	2.1611	2.0291	2.1037	2.0745	1.9597	2.1171	1.9615	2.0001	1.9884	1.9243	2.0846	1.9245	1.9508	1.9635	**1.9188**	1.9193
DIS	2.2613	2.4174	2.2645	2.3502	2.3062	2.2292	2.4122	2.2312	2.2751	2.2613	2.1877	2.3802	2.1886	2.2124	2.2247	**2.1839**	2.3119
GE	2.2720	2.4190	2.2739	2.3581	2.3446	2.2387	2.4134	2.2410	2.2729	2.2996	2.2373	2.4176	2.2373	2.2757	2.3192	**2.2317**	2.2326
HD	2.4353	2.5995	2.4376	2.5027	2.5065	2.3869	2.5833	2.3893	2.4227	2.4490	2.2124	2.4058	2.2128	2.2333	2.2399	**2.2066**	2.3126
HPQ	2.6861	2.8699	2.6894	2.7725	2.7757	2.6299	2.8397	2.6318	2.6600	2.7010	2.4894	2.7099	2.4906	2.5069	2.5347	**2.4859**	2.5672
IBM	1.9367	2.0531	1.9369	2.0043	2.0072	1.8891	2.0283	1.8895	1.9121	1.9294	1.7524	1.8882	1.7528	1.7695	1.7845	**1.7474**	1.8124
INTC	2.9163	3.1320	2.9197	3.0348	2.9633	2.8505	3.0989	2.8524	2.9010	2.9018	2.6918	2.9419	2.6919	2.7160	2.7159	**2.6837**	2.6843
JNJ	1.4008	1.5048	1.4032	1.4632	1.4337	1.3346	1.4506	1.3354	1.3692	1.3645	1.3062	1.4283	1.3066	1.3350	1.3317	**1.3028**	1.3030
JPM	3.0590	3.2884	3.0655	3.2097	3.1703	3.0355	3.3006	3.0378	3.0801	3.1091	3.0350	3.3260	3.0362	3.1382	3.1485	**3.0279**	3.1598
KFT	1.4872	1.5843	1.4876	1.5593	1.5423	1.4732	1.5897	1.4739	1.5011	1.5163	1.4623	1.5838	1.4626	1.4796	1.4932	**1.4576**	1.4580
KO	1.5502	1.6645	1.5532	1.6386	1.6059	1.4652	1.5826	1.4660	1.5176	1.5094	1.3810	1.4941	1.3809	1.4303	1.4316	**1.3766**	1.3772
MCD	1.7664	1.8910	1.7687	1.8248	1.8399	1.7057	1.8442	1.7061	1.7393	1.7685	1.6694	1.8161	1.6691	1.6871	1.7308	**1.6648**	**1.6648**
MMM	1.6426	1.7592	1.6444	1.6926	1.7037	1.5940	1.7272	1.5953	1.6249	1.6302	1.5683	1.7102	1.5688	1.5817	1.5888	**1.5649**	1.5653
MRK	2.0905	2.2271	2.0929	2.1708	2.1791	2.0483	2.2007	2.0490	2.0704	2.1038	2.0445	2.2123	2.0450	2.0545	2.0843	**2.0410**	2.0477
MSFT	2.2934	2.4510	2.2944	2.3819	2.3524	2.1932	2.3730	2.1943	2.2368	2.2226	2.0773	2.2666	2.0779	2.0952	2.0848	2.0708	**2.0704**
PFE	1.8746	2.0157	1.8776	1.9546	1.9185	1.8289	1.9883	1.8304	1.8610	1.8706	1.7680	1.9277	1.7685	1.7987	1.7977	**1.7636**	1.7644
PG	1.6305	1.7401	1.6335	1.6743	1.6662	1.3681	1.4820	1.3690	1.3969	1.4010	1.3017	1.4216	1.3023	1.3242	1.3232	**1.2994**	1.3306
T	2.0094	2.1557	2.0119	2.0848	2.0572	1.9469	2.1103	1.9478	1.9817	1.9840	1.8940	2.0660	1.8947	1.9163	1.9197	**1.8907**	1.8910
TRV	2.2826	2.4375	2.2853	2.4106	2.3564	2.2216	2.4127	2.2238	2.3234	2.2614	2.2056	2.4092	2.2063	2.2841	2.2647	**2.1997**	2.2008
UTX	2.0056	2.1431	2.0087	2.0699	2.0555	1.9436	2.0990	1.9453	1.9759	1.9768	1.9136	2.0739	1.9140	1.9391	1.9339	**1.9087**	1.9141
VZ	1.9126	2.0444	1.9140	1.9851	1.9923	1.8743	2.0299	1.8751	1.9121	1.9491	1.7844	1.9469	1.7849	1.8079	1.8432	**1.7799**	1.7800
WMT	1.7580	1.8919	1.7607	1.8168	1.7998	1.6716	1.8224	1.6733	1.6954	1.6899	1.5452	1.6910	1.5459	1.5621	1.5624	**1.5414**	**1.5414**
XOM	1.7846	1.9240	1.7888	1.9122	1.8262	1.7516	1.9087	1.7536	1.8361	1.7780	1.7485	1.9168	1.7496	1.8190	1.7770	**1.7460**	**1.7460**

B.3. RMSE of Financial Times Stock Exchange Index (FTSE) Stocks

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
AAL.L	3.0409	3.2715	3.0456	3.1590	3.1525	**3.0263**	3.2994	3.0300	3.0968	3.0970	3.1289	3.4245	3.1294	3.1684	3.1945	3.1209	3.2795
ABF.L	1.2963	1.3815	1.2978	1.3579	1.3321	**1.2764**	1.3786	1.2774	1.3127	1.2953	1.2926	1.4042	1.2928	1.3048	1.3095	1.2892	1.2895
ADM.L	**2.2987**	2.4574	2.3023	2.4392	2.3614	2.3224	2.5138	2.3238	2.4660	2.3679	2.4256	2.6492	2.4269	2.4891	2.4640	2.4224	2.4208
AGK.L	2.4149	2.5769	2.4171	2.5278	2.4745	2.3637	2.5546	2.3657	2.4068	2.4056	2.2870	2.4817	2.2870	2.3131	2.3137	**2.2810**	2.2812
AMEC.L	2.2203	2.3746	2.2224	2.3315	2.3206	**2.2010**	2.3800	2.2012	2.2565	2.2689	2.2192	2.4175	2.2196	2.2609	2.2941	2.2144	2.2152
ANTO.L	**4.6118**	4.8808	4.6159	4.6858	4.6876	4.6247	4.9348	4.6285	4.6619	4.6534	4.7816	5.1176	4.7829	4.8097	4.8045	4.7727	5.2852
ARM.L	4.0450	4.3033	4.0457	4.1672	4.1136	3.9889	4.3129	3.9929	4.0167	4.0220	3.8289	4.1403	3.8284	3.9087	3.8512	**3.8183**	4.1647
AU.L	4.0882	4.3041	4.0869	4.2205	4.1260	3.9556	4.2179	3.9556	4.0329	3.9806	3.4568	3.7218	3.4551	3.4904	3.5026	**3.4417**	3.5258
AV.L	2.9569	3.1675	2.9605	3.0738	3.0272	**2.9008**	3.1409	2.9043	2.9828	2.9643	2.9763	3.2351	2.9775	3.0324	3.0258	2.9700	2.9711
AZN.L	1.6631	1.7696	1.6642	1.7345	1.7106	1.6135	1.7370	1.6148	1.6441	1.6471	1.6089	1.7418	1.6092	1.6254	1.6348	1.6054	**1.6049**
BA.L	1.9501	2.0964	1.9541	2.0315	1.9887	1.8690	2.0278	1.8703	1.9027	1.8743	1.8328	2.0019	1.8336	1.8556	1.8418	**1.8303**	1.8307
BARC.L	3.5367	3.7523	3.5395	3.7050	3.6489	**3.5341**	3.7669	3.5347	3.5978	3.6030	3.6622	3.9091	3.6617	3.7234	3.7048	3.6505	3.9254
BATS.L	**2.4340**	2.6098	2.4385	2.4982	2.4775	2.4348	2.6260	2.4373	2.4772	2.4787	2.5006	2.7084	2.5015	2.5370	2.5451	2.4953	2.8425
BAY.L	2.8878	3.0805	2.8894	2.9722	2.9611	**2.8016**	3.0246	2.8036	2.8411	2.8602	2.8103	3.0467	2.8104	2.8436	2.8558	2.8042	2.8055
BG.L	2.1106	2.2650	2.1155	2.1888	2.1652	**2.0856**	2.2635	2.0879	2.1283	2.1203	2.1509	2.3463	2.1515	2.1810	2.1833	2.1453	2.1457
BLND.L	2.0902	2.2468	2.0946	2.1889	2.1671	**2.0894**	2.2718	2.0917	2.1261	2.1045	2.0982	2.2901	2.0987	2.1175	2.1226	2.0947	2.0946
BLT.L	2.7814	2.9788	2.7841	2.8889	2.8318	**2.7646**	3.0032	2.7678	2.8328	2.8118	2.8448	3.1070	2.8458	2.8912	2.8972	2.8382	2.8394
BNZL.L	**1.6484**	1.7679	1.6513	1.7319	1.6846	1.6575	1.8006	1.6587	1.6954	1.6850	1.7195	1.8854	1.7201	1.7487	1.7553	1.7150	1.7154
BP.L	1.6390	1.7520	1.6409	1.7210	1.6746	**1.6111**	1.7433	1.6126	1.6695	1.6469	1.6448	1.7939	1.6455	1.6889	1.6868	1.6415	1.6417
BRBY.L	2.3860	2.5459	2.3881	2.4593	2.4213	2.3609	2.5451	2.3614	2.3884	2.3920	2.3468	2.5471	2.3468	2.3825	2.3546	**2.3433**	2.3450
BSY.L	3.5161	3.7513	3.5297	4.2781	3.5050	3.5212	3.7846	3.5265	4.7462	3.5060	1.7958	1.9441	1.7965	1.9799	1.8052	1.7921	**1.7920**
BT-A.L	2.2055	2.3699	2.2094	2.2790	2.2703	2.1801	2.3679	2.1813	2.2179	2.2334	2.0519	2.2397	2.0520	2.0767	2.0827	**2.0482**	2.0487
CCL.L	**2.1098**	2.2583	2.1117	2.2173	2.1846	2.1140	2.2907	2.1156	2.1565	2.1768	2.1611	2.3524	2.1618	2.1899	2.2203	2.1570	2.1594
CNA.L	**1.7414**	1.8456	1.7447	1.8434	1.7797	1.7489	1.8743	1.7508	1.7892	1.7877	1.8083	1.9482	1.8089	1.8387	1.8625	1.8051	1.8058
CNE.L	12.767	13.606	12.820	14.511	**12.703**	12.895	13.822	12.915	15.565	12.860	13.417	14.404	13.425	16.241	13.445	13.391	13.108
COB.L	1.6476	1.7505	1.6486	1.7327	1.7080	**1.6429**	1.7689	1.6445	1.6885	1.6775	1.6808	1.8202	1.6815	1.6977	1.7045	1.6769	1.6778
CPG.L	2.2083	2.3665	2.2113	2.3076	2.2590	2.1969	2.3786	2.1987	2.2478	2.2256	2.1477	2.3361	2.1480	2.1776	2.1742	**2.1427**	2.1429
CPI.L	1.6359	1.7611	1.6397	1.6838	1.6998	1.5713	1.7064	1.5729	1.5866	1.6241	1.4713	1.6098	1.4719	1.4836	1.5018	1.4683	**1.4681**
CW.L	2.0723	2.2121	2.0744	2.1451	2.1241	1.9465	2.0946	1.9475	1.9831	1.9671	1.8821	2.0227	1.8815	1.9022	1.8949	**1.8750**	1.8759

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
DGE.L	1.3003	1.3979	1.3025	1.3492	1.3395	**1.2685**	1.3801	1.2698	1.2976	1.2985	1.2758	1.3978	1.2765	1.2970	1.3061	1.2734	1.2736
EMG.L	**3.9686**	4.2633	3.9784	4.2214	4.1830	4.0697	4.4097	4.0728	4.2125	4.2583	4.4412	4.8306	4.4414	4.5283	4.5913	4.4274	4.6870
ENRC.L	5.7062	6.1952	5.7191	5.9252	5.8463	5.8936	6.4642	5.8949	6.0060	5.9777	4.6367	5.0292	4.6348	4.6478	4.6594	4.5828	**4.5808**
EXPN.L	**2.4486**	2.6116	2.4503	2.5571	2.4873	2.4935	2.7064	2.4970	2.5600	2.5426	2.5965	2.8232	2.5980	2.6346	2.6731	2.5940	2.5941
FRES.L	4.8129	4.9852	4.7974	4.9554	4.9476	5.0615	5.2475	5.0475	5.1670	5.2004	3.7035	3.9495	3.6986	3.6830	3.7660	3.6719	**3.6543**
GFS.L	1.7506	1.8716	1.7524	1.8275	1.7938	1.7327	1.8778	1.7344	1.7738	1.7579	1.6921	1.8449	1.6928	1.7184	1.7090	**1.6879**	1.6888
GSK.L	1.6939	1.8190	1.6980	1.7880	1.7569	1.6691	1.8107	1.6708	1.7932	1.7099	1.6563	1.8077	1.6569	1.6711	1.6643	1.6526	**1.6502**
HMSO.L	2.4105	2.5624	2.4144	2.5618	2.4209	2.4008	2.5815	2.4026	2.6236	**2.3976**	2.4557	2.6486	2.4558	2.7011	2.4375	2.4508	2.4618
HOME.L	3.9261	4.1652	3.9306	3.9879	3.9702	3.9996	4.2788	4.0022	4.0259	4.0277	2.9743	3.2206	2.9753	2.9980	3.0080	2.9636	**2.9613**
HSBA.L	1.9403	2.0823	1.9432	2.0077	1.9838	1.9293	2.0939	1.9308	1.9676	1.9623	1.8981	2.0687	1.8983	1.9312	1.9298	**1.8924**	1.8943
IAP.L	**2.9319**	3.1448	2.9372	3.1038	3.0466	2.9490	3.2046	2.9517	3.0710	3.0542	3.0501	3.3294	3.0501	3.1347	3.1573	3.0411	3.2274
IHG.L	**2.5445**	2.7231	2.5462	2.6114	2.6138	2.5914	2.8140	2.5946	2.6257	2.6330	2.7823	3.0309	2.7819	2.7907	2.8295	2.7740	2.7754
III.L	2.9582	3.1349	2.9595	3.0857	3.0130	**2.9211**	3.1273	2.9224	2.9603	2.9679	3.0030	3.2297	3.0031	3.0414	3.0549	2.9969	3.1391
IMT.L	1.5161	1.6304	1.5185	1.5946	1.5294	**1.5004**	1.6319	1.5018	1.5404	1.5265	1.5305	1.6761	1.5311	1.5460	1.6062	1.5281	1.5283
IPR.L	2.1330	2.2532	2.1342	2.2666	2.2150	2.0458	2.1902	2.0473	2.0935	2.0828	2.0301	2.1844	2.0304	2.0559	2.0466	2.0267	**2.0261**
ISAT.L	**2.2033**	2.3584	2.2065	2.2956	2.3284	2.2071	2.3965	2.2092	2.2620	2.2991	2.2615	2.4771	2.2627	2.2850	2.3330	2.2568	2.2536
ISYS.L	6.7111	7.0706	6.7145	6.7867	6.8751	6.6651	7.0371	**6.6638**	6.6821	6.7231	6.7807	7.1837	6.7801	6.7882	6.8037	6.7575	7.6593
ITRK.L	1.8461	1.9739	1.8485	1.9256	1.8805	**1.8327**	1.9862	1.8335	1.9317	1.8565	1.8419	2.0090	1.8423	1.8862	1.8720	1.8369	1.8367
JMAT.L	1.9899	2.1152	1.9921	2.0625	2.0295	**1.9620**	2.1082	1.9636	2.0018	1.9857	2.0072	2.1633	2.0068	2.0291	2.0271	2.0009	2.0010
KAZ.L	**4.5624**	4.9060	4.5689	4.7499	4.7225	4.6553	5.0420	4.6544	4.7387	4.7556	4.8788	5.2882	4.8734	4.9265	4.9770	4.8572	5.1372
KGF.L	2.2026	2.3383	2.2037	2.2558	2.2750	**2.1975**	2.3734	2.2004	2.2310	2.2395	2.2731	2.4631	2.2736	2.2862	2.3065	2.2690	2.2689
LAND.L	**2.0351**	2.1503	2.0365	2.0855	2.0839	2.0406	2.1820	2.0425	2.0791	2.0605	2.0962	2.2441	2.0959	2.1243	2.1319	2.0926	2.0907
LGEN.L	3.0096	3.2259	3.0140	3.0957	3.0728	**2.9325**	3.1784	2.9364	2.9803	2.9785	3.0140	3.2716	3.0146	3.0533	3.0795	3.0062	3.0078
LII.L	**2.3475**	2.4908	2.3505	2.4144	2.3980	2.3525	2.5140	2.3533	2.3895	2.3879	2.3658	2.5440	2.3658	2.3996	2.3914	2.3613	2.4711
LLOY.L	3.5642	3.7819	3.5671	3.8040	3.6664	**3.5537**	3.8067	3.5565	3.7066	3.6615	3.6241	3.8929	3.6251	3.7156	3.7550	3.6176	4.1650
LMI.L	3.2873	3.4871	3.2902	3.4016	3.3835	3.2843	3.5071	**3.2831**	3.3102	3.3760	3.3844	3.6407	3.3844	3.4080	3.4777	3.3770	3.3778
LSE.L	2.6277	2.7821	2.6299	2.7666	2.8182	**2.6147**	2.7995	2.6157	2.6975	2.7528	2.6714	2.8690	2.6707	2.6995	2.7388	2.6646	2.7643
MKS.L	2.1194	2.2462	2.1208	2.1821	2.1542	**2.0847**	2.2340	2.0858	2.1095	2.1018	2.1284	2.2902	2.1283	2.1440	2.1532	2.1254	2.2717
MRW.L	2.4790	2.6487	2.4863	2.8810	2.5584	**2.4574**	2.6493	2.4600	3.1720	2.5366	2.5265	2.7402	2.5279	3.6695	2.6023	2.5213	2.5188
NG.L	**1.6416**	1.7785	1.6463	1.8021	1.7553	1.6579	1.8095	1.6598	1.8264	1.7781	1.7404	1.9093	1.7412	1.8577	1.8932	1.7371	1.7378
NXT.L	2.1289	2.2840	2.1319	2.1847	2.1831	**2.1095**	2.2944	2.1112	2.1340	2.1434	2.1702	2.3746	2.1707	2.1876	2.2021	2.1672	2.1684
OML.L	**5.9519**	6.2569	5.9585	6.0490	5.9686	5.9621	6.2996	5.9671	6.0469	6.0261	6.1913	6.5577	6.1937	7.0656	6.2814	6.1777	6.8110
PFC.L	**2.8775**	3.0969	2.8832	3.0665	2.9581	2.9126	3.1547	2.9130	3.0002	2.9770	2.9253	3.1958	2.9248	2.9608	3.0066	2.9150	2.9150

Stock	Local RMSE K=40 Mean	HP	KF	EWMA	NW	Local RMSE K=100 Mean	HP	KF	EWMA	NW	Local RMSE K=250 Mean	HP	KF	EWMA	NW	Global RMSE Mean	GARCH
PRU.L	3.0903	3.3444	3.0951	3.2163	3.2075	**3.0226**	3.3102	3.0278	3.0940	3.1121	3.1075	3.4103	3.1082	3.1706	3.1758	3.0991	3.1022
PSON.L	1.6084	1.7304	1.6110	1.6726	1.6484	1.5038	1.6298	1.5049	1.5394	1.5288	1.4838	1.6218	1.4844	1.5002	1.4997	**1.4811**	1.4815
RB.L	1.9108	2.0640	1.9141	2.0299	1.9795	1.8758	2.0626	1.8783	1.9496	1.9483	1.7159	1.9091	1.7170	1.7295	1.7553	**1.7112**	1.7120
RBS.L	**4.4833**	4.7036	4.4834	4.6537	4.6622	4.4941	4.7649	4.4964	4.5916	4.7423	4.6784	4.9701	4.6780	4.8068	4.9960	4.6693	5.0577
RDSA.L	**1.8818**	2.0071	1.8834	2.0062	1.9245	1.8995	2.0512	1.9008	1.9758	1.9388	1.9855	2.1636	1.9867	2.0462	2.0218	1.9817	1.9825
REL.L	1.9002	2.0370	1.9027	1.9753	1.9466	1.8822	2.0480	1.8841	1.9189	1.9147	1.8434	2.0220	1.8443	1.8545	1.8537	**1.8389**	1.8390
REX.L	1.9099	2.0150	1.9125	1.9981	1.9696	**1.8902**	2.0144	1.8916	1.9320	1.9296	1.9106	2.0461	1.9117	1.9288	1.9449	1.9075	1.9079
RIO.L	**3.2647**	3.4916	3.2720	3.3873	3.3732	3.2825	3.5371	3.2839	3.3537	3.3569	3.3946	3.6786	3.3945	3.4364	3.4815	3.3858	3.3850
RR.L	2.0908	2.2368	2.0925	2.1659	2.1552	2.0679	2.2444	2.0704	2.1074	2.1074	2.0595	2.2469	2.0599	2.0789	2.1128	**2.0557**	2.0567
RRS.L	**3.1764**	3.3790	3.1793	3.2703	3.2433	3.1816	3.4293	3.1844	3.2212	3.2507	3.2289	3.5010	3.2304	3.2533	3.2893	3.2213	3.2191
RSA.L	2.3939	2.5627	2.3957	2.4928	2.4537	2.2188	2.3983	2.2186	2.2555	2.2548	2.0628	2.2642	2.0637	2.0866	2.0700	**2.0580**	2.0930
RSL.L	2.3462	2.5177	2.3555	2.3814	2.3142	1.9039	2.0357	1.9060	1.9192	1.8905	1.7551	1.7708	1.7560	1.7772	1.7829	1.7508	**1.7305**
SAB.L	2.0823	2.2086	2.0814	2.1550	2.1424	**2.0614**	2.2114	2.0624	2.1035	2.0955	2.1184	2.2870	2.1188	2.1422	2.1448	2.1145	2.1822
SBRY.L	1.8747	1.9974	1.8772	1.9602	1.9364	**1.8459**	1.9913	1.8486	1.8874	1.8768	1.8660	2.0193	1.8664	1.8771	1.8841	1.8627	1.8637
SDRC.L	2.7020	2.9015	2.7089	2.9268	2.7427	**2.6256**	2.8505	2.6282	2.9211	2.6450	2.6336	2.8773	2.6345	2.8053	2.6454	2.6276	2.6283
SDR.L	2.5853	2.7714	2.5907	2.7946	2.6519	**2.5161**	2.7286	2.5185	2.7573	2.5549	2.5582	2.7953	2.5589	2.7151	2.5281	2.5521	2.6254
SGE.L	1.9495	2.0922	1.9529	2.0202	1.9891	1.8385	1.9953	1.8401	1.8660	1.8746	1.7711	1.9338	1.7717	1.7870	1.7912	**1.7671**	1.7679
SGRO.L	**8.4583**	8.9473	8.4710	8.4844	8.5108	8.8479	9.4139	8.8505	8.9252	8.9057	10.477	11.156	10.477	10.552	10.547	10.444	12.163
SHP.L	2.3497	2.5071	2.3497	2.4240	2.4079	2.3194	2.5096	2.3213	2.3542	2.3808	2.2167	2.4083	2.2176	2.2256	2.2354	**2.2149**	2.2155
SL.L	**3.1782**	3.4196	3.1845	3.3238	3.2685	3.2443	3.5423	3.2496	3.3441	3.3384	3.5362	3.8726	3.5378	3.6110	3.6948	3.5267	3.5292
SMIN.L	1.9765	2.1076	1.9779	2.0921	2.0453	1.9187	2.0713	1.9197	1.9644	1.9543	1.9016	2.0658	1.9019	1.9275	1.9441	**1.8966**	1.8987
SN.L	2.4629	2.6283	2.4683	2.6963	2.5492	1.8906	2.0529	1.8918	1.9515	1.9396	1.8816	2.0575	1.8821	1.8956	1.9124	**1.8768**	1.8773
SRP.L	1.8534	1.9912	1.8548	1.9336	1.8897	1.7616	1.9177	1.7626	1.7850	1.7899	1.6648	1.8191	1.6656	1.6781	1.6794	**1.6617**	1.6618
SSE.L	1.4309	1.5465	1.4351	1.5536	1.5325	**1.4168**	1.5452	1.4185	1.6387	1.5282	1.4449	1.5822	1.4456	1.5719	1.5806	1.4428	1.4429
STAN.L	2.6423	2.8325	2.6465	2.7637	2.7351	2.6144	2.8372	2.6171	2.6983	2.6783	2.5793	2.8115	2.5794	2.6325	2.6738	**2.5715**	2.6864
SVT.L	1.6957	1.8202	1.6983	1.7433	1.7317	**1.6872**	1.8247	1.6882	1.7376	1.7183	1.7316	1.8836	1.7322	1.7670	1.7702	1.7279	1.7321
TLW.L	2.6609	2.8220	2.6625	2.7726	2.7551	**2.6483**	2.8452	2.6496	2.7071	2.7074	2.6869	2.9009	2.6875	2.7134	2.7311	2.6794	2.6789
TSCO.L	1.5823	1.7058	1.5853	1.6724	1.6354	**1.5415**	1.6877	1.5432	1.5638	1.5644	1.5453	1.7005	1.5459	1.5618	1.5511	1.5423	1.5423
TT.L	2.4277	2.6005	2.4315	2.5329	2.4819	**2.3521**	2.5565	2.3543	2.4080	2.3832	2.3736	2.6001	2.3744	2.3991	2.3898	2.3677	2.4132
UU.L	1.4694	1.5764	1.4721	1.5331	1.5248	1.4487	1.5717	1.4497	1.4938	1.5067	1.4336	1.5663	1.4341	1.4636	1.4867	**1.4307**	1.4312
VED.L	**3.6749**	3.9164	3.6772	3.8084	3.8063	3.7054	3.9908	3.7070	3.7918	3.8425	3.8611	4.1583	3.8590	3.9132	3.9923	3.8487	4.0298
VOD.L	1.8849	2.0329	1.8891	1.9456	1.9593	**1.8700**	2.0358	1.8713	1.9642	1.9181	1.8975	2.0798	1.8983	1.9164	1.9032	1.8936	1.8944
WOS.L	5.7584	6.1070	5.7675	6.3599	5.7959	**5.7527**	6.1594	5.7598	6.4344	5.8165	5.9021	6.3415	5.9047	6.7940	5.8839	5.8899	7.4229

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
WPP.L	2.3404	2.5156	2.3428	2.4324	2.4022	2.3256	2.5351	2.3278	2.3664	2.3702	2.2291	2.4359	2.2293	2.2448	2.2447	**2.2230**	2.2235
WTB.L	**2.4599**	2.6142	2.4615	2.5673	2.5119	2.5050	2.6991	2.5075	2.5730	2.5459	2.6882	2.9100	2.6881	2.7052	2.7109	2.6832	2.6825
XTA.L	3.5601	3.8295	3.5676	3.6787	3.6358	**3.5373**	3.8439	3.5400	3.6051	3.6196	3.6024	3.9242	3.6010	3.6444	3.6837	3.5923	3.7967

B.4. RMSE of Hang Seng Index (HSI) Stocks

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
0001.HK	2.1790	2.3373	2.1816	2.2973	2.2270	**2.1713**	2.3547	2.1725	2.2274	2.1823	2.1972	2.3942	2.1976	2.2276	2.2183	2.1917	2.1919
0002.HK	**1.2808**	1.3782	1.2847	1.4289	1.2821	1.2839	1.3965	1.2856	1.3925	1.2917	1.3216	1.4448	1.3220	1.4156	1.3530	1.3179	1.3175
0003.HK	**1.7459**	1.8723	1.7487	1.9167	1.8130	1.7461	1.8933	1.7475	1.9096	1.8214	1.7985	1.9555	1.7981	1.9302	1.8821	1.7921	1.7916
0004.HK	2.6051	2.7889	2.6078	2.6832	2.6957	**2.5794**	2.7948	2.5812	2.6626	2.5998	2.6236	2.8483	2.6231	2.6582	2.6455	2.6154	2.6161
0005.HK	**1.9257**	2.0482	1.9281	2.2329	2.1112	1.9370	2.0759	1.9378	2.1787	2.1719	2.0062	2.1519	2.0057	2.1380	2.3033	1.9996	2.0004
0006.HK	1.2694	1.3711	1.2728	1.3298	1.3244	**1.2626**	1.3813	1.2641	1.3131	1.3282	1.3043	1.4369	1.3051	1.3310	1.3495	1.3016	1.3017
0011.HK	**1.6124**	1.7071	1.6133	1.7189	1.7350	1.6170	1.7262	1.6173	1.6761	1.7133	1.6669	1.7888	1.6671	1.7075	1.7606	1.6629	1.6656
0012.HK	2.3683	2.5383	2.3707	2.5042	2.4285	**2.3543**	2.5502	2.3554	2.4406	2.3843	2.3721	2.5701	2.3714	2.4079	2.4306	2.3637	2.3634
0013.HK	1.8440	1.9711	1.8458	1.9639	1.9056	1.8336	1.9754	**1.8330**	1.8980	1.8875	1.8583	2.0113	1.8580	1.8928	1.8673	1.8531	1.8522
0016.HK	2.2560	2.4161	2.2584	2.3775	2.3094	2.2484	2.4311	2.2487	2.3133	2.2831	2.2437	2.4291	2.2426	2.2665	2.2841	**2.2346**	2.2348
0017.HK	3.0948	3.2990	3.0955	3.2209	3.1687	3.0834	3.3088	3.0819	3.1691	3.1184	3.0307	3.2716	3.0285	3.0621	3.0360	3.0180	**3.0179**
0019.HK	2.0846	2.2342	2.0872	2.2004	2.1498	2.0552	2.2282	2.0567	2.1303	2.0799	2.0600	2.2378	2.0599	2.0886	2.0777	**2.0541**	2.0543
0023.HK	**2.2519**	2.4033	2.2553	2.3962	2.3501	2.2612	2.4275	2.2615	2.3418	2.3804	2.2978	2.4693	2.2966	2.3342	2.3551	2.2905	2.2920
0066.HK	1.7555	1.8634	1.7570	1.9060	1.8238	1.7479	1.8778	1.7487	1.8591	1.7927	1.7425	1.8828	1.7424	1.7916	1.7573	1.7365	**1.7361**
0083.HK	**3.0399**	3.2602	3.0426	3.1524	3.1351	3.0521	3.3053	3.0526	3.1015	3.1196	3.0662	3.3317	3.0654	3.0900	3.1128	3.0571	3.0565
0101.HK	2.6663	2.8713	2.6714	2.7561	2.7328	**2.6633**	2.8995	2.6656	2.7054	2.7075	2.7373	2.9992	2.7378	2.7505	2.7613	2.7305	2.7316
0144.HK	3.0761	3.2977	3.0815	3.2400	3.2242	**3.0754**	3.3356	3.0783	3.1570	3.2194	3.1134	3.3906	3.1135	3.1518	3.2335	3.1054	3.1065
0267.HK	3.3951	3.5326	**3.3882**	3.6658	3.4786	3.4006	3.5784	3.4004	3.5170	3.4507	3.5353	3.7171	3.5335	3.6190	3.5787	3.5236	3.5682
0291.HK	2.8190	3.0254	2.8225	3.0233	2.9347	**2.8145**	3.0601	2.8175	2.9315	3.0002	2.8800	3.1450	2.8801	2.9552	3.0840	2.8732	2.8773

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
0293.HK	2.2322	2.3921	2.2353	2.5006	2.4783	**2.1917**	2.3788	2.1935	2.4585	2.4587	2.2102	2.4121	2.2104	2.4283	2.5504	2.2053	2.2064
0330.HK	2.7637	2.9679	2.7691	2.8779	2.8519	**2.7572**	2.9961	2.7600	2.8044	2.8119	2.7728	3.0284	2.7736	2.7990	2.8257	2.7693	2.7683
0386.HK	2.7924	3.0068	2.7966	2.9368	2.8986	2.7663	3.0103	2.7674	2.8386	2.8533	2.7556	3.0207	2.7564	2.7862	2.7911	2.7502	**2.7488**
0388.HK	2.5576	2.7130	2.5560	2.6658	2.6090	2.5406	2.7253	**2.5392**	2.5947	2.5622	2.5509	2.7423	2.5493	2.5610	2.5622	2.5443	2.5871
0494.HK	3.0161	3.2441	3.0232	3.1338	3.1096	2.9743	3.2298	2.9760	3.0439	3.0385	2.9505	3.2286	2.9510	2.9978	2.9818	2.9409	**2.9398**
0688.HK	3.3117	3.5666	3.3178	3.4372	3.4004	**3.3107**	3.6020	3.3121	3.3672	3.4003	3.3465	3.6585	3.3465	3.3645	3.3914	3.3373	3.3387
0700.HK	3.2892	3.5432	3.2941	3.4714	3.3796	**3.2887**	3.5797	3.2904	3.3794	3.3576	3.3349	3.6642	3.3362	3.3901	3.3557	3.3279	3.3285
0762.HK	3.1603	3.4120	3.1660	3.2912	3.2986	3.1534	3.4378	3.1553	3.2074	3.2628	3.0986	3.4105	3.0996	3.1262	3.1823	**3.0931**	3.0966
0836.HK	3.2176	3.4514	3.2239	3.3941	3.3290	3.2068	3.4736	3.2085	3.3059	3.2723	3.1962	3.4952	3.1975	3.2284	3.2756	**3.1924**	**3.1924**
0857.HK	2.4895	2.6581	2.4903	2.6450	2.6053	2.4476	2.6397	2.4483	2.5133	2.4850	2.4160	2.6168	2.4164	2.4500	2.4494	2.4112	**2.4111**
0883.HK	**2.9552**	3.1569	2.9561	3.1425	3.0052	2.9575	3.1989	2.9589	3.0209	2.9960	3.0635	3.3261	3.0636	3.1026	3.0748	3.0547	3.0919
0939.HK	**2.9834**	3.1869	2.9865	3.2217	3.1878	3.0108	3.2581	3.0123	3.1695	3.1984	3.2301	3.5158	3.2308	3.3010	3.4266	3.2225	3.2565
0941.HK	2.2298	2.3786	2.2315	2.3238	2.2927	**2.2144**	2.3905	2.2153	2.2466	2.2558	2.2396	2.4300	2.2395	2.2579	2.2596	2.2347	2.2344
1088.HK	**3.5177**	3.7718	3.5221	3.7084	3.7133	3.5665	3.8632	3.5681	3.7900	3.8331	3.7395	4.0604	3.7379	3.9184	4.0804	3.7277	3.7325
1199.HK	3.2377	3.4355	3.2397	3.5187	3.3433	**3.2242**	3.4610	3.2267	3.3577	3.3547	3.2975	3.5489	3.2977	3.4072	3.4101	3.2886	3.3811
1398.HK	**3.0384**	3.2614	3.0419	3.2670	3.2249	3.0604	3.3267	3.0616	3.1844	3.2221	3.2306	3.5328	3.2306	3.2823	3.3702	3.2179	3.2288
2038.HK	**4.1934**	4.5035	4.1965	4.4627	4.3267	4.2400	4.6143	4.2428	4.3977	4.2896	4.4171	4.8210	4.4166	4.5511	4.4855	4.4134	4.6214
2318.HK	**3.0968**	3.3044	3.0984	3.3137	3.2177	3.1143	3.3615	3.1151	3.2132	3.1730	3.2653	3.5450	3.2656	3.3053	3.2765	3.2599	3.2614
2388.HK	**2.0690**	2.2216	2.0725	2.1731	2.1299	2.0824	2.2501	2.0820	2.1465	2.1202	2.1547	2.3336	2.1533	2.1795	2.1691	2.1467	2.1474
2600.HK	3.7029	3.9385	3.7054	3.8867	3.7821	3.6982	3.9664	**3.6977**	3.7786	3.7588	3.7528	4.0374	3.7499	3.7946	3.8046	3.7388	3.7389
2628.HK	2.7207	2.9063	2.7237	2.9592	2.9102	**2.7145**	2.9297	2.7155	2.8824	2.8976	2.7900	3.0361	2.7911	2.8510	2.9751	2.7884	2.8170
3328.HK	**2.9362**	3.1381	2.9386	3.1463	3.0228	2.9809	3.2198	2.9811	3.0827	3.0894	3.1229	3.3882	3.1221	3.1624	3.1647	3.1127	3.1472
3988.HK	**2.7662**	2.9783	2.7702	2.9984	2.9452	2.8454	3.0936	2.8459	2.9559	3.0709	3.0634	3.3542	3.0631	3.1342	3.2125	3.0536	3.0553

B.5. RMSE of Nasdaq Canada (CND) Stocks

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
AEZS	5.0282	5.3383	5.0350	5.1472	5.3142	**5.0141**	5.3589	5.0144	5.0703	5.2406	5.0333	5.4197	5.0349	5.0689	5.1555	5.0224	5.2992
ALTI	6.4918	6.9475	6.4996	6.8816	6.7205	6.4222	6.9528	6.4266	6.5970	6.5929	6.2002	6.7561	6.2022	6.2581	6.3196	**6.1861**	6.4383
ANPI	5.0971	5.4962	5.1033	5.4290	5.3676	**5.0457**	5.4690	**5.0457**	5.3108	5.2893	5.1087	5.5624	5.1073	5.2074	5.1873	5.0954	5.9075
BLDP	4.7608	5.0584	4.7602	5.0783	4.9231	4.6420	4.9963	4.6432	4.8024	4.7198	4.6137	4.9978	4.6150	4.7117	4.7222	**4.6034**	4.7645
CFK	3.9190	4.1547	3.9214	4.1738	4.0586	3.8791	4.1552	3.8801	4.0273	3.9944	3.7070	3.9977	3.7079	3.7985	3.7761	**3.7010**	3.7780
CNIC	8.1544	8.7375	8.1730	8.7220	8.3041	8.0821	8.7547	8.0889	8.8408	8.3297	8.0377	8.7723	8.0398	8.4180	8.3467	**8.0217**	8.3218
CRME	3.8896	4.1350	3.8915	4.0963	4.0734	3.7823	4.0547	3.7840	3.8530	3.8916	3.7414	4.0376	3.7425	3.7721	3.8242	**3.7335**	3.9737
CSIQ	**6.5372**	6.9198	6.5398	6.7736	6.7099	6.6307	7.0742	6.6291	6.7224	6.6832	7.1367	7.6148	7.1285	7.1824	7.1970	7.0973	7.2702
DDSS	6.1410	6.4494	**6.1332**	6.4355	6.2495	6.2526	6.6411	6.2521	6.3113	6.2834	6.7220	7.1929	6.7244	6.7286	6.7256	6.7132	6.8791
DRWI	6.5706	6.8628	6.5693	6.7696	6.8696	5.7103	6.1199	5.7086	5.7457	5.9196	4.4462	4.7183	4.4299	4.4220	4.4471	**4.4136**	4.5225
DSGX	4.4363	4.7461	4.4416	4.5472	4.6557	4.1799	4.4937	4.1803	4.2436	4.2877	3.9597	4.2831	3.9604	3.9963	4.0204	**3.9543**	4.1413
ECGI	7.1174	7.5634	7.1271	7.3710	7.2313	**7.1077**	7.6358	7.1126	7.2839	7.1800	7.1687	7.7392	7.1689	7.2685	7.2428	7.1518	7.3959
EXFO	4.5536	4.8284	4.5546	4.7481	4.7167	4.4234	4.7290	4.4251	4.4922	4.5599	3.9215	4.2269	3.9225	3.9579	3.9906	**3.9192**	3.9496
FSRV	2.4120	2.5624	2.4129	2.4918	2.4693	2.3885	2.5673	2.3904	2.4080	2.4146	2.3937	2.5772	2.3927	2.4086	2.4699	**2.3876**	2.3878
GLGL	5.5885	5.9631	**5.5857**	5.9413	5.8737	5.7698	6.2022	5.7689	5.9164	6.0606	6.2022	6.7221	6.2002	6.2774	6.5779	6.1754	6.2982
HYGS	5.0778	5.4079	5.0778	5.2990	5.2471	4.9174	5.3000	4.9173	5.0338	5.0505	4.6524	5.0605	4.6540	4.6868	4.7629	**4.6419**	4.7868
IMAX	5.3152	5.6038	5.3175	5.4657	5.4412	5.3125	5.6470	5.3118	5.4046	5.3792	4.6248	4.9828	4.6241	4.6629	4.7119	**4.6107**	4.8042
IVAN	**5.6291**	5.9967	5.6343	5.8577	5.7242	5.6699	6.0823	5.6682	5.7961	5.7667	5.6539	6.0990	5.6521	5.7248	5.7749	5.6353	5.8017
JCTCF	**3.4487**	3.7145	3.4570	3.6744	3.6952	3.4517	3.7599	3.4557	3.5413	3.6308	3.4867	3.8199	3.4881	3.5363	3.6215	3.4782	3.7477
LBIX	7.0282	7.5491	7.0405	7.3448	7.1391	6.8899	7.4971	6.8952	6.9970	6.9579	6.7528	7.3782	6.7536	6.8412	6.7904	**6.7377**	7.0456
LMLP	6.2550	6.5856	6.2543	6.5668	6.5593	5.7944	6.1848	5.7966	5.9797	5.9198	5.3793	5.7810	5.3808	5.4921	5.5254	**5.3675**	5.6148
MDCA	4.9723	5.2578	4.9759	5.0723	5.0762	3.3547	3.5442	3.3454	3.4292	3.4302	3.3325	3.5624	3.3301	3.3812	3.3901	**3.3231**	3.3375
MEOH	2.9417	3.1340	2.9436	3.0491	3.0145	2.8031	3.0139	2.8034	2.8327	2.8731	2.6383	2.8386	2.6369	2.6477	2.6701	**2.6290**	2.6299
NEPT	**7.3249**	7.8394	7.3408	7.5674	7.3548	7.6013	8.1985	7.6043	7.7410	7.7086	8.4058	9.0903	8.4025	8.5077	8.5478	8.3756	8.6388
NGAS	5.4801	5.8768	5.4877	5.7389	5.6800	5.1825	5.6113	5.1872	5.3341	5.3631	5.0876	5.5284	5.0885	5.1578	5.2252	**5.0785**	5.1209
NICK	3.2140	3.4446	3.2179	3.3345	3.2537	3.1280	3.3869	3.1308	3.1748	3.1680	3.0719	3.3300	3.0717	3.1004	3.0832	**3.0656**	3.0663
NYMX	4.9403	5.2589	4.9446	5.1756	5.0833	4.5576	4.8895	4.5598	4.7116	4.7126	4.1758	4.5260	4.1777	4.2491	4.3067	**4.1671**	4.2983
ONCY	5.0116	5.3731	5.0154	5.2556	5.2135	4.6387	5.0223	4.6420	4.7499	4.7640	4.6245	5.0364	4.6254	4.6760	4.6877	**4.6131**	4.6298
OPMR	4.4529	4.7063	4.4502	4.6793	4.5832	4.3181	4.6305	4.3211	4.4248	4.4292	4.2792	4.6051	4.2792	4.3329	4.4186	**4.2722**	4.5301

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
OTEX	3.2480	3.4139	3.2438	3.3559	3.3501	3.0325	3.2282	3.0332	3.0722	3.0764	2.8220	3.0362	2.8237	2.8389	2.8522	**2.8191**	2.9690
PAAS	3.6620	3.9097	3.6670	3.7764	3.7775	**3.6350**	3.9212	3.6384	3.6826	3.7286	3.6596	3.9603	3.6604	3.6897	3.7515	3.6503	3.6501
QLTI	3.8436	4.0786	3.8446	4.0177	4.0249	3.7116	3.9849	3.7144	3.8275	3.9343	3.4981	3.7842	3.4981	3.5213	3.6531	**3.4914**	3.6362
RIMM	4.8275	5.1313	4.8279	5.0298	4.9278	4.5449	4.8866	4.5455	4.6024	4.6204	4.1522	4.4975	4.1525	4.1924	4.2149	**4.1493**	4.2785
SSRI	4.1443	4.4012	4.1464	4.2955	4.2717	**4.1024**	4.3960	4.1043	4.1861	4.1712	4.1393	4.4539	4.1403	4.1803	4.1886	4.1305	4.1316
STKL	4.3319	4.5387	4.3265	4.5375	4.4737	4.1569	4.4361	4.1589	4.2032	4.2369	3.9382	4.1970	3.9382	3.9753	3.9669	**3.9312**	4.1000
SWIR	4.8136	5.0609	4.8095	4.9409	4.9167	4.8031	5.1032	4.8015	4.8626	4.8591	4.5496	4.8620	4.5478	4.5926	4.6085	**4.5410**	4.7164
SXCI	**3.3347**	3.5418	3.3360	3.4725	3.4866	3.3854	3.6246	3.3850	3.4524	3.5062	3.6033	3.8867	3.6032	3.6298	3.6998	3.5958	3.7376
TESO	3.5757	3.7934	3.5771	3.6516	3.6791	3.5219	3.7652	3.5201	3.5552	3.6023	3.4511	3.7095	3.4514	3.4784	3.5362	**3.4449**	3.5581
TGA	5.6223	6.0506	5.6350	5.8288	5.6190	5.3497	5.8375	5.3554	5.4243	5.3631	5.1233	5.6259	5.1251	5.1786	5.1693	**5.1141**	5.2150
TTHI	5.3936	5.6811	**5.3921**	5.6014	5.5101	5.5509	5.8559	5.5438	5.6827	5.7195	6.2655	6.6144	6.2613	6.3414	6.4083	6.2354	6.5436
VTNC	3.3002	3.5047	3.3038	3.4957	3.3378	3.1278	3.3428	3.1271	3.1818	3.1634	3.0807	3.3008	3.0801	3.1270	**3.0639**	3.0736	3.2075
WPRT	5.6743	6.0449	5.6791	5.9338	6.0540	4.9333	5.3142	4.9391	4.9811	5.0613	4.2109	4.4954	4.2023	4.2986	4.1889	4.1806	**4.1337**

B.6. RMSE of Nasdaq Technology Index (NDXT) Stocks

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
AAPL	3.3784	3.5765	3.3789	3.4628	3.4457	3.3119	3.5358	3.3111	3.3321	3.3636	2.8387	3.0741	2.8393	2.8560	2.9038	2.8309	**2.8296**
ADBE	3.4449	3.6895	3.4514	3.5800	3.5352	3.2968	3.5585	3.2971	3.3446	3.3669	3.0427	3.2945	3.0432	3.0651	3.1084	**3.0354**	3.2183
ADSK	3.0027	3.1839	3.0033	3.0915	3.0543	2.9382	3.1525	2.9387	2.9869	2.9704	2.8366	3.0760	2.8372	2.8537	2.8516	**2.8330**	2.8751
ALTR	3.7243	3.9923	3.7305	3.8305	3.8111	3.5898	3.8995	3.5937	3.6429	3.6464	3.2653	3.5638	3.2665	3.2746	3.2989	**3.2577**	3.3323
AMAT	3.3331	3.5789	3.3390	3.4840	3.3827	3.2117	3.4895	3.2145	3.2625	3.2488	3.0206	3.2988	3.0219	3.0458	3.0480	**3.0135**	3.0136
BIDU	4.1733	4.4806	4.1801	4.3119	4.2559	4.1692	4.4928	4.1674	4.1943	4.2192	4.0849	4.4435	4.0838	4.0968	4.1664	**4.0737**	4.2761
BMC	3.2353	3.4158	3.2329	3.3232	3.4326	3.1507	3.3695	3.1508	3.1988	3.3176	2.7302	2.9894	2.7317	2.7493	2.9495	**2.7260**	2.8598
BRCM	4.4426	4.7110	4.4422	4.5814	4.5660	4.3115	4.6277	4.3125	4.3926	4.3999	4.1225	4.4553	4.1221	4.1432	4.2017	**4.1116**	4.1119
CA	3.2229	3.3816	3.2190	3.3977	3.3503	3.1505	3.3539	3.1513	3.2156	3.1956	2.8042	3.0241	2.8044	2.8269	2.8864	**2.7971**	3.0315

Stock	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
CERN	3.3033	3.5126	3.3074	3.4360	3.3407	3.1316	3.3617	3.1333	3.1625	3.1895	2.9761	3.2021	2.9767	2.9955	3.0222	**2.9690**	3.1119
CHKP	3.7441	4.0043	3.7494	3.9142	3.7883	3.5134	3.8054	3.5167	3.5624	3.5306	3.2592	3.5419	3.2601	3.2699	3.2558	**3.2535**	3.4428
CSCO	3.0387	3.2574	3.0436	3.1379	3.1051	2.9708	3.2188	2.9727	3.0088	3.0031	2.8531	3.1062	2.8535	2.8700	2.8963	**2.8478**	2.8496
CTSH	3.5093	3.7342	3.5116	3.6179	3.6203	3.3493	3.6289	3.3518	3.3994	3.3834	3.1675	3.4472	3.1683	3.1719	3.1968	**3.1606**	3.2473
CTXS	4.1526	4.4234	4.1556	4.3337	4.2491	3.9564	4.2352	3.9550	4.0294	4.0177	3.2797	3.5526	3.2784	3.2979	3.3127	**3.2697**	3.4213
DELL	2.8162	3.0154	2.8185	2.9044	2.8653	2.7605	2.9999	2.7621	2.8022	2.7860	2.5647	2.8039	2.5654	2.5736	2.5761	2.5563	**2.5556**
GOOG	2.4028	2.5587	2.4033	2.5250	2.4588	2.3200	2.4841	**2.3177**	2.3541	2.3790	2.3364	2.5268	2.3362	2.3483	2.4021	2.3316	2.3329
INFY	3.6543	3.9205	3.6567	3.7599	3.7708	3.4248	3.7186	3.4276	3.4614	3.4872	3.2424	3.5489	3.2439	3.2620	3.2720	**3.2383**	3.3454
INTC	2.9163	3.1320	2.9197	3.0348	2.9633	2.8505	3.0989	2.8524	2.9010	2.9018	2.6918	2.9419	2.6919	2.7160	2.7159	**2.6837**	2.6843
INTU	3.1593	3.3870	3.1641	3.2495	3.2468	2.9506	3.2012	2.9528	2.9824	2.9894	2.7117	2.9802	2.7135	2.7209	2.7295	**2.7068**	2.8078
KLAC	3.5777	3.8411	3.5827	3.6827	3.6648	3.4012	3.6958	3.4045	3.4414	3.4477	3.0550	3.3194	3.0555	3.0739	3.0743	3.0473	**3.0466**
LLTC	3.1648	3.3982	3.1694	3.2543	3.2185	3.0258	3.2996	3.0296	3.0675	3.0606	2.7919	3.0525	2.7934	2.8047	2.7973	**2.7866**	2.8082
LOGI	3.2902	3.5067	3.2909	3.4189	3.3542	3.1936	3.4484	3.1950	3.2570	3.2230	3.0236	3.2837	3.0243	3.0449	3.0645	**3.0169**	3.0568
LRCX	3.9403	4.2134	3.9446	4.0923	4.0361	3.7873	4.0931	3.7902	3.8377	3.8169	3.5487	3.8538	3.5495	3.5747	3.5700	**3.5403**	3.5405
MCHP	3.3380	3.5982	3.3455	3.4840	3.4254	3.1980	3.4854	3.2013	3.2360	3.2302	2.9100	3.1868	2.9112	2.9341	2.9518	**2.9031**	2.9033
MRVL	4.4276	4.6937	4.4253	4.5453	4.5625	4.2713	4.5955	4.2724	4.3065	4.3219	3.8887	4.2539	3.8889	3.9129	3.9685	**3.8791**	3.9319
MSFT	2.2934	2.4510	2.2944	2.3819	2.3524	2.1932	2.3730	2.1943	2.2368	2.2226	2.0773	2.2666	2.0779	2.0952	2.0848	2.0708	**2.0704**
MXIM	3.3937	3.6357	3.3983	3.5097	3.5006	3.2045	3.4807	3.2081	3.2474	3.2870	2.9993	3.2663	3.0005	3.0155	3.0376	**2.9928**	2.9930
NTAP	4.7024	4.9918	4.7026	4.8283	4.8373	4.4818	4.8240	4.4851	4.5333	4.5279	4.2262	4.5757	4.2250	4.2446	4.2922	**4.2139**	4.3533
NVDA	4.7944	5.0890	4.7969	4.9885	4.9427	4.5540	4.8752	4.5533	4.6210	4.6307	4.3583	4.6911	4.3579	4.3829	4.4548	**4.3479**	4.5447
ORCL	3.0823	3.3196	3.0880	3.1813	3.1558	2.9929	3.2574	2.9955	3.0265	3.0213	2.8264	3.0930	2.8271	2.8443	2.8370	**2.8202**	2.8205
QCOM	3.2727	3.5062	3.2774	3.4133	3.3318	3.1620	3.4380	3.1643	3.1979	3.2209	2.8849	3.1377	2.8859	2.8984	2.9173	**2.8796**	2.9314
RIMM	4.8275	5.1313	4.8279	5.0298	4.9278	4.5449	4.8866	4.5455	4.6024	4.6204	4.1522	4.4975	4.1525	4.1924	4.2149	**4.1493**	4.2785
SNDK	4.9493	5.2327	4.9508	5.0739	5.1062	4.7682	5.1057	4.7712	4.8176	4.8838	4.5698	4.9204	4.5705	4.6032	4.6207	**4.5619**	4.7262
STX	3.3590	3.5792	3.3611	3.4593	3.4399	3.3508	3.6021	3.3498	3.4049	3.4162	3.2932	3.5400	3.2901	3.3280	3.3341	3.2812	**3.2805**
SYMC	3.3431	3.5913	3.3482	3.4712	3.4246	3.2434	3.5192	3.2452	3.2821	3.2811	3.0608	3.3401	3.0628	3.0748	3.1159	**3.0558**	3.1052
VRSN	4.5425	4.8388	4.5448	4.7488	4.6636	4.2942	4.6071	4.2951	4.3779	4.3835	4.0780	4.3923	4.0780	4.1374	4.1383	**4.0697**	4.0698
XLNX	3.5596	3.8010	3.5636	3.6580	3.6346	3.4352	3.7235	3.4384	3.4738	3.4804	3.1568	3.4357	3.1581	3.1730	3.1927	**3.1503**	3.2168
YHOO	3.8845	4.1361	3.8863	3.9779	3.9756	3.8119	4.1085	3.8130	3.8693	3.8692	3.6164	3.9226	3.6173	3.6592	3.6408	**3.6095**	3.6609

B.7. RMSE of Deutscher Aktien Index Technologiewerte (TecDAX) Stocks

	Local RMSE K=40					Local RMSE K=100					Local RMSE K=250					Global RMSE	
Stock	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	HP	KF	EWMA	NW	Mean	GARCH
AFX.DE	3.5392	3.7663	3.5415	3.7384	3.6523	3.4838	3.7516	3.4851	3.6194	3.5302	3.4280	3.7157	3.4286	3.5625	3.4708	**3.4199**	3.5919
AIXA.DE	4.6198	4.9326	4.6219	4.7769	4.7389	4.5902	4.9422	4.5907	4.6624	4.6774	4.3861	4.7538	4.3843	4.4054	4.4345	**4.3785**	4.4429
BBZA.DE	4.6712	4.9462	4.6755	4.7593	4.7096	**4.5841**	4.8672	4.5866	4.6170	4.6296	4.5958	4.8777	4.5948	4.5968	4.5990	4.5854	4.6865
BC8.DE	2.8172	3.0101	2.8214	3.0115	2.9472	2.7922	3.0140	2.7936	2.9151	2.9058	2.6558	2.8924	2.6562	2.6881	2.7549	2.6505	**2.6501**
CGY.DE	**7.2013**	7.6144	7.2032	7.5599	7.6277	7.3208	7.7899	7.3197	7.5549	7.7036	7.7666	8.2997	7.7654	7.8468	8.1310	7.7424	8.2534
CTN.DE	5.0805	5.4617	5.0879	5.5148	5.2485	4.8868	5.2995	**4.8854**	4.9995	5.0194	5.0481	5.5502	5.0476	5.0888	5.0924	5.0285	5.1543
DRI.DE	3.6266	3.8675	3.6306	3.7099	3.7179	3.5097	3.7694	3.5097	3.5925	3.5519	3.1912	3.4277	3.1871	3.2270	3.2174	**3.1777**	3.2688
DRW3.DE	2.8466	3.0389	2.8492	3.0039	2.9258	**2.6791**	2.9008	2.6813	2.7397	2.7061	2.6913	2.9258	2.6907	2.7085	2.7076	2.6847	2.6873
EVT.DE	3.4322	3.6369	3.4317	3.5959	3.5725	3.2702	3.5248	3.2720	3.3205	3.3922	3.2622	3.5337	3.2610	3.3091	3.3511	3.2538	**3.2529**
FNTN.DE	5.5412	5.9509	5.5482	5.9630	5.7589	5.4745	5.9207	5.4782	5.8442	5.7662	5.4692	5.9375	5.4685	5.8108	5.8466	**5.4528**	5.7347
JEN.DE	2.7575	2.9205	2.7589	2.8861	2.8635	2.7181	2.9183	2.7194	2.7696	2.8118	2.7231	2.9449	2.7242	2.7606	2.7917	2.7166	**2.7159**
KBC.DE	2.9360	3.1138	2.9411	3.2395	2.9958	2.7291	2.9505	2.7307	2.9295	2.7701	2.5774	2.8058	2.5777	2.6030	2.6047	**2.5724**	2.6207
M5Z.DE	**5.1071**	5.4400	5.1168	5.4704	5.3316	5.2502	5.6301	5.2523	5.4339	5.4014	5.4288	5.8260	5.4252	5.5073	5.6332	5.4138	5.6080
MDG.DE	4.8674	5.1877	4.8710	5.0715	5.0104	4.7738	5.1524	4.7755	4.8935	4.8820	4.4240	4.7961	4.4242	4.4710	4.5530	**4.4105**	4.6041
MOR.DE	4.6842	4.9878	4.6837	5.0227	4.8687	4.5805	4.9435	4.5824	4.7112	4.8627	4.4996	4.8871	4.5009	4.5485	4.8025	**4.4944**	4.5872
NDX1.DE	4.3295	4.5616	4.3279	4.4577	4.3959	**4.3015**	4.5949	4.3030	4.3898	4.3392	4.3375	4.6633	4.3384	4.3949	4.4277	4.3325	4.7085
PFV.DE	2.3376	2.4969	2.3407	2.4623	2.4264	2.1732	2.3543	2.1752	2.2326	2.2360	2.1479	2.3406	2.1484	2.1622	2.1759	**2.1421**	2.1461
PS4.DE	4.0892	4.4007	4.0971	4.3314	4.2685	4.0696	4.4090	4.0706	4.1532	4.1537	4.0647	4.4295	4.0653	4.1081	4.1169	**4.0533**	4.1565
QCE.DE	5.1776	5.5275	5.1838	5.4138	5.3482	5.1327	5.5390	5.1374	5.2167	5.2387	4.8880	5.3208	4.8884	4.9715	5.0369	**4.8774**	5.1034
QSC.DE	4.3442	4.6239	4.3468	4.5156	4.4227	4.3107	4.6388	4.3115	4.3920	4.4053	4.0105	4.3351	4.0102	4.0287	4.0510	4.0061	**4.0060**
R8R.DE	**6.2215**	6.6091	6.2254	6.4437	6.2776	6.3501	6.8233	6.3545	6.3954	6.4492	6.9128	7.4175	6.9071	6.9379	6.9585	6.8922	7.4137
RSI.DE	3.5835	3.8349	3.5885	3.7010	3.6512	3.5626	3.8534	3.5658	3.6170	3.6170	3.4245	3.7117	3.4256	3.4372	3.4454	**3.4184**	3.5774
S92.DE	4.5862	4.8756	4.5886	4.7203	4.7301	4.2304	4.5832	4.2351	4.3540	4.3338	3.5674	3.8756	3.5677	3.6030	3.7022	**3.5636**	3.5850
SM7.DE	**3.7562**	3.9704	3.7621	3.9305	3.8522	3.8345	4.1042	3.8389	3.8743	3.9150	4.0998	4.3857	4.0986	4.1410	4.2001	4.0897	4.0941
SOW.DE	2.7794	2.9808	2.7846	2.8927	2.8314	2.7576	2.9917	2.7591	2.8119	2.7867	2.7379	2.9998	2.7389	2.7693	2.7667	**2.7333**	2.7340
SWV.DE	4.8146	5.1565	4.8220	5.0124	5.0212	4.6755	5.0483	4.6786	4.7809	4.6847	**4.1787**	4.5257	4.1804	4.2282	4.3159	4.1842	4.2523
UTDI.DE	2.8826	3.0855	2.8876	3.0117	2.9396	2.8290	3.0604	2.8305	2.8724	2.8469	2.8236	3.0625	2.8231	2.8585	2.8493	**2.8158**	2.8169
WDI.DE	4.1353	4.4299	4.1420	4.3944	4.2813	4.0102	4.3640	4.0136	4.0806	4.1155	3.7561	4.1044	3.7565	3.8441	3.7764	**3.7467**	3.7937

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