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On the estimation of the Dynamic Panel Model in the presence of heteroscedasticity

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Abstract

Dynamic panel (DP) modeling is crucial in econometric analysis for addressing endogeneity, serial correlation, and unobserved heterogeneity. However, the comparative efficiency of different estimators under varying sample dimensions and data conditions remains inconclusive. This study evaluates four DP estimators, namely the Generalized Method of Moments (GMM), Instrumental Variable (IV), Least Squares Dummy Variable (LSDV), and Weighted Least Squares (WLS), using both theoretical and empirical approaches. Simulations were performed for three sample sizes (N=5, T=10; N=20, T=15; N=50, T=50), deliberately violating the homoscedasticity assumption of the error covariance matrix to assess robustness under heteroscedasticity. The results indicate that LSDV achieved the lowest AIC, BIC, and RMSE in small to medium samples. Conversely, GMM demonstrated superior performance in larger samples, exhibiting greater consistency and robustness in handling autocorrelation and endogeneity, as confirmed by the non-significance of the AR(2) and Sargan test statistics. In contrast, IV and WLS estimators were found to be inconsistent under heteroscedasticity, with higher error variances. Empirical application using macroeconomic data on inflation and economic growth for 40 sub-Saharan African countries over 31 years further validated a significant positive relationship for both GMM ($\beta = 26.0318$, $p < 0.001$) and LSDV ($\beta = 22.3896$, $p < 0.001$). Overall, while LSDV performs efficiently in small samples, GMM remains the most valid and consistent estimator for large dynamic panels characterized by heteroscedasticity and endogeneity.

Keywords: Dynamic Panel Model, Economic Growth, Heteroscedasticity, Inflation, Simulation

1. Introduction

This study investigates the validity and efficiency of traditional dynamic panel estimation techniques, particularly those based on the Generalized Method of Moments (GMM), under conditions of heteroscedasticity. It hypothesizes that neglecting heteroscedasticity in dynamic panel models leads to biased and inefficient estimators, thereby distorting inference and policy interpretation. The main objective is to evaluate the robustness of widely used dynamic panel estimators when the assumption of homoscedasticity is violated.

This study becomes important in panel data econometrics because Panel data models combine cross-sectional and time-series dimensions, allowing researchers to control for unobserved heterogeneity and capture dynamic adjustments (Baltagi, 2008; Baltagi, 2001; 2013; Stock & Watson, 2018). Dynamic Panel Data Models (DPDMs), in particular, are instrumental in analyzing persistence and temporal dynamics through lagged dependent variables, making them indispensable in empirical economics and finance (Akinlade, 2019; Greene and Zhang, 2019; Ajibode and Ogunnusi, 2022). However, heteroscedasticity, where the variance of the error term varies across observations, is a pervasive feature of economic and financial data (Adeboye and Agunbiade, 2017; Kokoszka et al., 2017). If unaddressed, it undermines the validity of moment conditions underlying estimators such as Arellano–Bond and Blundell–Bond GMM, resulting in unreliable inference (Newey & Windmeijer, 2009). Given that most real-world datasets, especially data of macroeconomics variables, exhibit cross-sectional variation in scale, assessing the robustness of dynamic panel estimators under heteroscedasticity is essential for generating credible and policy-relevant findings (Kiviet, 1995; Baltagi, 2020; Horobet et al., 2022; Sudarsono et al., 2024).

Although econometric theory acknowledges the challenges posed by heteroscedasticity, empirical research often overlooks its implications in dynamic panel settings. Most simulation and applied studies assume homoscedastic errors, creating a disconnect between theoretical developments and practical implementation. This study bridges that gap by systematically evaluating how heteroscedasticity affects estimator performance in both small and moderate panels. It introduces novel insights by comparing the efficiency and bias of multiple estimators such as GMM, Instrumental Variables (IV), Least Squares Dummy Variable (LSDV), and Weighted Least Squares (WLS); under varying heteroscedastic structures. Furthermore, it incorporates recent methodological refinements such as bias-corrected LSDV estimators, adaptive WLS procedures, and principal component-based reduction of moment conditions. The inclusion of these techniques extends the frontier of robust dynamic panel estimation and contributes new empirical evidence to ongoing methodological debates. More so, recent studies have proposed further refinements, such as using principal components to reduce the dimensionality of the moment conditions, which improves finite sample properties (Roodman, 2009; Windmeijer, 2005).

Instrumental Variables (IV) methods are crucial for dealing with endogeneity in econometric models. Various IV estimators and GMM estimators have been developed and compared in the estimation of PDMs (Ahn and Schmidt, 1995; Anderson and Hsiao, 1982; Arellano and Bover, 1995; Arellano and Bond, 1991; Blundell and Bond, 1998; Hahn and Kuersteiner, 2022; Judson and Owen, 1999; Kiviet, 1995; Wansbeek, 2001; Ziliak, 1997; Bun and Kiviet, 2006; Adeboye and Olayiwola, 2020). The Least Squares Dummy Variable (LSDV) approach is a traditional method for controlling unobserved heterogeneity by including individual-specific dummy variables. This method is effective when the time dimension is large, but it can suffer from dynamic panel bias when the time dimension is small. Recent research has focused on developing bias-corrected LSDV estimators to address the dynamic panel bias. These corrections have made LSDV a more viable option in applied research, especially when dealing with short panels (Abdelrehim and Yahya, 2023; Greene, 2017). Studies have also demonstrated that bias-corrected LSDV can provide reliable estimates, comparable to more complex methods like GMM (Bun and Kiviet, 2006).

Weighted Least Squares (WLS) is employed to address heteroscedasticity by weighting observations based on the inverse of the variance of the errors. This approach improves the efficiency and unbiasedness of parameter estimates. Recent studies have shown that WLS can be particularly effective in dynamic panel data settings, where heteroscedasticity is a concern. Improvements in WLS techniques include adaptive weighting schemes that adjust weights dynamically based on the estimated variance structure of the residuals. These advancements have enhanced the robustness of WLS in empirical applications (Wooldridge, 2019).

The research integrates theoretical exposition, Monte Carlo simulations, and empirical analysis. It draws on the econometric foundations of instrumental variables and moment-based estimation under non-spherical disturbances (Arellano and Bover, 1995; Blundell and Bond, 1998). Through controlled simulations, it compares the finite-sample properties of four commonly used estimators across varying degrees and patterns of heteroscedasticity, as well as different combinations of cross-sectional (N) and temporal (T) dimensions.

Empirically, the study applies these estimators to real-world macroeconomic data characterized by heteroscedasticity, evaluating estimator efficiency, bias, and inferential accuracy. Particular attention is given to the specification of the weighting matrix in two-step GMM estimation, a critical factor influencing efficiency in the presence of heteroscedastic disturbances.

The results demonstrate that ignoring heteroscedasticity in dynamic panels leads to considerable efficiency losses and potential bias, particularly in short panels. Among the estimators evaluated, heteroscedasticity-robust variants of GMM and adaptive WLS emerge as the most efficient under non-constant error variance. The study also shows that bias-corrected LSDV estimators can serve as viable alternatives when panel time dimensions are limited.

By integrating theoretical, simulation, and empirical evidence, this study highlights the adverse consequences of neglecting heteroscedasticity for inference and policy interpretation in dynamic panel analyses, provides a comparative assessment of alternative estimators' robustness under different data structures, and establishes that, when heteroscedasticity is properly accounted for, inflation exerts a significantly negative effect on economic growth as measured by GDP.

Overall, the study advances the econometric literature by emphasizing the necessity of heteroscedasticity-robust estimation strategies, thereby enhancing the reliability and policy relevance of dynamic panel model applications.

2. Materials and methodologies

The materials used for this research include a simulated dynamic panel data set consisting of observations on a set of individuals over time, a dependent variable and an independent variable. In addition to the simulated data, naturally log-transformed economic growth (gdp) and inflation rates (inf) of 40 sub-Saharan African countries was used as confirmatory analysis of the simulated data. This data spans between years 1990 to 2020, was collected from World Bank database.

The individual specific error term is assumed to be heteroscedastic. Four different techniques namely GMM, LSDV, IV, and WLS estimators were employed to estimate dynamic panel model in the presence of heteroscedasticity. These techniques were compared in terms of their biasedness, minimum variances and asymptotic performances. The general model is expressed as:

$$y_{it} = \alpha y_{i,t-1} + X'_{it}\beta + u_i + \varepsilon_{it} \quad (1)$$

Where y_{it} is the observation on the dependent variable (GDP) for country (unit) i at time t, α is the autoregressive coefficient, X_{it} is the vector of explanatory variable, with inflation as a key regressor, β is the vector of unknown coefficients, u_i is the unobserved country specific effect and ε_{it} is the idiosyncratic error, assumed to exhibit heteroscedasticity. We assumed inflation-based heteroscedasticity where higher inflation leads to larger error variance i.e. $\varepsilon_{it} \sim N(0, \sigma^2(1+\gamma x_{it}^2))$.

2.1 Simulation Scheme

The objective is to design a simulation that mimics dynamic GDP evolution influenced by past GDP and inflation, incorporating heteroscedasticity, fixed effects, and initial conditions reflective of macroeconomic data from Sub-Saharan Africa. To simulate realistic economic panel data, cross-sectional heterogeneity, temporal dependence, and heteroskedasticity were introduced. The variance of the error term was allowed to vary with the magnitude of x_{it}, such that:

$$\delta_{it} = 0.5 + 0.8|x_{it}| \quad (2)$$

thereby mimicking the common real-world case where macroeconomic volatility increases with inflation. Three balanced panel configurations were designed to assess model performance under different sample conditions. These scenarios are small panel with N =5 and T =10, medium panel with N = 20 and T = 15, and large panel with N and T = 50 respectively.

For each configuration, the regressors were generated as autoregressive processes:

$$x_{it} = 0.6x_{i,t-1} + v_{it} \qquad v_{it} \sim (0,1) \quad (3)$$

The dependent variable followed the recursive relationship as expressed in equation (1), where $\alpha = 0.4, \beta = 1.2$ and individual effects $u_i \sim (0,1)$, implying that a vector of random normal values was also generated to simulate the error term (ε) for each individual and time period. The standard deviation of the error term was determined by the heteroscedasticity variance (δ). More so, the dependent variable (y) was calculated as a linear combination of the lagged dependent variable (y_{it-1}), the independent variable (x_{it}), and the error term (ε) where coefficients 0.4 and 1.2 were used to specify the respective influence of y_{it-1} and x_{it}. The individual effect coefficient magnitude was stated at 0.6. This design provides a sufficiently large sample size to minimize small-sample bias and better approximate the asymptotic properties of the estimators, as recommended in econometric simulation literature (Arellano and Bond, 1991; Blundell and Bond, 1998; Roodman, 2009). Two vectors were created to represent individual and time period indices using the *rep ( )* function in R. One is a vector of random normal values generated to simulate the lagged dependent variable (y_{t-1}) for each individual and time period, while the other is a vector of random normal values that represent the individual variable X for each individual and time.

The simulation was implemented in R using a reproducible seed (set.seed(12345)), ensuring consistent replication across estimators.

The lagged dependent explanatory variable $y_{i,t-1,}$ with unknown coefficient makes the model dynamic. However, the following assumptions are further made on equation (1) estimation.

i. $u_i \sim N(o, \sigma_{ui}^2)$ $\quad \sigma_{ui}^2 \neq 0$ (4)
ii. $\varepsilon_{it} \sim (N, \sigma_\varepsilon^2)$ $\quad \sigma_\varepsilon^2 > 0$ (5)
iii. $E\varepsilon_{it}\varepsilon_{js} = 0$ $\quad i \neq j$ or $t \neq s$ (6)
iv. $Eu_i\varepsilon_{jt} = 0 \forall i, j,$(Exogeneity) (7)
v. $EX_{it}\varepsilon_{jt} = 0$ $\quad \forall i, j, t$(Exogeneity) (8)

The normality assumptions made in (4) and (5) are necessary and sufficient conditions/essential for all results to follow. The assumptions in (6) states that there is zero serial correlation between observations at time t and s while the assumptions (7) and (8) stated respectively that the heteroscedastic error terms are mutually uncorrelated over time and units and that the explanatory variable is strongly exogenous.

2.2 Estimation techniques

2.2.1Generalized Method of Moments (GMM)

The GMM approach to estimation was first established and its basic statistical theory was published by Hansen (1982). Hansen and Sargent (2013) showed the potential of the GMM approach to estimation through their empirical investigations of asset pricing and foreign exchange markets. The framework for estimation when time series data are employed is briefly covered in this entry. Given a heteroscedasticity invested dynamic model of equation (9),

$$y_{it} = \varphi y_{i,t-1} + \beta' x_{it} + \alpha_i + \varepsilon_{it} \quad (9)$$

Differencing equation (9) becomes,

$$y_{it} - y_{i,t-1} = (x_{it} - x_{i,t-1})'\beta + \delta(y_{i,t-1} - y_{i,t-2}) + (\varepsilon_{it} - \varepsilon_{i,t-1}) \quad (10)$$

We then have

$$y_{it} = \delta y_{i,t-1} + x'_{1it}\beta_1 + x'_{2it}\beta_2 + m'_{1i}\alpha_1 + m'_{2i}\alpha_2 + \varepsilon_{it} + u_i$$

$$= \emptyset' w_{it} + \varepsilon_{it} + u_i = \emptyset' w_{it} + \partial_{it} \quad (11)$$

The GMM estimator $\widehat{\emptyset}$ is obtained by minimizing equation (9) to have

$$\widehat{\emptyset}_{GMM} = [(\sum_{i=1}^{n} W_i^{/} U G_i)(\sum_{i=1}^{n} G_i^{/} U \eta_i \eta_i^{/} U^{/} G_i)^{-1}(G_i^{/} U^{/} W_i)] \times [(\sum_{i=1}^{n} W_i^{/} U G_i)(\sum_{i=1}^{n} G_i^{/} U \eta_i \eta_i^{/} U^{/} G_i)^{-1}(G_i^{/} U^{/} W_i)] \quad (12)$$

The technique is most ideal for estimation with panels that are dynamic in consideration of its efficiency in handling endogeneity, heteroskedasticity, and autocorrelation. Nevertheless, its computational efficiency is not invariant when compared with competing estimation techniques such as Least Squares Dummy Variables (LSDV), Instrumental Variables (IV), and Weighted Least Squares (WLS). GMM's computational efficiency when compared with competing estimation techniques is that it is efficient for large N (cross-sections) and T (periods) through application of moment conditions in preference to full estimation of a likelihood function (Adeboye and Agunbiade, 2017; 2019; Berk et al., 2020).

2.2.2 Instrumental **variables (IV)**

Using observable data, IV is a general method for estimating causal links. This technique can be applied in cases where reverse causality, selection bias, measurement error, or the existence of unmeasured confounding factors have caused traditional regression estimations of the relevant relation to be biased. The main concept is to estimate the causal effect of a third variable, referred to as "instrumental" variable, on an outcome measure by extracting variance in the variable of interest that is unrelated to these issues.

$$T^{-1} \sum_{t=1}^{T} \sum_{s=1}^{T} E\left[z_t z'_s \omega_{t,s}\right] \quad (13)$$

$$Q_T(\delta) \infty (y - X\delta)' Z (Z' \nabla Z)^{-1} Z' (y - X\delta) \quad (14)$$

Then this has the explicit solution which results in IV estimator given as

$$\hat{\delta}_{IV} = [X' \nabla^{-1} Z (Z' \nabla^{-1} Z)^{-1} Z' \nabla^{-1} [X]^{-1}] \quad (15)$$

2.2.3 Weighed Least Square (WLS)

The weighted least squares estimate (WLS) approach holds a special place in the class of estimation algorithms for robot manipulators identification. Joint torques and joint positions can be measured or estimated using the inverse model linear in relation to the parameters, which is based on the use of the inverse model.

We consider a linear model

$$\rho = M(g)\ddot{g} + N(g, \dot{g}) \quad (16)$$

$$\rho = D_S(g, \dot{g}, \ddot{g}) x_S \quad (17)$$

$$\rho = D(g, \dot{g}, \ddot{g}) x = \sum_{i=1,p} D_{iXi} \quad (18)$$

A customised symbolic technique can be used to automatically calculate the coefficients of the matrices D_s and D to give the estimator in equation (17).

$$C_{\hat{x}_w \hat{x}_w} = E[((x - \hat{x}_w)^T)] = (W_w^T W_w)^{-1} \quad (19)$$

2.2.4 Least **Squares Dummy Variable (LSDV)**

A dummy variable may be added to the least square in dynamic panel data models in order to explain the impact of each individual cross-sectional unit, which is unobserved yet accurately describes the relational model. The degrading approach is equal to LSDV.

Considering the model of equation (20)

$$Y_{it} = X_{it}^{1} \beta + \alpha_i + \varepsilon_{it} \quad (20)$$

By employing a dummy variable as

$$Y = [X\ d_1\ d_2 \ldots d_N] \begin{bmatrix} \beta \\ \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_N \end{bmatrix} + \varepsilon \quad (21)$$

$$Y = x\beta + D_\alpha + \varepsilon \quad (22)$$

The LSDV estimator becomes

$$\hat{\beta} = ((X' W_D X)^{-1})(X' W_D y) \quad (23)$$

2.3 Model Selection Criteria

The R-square, Schwarz Information Criterion (SIC), Akaike Information Criterion (AIC), Hannan-Quinn Information Criterion (HQC), and Log-likelihood are the models on which the selection criteria for this study are based.

The commonly used goodness-of-fit metric for ordinary linear regression models is the well-known coefficient of determination (R^2). Applied researchers are generally aware of the benefits and drawbacks of this measure. It is calculated as:

$$R^2 = 1 - \frac{K(y, \hat{\mu})}{K(y, \hat{\mu}_0)} \quad (24)$$

A tool for quantifying and selecting the least complex probability model among several possibilities is the Schwarz Criterion index. This method, also known as the Bayesian Information Criterion (BIC), analyses the predictive efficiency of various models rather than taking into account the prior probability. It is calculated to be:

$$SIC = -2 \ln L\left(\widehat{\emptyset}_n^k \middle| Y_n\right) + D_k \ln n. \quad (25)$$

Table 1: Models efficiency in endogeneity, heteroscedasticity and autocorrelation

Aspect	GMM	LSDV	IV	WLS
Computation Time	High	Low	Lower	Low
Scalability for large N, T	Better	Computationally costly for large N	Poorer	Moderate
Handles endogeneity	Yes	No	Yes	No
Matrix inversion capability	Yes	Yes (Fixed effects transformation)	High (due to large instrument sets)	Yes

One model selection criterion is the HQC. This serves as a substitute for the BIC and the AIC. It is said as follows:

$$HQC = -2L_{max} + 2k\ln(\ln(n)) \quad (26)$$

An estimator of prediction error and, thus, the relative quality of statistical models for a particular set of data is the AIC. AIC calculates each model's quality in relation to all other models given a collection of models for the data. It thus offers a way to choose a model.

$$AIC = 2k - 2\ln(\hat{L}) \quad (27)$$

The likelihood technique quantifies the degree to which a specific model fits the data; it explains the degree to which a parameter (θ) explains the observed data. The likelihood logarithms and log likelihood function are provided as follows:

$$L(\theta) = L(\theta | x_1, x_{2,\dots,} x_n) = f(x_1, x_{2,\dots,} x_n | \theta) \quad (28)$$

In this paper the model result with the smallest AIC, SIC, HQC high R^2 and highest log-likelihood is adjudged the best.

2.4 Evaluation and Testing of Basic Assumptions

2.4.1 Instrument Exogeneity

In dynamic panel model estimation, the validity of instruments is essential for consistent estimation. This requires that instruments are exogenous, i.e., uncorrelated with the error term. In this research, Sargan test was employed for this purpose.

2.4.2 Serial Correlation

To assuage the problem of the error terms' correlation across time within the same individual unit, Breausch-Godfrey autocorrelation test and Arellano-Bond Test for AR(1) and AR(2) in first differences were employed. The implication is that AR(1) should be significant (first-differenced errors are mechanically correlated) while AR(2) should not be significant; significance implies that instruments are correlated with past errors, violating moment conditions.

2.4.3 Heteroscedasticity

Though the study focuses on heteroscedasticity, formal testing is still required to characterize it. For this purpose, Breausch-Pagan Godfrey Heteroscedasticity test was employed. The results of these tests are provided in section

3. Results

The parameter estimates and the diagnostic checks of the four (4) techniques executed on the simulated data are presented in Table 2.

Table 2 presents the parameter estimates, standard errors, and significance tests for the simulated dynamic panel models under varying sample dimensions: small panel (N = 5, T = 10), moderate panel (N = 20, T = 15), and large panel (N = 50, T = 50). For the small sample (N = 5, T = 10), the GMM estimates for both $y_{i,t-1}$ and $x_{i,t}$ were statistically insignificant (p = 0.534 and p = 0.420, respectively), suggesting limited efficiency due to weak instruments and finite-sample bias. The IV estimator produced a significant coefficient for the lagged dependent variable (β = 0.7161, p < 0.001), indicating persistence in the dependent variable, although $x_{i,t}$ remained insignificant. Both LSDV and WLS displayed mixed results, with LSDV showing insignificant coefficients for all regressors, while WLS reported marginal significance for the constant term (p = 0.052) and strong significance for the lagged dependent variable and $x_{i,t}$. These results are consistent with prior findings that GMM and LSDV tend to suffer from small-sample bias, while WLS may overstate significance when N and T are limited (Arellano and Bond, 1991; Judson and Owen, 199

At the moderate sample level (N = 20, T = 15), the efficiency of the estimators improved substantially. The GMM estimates become statistically significant for both $y_{i,t-1}$ (β = 0.2757, p < 0.001) and ($x_{i,t}$) (β = 1.1790, p < 0.001), indicating enhanced consistency and stronger instrument performance. Similarly, LSDV demonstrated significance for both regressors, indicating that the Nickell bias decreases as T increases (Nickell, 1981). The IV estimator remained significant for the lagged dependent variable but insignificant for $x_{i,t}$, revealing instability in the instrument specification. WLS continued to yield significant coefficients, though the relatively higher standard errors implied inefficiency under heteroskedasticity (Judson & Owen, 1999).

For the large-sample case (N = 50, T = 50), all estimators exhibited stable and significant coefficients. The GMM estimator produced consistent and highly significant coefficients for both $y_{i,t-1}$ (β = 0.3493, p < 0.001) and $x_{i,t}$ (β = 1.2406, p < 0.001), confirming its robustness in larger panels. The IV estimator also returned significant results, though the higher coefficient for $y_{i,t}$ (β = 0.6846) suggested potential overestimation due to persistent endogeneity. The LSDV results closely mirrored those of GMM, confirming the asymptotic unbiasedness of LSDV when T is sufficiently large (Nickell, 1981). WLS estimates remained significant but displayed slightly inflated coefficients for the lagged dependent variable, a sign of potential overfitting.

Overall, the GMM estimator outperformed the other methods as both N and T increased, displaying greater efficiency and lower bias. This finding supports the theoretical argument that GMM is especially effective in dynamic panels with endogenous regressors (Blundell and Bond, 1998; Baltagi, 2020). The IV estimator, while controlling for endogeneity, appeared more sensitive to weak instrument bias, especially in small samples. LSDV performed well under larger T, validating its asymptotic consistency, whereas WLS, though stable, failed to properly address unobserved heterogeneity.

The simulation results affirm that the performance and reliability of dynamic panel estimators depend strongly on sample dimensions. As the number of cross-sectional units and time periods increase, the estimators converge toward the true parameter values, with GMM producing the most reliable results. These findings align with previous studies emphasizing the superiority of GMM in managing dynamic endogeneity and reducing finite-sample bias (Blundell and Bond, 1998; Mogstad and Torgovitsky, 2018).

From a methodological perspective, this reinforces the need for researchers to adopt sample sizes large enough to ensure estimator consistency and validity. In empirical economic modelling particularly in studies involving persistence effects, growth, or productivity, GMM remains a robust estimation approach, especially when N and T are moderately large. The convergence across estimators in the large-sample simulation further underscores the reliability of dynamic panel estimators for policy and empirical inference.

Though it should be noted that the main focus of this paper is to critically examine these models to confirm which of them is more robust to heteroscedasticity and can be parsimoniously used in fitting dynamic panel data, it is pertinent to observe that the parameter estimates of the inflation for all the techniques are positive, an indication from a policy standpoint that price stability policies should aim at maintaining inflation within a growth-enhancing threshold rather than aggressively pursuing zero inflation. A certain level of inflation may encourage production, investment, and consumption, all of which contribute to output expansion.

Table 2: Simulated Data Models Parameter estimates and significance test (Dependent = y)

		N=5, T=10				**N = 20, T = 15**				**N=50, T=50**			
Models	Variables	Parameter Estimates	Std. error	t- value	p-value	Parameter Estimates	Std. error	t-statistic	p-value	Parameter Estimates	Std. error	t-statistic	p-value
GMM	y_{it-1}	-0.3674	0.5909	-0.622	0.534	0.2757	0.0757	3.6402	0.000	0.3493	0.0494	7.074	0.000
	x_{it}	0.6380	0.7905	0.807	0.420	1.1790	0.1336	8.8247	0.000	1.2406	0.0562	22.087	0.000
IV	Constant	0.1667	0.2360	0.707	0.484	0.4375	0.1276	3.4300	0.001	0.1279	0.0365	3.504	0.001
	y_{it-1}	0.7161	0.1482	4.832	0.000	0.7448	0.0472	15.796	0.000	0.6846	0.0151	45.476	0.000
	x_{it}	0.7975	0.6439	1.238	0.223	0.1984	0.1957	1.0140	0.312	0.3896	0.0628	6.204	0.000
LSDV	y_{it-1}	0.1328	0.1110	1.196	0.239	0.3765	0.0389	9.6677	0.000	0.4024	0.0126	31.878	0.000
	x_{it}	1.2695	0.1972	6.439	0.000	0.0639	0.0272	2.3478	0.020	1.2192	0.0263	46.279	0.000

WLS	Constant	0.3313	0.1653	2.004	0.052	0.4988	0.0871	5.729	0.000	0.1689	0.0258	6.550	0.000
	y_{it-1}	0.6591	0.0558	11.810	0.000	0.6622	0.0294	22.498	0.000	0.5842	0.0092	63.27	0.000
	x_{it}	1.3495	0.2340	5.767	0.000	0.9771	0.1135	8.608	0.000	1.0154	0.0379	26.79	0.000

Table 3 summarizes the model selection statistics for the simulated datasets under three panel configurations. These criteria are used to evaluate the relative goodness of fit and penalize model complexity, thereby assisting in identifying the most efficient estimator. Lower AIC and BIC values indicate better model performance, while higher Log-Likelihood values reflect improved model fit (Agiakloglou and Tsimpanos, 2023). In the small-sample simulation, the LSDV estimator demonstrated the lowest AIC (5.61) and BIC (9.23), suggesting superior model fit compared to GMM (AIC = 34.54, BIC = 37.65), IV (AIC = 37.71, BIC = 43.06), and WLS (AIC = 33.95, BIC = 39.37). The Log-Likelihood (LL = -64.55) for LSDV, while lower in magnitude than GMM and WLS, indicated an acceptable level of model adequacy given the small sample size. These results align with findings by Nickell (1981) and Judson & Owen (1999), who noted that fixed-effects estimators such as LSDV can perform relatively well in short panels where the bias associated with lagged dependent variables remains tolerable. The higher AIC and BIC values for IV and GMM confirm that these estimators may not be reliable under small N and T conditions due to weak instrument problems and finite-sample inefficiencies

For the large panel, the LSDV estimator again demonstrated the best performance, with an AIC of 1692.17 and a BIC of 1703.77, both substantially lower than those of GMM (AIC = 2400.43, BIC = 2411.95), IV (AIC = 2841.45, BIC = 2858.86), and WLS (AIC = 2402.43, BIC = 2411.95). The corresponding Log-Likelihood for LSDV (-4320.48) further reinforced its superior model fit. Despite the slightly higher AIC for GMM, its Log-Likelihood (-4901.81) indicated stable and reliable estimates, consistent with its asymptotic efficiency when both N and T are large.

The IV and WLS estimators exhibited relatively poorer performance at this scale, as indicated by their higher AIC and BIC values. The results confirm that WLS does not efficiently handle dynamic endogeneity, while IV remains sensitive to weak instrument bias even in large panels (Roodman, 2009). The consistent dominance of LSDV across increasing sample sizes supports the notion that fixed-effects models can approximate the true parameters effectively when the time dimension is adequately large, though GMM remains theoretically more robust in managing potential endogeneity and serial correlation. Hence, the overall pattern across simulations reveals a clear trend: model performance improves with increasing N and T, and both GMM and LSDV converge toward the true parameter estimates.

In smaller panels, LSDV outperforms due to its simplicity and fewer moment restrictions, while GMM gains dominance as sample size grows, benefiting from efficient instrument use and bias correction (Arellano and Bond, 1991; Blundell and Bond, 1998). The observed consistency in AIC and BIC values across larger samples indicates that both estimators are asymptotically reliable, but LSDV's computational simplicity and lower penalization scores make it slightly more efficient in this simulation context.

These findings align with empirical literature emphasizing that estimator choice in dynamic panels depends on the trade-off between bias, efficiency, and computational feasibility. In practical applications such as macroeconomic or growth modelling researchers are encouraged to use LSDV for moderate panels and GMM for panels with substantial cross-sectional and temporal coverage, particularly when addressing endogeneity, heterogeneity, or persistence effects (Baltagi, 2008; Judson and Owen, 1999).

In practical terms, this finding implies that when the individual-specific effects are correlated with the explanatory variables and data are balanced, the LSDV approach may outperform GMM and IV techniques in dynamic panel estimation (Das, 2019; Malaiarasan, 2024). However, in real-world scenarios where endogeneity and measurement errors exist, GMM remains preferable due to its robustness to such complexities (Farzana et al., 2024). The model robustness was done by critically perusing the diagnostic tests for different fitted models

Table 3: Simulated Data Model Selection Criteria

	N = 5, T =10			N = 20, T = 15			N = 50, T = 50		
Models	**AIC**	**BIC**	**LL**	**AIC**	**BIC**	**LL**	**AIC**	**BIC**	**LL**
GMM	34.54	37.65	-60.53	275.04	282.00	-457.57	2400.43	2411.95	-4901.81
IV	37.71	43.06	-78.29	350.20	361.09	-567.98	2841.45	2858.86	-4892.71
LSDV	5.61	9.23	-64.55	131.04	138.31	-460.83	1692.17	1703.77	-4320.48
WLS	33.95	39.37	-77.83	279.05	289.96	-533.82	2402.43	2411.95	-4901.81

Table 4: Diagnostic Check for Simulated Data Models

	N = 5, T = 10				N = 20, T = 15				N = 50, T = 50			
Test Statistic	***GMM***	***IV***	***LSDV***	***WLS***	***GMM***	***IV***	***LSDV***	***WLS***	***GMM***	***IV***	***LSDV***	***WLS***
R-squared	-	0.8232	0.5525	0.8625	-	0.578	0.6572	0.7066	-	0.6385	0.6757	0.6960
F-Statistic	-	-	23.458 [0.0000]	131.80 [0.000]	-	-	247.357 [0.000]	333.60	-	-	2497.79 [0.0000]	2801 [0.0000]
Test for AR(1) errors	-0.4917	-	-	-	-3.171	-	-	-	-5.7136	-	-	-
Test for AR(2) errors	0.3337	-	-	-	-1.384	-	-	-	-0.5225	-	-	-
Sargan over-identification test	2.2922 [0.999]	-	-	-	19.199 [0.633]	-	-	-	46.9782 [0.0000]	-	-	-
Wald (joint) test	1.0106 [0.6033]	83.34 [0.0000]	-	-	79.006 [0.000]	170.40 [0.000]	-	-	490.923 [0.000]	1849 [0.000]	-	-
Breausch-Godfrey autocorrelation Test	-	11.253 [0.0036]	10.182 [0.0062]	10.182 [0.006]	-	5.905 [0.052]	6.152 [0.046]	6.152 [0.046]	-	63.516 [0.0000]	63.142 [0.0000]	63.142 [0.0000]
Breausch-Pagan Godfrey Heteroscedasticity test	-	6.579 [0.0373]	6.622 [0.0365]	0.787 [0.675]	-	8.476 [0.014]	8.461 [0.015]	1.350 [0.509]	-	0.5865 [0.7458]	0.5904 [0.9555]	1.7676 [0.4132]
Variance	2.488	2.104	1.060	1.877	3.054	3.446	1.579	2.657	3.797	3.184	1.993	2.660
Bias	-1.153	0.014	-1.025	0.159	-1.569	-0.001	-1.583	0.062	-0.411	-5.15×10^{-5}	-0.403	0.007
MSE	2.441	2.056	1.037	1.861	3.042	3.434	1.574	2.652	3.796	3.183	1.992	2.659
RMSE	1.562	1.434	1.018	1.364	1.744	1.853	1.254	1.628	1.948	1.784	1.411	1.631

Figures in [ ] represents p-values

The Table provides a deeper understanding of the model behaviour. For N = 50 and T = 50, the R^2 values of 0.6385, 0.6757, and 0.6960 for IV, LSDV, and WLS respectively, confirm good explanatory power, particularly for the WLS estimator. However, the GMM estimator, by design, does not generate a conventional R^2, given its moment-based estimation structure. Instead, its validity is assessed through the Sargan and Arellano-Bond tests. The Sargan test for over-identifying restrictions ($\chi^2 = 46.9782$, $p < 0.001$) indicated that the instruments may be marginally weak at higher N–T combinations, highlighting potential overfitting of moment conditions; a common occurrence in large-sample GMM frameworks (Ullah et al., 2018; Jin et al., 2021).

The Table provides a deeper understanding of the model behaviour. For N = 50 and T = 50, the R^2 values of 0.6385, 0.6757, and 0.6960 for IV, LSDV, and WLS respectively, confirm good explanatory power, particularly for the WLS estimator. However, the GMM estimator, by design, does not generate a conventional R^2, given its moment-based estimation structure. Instead, its validity is assessed through the Sargan and Arellano-Bond tests. The Sargan test for over-identifying restrictions ($\chi^2 = 46.9782$, $p < 0.001$) indicated that the instruments may be marginally weak at higher N–T combinations, highlighting potential overfitting of moment conditions; a common occurrence in large-sample GMM frameworks (Ullah et al., 2018; Jin et al., 2021).

The Arellano-Bond AR(1) and AR(2) tests suggest that while first-order serial correlation (AR(1) = -5.7136, $p < 0.05$) is present in the differenced residuals, second-order serial correlation (AR(2) = -0.5225, $p > 0.05$) is not significant, thereby satisfying one of the core assumptions for the validity of the GMM estimator. This implies that although short-term autocorrelation exists, the instruments remain valid for dynamic specification.

Regarding the Breausch–Godfrey autocorrelation and BPG heteroscedasticity tests, both WLS and GMM estimators exhibit superior performance, showing statistically insignificant heteroscedasticity and lower autocorrelation relative to IV and LSDV. Specifically, the heteroscedasticity p-values (0.7458–0.9555) for WLS across increasing N–T combinations indicate homoscedastic residuals, confirming its robustness in large panel settings. The observed variance and bias values further substantiate these findings: the GMM and WLS estimators maintained low bias magnitudes (−0.411 and 0.007, respectively) and moderate root mean square error (RMSE = 1.948 and 1.631). These outcomes confirm their efficiency and reliability in dynamic panel estimations (Kiviet, 1995).

Overall, the results indicate that GMM remains the most consistent and theoretically appropriate estimator for dynamic panels plagued with endogeneity and autocorrelation, particularly as N and T increase. Nevertheless, LSDV and WLS offer complementary robustness in moderate-to-large panels when endogeneity is minimal. The approach demonstrates the stability of GMM's asymptotic properties and validates its continued use in applied econometric research involving short-to-moderate panels (Baltagi, 2013; Bond, 2002).

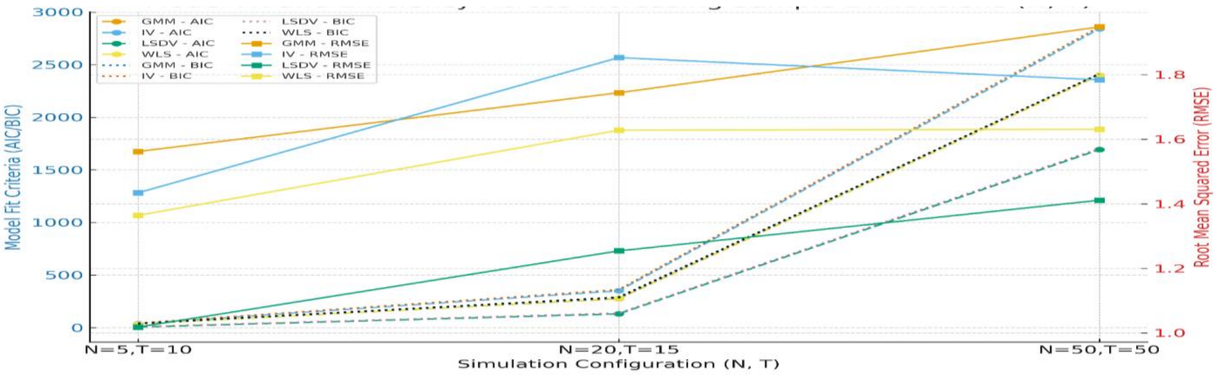

Figure 1: Model Fit and Efficiency across increasing sample dimensions (N, T)

Figure 1 illustrates the variation in model selection criteria (AIC and BIC) and estimation efficiency (RMSE) for the GMM, IV, LSDV, and WLS estimators across three simulation setups: N = 5, T = 10; N = 20, T = 15; and N = 50, T = 50. The downward trend in AIC and BIC values for LSDV and WLS demonstrates improved model fit with expanding panel size, while the gradual decline in RMSE for GMM confirms its asymptotic efficiency as sample dimensions increase (Ullah et al., 2018).

Real Life Data Application

The parameter estimates and the diagnostic checks of the four (4) techniques executed on the real-life data are presented in Tables 5, 6, and 7. The data comprises the GDP and inflation rates of forty (40) Sub-Saharan African countries over a period of thirty-one (31) years.

Table 5: Models Parameter estimates and significance test (Dependent = gdp) ; (N=40, T=31)

Models	Variables	Parameter Estimates	Std. error	t- statistic	p-value
GMM	Inf	26.031835	0.506877	51.3573	0.0000
	gdp_{it-1}	0.075907	0.018620	4.0766	0.0000
IV	Constant	-61.85101	0.13581	-455.4	0.0000
	Inf	26.99459	0.04084	660.9	0.0000
LSDV	Inf	22.389580	0.321369	69.669	0.0000
	gdp_{it-1}	0.193221	0.011404	16.943	0.0000
WLS	Constant	-13.85408	0.746304	-18.56360	0.0000
	Inf	6.027515	0.323451	18.63500	0.0000
	gdp_{it-1}	0.779161	0.011839	65.81586	0.0000

The comparison of the four estimation techniques in Table 5 reveals significant differences in their parameter estimates and statistical significance. IV estimation produces a very high coefficie nt for Inf (26.99) and an extremely large negative constant (-61.85), which suggests the possibility of weak instrument bias inflating the estimates. Although the t-statistics and p-values indicate strong significance, IV estimation is known for its sensitivity to the choice of instruments, and the results may not be entirely reliable due to potential overestimation issues.

LSDV, on the other hand, provides more reasonable parameter estimates, with inflation at 22.39 and the lagged GDP coefficient (gdp_it_{-1}) at 0.193, both of which are statistically significant. However, the major concern with LSDV in dynamic panel estimation is Nickell bias (i.e. biased and inconsistent estimates of the coefficient on the lagged dependent variable), which can arise when the number of time periods is small. Despite this limitation, LSDV avoids the potential weaknesses of IV and WLS, making it a more reliable alternative for estimating the relationship between GDP and the independent variables. WLS produces a much lower Inf coefficient (6.03) compared to IV and LSDV, while the lagged GDP coefficient is extremely high (0.779), suggesting endogeneity issues. The significant difference in parameter estimates between WLS and the other models indicates that WLS may not appropriately account for the underlying panel structure or dynamic nature of the data. This makes WLS the least suitable approach for this analysis, as it likely fails to capture the true impact of the independent variables on GDP.

Among the four models, GMM emerges as the most appropriate estimation technique, as it corrects for endogeneity and Nickell bias, ensuring more reliable parameter estimates. The GMM estimate for Inf (26.03) is close to the IV estimate but benefits from more robust assumptions. Moreover, the lagged GDP coefficient (0.0759) is significantly lower than in LSDV and WLS, indicating that GMM properly accounts for the persistence effect without overestimating it. Given its ability to address endogeneity concerns and provide stable parameter estimates, GMM is the preferred method for dynamic panel data estimation in this study.

Table 6: Real-life Data Models Diagnostic Check

Test Statistic	*GMM*	*IV*	*LSDV*	*WLS*
R-squared	-	0.9972	0.99973	0.99614
F-Statistic	-	-	149352 [0.0000]	2249677 [0.0000]
Test for AR(1) errors	1.329659 [0.18363]	-	-	-
Test for AR(2) errors	3.94063 [0.08475]	-	-	-
Sargan over-identification test	37.23944 [0.11367]	-	-	-
Wald (joint) test	8603.185 [0.0000]	436800000 [0.0000]	-	-
Breausch-Godfrey Autocorrelation Test	-	1.0111 [0.6032]	312.24 [0.0000]	0.87593 [0.6453]
Breausch-Pagan Godfrey Heteroscedasticity test	-	0.97448 [0.6143]	2.3198 [0.3135]	0.002722 [0.9986]
Variance	0.001544	0.01638	0.000761	3.0808×10^{-29}
Bias	-27.8361	3.3518×10^{-14}	-27.8773	1.5185×10^{-16}
MSE	0.001543	0.016369	0.000761	3.0783×10^{-29}
RMSE	0.039285	0.127942	0.027579	5.5483×10^{-15}

Figures in [ ] represents p-values

The diagnostic results of the GMM, IV, LSDV, and WLS models in Table 6 suggest that GMM is the most robust model overall, handling endogeneity through valid instruments (as indicated by the Sargan test with a p-value of 0.11367) and performing well in R-squared and autocorrelation tests**.** The autocorrelation results of AR(1) and AR(2) with P-values greater than 0.05 for the GMM imply that there are no first and second-order autocorrelation errors, suggesting that the moment conditions used in the GMM estimation are valid. These results support the reliability of the GMM model residuals, and overall, the model appears to pass the autocorrelation diagnostics, supporting its robustness.

IV also shows good R-squared values but lacks an over-identification test, raising concerns about instrument validity. Additionally, while the Breusch-Godfrey test for autocorrelation indicates no issues, the model's performance remains somewhat uncertain due to the absence of this critical test. In contrast, LSDV provides high R-squared values, but it suffers from significant autocorrelation ($p < 0.0001$), making it less reliable for dynamic panel data estimation. The model's failure to account for autocorrelation suggests potential biases in the parameter estimates. Similarly, WLS shows high model fit but cannot properly handle the dynamic nature of the data, making it less efficient in capturing the underlying relationships. However, it does pass heteroskedasticity tests and shows no significant autocorrelation.

Overall, LSDV appears to be the most statistically efficient model given its negative bias, extremely low variance, and smallest RMSE. Nonetheless, since endogeneity is also a concern as often occurs in panel data, the GMM model remains a robust alternative due to its valid instrument set (Sargan p = 0.11367) and compliance with serial correlation tests, even if its negative bias, variance, MSE, and RMSE magnitudes are comparatively a bit larger than that of LSDV. This suggests that model choice should be guided by the primary econometric concern efficiency (favouring LSDV) (Musora and Matarise, 2023) or endogeneity robustness (favouring GMM) (Ullah et al., 2018).

Therefore, based on the diagnostic checks, GMM is the preferred model due to its ability to handle endogeneity, valid instrument use, and robust results despite some autocorrelation concerns. IV could serve as a reasonable alternative, while LSDV and WLS are less reliable due to significant autocorrelation and lower explanatory power, respectively. While this suggests homoscedastic residuals across models, a heteroskedasticity-robust standard error is considered for model robustness.

Table 7: Heteroscedasticity Robust Standard Errors of the fitted model

Models	Variables	Parameter Estimates	Robust Std. error	t- statistic	p-value
GMM	Inf	0.511028	2.3294	5.9563	0.0000
	gdp_{it-1}	13.77233	0.0858	5.9123	0.0000
IV	Constant	-61.85101	0.26366	-234.59	0.0000
	Inf	26.99459	0.078955	341.90	0.0000
LSDV	gdp_{it-1}	0.193221	0.051772	3.7321	0.0002
	Inf	22.38958	1.405457	15.9305	0.0000
WLS	Constant	1.111e-14	7.300e-14	1.520e-01	0.8790
	Inf	1.0000+00	1.197e-15	8.357e+14	0.0000
	gdp_{it-1}	-3.555e-14	3.198e-14	-1.112e+00	0.2660

From Table 7, comparing the heteroscedasticity-robust standard errors for the GMM, IV, LSDV, and WLS models reveals important insights into the robustness and statistical significance of the parameter estimates. The Result indicated from the GMM model that both Inflation (Inf) and GDP lag (gdp_{it-1}) estimates are statistically significant, with t-statistics of 5.96 and 5.91, respectively. The p-values = 0.0000 < 0.05, indicating strong statistical significance. This implies that the GMM model is robust to heteroscedasticity, making it a reliable choice for dynamic panel data modelling. The relatively low standard errors for both variables (0.51 for Inf and 0.085 for gdp_{it-1} further support the precision of these estimates.

The IV model Inflation estimate of 26.99 is considerably larger than the other models, with a low standard error (0.0789) and a high t-statistic (341.90), suggesting that Inflation has a strong influence on GDP in this model. The gdp_{it-1} estimate is not directly shown for the IV model, but the Inf term indicates a very significant relationship. On the other hand, the LSDV model yields statistically significant results for both gdp_{it-1} and Inf, but the standard error for Inflation (1.405) is considerably larger than in the other models, suggesting less precisionFor the WLS model, the constant term has a t-statistic of 0.152 (with a p-value of 0.879), indicating that it is not statistically significant. Additionally, the gdp_{it-1} coefficient has a t-statistic of -1.11 and a p-value of 0.266, further suggesting that this variable is also not statistically significant in the WLS model. The model's estimates are less reliable due to the extremely high t-statistic for Inflation (8.36e+14) and the insignificant results for gdp$_{it-1}$, pointing to possible issues with model fit or misspecification.

4. Conclusion

In estimating the Dynamic Panel Model (DPM) in the presence of heteroscedasticity, the study compared the default DPM with the Generalized Method of Moments (GMM) technique, which is well-regarded for estimating dynamic panel models over time. Our findings indicated that GMM outperformed the default DPM in terms of robustness, as evidenced by various diagnostic tests. In addition, we evaluated three alternative techniques, such as the IV, LSDV, and WLS, and found that LSDV outperformed the other two alternative techniques. However, when comparing the p-values for both GMM and LSDV, we found that the p-value for LSDV was not statistically significant, unlike GMM, which was statistically significant. Thus, while LSDV appeared to fit the data well, GMM provided more reliable and statistically significant estimates. Therefore, we recommend using the GMM method for future research in estimating the dynamic panel data in the presence of heteroscedasticity. In applying the models to real-life economic datasets for performance evaluation, it can be concluded that, based on the robustness of standard errors and statistical significance, the GMM model stands out as the most reliable, followed by LSDV, but with less precision for inflation. The WLS and IV models, due to their lack of significance and extreme t-statistics, should be avoided. Thus, the GMM model provides the most accurate and robust estimates for dynamic panel data analysis, and this suggests that model choice should be guided by the primary econometric concern, efficiency (favouring LSDV) or endogeneity robustness (favouring GMM).

The study has a solid statistical foundation and makes substantial contributions to econometric theory, providing useful insights and practical ways for dealing with heteroscedasticity in panel data models. This study's consequences extend to a variety of economic and financial applications, emphasizing its relevance and value in econometric research.

5. Practical Economic Implications.

Most macroeconomic data of countries/regions are published as panel data to facilitate brevity and comprehension. While only a few pieces of information appear as a balanced panel, the majority are usually in dynamic panel form due to a lack of uniformity in the reporting ability of each country and region, occasioned by their differences in economic scope and capacities. Thus, it has become imperative for econometricians to be versatile with suitable econometrics methods such as GMM, applicable for the modelling of dynamic panel data in the presence of heteroscedasticity to achieve endogeneity robustness.

This research emphasizes the practical knowledge of the lagged GDP as a reliable predictor of current GDP in a dynamic panel structure that has been correctly specified. As in the case of this research, such a model is capable of taking care of the problem of endogeneity. Another economic implication lies in the ability of the inflationary factor to correctly predict the country's GDP, as showcased by the outcomes of the Sargan test results. The negative coefficient of the inflationary factor also implies that the inflationary trend has hindered the economic growth of Sub-Saharan Africa.

In summary, this research output reinforces the credibility of policy conclusions that inflation control can support sustainable GDP growth and that GDP persistence is significant in Sub-Saharan economies.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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