HAS THE COVID-19 PANDEMIC CHANGED PEOPLE'S ATTITUDE ABOUT WHERE TO LIVE? SOME PRELIMINARY ANSWERS FROM A STUDY OF THE ATLANTA HOUSING MARKET

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HAS THE COVID-19 PANDEMIC CHANGED PEOPLE'S ATTITUDE ABOUT WHERE TO LIVE? SOME PRELIMINARY ANSWERS FROM A STUDY OF THE ATLANTA HOUSING MARKET

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SUMMARY

In March 2020, the national lockdowns and social distancing mandates to contain the COVID-19 pandemic in the US abruptly disrupted all aspects of urban life, requiring people to conduct daily activities including work, shopping, learning, schooling, and socializing, from home using online tools. These lockdowns and stay-at-home orders sharply increased unemployment and hindered active transactions in the housing market in the second quarter of 2020 (Liu & Su, 2021). While the high unemployment rate was a severe economic and social concern affecting housing demand, monetary easing and low interest rates increased liquidity and the flow of money into the housing market (Zhao, 2020).

A growing body of work started to examine the overall vitality of the housing market in response to the disruptions caused by the pandemic (D'Lima et al., 2020; Liu & Su, 2021; Yoruk, 2020; Zhao, 2020). In addition, reports in popular media have highlighted trends in cities like New York and San Francisco, where many households were giving up expensive central city residences for low-density suburban houses with large yards. This finding implied that cities were losing their appeal given the reduction in the need for commuting in a work-from-home culture and the desire for security and open space in a low-density environment in the suburbs. Despite this type of anecdotal evidence, we know very little about how the preferences for housing in different locations are changing in response to the COVID-19 pandemic.

This study explores whether and how the pandemic affected the housing preferences in the Atlanta single-family housing market. The focus goes to locational

characteristics such as the accessibility to the rail transit system, accessibility to freeway systems, and walkability. The housing market participants' attitudes toward the different travel modes can be revealed with the price effects of the accessibility-related locational characteristics. The impact of whether a house is in the inner city, inner-ring suburb, or outer-ring suburb on housing prices is also examined.

A few main findings are derived from comparing the descriptive statistics and hedonic price models for 2018, 2019, and 2020. First, a steep drop in the number of transactions in the second quarter of 2020 was followed by an increase in the number of transactions and housing prices. The observed boom in the Atlanta single-family housing market aligns with the arguments of Zhao (2020) and Liu and Su (2021) that the lowered mortgage rate caused the influx of money to the housing markets across the US. Second, the positive price effect of parcel size and a pool increased in 2020 while that of square footage decreased. Third, the recently increasing preference for the inner city over the suburban area was restrained in 2020, which might have resulted from the diminished advantage of staying near the city center for job accessibility. Fourth, the pandemic did not substantially change the capitalization effect of the accessibility to a MARTA rail station and freeway.

A few suggestions are made for future studies. First, the endeavor to further clarify the underlying reasons for the observations from this study would be necessary, which hedonic price models alone cannot do. Conducting a customized survey is one way to reveal the existence of and reasons for the changes in the attitudes, lifestyle, and travel patterns of diverse market participants covering both the supply and demand sides. Second, investigating the parts of the housing market that are not examined in this study will bring a comprehensive and detailed understanding of the housing market and the changes the market went through. The houses for rent and the houses other than detached single-family houses are not included in this study. Moreover, the transactions of the newly constructed houses are not usually in the FMLS data even though they take up a significant proportion of the transactions in the Atlanta region. Third, the analyses with some submarket segmentation using such criteria as the housing price, number of rooms, and location are expected to bring useful policy implications enabling detailed and customized solutions to the issues that planners are tackling.

CHAPTER 1. INTRODUCTION

Understanding the intrinsic value of—or the willingness to pay for—each housing and locational characteristic determined in the housing market is one of the main interests of urban and transportation planners and governments. A firm understanding of the values can contribute to predicting the housing price changes following a real estate development or transportation infrastructure investment. For instance, the willingness to pay for increased accessibility to a rail transit service can help predict the housing price changes in the area around a new rail transit station. The changes matter to local governments interested in predicting the property tax revenues, financing expansion projects through value capture, and identifying who will benefit from the projects. Moreover, the willingness to pay indicates the attitudes of housing market participants toward the rail transit service, which helps understand travel behavior and helps prepare for transit-oriented development (TOD) plans and housing supply plans.

The COVID-19 pandemic brought drastic changes in the preference for various housing and locational characteristics and the housing market's vitality. An unprecedented number of workers started working from home to avoid the transmission of the disease with different proportions of remote workers by job category and industry (Bartik et al., 2020; Bick et al., 2020). How people socialize and spend their free time has also been notably altered; visitors to crowded places such as shops, restaurants, and gyms as well as the expenditure at such places have decreased (Allcott et al., 2020). Lockdowns and stay-at-home orders in some states since March 2020 hindered active transactions in the housing market (Liu & Su, 2021). While the increased unemployment rate has arisen as a serious economic and social concern (Blustein et al., 2020; Gallant et al., 2020; Gangopadhyaya & Garrett, 2020), the monetary easing with a low interest rate that the Federal government introduced to fight the recession from the pandemic resulted in the increased money flow to the housing market (Zhao, 2020).

Emerging literature on the impacts of the pandemic on the US housing market, however, is mainly focused on the immediate alterations in the overall vitality of the housing market. The primary attention has been attracted to the number of sales and new listings, housing sale prices, and online viewings of properties after the pandemic outbreak (D'Lima et al., 2020; Liu & Su, 2021; Yoruk, 2020; Zhao, 2020). Less attention has been given to whether and to what extent the housing price determination mechanism has changed. Even though Liu and Su (2021) confirmed the decreased demand for density in the US housing market, they did not look into the changes in the impact of density on housing prices with a detailed housing-unit-level analysis.

To address this research gap, this study explores whether and how the COVID-19 pandemic affected the housing price determination mechanism. The focus lies on the impact of accessibility-related locational characteristics on housing prices including the accessibility to a rail transit system, accessibility to freeway systems, and walkability, each of which reflects the housing market participants' attitudes toward the associated travel mode and expected travel behavior. In addition, the impacts of other locational characteristics such as whether a house is in the inner city, inner-ring suburb, or outer-ring suburb are also of primary interest. These attributes are carefully examined when purchasing a home, which entails careful consideration of the long-term expectations regarding the permanent income (Olsen, 1987), lifestyle, travel patterns, and telecommuting status of a household. The modifications of these long-term expectations, if any, need to be identified to build well-informed housing, land-use, and transportation plans.

A before-and-after comparison is conducted to clarify the existence and degree of such modifications in the Atlanta single-family housing market. The single-family house transactions, which take up the majority of the residential property transactions, from 2018 to 2020 are collected from the First Multiple Listing System (FMLS) while some explanatory variables are created to measure various locational characteristics of the houses in the transaction data. The comparison of the descriptive statistics (i.e., the mean and median values of the attributes of the houses sold) and hedonic price models for 2018, 2019, and 2020 is expected to bring insight into whether the COVID-19 pandemic had a substantial impact on the characteristics of houses sold and the intrinsic values of the characteristics. Especially, a close examination of the intrinsic value of each housing or locational characteristic, represented by the associated coefficients, can shed light on what people expect regarding the future of their travel behavior and lifestyles after the pandemic ends.

The organization of the rest of this paper is as follows: Chapter 2 explains the research background including the research framework and literature review, Chapter 3 elaborates on the data and methods used in this study, Chapter 4 presents the results from the analyses conducted, and Chapter 5 concludes the paper by summarizing the findings and suggesting future steps to overcome the limitations.

CHAPTER 2. RESEARCH BACKGROUND

2.1 Research Framework

This study uses hedonic price models to uncover the "implicit prices" of "utility-bearing attributes" (Rosen, 1974) of houses. Hedonic price models are based on the "hedonic hypothesis that goods are valued for their utility-bearing attributes" (Rosen, 1974). Therefore, the sale price becomes the dependent variable and the utility-bearing attributes serve as explanatory variables of the regression analysis. Investigating the implicit prices (i.e., the regression coefficients) of the attributes and their changes over time enables the understanding of how housing prices are determined and how the contribution of each attribute has changed, which is conducted in this study in conjunction with the examination on the descriptive statistics of the houses sold.

2.2 The Impacts of COVID-19 on the Housing Market

As soon as the COVID-19 pandemic started to exert a strong influence on economic and social activities in March 2020, the impacts of the pandemic on transactions in the US housing market gained great interest. Yoruk (2020) detected a considerable decrease in the new listings and pending sales started in the second half of March across the 50 major cities in the US by examining the data from Zillow from February to April. D'Lima et al. (2020) discovered that the housing transactions shrank during the shutdown and re-opening periods. Liu and Su (2021, p.24) also reported a sharp drop in the number of new listings and homes sold in April based on the data from Redfin Data Center, but the new listings and home sales fully recovered and even posted the record for the past year in July with a lowered interest rate and monetary-easing policies from the Federal government. In other words, the transactions in the housing market were negatively influenced in the short term, but the impact lasted only during the second quarter of 2020 and the market recovered quite soon.

The short-term negative ‘price’ effect of the pandemic in the US was less prominent than the negative short-term ‘sales’ effect, whereas the longer-term price effect was positive and definite. According to D’Lima et al. (2020), who investigated the housing transactions of 31 US states and the District of Columbia in many multiple listing services from January 2019 to June 2020, housing prices decreased by 1.3% on average during the shutdown period. On the other hand, Zhao (2020) argued that the overall growing trend of the housing price per square foot in the US experienced just a “temporary slow-down in March and April 2020” (p. 13) but the growth rate surged back immediately and surpassed the level before the pandemic in June, with the analysis on the zip-code level residential listings database from realtor.com from July 2017 and August 2020.

Even though the decreased interest rate was regarded as one of the possible reasons for the rising housing purchases and prices (Liu & Su, 2021; Zhao, 2020), the changes in the household preference and behavior also have been suggested as a potential driving force (Zhao, 2020). The possible changes include putting a higher value on owning larger houses as the time spent in houses increases and saving more money as the consumption on daily activities decreases (Zhao, 2020). This implies that the pandemic could have changed the housing market participants’ preferences such that some housing-unit and locational characteristics of a house are more valued or less valued.

Few studies, however, analyzed how the preferences for various characteristics of a house have altered after the pandemic began. Liu and Su (2021) studied the change in demand for density. They concluded that the housing demand had shifted away from the city centers with high population density, which was partially driven by the reduced need to be close to workplaces and consumption amenities. With the investigation on sales, new listing, home-price index, and inventory data across the US from diverse sources from March and October 2020, they insisted that the trend persisted even after the housing market recovery (Liu & Su, 2021). However, they only used the number of sales, number of new listings, and housing inventory to draw their conclusion but did not use a direct way (e.g., the hedonic model approach) to check the implicit prices of various characteristics and their changes.

With the hedonic model approach, some of the observations from the literature can be better understood. For example, Liu and Su (2021) pointed out that the housing prices in the central cities with high population density dropped less than expected, considering the decreased demand and increased supply in such areas. The outputs from the hedonic model calibration (i.e., coefficients) can reveal the implicit prices related to population density or distance to city centers as well as their changes since the pandemic.

This study is expected to provide additional insight on the impacts of the COVID-19 pandemic on the housing market using yearly-calibrated hedonic price models with a sophisticated model specification to examine the implicit prices of the varied characteristics associated with houses. Even though D'Lima et al. (2020) used a hedonic price model approach to check the impact of shutdown orders on housing prices, they only included a limited number of characteristics and the main focus was just the price impact of the shutdown orders across the US. Liu and Su (2021) also conducted regression analyses using a housing price index as the dependent variable, but they were county-level and ZIP-code-level analyses without housing-unit characteristics in the models. The hedonic price models in this study, on the other hand, includes not only the locational characteristics related to accessibility and subarea classification, which are the main variables of interest, but also many other utility-bearing characteristics to control for their effects and to create models with a high explanatory power.

2.3 The Relationship between Accessibility-Related Variables and Housing Prices

Numerous studies have tried to check the existence and magnitude of the premium given to a house with high accessibility, the results from which are briefly reviewed in this section. This section focuses on the studies that regard transit accessibility or freeway accessibility as the main variables.

The premium related to easy access to bus rapid transit (BRT) services, the type of transit service gaining more popularity these days, has recently received great attention and conflicting results have been reported. Zhang and Yen (2020) conducted a meta-analysis using 23 recent studies across the world on how BRT services impact the property and land values. Some of the studies found a positive price impact, which agrees with the land rent theory that considers the transportation cost and housing cost as complements (Alonso, 1964). In contrast, the others confirmed no significant impact or a negative impact.

The existence and magnitude of the land and property price impact of rail transit services have long been examined as well. Zuk et al. (2015), Mohammad et al. (2013), Hess and Almeida (2007), and Landis et al. (1994) provided neatly organized, comprehensive summaries of the results from relevant studies. According to the comparison of the price impact of BRT and rail transit from the studies reviewed by Zhang and Yen (2020) and Mohammad et al. (2013), rail transit services have a higher positive price impact on average and a larger variation in the impact (Zhang & Yen, 2020).

As such, accessibility to a transit system positively affects the housing price in general, even though the degree and direction of the impact vary with diverse factors such as the spatial and temporal contexts, transit system characteristics, dataset used, and research methods (Duncan, 2008; Wardrip, 2011; Zhang & Yen, 2020). For example, Chapple and Zuk (2020) contended that the price impact of heavy rail systems is larger than that of light rail systems. Ke and Gkritza (2019) suggested the preference of the residents of the Charlotte-Mecklenburg area (an urban area with low density in North Carolina) for taking private vehicles may be the reason for the negative housing price impact of a new light-rail transit in the nearby area after the operation. The difference can exist even within a city; Li (2020) found that the willingness to pay for better accessibility to transit increases in a more congested area in his study on the housing market of Beijing, China.

One noteworthy observation is that houses located too close to transportation facilities including rail and BRT lines, and freeways can suffer from the disutility from the noise, vibration, and pollution (Golub et al., 2012; Landis et al., 1994; Mikelbank, 2005; Mulley et al., 2016; Welch et al., 2016; Yang et al., 2020). This implies the importance of controlling for the possible negative price effect when constructing a hedonic price model to precisely extract the price effect that the accessibility to a transportation facility has.

The relationship between the accessibility to freeway systems and housing/land prices, of course, has been widely studied. The positive price effect of accessibility-related benefits as well as the negative price effect of disamenities from being close to a freeway segment have been argued in some of the studies reviewed by Landis et al. (1994). Just like the results from the studies focused on transit accessibility, these divergent results are expected to stem from the different contexts, data, and research methods.

More recent studies also reported the observations corresponding to the previous findings that both positive and negative price effects occur near a freeway (Iacono & Levinson, 2011; Levkovich et al., 2016; Mikelbank, 2005; Tian et al., 2017). Tian et al. (2017) claimed that the accessibility via car is valued more than the accessibility via transit and that locating too close to a highway exit harms housing prices after examining the single-family housing market in Salt Lake County. Levkovich et al. (2016) collected the housing transaction data from the areas near two new freeway construction sites in the Netherlands. They concluded that both the positive effect from accessibility and negative effect from nuisance exist, while the positive effect is stronger in general. Iacono and Levinson (2011) pointed out that the accessibility to freeway interchanges has a positive association with sales price, whereas being close to a freeway segment has a negative price effect in the housing market of Hennepin County, Minnesota.

A few studies investigated the relationship between accessibility and housing prices in the Atlanta context. Nelson (1992) found that the single-family house prices near the east line of Metropolitan Atlanta Rapid Transit Authority (MARTA) rail transit increase as a house gets closer to a station in low-income neighborhoods, but a slight negative effect is detected in high-income neighborhoods. This result implied that the accessibility benefit from the MARTA rail service is valued more in low-income neighborhoods and people in high-income neighborhoods are more concerned about nuisances (e.g., the noise and traffic). Bowes and Ihlanfeldt (2001) argued that the positive effect of accessibility to a station generally outweighs the negative effect of nuisances, whereas locating within a quarter mile from a station gives a neutral or negative price effect, which indicates that the negative impact is strong within a quarter-mile radius from stations. They also included the proximity to the freeway in their hedonic models as dummy variables; the houses located between 1 and 3 miles from a freeway interchange had higher housing prices but no significant positive price effect was found in houses within 1 mile,

This study will contribute to the literature by 1) constructing hedonic price models of the single-family houses that explains the housing price determination mechanism in current Atlanta contexts, 2) measuring the accessibility to freeway exits and MARTA rail stations using network distances for improved accuracy and precision, and 3) checking the changes in the premiums associated with locational characteristics regarding accessibility and subarea classification after the pandemic by a before-and-after comparison.

CHAPTER 3. METHODS AND DATA

3.1 Study Area

The area within five miles from the MARTA rail transit lines is examined in this study. The area lying in Clayton County is ruled out because a large proportion of the area is occupied by the Hartsfield-Jackson Atlanta International Airport and related industrial facilities. This study area is set to exclude the area where the MARTA rail service would not substantially influence the housing prices. As illustrated in Figure 1, the study area covers most of the city of Atlanta and the area inside the I-285 loop.

3.2 Housing Transaction Data

The transaction data of single-family houses are from FMLS, one of the two multiple listing services (MLSs) that mainly cover residential properties in the Atlanta metropolitan region. FMLS has more listings inside the I-285 loop compared with the other MLS, the Georgia Multiple Listing Service (GAMLS) (Metro Atlanta Home Group, 2016). The listings in FMLS are more suitable for this study because most of the study area lies inside the loop.

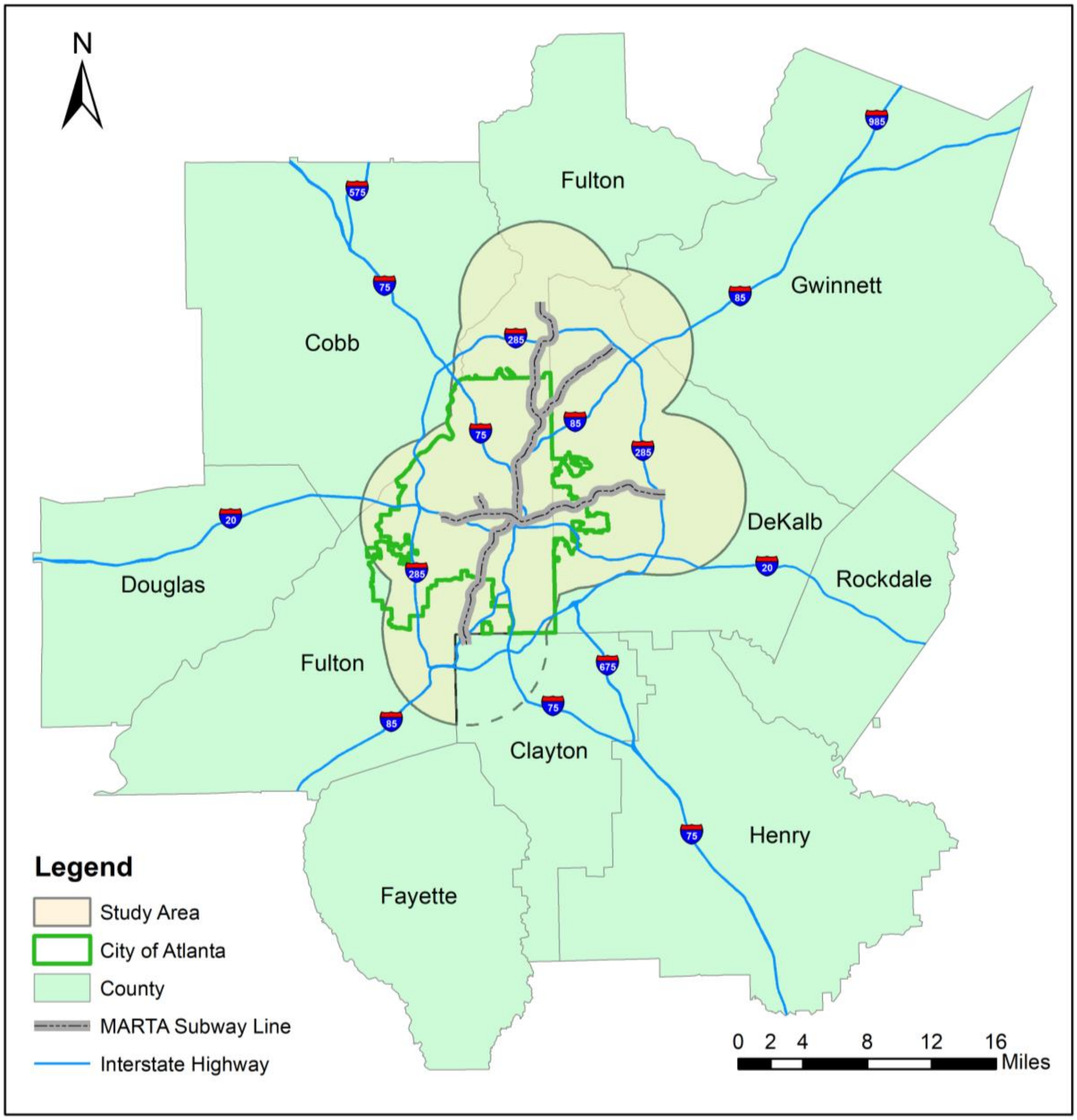

Figure 1 - Study Area

A great majority of the listings in FMLS consist of detached single-family houses for sale. Table 1 shows the number of listings by property type in FMLS from the search result on June 8th, 2016 (Metro Atlanta Home Group, 2016). Two thirds of the listings are detached single-family houses for sale. On the other hand, the commercial properties for sale take up just a small proportion, 3.4%, which indicates that they are listed on other services by agents mainly dealing with commercial properties (Metro Atlanta Home Group, 2016). Moreover, only 4.2% are for rent because most rental transactions are for apartments, and such transactions are usually done without a realtor.

Table 1 - The Number of Listings in FMLS by Property Type

Property Type	Number of Listings	
Single Family Detached	34,195	(66.6%)
Single Family Attached	5,301	(10.3%)
Developed Lot	4,523	(8.8%)
Land / Farm	3,108	(6.1%)
Rental	2,156	(4.2%)
Multi-family	294	(0.6%)
Commercial for Sale	1,747	(3.4%)
Total	51,324	(100.0%)

(Source: Metro Atlanta Home Group (2016))

This study uses the transaction data categorized as ‘Single Family Detached,’ detached single-family houses for sale excluding condominiums and townhouses. The transactions in Fulton, DeKalb, Cobb, and Gwinnett Counties in the 2nd, 3rd, and 4th quarters of 2018, 2019, and 2020 were downloaded from the Matrix dataset of FMLS. The transactions from the 1st quarter of 2020 are excluded because they are barely affected by the pandemic. Most of the universities, schools, companies, and government offices in Georgia started to close in mid-March 2020, and the statewide lockdown was implemented in early April 2020. The transactions from the 1st quarters of 2018 and 2019 are also ruled out to control for fair comparison among different years.

The number of transactions collected is 101,064. Google Maps Geocoding API service is employed to geocode each transaction based on the address. Of the 101,064 requests, 96,189 (95.2%) successful, street-address level geocoding results are returned.

After the geocoding process, 31,163 transactions within five miles from the MARTA rail tracks are selected.

3.3 Network Distance to Transportation Facility

The network distance to the closest MARTA rail station from each house in the dataset measures the accessibility to the MARTA rail transit service. Google Maps Distance Matrix API service was utilized to calculate the network distances for driving. The longitude and latitude of each of the 38 MARTA rail stations, which are the inputs for the API requests, are from a manual search on the Google Maps webpage.

The network distance between each house and its closest freeway exit was calculated with the same method; the only difference is that the closest exit could be either an accessing or egressing point of a freeway system. Freeway exits are defined to include both the accessing points and egressing points to freeway systems in this study. The exits are extracted from the roads in Open Street Maps classified as a “motorway_link” indicating ramps connecting a motorway (i.e., a controlled-access highway including interstate highways and some state highways such as Georgia State Route 141, 154, 166, 400, and 410) with a road. The mixture of accessing and egressing points can result in inaccurate network distances that are far different from the exact measurements of the accessibility to freeway systems. For example, when calculating the network distance from an “accessing” point to a house, the Google Maps Distance Matrix API request outputs a route entering the freeway, exiting at another exit, and then getting to the house. However, when the origin and destination are switched, the API gives the intended route. To resolve this issue, both the network distance from a house to its closest freeway exit and that in the opposite direction are calculated and the shorter one is chosen.

Figure 2 illustrates the MARTA rail stations and freeway exits used in this study. The MARTA rail system consists of four lines: Red, Gold, Green, and Blue, with 38 stations. The Red and Gold lines share a line stretching from south to north, but the Gold line diverts to a northeastern direction at the end. The Blue line connects from west to east. The Green line shares most of its track with the Blue line, but it is shorter and has a station (i.e., the Bankhead Transit station) that sticks out to the north at the west end. Because a freeway exit (i.e., a blue dot in Figure 2) is defined as the point at which a road intersects with a ramp connected to a freeway segment, multiple exits exist for one interchange.

3.4 Walkability

The Walk Score is employed to assess the walkability of a housing location. Ranging from 0 to 100, the Walk Score is the weighted sum of the distances to various types of amenities such as restaurants, parks, and entertainment (Hirsch et al., 2013). Nine categories of amenities are defined and the amenities closer than 1.5 miles from a location are considered (Walk Score, 2011). A location with low intersection density and a large average block length around the location are penalized up to 10% (Walk Score, 2011). The Walk Score values extracted from the Walk Score API service are assigned to the corresponding houses.

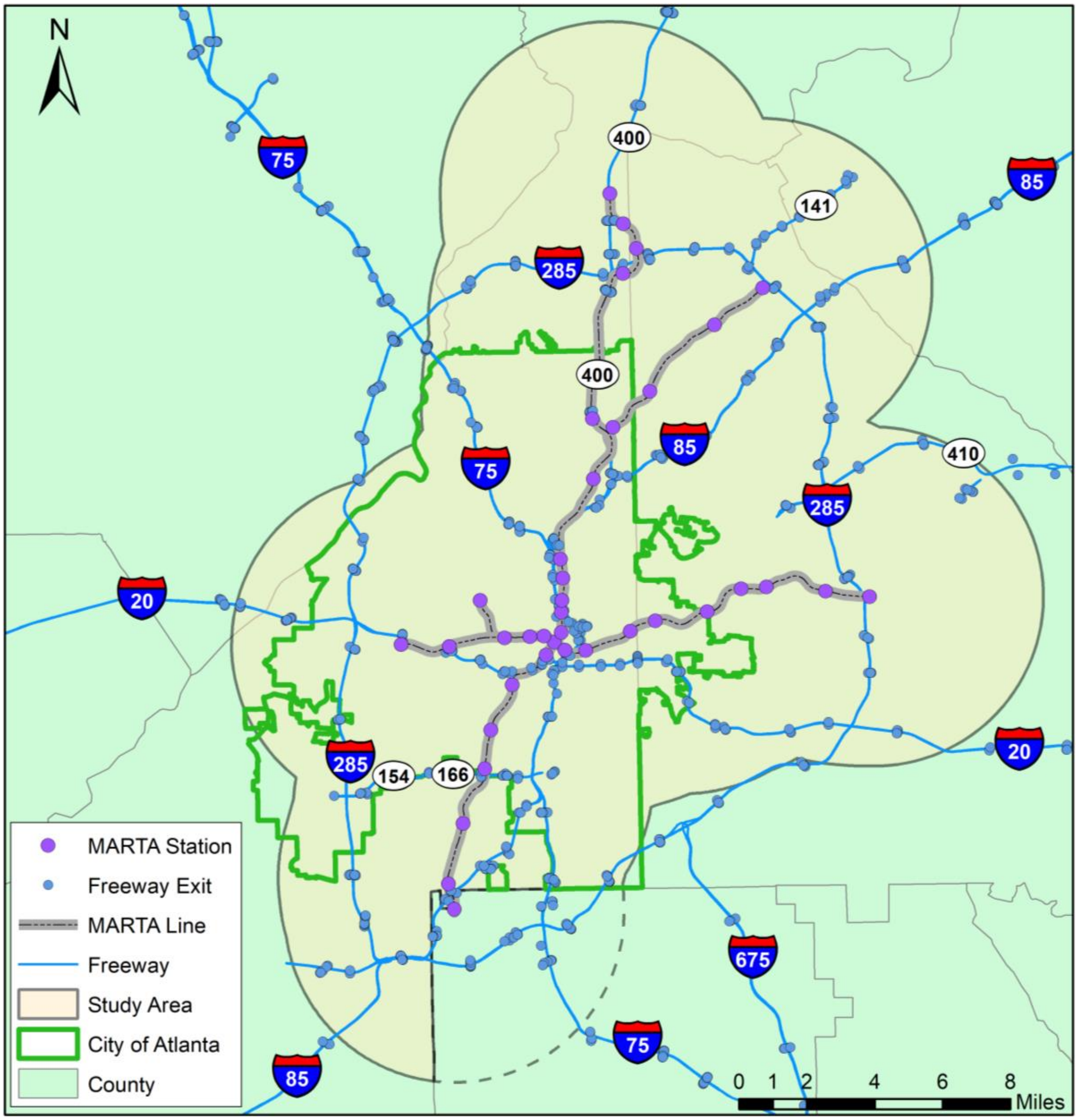

Figure 2 - MARTA Stations and Freeway Exits

3.5 School Quality

The source of the school quality information is the School Level Data 2019 from the Georgia School Grades Reports prepared by the Governor's Office of Student Achievement. The reports grade all public elementary, middle, and high schools in Georgia with scores from 0 to 100, based on which A-F letter grades are assigned. (Governor's

Office of Student Achievement, n.d.). The score reflects various aspects of a school closely linked with the quality of education, such as the "performance on statewide assessments, [make-up] of the school's student body, [graduation] rate, and additional academic information" (Governor's Office of Student Achievement, n.d.).

The school quality variable is created by averaging the elementary, middle, and high school scores for each house. Every house in the FMLS transaction dataset is assigned to one elementary, one middle, and one high school based on public school districts, even though missing values exist for a small proportion of the houses. The scores from the School Level Data 2019 are joined to the FMLS transaction dataset by using the school name as the key variable. Houses with missing school information, on the other hand, are joined with the scores of their closest schools.

3.6 Subarea Identification

The differentiation of the inner city, inner-ring suburb, and outer-ring suburb area is implemented to compare the number of houses sold and the housing-price difference in each of the areas. The basic approach for the classification is similar to the one used by Lee and Leigh (2007), who classified the downtown, inner city, inner-ring suburb, and outer-ring suburb in the Atlanta, Cleveland, Philadelphia, and Portland metropolitan areas in their study. They defined the inner city as the area with "a concentration of housing stock built mostly before 1950." The inner-ring suburb is defined as the area surrounding the inner city and having a "relatively higher percentage" of housing units built in the 50s and 60s, using the 2000 Census tract-level housing unit data (Lee & Leigh, 2007).

Using the tract-level 2015-2019 American Community Survey (ACS) estimates of housing units, the outer boundary of the inner city is specified by the chunk of tracts around the downtown area satisfying the following conditions: 1) housing units built before 1950 are "more" than those built in the 1950s and 1960s and 2) more than 20% of the housing units were built before 1950. The only exception is the tracts around the Atlantic station, which have been recently redeveloped. The development plan was produced in the mid-1990s (Atlantic Station - Jacoby Development, n.d.); more than 80% of the housing units in the two census tracts adjacent to the south-eastern side of the station were built after 1990. The two census tracts are included in the inner city so that the boundary becomes smooth and aligns with the rail track.

The outer boundary of inner-ring suburb is defined as the chunk of tracts surrounding the inner city with three conditions met: 1) housing units built before 1950 are "less" than those built in the 1950s and 1960s, 2) more than 20% of the housing units were built in the 1950s and 1960s, and 3) the tract lies inside or on the I-285 loop. To smooth out the boundary, the two census tracts covering the Hartsfield-Jackson Atlanta International Airport are included. In addition, the small gaps of the chunk at the north-western side and northern side are filled with the city of Atlanta boundary and I-285 loop.

Figure 3 shows the classification result, which closely replicates that of Lee and Leigh (2007). Different from their result, the downtown area is not defined because it is mainly used for office and commercial purposes, which makes drawing its boundary irrelevant to this study.

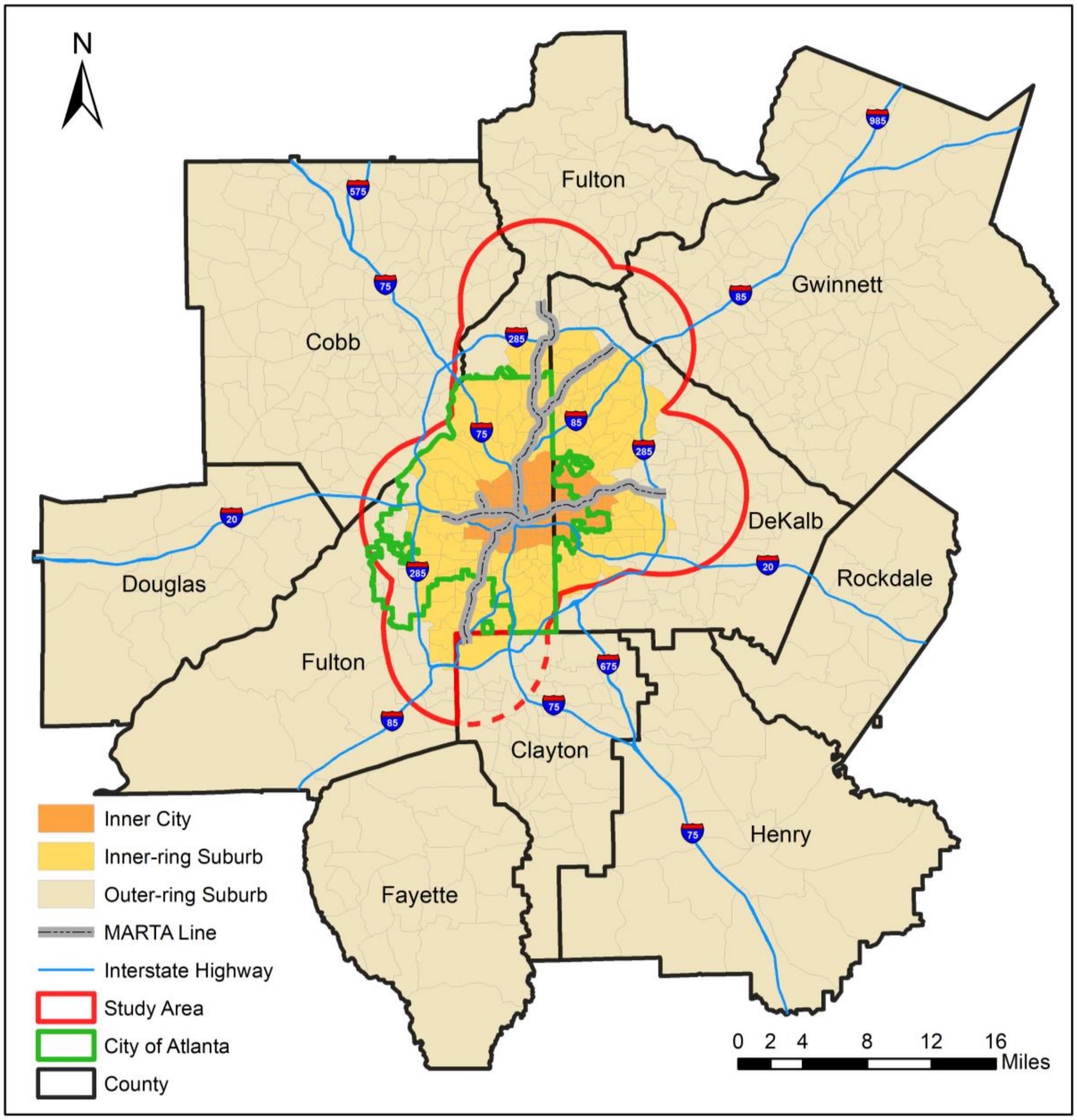

Figure 3 - Subarea Identification

3.7 Other Variables

Land parcel data are spatially joined with the FMLS transaction data to include the land lot size as one of the explanatory variables. Even though two columns (i.e., "Landlot" and "Lot Dimensions") in the original FMLS dataset contain information about the land lot size, neither is coded with a unified unit of measure. Even worse, they are mostly filled with invalid or missing values. Therefore, the tax parcel GIS data from Fulton County GIS Portal (2020 data of Fulton) and from Koordinates (2019 data of Dekalb, Cobb, and Gwinnett) are utilized to add the land lot size variable to the dataset.

The adjacency (i.e., proximity) to freeways and MARTA rail tracks are also measured to check the housing price impact of locating adjacent to transportation facilities that can be are sources of noise, vibration, and pollution. The distance used for the dummy variable for the proximity to a transportation facility ranges mostly from 0.03 miles to 0.25 miles (sometimes up to 0.5 miles), depending on the study area and type of facility. Because the MARTA rail transit system can be regarded as a heavy rail system and the great majority of its tracks are aboveground, which causes relatively loud noises, a quarter mile from the tracks is used to determine the proximity. Similarly, considering the heavy traffic volumes on the freeways in the Atlanta region, the one-quarter-mile criterion is also adopted for the proximity to a freeway.

A few neighborhood characteristics are collected and combined with the dataset: the tract-level 5-year median household income estimates from the 2015-2019 ACS, block-group-level 5-year population estimates from the 2015-2019 ACS, and block-group-level employment counts from the 2018 Longitudinal and Employer Household Dynamics Origin-Destination Employment Statistics (LODES). The population and employment data are transformed into block-group-level population density and employment density before being joined with the dataset.

Table 2 contains basic descriptions regarding all the variables collected and calculated in this study. Variables from the top to *Days on Market* are directly from the

FMLS transaction dataset except for *Parcel Size*, obtained from a spatial join of the tax parcel GIS data with the transaction dataset after geocoding. The rest are created based on the geolocation of each house in the dataset.

Table 2 - Variables

Variable	Unit	Source	Description
Sale Price	$	FMLS	-
Days on Market	day	FMLS	The number of days during which the house was listed
Floor Area	ft^2	FMLS	-
Parcel Size	ft^2	Koordinates & Fulton County	-
Bed	-	FMLS	The number of bedrooms
Full Bath	-	FMLS	The number of full bathrooms
Half Bath	-	FMLS	The number of half bathrooms
Pool	dummy	FMLS	Whether the house has a pool
Fireplace	-	FMLS	The number of fireplaces
Multi-story	dummy	FMLS	Whether the house is multistory
Age	year	FMLS	-
Inner City	dummy	Authors	1, if the house is in the inner city
Inner-ring Suburb	dummy	Authors	1, if the house is in the inner-ring suburb
Outer-ring Suburb	dummy	Authors	1, if the house is in the outer-ring suburb
Freeway Exit Dist	mile	Google Maps	The network distance to the closest freeway exit
Freeway Adjacency	dummy	Authors	1, if the house is within 1/4 miles from a freeway
Subway Station Dist	mile	Google Maps	The network distance to the closest MARTA subway station
Subway Adjacency	dummy	Authors	1, if the house is within ¼ miles from MARTA subway tracks
Median HH Income	$1000	ACS	The median household income of the associated tract
Pop Density	persons/mi^2	ACS	The population density of the associated block group
Emp Density	persons/mi^2	LODES	The employment density of the associated block group
Walk Score	-	Walk Score	The Walk Score given to the house
School Quality	-	Georgia School Grades Reports	The average of the associated elementary, middle, and high school scores

Note: the value for a dummy variable is 0 when the associated condition is not met

3.8 Hedonic Price Model Analysis

This study builds separate hedonic price models for 2018, 2019, and 2020, using the dataset including the variables in Table 2. However, two variables from Table 2, *Days on Market* and *Inner City*, are excluded when calibrating the models. *Days on Market* is useful in checking how active the transactions in the market are, while not being a strong predictor of housing prices. The exclusion of *Inner City* lets the inner city become the base location, which enables the observation of the price effect of locating either the inner-ring suburb or outer-ring suburb instead of the base location.

Before being used as inputs of the hedonic price models, variables except for dummy variables (i.e., *Pool*, *Multi-story*, *Inner-ring Suburb*, *Outer-ring Suburb*, *Freeway Adjacency*, and *Subway Adjacency*) and simple counts (i.e., *Bed*, *Full Bath*, *Half Bath*, and *Fireplace*) are log-transformed. For the variables with at least one 0 value (i.e., *Age*, *Freeway Exit Dist*, *Emp Density*, and *Walk Score*), one is added before the transformation. The only exception is *Age*, to which two are added because it has the value of -1 for houses sold before the construction ends. In this study, this log-log approach gives the models better explanatory powers than the approach with no log-transformations or with only the log-transformed dependent variable.

Outliers were detected and reviewed in detail twice: before and after the first model calibration. The before-calibration review dealt with errors from manual input from realtors. Since a huge proportion of the FMLS dataset was filled with information from the manual input, it was necessary to check the transactions with suspicious values (e.g., an extremely large floor area). If the values were correct or easily correctable, the corresponding transactions were kept in the dataset. The after-calibration review examined the cases with a large absolute residual value, most of which had negative residuals, indicating that the predicted sale prices were substantially larger than the observed sale prices. Although a few such cases were with errors from manual input, most of them were fired-damaged houses or fixer-uppers requiring complete renovation. The final model calibration was implemented after removing or fixing these outliers.

CHAPTER 4. RESULTS

4.1 Descriptive Statistics

The descriptive statistics (i.e., the mean and median) of the variables in the datasets used in the final model calibration are shown in Table 3. The descriptive statistic tables with more statistics including the standard deviation, minimum, and maximum (i.e., Table 7, Table 8, and Table 9) can be found in Appendix A. The interpretation in this section mainly focuses on the mean and median values illustrated in Table 3.

It is possible to observe from the transaction characteristics in Table 3 that the Atlanta single-family housing market boomed after the COVID-19 pandemic even after taking the pre-existing growing trend into consideration. First of all, the median housing price increased 4.48% (from 335k to 350k) between 2018 and 2019, but the rate of increase between 2019 and 2020 was 12.86%, almost triple in comparison to the previous year. The mean housing price also followed a similar pattern. Secondly, the median number of days on market was increasing before the pandemic but dropped sharply after the pandemic, implying the increased vitality stemming from the raised demand. Lastly, the number of transactions in 2019 and 2020 were about the same, even though the 2nd quarter of 2020 was affected by a stay-at-home order which hindered active transactions.

Table 3 - Descriptive Statistics

Type	Variable Name	Unit	Median			Mean		
			2018	2019	2020	2018	2019	2020
Transaction Characteristics	Sale Price	$	335,000	350,000	395,000	423,847	441,209	500,643
	Days on Market	day	16	22	14	36.03	41.11	35.51
Housing-unit Characteristics	Floor Area	ft^2	1,952	1,989	2,066	2,351	2,381	2,466
	Parcel Size	ft^2	12,233	12,170	12,237	16,051	16,244	16,412
	Bed	-	3	3	4	3.64	3.65	3.70
	Full Bath	-	2	2	2	2.46	2.47	2.56
	Half Bath	-	0	0	0	0.44	0.44	0.46
	Pool	dummy	0	0	0	0.05	0.05	0.06
	Fireplace	-	1	1	1	0.91	0.93	0.97
	Multi-story	dummy	1	1	1	0.56	0.57	0.59
	Age	year	53	55	55	48.65	49.76	50.42
Locational Characteristics	Inner City	dummy	0	0	0	0.17	0.17	0.17
	Inner-ring Suburb	dummy	1	1	1	0.50	0.51	0.52
	Outer-ring Suburb	dummy	0	0	0	0.33	0.33	0.31
	Freeway Exit Dist	mile	1.62	1.62	1.62	1.87	1.87	1.88
	Freeway Adjacency	dummy	0	0	0	0.10	0.11	0.11
	Subway Station Dist	mile	2.98	2.94	2.88	3.32	3.32	3.27
	Subway Adjacency	dummy	0	0	0	0.04	0.05	0.05
	Median HH Income	$1000	71.62	71.62	72.54	78.86	78.87	81.30
	Pop Density	persons/mi^2	448.58	448.99	448.43	528.02	530.84	528.94
	Emp Density	persons/mi^2	71.30	71.30	77.63	215.44	224.09	228.88
	Walk Score	-	28	27	28	30.93	30.41	31.08
	School Quality	-	73.43	73.43	74.50	73.37	73.40	73.90
	N	-	9,461	9,995	9,960			

The change in the median floor area seems to partially explain the growth of housing prices. The median floor area increased by 1.90% between 2018 and 2019 and by 3.87% between 2019 and 2020. Accordingly, the average number of bedrooms, full baths, half baths, and fireplaces also rose during the three years. However, such changes were not as large as that of housing prices. Therefore, the steep increase in housing prices between

2019 and 2020 might have resulted from the monetary easement policies implemented to combat the negative economic impacts of the pandemic or from the changes in the preference of housing market participants. The hedonic price model outputs will help understand whether the slight changes in housing-unit characteristics and the inflation with the influx of money led to the observed housing price increment or the changes in the preferences (i.e., the implicit prices of characteristics) also contributed to it.

The proportion of transactions in each subarea slightly changed. The proportion of transactions in the inner-ring suburb (i.e., the mean value of *Inner-ring Suburb*) steadily increased from 50% to 52% as the proportion in the outer-ring suburb (i.e., the mean value of *Outer-ring Suburb*) decreased from 33% to 31%. At this stage of the analysis on descriptive statistics, it is not clear what caused the observed change. For example, it could be from the increased supply in the inner-ring suburb area, the raised demand to live in the area, or the increased housing prices in the outer-ring suburb area pushing people out of the area.

Looking into the accessibility-related locational characteristics, the mean and median network distance to the closest freeway exit remained almost unchanged. In contrast, the mean and median network distance to the closest MARTA rail station slightly decreased over time. The proportion of houses sold adjacent to a freeway (i.e., located within a quarter mile from a freeway) is 10~11%, and the proportion of those adjacent to a MARTA rail track (i.e., located within a quarter mile from a MARTA rail track) is 4~5%. The Walk Score values of houses sold indicated neither a positive nor negative trend but fluctuated a little.

Overall, the descriptive statistics in Table 3 reveal that the median sale price and median floor area increased substantially between 2019 and 2020 even though the median number of days on market of the sold house sharply dropped. However, other variables did not show a notable change between 2019 and 2020 compared to a pre-existing trend observed from the difference between 2018 and 2019.

Table 4, which contains the quarterly median values of all the variables in the dataset, is for a more detailed analysis of the changes in the sale price, days on market, floor area, and the number of transactions. In 2018 and 2019, the number of transactions, the median sale price, and the median floor area went down while the median number of days on market went up, as it became closer to the end of the year. This trend agrees with the usual seasonal fluctuation of typical rises in the spring in the US housing market (Yoruk, 2020). This trend also indicates the seasonal pattern that large houses with a high price are traded more actively in the spring and new listings are sold out quickly in the spring.

The seasonal pattern, however, reversed in 2020. The number of transactions shrank in the second quarter but surged back in the third quarter, implying that transactions were suppressed by the statewide lockdown and the requirement for social distancing. In addition, the median housing price and floor area increased from the second quarter to the fourth quarter while the median number of days on market decreased. The values of median housing price and floor area are substantially larger than those of 2018 and 2019.

Even though these observations from Table 3 and Table 4 imply a housing market boom in the Atlanta single-family housing market after the pandemic, the necessity remains for the comparison among hedonic price models for 2018, 2019, and 2020 for an improved understanding of the observations.

Table 4 - Median Values by Quarter

Variable	Unit	2018			2019			2020		
		2Q	3Q	4Q	2Q	3Q	4Q	2Q	3Q	4Q
Sale Price	$	353,000	336,000	313,000	370,000	341,504	324,000	383,750	396,050	400,000
Days on Market	day	12	17	22	17	24	28	17	15	13
Floor Area	ft^2	2,004	1,920	1,910	2,024	1,974	1,953	2,029.5	2,068	2,101
Parcel Size	ft^2	12,252	12,157	12,241	12,071	12,343	12,097	12,292	12,197	12,184
Bed	-	4	3	3	3	3	3	4	4	4
Full Bath	-	2	2	2	2	2	2	2	2	2
Half Bath	-	0	0	0	0	0	0	0	0	0
Pool	dummy	0	0	0	0	0	0	0	0	0
Fireplace	-	1	1	1	1	1	1	1	1	1
Multi-story	dummy	1	1	1	1	1	1	1	1	1
Age	year	53	54	53	54	54.5	55	55	56	54
Inner City	dummy	0	0	0	0	0	0	0	0	0
Inner-ring Suburb	dummy	1	1	0	1	1	1	1	1	1
Outer-ring Suburb	dummy	0	0	0	0	0	0	0	0	0
Freeway Exit Dist	mile	1.65	1.60	1.62	1.66	1.62	1.58	1.64	1.62	1.60
Freeway Adjacency	dummy	0	0	0	0	0	0	0	0	0
Subway Station Dist	mile	3.01	2.94	2.98	2.86	2.94	3.03	2.89	2.86	2.89
Subway Adjacency	dummy	0	0	0	0	0	0	0	0	0
Median HH Income	$1000	72.54	71.62	66.64	72.65	71.62	66.64	72.54	72.54	73.43
Pop Density	$persons/mi^2$	446.42	448.43	451.02	448.58	448.58	449.63	449.63	448.99	441.29
Emp Density	$persons/mi^2$	75.97	70.77	70.05	77.63	69.26	69.91	77.10	77.63	78.68
Walk Score	-	28	28	28	28	27	27	27	28	28
School Quality	-	74.83	73.43	72.80	74.83	73.23	72.50	74.32	73.47	74.77
N	-	3,671	3,111	2,679	3,651	3,340	3,004	2,832	3,821	3,307

4.2 Modeling Result

Table 5 shows the final hedonic model outputs from 2018 to 2020 with the comparison between the coefficients between two consecutive models. Coefficients with standard errors in parentheses are shown in the columns for the model outputs (i.e., 2018

Model, 2019 Model, and 2020 Model). The columns named “Comparison (p-value)” are filled with p-values from one-tailed z-tests of the difference between two coefficients of the same variable in two models. The reason for using one-tailed tests is that the direction of a change between two years matters. The formula for the z-statistic in this study (i.e., the z-statistic equals the difference between two coefficients divided by the square root of the squared sum of the standard errors of the two coefficients) is known to produce the unbiased estimate of the standard deviation of the difference between two coefficients and is recommended by Paternoster et al. (1998). The significance level of a coefficient or comparison is marked with asterisks.

Each model has more than 9000 cases and has an R-squared value higher than 0.85. The R-squared values of the three models that are almost the same imply that the explanatory power of the set of explanatory variables has not been altered. Most of the explanatory variables have statistically significant coefficients at the significance level of 0.01, with only two exceptions being *Freeway Adjacency* and *Subway Adjacency*.

No serious multicollinearity issue is detected according to the Variance Inflation Factor (VIF) values in Table 6. The VIF values of all the explanatory variables except *log(Floor Area)* are smaller than 5. Only *log(Floor Area)* has VIF values slightly higher than 5, the reason being that it is highly correlated with the number of rooms and bathrooms.

Table 5 - Hedonic Price Modeling Result

	Dependent variable: log(Sale Price)				
	2018 Model	Comparison (p-value)	**2019 Model**	Comparison (p-value)	**2020 Model**
log(Floor Area)	**0.577*** (0.017)**	0.238	**0.560*** (0.015)**	0.055*	**0.526*** (0.015)**
log(Parcel Size)	**0.057*** (0.007)**	0.226	**0.050*** (0.006)**	0.019**	**0.068*** (0.006)**
Bed	**-0.050*** (0.006)**	0.354	**-0.047*** (0.005)**	0.379	**-0.044*** (0.005)**
Full Bath	**0.119*** (0.006)**	0.020**	**0.136*** (0.006)**	0.341	**0.132*** (0.005)**
Half Bath	**0.048*** (0.007)**	0.158	**0.057*** (0.006)**	0.217	**0.063*** (0.006)**
Pool	**0.088*** (0.016)**	0.419	**0.084*** (0.014)**	0.036**	**0.117*** (0.012)**
Fireplace	**0.033*** (0.005)**	0.248	**0.028*** (0.004)**	0.276	**0.032*** (0.004)**
Multi-story	**-0.031*** (0.009)**	0.324	**-0.036*** (0.008)**	0.448	**-0.035*** (0.008)**
log(Age)	**-0.062*** (0.004)**	0.077*	**-0.055*** (0.004)**	0.405	**-0.053*** (0.004)**
Inner-ring Suburb	**-0.094*** (0.010)**	0.003***	**-0.131*** (0.009)**	0.291	**-0.138*** (0.009)**
Outer-ring Suburb	**-0.403*** (0.012)**	0.217	**-0.416*** (0.011)**	0.376	**-0.411*** (0.011)**
log(Freeway Exit Dist)	**-0.088*** (0.010)**	0.080*	**-0.068*** (0.009)**	0.255	**-0.060*** (0.009)**
Freeway Adjacency	**-0.026** (0.012)**	0.486	**-0.027*** (0.010)**	0.107	**-0.044*** (0.010)**
log(Subway Station Dist)	**-0.069*** (0.007)**	0.300	**-0.064*** (0.006)**	0.329	**-0.060*** (0.006)**
Subway Adjacency	**-0.017 (0.017)**	0.190	**-0.037** (0.015)**	0.022**	**0.004 (0.014)**
log(M HH Income)	**0.481*** (0.011)**	0.000***	**0.397*** (0.010)**	0.000***	**0.351*** (0.009)**
log(Pop Density)	**0.098*** (0.007)**	0.034**	**0.080*** (0.007)**	0.004***	**0.057*** (0.006)**
log(Emp Density)	**0.020*** (0.003)**	0.236	**0.023*** (0.002)**	0.303	**0.021*** (0.002)**
log(Walk Score)	**0.033*** (0.004)**	0.315	**0.035*** (0.004)**	0.349	**0.038*** (0.004)**
log(School Quality)	**0.909*** (0.037)**	0.192	**0.865*** (0.034)**	0.002***	**0.732*** (0.031)**
Constant	**1.416*** (0.161)**	0.000***	**2.221*** (0.146)**	0.000***	**3.300*** (0.140)**
Observations	9,461		9,995		9,960
R^2	0.852		0.853		0.852
Adjusted R^2	0.852		0.853		0.851
Residual Std. Error	0.302 (df = 9440)		0.284 (df = 9974)		0.268 (df = 9939)
F Statistic	2426.026*** (df = 20; 9440)		2526.075*** (df = 20; 9974)		2385.970 (df = 20; 9939)
Breusch–Pagan (BP)	913.12***		747.14***		643.65***
Moran's I	0.053***		0.056***		0.041***
Note:					*p<0.1; **p<0.05; ***p<0.01

Heteroskedasticity-robust standard errors are calculated to replace the original standard errors because of the heteroskedasticity found in all the three models by Breusch-Pagan (BP) tests shown in Table 5. Heteroskedasticity biases the standard errors of coefficients, thereby affecting the reliability of the statistical significance of the coefficients and leading to the incorrect comparison of the coefficients between two models. One of the potential inducers of heteroskedasticity is the spatial autocorrelation of residuals, and Moran's I is one way to check the existence of the issue. Moran's I values of the models in Table 5 are minimal even though being statistically significant (from 4.1% to 5.6%). Thus, White robust standard errors are employed, which would suffice to resolve the heteroskedasticity in this study.

Table 6 - VIF

Variable	VIF Value		
	2018 Model	2019 Model	2020 Model
log(Floor Area)	6.15	5.93	6.31
log(Parcel Size)	1.75	1.75	1.80
Bed	3.03	2.95	3.13
Full Bath	4.18	4.04	4.08
Half Bath	1.61	1.58	1.63
Pool	1.21	1.22	1.20
Fireplace	1.76	1.73	1.72
Multi-story	1.95	1.84	1.84
log(Age)	1.72	1.58	1.60
Inner-ring Suburb	2.64	2.64	2.63
Outer-ring Suburb	3.56	3.63	3.56
log(Freeway Exit Dist)	1.64	1.65	1.64
Freeway Adjacency	1.19	1.19	1.20
log(Subway Station Dist)	2.16	2.19	2.16
Subway Adjacency	1.21	1.22	1.22
log(M HH Income)	2.89	2.92	2.87
log(Pop Density)	1.43	1.48	1.50
log(Emp Density)	1.37	1.37	1.36
log(Walk Score)	2.03	2.10	2.15
log(School Quality)	2.76	2.86	2.78

One noteworthy aspect regarding the interpretation of the output table (Table 5) is that a coefficient does not directly represent the monetary value (i.e., the implicit price) of the associated characteristic. For a log-transformed variable, the coefficient being β indicates that a 1% percent increase in the variable changes the housing price by a factor of $(1 + 0.01)\beta$. On the other hand, for a non-log-transformed variable, a one-unit change in the variable changes the housing price by a factor of e β (please refer to UCLA Institute for Digital Research and Education (n.d.) for more details).

The two main reasons for using the log-transformation are its robustness to inflation and the high R-squared values. A coefficient value in this study is related to a "percent change" in the housing price rising from a change in the corresponding explanatory variable, which can have an effect of adjusting the inflation or deflation in the housing market when comparing the coefficients between two years. Considering the inflation that the single-family house market of the study area has been experiencing, the same coefficients of a variable in two models do not mean the unchanged impact of the variable between two years if the model is without any log transformation. However, using the current model specification can mitigate the inflation effect and provide high R-squared values for all three models. Since one of the main purposes of this study is to check the changes in preferences for various characteristics related to a house, which can be observed from how elastic the housing price is to a change in a variable, the log-log transformation would be the most proper model specification for this study.

The positive coefficients of *log(Floor Area)* and *log(Parcel Size)* in all three models confirm that residents are willing to pay more for a larger floor area and parcel size. The willingness to pay for an additional 1% of floor area, however, is much larger than that of parcel size. The coefficients did not change with a statistical significance between 2018 and 2019 but did between 2019 and 2020; the coefficient of *log(Floor Area)* decreased (even though the p-value is slightly larger than 0.05), and that of *log(Parcel Size)* increased. It can be inferred that the preference for a larger parcel size grew with a slight compromise on the floor area. Considering that residents started social distancing and the time spent in their houses increased after the pandemic began, they might have raised the desire for being outside while keeping themselves away from others.

Full Bath and *Half Bath* show positive relationships with housing prices, but *Bed* is negatively related to housing prices. Even though the negative relationship may look counterintuitive, it does not necessarily indicate the disinclination for having one more bedroom. The proper interpretation of the negative coefficient of *Bed* would be that "people prefer their additional square footage in a form other than additional bedrooms" (Landis et al., 1994), or people do not want an additional bedroom without increasing the square footage of their houses. A significant increase in the coefficient of *Full Bath* between 2018 and 2019 is detected but the reason behind the change is not apparent.

In terms of other housing-unit characteristics, a young, one-story house with a pool and fireplaces gains a premium in price, according to the coefficients of *Pool*, *Fireplace*, *Multi-story*, and *log(Age)*. In 2020, the premium given to houses with a pool became larger than before. This result is consistent with the change in the coefficients of *log(Floor Area)* and *log(Parcel Size)*, corroborating that social distancing and work-at-home encouraged people to spend more time in their backyards instead of going to crowded places.

Looking at the coefficients of *Inner-ring Suburb*, a house in the inner-ring suburb area was sold at a 9.0% discount ($e^{-0.094} = 0.910$) compared to a house in the inner city in 2018, ceteris paribus. The discount rate significantly increased to 12.3% ($e^{-0.131} = 0.877$) in 2019 but not significantly changed between 2019 and 2020 (the discount rate in 2020 is 12.9% ($e^{-0.138} = 0.871$)). The recent trend of increasing preference for the inner city over the inner-ring suburb was put on hold in 2020. The increasing premium given to houses in the inner city stands to reason because the inner-city area of Atlanta has recently been experiencing active urban redevelopments including the BeltLine project, which has attracted more people into the inner city. The hold on this trend might have stemmed from the reduced desire to stay in the inner city with a high risk of transmission and the decreased need to stay near the downtown area for easy access to workplaces.

The change in the coefficient of *Outer-ring Suburb* accords with the trend shown in the coefficient of *Inner-ring Suburb*, even though the coefficient has not changed significantly during the three years. The discount rate for a house in the outer-ring suburb area compared to the same house in the inner city increased from 33.2% ($e^{-0.403} = 0.668$) in 2018 to 34.0% ($e^{-0.416} = 0.660$) in 2019, but decreased to 33.7% ($e^{-0.411} = 0.663$) in 2020.

The negative coefficients of *log(Freeway Exit Dist)* and *log(Subway Station Dist)* imply the capitalization of accessibility to a freeway exit and MARTA rail station to housing prices. For example, the 1% increase in the network distance to its closest MARTA rail station induces a 0.088% decrease in the housing price ($1.01^{-0.088} = 0.99912$). The capitalization effects of the accessibility to freeway exits and MARTA rail stations continuously decreased from 2018 to 2020. The decreasing trends have not accelerated after the pandemic began but have slightly decelerated, meaning that people still value the accessibility to transportation facilities despite the decreased trip length and frequency via both public transit and personal vehicles since the pandemic. This result signifies that residents in Atlanta either expect their lifestyles will get back to normal quite soon or at least forecast that the accessibility to transportation facilities is going to keep its importance even if the new lifestyle introduced with the pandemic persists.

The adjacency to a freeway turned out to negatively affect housing prices while the impact of the adjacency to a MARTA rail station on housing prices varies across the three models, being insignificant or slightly negative. Therefore, the disutility from locating too close to freeway segments is more certain than that of MARTA rail tracks.

Walk Score, the diversity of and easy access to amenities within walking distance, are positively related to housing prices. The magnitude of the impact has increased since 2018 even though the change is not statistically significant. The outbreak of the pandemic does not seem to accelerate, brake, or reverse the trend; the premium for walkable communities keeps growing.

Summarizing the findings from accessibility-related variables, a house in a walkable community with good accessibility to the MARTA rail service and a freeway has a high price in the study area. Such a preference has not been evidently affected by the outbreak of the pandemic despite the changes in travel behavior including the decrease in public transit ridership and vehicle miles traveled (VMT) as well as the increase in telecommuting. Especially, the not-significantly-impaired capitalization effect of a MARTA rail station is good news to transportation planners.

Median household income, population density, employment density, and school quality exert a positive influence on housing prices. However, the coefficients of the associated variables except for the employment density (i.e., *log(Emp Density)*) have shown significant decreases not only between 2018 and 2019 but also between 2019 and 2020. The preference of housing market participants and the impacts of these variables are changing but probably not because of the pandemic considering the trend before the pandemic.

CHAPTER 5. CONCLUSION

This study examined what the Atlanta single-family housing market experienced in 2020 with the emergence of the COVID-19 pandemic that completely transformed people's daily lives with social distancing, telecommuting, and mass unemployment. The decreased mortgage rates and increased unemployment are the potential factors influencing the housing market. In addition, the preference change for some features of a house can substantially affect the housing market considering that a fair amount of companies expect that the proportion of telecommuters will not get back to the previous level after the pandemic ends (Bartik et al., 2020). Thus, this study investigated 1) the prices and characteristics of single-family houses sold from 2018 to 2020 and 2) the changes in the housing price determination mechanism in 2020 using the comparison between hedonic price models, while the differences between 2018 and 2019 being benchmarks.

A few main findings are extracted from the analyses. First, after the COVID-19 pandemic began, the median housing price of the single-family houses in the study area increased to a large extent, and transactions were more activated after a sharp drop in the number of transactions in the second quarter of 2020. This implies that the Atlanta single-family housing market boomed with the lowered mortgage rates that induced an influx of money into the housing market, which aligns with the housing market boom across the US after the pandemic argued by Zhao (2020) and Liu and Su (2021). Second, the preference for a house with a larger parcel size and a pool increased in 2020, while the positive impact of the square footage of a house on housing prices slightly decreased. The increase in the time spent at home owing to social distancing and work-at-home might have caused this change. Third, the preference for the inner city over the suburban area exists, and the recently increasing preference was restrained in 2020, which might reflect the diminished desire for staying close to the city center for job accessibility. Fourth, the capitalization effects of the accessibility to a MARTA rail station and freeway have become slightly smaller (even though without a statistical significance), but the pandemic did not exert a substantial impact on the decrease or increase of the effects.

The hedonic models developed in this study have high explanatory powers with a large number of transactions. Moreover, they can be easily updated as new data are released and can be reproduced with similar transaction data from other regions as well. This hedonic price model approach provides valuable insight into the preference of the market participants without conducting expensive data collection processes such as surveys. The information gained from the model outputs can help planners and policymakers in their decision-making regarding the value capture policies, housing supply plans, and transportation infrastructure investments.

The above findings suggest that the pandemic affected not only the macroeconomic situations but also the preferences of housing market participants in Atlanta. However, follow-up studies will be required to monitor whether these changes will last for an extended period. Studies that further verify the findings from this study and conduct more detailed analyses will also be necessary. Some suggestions for future studies to overcome the limitations of this study are presented below.

First, additional information from other data sources would reveal the underlying causes of the observations from this study. The hedonic price models do not provide the underlying reasons for some changes detected from the comparison between models. When a change in a coefficient between 2019 and 2020 is revealed by the model outputs, it is possible to test whether the change is substantial considering the pre-existing trend and the z-test result. Also, possible explanations taking into account the observed changes in travel behavior, lifestyles, and macroeconomic indicators in 2020 can be proposed. However, in some cases, suggesting plausible explanations is not possible nor do they suffice. Consequently, the information from a survey directly asking the modification of various market participants' attitudes, lifestyle, and travel patterns would enable more in-depth further studies. With the help of such additional information, further understanding the impacts of the pandemic with a balanced consideration of both the demand and supply sides would be possible.

Second, further investigations on the rental market, new construction sector, and other types of houses than detached single-family houses will enhance the overall understanding of the housing market. This study analyzed the sales data of single-family houses from an MLS, excluding the other types of houses (e.g., condominiums and townhouses for sale) and the houses for rent. Because the market participants of different submarkets (e.g., the sales market and the rental market) have different characteristics and considerations, the impacts of the pandemic can differ. For example, the pandemic might have had a greater influence on the rental market given the short duration of rental contracts with no transfer of ownership involved. Also, the new construction sector, which takes up about 25% of the sales transactions in the Atlanta region, is not usually included in the FMLS data (R. Porter, personal communication, March 30, 2021).

Lastly, more detailed submarket-level analyses will bring additional observations and insights that give useful policy implications. The housing market of a region can be divided into submarkets using some criteria such as the housing price, size, number of rooms, and neighborhood. The improved grasp of how the pandemic affected each housing submarket will assist planners in devising customized solutions to various planning issues.

APPENDIX A. DESCRIPTIVE STATISTICS

Table 7 - 2018 Descriptive Statistics (N = 9,461)

Variable	Unit	Median	Mean	St. Dev.	Min	Max
Sale Price	$	335,000	423,847	383,734	27,900	7,500,000
Days on Market	day	16	36.03	53.47	0	1,123
Floor Area	ft^2	1,952	2,351	1,402	510	18,158
Parcel Size	ft^2	12,233	16,051	15,043	800	343,249
Bed	-	3	3.64	0.98	0	8
Full Bath	-	2	2.46	1.11	0	10
Half Bath	-	0	0.44	0.57	0	5
Pool	dummy	0	0.05	0.21	0	1
Fireplace	-	1	0.91	0.92	0	10
Multi-story	dummy	1	0.56	0.50	0	1
Age	year	53	48.65	27.53	-1	158
Inner City	dummy	0	0.17	0.38	0	1
Inner-ring Suburb	dummy	1	0.50	0.50	0	1
Outer-ring Suburb	dummy	0	0.33	0.47	0	1
Freeway Exit Dist	mile	1.62	1.87	1.22	0.00	8.32
Freeway Adjacency	dummy	0	0.10	0.31	0	1
Subway Station Dist	mile	2.98	3.32	2.05	0.17	11.06
Subway Adjacency	dummy	0	0.04	0.21	0	1
Median HH Income	$1000	71.62	78.86	42.94	12.48	208.75
Pop Density	persons/mi^2	448.58	528.02	303.68	38.15	3,825.13
Emp Density	persons/mi^2	71.30	215.44	577.48	0.00	8,528.37
Walk Score	-	28	30.93	21.91	0	94
School Quality	-	73.43	73.37	11.21	37.93	96.97

Table 8 - 2019 Descriptive Statistics (N = 9,995)

Variable	Unit	Median	Mean	St. Dev.	Min	Max
Sale Price	$	350,000	441,209.40	397,648.50	30,000	8,000,000
Days on Market	day	22	41.11	53.98	0	843
Floor Area	ft^2	1,989	2,381.06	1,427.65	512	24,800
Parcel Size	ft^2	12,169.94	16,243.86	17,272.76	871.20	427,092.00
Bed	-	3	3.65	0.99	0	9
Full Bath	-	2	2.47	1.08	0	10
Half Bath	-	0	0.44	0.58	0	5
Pool	dummy	0	0.05	0.22	0	1
Fireplace	-	1	0.93	0.91	0	8
Multi-story	dummy	1	0.57	0.49	0	1
Age	year	55	49.76	27.83	-1	139
Inner City	dummy	0	0.17	0.37	0	1
Inner-ring Suburb	dummy	1	0.51	0.50	0	1
Outer-ring Suburb	dummy	0	0.33	0.47	0	1
Freeway Exit Dist	mile	1.62	1.87	1.22	0.03	8.58
Freeway Adjacency	dummy	0	0.11	0.31	0	1
Subway Station Dist	mile	2.94	3.32	2.04	0.12	10.99
Subway Adjacency	dummy	0	0.05	0.21	0	1
Median HH Income	$1000	71.62	78.87	43.26	12.48	208.75
Pop Density	persons/mi^2	448.99	530.84	314.23	38.15	3,825.13
Emp Density	persons/mi^2	71.30	224.09	610.38	0.00	11,000.51
Walk Score	-	27	30.41	21.98	0	94
School Quality	-	73.43	73.40	11.30	42.50	96.97

Table 9 - 2020 Descriptive Statistics (N = 9,960)

Variable	Unit	Median	Mean	St. Dev.	Min	Max
Sale Price	$	395,000	500,643.10	469,001.30	47,000	15,000,000
Days on Market	day	14	35.51	54.82	0	1,224
Floor Area	ft^2	2,066.5	2,466.46	1,494.75	576	34,688
Parcel Size	ft^2	12,237.23	16,411.62	17,318.20	953.80	751,608.50
Bed	-	4	3.70	1.00	0	9
Full Bath	-	2	2.56	1.12	0	9
Half Bath	-	0	0.46	0.59	0	5
Pool	dummy	0	0.06	0.23	0	1
Fireplace	-	1	0.97	0.96	0	10
Multi-story	dummy	1	0.59	0.49	0	1
Age	year	55	50.42	28.07	-1	134
Inner City	dummy	0	0.17	0.38	0	1
Inner-ring Suburb	dummy	1	0.52	0.50	0	1
Outer-ring Suburb	dummy	0	0.31	0.46	0	1
Freeway Exit Dist	mile	1.62	1.88	1.25	0.01	8.55
Freeway Adjacency	dummy	0	0.11	0.31	0	1
Subway Station Dist	mile	2.88	3.27	2.07	0.06	10.99
Subway Adjacency	dummy	0	0.05	0.22	0	1
Median HH Income	$1000	72.54	81.30	44.11	12.48	208.75
Pop Density	persons/mi^2	448.43	528.94	312.35	38.15	3,234.54
Emp Density	persons/mi^2	77.63	228.88	582.85	0.00	8,528.37
Walk Score	-	28	31.08	22.36	0	96
School Quality	-	74.50	73.90	11.38	37.93	96.97

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