# The Impact of Close Proximity to Metrorail Stations on Property Values during COVID-19 in Miami-Dade County

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**Abstract**

This paper examines the impact of proximity to Metrorail transit stations on property values in Miami-Dade County during the COVID-19 pandemic. Utilizing a difference-in-differences methodology, the analysis compares property values within one-third mile of a Metrorail station to those between one-third and one mile, using data from 2017 to 2021. Results indicate a 12.2% decrease in property values within one-third mile of a station post-COVID-19, with a 3.9% decrease up to one mile, both significant at the 10% level. The negative effects are more pronounced in Democrat-leaning, high-density, high-income, and older neighborhoods. These findings suggest that the pandemic has significantly altered households' valuation of urban amenities, emphasizing the need for targeted policy interventions to support affected communities and enhance urban resilience.

## 3.1 Introduction

There is a vast literature that examines how access to mass transit impacts the housing market (Gibbons & Machin, 2005), household sorting (Voith, 1991), land use (Cervero, 1994), industrial concentration (Billings & Johnson, 2012), and agglomeration economies (Ahlfeldt & Feddersen, 2018). At the same time, there is growing evidence that the COVID-19 pandemic shifted residential and commercial demand from dense urban centers to suburban and rural areas for reasons related to the growing use of remote work (Dingel & Neiman, 2020). The authors show remote work during COVID-19 made rural areas more attractive due to a lower cost of living. This raises questions concerning the extent to which households have altered their valuation of urban amenities like mass transit systems, which are largely situated in urban cores of major cities.

Theoretical foundations, such as the monocentric city model proposed by Alonso (1964) and Mills (1972), suggest that residential location choices are influenced by a trade-off between commuting costs and housing consumption. This model predicts a negative relationship between housing prices and distance from employment centers, known as the bid rent curve. Empirical studies have shown that investments in rapid transit systems can flatten the bid rent gradient and reduce the housing price gap between urban and rural areas (Gatzlaff & Smith, 1993; Landis et al., 1995; McDonald & Osuji, 1995; Bowes & Ihlanfeldt, 2001; McMillen & McDonald, 2004). Increased accessibility from new transit investments is capitalized into higher property values (Edel & Sclar, 1974; Hilber & Mayer, 2009; Diao et al., 2017). Research consistently finds positive capitalization effects of proximity to transit stations on housing values (Gibbons & Machin, 2005; Hess & Almeida, 2007; Diao & Ferreira, 2010), though some studies report mixed or negative effects due to noise and crime (Bowes & Ihlanfeldt, 2001). Meta-analyses indicate property values rise by approximately 2.3% for every 250 meters closer to a railway station (Debrezion et al., 2007).

The literature on COVID-19's impact on property prices remains limited. Some studies suggest no adverse effects on U.S. property prices (Zhao, 2020) and significant rebounds in developed countries (Yiu, 2021), while others report varied impacts across different regions and property characteristics (Yang & Zhou, 2022; Tomal & Marona, 2021; Oyedeji, 2020). Gupta et al. (2021) notes a reduced price differential between city centers and outskirts, driven by remote work trends. Studies using difference-in-differences models confirm lower prices in areas with high COVID-19 infection rates, though these effects are short-lived (Liu & Tang, 2021; Qian et al., 2021). Additionally, gated communities in China have seen property value increases due to heightened security measures during the pandemic (Li et al., 2021).

This paper contributes to the existing literature by investigating the effect of proximity to Miami Metrorail transit stations on property values in Miami-Dade County in the aftermath of the COVID-19 pandemic. The Miami Metrorail system, established in 1984 and operated by Miami-Dade Transit, is Florida's only rapid transit system. Designed to alleviate traffic congestion and enhance connectivity across Miami-Dade County, the Metrorail spans 25 miles with 23 stations, including a significant stop at Miami International Airport (Miami-Dade County, 2011; Chardy, 2012). The pandemic led to a severe decline in Metrorail ridership, though recent data shows a recovery, with the first quarter of 2024 recording nearly 3.78 million riders (American Public Transportation Association, 2024). Figure 1 shows a map of the Metrorail system displaying each of the 23 transit locations.

Employing a difference-in-differences methodology, I analyze single-family property values from 2017 to 2021, comparing properties within one-third mile of a Metrorail station to those between one-third and one mile from a station. Data from the Florida Department of Revenue and the Miami-Dade County Property Appraiser provides a robust set of controls, including property characteristics such as the number of bedrooms, bathrooms, and square footage. Additional data on COVID-19 cases by zip code is sourced from the Florida Department of Health, and census block group data on population density, income, and age is obtained from the American Community Survey. Election data from the Harvard Dataverse repository offers insights into political heterogeneity (Bryan, 2022).

My findings indicate that housing prices within one-third mile of a Metrorail transit station decreased by 12.2% post-COVID-19, significant at the 10% level. This decline persists up to one mile, with a 3.9% decrease in property values, also significant at the 10% level. The effect is more pronounced in areas with a higher share of Democrat voters, with no significant effect observed in predominantly Republican neighborhoods. Additionally, property values are lower in census blocks with above-median population density, income, and age demographics.

### 3.2 Data

My dataset comes from several sources in Miami-Dade County over the period January 2017- May 2021. My sales data comes from the Florida Department of Revenue (FDOR). Data is merged this with the Miami-Dade Property Appraiser to obtain a more extensive set of controls such as bedrooms, baths, square feet, etc. Observations are restricted to qualified arm's length transactions and drop prices in the 1st and 99th percentile of my distribution. Prices are deflated to January of 2017. I geocode addresses for each property and Metrorail transit station using Google API and calculate the distance to each transit station. Following Diao et al. (2018), I classify treated single-family households as those within 1/3 miles of a transit station and control households as those between 1/3 miles and 1 mile. Following Linden & Rockoff (2008), observations from outside the Metrorail transit station area are included to increase the statistical power of my sample. As a sensitivity check, observations are restricted in Table 3.3 column 4 to only those within 1 mile of transit rail stations to check the robustness of my main result.

My second main source of data comes from the Florida Department of Health, which provides daily COVID-19 cases by zip code starting in April of 2020 and ending at the end of May of 2021. Furthermore, supplemental data from the American Community Survey is used to obtain data on income, age, and population density for census block groups. Finally, data is used from the Harvard Dataverse repository, where Bryan (2022) provides 2020 United States election results by census block groups. Table 3.1 provides summary statistics for my dataset. In total, my sample contains 68,571 single- family homes sold within the time frame of my study. Furthermore, there are a total of 12,294 single-family homes sold within 1 mile of a transit Metrorail station.

## 3.3 Methodology

To identify the causal impact of mass transit access on nearby property values during the COVID-19 pandemic, I use a difference-in-differences methodology to estimate housing prices pre and post pandemic with a treatment group of single-family households within a radius of 1/3 miles and a control group of single-family households between 1/3 miles to 1 mile of a Metrorail transit station. Bartik (1987) highlights a key identification challenge in estimating hedonic price functions for local (dis)amenities: the potential correlation between variations in local (dis)amenities and unobserved confounders. To address this omitted variables problem, researchers often examine short-run changes in property values resulting from a plausibly exogenous change in local (dis)amenities (Linden & Rockoff, 2008; Diao et al., 2018).

Following this approach, the current study compares the value of home sales before and after the pandemic within very small areas where homes are more homogeneous than they would be in typical aggregated comparisons. One of the key assumptions in my estimation strategy is the similarity between properties sold between my treatment and control group. If homes sold within 1/3 miles of a transit station are fundamentally different than homes sold up to a mile of a transit station, this would bias my estimates. Therefore, I first conduct balance tests using a cross-sectional estimator to provide evidence for the similarity between these properties in the period before COVID-19 occurred. Given the similarity of these geographic areas, I then use a difference- in-differences estimator—in which homes sold within 1/3 to 1 mile from a transit station are used as controls for homes sold within 1/3 miles of a transit station.

The cross-sectional difference estimator takes the form seen in Equation 3.1,

$$log(P_{ijt}) = \alpha_{jt} + \beta_1 Treated_{ijt} + \varepsilon_{ijt} \tag{3.1}$$

where $P_{ijt}$ is the sales price of home $i$ in census block $j$ at time $t$, $\alpha_{jt}$ is a block year specific fixed effect, $Treatedt_{ijt}$ is an indicator variable equal to 1 if a home is sold within 1/3 miles of a Metrorail transit station in the pre-period, and $\varepsilon_{ijt}$ is a random error term that allows for year specific correlation in prices by transit station area. This specification restricts observations merely to those within the transit station area of 1 mile. To examine variation in housing characteristics other than log sale price, I substitute those characteristics for log sale price as the dependent variable.

The difference-in-differences specification now allows observations from outside the transit station area and takes the form seen in Equation 3.2,

$$log(P_{ijt}) = \alpha_{jt} + H'_{ijt}\gamma + (\beta_1 Treated_{ijt} + \beta_2 Control_{ijt}) + (\Lambda_1 Treated_{ijt} + \Lambda_2 Control_{ijt}) * Post_{it} + \varepsilon_{ijt} \quad (3.2)$$

where $\alpha_{jt}$ is a block-year fixed effect and $H'$ is a vector of control variables for each household. These control variables include property characteristics and the monthly covid case rate per 100,000 by zip code for each household. Distance- based dummy variables are included ($Treated_{ijt}$ and $Control_{ijt}$) to account for price differences in properties in closer proximity to a transit rail station. Finally, I interact my spatial dummy variables with an indicator variable equal to one if the sale took place after the arrival of COVID-19 ($Post_{it}$). Thus, the counterfactual change in price for homes sold close to a transit rail station (i.e., $\Lambda_1$) can be estimated using homes sold just slightly further away (i.e., $\Lambda_2$).

## 3.4 Empirical Results

### 3.4.1 Impact of COVID-19 on Properties Values Near Metrorail Stations

Estimates are first provided from Equation 3.2 for balance tests that check for any pre-existing differences between the treatment and control group. This can be seen in Table 3.2. Findings indicate no statistically significant differences between properties in the treatment and control group for major housing characteristics. Table 3.3 presents the main results of the difference-in-differences analysis examining the impact of COVID-19 on property values near Metrorail transit stations in Miami-Dade County. Column 1 shows the baseline effect of being within 1/3 miles of a transit station on log sale prices before the COVID-19 pandemic. The coefficient is positive but not statistically significant, suggesting no significant price premium for properties near transit stations in the pre-pandemic period. Though surprising, this is supported by past research on the Miami Metrorail system that show property values in Miami-Dade county nearby a rail transit station were at most weakly impacted by the announcement of a new rail system (Gatzlaff & Smith, 1993). Columns 3 introduces the difference-in-differences specification, interacting the proximity to transit stations with a post-COVID-19 indicator. The results show that properties within 1/3 miles of a transit station experienced a 12.2% decrease in sale prices post-COVID-19, significant at the 10% level.

Furthermore, my findings show that properties between 1/3 miles and 1 mile of a transit station also experienced a decrease in sale prices post-COVID-19, albeit smaller at 3.9% and significant at the 10% level. This suggests that the negative impact of the pandemic on property values extends beyond the immediate vicinity of transit stations. Overall, these findings provide evidence that the COVID-19 pandemic has had a significant negative impact on property values near Metrorail transit stations in Miami-Dade County, with the effect being more pronounced for properties in close proximity to transit stations.

**3.4.2 Heterogeneous Impact of Results**

To further investigate the heterogeneous impact of COVID-19 on property values near Metrorail transit stations, I examine the differential effects across neighborhoods with varying population density, age, political affiliation, and income levels. Tables 3.4 to 3.7 present the results of these analyses. Table 3.4 and Table 3.5 investigate the heterogeneous impact by political affiliation, using the share of Democrat and Republican voters in each census block group based on the 2020 election results. The results indicate that the negative impact of COVID-19 on property values within 1/3 miles of a transit station is more pronounced in neighborhoods with a high share of Democrat voters (-13.9%), while the effect is not statistically significant in neighborhoods with a low share of Democrat voters or in both high and low Republican neighborhoods.

Table 3.6 shows the impact of COVID-19 on property values in low and high population density neighborhoods, defined as census blocks below and above the median population density in the dataset. The results indicate that the negative effect of the pandemic on property values within 1/3 miles of a transit station is more pronounced in high-density neighborhoods (-25.3%) compared to low-density neighborhoods, where the effect is not statistically significant. Similarly, the negative impact on properties within 1 mile of a transit station is only significant in high-density neighborhoods (-9.3%).

Table 3.7 presents the differential impact by neighborhood income levels, defined as census blocks below and above the median income in the dataset. The results show that the negative effect of the pandemic on property values within 1/3 miles of a transit station is significant only in high-income neighborhoods (-20.1%), while the effect is not statistically significant in low-income neighborhoods.

Finally, Table 3.8 examines the differential impact by neighborhood age, defined as census block groups below and above the median age in the dataset. The results show that the negative effect of COVID-19 on property values within 1/3 miles and 1 mile of a transit station is significant only in older neighborhoods (-18.2% and -6.9%, respectively). In younger neighborhoods, the effects are not statistically significant. These findings suggest that the impact of COVID-19 on property values near Metrorail transit stations in Miami-Dade County is pronounced in high-density, older, high-income, and Democrat-leaning neighborhoods. These results highlight the importance of considering neighborhood characteristics when assessing the impact of the pandemic on urban housing markets and the potential for targeted policy interventions to mitigate the negative effects on specific communities.

### 3.5 Sensitivity Tests

#### 3.5.1 Metrorail Transit Area by Year Fixed Effects

Implicit in my analysis is the assumption that transactions outside of the Metrorail transit area are valuable in estimating the relationship between characteristics and prices within the Metrorail area. If the two areas are fundamentally different, this will bias my results. I therefore estimate Equation 3.3 seen below,

$$log(P_{ijt}) = \alpha_{jt} + H'_{ijt}\gamma + \beta_1 Treated_{ijt} + \Lambda_1 Treated_{ijt} * Post_{it} + \varepsilon_{ijt} \tag{3.3}$$

which is a modified version of equation 3.2 that now restricts my analysis to properties sold within 1 mile of a transit station area and substitutes block-year fixed effects with transit station area by year fixed effects. Results can be found in column 4 of Table 3.3. My results are relatively consistent with column 3 suggesting that using additional data from outside the transit station area does not bias my results.

#### 3.5.2 Falsification Tests

Although my analysis shows little evidence of pre-existing differences in homes located within 1/3 miles and a 1 mile of a transit station, the decrease in value ascribed to COVID-19 could be a result of differential trends in property value growth leading to a spurious result. This possibility is checked for by running a series of falsification tests using false start dates to the COVID-19 pandemic set one and two years prior to March of 2020. Equation 3.2 is re-estimated using these false pandemic dates, and Table 3.8 presents statistically insignificant results in columns 2 and 3. Therefore, I find no evidence of a spurious effect.

### 3.6 Conclusion

This study contributes to the existing literature by examining the impact of the COVID-19 pandemic on property values near Metrorail transit stations in Miami-Dade County from 2017-2021. Using a difference-in-differences methodology and data from various sources, the results show that housing prices within 1/3 miles of a Metrorail station decreased by 12.2% post-COVID-19, with a persistent effect up to 1 mile. The effect was more pronounced in census block groups with a higher share of Democrat voters in the 2020 election and in neighborhoods above the 50th percentile of the distribution in population density, income, and age.

These findings suggest that the COVID-19 pandemic has altered households' valuation of urban amenities like mass transit systems. Democrat-leaning areas, more likely to adopt stringent public health measures and embrace remote work, saw a sharper decline in the demand for properties near transit (Allcott et al., 2020). High-density neighborhoods faced greater health risks and quality of life declines, reducing their desirability (Hamidi et al., 2020). Higher-income areas, with greater remote work opportunities, experienced more significant market corrections due to their initial price premiums (Dingel & Neiman, 2020). Older neighborhoods, with aging infrastructure and a higher proportion of elderly residents, became less attractive during the health crisis (Dowd et al., 2020).

However, several limitations warrant consideration. The study's focus on Miami-Dade County limits the generalizability of the findings to other regions with different transit systems or socioeconomic contexts. Additionally, the reliance on available data may not capture all relevant factors influencing property values, such as changes in local amenities or long-term shifts in transportation usage. Future research should explore these dimensions to provide a more comprehensive understanding of the pandemic's impact on urban housing markets. Despite these limitations, the findings underscore the importance of considering neighborhood characteristics in urban policy planning. Targeted interventions are essential to mitigate the negative impacts on specific communities, ensuring equitable recovery and enhancing resilience in the post-pandemic landscape.

In conclusion, this study highlights the significant impact of the COVID-19 pandemic on property values near Metrorail transit stations in Miami-Dade County. The pronounced declines in property values, particularly in high-density, high-income, and Democrat-leaning neighborhoods, underscore the evolving dynamics of urban housing markets. These findings emphasize the need for policymakers to consider the interplay between public health crises, urban amenities, and housing market resilience. By addressing the specific needs of affected communities, targeted interventions can help stabilize property values and foster recovery, ultimately contributing to a more equitable and resilient urban landscape in the face of future challenges.

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## 3.7 Tables

**Table 3.1:** Summary Statistics for Parcels Sold in Miami-Dade County from 2017-2021

| | All Parcels | Within 1 Mile of Transit Station |
|---|---|---|
| | Mean *(SD)* | (Mean) *(SD)* |
| Sale Price ($100,000) | 3.310 (1.831) | 3.482 (2.244) |
| Square Footage (1,000 sq. ft.) | 2.165 (0.941) | 1.915 (0.867) |
| Stories | 1.337 (0.346) | 1.057 (0.260) |
| Bedrooms | 3.158 (0.822) | 2.891 (0.878) |
| Bathrooms | 1.912 (0.751) | 1.708 (0.806) |
| Year Built | 1965.199 (19.662) | 1953.559 (18.378) |
| Effective Year Built | 1985.346 (20.133) | 1978.363 (25.906) |
| Sample size | 68,571 | 12,294 |

**Table 3.2:** Balance Tests for Pre-Pandemic Differences in Observable Housing Characteristics

| | Log Price | Square Feet | Bedrooms | Bathrooms | Year Built |
|---|---|---|---|---|---|
| Within 1/3 Miles of Transit Station | 0.024<br>(0.054) | -85.883<br>(93.314) | -0.038<br>(0.072) | -0.006<br>(0.111) | -0.048<br>(1.627) |
| Constant | 12.577** | 1928.336** | 2.888** | 1.207** | 1952.843** |

Note: This table tests for pre-pandemic differences in key observable characteristics among properties in the treatment and control group. Standard errors are in parentheses and clustered at the Transit Station Level. N = 5,026.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

**Table 3.3:** The Impact of COVID-19 on Property Values Near Metrorail Transit Stations

| | Log (Sale Price) Pre COVID-19 | Log (Sale Price), Pre and Post COVID-19 | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Within 1/3 mi of Transit Station | 0.031<br>(0.071) | -0.012<br>(0.161) | 0.101<br>(0.178) | 0.075<br>(0.057) |
| Within 1/3 mi x Post-COVID | | -0.118†<br>(0.049) | -0.122†<br>(0.064) | -0.110*<br>(0.047) |
| Within 1 mi of Transit Station | 0.049<br>(0.101) | | 0.094<br>(0.063) | |
| Within 1 mi x Post-COVID | | | -0.039†<br>(0.016) | |
| Property Characteristics | Yes | Yes | Yes | Yes |
| Block-Year Fixed Effects | Yes | Yes | Yes | No |
| Transit Area-Year Fixed Effects | No | No | No | Yes |
| Restricted to Transit Station Areas | No | No | No | Yes |
| Restricted to Pre-COVID | Yes | No | No | No |
| Standard errors clustered by… | Census Block | Census Block | Census Block | Transit Station |
| Sample size | 40,088 | 68,571 | 68,571 | 12,294 |

Note: This table estimates the impact of COVID-19 on property values near transit station areas.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

**Table 3.4:** The Differential Impact by Neighborhood Democrat Share in the US 2020 Election

| | Baseline Estimate | Low Democrat Neighborhood | High Democrat Neighborhood |
|---|---|---|---|
| | (1) | (2) | (3) |
| Within 1/3 mi of Transit Station | 0.101<br>(0.178) | 0.162<br>(0.321) | 0.036<br>(0.201) |
| Within 1/3 mi x Post-COVID | -0.122†<br>(0.064) | -0.040<br>(0.155) | -0.139*<br>(0.067) |
| Within 1 mi of Transit Station | 0.094<br>(0.063) | 0.213<br>(0.123) | 0.048<br>(0.072) |
| Within 1 mi x Post-COVID | -0.039†<br>(0.016) | -0.036<br>(0.030) | -0.040<br>(0.031) |
| Property Characteristics | Yes | Yes | Yes |
| Block-Year Fixed Effects | Yes | Yes | Yes |
| Transit Area-Year Fixed Effects | No | No | No |
| Restricted to Transit Station Areas | No | No | No |
| Restricted to Pre-COVID | No | No | No |
| Sample size | 68,571 | 33,273 | 35,298 |

Note: This table estimates the impact of COVID-19 on property values near transit station areas in low and high democrat neighborhoods, which I define as census blocks above or below the median democrat share in my dataset. Standard errors are clustered at the census block level.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

**Table 3.5:** The Differential Impact by Neighborhood Republican Share in the US 2020 Election

| | Baseline Estimate | Low Republican Neighborhood | High Republican Neighborhood |
|---|---|---|---|
| | (1) | (2) | (3) |
| Within 1/3 mi of Transit Station | 0.101<br>(0.178) | 0.059<br>(0.201) | 0.142<br>(0.321) |
| Within 1/3 mi x Post-COVID | -0.122†<br>(0.064) | -0.139*<br>(0.067) | -0.041<br>(0.155) |
| Within 1 mi of Transit Station | 0.094<br>(0.063) | 0.074<br>(0.070) | 0.190<br>(0.121) |
| Within 1 mi x Post-COVID | -0.039†<br>(0.016) | -0.047<br>(0.032) | -0.032<br>(0.029) |
| Property Characteristics | Yes | Yes | Yes |
| Block-Year Fixed Effects | Yes | Yes | Yes |
| Transit Area-Year Fixed Effects | No | No | No |
| Restricted to Transit Station Areas | No | No | No |
| Restricted to Pre-COVID | No | No | No |
| Sample size | 68,571 | 35,429 | 33,142 |

Note: This table estimates the impact of COVID-19 on property values near transit station areas in low and high republican neighborhoods, which I define as census blocks above or below the median republican share in my dataset. Standard errors are clustered at the census block level.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

**Table 3.6:** The Differential Impact by Neighborhood Population Density

| | Baseline Estimate | Low Population Density Neighborhood | High Population Density Neighborhood |
|---|---|---|---|
| | (1) | (2) | (3) |
| Within 1/3 mi of Transit Station | 0.101<br>(0.178) | -0.068<br>(0.240) | 0.297<br>(0.217) |
| Within 1/3 mi x Post-COVID | -0.122†<br>(0.064) | 0.113<br>(0.115) | -0.253**<br>(0.062) |
| Within 1 mi of Transit Station | 0.094<br>(0.063) | 0.069<br>(0.090) | 0.137<br>(0.108) |
| Within 1 mi x Post-COVID | -0.039†<br>(0.016) | 0.009<br>(0.029) | -0.093<br>(0.025) |
| Property Characteristics | Yes | Yes | Yes |
| Block-Year Fixed Effects | Yes | Yes | Yes |
| Transit Area-Year Fixed Effects | No | No | No |
| Restricted to Transit Station Areas | No | No | No |
| Restricted to Pre-COVID | No | No | No |
| Sample size | 68,571 | 32,666 | 35,905 |

Note: This table estimates the impact of COVID-19 on property values near transit station areas in low and high population density neighborhoods, which I define as census blocks above or below the median population density in my dataset. Standard errors are clustered at the census block level.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

**Table 3.7:** The Differential Impact by Neighborhood Median Income

| | Baseline Estimate | Low Income Neighborhood | High Income Neighborhood |
|---|---|---|---|
| | (1) | (2) | (3) |
| Within 1/3 mi of Transit Station | 0.101<br>(0.178) | 0.071<br>(0.162) | -0.096<br>(0.210) |
| Within 1/3 mi x Post-COVID | -0.122†<br>(0.064) | 0.030<br>(0.141) | -0.201**<br>(0.067) |
| Within 1 mi of Transit Station | 0.094<br>(0.063) | 0.035<br>(0.062) | 0.025<br>(0.126) |
| Within 1 mi x Post-COVID | -0.039†<br>(0.016) | 0.001<br>(0.034) | -0.048<br>(0.029) |
| Property Characteristics | Yes | Yes | Yes |
| Block-Year Fixed Effects | Yes | Yes | Yes |
| Transit Area-Year Fixed Effects | No | No | No |
| Restricted to Transit Station Areas | No | No | No |
| Restricted to Pre-COVID | No | No | No |
| Sample size | 68,571 | 35,498 | 33,073 |

Note: This table estimates the impact of COVID-19 on property values near transit station areas in low- and high-income neighborhoods, which I define as census blocks above or below the median income in my dataset. Standard errors are clustered at the census block level.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

**Table 3.8:** The Differential Impact by Neighborhood Age

| | Baseline Estimate | Young Neighborhood | Old Neighborhood |
|---|---|---|---|
| | (1) | (2) | (3) |
| Within 1/3 mi of Transit Station | 0.101<br>(0.178) | 0.104<br>(0.240) | 0.264<br>(0.248) |
| Within 1/3 mi x Post-COVID | -0.122†<br>(0.064) | 0.056<br>(0.122) | -0.182**<br>(0.058) |
| Within 1 mi of Transit Station | 0.094<br>(0.063) | 0.211<br>(0.101) | 0.142<br>(0.115) |
| Within 1 mi x Post-COVID | -0.039†<br>(0.016) | -0.039<br>(0.029) | -0.069**<br>(0.024) |
| Property Characteristics | Yes | Yes | Yes |
| Block-Year Fixed Effects | Yes | Yes | Yes |
| Transit Area-Year Fixed Effects | No | No | No |
| Restricted to Transit Station Areas | No | No | No |
| Restricted to Pre-COVID | No | No | No |
| Sample size | 68, 571 | 33,492 | 35,079 |

Note: This table estimates the impact of COVID-19 on property values near transit station areas in young and old neighborhoods, which I define as census blocks above or below the median age in my dataset. Standard errors are clustered at the census block level.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

**Table 3.9:** Falsification Tests

| | Baseline Estimate | March 2018 | March 2019 |
|---|---|---|---|
| | (1) | (2) | (3) |
| Within 1/3 mi of Transit Station | 0.101<br>(0.178) | -0.057<br>(0.085) | -0.007<br>(0.091) |
| Within 1/3 mi x Post-COVID | -0.122†<br>(0.064) | 0.093<br>(0.085) | 0.089<br>(0.079) |
| Within 1 mi of Transit Station | 0.094<br>(0.063) | 0.097<br>(0.104) | 0.128<br>(0.102) |
| Within 1 mi x Post-COVID | -0.039†<br>(0.016) | 0.053<br>(0.032) | 0.005<br>(0.029) |
| Property Characteristics | Yes | Yes | Yes |
| Block-Year Fixed Effects | Yes | Yes | Yes |
| Transit Area-Year Fixed Effects | No | No | No |
| Restricted to Transit Station Areas | No | No | No |
| Restricted to Pre-COVID | No | No | No |
| Sample size | 68, 571 | 40,088 | 40,088 |

Note: This table estimates falsification tests by running regressions as if COVID-19 appeared in March 2018 or March 2019. I restrict my dataset to the pre-pandemic period. Standard errors are clustered at the census block level. ** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

## 3.8 Figures


**Figure 3.1:** Map of Miami-Dade Transit Metrorail System

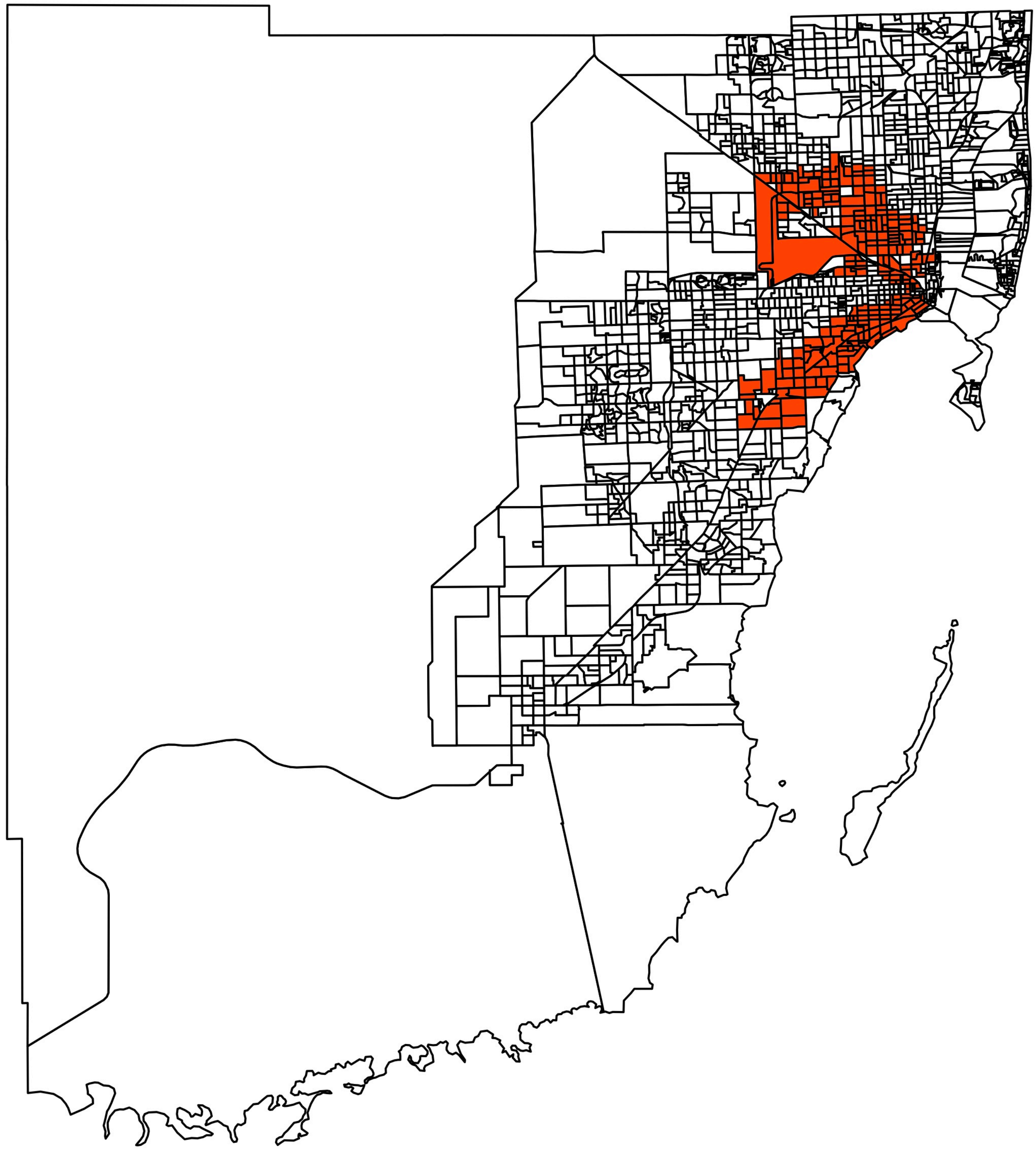

**Figure 3.2:** Map of Census Block Groups Where at Least One Property Was Sold Within 1 Mile

Note: This is a map of the census block groups in Miami-Dade County in which at least one property was sold within 1 mile of a Metrorail transit station.