

IMPACTS OF THE COVID-19 PANDEMIC ON HOUSING MARKETS

A Thesis
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

Tuhinur Rahman Chowdhury

In Partial Fulfillment of the Requirements
for the Degree of
MASTER OF SCIENCE

Major Department:
Agribusiness and Applied Economics

June 2022

Fargo, North Dakota

North Dakota State University
Graduate School

Title

IMPACTS OF THE COVID-19 PANDEMIC ON HOUSING MARKETS

By

Tuhinur Rahman Chowdhury

The Supervisory Committee certifies that this *disquisition* complies with North Dakota State University's regulations and meets the accepted standards for the degree of

MASTER OF SCIENCE

SUPERVISORY COMMITTEE:

Prof. Lei Zhang

Chair

Prof. Siew Hoon Lim

Prof. Cheryl Wachenheim

Prof. Ruilin Tian

Approved:

07/05/2022

Date

Prof. William Nganje

Department Chair

ABSTRACT

Efficient housing markets are critical for economic stability in the United States. Over one million people died in the United States from COVID-19. One method employed to halt the spread of the virus were stay-at-home orders. The effects of stay-at-home orders on different distributions of housing prices in 101 housing markets were investigated in this study. To estimate the effects of executive orders on house prices, an unconditional quantile regression model was employed for analysis. Results suggest that lower-priced houses experienced a larger price increase while the executive order was in effect. Following the expiration of the executive order, larger price increases were observed in both lower and higher priced house markets. Using a binary logit model, we examined whether socioeconomic or demographic characteristics affect executive orders. Results suggest that more black individuals and democrats make home price increases more likely under an executive order at certain quantiles.

ACKNOWLEDGMENTS

I would like to convey my profound appreciation to Dr. Lei Zhang, my adviser and committee chair for my thesis, for her outstanding assistance during my research work. Without her direction and competent assistance, it would be impossible to complete my project and write my thesis. I am grateful to her for allowing me to work under her supervision, and I learned a lot from her vast experience.

I would also like to thank my committee members, Dr. Cheryl Wachenheim, Dr. Siew Hoon Lim, and Dr. Ruilin Tian, for their unwavering support and for the inspiration they have provided.

Last but not least, I am grateful to my colleagues and family members, who have always supported me and encouraged me to continue my studies. I would also like to acknowledge the financial support I have received from the Department of Agribusiness and Applied Economics.

TABLE OF CONTENTS

ABSTRACT.....	iii
ACKNOWLEDGMENTS	iv
LIST OF TABLES.....	vii
LIST OF FIGURES	viii
LIST OF APPENDIX FIGURES.....	ix
1. INTRODUCTION	1
1.1. Background of the Study.....	1
1.2. Problem Statement	3
1.3. Objectives.....	4
1.3.1. General Objectives	4
1.3.2. Specific Objectives.....	4
1.4. Paper Organization.....	4
2. LITERATURE REVIEW	6
2.1. The Housing Market and the United States Economy.....	6
2.2. COVID-19 Outbreak and the United States Response.....	7
2.3. COVID-19 and Housing Market Response.....	9
3. DATA AND METHODS	13
3.1. Data Sources.....	13
3.1.1. Housing Data.....	13
3.1.2. Socio-demographic Data	13
3.2. Stay-at-Home Orders.....	16
3.3. Empirical Models	20
3.3.1. Unconditional Quantile Regression Model	20
3.3.2. Binary Logistic Regression Model.....	21

4. RESULTS & DISCUSSION.....	23
4.1. Estimation Results from Unconditional Quantile Regression Model	23
4.2. Estimation Results from Binary Logistic Regression Model.....	30
5. CONCLUSION.....	34
REFERENCES	36
APPENDIX A. ESTIMATED COEFFICIENTS ASSOCIATED WITH THE ORDER POST-ORDER PERIOD FOR 101 MSAS WITH MORE THAN 500 OBSERVATIONS	39
APPENDIX B. COEFFICIENTS PLOT FROM UNCONDITIONAL QUANTILE REGRESSION IN 10 LARGEST MSAS.....	43

LIST OF TABLES

<u>Table</u>	<u>Page</u>
3.1. Description and summary statistics of variables included in UQR model	16
3.2. Description and summary statistics of variables included in binary logistic regression model	16
3.3. Stay-at-home order period and post-order period across MSA.	18
4.1. Summary table of coefficient estimates from unconditional quantile regression in 101 MSA.	23
4.2. Estimated coefficients associated with the order and post-order period for the ten largest MSAs with more than 50,000 observations.	26
4.3. Effects of socioeconomic and demographic factors on statistical significance of order coefficients.	31
4.4. Effects of socioeconomic and demographic factors on statistical significance of post order coefficients.	31

LIST OF FIGURES

<u>Figure</u>	<u>Page</u>
1.1. Trend of Newly Built House Price in the United States	2
3.1. Mean Sales Price of Houses across MSA.	14
4.1. Mean of Order and Post-order Coefficients over 101 MSA.	24
4.2. Order and Post-order Effects across Quantiles.	27

LIST OF APPENDIX FIGURES

<u>Figure</u>	<u>Page</u>
B1. Coefficients Plot from Unconditional Quantile Regression, Hartford-West Hartford-East Hartford, CT.....	43
B2. Coefficients Plot from Unconditional Quantile Regression, North Port-Sarasota-Bradenton, FL.	44
B3. Coefficients Plot from Unconditional Quantile Regression, Atlanta-Sandy Springs-Roswell, GA.	45
B4. Coefficients Plot from Unconditional Quantile Regression, Cincinnati, OH-KY-IN.	46
B5. Coefficients Plot from Unconditional Quantile Regression, Memphis, TN-MS-AR.	47
B6. Coefficients Plot from Unconditional Quantile Regression, Rochester, NY.....	48
B7. Coefficients Plot from Unconditional Quantile Regression, Cleveland-Elyria, OH.	49
B8. Coefficients Plot from Unconditional Quantile Regression, Columbus, OH.	50
B9. Coefficients Plot from Unconditional Quantile Regression, Seattle-Tacoma-Bellevue, WA.....	51
B10. Coefficients Plot from Unconditional Quantile Regression, Washington-Arlington-Alexandria, DC, VA.....	52

1. INTRODUCTION

1.1. Background of the Study

As of June 10, 2022, the United States had over 85 million confirmed COVID-19 cases and over 1 million deaths (CDC COVID Data Tracker: Daily and Total Trends, 2022). The COVID-19 outbreak in the United States caused massive damage to the United States healthcare system and the economy as well (D’Lima et al., 2022). Most notable metrics reported associated with the pandemic are rates of infection, illness, and deaths, although indirect repercussions of the pandemic should not be overlooked. Indirect repercussions of the pandemic, including job losses, educational institution closures, business firm closures, and a drop in overall GDP, should not be overlooked. COVID-19 pandemic has wreaked havoc on the economy, disrupting supply chains, labor markets, international trade, and so on (D’Lima et al., 2022). The COVID-19 pandemic has had a tremendous impact on the housing market, as it has on other sectors of the United States economy.

Although home prices in the United States had been increasing prior to the outbreak of COVID-19, the rate of increase accelerated following the pandemic. Figure 1.1. depicts the trend in newly built house prices in the United States from 2015 to 2021. The graph shows that housing prices began to rise substantially in the year 2020 and beyond.

In the United States, policies to counteract the COVID-19 epidemic were implemented on three levels: federal, state, and local governments. Travel restrictions, recommendations on public gatherings, monetary policy, and a ban on evictions and foreclosures were among the federal policy responses (Zhang et al., 2022). Stay-at-home orders were implemented on state levels, and these executive orders required restrictions on non-essential activities. Although it is

thought that all these restrictions managed to slow the spread of COVID-19 infection and save many lives, they came at a price.

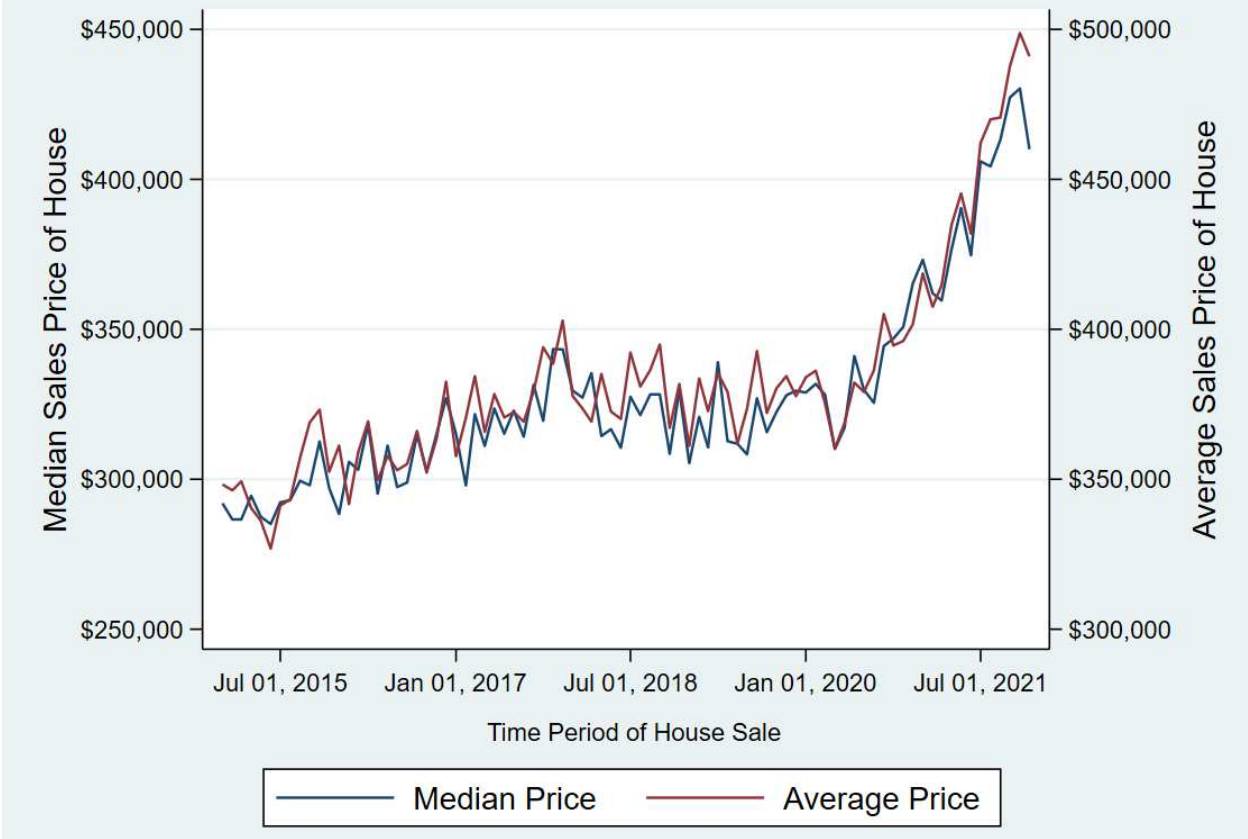


Figure 1.1. Trend of Newly Built House Price in the United States.

It has been reported that the policy of shutting down non-essential businesses and encouraging people to stay at home led to an economic downturn as well as decreased consumer spending, increased the unemployment rate, and increased instability in the stock market (Beland et al., 2020; D’Lima et al., 2022). The COVID-19 pandemic and mandatory closures have clearly affected economic growth and job markets, but the effect of the mandated closure policy connected with COVID-19 on housing markets is unclear. The COVID-19 pandemic and the stay-at-home orders must be studied to understand their impact on housing markets.

1.2. Problem Statement

Housing markets are critical for overall economic growth in the United States, and their collapse can result in a recession. Understanding housing market performance and the effects of any policy or event on the housing market is therefore critical. On March 19, California became the first state to issue a shelter in place order (SIPO) in response to the COVID-19 pandemic. Residents with a stay-at-home order or shelter in place order were prohibited from engaging in any non-essential activity outside of the home. Following California's lead, 39 more states implemented SIPO statewide between March 19th and April 20th, 2020 (Dave et al., 2021). The Stay-at-home orders implemented by governments had an impact on the housing market by altering supply and demand. But studies done to look at the effects of the COVID-19 pandemic showed that it had different effects on housing prices.

For instance, Yilmazkuday (2020) found a negative association between home prices and the number of COVID-19 cases and deaths. Additionally, they discovered that the COVID-19 had a significant negative impact on home values in counties where individuals lack access to a variety of employment opportunities. Wang (2021) , utilizing data from Santa Clara, Honolulu, Irvine, and Des Moines in the United States and using the difference-in-difference method, analyzed the impact of COVID-19 on housing prices. This study discovered that only Honolulu saw a decrease in house price, while the other 4 areas saw an increase in house price. However, most studies examined the effect of COVID-19 cases on home prices while neglecting the impact of COVID-19 related governmental responses on house prices.

The following questions are the focus of our efforts in this study:

- i. What effect does the stay-at-home order have on housing prices? How can those effects be quantified?

- ii. What factors influence the likelihood of a price increase as a result of an executive order at different price distributions?

1.3. Objectives

Objectives have been broken down into two categories: general objectives and specific objectives.

1.3.1. General Objectives

Our primary objective is to investigate the effects of the COVID-19 related stay-at-home order regulations on housing markets. Furthermore, we intend to investigate the socioeconomic and demographic characteristics that influence the probability of a price increase at a specific price distribution.

1.3.2. Specific Objectives

Our research has two specific objectives.

- i. To quantify the effects of stay-at-home orders across different distributions of house prices
- ii. To identify whether demographic and socioeconomic factors influence the effects of stay-at-home orders

1.4. Paper Organization

This paper contains five chapters. In chapter 2, we give a review of the literature. We address the housing market's contribution to the United States economy, the strategies adopted by the United States government to combat the COVID-19 pandemic, and the housing market's reaction to these efforts. We reported on more studies that explored the implications of COVID-19 on the housing market. Chapter 3 presents the methodology and data. In this section, we present our empirical model as well as a complete variable description and estimation technique.

Chapter 4 contains the results and discussion. In Chapter 5, we present our study's conclusions, limitations, and future research opportunities.

2. LITERATURE REVIEW

2.1. The Housing Market and the United States Economy

Household spending is heavily influenced by home equity, which is defined as the difference between the value of a home and its mortgage debt. Home equity is thought to stimulate the economy and economic growth by allowing people to spend more. This is especially essential given that most of the American households' main investment is their home. Any drop in the house value slows economic growth by reducing private consumption spending (Nothaft, 2004).

Given that the residential property stock in the United States accounts for a sizable amount of family wealth, every change in house prices has an influence on both household wealth and spending (Leung, 2004). Winkler & Donald Jud (2002) examined city-level data and discovered that interest rates, construction costs, and population growth all influence home prices. Over time, home equity has developed into a source of liquidity (Domanski & Deep, 2002). Homeowners are refinancing their mortgages and cashing out funds to help them through financial difficulties or wealth loss. Additionally, refinancing combined with a lower interest rate generates additional money for households that can be used for other purposes. So, housing markets are very important for the United States economy to grow (Domanski & Deep, 2002).

Consumer expenditures, investment spending, government spending, and net exports are the four components of national spending, with consumption spending being the least volatile of the four (Leonard, 2010). The reason for this is that consumers do not like to change their consumption patterns, even if their income declines. If they believe their income reduction is temporary, they are more likely to continue with their current consumption pattern. For example, even during the recession, consumer spending in the United States did not fall drastically

(Leonard, 2010). People, on the other hand, see rising housing prices as an increase in permanent income, encouraging them to spend more. As a result, the impact of rising property prices on consumer spending is substantially greater than that of increased income from other sources. Also, refinancing makes it more liquid than ever, which means that private spending goes up quickly as property prices go up (Leonard, 2010)

The collapse of the housing market following the burst of the bubble is widely regarded as the primary cause of the 2008 Great Recession in the United States (Bahmani-Oskooee & Ghodsi, 2018). Stock prices fell in response to the reduction in house prices, implying that house prices are a determinant of stock prices. Bahmani-Oskooee & Ghodsi (2018) used the housing price index and the S&P 500 index to determine if there was any causal relationship between these two variables, and they were able to establish one. They found housing markets are critical to the growth of the stock market and the economy.

2.2. COVID-19 Outbreak and the United States Response

COVID-19, an infectious disease that is rapidly spreading, was initially detected in Wuhan, China in December 2019. It is one of the worst pandemics the world has ever seen, having claimed more than 6 million people as of June 2022 (*COVID-19 Map - Johns Hopkins Coronavirus Resource Center*, n.d.) and is predicted to claim many more in the coming months. Within 4 months of the COVID-19 virus's debut, people from over 183 different countries had been infected with the virus, which had spread in a very short period (Fang et al., 2020). The first Covid-19 patient in the United States was discovered on January 20th in Washington State, and since then, a rapidly increasing number of cases have been recorded around the country. On the 18th of March, the number of confirmed COVID-19 cases reached 18747, up from 1629 on the 12th of March (Dave et al., 2021). The number of verified cases climbed swiftly, reaching

778,328 by late April, accounting for one-third of all reported COVID-19 cases worldwide (Dave et al., 2021). Even though many countries, including the United States, initially discounted the prospect of a deadly epidemic of COVID-19, the entire world became aware of the disease's devastating breakout after the World Health Organization (WHO) proclaimed it a global pandemic in early March (Hiscott et al., 2020).

Immediately following COVID-19, output dropped precipitously, with the low-tech industry bearing the brunt of the fallout from the disaster. In contrast, the high-tech industry, driven by Google and Microsoft, was able to respond quickly and outpace the rest of the economy (Pagano et al., 2020). The unemployment rate in the United States fell to 3.5 percent in February 2020, the lowest level in 67 years, and around 10 million people applied for unemployment benefits within six weeks of the rate's reaching 3.5 percent in February 2020 (Baker et al., 2020), and the effects were borne disproportionately by the general population. As a result of a lack of access to healthcare and because they work in low-wage occupations where social distancing is almost impossible, minorities and low-income people face a disproportionate amount of the cost of COVID-19 (Louis-Jean et al., 2020). According to this study, 70% of total death in Louisiana from COVID-19 were attributed to African American, even though they constituted just 32 percent of the state's entire population. At the same time, white Americans accounted for 28 % of COVID-19 deaths in Louisiana, despite the fact that they constituted 62 % of the state's population (Louis-Jean et al., 2020). In the same vein, rural Americans were more adversely affected by COVID-19, and the death rate among them was higher as well (Dorn et al., 2020).

2.3. COVID-19 and Housing Market Response

As a result of COVID-19 pandemic, more than half a million individuals have died in the United States, and the indirect consequences have included growing unemployment, decreasing GDP growth, a drop in international trade, and the closure of several enterprises and financial institutions throughout the country. Real estate value changes are one of the most major indirect repercussions of COVID-19 pandemic. The price of housing, like the price of other things, is determined by the demand for and supply of housing. Any increase in demand for housing is expected to have a positive influence on the price, whilst any increase in supply is expected to have a negative impact on the price of housing. Housing prices fall because of any uncertainty or income loss, because uncertainty and income loss lessen the desire to purchase housing (Granja et al., 2020; Haurin et al., 2005; Mayer & Somerville, 2000). COVID-19 pandemic has had an impact on both the demand for and the supply of housing, making it impossible to forecast changes in the value of real estate.

Zhao (2020) investigated data at the zip code level and observed an upward trend in housing values. Even though costs originally fell as Covid extended across the United States, they began to climb quickly in mid-April and thereafter because of the Covid problem and the government shutdown restrictions imposed by the shutdown. According to Zhao, availability of residences for sale decreased during the same period, which contributed to the increase in housing costs.

Liu & Su (2021) evaluated the impact of COVID-19 pandemic on the demand for density, and in their study, they had some intriguing findings regarding how the demand for density transfers from neighborhoods with high-end amenities to suburban areas with lower-end amenities and fewer consumption opportunities. They discovered that the demand for density

had decreased in neighborhoods where the prices were higher prior to the outbreak of COVID-19. These researchers speculate that the ability to work from home may have played a role in this shift. In addition to this, because it is understandable that it was more expensive to live in larger towns with more amenities, the option to work from home facilitated their decision to relocate to more remote neighborhoods with lower living expenses. The research is particularly relevant in explaining why prices in larger cities are declining even though the quantity of homes on the market has decreased because of the COVID-19 pandemic. According to the findings of the study, there has been a decrease in demand for homes in densely populated areas, particularly in areas with more pubs and restaurants. In addition, the study found that prices were declining in larger cities with a higher population density. Further investigation is needed to examine the impact of COVID-19 pandemic on property prices, including whether they are increasing or falling.

Qian et al. (2021) attempted to explore the impact of COVID-19 pandemic on housing price. In their study, number of COVID-19 cases was used as an independent variable to evaluate the direct consequences of the disease in the community, and a Difference in Difference (DID) technique is used to examine how confirmed Covid cases affect property values. They noted a reduction in the value of homes in correlation with the number of confirmed cases of COVID-19 infection. Their research suggests that the effect lasts for three months and then grows in amplitude. His findings are consistent with the notion that the assumption of risk lowers the value of real estate. Because of the increased number of confirmed COVID cases, consumers can better predict the unsafe condition, which ultimately results in a decline in property values.

The increase in the number of COVID cases had a particularly negative impact on the real estate market, and the impact was not consistent across counties. Using DID technique,

Yilmazkuday (2020) evaluated the effects of COVID-19 on home prices at the county level in the United States. According to this research, a fall in housing prices of 501 dollars was connected with an increase in the number of fatalities by 1000. According to the study, average prices increased in certain areas while decreasing in others, particularly in counties in the Midwestern United States. Following the adjustment for time and county effects, however, the overall impacts were assessed to be negative and statistically significant. According to the findings of the study, the negative effects of COVID-19 on housing markets are likely to be greater in counties with restricted access to a diverse range of jobs.

Although housing transactions were not suspended since they were not deemed non-essential, the shutdown order had an impact on housing demand and pricing, which changed because of consumer behavior. Individuals can choose to work from home under the terms of the shutdown order, which is likely to reduce the demand for housing in city areas and, consequently, the price of housing. Nonetheless, it is understandable that the order to stay at home could generate increased demand for specific types of homes, hence raising the price for those homes. It is still unclear how the shutdown order affected the housing market, whether it will have a favorable or negative impact, and how they will be affected.

When researching the influence of shutdown orders on house prices, Lima looked at data from several states in the United States (D'Lima et al., 2022). Despite the fact that the study discovered a decline in house sales following a shutdown order, it was unable to identify whether shutdown orders had a meaningful impact on property prices. Results suggest a decrease in price for a house in more densely populated area, whereas an increase in price for a house less densely populated area. When considering whether to implement limits in a more densely populated area or a less densely populated one, research is particularly crucial. Other authors came to similar

conclusions. They said that property prices in big cities or areas with a lot of people were going down, while prices in suburbs or areas with less people were going up.

Even though numerous research studies have been conducted to study the impact of COVID-19 on housing markets, most of them were either confined to small sample sizes or used ordinary least squares regressions. As a result, some research found that COVID-19 had a favorable influence on house prices, while others found that it had a negative effect. The importance of examining diverse price distributions in the housing market to better understand whether the price effects are different across different house price quantiles cannot be overlooked. As a result, we intend to explore the impact of COVID-19 on different price distributions of houses using a quantile regression approach.

3. DATA AND METHODS

3.1. Data Sources

There are two primary sources of data that we have used in various stages of analysis.

3.1.1. Housing Data

We received housing data from the ZTRAX database, which has over 400 million home transaction records. Our data from the ZTRAX database includes housing attributes, sales prices, and sales dates for homes sold between 2015 and 2020. Figure 3.1. shows the average price of a home sold in each metropolitan statistical area. Table 3.1. contains a description and summary statistics for the variables included in our unconditional quantile regression model (UQR). The average sale price of a home in our sample was \$292,005, and it featured two bedrooms and three baths. On average, houses were 41 years old and had 2,000 square feet of living space. About 64% of the homes were in average condition, while 24% of the homes were in good condition. Nearly 20% of home sales occurred in 2019 and 18% occurred in 2020.

3.1.2. Socio-demographic Data

We obtained socio-demographic data at the MSA level from the United States Census Bureau, specifically from the American Community Survey 2-year estimates. This information was used in a binary logistic regression model to predict the likelihood of a price increase connected with an executive order being seen in a particular house price distribution. Table 3.2. shows the description and summary statistics of the variables used in the binary logit model. The percentages of black people and hispanic people in our sample were roughly 13% and 9%, respectively. With a standard deviation of 1.03, the average unemployment rate was nearly 5%.

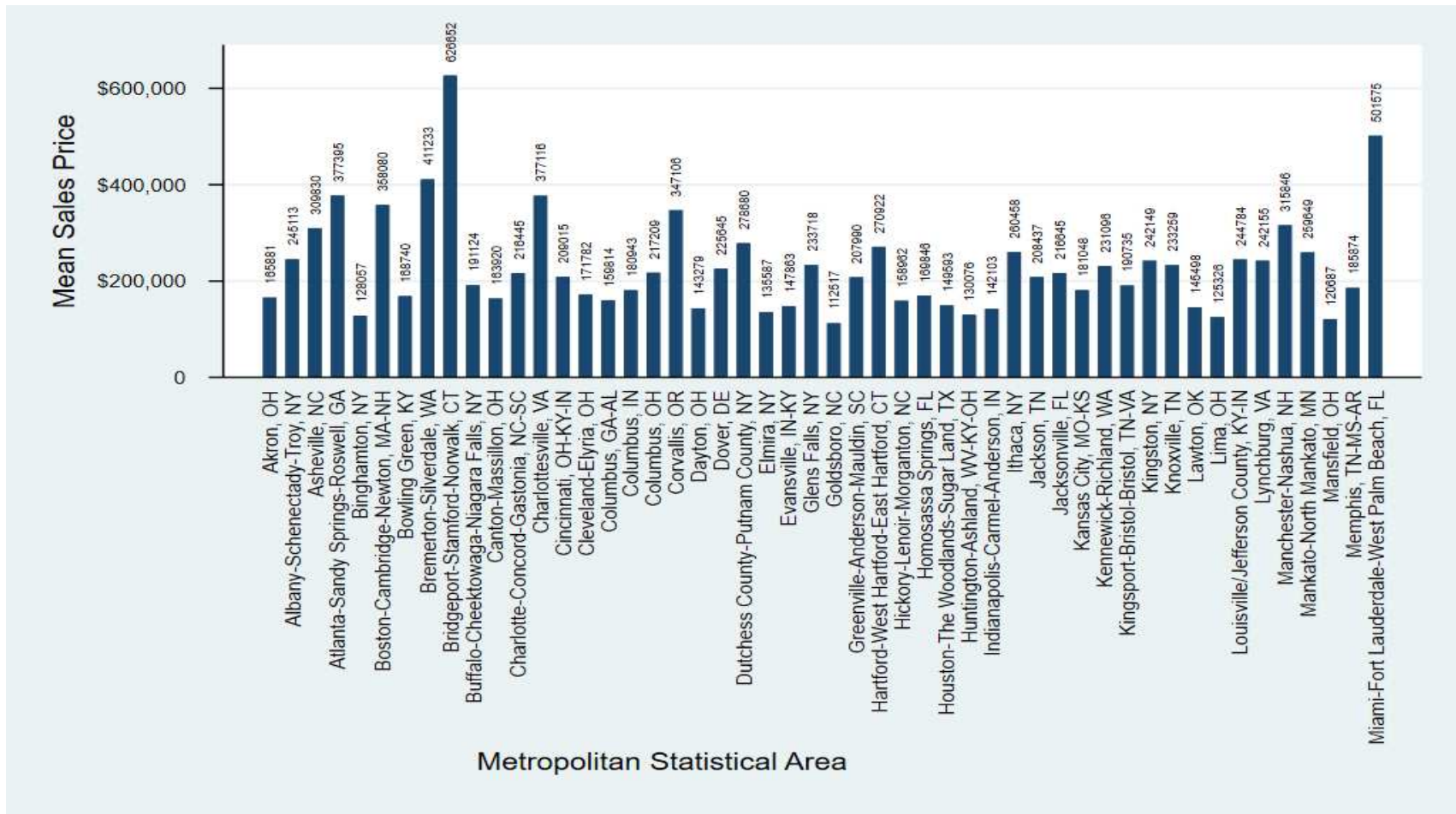


Figure 3.1. Mean Sales Price of Houses across MSA.

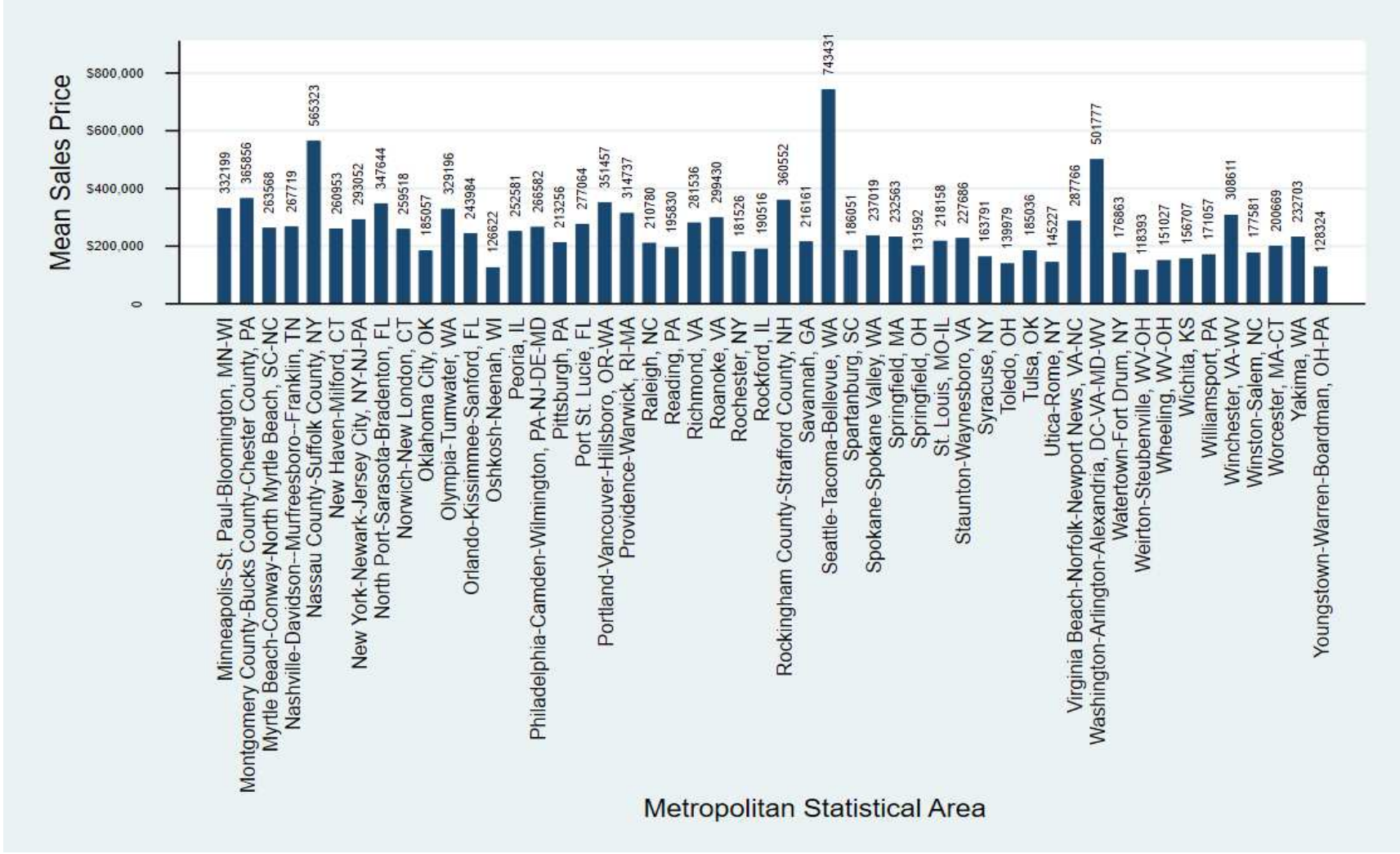


Figure 3.1. Mean Sales Price of Houses across MSA (continued).

Table 3.1. Description and summary statistics of variables included in UQR model.

Variable	Mean	Std. Dev.	Min	Max
<i>House Characteristics</i>				
Natural log of sales price	12.29	0.76	10.13	15.42
Living area in 1000 square foot	2.14	1.18	0.02	10.00
Lot area in 1000 square foot	24.61	37.74	0.01	300.00
Number of bedrooms	3.23	0.80	1.00	43.00
Number of bathrooms	2.09	0.89	0.50	10.00
Age of house	41.50	26.98	0.00	100.00
<i>House Conditions</i>				
Excellent	0.04	0.20	0.00	1.00
Good	0.24	0.43	0.00	1.00
Average	0.64	0.48	0.00	1.00
Fair	0.04	0.19	0.00	1.00
<i>Time Variable</i>				
2015 (Dummy variable; takes value 1 if house is sold in year 2015; 0 otherwise)	0.13	0.34	0.00	1.00
2016 (Dummy variable; takes value 1 if house is sold in year 2016; 0 otherwise)	0.16	0.36	0.00	1.00
2017 (Dummy variable; takes value 1 if house is sold in year 2017; 0 otherwise)	0.17	0.37	0.00	1.00
2018 (Dummy variable; takes value 1 if house is sold in year 2018; 0 otherwise)	0.18	0.38	0.00	1.00
2019 (Dummy variable; takes value 1 if house is sold in year 2019; 0 otherwise)	0.19	0.39	0.00	1.00
2020 (Dummy variable; takes value 1 if house is sold in year 2020; 0 otherwise)	0.18	0.38	0.00	1.00

The order period dummy takes the value of 1 if the house is sold during the stay-at-home period and 0 otherwise. The post-order dummy takes the value of 1 if the house is sold after the expiration of the stay-at-home period, 0 otherwise. Due to space limitations, we could not provide summary statistics of order period dummy and post-order period dummy. As executive orders had different time periods across the states, different MSAs had different timing for orders and post-order dummies. Number of observations = 2,203,758

Table 3.2. Description and summary statistics of variables included in binary logistic regression model.

Variables	Mean	Std. Dev	Min	Max
Black (%)	12.55	9.52	1.36	47.58
Hispanic (%)	8.80	7.62	0.70	46.10
Unemployment Rate (%)	4.51	1.03	2.30	9.00
Vote received by Democratic Party (%)	50.70	8.12	32.30	65.60

3.2. Stay-at-Home Orders

On the 18th of January, when the first COVID-19 patient was detected in the state of Washington, the United States government promptly began enacting steps to prevent the nationwide spread of COVID-19 infections. Among other measures, travel prohibitions, the

shutdown of educational institutions, bars, and restaurants were being discussed. Nonetheless, each state kept the authority to enforce a stay-at-home order, which it did on its own timetable, with California being the first to do so. Other states soon followed suit, enacting their own versions of the stay-at-home order. The order period is the time during which the stay-at-home order was in effect, and post-order period is the time after the order has expired. Some MSAs were located in multiple states, in which case we considered a stay-at-home order depending on the state from where the majority of observations originated. For example, the Evansville, IN-KY MSA is located in both Indiana and Kentucky, but Kentucky accounts for more than 90% of the observations. So, to get rid of as much bias as possible, we determined the order and post-order period for the Evansville, IN-KY MSA based on the stay-at-home order in Kentucky. Table 3.3. provides detailed information regarding the stay-at-home order period and post-order period (D’Lima et al., 2022). Table 3.3. also shows the number of observations in each MSA.

Table 3.3. Stay-at-home order period and post-order period across MSA.

MSA Name	State	Order Period	Post-order Period	N
Akron, OH	Ohio	3/23/2020	6/10/2020	36095
Albany-Schenectady-Troy, NY	New York	3/22/2020	5/28/2020	32431
Asheville, NC	North Carolina	3/30/2020	5/20/2020	3826
Atlanta-Sandy Springs-Roswell, GA	Georgia	3/21/2020	4/30/2020	91330
Binghamton, NY	New York	3/22/2020	5/28/2020	6061
Boston-Cambridge-Newton, MA-NH	Massachusetts	3/24/2020	5/18/2020	1905
Bowling Green, KY	Kentucky	3/26/2020	5/31/2020	6216
Bremerton-Silverdale, WA	Washington	3/23/2020	5/31/2020	13869
Bridgeport-Stamford-Norwalk, CT	Connecticut	3/23/2020	5/20/2020	43520
Buffalo-Cheektowaga-Niagara Falls, NY	New York	3/22/2020	5/28/2020	47624
Canton-Massillon, OH	Ohio	3/23/2020	6/10/2020	9783
Charlotte-Concord-Gastonia, NC-SC	North Carolina	3/30/2020	5/20/2020	29687
Charlottesville, VA	Virginia	3/30/2020	5/13/2020	8333
Cincinnati, OH-KY-IN	Ohio	3/23/2020	6/10/2020	89693
Cleveland-Elyria, OH	Ohio	3/23/2020	6/10/2020	87882
Columbus, GA-AL	Georgia	3/21/2020	4/30/2020	15202
Columbus, IN	Illinois	3/24/2020	5/4/2020	974
Columbus, OH	Ohio	3/23/2020	6/10/2020	88193
Corvallis, OR	Oregon	3/23/2020	5/9/2020	4429
Dayton, OH	Ohio	3/23/2020	6/10/2020	25937
Dover, DE	Delaware	3/24/2020	5/18/2020	11961
Dutchess County-Putnam County, NY	New York	3/22/2020	5/28/2020	10938
Elmira, NY	New York	3/22/2020	5/28/2020	5449
Evansville, IN-KY	Kentucky	3/26/2020	5/31/2020	2024
Glens Falls, NY	New York	3/22/2020	5/28/2020	6588
Goldsboro, NC	North Carolina	3/30/2020	5/20/2020	1208
Greenville-Anderson-Mauldin, SC	South Carolina	4/7/2020	5/1/2020	2740
Hartford-West Hartford-East Hartford	Connecticut	3/23/2020	5/20/2020	60941
Hickory-Lenoir-Morganton, NC	North Carolina	3/30/2020	5/20/2020	5071
Homosassa Springs, FL	Florida	3/25/2020	6/18/2020	17882
Houston-The Woodlands-Sugar Land, TX	Texas	3/23/2020	6/5/2020	2136
Huntington-Ashland, WV-KY-OH	Ohio	3/23/2020	6/10/2020	3381
Indianapolis-Carmel-Anderson, IN	Illinois	3/24/2020	5/4/2020	1507
Ithaca, NY	New York	3/22/2020	5/28/2020	2887
Jackson, TN	Tennessee	3/25/2020	5/15/2020	903
Jacksonville, FL	Florida	3/25/2020	6/18/2020	12659
Kansas City, MO-KS	Kansas	3/24/2020	5/15/2020	1253
Kennewick-Richland, WA	Washington	3/23/2020	5/31/2020	943
Kingsport-Bristol-Bristol, TN-VA	Virginia	3/30/2020	5/13/2020	2107
Kingston, NY	New York	3/22/2020	5/28/2020	9373
Knoxville, TN	Tennessee	3/25/2020	5/15/2020	38274
Lawton, OK	Oklahoma	3/25/2020	6/5/2020	3789
Lima, OH	Ohio	3/23/2020	6/10/2020	5110
Louisville/Jefferson County, KY-IN	Kentucky	3/26/2020	5/31/2020	25401
Lynchburg, VA	Virginia	3/30/2020	5/13/2020	7546
Manchester-Nashua, NH	New Hampshire	3/27/2020	6/15/2020	22190
Mankato-North Mankato, MN	Minnesota	3/27/2020	5/15/2020	512
Mansfield, OH	Ohio	3/23/2020	6/10/2020	5682
Memphis, TN-MS-AR	Tennessee	3/25/2020	5/15/2020	58514
Miami-Fort Lauderdale-West Palm Beach	Florida	3/25/2020	6/18/2020	42845
Minneapolis-St. Paul-Bloomington, MN-WI	Minnesota	3/27/2020	5/15/2020	27271
Montgomery County-Bucks County-Cheste	Pennsylvania	3/23/2020	5/4/2020	53231

Table 3.3. Stay-at-home order period and post-order period across MSA (continued).

MSA Name	State	Order Period	Post-order Period	N
Myrtle Beach-Conway-North Myrtle Beac	South Carolina	4/7/2020	5/1/2020	50391
Nashville-Davidson--Murfreesboro--Franklin, TN	Tennessee	3/25/2020	5/15/2020	949
Nassau County-Suffolk County, NY	New York	3/22/2020	5/28/2020	4086
New Haven-Milford, CT	Connecticut	3/23/2020	5/20/2020	39653
New York-Newark-Jersey City, NY-NJ-PA	New York	3/22/2020	5/28/2020	31060
North Port-Sarasota-Bradenton, FL	Florida	3/25/2020	6/18/2020	65832
Norwich-New London, CT	Connecticut	3/23/2020	5/20/2020	13888
Oklahoma City, OK	Oklahoma	3/25/2020	6/5/2020	12180
Olympia-Tumwater, WA	Washington	3/23/2020	5/31/2020	12936
Orlando-Kissimmee-Sanford, FL	Florida	3/25/2020	6/18/2020	49082
Oshkosh-Neenah, WI	Wisconsin	3/25/2020	5/13/2020	694
Peoria, IL	Illinois	3/21/2020	5/30/2020	4700
Philadelphia-Camden-Wilmington, PA-NJ..	Delaware	3/24/2020	5/18/2020	25278
Pittsburgh, PA	Pennsylvania	3/23/2020	5/4/2020	32196
Port St. Lucie, FL	Florida	3/25/2020	6/18/2020	44430
Portland-Vancouver-Hillsboro, OR-WA	Washington	3/23/2020	5/31/2020	32321
Providence-Warwick, RI-MA	Rhode Island	3/28/2020	5/26/2020	56482
Raleigh, NC	North Carolina	3/30/2020	5/20/2020	4769
Reading, PA	Pennsylvania	3/23/2020	5/4/2020	23752
Richmond, VA	Virginia	3/30/2020	5/13/2020	49881
Roanoke, VA	Virginia	3/30/2020	5/13/2020	5133
Rochester, NY	New York	3/22/2020	5/28/2020	59489
Rockford, IL	Illinois	3/21/2020	5/30/2020	3001
Rockingham County-Strafford County, NH	New Hampshire	3/27/2020	6/15/2020	25807
Savannah, GA	Georgia	3/21/2020	4/30/2020	16720
Seattle-Tacoma-Bellevue, WA	Washington	3/23/2020	5/31/2020	114961
Spartanburg, SC	South Carolina	4/7/2020	5/1/2020	18439
Spokane-Spokane Valley, WA	Washington	3/23/2020	5/31/2020	28471
Springfield, MA	Massachusetts	3/24/2020	5/18/2020	8871
Springfield, OH	Ohio	3/23/2020	6/10/2020	6701
St. Louis, MO-IL	Missouri	3/23/2020	5/4/2020	36237
Staunton-Waynesboro, VA	Virginia	3/30/2020	5/13/2020	3894
Syracuse, NY	New York	3/22/2020	5/28/2020	30547
Toledo, OH	Ohio	3/23/2020	6/10/2020	23675
Tulsa, OK	Oklahoma	3/25/2020	6/5/2020	7658
Utica-Rome, NY	New York	3/22/2020	5/28/2020	9899
Virginia Beach-Norfolk-Newport News,	Virginia	3/30/2020	5/13/2020	25444
Washington-Arlington-Alexandria, DC-V	Virginia	3/30/2020	5/13/2020	63318
Watertown-Fort Drum, NY	New York	3/22/2020	5/28/2020	3216
Weirton-Steubenville, WV-OH	Ohio	3/23/2020	6/10/2020	2016
Wheeling, WV-OH	Ohio	3/23/2020	6/10/2020	1873
Wichita, KS	Kansas	3/24/2020	5/15/2020	1340
Williamsport, PA	Pennsylvania	3/23/2020	5/4/2020	3564
Wilmington, NC	North Carolina	3/30/2020	5/20/2020	8589
Winchester, VA-WV	Virginia	3/30/2020	5/13/2020	2757
Winston-Salem, NC	North Carolina	3/30/2020	5/20/2020	6938
Worcester, MA-CT	Connecticut	3/23/2020	5/20/2020	6417
Yakima, WA	Washington	3/23/2020	5/31/2020	1473
Youngstown-Warren-Boardman, OH-PA	Ohio	3/23/2020	6/10/2020	18575

3.3. Empirical Models

3.3.1. Unconditional Quantile Regression Model

Our main purpose is to quantify the effects of stay-at-home order and post-order on housing prices in 101 metropolitan statistical areas (MSA). The most commonly used method for determining the influence of property attributes and other neighborhood features on housing prices is the hedonic price model. The following is the hedonic baseline model for our research:

$$P = \beta X + \alpha T + \varepsilon \quad (3.1)$$

Where P is a vector that holds the natural log of each house's sale price during the study period (2015–2020). X is a matrix with the values of house characteristics like the number of bedrooms, the number of bathrooms, the size of the living room, the condition of the house, and the year it was sold. T is a vector that has two pandemic dummies in it: one for the order period and one for the post-order period. Order period dummy = 1 if the house was sold during the stay-at-home order period. Post-order period dummy = 1 if the house was sold after the stay-at-home order period ended.

Although OLS regression is commonly used to estimate equation 1, quantile regression has a fundamental advantage over OLS regression. Unlike OLS, which estimates the effects of a covariate on an endogenous variable around its mean, quantile regression estimates the effects of a covariate on the entire distribution. So, for estimating our hedonic price model, the conditional quantile regression model (CQR) would allow us to estimate the effects of stay-at-home orders or any other covariate on house prices at various points of the house price distribution, such as the 25th, 50th, and 75th percentiles. Thus, this estimation technique can provide us with the heterogeneous price effects of stay-at-home orders in the United States housing markets.

Nonetheless, there are issues with conditional quantile regression estimates in the context of policy formation. Since the CQR model estimates the effects of a covariate on an endogenous

variable conditional on other covariates in the model, it is frequently challenging to generalize the result and formulate the policy, as the impacts would vary with the change of other covariates. This issue can be resolved by estimating the hedonic price model employing the unconditional quantile regression model (UQR). Unconditional quantile regression can be used directly to estimate the effect of any covariate on different quantiles of the unconditional distribution of sale price. This makes the estimations more interpretable and generalizable.

To quantify the heterogeneous price impacts throughout the house price distribution, we fitted an unconditional quantile regression model. Firpo et al. (2009) proposed regressing covariates on the Recentered Influence Function (RIF) to estimate the UQR model:

$$RIF(Y; Pq_{\tau}, Fp_{q_{\tau}}) = P_{q_{\tau}} + \frac{(\tau - I\{P \leq Pq_{\tau}\})}{f_y(Pq_{\tau})} = \beta X + \alpha T + \epsilon \quad (3.2)$$

Where $P_{q_{\tau}}$ is the sale price, p , at the τ^{th} percentile (q). I is the indicator function which takes the value 1 when P is less than Pq_{τ} , and $f_y(Pq_{\tau})$ is the density of P at the τ^{th} quantile.

Before estimating (3.2), the data were cleaned. If sample size is too small, significant result cannot be obtained, so MSAs with fewer than 500 observations were omitted from the analysis and finally we had 101 MSA with at least 500 observations. We also eliminated observations for which sales price data was absent.

3.3.2. Binary Logistic Regression Model

After obtaining the order and post-order coefficients at three quantiles (0.25, 0.50, and 0.75) for 101 MSA, we analyzed whether they were positive and statistically significant. A coefficient that is statistically significant and positive suggests an increase in home prices. Now, our purpose is to determine how socioeconomic and demographic characteristics, as stated in table 3.2. influence the probability of a statistically significant price increase in these quantiles.

Now we want to figure out what factors influence the likelihood of a price increase at the 0.25th quantile due to stay-at-home orders. Our response variable, z_i is a binary variable which can take on the values of 1 or 0. If coefficient value of order period is positive at 0.25th quantile, $z_i=1$; 0 otherwise. In such a situation, our binary logistic model may be represented as follows:

$$\ln \left[\frac{\pi_i}{1-\pi_i} \right] = x_i^T \beta \quad (3.3)$$

where $\pi_i = p_r(z_i = 1|x_i^T) = \frac{e^{x_i^T \beta}}{(1+e^{x_i^T \beta})}$ is the conditional probability of $z_i = 1$ given x_i^T and x_i

denotes the matrix containing the values of explanatory variables. Similarly, the binary logistic regression model was fit for the following quantiles: order (0.5th quantile); order (0.75th quantile); post-order (0.25th quantile); post-order (0.50th quantile); and post-order (0.75th quantile).

We removed some other racial variables from our estimation model, such as white, Asian, and other socioeconomic characteristics, because they were highly correlated with other variables.

4. RESULTS & DISCUSSION

4.1. Estimation Results from Unconditional Quantile Regression Model

Table 4.1. shows the summary statistics of coefficients from unconditional quantile regression in 101 MSAs. Table 4.1. shows that every extra 1000 square feet of living space was related to a 14% rise in house price at the 0.25th quantile and a 35% increase at the 0.75th quantile. Older homes were sold at a discount across all quantiles.

Table 4.1. Summary table of coefficient estimates from unconditional quantile regression in 101 MSA.

Variables	Q25			Q50			Q75		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Living Area	0.14	-0.13	0.42	0.23	0.00	0.53	0.35	0.02	0.67
Lot Area	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01
Bedroom	0.05	-0.22	0.24	0.02	-0.14	0.13	-0.01	-0.14	0.14
Bathroom	0.15	-0.26	0.53	0.13	-0.08	0.39	0.15	-0.14	0.40
Age	-0.01	-0.02	0.00	0.00	-0.02	0.01	0.00	-0.01	0.01
Excellent Condition	0.40	-1.57	1.86	0.12	-1.21	1.07	0.13	-1.55	1.17
Good Condition	0.63	-1.62	1.81	0.25	-1.43	0.86	0.13	-1.77	0.87
Average Condition	0.50	-1.93	1.61	0.13	-1.61	0.62	-0.03	-1.81	0.44
Fair Condition	0.10	-2.56	0.99	0.00	-1.76	0.52	-0.04	-1.67	0.36
Year 2016	0.06	-0.27	0.32	0.05	-0.18	0.37	0.03	-0.53	0.42
Year 2017	0.10	-0.86	0.49	0.09	-0.30	0.35	0.06	-0.26	0.37
Year 2018	0.19	-0.78	0.92	0.15	-0.31	0.61	0.11	-0.21	0.34
Year 2019	0.25	-0.87	0.96	0.22	-0.36	0.69	0.17	-0.16	0.59
Year 2020	0.28	-0.74	1.10	0.22	-0.41	0.75	0.17	-0.17	0.43
Order	0.04	-1.64	0.70	0.06	-0.57	0.67	0.05	-0.52	0.73
Post-order	0.08	-1.27	0.67	0.10	-0.70	0.40	0.10	-0.65	0.47

The coefficients associated with variables were estimated using unconditional quantile regression model.

Variables included in the models are living area, lot area, bedroom, bathroom, age of house, condition excellent, condition good, condition average, condition fair, and 6 years as dummy variables such as year 2015, year 2016, year 2018, year 2019, year 2020, order period dummy, and post-order period dummy.

At both the 0.25th and 0.75th quantiles, an additional bathroom was shown to be associated with a 15% price increase. Figure 4.1 shows the average effects of order and post-order period. Across all quantiles, we found that order and post-order had a favorable impact on

house prices. In comparison to order effects, post-order effects were significantly greater at every quantile.

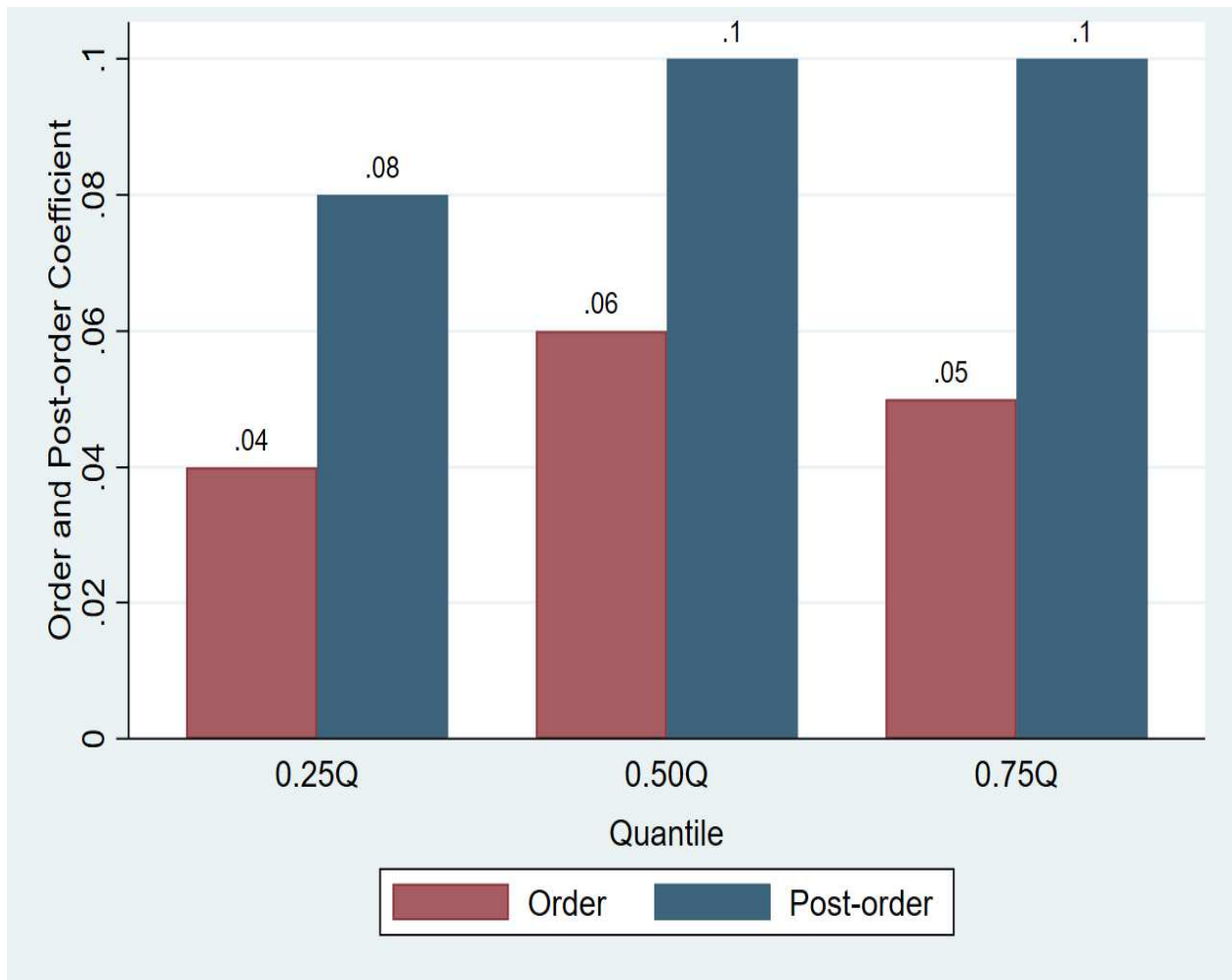


Figure 4.1. Mean of Order and Post-order Coefficients over 101 MSA.

In table 4.2, we present the order and post-order effects on home prices in the 10 largest MSAs. During the period while the executive order was in effect, nine out of ten MSAs experienced price increases at the 0.25th, 0.50th, and 0.75th quantiles. In the majority of MSAs, low-priced homes experienced the highest price increases. For instance, during the order period in the Cleveland-Elyria MSA, the housing price at the 0.25th quantile increased by 10%, while the prices at the 0.5th and 0.75th quantiles increased by around 8% and 6%, respectively. All MSAs had price appreciation throughout the post-order period, which was statistically significant

at the 95% confidence interval. When comparing the price increases at each quantile during order and post-order period, it is evident that the price increase at each quantile during the post-order period were larger. In the Columbus MSA, the price at the 0.25th quantile increased by 10 percent during the order period and 16 percent after the order period. Similarly, the 0.25th quantile house price in Rochester increased by 5% during the order period and 17% after the expiration of executive orders.

Figures 4.2. shows order and post-order effects in the 10 largest MSAs across the home price distribution. Statistical significance was indicated with + over the bar (small plus sign). We can see that post-order effects were larger than order effects in virtually all MSAs throughout the quantiles. One key finding from the graph is that, while most MSAs see larger pricing effects on lower-priced housing during the executive order era, higher-priced housing sees stronger price effects during the post-order period. Appendix A contains the complete results on order and post-order impacts across quantiles in all 101 MSAs. We plotted order and post-order effects on different quantiles for 10 major MSAs to better visualize the effects of order and post-order across the pricing distribution. (Figure B1 through Figure B10 in Appendix B).

Table 4.2. Estimated coefficients associated with the order and post-order period for the ten largest MSAs with more than 50,000 observations.

MSA Name	N	Order Q25	Q50	Q75	Q75- Q25	Post Order Q25	Q50	Q75	Q75- Q25
Atlanta-Sandy Springs-Roswell, GA	91,330	0.1131***	0.1602***	0.1503***	0.0372	0.1114***	0.1223***	0.1545***	0.0431
Cincinnati, OH-KY-IN	89,693	0.0226	0.0112	0.0470***	-0.6153	0.0468***	0.0581***	0.0996***	-0.4132
Cleveland-Elyria, OH	87,882	0.1410***	0.0763***	0.0565***	-0.0845#	0.1836***	0.1366***	0.1335***	-0.0501
Columbus, OH	88,193	0.1218***	0.1014***	0.1219***	0	0.1608***	0.1318***	0.1589***	-0.0019
Hartford-West Hartford-East Hartford	60,941	0.0867***	0.0817***	0.0201	-0.0666	0.1651***	0.1546***	0.1109***	-0.0542
Memphis, TN-MS-AR	58,514	0.1508***	0.1135***	0.0494**	-0.1014	0.1792***	0.1703***	0.1522***	-0.027
North Port-Sarasota-Bradenton, FL	65,832	0.0407**	0.0350**	0.005	-0.0357	0.0606***	0.0780***	0.0875***	0.0269
Rochester, NY	59,489	0.0579**	0.1109***	0.1181***	0.0602	0.1662***	0.1749***	0.1543***	-0.0119
Seattle-Tacoma-Bellevue, WA	114,961	0.0584***	0.0541***	0.0440***	-0.0144	0.1014***	0.1016***	0.1073***	0.0059
Washington-Arlington-Alexandria, DC-V..	63,318	0.0609***	0.0784***	0.0774***	0.0165	0.1219***	0.1594***	0.1225***	0.0006

***p<0.01, **p<0.05, *p<0.1

The CI at 0.75th quantile doesn't overlap with the CI at 0.25th quantile

Coefficients associated with order and post-order were estimated using unconditional quantile regression model.

Variables included in the models are living area, lot area, bedroom, bathroom, age of house, condition excellent, condition good, condition average, condition fair, and 6 years as dummy variable such as year 2015, year 2016, year 2018, year 2019, year 2020, order period dummy, and post-order period dummy

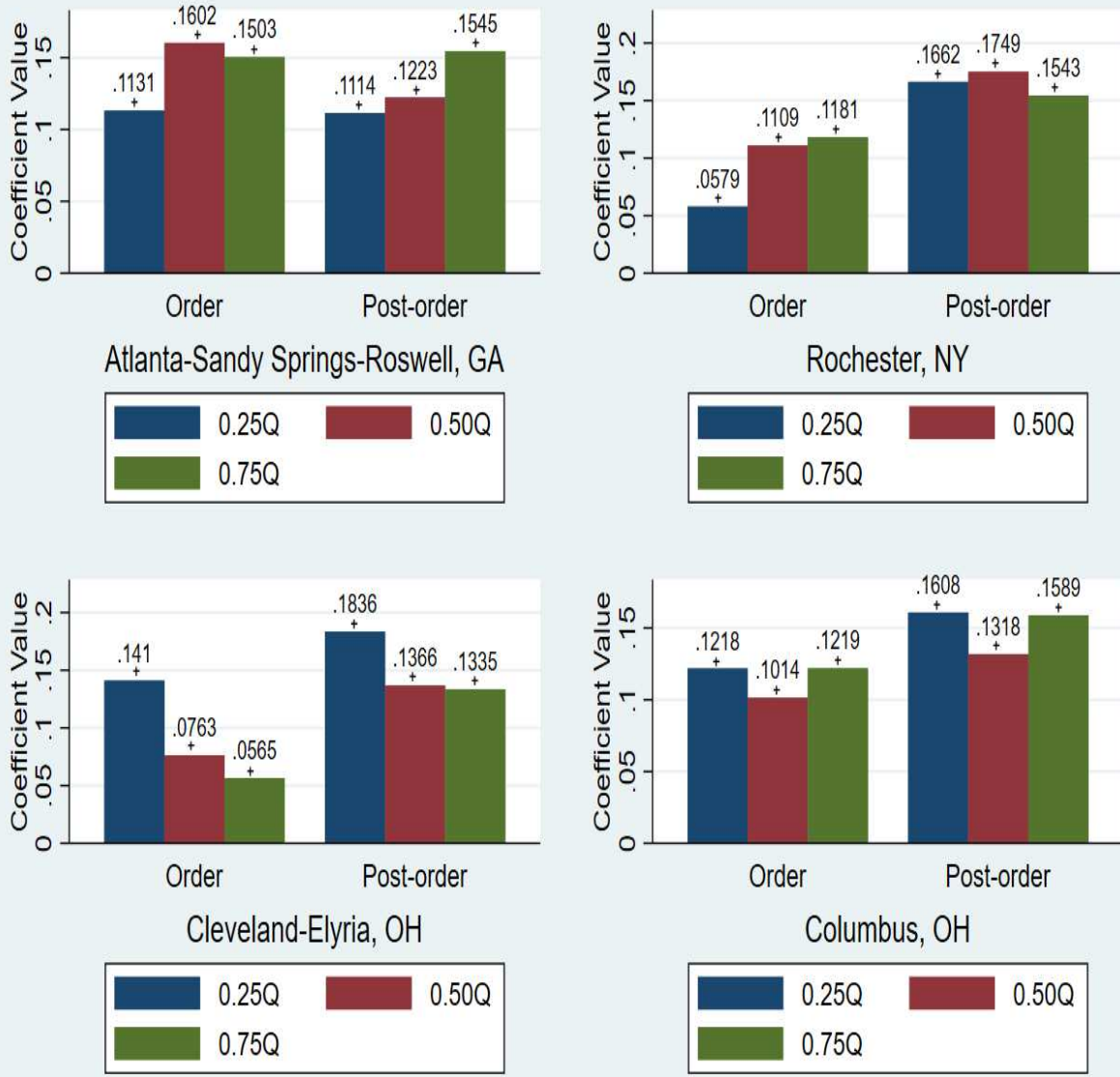


Figure 4.2. Order and Post-order Effects across Quantiles.

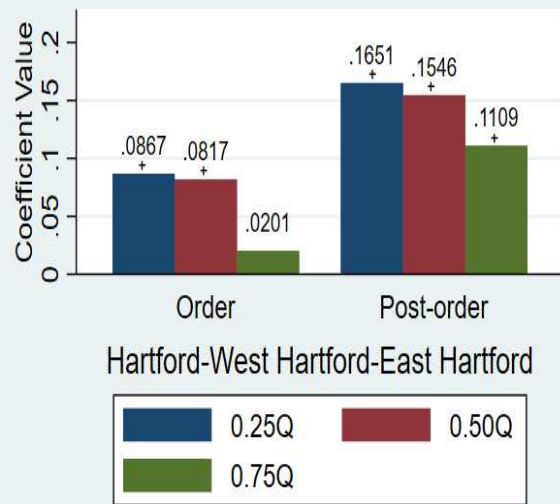
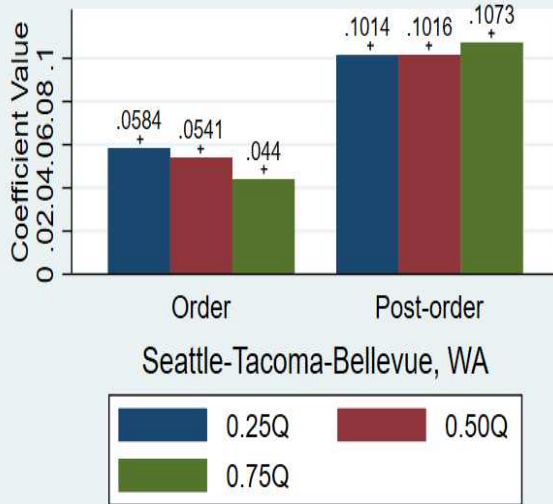
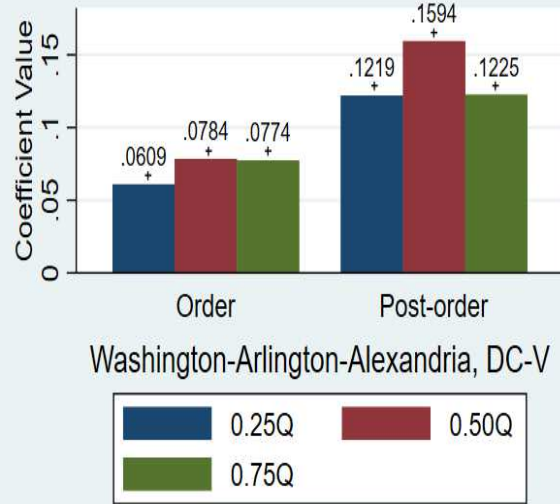
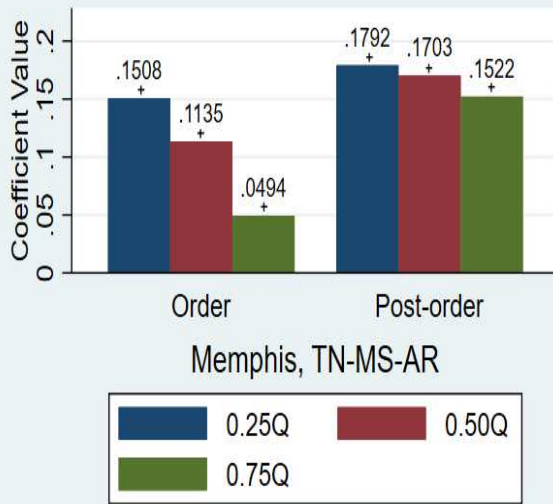


Figure 4.2. Order and Post-order Effects across Quantiles (continued).

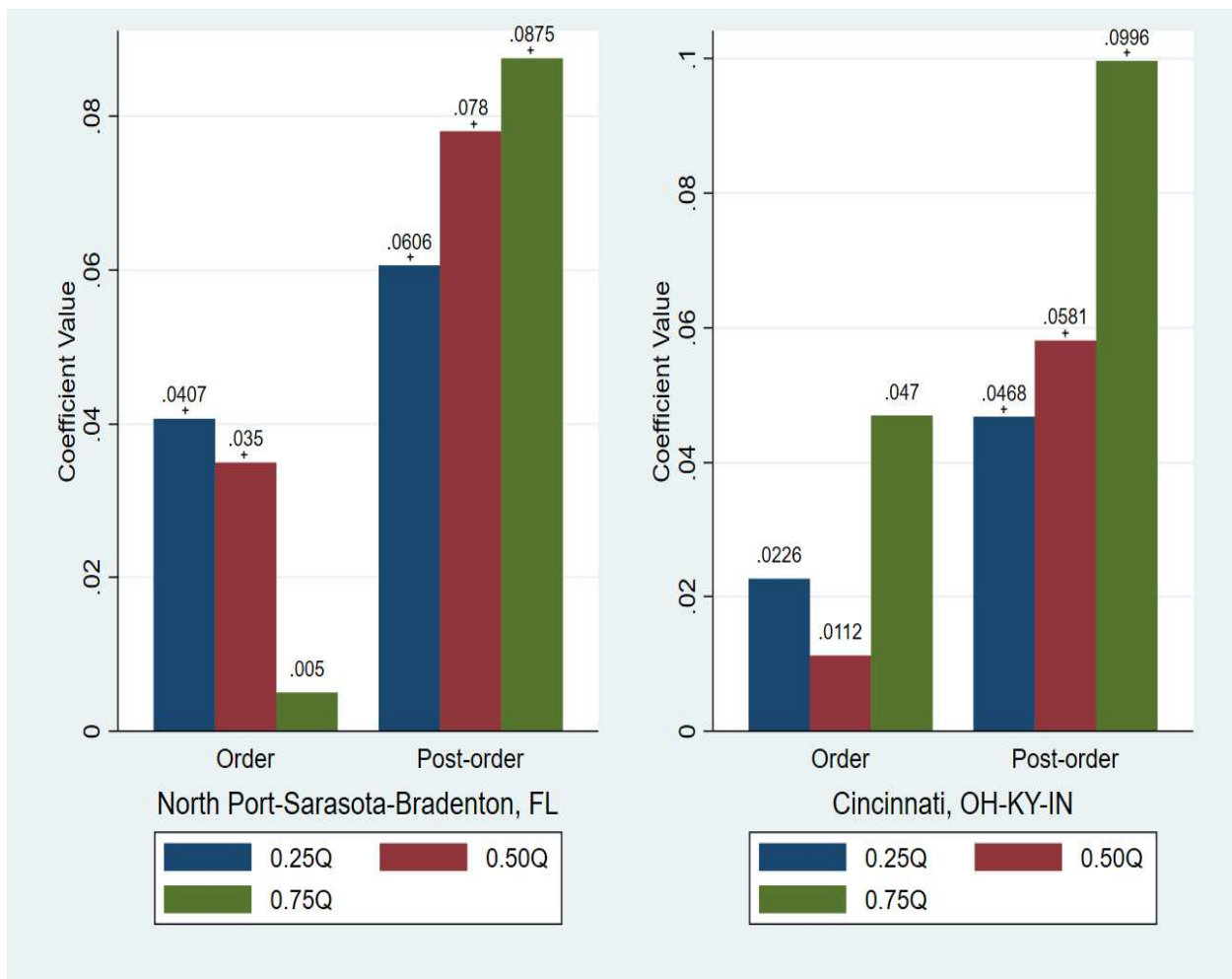


Figure 4.2. Order and Post-order Effects across Quantiles (continued).

If we examine the figures in Appendix B, it is evident that throughout the time the executive order was in place, the greatest price increase occurred for houses with the lowest prices. In contrast, the price increases associated with the post-order period were greater for both the less expensive and more expensive homes. This pattern of price fluctuations in the housing markets in response to the introduction of the stay-at-home order can be explained using a framework of demand and supply. Housing markets were significantly influenced by the executive order, which changed housing supply and demand. The majority of MSAs saw price increases during the stay-at-home order. Supply shock was the primary driver of this price spike. The order to stay at home caused a labor shortage and increased housing costs. Fewer people

were interested in displaying properties for sale, which resulted in fewer homes being advertised for sale. The supply chain was disrupted, manpower was limited, and the price of lumber and other supplies skyrocketed, all of which contributed to supply shock and price hikes (Dunn & Brizuela, 2021). It was reported that active listings fell by half in January 2021 when compared to active listings in January 2019 (Dunn & Brizuela, 2021). On the other hand, demand for lower-priced housing continued to rise as a result of the stay-at-home order. People began working from home, and the demand for housing in the suburbs increased. People began to flee congested cities, and the demand for housing in these cities fell. A study looked at the effects of COVID-19 on density demand and discovered that demand for density in city areas with more amenities decreased (Liu & Su, 2021). As a result, we can conclude that the price increase in lower-priced houses was caused by an increase in demand and a constant decrease in housing supply.

Following the expiration of the executive order, price increases were more prevalent across the price distribution. During the post-order period, housing demand continued to rise, but supply fell short of meeting demand. Housing supply has been limited by a lack of manpower and a rise in the cost of construction materials. People were also hesitant to put their homes up for sale because finding a new one was extremely tough. People began returning to work once the stay-at-home order expired, and demand for property in metropolitan areas surged, resulting in a house price rise in higher-priced homes.

4.2. Estimation Results from Binary Logistic Regression Model

The estimation outcomes of the binary logit model are displayed in tables 4.3 and 4.4. Table 4.3 shows how demographic and economic characteristics influence the likelihood of a statistically significant price rise associated with a stay-at-home order at various quantiles. We

discovered that for every 1% rise in the black population, there was a 9% increase in the likelihood of seeing a price increase at the 0.25 quantile and a 7% increase at the 0.5th and 0.75th quantiles. Post-order effects at other quantiles yielded similar results. Table 4.4 shows that at the 0.25th quantile, there was a 10% higher risk of a price increase connected with the expiration of a stay-at-home order.

Table 4.3. Effects of socioeconomic and demographic factors on statistical significance of order coefficients.

Factors	0.25 Quantile		0.50 Quantile		0.75 Quantile	
	Odds Ratio	P Value	Odds Ratio	P Value	Odds Ratio	P Value
Black	1.09***	0.004	1.07**	0.011	1.07**	0.010
Hispanic	0.96	0.166	1.02	0.424	1.06*	0.073
Unemployment Rate	1.32	0.202	0.99	0.965	0.66	0.117
Vote obtained by Democratic	1.07**	0.031	1.03	0.311	1.02	0.515
Constant	0.00	0.005	0.09	0.168	0.36	0.592

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.4. Effects of socioeconomic and demographic factors on statistical significance of post order coefficients.

C Factors	0.25 Quantile		0.50 Quantile		0.75 Quantile	
	Odds Ratio	P Value	Odds Ratio	P Value	Odds Ratio	P Value
Black	1.10***	0.008	1.10**	0.029	1.05*	0.096
Hispanic	1.00	0.897	0.97	0.432	1.02	0.598
Unemployment Rate	0.96	0.844	1.01	0.956	0.97	0.906
Vote obtained by Democratic	1.07**	0.025	1.06*	0.088	1.05*	0.093
Constant	0.03	0.067	0.10	0.274	0.12	0.275

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The possibility of price increase with more black population can be explained by existing racial discrimination in the United States housing market. The kernel report revealed institutional racism in the United States which included discrimination against black communities in education, employment, and housing. All these adversely affected black communities and were responsible for racial segregation (Zonta, 2019). The Fair Housing Act, Title VIII of the Civil Right Act, was passed in 1968 to address this racial discrimination. This act prohibited discrimination in sale or rental of housing against any community based on their color or

national origin (Zonta, 2019). The Fair Housing Act was further amended in the year 1988. The amended act included the penalty for not abiding by the act. Although, racial discrimination against black communities declined significantly following the passage of this law, non-institutional discrimination still exists today.

It is reported by many studies that black communities face substantial discrimination in terms of house ownership, sale of houses and even rental of houses (Bayer et al., 2017; Thomas et al., 2018; Zonta, 2019). It was also reported that black communities get fewer options to purchase houses, and real estate agents are also less willing to show them houses. There is evidence that black residents are more likely to be denied for appointment to see the house compared to white residents (Zonta, 2019). A recent study by Bayer et al. (2017) also documented that black and hispanic house buyers paid more price for the same type of house compared to white buyers. Their study suggests that black people had to bid substantially higher prices to be taken seriously resulting in a higher price to be paid.

We also discovered a positive pricing impact of the executive order at the 0.25th quantile, which was linked to the democratic party receiving a higher share of the vote. At the 0.25th quantile, each additional percent of vote received by the democratic party was associated with a 7% higher likelihood of price increase. The percentage of votes obtained by the democratic party was likewise linked to a statistically significant price increase during the post-order period. According to our findings in table 4.4, there was a 7% higher chance for price increase during the post-order period for every extra 1% increase in the democratic party's vote. The fact that democratic states were more likely to strictly follow stay-at-home orders could explain how executive orders affected house prices in places with more democratic supporters or in democratic states.

According to studies, democratic states were more inclined to enact stay-at-home orders, and they also wanted them to last longer (Patterson, 2022; Pew Research Center, 2022). Republican governors emphasized the importance of individuals taking the required precautions and were hesitant to issue a statewide stay-at-home order or to announce it for a prolonged period. It was also discovered that citizens in states with democratic governors stayed at home more than those in states with republican governors (Patterson, 2022). Price increases at different quantiles are more likely to be caused by strict adherence to executive orders or extending the length of stay orders in states with more democratic voters.

5. CONCLUSION

COVID-19 not only killed hundreds of thousands of people in the United States, but it also harmed the country's economic growth. Millions of people lost their jobs, many businesses were permanently shuttered, and there was widespread fear. COVID-19's effects on property markets compounded the suffering of people who were already in a bad situation. House prices rose dramatically, making it impossible for people to afford property, even when they needed it more than ever before, owing to work from home or isolation. Our research investigated the effects of different price distributions on housing prices as a result of stay-at-home orders. This study used unconditional quantile regression to assess order and post order effects throughout the housing price distribution. We can generalize the results because coefficient estimates from unconditional quantile regression are not conditional on other factors, and the interpretation of coefficient is simple. Our research shows that executive orders have statistically significant effects on house prices across different quantiles. According to the study, post-order effects were more dominant, and more MSAs saw positive price effects than in the order period. Price appreciation was greatest for lower-priced houses in the majority of MSAs during the period when the executive order was in force. However, after the executive order was repealed, the price of higher-priced homes rose at a faster rate.

Our study's strength is that it used an unconditional quantile regression model, which has several advantages over OLS and conditional regression. We also used over 2 million observations from 101 MSAs across 25 states for our investigation. As a result, our findings are more generalizable and robust. We also looked into how socioeconomic and demographic factors influence executive orders. We discovered that having a larger black population or being a

democratic supporter is linked to a higher risk of price increases because of the executive order's execution.

This study has certain shortcomings that must be addressed. The stay-at-home order was not applied statewide in all states. In many states, certain counties implemented executive order earlier than others. If any county within a state began enforcing a stay-at-home order, however, we were required to define the stay-at-home order duration statewide according to that county. Furthermore, because several MSAs were located in different states, it was impossible to define the stay-at-home order with 100% precision.

Increased demand due to low interest rates and supply constraints were more likely reasons for house prices to continue to rise. Although price growth was higher for lower-priced houses during the executive order, once it expired, price growth was higher across all quantiles, and several MSAs saw the highest price rise for higher-priced houses. If housing price continues to grow, it will have an especially negative impact on low-income people looking for housing. It will also cause distress among those who are currently experiencing financial hardship as a result of the COVID-19 pandemic. It's also critical to take steps to expand housing supply to alleviate price pressure. While developing policy, it is also critical to consider existing racial composition, as we discovered that price effects change depending on racial composition.

REFERENCES

- Bahmani-Oskooee, M., & Ghodsi, S. H. (2018). Asymmetric causality between the U.S. housing market and its stock market: Evidence from state level data. *Journal of Economic Asymmetries*, 18(March), e00095. <https://doi.org/10.1016/j.jeca.2018.e00095>
- Baker, S., Bloom, N., Davis, S., & Terry, S. (2020). COVID-Induced Economic Uncertainty. *National Bureau of Economic Research*. <https://doi.org/10.3386/w26983>
- Bayer, P., Casey, M., Ferreira, F., & McMillan, R. (2017). Racial and ethnic price differentials in the housing market. *Journal of Urban Economics*, 102, 91–105. <https://doi.org/10.1016/j.jue.2017.07.004>
- Beland, L.-P., Brodeur, A., & Wright, T. (2020). COVID-19, Stay-at-Home Orders and Employment: Evidence from CPS Data. *IZA Discussion Paper*, 13282.
- CDC COVID Data Tracker: Daily and Total Trends*. (n.d.). Retrieved June 9, 2022, from <https://covid.cdc.gov/covid-data-tracker/#datatracker-home>
- COVID-19 Map - Johns Hopkins Coronavirus Resource Center*. (n.d.). Retrieved June 10, 2022, from <https://coronavirus.jhu.edu/map.html>
- Dave, D., Friedson, A. I., Matsuzawa, K., & Sabia, J. J. (2021). When Do Shelter-in-Place Orders Fight Covid-19 Best? Policy Heterogeneity Across States and Adoption Time. *Economic Inquiry*, 59(1), 29–52. <https://doi.org/10.1111/ecin.12944>
- D’Lima, W., Lopez, L. A., & Pradhan, A. (2022). COVID-19 and housing market effects: Evidence from U.S. shutdown orders. *Real Estate Economics*, 50(2), 303–339. <https://doi.org/10.1111/1540-6229.12368>
- Domanski, D., & Deep, A. (2002). Housing markets and economic growth: lessons from the US refinancing boom 1. *BIS Quarterly Review*, 8353(September), 37–45. https://www.bis.org/publ/qtrpdf/r_qt0209e.pdf
- Dorn, A. van, Cooney, R. E., & Sabin, M. L. (2020). COVID-19 exacerbating inequalities in the US. *Lancet (London, England)*, 395(10232), 1243. [https://doi.org/10.1016/S0140-6736\(20\)30893-X](https://doi.org/10.1016/S0140-6736(20)30893-X)
- Dunn, J., & Brizuela, I. (2021). *Strong Demand, Limited Supply, and Rising Prices: The Economics of Pandemic-Era Housing*. <https://doi.org/10.26509/frbc-ddb-20210929>
- Fang, H., Wang, L., & Yang, Y. (2020). Human mobility restrictions and the spread of the novel coronavirus (2019-nCoV) in China. *Journal of Public Economics*, 191, 104272.
- Firpo, S., Fortin, N. M., & Lemieux, T. (2009). Unconditional Quantile Regressions. *Econometrica*, 77(3), 953–973. <https://doi.org/10.3982/ecta6822>

- Granja, J., Makridis, C., Yannelis, C., & Zwick, E. (2020). Did the Paycheck Protection Program Hit the Target? *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3585258>
- Haurin, D. R., Dietz, R. D., & Weinberg, B. A. (2005). The Impact of Neighborhood Homeownership Rates: A Review of the Theoretical and Empirical Literature. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.303398>
- Hiscott, J., Alexandridi, M., Muscolini, M., Tassone, E., Palermo, E., Soultsioti, M., & Zevini, A. (2020). The global impact of the coronavirus pandemic. *Cytokine and Growth Factor Reviews*, 53(May), 1–9. <https://doi.org/10.1016/j.cytogfr.2020.05.010>
- Leonard, J. A. (2010). The impact of the housing market boom and bust on consumption spending. *Business Economics*, 45(2), 83–93. <https://doi.org/10.1057/be.2010.11>
- Leung, C. (2004). Macroeconomics and housing: A review of the literature. *Journal of Housing Economics*, 13(4 SPEC.ISS.), 249–267. <https://doi.org/10.1016/j.jhe.2004.09.002>
- Liu, S., & Su, Y. (2021). The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market. *Economics Letters*, 207. <https://doi.org/10.1016/j.econlet.2021.110010>
- Louis-Jean, J., Cenat, K., Njoku, C. v., Angelo, J., & Sanon, D. (2020). Coronavirus (COVID-19) and Racial Disparities: a Perspective Analysis. *Journal of Racial and Ethnic Health Disparities*, 7(6), 1039–1045. <https://doi.org/10.1007/s40615-020-00879-4>
- Mayer, C. J., & Somerville, C. T. (2000). Residential Construction: Using the Urban Growth Model to Estimate Housing Supply. *Journal of Urban Economics*, 48(1), 85–109. <https://doi.org/10.1006/JUEC.1999.2158>
- Nothaft, F. E. (2004). The contribution of home value appreciation to us economic growth. *Urban Policy and Research*, 22(1), 23–34. <https://doi.org/10.1080/0811114042000185464>
- Pagano, M., Wagner, C., & Zechner, J. (2020). Disaster Resilience and Asset Prices. *ArXiv*. <https://doi.org/10.2139/ssrn.3603666>
- Patterson, S. (2022). The Politics of Pandemics: The Effect of Stay-At-Home Orders on COVID-19 Mitigation. *State Politics & Policy Quarterly*, 22(1), 1–23. <https://doi.org/10.1017/SPQ.2021.14>
- Qian, X., Qiu, S., & Zhang, G. (2021). The impact of COVID-19 on housing price: Evidence from China. *Finance Research Letters*. <https://doi.org/10.1016/j.frl.2021.101944>
- Republicans, Democrats Move Even Further Apart in Coronavirus Concerns | Pew Research Center*. (n.d.). Retrieved May 26, 2022, from <https://www.pewresearch.org/politics/2020/06/25/republicans-democrats-move-even-further-apart-in-coronavirus-concerns/>

- Thomas, M. E., Moye, R., Henderson, L., & Horton, H. D. (2018). The Deepening Racial Divide Separate and Unequal: The Impact of Socioeconomic Status, Segregation, and the Great Recession on Racial Disparities in Housing Values. *Lewin-Epstein, Elmelech, and Semyonov*, 4(2), 229–244. <https://doi.org/10.1177/2332649217711457>
- Wang, B. (2021). How Does COVID-19 Affect House Prices? A Cross-City Analysis. *Journal of Risk and Financial Management*, 14(2), 47. <https://doi.org/10.3390/jrfm14020047>
- Winkler, D. T., & Donald Jud, G. (2002). The Dynamics of Metropolitan Housing Prices. *Journal of Real Estate Research*, 23(2), 29–45.
- Yilmazkuday, H. (2020). COVID-19 and Housing Prices: Evidence from U.S. County-Level Data. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3746552>
- Zhang, L., Leonard, T., & Bitzan, J. (2022). Impacts of the COVID-19 Pandemic on House Prices: Heterogeneous Impacts over Time and across the House Price Distribution. *Journal of Real Estate Research*, 1–22. <https://doi.org/10.1080/08965803.2022.2041272>
- Zhao, Y. (2020). US Housing Market during COVID-19: Aggregate and Distributional Evidence. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3677651>
- Zonta, M. (2019). Racial Disparities in Home Appreciation Implications of the Racially Segmented Housing Market for African Americans' Equity Building and the Enforcement of Fair Housing Policies. *American Progress*. <https://www.americanprogress.org/article/racial-disparities-home-appreciation/>

**APPENDIX A. ESTIMATED COEFFICIENTS ASSOCIATED WITH THE ORDER
POST-ORDER PERIOD FOR 101 MSAS WITH MORE THAN 500 OBSERVATIONS**

MSA Name	Order				Post Order			
	Q25	Q50	Q75	Q75- Q25	Q25	Q50	Q75	Q75- Q25
Akron, OH	0.1608***	0.1066***	0.0601**	-0.1007	0.1927***	0.1414***	0.1201***	-0.0726
Albany-Schenectady-Troy, NY	0.0810**	0.0907***	0.0387	-0.0423	0.1726***	0.1673***	0.1280***	-0.0446
Asheville, NC	0.0826	0.0433	0.0238	-0.0588	0.0398	0.0120	0.0506	0.0108
Atlanta-Sandy Springs-Roswell, GA	0.1131***	0.1602***	0.1503***	0.0372	0.1114***	0.1223***	0.1545***	0.0431
Binghamton, NY	0.0131	0.0081	0.2214***	0.2083	-0.0315	0.1233*	0.2352***	0.2667
Boston-Cambridge-Newton, MA-NH	-0.1129	0.1345	0.1513	0.2642	-0.1479	0.1307	0.1967	0.3446
Bowling Green, KY	0.0397	0.0326	-0.0027	-0.0424	0.035	0.0787*	0.0939*	0.0589
Bremerton-Silverdale, WA	-1.3296***	-0.5684	-0.2770	1.0526	0.0831	0.1374*	0.1769	0.0938
Bridgeport-Stamford-Norwalk, CT	0.1224***	0.0615**	-0.0326	-0.155*	0.2280***	0.1965***	0.1490***	-0.079
Buffalo-Cheektowaga-Niagara Falls, NY	0.1609***	0.0697***	0.0656***	-0.0953	0.2099***	0.1851***	0.1681***	-0.0418
Canton-Massillon, OH	-0.0775	0.0552	0.0236	0.1011	0.0323	0.1278***	0.0834**	0.0511
Charlotte-Concord-Gastonia, NC-SC	0.0510	0.0373	0.0416*	-0.0094	0.0938***	0.0901***	0.0990***	0.0052
Charlottesville, VA	0.1088*	0.0849*	-0.0171	-0.1259	0.1300***	0.0726**	0.0653*	-0.0647
Cincinnati, OH-KY-IN	0.0226	0.0112	0.0470***	-0.6153	0.0468***	0.0581***	0.0996***	-0.4132
Cleveland-Elyria, OH	0.1410***	0.0763***	0.0565***	-0.0845*	0.1836***	0.1366***	0.1335***	-0.0501
Columbus, GA-AL	0.2132**	0.0693	-0.03	-0.2432	0.1644***	0.1206***	0.0591**	-0.1053
Columbus, IN	-0.2239	0.0088	0.1459	0.3698	0.0607	0.1228	-0.1589	-0.2196
Columbus, OH	0.1218***	0.1014***	0.1219***	0	0.1608***	0.1318***	0.1589***	-0.0019
Corvallis, OR	0.0237	0.0285	-0.0462	-0.0699	0.0548	0.0755**	0.0695**	0.0147
Dayton, OH	0.1387***	0.1139***	0.1035***	-0.0352	0.1419***	0.1398***	0.1644***	0.0225
Dover, DE	0.0525	0.0164	0.0499**	-0.0026	0.1037***	0.0727***	0.0601***	-0.0436
Dutchess County-Putnam County, NY	0.1399	0.1006*	0.0486	-0.0913	0.2378***	0.2096***	0.2949***	0.0571
Elmira, NY	0.2100*	0.2608***	0.0883	-0.1217	0.2132***	0.2136***	0.1667***	-0.0465
Evansville, IN-KY	-0.1129	0.1345	0.1513	0.2078	-0.1479	0.1307	0.1967	0.6251
Glens Falls, NY	0.1149	-0.0423	0.0282	-0.0867	0.2149***	0.1179***	0.2080***	-0.0069
Goldsboro, NC	0.0600	-0.1429	-0.0751	-0.1351	0.1242	0.1883**	0.0144	-0.1098
Greenville-Anderson-Mauldin, SC	0.1450	-0.0188	-0.0294	-0.1744	0.1100*	0.0996**	0.0020	-0.108
Hartford-West Hartford-East Hartford,..	0.0867***	0.0817***	0.0201	-0.0666	0.1651***	0.1546***	0.1109***	-0.0542
Hickory-Lenoir-Morganton, NC	0.0230	0.0399	0.0402	0.0172	0.1237*	0.1508***	0.1526***	0.0289
Homosassa Springs, FL	0.0177	0.0172	-0.0067	-0.0244	0.0980***	0.1013***	0.0945***	-0.0035
Houston-The Woodlands-Sugar Land, TX	0.0667	-0.1641	0.3405	0.2738	0.0694	0.1880	0.4083**	0.3389
Huntington-Ashland, WV-KY-OH	-0.1393	0.0297	-0.0806	-0.0846	0.0082	0.1197**	0.1263**	-0.1016
Indianapolis-Carmel-Anderson, IN	-0.2049	0.0363	0.1158	0.3207	0.1768	0.1125	0.3387***	0.1619
Ithaca, NY	0.1323	-0.0159	0.1419	0.0096	0.1542*	0.0665	0.2720***	0.1178
Jackson, TN	0.4424**	0.3732***	0.1301	-0.3123	0.5165***	0.4038***	0.3312***	-0.1853
Jacksonville, FL	0.0071	0.0439**	0.0670***	0.0599	0.0309	0.0748***	0.1210***	0.0901*

MSA Name	Order				Post Order			
	Q25	Q50	Q75	Q75- Q25	Q25	Q50	Q75	Q75- Q25
Kansas City, MO-KS	0.7045	0.5604	0.0213	-0.6832	0.2166	0.1092	-0.0936	-0.3102
Kennewick-Richland, WA	0.0000	0.0000	0.0000	0	0.3178	0.1067	0.4712	0.1534
Kingsport-Bristol-Bristol, TN-VA	0.2804	-0.1745	-0.1160	0	0.0494	0.0387	0.0102	0
Kingston, NY	-0.0753	0.0083	0.1164**	0.1917	0.1727***	0.2775***	0.2966***	0.1239
Knoxville, TN	0.0370	0.0523**	0.0243	-0.0127	0.0785***	0.1182***	0.1155***	0.037
Lawton, OK	-0.0820	-0.0325	-0.1275**	-0.0455	-0.1032	0.0375	0.0193	0.1225
Lima, OH	0.2141***	-0.0379	0.0653	-0.1488	0.1800***	0.0821	0.0659	-0.1141
Louisville/Jefferson County, KY-IN	0.1014**	0.1490***	0.1209***	0.6151	0.1817***	0.1991***	0.1772***	0.023
Lynchburg, VA	-0.0129	0.0338	-0.0239	-0.011	0.0352	0.0548	0.0581	0.0229
Manchester-Nashua, NH	0.0592***	0.0974***	0.0609***	0.0017	0.0751***	0.1107***	0.1203***	0.0452
Mankato-North Mankato, MN	0.0845	0.121	0.1505*	0.066	0.1300**	0.1889***	0.1330**	0.003
Mansfield, OH	0.1453*	0.1266**	0.1351***	-0.0102	0.2437***	0.1740***	0.1957***	-0.048
Memphis, TN-MS-AR	0.1508***	0.1135***	0.0494**	-0.1014	0.1792***	0.1703***	0.1522***	-0.027
Miami-Fort Lauderdale-West Palm Beach..	0.0251	0.0588***	0.0485*	0.0234	0.0601***	0.1088***	0.1457***	0.0856*
Minneapolis-St. Paul-Bloomington, MN-WI	0.0490*	0.0583**	0.0401	-0.0089	0.0839***	0.1287***	0.0749***	-0.009
Montgomery County-Bucks County-Cheste..	0.0538**	0.0526**	0.0839***	0.0301	0.1095***	0.0995***	0.1159***	0.0064
Myrtle Beach-Conway-North Myrtle Beac..	-0.0375	-0.0939***	-0.1328***	0.024	0.0093	0.0146	-0.0380***	0.1221*
Nashville-Davidson--Murfreestboro--Franklin, TN	0.0473	0.1304	0.1930	0.1457	0.0326	0.0371	0.0512	0.0186
Nassau County-Suffolk County, NY	0.0533	0.0535	0.1016*	0.0483	0.0837**	0.0612**	0.0825**	-0.0012
New Haven-Milford, CT	0.1634***	0.1046***	0.0474**	-0.116*	0.2130***	0.1876***	0.1100***	-0.103*
New York-Newark-Jersey City, NY-NJ-PA	0.2096***	0.2329***	0.1160***	-0.0936	0.3030***	0.3671***	0.2706***	-0.0324
North Port-Sarasota-Bradenton, FL	0.0407**	0.0350**	0.005	-0.0357	0.0606***	0.0780***	0.0875***	0.0269
Norwich-New London, CT	0.1180**	0.0702**	0.0219	-0.0961	0.2094***	0.1837***	0.1468***	-0.0626
Oklahoma City, OK	0.0618*	0.0550**	0.0699**	-0.0961	0.1275***	0.1227***	0.1731***	-0.0626
Olympia-Tumwater, WA	0.0000	0.0000	0.0000	0	0.0000	0.0000	0.0000	0
Orlando-Kissimmee-Sanford, FL	0.0075	0.0338***	0.0254*	0.0179	0.0333***	0.0645***	0.0757***	0.0424
Oshkosh-Neenah, WI	0.0947	0.2631**	0.1024	0.0077	0.1819*	0.3654***	0.2559***	0.074
Peoria, IL	-0.0513	-0.0321	-0.0205	0.0308	0.0575	0.0215	0.0298	-0.0277
Philadelphia-Camden-Wilmington, PA-NJ..	0.0835***	0.0421**	0.0371*	-0.0464	0.1557***	0.1119***	0.0896***	-0.0661
Pittsburgh, PA	0.1491**	0.1114**	0.0796	-0.0695	0.2074***	0.2008***	0.1722***	-0.0352
Port St. Lucie, FL	0.0471***	0.0382**	0.0342	-0.0129	0.0691***	0.0962***	0.1177***	0.0486
Portland-Vancouver-Hillsboro, OR-WA	0.1478	0.0217	0.0843	-0.0635	-0.1660	-0.1848*	-0.1589	0.0071
Providence-Warwick, RI-MA	0.0674***	0.0559***	0.0417**	0.217	0.1151***	0.1371***	0.1243***	0.348*
Raleigh, NC	0.1092	0.0768	0.1001***	-0.0091	0.2016***	0.1854***	0.1104***	-0.0912

MSA Name	Order				Post Order			
	Q25	Q50	Q75	Q75- Q25	Q25	Q50	Q75	Q75- Q25
Reading, PA	0.0580	0.0772***	0.0827***	0.0247	0.0950***	0.0752***	0.0856***	-0.0094
Richmond, VA	0.0789***	0.0677***	0.0265	-0.0524	0.1174***	0.1152***	0.0540***	-0.0634*
Roanoke, VA	-0.0676	0.0815	0.0723	0.1399	0.0286	0.2062***	0.2761***	0.2475
Rochester, NY	0.0579**	0.1109***	0.1181***	0.0602	0.1662***	0.1749***	0.1543***	-0.0119
Rockford, IL	0.0055	0.0459	-0.0775	-0.083	0.1719**	0.0591	0.0666	-0.1053
Rockingham County-Strafford County, NH	0.0347	0.0562***	0.0729***	0.0382	0.0732***	0.1263***	0.1574***	0.0842*
Savannah, GA	0.1234**	0.1083***	0.0216	-0.1018	0.1622***	0.0893***	0.0808***	-0.0814
Seattle-Tacoma-Bellevue, WA	0.0584***	0.0541***	0.0440***	-0.0144	0.1014***	0.1016***	0.1073***	0.0059
Spartanburg, SC	0.0459	0.0290	-0.0329	-0.0788	0.0744***	0.0678***	0.1262***	0.0518
Spokane-Spokane Valley, WA	-0.5277*	-0.1901	0.1498	0.6775	-0.2538	-0.1065	0.1503	0.4041
Springfield, MA	0.1558***	0.1607***	0.0734*	-0.0824	0.1557***	0.1991***	0.1370***	-0.0187
Springfield, OH	-0.0173	0.0082	0.0122	0.0295	0.0527	0.0961**	0.1006***	0.0479
St. Louis, MO-IL	0.2217	-0.1206	-0.1252	-0.3469	0.6681***	0.1791**	-0.0494	-0.7175*
Staunton-Waynesboro, VA	0.1093	0.0190	-0.0505	-0.1598	0.2745***	0.1386***	0.0059	-0.2686*
Syracuse, NY	0.1567***	0.1155***	0.0663*	-0.0904	0.2298***	0.1776***	0.1572***	-0.0726
Toledo, OH	0.0988**	0.0649**	0.0457	-0.0531	0.1516***	0.1374***	0.0963***	-0.0553
Tulsa, OK	0.0282	0.0409	-0.0584	-0.0866	0.0512	0.0632**	0.0463	-0.0049
Utica-Rome, NY	0.1402*	0.0364	0.0253	-0.1149	0.1922***	0.2057***	0.1758***	-0.0164
Virginia Beach-Norfolk-Newport News, ...	0.1023***	0.1107***	0.0105	-0.8866	0.1227***	0.1302***	0.0287	-0.1809
Washington-Arlington-Alexandria, DC-V..	0.0609***	0.0784***	0.0774***	0.0165	0.1219***	0.1594***	0.1225***	0.0006
Watertown-Fort Drum, NY	-0.1228	0.1277	-0.0012	0.1216	0.1178	0.2403***	0.1699***	0.0521
Weirton-Stebenville, WV-OH	0.2422*	0.1275	0.0539	-0.1883	0.2591**	0.1879**	0.1483*	-0.1108
Wheeling, WV-OH	0.0908	-0.0599	0.1798	0.089	-0.1679	-0.0229	0.0927	0.2606
Wichita, KS	-1.6432	0.422	0.403	2.0462	-0.9796	0.2535	-0.006	0.9736
Williamsport, PA	-0.1452	0.0751	0.1185	0.2637	0.0961	0.1870***	0.1312**	0.0351
Wilmington, NC	0.0919	0.1340***	-0.0561	-0.148	0.0455	0.1306***	0.1393***	0.0938
Winchester, VA-WV	0.1306	0.0294	0.0892**	-0.0414	0.1705**	0.0532	0.1208***	-0.0497
Winston-Salem, NC	0.0892	0.0948**	0.0926	0.0034	0.1536**	0.1297***	0.1844***	0.0308
Worcester, MA-CT	0.2146	0.0383	0.0433	-0.0058	0.0799	0.0766	0.0962	-0.0348
Yakima, WA	0.0000	0.0000	0.0000	0	-0.5926	-0.5012	-0.1714	0.4212
Youngstown-Warren-Boardman, OH-PA	0.0717	0.1113**	0.0854**	0.0137	0.1431***	0.1874***	0.1751***	0.032

***p<0.01, **p<0.05, *p<0.1

The CI at 0.75th quantile doesn't overlap with the CI at 0.25th quantile

Coefficients associated with order and post-order were estimated using unconditional quantile regression model.

Variables included in the models are living area, lot area, bedroom, bathroom, age of house, condition excellent, condition good, condition average, condition fair, and 6 years as dummy variable such as year 2015, year 2016, year 2018, year 2019, year 2020, order period dummy, and post-order period dummy.

**APPENDIX B. COEFFICIENTS PLOT FROM UNCONDITIONAL QUANTILE
REGRESSION IN 10 LARGEST MSAS.**

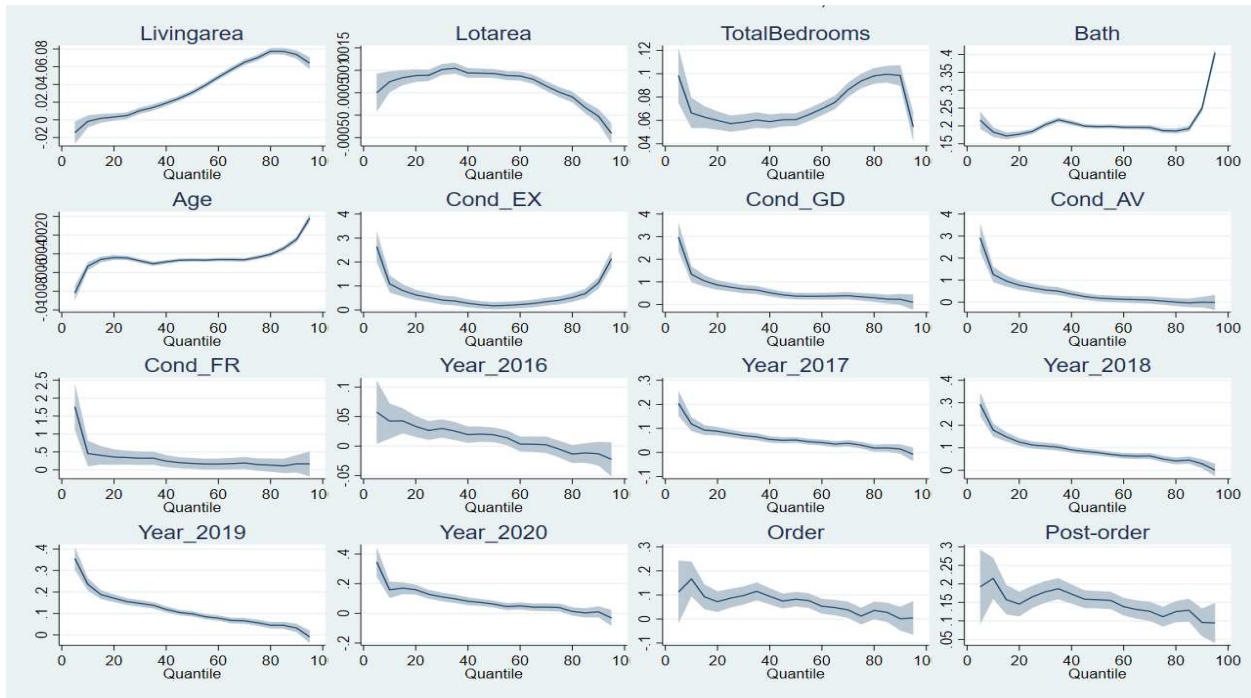


Figure B1. Coefficients Plot from Unconditional Quantile Regression, Hartford-West Hartford-East Hartford, CT.

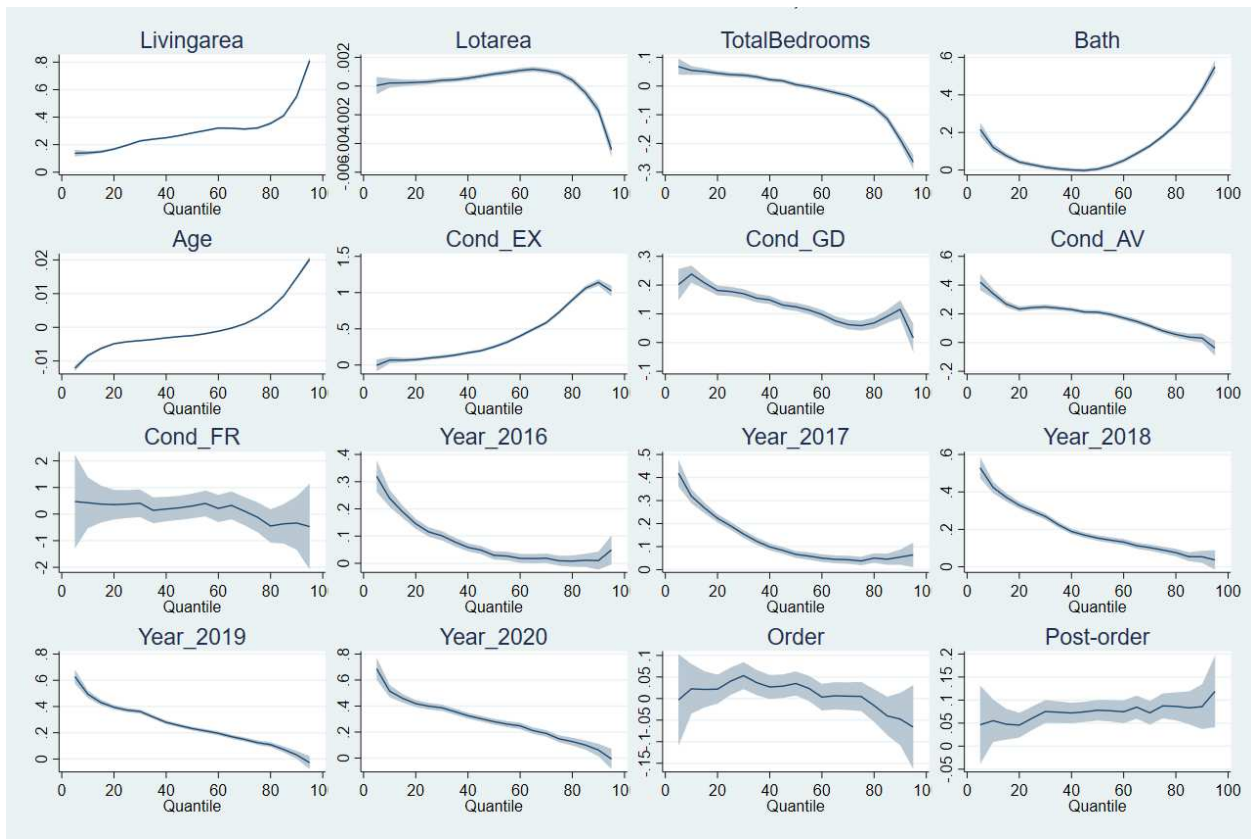


Figure B2. Coefficients Plot from Unconditional Quantile Regression, North Port-Sarasota-Bradenton, FL.

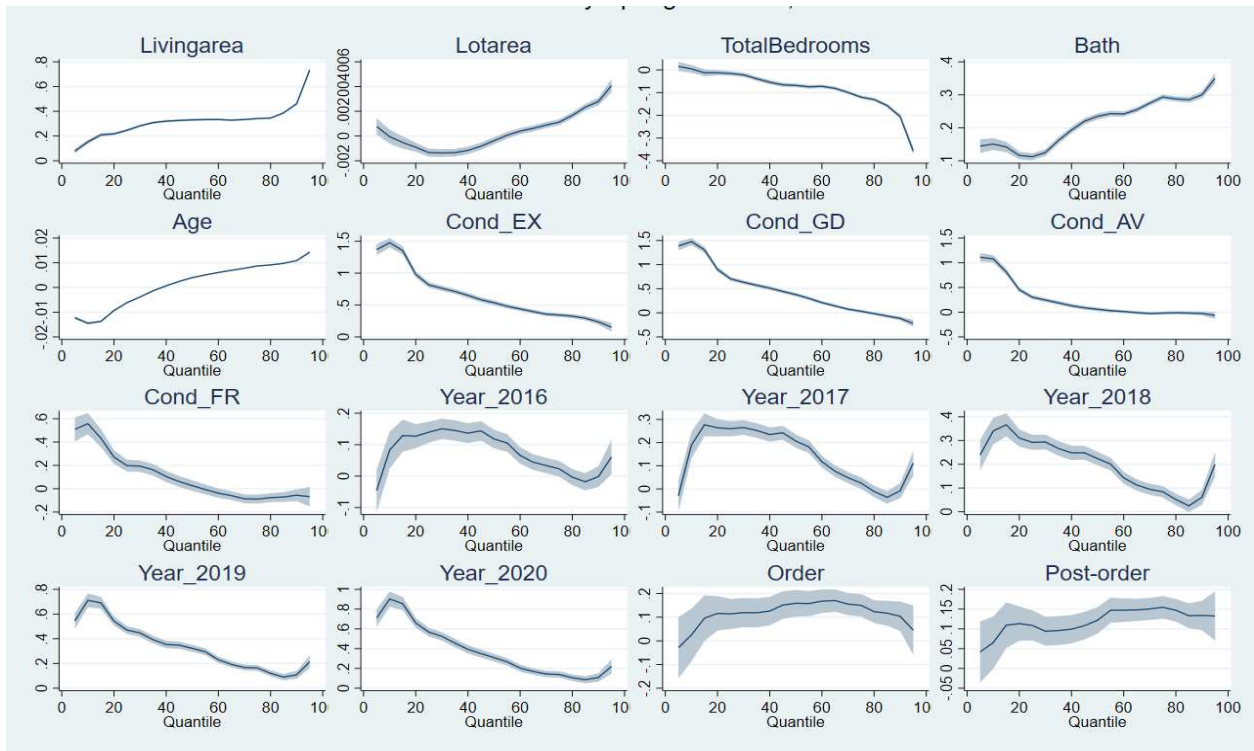


Figure B3. Coefficients Plot from Unconditional Quantile Regression, Atlanta-Sandy Springs-Roswell, GA.

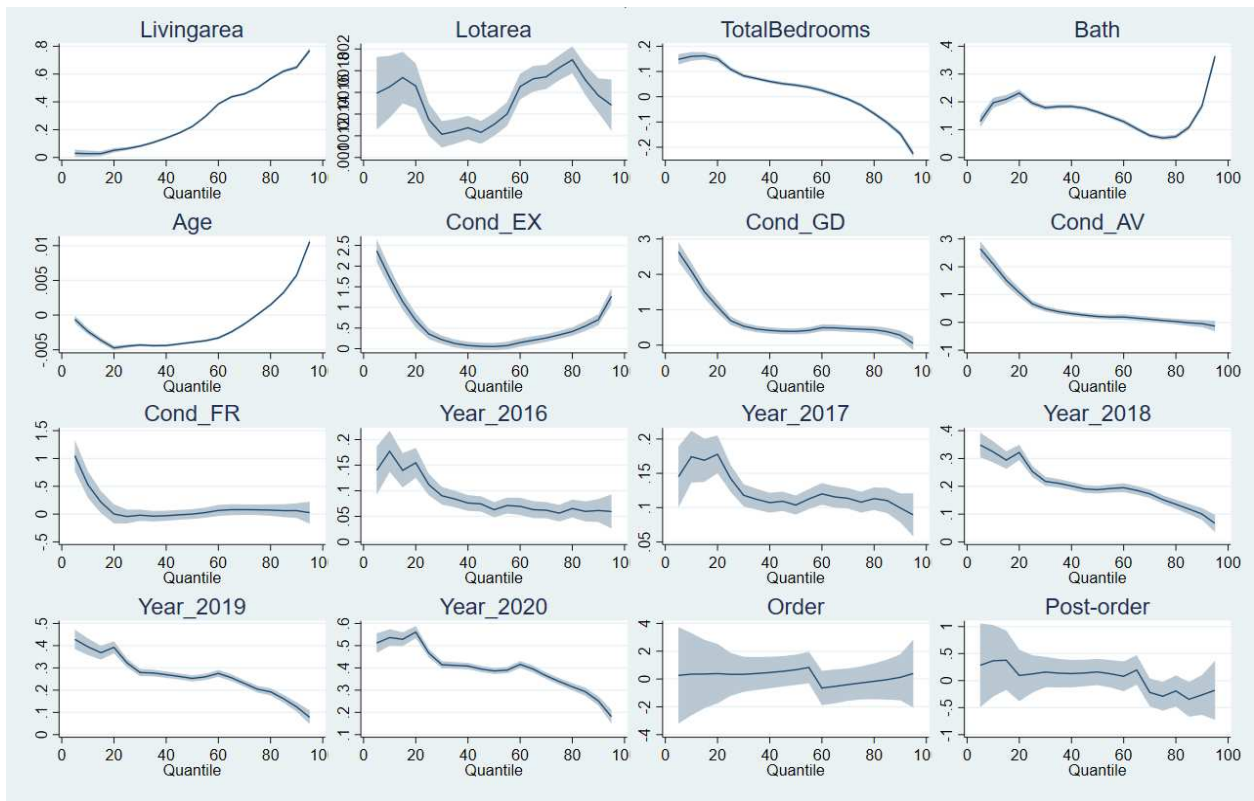


Figure B4. Coefficients Plot from Unconditional Quantile Regression, Cincinnati, OH-KY-IN.

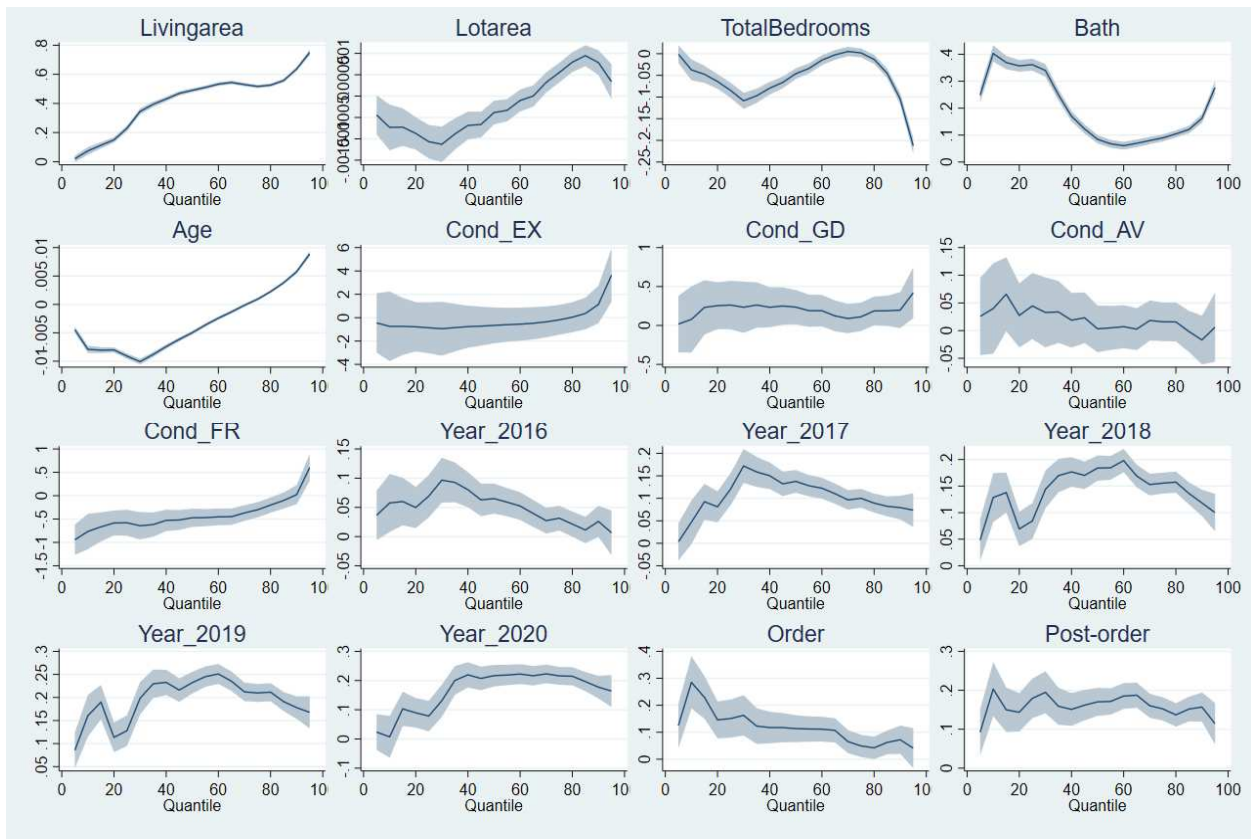


Figure B5. Coefficients Plot from Unconditional Quantile Regression, Memphis, TN-MS-AR.

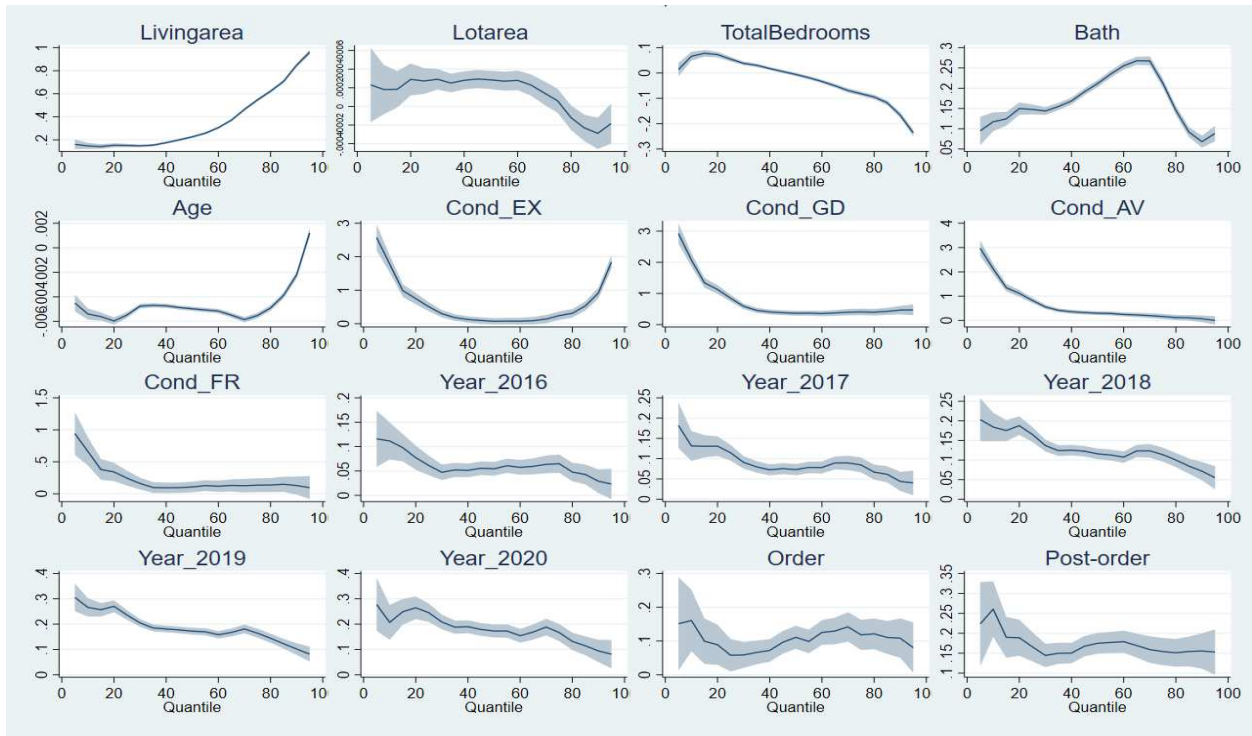


Figure B6. Coefficients Plot from Unconditional Quantile Regression, Rochester, NY.

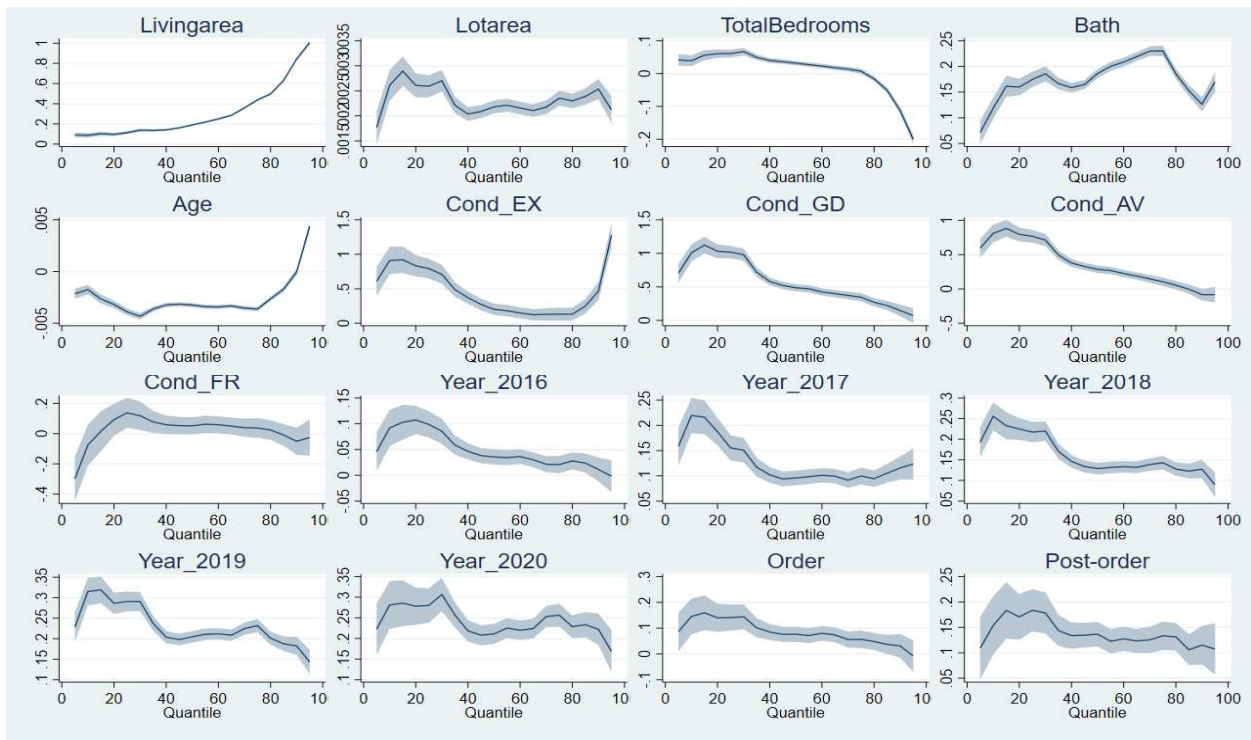


Figure B7. Coefficients Plot from Unconditional Quantile Regression, Cleveland-Elyria, OH.

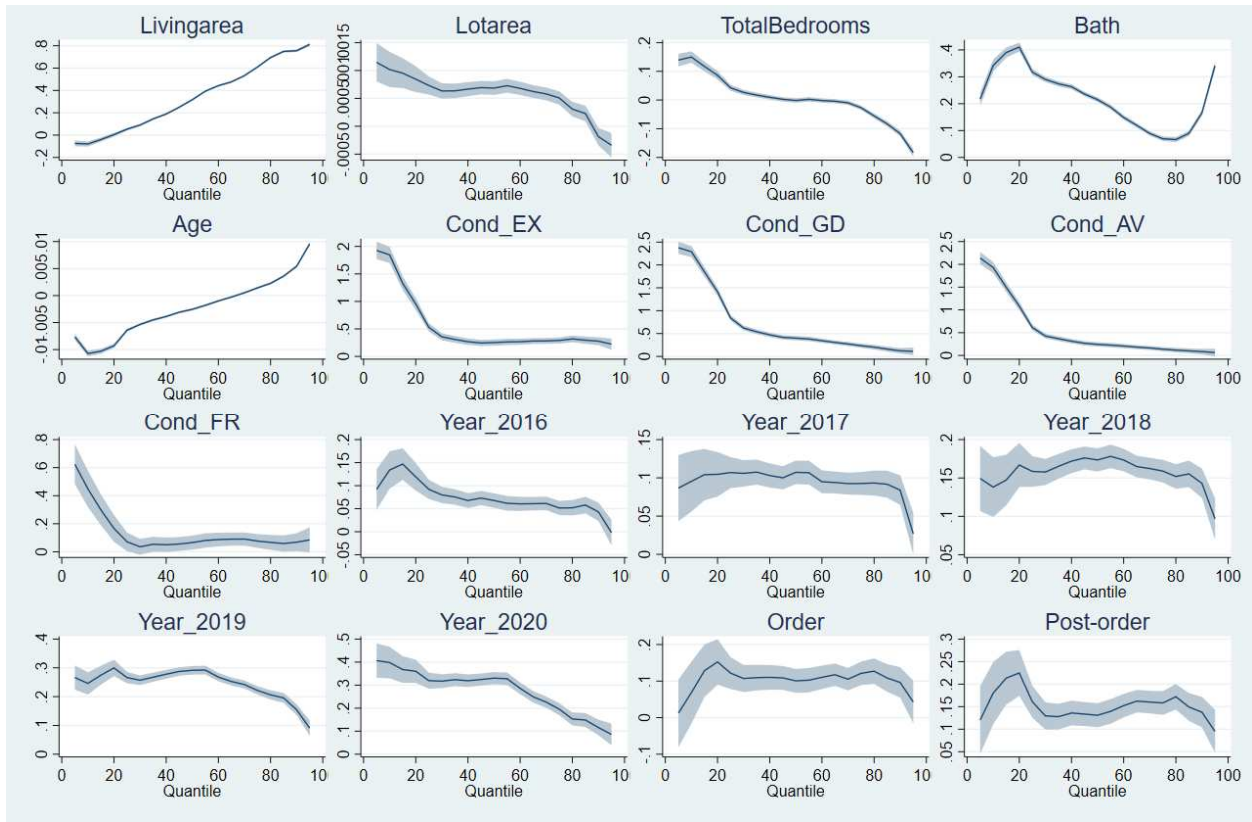


Figure B8. Coefficients Plot from Unconditional Quantile Regression, Columbus, OH.

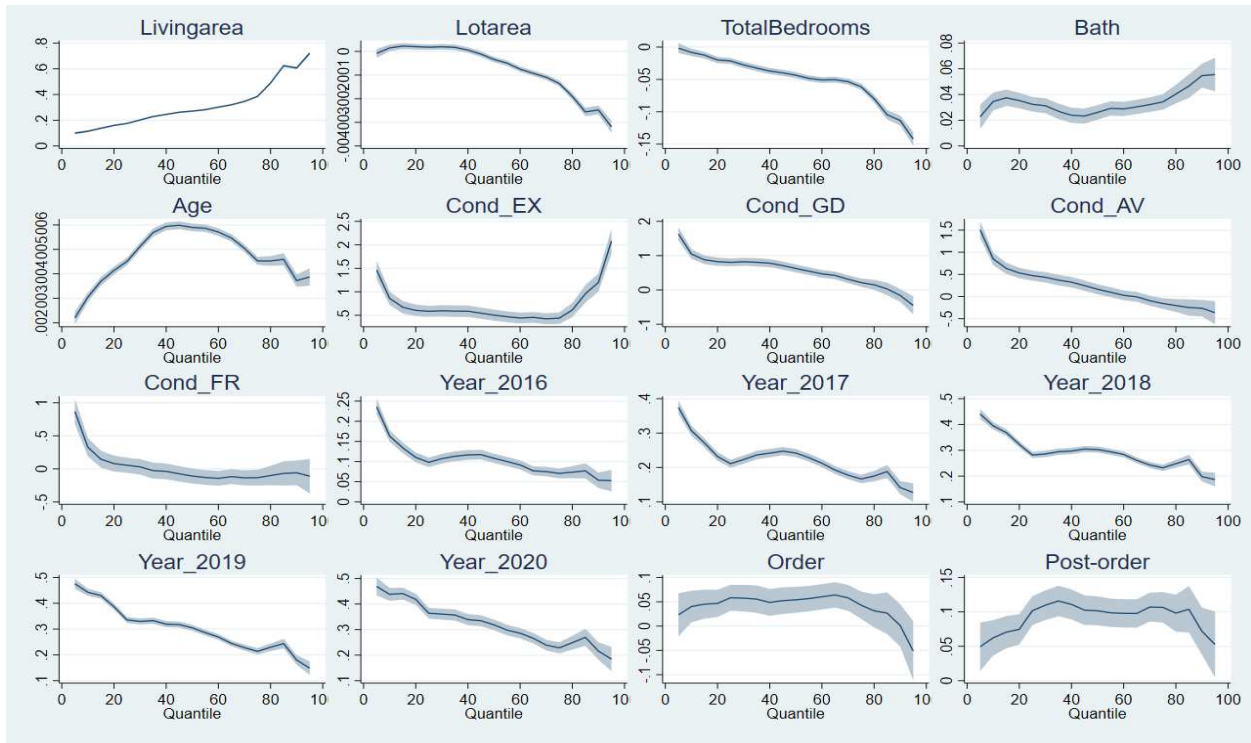


Figure B9. Coefficients Plot from Unconditional Quantile Regression, Seattle-Tacoma-Bellevue, WA.

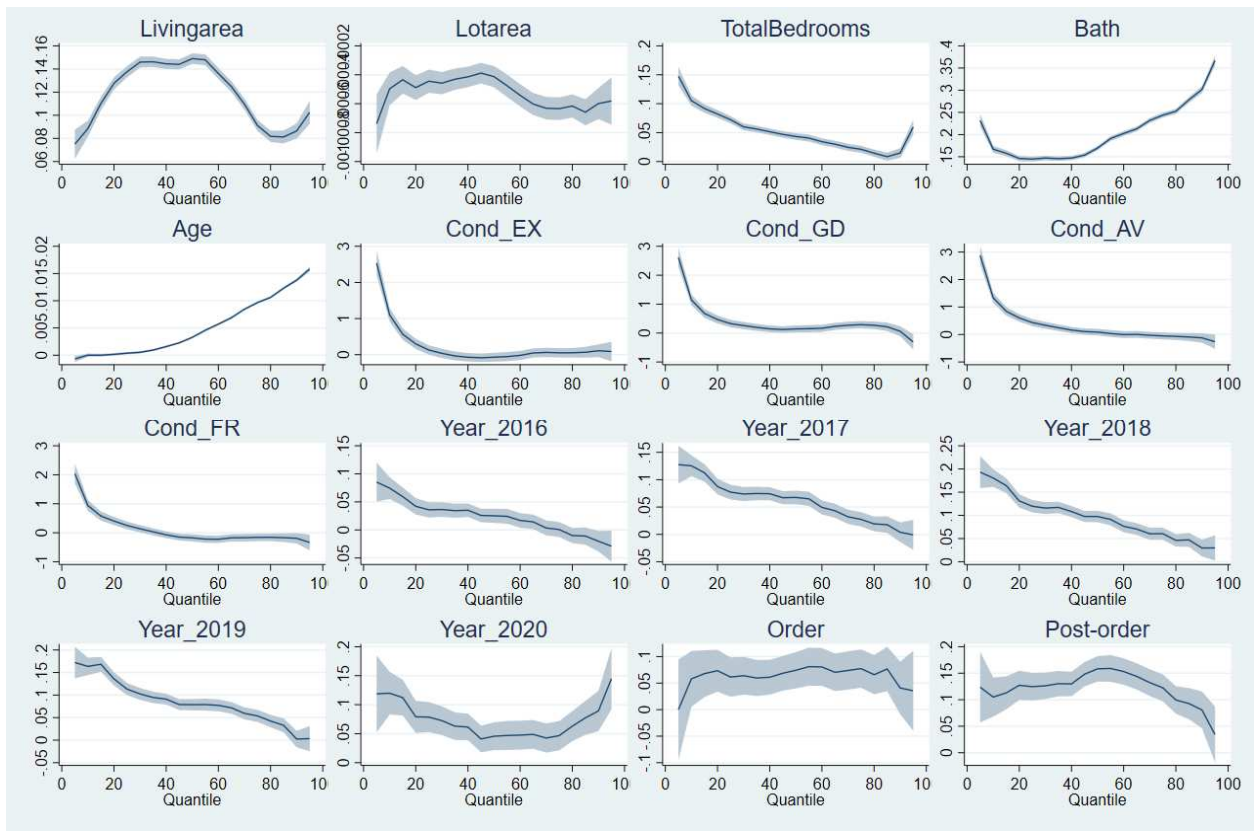


Figure B10. Coefficients Plot from Unconditional Quantile Regression, Washington-Arlington-Alexandria, DC, VA.