Forecasting Stock Market (Realized) Volatility in the United Kingdom: Is There a Role of Inequality?

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Abstract

In this paper, we analyze the potential role of growth in inequality for forecasting realized volatility of the stock market of the United Kingdom (UK). In our forecasting exercise, we use linear and nonlinear models, as well as, measures of absolute and relative consumption and income inequalities at quarterly frequency over the period of 1975 to 2016. Our results indicate that, while linear models incorporating the information of growth in inequality does produce lower forecast errors, these models do not necessarily outperform the univariate linear and nonlinear models based on formal statistical forecast comparison tests, especially in short- to medium-runs. However, at a one-year-ahead horizon, absolute measure of consumption inequality results in significant statistical gains for stock market volatility predictions - possibly due to consumption inequality translating into both political and social uncertainty in the long-run.

Keywords: Income and Consumption Inequalities; Stock Markets; Realized Volatility; Forecasting; Linear and Nonlinear Models; United Kingdom.
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1. Introduction

Accurate forecasting of the process of volatility has implications for portfolio selection, the pricing of derivative securities and risk management (Poon and Granger, 2003). In addition, financial market volatility, as witnessed during the recent global financial crisis, can have widespread repercussions on the economy as a whole, via its effect on real economic activity and public confidence. Hence, forecasts of market volatility, can serve as a measure for the vulnerability (uncertainty) of financial markets and the economy (Gupta et al., 2018a), and can help policymakers design appropriate policies to neutralize the negative impacts. Not surprisingly, given the importance of information on volatility for both investors and in policy-making, the literature on forecasting of volatility is quite large (see Rapach et al. (2008), Babikir et al. (2012) and Ben Nasr et al. (2014, 2016) for details reviews).

While prediction of volatility has historically relied on high-frequency univariate (Generalized Autoregressive Conditional Heteroskedasticity (GARCH)-type) models, more recently, Engle and Rangel (2008), Rangel and Engle (2011) and Engle et al. (2013) have highlighted the importance of low-frequency financial and macroeconomic variables in capturing future movements in the volatility process of financial assets. In this strand of the literature, despite the ample evidence linking stock market volatility to real economic activity (e.g. Hamilton and Lin (1996); Schwert (2011)) and the business cycle (e.g. Choudhry (2016)), the approach has largely been from a cashflow perspective, focusing on how economic fundamentals drive fluctuations in earnings and cashflow projections, which then contribute to volatility at the aggregate market level. From a non-cashflow perspective, however, one might argue that investors' perception of economic stability (or lack thereof), which may be driven by social and political risk factors, also plays a role in driving fluctuations in financial markets as investors adjust their expectations of risk exposures with respect to economic instability worries.

In this regard, given an upward trend in inequality globally (Piketty and Saez, 2014), which in turn, can lead to both political and social uncertainty (Barro, 2000), one could hypothesize that inequality might result in second-moment effects on stock prices (specifically, increased volatility). In addition, with income inequality representing a higher payoff for human capital (Becker and Chiswick, 1966; Lucas, 1977; Becker and Murphy, 2007), the most highly skilled individuals would be left to make the most important investment decisions for the firm, which in turn, is also likely to affect (decrease) stock market volatility, as observed in an in-sample analysis by Blau (2015)[1].

Against this backdrop, given the fact that in-sample predictability does not guarantee out-of-sample forecasting gain, and considering that the ultimate test of any predictive model is its out-of-sample performance (Campbell, 2008), the objective of this paper is to investigate, for the first time, whether inequality forecasts stock market volatility in the United Kingdom (UK). For this purpose, we use a unique data set at the (highest possible) quarterly frequency, over 1975Q1 to 2016Q1 which includes both income- and consumption-based relative and absolute measures of inequality. Given that stock market data over this period is available at daily frequency, we capture the latent process of volatility using a model-free estimate, namely realized volatility, i.e. sum of daily squared returns over a quarter. Furthermore, observing that realized volatility is nonlinearly related with its predictors (as highlighted by Gupta et al., 2018c), we not only use linear models for forecasting, but also nonparametric models to control against possible misspecification.

Our findings generally underscore the long-run predictive information captured by measures of inequality. Although incorporating measures of growth in inequality in the forecasting model produces smaller forecast errors in the short- to medium-runs, these models do not necessarily outperform the benchmark univariate linear and nonlinear models based on formal statistical forecast comparison tests. In the long-run, in particular one-year-ahead horizon, however, we observe that absolute measure of consumption inequality yields significant statistical gains for stock market volatility predictions. We argue that the long-run predictive power of consumption inequality is driven by its informational content over both political and social uncertainty in the long-run. The remainder of the paper is organized as follows: Section 2 outlines the alternative econometric models used for our forecasting analysis, while, Section 3 discusses the data and results, with Section 4 concluding the

[1] Note that, a recent line of research has already related prediction of stock market returns with measures of inequality (see for example, Brogaard et al. (2015), Christou et al. (2017) and Gupta et al. (2018b) for detailed reviews of the theoretical and empirical literature in this regard).

paper.

2. Forecasting Models and Accuracy Measures

2.1. Functional-Coefficient Autoregressive with Exogenous variables

The Functional-Coefficient Autoregressive with Exogenous variables ($FARX$) formulates the time series y_t as follows (Cai et al., 2000; Chen and Tsay, 1993a):

$$y_t = \sum_{i=1}^{p} f_i(y_{t-d}) y_{t-i} + \sum_{i=1}^{q} g_i(y_{t-d}) x_{t,i} + \varepsilon_t,$$

where ε_t is white noise and $x_i (i = 1, \ldots, q)$ are exogenous variables (and may contain the exogenous variables' lags). d, p and q are the orders of the model. The nonlinear functions $f_i(y_{t-d})$ and $g_i(y_{t-d})$ are estimated using local linear regression (Cai et al., 2000).

2.2. Nonlinear Additive Autoregressive with Exogenous variables

The Nonlinear Additive Autoregressive with Exogenous variables model ($NAARX$) uses the following formulation for time series modeling (Chen and Tsay, 1993b):

$$y_t = \sum_{i=1}^{p} f_i(y_{t-i}) + \sum_{i=1}^{q} g_i(x_{t,i}) + \varepsilon_t,$$

where ε_t is white noise and $x_i (i = 1, \ldots, q)$ are exogenous variables (and may contain the exogenous variables' lags). p and q are the orders of the model. The nonlinear functions $f_i(y_{t-i})$ and $g_i(x_{t,i})$ can be estimated using local linear regression (Cai and Masry, 2000).

2.3. Linear State Space Model

A Linear State Space Model (LSS) uses the following formulation to represent a linear Autoregressive with Exogenous variables (ARX) model:

$$\begin{cases} \boldsymbol{s}_t = \boldsymbol{A}\boldsymbol{s}_{t-1} + \boldsymbol{b}u_t \\ y_t = \boldsymbol{c}'\boldsymbol{s}_t + \boldsymbol{\beta}'\boldsymbol{x}_t + \varepsilon_t \end{cases}$$

where $\boldsymbol{s}_t$ is the state vector, u_t and ε_t are mutually *iid* Gaussian random variables (with variances η^2 and σ^2) and $\boldsymbol{x}_t$ is a vector of exogenouse variables.

The system's matrices $\boldsymbol{A}$, $\boldsymbol{b}$, $\boldsymbol{c}$ and $\boldsymbol{\beta}$ and the exogenous vector are defined as follows (Pearlman, 1980):

$$\boldsymbol{A} = \begin{bmatrix} 0 & 1 & 0 & \cdots & 0 \\ 0 & 0 & 1 & \cdots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 1 \\ \phi_p & \phi_{p-1} & \phi_{p-2} & \cdots & \phi_1 \end{bmatrix}_{p\times p},$$

$$\boldsymbol{b} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ b \end{bmatrix}_{p\times 1}, \quad \boldsymbol{c} = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ c \end{bmatrix}_{p\times 1}, \quad \boldsymbol{\beta} = \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_q \end{bmatrix}_{(q+1)\times 1}, \quad \boldsymbol{x}_t = \begin{bmatrix} 1 \\ x_{t,1} \\ \vdots \\ x_{t,q} \end{bmatrix}_{(q+1)\times 1}.$$

$\phi_1, \ldots, \phi_p$, $\beta_0, \ldots, \beta_q$, b and c are model's paramters. One may use an EM algorithm based on Kalman recursions to estimate the parameters (Shumway and Stoffer, 2011).

2.4. Heterogeneous Autoregressive Model of Realized Volatility

Consider the classical estimator of realized volatility (RV) of a market or an asset(Andersen and Bollerslev, 1998):

$$RV_t^{\Omega} = \sqrt{\sum_{i=1}^{M} r_{t,i}^2} \qquad (1)$$

where Ω is the frequency which RV is calculated in (i.e. daily, weekly, monthly, quarterly, etc.) and $r_{t,i}$, $(i = 1, \ldots, M)$ are log-return (first-differences of the natural logarithmic values) of the market's index or asset's price in tth period (in Ω frequency). The RV is an approximation to the volatility of high frequency data(Andersen et al., 2001a,b; Barndorff-Nielsen and Shephard, 2002a,b). The Heterogeneous Autoregressive Model of Realized Volatility ($HAR - RV$) is a cascade model based on RVs in lower frequencies(Corsi, 2009)[2]:

$$RV_{t+1}^{\Omega} = \beta_0 + \beta_1 RV_t^{\omega_1 \Omega} + \cdots + \beta_k RV_t^{\omega_k \Omega} + \nu_{t+1},$$

[2]It should be noted that the original $HAR - RV$ model in Corsi (2009) is formulated based on daily, weekly and monthly frequencies. The formulation is generalized to match the structure of data in this research. Details on structure of the data is given in next section.

where $\omega_1 = 1$, $RV_t^{j\Omega} = \frac{1}{j}\left(RV_t^{\Omega} + \cdots + RV_{t-j+1}^{\Omega}\right)$, $(j > 1)$, are RV in lower frequencies and ν_{t+1} is the innovation term. The sequence $\omega_1, \ldots, \omega_k$ shows the lag-structure of the $HAR - RV$ model (i.e. the lags included in the forecasting equation).

2.5. Forecasting Evaluation

Suppose $E(RV_t|\mathcal{F}_{t-1})$ is the realized volatility forecast and the ε_t is the square residual of the conditional mean model at time t:

$$\varepsilon_t = \left(RV_t - E(RV_t|\mathcal{F}_{t-1})\right)^2,$$

The Root Mean Square Error is formulated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\varepsilon_t}$$

In this research, the Kolmogorov-Smirnov Prediction Accuracy test (KSPA test) of Hassani and Silva (2015) is used to compare two forecasting models. The null hypothesis and the alternative for the two-tailed KSPA test are as follows:

$$\begin{cases} H_0 : F_{\varepsilon_{t,1}}(z) = F_{\varepsilon_{t,2}}(z) \\ H_1 : F_{\varepsilon_{t,1}}(z) \neq F_{\varepsilon_{t,2}}(z) \end{cases},$$

where $\varepsilon_{t,i}$ is the h-steps ahead out-of-sample forecast square errors generated by i-th forecasting model and $F_{\varepsilon_{t,i}}(.)$ is the cumulative distribution function. Rejecting the null hypothesis implies that the two competing models have different forecasting accuracy.

3. Data and Results

Data on daily FTSE All Share Stock Index (ALSI) for the UK is obtained from Data stream of Thomson Reuters. Since the inequality data is available quarterly, we compute the quarterly realized volatility of the FTSE ALSI using daily data. The measure that we consider RV in quarterly frequency (given by (1) with $\Omega = Quarter$). The three measures of inequality used are the Gini coefficient, standard deviation (of the data in natural logarithms), and the difference between the 90th and 10th percentile (with the data in natural logarithms). In other words, we include both absolute and relative measures of inequality. The various inequality measures are calculated using survey data on income and consumption from the family expenditure survey[3]. Further details on the construction of the data and the survey are documented in Mumtaz and Theophilopoulou (2017)[4]. Note that we work with the growth rates of the inequality measures to ensure that our predictors under consideration (taken into account one at a time) are stationary as required by the empirical models. We abbreviate the growth rates of the three income-based inequality measures as x_1, x_2, and x_3, while the growth rates of the three consumption-based inequality measures are denoted as x_4, x_5, and x_6. In Table 1, we provide a list of the inequality measures utilized along with model abbreviations.

Tables 2 and 3 show the RMSE for out-of-sample forecasting of RV using different models and predictors. Note, given that we have 164 observations to work with, following Rapach et al. (2005), we use 50% of the observations as in-sample, while the remaining 50% is used as the out-of-sample period, over which all our models are recursively estimated to mimic a pseudo out-of-sample forecasting scenario. As it can be seen, the best model with a specific-type of inequality (in the sense of minimum RMSE), is the linear ARX model with x_3 (i.e., the income inequality measure as given by the difference between the 90th and 10th percentile) for $h = 1, 2$. For $h = 4$, the best model is LSS with the x_5 (i.e., the consumption inequality measure as given by the standard deviation) as the predictor. Table 4 summarizes the best models for the three horizons considered. Although the RMSE metric suggests that the models with highest accuracy in forecasting RV are the linear ARX and the LSS with predictor variables x_3 and x_5, respectively, concluding which models and predictors are the best, needs statistical hypothesis testing. In this regard, we use KSPA statistic to test the null hypothesis that an model has the same forecasting accuracy as the best performing model (in the sense of minimum RMSEs).

[3] The data is downloadable from: `https://discover.ukdataservice.ac.uk/series/?sn=200016` and `https://discover.ukdataservice.ac.uk/series/?sn=2000028`.

[4] We would like to thank Professor Haroon Mumtaz for kindly sharing the inequality data with us.

Table 1: Inequality measures and model abbreviation

Abbreviation	Description
x_1	Gini coefficient of income growth rate
x_2	Standard deviation of income growth rates[1]
x_3	Difference between the 90th and 10th percentile of the income growth rates[1]
x_4	Gini coefficient of consumption growth rate
x_5	Standard deviation of consumption growth rate[1]
x_6	Difference between the 90th and 10th percentile of consumption growth rate[1]
ARX	Autoregressive with Exogenous variables
$FARX$	Functional-Coefficient Autoregressive with Exogenous variables
$NAARX$	Nonlinear Additive Autoregressive with Exogenous variables
LSS	Linear State Space
RV	Realized Volatility
$HAR-RV$	Heterogeneous Autoregressive - Realized Volatility
$KSPA$	Kolmogorov-Smirnov Prediction Accuracy

[1] Data in natural logarithms.

Tables 5 and 6 show the p-values for KSPA test, comparing the models and predictors with the minimum RMSE model in terms of the out-of-sample forecasts of RV. Table 7 shows the models and predictors for which the null hypothesis of the KSPA test is retained at $\alpha = 0.05$ significance level, (i.e. the models and predictors with same accuracy as the minimum RMSE model).

According to the KSPA test results, for one-step-ahead forecasts, the linear ARX, $HAR-RV$ and $NAARX$ models with predictors, have the same accuracy as the minimum RMSE model. Further, there is no significant difference between the accuracy of the minimum RMSE model and the $NAAR$, AR, $HAR-RV$ models without any predictors. Almost similar results are obtained for the two-step-ahead forecasts as well. However, the $NAARX$ with x_2 as the predictor and $NAAR$ model does not have the same accu-

Table 2: Out-of-sample RMSE for RV forecasting (based on 82 out-of-sample forecasts)

Predictor	Model	$h = 1$	$h = 2$	$h = 4$
x_1	$FARX$	1.5104	228.410	2.671E+03
	$NAARX$	0.3472	0.3961	0.4301
	LSS	5.1227	5.3190	5.7348
	ARX	0.3413	0.3954	0.4278
	$HAR - RV^a$	0.3484	0.4075	0.4293
x_2	$FARX$	2.2922	3.115E+04	7.633E+04
	$NAARX$	0.6657	5.9579	0.9081
	LSS	4.3694	4.5020	4.7727
	ARX	0.3380	0.3935	0.4254
	$HAR - RV^a$	0.3474	0.4073	0.4286
x_3	$FARX$	1.5233	449.42	396.288
	$NAARX$	0.3649	0.3934	0.4980
	LSS	4.7007	4.8085	5.1005
	ARX	0.3358	0.3921	0.4236
	$HAR - RV^a$	0.3449	0.4062	0.4277
x_4	$FARX$	1.3477	38.6539	1.520E+06
	$NAARX$	4.7721	1.7204	0.5971
	LSS	4.6861	4.8258	5.1411
	ARX	0.3422	0.3949	0.4283
	$HAR - RV^a$	0.3508	0.4067	0.4287

[a]. The lag-structure of the model is $\omega_1 = 1, \omega_2 = 4$.

Table 3: Out-of-sample RMSE for RV forecasting (continued)

Predictor	Model	$h = 1$	$h = 2$	$h = 4$
x_5	$FARX$	1.3637	51.6935	1.299E+07
	$NAARX$	0.3414	0.3992	0.4394
	LSS	1.2157	0.5571	0.1744
	ARX	0.3414	0.3946	0.4274
	$HAR-RV^a$	0.3514	0.4070	0.4282
x_6	$FARX$	1.4523	82.0759	9.746E+06
	$NAARX$	0.3456	0.3953	0.4291
	LSS	4.3086	4.4380	4.6928
	ARX	0.3403	0.3951	0.4268
	$HAR-RV^a$	0.3495	0.4087	0.4289
Without Predictors	$FARX$	1.3657	51.1659	2.801E+03
	$NAARX$	0.3941	0.4053	0.4198
	LSS	3.7939	3.8810	4.0633
	ARX	0.3384	0.3938	0.4257
	$HAR-RV^a$	0.3452	0.4063	0.4278
	RW	0.3593	0.4272	0.4890

[a]. The lag-structure of the model is $\omega_1 = 1, \omega_2 = 4$.

Table 4: Summary table (minimum out-of-sample RMSE models and predictors for RV forecasting)

	$h = 1$	$h = 2$	$h = 4$
Model	ARX	ARX	LSS
Predictor	x_3	x_3	x_5

Table 5: KSPA test p-values (two tailed) for comparing the forecasting models to minimum RMSE RV forecast. (based on 82 out-of-sample forecasts)

	$h = 1$	$h = 2$	$h = 4$
Minimum RMSE model → Comparing to ↓	ARX (x_3)	ARX (x_3)	LSS (x_5)
$FARX$ (x_1)	0.0000	0.0000	0.0000
$NAARX$ (x_1)	0.7027	0.9794	0.0000
LSS (x_1)	0.0000	0.0000	0.0000
ARX (x_1)	0.9806	1.0000	0.0000
$HAR - RV^a$ (x_1)	0.9806	0.8219	0.0000
$FARX$ (x_2)	0.0000	0.0000	0.0000
$NAARX$ (x_2)	0.0562	0.0216	0.0000
LSS (x_2)	0.0000	0.0000	0.0003
ARX (x_2)	0.9981	1.0000	0.0000
$HAR - RV^a$ (x_2)	0.8277	0.9220	0.0000
$FARX$ (x_3)	0.0000	0.0000	0.0000
$NAARX$ (x_3)	0.7027	0.9794	0.0000
LSS (x_3)	0.0000	0.0000	0.0006
ARX (x_3)			0.0000
$HAR - RV^a$ (x_3)	0.7027	0.8219	0.0000
$FARX$ (x_4)	0.0000	0.0000	0.0000
$NAARX$ (x_4)	0.7027	0.9220	0.0000
LSS (x_4)	0.0000	0.0000	0.0311
ARX (x_4)	0.9806	1.0000	0.0000
$HAR - RV^a$ (x_4)	0.9254	0.9220	0.0000

[a]. The lag-structure of the model is $\omega_1 = 1, \omega_2 = 4$.

Table 6: KSPA test p-values (two tailed) for comparing the forecasting models to minimum RMSE RV forecast. (continue)

	$h = 1$	$h = 2$	$h = 4$
Minimum RMSE model → Comparing to ↓	ARX (x_3)	ARX (x_3)	LSS (x_5)
$FARX$ (x_5)	0.0000	0.0000	0.0000
$NAARX$ (x_5)	0.8277	0.9220	0.0000
LSS (x_5)	0.0000	0.0000	
ARX (x_5)	0.9981	1.0000	0.0000
$HAR-RV^a$ (x_5)	0.4462	0.9794	0.0000
$FARX$ (x_6)	0.0000	0.0000	0.0000
$NAARX$ (x_6)	0.5705	0.9794	0.0000
LSS (x_6)	0.0000	0.0000	0.0000
ARX (x_6)	0.9806	1.0000	0.0000
$HAR-RV^a$ (x_6)	0.5705	0.9220	0.0000
FAR	0.0000	0.0000	0.0000
$NAAR$	0.8277	0.9794	0.0000
LSS (Without Predictors)	0.0000	0.0000	0.0000
AR	0.9981	1.0000	0.0000
$HAR-RV^a$ (Without Predictors)	0.5705	0.8219	0.0000
RW	0.1245	0.6953	0.0000

[a]. The lag-structure of the model is $\omega_1 = 1, \omega_2 = 4$.

Table 7: Forecasts similar to the Minimum RMSE for RV forecasting.[a]

Minimum RMSE model →	$h = 1$ ARX (x_3)	$h = 2$ ARX (x_3)	$h = 4$ LSS (x_5)
	$NAARX$ (x_1)	$NAARX$ (x_1)	
	ARX (x_1)	ARX (x_1)	
	$HAR-RV^b$ (x_1)	$HAR-RV^b$ (x_1)	
	$NAARX$ (x_2)	ARX (x_2)	
	ARX (x_2)	$HAR-RV^b$ (x_2)	
	$HAR-RV^b$ (x_2)	$NAARX$ (x_3)	
	$NAARX$ (x_3)	$HAR-RV^b$ (x_3)	
Similar forecasts	$HAR-RV^b$ (x_3)	$NAARX$ (x_4)	
($\alpha = 0.05$)	$NAARX$ (x_4)	ARX (x_4)	
	ARX (x_4)	$HAR-RV^b$ (x_4)	
	$HAR-RV^b$ (x_4)	$NAARX$ (x_5)	
	$NAARX$ (x_5)	ARX (x_5)	
	ARX (x_5)	$HAR-RV^b$ (x_5)	
	$HAR-RV^b$ (x_5)	$NAARX$ (x_6)	
	$NAARX$ (x_6)	ARX (x_6)	
	ARX (x_6)	$HAR-RV^b$ (x_6)	
	$HAR-RV^b$ (x_6)	AR	
	$NAAR$	$HAR-RV^b$ (Without Predictors)	
	AR	RW	
	$HAR-RV$ (Without Predictors)		
	RW		

[a]. H_0 Retained at 0.05 significance level .

[b]. The lag-structure of the model is $\omega_1 = 1, \omega_2 = 4$.

racy as the minimum RMSE, at two-step-ahead forecasting. Accordingly, the effect of x_3 in short- and medium-term forecasting of RV is not significant. Furthermore, using the ARX model with x_3 as the predictor, does not improve the short-term forecasting accuracy of the RW model. At the one-year-ahead forecasting horizon, however, there is a significant improvement to the forecasting ability of the RW model, using LSS. Furthermore, using x_5 (i.e., the consumption inequality measure as given by the standard deviation) as predictor, improves the accuracy of one-year-ahead forecasting.[5]

Note that, as indicated in the introduction, theory tends to suggest that inequality can either increase volatility by enhancing both political and social uncertainty, or reduce volatility if income inequality is a signal about skilled decision making. The lack of predictive evidence of inequality for RV, especially at short- to medium-runs could be an indication that these two effects are possibly cancelling each other out in our data set for the UK. However, the information content in the increased absolute consumption inequality (as given by the standard deviation), is likely to enhance stock market volatility in the longer run via the heightened political and social risks that is generated.

4. Conclusion

Financial market volatility is used as an important input in investment decisions, option pricing and financial market regulation, thus making forecasting of volatility an important area of research for academics, investors and policymakers. Given this, we investigate whether income- and consumption-based relative and absolute measures of inequality can forecast stock market realized volatility of the UK, based on a unique high-frequency (quarterly) data set over 1975Q1 to 2016Q1. Using an array of univariate and bivariate linear and nonlinear models, we find that, while linear models with inequality can produce lower forecast errors, their performance is not statistically different from other univariate (and even bivariate) linear and nonlinear models in the short- to medium-runs. But, growth in inequality, and in particular absolute consumption inequality, carries additional information in forecast-

[5]Using the Minimum Absolute Error and AE function in KSPA test tends to provide similar results, which in turn, are available upon request from the authors.

ing stock market volatility in the UK in the long-horizon. As part of future research, given that inequality data is traditionally only available at annual frequency, it would be interesting to extend our analysis to multiple countries using panel data-based forecasting methods. This will, in the process, provide a more robust test (from the perspective of obtaining cross-country evidence) of the theoretical arguments relating inequality with stock market volatility.

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