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Does the choice of estimator matter for forecasting? A revisit

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Abstract

In this study, we further examine whether the choice of estimator matters for forecasting based on the conclusion of Westerlund and Narayan [WN, hereafter] (2012, 2015). A similar but small simulation study was conducted by WN (2012, 2015) to validate the need to account for salient features of predictors such as persistence, endogeneity and conditional heteroscedasticity in a forecast model. In addition to considering a more representative number of observations for high frequency, extensive replications and four competing estimators, we offer alternative functions for these effects and thereafter, we test whether the conclusion of WN (2012, 2015) will still hold. Our results further lend support to the WN (2012, 2015) findings and thus suggest that the choice of estimator matters for forecasting notwithstanding the alternative functions and scenarios considered in our study. Thus, pre-testing the predictors in a forecast model for the mentioned features is required to identify the appropriate estimator to apply.

Keywords: Endogeneity, Heteroscedasticity, Persistence, Forecast evaluation

JEL Classification: C15, C52, C53

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1.0 Introduction

The need to evaluate the forecast performance of a predictive model is important for at least three reasons. One, it helps to ascertain whether such predictive model will be good enough for making future projections. Second, when there are alternative models for forecasting, the analysis of their forecast performance is necessary to rank these models particularly when dealing with out-of-sample forecasts. Thirdly, when there are competing estimators for a predictive model, forecast evaluation becomes necessary to choose the estimator that is more likely to produce accurate forecasts. In reality, researchers are often confronted with alternative estimators for modeling and forecasting and therefore, understanding the predictive power of these estimators is crucial for desirable outcomes to become realizable. Also, from policy perspective, the need to produce accurate forecasts by fiscal and monetary authorities is a strong prerequisite for the actualization of policy targets and that partly explains why models are constantly updated to account for more information that can produce better forecast outcomes.

Recently, Westerlund and Narayan [WN hereafter] (2012, 2015) offer a small-scale simulation study to justify that the choice of estimator matters for forecasting returns. They argue that the choice of estimator should be rooted in the salient features of the data such as heteroscedasticity, persistence and endogeneity and an empirical application to stock returns further validates their simulation evidence. This approach of accounting for the salient features of predictors in forecasting was first formalized by Lewellen [LW hereafter] (2004) to account for endogeneity and persistence effects and was later extended by WN (2012, 2015) to capture conditional heteroscedasticty. Both the theoretical and empirical results favour the consideration of conditional heteroscedsticity in forecasting if it is found to be significant. Thus, the ability of the WN approach to deal with the inherent characteristics of the predictors simultaneously in a predictive model is a major attraction and its application has continued to gain recognition in the literature. For instance, the approach has been applied to model borrowing and expenditure (see, Makin et al., 2014); forecast stock returns (see for example, Narayan and Bannigidadmath, 2015; Narayan and Gupta, 2015; Phan et al., 2015; Bannigidadmath and Narayan, 2016; Devpura et al., 2017); predict gold price returns using consumer prices (see, Sharma, 2016); predict inflation using oil price (see Salisu and Isah, 2017; Salisu et al., 2018), forecast CO_2 emissions using the EKC hypothesis (see Salisu, Akanni and Ogbonna, 2018). While these studies seem to support this approach, their findings are limited to the series considered.

Thus, in this study, we offer a more extensive and alternative simulation study to further verify the strength and limits of this new approach of forecasting financial series. We do acknowledge that such an experiment has been previously conducted by WN (2012, 2015) as noted earlier. However, the strict assumption of “either or” for persistence does not allow for variations that are often confronted when dealing with real economic datasets. Motivated by the fractional integration procedure, we vary the parameter for persistence effect from mild to severe rather than the strict 0 and 0.9 considered in the WN (2012) study. This permits the analysis of the extent to which persistence becomes a concern in forecasting. Also, we consider an alternative functional form of heteroscedasticity different from the ARCH structure considered in WN (2012) paper. The idea here is to examine whether the choice of functional form for heteroscedasticity matters for forecasting. In other words, if we pre-weight the data in a typical predictive model as specified in WN (2012, 2015) by the inverse of standard deviation of the regression that follows a different functional form for heteroscedasticity, will the conclusion remains the same as regard the superiority of the estimator that accounts for such effect relative to others such as Ordinary Least Squares (OLS) and LW (2004) estimators which ignore same? We also compare the WN estimator with the conventional Generalized Least Squares (GLS) estimator that ignores persistence and endogeneity effects. Finally, we consider a more representative number of observations particularly for high frequency series and extensive replications than those used in the WN (2012). All these considerations in this study further enrich the small simulation study conducted by WN (2012) and offer more meaningful generalizations on the proposed approach to forecasting.

On the whole, our results further validate the conclusion of WN (2012, 2015) and more importantly it demonstrates that the WN estimator compares favourably with traditional GLS estimator in the presence of an alternative functional form for heteroscedasticity but mild persistence and produces forecast outcomes that are superior to the latter including OLS and LW estimators in the presence of severe persistence and heteroscedasticity.

The remainder of this study is organized as follows: Section 2 describes the methodology for the Monte Carlo experiment; Section 3 discusses the simulation results under different scenarios while Section 4 concludes the paper.

2.0 Monte Carlo experiment

In a view to ascertain the performance of four selected linear model estimators (OLS, GLS, LW and WN) in the presence or otherwise of salient features of predictors, we subject these estimators to series of linear regression estimations using the Monte Carlo (hereafter, MC) approach. Let us consider a simple linear regression model as follows:

$$y_t = \beta_0 + \beta_1 x_t + u_t \qquad (1)$$

where $u_t \sim iid\, N(0,1)$ is the error term, y_t is the dependent variable, the independent variable x_t is uniformly distributed on an interval [0,10], while the intercept β_0 and slope coefficient β_1 are initialized to be 0 and 0.5, respectively. This model serves here as the baseline scenario, under which all four estimators would be tested. We allow for four number of replications ($R=1000$, $R=2500$, $R=5000$ and $R=10000$), four sample sizes ($n=100$, $n=250$, $n=500$ and $n=1000$) and four correlation coefficients ($\rho=.1$, $\rho=.2$, $\rho=.6$ and $\rho=.9$) for persistence effect from mild 0.1, 0.2 to severe 0.6 and 0.9 and four data generating processes [DGP hereafter]. On generating any given sample size, an extra 200 observations are added such that for a sample size of 100, we generate 300 observation and for 250, we generate 450 observations. The extra 200 observations are meant to serve as burn-ins (observations which are only required for the simulation process to stabilize and are afterwards, discarded before the estimation procedure).

The first DGP assumes homoscedastic error/disturbance term and exogenously determined independent variable(s) (which are uncorrelated with the error term). The second DGP, while defined similarly as the model in equation (1), assumes that the disturbance term is heteroscedastic i.e., $u_t \sim iid\, N(0,\sigma_t^2)$ such that $\sigma_t^2 = \sigma^2(\gamma z_t)$, where $z_t = \rho x_t + e_t$,

$e_t \sim iid\, N(0,1)$, the innovation vector (u_t, e_t) is independently distributed for each specified sample size, while $\sigma^2 = 1$ and $\gamma = 1$, x_t, β_0 and β_1 remain as previously defined. The correlation between x_t and z_t are varied as earlier specified ranging from mild $(\rho = 0.1, 0.2)$ to severe $(\rho = 0.6, 0.9)$ correlation.

In the third DGP, we introduce persistence in the independent variable, defined by $x_t = \rho x_{t-1} + e_t$ with $e_t \sim iid\, N(0,1)$ and incorporate x_t into equation (1), leaving all other parameters as previously defined with respect to the first DGP. The ρ here, representing the correlation between the independent variable, (x_t) and its immediate past value (x_{t-1}), are also varied on the basis of correlation severity.

Finally, in the fourth case, we simulate datasets that are characterized by heteroscedasticity, persistence and endogeneity. The model is defined by equation (2)

$$y_t = \beta_0 + \beta_1 x_t + \beta_2 z_t + u_t \qquad (2)$$

where $u_t \sim iid\, N(0, \sigma_t^2)$ such that $\sigma_t^2 = \sigma^2(\gamma z_t)$, where $z_t = \rho x_t + e_t$, $e_t \sim iid\, N(0,1)$ and $\beta_2 = .45$, while σ^2, γ, x_t, β_0 and β_1 remain as previously defined. In order to capture the endogeneity in the dataset, z_t, which is simulated to be correlated with x_t, would intentionally be omitted in the estimation procedure.

3.0 Discussion of results

3. 1 Theoretical expectations

Here, we discuss the results of our Monte Carlo experiment, which is targeted at providing further evidence(s) on the performance of selected linear model estimators when one or more of the highlighted features as endogeneity, heteroscedasticity and persistence is/are present. The selected estimators differ in their ability to account for the characteristic features of predictors. For instance, the OLS estimator does not account for any of these effects and therefore it is expected to underperform any estimator that accounts for one or more of the effects. In the same vein, the WN estimator which accounts for all three effects is expected to outperform any other estimator such as LW and the traditional GLS estimator that account for less. The forecast performance of the competing model estimators is evaluated singly using the root mean square error (RMSE) statistic and pair-wisely using the Campbell Thompson (C-T) statistic. The percentage outperformance of each estimator over other competing estimators is also examined. Using the Monte Carlo simulation, the experimental process is replicated using $R = 1000,\ 2500,\ 5000,\ 10000$ times, four sample sizes $\left(n = 100,\ 250,\ 500,\ 1000\right)$ and correlation severity $\left(\rho = 0.1,\ 0.2,\ 0.6,\ 0.9\right)$ as previously mentioned. This consequently results in four different scenarios on the basis of earlier defined DGPs, which include homoscedasticity assumption (see Tables 1a – 1c); presence of heteroscedasticity (see Tables 2a – 2c); presence of persistence (see Tables 3a – 3c); and presence of heteroscedasticity with persistence and endogeneity (see Tables 4a – 4c). The results are discussed in subsequent sections.

3.2 Does the choice of estimator matter when residuals are homoscedastic?

On the assumption of homoscedastic error in the DGP, we examine the forecast performance of the competing estimators under different combinations of number of replications and sample sizes using RMSE (Table 1a), Campbell Thompson statistic (Table 1b) and probability values (Table 1c). We find LW, which accounts for both persistence and endogeneity, to have the least RMSE value in comparison with other competing estimators. While the OLS estimator outperforms both the GLS and WN estimators as expected given the homoscedasticity assumption, it underperforms in comparison to the LW estimator. On the pairwise comparison, we again find the LW estimator to out-perform the OLS estimator, while the OLS estimator outperforms both the GLS and WN estimators (see Campbell Thompson result in Table 1b). This performance is further confirmed probabilistically determined by the number of cases of superior performance of a given estimator relative to others (in percentages). While the LW estimator consistently outperforms the OLS estimator across the different combinations of sample sizes and replications, the outperformance of latter in comparison with the GLS and WN is relative.

Although, the error term in the DGP is simulated to be homoscedastic, the persistence of the regressor is not explicitly specified, implying some level of persistence in the regressor, which gives leverage to the LW estimator over the OLS estimator. Our finding affirms the importance of the choice of estimator when the DGP assumes homoscedastic error term without an explicitly specified persistence of model regressors. Any estimator that accounts for persistence in regressor(s) would most probably outperform other competing estimators that do not. With similar patterns also observed across the different combinations of sample sizes and number of replications, showing the insensitivity of the forecast performance of the examined estimators to the sample size and number of replications, we convincingly conclude that the choice of estimator does matter and the LW estimator is preferred under this scenario.

Table 1a: RMSE results for Estimators' Forecast Performance(s) under Homoscedasticity Assumption

Estimators	Number of Observations = 100				Number of Observations = 250				Number of Observations = 500				Number of Observations = 1000			
	R=1,000	*R=2,500*	*R=5,000*	*R=10,000*	*R=1,000*	*R=2,500*	*R=5,000*	*R=10,000*	*R=1,000*	*R=2,500*	*R=5,000*	*R=10,000*	*R=1,000*	*R=2,500*	*R=5,000*	*R=10,000*
OLS	0.9878	0.9868	0.9875	0.9879	0.9920	0.9942	0.9949	0.9944	0.9972	0.9980	0.9976	0.9973	0.9981	0.9987	0.9986	0.9989
GLS	0.9971	0.9982	0.9975	0.9972	1.0021	0.9998	0.9991	0.9996	0.9997	0.9990	0.9994	0.9997	1.0003	0.9998	0.9999	0.9996
LW	0.9827	0.9816	0.9824	0.9828	0.9900	0.9922	0.9929	0.9924	0.9963	0.9970	0.9966	0.9963	0.9976	0.9982	0.9980	0.9984
WN	0.9920	0.9929	0.9923	0.9920	1.0000	0.9978	0.9970	0.9976	0.9988	0.9980	0.9984	0.9987	0.9998	0.9993	0.9994	0.9991

Table 1b: Campbell Thompson results for Estimators' Forecast Performance(s) under Homoscedasticity Assumption

Estimators	Number of Observations = 100				Number of Observations = 250				Number of Observations = 500				Number of Observations = 1000			
	R=1,000	*R=2,500*	*R=5,000*	*R=10,000*	*R=1,000*	*R=2,500*	*R=5,000*	*R=10,000*	*R=1,000*	*R=2,500*	*R=5,000*	*R=10,000*	*R=1,000*	*R=2,500*	*R=5,000*	*R=10,000*
GLS_OLS	-0.0617	-0.0667	-0.0640	-0.0629	-0.0382	-0.0285	-0.0250	-0.0271	-0.0128	-0.0097	-0.0116	-0.0130	-0.0084	-0.0060	-0.0066	-0.0053
LW_OLS	0.0102	0.0106	0.0103	0.0103	0.0041	0.0041	0.0041	0.0041	0.0019	0.0019	0.0020	0.0020	0.0011	0.0010	0.0010	0.0010
WN_OLS	-0.0509	-0.0555	-0.0531	-0.0520	-0.0339	-0.0243	-0.0208	-0.0230	-0.0109	-0.0077	-0.0096	-0.0110	-0.0073	-0.0050	-0.0056	-0.0043
LW_GLS	-0.0103	-0.0065	-0.0099	-0.0122	0.0072	-0.0014	-0.0039	-0.0018	-0.0008	-0.0038	-0.0023	-0.0011	0.0015	-0.0009	-0.0001	-0.0016
WN_GLS	0.0102	0.0106	0.0103	0.0103	0.0041	0.0041	0.0041	0.0041	0.0019	0.0019	0.0020	0.0020	0.0011	0.0010	0.0010	0.0010
WN_LW	-0.0617	-0.0667	-0.0640	-0.0629	-0.0382	-0.0285	-0.0250	-0.0271	-0.0128	-0.0097	-0.0116	-0.0130	-0.0084	-0.0060	-0.0066	-0.0053

Note: The table presents a pairwise comparison of two competing estimators using the Campbell Thompson Statistic, with positive values indicating out-performance in favour of the first listed estimator and vice versa for negative values. Each column represents the number of replications considered under each of the four different sample sizes employed.

Table 1c: Probability values of Estimators' Forecast Performance(s) under Homoscedasticity Assumption

Estimators	Number of Observations = 100				Number of Observations = 250				Number of Observations = 500				Number of Observations = 1000			
	R=1,000	*R=2,500*	*R=5,000*	*R=10,000*	*R=1,000*	*R=2,500*	*R=5,000*	*R=10,000*	*R=1,000*	*R=2,500*	*R=5,000*	*R=10,000*	*R=1,000*	*R=2,500*	*R=5,000*	*R=10,000*
GLS_OLS	48.00	47.32	48.06	48.41	46.00	48.16	48.48	48.22	48.80	49.04	49.44	48.88	49.60	50.12	49.66	49.82
LW_OLS	100.00	99.96	99.9	99.91	100.00	99.96	99.98	99.97	99.70	99.84	99.88	99.92	99.90	99.88	99.88	99.93
WN_OLS	49.80	49.08	49.74	49.91	47.00	49.08	49.34	49.03	49.30	49.76	50.24	49.71	49.90	50.48	50.12	50.29
LW_GLS	53.30	53.76	53.18	52.81	54.50	52.68	52.44	52.70	51.90	51.56	51.38	51.89	51.10	50.40	50.86	50.67
WN_GLS	100.00	99.92	99.92	99.94	99.90	99.88	99.92	99.92	99.90	99.96	99.96	99.95	99.90	99.92	99.9	99.91
WN_LW	48.00	47.32	48.06	48.41	46.00	48.16	48.48	48.22	48.80	49.04	49.44	48.88	49.60	50.12	49.66	49.82

Note: The table presents a pairwise comparison of two competing estimators using the percentage number of times an estimator out-performs its competing estimator. Each column represents the number of replications considered under each of the four different sample sizes employed.

3.3 Does the choice of estimator matter when residuals are heteroscedastic?

We try to examine here the importance of the choice of estimator when the assumption of homoscedasticity is violated. While following the procedure for the homoscedastic residual case earlier discussed, we consider a scenario when the variance of the residuals is no longer constant and again allow for implicit persistence of the regressor. Our interest here is to vary the correlation coefficient (between x_t and z_t as previously defined in the Monte Carlo section) from mild to severe, while observing the pattern of performance across the competing estimators. Under this scenario, we find the WN and GLS estimators that try to correct for heteroscedasticity, to be relatively similar in outperforming OLS and LW, with the WN estimator being the most preferred across the different combinations of sample sizes, correlation coefficients and number of replications (see Table 2a). The forecast performance (in terms of RMSE) of the WN estimator also improves as the sample size increases regardless of the severity of the correlation coefficient specified. On the pairwise comparison of the competing estimators, we find positive C-T statistics (see Table 2b) and probability values (see Table 2c) close to unity whenever the WN estimator is compared with other estimators, which further confirms the stance of the RMSE results. Again, given the implicit persistence in the regressor, the LW estimator is observed to consistently outperform the OLS estimator. Generally, while the forecast performance of the WN and GLS estimators improve as heteroscedasticity severity increases, the forecast performance of the OLS and LW estimators seem to worsen. By implication, when a dataset exhibits characteristics suggesting any form of the violations of the least squares assumptions, estimators that try to correct/adjust for these violations tend to outperform those that ignore them. Therefore, in the presence of heteroscedastic error term and implicit persistence, the choice of estimator does matter and in this case, the WN estimator is preferred in line with our expectation. The pattern of outperformance is also not sensitive to the sample size, heteroscedasticity severity and number of replications. Hence, in the presence of a specified form of heteroscedasticity, our results are robust.

TABLE 2a: RMSE results for Estimators' Forecast Performance(s) under Heteroscedasticity Scenario

Estimator	$\rho = 0.1$				$\rho = 0.2$				$\rho = 0.6$				$\rho = 0.9$			
	R=1,000	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***
Number of Observations = 100																
OLS	1.5602	1.5643	1.5707	1.5720	1.6834	1.6893	1.6957	1.6935	2.3588	2.3611	2.3692	2.3588	2.7615	2.7579	2.7681	2.7560
GLS	0.6792	0.6798	0.6789	0.6790	0.6414	0.6424	0.6419	0.6425	0.5003	0.5009	0.5010	0.5023	0.4518	0.4508	0.4517	0.4532
LW	1.5522	1.5566	1.5629	1.5640	1.6747	1.6809	1.6872	1.6849	2.3466	2.3491	2.3573	2.3470	2.7472	2.7438	2.7541	2.7422
WN	0.6757	0.6764	0.6755	0.6755	0.6380	0.6392	0.6387	0.6393	0.4976	0.4982	0.4985	0.4998	0.4493	0.4484	0.4494	0.4509
Number of Observations = 250																
OLS	1.6382	1.6524	1.6421	1.6441	1.7823	1.7995	1.7846	1.7860	2.5684	2.6006	2.5676	2.5688	3.0534	3.0941	3.0480	3.0506
GLS	0.6354	0.6295	0.6327	0.6322	0.5912	0.5858	0.5895	0.5892	0.4311	0.4272	0.4307	0.4303	0.3727	0.3694	0.3729	0.3722
LW	1.6349	1.6492	1.6389	1.6408	1.7787	1.7961	1.7811	1.7824	2.5631	2.5955	2.5624	2.5637	3.0471	3.0879	3.0418	3.0445
WN	0.6341	0.6283	0.6314	0.6309	0.5901	0.5847	0.5884	0.5880	0.4302	0.4263	0.4299	0.4295	0.3719	0.3687	0.3722	0.3715
Number of Observations = 500																
OLS	1.6689	1.6620	1.6646	1.6713	1.8217	1.8155	1.8170	1.8245	2.6541	2.6577	2.6528	2.6641	3.1735	3.1851	3.1759	3.1898
GLS	0.6155	0.6167	0.6158	0.6137	0.5690	0.5695	0.5689	0.5669	0.4029	0.4017	0.4020	0.4002	0.3423	0.3408	0.3414	0.3397
LW	1.6673	1.6605	1.6630	1.6696	1.8201	1.8138	1.8152	1.8226	2.6517	2.6553	2.6502	2.6614	3.1705	3.1822	3.1728	3.1866
WN	0.6150	0.6161	0.6152	0.6131	0.5684	0.5690	0.5683	0.5663	0.4025	0.4013	0.4016	0.3998	0.3420	0.3405	0.3411	0.3393
Number of Observations = 1000																
OLS	1.6791	1.6843	1.6856	1.6840	1.8377	1.8440	1.8467	1.8448	2.7152	2.7306	2.7369	2.7329	3.2689	3.2922	3.3005	3.2939
GLS	0.6060	0.6033	0.6031	0.6034	0.5566	0.5541	0.5537	0.5541	0.3837	0.3819	0.3814	0.3819	0.3222	0.3204	0.3198	0.3203
LW	1.6783	1.6835	1.6848	1.6831	1.8368	1.8431	1.8458	1.8439	2.7138	2.7292	2.7355	2.7315	3.2672	3.2906	3.2989	3.2922
WN	0.6057	0.6030	0.6028	0.6032	0.5563	0.5538	0.5534	0.5538	0.3835	0.3817	0.3812	0.3817	0.3220	0.3203	0.3197	0.3202

TABLE 2b: Campbell Thompson results for Estimators' Forecast Performance(s) under Heteroscedasticity Scenario

Estimators	$\rho = 0.1$				$\rho = 0.2$				$\rho = 0.6$				$\rho = 0.9$			
	R=1,000	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***
Number of Observations = 100																
GLS_OLS	0.6800	0.6757	0.6735	0.6738	0.7243	0.7173	0.7150	0.7155	0.8468	0.8409	0.8361	0.8337	0.8577	0.8606	0.8479	0.8473
LW_OLS	0.0103	0.0099	0.0100	0.0101	0.0103	0.0100	0.0099	0.0100	0.0105	0.0102	0.0100	0.0100	0.0104	0.0103	0.0101	0.0100
WN_OLS	0.6834	0.6791	0.6769	0.6772	0.7273	0.7202	0.7179	0.7184	0.8485	0.8427	0.8377	0.8354	0.8593	0.8622	0.8494	0.8489
LW_GLS	-12.3771	-12.2725	-13.5802	-14.7450	-22.9453	-22.5225	-24.4549	-25.6909	-173.6606	-187.9524	-188.5308	-184.5334	-401.5506	-470.9464	-449.3941	-434.1580
WN_GLS	0.0103	0.0099	0.0100	0.0101	0.0103	0.0100	0.0099	0.0100	0.0105	0.0102	0.0100	0.0100	0.0104	0.0103	0.0101	0.0100
WN_LW	0.6800	0.6757	0.6735	0.6738	0.7243	0.7173	0.7150	0.7155	0.8468	0.8409	0.8361	0.8337	0.8577	0.8606	0.8479	0.8473
Number of Observations = 250																
GLS_OLS	0.7953	0.8025	0.8001	0.8000	0.8392	0.8436	0.8415	0.8415	0.9436	0.9440	0.9432	0.9437	0.9635	0.9638	0.9627	0.9635
LW_OLS	0.0040	0.0039	0.0039	0.0040	0.0040	0.0038	0.0039	0.0040	0.0041	0.0039	0.0040	0.0040	0.0041	0.0039	0.0040	0.0040
WN_OLS	0.7961	0.8033	0.8009	0.8008	0.8398	0.8442	0.8421	0.8421	0.9439	0.9442	0.9434	0.9439	0.9637	0.9640	0.9629	0.9637
LW_GLS	-15.5838	-12.8367	-11.9454	-11.8599	-32.8391	-24.5215	-22.5117	-21.7470	-259.6419	-187.8045	-183.2504	-174.0742	-525.3498	-407.3296	-423.2472	-409.6265
WN_GLS	0.0040	0.0039	0.0039	0.0040	0.0040	0.0038	0.0039	0.0040	0.0041	0.0039	0.0040	0.0040	0.0041	0.0039	0.0040	0.0040
WN_LW	0.7953	0.8025	0.8001	0.8000	0.8392	0.8436	0.8415	0.8415	0.9436	0.9440	0.9432	0.9437	0.9635	0.9638	0.9627	0.9635
Number of Observations = 500																
GLS_OLS	0.8341	0.8335	0.8345	0.8366	0.8747	0.8747	0.8754	0.8769	0.9635	0.9644	0.9645	0.9652	0.9793	0.9800	0.9800	0.9805
LW_OLS	0.0019	0.0018	0.0020	0.0020	0.0019	0.0018	0.0020	0.0020	0.0019	0.0018	0.0020	0.0020	0.0019	0.0018	0.0020	0.0020
WN_OLS	0.8344	0.8338	0.8349	0.8369	0.8749	0.8750	0.8757	0.8771	0.9636	0.9644	0.9645	0.9652	0.9794	0.9800	0.9800	0.9806
LW_GLS	-9.9155	-9.2018	-9.2832	-9.5396	-16.9724	-15.4409	-15.2695	-15.3021	-115.9958	-105.5925	-104.1128	-104.0693	-267.8414	-252.6978	-253.6524	-259.3002
WN_GLS	0.0019	0.0018	0.0020	0.0020	0.0019	0.0018	0.0020	0.0020	0.0019	0.0018	0.0020	0.0020	0.0019	0.0018	0.0020	0.0020
WN_LW	0.8341	0.8335	0.8345	0.8366	0.8747	0.8747	0.8754	0.8769	0.9635	0.9644	0.9645	0.9652	0.9793	0.9800	0.9800	0.9805
Number of Observations = 1000																
GLS_OLS	0.8529	0.8555	0.8554	0.8552	0.8928	0.8948	0.8948	0.8945	0.9736	0.9741	0.9742	0.9740	0.9862	0.9865	0.9866	0.9865
LW_OLS	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
WN_OLS	0.8530	0.8556	0.8556	0.8553	0.8929	0.8949	0.8949	0.8947	0.9736	0.9741	0.9742	0.9741	0.9862	0.9865	0.9866	0.9865
LW_GLS	-11.6655	-9.7195	-9.2944	-8.8152	-16.2147	-14.6145	-14.7635	-14.0139	-81.7589	-92.7788	-101.2435	-93.4846	-189.1821	-235.2190	-253.1982	-228.5711
WN_GLS	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
WN_LW	0.8529	0.8555	0.8554	0.8552	0.8928	0.8948	0.8948	0.8945	0.9736	0.9741	0.9742	0.9740	0.9862	0.9865	0.9866	0.9865

Table 2c: Probability values of Estimators' Forecast Performance(s) under Heteroscedasticity Scenario

Estimators	$\rho = 0.1$				$\rho = 0.2$				$\rho = 0.6$				$\rho = 0.9$			
	R=1,000	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***
Number of Observations = 100																
GLS_OLS	94.90	94.92	95.14	95.01	95.60	95.28	95.48	95.63	98.00	97.56	97.40	97.42	97.40	97.44	97.28	97.36
LW_OLS	100.00	100.00	99.98	99.99	99.90	99.96	99.98	99.95	100.00	100.00	100.00	99.99	100.00	100.00	100.00	99.98
WN_OLS	94.90	94.92	95.18	95.10	95.60	95.32	95.52	95.70	98.00	97.56	97.50	97.47	97.40	97.48	97.32	97.39
LW_GLS	5.30	5.20	4.96	5.16	4.60	4.80	4.60	4.45	2.00	2.44	2.60	2.59	2.60	2.56	2.72	2.64
WN_GLS	100.00	100.00	99.98	99.99	99.80	99.88	99.92	99.92	100.00	99.96	99.94	99.94	100.00	100.00	99.94	99.94
WN_LW	94.90	94.92	95.14	95.01	95.60	95.28	95.48	95.63	98.00	97.56	97.40	97.42	97.40	97.44	97.28	97.36
Number of Observations = 250																
GLS_OLS	99.80	99.72	99.78	99.80	99.90	99.84	99.86	99.86	99.90	99.96	99.92	99.94	99.90	99.96	99.92	99.95
LW_OLS	99.80	99.92	99.94	99.93	100.00	99.92	99.96	99.92	100.00	100.00	100.00	99.94	99.90	99.92	99.96	99.96
WN_OLS	99.80	99.72	99.78	99.81	99.90	99.84	99.86	99.86	99.90	99.96	99.94	99.95	100.00	100.00	99.94	99.96
LW_GLS	0.20	0.28	0.22	0.20	0.10	0.16	0.14	0.14	0.10	0.04	0.08	0.06	0.10	0.04	0.08	0.05
WN_GLS	99.90	99.96	99.94	99.91	99.90	99.92	99.94	99.93	100.00	100.00	99.96	99.89	99.90	99.96	99.94	99.95
WN_LW	99.80	99.72	99.78	99.80	99.90	99.84	99.86	99.86	99.90	99.96	99.92	99.94	99.90	99.96	99.92	99.95
Number of Observations = 500																
GLS_OLS	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
LW_OLS	99.90	99.92	99.96	99.96	99.90	99.92	99.88	99.91	99.70	99.88	99.94	99.94	99.80	99.88	99.92	99.91
WN_OLS	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
LW_GLS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WN_GLS	100.00	99.92	99.96	99.93	100.00	99.96	99.94	99.91	99.70	99.88	99.94	99.95	99.80	99.88	99.94	99.94
WN_LW	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
Number of Observations = 1000																
GLS_OLS	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
LW_OLS	99.90	99.92	99.96	99.93	99.80	99.92	99.96	99.96	99.90	99.96	99.94	99.91	100.00	100.00	99.98	99.93
WN_OLS	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00
LW_GLS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
WN_GLS	99.80	99.92	99.96	99.92	99.90	99.92	99.94	99.92	99.90	99.92	99.94	99.92	100.00	99.96	99.96	99.96
WN_LW	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00

3.4 Does the choice of estimator matter when persistence exists in the regressors?

Here, having explicitly specified the persistence in the regressor of our linear model used in the DGP while allowing for homoscedastic error term, we expect the estimator that accounts for persistence to perform better than the one that neglects this feature. Our results (see Tables 3a – 3c) provide evidence that lends support to our expectations. On the RMSE results, we find the LW estimator, which is developed to capture persistence in model regressor(s), to relatively but consistently outperform the OLS, WN and GLS estimators. The WN estimator, which accounts not only for persistence in the regressors, but also for endogeneity and conditional heteroscedasticity, seems to further contaminate the data by correcting for violations that are originally nonexistent in the data. By implication, estimators that either correct for fewer inherent violations or focus on the exact violation tend to perform better. The stance is also confirmed by the C-T statistics and the probability values in Tables 3b and 3c, respectively. On the robustness of our findings, we examine the trend across sample sizes, correlation coefficients (autocorrelation) and number of replications and find our stance to be upheld. The effect of persistence on forecast performance seems to be relatively similar regardless of the degree (whether mild or severe). Again, while our results are not sensitive to the different combinations of examined features, we show that the choice of estimator does matter, our preference under the persistence scenario being the LW estimator.

Table 3a: RMSE results for Estimators' Forecast Performance(s) under Persistence Scenario

Estimator	$\rho = 0.1$				$\rho = 0.2$				$\rho = 0.6$				$\rho = 0.9$			
	R=1,000	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***
Number of Observations = 100																
OLS	0.9873	0.9885	0.9885	0.9873	0.9872	0.9885	0.9884	0.9873	0.9869	0.9882	0.9884	0.9873	0.9867	0.9880	0.9884	0.9874
GLS	0.9980	0.9966	0.9965	0.9977	0.9981	0.9966	0.9965	0.9977	0.9984	0.9970	0.9965	0.9977	0.9986	0.9972	0.9966	0.9977
LW	0.9822	0.9834	0.9835	0.9823	0.9822	0.9833	0.9834	0.9823	0.9820	0.9830	0.9833	0.9823	0.9818	0.9829	0.9833	0.9822
WN	0.9929	0.9914	0.9914	0.9926	0.9930	0.9914	0.9914	0.9926	0.9934	0.9917	0.9914	0.9925	0.9937	0.9921	0.9914	0.9925
Number of Observations = 250																
OLS	0.9945	0.9962	0.9946	0.9946	0.9946	0.9962	0.9946	0.9946	0.9946	0.9962	0.9946	0.9946	0.9947	0.9963	0.9946	0.9946
GLS	0.9994	0.9977	0.9993	0.9994	0.9994	0.9977	0.9993	0.9994	0.9993	0.9977	0.9993	0.9994	0.9992	0.9977	0.9994	0.9994
LW	0.9926	0.9942	0.9926	0.9926	0.9926	0.9942	0.9926	0.9926	0.9927	0.9942	0.9926	0.9926	0.9928	0.9943	0.9926	0.9926
WN	0.9974	0.9957	0.9973	0.9974	0.9974	0.9957	0.9973	0.9973	0.9973	0.9957	0.9973	0.9973	0.9972	0.9957	0.9974	0.9974
Number of Observations = 500																
OLS	0.9977	0.9966	0.9967	0.9973	0.9977	0.9966	0.9967	0.9973	0.9977	0.9966	0.9967	0.9973	0.9977	0.9966	0.9967	0.9973
GLS	0.9993	1.0004	1.0003	0.9997	0.9993	1.0004	1.0003	0.9997	0.9994	1.0004	1.0003	0.9998	0.9994	1.0004	1.0003	0.9997
LW	0.9967	0.9956	0.9957	0.9963	0.9967	0.9956	0.9957	0.9963	0.9967	0.9956	0.9957	0.9963	0.9967	0.9956	0.9957	0.9963
WN	0.9983	0.9994	0.9993	0.9987	0.9983	0.9994	0.9993	0.9987	0.9984	0.9994	0.9993	0.9988	0.9984	0.9994	0.9994	0.9987
Number of Observations = 1000																
OLS	0.9979	0.9982	0.9983	0.9986	0.9979	0.9982	0.9984	0.9986	0.9979	0.9982	0.9983	0.9986	0.9979	0.9982	0.9984	0.9986
GLS	1.0006	1.0003	1.0001	0.9999	1.0006	1.0003	1.0001	0.9999	1.0006	1.0003	1.0001	0.9999	1.0006	1.0003	1.0001	0.9999
LW	0.9974	0.9977	0.9979	0.9981	0.9974	0.9977	0.9979	0.9981	0.9974	0.9977	0.9978	0.9981	0.9974	0.9977	0.9979	0.9981
WN	1.0001	0.9998	0.9996	0.9994	1.0001	0.9998	0.9996	0.9994	1.0001	0.9998	0.9996	0.9994	1.0001	0.9998	0.9996	0.9994

Table 3b: Campbell Thompson results for Estimators' Forecast Performance(s) under Persistence Scenario

Estimators	$\rho = 0.1$				$\rho = 0.2$				$\rho = 0.6$				$\rho = 0.9$			
	R=1,000	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***
Number of Observations = 100																
GLS_OLS	-0.0676	-0.0608	-0.0591	-0.0645	-0.0679	-0.0610	-0.0592	-0.0645	-0.0692	-0.0625	-0.0594	-0.0644	-0.0709	-0.0639	-0.0597	-0.0644
LW_OLS	0.0101	0.0103	0.0101	0.0101	0.0101	0.0103	0.0101	0.0101	0.0098	0.0104	0.0103	0.0102	0.0099	0.0102	0.0103	0.0103
WN_OLS	-0.0567	-0.0497	-0.0482	-0.0536	-0.0570	-0.0499	-0.0482	-0.0536	-0.0585	-0.0513	-0.0484	-0.0535	-0.0603	-0.0530	-0.0488	-0.0533
LW_GLS	-0.0103	-0.0149	-0.0138	-0.0095	-0.0100	-0.0146	-0.0137	-0.0095	-0.0091	-0.0133	-0.0135	-0.0095	-0.0086	-0.0129	-0.0135	-0.0094
WN_GLS	0.0101	0.0103	0.0101	0.0101	0.0101	0.0103	0.0101	0.0101	0.0098	0.0104	0.0103	0.0102	0.0099	0.0102	0.0103	0.0103
WN_LW	-0.0676	-0.0608	-0.0591	-0.0645	-0.0679	-0.0610	-0.0592	-0.0645	-0.0692	-0.0625	-0.0594	-0.0644	-0.0709	-0.0639	-0.0597	-0.0644
Number of Observations = 250																
GLS_OLS	-0.0257	-0.0190	-0.0257	-0.0261	-0.0257	-0.0190	-0.0257	-0.0261	-0.0254	-0.0188	-0.0258	-0.0262	-0.0248	-0.0188	-0.0258	-0.0262
LW_OLS	0.0040	0.0041	0.0041	0.0040	0.0040	0.0041	0.0041	0.0041	0.0039	0.0041	0.0041	0.0041	0.0040	0.0040	0.0040	0.0040
WN_OLS	-0.0216	-0.0149	-0.0216	-0.0220	-0.0216	-0.0149	-0.0216	-0.0220	-0.0214	-0.0147	-0.0216	-0.0220	-0.0207	-0.0147	-0.0217	-0.0221
LW_GLS	-0.0017	-0.0085	-0.0023	-0.0025	-0.0018	-0.0085	-0.0023	-0.0025	-0.0021	-0.0086	-0.0023	-0.0025	-0.0025	-0.0088	-0.0023	-0.0026
WN_GLS	0.0040	0.0041	0.0041	0.0040	0.0040	0.0041	0.0041	0.0041	0.0039	0.0041	0.0041	0.0041	0.0040	0.0040	0.0040	0.0040
WN_LW	-0.0257	-0.0190	-0.0257	-0.0261	-0.0257	-0.0190	-0.0257	-0.0261	-0.0254	-0.0188	-0.0258	-0.0262	-0.0248	-0.0188	-0.0258	-0.0262
Number of Observations = 500																
GLS_OLS	-0.0119	-0.0162	-0.0155	-0.0132	-0.0120	-0.0162	-0.0156	-0.0132	-0.0121	-0.0163	-0.0157	-0.0132	-0.0121	-0.0162	-0.0156	-0.0131
LW_OLS	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020
WN_OLS	-0.0099	-0.0142	-0.0135	-0.0111	-0.0099	-0.0142	-0.0135	-0.0112	-0.0101	-0.0142	-0.0136	-0.0112	-0.0101	-0.0142	-0.0137	-0.0111
LW_GLS	-0.0033	0.0012	0.0010	-0.0011	-0.0033	0.0012	0.0010	-0.0011	-0.0031	0.0013	0.0011	-0.0010	-0.0032	0.0012	0.0011	-0.0011
WN_GLS	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020
WN_LW	-0.0119	-0.0162	-0.0155	-0.0132	-0.0120	-0.0162	-0.0156	-0.0132	-0.0121	-0.0163	-0.0157	-0.0132	-0.0121	-0.0162	-0.0156	-0.0131
Number of Observations = 1000																
GLS_OLS	-0.0096	-0.0082	-0.0075	-0.0065	-0.0096	-0.0082	-0.0075	-0.0065	-0.0096	-0.0081	-0.0075	-0.0065	-0.0096	-0.0082	-0.0075	-0.0065
LW_OLS	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
WN_OLS	-0.0086	-0.0072	-0.0065	-0.0055	-0.0086	-0.0072	-0.0065	-0.0055	-0.0086	-0.0071	-0.0065	-0.0055	-0.0086	-0.0072	-0.0065	-0.0055
LW_GLS	0.0025	0.0013	0.0007	-0.0005	0.0025	0.0013	0.0007	-0.0005	0.0026	0.0013	0.0007	-0.0005	0.0025	0.0013	0.0007	-0.0005
WN_GLS	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
WN_LW	-0.0096	-0.0082	-0.0075	-0.0065	-0.0096	-0.0082	-0.0075	-0.0065	-0.0096	-0.0081	-0.0075	-0.0065	-0.0096	-0.0082	-0.0075	-0.0065

Table 3c: Probability Values for Estimators' Forecast Performance(s) under Persistence Scenario

Estimators	$\rho = 0.1$				$\rho = 0.2$				$\rho = 0.6$				$\rho = 0.9$			
	R=1,000	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***
Number of Observations = 100																
GLS_OLS	49.20	49.88	49.40	48.43	49.00	49.84	49.48	48.50	48.60	49.40	49.34	48.48	48.40	49.52	49.36	48.61
LW_OLS	100.00	100.00	99.98	99.99	100.00	99.96	99.98	99.99	100.00	100.00	99.98	99.97	100.00	100.00	99.98	99.96
WN_OLS	50.30	51.48	50.86	49.85	50.20	51.32	50.86	49.87	50.20	51.32	50.94	50.14	49.80	50.76	50.96	50.14
LW_GLS	53.20	52.12	52.40	53.08	52.90	51.96	52.32	53.05	52.60	51.88	52.10	52.82	52.30	51.84	52.08	52.90
WN_GLS	100.00	100.00	99.96	99.98	100.00	100.00	100.00	99.99	100.00	100.00	99.98	99.99	100.00	100.00	99.96	99.97
WN_LW	49.20	49.88	49.40	48.43	49.00	49.84	49.48	48.50	48.60	49.40	49.34	48.48	48.40	49.52	49.36	48.61
Number of Observations = 250																
GLS_OLS	48.10	49.84	48.08	48.25	48.20	50.00	48.10	48.27	48.40	49.96	47.90	48.13	49.10	50.24	48.14	48.23
LW_OLS	99.90	99.96	99.98	99.96	100.00	100.00	99.98	99.97	99.90	99.96	99.98	99.98	100.00	99.96	99.88	99.91
WN_OLS	49.10	50.76	48.94	49.11	49.00	50.72	48.86	49.09	49.20	50.68	48.68	49.02	49.70	50.84	48.86	49.09
LW_GLS	52.60	51.00	53.02	52.78	52.60	51.12	53.12	52.89	52.60	51.00	53.02	52.83	52.20	51.00	52.92	52.69
WN_GLS	99.90	99.92	99.96	99.95	100.00	100.00	99.96	99.97	99.90	99.96	99.96	99.97	100.00	99.92	99.88	99.93
WN_LW	48.10	49.84	48.08	48.25	48.20	50.00	48.10	48.27	48.40	49.96	47.90	48.13	49.10	50.24	48.14	48.23
Number of Observations = 500																
GLS_OLS	49.70	47.20	48.06	48.82	49.70	47.28	48.06	48.79	49.20	47.00	47.80	48.78	49.50	47.12	48.02	48.84
LW_OLS	100.00	99.96	99.98	99.97	100.00	99.96	99.96	99.96	99.90	99.88	99.94	99.95	99.80	99.88	99.94	99.97
WN_OLS	50.20	47.80	48.62	49.48	50.30	47.88	48.74	49.54	49.70	47.56	48.36	49.48	49.90	47.48	48.44	49.47
LW_GLS	51.30	53.40	52.54	51.82	51.30	53.40	52.54	51.79	51.50	53.44	52.66	51.85	51.50	53.60	52.58	51.87
WN_GLS	100.00	99.96	99.96	99.95	100.00	99.96	99.96	99.97	100.00	99.88	99.94	99.95	99.70	99.80	99.90	99.93
WN_LW	49.70	47.20	48.06	48.82	49.70	47.28	48.06	48.79	49.20	47.00	47.80	48.78	49.50	47.12	48.02	48.84
Number of Observations = 1000																
GLS_OLS	47.10	48.36	48.74	49.49	47.10	48.32	48.70	49.45	47.20	48.56	48.78	49.50	47.30	48.72	48.78	49.48
LW_OLS	99.90	99.96	99.96	99.96	100.00	100.00	99.98	99.93	100.00	99.96	99.96	99.96	100.00	100.00	99.94	99.95
WN_OLS	47.40	48.76	49.16	49.93	47.40	48.80	49.22	49.98	47.30	48.72	49.12	49.91	47.50	49.04	49.14	49.85
LW_GLS	53.10	51.92	51.54	50.86	53.10	51.92	51.54	50.85	52.90	51.72	51.48	50.80	53.10	51.68	51.60	50.89
WN_GLS	99.90	99.96	99.96	99.95	100.00	100.00	99.98	99.96	99.70	99.84	99.86	99.91	99.90	99.96	99.88	99.89
WN_LW	47.10	48.36	48.74	49.49	47.10	48.32	48.70	49.45	47.20	48.56	48.78	49.50	47.30	48.72	48.78	49.48

3.5 Does the choice of estimator matter when data is characterized by heteroscedastic error with persistence and endogeneity in regressors?

Earlier, we examined three different cases - homoscedastic error term with implicit persistence (Tables 1a – 1c), heteroscedastic error term with implicit persistence (Tables 2a – 2c) and explicitly specified persistence in regressors with the assumption of homoscedastic error term (Tables 3a – 3c). Our findings have not only corresponded to our expectations, but also reflected the importance of the choice of estimator in estimating the model used in DGP and the insensitivity of the results to sample sizes, correlation coefficients and replications. We further subject the four estimators to another scenario, where the DGP incorporates heteroscedastic errors with explicitly specified degrees of persistence and endogeneity. Our expectation here is to ascertain how well the WN estimator would outperform the other competing models, given that it is developed to capture all the three features jointly. Quite interestingly, our findings correspond to our earlier expectations in terms of outperformance and robustness of results. Again, we see that the effect of heteroscedasticity (whether mild or severe) poses greater challenge to the model used in the DGP compared to the effect of persistence and endogeneity on same, since both the WN and GLS estimators (which correct for inherent heteroscedasticity) consistently outperform the estimators that fail to account for same (see Tables 4a – 4c). Conclusively, when the data is characterized by heteroscedastic error term with persistence and endogeneity in the regressors, the choice of estimator (here, the WN estimator) does matter, as well as the degree of persistence, endogeneity and heteroscedasticity.

TABLE 4a: RMSE results for Estimators' Forecast Performance(s) under Heteroscedasticity, Persistence and Endogeneity Scenario

Estimator	$\rho = 0.1$				$\rho = 0.2$				$\rho = 0.6$				$\rho = 0.9$			
	R=1,000	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***
Number of Observations = 100																
OLS	1.5942	1.6000	1.6025	1.5975	1.6068	1.6122	1.6142	1.6078	1.7081	1.6967	1.7037	1.6892	2.1421	2.1827	2.2159	2.2005
GLS	0.6608	0.6573	0.6575	0.6581	0.6584	0.6552	0.6555	0.6561	0.6834	0.6860	0.6833	0.6868	0.9557	0.9621	0.9586	0.9705
LW	1.5865	1.5917	1.5945	1.5894	1.5991	1.6038	1.6061	1.5996	1.6994	1.6880	1.6952	1.6807	2.1310	2.1722	2.2048	2.1897
WN	0.6576	0.6539	0.6542	0.6547	0.6553	0.6518	0.6522	0.6528	0.6801	0.6826	0.6800	0.6834	0.9511	0.9576	0.9539	0.9656
Number of Observations = 250																
OLS	1.6697	1.6523	1.6473	1.6496	1.6873	1.6677	1.6628	1.6650	1.8931	1.8561	1.8497	1.8506	2.9795	2.9647	2.9846	2.9656
GLS	0.6173	0.6222	0.6249	0.6244	0.6128	0.6179	0.6206	0.6201	0.5914	0.5944	0.5961	0.5959	0.6533	0.6454	0.6431	0.6457
LW	1.6663	1.6490	1.6441	1.6464	1.6839	1.6645	1.6596	1.6617	1.8895	1.8525	1.8461	1.8471	2.9739	2.9590	2.9790	2.9598
WN	0.6160	0.6210	0.6237	0.6232	0.6116	0.6167	0.6194	0.6188	0.5902	0.5932	0.5949	0.5947	0.6521	0.6442	0.6419	0.6445
Number of Observations = 500																
OLS	1.6580	1.6701	1.6709	1.6743	1.6746	1.6877	1.6881	1.6924	1.9095	1.9348	1.9385	1.9493	3.6353	3.6848	3.7183	3.7616
GLS	0.6130	0.6099	0.6098	0.6089	0.6078	0.6044	0.6044	0.6032	0.5579	0.5506	0.5496	0.5467	0.4588	0.4520	0.4537	0.4474
LW	1.6565	1.6685	1.6693	1.6727	1.6731	1.6861	1.6865	1.6907	1.9078	1.9330	1.9366	1.9474	3.6318	3.6813	3.7148	3.7580
WN	0.6124	0.6093	0.6092	0.6083	0.6072	0.6038	0.6038	0.6026	0.5574	0.5501	0.5491	0.5461	0.4584	0.4516	0.4532	0.4470
Number of Observations = 1000																
OLS	1.6942	1.6950	1.6964	1.6929	1.7168	1.7150	1.7168	1.7138	2.0537	2.0412	2.0516	2.0492	4.6631	4.6167	4.6716	4.6675
GLS	0.5976	0.5976	0.5972	0.5983	0.5904	0.5911	0.5906	0.5915	0.5072	0.5092	0.5082	0.5090	0.3221	0.3210	0.3180	0.3149
LW	1.6933	1.6942	1.6956	1.6921	1.7159	1.7141	1.7159	1.7129	2.0527	2.0402	2.0505	2.0481	4.6610	4.6146	4.6694	4.6653
WN	0.5973	0.5973	0.5969	0.5980	0.5901	0.5908	0.5903	0.5912	0.5070	0.5090	0.5079	0.5088	0.3220	0.3208	0.3179	0.3148

Table 4b: Campbell Thompson results for Estimators' Forecast Performance(s) under Heteroscedasticity, Persistence and Endogeneity Scenario

Estimators	$\rho = 0.1$				$\rho = 0.2$				$\rho = 0.6$				$\rho = 0.9$			
	R=1,000	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***
Number of Observations = 100																
GLS_OLS	0.7197	0.7313	0.7302	0.7317	0.7205	0.7311	0.7298	0.7315	0.4096	0.4223	0.4540	0.4453	-3.7082	-3.8570	-3.8105	-3.9721
LW_OLS	0.0095	0.0103	0.0100	0.0101	0.0095	0.0103	0.0100	0.0101	0.0101	0.0101	0.0098	0.0100	0.0099	0.0095	0.0098	0.0098
WN_OLS	0.7224	0.7342	0.7329	0.7344	0.7231	0.7339	0.7324	0.7342	0.4149	0.4275	0.4589	0.4510	-3.6659	-3.8132	-3.7642	-3.9224
LW_GLS	-11.4389	-12.4619	-13.9631	-13.5838	-12.5523	-13.5549	-14.8964	-13.9814	-56.9766	-46.0664	-44.5412	-41.1701	-2310.0010	-1812.8780	-1854.8380	-1961.8720
WN_GLS	0.0095	0.0103	0.0100	0.0101	0.0095	0.0103	0.0100	0.0101	0.0101	0.0101	0.0098	0.0100	0.0099	0.0095	0.0098	0.0098
WN_LW	0.7197	0.7313	0.7302	0.7317	0.7205	0.7311	0.7298	0.7315	0.4096	0.4223	0.4540	0.4453	-3.7082	-3.8570	-3.8105	-3.9721
Number of Observations = 250																
GLS_OLS	0.8242	0.8195	0.8156	0.8165	0.8273	0.8229	0.8191	0.8200	0.7558	0.7656	0.7619	0.7618	-0.7541	-0.6977	-0.6991	-0.7209
LW_OLS	0.0041	0.0039	0.0040	0.0040	0.0040	0.0039	0.0040	0.0040	0.0038	0.0039	0.0039	0.0039	0.0038	0.0037	0.0037	0.0038
WN_OLS	0.8249	0.8202	0.8164	0.8172	0.8280	0.8236	0.8198	0.8208	0.7567	0.7666	0.7629	0.7628	-0.7481	-0.6914	-0.6926	-0.7142
LW_GLS	-9.9719	-9.1480	-9.3824	-9.9308	-10.8269	-9.8172	-10.0241	-10.6546	-60.0995	-40.5455	-34.6447	-33.2767	-6071.2720	-4218.4610	-3377.2010	-3135.3160
WN_GLS	0.0041	0.0039	0.0040	0.0040	0.0040	0.0039	0.0040	0.0040	0.0038	0.0039	0.0039	0.0039	0.0038	0.0037	0.0037	0.0038
WN_LW	0.8242	0.8195	0.8156	0.8165	0.8273	0.8229	0.8191	0.8200	0.7558	0.7656	0.7619	0.7618	-0.7541	-0.6977	-0.6991	-0.7209
Number of Observations = 500																
GLS_OLS	0.8425	0.8448	0.8450	0.8456	0.8469	0.8495	0.8496	0.8505	0.8364	0.8571	0.8602	0.8641	0.3366	0.4221	0.4079	0.4274
LW_OLS	0.0019	0.0019	0.0020	0.0020	0.0018	0.0020	0.0020	0.0020	0.0018	0.0019	0.0020	0.0020	0.0018	0.0019	0.0019	0.0019
WN_OLS	0.8428	0.8451	0.8453	0.8459	0.8472	0.8498	0.8499	0.8508	0.8366	0.8573	0.8605	0.8644	0.3376	0.4234	0.4091	0.4286
LW_GLS	-7.9045	-8.5803	-8.7015	-8.8599	-8.4358	-9.1439	-9.2962	-9.4745	-23.1453	-25.4458	-28.8501	-28.5768	-2100.2900	-2990.9740	-3695.4280	-4445.1900
WN_GLS	0.0019	0.0019	0.0020	0.0020	0.0018	0.0020	0.0020	0.0020	0.0018	0.0019	0.0020	0.0020	0.0018	0.0019	0.0019	0.0019
WN_LW	0.8425	0.8448	0.8450	0.8456	0.8469	0.8495	0.8496	0.8505	0.8364	0.8571	0.8602	0.8641	0.3366	0.4221	0.4079	0.4274
Number of Observations = 1000																
GLS_OLS	0.8627	0.8623	0.8628	0.8621	0.8686	0.8677	0.8684	0.8677	0.9170	0.9156	0.9149	0.9139	0.8167	0.8374	0.8432	0.8545
LW_OLS	0.0010	0.0010	0.0010	0.0010	0.0011	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0009	0.0010	0.0009
WN_OLS	0.8629	0.8625	0.8630	0.8622	0.8687	0.8679	0.8685	0.8678	0.9171	0.9157	0.9149	0.9140	0.8169	0.8375	0.8433	0.8546
LW_GLS	-8.2865	-8.3506	-8.5418	-8.4671	-8.9243	-8.8838	-9.0293	-9.0497	-27.9791	-25.0193	-27.8845	-29.9086	-7626.4180	-6511.0000	-8030.1920	-8728.2100
WN_GLS	0.0010	0.0010	0.0010	0.0010	0.0011	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010	0.0009	0.0010	0.0009
WN_LW	0.8627	0.8623	0.8628	0.8621	0.8686	0.8677	0.8684	0.8677	0.9170	0.9156	0.9149	0.9139	0.8167	0.8374	0.8432	0.8545

Table 4c: Probability Values for Estimators' Forecast Performance(s) under Heteroscedasticity, Persistence and Endogeneity Scenario

Estimators	$\rho = 0.1$				$\rho = 0.2$				$\rho = 0.6$				$\rho = 0.9$			
	R=1,000	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***	***R=1,000***	***R=2,500***	***R=5,000***	***R=10,000***
Number of Observations = 100																
GLS_OLS	97.30	97.84	97.60	97.74	97.40	97.88	97.60	97.60	88.50	88.40	88.72	88.33	60.10	59.44	59.22	58.58
LW_OLS	100.00	100.00	99.98	99.98	100.00	100.00	99.98	99.99	100.00	100.00	99.98	99.97	99.90	99.96	99.98	99.97
WN_OLS	97.30	97.88	97.68	97.80	97.40	97.92	97.64	97.63	88.60	88.52	88.88	88.53	60.10	59.48	59.34	58.74
LW_GLS	2.70	2.24	2.46	2.33	2.60	2.16	2.48	2.46	11.50	11.68	11.36	11.84	40.20	40.68	40.84	41.49
WN_GLS	100.00	100.00	100.00	99.98	99.90	99.96	99.98	99.99	100.00	100.00	99.94	99.94	99.90	99.96	99.96	99.98
WN_LW	97.30	97.84	97.60	97.74	97.40	97.88	97.60	97.60	88.50	88.40	88.72	88.33	60.10	59.44	59.22	58.58
Number of Observations = 250																
GLS_OLS	100.00	100.00	99.96	99.97	100.00	100.00	99.96	99.98	96.60	96.92	96.68	96.71	78.40	79.20	79.46	79.43
LW_OLS	100.00	100.00	100.00	99.99	100.00	100.00	100.00	100.00	100.00	99.92	99.96	99.98	100.00	99.96	99.92	99.90
WN_OLS	100.00	100.00	99.96	99.97	100.00	100.00	99.96	99.98	96.60	96.96	96.72	96.74	78.50	79.24	79.48	79.46
LW_GLS	0.00	0.00	0.06	0.04	0.00	0.00	0.04	0.02	3.40	3.08	3.32	3.29	21.60	20.84	20.58	20.64
WN_GLS	100.00	100.00	100.00	99.98	100.00	100.00	99.98	99.99	100.00	100.00	100.00	99.99	100.00	100.00	99.88	99.87
WN_LW	100.00	100.00	99.96	99.97	100.00	100.00	99.96	99.98	96.60	96.92	96.68	96.71	78.40	79.20	79.46	79.43
Number of Observations = 500																
GLS_OLS	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	98.90	99.28	99.10	99.16	90.70	91.72	91.34	91.52
LW_OLS	100.00	100.00	100.00	100.00	100.00	100.00	100.00	99.99	99.80	99.92	99.92	99.94	99.90	99.96	99.94	99.93
WN_OLS	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	98.90	99.28	99.10	99.16	90.70	91.76	91.36	91.54
LW_GLS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.10	0.72	0.90	0.84	9.30	8.28	8.66	8.48
WN_GLS	100.00	99.96	99.98	99.98	100.00	100.00	99.96	99.98	99.70	99.88	99.90	99.92	99.90	99.96	99.94	99.95
WN_LW	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	98.90	99.28	99.10	99.16	90.70	91.72	91.34	91.52
Number of Observations = 1000																
GLS_OLS	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	99.80	99.84	99.72	99.79	96.80	97.28	97.42	97.64
LW_OLS	99.80	99.92	99.94	99.97	100.00	99.96	99.96	99.97	99.90	99.84	99.92	99.96	99.90	99.88	99.92	99.93
WN_OLS	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	99.80	99.84	99.72	99.79	96.80	97.28	97.42	97.64
LW_GLS	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.16	0.28	0.21	3.20	2.72	2.58	2.36
WN_GLS	99.90	99.96	99.94	99.97	100.00	100.00	99.98	99.97	99.90	99.92	99.94	99.97	100.00	99.92	99.90	99.94
WN_LW	100.00	100.00	100.00	100.00	100.00	100.00	100.00	100.00	99.80	99.84	99.72	99.79	96.80	97.28	97.42	97.64

4.0 Conclusion

We attempt to provide an alternative and extensive simulation study, which examines the importance of the choice of estimator in forecasting financial series. This study offers more meaningful generalizations for the estimator proposed by WN (2012, 2015), while accounting for salient features of predictors. Rather than being restricted to the case(s) of presence or absence (“either or”) of the one or more salient features in model predictors, we vary the degree from mild to severe in order to observe the plausible effects on forecast performance of each selected linear estimator. We employ the Monte Carlo simulation with a combination of four different sample sizes (100, 250, 500 and 1000), correlation coefficients to capture the severity of heterogeneity, persistence and endogeneity (0.1, 0.2, 0.6 and 0.9) and number of replications (1000, 2500, 5000 and 10000) for robustness purpose. This produces four different distinct scenarios – (i) homoscedastic error with implicit persistence, (ii) heteroscedastic error with implicit persistence, (iii) explicitly specified persistence, and (iv) explicitly specified heteroscedastic error with persistence and endogeneity.

Under the different scenarios, we compare the four selected linear estimators (OLS, GLS, LW and WN) that vary by how much of the salient features of the considered model predictor(s) they account for. While answering the question of the importance of the choice of estimator in forecasting, generally and more specifically, in financial series, we find that the choice of estimator does matter. The LW estimator dominates in the first and third scenarios, where the datasets are characterized by persistence (either implicitly or explicitly specified), while the WN estimator dominates in the second and fourth scenarios, where the datasets are majorly characterized by heteroscedastic errors. We also find the forecast errors under different degrees of persistence to be relatively similar, while for heteroscedasticity, it improves with increase in severity. By implication, estimators that account for fewer salient features or focus on the exact salient feature(s) in the predictor(s) tend to perform better. Again, the presence of heteroscedasticity (mild or severe) might pose a greater challenge when forecasting financial series compared to the persistence and endogeneity.

On robustness grounds, our results are consistent across specified sample sizes and number of replications, and are therefore not sensitive to the choice of both, thus supporting the stance of

WN (2012, 2015) with more verifiable evidence(s) for generalization. We can conclusively say here that the choice of estimator does matter in forecasting as estimator(s) that account(s) for salient features of any given predictor would perform better.

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