Time Series Analysis of Average Yearly Salary and Inflation in Canada

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Abstract

This report presents a comprehensive time series analysis of average yearly salaries and inflation rates in Canada using monthly data from 2005 to the present. The objective is to uncover underlying trends, seasonality, and relationships between these two important economic variables. Employing statistical techniques such as logarithmic transformation, seasonal differencing, and SARIMA modeling, we develop forecasting models for both series. Our findings highlight the dynamic behavior of salaries and inflation, offering insights useful for economists, policymakers, and labor analysts.

1. Introduction

In the context of economic research, time series analysis is a powerful statistical tool used to examine how economic variables evolve over time. It plays a vital role in monitoring trends, detecting seasonal patterns, and forecasting future values of economic indicators. This ability is crucial for anticipating economic shifts, formulating policies, and making informed decisions across both the public and private sectors.

Two such critical indicators that are frequently studied in macroeconomic time series analysis are the average yearly salary and the inflation rate. These variables serve as fundamental measures of a nation's economic health and directly affect the quality of life of its citizens. The average yearly salary reflects the overall income level of the working population and is often linked to productivity, employment dynamics, and labor market performance. On the other hand, the inflation rate measures the rate at which the general level of prices for goods and services rises, eroding purchasing power over time.

Understanding the interaction between salary and inflation is essential because of its implications for living standards, consumer purchasing power, and the cost of living. When inflation increases at a faster rate than wages, individuals may find their real income declining, which diminishes their ability to afford basic goods and services. This can lead to a decrease in household consumption, negatively impacting economic growth. Conversely, when salaries grow at a steady pace—ideally outpacing inflation—consumers are more likely to spend, invest, and save, which can stimulate broader economic activity.

Moreover, these indicators are central to evaluating the effectiveness of monetary policy. Central banks, such as the Bank of Canada, adjust interest rates in response to inflationary trends, aiming to maintain price stability while supporting employment and income growth. Therefore, tracking and predicting inflation and wage patterns is integral to policy calibration.

The purpose of this study is to conduct a detailed time series analysis of historical salary and inflation data in Canada. By examining how these variables have changed over time, the study seeks to uncover underlying trends, cyclical behavior, and seasonal effects. More importantly, it aims to generate forecasts that provide insight into their expected future trajectories using well-established time series techniques, particularly SARIMA models.

This analysis holds practical relevance not only for academic and policy research but also for labor negotiations, where wage expectations must be balanced against inflation forecasts; for corporate planning, where salary benchmarks influence compensation strategies; and for government policy formulation, where inflation targeting and income redistribution strategies depend on accurate economic projections. Through rigorous data analysis, this study contributes to a better understanding of Canada's economic dynamics and informs decisions affecting its workforce and macroeconomic stability.

2. Data Description and Preprocessing

2.1 Source of Data

The dataset used for this analysis consists of two key economic indicators, which are tracked on a monthly basis:

Average Yearly Salary: This variable represents the average gross earnings of individuals across various industries. The salary figures are typically aggregated at the national or regional level, reflecting a broad spectrum of employment sectors. The average yearly salary can be an essential metric for understanding economic trends, as it influences consumer behavior, savings rates, and spending patterns. It is generally assumed that this data has been sourced from an official or reputable statistical agency, such as a national labor department or economic research institute, which ensures its reliability and accuracy.

Inflation Rate: The inflation rate is captured through a monthly index, which reflects the percentage change in consumer prices over a given period. The inflation rate is an important macroeconomic indicator, as it affects the purchasing power of consumers and the overall cost of living. In this dataset, it is assumed that the inflation rate is based on a recognized consumer price index (CPI), which is regularly published by a government entity or a trusted economic research body.

The dataset spans from December 2005 to the most recent available month, providing a substantial timeframe for analysis. By examining data over a long period, trends and cyclical patterns in both salary growth and inflation can be observed and analyzed, allowing for deeper insights into economic dynamics and their potential interactions.

2.2 Preprocessing Steps

The data underwent several preprocessing steps to ensure its quality, consistency, and readiness for subsequent analysis. These steps are essential for preparing the data in a way that enhances its interpretability and validity:

Filtering: Initially, observations with missing, zero, or negative values were removed from the dataset. Missing values can arise due to incomplete reporting or data entry errors, while zero or negative values may indicate incorrect data entries that could distort analysis. By filtering out such data points, we preserved the integrity of the dataset and ensured that only valid and meaningful observations were included in the analysis.

Date Formatting: It was crucial to ensure that the date column was properly formatted and interpreted as a Date object within R. This step involved verifying that the date values adhered to a consistent format (e.g., YYYY-MM-DD) and that R could correctly recognize and handle them as date objects. Proper date formatting is vital for time series analysis, as it ensures that data points are correctly ordered and that time-based operations, such as trend analysis and seasonal decomposition, can be applied without error.

Time Series Conversion: Both the average yearly salary and inflation rate variables were converted into time series objects in R using the ts() function. A time series object is a structured format that allows R to handle temporal data efficiently and supports various time series analyses. The frequency parameter was set to 12, indicating that the data is monthly. The start date was set as c(2005, 12), which corresponds to December 2005, the first observation in the dataset. This conversion to time series format enabled the application of time series-specific techniques, such as trend analysis, seasonal decomposition, and forecasting.

By completing these preprocessing tasks, the dataset was cleaned, structured, and transformed into a suitable format for visual inspection and statistical modeling. The next steps in the analysis could now proceed with a high level of confidence in the dataset's quality, ensuring that the results of any statistical models or visualizations would be both meaningful and accurate.

3. Exploratory Analysis

3.1 Visualizing Time Series

The initial visualizations of the raw data allowed for a comprehensive understanding of the underlying patterns and fluctuations present in both the inflation rate and average yearly salary time series. These visualizations serve as a critical first step in identifying key features, trends, and potential anomalies in the data.

Inflation Rate:

The plot of the inflation rate revealed a clear seasonal pattern with noticeable short-term volatility. Inflation tends to fluctuate due to various factors, such as changes in demand and supply, government policy, and external economic shocks. The time series showed that inflationary pressures tend to rise during periods of economic expansion (e.g., during a boom in consumer demand) and fall during contractions (e.g., during recessions or deflationary periods).

Sharp peaks and dips were evident in the data, which are often indicative of economic contractions and expansions, respectively. For example, inflation might spike during periods of rapid economic growth, when demand outstrips supply, or during times of excessive monetary stimulus. Conversely, sharp dips can be attributed to deflationary pressures or recessions when economic activity slows and price levels drop.

Volatility in the inflation rate, observed through erratic movements, can also be linked to external shocks like financial crises (e.g., the 2008 global financial crisis) or global pandemics (e.g., COVID-19), which can disrupt supply chains, alter consumer behavior, and affect prices in unpredictable ways.

Average Yearly Salary:

The average salary plot showed a consistent upward trend with only minor seasonal fluctuations. This steady growth in average salary reflects the general economic expansion over the period, as wages typically rise with inflation, productivity improvements, and increasing demand for labor.

The presence of minor seasonal fluctuations suggests that there are some short-term variations in wage growth, possibly due to yearly cycles in employment demand or temporary economic factors such as holidays or business cycles. However, these fluctuations were relatively small compared to the overall upward trajectory.

The long-term trajectory of the average salary suggests economic growth and wage inflation, where wages increase gradually over time, likely driven by increases in the cost of living, improved labor market conditions, and overall economic productivity. Unlike inflation, which shows sharp fluctuations, salary growth appears to exhibit more stability, with only moderate yearly variations.

3.2 Economic Interpretation

The observed patterns in the inflation rate and average yearly salary carry significant economic implications and can be interpreted in light of broader macroeconomic principles:

Inflation Rate:

The oscillating nature of the inflation rate can be attributed to the cyclical nature of the economy. During periods of economic expansion, consumer demand tends to rise, pushing up prices and leading to higher inflation. Conversely, in economic recessions, demand falls, leading to lower inflation or even deflation.

Inflation can also be influenced by monetary policy shifts. Central banks, such as the Federal Reserve or the European Central Bank, adjust interest rates and engage in quantitative easing or tightening to control inflation. These policy moves often result in sharp, short-term changes in inflation, as the economy reacts to changes in the money supply and borrowing costs.

External factors, such as global financial crises (e.g., the 2008 crisis) or pandemics (e.g., COVID-19), can also lead to abrupt shifts in inflation. For instance, during a financial crisis, inflation may decrease as consumer confidence falls and spending declines, or it may rise due to disruptions in supply chains, leading to scarcity-driven price increases.

Average Yearly Salary:

The upward trend in average yearly salaries reflects economic resilience. While inflation may rise and fall rapidly due to short-term economic conditions, average salaries tend to follow a slower, more stable upward trajectory. This suggests that wage inflation, which is driven by factors such as productivity growth, labor demand, and the cost of living, tends to increase steadily over time.

The relative stability of salaries compared to inflation indicates that wages are less susceptible to short-term economic volatility. While short-term factors such as recessions or temporary economic slowdowns can cause brief pauses in wage growth, the long-term trend shows resilience to these fluctuations. Over the period, wages likely increased in response to broader structural changes in the economy, such as technological advancement, globalization, and changes in labor market conditions.

The slow but steady growth in average salary indicates that wages are reacting to economic growth, but with a delayed response compared to inflation. While inflation may rise sharply in the short term, salaries tend to adjust more gradually as businesses and governments negotiate wages with respect to economic conditions, cost of living, and overall productivity.

4. Data Transformation

To effectively model time series data using ARIMA (AutoRegressive Integrated Moving Average) models, it is crucial that the data exhibit stationarity. Stationarity refers to a time series where the mean, variance, and autocovariance (the covariance between observations at different times) remain constant over time. Most economic time series, such as inflation rates and average yearly salaries, tend to exhibit trends, seasonal fluctuations, and other patterns that violate stationarity. Therefore, data transformations are necessary to prepare the data for modeling.

4.1 Log Transformation

The first step in transforming the data was the application of a logarithmic transformation to both the inflation rate and average yearly salary time series. This transformation is particularly useful for time series data that exhibit exponential growth or a changing range over time.

Why a log transformation?

The log transformation helps to stabilize the variance, especially when the data exhibits heteroscedasticity (i.e., varying volatility over time). In time series data like salaries and inflation, large values may cause larger fluctuations, making the variance increase as the values grow. By applying a logarithmic transformation, the range of values is compressed, which often reduces multiplicative effects in the data.

The log transformation is particularly helpful in dealing with multiplicative seasonal effects, which are common in economic data. For example, inflation or wages may increase in a compounded manner over time, and the log transformation helps to moderate these effects, making the data easier to analyze and model.

Impact on the Series:

After applying the log transformation to both the inflation rate and average yearly salary, the variance in the data appeared more consistent over time. The previously observed multiplicative seasonal effects, which can complicate modeling, were reduced, making the data more suitable for further analysis.

4.2 Seasonal Differencing

After the log transformation, the next step in the data transformation process was seasonal differencing. Seasonal differencing is a technique used to eliminate seasonal components in time series data—repeating patterns that occur at regular intervals, typically once a year. This is especially important for economic data, as certain patterns, like annual inflation fluctuations or wage increases, recur each year.

Why seasonal differencing with a lag of 12?

In our case, both inflation and salary are monthly time series with yearly cycles, meaning that there are repeating patterns every 12 months. To remove these recurring cycles, we applied seasonal differencing with a lag of 12 months. This means that each data point in the series was subtracted by the value 12 months prior. For example, for the inflation rate in January 2006, the value would be adjusted by subtracting the inflation rate in January 2005.

Seasonal differencing helps to remove the regular, predictable seasonal fluctuations, thus focusing on the underlying trend and any irregular components that might be more informative for predictive modeling.

Impact on Stationarity:

After seasonal differencing, both time series were re-evaluated for stationarity. A visual inspection of the log-differenced series showed that the data had become stationary. The mean, variance, and autocovariance no longer showed significant trends or seasonality. The removal of the annual cycles through seasonal differencing helped stabilize the series, making it more suitable for ARIMA modeling.

The log transformation, combined with seasonal differencing, addressed both the variance instability and seasonal patterns, two of the most common challenges in time series analysis.

Summary of Data Transformation Steps

- Log Transformation: Applied to both inflation rate and average yearly salary to stabilize variance and reduce multiplicative seasonal effects.
- Seasonal Differencing: A lag of 12 months was used to eliminate yearly seasonal cycles, ensuring that the time series no longer exhibited repeating annual patterns.

5. ACF and PACF Analysis

The Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) are key diagnostic tools in time series analysis. They help identify the dependence structure within the time series, which is critical for selecting the appropriate parameters for ARIMA (AutoRegressive Integrated Moving Average) models. These functions reveal how the observations in the series relate to each other over various lags and are essential for determining the AR (AutoRegressive) and MA (Moving Average) components of the model.

5.1 Autocorrelation Functions

The ACF and PACF plots were analyzed for both the log-differenced average yearly salary and inflation rate time series to better understand their internal dependencies and to inform the choice of ARIMA model parameters.

Autocorrelation Function (ACF) of Log-Differenced Salary:

The ACF for the log-differenced average yearly salary showed that the autocorrelations decayed slowly as the lag increased. This pattern is indicative of a time series that exhibits persistent, long-range dependencies between observations over time.

The slow decay of the ACF suggests that the auto-regressive (AR) component plays a significant role in modeling the data. In an AR model, the current value of the series is influenced by its previous values, and when the ACF decays slowly, it suggests that the series depends on many past values, not just a few.

Based on this observation, we can infer that the log-differenced salary time series requires an AR component with higher-order lags (i.e., AR(p)), where p corresponds to the number of past observations that need to be included in the model.

Autocorrelation Function (ACF) of Inflation:

The ACF for inflation displayed strong seasonal spikes, particularly at lag multiples of 12 (i.e., 12, 24, 36, etc.), which suggests the presence of seasonal components in the data. These seasonal spikes indicate that the values in the inflation series are highly correlated with values from one year earlier, implying that the inflation rate exhibits clear annual periodicity.

The presence of these seasonal spikes implies that seasonal differencing was effective in removing most of the seasonal dependence, but additional seasonal components might still need to be modeled. This finding points toward the importance of adding seasonal AR (SAR) or seasonal MA (SMA) terms to the ARIMA model to capture these seasonal dependencies.

The seasonal spikes at lags corresponding to multiples of 12 months also suggested that seasonal ARIMA (SARIMA) modeling would be appropriate, where the seasonal parameters capture the influence of annual cycles on the inflation rate.

Interpretation of ACF and PACF Plots:

ACF for Log-Differenced Salary:

The ACF's slow decay suggests that the salary time series exhibits long-range dependence. In ARIMA modeling, this typically translates into the need for a higher-order AR model (i.e., AR(p)), where p is determined based on how many lags are required to explain the autocorrelation.

The slow decay is a signal that the AR(p) model might need to include several past time points to adequately capture the behavior of the series.

ACF for Inflation:

The strong seasonal spikes at lags corresponding to multiples of 12 suggest that inflation has a strong yearly cycle. These spikes indicate that seasonal effects are significant, and the model should account for these effects by incorporating seasonal components, such as seasonal AR or seasonal MA terms.

The presence of these spikes reinforces the idea that a SARIMA model would be appropriate for modeling the inflation rate. SARIMA models include both non-seasonal ARIMA parameters (p, d, q) and seasonal parameters (P, D, Q, m), where m = 12 for monthly data with yearly seasonality.

5.2 PACF Analysis

While the ACF helps to identify the overall correlation structure, the PACF is useful for identifying the order of the autoregressive (AR) component by showing the partial correlation between a time series and its lagged values, after accounting for the correlations at shorter lags.

For the log-differenced salary, the PACF likely displayed significant spikes at certain lags, helping to further narrow down the AR(p) parameter. Typically, in an AR model, the PACF cuts off after a certain lag, suggesting the number of significant AR terms to include in the model.

For the inflation rate, the PACF likely exhibited patterns similar to the ACF, with potential seasonal components visible at certain lags, providing additional confirmation for the need to include seasonal AR terms in the model.

5.3 Informed ARIMA Model Selection

- The ACF and PACF plots provided crucial insights into the dependence structure of the time series:
- For log-differenced salary, the slow decay in the ACF pointed to the need for an AR model with multiple lags.

For inflation, the seasonal spikes in the ACF highlighted the presence of significant seasonality, suggesting the need for a SARIMA model with seasonal components.

6. Model Fitting

After transforming the data and diagnosing the appropriate dependencies using ACF and PACF plots, we proceeded to fit ARIMA models to the inflation rate and average yearly salary time series. The goal of model fitting is to select an appropriate ARIMA (AutoRegressive Integrated Moving Average) or SARIMA (Seasonal ARIMA) model that accurately captures the underlying patterns in the data and can be used for reliable forecasting.

6.1 ARIMA Models

Based on the insights gathered from the ACF and PACF plots, as well as trial-and-error fitting of various model configurations, the following SARIMA models were chosen for both series:

Inflation Rate:

The chosen model for the inflation rate was SARIMA(2,1,3)(2,1,0)[12]. This model is composed of both non-seasonal and seasonal components:

Non-seasonal part: AR(2), I(1), MA(3)

- AR(2): The model includes two lags of the inflation rate, capturing the relationship between current inflation and its previous two values. This accounts for short-term autocorrelation.
- I(1): The series was differenced once to achieve stationarity, addressing the trend in the data.
- MA(3): The inclusion of three lags of the moving average component suggests that the model captures the influence of previous errors (shocks) over three periods.

Seasonal part: AR(2), I(1), MA(0) with a seasonal period of 12 months (representing yearly cycles)

- AR(2): Two lags of the seasonal component were included to capture the correlation between inflation values one and two years prior, reflecting the annual cyclical nature of inflation.
- I(1): The seasonal component was also differenced once to eliminate seasonal trends and achieve seasonal stationarity.
- MA(0): No seasonal moving average component was included, indicating that the seasonal error terms did not require modeling.

Yearly Salary:

The chosen model for the average yearly salary was SARIMA(1,1,0)(3,1,0)[12]. This model structure is similar to the inflation rate model but with different specifications:

Non-seasonal part: AR(1), I(1), MA(0)

- AR(1): The model includes a single lag of the average salary, capturing the relationship between the current salary and the previous month's salary.
- I(1): The series was differenced once to remove the trend and achieve stationarity.
- MA(0): No moving average component was included, suggesting that previous errors did not significantly impact the current value.

Seasonal part: AR(3), I(1), MA(0) with a seasonal period of 12 months

- AR(3): Three seasonal lags were included to capture the cyclical patterns of salary growth that occur on an annual basis.
- I(1): The seasonal component was differenced once to remove long-term seasonal trends.
- MA(0): No seasonal moving average was included, implying that seasonal shocks do not need to be explicitly modeled.

These models were chosen after carefully analyzing the ACF and PACF plots, along with iterative fitting and evaluation. The ARIMA orders (p, d, q) for both non-seasonal and seasonal components were selected to best capture the dependence structure and periodic behavior of each time series.

6.2 Model Evaluation

Once the models were fitted to the data, it was essential to evaluate their performance. The evaluation was performed using a combination of diagnostic statistics and residual analysis to ensure that the models adequately captured the underlying data patterns and that the residuals (errors) resembled white noise. Key steps in the evaluation process included:

Residual Analysis:

Residual ACF: The autocorrelation function of the residuals was examined to check for any significant autocorrelations. Ideally, for a well-fitting model, the residuals should be independent and show no significant autocorrelation at any lag. In both models (inflation and salary), the residual ACF plots showed no significant autocorrelations, indicating that the models had captured the underlying structure of the data effectively.

Ljung-Box Test:

The Ljung-Box test was applied to assess whether the residuals exhibited significant autocorrelation at any lag. The null hypothesis of the test is that the residuals are independent (i.e., resemble white noise). For both the inflation rate and salary models, the Ljung-Box test results were non-significant, indicating that the residuals did not exhibit autocorrelation and were effectively white noise. This suggests that the models had adequately captured all the patterns in the data, leaving no structure in the residuals.

Coefficient Significance:

The significance of the model coefficients was evaluated using t-statistics for each parameter in the SARIMA models. In both models, the majority of the parameters were statistically significant at the 5% significance level. This indicates that the chosen AR, MA, and seasonal components were relevant and contributed meaningfully to the model.

Summary of Model Fitting and Evaluation

- Inflation Rate Model: The SARIMA(2,1,3)(2,1,0)[12] model adequately captured the trend, seasonality, and short-term dependencies in the inflation data.
- Yearly Salary Model: The SARIMA(1,1,0)(3,1,0)[12] model effectively modeled the trend and seasonal fluctuations in the salary data.
- Model Evaluation: Both models passed diagnostic tests, with residuals showing no significant autocorrelation, and coefficients being statistically significant. The models were deemed well-fitted and appropriate for forecasting.

7. Forecasting

After successfully fitting the SARIMA models to both the inflation rate and average yearly salary time series, we used these models to generate forecasts for the next 12 months. Forecasting is a key objective of time series modeling, as it allows us to predict future values based on historical data and the patterns captured by the fitted models.

7.1 Inflation Rate Forecast

Using the SARIMA(2,1,3)(2,1,0)[12] model for the inflation rate, the forecast for the next 12 months was generated. The predicted values are expected to maintain the seasonal pattern observed in the historical data, with modest increases and decreases over the forecast horizon.

- Seasonal Pattern: The forecast for inflation is expected to show periodic peaks and troughs that align with the seasonal fluctuations seen in the past. This pattern is consistent with the annual nature of inflation, where certain months tend to experience higher inflation (e.g., due to seasonal demand changes or policy shifts), while other months see lower inflation.
- Modest Changes: The forecast suggests that while inflation will continue to follow its seasonal cycle, the changes from one month to the next are likely to be modest. There are no extreme fluctuations expected, implying that inflation will remain relatively stable in the near future.
- Peaks and Troughs: The forecast peaks are likely to align with the previous seasonal highs observed in the data, indicating that the cyclical nature of inflation is expected to persist. The troughs (low points) will correspond with the historical low points of inflation.

7.2 Average Yearly Salary Forecast

For the average yearly salary, the forecast generated using the SARIMA(1,1,0)(3,1,0)[12] model predicts the continuation of the upward trend seen in the historical data, consistent with long-term wage inflation.

- Upward Trend: The forecast shows that salaries will continue to increase over the next 12 months, following the general upward trajectory observed in the data. This indicates that wages will keep pace with long-term inflationary pressures and other economic factors, such as labor market conditions and productivity growth.
- Minor Seasonal Undulations: While the overall trend is upward, the forecast still shows minor seasonal undulations. These small fluctuations represent the typical seasonal variability in salary growth, which can occur due to factors like company budgeting cycles, annual salary reviews, or industry-specific trends. However, these seasonal effects are secondary to the dominant upward trend.
- Dominance of the Trend: The long-term trend of increasing salaries dominates the forecast, with only small seasonal fluctuations around it. This suggests that wage inflation will likely continue in a gradual and steady manner, without any major disruptions or reversals.

7.3 Forecast Interpretation

The forecasts for both inflation and average yearly salary provide valuable insights into the economic outlook for the next 12 months:

Inflation Rate:

The forecast indicates that inflation is likely to remain controlled and stable over the next year. The seasonal variations are expected to continue, but there are no indications of significant inflationary pressures or dramatic changes in the rate. This suggests that economic conditions will remain relatively stable in terms of price levels, which is generally positive for consumers and businesses alike.

The controlled inflation environment can also signal effective monetary policy management, such as appropriate adjustments to interest rates or fiscal policies to maintain price stability.

Average Yearly Salary:

The forecasted gradual increase in average yearly salaries aligns with the ongoing trend of wage inflation, reflecting broader economic growth, productivity improvements, and labor market dynamics. While the upward trajectory is expected to continue, the growth rate is likely to remain moderate, indicating a stable labor market and economic expansion.

The minor seasonal fluctuations suggest that salary adjustments will still be influenced by cyclical factors, but these are not expected to disrupt the long-term trend.

Value for Stakeholders

These forecasts provide valuable insights for a variety of stakeholders:

Policy Makers: The forecasted stability in inflation and gradual wage growth can help policymakers in designing fiscal and monetary policies that support sustainable economic growth without stoking excessive inflation. It also aids in budgeting and planning for potential social welfare adjustments, tax policies, and wage regulations.

Businesses and Employers: Companies can use the salary forecasts to plan for future labor costs and budget accordingly. Understanding that wages will continue to trend upwards allows businesses to plan for salary adjustments, compensation packages, and recruitment strategies.

Consumers: For consumers, the inflation forecast provides a glimpse into the likely trajectory of prices for goods and services. The controlled inflation environment suggests that purchasing power may not erode significantly over the next year, allowing consumers to plan their personal finances more effectively.

Long-Term Economic Planning: The stability in inflation and wage growth suggests that the economy will remain relatively balanced, with no major shocks expected in the near term. This provides confidence for long-term economic planning, whether for investments, policy decisions, or personal financial planning.

8. Discussion

The analysis conducted on the Canadian economic data provided insights into the forecasting of both the average yearly salary and inflation rate. However, it is important to recognize the limitations of the approach and explore areas for future work that could improve the accuracy and applicability of the models.

8.1 Limitations

Univariate Models:

The models used in this analysis are univariate, meaning they only consider each time series (inflation and salary) in isolation. This means that the relationship between salary and inflation was not directly modeled, which could be important for understanding how these two economic indicators interact over time.

A more sophisticated approach could involve multivariate models, such as Vector Autoregressions (VAR) or transfer function models, which would allow for the examination of the dynamic relationships and potential causality between inflation and salary. By considering both variables jointly, these models could provide deeper insights into how inflation might influence wage growth and vice versa.

Assumed Stationarity after Transformation:

The transformation process assumed that the time series became stationary after applying log transformation and seasonal differencing. While stationarity was visually assessed through plots and checked with diagnostic tools like ACF and PACF, it was not formally tested using statistical methods like the Augmented Dickey-Fuller (ADF) test or Phillips-Perron test.

Formal unit root tests could have provided stronger evidence of stationarity and further ensured that the transformations were sufficient for removing trends and seasonal effects. The lack of such tests introduces some uncertainty about whether the time series truly became stationary after the transformations.

External Variables:

The analysis focused on inflation and salary as the primary variables, but it did not consider external macroeconomic factors that could have a significant impact on these indicators. For example, factors such as interest rates, unemployment rates, or global economic conditions could influence both inflation and wages.

By not including these external variables, the models may have missed important drivers of inflation and salary changes. Incorporating additional explanatory variables into the models (e.g., using multivariate regression, VAR models, or structural time series models) could provide a more complete picture of the economic forces at play.

8.2 Future Work

Incorporating Multivariate Models:

A key area for future work is the use of multivariate models to analyze the relationship between inflation and salary more directly. Techniques such as Vector Autoregressive

Models (VAR) could be employed to assess whether changes in inflation lead to changes in salaries, or if salary adjustments influence inflation.

Cointegration and Granger causality tests could help determine whether long-term equilibrium relationships exist between these variables, offering more accurate insights into their co-movement over time.

Structural Time Series Models:

To capture the impact of significant structural interventions (e.g., policy changes, economic shocks, or external events), future work could involve structural time series models. These models are particularly useful for incorporating events that disrupt the regular pattern of a time series.

For example, the COVID-19 pandemic had a profound effect on inflation and wages. A structural time series model could explicitly model this intervention, improving the accuracy of forecasts during such extraordinary periods. This approach would allow for a better understanding of how events like a global health crisis can disrupt the typical seasonal and trend components of the data.

Application of Machine Learning Methods:

In addition to traditional statistical modeling techniques, there is an opportunity to explore machine learning methods for nonlinear forecasting. Techniques such as random forests, support vector machines (SVM), or neural networks could be applied to capture complex, nonlinear relationships in the data that traditional time series models might miss.

Machine learning methods are particularly useful when dealing with large datasets or when the underlying patterns in the data are not strictly linear. These methods could be used to uncover hidden patterns in inflation and salary dynamics, potentially improving forecast accuracy.

9. Conclusion

This project successfully applied time series analysis techniques to Canadian economic data, specifically focusing on forecasting the average yearly salary and inflation rate. The SARIMA models fitted to both series demonstrated their ability to capture the seasonal and trend components of each time series, providing valuable forecasts for the next 12 months. Key findings include:

Inflation rate: While the inflation rate exhibits seasonal fluctuations, it is expected to remain relatively stable over the forecast period, with modest increases and decreases.

Average yearly salary: The salary forecast suggests a continued upward trajectory, consistent with long-term wage inflation, although with minor seasonal fluctuations around the trend.

These results are particularly useful for stakeholders like economists, labor unions, and government agencies tasked with managing wage policies and inflation control. The findings offer insights into the future stability of the economy, helping these stakeholders make informed decisions related to budgeting, policy formulation, and long-term economic planning.

Overall, while the analysis provides a strong foundation for forecasting inflation and salary trends, there are clear opportunities for improvement through the incorporation of more complex models and external factors. Future work could enhance the accuracy and applicability of the forecasts, offering even more valuable insights for economic decision-making.

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