Impacts of COVID-19 Regulations on Housing Prices in Manhattan, Brooklyn, and Queens

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Abstract

It is well-known that the unexpected shock of the COVID-19 pandemic severely affected the global economy, which led to large impacts on multiple markets. This study seeks to explore the impact of the introduction of COVID-19 regulations in March 2020 on the housing market in select New York City boroughs. We employed a "before - after" study framework, which is well suited to analyze this impact as COVID-19 caused a large structural break in the housing market. Time series data is utilized in this study, and the impact is estimated using Newey-West HAC-Robust Standard Errors under the Ordinary Least Squares (OLS) regression model. The model follows an autoregressive process with four lags and includes economic and housing characteristic control variables, such as the median square feet of a listing in a given month, while accounting for time trends in the data. The results of this study indicate the introduction of COVID-19 regulations in March 2020 led to a statistically insignificant decrease in monthly housing price indexes in Manhattan and Brooklyn, while they led to a statistically significant increase in Queens.

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1 Introduction

COVID-19 is a respiratory virus that can be transmitted by air. The outbreak started at the end of 2019, and started to dangerously spread, and it was declared a pandemic in March 2020 by the World Health Organization (WHO) (Yörük, 2022) The unforgettable recent global COVID-19 pandemic brought many consequences to the world, especially economic consequences. Many of the governments across the globe enforced lockdowns, leading many individuals being laid off due to many businesses pausing or even closing down. Hence, there is no doubt that the pandemic had a huge and rapid impact on the global economy (World Bank Group, 2023), even big economies such as the United States suffered from this outbreak with the highest reported numbers of cases and deaths (Yörük, 2022). It certainly affected many markets within the USA, and in this paper we are going to focus on its effects on the housing market.

The primary objective of this paper is to estimate the magnitude and direction of the impact COVID-19 regulations had on housing prices in New York, specifically in Manhattan, Brooklyn, and Queens. To achieve this, the effect on each borough will be modelled by a time series regression using data spanning a 103 months, from June 2016 to January 2025, with housing price index for each borough as the primary endogenous variable for each model. These key variables will be analyzed using a level-level functional form, facilitating a clear interpretation of changes in the prices of houses for different areas in New York. Additionally, the data sets were obtained from multiple sources, the main ones being Federal Reserve Economic Data, Realtor.com, and StreetEasy. The first two sources offer crucial data on the control variables used in this study, controlling for a mix of economic and housing market shifters in the cost of housing. The last source provides data on the market in various boroughs in New York City. Additionally, the type of regression model used in this study is a Before-After Autoregressive Model with four lags using the housing price index for each borough as the outcome variable of interest, and a dummy variable, *COVID*, indicating if the period observed is before or after COVID-19 as the primary explanatory variable.

2 Literature Review

The impacts of the COVID-19 on various economic sectors, including real estate, has been extensively studied in economics and finance. A key sector of interest is the effects of the unexpected pandemic economic shock on the housing market. Specifically, authors have researched the effects of COVID-related policies on housing market activities and prices, considering house characteristics, type of job, and house prices. This section explores relevant literature that provides key insights on this topic, with a focus on temporary price changes and impact differences in urban and suburban areas.

Most studies used similar methods such as Difference in Difference models and event studies, concluding that the COVID-related policies had short-term negative effects on housing prices, specifically in urban areas, but the conclusions vary across studies depending on the type of observations used. For example, Cohen et al. (2022) used a hedonic pricing model to estimate a decrease of 8% on sale prices for one- or two-family properties for every 1,000 additional infections per 100,000 residents, and 10% increase in unemployment of specific Zip Code area (MODZCTA). Additionally, the property values in most affected areas decreased by 0.8% to 50%. However, shutdown effects on sales prices were not statistically significant. Moreover, D'Lima et al. (2022) used an event studies and a difference in difference model, showing that shutdown orders led to a decline of 1.4% in housing prices located in urban areas, but a 1.5% increase in suburban areas. This suggests that demand shifted to larger properties in the suburbs. They also observed a temporary decrease of 2% in home sales due to in-person viewing restrictions and temporary market slowdown before the market's recovery.

Some of the literature emphasize the different impacts on different market segments. Wang (2022) found that housing prices, supply, and demand decreased for a short period in March to May 2020, with a maximum decline of 9% in May, New York City (NYC) for example, where the share of the labour force working in entertainment, accommodation and food were high while the homeownership rates were low, recovering in September 2020.

Yörük (2022) studied the impacts of non-essential businesses and school closures, due to the virus, on the housing market. He found that there was a significant decline in new home listings of 11%, and in total housing inventory of 3.5%. The effects of school closures were less precise since the results were marginally significant, a decrease of 5% to 9.1% in inventory. Nonetheless, most state-level policies had insignificant impacts on key housing market indicators, indicating the fast adaptation of the market to the COVID-related policies.

Heiniger et al. (2024) used causal machine learning techniques to estimate the COVID-related policies on Germany's well-developed real estate market, concluding that commercial properties, specially in urban areas, suffered more than residential real estate. On one hand, retail rents experienced an insignificant decrease of 3.5% in municipalities with a lot of COVID cases, while office rents significantly decreased by 3.2% where there was high short-time work. On the other hand, residential rents suffered from a neglectable insignificant decrease of 0.5% in municipalities with large COVID cases. They compared the German house market performance to the US market and concluded that the effects of COVID-19 regulations were less intense in Germany compared to the United States.

Although these papers positively contribute to the understanding of this relationship, several gaps still remain to be further explored. Most studies focused on short-term effects and were estimated with data available while the pandemic was still happening. However, long-term effects remain unclear. Additionally, it is clear that the pandemic led to a shift to remote work, which fundamentally changed housing demand. Further research can explore this change in housing prices.

This literature review highlights the temporary effects of COVID-19 policies, particularly in urban areas, and how different segments of the market reacted to the outbreak. Although the general consensus is short-term negative effects, we want to investigate the long-term effects. This paper builds on this framework by providing a different estimation approach to assess the before-and-after impacts of COVID-related regulations on housing prices, with a focus on unemployment levels, prevailing interest rates, and minimum wages.

3 Data

3.1 Description

The endogenous variable used in this experiment will be from Streeteasy (2021) housing price indexes, in 2016 dollars amounts of the New York City boroughs Manhattan, Queens, and Brooklyn, observed over a 14-year period, from January 2012 to January 2025, meaning 157 observations for the unrestricted dataset. The restricted dataset will include data from June 2016 to January 2025, which contains 103 observations. The price indexes for each borough take into account the "for geographic submarkets and price tiers within each borough" (Long, 2022).

There are 7 exogenous variables used in this model. The data that we used from FRED is the state minimum wage and unemployment rate in New York, and the 30-year fixed mortgage rate in the US over time. This data covers the time period January 2012 to January 2025, but are all observed in different intervals. As the housing data is observed monthly, the yearly observed minimum wage data was converted to monthly observation, with each month in a year having the same value. However, another issue with the minimum wage is that it is measured in nominal dollar amounts. The data was deflated by standardizing it to 2016, the base year, meaning that in the model the standardized values of the minimum wage are used as opposed to the actual minimum wage. The weekly observed mortgage rate data was converted to monthly data by averaging the data in a given month. The unemployment rate was observed monthly, so no transformations were required there. Both the unemployment and mortgage rates are measured in terms of percentages, so there is no need for deflation.

The data from the Realtor.com (2025) is the monthly amount of new listings and the median square footage per listing in the State of New York. Since these variables are observed monthly, there was no need to alter the observation intervals. However, since this data only covers the time period beginning from June 2016 and ending in January 2025, we will restrict the data from FRED and the endogenous variable to the same period range. We also included a variable to control for time trends, which assigns each observation a value indicating its order in the chronological sequence of time (first period = 1 and last = 103). Lastly, our main parameter of interest is the

COVID-19 indicator variable, which is explained below.

As the main focus of this experiment is to see how COVID-19 policies affected the housing market in NYC, the methodology of this experiment follows the framework of a 'before-after' analysis. Because initial lockdown regulations began in March 2020, this date was used as it is where we identify the COVID-19 structural break. This means that the main explanatory variable is the COVID dummy variable, indicating whether the time period being observed is pre or post COVID-19. The COVID dummy will take values of zero during any time prior to March 2020 and will take a value of one any time after that. The coefficient on this dummy will give an idea into what effect COVID-19 policies had on the housing prices in three different NYC boroughs.

3.2 Summary Statistics

The statistics for the unrestricted model are taken from B.1 and the restricted model are taken from B.2. The statistics for the housing prices in the three boroughs are as follows in the unrestricted data. Manhattan had a lowest price index of \$890,966 and a highest of \$1,170,453, with a mean purchase price of \$1,074,139 and standard deviation of about \$72,312.07, over the 14 year period. Queens on the other hand was much cheaper, with a lowest recorded housing index of \$392,400 and highest of \$527,845. The average price was \$477,394.40, with a standard error of about \$47,145.71. Brooklyn comes in between both of these boroughs, with a lowest purchase price of \$525,312 and highest of \$734,938. The mean price index in Brooklyn was \$672,823.40, with a standard deviation of \$65,638.45. In the restricted dataset, the data for Manhattan was a lowest index of \$1,023,761 and highest of \$1,170,453, with a mean price of \$1,099,055 and standard error of \$44,083.55. Queens had a lowest price index of \$456,433 and highest of \$527,845, with a mean index of \$508,914.10 and standard error of \$16,264.97. Brooklyn had a lowest index of \$672,522 and highest of \$734,978, with a mean of \$712,149.50 and standard deviation of \$14,127.66.

In the unrestricted dataset, the average of the weekly data for the 30-year fixed mortgage rate had a minimum mortgage rate of 2.684% and a maximum of 7.62%. The mean rate was 4.39% with a standard deviation of 1.26%. In the restricted dataset, lowest and highest rates remained unchanged, however the mean shifted up to a rate of 4.63% and a standard deviation of 1.46%.

The lowest unemployment rate over this time period in the unrestricted dataset was 3.8% and rose to a highest of 16.7%. The average rate was about 5.77% with a standard deviation of 2.26%. The restricted dataset did not have any changes in the highest and lowest rates, but the mean unemployment rate shifted to 5.25% and standard deviation of 2.43%.

The unrestricted dataset shows the lowest minimum wage over this time period of $7.25 and highest of $16.50. The mean minimum wage was around $10.78 with a standard deviation of about $2.70. In the restricted dataset, the highest observed minimum wage remained constant, with the lowest hourly wage increasing to $9. This shifted the mean hourly wage up to about $12.21, with a standard error of around $2.09.

The next set of control variables used in the model are housing market characteristics for the entire state of New York. These variables are the number of new listings in the market, and the median square footage of the listing. The lowest number of new listings per month was 7,100 and highest of 26,296 with an average of 16,504.31 and standard error of 4,247.87. The lowest median square footage of a listing was 1500 with a highest of 1829 sq ft. The mean square footage of a listing in a given month was 1,687.01 with a standard deviation of 106.17.

4 Empirical Framework

4.1 Estimation Framework

This study discussed in this paper follows a “before and after” analysis method, which involves using an indicator variable for the pre and post structural break period, with the coefficient on the indicator variable displaying the effect of being in the post-period on the explained variable. This framework is appropriate to this study as it allows a proper analysis of structural breaks to take place. When the COVID-19 pandemic took over the world in March of 2020, there was immediate action taken by governments around the world, calling for lockdowns and putting in restrictive regulations attempting to reduce the spread of the virus. These regulations and sudden decrease in economic activity across the globe led to the economies of many countries falling into a recession, causing many structural breaks to occur in various markets, with the housing market undoubtedly being one of them. One good thing that these regulations do, however, is provide a very distinct before and after period. This allows for the COVID indicator to take values of one for the correct time period and ensures that the coefficient on the variable measures the effect from the accurate starting point of the break.

Due to the period restrictions of the two housing characteristics data, there were three possible models variations of this before-after framework, each containing the 30-year fixed mortgage average monthly rate for the US, the New York State annual standardized minimum wage, and the monthly New York State unemployment rate that capture the effect of some economic shifters. The unrestricted model utilizes all the data from January 2012 to January 2025. The other two are restricted models using the dataset restricted from July 2016 to January 2025, with one using the same parameters as the unrestricted model to see how this restriction affects the estimated effect in each borough, while the other one includes two more housing characteristic control variables. One of which is the monthly number of new listings in the housing market, which helps to understand whether it is a buyers or sellers market, a factor that influences the housing price. The second is the New York state level median square footage of a listing in a given month, as the larger the house, the more it will cost, so this variable allows for the model to control for variations in the size of the houses available on the market.

After comparing results from running the Newey-West HAC Robust S.E OLS regressions in each of these three models, we will discuss the results of the restricted model with two additional housing characteristic control variables. This is due to the importance of having the housing market characteristics control variables in the model, in the attempt to minimize any biases in the results.

As with every regression model, there is a risk of omitted variable bias (OVB) in this framework. This model attempts to minimize the amount of OVB present through the selection of control variables. However, despite attempting to control for some of the housing market characteristics, there is still OVB present in this model. This bias arises in the model when some important metrics are not included as control variables, such as the number of bedrooms in the home and the average income level per borough. The number of bedrooms was not included in our model since the data was not available for the period this study is observing. Nonetheless, to adequately account for the size of the property and its effect on housing prices, the square footage of the listing data was controlled for.

Another variable that is not included in this regression is the average household income in each of the boroughs over time. This is an extremely important economic metric that has a large effect on the price index of housing as it helps to determine the proportion of the population that is in the market for a house, hence, affecting housing prices. This variable was omitted as the data available does not cover enough of the time period past the implementation of COVID-19 policies to provide an accurate estimation of the effect income has on the post-COVID housing market. This means that the effects of these two variables now reside in the unobservables, meaning the effect of the COVID indicator might be underestimated in the model. To address this issue, minimum wage was used to attempt to control for some the level of income in each borough.

Apart from OVB, there is one more issue that this model suffers from. The explanatory power of COVID weakens because the data available for the control variables is for the state of New York as a whole, with the exception of the 30-year mortgage rate, which is for the entirety of the USA, as borough level data was not available. Since the explained variables are all monthly HPI's for specific boroughs in New York City, using state level data will of course include the data from these areas as well as from the entire state of New York, meaning the coefficients on these controls will not accurately reflect the effect that the control has on the variable of interest.

4.2 Regression Model

To evaluate the COVID shut downs regulation effects on housing prices, we are modeling three time series models for three different boroughs from New York, which are Manhattan, Brooklyn, and Queens. This level-level 'before-after' model allows for the estimation of the change in housing prices caused by the required COVID shut downs in terms of 2016 dollars. Each equation is represented by the following general format of the autoregressive (AR(4)) model for each of the boroughs. The variables $borough_{it}$ and $borough_{it-h}$, where h = {1, 2, 3, 4} and t $\in$ [1, 103], and

$borough_i$ = {Manhattan, Brooklyn, Queens}, are name place holders.

$$\begin{aligned} borough_{it} = \beta_0 + \beta_1 COVID_t + \beta_2 borough_{it-1} + \beta_3 borough_{it-2} + \beta_4 borough_{it-3} + \\ \beta_5 borough_{it-4} + \beta_6 nyur_t + \beta_7 std\_min\_wage_t + \beta_8 mortgage\_rate_t + \\ \beta_9 median\_square\_feet_t + \beta_{10} new\_listing\_count_t + \beta_{11} t_t + \epsilon_{it} \end{aligned} \quad (1)$$

Where $borough_{it}$ denotes the HPI of borough i at period t. The indicator variable is $COVID_t$ which takes the value of 0 when the observed period is before March 2020, and takes the value of 1 when the observed period is after March 2020. The lag variables $borough_{it-h}$, are the values of housing prices in previous periods, which are included since HPI is believed to depend on previous HPI levels and the Newey-West lag formula indicates that the optimal amount of lags should be 4 months. t_t represents a time trend variable that indicates which period we are observing, which controls for time trends in the model. The remaining are controlled variables: $nyur_t$, $std\_min\_wage_t$, $mortgage\_rate_t$, $median\_square\_feet_t$, $new\_listing\_count_t$.

4.3 Model Specification

To effectively construct the model, it is essential to define the assumptions that it needs to hold. First, the models are assumed to be linear in parameters, to not have perfect collinearity, and to have a level-level functional form. Ideally, at period t, the unobservables term should not be correlated with the explanatory variables to mitigate the risk of endogeneity issues in the model. This seems to be the case for our parameter of interest, β_1, representing the effect of the dummy variable COVID, is not correlated with the unobservables.

In time series data, time trends and seasonality in the data are always a large concern that can lead to biased and inconsistent estimates on the parameter of interest. Since the housing prices this month depend on the previous month's housing prices, there are definitely time trends present in this model. To address this issue, we included a time trending variable t to capture the effect of moving from one time period to the next, in order to control for any time trends that affect the estimate on COVID. By analyzing the graphs of the HPI in each borough over time, A.1, A.2, and A.3, we can see that there are definitely some linear time trends present in certain periods for each borough. However, we believe that there is no seasonality present in this model. Once again, based on the graphs for the HPI's, there does not seem to be any seasonal trends occurring within the housing markets each year, indicating that seasonality is not an issue that the endogenous variable suffers from. However, one of the control variables, unemployment rate, would likely suffer from seasonality as there are certain times in the year where employers tend to hire more workers, or lay off their staff. Fortunately, the data available for the New York unemployment rate was already seasonally adjusted, meaning that there was no need to adjust for it further in the model.

Additionally, to ensure that the model is consistent, it is required that for any value of $COVID_t$, the expected value of the unobservables term equals zero at period t. Although $new\_listing\_count_t$ and $Queens_t$ are stationary, the remaining variables follow a unit root process but they are cointegrated. Plugging the residuals of each model over time, which can be seen in A.4 and A.5, which show the residuals for Manhattan and Brooklyn respectively, the residuals seem to be weakly dependent and stationary, therefore, with the sufficiently large sample size of 103, the sample distribution is approximately normal, according to the Central Limit Theorem. Hence, the model allows for inference of confidence intervals and hypothesis testing using Newey-West HAC-Robust standard errors.

Furthermore, three key tests are employed: 1) F-test to assess the joint significance of the model, 2) unit root test on all variables except for time trend, 3) cointegration test on the models that follow a unit root process, and repeated test 2) on the residuals of those models to ensure that they are stationary and the unit root processes are cointegrated.

The F-statistics of the HAC-robust estimated models are 2,113.51, 108.59, and 309.37, respectively for Manhattan, Brooklyn, and Queen model. The critical value of the F-distribution at the 1% significance level is approximately 2.52, based on 10 degrees of freedom in the numerator and 90 degrees of freedom in the denominator which are the closest degrees of freedom to the ones from the models (11 df in the numerator and 87 df in the numerator). Since the F-tests exceeds the critical value and the p-value = 0.0 is lower than 0.01, the null hypothesis is rejected, suggesting that at least one of the explanatory variables in the model is statistically significant in relationship with HPI for each borough, thereby confirming that the model is statistically significant.

To test for unit root processes, we ran the Dickey-Fuller (DF) test on each variable used in the regression other than the time trending variable, where the null hypothesis of the variable following a unit root process is rejected if the t-test is lower than the DF critical value, concluding stationarity. This is not the case for all the variables other than $new\_listing\_count_t$ and $Queens_t$, meaning that we fail to reject that they are non-stationary. The results from these tests can be found in Appendix B, tables B.4 to B.24. This leads to a violation of the stationarity assumption of the time series data. To address this concern, we checked if the endogenous variables cointegrate with their explanatory variables. This would ensure that there is a stable long term relationship that will keep the variances of the variables from becoming excessively large, making the model behave stationary, thus allowing the use of an OLS regression with robust standard errors with better results.

The Engle-Granger test was used to test for cointegration. We first ran the OLS regression of Brooklyn and Manhattan on their respective lagged and control variables as seen in table B.25, allowing us to obtain the residuals for each regression. Secondly, we performed the DF unit root test on the residuals (B.26, B.27), indicating whether the model is cointegrated. Since both t-tests were much less than the DF critical values, we conclude that the model is cointegrated. Performing the DF test on the residuals, we also conclude that the residuals are stationary, as the coefficients on both are statistically significant at the 1% level (B.28), further supporting the cointegration of each model.

Given the autocorrelation and uncertainty surrounding the presence of heteroskedasticity or homoskedasticity in the models, employing the Heteroskedasticity Autocorrelation Consistent (HAC) Robust Standard Errors method is appropriate for these models. While HAC-robust standard errors may be less efficient than OLS standard errors in absence of serial correlation or heteroskedasticity, they still provide consistent inference even when these issues arise. The large sample size suggests that this difference may be negligible. Furthermore, employing robust standard errors is more appropriate, as heteroskedasticity is often prevalent in real-world data (Alexander, 2018).

5 Results

Based on the results from the regressions, seen in table B.3, the effect of COVID-19 policies on housing prices in 2016 dollar amounts for each observed borough is discussed in this section. We observed a negative effect in Manhattan and Brooklyn housing prices, and a positive effect in Queens.

Manhattan experienced a negative effect from the COVID-19 regulations on the monthly HPI of $2,627.12 with a robust standard error of $2,130.28. This result however, is not statistically significant at any level. Similarly, Brooklyn monthly HPI insignificantly decreased by $160.75 because of these regulations, with a robust standard error of $2348.03. On the other hand, COVID-19 regulations significantly increased its monthly HPI in Queens by $4,195.22 at the 5% level, with a robust standard error of $1,020.07.

Although the negative effects are statistically insignificant, they are consistent with the results from D'Lima et al. (2022), and are what was expected. Their findings were arguing that the housing market experienced a decrease in demand, thus housing price (HPI) decreased, in more densely populated areas because individuals wanted to move to less clustered neighborhoods to decrease the risk of contagency, while the opposite was observed in lower populated areas. On that account, Manhattan and Brooklyn have higher populations than Queens, explaining the negative and positive effects observed respectively. In short, the signs of all effects were within expectation.

The limitations to the model comes from the data used in the model. As the control variables are used for the New York State level, which includes many more cities and boroughs than Manhattan, Brooklyn, and Queens, they do not accurately control for the effects that the unemployment rate, number of new listings, and median square footage in each borough have on their respective borough. This means that the coefficients on the controls and the COVID indicator suffer from a form of measurement error in the controls as the observed value in the data is the data for the borough level plus all the other cities in the New York State. This results in a potential attenuation bias on the estimates on the controls and COVID, meaning that the estimation of the coefficients are biased towards zero.

6 Conclusion

The findings presented in this paper follow similar results to the previously reviewed literature. The statistical analysis indicates that the introduction of COVID-19 regulations in March 2020 lead to a statistically insignificant decrease in the monthly HPI in Manhattan and Brooklyn, while it leads to a statistically significant increase in the monthly HPI in Queens. While these findings align with other literature, we must remember that the results from this paper are not entirely without error. The specified model suffers from omitted variable bias, measurement error, and potential attenuation bias. Additionally, the power of the explanatory variables are weakened due to the quality of the data being used in the time series regressions. While the model is believed to hold the necessary OLS asymptotic properties and controls for time trends, it is likely downwards biased. This means that the results in this paper are potentially an underestimate of the true effect COVID-19 regulations had on the HPI in Manhattan, Brooklyn, and Queens.

Moreover, this paper can contribute to the field in the investigation of longer term effects since most reviewed papers were published within two to three years after the initial COVID-19 regulations were implemented, thus, their results are more of a short-term interpretation. Due to different methodologies, model specifications, time periods, and geographical considerations, our estimated magnitude differs from the results obtained by other authors. Nonetheless, the economy seems to have bounced back from the pandemic, and we concluded very similar results of the estimated direction as in the literature. Further contributions can be made by simply trying to address the data issues encountered in this paper, by applying the motive of this study to other areas where better data is available, or focusing on a more specific section of the housing markets.

One of the steps that can be taken to improve this study is to improve the quality of the data used. As discussed in the econometric model section, the data used in this study, apart from the borough specific HPI's, are either New York State or U.S. level data. Such data does not allow for a fully accurate representation of the impact, as the effect the overall unemployment rate in New York has on Manhattan's HPI will not be as informative as the effect of Manhattan's unemployment rate on its HPI. Due to this loss in explanatory power in the control variables, resulting from essentially a measurement error, the overall effect of COVID-19's regulations on each borough's

HPI is biased towards zero. Another aspect in which the data proved inadequate in this study was the inability to incorporate two significant control variables, average household income in each borough and the number of bedrooms in homes being sold. Having these two variables included in the model would have definitely enhanced the explanatory power of the model. Given more time and resources, researchers looking into this same relationship should definitely focus on two things: finding borough specific data and being able to find all necessary controls. If the data meets these two conditions, these regressions would provide a more precise representation of COVID-19 regulation's impact on each borough's HPI.

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A Appendix A: Graphs

Figure A.1: This graph shows the monthly movement of Manhattan's HPI between June 2016 and January 2025

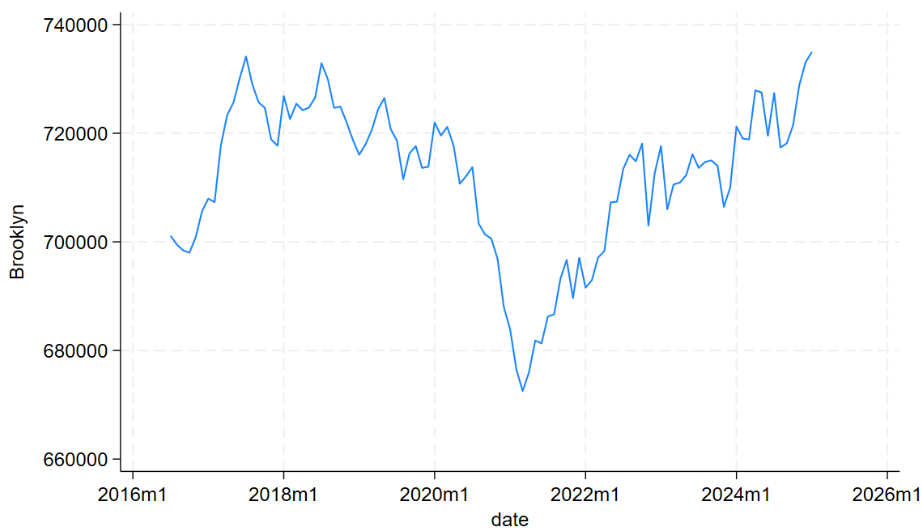

Figure A.2: This graph shows the monthly movement of Brooklyn's HPI between June 2016 and January 2025

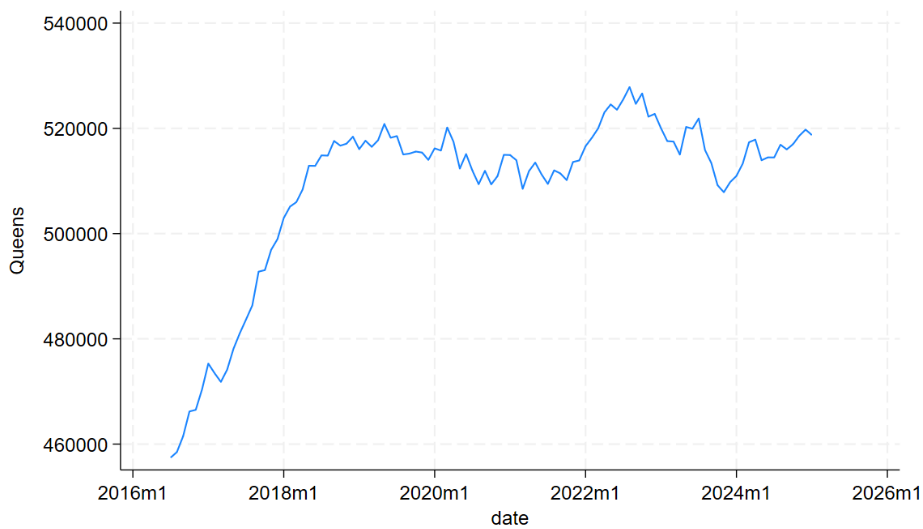

Figure A.3: This graph shows the monthly movement of Queens' HPI between June 2016 and January 2025

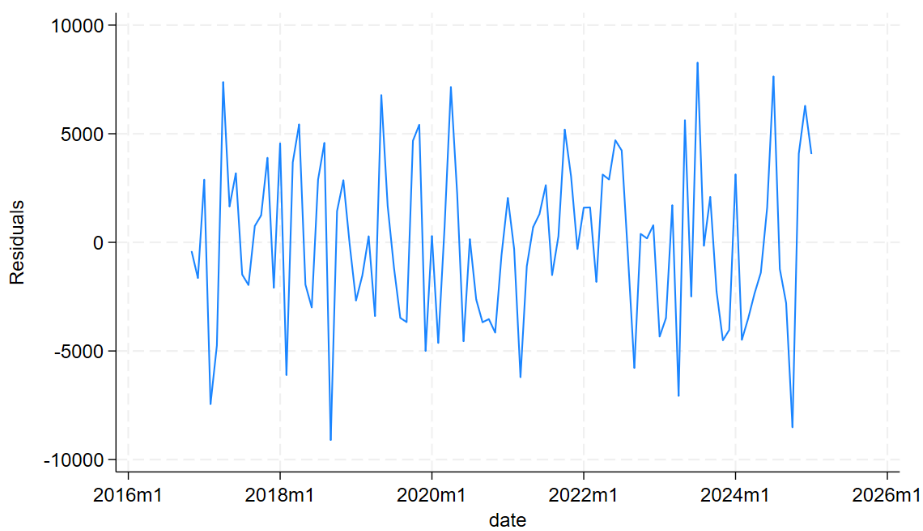

Figure A.4: This graph shows the monthly movement of Manhattan's residuals between June 2016 and January 2025

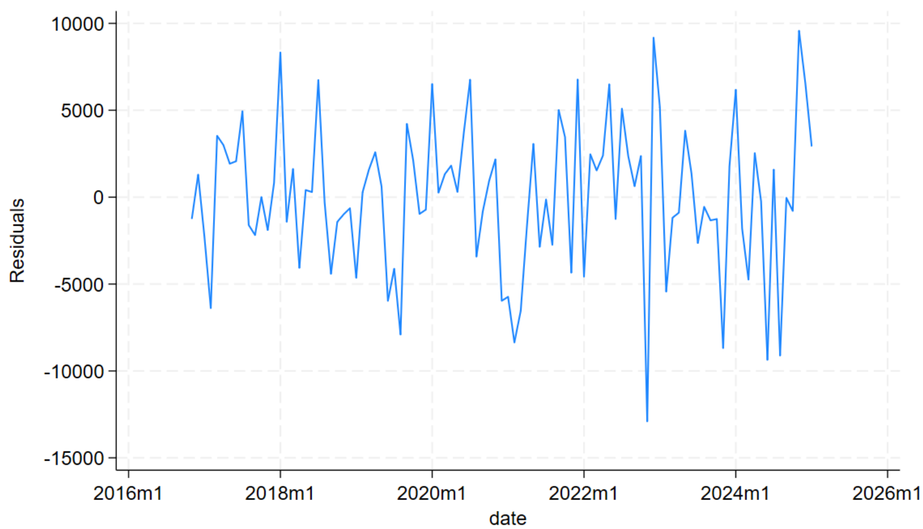

Figure A.5: This graph shows the monthly movement of Brooklyn's residuals between June 2016 and January 2025

B Appendix B: Regression Tables

Table B.1: Summary Statistics (Unrestricted)

Variable	Obs	Mean	Std. Dev.	Min	Max
min_wage	157	10.741	2.673	7.25	16.5
date	157	702	45.466	624	780
nyur	157	5.769	2.261	3.8	16.7
mortgage_rate	157	4.377	1.25	2.684	7.62
brooklyn	157	672823.43	65638.45	525312	734978
manhattan	157	1074138.9	72312.07	890966	1170453
queens	157	477394.44	47145.71	392400	527845
covid	157	0.376	0.486	0	1
std_min_wage	157	1.193	0.297	0.806	1.833

Table B.2: Summary Statistics (Restricted)

Variable	Obs	Mean	Std. Dev.	Min	Max
new_listing_count	103	16504.31	4247.87	7100	26296
median_square_feet	103	1687.01	106.17	1500	1829
date	103	729	29.88	678	780
min_wage	103	12.207	2.088	9	16.5
nyur	103	5.254	2.432	3.8	16.7
mortgage_rate	103	4.634	1.464	2.684	7.62
brooklyn	103	712149.54	14127.66	672522	734978
manhattan	103	1099055.4	44083.55	1023761	1170453
queens	103	508914.11	16264.97	457433	527845
covid	103	0.573	0.497	0	1
std_min_wage	103	1.356	0.232	1	1.833
t	103	52	29.88	1	103

Table B.3: Results From Each Model

Variable	Manhattan	Brooklyn	Queens
covid	-2627.1 (-1.23)	-160.7 (-0.07)	4195.2*** (4.11)
$Manhattan_{t-1}$	1.149*** (11.80)		
$Manhattan_{t-2}$	0.181 (1.06)		
$Manhattan_{t-3}$	-0.266 (-1.51)		
$Manhattan_{t-4}$	-0.146 (-1.36)		
$Brooklyn_{t-1}$		0.655*** (5.35)	
$Brooklyn_{t-2}$		0.0853 (0.75)	
$Brooklyn_{t-3}$		0.255* (2.14)	
$Brooklyn_{t-4}$		-0.300*** (-4.12)	
$Queens_{t-1}$			0.820*** (9.69)
$Queens_{t-2}$			0.143 (1.09)
$Queens_{t-3}$			0.0641 (0.38)
$Queens_{t-4}$			-0.0780 (-0.63)
nyur	164.1 (0.80)	-527.3* (-2.33)	-711.8*** (-7.52)
std_min_wage	13612.3 (1.75)	30992.4* (2.51)	11200.9 (1.68)
mortgage_rate	1475.7 (1.91)	1456.4* (2.40)	-731.8* (-2.43)
median_square_feet	-15.75* (-2.01)	25.94* (2.45)	7.802 (1.28)
new_listing_count	0.152 (1.32)	0.0639 (0.63)	-0.0456 (-0.77)
t	-242.0** (-3.26)	-220.9* (-2.02)	-111.0 (-1.37)
_cons	102571.0** (2.80)	137463.4*** (4.52)	9447.8 (0.67)
N	99	99	99

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.4: DF Test for Unit Root in $Manhattan_t$ Variable

Statistic	Value
Test statistic $z(t)$	-1.048
1% critical value	-3.509
5% critical value	-2.890
10% critical value	-2.580
Number of observations	102

Table B.5: DF Test for Unit Root in $Manhattan_{t-1}$ Variable

Statistic	Value
Test statistic $z(t)$	-0.958
1% critical value	-3.510
5% critical value	-2.890
10% critical value	-2.580
Number of observations	101

Table B.6: DF Test for Unit Root in $Manhattan_{t-2}$ Variable

Statistic	Value
Test statistic $z(t)$	-0.894
1% critical value	-3.510
5% critical value	-2.890
10% critical value	-2.580
Number of observations	100

Table B.7: DF Test for Unit Root in $Manhattan_{t-3}$ Variable

Statistic	Value
Test statistic $z(t)$	-0.832
1% critical value	-3.511
5% critical value	-2.891
10% critical value	-2.580
Number of observations	99

Table B.8: DF Test for Unit Root in $Manhattan_{t-4}$ Variable

Statistic	Value
Test statistic $z(t)$	-0.951
1% critical value	-3.513
5% critical value	-2.892
10% critical value	-2.581
Number of observations	98

Table B.9: DF Test for Unit Root in $Brooklyn_t$ Variable

Statistic	Value
Test statistic $z(t)$	-1.562
1% critical value	-3.509
5% critical value	-2.890
10% critical value	-2.580
Number of observations	102

Table B.10: DF Test for Unit Root in $Brooklyn_{t-1}$ Variable

Statistic	Value
Test statistic $z(t)$	-1.622
1% critical value	-3.510
5% critical value	-2.890
10% critical value	-2.580
Number of observations	101

Table B.11: DF Test for Unit Root in $Brooklyn_{t-2}$ Variable

Statistic	Value
Test statistic $z(t)$	-1.730
1% critical value	-3.510
5% critical value	-2.890
10% critical value	-2.580
Number of observations	100

Table B.12: DF Test for Unit Root in $Brooklyn_{t-3}$ Variable

Statistic	Value
Test statistic $z(t)$	-1.850
1% critical value	-3.511
5% critical value	-2.891
10% critical value	-2.580
Number of observations	99

Table B.13: DF Test for Unit Root in $Brooklyn_{t-4}$ Variable

Statistic	Value
Test statistic $z(t)$	-1.877
1% critical value	-3.513
5% critical value	-2.892
10% critical value	-2.581
Number of observations	98

Table B.14: DF Test for Unit Root in $Queens_t$ Variable

Statistic	Value
Test statistic $z(t)$	-4.135
1% critical value	-3.509
5% critical value	-2.890
10% critical value	-2.580
Number of observations	102

Table B.15: DF Test for Unit Root in $Queens_{t-1}$ Variable

Statistic	Value
Test statistic $z(t)$	-4.080
1% critical value	-3.510
5% critical value	-2.890
10% critical value	-2.580
Number of observations	101

Table B.16: DF Test for Unit Root in $Queens_{t-2}$ Variable

Statistic	Value
Test statistic $z(t)$	-4.086
1% critical value	-3.510
5% critical value	-2.890
10% critical value	-2.580
Number of observations	100

Table B.17: DF Test for Unit Root in $Queens_{t-3}$ Variable

Statistic	Value
Test statistic $z(t)$	-4.100
1% critical value	-3.511
5% critical value	-2.891
10% critical value	-2.580
Number of observations	99

Table B.18: DF Test for Unit Root in $Queens_{t-4}$ Variable

Statistic	Value
Test statistic $z(t)$	-4.093
1% critical value	-3.513
5% critical value	-2.892
10% critical value	-2.581
Number of observations	98

Table B.19: DF Test for Unit Root in $COVID_t$ Variable

Statistic	Value
Test statistic $z(t)$	-1.150
1% critical value	-3.509
5% critical value	-2.890
10% critical value	-2.580
Number of observations	102

Table B.20: DF Test for Unit Root in $nyur_t$ Variable

Statistic	Value
Test statistic $z(t)$	-2.570
1% critical value	-3.509
5% critical value	-2.890
10% critical value	-2.580
Number of observations	102

Table B.21: DF Test for Unit Root in $std\_min\_wage_t$ Variable

Statistic	Value
Test statistic $z(t)$	0.125
1% critical value	-3.509
5% critical value	-2.890
10% critical value	-2.580
Number of observations	102

Table B.22: DF Test for Unit Root in $mortgage\_rate_t$ Variable

Statistic	Value
Test statistic $z(t)$	-0.182
1% critical value	-3.509
5% critical value	-2.890
10% critical value	-2.580
Number of observations	102

Table B.23: DF Test for Unit Root in $new\_listing\_count_t$ Variable

Statistic	Value
Test statistic $z(t)$	-3.569
1% critical value	-3.509
5% critical value	-2.890
10% critical value	-2.580
Number of observations	102

Table B.24: DF Test for Unit Root in $median\_square\_feet_t$ Variable

Statistic	Value
Test statistic $z(t)$	-0.534
1% critical value	-3.509
5% critical value	-2.890
10% critical value	-2.580
Number of observations	102

Table B.25: Engle-Granger Test For Cointegration Step 1

Variable	Manhattan	Brooklyn
covid	-2627.1 (-0.67)	-160.7 (-0.04)
L.manhattan	1.149*** (11.03)	
L2.manhattan	0.181 (1.13)	
L3.manhattan	-0.266 (-1.69)	
L4.manhattan	-0.146 (-1.35)	
L.brooklyn		0.655*** (6.44)
L2.brooklyn		0.0853 (0.69)
L3.brooklyn		0.255* (2.09)
L4.brooklyn		-0.300** (-3.15)
nyur	164.1 (0.41)	-527.3 (-1.19)
std_min_wage	13612.3 (1.35)	30992.4** (2.71)
mortgage_rate	1475.7 (1.75)	1456.4* (2.03)
median_square_feet	-15.75 (-1.28)	25.94 (1.51)
new_listing_count	0.152 (1.26)	0.0639 (0.46)
t	-242.0* (-2.24)	-220.9* (-2.00)
_cons	102571.0* (2.42)	137463.4** (3.26)
N	99	99

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table B.26: DF Test for Unit Root in the Manhattan Residuals (EG Test Step 2)

Statistic	Value
Test statistic $z(t)$	-9.952
1% critical value	-3.513
5% critical value	-2.892
10% critical value	-2.581
Number of observations	98

Table B.27: DF Test for Unit Root in the Brookyln Residuals (EG Test Step 2)

Statistic	Value
Test statistic $z(t)$	-9.621
1% critical value	-3.513
5% critical value	-2.892
10% critical value	-2.581
Number of observations	98

Table B.28: Unit Root test on the residuals for Manhattan and Brooklyn

Variable	deltamres	deltabres
lagmres	-1.021*** (-9.95)	
lagbres		-0.984*** (-9.62)
_cons	3.188 (0.01)	13.30 (0.03)
N	98	98

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

C Appendix C: AI Usage

We completed this assignment independently, but with some support from ChatGPT. We asked ChatGPT how to understand the concepts and tests learned in class in a more practical way, as we were struggling to apply them in the paper. We wrote the first draft, and we corrected the grammar and spelling on our own. The our interaction with ChatGPT can be accessed through: https://chatgpt.com/share/67f96bed-b568-800a-a146-ac45be23b893.