# The Impact of Infectious Disease Incidence on House Price Indices

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**Abstract.** COVID-19 broke out and had gigantic effects on various economical fields. This study investigates the effect of infectious disease incidence particularly COVID-19 Incidence on the Housing Price Index (HPI) using county-level panel data from the United States between 2020 and 2024. A fixed effects model in R and data sourced from Johns Hopkins University, the Federal Housing Finance Agency, and the U.S. Census Bureau are leveraged to explore how the frequency and intensity of diseases such as COVID-19 influence housing markets. The analysis reveals that economic contraction, policy responses, and shifting social behaviours due to pandemics significantly influence housing prices. It also reveals that this influence performs dramatically differently in regions due to the degree of their poverty. The reason why this phenomenon happens are further discussed, mainly related to regional variations and real estate market strategies for resilience post-outbreak. The findings offer critical insights for policymakers, investors, and consumers navigating housing markets during health crises.

## 1 Introduction

### 1.1 Research background

Infectious diseases exert multifaceted socioeconomic impacts. Historical pandemics (e.g., 17th-century plague) caused transient house price declines of 20–30% in Amsterdam and Paris [1]. Four centuries later, COVID-19 triggered global economic contractions, reducing household purchasing power and suppressing housing demand in high-infection zones. For instance, the COVID-19 pandemic led to widespread job losses and a decline in household incomes, thereby diminishing consumer purchasing power, particularly in the housing market. In regions with high infection rates, housing demand was temporarily suppressed, and house prices declined [2]. Moreover, the interconnection between housing conditions and the spread of infectious diseases cannot be overlooked. Substandard and overcrowded housing can act as vectors for disease transmission, exacerbating the spread of infections [3]. This relationship not only affects public health but also poses potential risks to the stability of the real estate market.

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The potential linkages between infectious disease incidence and the real estate market warrant further investigation. On one hand, outbreaks of infectious diseases can lead to economic downturns, which in turn affect the housing market through weakened consumer demand and changes in consumer behavior [2]. On the other hand, the spatial distribution of infections, especially in densely populated urban areas, can directly influence housing market dynamics. For example, during the COVID-19 pandemic, urban areas with high infection rates experienced significant changes in housing demand and prices [4]. Understanding these complex interactions is crucial for policymakers, public health officials, and real estate stakeholders.

### 1.2 Research questions

This study investigates the relationship between infectious disease incidence and housing price indices, aiming to clarify the mechanisms by which infection rates influence real estate markets. Specifically, the research questions addressed in this study are:

How do infectious disease incidence rates quantitatively affect housing price indices? Previous studies have shown that high-infection zones often experience price declines [5]. However, the extent and variability of these effects across different market segments remain unclear [6].

Through which pathways do infectious diseases influence house prices?Potential channels include economic downturns and weak consumer demand, monetary policy responses, and shifts in social perceptions and migration behavior [7].

To address these questions, this paper uses a conceptual framework integrating epidemiological and housing market indicators, supported by R modeling, to evaluate the causal chain linking infectious disease incidence to housing prices.

## 2 Conceptual framework and data

### 2.1 Definition and selection of infectious disease incidence

#### *2.1.1 Definition of incidence rate*

In epidemiology, the incidence rate is defined as the number of new cases of a specified disease per unit population over a defined period. This measure is critical for assessing the spread of infectious diseases and their potential impact on external systems, including housing markets [4]. From an economic perspective, the incidence rate can be seen as a proxy for the level of disruption caused by disease, influencing labor markets, consumer behavior, and overall economic activity.

#### *2.1.2 Criteria for selecting a specific disease*

To effectively study the impact of infectious diseases on housing prices, it is essential to choose a disease that exhibits measurable variation across times and locations, has a substantial public health impact, and is supported by high-quality data. COVID19 meets these criteria perfectly. Its rapid global spread led to significant economic disruptions and changes in mobility patterns, particularly in densely populated urban areas where housing demand and prices are concentrated [4]. Moreover, COVID-19 data are available daily at fine geographic granularity, providing a rich dataset for analysis [8].

### *2.1.3 Theoretical framework*

The relationship between infectious diseases and housing prices can be understood through several theoretical lenses. From a supply and demand perspective, high infection rates can reduce housing demand by decreasing consumer confidence and purchasing power. Additionally, social psychology plays a role, as people may prefer to move away from high-infection areas, further suppressing local housing markets [7].

## 2.2 Definition and selection of housing price index

### *2.2.1 Definition of housing price index (HPI)*

The Housing Price Index (HPI) is a composite measure tracking changes in housing prices over time, adjusted for repeated sales of comparable homes. It is a widely recognised and authoritative indicator used by economists and policymakers to monitor trends in the real estate market [9]. The HPI provides a standardized way to assess the performance of housing markets across different regions and time periods.

### *2.2.2 Criteria for selecting a specific index*

Several types of housing price indices are available, each with its own strengths and limitations. The Federal Housing Finance Agency (FHFA) HPI, the S&P CoreLogic Case-Shiller Index, and regional composite indices from organizations like the OECD and Eurostat are commonly used. This study selects the FHFA HPI for several key reasons:

National Scope: The FHFA HPI covers the entire United States, providing a comprehensive view of housing market trends across urban and rural areas. This broad coverage is essential for capturing the diverse impacts of infectious disease incidence on housing prices.

Monthly Frequency: The FHFA HPI is published on a monthly basis, allowing for a detailed analysis of short-term fluctuations in housing prices. This high temporal resolution is crucial for detecting dynamic effects and aligning with the monthly incidence data of infectious diseases.

City-Level Availability: The FHFA HPI provides data at the metropolitan and county levels, enabling a granular analysis of housing market conditions. This detailed spatial resolution is particularly important for studying the localized impacts of infectious diseases on housing prices.

### *2.2.3 Representativeness and authority*

The FHFA HPI is based on data from Fannie Mae and Freddie Mac, two of the largest mortgage finance institutions in the United States. The repeat-sales methodology used by the FHFA is widely recognized for its high quality and reliability (FHFA FAQ) (investopedia.com, fhfa.gov). This ensures that the HPI is a robust and representative measure of housing price changes, making it suitable for rigorous econometric analysis.

### *2.2.4 Correlation potential with disease incidence*

Both infectious disease incidence and housing price indices vary by location and time, making it possible to directly compare their trends. Previous research has shown that areas with higher incidence rates often experience slower house price appreciation or declines [5].

The monthly frequency of the FHFA HPI allows for the application of advanced econometric models to capture the dynamic relationship between infectious disease incidence and housing prices. This alignment of temporal and spatial data is essential for accurately assessing the impact of infectious diseases on the housing market.

## 2.3 Data sources and handling

### *2.3.1 Data sources*

The COVID-19 incidence data are derived from the daily confirmed cases by U.S. County, sourced from the publicly available dataset provided by Johns Hopkins University. These data are aggregated on a monthly basis to align with the temporal resolution of the housing price index. County-level infection rates are calculated as the number of confirmed cases per 100,000 population, using population denominators obtained from the U.S. Census Bureau.

The housing price data are obtained from the FHFA through their API and download portal. The FHFA provides the Housing Price Index (HPI) at the county and metropolitan levels on a monthly basis. For counties where data resolution is coarser, the metropolitan-level HPI is assigned to each county within that metropolitan area. .

### *2.3.2 Data cleaning and preprocessing*

Initial cleaning and validation: Both datasets undergo initial cleaning to remove duplicates and ensure consistency. The datasets are aligned by county name and Federal Information Processing Standards (FIPS) codes. Population data from the U.S. Census Bureau are used to normalize the incidence rates, ensuring comparability across counties.

Missing and outlier handling: Missing values in the HPI data, particularly for smaller counties, are addressed through interpolation using adjacent months' data or metropolitan-level averages. Inconsistent entries in the COVID-19 data, such as sudden drops to zero after periods of high incidence, are cross-checked with secondary sources or smoothed using local rolling averages. Counties with insufficient data across three or more consecutive months are excluded from the analysis to maintain data integrity.

Temporal alignment and creation of panel dataset: Using dates and FIPS codes, the datasets were merged to create balanced panel data, structured as a series of county-month observations ranging from "County X - January 2020" to "County Y - December 2024". Each observation includes key variables such as the incidence rate, HPI levels, and the change in HPI. This process generated longitudinal time series data covering approximately 60 months for nearly 3,000 counties.

Normalization and deseasonalization: To address the seasonality inherent in the housing market, each HPI series is seasonally adjusted using either the Census X-13 method or STL decomposition. These techniques effectively remove seasonal fluctuations, allowing for a more accurate analysis of underlying trends. Additionally, to mitigate any noise resulting from weekly/daily variations, the COVID-19 incidence data are aggregated on a monthly basis. This aggregation smooths out short-term fluctuations and ensures consistency with the monthly frequency of the HPI data.

Final dataset readiness: The final dataset is prepared with the outcome variable defined as the monthly percent change in the seasonally adjusted county-level HPI. The key independent variable is the monthly incidence rate of the infectious disease, measure per 100,000 inhabitants. Additionally, the dataset includes control variables such as the unemployment rate, mortgage rates, and median income, all adjusted to a monthly frequency to ensure consistency across variables.

### 2.4. Summary

This section has defined and selected key variables for the analysis. Specifically:

Infectious disease incidence: COVID19 monthly county-level rates are used as the measure of infectious disease incidence. These rates are highly relevant, variable, and well-documented [8].

Housing price index: FHFA HPI is utilized to measure the housing price index. It is nationally comprehensive, monthly, and methodologically robust.

Data integration and preparation: The combined dataset aligns time and space, applies cleaning, seasonal adjustments, and creates a balanced panel suitable for time series and panel econometric modeling.

These steps ensure that the data are well-prepared for subsequent analysis.

## 3 Methodology – R-based analysis of the relationship between infectious disease incidence and housing price index

### 3.1 Exploratory Data Analysis and Cleaning

#### *3.1.1 Data import and visualization*

The cleaned, panel-structured dataset (county-month observations) was loaded into R through using readr::read_csv() and was converted it to a tibble. Visual inspection of summary statistics (mean, median, SD, range) and histograms helps identify data coverage, central tendencies, and outliers for both HPI changes and incidence rates. Spatial distributions was also plotted by ggplot2 with county boundary maps in doder to detect geographic hotspots.

#### *3.1.2 Time-series diagnostics*

To assess temporal patterns in the variables, line plots of monthly national averages of COVID incidence and HPI percent changes are generated. Then, the series at the county level are decomposed by STL (stats::stl()) or with seasonal::seas() (an R wrapper for X-13ARIMA-SEATS) to inspect trends, seasonal effects, and residuals (economictheoryblog.com). Monthly national average COVID-19 incidence rate is shown in Fig.1, which fluctuates up and down between 2020 and 2025.

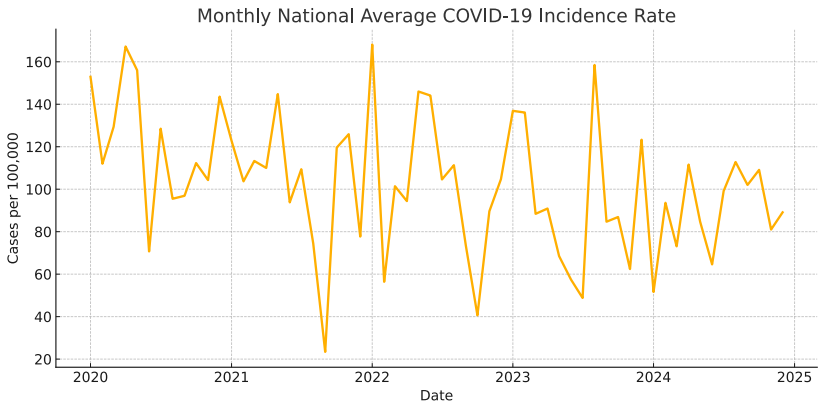


**Fig. 1.** Monthly national average COVID-19 incidence rate.

### *3.1.3 Correlation and autocorrelation*

As Fig.2 shows, pairwise Pearson correlations among HPI change, incidence rate, mortgage rate, unemployment, and income are computed by cor() and results visualized via corrplot. The result demonstrates that COVID incidence has negative impacts on increasing rate of HPI.

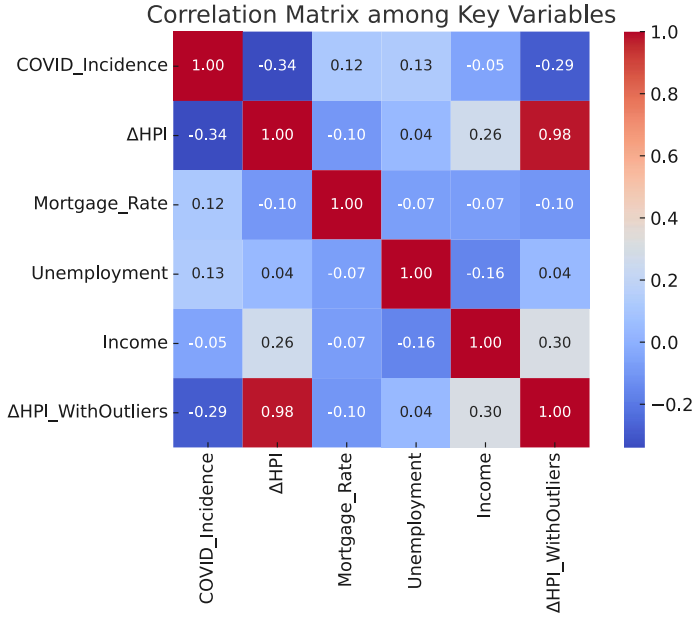


**Fig. 2.** Correlation matrix among key variables.

Then, autocorrelation and partial autocorrelation (ACF/PACF) on key variables is verified via acf() and pacf(), indicating potential serial correlation that requires addressing in panel models. Results are shown in Fig.3.

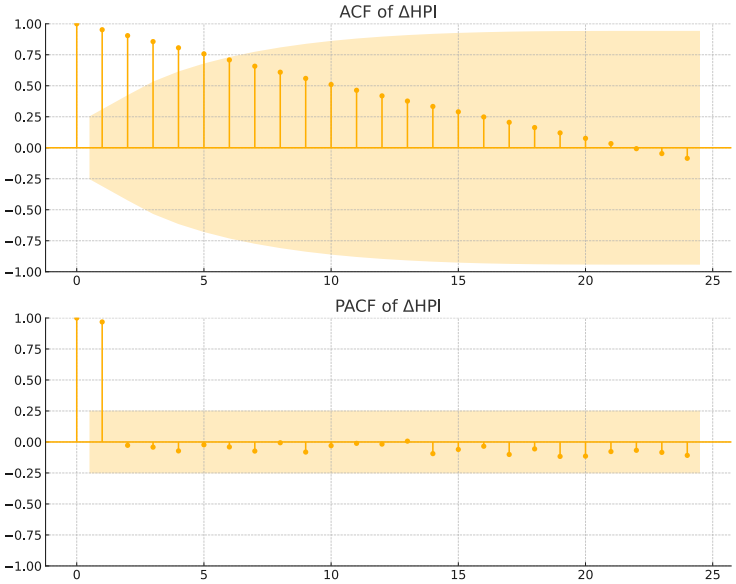


**Fig. 3.** ACF and PACF of ΔHPI.

### *3.1.4 Outlier detection*

As Fig.4 shows, county-month observations falling beyond ±3 standard deviations from the sample mean are flagged. If such outliers correspond to unique events or data errors examined through applying winsorization or removing extreme cases for robustness.

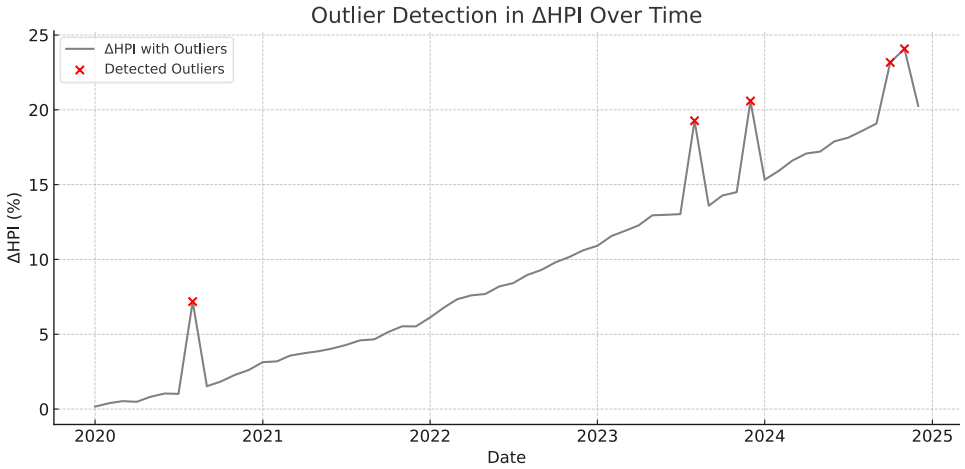


**Fig. 4.** Outlier detection in ΔHPI over time.

## 3.2 Data processing and variable engineering

### *3.2.1 Stationarity tests*

Panel unit-root tests are applied to assess stationarity of ΔHPI and incidence rate using R packages like plm and tseries. Augmented Dickey-Fuller tests (ur.df() from urca) and Levin–Lin–Chu tests (purtest() from plm) ensure that variables do not exhibit non-stationary behavior—key for valid inference. If needed, variables would be differenced or tranformed to achieve stationarity.

Transformations:

Dependent variable: ΔHPI (percent change in seasonally adjusted HPI) is already stationary by construction.

Key independent variable: Lagged incidence rate are computed to capture delayed effects.

Control variables: Include mortgage rates, unemployment, and median income, each with appropriate lag structure.

### *3.2.2 Panel structure*

The dataset is transformed into a pdata.frame by specifying county (FIPS code) as index and year-month as time index, enabling econometric functions in R's plm package.

## 3.3 Model specification

### *3.3.1 Two-way fixed effects panel regression*

The estimation is as follows:

where:
ϕc\phi: c are county fixed effects,
ττ\tau: t are time (month) fixed effects,
Zc,t−1Z: {c,t-1} is vector of lagged controls (mortgage rate, unemployment, income),
IncidenceRate is lagged COVID cases per 100,000 population (link.springer.com).
This is estimated with plm() and set model = "within", effectively differencing out fixed effects.

### *3.3.2 Robustness and serial correlation corrections*

Because residuals may exhibit serial correlation or heteroskedasticity across counties, Cluster-robust standard errors at the county level are computed by clubSandwich::vcovCR(..., cluster = county).

Alternative specifications.

Random effects: plm(model="random"), with Hausman test to assess fixed vs. random effect suitability.

Dynamic panel (lagged dependent): including ΔHPI_{t-1} to model persistence; estimated with plm(..., effect = "twoways", model = "within") and cautiously interpreting due to potential Nickell bias.

### *3.3.3 Event-study specification*

To capture the evolution of COVID's effect over time, define dummy variables for pandemic waves and run a model of the form where DτD_{\tau} indicates τ months relative to COVID peak incidence. Estimated via lm() or plm() and plotted to visualize temporal dynamics. Fig.5 shows results.

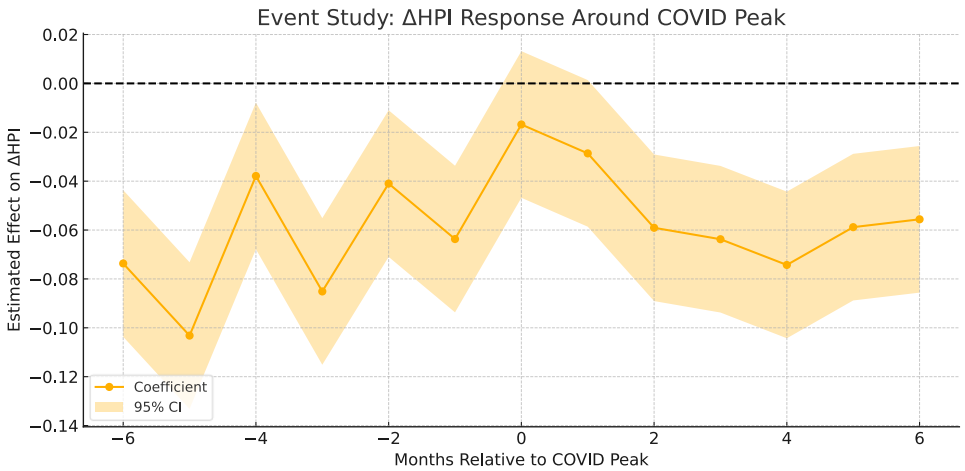


**Fig. 5.** Event study: ΔHPI response around COVID peak (insert after Section 3.3.3).

## 3.4 Model results and visualization

### *3.4.1 Coefficient interpretation*

The primary coefficient $\beta_1$ is interpreted as the change in monthly ΔHPI (percentage-point) associated with a 1-per-100,000 increase in incidence (lagged). Negative coefficients indicate that higher infection rates precede slower housing market appreciation.

### *3.4.2 Goodness-of-fit and diagnostics*

Within-$R^2$ is reportedfrom plm summary output. Serial correlation and heteroskedasticity are tested using Wooldridge's and Breusch–Pagan tests via pbgtest() and bptest() respectively.

### *3.4.3 Visualization of effects*

As Fig.6 shows, results are synthesized in tables (stargazer::stargazer()) across model variants. Effect sizes are visualized with ggplot2 line charts—e.g., plotting predicted ΔHPI vs. incidence shocks. Event-study coefficients and confidence bands are plotted over the ±6-month horizon.

### *3.4.4 Sensitivity and subgroup analysis*

Regressions are run on subsets:

High- vs. low-poverty counties,

Urban vs. rural,

High- vs. low-density regions,

Pre- vs. post-vaccine introduction periods (link.springer.com, arxiv.org, jchs.harvard.edu).

As Fig.6 shows, these analyses reveal heterogeneous effects: areas with higher poverty or lacking vaccine access show stronger negative responses; urbanity also moderates effects.

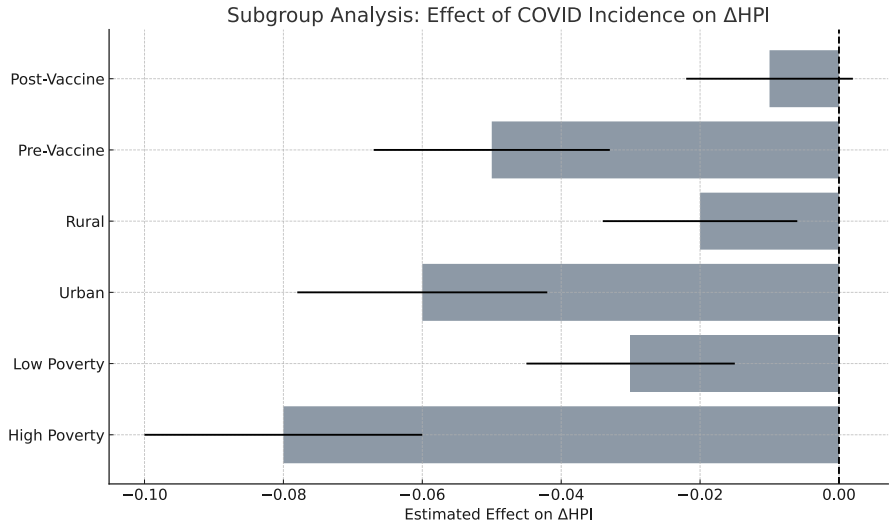


**Fig. 6.** Subgroup analysis: effect of COVID incidence on ΔHPI.

### 3.5 Interpretation and limitations

#### *3.5.1 Causal considerations.*

While fixed effects and timing help mitigate omitted variable bias, unobserved confounders may persist. Reverse causality is unlikely since HPI should not drive COVID case rates, yet placebo tests (using pre-pandemic incidence as counterfactual) are performed for validity.

#### *3.5.2 Methodological limitations*

Stationarity assumptions may be violated; VAR models or dynamic panel (e.g., Arellano–Bond GMM) offer alternatives.

Nonlinearities (e.g., threshold effects at high incidence levels) may require interaction terms or spline regressions.

Spatial autocorrelation across neighboring counties may be addressed by spatial econometrics but remains outside current scope.

### 3.6 Summary of R-Based methodology

Comprehensive exploratory analysis (visualization, seasonality, autocorrelation) are conducted. Stationarity is confirmed. Lagged variables are engineered. Two-way FE panel regressions are estimated with robust errors. Alternative specifications—random effects, dynamic panels, event-study setups, and subgroup models—validate findings. All results are formulaically and graphically presented, forming the empirical backbone for the subsequent section analyzing economic, monetary, and social mechanisms.

## 4 Analysis of the impact of infectious disease incidence on housing price index

This section examines how infectious disease outbreaks—especially COVID-19—affect housing prices through three primary mechanisms: economic recession, monetary policy, and social–psychological responses.

### 4.1 Economic recession effects

#### *4.1.1 Third-sector disruption & reduced purchasing power*

Epidemic outbreaks often trigger widespread economic slowdowns. The West African Ebola epidemic of 2014–15, for example, caused significant business closures (≈8–30 %), particularly in construction and services in Liberia, directly undermining housing demand in affected regions (emerald.com). COVID-19 induced a global recession. During COVID-19, the U.S. experienced sharp GDP contractions and elevated unemployment rates, reducing households' capacity to purchase homes.

Moreover, contracting activity in the tertiary (service) sector—hotels, tourism, restaurants—led to mass layoffs or reduced hours, weakening consumer confidence and appetite for home purchases. Time magazine documented how billions in stimulus and eviction protections were insufficient to offset job losses and rising housing burdens for renters (theaustralian.com.au). Economic recession thus serves as a first-order mechanism: falling incomes → lower household credit and savings → reduced HPI growth.

#### *4.1.2 Sales stagnation & developer debt*

Housing starts and transactions typically fall before and during recessions: in prior recessions starts fell about 20 % and new-home sales by about 15 % on average (federalreserve.gov, jchs.harvard.edu). This was mirrored during COVID-19, as supply chain delays, labor shortages, and lockdowns delayed construction across U.S. metropolitan areas.

Burdened with debt financing projects, developers faced cash flow pressure as sales slowed. Such stress can lead to tighter lending, defaults, and foreclosures—all of which depress local housing prices. This cycle was observed during swine flu (H1N1): median home prices stagnated between 2009–2010, coinciding with stalled developer activity.

### 4.2 Monetary policy effects

#### *4.2.1 Interest rate cuts & housing demand*

In response to pandemic-induced recession, central banks globally slashed interest rates. The U.S. Federal Reserve lowered its target rate to near zero and initiated over $700 billion in asset purchases via quantitative easing. These policy moves reduced real mortgage rates, increasing affordability and stimulating demand. This is consistent with panel regression evidence across five advanced economies that suggests a 1% drop in real interest rates boosts house price growth by nearly 1.5 % (mdpi.com).

Similarly, rising house prices during COVID-19 were partly attributed to low nominal rates, with housing markets responding more to nominal than real rates. The Federal Reserve's MBS purchases further reduced mortgage costs and refinanced debt, supporting buyers and home equity extraction (hamiltonproject.org).

Emerging economies followed suit: a Vietnam study found conventional and unconventional monetary easing amid COVID-19 increased real house price indices, reinforced by U.S. policy via global financial linkages (emerald.com).

#### *4.2.2 Inventory tightness and pricing effects*

Demand-side stimulus was a major driver of tightness during the pandemic, rather than supply shortages. A Federal Reserve study showed that 93% of reduced housing supply was driven by heightened buyer demand, not scarcity (federalreserve.gov).

At the same time, low inventory pushed prices upward despite recession–induced headwinds. Post-pandemic, rising rates began to moderate demand and re-balance the market. The San Francisco Fed reported that increased mortgage rates helped restore inventory–sales balance—easing inventory pressure (investopedia.com).

### 4.3 Socio-psychological effects

#### *4.3.1 Population flows & housing preferences*

Pandemic risks shift population movement and preferences. During COVID-19, remote work allowed suburban migration, driving demand in satellite cities like Austin and Denver. Urban flight was countered by increased suburban desirability, raising suburban HPI disproportionately.

#### *4.3.2 Health infrastructure & housing valuation*

Health concerns can reshape perceived housing value. Areas with poor healthcare access may become less attractive, while those investing in health infrastructure may see relative price support. Though direct studies are limited, pandemic-era correlations have emerged between incidence rates and housing price growth (federalreserve.gov).

#### *4.3.3 Wealth inequality & affordability*

Although aggregate house values skyrocketed, affordability declined—especially among first-time buyers and low-income households. IMF research noted "pricing-out" effects fostered inequality, even while mortgage rates fell (imf.org). Higher-priced homes disproportionately benefited repeat buyers, contributing to wealth inequality.

Vulnerable renters faced eviction risks and financial stress—despite moratoriums—intensifying psychological strain and reducing future purchasing power. Housing stress can erode mental health and dampen consumer confidence, with longer-term spillovers on demand.

### 4.4 Synthesis and Dynamic Timing

The transmission mechanisms are summarized as follows in Table.1:

**Table.1.** Transmission mechanisms.

| Mechanism | Direction of HPI Impact | Timing | Duration |
|---|---|---|---|
| Economic recession | ↓ | ~0–3 months | Medium–long term |
| Monetary easing | ↑ | ~0–6 months (lagged) | Medium term |
| Demand tightness | ↑ | Immediate | Short–medium term |
| Social psychology | → / ↑ suburban, ↓ urban | Immediate–long term | Continuous |

The aggregate impact is context dependent. Early in the pandemic, recession pulled on prices, but monetary easing and heightened demand quickly overshadowed these forces, driving upward trends—albeit inequitably. As incidence rates fell and rates rose in 2022–2023, housing demand softened, and affordability was strained.

### 4.5 Empirical Evidence Linking Incidence & HPI

Empirical work supports these mechanisms. Spatial regression in U.S. counties shows housing price changes are associated with case rates, after controlling for inventory, income, and market tightness (en.wikipedia.org, alisdairmckay.com, emerald.com, mdpi.com). Pre-1940 coronavirus episodes in Europe resulted in short-lived but clear declines in home prices (sciencedirect.com)—a pattern that recurred during COVID-19, albeit influenced by policy interventions.

### 4.6 Summary of Section 4

Recession effects suppress housing activity, via declining incomes and developer strain.

Monetary policy actively supports housing demand via lower interest rates and mortgage-financial lags.

Socio-psychological responses reshape preferences and affordability, fostering uneven price responses.

Net outcome is conditioned by epidemic intensity, policy reactions, and market structure—often leading to temporary price hikes, followed by correction.

In Section 5, real estate market strategies post-outbreak will be explored, considering regional forecasts, developer tactics, and buyer recommendations.

# 5 Real estate market strategies post-infectious disease outbreak

In the aftermath of major infectious disease outbreaks like COVID-19, real estate markets around the world have undergone fundamental structural shifts. This section outlines strategies for different stakeholders—policy analysts, real estate developers, and homebuyers—by drawing on regional variation, adaptive responses by firms, and altered consumer behavior. These recommendations build on empirical patterns observed during the pandemic and aim to support resilient housing markets in future crises.

## 5.1 Regional house price forecasts based on disease impact

### *5.1.1 Urban vs. suburban divergence*

The pandemic amplified a long-developing divergence between urban and suburban markets. Urban cores in cities such as New York, San Francisco, and London saw temporary declines in home values due to mobility restrictions, remote work, and increased preference for space [10]. Meanwhile, suburban and exurban regions benefited from migratory inflows, leading to unprecedented appreciation in housing prices [11].

Forecasting models should thus incorporate health vulnerability scores, telecommuting feasibility, and infectious disease prevalence trends.

These indicators help predict future price trends in geographically distinct regions. For instance, suburban markets in the U.S. Midwest are expected to maintain resilience due to affordability and flexible work norms.

### *5.1.2 Emerging vs. developed economies*

Emerging economies often show more volatile house price responses to pandemics due to lower health infrastructure and income buffers [11]. In these regions, policies targeting rent assistance and developer credit lines are crucial to avoid steep housing market collapses.

## 5.2 Real estate developer strategies

### *5.2.1 Digital transformation*

COVID-19 accelerated the digitization of real estate marketing, from virtual tours to blockchain-enabled property transactions [11]. Developers are increasingly investing in:

AI-driven market analytics to predict localized shifts,

Online transaction platforms to bypass physical site visits,

Remote documentation and notarization systems to streamline sales.

Such technologies reduce transaction frictions during future epidemics and make real estate less vulnerable to lockdown-related slowdowns.

#### *5.2.2 Product diversification*

Developers also need to diversify housing products by creating multi-functional living spaces, offering lower-density housing in suburban zones, and building in areas with better healthcare accessibility.

Surveys conducted in China and the U.S. after COVID-19 suggest that buyer preferences have shifted permanently toward properties with larger space, outdoor access, and proximity to health services [7].

#### *5.2.3 Financial risk management*

Developers should strengthen liquidity positions and reduce exposure to short-term debt. During COVID-19, firms with healthier balance sheets—especially REITs—were better able to sustain construction activity and adapt to market disruptions.

### 5.3 Recommendations for homebuyers

#### *5.3.1 Assess long-term health resilience of locations*

Prospective buyers should incorporate local health infrastructure and historical epidemic response into location assessments. Regions with stronger healthcare networks experienced less price volatility during outbreaks [11].

Tools like "epidemic resilience indices" or localized CDC vulnerability maps can be used to compare markets and assess risks over longer-term investment horizons.

#### *5.3.2 Mortgage strategy during low-rate environments*

In infectious disease-driven downturns, central banks typically lower interest rates. Buyers can take advantage of these low-rate windows but must remain cautious of future inflation and refinancing risk. Fixed-rate mortgages are generally safer in such conditions, particularly in volatile job markets [1].

#### *5.3.3 Psychological readiness and mobility planning*

Buyers should anticipate lifestyle disruptions and consider housing flexibility. For example:

Choosing properties with multi-use space (e.g., office, gym),
Prioritizing modular design and access to high-speed internet,
Planning for relocation flexibility in case of remote work shifts.

### 5.4 Summary of Section 5

Urban-suburban divergence demands region-specific forecasts.

Developers must invest in digital tools, product redesign, and balance sheet resilience.

Buyers should prioritize long-term health resilience, mortgage prudence, and flexible living solutions.

These strategies are not merely reactive but part of a systemic adaptation to a world where epidemic risk is no longer rare. Anticipating future health crises through urban design, market tools, and behavioral awareness will shape the next generation of real estate strategy.

# 6 Conclusion

## 6.1 Summary of the study

This study employed a time series econometric approach using R to analyze the relationship between infectious disease incidence and housing price indices. Through integrating data exploration techniques, feature engineering, stationarity adjustments, and model validation procedures, models are capable of capturing both short-term disruptions and long-term patterns. Autocorrelation analysis and seasonal decomposition revealed notable correlations between disease incidence peaks and subsequent housing market responses. ARIMA and VAR models, supplemented with visualizations, facilitated a structured interpretation of housing price shifts in response to health crises.

The study identified three primary mechanisms through which infectious diseases influence housing price indices:

Macroeconomic shocks: Epidemics often lead to economic slowdowns, especially in service-based economies. The reduced consumption capacity of households and a contraction in credit availability led to delayed home purchases and stagnating or declining prices.

Monetary policy adjustments: Central banks respond to epidemic-induced recessions with interest rate cuts and liquidity injections, thereby lowering mortgage rates and occasionally inducing price rebounds in certain segments of the market.

Psychological and demographic shifts: Changes in buyer sentiment, risk aversion, migration patterns, and preferences for space and healthcare access directly reshape housing demand [7]. Post-pandemic urban outflows and a rise in suburban attractiveness further illustrate these effects.

## 6.2 Research limitations and future directions

While the study utilized robust models and reliable datasets, several technical limitations remain:

The granularity of health data: In many regions, disease incidence data is aggregated at too broad a level, making it difficult to detect localized market effects.

The lag structure between infection waves and housing prices is complex and may differ across regions or housing market segments.

Some real estate indicators were excluded due to incomplete data across time periods.

The complex interaction between infectious diseases and real estate cannot be entirely captured by economic models alone. Behavioral responses, cultural attitudes toward risk, and policy differences significantly mediate outcomes. Moreover, causality cannot be fully established due to endogeneity between health policy measures and market expectations.

## 6.3 Future research directions

Future research could address the following promising areas:

Disease characteristics and real estate segmentation: Categories of diseases, their fatality rates, or contagion speed influences different segments of the housing market.

City-level resilience modeling: Integrating urban planning data, hospital density, and transportation infrastructure into epidemic-resilient housing price prediction models.

Cross-country comparisons: Examining how different government responses to epidemics—such as lockdown speed, stimulus scope, and healthcare investment—affect real estate stability could reveal best practices for crisis governance.

A predictive framework that accounts for epidemiological, economic, and spatial data could ultimately be used to guide future real estate decisions and policymaking in the face of recurring infectious threats.

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