The Heterogeneous Impact of a Homicide on Nearby Property Values Across Demographic Characteristics

Preston Monk

Department of Economics

Florida State University

Tallahassee, FL. 32306-2180

Abstract

This paper investigates the heterogeneous impact of homicides on property values in Miami-Dade County from 2010 to 2018, focusing on demographic characteristics of offenders and victims using a difference-in-difference-in-differences methodology. The findings reveal a significant 4.8% decrease in property values within 0.1 miles of a homicide, with the effect dissipating beyond this distance. Importantly, the study uncovers no significant impact based on offender demographics but identifies substantial negative effects for homicides involving victims under 18. Homes near such incidents, especially those involving young white female victims, see a 16.3% reduction in value. These results highlight the critical role of demographic factors in shaping the housing market's response to crime, emphasizing the need for targeted policies to mitigate these impacts and enhance community resilience.

1.1 Introduction

Crime is a major social problem that costs the United States an estimated 2.6 Trillion dollars annually (Cohen, 2016). A majority of violent and nonviolent criminal offenses take place within a mile of the victim's place of residence (Bureau of Justice Statistics, 2022), making crime a local disamenity. The literature has established a negative relationship between such disamenities and housing prices, documenting that households "vote with their feet" in response to neighborhood conditions (Dugan, 1999; Cullen & Levitt, 1999). This study extends the existing literature on the implicit pricing of neighborhood disamenities by examining heterogeneity in the price effects of crime, specifically homicides. I postulate that not all homicides elicit the same market response, and variations may exist based on the characteristics of the individuals involved.

One of the seminal early works on this topic is Rosen (1974), who posited that the price of a house can be seen as a function of its individual attributes, each contributing a specific amount to the total price. Amenities in the literature often include access to quality schools (Black, 1999; Card & Krueger, 1992), public transportation (Gibbons & Machin, 2005), and proximity to parks (Tyrväinen & Miettinen, 2000). Disamenities discussed in the literature include crime (Aliyu et al., 2016), environmental pollution (Greenstone & Gallagher, 2008), and noise pollution (Cohen & Coughlin, 2008). These studies demonstrate that properties near amenities (disamenities) command a higher (lower) price on average because they contribute to a higher (lower) quality of life.

Violent crime, in particular, has been shown to reduce the perception of neighborhood safety (Putrik et al., 2019), possibly due to the stigma associated with these crimes. Chang & Li (2018) studied Hong Kong, where they examined the impact of the stigma of unnatural death on housing prices. They estimate that homes sold in the same unit as an unnatural death sell at a 25% discount, and these effects can last up to five years. Gourley (2019) studied the impact of the Columbine School Shooting on nearby housing prices, where they claim it is a pure stigma effect because it was perceived as a one-off event in the area. They find a decrease in prices of a little over 5% for homes closest to the school.

There is also a growing literature that documents violent crime's negative effect on both physical and mental health outcomes for neighborhood residents (Curry et al., 2008; Putrik et al., 2015; Thayer, 2017). Ang (2020) documents that exposure to police violence leads to a persistent decrease in GPA and a lower high school completion rate for inner-city students. Dugan (1999) found that an attack or victimization near one's residence increases the probability of residents moving to a different location. Furthermore, Cullen & Levitt (1999) found that residential relocation resulted from increasing crime in their study on urban flight from high-crime cities. They find a 10% increase in crime leads to a 1% decrease in population. Furthermore, Lacoe et al. (2018) show that fear of crime leads to a decrease in neighborhood investment.

A crucial aspect of this relationship is the heterogeneity in preferences among different households, which influences how they respond to crime. The literature on preference heterogeneity suggests that demographic factors, such as race, income, and age, can significantly influence how households perceive and react to neighborhood disamenities like crime (Ioannides & Zabel, 2008; Caetano, 2019). For example, Caetano (2019) shows that households with children place a higher premium on neighborhood safety and quality schools, whereas single professionals may prioritize proximity to work and urban amenities. These differences underscore the importance of considering heterogeneity in household preferences when studying the impact of crime on housing prices.

Households can respond to crime risk by electing local representatives with policies to reduce crime, or they can elect to vote with their feet (Tiebout, 1956). When households vote with their feet, local response to crime will be observed in the housing market. However, establishing robust and credible estimates of the causal relationship between crime rates and housing prices has presented substantial methodological challenges. Many of the pioneering studies on this issue used an instrumental variables strategy to control for the endogeneity of crime in a hedonic price model. Ihlanfeldt & Mayock (2010) review six of these studies[1] that use instrumental variables, and only two provide identification tests. Of the two, only Gibbons (2004) passes the overidentification test. Thus, this strategy has proven challenging because it is difficult to identify instruments that are both strongly correlated with crime and plausibly excludable from the primary home price hedonic regression.

Linden & Rockoff (2008) and a similar paper by Pope (2008) propose a different estimation strategy in their papers on the arrival of a sex offender in the neighborhood. The authors propose examining short-term property value changes in response to unexpected local amenity shifts as an effective way to identify capitalization. They focus on small areas with uniform housing to isolate these effects. A number of papers have used the methodology first proposed by Linden & Rockoff (2008) to examine an exogenous shock to neighborhood property values due to an event like the arrival of a sex offender (Linden & Rockoff, 2008; Pope, 2008), discovery of a methamphetamine laboratory (Dealy et al., 2017), a local school shooting (Gourley, 2019), or a nearby homicide (Klimova & Lee, 2014; Chang & Li, 2018). These papers found that properties closest to the disamenity experience the largest drop in property values.

[1] See Rizzo (1979), Naroff et al. (1980), Burnell (1988), Buck et al. (1993), Gibbons (2004), and Tita et al. (2006)

The radius of homes affected tends to be within 0.1 miles, and the effect dissipates with time. In the case of Pope (2008), the author had data on both the arrival and departure of sex offenders within neighborhoods. The findings revealed that the adverse effects on property values dissipated following the departure of sex offenders from the neighborhood.

The present study extends this literature by treating homicides as random local shocks and examining demographic differences in the incidents. Specifically, my research question examines how the demographics of crime victims and offenders affect the relationship between crime and housing prices. No other known studies have examined demographic characteristics of offenders and victims in relation to housing prices. Investigating this issue could have implications for economists and other stakeholders, underscoring the importance of addressing specific types of crime. This chapter uses a difference-in-difference-in-differences methodology to examine the differential impact of a homicide across demographic groups on nearby property values within a radius of 0.1 miles, 0.1-0.2 miles, and 0.2-0.3 miles within a four-year temporal window, encompassing two years prior and after the incident using data on single-family homes in Miami-Dade County over the period 2010-2018.

First, using a difference-in-differences similar to Linden & Rockoff (2008), this study finds the average impact of a homicide on properties values produces a 4.8% decrease in home values within 0.1 miles of a homicide, with effects diminishing rapidly beyond this distance. The impact is more pronounced in areas with lower pre-existing crime rates. The difference-in-difference-in-differences specification finds no statistically significant impact on housing prices post-homicide based on offender characteristics. However, a significant negative effect is observed for all homicides with victims under 18, regardless of their race or gender. This effect is most pronounced when the victim is a white female under the age of 18 years, with nearby homes (within 0.1 miles) selling for 16.3% less after such incidents. These findings suggest that crimes involving young victims, particularly young white females, may have a more substantial impact on community perception of safety and desirability, potentially due to increased media attention or heightened emotional response to such tragedies (Gourley, 2019).

1.2 Data

My dataset comes from several sources in Miami-Dade County over the period 2010-2018. My sales data comes from the Florida Department of Revenue (FDOR) property tax data files. This data was merged with data from the Miami-Dade County Property Appraiser to obtain a more extensive set of property characteristics. This includes variables like bedrooms, bathrooms, square feet, and more that are not available in the FDOR dataset. Included are single-family residential sales that are arms-length transactions, and prices are deflated to January 2010 dollars.

Property and homicide addresses were geocoded using Google Map API to find the latitude and longitude of each address. Properties kept include those within 0.3 miles of a homicide only once and properties that were never within 0.3 miles of a homicide (but in a census block that had a homicide). Census blocks excluded include those in which a property was not sold within 0.3 miles of a homicide, as census blocks in which a homicide did not occur may be fundamentally different from census blocks in which a homicide did occur. After these restrictions, Table 1.1 presents summary statistics for my entire sample and a subsample of homes sold within 0.3 miles of a homicide. In total, this dataset includes 73,082 single-family home sales and 13,012 single-family homes sold within 0.3 miles of a homicide.

My second main source of data comes from Police Incident Reports from both the Miami-Dade Police Department (MDPD) and the Miami Police Department (MPD), which give the date and location of homicides. Figure 1.1 presents a map of Miami-Dade County with locations of each homicide plotted from 2010-2018. This data was merged with the Florida Supplemental Homicide Report (FSHR) to gather demographic data on both the offender and victim in each case. Table 1.2 presents homicide summary statistics for victims and offenders. Over the period 2010-2018, the MDPD and MPD report a total of 1,504 homicide victims and 1,704 offenders. In each case, the vast majority of both victims and offenders are male and black. The average victim age is around 34 years old, and the average offender age is around 32 years old. The vast majority of homicides are committed using a firearm. This sample is restricted to only include victims and offenders who are either white or black. This leaves 1,501 victims and 1,703 offenders. The FSHR does not provide data on ethnicity. They classify individuals as White, Black, Asian, and Unknown. Given the heavy presence of Hispanics in Miami-Dade County, this is a limitation of this study.

In total, the dataset includes 1200 distinct homicide cases, 1086 of which are within 0.3 miles of a single-family home sale. Eight hundred-six homicide cases come from the MDPD, and 394 cases come from the MPD. For homes sold within 0.3 miles of a homicide, 713 come from the MDPD, and 373 come from the MPD. Finally, the MDPD and MPD Police Incident Reports were used to create other variables in my dataset, which includes the violent crime rate, property crime rate, and total crime rate by census block to examine differences in the impact of a homicide on property values by pre-period crime rates.

1.3 Methodology

In this section, I adopt the methodological framework established by Linden & Rockoff (2008), first testing for pre-period differences in homes sold near a homicide using a cross-sectional differences estimator. Subsequently, I use a difference-in-differences methodology to estimate housing prices pre- and post-homicide within a radius of 0.1 miles, 0.1 to 0.2 miles, and 0.2 to 0.3 miles. I extend this work by using a difference-in-difference-in-differences methodology to examine the heterogeneous impact across demographic characteristics.

1.3.1 Cross-Sectional Difference Estimator

One of the key assumptions in my estimation strategy is the similarity between properties sold inside the homicide area of 0.3 miles. If homes sold within 0.1 miles of a homicide are fundamentally different than homes sold between 0.1 miles and 0.3 miles, this would bias my estimates. Therefore, I first use a cross-sectional estimator similar to Linden & Rockoff (2008) to provide evidence for the similarity between these properties in the period before the homicide occurred. This specification limits observations only to those inside the homicide area in the pre-period.

The cross-sectional difference estimator can be seen in Equation 1.1,

$$log(P_{ijt}) = \alpha_t + \pi_1 D_{ijt}^{1/10} + \pi_2 D_{ijt}^{2/10} + \varepsilon_{ijt} \tag{1.1}$$

where P_{ijt} is the sales price of home *i* in census block *j* at time *t*, α_t is a year specific fixed effect, $D_{ijt}^{1/10}$ and $D_{ijt}^{2/10}$ are dummy variables equal to 1 if a home is sold within 0.1 miles and 0.1-0.2 miles of a homicide in the pre-period, and ε_{ijt} is a random error term that allows for year specific correlation in prices by homicide area. To analyze how other housing characteristics vary, those characteristics are replaced as the dependent variable for the logarithm of sale price.

1.3.2 Difference-in-Differences Estimator

To identify the average causal impact of a homicide on property values, I used a difference-in-differences methodology similar to Linden & Rockoff (2008) to estimate housing prices pre- and post-homicide within a radius of 0.1 miles, 0.1 to 0.2 miles, and 0.2 to 0.3 miles.

The only difference to the specification of Linden & Rockoff (2008) is the inclusion of a 0.2-0.3 miles dummy variable following Klimova & Lee (2014) to test whether there is an effect for slightly further distances from the homicide. I subsequently include observations outside the homicide area in order to increase sample size and power for the analysis (Linden & Rockoff, 2008).

The difference-in-differences estimator can be seen in Equation 1.2,

$$\begin{aligned} log(P_{ijt}) = \alpha_{jt} + \sum_{c=1}^{c} b_{jtc}x_{ijtc} + (\pi_1 D_{ijt}^{1/10} + \pi_2 D_{ijt}^{2/10} + \pi_3 D_{ijt}^{3/10}) \\ +(\omega_1 D_{ijt}^{1/10} + \omega_2 D_{ijt}^{2/10} + \omega_3 D_{ijt}^{3/10}) * Post_{it} + \varepsilon_{ijt} \end{aligned} \tag{1.2}$$

where α_{jt} is a block year fixed effect and x_{ijtc} is my set of c control variables. These control variables include property characteristics for each home and demographic characteristics for each homicide. Included are distance-based dummy variables ($D_{ijt}^{1/10}$, $D_{ijt}^{2/10}$, and $D_{ijt}^{3/10}$) to account for price differences in properties in closer proximity to homicide incidents. Finally, I interact the spatial dummy variables with an indicator variable equal to one if the sale took place after the homicide occurred ($Post_{it}$). This equation allows one to estimate the impact on properties in close proximity to a homicide (represented by ω1) by comparing them to properties sold at slightly greater distances (denoted by ω2 and ω3).

1.3.3 Difference-in-Difference-in-Differences Estimator

This section will examine the extent to which the demographic characteristics of a victim or offender group affect housing prices. I first classify groups into a single victim (offender) demographic, such as sex, race, or age. Therefore, Equation 1.2 was modified to include indicator variables that account for a single demographic group. This equation was run separately for homicide victims and offenders. This can be seen below in Equation 1.3,

$$
\begin{aligned}
\log(P_{ijt}) = \alpha_{jt} &+ \sum_{c=1}^{C} b_{jtc} x_{ijtc} + (\pi_1 D_{ijt}^{1/10} + \pi_2 D_{ijt}^{2/10} + \pi_3 D_{ijt}^{3/10}) \\
&+ (\omega_1 D_{ijt}^{1/10} + \omega_2 D_{ijt}^{2/10} + \omega_3 D_{ijt}^{3/10}) * Post_{it} \\
&+ (\delta_1 D_{ijt}^{1/10} + \delta_2 D_{ijt}^{2/10} + \delta_3 D_{ijt}^{3/10}) * Dem_g \\
&+ (\gamma_1 D_{ijt}^{1/10} + \gamma_2 D_{ijt}^{2/10} + \gamma_3 D_{ijt}^{3/10}) * Dem_g * Post_{it} + \varepsilon_{ijt}
\end{aligned}
\tag{1.3}
$$

where the δ's control for variation in homes that sell in close proximity to a specific homicide victim (offender) of group g. The γ's examine the impact of a particular homicide victim (offender) group on property values post-homicide. Finally, I classify homicide victims (offenders) into a group of sex *s*, race *r*, and age *a*. This can be seen in Equation 1.4 below. This equation was estimated for each victim (offender) group.

$$
\begin{aligned}
\log(P_{ijt}) = \alpha_{jt} &+ \sum_{c=1}^{-} b_{jtc} x_{ijtc} + (\pi_1 D_{ijt}^{1/10} + \pi_2 D_{ijt}^{2/10} + \pi_3 D_{ijt}^{3/10}) \\
&+ (\omega_1 D_{ijt}^{1/10} + \omega_2 D_{ijt}^{2/10} + \omega_3 D_{ijt}^{3/10}) * Post_{it} \\
&+ (\delta_1 D_{ijt}^{1/10} + \delta_2 D_{ijt}^{2/10} + \delta_3 D_{ijt}^{3/10}) * Dem_{sra} \\
&+ (\gamma_1 D_{ijt}^{1/10} + \gamma_2 D_{ijt}^{2/10} + \gamma_3 D_{ijt}^{3/10}) * Dem_{sra} * Post_{it} + \varepsilon_{ijt}
\end{aligned}
\tag{1.4}
$$

1.4 Empirical Results

1.4.1 Homogeneity of Properties within 0.3 Miles of a Homicide

Results for Equation 1.1 can be found in Table 1.3. By limiting the sample to properties sold in the pre-period within 0.3 miles of a homicide, Equation 1.1 allows me to examine whether there are statistically significant differences between properties within 0.1 miles, 0.1-0.2 miles, and 0.2-0.3 miles in the pre-period. Each variable is statistically insignificant and near zero. In column 1 of Table 1.3, we see that homes within 0.1 miles pre-homicide have a statistically insignificant point estimate of -0.021 for log price, and homes between 0.1-0.2 miles pre-homicide have a statistically insignificant point estimate of -0.01 for log price. This provides evidence that homes within 0.1 miles of a homicide, as well as homes between 0.1-0.2 miles of a homicide, were not systematically different to homes between 0.2-0.3 miles of a homicide before the homicide took place. Results for other pre-period property characteristics can be found in columns 2-5 of Table 1.3. Given insignificant differences in properties pre-homicide, I now move on to estimate the difference-in-differences specification.

1.4.2 Impact of a Homicide on Property Values

Figure 1.2 illustrates the variation in property prices with respect to distance pre- and post-homicide. If proximity to a homicide is a disamenity, one would expect to see a decrease in the prices of homes near the site of the homicide following the incident. This effect is anticipated to be more pronounced for properties closer to the location of the homicide. There is a drop in price post-homicide for homes closest to a homicide, and the drop in price stabilizes after around 0.15 miles post-homicide.

Figure 1.3 extends this analysis by illustrating price trends two years pre- and post-homicide for homes sold within 0.1 miles, 0.1-0.2 miles, and 0.2-0.3 miles of a homicide. The comparison shows relatively consistent price trends for properties in each group in the pre-period. In the post-period, there is a distinct decrease in property values for homes sold within 0.1 miles post-homicide and a slight decrease in property values for homes sold within 0.1-0.2 miles post-homicide. For homes sold within 0.1 miles post-homicide, the illustration shows prices stabilize to pre-period levels after a period of around 365 days. For homes within 0.1-0.2 miles, prices quickly stabilize. There are no changes in the pre- and post-trends for homes within 0.2-0.3 miles of a homicide. To formally test this, I now present results for the difference-in-differences specification.

My results for the difference-in-differences specification can be found in Table 1.4. I first present estimates of a modified version of equation 1.1, but this specification now includes my entire pre-period sample both inside and outside the homicide area with only sale-year fixed effects. The estimate of π_1 and π_2 from this specification measures the average difference in price between homes within 0.1 miles and 0.1-0.2 miles of a future homicide location and other properties sold within the same pre-period. The difference is approximately -54.9% and -37.8%, respectively, and demonstrates that homes sold near future homicide locations are cheaper than in other parts of Miami-Dade County. However, column 2 shows the inclusion of block-year fixed effects and property characteristics reduces this difference to statistically insignificant point estimates of -1.1% and 2.0% respectively. This result provides evidence that the systematic difference largely vanishes after the inclusion of property controls and block-year fixed effects.

Column 3 presents a similar specification to Equation 1.2, but it omits my indicator variables for homes selling within 0.2-0.3 miles of a homicide. Column 4 presents the results for a specification similar to papers like Klimova & Lee (2014) that introduces indicator dummies for homes slightly further away at 0.2-0.3 miles. Finally, column 5 presents the results for Equation 1.2 that now includes controls for homicide demographics. In each of the three columns, there is a clear statistically significant relationship that homes sold closer to a homicide sell for less. However, only homes sold within 0.1 miles post-homicide sell for a statistically significant discount. The results for $\omega 1$ in column 5 show that homes sold within 0.1 miles post-homicide sell at a discount of 4.8%. This is statistically significant at the 1% level.

1.4.2.1 Differential Impact Across Crime Areas. In this subsection, I examine the differential impact across various crime areas. First, I break down the impact of a homicide on properties sold by police jurisdiction (i.e., MDPD vs MPD). Table 1.5 presents the estimates for

Equation 1.2 restricted to a particular police jurisdiction. Findings indicate that homes sold near a homicide in the MDPD jurisdiction sell at a higher discount (-0.077) compared to homes sold near a homicide in the MPD jurisdiction (-0.044). As the MPD patrols neighborhoods with higher crime rates compared to the MDPD, this suggests that the housing market is more sensitive to a homicide with lower crime rates.

Furthermore, I consider pre-period block crime data in the two-year period before the homicide occurred from police incident reports provided by the MDPD and MPD to categorize blocks into high crime versus low crime. I specifically break blocks down by pre-period total crime, pre-period property crime, and pre-period violent crime and re-estimate Equation 1.2 with these restrictions. See Table 1.6 for these results. In each case, homes sold in blocks with lower pre-period crime receive larger discounts post- homicide. Homes sold in blocks with low pre-period violent crime receive the highest discount at 12.8%, significant at the 1% level.

1.4.3 Impact of a Homicide Across Demographic Groups

Tables 1.7 and 1.10 presents results for Equation 1.3, where I use a difference-in-difference-in-differences methodology to better understand the impact of a homicide across demographic groups. As shown in Table 1.7, female victims and victims under age 18 have a negative statistically significant impact on property values post-homicide at -0.078 and -0.065, respectively. In fact, the effect remains statistically significant up to 0.2 miles post-homicide in each case. For Table 1.10, each offender demographic has a statistically insignificant impact on property values post-homicide.

Tables 1.8 and 1.9 presents results for Equation 1.4 for male victims and female victims respectively. Results are displayed by demographic group of sex s, race r, and age a. Each victim group under 18, irrespective of sex or race, has a statistically significant negative impact on property values post-homicide. White female victims under 18 have the largest negative impacts at -16.3%, significant at the 5% level. In Tables 1.11 and 1.12, results are displayed by male and female offenders respectively by demographic group of sex *s*, race *r*, and age *a*. Each offender demographic group has a statistically insignificant effect on property values post-homicide.

1.5 Sensitivity Tests

1.5.1 Homicide Area by Year Fixed Effects

Implicit in my analysis is the assumption that transactions outside of the homicide area are valuable in estimating the relationship between characteristics and prices within the homicide area. If the two areas are fundamentally different, this will bias my results. I therefore estimate Equation 1.5, seen below,

$$\begin{aligned} log(P_{ijt}) = \alpha_{jt} + \sum_{c=1}^{c} b_{jtc}x_{ijtc} + (\pi_1 D_{ijt}^{1/10} + \pi_2 D_{ijt}^{2/10}) \\ + (\omega_1 D_{ijt}^{1/10} + \omega_2 D_{ijt}^{2/10}) * Post_{it} + \varepsilon_{ijt} \end{aligned} \tag{1.5}$$

which is a modified version of Equation 1.2 that now restricts my analysis to properties sold within 0.3 miles of a homicide area and substitutes block-year fixed effects with homicide area by year fixed effects. Results can be found in column 6 of Table 1.4. My results are relatively consistent with column 5, suggesting that using additional data from outside the homicide area does not bias my results.

1.5.2 Falsification Tests

Although my analysis shows little evidence of pre-existing differences in homes located within 0.1, 0.1-0.2, and 0.2-0.3 miles of a homicide, the decrease in value ascribed to a homicide could be a result of differential trends in property value growth leading to a spurious result. I check for this possibility by running a series of falsification tests using false homicide dates set one and two years prior to actual property transactions. I re-estimate Equation 1.2 with these false homicide dates, and Table 1.13 presents statistically insignificant results in columns 2 and 3. Therefore, there was no evidence of a spurious effect.

1.6 Conclusion

This paper uses a difference-in-difference-in-differences methodology to examine the impact of a homicide on property values across demographic groups. I have a rich sales dataset from the Florida Department of Revenue that I merged with the Miami Dade Property Appraiser for a more extensive set of property characteristics. My crime data comes from police incident reports from the Miami Dade Police Department and the Miami Police Department. Homicide case numbers from this data was then merged with the Florida Supplemental Homicide Reports (FSHR) to obtain demographic characteristics of the victim(s) and offender(s) in each homicide case.

The findings reveal that homes within 0.1 miles of a homicide on average experience a 4.8% decrease in value compared to those slightly further away, with the effect being statistically significant at the 1% level. This impact diminishes rapidly with distance, as properties located 0.1-0.2 miles from a homicide do not exhibit significant price changes. This aligns with previous studies that also document localized and short-term declines in property values following violent crimes (Klimova & Lee, 2014; Chang & Li, 2018; Gourley, 2019).

The study further reveals that the negative impact of homicides on property values is more pronounced in census blocks with lower pre-existing crime rates. This suggests that homicides are particularly disruptive in areas where violent crime is less common, likely due to the heightened sense of shock and perceived risk. This finding has important policy implications, indicating that crime prevention efforts in low-crime areas can have substantial benefits in maintaining property values and neighborhood stability.

This study, despite its comprehensive methodology, acknowledges several limitations that warrant consideration when interpreting its findings. First, the use of spatial dummies, while helpful in controlling for neighborhood-specific effects, may not fully capture the complex spatial dynamics of crime and housing markets, potentially overlooking important spillover effects or spatial heterogeneity. Furthermore, the demographic focus on only white and black victims and offenders might not fully capture the nuanced responses of diverse communities to crime, potentially limiting result generalizability. Finally, the study's exclusive focus on Miami-Dade County, while providing valuable insights into this specific urban area, may limit the applicability of findings to other regions with different socioeconomic characteristics, urban layouts, or crime patterns. Future research could benefit from more sophisticated econometric techniques, natural experiments, exploration of additional demographic dimensions, and comparative studies across diverse urban and rural settings to offer a more comprehensive and generalizable view of the crime-housing relationship.

Despite these limitations, this study contributes to the literature by demonstrating how the housing market's response to homicides varies depending on victims' demographic characteristics. Notably, homicides involving victims under 18 years old lead to significant declines in nearby property values, regardless of the victim's race or gender. This effect is most pronounced for cases involving white female victims under 18, with property values dropping by 16.3% within 0.1 miles of the homicide.

These results contribute to the broader literature on the social and economic impacts of crime, underscoring the importance of addressing violent crime not only for public safety but also for economic stability and community well-being. These findings suggest that researchers may misattribute differences in willingness to pay to variations in preferences or risk tolerance, when in fact, these differences stem from unobserved variations in the nature of the crime itself. Economists and policymakers should note the differential impacts of crime on housing markets and consider targeted interventions to mitigate these effects. Strategies to enhance neighborhood security and to support communities affected by youth violence can help preserve property values and promote social cohesion. Overall, this study provides valuable insights into the localized economic repercussions of violent crime, offering guidance for future research and informing policies aimed at fostering safer and more resilient communities.

REFERENCES

Aliyu, A. A., Muhammad, M. S., Bukar, M. G., & Singhry, I. M. (2016). Impact of crime on property values: Literature survey and research gap identification. *African Scholar Journal of Humanities and Social Science, 4*, 68-99.

Ang, D. (2021). The effects of police violence on inner-city students. *The Quarterly Journal of Economics, 136*(1), 115-168. https://doi.org/10.1093/qje/qjaa027

Bartik, T. J. (1987). The Estimation of Demand Parameters in Hedonic Price Models. *Journal of Political Economy, 95*(1), 81–88. https://doi.org/10.1086/261442

Black, S. E. (1999). Do better schools matter? Parental valuation of elementary education. *The Quarterly Journal of Economics, 114*(2), 577-599. https://doi.org/10.1162/003355399556070

Bowes, D. R., & Ihlanfeldt, K. R. (2001). Identifying the impacts of rail transit stations on residential property values. *Journal of Urban Economics, 50*(1), 1-25. https://doi.org/10.1006/juec.2001.2214

Bryan, M. (2022). U.S. Voting by Census Block Groups (Version V3) [dataset]. Harvard Dataverse. https://doi.org/10.7910/DVN/NKNWBX

Buck, A.J., Hakim, S., Spiegel, U., 1993. Endogenous crime victimization, taxes, and property values. Social Science Quarterly 74 (2), 334–348.

Bureau of Justice Statistics. (2022). Criminal Victimization, 2022. U.S. Department of Justice NCJ 307089. Washington, DC: Government Printing Office.

Burnell, J. D. (1988). Crime and racial composition in contiguous communities as negative externalities: Prejudiced household's evaluation of crime rate and segregation nearby reduces housing values and tax revenues. *American Journal of Economics and Sociology, 47*(2), 177-193. https://doi.org/10.1111/j.1536-7150.1988.tb02025.x

Caetano, G. (2019). Neighborhood sorting and the value of public school quality. *Journal of Urban Economics, 114*, 103193. https://doi.org/10.1016/j.jue.2019.103193

Card, D., & Krueger, A. B. (1992). Does school quality matter? Returns to education and the characteristics of public schools in the United States. *Journal of Political Economy, 100*(1), 1-40. https://doi.org/10.3386/w3358

Chang, Z., & Li, J. (2018). The impact of in-house unnatural death on property values: Evidence from Hong Kong. *Regional Science and Urban Economics, 73*, 112-126. https://doi.org/10.1016/j.regsciurbeco.2018.08.003

Cohen, J. P., & Coughlin, C. C. (2008). Spatial hedonic models of airport noise, proximity, and housing prices. *Journal of Regional Science, 48*(5), 859-878. https://doi.org/10.2139/ssrn.898635

Cohen, M. A. (2016). The cost of crime and benefit-cost analysis of criminal justice policy: Understanding and improving upon the state-of-the-art. *Journal of Criminal Justice, 45*, 14-23. https://doi.org/10.2139/ssrn.2832944

Cullen, J., & Levitt, S. (1999). Crime, urban flight, and consequences for cities. *Review of Economics and Statistics, 81*(2), 159-169. https://doi.org/10.3386/w5737

Curry, A., Latkin, C., & Davey-Rothwell, M. (2008). Pathways to depression: The impact of neighborhood violent crime on inner-city residents in Baltimore, Maryland, USA. *Social Science & Medicine, 67*(1), 23-30. https://doi.org/10.1016/j.socscimed.2008.03.007

Dealy, B. C., Horn, B. P., & Berrens, R. P. (2017). The impact of clandestine methamphetamine labs on property values: Discovery, decontamination and stigma. *Journal of Urban Economics, 99*, 161-172. https://doi.org/10.1016/j.jue.2017.03.002

Dugan, L. (1999). The effect of criminal victimization on a household's moving decision. *Criminology, 37*(4), 903-930. https://doi.org/10.1111/j.1745-9125.1999.tb00509.x

Gibbons, S. (2004). The Costs of Urban Property Crime. *The Economic Journal*, *114*(499), F441–F463. https://doi.org/10.1111/j.1468-0297.2004.00254.x

Goodstein, R., & Lee, Y. Y. (2010). Do Foreclosures Increase Crime? SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1670842

Gourley, P. (2019). Social stigma and asset value. *Southern Economic Journal, 85*(3), 919-938. https://doi.org/10.1002/soej.12315

Greenstone, M., & Gallagher, J. (2008). Does hazardous waste matter? Evidence from the housing market and the superfund program. *The Quarterly Journal of Economics, 123*(3), 951-1003. https://doi.org/10.2139/ssrn.840207

Hilber, C. A. L., & Mayer, C. J. (2009). Why do households without children support local public schools? Linking house price capitalization to school spending. *Journal of Urban Economics, 65*(1), 74-90. https://doi.org/10.1016/j.jue.2008.09.001

Ihlanfeldt, K., & Mayock, T. (2010). Panel data estimates of the effects of different types of crime on housing prices. *Regional Science and Urban Economics, 40*(2-3), 161-172. https://doi.org/10.1016/j.regsciurbeco.2010.02.005

Klimova, A., & Lee, A. D. (2014). Does a nearby murder affect housing prices and rents? The case of Sydney. *Economic Record, 90*, 16-40. https://doi.org/10.1111/1475-4932.12118

Kohlhase, J. E. (1991). The impact of toxic waste sites on housing values. *Journal of Urban Economics, 30*(1), 1-26. https://doi.org/10.1016/0094-1190(91)90042-6

Lacoe, J., Bostic, R. W., & Acolin, A. (2018). Crime and private investment in urban neighborhoods. *Journal of Urban Economics, 108*, 154-169. https://doi.org/10.1016/j.jue.2018.11.001

Linden, L., & Rockoff, J. E. (2008). Estimates of the impact of crime risk on property values from Megan's laws. *American Economic Review, 98*(3), 1103-1127. https://doi.org/10.1257/aer.98.3.1103

Naroff, J. L., Hellman, D., & Skinner, D. (1980). Estimates of the impact of crime on property values. *Growth and Change, 11*(4), 24-30. https://doi.org/10.1111/j.1468-2257.1980.tb00878.x

Pope, J. C. (2008). Fear of crime and housing prices: Household reactions to sex offender registries. *Journal of Urban Economics, 64*(3), 601-614. https://doi.org/10.1016/j.jue.2008.07.001

Putrik, P., van Amelsvoort, L., De Vries, N. K., Mujakovic, S., Kunst, A. E., van Oers, H., ... & Kant, I. (2015). Neighborhood environment is associated with overweight and obesity, particularly in older residents: Results from cross-sectional study in Dutch municipality. *Journal of Urban Health, 92*, 1038-1051. https://doi.org/10.1007/s11524-015-9991-y

Putrik, P., Van Amelsvoort, L., Mujakovic, S., & Kunst, A. E. (2019). Assessing the role of criminality in neighborhood safety feelings and self-reported health: Results from a cross-sectional study in a Dutch municipality. *BMC Public Health, 19*, 1-12. https://doi.org/10.1186/s12889-019-7197-z

Rizzo, M. J. (1979). The effect of crime on residential rents and property values. *The American Economist, 23*(1), 16-21. https://doi.org/10.1177/056943457902300103

Rosen, S. (1974). Hedonic prices and implicit markets: Product differentiation in pure competition. *Journal of Political Economy, 82*(1), 34-55. https://doi.org/10.1086/260169

Thayer, Z. M. (2017). Dark shadow of the long white cloud: Neighborhood safety is associated with self-rated health and cortisol during pregnancy in Auckland, Aotearoa/New Zealand. *SSM-Population Health, 3*, 75-80. https://doi.org/10.1016/j.ssmph.2016.11.004

Tiebout, C. M. (1956). A Pure Theory of Local Expenditures. Journal of Political Economy, 64(5), 416–424. http://www.jstor.org/stable/1826343

Tita, G. E., Petras, T. L., & Greenbaum, R. T. (2006). Crime and residential choice: A neighborhood level analysis of the impact of crime on housing prices. *Journal of Quantitative Criminology, 22*, 299–317. https://doi.org/10.1007/s10940-006-9013-z

Tyrväinen, L., & Miettinen, A. (2000). Property prices and urban forest amenities. *Journal of Environmental Economics and Management, 39*(2), 205-223. https://doi.org/10.1006/jeem.1999.1097

1.7 Tables

Table 1.1: Characteristics of Parcels Sold in Miami-Dade County, 2010-2018

	All Parcels	Within 1/3 Mile of Homicide
	Mean *(SD)*	Mean *(SD)*
Sale price ($100,000)	3.545 (2.168)	2.420 (1.799)
Square footage (1,000 sq ft)	2.378 (1.134)	1.854 (0.706)
Stories	1.109 (0.312)	1.059 (0.236)
Bedrooms	3.268 (0.817)	2.993 (0.739)
Bathrooms	2.075 (0.877)	1.737 (0.666)
Half-Baths	0.099 (0.298)	0.054 (0.227)
Year Built	1967.122 (21.113)	1962.078 (21.474)
Effective Year Built	1981.511 (20.133)	1978.363 (22.415)
Quality rating (1 to 5)	3.247 (1.210)	2.583 (1.159)
Sample Size	73,082	13,012

Table 1.2: Homicide Demographic Characteristics

	(1)	(2)
	Count	Percent
Victims		
Male	1,265	84.11%
Female	239	15.89%
White	528	35.11%
Black	973	64.69%
Asian	3	0.20%
Average Age	34	--
Offenders		
Male	1,079	63.32%
Female	76	4.46%
Unknown Sex	549	32.22%
White	447	26.23%
Black	676	39.67%
Asian	1	0.06%
Unknown Race	580	34.04%
Average Age	32	51.88%
Unknown Age	820	48.12%
Weapons		
Firearm	1,155	72.92%
Stabbing	131	8.27%
Strangulation	46	2.90%
Blunt Object	23	1.45%
Unknown	229	14.46%

Table 1.3: Pre-Homicide Differences in Homes Sold Near a Homicide

	Log Price	Sq. Feet	Bedrooms	Bathrooms	Year Built
Within 0.1 miles of Homicide	-0.021	-12.937	0.007	-0.006	-1.196
	(0.019)	(31.913)	(0.043)	(0.037)	(0.939)
Within 0.2 miles of Homicide	-0.010	-19.657	-0.019	-0.019	-0.503
	(0.013)	(23.900)	(0.031)	(0.027)	(0.593)
Constant	12.492**	1,835.678**	2.998**	1.753**	1963.158**
	(0.008)	(10.055)	(0.018)	(0.012)	(0.347)
R^2	0.053	0.053	0.024	0.035	0.025

Note: Pre-homicide refers to the two-year period before the homicide occurred. Standard errors are in parentheses and clustered at the Homicide Area Level. *N*= 6,555.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

Table 1.4: Impact of a Homicide on Nearby Property Values

	Log (Sale Price) Pre-Homicide		Log (Sale Price), Pre- and Post-Homicide			
	(1)	(2)	(3)	(4)	(5)	(6)
Within 0.1 mi of Homicide	-0.549** (0.018)	-0.011 (0.010)	-0.025† (0.013)	-0.033* (0.013)	-0.034* (0.014)	-0.021† (0.012)
Within 0.1 mi x Post-Homicide			-0.055** (0.015)	-0.053** (0.015)	-0.048** (0.016)	-0.064** (0.015)
Within 0.2 mi of Homicide	-0.378** (0.014)	0.020 (0.016)	-0.022** (0.007)	-0.029** (0.008)	-0.031** (0.007)	-0.014 (0.009)
Within 0.2 mi * Post-Homicide			0.014 (0.008)	0.013 (0.009)	0.015 (0.010)	0.006 (0.011)
Within 0.3 mi of Homicide				0.024** (0.007)	-0.029** (0.009)	
Within 0.3 mi * Post-Homicide				0.011 (0.008)	0.016 (0.011)	
Property Characteristics	No	Yes	Yes	Yes	Yes	Yes
Homicide Characteristics	No	No	No	No	Yes	Yes
Year Fixed Effects	Yes	No	No	No	No	No
Census Block-Year Fixed Effects	No	Yes	Yes	Yes	Yes	No
Homicide Area-Year Fixed Effects	No	No	No	No	No	Yes
Restricted to Homicide Areas	No	No	No	No	No	Yes
2 Years Pre- and Post-Arrival	No	No	Yes	Yes	Yes	Yes
Sample size	36,839	36,839	73,082	73,082	73,082	13,082

Note: Pre-homicide (post-homicide) refers to the two-year period before (after) the homicide occurred. Standard errors in parentheses. 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 1.5: Impact of a Homicide on Property Values by Police Jurisdiction

	Baseline Estimate	Miami- Dade Police Department	Miami Police Department
	(1)	(2)	(3)
Within 0.1 mi of Homicide	-0.034* (0.014)	-0.031* (0.014)	-0.065* (0.027)
Within 0.1 mi x Post-Homicide	-0.048* (0.016)	-0.077* (0.038)	-0.044** (0.017)
Within 0.2 mi of Homicide	-0.031** (0.007)	-0.028** (0.009)	-0.026 (0.045)
Within 0.2 mi * Post-Homicide	0.015 (0.010)	0.007 (0.010)	0.041 (0.028)
Within 0.3 mi of Homicide	-0.029** (0.009)	-0.025** (0.008)	-0.022 (0.028)
Within 0.3 mi * Post-Homicide	0.016 (0.011)	0.008 (0.009)	0.057 (0.035)
Property Characteristics	Yes	Yes	Yes
Homicide Characteristics	Yes	Yes	Yes
Census Block-Year Fixed Effects	Yes	Yes	Yes
Homicide Area-Year Fixed Effects	No	No	No
Restricted to Homicide Areas	No	No	No
Sample size	73,082	48,587	24,495

Note: Columns (2) and (3) refer to homes that match to a homicide occurring in the jurisdiction of the Miami-Dade Police Department or Miami Police Department, respectively. 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 1.6: Impact of a Homicide on Property Values by Pre-Period Crime

	Pre-Period Total Crime		Pre-Period Property Crime		Pre-Period Violent Crime	
	(1a) Low	(1b) High	(2a) Low	(2b) High	(3a) Low	(3b) High
Within 0.1 mi of Homicide	0.039 (0.038)	-0.030† (0.016)	0.026 (0.031)	-0.037 (0.016)	-0.003 (0.028)	-0.029** (0.008)
Within 0.1 mi x Post-Homicide	-0.090** (0.030)	-0.053** (0.018)	-0.118** (0.036)	-0.044* (0.018)	-0.128** (0.043)	-0.046* (0.019)
Within 0.2 mi of Homicide	0.013 (0.022)	-0.029** (0.009)	-0.018 (0.021)	-0.027* (0.011)	-0.009 (0.020)	-0.028* (0.010)
Within 0.2 mi * Post-Homicide	0.013 (0.026)	0.015 (0.011)	-0.007 (0.023)	0.013 (0.012)	0.026 (0.021)	0.010 (0.011)
Within 0.3 mi of Homicide	-0.037** (0.014)	-0.026* (0.009)	-0.033* (0.014)	-0.029** (0.010)	-0.016 (0.021)	-0.017 (0.016)
Within 0.3 mi * Post-Homicide	0.015 (0.016)	0.026 (0.019)	-0.017 (0.016)	0.024 (0.017)	0.013 (0.027)	0.008 (0.009)
Property Characteristics	No	Yes	Yes	Yes	Yes	Yes
Homicide Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Census Block -Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Homicide Area-Year Fixed Effects	No	No	No	No	No	No
Restricted to Homicide Areas	No	No	No	No	No	No
Sample size	27,515	45,567	27,764	45,318	28,173	44,909

Note: Pre-period crime refers to the two-year period crime level before the homicide occurred. Standard errors in parentheses. Property crime refers to burglary, larceny, and motor vehicle theft. Violent crime refers to homicide, aggravated assault, and armed robbery. Total crime is a combination of the two. 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 1.7: Differential Impact by Victim Demographic

	Victim Sex		Victim Race		Victim Age	
	(1a) Female	(1b) Male	(2a) White	(2b) Black	(3a) Under 18	(3b) Over 18
0.1 mi * vict. dem * post	-0.078* (0.036)	0.035 (0.021)	-0.038 (0.028)	-0.038 (0.030)	-0.065** (0.024)	-0.024 (0.035)
0.2 mi * vict. dem * post	-0.054* (0.022)	0.039 (0.036)	-0.028 (0.020)	0.024 (0.020)	-0.046* (0.022)	0.034 (0.024)
0.3 mi * vict. dem * post	-0.002 (0.022)	-0.003 (0.025)	0.034 (0.030)	0.038 (0.023)	-0.034 (0.030)	0.045 (0.029)
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Homicide Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Census Block -Year fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Homicide Area-Year Fixed Effects	No	No	No	No	No	No
Restricted to Homicide Areas	No	No	No	No	No	No

Note: Vict. dem refers to the particular victim demographic in each column. Standard errors are clustered at the census block level. N = 73,082.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

Table 1.8: Differential Impact by Male Victim Demographic

	Male Victim			
	(1a) White < 18	(1b) White ≥ 18	(2a) Black < 18	(2b) Black ≥ 18
0.1 mi * r * s * a * post	-0.058** (0.022)	0.054 (0.042)	-0.112** (0.032)	-0.046 (0.029)
0.2 mi * r * s * a * post	-0.051 (0.034)	-0.013 (0.024)	0.004 (0.021)	-0.018 (0.015)
0.3 mi * r * s * a * post	0.018 (0.026)	-0.001 (0.021)	0.027 (0.019)	0.021 (0.023)
Property Characteristics	Yes	Yes	Yes	Yes
Homicide Characteristics	Yes	Yes	Yes	Yes
Census Block -Year Fixed Effects	Yes	Yes	Yes	Yes
Homicide Area-Year Fixed Effects	No	No	No	No
Restricted to Homicide Areas	No	No	No	No

Note: Each column refers to a victim consisting of race r, sex s, and age a. Standard errors are clustered at the census block level. N = 73,082.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

Table 1.9: Differential Impact by Female Victim Demographic

	Female Victim			
	(1a) White < 18	(1b) White ≥ 18	(2a) Black < 18	(2b) Black ≥ 18
0.1 mi * r * s * a * post	-0.163* (0.066)	0.050 (0.041)	-0.108* (0.049)	0.045 (0.068)
0.2 mi * r * s * a * post	-0.055 (0.048)	0.025 (0.022)	-0.083 (0.056)	0.069 (0.045)
0.3 mi * r * s * a * post	0.037 (0.037)	0.001 (0.024)	0.045 (0.079)	-0.049 (0.048)
Property Characteristics	Yes	Yes	Yes	Yes
Homicide Characteristics	Yes	Yes	Yes	Yes
Census Block -Year Fixed Effects	Yes	Yes	Yes	Yes
Homicide Area-Year Fixed Effects	No	No	No	No
Restricted to Homicide Areas	No	No	No	No

Note: Each column refers to a victim consisting of race r, sex s, and age a. Standard errors are clustered at the census block level. *N* = 73,082.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

Table 1.10: Differential Impact by Offender Demographic

	Offender Sex		Offender Race		Offender Age	
	(1a) Female	(1b) Male	(2a) White	(2b) Black	(3a) Under 18	(3b) Over 18
0.1 mi * off. dem * post	0.051	0.011	0.032	-0.020	-0.057	0.038
	(0.034)	(0.030)	(0.029)	(0.029)	(0.043)	(0.030)
0.2 mi * off. dem * post	0.004	-0.002	0.007	-0.002	-0.045	0.006
	(0.042)	(0.025)	(0.021)	(0.022)	(0.033)	(0.021)
0.3 mi * off. dem * post	0.014	-0.022	0.006	-0.013	-0.023	0.024
	(0.025)	(0.022)	(0.020)	(0.023)	(0.043)	(0.020)
Property Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Homicide Characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Census Block -Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Homicide Area-Year Fixed Effects	No	No	No	No	No	No
Restricted to Homicide Areas	No	No	No	No	No	No

Note: Off. dem refers to the particular offender demographic in each column. Standard errors are clustered at the census block level. *N* = 73,082.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

Table 1.11: Differential Impact by Male Offender Demographic

	Male Offender			
	(1a) White < 18	(1b) White ≥ 18	(2a) Black < 18	(2b) Black ≥ 18
0.1 mi * r * s * a * post	-0.073 (0.045)	0.058 (0.037)	0.056 (0.039)	-0.091 (0.057)
0.2 mi * r * s * a * post	-0.008 (0.025)	0.006 (0.021)	-0.009 (0.027)	-0.044 (0.035)
0.3 mi * r * s * a * post	0.002 (0.021)	-0.016 (0.019)	0.029 (0.024)	-0.041 (0.031)
Property Characteristics	Yes	Yes	Yes	Yes
Homicide Characteristics	Yes	Yes	Yes	Yes
Census Block -Year Fixed Effects	Yes	Yes	Yes	Yes
Homicide Area-Year Fixed Effects	No	No	No	No
Restricted to Homicide Areas	No	No	No	No

Note: Each column refers to an offender consisting of race r, sex s, and age a. Standard errors are clustered at the census block level. $N = 73{,}082$.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

Table 1.12: Differential Impact by Female Offender Demographic

	Female Offender			
	(1a) White < 18	(1b) White ≥ 18	(2a) Black < 18	(2b) Black ≥ 18
0.1 mi * r * s * a * post	-0.072 (0.047)	-0.109 (0.072)	-0.151 (0.343)	-0.116 (0.158)
0.2 mi * r * s * a * post	0.046 (0.041)	0.066 (0.103)	0.083 (0.099)	-0.018 (0.087)
0.3 mi * r * s * a * post	0.036 (0.035)	0.011 (0.072)	-0.014 (0.071)	0.012 (0.112)
Property Characteristics	Yes	Yes	Yes	Yes
Homicide Characteristics	Yes	Yes	Yes	Yes
Census Block -Year Fixed Effects	Yes	Yes	Yes	Yes
Homicide Area-Year Fixed Effects	No	No	No	No
Restricted to Homicide Areas	No	No	No	No

Note: Each column refers to an offender consisting of race r, sex s, and age a. Standard errors are clustered at the census block level. *N* = 73,082.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

Table 1.13: Falsification Tests

	Baseline Estimate	One-Year Prior Homicide Dates	Two-Year Prior Homicide Dates
	(1)	(2)	(3)
Within 0.1 mi of homicide	-0.034* (0.014)	-0.073** (0.014)	-0.096** (0.022)
Within 0.1 mi x post-homicide	-0.048* (0.016)	0.013 (0.008)	0.023 (0.024)
Within 0.2 mi of homicide	-0.031** (0.007)	-0.018* (0.007)	-0.030* (0.012)
Within 0.2 mi * post-homicide	0.015 (0.010)	-0.008 (0.016)	-0.016 (0.014)
Within 0.3 mi of homicide	-0.029** (0.009)	-0.022** (0.009)	-0.021* (0.010)
Within 0.3 mi * post-homicide	0.016 (0.011)	-0.003 (0.008)	-0.009 (0.013)
Property Characteristics	Yes	Yes	Yes
Homicide Characteristics	Yes	Yes	Yes
Census Block -Year Fixed Effects	Yes	Yes	Yes
Homicide Area-Year Fixed Effects	No	No	No
Restricted to Homicide Areas	No	No	No

Note: Standard errors are clustered at the census block level. N = 73,082.
** Significant at 1 percent level. * Significant at 5 percent level. † Significant at 10 percent level.

1.8 Figures

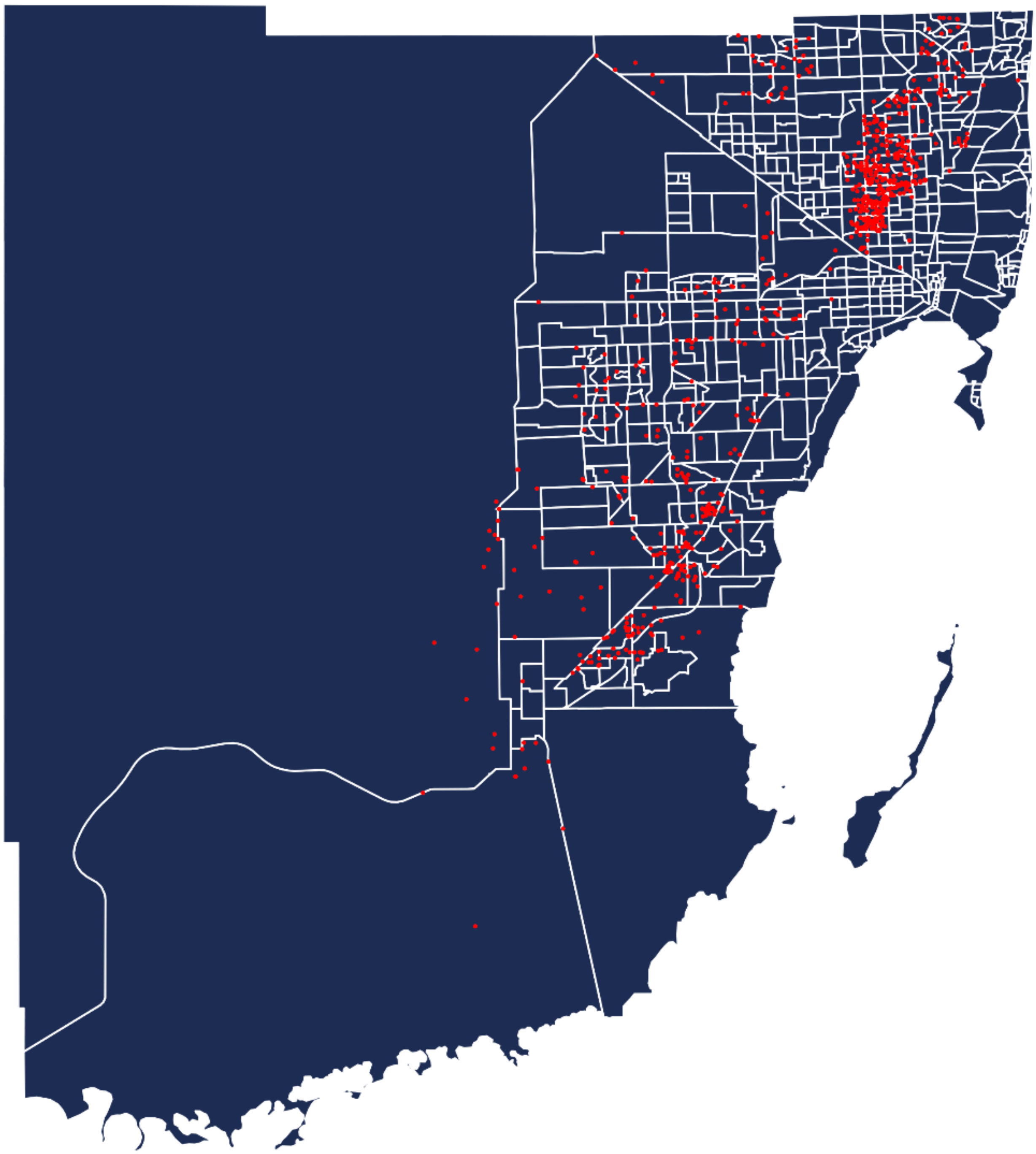

Figure 1.1: Homicide Locations for MDPD and MPD in Miami-Dade County from 2010-2018

Note: This map highlights homicide locations in red for the Miami-Dade police department and the Miami police department for the period 2010 to 2018.

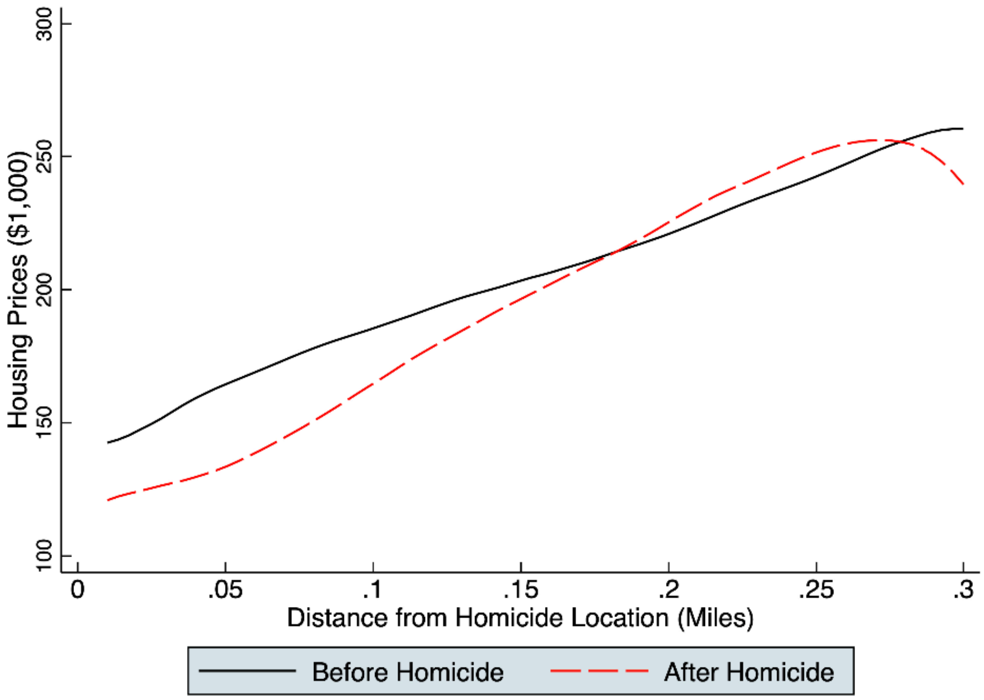

Figure 1.2: Prices Within 0.3 Miles Pre & Post Homicide

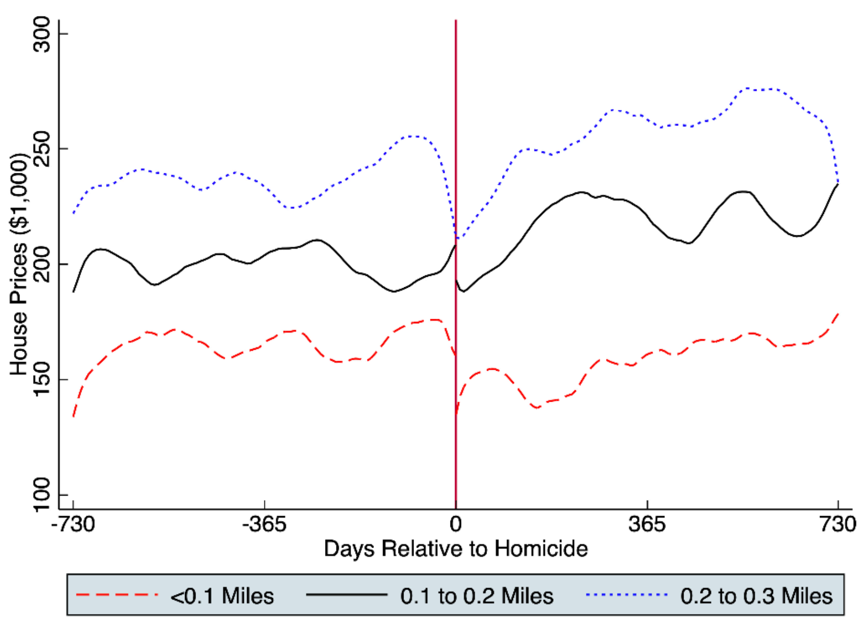

Figure 1.3: Price Trends Pre & Post Homicide