Housing Prices and Crime Perceptions: How Do Partisanship and Media Exposure Affect the Housing Market?

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Abstract

This paper examines the effects of crime perception and media depictions of crime on property prices and investigates how these effects vary across neighborhoods with different partisan compositions. I develop a theoretical framework of Bayesian updating with noisy signals and partisan weighting of information, showing how the use of realized crime, rather than perceived crime, can bias the estimated relationship. I construct a comprehensive dataset combining longitudinal ZIP-code-level housing price data with crime perception surveys, housing characteristics, media market information, ZIP-code partisan vote shares derived from precinct-level election returns, and annual counts of crime-related news reports on FOX News obtained using a machine-learning classification approach based on random forests and TF-IDF features. To strengthen causal identification, I exploit spatial discontinuities at media market boundaries. Because the limited number of survey responses provides only sparse measurements of crime perception at the ZIP-code level, I employ a Battese–Harter–Fuller small-area estimator to construct partially pooled estimates of crime perception. I then estimate hedonic price models with spatial-bundle, DMA, and time fixed effects and apply Murphy–Topel standard-error corrections to account for the generated-regressor problem. I find that higher crime perception is associated with lower neighborhood property values and that

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this effect becomes progressively stronger during the Trump and Biden administrations. I also find substantial heterogeneity across neighborhoods: Republican-leaning ZIP codes exhibit lower property values on average, while a higher Republican vote share significantly attenuates the negative relationship between crime perception and property values. Finally, I exploit geographic discontinuities at media market boundaries and use local television channel availability as an instrument for exposure to crime-related content on FOX News. I find that greater exposure to crime-related content on FOX News is positively associated with future property values.

1 Introduction

Crime is often cited as an important determinant of housing prices. A large literature, beginning with Ridker and Henning (1967a) and continuing through recent work, uses realized crime rates to explain property values. The vast majority of these studies find that increases in crime are associated with significantly lower neighborhood property values. Nevertheless, households rarely know the exact realized crime rate in their neighborhoods at the time of purchase or valuation. Instead, they are likely to rely on beliefs about crime, which may differ from the crime measures observed by researchers ex post. This distinction has motivated a related literature that focuses on crime perceptions rather than realized crime (Raya et al., 2012). Because direct victimization is relatively rare, households often form beliefs about neighborhood safety based on news coverage (**mastrorocco2025**). Consequently, news coverage can influence residential property values by shaping perceptions of crime risk. However, partisan media sources differ in how they depict crime. These differences may distort housing valuations in ways that vary systematically across groups of voters.

This paper investigates the causal effect of crime perception on property values in American neighborhoods, examines how this effect varies across neighborhoods with different partisan alignments, and studies whether exposure to crime-related coverage on FOX News affects property prices. In addition, the paper develops an extension of a Bayesian updating framework with noisy signals and group-specific information weighting to account for these mechanisms.

To address these questions, I first construct a novel dataset that combines neighborhood housing values, survey-based crime perceptions, spatially measured political alignment, and media exposure. I use ZIP-code-level data, the smallest geographic unit consistently available for the analysis, to capture the local nature of crime and housing markets. This level of geographic aggregation is important because counties often contain many neighborhoods with substantially different crime experiences and housing-market conditions. Property values are measured using the Zillow Home Value Index (ZHVI). To expand the usable sample, I supplement missing housing-value observations through a hierarchical imputation procedure. I then combine these housing data with Gallup survey measures of respondents' perceptions of crime in their neighborhoods. Because no direct measure of voting behavior is available at the ZIP-code level, I use Geographic Information System (GIS) methods to estimate ZIP-code-level electoral patterns from precinct-level election returns based on the geographic overlap between ZIP-code and precinct boundaries. These estimates are then used to construct historical measures of political alignment for each ZIP code.

I further complement these data by constructing annual measures of crime-related coverage on FOX News using textual analysis of television news transcripts. Specifically, I classify FOX News transcripts to identify crime-related segments and construct annual measures of FOX News crime-reporting intensity. These measures allow me to distinguish general FOX News viewership from exposure to crime-related content on FOX News. Consequently, the media-exposure analysis focuses not only on whether individuals watch FOX News, but also on the intensity of crime-related coverage to which they are exposed through the network.

Estimating the effect of crime perception is complicated by endogeneity concerns that would preclude a causal interpretation of the estimates if left unaddressed. To overcome this challenge, I exploit the institutional features of U.S. media markets and the spatial discontinuities at Designated Market Area (DMA) boundaries to identify a local average treatment effect. Specifically, I first isolate variation in media exposure arising from differences in the number and programming of local television stations across neighboring DMAs. I then use exogenous variation in the availability of local news stations as an instrument for FOX News viewership among residents living near DMA borders.

However, restricting the analysis to observations near DMA boundaries substantially reduces the sample size and results in limited survey observations within many ZIP codes. To address this sparsity, I employ a Battese–Harter–Fuller small-area estimator to construct partially pooled ZIP-year estimates of crime perception. This approach combines ZIP-specific information with information from the broader sample, thereby reducing estimation noise in areas with few survey respondents. Because the crime-perception measure is generated in a first-stage estimation procedure, I apply Murphy–Topel standard-error corrections in the second-stage regressions to account for the generated-regressor problem.

The empirical analysis proceeds through four main specifications. First, I estimate hedonic price equations in which future neighborhood property prices are regressed on the BHF estimate of crime perception, hedonic housing controls, spatial-bundle fixed effects, DMA fixed effects, and time fixed effects. Second, I allow the effect of crime perception to vary with ZIP-code partisan alignment by interacting crime perception with the Republican vote share at the ZIP-code level. Third, I estimate property-price appreciation specifications that focus on changes in property prices rather than property price levels. Fourth, I estimate the effect of exposure to crime-related content on FOX News on property prices using an instrumental-variables strategy based on local television station availability near DMA borders. This final specification exploits the idea that local station availability shifts exposure to FOX News while remaining unrelated to unobserved local housing-market shocks within comparable spatial bundles.
The results indicate that higher perceived crime is associated with lower future property values. This relationship is also heterogeneous across presidential administrations and neighborhood partisan composition. In the hedonic price specifications, the negative association between crime perception and property values becomes progressively stronger during the Trump and Biden administrations. In the neighborhood-partisanship specifications, Republican-leaning ZIP codes have lower property values on average, while a higher Republican vote share attenuates the negative relationship between crime perception and property values. The property-price appreciation specifications show that crime perception is also associated with subsequent changes in property prices, not only with property price levels, particularly during the Trump administration. Finally, the FOX News specifications suggest that greater exposure to crime-related content on FOX News is positively associated with future property values when FOX News exposure is instrumented using local television station availability.

1.1 Literature Review

This paper builds on and contributes to several strands of literature. First, it contributes to the literature on the effect of crime on property prices. This line of research has a long tradition in economics (Ihlanfeldt & Mayock, 2010). Most studies estimating the effect of crime on property prices find a negative and statistically significant relationship, as in Thaler (1978), Bowes and Ihlanfeldt (2001), and Gibbons (2004). However, some studies report positive effects (Case & Mayer, 1996), while others find no statistically significant relationship (Buck et al., 1993; Kain & Quigley, 1970; Ridker & Henning, 1967b). As discussed in the theoretical framework below, estimates in this literature may be biased when realized crime rates are used in place of the crime perceptions that enter households' valuation decisions.

Second, the paper contributes to the literature on the effect of crime perceptions on property values. As shown by Gibbons (2004) and MacDonald (2002), official crime statistics may understate the intensity of crime, and reporting rates can vary across space and time. Motivated by this concern, Buonanno et al. (2013) use crime perceptions as regressors in a hedonic model of property prices in Barcelona and estimate a 2SLS specification to address the endogeneity of crime perception. Related studies by Linden and Rockoff (2008) and Pope (2008) examine how information shocks associated with the arrival of sex offenders affect neighborhood housing markets in a natural-experiment setting.

This paper also builds directly on Raab (2026) and contributes to the literature on the effect of media on housing markets through crime perception. The closest related paper is Moreno-Medina (2026), which similarly studies how media depictions of crime affect property prices through changes in crime perceptions.

More broadly, the paper contributes to research on the influence of local media on policing outcomes (Mastrorocco & Ornaghi, 2025), Republican vote shares (Miho, 2024), local crime reporting (Martin & McCrain, 2019), political preferences (Martin & Yurukoglu, 2017), and voter turnout (DellaVigna & Kaplan, 2007). I extend this literature by examining how partisan crime coverage shapes crime perceptions and how those perceptions are capitalized into housing prices.

From a methodological standpoint, this paper follows Raab (2026) in applying a spatial discontinuity design to assure causal interpretation of the coefficients. It also builds on empirical strategies developed by Kaplan and Yuan (2020), Spenkuch and Toniatti (2018), and Snyder and Strömberg (2010).

2 U.S. Media Markets Overview

The empirical strategy exploits institutional features of the U.S. television market, following Raab (2026). As television became the dominant medium in the 1950s, the U.S. broadcasting system divided the country into geographically distinct media markets to organize local advertising and programming. These markets, known as Designated Market Areas (DMAs), are mutually exclusive geographic units that determine which local television stations households receive. The United States is currently divided into 210 non-overlapping DMAs (Nielsen, 2025).

DMAs differ in the composition and number of local stations available to viewers. As a result, households in different media markets face different local television environments. This institutional variation is central to the empirical design because the number of local stations can shift exposure to news programming without being directly chosen by individual households. The analysis therefore uses cross-DMA variation in local station availability as a source of plausibly exogenous variation in media exposure.

3 Main Framework

This section presents the modeling framework represented by the hedonic price function. The framework builds on the canonical model of Rosen (1974), incorporates uncertainty following Moreno-Medina (2026), and introduces partisan heterogeneity as in Raab (2026). Combining these models illustrates the mechanism through which partisan, group-specific crime-reporting bias may affect the hedonic price function and distort the marginal willingness to pay (MWTP) that would be recovered if unbiased crime information were observed.

3.1 Simple Hedonic Price Model

The standard hedonic price model was developed by Rosen (1974). In this model, when a decision maker purchases a property, utility depends on the property's embedded characteristics. An individual seeking to maximize utility therefore considers the property characteristics x, the crime rate in the neighborhood where the property is located θ, and consumption of a numeraire good z. The parameter α captures individual heterogeneity across decision makers. The decision maker solves:

$$\max_{x,z} \; u(x, \theta, z; \alpha)$$

subject to income y. The numeraire good z and the property price, which depends on property characteristics and surrounding crime, $P(x, \theta)$, satisfy the budget constraint:

$$y = z + P(x, \theta)$$

The first-order conditions imply that marginal willingness to pay for a change in crime is:

$$MWTP_\theta = \frac{\frac{\partial u}{\partial \theta}}{\frac{\partial u}{\partial z}} = \frac{\partial P(x,\theta)}{\partial \theta}.$$

3.2 Hedonic Price Model under Uncertainty

Following the framework of Moreno-Medina (2026), suppose that the decision maker does not have perfect information about crime at the time of utility maximization. The decision maker does not observe θ directly, but instead receives a signal about the state of the world, denoted by S. Rather than responding to the true crime rate, the decision maker observes the signal and forms beliefs using Bayes' rule. Perceived crime is therefore:

$$\theta_S = P(\theta = 1 \mid S) = \frac{P(S \mid \theta = 1)\, P(\theta = 1)}{P(S)}.$$

The maximization problem becomes:

$$\max_{x,z} \; E_{\theta|S}[u(x,\theta,z;\alpha)] \quad \text{s.t.} \quad y = z + P(x,\theta_S)\,.$$

where θ_S is a function of true crime θ.
Under uncertainty, the decision maker maximizes expected utility. Given the stochastic nature of crime, expected utility is:

$$E[u(x,\theta,z;\alpha)] = \theta_S u(x,1,z;\alpha) + (1-\theta_S)u(x,0,z;\alpha).$$

The first-order conditions are:

$$\frac{\partial E[u(x,\theta,z;\alpha)]}{\partial z} - \lambda = 0,$$

and

$$\frac{\partial E[u(x,\theta,z;\alpha)]}{\partial \theta_S} - \lambda \frac{\partial P(x,\theta_S)}{\partial \theta_S} = 0.$$

Replacing λ yields:

$$MWTP_{\theta_S} = \frac{\frac{\partial E[u]}{\partial \theta_S}}{\frac{\partial E[u]}{\partial z}} = \frac{\partial P(x,\theta_S)}{\partial \theta_S}.$$

3.3 Hedonic Price Model under Uncertainty with a Group-Specific Noisy Signal

I next adjust the framework to incorporate the influence of partisan media on viewers' beliefs. I do so using the signal-weighting function developed by Raab (2026).

Assume that the decision maker is Bayesian and has prior beliefs about θ. Specifically,

$$\theta \sim N(\mu_\theta, \sigma_\theta^2).$$

The decision maker then receives a signal $S = s$ and uses it to infer the underlying state θ. In the canonical signal-extraction framework,

$$S = \theta + \varepsilon,$$

where

$$\varepsilon \sim N(0, \sigma_\varepsilon^2).$$

In the present setting, however, the noise component is allowed to include a group-specific systematic component. Let $G \in \{R, D\}$ denote group membership, where R denotes a Republican voter and D denotes a Democratic voter. The observed signal can then be written as:

$$S = \theta + \varepsilon_G,$$

where

$$\varepsilon_G = \gamma_G + \eta,$$

and

$$\eta \sim N(0, \sigma_\eta^2).$$

Substituting the decomposition of the error term yields:

$$S = \theta + \gamma_G + \eta.$$

The parameter γ_G represents a group-specific fixed component embedded in the informational environment. Conceptually, this term captures systematic distortions in signal processing across groups. In the context of media consumption, it

represents the weight associated with the common partisan affiliation between the receiver of the signal and the source of the signal.
Define the composite group-specific distortion term as:

$$\gamma_G = -1(w_R B_{Rep} + w_D B_{Dem}).$$

where B_{Rep} and B_{Dem} denote partisan source-specific biases, and w_R and w_D are the decision maker's weights assigned to each partisan signal.
Using the restriction $w_R + w_D = 1$ and moving the weighted biases to the left-hand side yields:

$$w_R(S + B_R) + w_D(S + B_D).$$

This expression defines the resulting composite signal, denoted by S_G.
The conditional mean considered by the individual can be expressed as:

$$\mu_{\theta|S_G} = \beta S_G + (1 - \beta)\mu_\theta.$$

Replacing S_G gives:

$$\mu_{\theta|S_G} = \beta(S + w_R B_R + (1 - w_R)B_D) + (1 - \beta)\mu_\theta.$$

with weighting parameter

$$\beta = \frac{\sigma_\theta^2}{\sigma_\theta^2 + \sigma_\eta^2}.$$

The decision maker therefore uses two types of weights in this model. First, β determines the relative weight placed on the signal versus the prior, according to their respective noisiness. Second, the decision maker assigns different weights to each signal depending on its alignment with the partisanship of the news source. A detailed derivation of the weighting function can be found in Raab (2026).
The maximization problem becomes:

$$\max_{x,z} \; E_{\theta|S}[u(x, \theta, z; \alpha)] \quad \text{s.t.} \quad y = z + P(x, \mu_{\theta|S_G}).$$

where $\mu_{\theta|S_G}$ is a function of true crime θ.
The decision maker again maximizes expected utility, now incorporating the conditional mean generated by the double-weighting function:

$$E[u(x, \theta, z; \alpha)] = \mu_{\theta|S_G} u(x, 1, z; \alpha) + (1 - \mu_{\theta|S_G})u(x, 0, z; \alpha).$$

The first-order conditions are:

$$\frac{\partial E[u(x,\theta,z;\alpha)]}{\partial z} - \lambda = 0,$$

and

$$\frac{\partial E[u(x,\theta,z;\alpha)]}{\partial \mu_{\theta|S_G}} - \lambda \frac{\partial P(x,\mu_{\theta|S_G})}{\partial \mu_{\theta|S_G}} = 0.$$

Replacing λ yields:

$$MWTP_{\mu_{\theta|S_G}} = \frac{\frac{\partial E[u(x,\theta,z;\alpha)]}{\partial \mu_{\theta|S_G}}}{\frac{\partial E[u(x,\theta,z;\alpha)]}{\partial z}} = \frac{\partial P(x,\mu_{\theta|S_G})}{\partial \mu_{\theta|S_G}}.$$

4 Bias in the Hedonic Regression with Realized Crime

Following Moreno-Medina (2026), I characterize the potential bias that arises when the true realized crime rate is included in a hedonic price regression even though decision makers respond to perceived crime. Suppose we estimate:

$$\ln P_i = \alpha_0 + \alpha_1 \theta_i + x_i'\beta + \epsilon_i.$$

True crime statistics are only an approximation of individual beliefs at the time of hedonic valuation. Consequently, estimating the regression using realized crime can introduce bias. More specifically:

$$\alpha_1 \approx \frac{\partial P(x_i,\mu_{\theta|S_G})}{\partial \mu_{\theta|S_G}} \left[\beta\left(\frac{dS(\theta_i)}{d\theta_i} + w_R \frac{dB_R(\theta_i)}{d\theta_i} + (1-w_R)\frac{dB_D(\theta_i)}{d\theta_i}\right) + (1-\beta)\frac{d\mu_\theta}{d\theta_i}\right].$$

This expression highlights several issues for the recovery of MWTP. First, even if the decision maker places substantial weight on the prior, signal noisiness implies that there is no guarantee that $\frac{d\mu_\theta}{d\theta_i}$ equals one. The resulting estimate may therefore be biased, with the magnitude of the bias depending on this derivative. Second, if the decision maker places all weight on the composite signal, and even if the signal S perfectly represents the crime environment so that $\frac{dS(\theta_i)}{d\theta_i} = 1$, media bias can still distort the magnitude of the price response to crime. If media bias overreacts to crime, the implied price decline will be too large; conversely, if media bias underreacts to an increase in crime, the implied price decline will be too small. Third, the model shows that decision makers consciously weight partisan biases according to predetermined characteristics. Thus, the response of prices to crime fluctuations depends on the shared partisan affiliation between viewers and the news source.

5 Data and Measurement

5.1 Data Used

Crime Perception and Demographics. The main survey data come from the Gallup Poll Social Series (GPSS). Each October, Gallup asks respondents about crime, policing, criminal justice, and related issues. I use the questions measuring perceptions of neighborhood crime, together with respondent demographics and ZIP-code identifiers. Although the crime module has been fielded for a long period, ZIP-code information is available only beginning in 2008.

Neighborhood Housing Values. I measure neighborhood housing values using ZIP-code-level Zillow Home Value Index (ZHVI) data. The ZIP code is the smallest geographic unit available in the Gallup data and is therefore the most disaggregated spatial unit at which crime perceptions can be linked to local housing values. While ZIP codes are imperfect geographic units (Grubesic, 2008), they provide a substantially finer approximation of respondents' local environments than counties, especially in dense urban areas. ZHVI measures the typical home value in a region, focusing on homes between the 35th and 65th percentiles of the local value distribution.

Neighborhood Partisanship. I measure ZIP-code-level partisan affiliation using precinct-level presidential election returns and spatial boundary files. ZIP-code polygons are taken from the U.S. Census, and precinct-level election data are drawn from *The New York Times* and supplemented with data from the University of Florida Election Lab where coverage is incomplete. I assign precinct votes to ZIP codes using the proportional spatial overlap between precinct and ZIP-code polygons. This produces a ZIP-code-level measure of partisan vote shares. The detailed construction of these measures follows Raab (2026).

Spatial Structure. The spatial discontinuity design relies on Designated Market

Areas (DMAs), which determine local television media markets. I combine publicly available DMA boundary files with Census ZIP-code shapefiles to identify ZIP codes located near DMA borders. These boundary ZIP codes form the basis for comparing nearby neighborhoods that are geographically close but exposed to different local media markets. Details on DMA boundary construction, ZIP-code assignment, and distance-to-border measures follow Raab (2026).

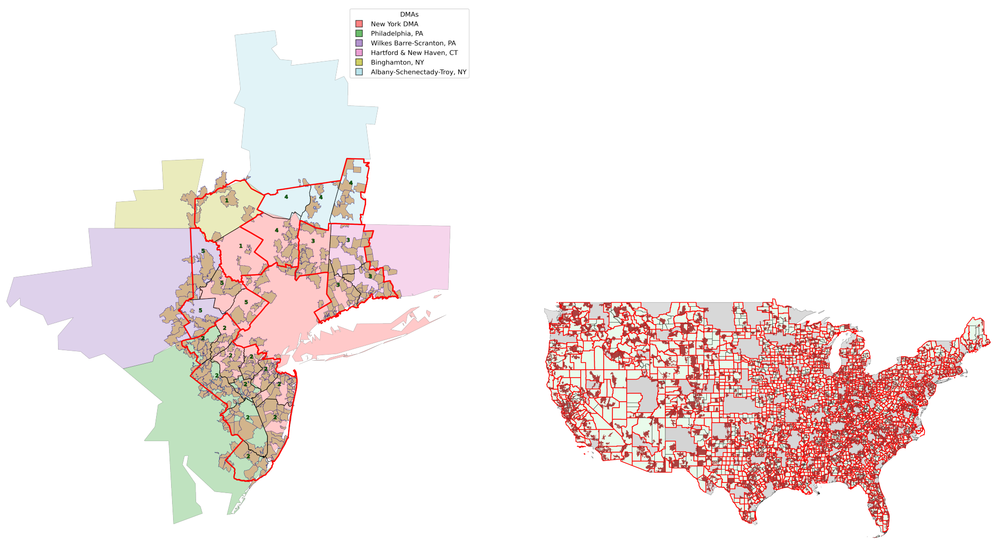
FOX News Viewership. The model predicting FOX News viewership is estimated using data from the Cooperative Election Study (CCES). The survey includes questions on FOX News viewership only in the 2020–2022 waves. Because the CCES is publicly available and contains both media-consumption measures and the individual-level covariates required for the first-stage estimation, it serves as the data source for estimating the instrumental-variable model of FOX News viewership.

Housing and Neighborhood characteristics. Hedonic models require information on property characteristics that intrinsically determine property values. Dwelling characteristics at the ZIP-code level are obtained from the American Community Survey (ACS) published by the U.S. Census Bureau for the years 2011 through 2024. Because these data are unavailable prior to 2011, the 2011 dwelling characteristics are matched to the years 2008–2010, as average housing characteristics are unlikely to change substantially over such a short period. In addition, missing dwelling characteristics for specific ZIP codes and years are imputed using the geographically closest ZIP code with available data. Specifically, when a particular housing characteristic is missing for a ZIP code in a given year, it is replaced with the corresponding characteristic from the nearest ZIP code, where proximity is measured by the distance between ZIP-code centroids, for which the information is available in the same year.

5.2 Spatial Matching of Comparable Units

Spatial Bundles. The empirical design compares ZIP codes located near the same DMA boundary. Following Raab (2026), I first identify counties near DMA borders and group adjacent counties into comparable cross-border bundles. Each bundle contains locations that are geographically close but assigned to different DMAs. ZIP codes are then assigned to these bundles based on their spatial overlap with the underlying counties. Within each bundle, observations closer to the DMA border receive greater weight, using the distance from the ZIP-code centroid to the DMA boundary. Figure 1 illustrates the bundle construction for the New York DMA border and for the full ZIP-code bundle sample. This approach preserves ZIP-code-level variation while restricting comparisons to nearby areas exposed to different local media markets.

Figure 1: Spatial Bundle Construction



(a) New York DMA border bundles **(b) Full ZIP-code bundle sample**

Notes: Panel (a) illustrates the construction of comparable ZIP-code bundles around the New York DMA border. Panel (b) shows the resulting ZIP-code bundle structure across all DMA borders used in the analysis. Detailed construction rules are described in Raab (2026).

ZIP-Code Partisan Affiliation. I use ZIP-code-level partisan vote shares to capture the political composition of each respondent's neighborhood. Because national partisan media may emphasize crime in politically opposed areas, neighborhood partisanship is central to the heterogeneity analysis. I construct these measures by overlaying precinct-level presidential election returns with ZIP-code polygons and assigning votes to ZIP codes according to proportional area overlap. Appendix Figure 5 illustrates the precinct-to-ZIP overlay used for this assignment. Coverage gaps in the New York Times precinct data are filled using the University of Florida Election Lab data. The full algorithm, including rules for incomplete precinct coverage and boundary changes, is described in Raab (2026).

5.3 Classification of transcripts about crime

FOX News transcripts were collected from LexisNexis for the years 2008 through 2024. October transcripts are excluded so that the annual FOX crime-coverage measure precedes the survey used in the main analysis. The transcript search was conducted in two parts. The first collected transcripts containing the word "crime," and the second collected transcripts containing other crime-related terms.[1]

The word "crime" is relatively precise because it usually refers to actual criminal activity. The broader crime-related keyword search increases coverage but also introduces noise, since some keywords are used metaphorically or in unrelated contexts. This makes systematic text classification necessary before constructing the FOX crime-coverage measure.

The transcript text was cleaned by removing reporter names, timestamps, transcript descriptions, and other formal elements that could affect classification. Because a single broadcast transcript may contain several unrelated segments, I retained only sentences containing at least one crime-related keyword, together with the immediately preceding and following sentences. This procedure produces shorter excerpts that are more focused on the crime-relevant portion of the transcript.

Spanish-language transcripts were removed using the `langdetect` library, since language classifications in LexisNexis are not always reliable. Transcripts classified as international or mixed were also removed. I then applied a separate international-news classifier to remove remaining transcripts focused on international events, because domestic FOX News segments may still contain references to foreign crime and because NexisNexis categories do not always separate these cases cleanly. Very short excerpts, especially those generated by keywords other than "crime," were also removed to reduce classification noise.

The crime classifier was trained and validated using manually coded FOX News transcripts. I selected 600 transcripts for manual classification, with 300 drawn from the "crime" keyword pool and 300 drawn from the broader crime-keyword pool. An additional 300 FOX transcripts were manually coded for validation, producing 900 manually classified FOX transcripts in total. I evaluated logistic regression with TF-IDF features, logistic regression with embeddings, random forest models with TF-IDF features and embeddings, a convolutional neural net-

[1]The following terms, including their variations, were used: murder OR homicide OR assault OR shooting OR stabbing OR theft OR burglary OR robbery OR arson OR vandalism OR drug OR narcotics OR fraud OR embezzlement OR rape OR molestation OR arrest OR conviction OR investigation OR suspect OR victim.

work, and a BERT-style model. For each model, the binary classification cutoff was chosen to maximize the F1 score.
The FOX classifier results are reported in Appendix Table B.1. The random forest model with TF-IDF features produced the highest F1 score and was therefore used to classify FOX News crime coverage in the final data. Appendix Figure 6 shows the resulting annual number of FOX street-crime news stories from 2008 through 2024.

5.4 Descriptive Statistics

Home Values Evolution Through the Years. Appendix Figure 2 reports the average monthly Zillow Home Value Index (ZHVI) for the ZIP-code sample from 2017 through 2025, covering the Trump and Biden administrations. The ZIP-code universe is defined by ZIP codes observed in the CCES-linked sample over time and then matched to monthly Zillow housing values. The aggregate pattern is broadly consistent with the national series published by FRED and Zillow (Federal Reserve Bank of St. Louis, 2026b; Zillow, 2026). Average values in the analysis sample are higher than in the national series because the sample is restricted to ZIP codes that can be linked to the survey and spatial data used in the empirical analysis. This restriction excludes some ZIP codes with relatively low housing values.
Home values increased steadily between 2017 and 2020, flattened briefly in 2020, and then accelerated through approximately mid-2022. Prior research attributes the post-COVID increase to several related forces, including stronger demand for larger homes better suited to remote work, fiscal stimulus, demographic pressure from prime-age home buyers, historically low mortgage rates, and limited housing supply during the pandemic (Duca & Murphy, 2021; Federal Reserve Bank of St. Louis, 2026a; Klein & Cui, 2025).
The pace of appreciation slowed after mid-2022, when affordability deteriorated following several years of rapid price growth and borrowing costs rose sharply with higher mortgage rates (Federal Reserve Bank of St. Louis, 2026a; Richter & Zhou, 2024). After this adjustment, the series appears to move closer to its pre-pandemic trend.

Home Values by Neighborhood Partisan Affiliation. Appendix Figure 3 divides ZIP codes into quartiles based on the Republican presidential vote share, measured using Donald Trump's vote share in the 2016 and 2020 elections. The figure shows how average home values evolve across neighborhoods with different partisan compositions.

Partisan affiliation is correlated with several socioeconomic and geographic characteristics that are also related to housing values. Although income and partisanship are not perfectly aligned, lower- and lower-middle-income individuals tend to lean Democratic, middle- and upper-middle-income individuals tend to lean Republican, and the highest-income group tends to lean Democratic (Pew Research Center, 2024a). Democratic-leaning voters are also more likely to rent and to live in urban areas (Pew Research Center, 2024a, 2024b), where housing values are generally higher.

The partisan-quartile series display two notable patterns. First, the COVID-era increase in home values is more pronounced in ZIP codes with lower Republican vote shares. One possible explanation is that these areas had higher rates of remote work and experienced larger increases in working from home after 2020 (Cowan & Garcia, 2024), generating stronger demand pressure in Democratic-leaning areas. COVID policy responses and behavioral changes were also politically differentiated, which may have further contributed to heterogeneous housing-market dynamics across partisan neighborhoods.

Second, the gap between the least Republican and most Republican quartiles widens over time. In the baseline graph, the difference between these quartiles is approximately \$218,000 in 2017 and increases to roughly \$328,000 by 2025.

6 Empirical Strategy

This section describes the empirical strategy used to estimate the relationship between neighborhood crime perceptions and subsequent property values, as well as how this relationship varies with the partisan composition of ZIP codes. The design follows Raab (2026) by comparing geographically proximate ZIP codes located around the same DMA boundary. All specifications therefore include spatial-bundle fixed effects, so identification comes from variation within comparable cross-border units rather than from comparisons across distant neighborhoods. This restriction reduces the number of usable observations, but it makes the comparison groups more credible for causal interpretation.

6.1 Identification Strategy

Spatial Discontinuity at DMA Borders: The causal identification strategy relies on comparing observations located near DMA borders. The key identifying assumption is that households on opposite sides of the same DMA boundary are geographically close and therefore exposed to similar local economic conditions, amenities, labor markets, and housing market trends, while receiving different local television programming. As the geographic distance between two observations decreases, they become increasingly comparable in all respects except for their media market assignment. Consequently, among households located near a DMA border, differences in media exposure are more plausibly driven by the exogenous assignment of ZIP codes to media markets rather than by deliberate household sorting across media markets.

This spatial discontinuity design is especially useful in the present setting. Crime perceptions may respond to differences in local media coverage, and those perceptions may then be capitalized into housing prices. By restricting comparisons to neighborhoods located near the same DMA boundary and by controlling for spatial bundles of comparable border areas, the design reduces the role of broad regional differences and focuses on variation in media exposure across nearby locations.

The placement of DMA borders further supports this comparison. Because DMAs group counties into common television markets (Nielsen, 2025), counties located immediately on opposite sides of a DMA boundary are often contiguous and share similar levels of urban development, population density, commuting patterns, and local amenities. While these areas differ in the media market to which they are assigned, they are otherwise likely to experience similar economic, crime, and demographic trends. This geographic continuity makes it more plausible that discontinuities in media exposure are not accompanied by comparable discontinuities in other determinants of property values.

Instrumental-Variables Motivation: The instrumental-variables strategy follows Raab (2026), which uses the number of local stations around DMA borders as an instrument for FOX News viewership. The intuition is that the local station environment affects viewers' propensity to watch particular news sources, but conditional on spatial-bundle comparisons and observed controls, the number of stations should not directly affect crime perceptions or housing prices except through media exposure. Additional details on the institutional justification for this instrument are provided in Raab (2026).

6.2 Empirical Framework

This paper extends the preceding logic by asking whether media-induced differences in crime perceptions are capitalized into neighborhood property values. The empirical design combines cross-border variation in local media structure with ZIP-code-level housing values and survey-based measures of perceived crime.

Hedonic Price Equations. I first estimate hedonic price equations in the spirit of the standard hedonic literature, including Gibbons (2004), Ihlanfeldt and Mayock (2010), and Moreno-Medina (2026). In this setting, however, the survey data create an additional measurement problem. The housing-price outcome is observed at the ZIP-code level, while crime perceptions are reported by individuals. A direct ZIP-year average of survey responses would be very noisy because many ZIP-year cells contain only a small number of respondents.

To address this problem, I use a small-area-estimation approach following Battese et al. (1988). The model can be interpreted as a linear mixed model that produces partially pooled ZIP-year estimates of crime perception. The unit-level model is

$$CP_{ijt} = \mathbf{w}'_{ijt}\boldsymbol{\gamma} + v_{it} + e_{ijt}, \tag{1}$$

where i indexes ZIP codes, j indexes individuals within ZIP code i, and t indexes years. The dependent variable CP_{ijt} is individual j's reported perception of crime in ZIP code i and year t. The vector $\mathbf{w}_{ijt}$ includes individual-level covariates and the lagged property-price measure used in the prediction equation **(add robustness here without lag of price)**. The term v_{it} is a ZIP-year random effect, and e_{ijt} is an individual-level error term.

The model assumes

$$v_{it} \sim iid\, N(0, \sigma_v^2), \qquad e_{ijt} \sim iid\, N(0, \sigma_e^2), \qquad v_{it} \perp e_{ijt}.$$

Under this structure, the ZIP-year mean of crime perception can be written as

$$CP_{it} = \bar{\mathbf{w}}'_{it}\boldsymbol{\gamma} + v_{it}, \tag{2}$$

so predicting ZIP-year crime perception requires predicting the random effect v_{it}. Let $u_{ijt} = v_{it} + e_{ijt}$, and define the within-ZIP-year average residual as

$$\bar{u}_{it} = n_{it}^{-1} \sum_{j=1}^{n_{it}} u_{ijt}.$$

The conditional expectation of the ZIP-year random effect is

$$E(v_{it} \mid \bar{u}_{it}) = \bar{u}_{it} g_{it},$$

where

$$g_{it} = m_{it}^{-1} \sigma_v^2$$

and

$$m_{it} = \left(\sigma_v^2 + n_{it}^{-1} \sigma_e^2\right).$$

Thus, g_{it} acts as a shrinkage factor. In practice, σ_v^2, σ_e^2, and $\boldsymbol{\gamma}$ are estimated from the data. The feasible predictor of ZIP-year crime perception is therefore

$$\widetilde{CP}_{it} = \bar{\mathbf{w}}_{it}' \tilde{\boldsymbol{\gamma}} + \tilde{v}_{it}, \tag{3}$$

where

$$\tilde{v}_{it} = \tilde{u}_{it\cdot} g_{it},$$

with

$$\tilde{u}_{it\cdot} = n_{it}^{-1} \sum_{j=1}^{n_{it}} \tilde{u}_{ijt}$$

and

$$\tilde{u}_{ijt} = CP_{ijt} - \mathbf{w}_{ijt}' \tilde{\boldsymbol{\gamma}}.$$

This predictor is a weighted combination of the information contained in the ZIP-year cell and the information from the full sample. When a ZIP-year contains many respondents, the shrinkage factor places more weight on its own survey responses. When a ZIP-year contains few respondents, the estimate is pulled more strongly toward the model prediction based on the overall sample. This partial-pooling structure is useful in my setting because it strengthens crime-perception estimates for small areas with sparse and noisy survey information, while still allowing ZIP-year estimates to reflect local survey responses when those responses are informative.

The partial-pooling method provides a rigorous framework for small-area estimation. However, using the generated variable $\widetilde{CP}_{it}$ directly in the second-stage price equation would understate uncertainty, because $\widetilde{CP}_{it}$ is itself estimated in the first-stage BHF model. Standard errors from the second-stage regression alone would therefore treat predicted crime perception as observed without error and could lead to incorrect inference. To account for this generated-regressor problem, I apply a Murphy-Topel correction following Murphy and Topel (1985).

The second-stage price equation using predicted ZIP-year crime perception is

$$P_{it+1} = \alpha + \beta_1 \widetilde{CP}_{it} + \mathbf{x}_{it}'\boldsymbol{\beta}_2 + \delta_b + \lambda_d + \tau_t + \varepsilon_{it}. \tag{4}$$

Here, P_{it+1} is the future ZIP-code-level property price, measured using Zillow home values averaged over January through September. The vector $\mathbf{x}_{it}$ contains ZIP-code-level property characteristics commonly used in hedonic models. The terms δ_b, λ_d, and τ_t denote spatial-bundle fixed effects, DMA fixed effects, and time fixed effects, respectively. The coefficient β_1 captures the association between predicted perceived crime and subsequent property values within comparable DMA-border bundles.

The Murphy-Topel correction requires defining several sample quantities. Let z_{it} denote the second-stage regressor vector:

$$z_{it} = \begin{pmatrix} 1 \\ \widetilde{CP}_{it} \\ \mathbf{x}_{it} \\ \delta_b \\ \lambda_d \\ \tau_t \end{pmatrix}, \qquad Z = \begin{pmatrix} z_{11}' \\ z_{12}' \\ \vdots \\ z_{it}' \\ \vdots \\ z_{NT}' \end{pmatrix}.$$

The first-stage BHF prediction can be written as a function of the first-stage parameters and covariates:

$$\widetilde{CP}_{it} = f(\theta, \mathbf{w}_{it}),$$

where $\mathbf{w}_{it}$ is the ZIP-year mean of the individual-level covariates used in the BHF equation. In the implementation used here, the Murphy-Topel correction is based on the first-stage coefficient vector that enters the generated prediction. The derivative of the generated regressor with respect to the first-stage parameters is

$$D_{it} = \frac{\partial f(\tilde{\theta}, \mathbf{w}_{it})}{\partial \theta}.$$

Because the generated regressor enters the second-stage equation multiplied by β_1, the relevant derivative for the second-stage score is

$$f_{it}^* = \tilde{\beta}_1 D_{it}.$$

Stacking these derivatives gives

$$F^* = \begin{pmatrix} f_{11}^{*\prime} \\ f_{12}^{*\prime} \\ \vdots \\ f_{it}^{*\prime} \\ \vdots \\ f_{NT}^{*\prime} \end{pmatrix}.$$

In the BHF predictor, this derivative corresponds to the sensitivity of $\widetilde{CP}_{it}$ to the first-stage coefficients.
The sample analogues used for the Murphy-Topel correction are

$$\widetilde{Q}_0 = n^{-1} Z' Z,$$

$$\widetilde{Q}_1 = n^{-1} Z' F^*,$$

and

$$\widetilde{Q}_2 = n^{-1} Z' \widetilde{\varepsilon} \widetilde{S},$$

where $\widetilde{\varepsilon}$ is the second-stage residual and $\widetilde{S}$ stacks the first-stage score contributions:

$$\widetilde{S} = \begin{pmatrix} S'_{11} \\ S'_{12} \\ \vdots \\ S'_{it} \\ \vdots \\ S'_{NT} \end{pmatrix}, \qquad S_{it} = \sum_{j=1}^{n_{it}} \mathbf{w}_{ijt} \widetilde{u}_{ijt}.$$

Here, $\widetilde{u}_{ijt}$ is the residual from the first-stage BHF unit-level equation. The term Q_2 accounts for the dependence between the first-stage generated crime-perception

estimate and the second-stage price equation when both stages are estimated from related data.
The covariance matrix used for inference is therefore

$$\widetilde{\Sigma}_{MT} = \widetilde{\Sigma}_{HC1} + \frac{1}{n}\widetilde{Q}_0^{-1}\left[\widetilde{Q}_1\widetilde{V}_\theta\widetilde{Q}_1' - \widetilde{Q}_1\widetilde{V}_\theta\widetilde{Q}_2' - \widetilde{Q}_2\widetilde{V}_\theta\widetilde{Q}_1'\right]\widetilde{Q}_0^{-1}. \tag{5}$$

In this expression, $\widetilde{\Sigma}_{HC1}$ is the heteroskedasticity-robust covariance matrix from the second-stage regression, and $\widetilde{V}_\theta$ is the estimated asymptotic covariance matrix of the first-stage BHF parameters. This correction adjusts the second-stage standard errors for the fact that crime perception is not directly observed at the ZIP-year level but is instead estimated through the first-stage partial-pooling model. I estimate this specification with additional controls for presidential administrations to account for potential heterogeneity in the effect of crime perception on property prices during periods of partisan transition.

Hedonic Price Equations with Neighborhood Partisanship. I extend the previous specification by allowing the capitalization of perceived crime into property prices to vary with the partisan composition of the neighborhood. Partisan crime coverage may differ across several dimensions, including the types of neighborhoods emphasized in the news. If partisan media disproportionately highlight crime in neighborhoods associated with the opposing party, the relationship between perceived crime and property prices may vary with local partisan affiliation. I therefore estimate a specification that interacts predicted crime perception with ZIP-code Republican vote share.
Specifically, I estimate the following equation separately for the Trump and Biden periods:

$$\begin{aligned} P_{i,t+1,p} = \alpha_p + \beta_{1,p}\widetilde{CP}_{it} + \beta_{2,p}RZ_{i,p} + \beta_{3,p}\left(\widetilde{CP}_{it} \times RZ_{i,p}\right) \\ + \mathbf{x}_{it}'\boldsymbol{\gamma}_p + \delta_b + \lambda_d + \tau_t + \varepsilon_{it,p}, \qquad p \in \{\text{Trump}, \text{Biden}\}. \end{aligned} \tag{6}$$

Here, $P_{i,t+1,p}$ denotes future neighborhood property prices in ZIP code i during administration p, and $\widetilde{CP}_{it}$ denotes the BHF estimate of ZIP-year crime perception. The variable $RZ_{i,p}$ denotes the Republican vote share in ZIP code i used for administration p. The vector $\mathbf{x}_{it}$ contains ZIP-level property controls, and α_p is an administration-specific intercept. The terms δ_b, λ_d, and τ_t denote spatial-bundle fixed effects, DMA fixed effects, and time fixed effects, respectively. The coefficient $\beta_{1,p}$ captures the association between predicted crime perception and future property prices during administration p, while $\beta_{2,p}$ captures the direct association

between Republican vote share and property prices. The interaction coefficient $\beta_{3,p}$ is the main heterogeneity parameter: it measures whether the price gradient with respect to perceived crime differs in more Republican ZIP codes.
I estimate this model separately for the Trump and Biden administrations because the detailed precinct-level spatial information needed to construct ZIP-code partisan affiliation is available only for the later election cycles. This restriction makes the partisanship analysis comparable across ZIP codes with observed partisan measures, while avoiding extrapolation of ZIP-level partisan affiliation to earlier years without the required underlying spatial election data.

Property Price Appreciation Model. The second specification examines how crime perception affects property price appreciation rather than property price levels. Similar to the previous specification, this model builds on the small-area partial pooling estimator of Battese et al. (1988) and applies the Murphy and Topel (1985) correction to account for the uncertainty associated with the imputed crime perception measure. The estimated equation is:

$$\Delta P_{it+1} = \alpha + \beta_1 \widetilde{CP}_{it} + \mathbf{x}'_{it}\boldsymbol{\beta}_2 + \delta_b + \lambda_d + \tau_t + \varepsilon_{it}. \tag{7}$$

where ΔP_{it+1} denotes the property price change between periods t and $t+1$, such that $\Delta P_{it+1} = P_{it+1} - P_{it}$.

FOX News Viewership Effect on Property Prices. I also estimate the effect of FOX News crime exposure on subsequent neighborhood property prices. This specification follows the instrumental-variables strategy in Raab (2026), which uses the number of local stations available near DMA borders as an instrument for FOX News viewership. The purpose of this specification is not to use FOX News viewership alone as the relevant treatment. Instead, I combine viewership with the amount of crime-related content aired on FOX News, since the mechanism of interest is exposure to crime coverage rather than exposure to the channel in general.
Let FV_{it} denote FOX News viewership in ZIP code i and year t, and let CRI_{it} denote FOX News crime-reporting intensity. I define FOX crime intensity as

$$FCI_{it} = FV_{it} \times CRI_{it}.$$

The variable FV_{it} is potentially endogenous because individuals self-select into watching FOX News. In contrast, CRI_{it} is treated as exogenous to an individual respondent because a respondent does not determine the annual amount of crime coverage aired by FOX News. Since FCI_{it} contains the endogenous viewership component, I instrument it using local-station availability and its interaction with FOX crime-reporting intensity. The first-stage equation for the baseline specification is

$$FCI_{it} = \pi_0 + \pi_1 LS_{it} + \pi_2 (LS_{it} \times CRI_{it}) + \mathbf{x}'_{it}\boldsymbol{\kappa} + \delta_b + \nu_{it}. \tag{8}$$

Here, LS_{it} denotes the number of local stations available through DMA assignment, $\mathbf{x}_{it}$ contains the exogenous ZIP-level hedonic controls used in the second stage, and δ_b denotes spatial-bundle fixed effects. The excluded instruments are LS_{it} and $LS_{it} \times CRI_{it}$. The corresponding second-stage equation is

$$P_{it+1} = \alpha + \beta_1 \widehat{FCI}_{it} + \mathbf{x}'_{it}\boldsymbol{\gamma} + \delta_b + \varepsilon_{it}. \tag{9}$$

I then allow the FOX crime-news effect to vary with neighborhood partisanship. Let RZ_{it} denote the Republican neighborhood measure. In this specification, both FCI_{it} and $FCI_{it} \times RZ_{it}$ are treated as endogenous, so I estimate two first-stage regressions. The first predicts FCI_{it}:

$$\begin{aligned} FCI_{it} = {} & \pi_0 + \pi_1 RZ_{it} + \pi_2 LS_{it} + \pi_3 (LS_{it} \times CRI_{it}) \\ & + \pi_4 (LS_{it} \times RZ_{it}) + \pi_5 (LS_{it} \times CRI_{it} \times RZ_{it}) \\ & + \mathbf{x}'_{it}\boldsymbol{\kappa} + \delta_b + \nu_{it}. \end{aligned} \tag{10}$$

The second predicts the endogenous interaction $FCI_{it} \times RZ_{it}$:

$$\begin{aligned} FCI_{it} \times RZ_{it} = {} & \rho_0 + \rho_1 RZ_{it} + \rho_2 LS_{it} + \rho_3 (LS_{it} \times CRI_{it}) \\ & + \rho_4 (LS_{it} \times RZ_{it}) + \rho_5 (LS_{it} \times CRI_{it} \times RZ_{it}) \\ & + \mathbf{x}'_{it}\boldsymbol{\psi} + \delta_b + \omega_{it}. \end{aligned} \tag{11}$$

The excluded instruments in the neighborhood-interaction model are LS_{it}, $LS_{it} \times CRI_{it}$, $LS_{it} \times RZ_{it}$, and $LS_{it} \times CRI_{it} \times RZ_{it}$. The second-stage equation is

$$\begin{aligned} P_{it+1} = {} & \alpha + \beta_1 RZ_{it} + \beta_2 \widehat{FCI}_{it} + \beta_3 (\widehat{FCI_{it} \times RZ_{it}}) \\ & + \mathbf{x}'_{it}\boldsymbol{\gamma} + \delta_b + \varepsilon_{it}. \end{aligned} \tag{12}$$

In this equation, β_2 captures the association between instrumented FOX crime intensity and future property prices, while β_3 captures whether this association differs with neighborhood Republican alignment. The dependent variable P_{it+1} is measured either as future neighborhood property prices in hundreds of thousands of dollars or, in the log specification, as the natural logarithm of future

ZIP-code property prices. All specifications are estimated at the ZIP-code level, include hedonic housing controls and spatial-bundle fixed effects, and use composite ZIP weights that combine respondent counts with inverse-distance weights to the DMA border.

7 Results

Hedonic Price Equations. I begin with the baseline hedonic price regressions. The level-price specifications are reported in Table 1. The corresponding log specifications, together with the versions that include additional controls, are reported in Appendix B in Tables B.2, B.3, and B.4.

Table 1: Effect of Crime Perception on Neighborhood Property Price Appreciation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable : Neighborhood Property Prices (hundreds of thousands of dollars)								
Intercept	3.539***	3.063***	2.371***	1.723***	2.468***	1.831***	2.398***	2.366***
	(0.214)	(0.216)	(0.254)	(0.233)	(0.156)	(0.159)	(0.246)	(0.235)
Trump		0.470		0.715**		0.689***		-0.121
		(0.387)		(0.291)		(0.238)		(0.284)
Biden		1.607***		1.685***		1.689***		0.654**
		(0.420)		(0.296)		(0.267)		(0.289)
Crime Perception	-1.410***	-1.089***	-0.902***	-0.369***	-0.787***	-0.308***	-0.743***	-0.294***
	(0.254)	(0.249)	(0.162)	(0.130)	(0.142)	(0.097)	(0.136)	(0.096)
Crime Perception × Trump		-0.335		-0.769**		-0.687**		-0.692**
		(0.504)		(0.376)		(0.307)		(0.311)
Crime Perception × Biden		-1.074*		-1.332***		-1.204***		-1.248***
		(0.606)		(0.491)		(0.447)		(0.452)
N	3,050	3,050	3,050	3,050	3,050	3,050	3,050	3,050
Bundle Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance

Notes: Each observation is a ZIP-year area. Crime perception is a BHF/EBLUP prediction from the unit-level Gallup model, centered at its regression-sample 25th percentile and scaled by its interquartile range. Crime-perception coefficients therefore represent a 25th-to-75th percentile increase in predicted crime perception, and main effects are evaluated at the 25th percentile of predicted crime perception. Second-stage standard errors apply a Murphy-Topel correction for the generated crime-perception regressor. Controls include mean-centered ACS DP04 bedroom shares, year-built shares, units in structure, and vacancy variables. Omitted categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. Columns (7) and (8) add year fixed effects. Missing Census controls are filled from the nearest same-year ZCTA with complete controls. Bathrooms are not available in ACS DP04. The base second-stage covariance is HC1 robust; ZIP-year weights use only the DMA-border distance weight. No specification includes a lagged property-price control. * p<0.10, ** p<0.05, *** p<0.01.

Table 1 estimates a sequence of increasingly restrictive specifications that add bundle fixed effects, DMA fixed effects, and time fixed effects. All specifications include hedonic controls and use distance weights, giving greater weight to ZIP-years located closer to DMA borders because they provide more comparable observations for the spatial-discontinuity design. To make the intercept more interpretable, I mean-center the hedonic control variables. I also rescale crime perception by subtracting its 25th percentile and dividing by its interquartile range. The coefficient on crime perception can therefore be interpreted as the association between moving from the 25th to the 75th percentile of predicted crime perception and subsequent property prices.

Because the spatial-discontinuity design restricts the sample to areas near DMA borders, the estimates should be interpreted as local average treatment effects for less urbanized areas around these boundaries. Property values in this sample are therefore lower than in the broader national housing market. In the specifications without presidential-administration interactions, the intercept represents the predicted property price for a ZIP-year with average hedonic characteristics and crime perception at the 25th percentile. Accordingly, the first specification indicates a baseline predicted property price of approximately \$353,900 for a property in the sample period.

In the specifications with presidential-administration interactions, specifically the second specification, the intercept has a different interpretation: it represents the predicted property price for a ZIP-year with average hedonic characteristics and crime perception at the 25th percentile during the omitted Obama administration. These specifications indicate that presidential administration is associated with substantial differences in estimated property values. Relative to the omitted Obama administration, property prices are estimated to be approximately \$47,000 higher during the Trump administration, although the estimate is not statistically significant, and approximately \$113,700 higher during the Biden administration, with the latter estimate being highly statistically significant. This pattern is consistent with the post-COVID increase in housing values shown in Appendix Figure 2.

Across the specifications without presidential-administration interactions, predicted crime perception is negatively and statistically significantly associated with subsequent property prices. The magnitude declines as the fixed-effect structure becomes more restrictive, but the relationship remains highly significant. Moving from the 25th to the 75th percentile of predicted crime perception is associated with a decrease of approximately \$78,700 in the most restrictive specification without time fixed effects and approximately \$74,300 in the corresponding specification with time fixed effects.

The specifications with presidential-administration interactions provide a more nuanced pattern. The coefficient on crime perception captures the association during the omitted Obama period, while the Trump and Biden interaction terms show how this association changes during those administrations. In the most restrictive specification, moving from the 25th to the 75th percentile of predicted crime perception is associated with property-price declines of approximately \$29,400 during the Obama period, \$98,600 during the Trump period, and \$154,200 during the Biden period. This pattern is consistent with a stronger capitalization of perceived crime into housing values in later periods. Without time fixed effects, the negative crime-perception effects remain smaller than the overall increase in property prices across administrations. With time fixed effects included, however, the implied Trump-period and Biden-period effects are large enough to place high-crime-perception neighborhoods below comparable Obama-period neighborhoods with crime perception at the 25th percentile.

Hedonic Price Equations with Neighborhood Partisanship. The second set of specifications adds ZIP-code partisan composition to the hedonic price equation. I use the Republican presidential vote share in the ZIP code as the measure of neighborhood partisanship. This variable is included because partisan media may emphasize crime in neighborhoods associated with the opposing party, which would imply that the capitalization of perceived crime into property values differs with local partisan composition.

Because standardized precinct-level spatial data are not available for earlier presidential elections, I estimate these specifications separately for the Trump and Biden administration periods. As in the baseline hedonic price equations, I estimate progressively more restrictive specifications that add bundle fixed effects, DMA fixed effects, and time fixed effects. The level-price specification is reported in Table 2.

Table 2: Effect of Crime Perception on Neighborhood Property Prices: Republican ZIP Interaction

	Trump	Biden	Trump	Biden	Trump	Biden	Trump	Biden
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable : Neighborhood Property Prices (hundreds of thousands of dollars)								
Intercept	2.948***	5.311***	2.338***	3.119***	2.372***	3.368***	2.232***	3.345***
	(0.135)	(0.762)	(0.184)	(0.711)	(0.256)	(0.607)	(0.243)	(0.591)
Republican ZIP	-0.665***	-2.274***	-0.596***	-1.359**	-0.343**	-1.210*	-0.375**	-1.250*
	(0.134)	(0.799)	(0.144)	(0.640)	(0.159)	(0.732)	(0.158)	(0.743)
Crime Perception	-0.440***	-2.350***	-0.356***	-1.919***	-0.285***	-1.758***	-0.247***	-1.715***
	(0.124)	(0.729)	(0.101)	(0.597)	(0.093)	(0.589)	(0.083)	(0.572)
Crime Perception × Republican ZIP	0.238**	2.085***	0.244**	1.751**	0.197**	1.586**	0.220**	1.614**
	(0.107)	(0.740)	(0.098)	(0.686)	(0.099)	(0.672)	(0.097)	(0.672)
N	818	570	818	570	818	570	818	570
Bundle Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance

Notes: Each observation is a ZIP-year area. Crime perception is a BHF/EBLUP prediction from the unit-level Gallup model, centered at its regression-sample 25th percentile and scaled by its interquartile range. Republican ZIP is also centered at its regression-sample 25th percentile and scaled by its interquartile range. Crime-perception and Republican-ZIP coefficients therefore represent 25th-to-75th percentile increases, and main effects are evaluated at the 25th percentile of the interacted variable. Second-stage standard errors apply a Murphy-Topel correction for the generated crime-perception regressor. Controls include mean-centered ACS DP04 bedroom shares, year-built shares, units in structure, and vacancy variables. Omitted categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. Republican ZIP is the ZIP-year value of Trump_neighborhood. Odd-numbered columns keep Trump-period ZIP-years; even-numbered columns keep Biden-period ZIP-years. Columns (7) and (8) add year fixed effects. The base second-stage covariance is HC1 robust; ZIP-year weights use only the DMA-border distance weight. No specification includes a lagged property-price control. * p<0.10, ** p<0.05, *** p<0.01.

The first feature of the table is that baseline property prices are higher during the Biden period than during the Trump period. As a result, several coefficients are mechanically larger in dollar terms in the Biden-period columns. This pattern is consistent with the baseline hedonic results above and with the post-COVID increase in property values documented in Appendix Figure 2. As in the previous specifications, adding fixed effects generally attenuates the magnitude of the estimates.

The estimates also show that neighborhoods with higher Republican vote shares have lower baseline property values. Column (1) reveals that the predicted property price for a ZIP-year with average hedonic characteristics, crime perception at the 25th percentile, and a Republican vote share at the 25th percentile increases from approximately $294,800 during the Trump administration to approximately $531,100 during the Biden administration. For ZIP-years at the 75th percentile of the Republican vote share, the corresponding predicted property values increase from approximately $228,300 to approximately $303,700. Thus, the increase in property values is substantially larger in more Democratic neighborhoods, consistent with the descriptive pattern shown in Appendix Figure 3. Similarly, focusing on the two most restrictive Trump-period specifications, columns (5) and (7), moving from the 25th to the 75th percentile of the Republican vote share is associated with statistically significant declines in predicted property values of approximately $34,300 and $37,500, respectively. During the Biden administration, the corresponding declines are substantially larger, at approximately $121,000 and $125,000, respectively. This difference partly reflects the higher baseline level of property prices during the Biden administration.

The interaction between crime perception and Republican vote share shows that the association between perceived crime and property prices is more negative in more Democratic neighborhoods. In the specification with all fixed effects, moving from the 25th to the 75th percentile of predicted crime perception in neighborhoods at the 25th percentile of Republican vote share is associated with declines of approximately $24,700 during the Trump period and $171,500 during the Biden period. At the 75th percentile of Republican vote share, the implied declines are much smaller, approximately $2,700 during the Trump period and $10,100 during the Biden period.

One possible explanation is that partisan neighborhoods differ systematically in demographic and socioeconomic composition. Democratic-leaning voters are more likely to include racial and ethnic minority groups and are relatively more represented among lower-income and high-income voters, as well as among voters with college and postgraduate degrees. Republican-leaning voters are more represented among voters with a high-school degree or less, voters with some college but no bachelor's degree, and middle- and upper-middle-income groups (Pew Research Center, 2024c, 2024d). These differences suggest that more Democratic ZIP codes may combine higher-income households with greater demographic and economic heterogeneity, whereas more Republican ZIP codes may be more concentrated around middle-income housing markets. Such differences could help explain why perceived crime is more strongly capitalized into property values in more Democratic neighborhoods.

The descriptive evidence is consistent with this interpretation. Appendix Figure 4 plots partisan-quartile home-value series separately by RUCA classification.[2] The largest divergence appears in RUCA categories 10 and especially 4.

[2] RUCA codes classify areas into 10 categories, including metropolitan areas, micropolitan

RUCA category 4 captures small towns with populations between 10,000 and 50,000. Some ZIP codes in this category include high-value nonmetropolitan or small-town housing markets, such as the Hamptons, Jackson, and Nantucket. These places may have benefited disproportionately from the COVID-era housing shock because they offered larger homes in less urban settings while still retaining amenities comparable to larger metropolitan areas. This composition could widen partisan gaps in property values and contribute to the heterogeneous capitalization of perceived crime across neighborhoods.

Property Price Appreciation Model. In this section, I estimate the effect of crime perception on the next-year increase in property prices. The regression is reported in Table 3, and the corresponding log-price specification is reported in Table B.6.

areas, small towns, rural areas, and their commuting zones. I keep only categories with sufficient ZIP codes in each quartile, although RUCA categories 2, 4, and 10 would likely benefit from larger sample sizes.

Table 3: Effect of Crime Perception on Neighborhood Property Price Appreciation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable : First Difference in Neighborhood Property Prices (hundreds of thousands of dollars)								
Intercept	0.182***	0.095***	0.168***	0.030	0.120***	0.022	-0.110*	-0.121**
	(0.027)	(0.024)	(0.056)	(0.050)	(0.023)	(0.029)	(0.064)	(0.059)
Trump		0.214***		0.248***		0.251***		0.350***
		(0.062)		(0.063)		(0.060)		(0.081)
Biden		0.104***		0.124***		0.124***		0.256***
		(0.030)		(0.027)		(0.031)		(0.072)
Crime Perception	-0.092***	-0.031	-0.037**	0.043*	-0.025*	0.053**	-0.039***	0.038*
	(0.028)	(0.031)	(0.015)	(0.024)	(0.013)	(0.027)	(0.012)	(0.023)
Crime Perception × Trump		-0.160*		-0.212***		-0.217***		-0.198***
		(0.082)		(0.080)		(0.075)		(0.076)
Crime Perception × Biden		-0.035		-0.058**		-0.052		-0.064**
		(0.040)		(0.028)		(0.037)		(0.031)
N	3,050	3,050	3,050	3,050	3,050	3,050	3,050	3,050
Bundle Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance

Notes: Each observation is a ZIP-year area. The dependent variable is a first difference in future property prices, defined as $P_{t+1} - P_t$. These specifications omit the lagged price-change control. Crime perception is a BHF/EBLUP prediction from the unit-level Gallup model, centered at the 25th percentile and scaled by the interquartile range. Second-stage standard errors apply a Murphy-Topel correction for the generated crime-perception regressor. Controls include mean-centered ACS DP04 bedroom shares, year-built shares, units in structure, and vacancy variables. Omitted categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. Missing Census controls are filled from the nearest same-year ZCTA with complete controls. The base second-stage covariance is HC1 robust; ZIP-year weights use only the DMA-border distance weight. Columns (7) and (8) add year fixed effects. * p<0.10, ** p<0.05, *** p<0.01.

During the period spanning the Obama, Trump, and Biden administrations, the average increase in property values, evaluated with mean-centered hedonic control variables and ZIP codes at the 25th percentile of crime perception, was $18,200, as reported in the first regression. Comparing property-price appreciation across presidential administrations, the largest increase occurred during the Trump administration, at $30,900 per year, compared with $9,500 during the Obama administration and $19,900 during the Biden administration. It is useful to put these numbers in perspective by comparing them with the level-price regressions in Table 1. That table reports the largest increase in property prices during the Biden administration, mostly due to the post-COVID increase in housing values shown in Appendix Figure 2. Nevertheless, isolating the upward jump in property prices during the Biden administration and focusing only on the increase that occurred during the administration years confirms the intuition behind Appendix Figure 2.

Although property prices increased rapidly during the Biden administration because of the COVID shock, the adjustment after 2022 resulted in a property-price slump, likely pushing price appreciation downward.
Specifications without presidential interactions show how crime perception is associated with following-year property-price appreciation for mean-centered hedonic control variables. Focusing on the two most restrictive specifications, an increase in crime perception from the 25th percentile to the 75th percentile is associated with price depreciation of $2,500 and $3,900 in the specifications without and with time fixed effects, respectively.
Breaking these results into presidential-administration-specific effects, both of the most restrictive specifications confirm that the largest depreciation occurs during the Trump period, with highly significant reported depreciation of $16,400 and $16,000 in the specifications without and with time fixed effects, respectively. Interestingly, this might point to the fact that the Trump period was the only presidential administration in my data without a property-price slump. During the Obama and Biden administrations, price depreciation may therefore be more likely to occur because of overall macroeconomic conditions, whereas during the Trump administration, crime perception may have a larger effect on price decreases.

FOX News Viewership Effect on Property Prices. I next estimate whether exposure to FOX News crime coverage is associated with subsequent neighborhood property prices. This specification is designed to distinguish exposure to FOX News as a channel from exposure to the specific type of content that is relevant for this paper. The mechanism of interest is not general FOX News viewership, but exposure to crime-related FOX News segments. I therefore construct a compound measure of FOX crime exposure by interacting a respondent's propensity to watch FOX News with the annual number of FOX News crime stories aired prior to the survey interview. In the tables, FOX crime exposure is scaled so that one unit corresponds to FOX viewership multiplied by 100 FOX crime stories.
FOX News viewership is likely endogenous because respondents self-select into watching FOX News according to their preferences, ideology, and information environment. Following Raab (2026), I use the number of local news stations available near DMA borders as an instrument for FOX News exposure. The identifying assumption is that, within comparable spatial bundles close to DMA borders, variation in the number of available stations is driven by media-market assignment rather than by household sorting or local housing-market conditions. I estimate two weighted 2SLS specifications, one without neighborhood partisanship

interactions and one that allows the FOX crime-exposure effect to vary with the Republican vote share in the ZIP code. I also report the corresponding weighted OLS specifications, which do not address endogenous selection into FOX News viewership. The level-price results are reported in Table 4. The corresponding log-price specification and first-stage regressions are reported in Appendix B in Tables B.9, B.7, and B.8.

Table 4: Second Stage Regression: FOX Crime News Exposure and Future Neighborhood Property Prices with Hedonic Controls

	No Interaction		Neighborhood Interaction	
	OLS Weighted	2SLS Weighted	OLS Weighted	2SLS Weighted
Dependent Variable : Neighborhood Property Prices (hundreds of thousands of dollars)				
Intercept	1.473***	-0.124	2.366***	1.093**
	(0.111)	(0.317)	(0.238)	(0.507)
Trump Neighborhood			-0.145***	-0.148*
			(0.031)	(0.087)
FOX Crime Exposure	-0.005	0.169***	-0.071***	0.193
	(0.004)	(0.031)	(0.024)	(0.130)
FOX Crime Exposure x Trump Neighborhood			0.011***	-0.005
			(0.004)	(0.020)
N ZIP Codes	9,055	9,055	9,055	9,055
First-stage F-statistic (joint)		36.76		
First-stage F-statistic (FOX x Crime)				20.16
First-stage F-statistic (FOX x Crime x Trump)				18.19
Bundle Fixed Effects	Yes	Yes	Yes	Yes
Weights	Composite ZIP	Composite ZIP	Composite ZIP	Composite ZIP

Notes: ZIP-level weighted regressions. Columns (1)–(2) reproduce second_stage_regression_NEWS_HEDONIC; columns (3)–(4) reproduce second_stage_regression_NEWS_HEDONIC_INTERACTION. The dependent variable is non-detrended future neighborhood property price divided by 100,000, Neighborhood_wealth_nodetrend_T/100000. Hedonic controls are mean-centered and included but suppressed from the table. FOX Crime Exposure is defined as FOX viewership multiplied by FOX crime articles divided by 100. Trump Neighborhood is measured in 10-percentage-point units in the interaction columns; hedonic controls are mean-centered, so the intercept is evaluated at average hedonic characteristics. The no-interaction 2SLS column instruments FOX Crime Exposure with Number Stations and Number Stations x FOX Crime Intensity divided by 100. The interaction 2SLS column instruments FOX Crime Exposure and its interaction with Trump Neighborhood in 10-percentage-point units with Number Stations, Number Stations x FOX Crime Intensity divided by 100, and both station instruments interacted with Trump Neighborhood in 10-percentage-point units. All specifications include final harmonized bundle fixed effects, exclude Neighborhood Wealth controls, and use composite ZIP weights equal to ZIP respondent count times inverse-distance weight, normalized to mean one. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The FOX crime-exposure variable and the neighborhood partisanship measure are not centered at the 25th percentile or rescaled by their interquartile range in these specifications. This choice is deliberate. FOX viewership enters the construction of the exposure measure and is based on a binary individual response, so an IQR transformation of the compound exposure variable would be difficult to interpret. In the interaction specifications, Republican ZIP share is instead measured in 10-percentage-point units, which gives the interaction term a direct interpretation.

The hedonic housing controls are mean-centered, so the regressions compare ZIP codes at average observed housing characteristics, but the intercepts in the 2SLS specifications should not be interpreted as meaningful baseline property values. Because the FOX viewership measure is available only in the recent CCES waves used here, these results should be interpreted as applying to the 2020–2022 sample rather than to the full 2008–2024 housing-price period.

In the neighborhood-interaction specifications, the coefficient on Republican ZIP share is similar in the OLS and 2SLS columns. A 10-percentage-point increase in the Republican vote share is associated with approximately \$14,500 lower property values in the OLS specification and approximately \$14,800 lower property values in the 2SLS specification. This similarity is consistent with the spatial-discontinuity design comparing geographically close ZIP codes within the same harmonized bundle. The coefficient is less precisely estimated in the 2SLS specification, reflecting the larger standard errors typical of instrumental-variables estimation.

The FOX crime-exposure coefficient differs substantially between OLS and 2SLS. In the no-interaction specification, the OLS coefficient is small, negative, and statistically insignificant. The 2SLS coefficient is positive and statistically significant: a one-unit increase in FOX crime exposure, corresponding to FOX viewership multiplied by 100 additional FOX crime stories, is associated with approximately \$16,900 higher future property values. This sign reversal is consistent with endogenous selection into FOX News viewership. Respondents with stronger crime concerns may be more likely to watch FOX News, which can bias the OLS relationship between FOX crime exposure and property prices. The IV estimate uses variation in local station availability to isolate the component of exposure induced by the media-market environment.

The interaction specification separates the association between FOX crime exposure and property prices by neighborhood partisanship. In OLS, FOX crime exposure is negatively associated with property prices in less Republican ZIP codes, while the positive interaction term implies that this negative association becomes weaker as the Republican vote share rises. The 2SLS interaction estimates have the opposite sign pattern but are not statistically significant. The point estimates suggest that the positive IV association between FOX crime exposure and property values is larger in less Republican neighborhoods, but the confidence intervals are wide. One interpretation is that the 2020–2022 sample coincides with a period of unusually rapid housing-price growth, shown in Appendix Figure 2, and with a sharp increase in FOX crime coverage, shown in Appendix Figure 6. Because the relevant variation is concentrated in this short period, the estimates may partly reflect the interaction between media exposure and the COVID-era housing boom rather than a stable long-run effect of FOX crime coverage.

8 Conclusion

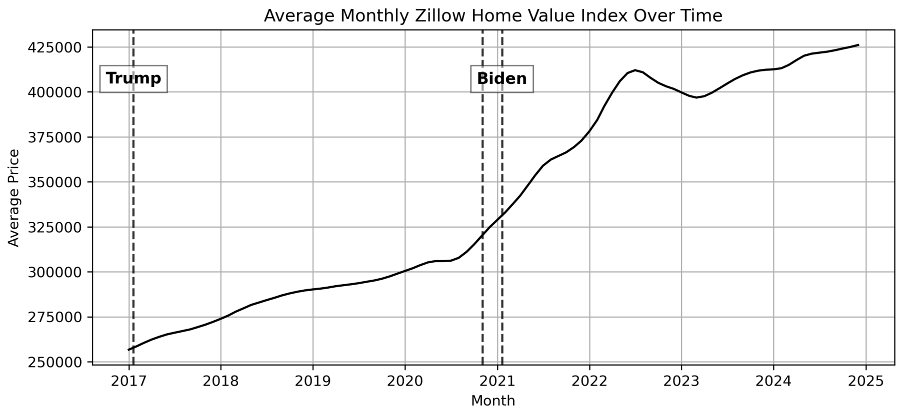
This paper studies how crime perception and media depictions of crime affect neighborhood property prices. To answer this question, I construct a novel dataset that combines ZIP-code-level housing prices, survey-based crime perceptions, spatial measures of neighborhood partisanship, and measures of crime coverage on FOX News. Because crime perception is observed only sparsely at the ZIP-year level, I use a Battese-Harter-Fuller small-area estimator to construct partially pooled measures of local crime perception and apply Murphy-Topel corrections to the second-stage standard errors.

The estimates show that higher perceived crime is associated with lower future property values and lower property-price appreciation. This relationship varies across presidential administrations and neighborhood partisan composition. In particular, the negative association between crime perception and property values is weaker in more Republican ZIP codes, suggesting that the capitalization of perceived crime into housing prices differs across politically distinct neighborhoods. The FOX News specifications provide additional evidence that media exposure matters for housing-market outcomes. When FOX News crime exposure is instrumented using local television station availability, the baseline IV estimates indicate a positive association between exposure to crime-related FOX News content and future property values.

These findings point to a broader role for information and perceptions in local housing markets. Housing prices may respond not only to realized neighborhood conditions but also to the way residents perceive those conditions and to the media environment through which those perceptions are formed. Future research could extend this framework by incorporating richer measures of local media content, longer panels of individual media consumption, and alternative measures of neighborhood beliefs to better understand how information frictions shape local housing markets.

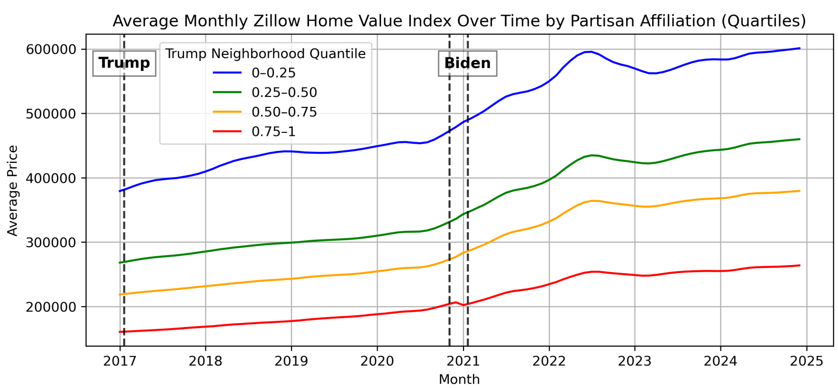
Appendix A. Graphs

Figure 2: Average Monthly Zillow Home Value Index Over Time



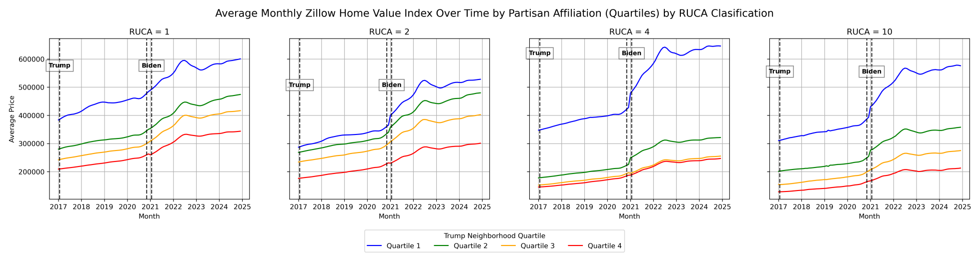
Notes: The figure plots the average monthly Zillow Home Value Index for the ZIP-code sample used in the descriptive analysis. Source: Author's elaboration based on Zillow Home Value Index monthly data.

Figure 3: Average Monthly Zillow Home Value Index Over Time by Partisan Affiliation



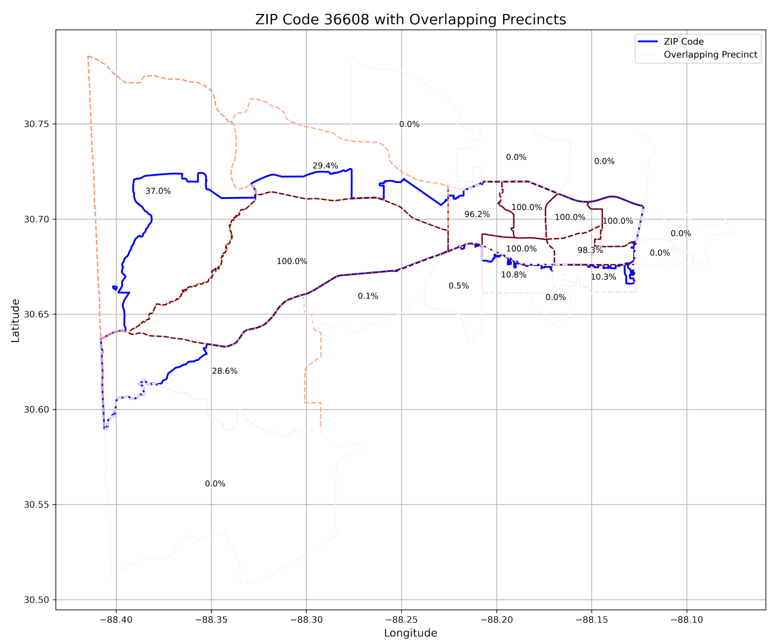
Notes: The figure plots average monthly Zillow Home Value Index values by ZIP-code partisan-affiliation quartile. Source: Author's elaboration based on Zillow Home Value Index monthly data, ZIP-code shapefiles from the U.S. Census Bureau, and ZIP-code voting patterns derived from precinct-level electoral data provided by *The New York Times* and the University of Florida Election Lab.

Figure 4: Average Monthly Zillow Home Value Index by Partisan Affiliation and RUCA Classification



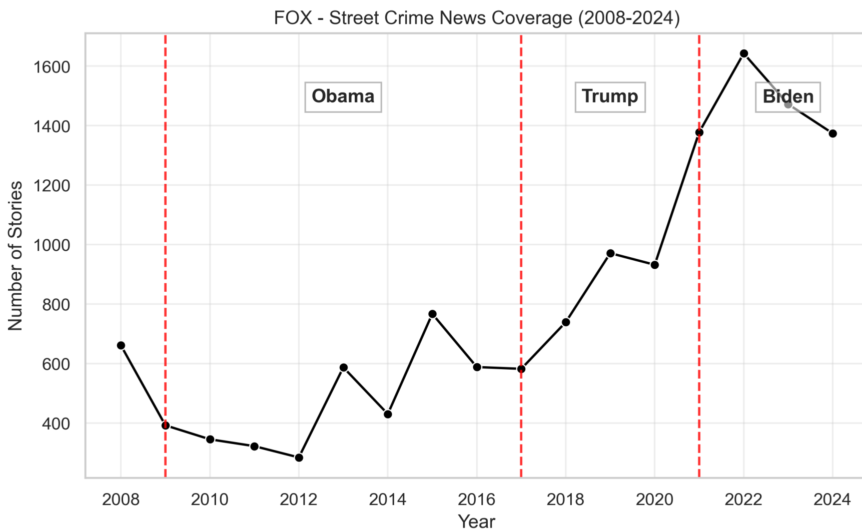
Notes: The figure plots average monthly Zillow Home Value Index values by ZIP-code partisan-affiliation quartile separately for RUCA categories 1, 2, 4, and 10. Source: Author's elaboration based on Zillow Home Value Index monthly data, ZIP-code shapefiles from the U.S. Census Bureau, ZIP-code voting patterns derived from precinct-level electoral data provided by *The New York Times* and the University of Florida Election Lab, and RUCA codes from the U.S. Department of Agriculture.

Figure 5: Precinct-to-ZIP Partisan Affiliation Assignment



Notes: The figure illustrates the spatial overlay used to assign precinct-level presidential election returns to ZIP codes. Votes are allocated to ZIP codes using proportional precinct-to-ZIP area overlap. The full construction procedure is described in Raab (2026).

Figure 6: FOX Street Crime News Coverage Over Time



Notes: The figure reports the annual number of FOX News transcripts classified as street-crime coverage. Classification uses the random forest model with TF-IDF features, with the binary cutoff chosen to maximize the F1 score. Source: Author's elaboration based on transcripts downloaded from Nexis Uni.

Table B.1: FOX News Crime Classification Model Evaluation

Model	Best Cutoff	Best F1	Precision	Recall
CNN Keras	0.4850	0.8108	0.8203	0.8015
Logit + TF-IDF	0.4497	0.8169	0.7582	0.8855
Logit + Embeddings	0.4326	0.7939	0.7939	0.7939
Random Forest + TF-IDF	0.5420	0.8178	0.8707	0.7710
Random Forest + Embeddings	0.4640	0.7645	0.7734	0.7557
BERT	0.9970	0.7344	0.7520	0.7176

Notes: The table reports validation metrics for the FOX News crime-transcript classifiers. The cutoff is chosen to maximize the F1 score for each model. Source: Author's elaboration based on transcripts downloaded from Nexis Uni.

Appendix B. Results

Hedonic Price Equations.

Table B.2: Effect of Crime Perception on Neighborhood Property Price Appreciation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable : Log of Neighborhood Property Prices								
Intercept	12.472***	12.400***	12.136***	12.035***	12.085***	11.960***	12.125***	12.125***
	(0.042)	(0.054)	(0.084)	(0.080)	(0.055)	(0.048)	(0.059)	(0.059)
Trump		0.043		0.098***		0.098***		-0.139***
		(0.055)		(0.026)		(0.024)		(0.043)
Biden		0.321***		0.369***		0.369***		0.080**
		(0.059)		(0.027)		(0.026)		(0.040)
Crime Perception	-0.376***	-0.413***	-0.215***	-0.201***	-0.199***	-0.184***	-0.166***	-0.172***
	(0.048)	(0.061)	(0.021)	(0.022)	(0.020)	(0.021)	(0.017)	(0.019)
Crime Perception × Trump		0.106		0.002		0.001		0.005
		(0.071)		(0.026)		(0.025)		(0.023)
Crime Perception × Biden		0.109		0.038		0.053*		0.034
		(0.080)		(0.029)		(0.029)		(0.029)
N	3,050	3,050	3,050	3,050	3,050	3,050	3,050	3,050
Bundle Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance

Notes: Each observation is a ZIP-year area. Crime perception is a BHF/EBLUP prediction from the unit-level Gallup model, centered at its regression-sample 25th percentile and scaled by its interquartile range. Crime-perception coefficients therefore represent a 25th-to-75th percentile increase in predicted crime perception, and main effects are evaluated at the 25th percentile of predicted crime perception. Second-stage standard errors apply a Murphy-Topel correction for the generated crime-perception regressor. Controls include mean-centered ACS DP04 bedroom shares, year-built shares, units in structure, and vacancy variables. Omitted categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. Columns (7) and (8) add year fixed effects. Missing Census controls are filled from the nearest same-year ZCTA with complete controls. Bathrooms are not available in ACS DP04. The base second-stage covariance is HC1 robust; ZIP-year weights use only the DMA-border distance weight. No specification includes a lagged property-price control. * p<0.10, ** p<0.05, *** p<0.01.

Table B.3: Effect of Crime Perception on Neighborhood Property Price Appreciation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable : Neighborhood Property Prices (hundreds of thousands of dollars)								
Intercept	3.539***	3.063***	2.371***	1.723***	2.468***	1.831***	2.398***	2.366***
	(0.214)	(0.216)	(0.254)	(0.233)	(0.156)	(0.159)	(0.246)	(0.235)
Trump		0.470		0.715**		0.689***		-0.121
		(0.387)		(0.291)		(0.238)		(0.284)
Biden		1.607***		1.685***		1.689***		0.654**
		(0.420)		(0.296)		(0.267)		(0.289)
Crime Perception	-1.410***	-1.089***	-0.902***	-0.369***	-0.787***	-0.308***	-0.743***	-0.294***
	(0.254)	(0.249)	(0.162)	(0.130)	(0.142)	(0.097)	(0.136)	(0.096)
Crime Perception × Trump		-0.335		-0.769**		-0.687**		-0.692**
		(0.504)		(0.376)		(0.307)		(0.311)
Crime Perception × Biden		-1.074*		-1.332***		-1.204***		-1.248***
		(0.606)		(0.491)		(0.447)		(0.452)
Bedrooms: 0-1 BR (%)	0.031***	0.033***	0.012**	0.014**	0.011**	0.014***	0.006	-0.006
	(0.009)	(0.009)	(0.006)	(0.006)	(0.005)	(0.005)	(0.009)	(0.008)
Bedrooms: 2 BR (%)	0.005	0.010	0.011**	0.014***	0.011**	0.015***	0.009*	0.003
	(0.011)	(0.010)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Bedrooms: 4 BR (%)	0.091***	0.090***	0.080***	0.073***	0.064***	0.057***	0.067***	0.058***
	(0.025)	(0.023)	(0.021)	(0.018)	(0.015)	(0.013)	(0.015)	(0.013)
Bedrooms: 5+ BR (%)	-0.000	-0.000	-0.000**	-0.000*	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Built 2000+ (%)	0.013	0.001	0.017**	0.006	0.009	-0.003	-0.003	-0.005
	(0.010)	(0.011)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)
Built 1960-1979 (%)	0.039***	0.033**	0.020**	0.015	0.007	0.002	0.002	0.002
	(0.014)	(0.014)	(0.010)	(0.009)	(0.008)	(0.007)	(0.008)	(0.007)
Built Pre-1960 (%)	-0.008	-0.013	0.011*	0.006	0.003	-0.002	0.001	0.001
	(0.008)	(0.008)	(0.006)	(0.006)	(0.004)	(0.004)	(0.004)	(0.004)
Single Detached (%)	0.004	0.010	0.003	0.011*	0.018***	0.026***	0.019***	0.021***
	(0.010)	(0.009)	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
Single Attached (%)	0.049***	0.053***	0.019**	0.026***	0.022***	0.030***	0.027***	0.029***
	(0.010)	(0.010)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Small Multiunit (%)	-0.003	-0.003	-0.003	-0.004	0.017**	0.016**	0.020***	0.021***
	(0.015)	(0.015)	(0.009)	(0.009)	(0.008)	(0.007)	(0.007)	(0.007)
Large Multiunit (%)	0.063***	0.061***	0.044***	0.045***	0.032***	0.033***	0.032***	0.040***
	(0.013)	(0.013)	(0.009)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)
Vacant Units (%)	0.017**	0.020***	0.011**	0.011**	0.009**	0.010***	0.011***	0.013***
	(0.008)	(0.008)	(0.005)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)
Homeowner Vacancy Rate	-0.119***	-0.102**	-0.105***	-0.077***	-0.091***	-0.065***	-0.055***	-0.068***
	(0.044)	(0.045)	(0.028)	(0.027)	(0.017)	(0.018)	(0.017)	(0.018)
Rental Vacancy Rate	-0.014	-0.013	0.006	0.007	0.009	0.008	0.009	0.007
	(0.012)	(0.011)	(0.007)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
N	3,050	3,050	3,050	3,050	3,050	3,050	3,050	3,050
Bundle Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance

Notes: Each observation is a ZIP-year area. Crime perception is a BHF/EBLUP prediction from the unit-level Gallup model, centered at its regression-sample 25th percentile and scaled by its interquartile range. Crime-perception coefficients therefore represent a 25th-to-75th percentile increase in predicted crime perception, and main effects are evaluated at the 25th percentile of predicted crime perception. Second-stage standard errors apply a Murphy-Topel correction for the generated crime-perception regressor. Controls include mean-centered ACS DP04 bedroom shares, year-built shares, units in structure, and vacancy variables. Omitted categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. Columns (7) and (8) add year fixed effects. Missing Census controls are filled from the nearest same-year ZCTA with complete controls. Bathrooms are not available in ACS DP04. The base second-stage covariance is HC1 robust; ZIP-year weights use only the DMA-border distance weight. No specification includes a lagged property-price control. * p<0.10, ** p<0.05, *** p<0.01.

Table B.4: Effect of Crime Perception on Neighborhood Property Price Appreciation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable : Log of Neighborhood Property Prices								
Intercept	12.472***	12.400***	12.136***	12.035***	12.085***	11.960***	12.125***	12.125***
	(0.042)	(0.054)	(0.084)	(0.080)	(0.055)	(0.048)	(0.059)	(0.059)
Trump		0.043		0.098***		0.098***		-0.139***
		(0.055)		(0.026)		(0.024)		(0.043)
Biden		0.321***		0.369***		0.369***		0.080**
		(0.059)		(0.027)		(0.026)		(0.040)
Crime Perception	-0.376***	-0.413***	-0.215***	-0.201***	-0.199***	-0.184***	-0.166***	-0.172***
	(0.048)	(0.061)	(0.021)	(0.022)	(0.020)	(0.021)	(0.017)	(0.019)
Crime Perception × Trump		0.106		0.002		0.001		0.005
		(0.071)		(0.026)		(0.025)		(0.023)
Crime Perception × Biden		0.109		0.038		0.053*		0.034
		(0.080)		(0.029)		(0.029)		(0.029)
Bedrooms: 0-1 BR (%)	0.005**	0.008***	-0.001	0.002	-0.002**	0.001	-0.006***	-0.005***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bedrooms: 2 BR (%)	-0.004	-0.001	-0.003**	-0.001	-0.002**	-0.001	-0.004***	-0.004***
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Bedrooms: 4 BR (%)	0.016***	0.019***	0.009***	0.011***	0.007***	0.008***	0.008***	0.009***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Bedrooms: 5+ BR (%)	-0.000	0.000	-0.000***	-0.000	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Built 2000+ (%)	-0.001	-0.003	0.002	-0.001	0.001	-0.001	-0.002**	-0.002**
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Built 1960-1979 (%)	0.002	0.000	0.001	-0.001	0.000	-0.001	-0.001	-0.001
	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Built Pre-1960 (%)	-0.009***	-0.010***	-0.005***	-0.006***	-0.005***	-0.007***	-0.006***	-0.006***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Single Detached (%)	0.007***	0.008***	0.007***	0.008***	0.009***	0.010***	0.008***	0.008***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Single Attached (%)	0.020***	0.021***	0.009***	0.011***	0.009***	0.011***	0.010***	0.010***
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Small Multiunit (%)	0.007*	0.007*	0.004**	0.004*	0.006***	0.005***	0.007***	0.007***
	(0.004)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Large Multiunit (%)	0.017***	0.016***	0.015***	0.014***	0.015***	0.014***	0.016***	0.016***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Vacant Units (%)	0.005**	0.005**	0.003**	0.003**	0.002**	0.002**	0.003***	0.003***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Homeowner Vacancy Rate	-0.044***	-0.036***	-0.039***	-0.029***	-0.040***	-0.029***	-0.030***	-0.029***
	(0.013)	(0.013)	(0.007)	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)
Rental Vacancy Rate	-0.006**	-0.006**	-0.001	-0.001	-0.000	-0.000	-0.000	-0.000
	(0.003)	(0.003)	(0.002)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
N	3,050	3,050	3,050	3,050	3,050	3,050	3,050	3,050
Bundle Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance

Notes: Each observation is a ZIP-year area. Crime perception is a BHF/EBLUP prediction from the unit-level Gallup model, centered at its regression-sample 25th percentile and scaled by its interquartile range. Crime-perception coefficients therefore represent a 25th-to-75th percentile increase in predicted crime perception, and main effects are evaluated at the 25th percentile of predicted crime perception. Second-stage standard errors apply a Murphy-Topel correction for the generated crime-perception regressor. Controls include mean-centered ACS DP04 bedroom shares, year-built shares, units in structure, and vacancy variables. Omitted categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. Columns (7) and (8) add year fixed effects. Missing Census controls are filled from the nearest same-year ZCTA with complete controls. Bathrooms are not available in ACS DP04. The base second-stage covariance is HC1 robust; ZIP-year weights use only the DMA-border distance weight. No specification includes a lagged property-price control.
* p<0.10, ** p<0.05, *** p<0.01.

Hedonic Price Equations with Neighborhood Partisanship.

Table B.5: Effect of Crime Perception on Neighborhood Property Prices: Republican ZIP Interaction

	Trump (1)	Biden (2)	Trump (3)	Biden (4)	Trump (5)	Biden (6)	Trump (7)	Biden (8)
Dependent Variable : Log of Neighborhood Property Prices								
Intercept	12.475***	12.885***	12.207***	12.593***	12.068***	12.316***	12.008***	12.314***
	(0.051)	(0.100)	(0.078)	(0.130)	(0.091)	(0.070)	(0.082)	(0.072)
Republican ZIP	-0.193***	-0.316***	-0.125***	-0.088*	-0.030	0.007	-0.040	0.006
	(0.044)	(0.084)	(0.037)	(0.051)	(0.038)	(0.060)	(0.036)	(0.061)
Crime Perception	-0.241***	-0.375***	-0.181***	-0.222***	-0.158***	-0.161***	-0.139***	-0.160***
	(0.058)	(0.080)	(0.044)	(0.049)	(0.043)	(0.044)	(0.038)	(0.044)
Crime Perception × Republican ZIP	0.098**	0.240***	0.076**	0.115**	0.065*	0.078	0.073**	0.078
	(0.038)	(0.071)	(0.034)	(0.047)	(0.035)	(0.049)	(0.035)	(0.048)
N	818	570	818	570	818	570	818	570
Bundle Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance

Notes: Each observation is a ZIP-year area. Crime perception is a BHF/EBLUP prediction from the unit-level Gallup model, centered at its regression-sample 25th percentile and scaled by its interquartile range. Republican ZIP is also centered at its regression-sample 25th percentile and scaled by its interquartile range. Crime-perception and Republican-ZIP coefficients therefore represent 25th-to-75th percentile increases, and main effects are evaluated at the 25th percentile of the interacted variable. Second-stage standard errors apply a Murphy-Topel correction for the generated crime-perception regressor. Controls include mean-centered ACS DP04 bedroom shares, year-built shares, units in structure, and vacancy variables. Omitted categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. Republican ZIP is the ZIP-year value of Trump_neighborhood. Odd-numbered columns keep Trump-period ZIP-years; even-numbered columns keep Biden-period ZIP-years. Columns (7) and (8) add year fixed effects. The base second-stage covariance is HC1 robust; ZIP-year weights use only the DMA-border distance weight. No specification includes a lagged property-price control. * p<0.10, ** p<0.05, *** p<0.01.

Property price appreciation model (need clarification)

Table B.6: Effect of Crime Perception on Neighborhood Property Price Appreciation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable : First Difference in Log Neighborhood Property Prices								
Intercept	0.035***	0.022***	0.084**	0.064*	0.035***	0.023**	-0.038***	-0.038***
	(0.004)	(0.007)	(0.040)	(0.039)	(0.009)	(0.009)	(0.010)	(0.010)
Trump		0.041***		0.038***		0.037***		0.089***
		(0.009)		(0.007)		(0.006)		(0.010)
Biden		0.009		0.010		0.007		0.068***
		(0.008)		(0.007)		(0.006)		(0.009)
Crime Perception	0.002	0.002	0.010**	0.010	0.011**	0.011*	0.006**	0.005
	(0.005)	(0.007)	(0.005)	(0.006)	(0.005)	(0.006)	(0.002)	(0.003)
Crime Perception × Trump		-0.008		-0.007		-0.008		0.003
		(0.007)		(0.006)		(0.006)		(0.004)
Crime Perception × Biden		0.009		0.007		0.006		0.003
		(0.008)		(0.007)		(0.007)		(0.005)
N	3,050	3,050	3,050	3,050	3,050	3,050	3,050	3,050
Bundle Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	Yes
DMA Fixed Effects	No	No	No	No	Yes	Yes	Yes	Yes
Time Fixed Effects	No	No	No	No	No	No	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weights	Distance	Distance	Distance	Distance	Distance	Distance	Distance	Distance
Lagged Log Price Change	No	No	No	No	No	No	No	No

Notes: Each observation is a ZIP-year area. The dependent variable is a first difference in future property prices, defined as $P_{t+1} - P_t$. These specifications omit the lagged price-change control. Crime perception is a BHF/EBLUP prediction from the unit-level Gallup model, centered at the 25th percentile and scaled by the interquartile range. Second-stage standard errors apply a Murphy-Topel correction for the generated crime-perception regressor. Controls include mean-centered ACS DP04 bedroom shares, year-built shares, units in structure, and vacancy variables. Omitted categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. Missing Census controls are filled from the nearest same-year ZCTA with complete controls. The base second-stage covariance is HC1 robust; ZIP-year weights use only the DMA-border distance weight. Columns (7) and (8) add year fixed effects. * p<0.10, ** p<0.05, *** p<0.01.

FOX News Viewership Effect on Property Prices.

Table B.7: First Stage Regression: FOX Crime Exposure

	FOX Crime Exposure
Dependent Variable : FOX Crime Exposure	
Intercept	9.473***
	(0.400)
Number Stations	-0.614***
	(0.094)
Number Stations x FOX Crime Intensity / 100	0.058***
	(0.007)
Bedrooms: 0-1 BR (%)	0.006
	(0.027)
Bedrooms: 2 BR (%)	-0.007
	(0.013)
Bedrooms: 4 BR (%)	-0.041**
	(0.018)
Bedrooms: 5+ BR (%)	-0.006
	(0.030)
Built 2000+ (%)	-0.014
	(0.010)
Built 1960-1979 (%)	-0.019
	(0.012)
Built Pre-1960 (%)	-0.018*
	(0.010)
Single Detached (%)	-0.009
	(0.011)
Single Attached (%)	-0.037**
	(0.018)
Small Multiunit (%)	0.002
	(0.015)
Large Multiunit (%)	-0.048***
	(0.017)
Vacant Units (%)	-0.003
	(0.010)
Homeowner Vacancy Rate	-0.043
	(0.059)
Rental Vacancy Rate	-0.021
	(0.015)
N ZIP Codes	9,055
First-stage F-statistic (joint)	36.76
Bundle Fixed Effects	Yes
Weights	Composite ZIP

Notes: ZIP-level weighted first-stage regression corresponding to the no-interaction 2SLS column in second_stage_regression_NEWS_HEDONIC. FOX Crime Exposure is defined as FOX viewership multiplied by FOX crime articles divided by 100. The excluded instruments are Number Stations and Number Stations x FOX Crime Intensity divided by 100. The reported joint F-statistic is an HC1 robust joint test of the excluded instruments. The specification includes mean-centered ACS DP04 property controls, final harmonized bundle fixed effects, and composite ZIP weights equal to ZIP respondent count times inverse-distance weight, normalized to mean one. Neighborhood Wealth controls are excluded. Omitted property-control categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. HC1 robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.8: First Stage Regressions: FOX Crime News Exposure and Trump-Neighborhood Interaction

	FOX Crime Exposure	FOX Crime Exposure x Trump
Dependent Variables : FOX Crime Exposure and FOX Crime Exposure x Trump Neighborhood		
Intercept	6.004***	17.751***
	(1.034)	(5.739)
Trump Neighborhood	0.474***	7.485***
	(0.151)	(0.829)
Number Stations	-0.447*	1.337
	(0.249)	(1.267)
Number Stations x FOX Crime Intensity / 100	0.045**	-0.050
	(0.018)	(0.094)
Number Stations x Trump Neighborhood	-0.028	-0.875***
	(0.043)	(0.263)
Number Stations x Crime x Trump / 100	0.002	0.069***
	(0.003)	(0.020)
Bedrooms: 0-1 BR (%)	0.018	0.015
	(0.027)	(0.122)
Bedrooms: 2 BR (%)	-0.005	0.011
	(0.013)	(0.074)
Bedrooms: 4 BR (%)	-0.017	-0.142
	(0.017)	(0.100)
Bedrooms: 5+ BR (%)	0.003	0.173
	(0.028)	(0.166)
Built 2000+ (%)	-0.013	-0.091*
	(0.010)	(0.054)
Built 1960-1979 (%)	-0.015	-0.122**
	(0.013)	(0.061)
Built Pre-1960 (%)	-0.013	-0.052
	(0.010)	(0.049)
Single Detached (%)	-0.002	-0.027
	(0.011)	(0.070)
Single Attached (%)	-0.014	-0.051
	(0.018)	(0.090)
Small Multiunit (%)	0.028*	0.056
	(0.016)	(0.085)
Large Multiunit (%)	-0.013	-0.015
	(0.018)	(0.087)
Vacant Units (%)	0.000	0.030
	(0.010)	(0.066)
Homeowner Vacancy Rate	-0.036	-0.211
	(0.056)	(0.334)
Rental Vacancy Rate	-0.027*	-0.216**
	(0.015)	(0.103)
N ZIP Codes	9,055	9,055
First-stage F-statistic	20.16	18.19
Bundle Fixed Effects	Yes	Yes
Weights	Composite ZIP	Composite ZIP

Notes: ZIP-level weighted first-stage regressions corresponding to the 2SLS column in second_stage_regression_NEWS_HEDONIC_INTERACTION. The endogenous second-stage regressors are FOX Crime Exposure and FOX Crime Exposure x Trump Neighborhood. FOX Crime Exposure is defined as FOX viewership multiplied by FOX crime articles divided by 100. The excluded instruments are Number Stations, Number Stations x FOX Crime Intensity divided by 100, and both station instruments interacted with Trump Neighborhood in 10-percentage-point units. The reported first-stage F-statistics are HC1 robust joint tests of the excluded instruments in each equation. Specifications include Trump Neighborhood in 10-percentage-point units, mean-centered ACS DP04 property controls, final harmonized bundle fixed effects, and composite ZIP weights equal to ZIP respondent count times inverse-distance weight, normalized to mean one. Neighborhood Wealth controls are excluded. Omitted property-control categories are 3 bedrooms, built 1980-1999, and mobile homes; median rooms are excluded. HC1 robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B.9: Second Stage Regression: FOX Crime News Exposure and Log Future Neighborhood Property Prices with Hedonic Controls

	No Interaction		Neighborhood Interaction	
	OLS Weighted	2SLS Weighted	OLS Weighted	2SLS Weighted
Dependent Variable : Log Neighborhood Property Prices				
Intercept	11.794***	11.372***	11.860***	11.646***
	(0.050)	(0.081)	(0.071)	(0.117)
Trump Neighborhood			-0.015**	-0.048**
			(0.007)	(0.021)
FOX Crime Exposure	-0.001	0.045***	-0.020***	0.012
	(0.001)	(0.008)	(0.005)	(0.028)
FOX Crime Exposure x Trump Neighborhood			0.003***	0.006
			(0.001)	(0.004)
N ZIP Codes	9,055	9,055	9,055	9,055
First-stage F-statistic (joint)		36.76		
First-stage F-statistic (FOX x Crime)				20.16
First-stage F-statistic (FOX x Crime x Trump)				18.19
Bundle Fixed Effects	Yes	Yes	Yes	Yes
Weights	Composite ZIP	Composite ZIP	Composite ZIP	Composite ZIP

Notes: ZIP-level weighted regressions. Columns (1)–(2) reproduce second_stage_regression_NEWS_HEDONIC_LOG; columns (3)–(4) reproduce second_stage_regression_NEWS_HEDONIC_INTERACTION_LOG. The dependent variable is the natural log of non-detrended future neighborhood property price, log(Neighborhood_wealth_nodetrend_T). Hedonic controls are mean-centered and included but suppressed from the table. FOX Crime Exposure is defined as FOX viewership multiplied by FOX crime articles divided by 100. Trump Neighborhood is measured in 10-percentage-point units in the interaction columns; hedonic controls are mean-centered, so the intercept is evaluated at average hedonic characteristics. The no-interaction 2SLS column instruments FOX Crime Exposure with Number Stations and Number Stations x FOX Crime Intensity divided by 100. The interaction 2SLS column instruments FOX Crime Exposure and its interaction with Trump Neighborhood in 10-percentage-point units with Number Stations, Number Stations x FOX Crime Intensity divided by 100, and both station instruments interacted with Trump Neighborhood in 10-percentage-point units. All specifications include final harmonized bundle fixed effects, exclude Neighborhood Wealth controls, and use composite ZIP weights equal to ZIP respondent count times inverse-distance weight, normalized to mean one. Robust standard errors are in parentheses. *** p<0.01, ** p<0.05, * p<0.1.