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# Forecasting Washington State's Housing Market: A Comparative Analysis of Time Series Models and Economic Indicators

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## ABSTRACT

This study examines Washington State's housing market by analyzing the relationship between new private housing units authorized by building permits and various economic indicators. Initially, an Ordinary Least Squares regression model was employed, which indicated significant autocorrelation in the residuals, as identified by the Durbin-Watson statistics. To address the autocorrelation and non-stationarity detected through the Augmented Dickey-Fuller and Ljung-Box tests, we employed differencing followed by ARIMA and Holt-Winters Exponential Smoothing models. The Holt-Winters model proved more effective, showing lower prediction errors and providing a more accurate forecast, thus emerging as the preferred method for forecasting in this market context.

## Introduction

### Data Sources and Description

In this project, we utilize data from FRED (Federal Reserve Economic Data) to analyze Washington State's housing construction market. The response variable is the number of new private housing units authorized by building permits, presented monthly and not seasonally adjusted. The predictor variable is the total of high-propensity business applications across all NAICS categories in Washington. Additional explanatory variables include the Labor Force Participation and the Washington Unemployment rates; all data are from 2004 July to 2023 Step.

The Labor Force Participation Rate dataset spans 231 entries, showing participation rates between 67.0% and 67.8% for mid-2004, with no missing data. The Business Applications dataset, with 232 entries, tracks monthly application counts ranging from 1873 to 2454 in the same timeframe. The Unemployment Rate dataset, also comprehensive and consisting of 231 rows, documents unemployment rates from 6.0% to 6.2% during this period. Lastly, the dataset on New Private Housing Units Authorized by Building Permits, encompassing 231 entries, details housing unit authorizations between 3625 and 5095 units.

### Attributes of data

The time series plot for new private housing units authorized by building permits reveals a fluctuation pattern over the studied period with notable variations that reflect broader economic trends(Figure 1). The plot for high-propensity business applications indicates an upward trend, suggesting increasing entrepreneurial activity(Figure 2). Labor force participation rate data depicts a decline followed by a gradual increase in recent years, while the unemployment rate demonstrates significant shifts likely tied to major economic events(Figures 3 and 4). Figure 5 illustrates Washington State's building permits not only recovered more robustly but also continue to show higher seasonal peaks compared to the national level, suggesting a more dynamic housing market in the state.

A potential correlation is observed in the combined plot of new housing units against high-propensity business applications, indicating that an increase in business applications could be associated with an uptick in housing construction activities(Figure 6). The correlation matrix plot reinforces this with a significant positive correlation between these two variables and a notable negative correlation between new housing units and the unemployment rate(Figure 7).

The cross-correlation function plot highlights the interdependencies between housing units authorized and business applications across different time lags, which can inform predictive modeling(Figure 8). Box plots segmented by year and quarter display the distribution of new housing units over time, showing annual variability and relatively consistent quarterly distribution(Figures 9 and 10). This suggests that the housing construction activity does not exhibit strong seasonal patterns.

The ACF suggests a strong autocorrelation for new private housing units that persists across multiple lags(Figure 11). At the same time, the PACF indicates a significant correlation at the first lag only, hinting at an AR(1) process(Figure 12). High-propensity business applications display a similar pattern, with persistent autocorrelation in the ACF and a significant first lag in the PACF(Figures 13 and 14). The labor force participation rate shows significant initial autocorrelation, which slowly diminishes, as seen in the ACF and a PACF that suggests a few significant lags(Figures 15 and 16). Finally, the unemployment rate demonstrates strong initial autocorrelation with a gradual decline, while the PACF again suggests an AR(1) process(Figures 17 and 18). These patterns suggest that each series likely contains a trend or cyclical components and may require differencing or transformation to achieve stationarity for modeling purposes.

### Model and Methods

We initially employed Ordinary Least Squares Regression to explore the relationships between the New Private Housing Units Authorized by Building Permits (our response variable) and a set of predictors, including High-Propensity Business Applications, Labor Force Participation Rate, and Unemployment Rate. However, to ensure the reliability of our regression analysis, we applied the Durbin-Watson Statistic, a test specifically designed to detect autocorrelation in the residuals of a regression model. Autocorrelation, if present, could invalidate our model assumptions and results.

The autocorrelation suggested by the Durbin-Watson Statistic led us to investigate the stationarity of our time series data using the Augmented Dickey-Fuller

Test. This test indicates that non-stationarity in time series data often necessitates differencing or transformation to achieve stationarity, a crucial aspect for many time series models. Concurrently, we employed the Ljung-Box Test to provide additional evidence of autocorrelation in the residuals over multiple lags, reinforcing the need for a modeling approach to handle these issues.

We adopted two advanced time series analysis techniques in response to these findings. First, we applied differencing to our series, a method effective in removing trends and seasonality, thereby achieving stationarity. Then, we employed the ARIMA (Autoregressive Integrated Moving Average) model, chosen for its capability to accommodate both autocorrelation and non-stationarity within the time series data. We utilized the Holt-Winters Exponential Smoothing technique to complement ARIMA and specifically address the seasonality detected in our data. This method is adept at forecasting time series data with trends and seasonal patterns, making it an ideal fit for our dataset characterized by such complexities.

**Finding and Forecasting results**

The Ordinary Least Squares regression model, with an R-squared value of 0.444, indicated that about 44.4% of the variance in the response variable is explained by the predictor and explanatory variables(Table 1). All predictors were statistically significant, with p-values less than 0.05. However, the Durbin-Watson statistic of 0.960 suggested moderate positive autocorrelation in the residuals(Table 2).

In the Augmented Dickey-Fuller test (test statistic: -2.1092, p-value: 0.53), since the p-value is greater than 0.05, we fail to reject the null hypothesis, indicating that the response variable is likely non-stationary(Table 3). The Ljung-Box test showed a statistic of 129.7 with a p-value close to 0, confirming significant autocorrelation in the residuals up to lag 10(Table 4).

We then applied ARIMA and Holt-Winters models to forecast the hold-out sample(Figures 19 and 20). The ARIMA model displayed high prediction errors with an MSE of 1,266,591.27, an MAE of 1004.861, and an RMSE of 1125.429(Table 7). In contrast, the Holt-Winters model with smoothing parameters $\alpha$=0.28, $\beta$=0 and $\gamma$=0.24(Table 6), which accounts for trends and seasonality, showed substantially lower errors (MSE: 966,858.02, MAE: 935.15, RMSE: 983.28) and provided more accurate forecasts (Table 7). The 12-month forecast from the Holt-Winters model predicted values ranging from approximately 2,318.62 to 5844.74(Table 9 and Figure 21). These results suggest that the Holt-Winters model, with its lower error metrics, is a more suitable and accurate approach for forecasting this time series data, particularly given the presence of trends and seasonal patterns in the dataset.

**Conclusion**

In conclusion, our analysis of Washington State's housing market, utilizing both Ordinary Least Squares Regression and advanced time series models, has provided a clear understanding of the market's dynamics. The study highlighted the limitations of the OLS model due to autocorrelation, leading to adopting ARIMA and Holt-Winters Exponential Smoothing models. The Holt-Winters model, in particular, emerged as superior, effectively accounting for seasonal patterns and trends and offering more accurate forecasts as evidenced by its lower error metrics. This model's ability to forecast housing market trends in Washington State is invaluable for policymakers and stakeholders, providing a reliable tool for future planning and decision-making. The interplay between housing construction activities and economic indicators like business applications and unemployment rates underlines the market's sensitivity to broader economic conditions. These insights are crucial for informed economic and urban planning strategies in Washington State

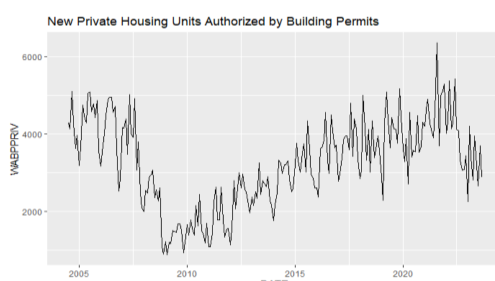
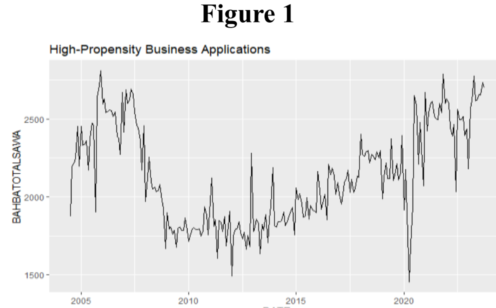



**Figure 1**

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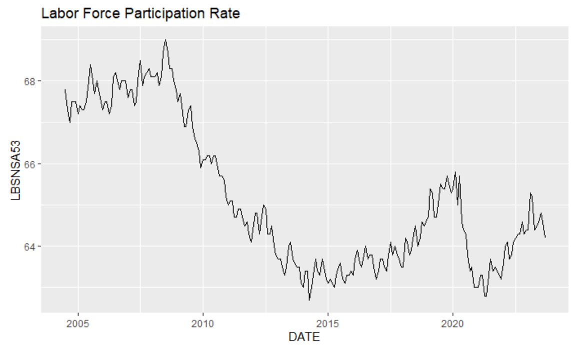


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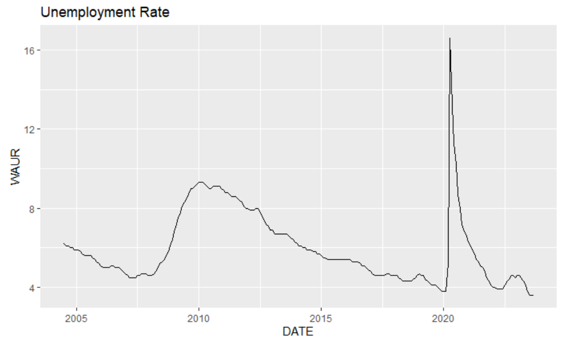


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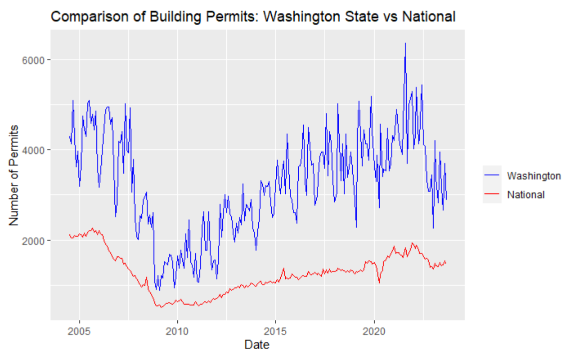


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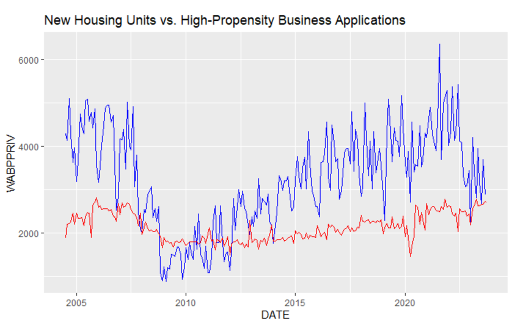


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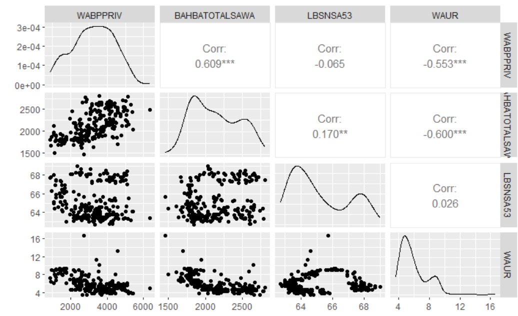


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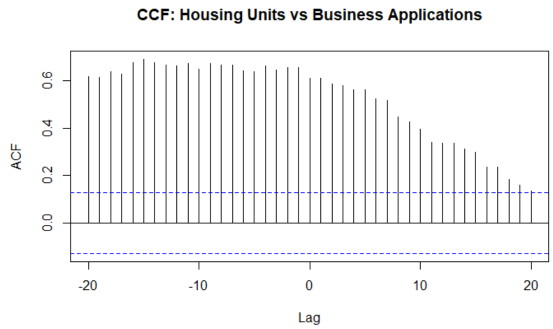


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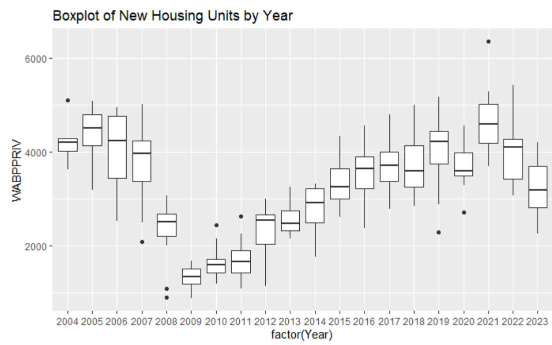


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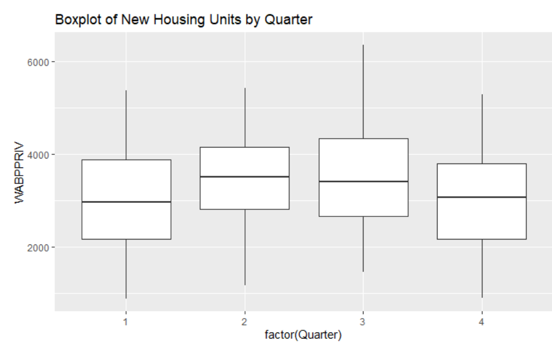


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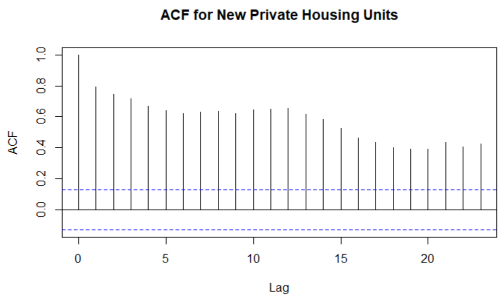


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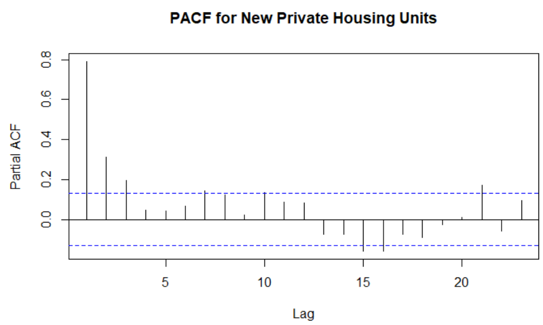


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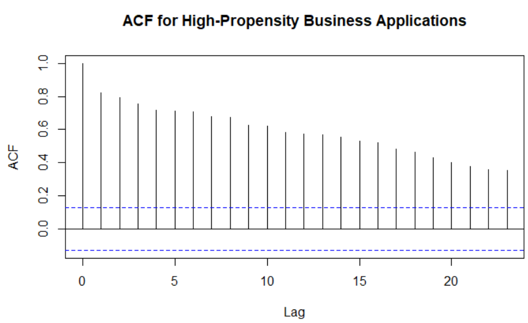


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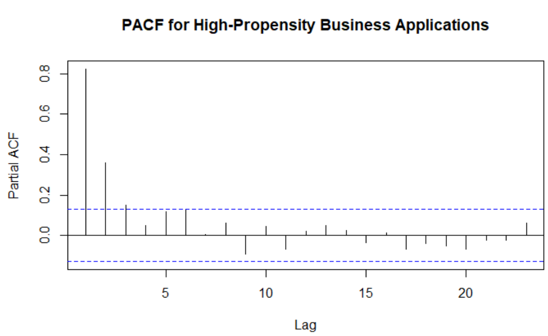


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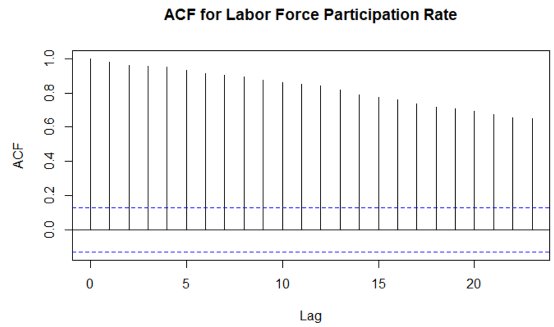


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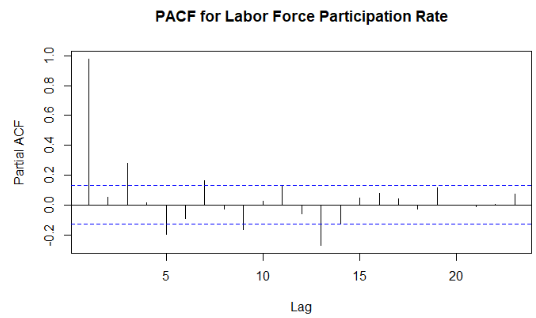


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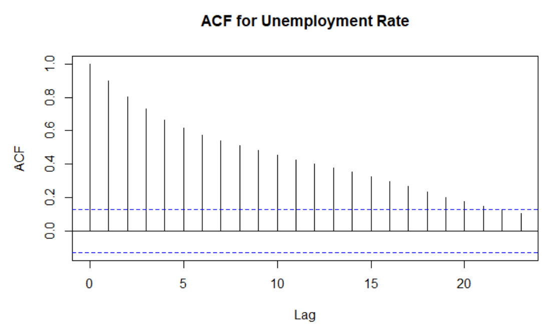


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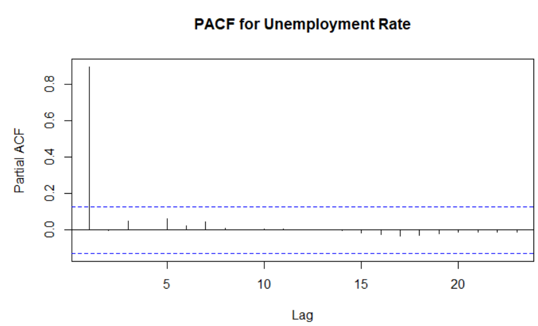


**Figure 18**

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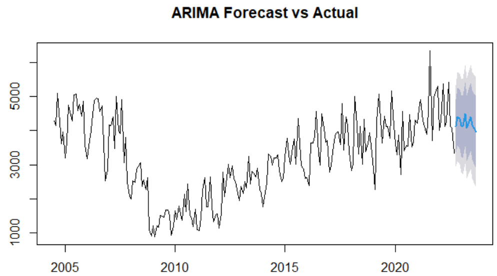


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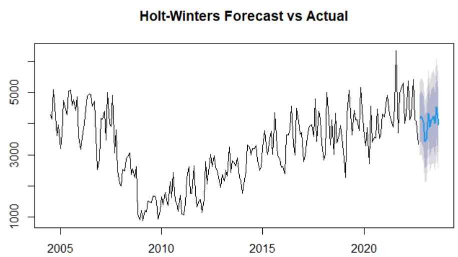


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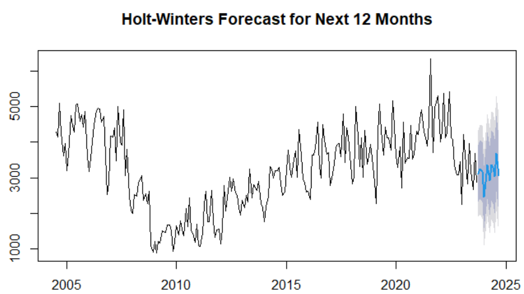


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