**Dayton Metro Real Estate Market Insights - Newsletter Edition**

**Welcome to the Dayton Metro Real Estate Market Insights!**

This edition delves into the latest trends, forecasts, and key insights impacting our local real estate market. We have conducted an in-depth analysis using various statistical models and economic indicators to provide a comprehensive view of the market dynamics. Hopefully, by having access to unique and specific data you will be able to develop a unique perspective on the driving forces of the trends affecting our market. Here’s what you need to know:

#### **Data Overview**

Our analysis spans from January 2010 to July 2024, including key metrics such as:

* **Active Listings:** The number of properties listed for sale.
* **Sales:** The number of properties sold.
* **CPI (Consumer Price Index):** Reflecting changes in the cost of consumer goods.
* **30-Year Fixed Rate Mortgage (30yrFRM):** Average interest rates for long-term mortgages.
* **Inflation Rate:** The rate of inflation impacting consumer prices.
* **Unemployment:** The percentage of unemployed individuals actively seeking work.
* **New\_Listings:** new listings entering the market during the month observed.
* **Sales\_Volume:** The raw total dollar amount of combined sales in the MSA.
* **Expired\_Listings:** The number of Listings that expired during the month observed.

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In our analysis we are attempting to drive actionable insights for professionals to be able to plan and prepare for opportunities and challenges in the market.

#### Summary of variables – Univariate Analysis

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#### The importance of a Correlation Heat Map **Overview of Residuals.**

**Importance of a Heat Map of Residual Correlations**

A heat map of residual correlations is a powerful visual tool used to understand and assess the relationships between variables in a model after accounting for their individual effects. Here’s why it’s important:

**1. Identifying Hidden Relationships**

* **Residual correlations** represent the relationships between variables that are not explained by the model. By analyzing these correlations, you can identify hidden or remaining patterns in the data that the model has not captured. This helps in understanding if there are any interactions or dependencies that occur.

**2. Diagnostics and Improvement**

* **Assessing model fit:** If the residuals are highly correlated, it indicates that the model might be missing important variables or interactions. A well-fitted model should have residuals that are uncorrelated, suggesting that the model has accounted for most of the relationships in the data.
* **Guiding model refinement:** High correlations in residuals might prompt the inclusion of additional variables, transformations, or interactions in the model, leading to improved performance.

**3. Detecting Multicollinearity**

* **Multicollinearity** refers to the situation where predictor variables are highly correlated with each other. A heat map can help visualize this issue, which might affect the stability and interpretability of the model's coefficients. This Correlation is represented in a range between 1 ( positive correlation) and -1 ( negative correlation) .

**4. Understanding Variable Contributions**

* A heat map of residual correlations can highlight which variables are contributing to unexplained variance, helping you focus on those areas for further investigation or data collection.

**5. Enhancing Interpretability**

* Visualizing residual correlations makes it easier to communicate complex model diagnostics to stakeholders. The intuitive nature of heat maps allows for a quick assessment of which variables may still be influencing each other, despite the model’s efforts to account for these effects.

**In Real Estate Market Analysis**

In a real estate context, a heat map of residual correlations could help identify relationships between economic indicators (like CPI, mortgage rates, etc.) that are not fully captured by the model. This could suggest additional factors or interactions, potentially leading to more accurate market predictions.

By providing these insights, heat maps of residual correlations serve as an essential tool in the iterative process of model development and refinement, ensuring that the final model is both robust and reliable.

A diagram of a heatmap

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Based on the **Vector Autoregression (VAR) model** summary provided, here's a ranked summary of the variables and their importance with respect to the forecasting model. The ranking is based on their significance (t-statistics and p-values) across the different equations in the VAR model.

**1. Sales**

* **Importance:** High
* **Key Observations:** Sales is a significant predictor in multiple equations, particularly within its own equation and in the New\_Listings equation. Its influence on the future values of Sales is notable, with significant coefficients for both the first and second lags. The t-statistics suggest that Sales has a strong predictive relationship with itself and influences other variables such as CPI and New\_Listings.

**2. CPI (Consumer Price Index)**

* **Importance:** High
* **Key Observations:** CPI shows significant self-predictive power (with a very high t-statistic) and also impacts other variables like Sales\_Volume, New\_Listings, and Sales. Notably, CPI’s coefficients in its own equation are highly significant, indicating it has a strong role in influencing future values within the dataset.

**3. Expired\_Listings**

* **Importance:** Medium to High
* **Key Observations:** Expired\_Listings demonstrates a significant influence in its own equation and in the New\_Listings equation. It has a notable negative relationship with New\_Listings and plays a role in the dynamics of Sales and CPI. The second lag of Expired\_Listings is particularly significant, emphasizing its role over time.

**4. New\_Listings**

* **Importance:** Medium
* **Key Observations:** New\_Listings has a strong self-predictive capability, as indicated by the significant coefficients in its equation. It also impacts the prediction of CPI and Expired\_Listings, although its influence on Sales is less direct.

**5. Unemployment**

* **Importance:** Medium
* **Key Observations:** Unemployment shows some significant relationships, particularly with Expired\_Listings and Inflation\_Rate. The influence of Unemployment is more evident in the dynamics involving Inflation\_Rate and 30yrFRM, although its direct effect on Sales is weaker compared to other variables.

**6. Inflation Rate**

* **Importance:** Medium
* **Key Observations:** The Inflation Rate is notably significant in its own equation and impacts the Unemployment equation. The coefficients related to the Inflation Rate indicate its role in the broader economic dynamics, though its direct influence on Sales is not as strong as CPI or Sales.

**7. 30yrFRM (30-Year Fixed Rate Mortgage)**

* **Importance:** Low to Medium
* **Key Observations:** 30yrFRM shows significant self-predictive power, but its influence on other variables such as Sales and Expired\_Listings is minimal. It mainly reflects interest rate trends rather than having a direct impact on sales .

**8. Active**

* **Importance:** Low
* **Key Observations:** The Active variable has some significant relationships, particularly within its own equation and with CPI. However, its overall impact on the forecasted Sales is not as pronounced as other variables like Sales or CPI.

**9. Sales\_Volume**

* **Importance:** Low
* **Key Observations:** Sales\_Volume has limited significance across the equations. While it is statistically significant in its own equation, its predictive power in influencing other variables like Sales or CPI is minimal.

**Ranking Summary:**

1. **Sales**
2. **CPI**
3. **Expired Listings**
4. **New Listings**
5. **Active Listings**
6. **Inflation Rate**
7. **30yrFRM**
8. **Unemployment Rate**
9. **Sales Volume**

**Models employed:**

**SARIMA**

The SARIMA (Seasonal Autoregressive Integrated Moving Average) model is an extension of the ARIMA model that specifically handles time series data with seasonality.

**Target Variable**: The model targets the differenced sales data (Sales\_diff) to address non-stationarity, making the time series more stable and predictable.

**Why Use SARIMA?**

SARIMA is chosen for time series data that exhibits both trend and seasonality, making it suitable for sales data with clear seasonal patterns. The model is powerful in capturing these regular seasonal effects while also managing the overall trend and noise in the data.

**Pros of SARIMA:**

1. **Seasonality Handling**: SARIMA effectively captures recurring seasonal effects, which is essential for datasets like sales that naturally fluctuate across seasons.
2. **Comprehensive Model**: By integrating both autoregressive (AR) and moving average (MA) components, along with differencing (I), SARIMA offers a flexible framework that can model a wide range of time series behaviors.
3. **Forecast Accuracy**: SARIMA models tend to provide accurate forecasts, especially for short to medium-term predictions, which is crucial for business planning.

**Challenges and Cons of SARIMA:**

1. **Complexity in Model Selection**: Choosing the correct parameters (p, d, q, P, D, Q, m) for SARIMA is challenging and requires careful analysis and testing. Incorrect parameter choices can lead to overfitting or underfitting, impacting forecast accuracy.
2. **Sensitivity to Non-Stationarity**: While SARIMA can handle non-stationary data through differencing, it still requires the data to be stationary after differencing. This process can sometimes oversimplify or lose essential dynamics in the data.
3. **Inflexibility to External Shocks**: SARIMA models are less adaptive to sudden changes or shocks in the data that do not follow historical patterns. This limitation makes it less effective in scenarios where unexpected events significantly impact sales.
4. **Seasonal Dependencies**: SARIMA assumes that seasonality is fixed and consistent over time. In real-world scenarios, seasonal effects may evolve, leading to model degradation if these changes are not accounted for.

**Model Fit and Probability Considerations:**

* **Fit Quality**: The model shows significant coefficients for autoregressive terms (L1 to L4) and seasonal terms (ar.S.L12, ma.S.L12, ma.S.L24), indicating that the model captures underlying patterns in the data. However, some variables like CPI and Inflation Rate have insignificant coefficients, suggesting that these factors might not be as predictive of sales in this context.
* **Challenges in Capturing All Energies**: Despite the SARIMA model's strengths, it may not fully capture all the complexities in the data, particularly those not tied to seasonal or trend components. This limitation highlights the need for complementary models or adjustments to capture additional dynamics.

In summary, while SARIMA is a robust model for handling seasonality in time series data, it comes with challenges such as model selection complexity and sensitivity to non-stationarity. The model's effectiveness is evident in its ability to forecast sales with a degree of accuracy, but it may miss out on capturing all underlying dynamics, particularly those that are non-seasonal or subject to abrupt changes.

**Forecast:**

Forecasted Values:

Sales mean mean\_se mean\_ci\_lower mean\_ci\_upper

2024-08-01 1485.206921 104.508319 1280.374380 1690.039462

2024-09-01 1472.377919 133.759042 1210.215014 1734.540824

2024-10-01 1564.962632 152.149884 1266.754339 1863.170926

2024-11-01 1370.875439 179.029302 1019.984456 1721.766423

2024-12-01 1293.211402 191.974514 916.948269 1669.474535

2025-01-01 1090.306300 205.461625 687.608915 1493.003685

2025-02-01 1143.916080 220.998790 710.766412 1577.065748

2025-03-01 1357.770758 232.194199 902.678490 1812.863026

2025-04-01 1447.490428 244.702625 967.882097 1927.098759

2025-05-01 1562.766774 256.866473 1059.317738 2066.215810

2025-06-01 1594.994365 267.293254 1071.109213 2118.879517

2025-07-01 1577.348196 278.291143 1031.907578 2122.788814

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**Conclusion**

The Sales and CPI variables are the most influential in the VAR model, with Expired\_Listings and New\_Listings also playing important roles in the dynamics of sales forecasting. Variables like 30yrFRM and Sales\_Volume, while significant within their own contexts, contribute less to the overall prediction of future sales. This ranking can help prioritize the focus areas for your analysis and communication.

**Summary and Explanation of CNN-LSTM Model for Addressing SARIMA and VAR Deficiencies**

**Model Overview:**

In this analysis, you've chosen to employ a **CNN-LSTM (Convolutional Neural Network - Long Short-Term Memory)** model to complement traditional models like SARIMA and VAR, which have limitations when dealing with highly seasonal and complex data. The CNN-LSTM model integrates both convolutional and recurrent layers to capture spatial patterns and long-term dependencies in the data, making it highly effective in forecasting complex time series like sales data.

**Why Use CNN-LSTM?**

1. **Handling Seasonality and Complexity**: The SARIMA and VAR models are effective in capturing trends and seasonal components in time series data. However, they often struggle with data that has intricate, non-linear relationships and evolving seasonal patterns. The CNN-LSTM model addresses these shortcomings by leveraging the strengths of both CNN and LSTM networks:
   * **CNN Layers**: Extract local features and patterns, such as sudden changes in sales within a short period, which traditional models might miss.
   * **LSTM Layers**: Capture long-term dependencies and memory effects, essential for understanding how sales evolve over time and how past events impact future sales.
2. **Generalization**: The primary reason for choosing the CNN-LSTM model is its ability to generalize better compared to the standalone LSTM or CNN models. This is crucial when dealing with complex, non-linear sales data, where overfitting is a significant concern. The CNN-LSTM model balances the network's complexity with generalization ability, reducing the risk of overfitting and providing more reliable forecasts.
3. **Focus on the Last 2 Years and Next 12 Months**: Given the emphasis on the last two years of sales data and the forecast for the next 12 months, the CNN-LSTM model is well-suited to capture both recent trends and anticipated seasonal effects. Its architecture allows it to learn from the nuanced patterns observed in the recent past and project them into the future, making it highly relevant for short- to medium-term forecasting.

**Model Performance and MSE Evaluation:**

* **Mean Squared Error (MSE)**: Among the models evaluated (DNN, CNN, LSTM, CNN-LSTM), the LSTM initially showed the lowest MSE, indicating it had the best fit on the test data. However, based on your goal of achieving better generalization, the CNN-LSTM was selected as the best model, even if its MSE wasn't the lowest. This decision underscores the importance of generalization over mere fit, particularly in dynamic environments like sales forecasting.
* **Forecasting Results**: The CNN-LSTM model forecasts a steady decline in sales over the next 12 months, which aligns with the patterns observed in the past data. The model's ability to incorporate moving averages and other temporal features ensures that the forecast is not only accurate but also realistic in terms of expected seasonal fluctuations.

**Complementing SARIMA and VAR with CNN-LSTM:**

* **Pros of CNN-LSTM**:
  1. **Advanced Pattern Recognition**: Unlike SARIMA, which assumes a fixed seasonal pattern, CNN-LSTM can adapt to evolving patterns, making it more flexible.
  2. **Long-Term Dependencies**: LSTM layers in the CNN-LSTM model can capture long-term dependencies that SARIMA might miss, especially when seasonal patterns change over time.
  3. **Robustness to Non-Linearities**: CNN-LSTM handles non-linearities more effectively than traditional linear models like SARIMA and VAR.
* **Cons of CNN-LSTM**:
  1. **Complexity**: The CNN-LSTM model is more complex and requires more computational resources and time to train compared to traditional models.
  2. **Interpretability**: While SARIMA and VAR provide clear insights into the influence of different variables, CNN-LSTM models are often seen as "black boxes," making it harder to interpret the results.

**Conclusion:**

By integrating the CNN-LSTM model into the forecasting framework, we are effectively addressing the limitations of SARIMA and VAR, particularly in capturing the non-linear, evolving seasonal patterns in sales data. This approach not only enhances the accuracy of the forecasts but also provides a more robust tool for understanding future market trends, especially over the critical next 12 months.

As you can see from below the trendline clearly shows a slowing trend and market. When balanced with the forecasts from the SARIMA and VAR we can deduce there are strong energies driving a new trendline.

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For an alternative - the **Convolutional Neural Network which performed with an exceptional MSE, however from an observation I felt it overfitted and potentially exaggerated the new trend emerging.**

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Last 12 months- Sales

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Next 12 months forecasted using **Convolutional Neural Network - Long Short-Term Memory model.**

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**Key Forecast Insights:**

* **Stable Active Listings**: The model forecasts that the number of active listings will remain relatively stable but with some fluctuations over the next year. For instance, in **August 2024**, the model predicts about **5,628 active listings**, which slightly increases to around **5,719** in **September** before gradually declining to **5,303** by **July 2025**.
* **Seasonal Variations**: The SARIMA model captures seasonal effects, such as fewer listings towards the end of the year and into early 2025, which aligns with typical seasonal slowdowns in the real estate market. Make note of the floor which was established in 2022 and 2023 combined with the establishment of a new trend direction.
* **Economic Influences**: The model incorporates exogenous factors like sales volume, CPI, mortgage rates, inflation rate, and unemployment, which have varying impacts on the forecasted active listings. For example, a higher CPI or sales volume might lead to more listings as property values increase or as the market becomes more active.

**Practical Implications for Real Estate Professionals:**

* **For Real Estate Agents**: Understanding the expected number of active listings can help agents prepare for the market dynamics. For instance, with fewer listings expected in early 2025, it might be a good time to focus on securing exclusive listings and preparing for a more competitive market.
* **For Mortgage Professionals**: The anticipated fluctuations in active listings, influenced by economic factors like mortgage rates and CPI, suggest that timing might be critical for homebuyers looking to secure the best mortgage deals before any market shifts.

**Conclusion**

The SARIMA model provides a data-driven forecast for active listings in the Dayton Metro area, helping real estate and mortgage professionals better anticipate market trends and prepare strategic actions for the coming year. With these insights, professionals can more effectively guide their clients in making informed decisions.

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**Concluding thoughts Summary: Disparity Between Active Listings and Sales- Market temperature**

**Overview of Disparity Metrics**

The disparity between active listings and sales provides a critical view of market dynamics. By examining this disparity, we can gain insights into whether the market is currently favoring buyers or sellers, as well as how liquid the market is. The key metrics used in this analysis are:

* **Disparity (Active Listings - Sales):** This raw metric shows the difference between the number of active listings and the number of sales. A higher disparity indicates a larger gap between supply (active listings) and demand (sales), suggesting a buyer’s market, where buyers have more options and leverage in negotiations. Conversely, a lower disparity would indicate a seller’s market.
* **Disparity% ((Active Listings - Sales) / Active Listings) \* 100):** This normalized measure of disparity provides a percentage that adjusts for the scale of the market. It allows us to compare the disparity over time more effectively, offering a clearer view of how market conditions are evolving.

**Market Trends Based on Disparity Analysis**

* **Current State (Last 2 Years)**: The analysis shows that over the past two years, the disparity percentage has consistently hovered around 70% to 75%. This range suggests a strong buyer's market, where the supply of active listings significantly outpaces the demand (sales). This could indicate a period of economic uncertainty or lower buyer confidence, where properties are not moving as quickly, and sellers may need to reduce prices to attract buyers.
* **Comparison with Historical Data**: Historically, the mean Disparity% has been around 80.4%, with a standard deviation of approximately 9%. The recent values are slightly below this average, indicating a slight trend toward a more balanced market, although it remains firmly in favor of buyers. The maximum disparity percentage recorded was 94.6%, reflecting times of extreme buyer advantage, while the minimum was 59.4%, closer to a balanced or seller's market.

**Market Implications and Forecast**

* **Future Market Movement (Next 12 Months)**: If the current trend of high disparity continues, it could signal ongoing downward pressure on prices, as sellers may need to compete more aggressively to close deals. This trend aligns with the forecasted decline in sales from the CNN-LSTM model, indicating that the market could continue to favor buyers over the next year.
* **Potential for Market Shift**: Should economic conditions improve, or if there is a significant reduction in the number of active listings without a corresponding drop in sales, the disparity could decrease, moving the market closer to a balanced state. However, given the historical and current data, a significant shift towards a seller’s market seems unlikely in the near term.

**Conclusion**

The disparity between active listings and sales, particularly when analyzed as a percentage, provides valuable insights into the current state of the real estate market. With a Disparity% consistently around 70% to 75% over the past two years, the market is clearly favoring buyers. This aligns with broader economic indicators suggesting lower buyer confidence and potentially lower demand. As the CNN-LSTM model suggests a continuing decline in sales, the market is likely to remain a buyer's market over the next 12 months, with ongoing downward pressure on prices unless significant changes occur in the broader economy or housing supply.

The disparity between active listings and sales in a real estate market can provide several insights into market dynamics and conditions:

Market Balance:

o Seller's Market: If active listings are low relative to sales, it indicates high demand and low supply, leading to a seller's market. In such a market, homes sell quickly, often at or above the asking price. o Buyer's Market: If active listings are high relative to sales, it indicates high supply and low demand, leading to a buyer's market. In such a market, buyers have more choices and can negotiate lower prices.

Market Liquidity:

o A low disparity (i.e., active listings close to sales) suggests a liquid market where properties are moving quickly. o A high disparity indicates less liquidity, meaning properties stay on the market longer.

Price Trends:

o A high number of active listings with stagnant or declining sales can lead to downward pressure on prices as sellers compete to attract buyers. o Conversely, low inventory with high sales can drive prices up due to competition among buyers.

Economic Indicators:

o The disparity can reflect broader economic conditions. For example, economic downturns might see a rise in active listings (as more people need to sell) but a drop in sales (as fewer people can afford to buy). o Economic growth periods might see the opposite, with fewer active listings and higher sales.

Market Sentiment:

o A growing disparity where listings outpace sales could indicate increasing seller pessimism or decreasing buyer confidence. o A shrinking disparity could signal growing confidence among buyers or fewer sellers willing to list their properties, expecting higher future prices.

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**Insights on Combining VAR, SARIMA, and CNN-LSTM Models**

In this analysis, I combined the strengths of three distinct models—VAR (Vector Autoregression), SARIMA (Seasonal AutoRegressive Integrated Moving Average), and CNN-LSTM (Convolutional Neural Network Long Short-Term Memory)—to forecast sales and better understand market trends. Each model brings unique capabilities to the table, addressing different aspects of the data and its complexities. Here's an overview of the approach and its benefits:

**1. VAR (Vector Autoregression):**

* **Strengths:** VAR is well-suited for capturing the interdependencies among multiple time series variables. It models the relationships between various economic indicators (like CPI, unemployment rate, and sales) and how they influence each other over time.
* **Challenges:** While VAR is effective in handling the relationships between variables, it might struggle with non-linear trends and complex seasonality inherent in sales data. This limitation makes it less effective in accurately predicting sudden market shifts or seasonal patterns.

**2. SARIMA (Seasonal AutoRegressive Integrated Moving Average):**

* **Strengths:** SARIMA excels in capturing seasonality and trends within time series data. It adjusts for seasonality by differencing and can handle periodic fluctuations in the data, which is crucial for accurate sales forecasting in markets with strong seasonal patterns.
* **Challenges:** SARIMA assumes that the seasonal patterns are consistent over time, which can be problematic if there are significant changes in market dynamics. Additionally, SARIMA might struggle with sudden changes or non-linear trends, which can lead to inaccuracies in the forecasts.

**3. CNN-LSTM (Convolutional Neural Network Long Short-Term Memory):**

* **Strengths:** The CNN-LSTM model combines the pattern recognition capabilities of CNNs with the temporal dependencies captured by LSTMs. This hybrid approach is powerful for modeling complex, non-linear relationships in data, making it more adaptable to changes and able to generalize better, especially when dealing with intricate patterns in sales data.
* **Challenges:** Although CNN-LSTM is highly effective in capturing complex patterns, it requires more data and computational resources compared to traditional models like VAR and SARIMA. Additionally, its forecasts can sometimes be less interpretable due to the black-box nature of neural networks.

**Ensemble Approach: Combining the Models**

To leverage the strengths of each model while mitigating their individual weaknesses, I combined their outputs to generate a more robust forecast:

* **Year-over-Year Forecasted Differences:** By aligning the last 12 months of actual sales data with the first 12 months of forecasted data from each model (VAR, SARIMA, CNN-LSTM), I calculated the year-over-year differences for each model.
* **Mean Sales Difference:** The final step involved averaging the differences from all three models to produce a consolidated forecast that accounts for the unique strengths of each approach.

**Insights and Market Implications**

* **Improved Generalization:** The CNN-LSTM component of the ensemble helps to address the non-linearities and complex patterns that might be missed by VAR and SARIMA, particularly when it comes to capturing sudden market shifts or changes in seasonal patterns.
* **Market Focus:** By focusing on the last two years and the upcoming 12 months, the ensemble model provides a comprehensive view of where the market is heading. It considers both the macroeconomic indicators modeled by VAR and the seasonal fluctuations captured by SARIMA, along with the deep learning capabilities of CNN-LSTM to adapt to evolving market conditions.
* **Enhanced Accuracy:** The combined approach results in a more accurate and generalizable forecast, as it integrates the strengths of traditional time series models with the advanced pattern recognition abilities of neural networks.

**Conclusion**

The integration of VAR, SARIMA, and CNN-LSTM models represents a sophisticated approach to sales forecasting. By combining these models, we can leverage their individual strengths to produce a more reliable and accurate forecast, particularly in a complex and dynamic market. This ensemble method not only improves forecast accuracy but also provides a more nuanced understanding of market trends, helping to anticipate where the market is likely to move in the near future.

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**Summary of Results: Sales Forecast for Real Estate and Mortgage Professionals**

The combined analysis of sales forecasts using SARIMA, VAR, and CNN-LSTM models provides valuable insights into the anticipated market trends over the next year. Here's what the results indicate:

1. **Near-Term Decline (August 2024 - December 2024):**
   * **August to October 2024:** All three models predict a decrease in sales compared to the previous year, with the **Mean Sales Difference** indicating a substantial decline. The highest drop is forecasted in September, with a mean difference of **-296.68 units**. This suggests a slowdown in the market, possibly due to seasonal factors or economic conditions affecting buyer confidence.
   * **November to December 2024:** Although the decline persists, it is less severe in December, with the mean sales difference improving slightly to **-89.73 units**. This might indicate early signs of market stabilization.
2. **Potential Rebound (January 2025):**
   * **January 2025:** The models suggest a potential rebound in sales, with a significant positive **Mean Sales Difference** of **113.08 units**. This could indicate a shift in market dynamics, where pent-up demand or favorable conditions (e.g., lower interest rates or improved economic indicators) might lead to an uptick in sales.
3. **Continued Uncertainty (February 2025 - July 2025):**
   * **February to July 2025:** The forecasts show mixed results, with some months indicating declines (e.g., **-198.80 units in May 2025**) and others showing smaller fluctuations during the main buying season. Notably, the decline is more pronounced in February and May, suggesting ongoing volatility and uncertainty in the market.

**Key Takeaways for Real Estate Agents and Mortgage Professionals:**

* **Short-Term Strategy:** Expect a challenging market in the latter half of 2024, particularly in the fall. Sellers might need to adjust pricing strategies, and buyers could benefit from increased negotiation power. Advising clients on the possibility of lower prices or longer time on the market could be prudent.
* **Mid-Term Opportunities:** January 2025 presents a potential opportunity for a market rebound. This could be a good time to re-engage with buyers who have been on the fence or to promote new listings as the market picks up. Understanding that despite the negative trend, the market is still well above the normal carrying capacity of the market historically. Reaching out to consumers to provide motivation to sell property and to price in accordance to a shifting market should provide the skill necessary to maneuver the new trends.
* **Market Volatility:** The forecasts highlight continued market volatility into 2025. Staying informed on broader economic trends and being prepared to pivot strategies quickly will be essential. Utilizing the data provided should help to provide insights to consumers on key performance indicators that move the market should elevate the professional as the market leader.

This analysis provides a data-driven foundation for anticipating market movements and helping clients make informed decisions in the coming year. Please be reminded that projections and forecasts are driven by statistically sound principles , however they should be used with caution as conditions can and often do shift to develop different market paradigms.

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**Disparity Analysis**

**Disparity Percentage** between active listings and sales shows the proportion of active listings that do not result in sales. This disparity has averaged 80.4% since January 2010, indicating a substantial number of listings remain unsold each month.

| **Date** | **Active** | **Sales** | **Disparity (%)** |
| --- | --- | --- | --- |
| 2023-08-01 | 5658 | 1584 | 72.00 |
| 2023-09-01 | 5903 | 1810 | 69.34 |
| 2023-10-01 | 6242 | 1809 | 71.02 |
| 2023-11-01 | 6097 | 1654 | 72.87 |
| 2023-12-01 | 5329 | 1521 | 71.46 |

*Figure: Disparity Percentage between Active Listings and Sales*

**Forecasting Models and Insights**

**SARIMAX Model for Active Listings**

The SARIMAX model, which includes exogenous variables such as Sales, CPI, 30yrFRM, Inflation Rate, and Unemployment, provides the following insights:

* **AIC:** 2458.434
* **BIC:** 2490.025
* Significant predictors include Sales, CPI, and autoregressive terms.

**Forecasted Values:**

| **Date** | **Active** |
| --- | --- |
| 2024-08-01 | 5605.08 |
| 2024-09-01 | 5694.87 |
| 2024-10-01 | 5741.88 |
| 2024-11-01 | 5539.64 |
| 2024-12-01 | 4878.09 |

**VAR Model**

The VAR model examines the interdependencies among multiple time series variables.

* **AIC:** 15.7550
* **BIC:** 17.1767

Key insights:

* Lower AIC and BIC values suggest a good model fit.
* Active Listings, Sales, and CPI are significant predictors in the VAR model.

**Forecasted Values:**

| **Date** | **Active** | **Sales** | **CPI** | **30yrFRM** | **Inflation Rate** | **Unemployment** |
| --- | --- | --- | --- | --- | --- | --- |
| 2024-08-01 | 5537.10 | 1570.30 | 315.38 | 6.82 | 3.02 | 4.21 |
| 2024-09-01 | 5388.27 | 1548.70 | 315.93 | 6.80 | 3.04 | 4.13 |
| 2024-10-01 | 5228.24 | 1521.61 | 316.52 | 6.79 | 3.06 | 4.08 |
| 2024-11-01 | 5080.57 | 1504.65 | 317.18 | 6.79 | 3.09 | 4.04 |
| 2024-12-01 | 4956.47 | 1500.07 | 317.89 | 6.79 | 3.12 | 4.00 |

**Year-Over-Year Estimated Difference in Sales by Models**

We used three models—SARIMA, CNN-LSTM, and VAR—to forecast sales differences and calculated the mean of their forecasts.

| **Date** | **SARIMASales** | **VARSales** | **CNNSales** | **MeanSalesDifference** |
| --- | --- | --- | --- | --- |
| 2024-08-01 | -107.85 | -13.70 | -64.95 | -62.17 |
| 2024-09-01 | -355.16 | -261.30 | -290.17 | -302.21 |
| 2024-10-01 | -257.86 | -287.39 | -291.94 | -279.06 |
| 2024-11-01 | -298.87 | -149.35 | -148.87 | -199.03 |
| 2024-12-01 | -246.34 | -20.93 | -24.10 | -97.12 |

**Plot:**

*Figure: Mean Sales Difference Over Time*

**Conclusion and Recommendations**

**For Buyers:**

* Monitor mortgage rate trends closely and take advantage of any dips to secure favorable financing.
* Be prepared for a competitive market with fewer active listings.

**For Sellers:**

* Pricing competitively and enhancing property appeal are crucial in a market with high inventory levels.
* Expect significant competition and strategize accordingly.

**For Investors:**

* Consider broader economic indicators such as CPI and unemployment rates to gauge market health and future trends.

## This comprehensive analysis aims to equip you with valuable insights into the Dayton Metro real estate market, helping you make informed decisions. Stay tuned for more updates in our next edition!

## **Dayton Metro Real Estate Market Insights - Newsletter Edition**

**Welcome to the Dayton Metro Real Estate Market Insights!**

This edition delves into the latest trends, forecasts, and key insights impacting our local real estate market. We have conducted an in-depth analysis using various statistical models and economic indicators to provide a comprehensive view of the market dynamics. Here’s what you need to know:

**Data Overview**

Our dataset spans from January 2010 to July 2024, capturing critical monthly metrics including:

* **Active Listings**: The number of active real estate listings.
* **Sales**: The number of property sales.
* **Consumer Price Index (CPI)**: Reflecting the average change over time in the prices paid by urban consumers for a basket of consumer goods and services.
* **30-Year Fixed Rate Mortgage (30yrFRM)**: The average interest rate for a 30-year fixed-rate mortgage.
* **Inflation Rate**: The annual percentage change in the cost to the average consumer of acquiring a basket of goods and services.
* **Unemployment**: The percentage of the labor force that is jobless and actively seeking employment.

**Key Statistics**

**Descriptive Statistics (2010-2024):**

|  | **Active Listings** | **Sales** | **CPI** | **30yrFRM** | **Inflation Rate** | **Unemployment** |
| --- | --- | --- | --- | --- | --- | --- |
| **Mean** | 8152 | 1386 | 252.39 | 4.33 | 2.59 | 6.01 |
| **Std Dev** | 2661 | 327 | 26.88 | 1.12 | 2.00 | 2.44 |
| **Min** | 3934 | 649 | 216.69 | 2.68 | -0.20 | 3.10 |
| **Max** | 14068 | 2021 | 314.80 | 7.62 | 9.10 | 15.10 |

**Recent Trends and Forecasts**

**Active Listings and Sales Over Time**

**Active Listings** have seen a noticeable decline from over 14,000 in early 2010 to around 5,600 in mid-2024. This indicates a tightening market where fewer properties are available.

**Sales** have fluctuated, with recent years showing stabilization. However, the number of sales remains lower than peak periods, reflecting changing market dynamics.

**Disparity Percentage** between active listings and sales shows the proportion of active listings that do not result in sales. This disparity has averaged 80.4% since January 2010, indicating a substantial number of listings remain unsold each month.

| **Date** | **Active** | **Sales** | **Disparity (%)** |
| --- | --- | --- | --- |
| 2023-08-01 | 5658 | 1584 | 72.00 |
| 2023-09-01 | 5903 | 1810 | 69.34 |
| 2023-10-01 | 6242 | 1809 | 71.02 |
| 2023-11-01 | 6097 | 1654 | 72.87 |
| 2023-12-01 | 5329 | 1521 | 71.46 |

**Plot: Disparity Percentage between Active Listings and Sales**

**Forecasting Key Metrics**

**SARIMAX Model for Active Listings**

The SARIMAX model, which includes exogenous variables such as Sales, CPI, 30yrFRM, Inflation Rate, and Unemployment, provides critical forecasts for the coming year.

**Forecasted Active Listings:**

| **Date** | **Active** |
| --- | --- |
| 2024-08-01 | 5605.08 |
| 2024-09-01 | 5694.87 |
| 2024-10-01 | 5741.88 |
| 2024-11-01 | 5539.64 |
| 2024-12-01 | 4878.09 |

These forecasts suggest a slight increase in active listings over the next few months, potentially easing some market tightness.

**VAR Model**

The VAR model examines the interdependencies among multiple time series variables and provides comprehensive forecasts.

**Forecasted Values:**

| **Date** | **Active** | **Sales** | **CPI** | **30yrFRM** | **Inflation Rate** | **Unemployment** |
| --- | --- | --- | --- | --- | --- | --- |
| 2024-08-01 | 5537.10 | 1570.30 | 315.38 | 6.82 | 3.02 | 4.21 |
| 2024-09-01 | 5388.27 | 1548.70 | 315.93 | 6.80 | 3.04 | 4.13 |
| 2024-10-01 | 5228.24 | 1521.61 | 316.52 | 6.79 | 3.06 | 4.08 |
| 2024-11-01 | 5080.57 | 1504.65 | 317.18 | 6.79 | 3.09 | 4.04 |
| 2024-12-01 | 4956.47 | 1500.07 | 317.89 | 6.79 | 3.12 | 4.00 |

The VAR model predicts a steady decrease in active listings and sales, while CPI and inflation rates are expected to continue their upward trend.

**Year-Over-Year Estimated Difference in Sales by Models**

We used three models—SARIMA, CNN-LSTM, and VAR—to forecast sales differences and calculated the mean of their forecasts.

| **Date** | **SARIMASales** | **VARSales** | **CNNSales** | **MeanSalesDifference** |
| --- | --- | --- | --- | --- |
| 2024-08-01 | -107.85 | -13.70 | -64.95 | -62.17 |
| 2024-09-01 | -355.16 | -261.30 | -290.17 | -302.21 |
| 2024-10-01 | -257.86 | -287.39 | -291.94 | -279.06 |
| 2024-11-01 | -298.87 | -149.35 | -148.87 | -199.03 |
| 2024-12-01 | -246.34 | -20.93 | -24.10 | -97.12 |

**Plot: Mean Sales Difference Over Time**

The forecasted sales differences highlight a negative trend in the coming months, with the mean sales difference remaining below zero. This suggests a challenging period ahead for sellers.

**Conclusion and Recommendations**

**For Buyers:**

* Monitor mortgage rate trends closely and take advantage of any dips to secure favorable financing.
* Be prepared for a competitive market with fewer active listings.

**For Sellers:**

* Pricing competitively and enhancing property appeal are crucial in a market with high inventory levels.
* Expect significant competition and strategize accordingly.

**For Investors:**

* Consider broader economic indicators such as CPI and unemployment rates to gauge market health and future trends.

This comprehensive analysis aims to equip you with valuable insights into the Dayton Metro real estate market, helping you make informed decisions. Stay tuned for more updates in our next edition!

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**Dayton Metro Real Estate Market Insights - Newsletter Edition Summary**

Welcome to the latest edition of Dayton Metro Real Estate Market Insights! In this edition, we provide a comprehensive analysis of the Dayton real estate market, focusing on the latest trends, forecasts, and key insights. Our goal is to equip you with valuable data and forecasts to help you navigate the market effectively.

**Data Overview**

Our analysis spans from January 2010 to July 2024, including key metrics such as:

* **Active Listings:** The number of properties listed for sale.
* **Sales:** The number of properties sold.
* **CPI (Consumer Price Index):** Reflecting changes in the cost of consumer goods.
* **30-Year Fixed Rate Mortgage (30yrFRM):** Average interest rates for long-term mortgages.
* **Inflation Rate:** The rate of inflation impacting consumer prices.
* **Unemployment:** The percentage of unemployed individuals actively seeking work.

**Key Statistics (2010-2024)**

* **Mean Active Listings:** 8152
* **Mean Sales:** 1386
* **Mean CPI:** 252.39
* **Mean 30yrFRM:** 4.33%
* **Mean Inflation Rate:** 2.59%
* **Mean Unemployment:** 6.01%

**Market Trends and Insights**

**Active Listings and Sales Over Time**

* **Trend:** Active Listings have decreased significantly from over 14,000 in 2010 to approximately 5,600 by mid-2024, indicating a tighter market.
* **Sales:** Although fluctuating, sales have stabilized in recent years but remain lower than peak levels.

**Disparity Analysis**

* **Disparity %:** Measures the proportion of active listings that do not result in sales. The average disparity since January 2010 is 80.4%, indicating a persistent surplus of listings relative to sales.
* **Recent Values:** The disparity percentage has remained around 70% to 75% over the past two years, suggesting a continued buyer's market where supply exceeds demand.

**Forecasting Models and Insights**

**SARIMAX Model**

* **Purpose:** Captures the impact of exogenous variables like Sales, CPI, and 30yrFRM on Active Listings.
* **Forecast:** Predicts an increase in active listings in the coming months, potentially easing the tight market conditions.

**VAR Model**

* **Purpose:** Examines the interdependencies between multiple economic indicators.
* **Forecast:** Suggests a steady decrease in active listings and sales, with CPI and inflation rates expected to rise despite recent data.

**Year-Over-Year Estimated Sales Difference**

* **Combined Models (SARIMA, CNN-LSTM, VAR):** These models were used to forecast sales differences. The forecasts show a general decline in sales from August 2024 to July 2025, with occasional rebounds, particularly in January 2025.

**Conclusion and Recommendations**

**For Buyers:**

* **Interest Rates:** Keep a close watch on mortgage rate trends. Lower rates may present opportunities to secure better financing.
* **Market Conditions:** Prepare for a competitive environment with limited listings.

**For Sellers:**

* **Competitive Pricing:** With high inventory levels, it’s crucial to price your property competitively and enhance its appeal to attract buyers.
* **Market Strategy:** Be aware of the competition and adjust your strategy accordingly.

**For Investors:**

* **Economic Indicators:** Monitor broader economic factors such as CPI and unemployment to gauge market health and make informed investment decisions.

This edition of the Dayton Metro Real Estate Market Insights provides you with critical data and forecasts to help you navigate the real estate market. Stay tuned for more updates in future editions!

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This newsletter aims to provide you with a data-driven foundation for making informed decisions in the Dayton Metro real estate market. Whether you’re buying, selling, or investing, the insights shared here are designed to keep you ahead of the curve.