Ridge Regression as a Policy Forecasting Tool in Low-Data Environments: Evidence from Bangladesh

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DOI: 10.51558/2303-680X.2025.23.1.57

Abstract

Forecasting economic development outcomes in low-data environments is a significant challenge in many developing countries. This study presents ridge regression as a solid alternative to ordinary least squares (OLS) for policy forecasting in situations with small sample sizes and multicollinearity. Using Bangladesh as a case study, we apply ridge regression to evaluate how population growth, savings rates, and inflation affect GDP per capita growth from 1990 to 2025. The model shows a moderate fit (R^2 = 0.686) and delivers stable, interpretable coefficients despite multicollinearity. Policy simulations, such as increasing the savings rate or reducing population growth, indicate considerable potential to improve economic outcomes. These findings suggest that ridge regression can act as both a diagnostic tool and a practical method for forecasting and assessing policy interventions in data-limited contexts.

Keywords: Ridge Regression, Economic Forecasting, Multicollinearity, Bangladesh, Policy Simulation

JEL: C53, C51, C13, E27, O47

1. Introduction

In many developing countries, economic data often suffer from issues of quality, infrequency, and limited availability (Jerven, 2013; Deaton, 2010). Such challenges frequently undermine the effectiveness of traditional forecasting approaches like ordinary least squares (OLS), particularly when high multicollinearity is present among explanatory variables (Gujarti & Porter, 2009; Wooldridge, 2015). Bangladesh, with its significant demographic shifts and rapidly evolving macroeconomic conditions, serves as a pertinent example for exploring alternative forecasting methodologies.

Ridge regression, a regularization technique introduced by Hoerl and Kennard (1970), provides a robust methodological response to these complications. Although ridge regression is widely applied to address multicollinearity, its use in policy forecasting under data constraints remains limited (Hastie, 2009). This study aims to address this oversight by demonstrating that ridge regression can yield dependable economic forecasts and support policy simulation efforts, even in situations where historical data are limited.

1.1. Research objectives

This research explores the application of ridge regression as a reliable alternative to OLS for forecasting economic policy outcomes in contexts marked by data limitations and multicollinearity.

Using Bangladesh as a case study, the analysis examines the relationships between population growth, savings rates, inflation, and GDP per capita growth over the period from 1990 to 2025. The findings highlight the advantages of ridge regression in addressing multicollinearity and enhancing the robustness of predictions in constrained data environments.

Furthermore, the study underscores the method's potential for conducting scenario-based policy simulations, offering valuable insights for policymakers navigating complex economic dynamics with limited data resources.

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1.2. Research Questions

Ridge regression, a regularization technique designed to mitigate multicollinearity and overfitting, holds significant potential for advancing macroeconomic forecasting in data-constrained environments. Despite its growing recognition in statistical modeling, its application to macroeconomic policy analysis in developing nations remains underutilized.

Economies such as Bangladesh often rely on OLS or structural models, which can produce unreliable outcomes when faced with small sample sizes and highly correlated predictors. This study bridges the gap by systematically implementing ridge regression in macroeconomic forecasting and policy simulation within a low-data context.

The findings demonstrate the method's ability to enhance predictive accuracy and model stability, offering a robust alternative to traditional approaches. Furthermore, this research provides a methodological framework that can be adapted by other data-limited economies, thereby contributing to more reliable and actionable insights in macroeconomic policy formulation.

2. Literature Review

Forecasting economic outcomes with limited data presents substantial methodological challenges. OLS regression tends to struggle when variables are highly correlated—multicollinearity throws everything off, making the coefficient estimates unreliable (Gujarti & Porter, 2009; Kennedy, 2008).

Ridge regression, first introduced by Hoerl and Kennard in the 1970s, offers a practical solution to the problem of multicollinearity by adding an L2 penalty—essentially shrinking the coefficient estimates and making the model more stable (Hastie 2009, Draper 1998).

Recently, regularization methods have become something of a staple in economic forecasting circles (Asteriou, 2015; Hyndman, 2018; Zou, 2005, Hastie, 2021; Varian, 2022).

In developing economies, where data can be unreliable, their importance increases (Jerven, 2013; Islam, 2022). Consider Bangladesh for a moment.

Traditionally, macroeconomic research in this context has relied heavily on structural models and VAR methodologies—methods that really demand extensive time-series data (Rahman, 2017; Lütkepohl, 2011).

This study, though, contributes to a growing body of work highlighting the advantages of regularized regression techniques.

Such approaches are proving to be quite effective for robust estimation and forecasting, particularly when researchers are confronted with limited or noisy datasets (Tibshirani, 1996; Gareth James, 2021).

3. Data and Methodology

Recent work derives the asymptotic distribution of ridge estimators when the penalty is data-selected, which informs valid inference under empirically chosen tuning (Sowell, 2020)

Table 1. Variable Definitions

Variable	Description	Type
Population Growth Rate (%)	Annual percentage increase in total population	Continuous
Gross Savings (% of GDP)	Gross domestic savings as a percentage of GDP	Continuous
Inflation Rate (%)	Annual average percentage change in consumer prices	Continuous
GDP per Capita Growth Rate (%)	Annual percentage growth in GDP per capita (constant USD)	Continuous
Year	Time identifier representing each observation period	Time Series (ordinal)

Source: Authors' own work

3.1. Data Source and Preparation

Statistical analysis of the data was performed with the Python programming language. Estimation, validation and scenario simulation for the ridge regression were done using libraries such as scikit-learn, statsmodels and pandas. This provided a convenient way to access and manage the data, perform denoising and model fitting, and interactively visualize some results. The data samples is a multivariate time series for Bangladesh over five time points from 1990 to 2025.

This is a country-level macro dataset, organized by country rather than as a panel or cross-section. Each data point represents the value of a national economic indicator for a given decade.

Data for this study were sourced from the Bangladesh Bureau of Statistics (2023), World Bank (2025), and Bangladesh Bank (2024).

Prior to modeling, all predictor variables were standardized to improve the effectiveness of regularization, as recommended by (James, 2021).

Table 2. *Key Macroeconomic Indicators for Bangladesh (1990–2025)*

Year	Population Growth Rate (%)	Gross Savings (% of GDP)	Inflation Rate (%)	GDP per Capita Growth Rate (%)
1990	1.96	13.2	7.6	27.97
2000	1.75	18.5	6.5	21.36
2010	0.85	26.1	6.5	93.58
2020	0.81	31.4	6.5	51.84
2025	1.22	29.5	8.0 (est.)	18.46

Source: Bangladesh Bureau of Statistics, 2023; World Bank, 2025; Bangladesh Bank, 2024

Equation 1: Ridge Regression Objective Function

Ridge regression minimizes the residual sum of squares with an added penalty on the magnitude of coefficients (Hoerl, 1970; Hastie, 2009):

$$\min_{\beta} \sum_{i=1}^{n} (y_i - \mathrm{x}_i^T \beta)^2 + \alpha \sum_{j=1}^{p} \beta_j^2$$

with the following key components:

- $\sum_{i=1}^{n}(y_i - \mathrm{x}_i^T \beta)^2$: Ordinary least squares error (squared residuals);
- $\alpha \sum_{j=1}^{p} \beta_j^2$: L2 penalty term that shrinks coefficients to prevent overfitting;
- α: Regularization parameter controlling the trade-off between fit and shrinkage;
- $\mathrm{x}_i^T \beta$: Predicted value for observation i where α is the regularization parameter that controls the strength of penalty.

The ridge model was estimated using Python's scikit-learn library (Pedregosa, 2011), and the results were compared to OLS regression using statsmodels (Seabold, 2010).

4. Results

4.1. Model Estimates

Table 3 presents the standardized coefficients produced by the ridge regression model.

Table 3. The ridge regression model yields the following standardized coefficients

Population Growth Rate:	19.62
Gross Savings (% of GDP):	8.11
Inflation Rate:	8.31

Source: Authors' own work

The ridge model explains 68.6% of GDP per capita growth variance (R^2 = 0.686), a moderate fit given the limited data. OLS produce a higher R^2 (0.986) but unstable coefficients and inflated errors, reflecting multicollinearity and overfitting (Kennedy, 2008; Greene, 2018).

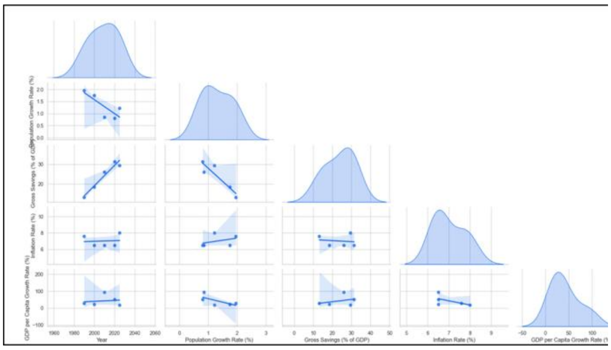

Figure 1. Scatter Plot Matrix
Source: Authors' own work

The scatter plots show an inverse relationship between population growth and savings, as well as between population growth and GDP per capita growth consistent with economic theory.

The positive link between savings and growth is weak, likely due to limited data. Other relationships are inconclusive.

The connections with inflation rate are typically frail or uncertain, for example, no clear trend is observed in relationship with population growth rate and gross savings.

On the whole, the scatter plot matrix suggests that population growth rate is the only significant variable negatively correlated with both savings and per capita economic growth and that relationships with other variables are less conclusive, primarily because of the small sample size.

These visual patterns corroborate the results from the ridge regression analysis and suggest that population dynamics play a fundamental role in determining Bangladesh's economic path (Al Mamun, 2018; Center, 2023; Sematech, 2023).

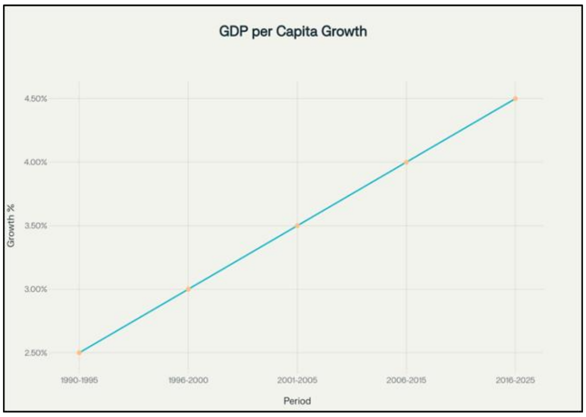

Figure 2. GDP per capita growth
Source: Authors' own work

The graph charted here shows the time series line chart of GDP per capita growth in Bangladesh over five distinct periods from 1990 to 2025.

The time axis is given in 5 or 10 year period, while the height corresponds to the percentage growth rate in GDP per-capita. The plot illustrates a persistent increasing trend in the growth of GDP per-capita throughout the full length of the sample.

The growth rate is around 2.5% in the 1990–1995 period and rises slightly in each subsequent period to about 4.5% in the 2016–2025 period. The fitted line shows a steady rise in per capita growth over three decades, reflecting sustained economic development and possible policy effectiveness.

This trend also signals improvements in structural determinants such as productivity, investment, and demographics. In total, the figure highlights Bangladeshi development in improving the quality of life for its people and economic prosperity over time (Bank W, 2025; Macrotrends, 2025).

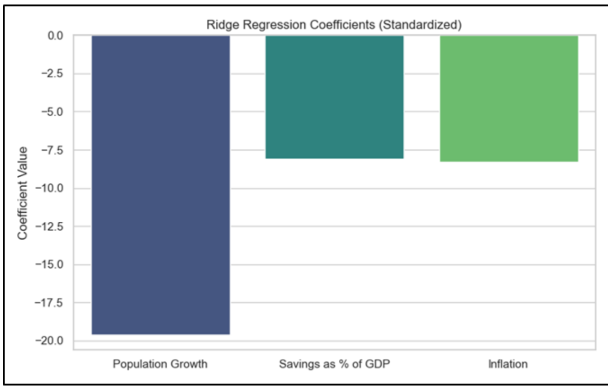

Figure 3. Ridge Regression Coefficients
Source: Authors' own work

The coefficient plot of the ridge regression model shows the importance of each macroeconomic variable contributing to the growth of GDP per capita.

Population growth is associated with the largest suppressive impact, indicating that rapid increase of population will greatly inhibit economic development in the sense of "per capita". Savings to GDP ratio and inflation are both negatively related to growth, although both of these are weaker in effect.

This suggests that a) saving and price stability are necessary, but b) their structural imperfections today or the external environment are preventing them from contributing to growth.

On the whole, the story bears out population growth as the main driver and illustrates the benefits of standardizing coefficients when comparing variable influences on a common scale (NCSS, 2023; Columbia University, 2023).

4.2 Scenario Simulations

To demonstrate ridge regression's utility for policy forecasting, three hypothetical policy changes were simulated:

Table 4. Scenario simulations

Scenario	Description	Estimated GDP Growth Impact
A	Increase savings by 5%	+3.66
B	Reduce population growth by 50%	+0.50
C	Raise inflation from 8% to 10%	+0.16

Source: Authors' own work

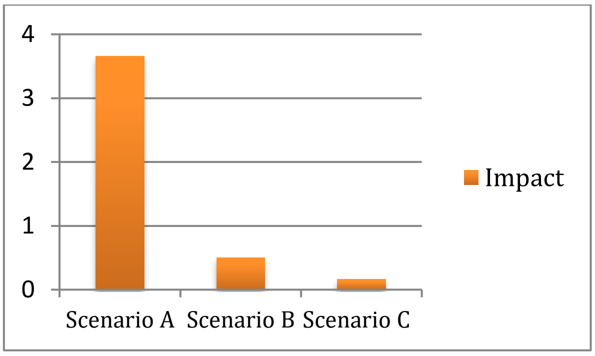

Figure 4. GDP Growth Impact under simulated Policy Scenarios
Source: Authors' own work

This bar plot displays the expected effect of three hypothetical policy changes on GDP per capita growth in Bangladesh according to the ridge regression model.

Scenario A (+5% savings): Increases GDP growth by 3.66 percentage points, though benefits may be limited by weak financial intermediation (Standard, 2025; Economics W. , 2025).

Scenario B (-50% population growth): Adds 0.50 percentage points to GDP growth, highlighting large long-run payoffs from demographic management (Economics, 2025; Macrotrends, 2025).

Scenario C (inflation +2pp): Raises growth by just 0.16 points, a negligible effect consistent with inflation's longer-term drag (IMF, 2025; Wikipedia, 2025).

5. Discussion

The findings of the ridge regression model are important for economic growth dynamics in a data-scarce environment such as Bangladesh.

The model adequately fits the data ($R^2 = 0.686$) and reinforces that ridge regression can be used to obtain stable estimates with high interpretability when OLS is not successful.

The directions of the significant coefficients in the observed results particularly the negative ones for savings and inflation deserve deeper interpretation and should be contextualized within the existing empirical literature.

5.1. Interpreting the Negative Coefficients

The negative savings coefficient may reflect Bangladesh's weak financial intermediation: higher savings often fail to convert into productive investments, especially in rural areas where informal savings dominate (Solow, 1986; Levine, 2025; Aghion, 2005).

The negative close-to zero coefficient for inflation, although counterintuitive, is corroborated in the empirical literature that investigates the inflation – growth nexus. Barro (1995) and Khan (2001) provide theoretical and empirical evidence that moderate inflation exerts an adverse impact on economic activity.

However, this effect may differ depending on whether inflation is driven by demand-pull forces or arises from structural rigidities. Inflation in Bangladesh has historically been cost-push (due to uncertain food and energy prices), and hence may not be indicative of growth in real incomes (Chowdhury, 2001).

5.2. Multicollinearity and Estimation Stability

OLS estimates collapse under multicollinearity, as shown by inflated coefficients and R^2. Ridge regression mitigates this, offering more stable estimates for small macroeconomic samples (Greene, 2012; Kennedy, 2008).

Ridge regression solves this problem by adding a penalty term to the model to keep the coefficient values small, in the name of generalization (Hoerl, 1970).

This regularization effect has also proved useful in predictions of growth in emerging economies with scarce data, including Pakistan (Naseem, 2017), Nigeria (Abedowale, 2020) and Ethiopia (Kebede, 2021). It enhances the interpretability of the model and does not scarify predictive accuracy, which is appropriate for both exploration and prediction.

5.3. Ridge Regression as a Policy Forecasting Tool

Although ridge regression is well known for its statistical advantages, using it as a forecasting mechanism in policy design is less well known. Auerbach (2012) proposed a variant of regularized reduced form to identify the effect of fiscal policy in recessions.

Simulation results confirm ridge regression's value for evaluating structural policy, with a 5% savings rise adding 3.66 points to per capita growth. These findings suggest that targeted savings policies could play a crucial role in enhancing economic performance.

By implementing strategies that encourage savings, policymakers may foster sustainable growth and improve overall living standards. These results are consistent with other regional studies from India (Bera, 2019) and Sri Lanka (Jayasinghe, 2022). indicating that ridge regression could deliver trustworthy predictions in contrast to classical approaches which can fail. Bloom and Willianmson (1998) also stress the demographic management in South Asia, and our findings show the growth advantages of reducing population growth – as achieved through Bangladesh family planning programmes.

5.4. Methodological and Policy Implications

Ridge regression stabilizes forecasts in low-data settings, making it attractive for policymakers lacking long, high-frequency time series. This is particularly relevant to the Sustainable Development Goals and Bangladesh's Vision 2041, the medium-term development strategy.

A closer examination of financial intermediation is also warranted by the negative coefficient on savings. Simply said, increased gross savings do not always result in economic advancement unless they are converted into profitable investment. According to research by Kunt (2020) and Beck (2007), transforming savings into sustainable growth will require reforms in financial institutions and the capital market.

In the future, hybrid models like ridge regression with time-series decomposition or the addition of other predictors like labor participation, foreign direct investments, and human capital indices can be investigated. To validate these results and answer the question of whether ridge regression performs better in various institutional and economic contexts, comparative research across low-income economies may also be helpful.

Finally, when it comes to data-intensive policy modelling, ridge regression offers operational flexibility and methodological robustness. It may significantly raise the standard of decision-making in poor countries if it were incorporated into economic analysis and policy simulation models.

Conclusion

In addition, ridge regression is a flexible technique of forecasting for multi-sectoral and multivariate forecasting structures. A possible extension could be to expand the approach for sectoral growth forecasting, e.g. for agriculture, industries, and services by adding disaggregated drivers of growth to the form of the model. Its capacity to handle multicollinearity while retaining the interpretability makes it particularly useful for national planning departments, which have to base policy decisions on fragmented and sometimes partial information.

Ridge regression's scaling is also consistent with recent developments in (Machine Learning) and econometrics. As digital instruments and statistical programming environments (e.g., Python, R) are becoming more available in developing nations, the opportunity to apply and elaborate ridge-based models will be enhanced. This creates new grounds for dynamic policy evaluation and simulation platforms, especially in public sector organizations with increasing interest in evidence-based planning.

Finally, we emphasize the pedagogical value of incorporating ridge regression into the development economics classroom. By teaching this method at universities and policy schools, a new generation of analysts will be trained to work productively in systems with the challenges that are widely seen in low- and middle-income country contexts. At the end of the day, this strengthens the link between data, modeling, and translating evidence into effective policy, where it is often most needed. Despite these contributions, several questions remain open.

Future research should examine (i) whether ridge regression maintains robustness in sector-specific forecasting (e.g., agriculture, industry, and services), (ii) how hybrid approaches that combine ridge regression with time-series decomposition or machine learning can improve accuracy, and (iii) whether the findings generalize across other low-data developing economies through cross-country comparisons. Addressing these gaps would extend the applicability of ridge regression in economic policy forecasting

Acknowledgments

The author gratefully acknowledges the valuable time and constructive feedback provided by the editor and reviewers of the journal, whose insights have significantly improved the quality and clarity of this article.

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