The Impact of Hybrid/Remote Work on the Real Estate Market

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INTRODUCTION

The COVID-19 pandemic has significantly increased work-from-home (WFH) opportunities, leading to a shift in residential preferences and impacting home prices, office demand, and migration trends. Our project aims to analyze these changes and develop an interactive dashboard for real estate developers to analyze the most profitable areas for residential real estate development. By examining various datasets and employing predictive modeling techniques, we seek to identify high-growth US counties and their shared characteristics.

LITERATURE SURVEY

The widespread adoption of work-from-home (WFH) policies during the COVID-19 pandemic has significantly influenced housing demand, property values, and local business activity. Barrero, Bloom, and Davis (2022) explore these dynamics in their study, "The Remote Work Revolution: Impact on Real Estate Values and the Urban Environment." They find that the transition to remote work has diminished demand for commercial office space, leading to declining prices in urban centers. Similarly, Arpit, Mittal, and Van Nieuwerburgh (2022) describe this trend as an "office real estate apocalypse," with businesses increasingly vacating urban spaces. In addition, Bloom, Han, and Liang (2022) identify a rise in hybrid work models, which sustain some urban office usage while promoting flexibility.

Azhdari, Sigler, & Pojani (2024) provided evidence of population and job declines in major cities with growth in suburban Sunbelt areas. As individuals seek larger living spaces facilitated by remote work, there is a noticeable shift toward suburban living, altering residential real estate markets. Capello and Caragliu (2024) note a growing preference for suburban and less dense areas in Europe, with access to outdoor amenities gaining importance. Furthermore, Dalton, Dey, and Loewenstein (2023) highlight how declining foot traffic in urban employment hubs has accelerated suburban migration, and census data analyzed by Johnson (2023) underscores the demographic impact of remote work, showing migration patterns favoring suburban and rural areas. This trend is echoed by Florida and Rodriguez-Pose (2023), who explain that "the impacts of the COVID-19 pandemic have spurred a shift away from superstar cities and tech hubs, leading to a surge of housing demand and prices in suburbs, second- and third-tier cities, and rural areas." This shift has exacerbated the "new urban crisis" and has resulted in a broader housing crisis across America.

Current research often focuses on short-term economic impacts, with studies such as Morris et al. (2023) examining changes in work allocation and income dynamics in remote occupations. Although there is increased demand for suburban housing, Howard et al. (2023) caution that predicting the sustainability of these trends remains challenging. This is supported by Duranton and Puga (2024) who suggest that cities may retain their appeal due to their cultural and economic resilience, particularly as hybrid work models stabilize. In addition, a significant limitation of existing research is the reliance on surveys, which may not fully capture the economic implications of WFH. For instance, Guerra (2023) investigates remote work preferences but does not address the structural changes in real estate. Reber (2024) discusses migration and urban sprawl without providing long-term frameworks for sustainability, while Matthew et al. (2022) focus solely on the LA area, limiting the diversity of their findings.

Our approach seeks to integrate data from multiple sources, including WFH trends, census data, and home prices, to provide a more comprehensive understanding of how remote work is reshaping urban and suburban areas. By employing advanced visualizations and analysis, we aim to make the data more accessible and facilitate the identification of meaningful patterns and trends. By building on insights from Matthew, Kwon, and Parkhomenko (2022) on WFH impact in LA and Stuart, Strange, and Urrego (2022) on commercial real estate, this study offers a broader perspective on post-pandemic residential housing market dynamics. Although our focus is on real estate developers, policymakers, urban planners, and more will benefit from our findings, which aim to provide valuable insights into the future impacts of remote work on real estate and urban planning.

PROPOSED METHOD

Our approach combines predictive modeling and dynamic visualization to analyze the pandemic's impact on urban and suburban housing markets. By integrating data from remote work trends, census statistics, Zillow real estate metrics, Federal Reserve Economic Data (FRED), and county adjacency information, we provide a comprehensive view of how these landscapes have evolved during the pandemic.

We start by identifying the top urban county in each state based on population density and housing unit density. To expand the scope beyond these urban hubs, we calculate adjacency relationships for up to five levels using a graph representation of counties, traversed iteratively with a depth-first search (DFS) algorithm. This systematic process clusters urban hubs with adjacent, lower-density counties, uncovering nuanced spatial and demographic relationships. Unlike traditional methods that often treat urban and suburban areas as distinct, isolated entities, our approach captures the interdependencies between them, offering richer insights into their shared dynamics. These insights also form the basis for our unique, highly interactive visualizations.

To forecast growth potential, we employed a variety of predictive models, including Linear Regression, Ridge, Lasso, Elastic Net, ARIMA, and ARIMAX. These models predict the highest-growth counties for each metro's surrounding area and also help identify key drivers of housing price trends, such as remote work prevalence, population growth, and income levels. Feature importance analysis further highlights the common characteristics of high-growth counties, enhancing our understanding of the factors shaping these trends. Unlike much of the existing literature, which focuses primarily on current pandemic-era trends using basic statistical analyses, we emphasize forward-looking predictions and nuanced insights. A detailed evaluation of the predictive models and their results is provided in the subsequent section.

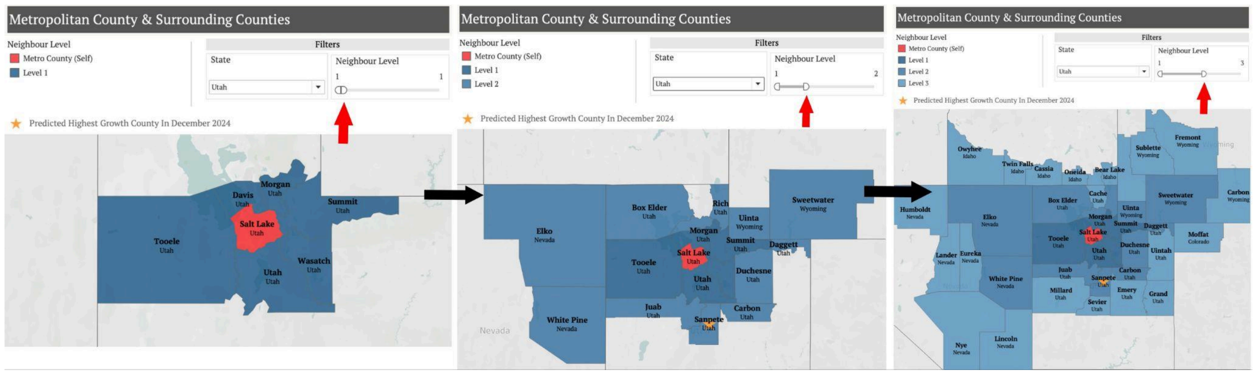


Figure 1: Visual representation of calculated county adjacency levels using DFS for an urban cluster in Tableau.

Our visualizations, developed in Tableau, make these findings accessible and actionable for stakeholders. The interactive urban-suburban map allows users to adjust filters like "Neighbor Level" to explore county adjacency relationships, represented with progressively lighter shades of blue for more distant counties and urban centers highlighted in red (as shown in Figure 1). High-growth counties, identified through our predictive models, are marked with yellow stars, enabling users to pinpoint areas of opportunity. Additional interactive features include toggling between states, zooming in for localized insights, and zooming out for a broader perspective.

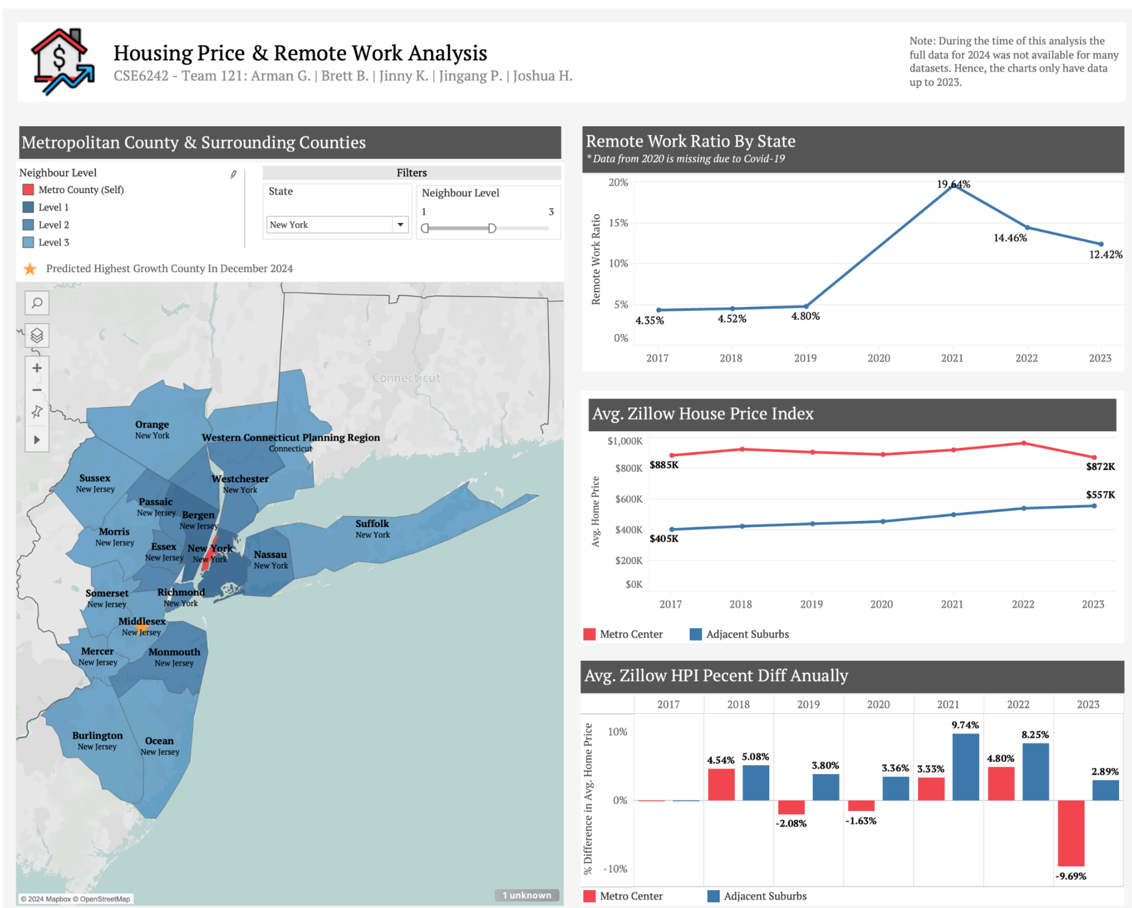


Figure 2 : Interactive Tableau map with house price growth comparison of urban center vs. suburbs by state.

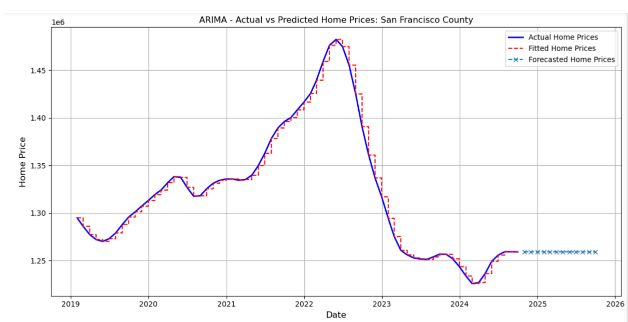
Figure 2 showcases complementary views for comparing metrics between the metro center and its surrounding areas. These views provide insights into variables such as the remote work ratio by state, average Zillow Home Value Index, and changes in housing prices over time. These dynamic tools empower real estate stakeholders to explore trends intuitively, compare urban and suburban metrics, and extract actionable insights to guide decision-making.

EXPERIMENTS / EVALUATION

The experiments were designed to answer three main research questions: (1) Which predictive model is most effective for forecasting housing prices? (2) What underlying factors contribute to the superior performance of specific models compared to others? (3) What shared attributes can be identified among counties experiencing high growth?

To ensure consistency across datasets, date columns were standardized, aligning the start date to the first day of each month for monthly data. In cases where monthly data was unavailable, year-level data was merged to fill the gaps. Missing data, particularly regarding remote work metrics, was addressed through a hierarchical imputation strategy, where county-level data was prioritized and state-level data served as a backup. This imputation method was crucial for maintaining a comprehensive dataset, especially since remote work was identified as a significant variable impacting housing price trends.

After data cleaning and preprocessing, we initiated modeling to predict housing prices, employing both regression and time series approaches. The regression models included linear, ridge, lasso, and elastic net regressions, while time series models comprised ARIMA and ARIMAX. These models were tested in parallel, with the regression and time series workflows proceeding separately to compare their predictive capabilities.



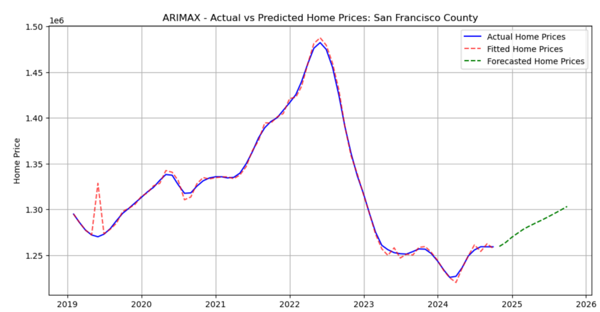
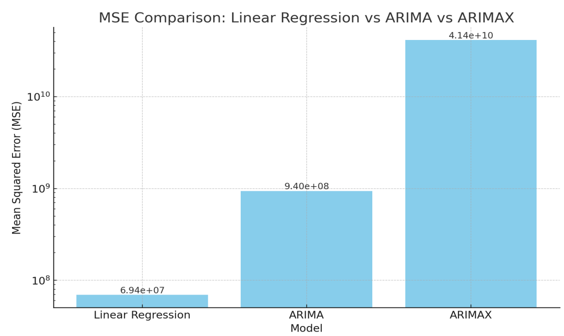


Figure 3 (left): ARIMA prediction of home price in San Francisco County.
Figure 4 (right): ARIMAX prediction of home price in San Francisco County.

For time series analysis, ARIMA was utilized, which required stationarity—a condition achieved by transforming the home price data to stabilize its mean and variance over time. While ARIMA effectively captured historical price trends, it was limited by its inability to incorporate external influences such as demographic and economic factors. This constraint made it less adaptable to market shifts. ARIMAX addressed this limitation by integrating external variables, including population density, income levels, and remote work rates, into its predictive framework, offering a more nuanced and comprehensive model of housing price dynamics. The results of these two workflows are illustrated in Figures 3 and 4 above, showcasing their predictions and comparative performance. As shown, ARIMAX (right) produces more reasonable results as it follows the upward trend in housing prices, while ARIMA (left) results in a flat, horizontal line, failing to capture the trajectory of the data.

The time series models, particularly ARIMA and ARIMAX, performed poorly and had significantly higher Mean Squared Errors (MSE) compared to the regression models as shown in Figure 5. This could be due to the nature of time series models, which require trends to be stationary or cyclic. Unfortunately, our dataset, which spanned from 2019 to 2023, was too small and volatile to exhibit the necessary trend patterns for effective time series modeling. As a result, despite ARIMAX's potential to incorporate both time series data and external factors, the regression models outperformed the time series models.



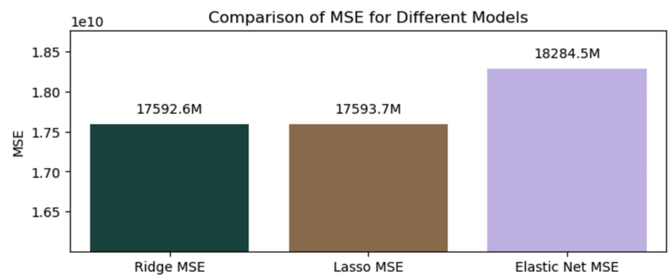


Figure 5 (left): MSE of Linear Regression, ARIMA, and ARIMAX models.
Figure 6 (right): MSE of Ridge, Lasso, and Elastic Net regression models.

These regression models were better equipped to handle overfitting and multicollinearity, especially given the complex interactions among the features in the dataset. Ridge regression, optimized through cross-validation to find the best hyperparameter (lambda), delivered the best results as shown in Figure 6. It effectively addressed multicollinearity, a key issue in our dataset due to the overlap between variables such as income, population demographics, and remote work trends. Ridge regression also minimized MSE more effectively than the other models and ended up having the lowest MSE amongst all models.

Lasso regression, which excels in feature selection by shrinking less important variables to zero, performed slightly worse than Ridge. This was likely because it excluded variables with smaller effects, which, while less significant, still contributed valuable information. Elastic Net, which combines both L1 and L2 penalties, did not show substantial improvements over Ridge in this context. Overall, the regression models provided more accurate predictions and helped identify key features influencing housing price changes, particularly factors such as remote work flexibility, demographic characteristics, and median income. Figure 7 below reveals these features which we will further discuss in the next section.

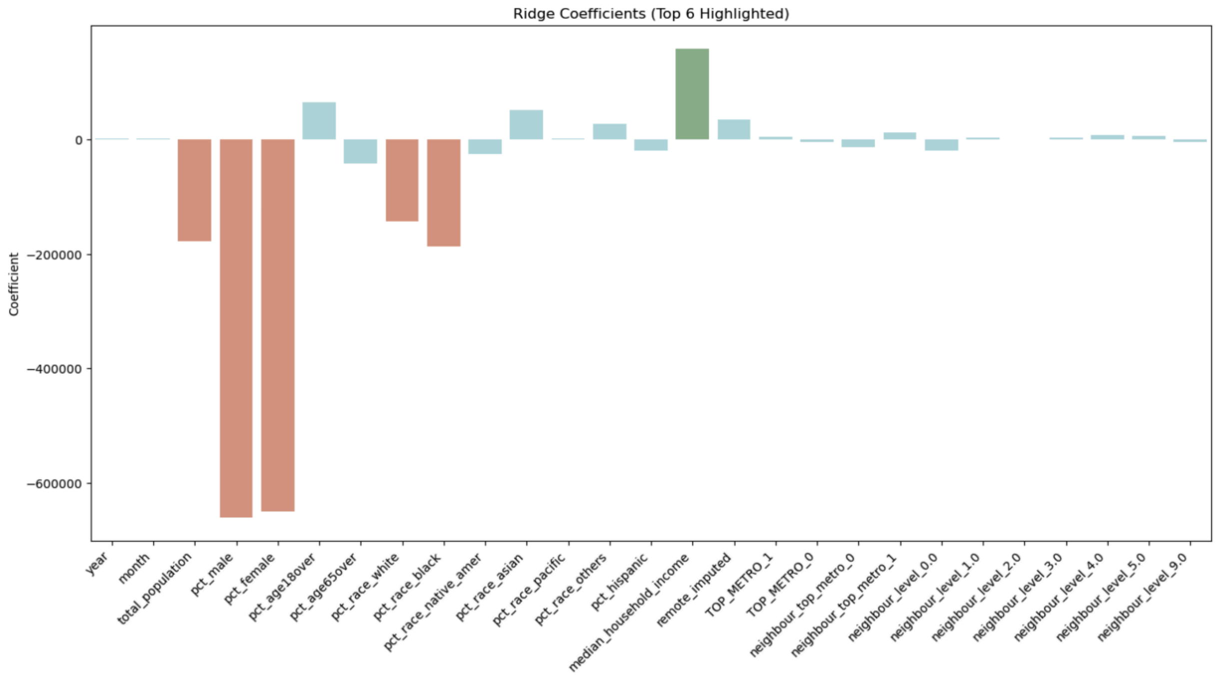


Figure 7: Ridge coefficients indicating the top predictors in predicting home price.

CONCLUSIONS

In conclusion, Linear Regression demonstrated higher accuracy than time series forecasting, with Ridge regression outperforming other models by effectively managing multicollinearity. Counties with lower population densities, higher remote work rates, and younger, more diverse populations with higher median household incomes experienced the largest increases in housing prices, as shown in Figure 7. Interestingly, features like “pct_male” and “pct_female” showed unexpectedly high negative correlations with housing prices, suggesting a need for further investigation.

Across all models, the remote work rate consistently exhibited a positive and significant effect on housing prices. Other consistently influential factors included ethnic diversity, median income, and a larger proportion of working-age individuals, all of which positively impacted housing prices. However, limitations arose from the use of state-level data as a proxy for county-level insights, potentially overlooking regional nuances, particularly in rural areas. This includes the absence of some remote work data for 2020, due to the pandemic. To address these issues, future research could explore additional features and incorporate advanced techniques such as community detection and neural networks (e.g., CNNs or LSTMs) to capture more detailed spatial and temporal patterns.

Ultimately, our interactive Tableau visualization can be a valuable tool in helping users explore housing market dynamics and remote work trends across urban and suburban areas, offering actionable insights for stakeholders. Team collaboration was instrumental, with all members contributing equally to research review, discussions, data cleaning, predictive modeling and visualization tasks.

APPENDIX

Arpit, C., Mittal, V., & Van Nieuwerburgh, S. (2022). Work from home and the office real estate apocalypse. *National Bureau of Economic Research*. https://www.nber.org/papers/w30526

Barrero, J. M., Bloom, N., & Davis, S. J. (2022). The remote work revolution: Impact on real estate values and the urban environment. *The Journal of Real Estate Finance and Economics*. https://onlinelibrary.wiley.com/doi/epdf/10.1111/1540-6229.12422

Bloom, N., Han, R., & Liang, J. (2022). How hybrid working from home works out (NBER Working Paper No. 30292). *National Bureau of Economic Research*. https://doi.org/10.3386/w30292

Capello, R., & Caragliu, A. (2024). Remote work and location preferences: A study of post-pandemic trends in Italy. *SpringerLink*. https://link.springer.com/article/10.1007/s00168-024-01295-w

Dalton, M., Dey, M., & Loewenstein, M. (2023). The impact of remote work on local employment, business relocation, and local home costs (BLS Working Paper No. 553). *U.S. Bureau of Labor Statistics*.

Duranton, G., & Puga, D. (2024). The appeal of cities may not wane due to the COVID-19 pandemic and remote working. *Nature Cities*. https://www.nature.com/articles/s42949-024-00151-2

Economic Innovation Group. (2023). The short- and long-run effects of remote work on U.S. housing markets. *Journal of Financial Economics*. https://eig.org/wp-content/uploads/2023/08/The-Short-and-Long-Run-Effects-of-Remote-Work-on-U.S.-Housing-Markets.pdf

Favilukis, J., Mabille, P., & Van Nieuwerburgh, S. (2021). Housing consumption and the cost of remote work. *National Bureau of Economic Research*. https://www.nber.org/system/files/working_papers/w28483/w28483.pdf

Florida, R., & Rodriguez-Pose, A. (2023). COVID-19, the new urban crisis, and cities: How COVID-19 compounds the influence of economic segregation and inequality on metropolitan economic performance. *National Institutes of Health*. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC9941007/

Guerra, T. (2023). 64% say they prefer to work remote: How is this changing real estate? *Bankrate*. https://www.bankrate.com/real-estate/remote-jobs-and-home-prices/

Johnson, K. (2023). New census data reflect the continuing impact of COVID on U.S. demographic trends. *Carsey School of Public Policy*. https://carsey.unh.edu/publication/new-census-data-reflect-continuing-impact-covid-us-demographic-trends

Milder, N. (2020). Remote work: An example of how to identify a downtown-related trend breeze that probably will outlast the COVID-19 crisis. *University of Wisconsin-Extension*. https://economicdevelopment.extension.wisc.edu/files/2020/10/Milder_paper.pdf

Matthew, J. D., Kwon, E., & Parkhomenko, A. (2022). How do cities change when we work from home? *JUE Insight*. https://www.sciencedirect.com/science/article/pii/S0094119021000139

Morris, A. D., Ghent, A. C., & Gregory, J. M. (2023). The work-from-home technology boon and its consequences. *National Bureau of Economic Research*. https://www.nber.org/papers/w28461

Ostrovsky, Y., & Lichtman, S. (2023). How hybrid working from home works out. *National Bureau of Economic Research*. https://www.nber.org/papers/w30292

Quadri, I. (2024). Impact of remote work on urban development. *Economic Policy Brief #62*. https://www.usresistnews.org/2024/07/02/remote-work-urban-impact/

Reber, S. (2024). American superstar cities fade as remote work sparks migration southward and inland, exacerbating urban sprawl. *Research Square*. https://assets-eu.researchsquare.com/files/rs-4831481/v1/001fc626-c749-4ff0-8653-9c6c54f174d4.pdf?c=1726734914

Rob, L. (2024). Managing a low urban emissions world. *Nature*. https://www.nature.com/articles/s44168-024-00117-1

Stebbins, S. (2022). The impact of remote work on local employment, business relocation, and local home costs. *Bureau of Labor Statistics*. https://www.bls.gov/osmr/research-papers/2022/ec220080.htm

Stuart, S. R., Strange, W. C., & Urrego, J. A. (2022). Are city centers losing their appeal? Commercial real estate, urban spatial structure, and COVID-19. *JUE Insight*. https://www.sciencedirect.com/science/article/pii/S0094119021000632

Dataset: County-level 2020 Census Urban and Rural Information for the U.S., Puerto Rico, and Island Areas (2020). *US Census Bureau.* https://www2.census.gov/geo/docs/reference/ua/2020_UA_COUNTY.xlsx

Dataset: 2024 County Adjacency (2024). *US Census Bureau.* https://www2.census.gov/geo/docs/reference/county_adjacency/county_adjacency2024.txt

Dataset: Zillow Home Value Index ZHVI (2024). *Zillow.* https://www.zillow.com/research/data/

Dataset: Means of Transportation to Work by Selected Characteristics (2023). *US Census Bureau.* https://data.census.gov/table/ACSST1Y2023.S0802?q=commuting%20to%20work&g=010XX00US$0400000