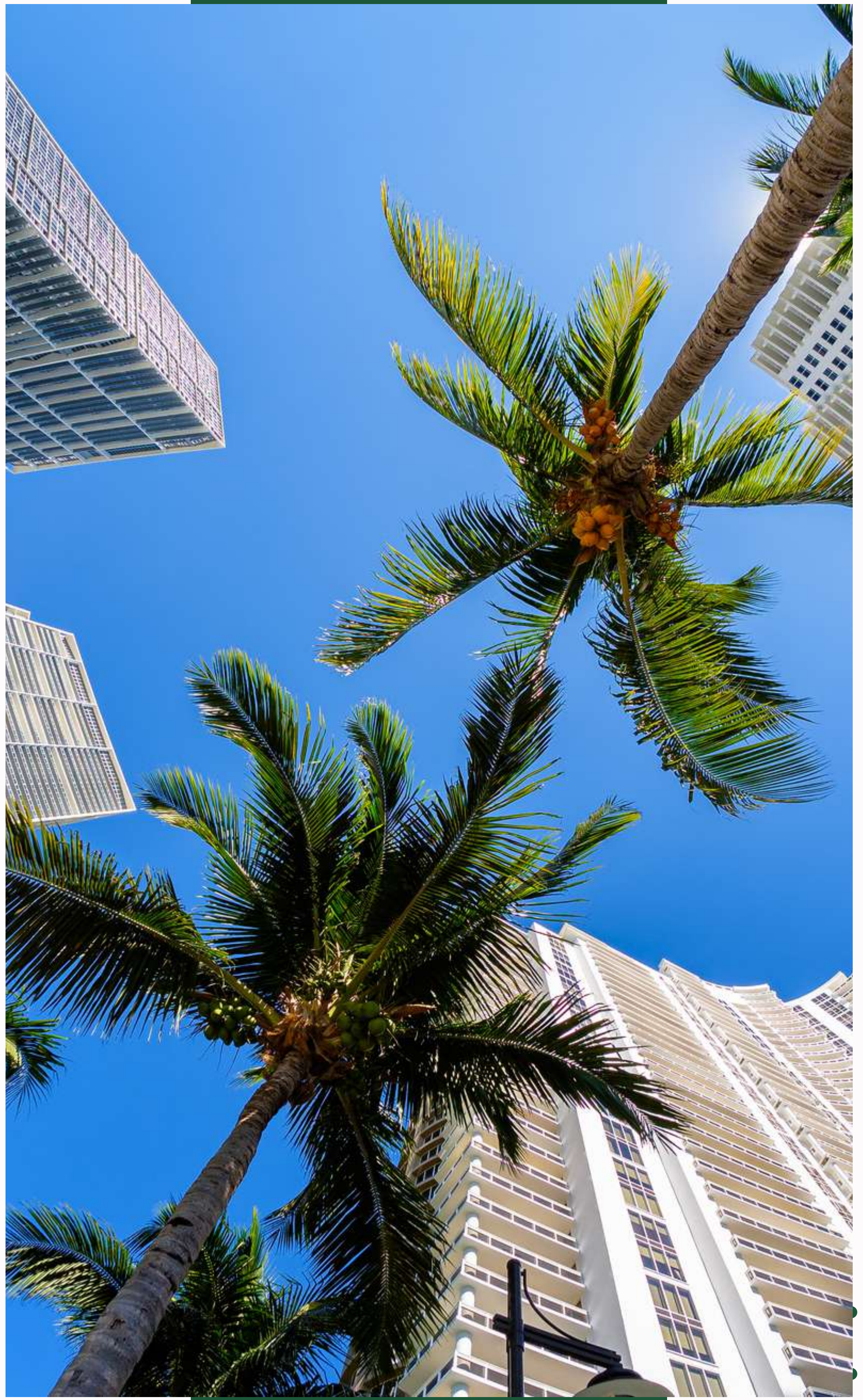
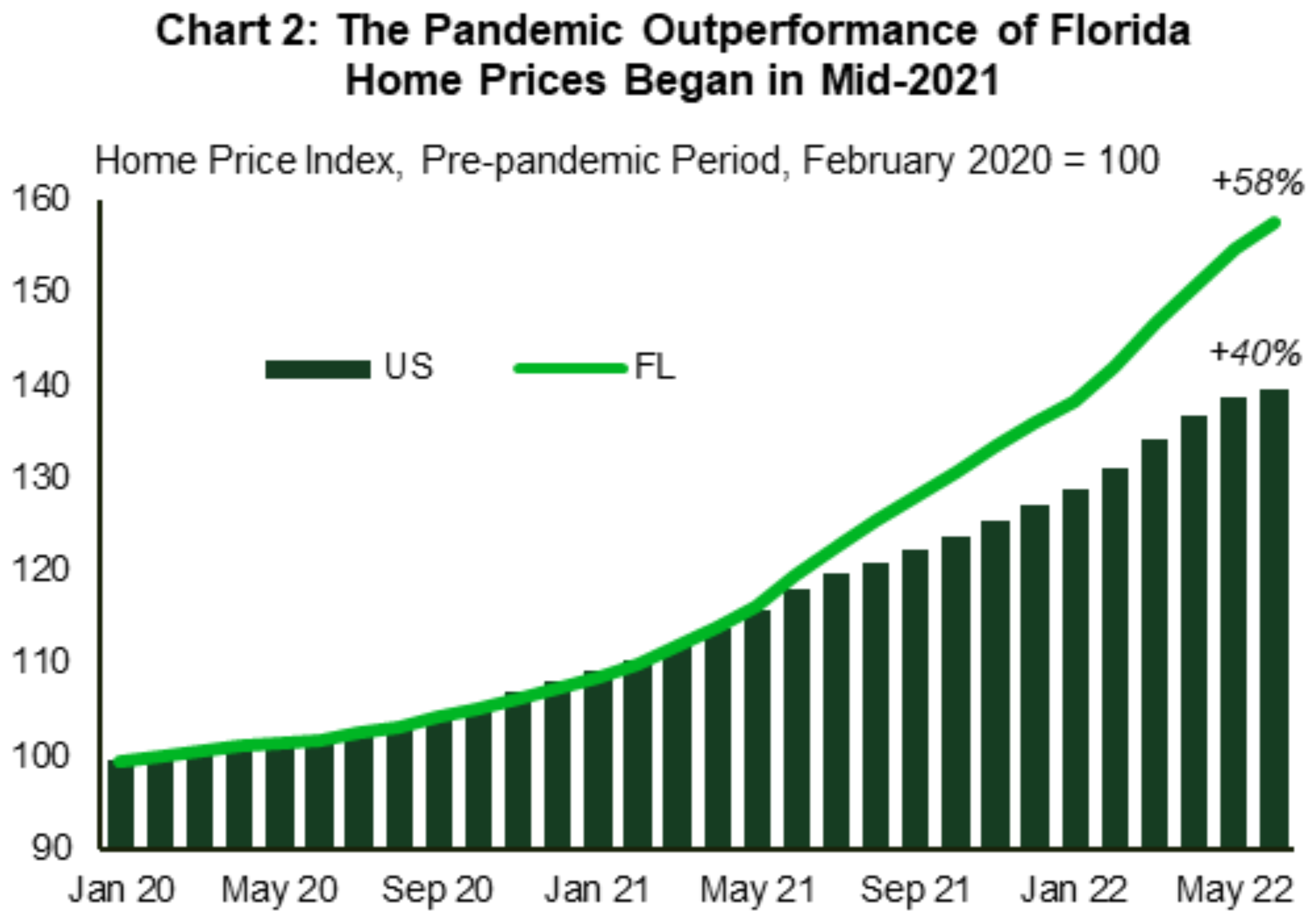
Group 1

PREDICTING HOUSE PRICES IN FLORIDA: AN ALTERNATIVE APPROACH

Capstone Project for Freddie Mac





A CAUTIONARY TALE: COVID-19

01. All economists thought house prices would tank during COVID-19

Instead, they rose almost 40% in 2 years.

- Positive housing demand shocks.
- Negative housing supply shocks.
- Swift and decisive policies to support the economy.

02. FL Housing Market Outperforms the U.S.

- Influx of residents from other parts of the country.
- Florida's market clocked in at $3.85 trillion, pulling in front of New York and Texas.
- Florida welcomed 655,000 new residents since the start of the pandemic.

Key Takeaway: We need a better way to predict house prices during Black Swan events!

AGENDA

01	Background
02	Business Objective
03	Solution #1: LLM
04	Solution #2: Sentiment Analysis
05	Conclusion

Florida's Housing Market

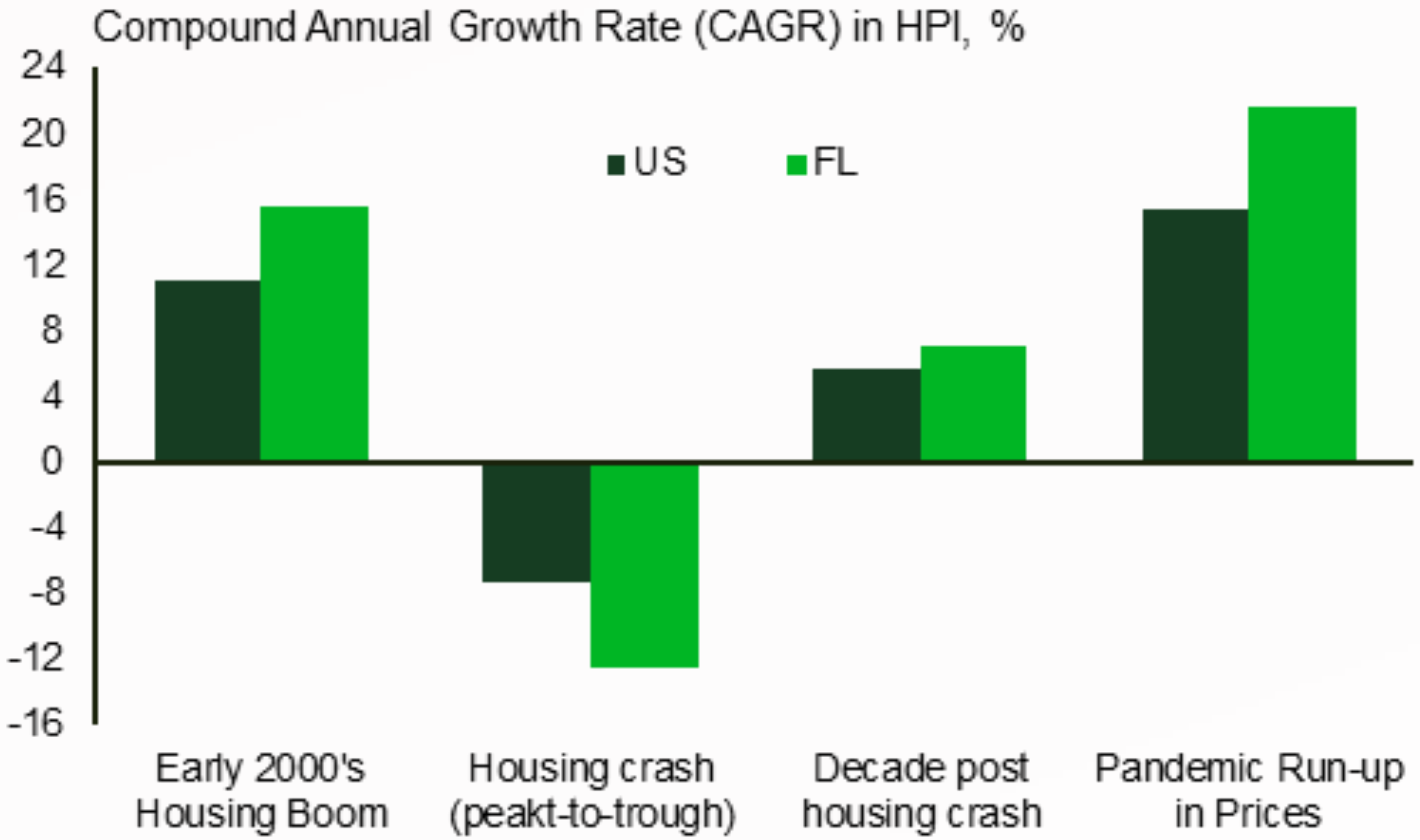
01
The state has led the country in net migration, and the pandemic accelerated that population growth.

02
Florida's weather has made it attractive for retirees, but it's now also become attractive for remote workers.

03
Florida is the second most-valuable real-estate market in the country, partially due to low taxes.

04
It is important to understand these recent trends and the state's value proposition in order to forecast home prices.

Chart 3: Florida's Housing Market Exhibits Above-average Volatility



Source: CoreLogic, TD Economics.

BUSINESS OBJECTIVES

Objective 01

Improve forecast accuracy for house prices (house price index) during the COVID-19 pandemic.

Objective 02

Test the use of AI, particularly LLMs, in accurately predicting house prices during Black Swan events.

Objective 03

Test the use of machine learning techniques in accurately predicting house prices during Black Swan events.

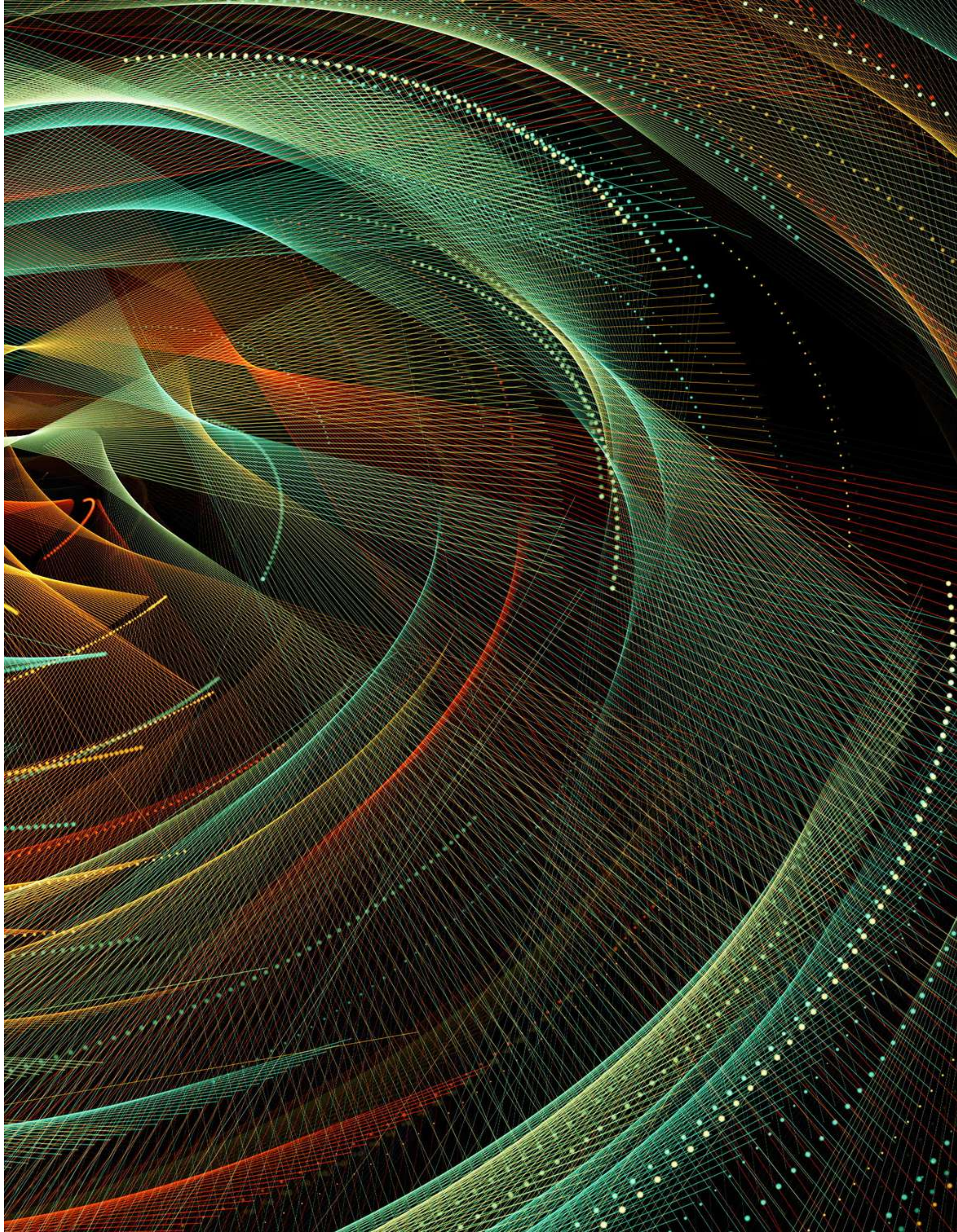
Objective 04

Test the use of sentiment analysis, measured by extracting data from community forums, social media sites, and online real estate marketplaces, in forecasting house prices.

SOLUTION #1: LARGE LANGUAGE MODELS

INTRO TO LLM'S

- Our team wanted to investigate the accuracy of Large Language Models (LLM's) in predicting house prices during COVID-19.
- We used two leading LLM's, Google's PaLM and OpenAI's GPT 3.5 and GPT 4.0 to provide us with forecasts for 2020-2022.
- We compared the results provided by the LLM model to a baseline model built on traditional economic indicators, such as GDP and unemployment rate.



METHODOLOGY

GPT 4.0

Prompt Engineering Techniques focusing on integrating key variables relevant to housing market analysis.

Incorporation of Critical Variables & Historical Data:

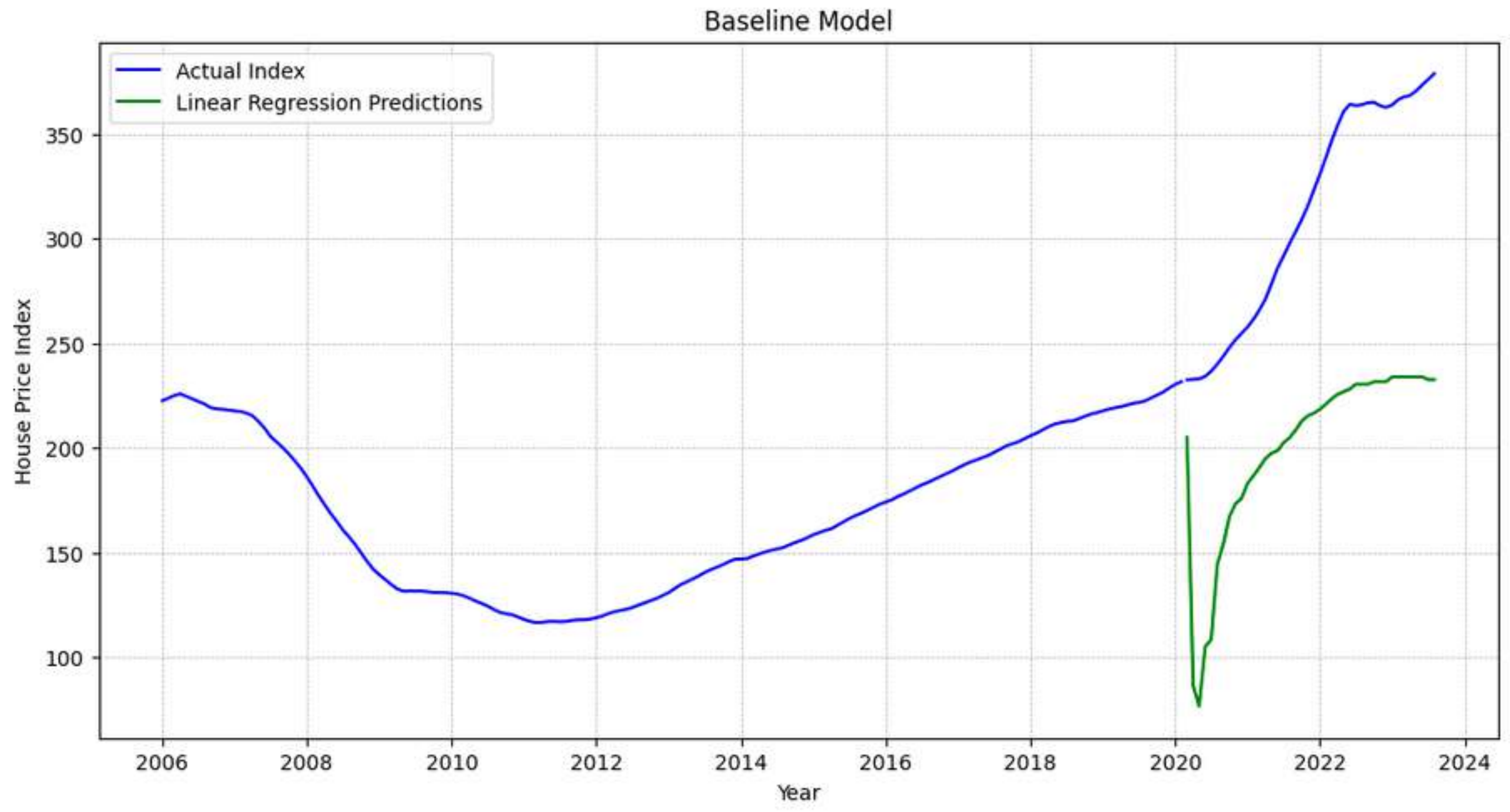
- Prompted GPT 4 to include data such as interest rates, employment rates, and GDP growth. Factored in historical trends, current market conditions, and supply-demand dynamics.
- Analyzed GPT-4's output against actual housing index data to evaluate prediction accuracy.
- Cross-referenced GPT-4 predictions with our baseline models for validation.

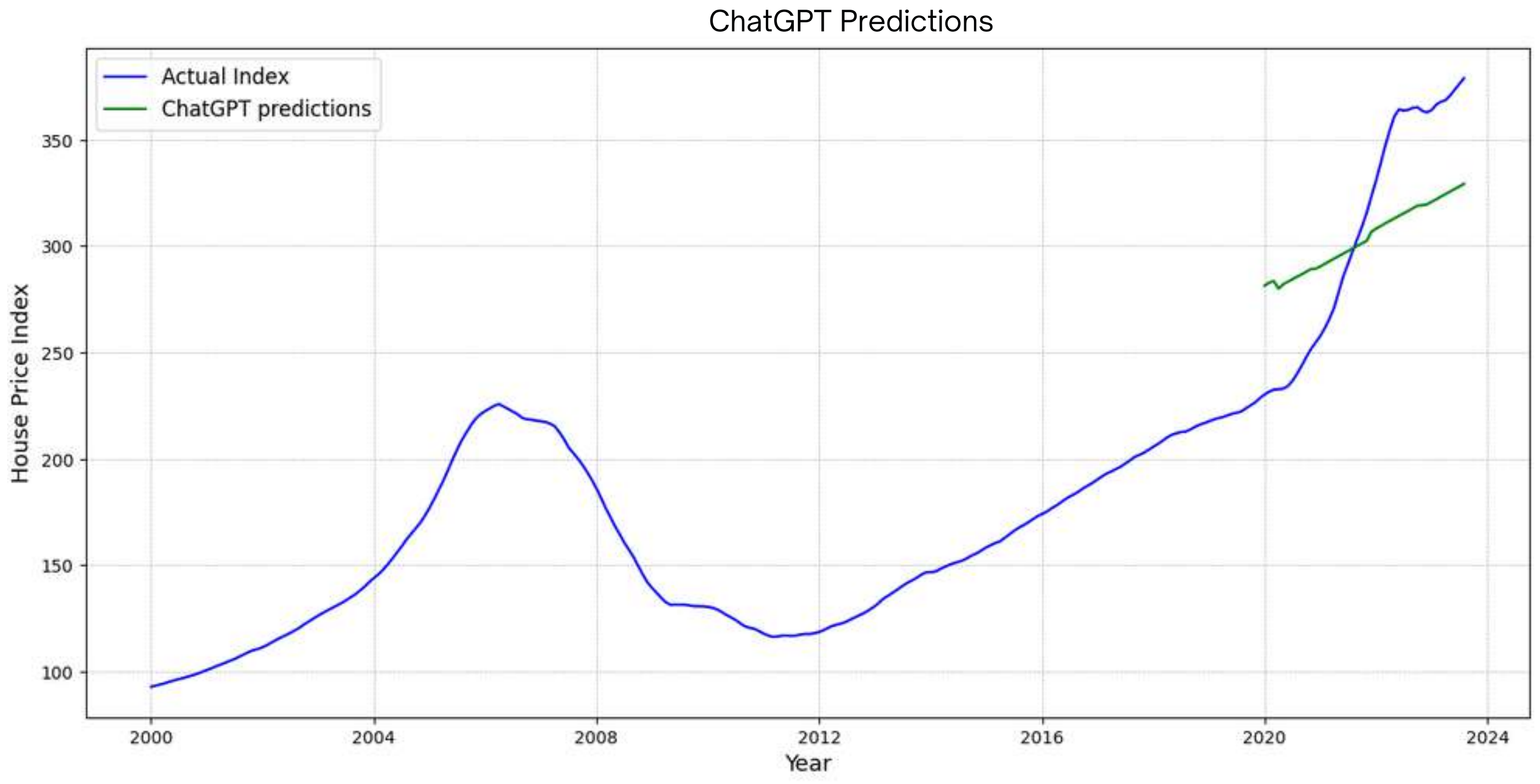
RESULTS

- GPT 4.0 was able to give fairly good predictions compared to our baseline model, and had an RMSE of 38.75, compared to an RMSE of 115.54.

- The baseline model predicts a sharp dip in 2020, in response to decreasing GDP and increasing unemployment. However, GPT was able to show a continued increase in house prices.

- However, the GPT model underestimated the growth rate we would see during COVID.





LIMITATIONS

Sensitivity
The results are highly dependent on prompts

Reproducibility
Difficult to replicate results consistently

Limited by data
GPT training data: we don't have access, and cannot expand on it

Low visibility
The models and forecast methods are a black box to user

COMPARATIVE ANALYSIS

	Chat GPT 4.0	Chat GPT 3.5	Google PaLM 2.0
Capable	✓	✗	✓
Consistent	✓	✗	✗
Transparent	✗	✗	✗

Recommendation

AI needs more time to grow. There is potential but it is currently a black box.

- Promising as a largely accessible tool for prediction.
- Useful due to the breadth of data the model is able to monitor.
- Freddie Mac should invest internally to continue monitoring AI developments.

"I AM STILL UNDER DEVELOPMENT, AND I AM ALWAYS LEARNING AND IMPROVING. AS I LEARN MORE ABOUT THE WORLD AND HOW IT WORKS, MY FORECASTS WILL BECOME MORE ACCURATE."

\- GOOGLE PALM

SOLUTION #2: SENTIMENT ANALYSIS

DATA USED

Reddit

Limited number of posts due to API restrictions (~1200 posts)

Traditional Economic Indicators

Publicly available indicators such as GDP, unemployment rate, etc.

Google Search

Web-scraping search results with keyword filtering

SENTIMENT ANALYSIS

Localized Insights

Gives us an idea of what the local community has to say about house prices.

Social Media Impact

Helps capture trending dialogue on social media platforms.

Economic Indicators

Helps capture the impact of important economic decisions on public sentiment.

Human Behavior Influence

Incorporates consumer sentiment and rationale into our analysis.

KEYWORDS

Real Estate

Housing bubble
Rental market
Home buying
Home selling
Foreclosure
Property taxes

+

Florida Specific

Bigger houses
Orlando housing
Florida Keys real estate
Hurricane impact (on housing)
Flood insurance
Snowbird influence
Retirement homes in Florida

=

Combined

Florida real estate trends
Miami housing bubble
Tampa foreclosure rates

MODELS AND METHODS

ARIMA

Time Series Forecasting with Trends

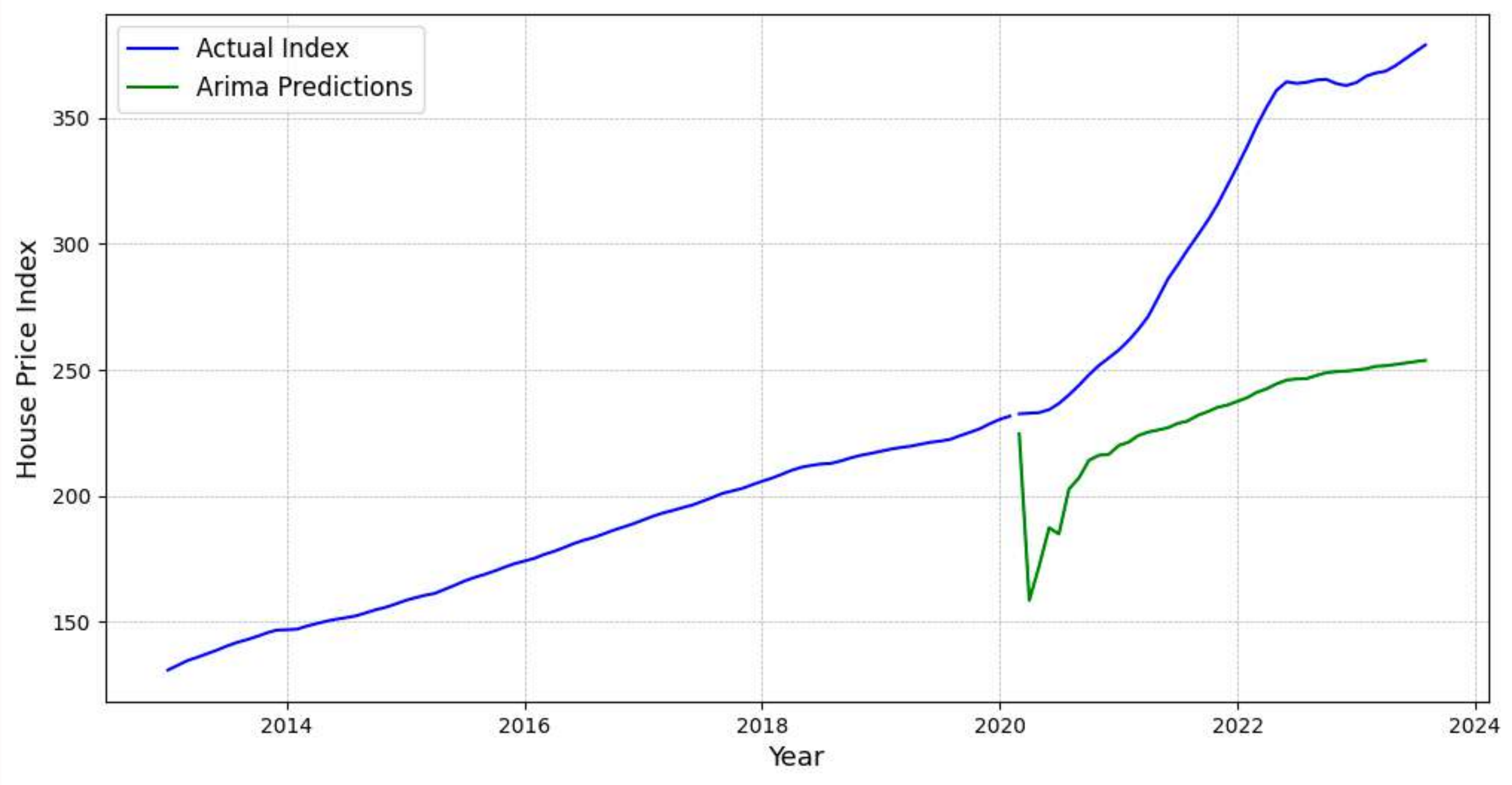
Random Forest

Ensemble of Decision Trees for Prediction

XGBoost

Optimized Gradient Boosting for Performance

ARIMA model



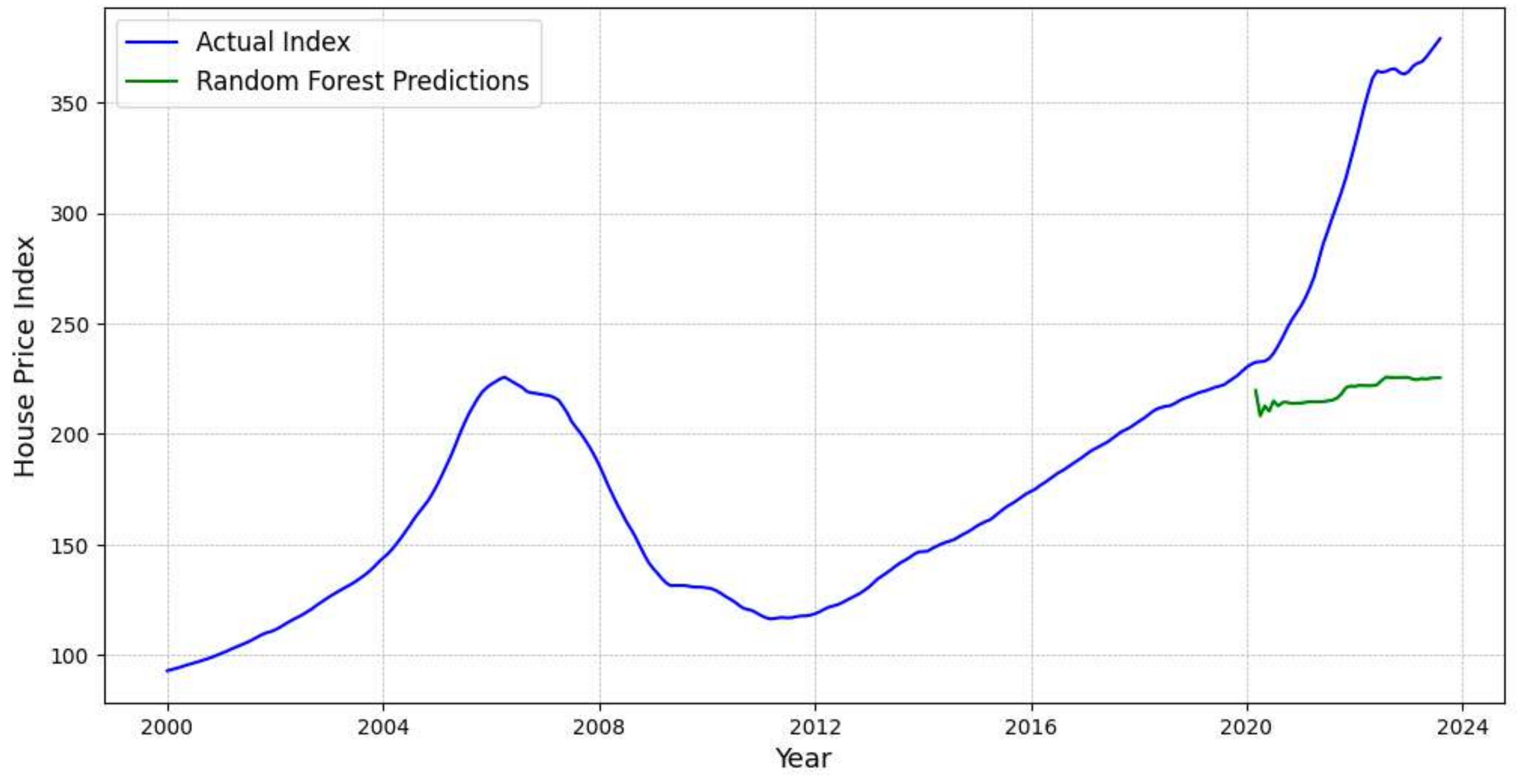
Root Mean Square Error: 88.81

Predictor Variables:

1. Federal Cost of Funds Index
2. Mortgage Rates
3. Number of eligible adults in the U.S. workforce
4. Unemployment rate
5. Sentiment score (Google search data)
6. GDP
7. Average value of appraisal
8. % of WFH employees in Florida

*some variables have been omitted from the ARIMA model due to large number of null values

Random Forest

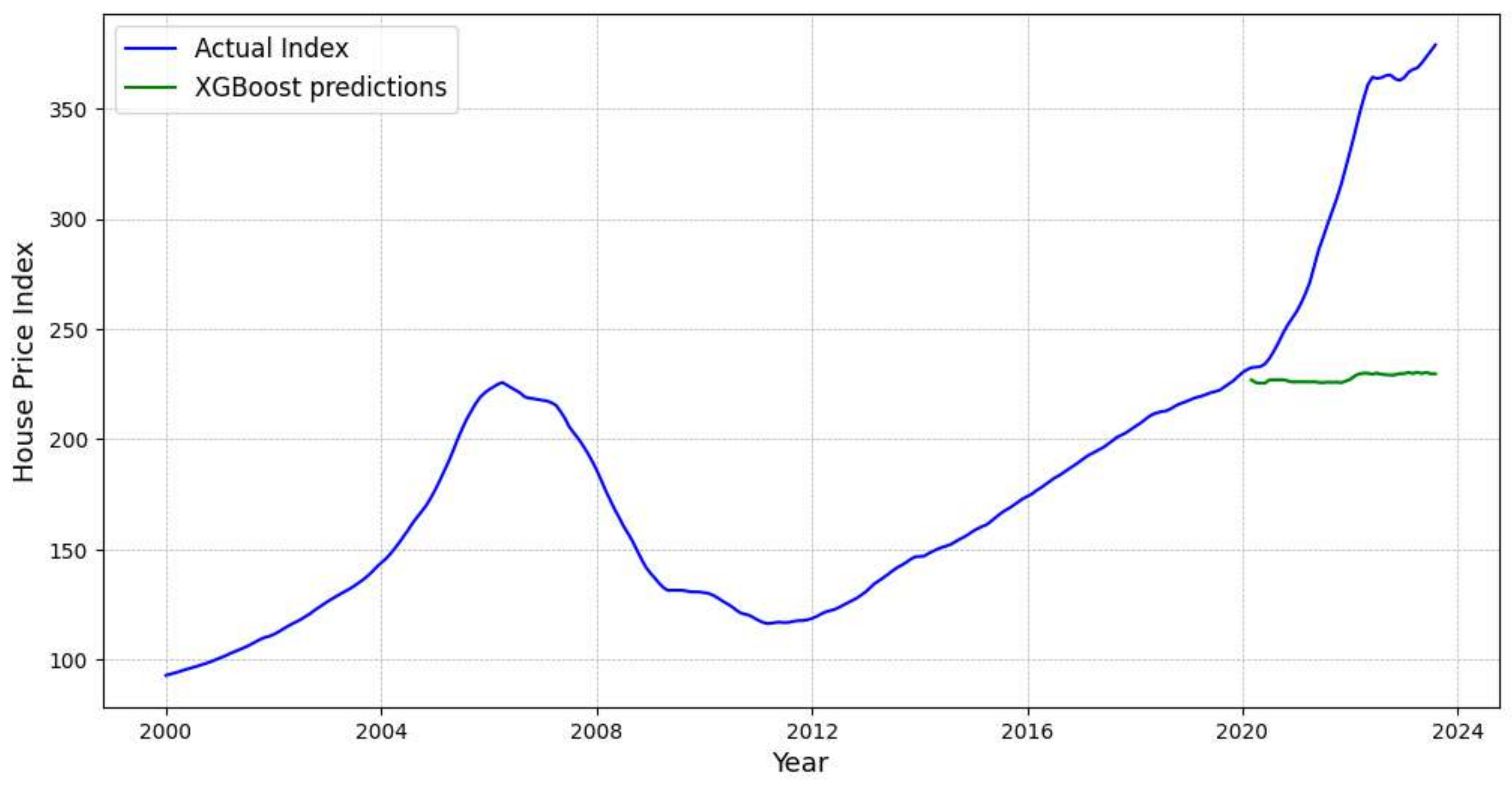


Root Mean Square Error: 104.44

Predictor Variables:

1. Federal Cost of Funds Index
2. Number of new private housing units (+ days since start)
3. Mortgage Rates
4. Number of eligible adults in the U.S. workforce
5. Unemployment rate
6. Sentiment score (Google search data)
7. Sentiment Score (Reddit data)
8. GDP
9. Average value of appraisal
10. % of WFH employees in Florida
11. Number of individuals flying into Florida
12. Number of individuals flying out of Florida
13. Number of active housing listings in Florida
14. Federal interest rates
15. Lag in Seasonal Adjusted Housing Index

XGBoost Model



Root Mean Square Error: 98.40

Predictor Variables:

1. Federal Cost of Funds Index
2. Number of new private housing units (+ days since start)
3. Mortgage Rates
4. Number of eligible adults in the U.S. workforce
5. Unemployment rate
6. Sentiment score (Google)
7. Sentiment Score (Reddit)
8. GDP
9. Average value of appraisal
10. % of WFH employees in Florida
11. Number of individuals flying into Florida
12. Number of individuals flying out of Florida
13. Number of active housing listings in Florida
14. Federal interest rates
15. Lag in Seasonal Adjusted Housing Index

RESULTS

	ARIMA	Random Forest	XGBoost
RMSE	88.81	104.44	98.40
Advantages	Ideal for time series with its focus on historical trends.	Reduces overfitting, enhancing robustness for complex datasets.	Fast and efficient with large datasets, versatile across data types.
Limitations	Cannot process missing data; limited training period excludes major events like the 2008 financial crisis.	Demonstrated lowest accuracy in this analysis, less optimal for time series.	Less suited for time series, didn't achieve the lowest error in this specific analysis.

RECOMMENDATIONS

Invest in Artificial Intelligence & Machine Learning

Implement machine learning based prediction models for real-time monitoring.

Text Mining Integration

Use text mining on social media platforms to extract consumer sentiment and enhance predictive accuracy.

Agile Indicators for Black Swan Events

Integrate frequent updates on policy and consumer sentiment to swiftly adapt to rapid shifts during black swan events.

LIMITATIONS

1. Exclusion of Post-2020 Data

By excluding data beyond the 2020 COVID lockdown, our analysis missed daily shifts in consumer needs and micro market trends, limiting our predictive capability.

2. Cost of Quality Data Acquisition

Accessing high-quality data from tools like Brandwatch for tracking social media trends incurs significant costs, posing a financial constraint on our analysis.

3. API Restrictions

Encountered difficulties in obtaining sufficient data due to API restrictions on various social media platforms

CONCLUSION

1

XGBoost Model, with sentiment score as one of the key predictors, shows a **14.83%** reduction in error rate.

2

LLM models, while promising, are **not sufficiently reliable** for analysis as of December 2023.

3

Public sentiment is **directly indicative** of the change in house price index.

THANK YOU!

NOW OPEN FOR Q&A