The Effect of Polynomial Feature Engineering on Regularised Regression Models for Inflation Forecasting Connor Smedley

1 Introduction

This research explores the question: **to what extent does increasing model complexity through polynomial feature engineering improve the predictive performance of regularised regression models for inflation forecasting?**

Inflation forecasting proves to be a central and increasingly difficult topic among econometrics and data science alike [10], with inflation demonstrating market changes and global economic stability. In this context, regression-based forecasting often persists as one of the most popular approaches, despite heavy performance dependency on capturing accurate non-linearity.

Following from the examples of [9] and [11], this study looks to resolve these issues by comparing the performance of Ridge and Lasso regression, both with and without polynomial feature transformations, and contrasts them against a baseline Ordinary Least Squares (OLS) model. The motivation lies in testing whether introducing higher-order interactions among predictors enhances model accuracy or, conversely, leads to overfitting and consequential loss in predictive capability.

The following hypotheses guide the analysis: H1: Polynomial features improve the predictive performance of regularised regression models for short-term inflation forecasting. H2: Polynomial features introduce unnecessary complexity, worsening model performance. H3: Neither regularised regression nor polynomial expansion provides adequate forecasting capability for inflation.

2 Dataset Description

The project uses three primary datasets: Money Supply: [4], Inflation: [3],Commodity Prices: [8].

Firstly, commodity prices include: metal price index, oil price index, gas price index and food price index, selected through domain knowledge as widely assumed determinants of inflation [2, 1].

All datasets cover the period from January 1992 to January 2024 to specifically look at post inflation-targetting monetary policy time-line. Preprocessing involved:Removing irrelevant columns from individual datasets, combining all datasets into a unified panel, applying Kalman smoothing to handle missing values and performing log-difference transformations on all predictor variables. These steps ensured stationarity and comparability across predictors such as food, oil, gas, metals, and money supply. The lagged and transformed dataset (before polynomial expansion) is 33 rows or months long, with columns for the transformed predictor values, lagged at both one- and three-month periods.

3 Methods

All experiments were executed in Python 3.12 using scikit-learn 1.5, using 6-fold time-series CV (expanding window, test = 3 months). Optimal hyperparameter selected for each independent model via grid search. Code and data cleaning scripts are available in the complementary Jupyter notebook. Feature engineering began with lagging all predictor variables to capture temporal dependencies and delayed effects of monetary and commodity indicators. A baseline OLS model was first trained to establish benchmark performance. Ridge and Lasso regression were then implemented to explore the benefits of regularisation [6, 11]. Both models underwent: time-series cross-validation, grid-search hyperparameter tuning, specifics within fig1 and predictor standardization. Subsequently, polynomial feature expansion (10 to 220 as per 3 degrees) was applied to all regularised models [5]. The optimal polynomial degree was determined via grid-search within the same validation framework. Evaluation metrics included Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), R^2, and Directional Accuracy (DA) [7]. This experimental setup allows for a clear comparison between linear and polynomial regularised models, controlling for hyperparameter tuning and temporal dependencies.

4 Results And Dicussion

H1 accepted, both models improved predictive capability after introduction of polynomial features, most significantly being an improvement from 0.15 to 0.27 (52% percent) increase in R squared for the Ridge model. However, an important consideration for model evaluation is differing results regarding directional accuracy. While polynomial features outperformed non-polynomial models in RMSE, MAE and R squared, all linear models performed better on directional accuracy, with OLS and Ridge both accurately predicting directional accuracy 82.3 percent of the time. Moreover, the linear coefficients were also extracted for the Ridge model, as the highest performing non-polynomial model, which demonstrated a strong exertion of food prices with the largest standardised effect, aligned with the findings of [2] on the role of global food price shocks on inflation. Food prices: 0.81, Oil and gas: 0.2–0.3, Money supply and metals: 0.1–0.2

Crucially, findings indicate that the introduction of polynomial features into regularized regression allowed for increased complexity without the introduction of damaging noise sensitivity. Most importantly, this allows for the model to move beyond linear relationships while still ensuring generalization is prevalent. Significantly, these results align with theoretical understanding, demonstrating the complex, versatile and multicellularity between commodity price indices, money supply and inflation. These inter dependencies reflect findings from [1] and [2]. However, differences in performance regarding directional accuracy, with a 4 pp decline between ridge, prior to and after polynomial transformation, suggest that linear models greater capture the underlying trend more and particularly, are more resistance to the high levels of noise. Conversely, polynomials demonstrate much higher variance and consequently, are more directionally unstable due to introduction of tight curves. Overall, while polynomial inflation forecasting models introduce drastic increases in capability to predict quantity of change, there exists a trade-off for introducing variance and therefore decreased directional accuracy.

Food index demonstrating high coefficient values appears indicative of accurate coefficient values. As a key mechanism in cost-of-living food presumably would play a very significant role in determining inflation. However, also notable is the potential for multi-collinearity to be demonstrating here, with food prices acting as a proxy for need to raise prices if oil, gas are increasing. Additionaly, these are exemplified through polynomial inflation of features and resulting coefficient inflation.

Considerably, while results only look to predict 1–3-month inflation, there is potential the mechanisms examined play much more determining roles over longer-term periods, hence lower coefficients here, most notably probable for money supply.

5 Conclusions

H1 accepted, H2 and H3 rejected. Polynomial feature engineering can meaningfully improve the predictive performance of regularized regression models for inflation forecasting, particularly in explaining variance [9]. However, this gain comes at the cost of reduced stability and interpretability as additional correlated terms are introduced. Importantly, there are several considerations regarding the research in: nature of regularized regression, possible data limitations and reverse causality. Firstly, due to the nature of hyperparameter sensitivity within regularized regression models, coefficient reports may alter significantly on different datasets with differing optimal parameters. Additionally, due to the nature of economic data, coefficients are not often stable and may be changing, future research may wish to employ a sliding window validation to cross-validate changes to coefficients as a result. Furthermore, there is risk of endogeneity, as inflation dynamics often involve large elements of expectation and psychological factors, often leading to self-fulfilling prophecy and consequently reverse causality in this instance. Additionally, the exemption of any significance tests implies potential existence of some sample variability as well limited inferable statistical significance. Lastly, the usage of monthly data within time frame results in potentially limiting sample size (33), further adding to statistical significance complications. In conclusion, the research provides clear exploration of the capability of polynomial regularization models to improve predictive capacity on inflation forecasting, also significantly demonstrating the outer limits of regularization ability to stabilize an over-parameterized system. However, due to structural risk of excessive N:P ratio, as a result of higher degree polynomial transformation and lacking significance tests, future work must develop on exploration and prioritize scaling the dataset to achieve a statistically robust ratio, which is the necessary precondition for confirming whether the observed non-linear gains are structural or merely statistical artifacts of over-parameterization. Consequently, future research should: Explore dynamic coefficient models (e.g., time-varying ridge), employ sliding-window validation to capture evolving relationships, investigate hybrid models combining regularisation with ensemble or neural techniques, utilize further model complexity such as kernelized Ridge or interaction-sparse Lasso, increase sample size by utilizing bi-weekly instead of monthly, to allow for larger folds and test sizes and/or expand inflation data sample size to reduce N:P ratio.

6 Figures

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--- Model Comparison ---
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	Model	Best Alpha	Poly Degree	RMSE	MAE	R^2	MAPE (%)	DA (%)
2	Ridge (poly degree 3)	100	3	1.957502	1.367222	0.276915	138.861539	76.470588
1	Ridge (no poly)	10	-	2.127197	1.598845	0.146113	191.330518	82.352941
3	Lasso (poly degree 3)	1	3	2.158252	1.352234	0.120999	100.026388	64.705882
0	Lasso (no poly)	0.1	-	2.186279	1.734186	0.098022	221.808270	76.470588
4	OLS (no poly)	-	-	2.515284	1.866163	-0.193875	234.255224	82.352941
5	OLS (poly degree 3)	-	3	3.519311	2.818801	-1.337224	343.706803	76.470588

Figure 1: Comparative performance of OLS, Ridge, and Lasso with and without polynomial features predicting 1-3 month inflation rate forecasting using money supply, inflation and commodity price index data from 1992-2024. Time series split using $\mathrm{N}_folds = 6, test_size = 3(months)$.

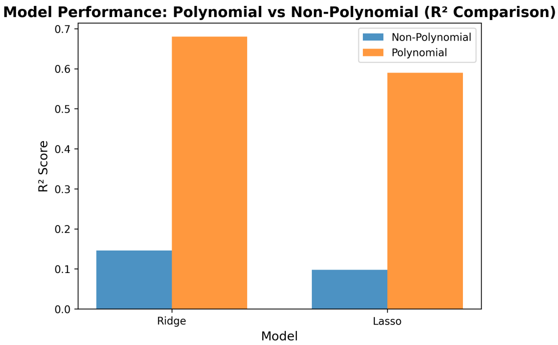

Figure 2: Regularised model performance comparison (polynomial vs. non-polynomial) when predicting inflation forecasting over 1-3 months using money supply, inflation and commodity price index data from 1992-2024. Ridge performed at an R squared of [0.146 and 0.277] while Lasso performed at [0.098 and 0.121] over their non-polynomial and 3 polynomial counterparts, selected via grid-search. Both models managed to outperform baseline OLS (-0.19). Time series split using $\mathrm{N}_folds = 6, test_size = 3(months)$

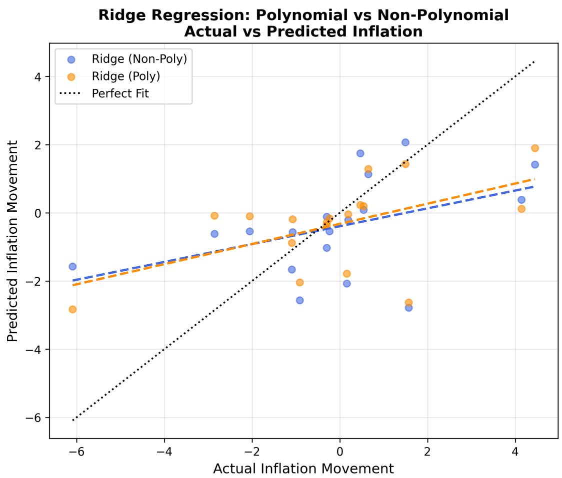

Figure 3: Actual vs. predicted inflation for the Ridge model (best performer with optimal polynomial degree selected via grid search), when predicting inflation forecasting over 1-3 months using money supply, inflation and commodity price index data from 1992-2024. Time series split using $\mathrm{N}_folds = 6, test_size = 3(months)$.

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