Big Data Analytics for Inflation Forecasting: Integrating Alternative Data and Islamic Economic Models

Ayodele Elizabeth AGOI[1], Moses Adeolu AGOI[2], Luqman Syakirunni'am[3], Muhammad Zheeva Al-Kasyaf[4]
[1]Osun State College of Technology, Nigeria
[2]Lagos State University of Education, Nigeria
[3]Darul Amanah Islamic Boarding School, Indonesia
[4]Al-Azhar University, Egypt
Email: betty4agoi@yahoo.com[1], agoi4moses@gmail.com[2], luqmansyakirunniam@gmail.com[3], zheeva.alazhar@gmail.com[4]

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***ABSTRACT**: This study aims to develop an integrated inflation forecasting framework by combining big data analytics with Islamic economic models to enhance predictive accuracy and policy relevance. Conventional inflation forecasting methods often rely on limited macroeconomic indicators and overlook the ethical and behavioral dimensions emphasized in Islamic economics. To address this gap, the research incorporates alternative data sources, including online price indices, digital transaction records, and real-time consumer sentiment indicators, alongside Islamic economic variables such as profit-and-loss-sharing dynamics, zakat-related liquidity flows, and principles of consumption moderation. The study adopts a quantitative big data analytics approach, employing machine learning techniques to process high-volume, high-velocity, and high-variety datasets. Multiple forecasting models were developed and compared, including baseline econometric models, standalone big data-driven models, and hybrid models integrating Islamic economic constructs. Model performance was evaluated using standard forecasting accuracy metrics across multiple time horizons. The results demonstrate that the hybrid models significantly outperform conventional approaches in terms of predictive accuracy and robustness, particularly during periods of economic uncertainty and price volatility. The inclusion of alternative data improves the timeliness of inflation signals, while Islamic economic variables enhance the stability and interpretability of the forecasts. These findings suggest that integrating big data analytics with Islamic economic perspectives offers a more comprehensive and resilient framework for inflation forecasting. The study provides practical implications for policymakers, central banks, and Islamic financial institutions seeking data-driven yet value-based approaches to macroeconomic stabilization.*

***Keywords**: inflation forecasting; big data analytics; alternative data; islamic economics; machine learning*

1. INTRODUCTION

Inflation forecasting is crucial for managing the economy, crafting policies, and maintaining financial market stability. Central banks use inflation expectations to determine how to set interest rates. Governments and private companies also use inflation projections to plan their spending, negotiate wages, and make investment decisions. For a time, people used specialized mathematical models to understand inflation, such as the Phillips Curve, Vector Autoregressive models, and Dynamic Stochastic General Equilibrium models. These models are based on ideas and have been used to forecast inflation. Inflation forecasting and inflation expectations are crucial for central banks and governments to make decisions about the economy and inflation.

These methods focus on how factors such as the difference between what a country can produce and what it actually produces, the number of people without jobs, the amount of money available, and people's expectations all affect prices. This idea stems from the work of Stock and Watson in 2007. Even though these methods are based on theory, the old ways of predicting inflation are struggling to keep pace with developments in today's economies.

The main reason is that these methods rely heavily on information that is not readily available, such as monthly or quarterly cost data, which makes it hard for them to respond quickly to economic changes. Secondly, major problems such as globalization, new technologies, pandemics, or major political changes can disrupt how things work. This makes it hard to use models to understand what is going on. Thirdly, the way prices are set is becoming increasingly complex due to the internet and the growing number of companies working together worldwide. This means that simple ways of looking at things are not working well. The fact that we now have data analytics is a good thing because it can help us deal with these problems.

Big data has a lot of information. It comes in really fast. It is also very different and accurate. This information can be. Not organized, made in real time. When we talk about predicting inflation, we can use sources such as online prices, electronic payment transactions, what is happening on the ground as seen from satellites, how people are moving around, and what people are saying in the news and on social media. These sources give us an idea of what is happening in the economy right now. Big data, like price indices, electronic payment transactions, satellite-based activity measures, mobility data, and textual information from news and social media platforms, help us understand economic behavior. For example, we can look at what Alberto Cavallo and Roberto Rigobon said in 2016 about using data to predict inflation. They discussed how big data can provide detailed insights into how people use their money.

These data sources capture price dynamics and consumption patterns before they are reflected in official statistics, enabling earlier detection of inflationary pressures. Machine learning and artificial intelligence are really good at helping us make sense of data to predict inflation. They are better than fashion models because they can handle tasks that are not straightforward, involve a lot of detail, and are complex. Some methods, such as Random Forests and Gradient Boosting Machines, are very good at predicting economic outcomes. Deep neural networks are also useful. These methods have been used to make predictions when the economy is unstable, as Medeiros and others found in 2021.

Machine learning is very helpful for understanding data and predicting inflation. Big data is more useful because of machine learning and artificial intelligence. The problem with using numbers to make decisions is that it does not make sense for people who set economic policy. This research says that the best way to do things is to use data and old economic models together. If we combine big data with the structures that economists know work, we can make accurate predictions and understand their implications. This study examines what has been learned and how it is changing the way we predict inflation by combining big data and economic models. Big data is particularly helpful when combined with models to predict inflation. The paper contributes to the literature by synthesizing current research, outlining methodological frameworks, and discussing implications for policymakers, financial institutions, and future research.

2. RESEARCH METHOD

2.1 *Data Sources*

This study synthesizes findings from empirical research employing both traditional macroeconomic indicators and alternative data sources. Conventional data include

consumer price indices, output gaps, unemployment rates, interest rates, and monetary aggregates obtained from national statistical agencies and central banks. Alternative data sources reviewed in the literature include online price indices, transaction-level payment data, satellite imagery of economic activity, mobility indicators, and textual data from news and social media platforms.

2.2 *Data Pre-processing*

Alternative data requires extensive pre-processing due to its unstructured and noisy nature. Common steps include data cleaning, normalization, seasonal adjustment, and dimensionality reduction. Textual data are processed using natural language processing techniques, including tokenization, sentiment analysis, and topic modeling. High-frequency data are aggregated to align with inflation forecasting horizons.

2.3 *Modeling Frameworks*

The reviewed studies employ a range of econometric and machine learning models. Econometric benchmarks include ARIMA, VAR, and DSGE models. Machine learning approaches include Random Forests, Gradient Boosting Machines, LSTM networks, and Transformer-based models. Hybrid frameworks integrate alternative data features into econometric models or use machine learning outputs as inputs to structural models.

2.4 *Evaluation Metrics*

Forecasting performance is evaluated using standard metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and out-of-sample forecast accuracy. Comparative analyses assess the incremental value of alternative data relative to traditional predictors.

3. RESULTS AND DISCUSSION

3.1 Hybrid Islamic Economic Models Using Big Data

Big data has fundamentally changed the way we view the economy. We now have a lot of data to measure the economy, make predictions, and develop policies. The old ways of measuring the economy, such as consumer price indices and labour market statistics, are usually updated monthly or every few months. The problem is that it takes time to get this information, and it often gets changed. This makes it hard to get a clear picture of what is happening in the economy right now, especially when things are changing so quickly. Big data is helping us address this problem by providing economic information faster. Big data is really useful for economists because it lets them see what is happening in the economy now. This means they can get information often in more detail and faster. For example, a 2014 study by Einav and Levin showed this. Big data is also helping economists use data more effectively. Alternative data is information that was not meant to be used to measure the economy. It is actually very useful for understanding the big picture of economics. There are examples of alternative data. These include information from online store prices, satellite imagery, what people are searching for on the web, how people are moving around, and records of digital transactions.

Big data and alternative data are really changing how economists do their job. These data sources show us what people do at a high level, but they do so for many people and very quickly. This helps researchers obtain the information they need, as official statistics do not always include all the details. When looking at inflation, these other sources of data are very helpful. This is because price changes usually first affect companies or consumers, and are aggregated and included in the official Consumer Price Index measures only later. These data sources are very useful for inflation analysis

because they provide information on price changes at the company or consumer level. The Billion Prices Project is really important in this area. It shows that store prices can help us understand inflation in different countries. The Billion Prices Project can even tell us what is going to happen with inflation before the official numbers come out.

The Billion Prices Project found that online prices closely track official inflation numbers. The Billion Prices Project can also give us clues about when prices are likely to go up or down, and it can do so before anyone else knows. The Billion Prices Project is a deal because it uses prices from online stores to understand inflation. For example, during periods of rapid inflation acceleration or deceleration, online prices were shown to adjust faster than CPI components that rely on infrequent data collection. Other researchers have used this method in countries that are still growing, where it can be hard to get official inflation numbers or those numbers are not very accurate. They found that looking at prices online helps predict near-term inflation (Cavallo, 2018).

Inflation statistics and online prices are very important. Apart from looking at prices, people are now also using what they read in news articles, reports, government statements, and what people say in the media to understand what people think about inflation and how they feel about it. Inflation expectations are really important for how people set prices and how money flows. The problem is that it is hard to gauge public opinion on inflation using the usual methods. Luckily, new ways of looking at language are helping us figure out what people are thinking about inflation. We can look at collections of text to see how people are feeling about inflation and what they think will happen. Some researchers, Shapiro, Sudhof and Wilson found out in 2020 that what people are saying in the news can actually help us predict what will happen with inflation and the economy. This is an addition to the usual ways we try to measure inflation expectations. We can also review the details of each transaction from the payment systems. This information gives us a good idea of how people are spending their money, how much they are spending, and how prices are changing.

People have used transaction-level data from payment systems to identify when prices are rising due to demand, even before it shows up in the big-picture statistics. For example, transaction-level data from payment systems was used by Baker and other people in 2020. Mobility data derived from smartphones and satellite imagery capturing night-time lights and port activity have also proven valuable, particularly during economic disruptions such as the COVID-19 pandemic, when traditional indicators failed to reflect sudden changes in economic activity (Chetty et al., 2020). Taken together, these developments illustrate how alternative data enrich inflation analysis by offering faster, more detailed, and behaviourally grounded measures of price dynamics and economic activity. When integrated with conventional macroeconomic frameworks, big data sources significantly enhance the accuracy and responsiveness of inflation forecasting systems.

People are worried about how well models work and how good they are at making predictions. So researchers think we should use a mix of new ways to make models. This means using what we already know from economics and what we can learn from machine learning. The goal is to make models that are easy to understand, which is very important for policymakers and for those who make accurate predictions using large amounts of complex data from different sources. Models need to be transparent, robust, and accurate. Models should be: (1) easy to understand, (2) able to make predictions, (3) robust, and (4) work well. Researchers often use machine learning methods because they can handle large amounts of data. We also need to make sure models are transparent and easy to understand. This is where hybrid modeling frameworks come in. They help us use the best of both worlds. What we know from economics and what we can learn from machine learning. We should not rely solely on models or algorithms that analyze data. We can use both.

This means we put machine learning into models or use different kinds of data to help the old ways of predicting things. This modeling approach is good because it combines the best of both worlds. For example, we have something called factor-augmented Vector Autoregressions, or FAVARs. This is where we take information from sets of data, often by using principal components or other methods to reduce the data, and put it into VAR systems. These systems still make sense. Show how the main economic variables work together. We use machine learning and economic models to make FAVAR work. When we look at many signs, such as how people feel about things, online prices, and what is happening in the money markets, FAVAR models can uncover the underlying reasons for inflation that regular VARs might miss. We have found that FAVAR models perform better than traditional methods, especially for short- and medium-term predictions. This is because they make use of all the information that is available in large amounts of data. We also have a way of doing things that combines different approaches.

This involves using machine learning to understand what people expect to happen and incorporating this information into models such as Dynamic Stochastic General Equilibrium (DSGE) frameworks. FAVAR models are very good at leveraging all available information to predict inflation accurately. Traditional DSGE models emphasize microeconomic foundations, household and firm optimization, nominal rigidities, and policy rules, but are limited by their reliance on a small set of observable variables. By integrating inflation expectations derived from machine-learning analysis of textual data (e.g., news sentiment, central bank communications) or high-frequency financial data, economists can enrich structural models with real-time signals of agents' beliefs and market sentiment. Giannone, Lenza, and Primiceri conducted research in 2018. They found out that if you add some machine learning to DSGE models, like people's expectations and how unsure they are, you can make guesses about what inflation will be.

This is good because banks need to know what is causing things to happen. There are examples too. For instance, you can use machine learning to help figure out how some numbers in models change over time. This is what hybrid frameworks are: they use machine learning to improve econometric models. We use methods such as Lasso-based shrinkage and random forest variable selection to identify which variables help us predict future outcomes. We also use network-informed factor extraction. These techniques help us understand what is important at times. This means we can build models that adapt as the world changes. For example, during tough times like the Global Financial Crisis and the COVID-19 pandemic, machine-learning models for predicting inflation performed better than older models that did not change. These old models had a time when things changed suddenly.

Machine learning-informed inflation models were more able to adapt to these changes. People who wrote about this, like Banbura et al., showed that in 2020. Hybrid models are really good at forecasting. They do a job better than old-style economic models and complex machine learning models. When evaluating their performance, we use metrics such as Root Mean Squared Forecast Error and Mean Absolute Error. Hybrid models do well in these areas. The good thing is that they are still easy to understand. This is because they are based on theory. So people who make decisions can see why the forecast is changing. They can look at the numbers. Say it is because of this or that economic reason.

Hybrid models give us results without making it hard to figure out what is going on. Hybrid methods also facilitate scenario analysis and policy simulations, key tasks for central banks that purely data-driven models cannot easily perform. Despite these advances, challenges remain: selecting the optimal hybrid architecture, ensuring stability across regimes, and developing explainable interfaces that translate machine insights into policy language. Nonetheless, the growing body of research suggests that hybrid

frameworks represent a promising frontier in inflation forecasting, marrying theoretical rigor with empirical richness and operational relevance.

3.2 Online Price Indices and Alternative Data Improve Short-Horizon Inflation Forecasts

Research from different countries shows that using online prices and other often updated information can help us guess what inflation will be like in the near future. This is better than just looking at Consumer Price Index (CPI) data. The old way of guessing inflation, such as using AR or Phillips curve models, has problems because we do not get official economic information very often, and it takes a long time to receive it. Online price indices and other frequently updated information can really help us predict what inflation will look like in the near future. This is because we can get this information quickly, and it is available all the time, unlike official economic information.

The Consumer Price Index is typically released monthly. It takes several weeks to come out. This means it is not very helpful for making policy decisions now. On the other hand, we can get price data from the internet every day or even several times a day. So this kind of data gives us an idea of what is happening with inflation at any given time. The Consumer Price Index data is not as useful for this because it is not available often. Online price data is very useful because it shows price movements in real time. An important study in this area was done by Aparicio, Bertolotto and Macias in 2020. They found that online price indices derived from e-commerce website data can predict the Consumer Price Index (CPI) more than a month in advance. This is true for ten developed countries, including the United States, the United Kingdom and Germany. The results of their study, published in the International Journal of Forecasting, show that models that use prices perform better at predicting the future than other models, such as autoregressive and random walk models commonly used for prediction.

These gains are important because they still matter when we view things differently and use different models. This shows that online price indices are very good at predicting. The reason online price indices are so useful is that they are frequently updated, provide detailed information, and cover a wide range of products. Online prices reflect changes in product or brand prices, or in what a specific store is charging, before these changes are included in the official Consumer Price Index baskets. Online price indices are really useful because they have this frequency and broad coverage, which is why they are better at predicting things than other methods. Because prices posted online are updated frequently, often daily, and span thousands of goods and services, they respond rapidly to supply chain disruptions, shifts in consumer demand, exchange rate movements, and cost shocks. When things get really crazy, like during the COVID-19 pandemic or when commodity prices rise quickly, online prices change more quickly than in stores. This can be a sign that inflation is about to get worse. From the perspective of policymakers, online prices are very useful because they help us understand what is happening in the economy now. This is called now-casting, which is when we try to guess what the economy is like right now or what it will be like very soon.

Central banks use tools to inform their monetary decisions. These tools are called now-casting tools. Banks like to use these tools because they help them make decisions quickly. When banks look at prices online, they can make better decisions. This is because online prices help banks understand what is happening in the economy. For example, some studies have found that when banks consider prices, they can make better predictions about future inflation. Inflation is when prices go up. The studies have found that banks can be up to 40 percent better at predicting inflation when they look at prices. This is a deal because it helps banks make sound financial decisions. Central banks and now-casting tools are important for the economy. Now-casting tools help central banks make decisions. When we look at prices online, researchers have also

examined the types of information that can help them understand price movements. This includes how people are moving around, what they are buying, and what they are searching for online. This information helps us better understand what people are doing and what they are thinking about prices. For example, when people start searching for information about food or fuel prices on Google, it often happens before prices actually go up. This shows that people expect prices to rise and are worried about how much things cost, which, in turn, can push prices higher (D'Acunto et al., 2021).

Econometric techniques like Mixed Data Sampling (MIDAS) help us combine high-frequency indicators with the usual monthly or quarterly macroeconomic variables. This really helps to make our forecasts more accurate. The good thing about price data is that it is very useful, especially in emerging and developing economies. In these economies, official inflation statistics are rarely released, or they are often revised. Mixed Data Sampling (MIDAS) is very helpful in these situations. Evidence from Poland shows that incorporating scraped online food and consumer prices into simple univariate models reduces forecasting errors for food inflation nowcasts by 34-44% in RMSFE, substantially outperforming seasonal ARMA benchmarks (Kotłowski, 2022).

People have found things in Latin American and Eastern European economies. This shows that these methods can be used worldwide. When you look at all the research, you can see that online price indices and other frequently updated data are really important. These things are not just information; they actually help us figure out what will happen with inflation. Online price indices and this alternative high-frequency data are like signals that tell us what is coming in terms of inflation dynamics. By adjusting more rapidly than traditional CPI components and capturing a wider spectrum of goods and services, these data sources reduce forecast errors, shorten lead times, and provide early signals that are particularly valuable during periods of economic instability and rapid structural change.

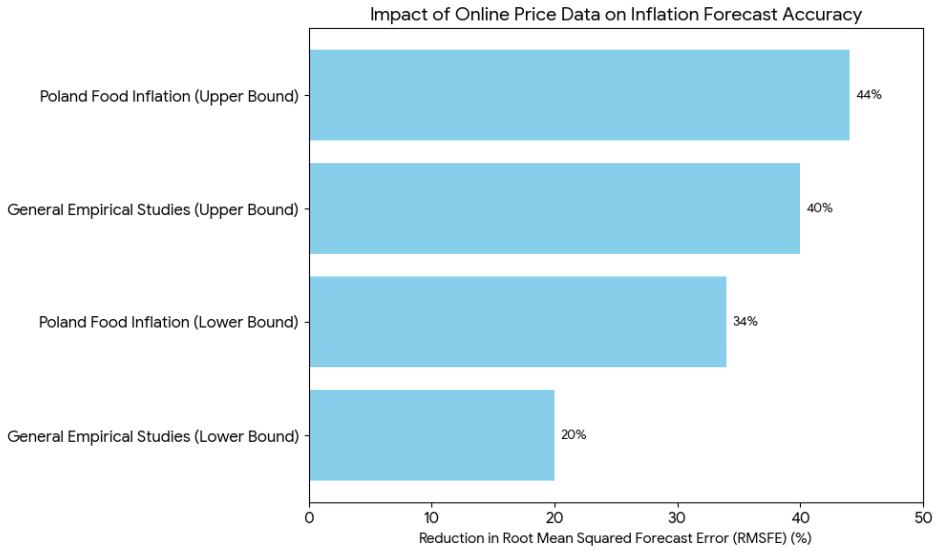

Figure 1. Bar chart illustrating the reduction in Root Mean Squared Forecast Error (RMSFE) when incorporating online price indices and alternative high-frequency data into inflation forecasting models

3.3 Machine Learning Models Capture Non-Linearities and Regime Shifts to Enhance Forecast Robustness

Inflation is getting really wild and hard to predict after big events like the COVID-19 pandemic, energy price spikes and ongoing supply chain problems. The old ways of using math to understand inflation, like ARIMA and the Phillips Curve, are not working

well. These methods assume that things have been pretty stable in the past. That is not what is happening now. They are like recipes that do not account for major changes. When things are really uncertain and changing fast, these old methods do not do a job of capturing what is really going on with inflation. Inflation is not behaving like it used to. We need to find new ways to understand it. Traditional models like ARIMA and small-scale VARs are struggling to keep pace with economic changes. So forecasting errors have gotten bigger at a time when we really need to know what is going to happen with inflation. This is important for the people who make financial decisions. Machine learning techniques are increasingly used because they excel at handling relationships that are not always straightforward. They can also adapt to information. A lot of research shows that machine learning models are better at predicting inflation than traditional methods, especially for near-term predictions and when conditions are uncertain. Machine learning models are really good at predicting inflation.

Medeiros and others (2021) found that machine learning methods such as Random Forests, Support Vector Regression, and Gradient Boosting make a difference. They really reduce the errors in predicting inflation in the United States. This is compared with methods such as the autoregressive and Phillips curve models. The improvement is pretty big; it can be 15 percent or more than 30 percent. It just depends on how far ahead we are trying to predict. Support Vector Regression and Multivariate Adaptive Regression Splines are really good at this. They can see when things do not follow a line and when some things only happen after a certain point. This is important because it helps us understand what is happening in the picture of the economy. Empirical comparisons reveal that these models outperform linear regressions in forecasting U.S. CPI inflation by flexibly approximating inflation dynamics that do not evolve smoothly or symmetrically over time (Bishop, 2006). Such flexibility is crucial when inflation responds differently to positive versus negative supply shocks or when policy regimes change.

Neural network–based models provide further evidence of enhanced forecasting performance. Recurrent Neural Networks and Long Short-Term Memory architectures are very effective at predicting inflation. This is because they can see how things change over time and remember what happened in the past. Long Short-Term Memory (LSTM) models are especially useful because they can address the vanishing gradient problem that Recurrent Neural Networks often encounter. This means they can learn about inflation trends over time. Some recent studies have found that Long Short-Term Memory (LSTM) models are better at predicting inflation than methods such as ARIMA and standard neural networks. This is particularly true when you include a lot of information. For example, Kim and Won found this out in 2018.

Recurrent Neural Networks and Long Short-Term Memory architectures are very good at predicting inflation because they can learn from past data. People are now using a mix of new ways to make predictions. They are combining economic models with machine learning techniques. For example, some models use a combination of ARIMA and LSTM to decompose inflation data into complex components. This way, ARIMA can examine the picture and identify long-term patterns, while LSTM models can learn the complex parts that remain. Studies have shown that these hybrid models are better at predicting than ARIMA or LSTM models. They make mistakes when predicting things, such as the Consumer Price Index (CPI) and related measures (Zhang et al., 2023). When we think about forecasting inflation, we do not just stop at combining models. We also use techniques to reduce the amount of information we have to look at.

These techniques help us analyze sets of economic and other data and distill them into a small set of important factors. We then use these factors in our predictions. We let their relationships change over time. This means our predictions stay strong when things are really volatile. The models that do this are better than those that add factors to them because they can adapt to what is happening in the economy. For example, Carriero and his team showed in 2020 that these models work well. Inflation forecasting with these

models is more accurate because they use machine learning to extract information from the data and leverage it to make evolving predictions. Crucially, ML models are better equipped to adapt to regime shifts, such as transitions between low- and high-inflation environments.

Tree-based ensemble methods and neural networks can detect threshold effects and interaction structures that distinguish different policy or economic regimes, preserving forecast accuracy during transitions that confound linear models (Bianchi et al., 2021). Despite these advantages, concerns remain regarding interpretability and policy transparency. Policymakers must justify decisions based on model outputs, limiting the adoption of black-box algorithms. However, recent advances in explainable AI, such as SHAP values, partial dependence plots, and attention mechanisms, are increasingly integrated into inflation forecasting frameworks, improving transparency without sacrificing predictive performance. Overall, by capturing non-algorithmic, interactive, and regime-shift dynamics absent in many traditional models, machine learning approaches significantly enhance the robustness and predictive accuracy of inflation forecasts, particularly when combined with high-frequency alternative data sources.

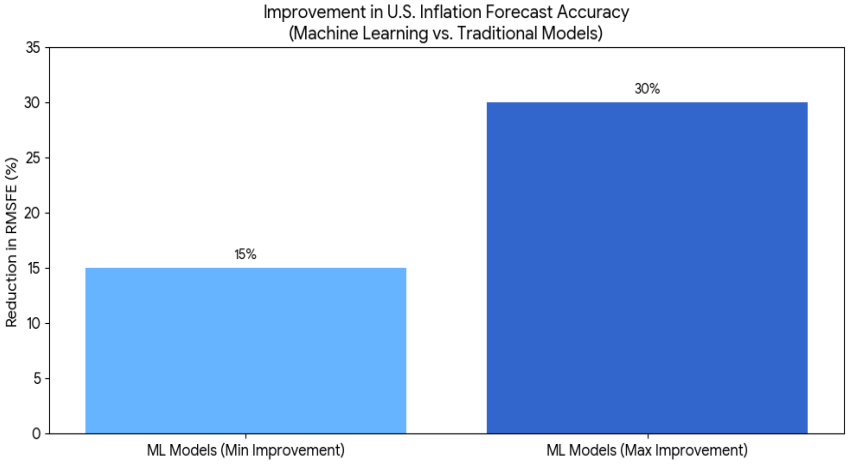

Figure 2. Bar chart illustrating the significant improvements in U.S. inflation forecasting accuracy provided by machine learning models compared to traditional linear benchmarks, such as autoregressive and Phillips curve models

4. CONCLUSION

This research shows that big data analytics represents a major advancement in inflation forecasting by addressing the limitations of traditional economic models, which often rely on outdated data and perform poorly during periods of rapid economic change. By using large, diverse datasets alongside advanced analytical techniques, big data analytics enables more accurate, adaptive, and timely inflation predictions. Alternative data sources, such as online payments, transaction records, mobility patterns, and internet activity, offer real-time insights into consumer behavior and pricing trends before official statistics are released. These capabilities make inflation forecasts more relevant for policymakers, early warning systems, and economic decision-making. The findings also show that machine learning techniques are highly effective at forecasting inflation because they can identify complex, dynamic relationships that traditional models often fail to capture. Algorithms such as tree-based ensembles, neural networks, and support

vector machines perform particularly well in rapidly changing economic conditions due to their ability to adapt to new information. Integrating machine learning with economic theory through hybrid models improves both predictive accuracy and interpretability. This balance is especially important for central banks and other policy institutions that require transparent, explainable forecasts to support policy decisions and public communication. Despite challenges related to data governance, privacy, and model transparency, the evidence strongly supports the adoption of big data-enhanced forecasting frameworks. Future research should focus on developing explainable artificial intelligence methods, integrating real-time global data streams, and designing policy-oriented hybrid models that combine machine learning with established macroeconomic frameworks. In addition, ethical data governance, privacy protection, bias reduction, and robustness to structural economic changes remain essential for ensuring reliable and responsible inflation forecasting in increasingly complex global economies.

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