# Appendix for The Distaste for Housing Density

Joe Gyourko and Sean McCulloch

## Appendix A. Additional figures and tables

Figure A1: WRLURI survey instruments on density restrictions

(a) 2006 survey instrument

**6.** To build, do developers have to meet these requirements?

| | Yes | No |
|---|---|---|
| - Meet the minimum lot size requirement?<br>If yes: ½ acre or more________ ½ acre or less _______<br>1 acre or more ________ 2 acres or more _______ | | |
| - Include "affordable housing" (however defined)? | | |
| - Supply mandatory dedication of space or open space (or fee in lieu of dedication)? | | |
| - Pay allocable share of costs of infrastructure improvement? | | |

(b) 2018 survey instrument

**7. Do you have a minimum lot size requirement?** ❒ a. Yes 1 ❒ b. No 2 *(If "No," skip to question 8.)*

**7A. If "Yes," do you have the same minimum lot size requirement across the entire jurisdiction?**

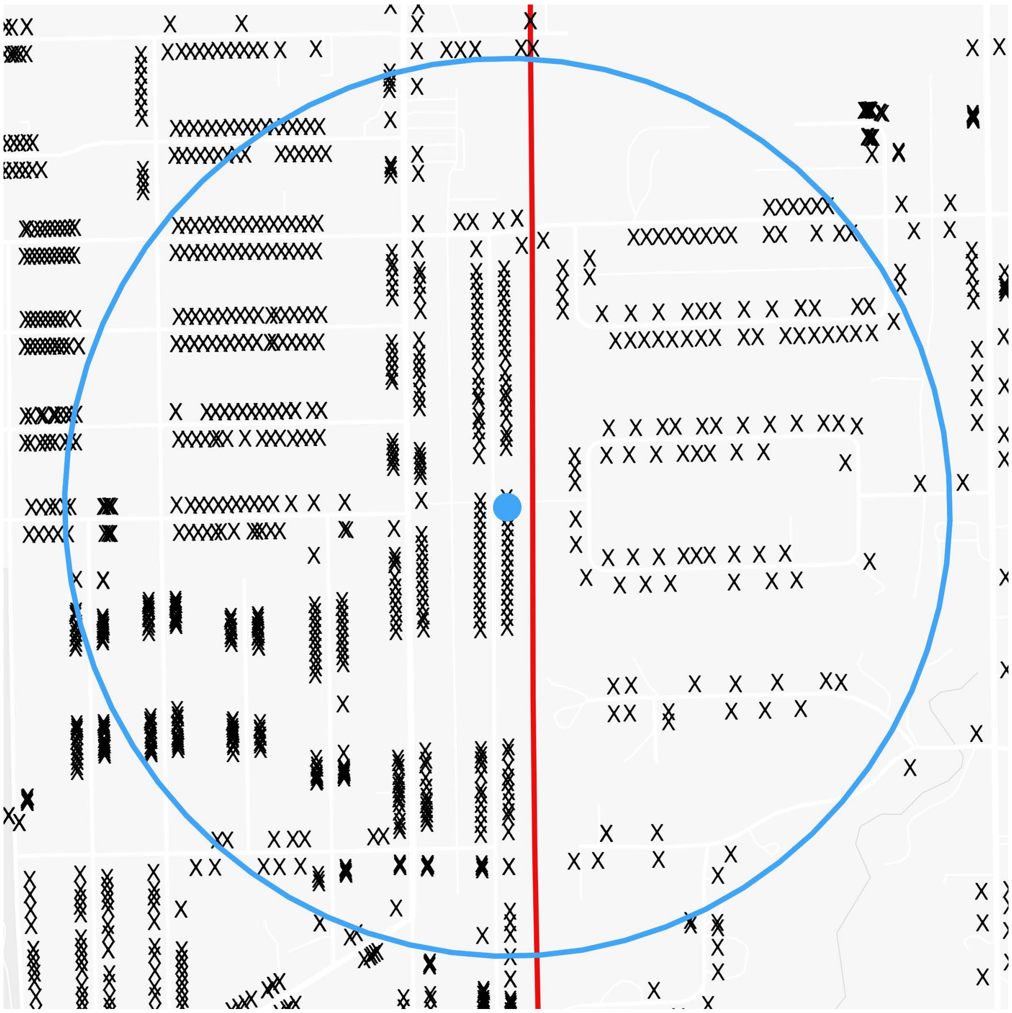
❒ a. Yes 1 ❒ b. No 2

**7B. If you have any minimum size requirement, what is the largest minimum requirement?** (*Check only one.)*

❒ Less than ½ acre 1 ❒ ½ to 1 acre 2 ❒ 1 to under 2 acres 3 ❒ 2 acres or more 4

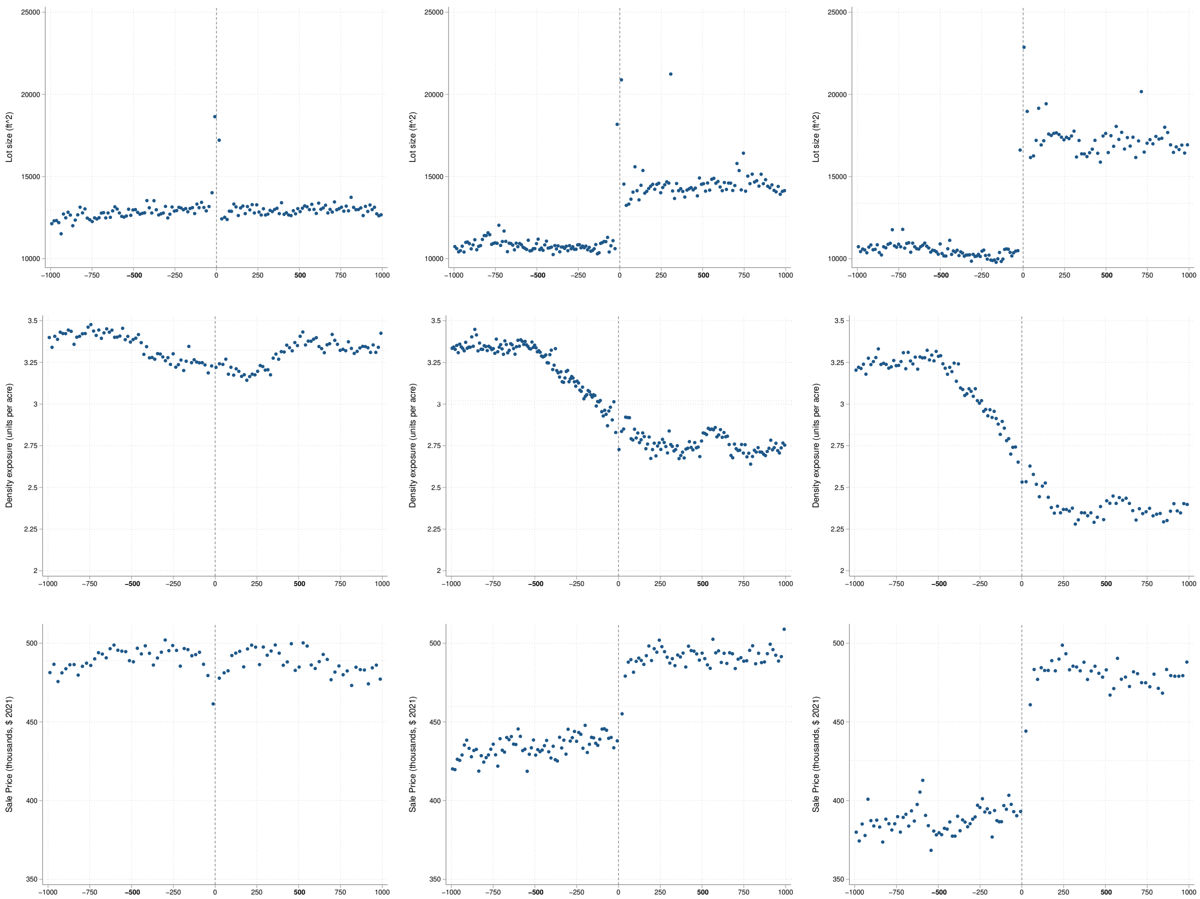
*Note: This figure shows the density restriction questions from the questionnaires disseminated in the 2006 and 2018 Wharton Residential Land Use Regulation survey (Gyourko et al., 2008, 2021).*

Figure A2: Construction of a density exposure measure using CoreLogic microdata



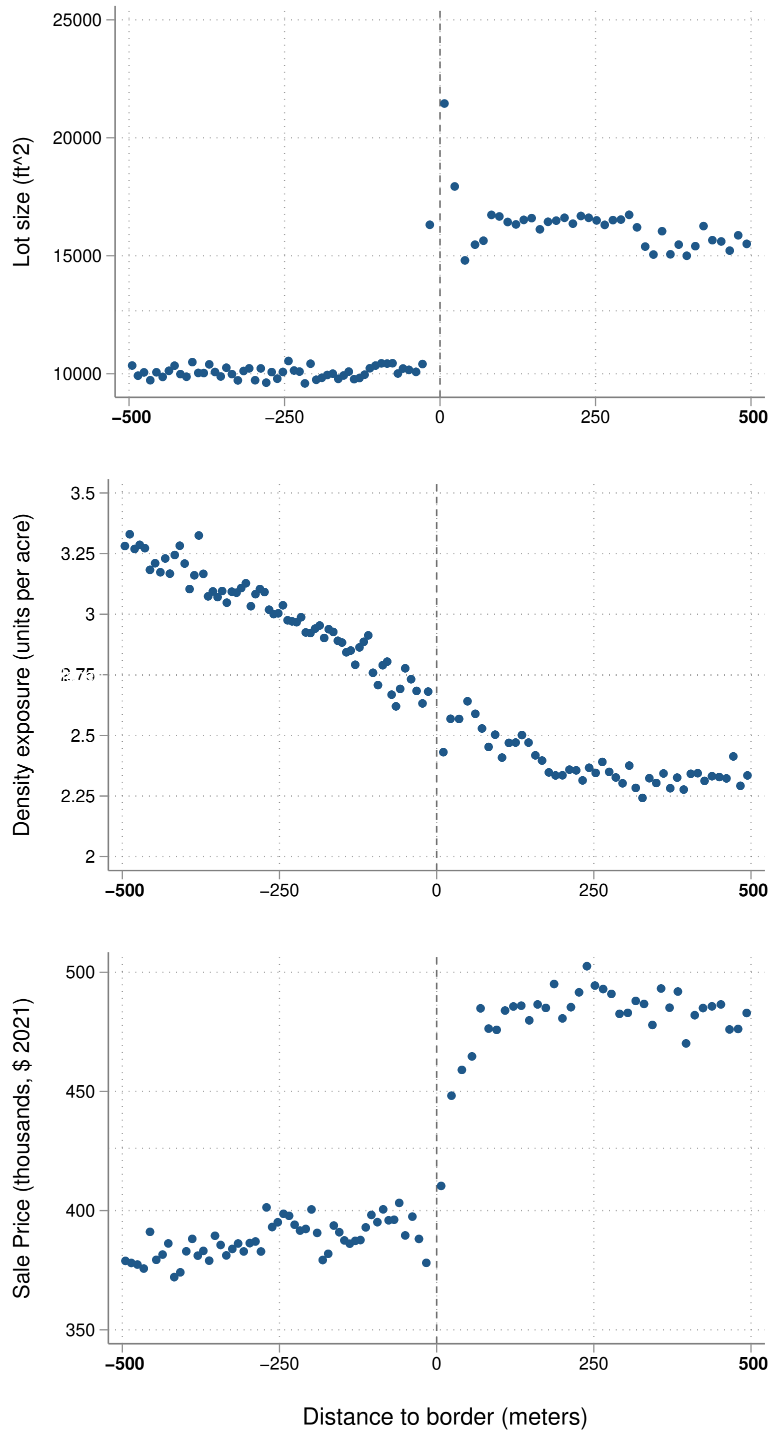
*Note: This figure shows the construction of a density exposure measure for one parcel close to the Golf Manor-Amberley border in the Cincinnati, OH metropolitan area using the location data in CoreLogic. The blue dot is the location reported by CoreLogic for the parcel of interest and the blue circle shows the area within 500 meters of that parcel. The black crosses mark other single family parcel locations reported by CoreLogic. To construct a measure of density we add up all the single family parcels within the blue circle and divide by the circle's geographic area ($\pi 500^2$ square meters). We then convert from square meters to acres. We apply this process to every single family parcel in the border areas in our sample. Basemap by ©OpenStreetMap ©CARTO.*

Figure A3: Distance gradients in borders with no density restriction change vs. $\Delta$DRI borders vs. $\Delta$Lot borders



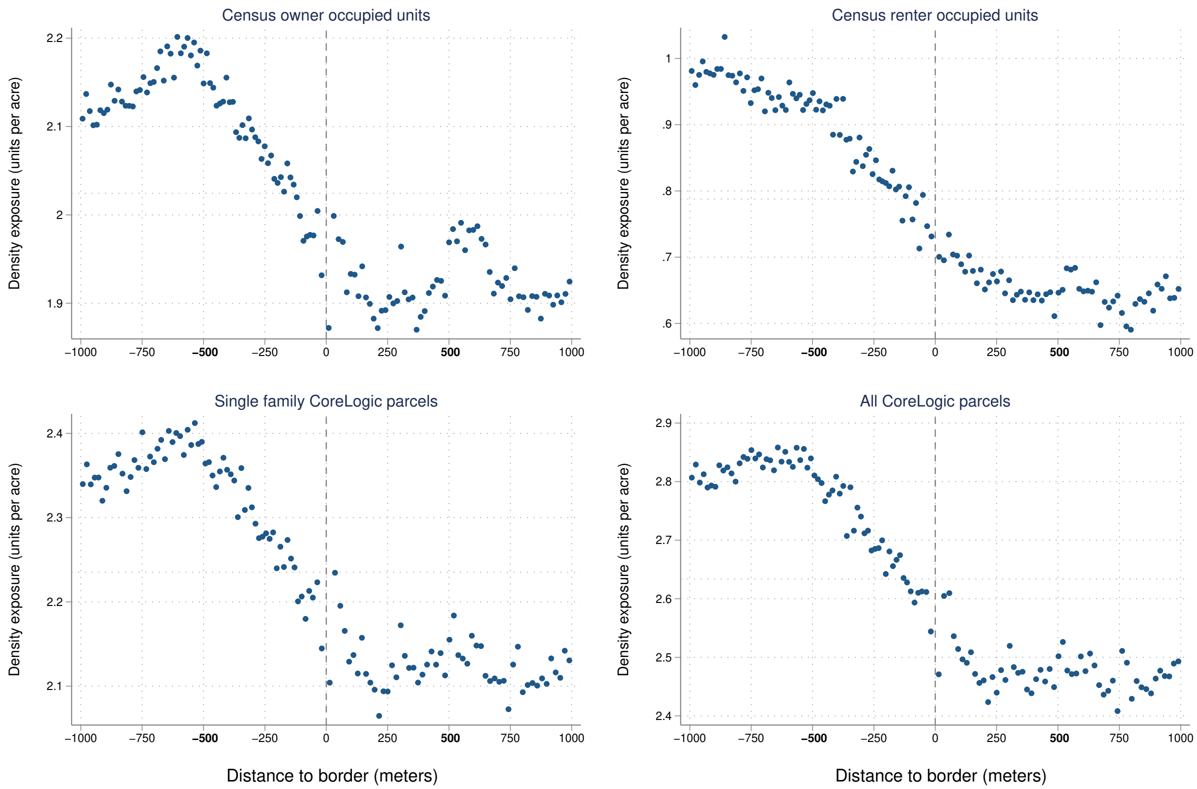
*Note: This figure compares binscatter plots constructed in the same way as Figure 5 for borders with no density restriction change (left column) vs. $\Delta$DRI borders (middle column) vs. $\Delta$Lot borders (right column). For the borders with no change, the "left" side of the border (negative distance values) was chosen randomly.*

Figure A4: Distance gradients in the hedonic sample




*Note: This figure presents binned scatter plots of the three outcomes lot size, density exposure, and sale price on distance to the municipal boundary pooling together the border areas used in the hedonic estimation sample. The plotted relationships between the outcomes and distance to the boundary adjust for border pair specific fixed effects following Cattaneo et al. (2024a,b). The top panel is the plot for lot size, the middle panel is for density exposure, and the final panel is for sale price. Note that the hedonic sample uses only observations < 500 meters from the borders so the x-axis reflects a smaller geographic area than Figure 5.*

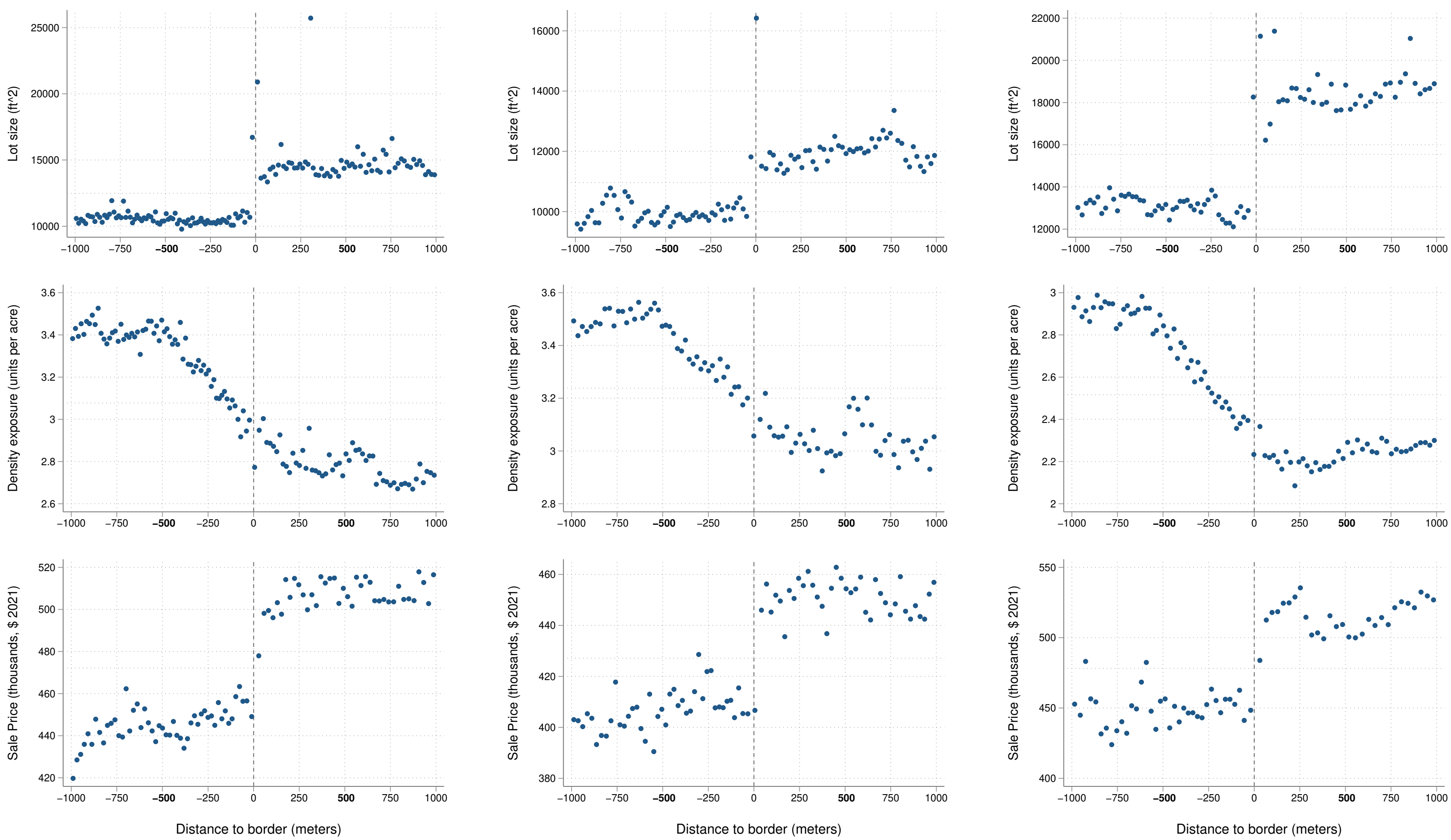
Figure A5: Density exposure gradients for alternative measures of exposure




*Note: This figure presents binned scatter plots of alternative measures of density exposure on distance to the border pooling together the ΔDRI border areas. The plotted relationships adjust for border pair specific fixed effects following Cattaneo et al. (2024a,b). The first row shows density exposure by housing tenure. In the top left panel, the density exposure is the number of owner occupied housing units found in census blocks within 500 meters converted to units per acre. In the top right panel, the density exposure is the number of renter occupied housing units found in census blocks within 500 meters converted to units per acre. The panels in the bottom row are constructed using the more granular location data in CoreLogic. In the bottom left panel, the density exposure is the number of single family housing units found in CoreLogic within 500 meters converted to units per acre. In the bottom right panel, the density exposure is the total number of parcels found in CoreLogic within 500 meters converted to parcels per acre.*

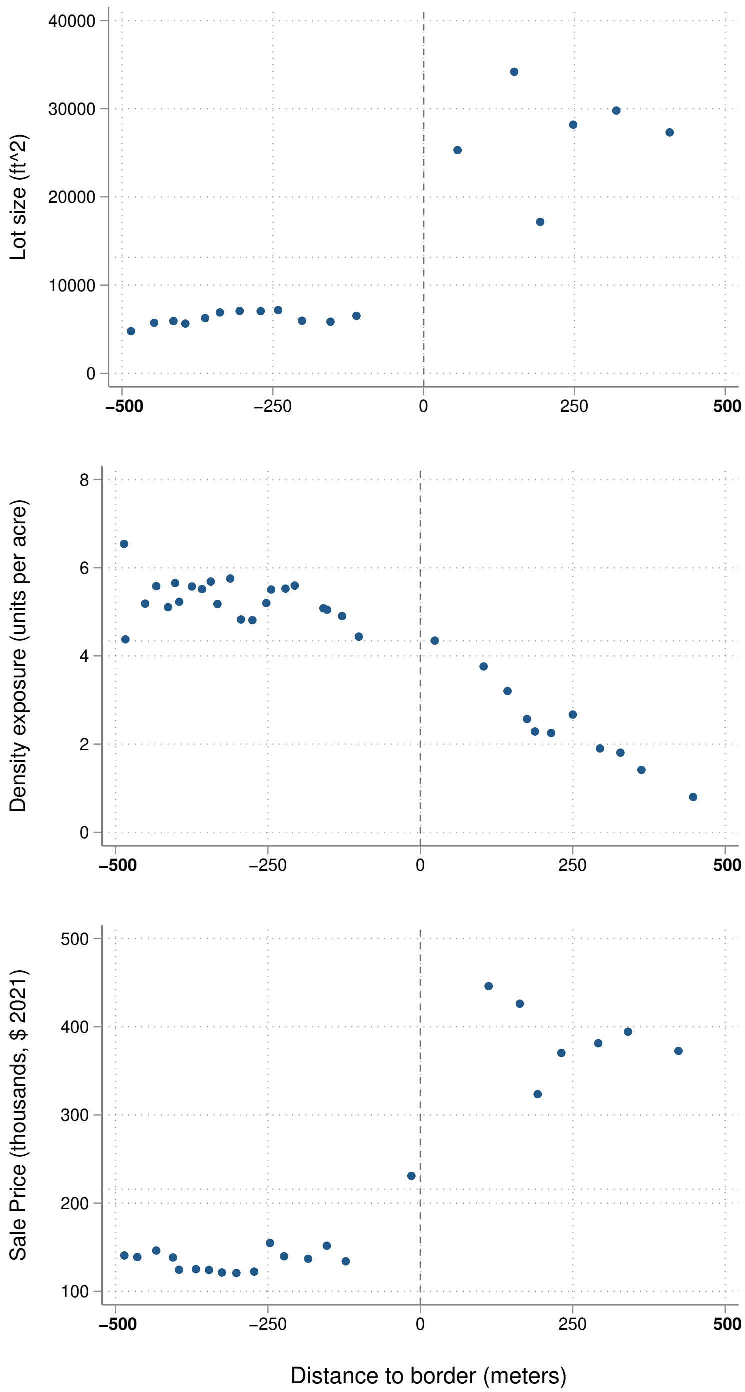
Figure A6: Distance gradients by ΔDRI subgroup

(a) Low-high (b) Low-medium (c) Medium-high



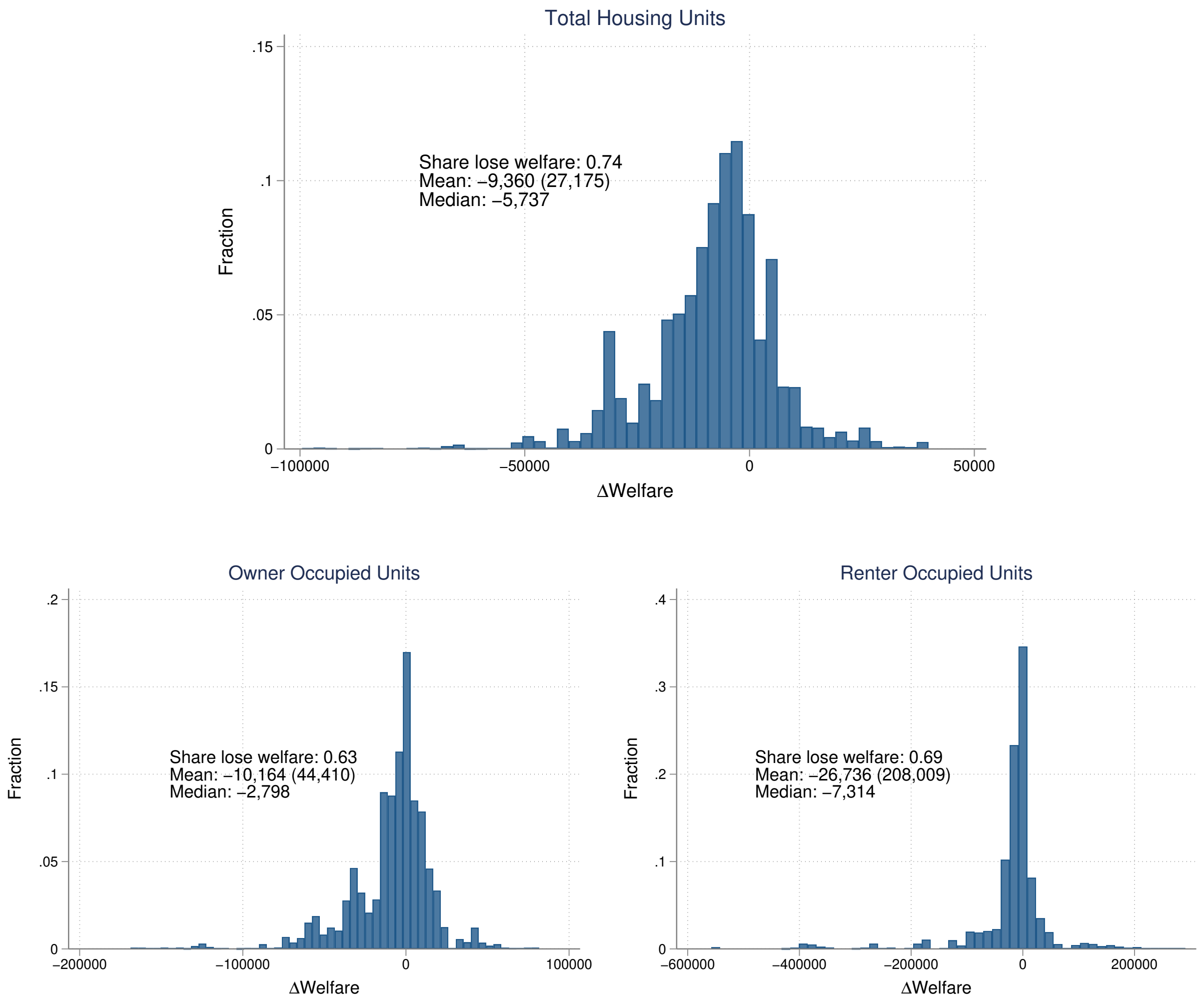

*Note: This figure presents binned scatter plots splitting the ΔDRI borders into subsamples by whether the density restriction index changed from low to high, low to medium, or medium to high, after adjusting for border pair specific fixed effects following Cattaneo et al. (2024a,b). Panel (a) plots the three outcomes, lot size, density exposure, and sale price, on distance to the municipal boundary for borders where the density restriction index changed from a low index value to a high value (201 borders). Panel (b) shows analogous plots for borders with a change from low to medium (132 borders). Panel (c) is borders with a medium to high density restriction index change (92 borders).*

Figure A7: Border gradients at the Golf Manor-Amberley border area, Cincinatti, OH, metropolitan area



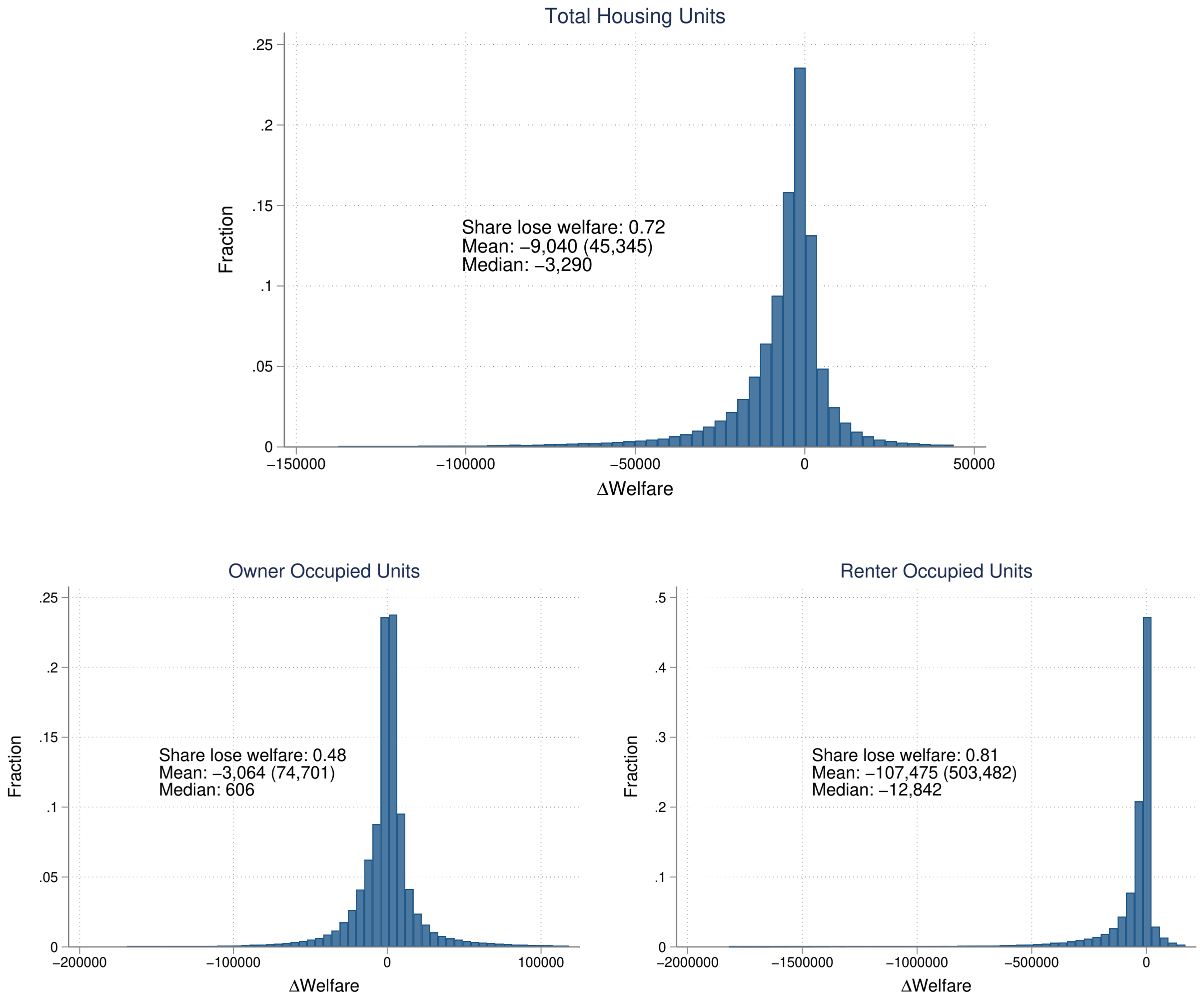

*Note: This figure presents binned scatter plots of the three outcomes lot size, density exposure, and sale price on distance to the municipal boundary using only observations within 500 meters of the Golf Manor-Amberley border. The top panel is for lot size, the middle panel is for density exposure, and the final panel is for sale price. The number of bins was selected to minimize the IMSE following Cattaneo et al. (2024b).*

Figure A8: Distribution of $\Delta$Welfare estimates, Linear specification




*Note: This figure shows distributions of welfare change estimates under a counterfactual increase of* 1/2 *unit per acre by housing type based on a linear hedonic specification controlling for parcel characteristics, school test scores, and distance to local amenities. The top panel plots the empirical distribution for the total housing unit density exposure from the 1st through 99th percentile. The bottom left panel plots the distribution of welfare changes from increasing owner occupied density exposure. The bottom right panel plots the distribution of welfare changes for increasing the renter occupied density exposure. Measures of central tendency for each distribution are reported in the accompanying text boxes.*

Figure A9: Distribution of $\Delta$Welfare estimates, Log-log specification




*Note: This figure shows distributions of welfare change estimates under a counterfactual increase of* 1/2 *unit per acre by housing type based on a log-log hedonic specification controlling for parcel characteristics, school test scores, and distance to local amenities. The top panel plots the empirical distribution for the total housing unit density exposure from the 1st through 99th percentile. The bottom left panel plots the distribution of welfare changes from increasing owner occupied density exposure. The bottom right panel plots the distribution of welfare changes for increasing the renter occupied density exposure. Measures of central tendency for each distribution are reported in the accompanying text boxes.*

## Appendix Tables

Table A1: Number of borders by CBSA

| Metro area | (1)<br>All < 1,000m | (2)<br>< 1,000m, $\Delta$DRI | (3)<br>< 500m, $\Delta$Lot |
|---|---|---|---|
| Albany-Schenectady-Troy, NY | 1 | 0 | 0 |
| Allentown-Bethlehem-Easton, PA-NJ | 6 | 1 | 0 |
| Atlanta-Sandy Springs-Alpharetta, GA | 6 | 3 | 1 |
| Boston-Cambridge-Newton, MA-NH | 73 | 22 | 7 |
| Buffalo-Cheektowaga, NY | 1 | 0 | 0 |
| Charlotte-Concord-Gastonia, NC-SC | 6 | 1 | 1 |
| Chicago-Naperville-Elgin, IL-IN-WI | 133 | 51 | 33 |
| Cincinnati-Middletown, OH-KY-IN | 56 | 33 | 21 |
| Cleveland, OH | 30 | 16 | 13 |
| Columbus, OH | 14 | 7 | 6 |
| Dallas-Fort Worth-Arlington, TX | 57 | 33 | 12 |
| Denver-Aurora-Lakewood, CO | 18 | 7 | 5 |
| Detroit-Warren-Dearborn, MI | 97 | 37 | 20 |
| Harrisburg-Carlisle, PA | 15 | 6 | 6 |
| Hartford-West Hartford-East Hartford, CT Metro Area | 25 | 6 | 1 |
| Houston-Baytown-Sugar Land, TX | 20 | 8 | 6 |
| Indianapolis-Carmel-Anderson, IN | 9 | 4 | 3 |
| Kansas City, MO-KS | 19 | 12 | 8 |
| Lancaster, PA | 15 | 3 | 1 |
| Los Angeles-Long Beach-Anaheim, CA | 91 | 26 | 7 |
| Miami-Fort Lauderdale-Pompano Beach, FL | 32 | 8 | 2 |
| Minneapolis-St. Paul-Bloomington, MN-WI | 69 | 21 | 12 |
| Nashville-Davidson–Murfreesboro–Franklin, TN | 4 | 1 | 1 |
| New York-Newark-Jersey City, NY-NJ-PA | 62 | 19 | 10 |
| Phoenix-Mesa-Chandler, AZ | 16 | 10 | 4 |
| Pittsburgh, PA | 70 | 33 | 15 |
| Portland-South Portland-Biddeford, ME | 15 | 0 | 0 |
| Portland-Vancouver-Hillsboro, OR-WA | 11 | 5 | 3 |
| Providence-New Bedford-Fall River, RI-M | 24 | 4 | 2 |
| Riverside-San Bernardino-Ontario, CA | 15 | 7 | 3 |
| Rochester, NY | 10 | 6 | 5 |
| St. Louis, MO-IL | 28 | 15 | 2 |
| San Antonio-New Braunfels, TX | 3 | 1 | 1 |
| San Francisco-Oakland-Berkeley, CA | 22 | 9 | 2 |
| Scranton–Wilkes-Barre, PA | 1 | 0 | 0 |
| Seattle-Tacoma-Bellevue, WA | 19 | 6 | 3 |
| Washington-Arlington-Alexandria, DC-VA-MD-WV | 3 | 1 | 0 |
| Worcester, MA-CT | 17 | 2 | 0 |
| Youngstown-Warren-Boardman, OH-PA | 5 | 1 | 1 |
| Total | 1,118 | 425 | 217 |

*Note: This table reports the number of borders of adjacent WRLURI municipalities by CBSA. Col. (1) reports the number for all borders between WRLURI municipalities. Col. (2) reports the number of borders for the $\Delta$DRI subsample. Col. (3) shows the number of borders where lot sizes increase used in the hedonic regressions ($\Delta$Lot).*

Table A2: Average $\Delta$Welfare estimates by housing tenure, additional hedonic specifications

| Tenure | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel (a): Linear** | | | | |
| All housing units | -$9,360 | -$7,906 | -$7,110 | -$4,181 |
| | ($1,351) | ($1,388) | ($1,488) | ($1,522) |
| Owner occupied | -$10,164 | -$11,197 | -$10,468 | -$10,062 |
| | ($2,434) | ($2,394) | ($2,425) | ($2,151) |
| Renter occupied | -$26,736 | -$23,613 | -$23,846 | -$5,503 |
| | ($8,488) | ($8,470) | ($8,363) | ($9,786) |
| **Panel (b): Log** | | | | |
| All housing units | -$9,040 | -$6,618 | -$6,293 | -$6,293 |
| | ($1,399) | ($1,657) | ($1,674) | ($1,674) |
| Owner occupied | -$3,064 | -$6,043 | -$7,500 | -$10,687 |
| | ($2,619) | ($2,435) | ($2,322) | ($2,269) |
| Renter occupied | -$107,475 | -$90,847 | -$76,306 | -$58,630 |
| | ($14,094) | ($14,816) | ($13,935) | ($17,031) |
| **Panel (c): Semiparametric** | | | | |
| All housing units | -$9,462 | -$7,771 | -$6,820 | -$4,648 |
| | ($1,457) | ($1,515) | ($1,547) | ($1,664) |
| Owner occupied | -$10,366 | -$11,777 | -$11,821 | -$12,748 |
| | ($3,053) | ($2,958) | ($2,986) | ($2,494) |
| Renter occupied | -$56,392 | -$48,953 | -$43,201 | -$20,998 |
| | ($12,552) | ($11,979) | ($11,506) | ($10,848) |
| Housing traits | Y | Y | Y | Y |
| Elevation/slope | Y | Y | Y | Y |
| Distance to amenities | Y | Y | Y | Y |
| School test score | Y | Y | Y | Y |
| Race | | Y | Y | Y |
| Income | | | Y | Y |
| Other demographics | | | | Y |

*Note: This table presents estimates of the average welfare change for individual homeowners from increasing their density exposure by 1/2 unit per acre. Each cell represents an average welfare change estimate under a different specification with the functional form tabulated by row and the set of included controls tabulated by column. Hedonic regression estimates are retrieved separately by border area. The hedonic regressions are estimated using 263,340 houses spread throughout 217 border areas. Standard errors are calculated by cluster resampled bootstrap. The 217 border areas were resampled with replacement for 1,000 bootstrap replications.*

Table A3: Average $\Delta$Welfare estimates by housing tenure, robustness checks

| Tenure | 250m border areas | 250m radius circles | CoreLogic density exposure | Separate sides of the border |
|---|---|---|---|---|
| All housing units | -\$7,988 | -\$3,672 | | -\$7,979 |
| | (\$1,952) | (\$652) | | (\$1,360) |
| Owner occupied | -\$12,416 | -\$1,884 | -\$13,330 | -\$7,773 |
| | (\$3,814) | (\$1,181) | (\$2,681) | (\$2,671) |
| Renter occupied | -\$75,697 | -\$39,513 | | -\$61,286 |
| | (\$19,073) | (\$9,206) | | (\$13,814) |
| Num parcels | 130,677 | 263,340 | 263,340 | 253,027 |
| Num borders | 200 | 217 | 217 | 178 |
| Housing traits | Y | Y | Y | Y |
| Elevation/slope | Y | Y | Y | Y |
| Distance to amenities | Y | Y | Y | Y |
| School test score | Y | Y | Y | Y |

*Note: This table presents estimates of the average welfare change for individual homeowners from increasing their density exposure by 1/2 unit per acre by housing tenure. Each column shows average welfare change estimates under an alternative construction for the hedonic regressions. The first column shows results only using housing sales within 250 meters of the borders. The second column shows results calculating density exposure measures using 250 meter radius circles. The third column shows results where the owner occupied density exposure is constructed using the precise location of single family parcels reported in CoreLogic. The final column runs separate hedonic regressions for each side of the border only forming comparisons within the same municipality. All regression estimates were retrieved separately by border area or border side. Standard errors are calculated by cluster resampled bootstrap. The border areas were resampled with replacement for 1,000 bootstrap replications.*

Table A4: Preference estimates by neighborhood type

| | | Q1 | Q2 | Q3 | Q4 |
|---|---|---|---|---|---|
| **Panel (a)** | **Avg. density exposure (total units per acre)** | 0.99 | 2.07 | 3.07 | 4.91 |
| | Share who dislike density | 0.65 | 0.70 | 0.65 | 0.62 |
| | Avg. $\Delta$Welfare, All | -$18,257 | -$8,873 | -$6,967 | -$3,696 |
| | Avg. $\Delta$Welfare, Owner | -$18,850 | -$9,698 | -$7,947 | -$4,920 |
| | Avg. $\Delta$Welfare, Renter | -$151,842 | -$44,347 | -$21,419 | -$7,409 |
| | | Q1 | Q2 | Q3 | Q4 |
| **Panel (b)** | **Avg. household income ($ 2021)** | $50,972 | $78,998 | $105,680 | $157,261 |
| | Share who dislike density | 0.65 | 0.65 | 0.64 | 0.68 |
| | Avg. $\Delta$Welfare, All | -$4,494 | -$6,936 | -$7,423 | -$19,003 |
| | Avg. $\Delta$Welfare, Owner | -$6,092 | -$8,377 | -$9,759 | -$17,246 |
| | Avg. $\Delta$Welfare, Renter | -$10,038 | -$27,849 | -$44,834 | -$142,957 |
| | | Q1 | Q2 | Q3 | Q4 |
| **Panel (c)** | **Share college degree** | 0.16 | 0.34 | 0.50 | 0.69 |
| | Share who dislike density | 0.63 | 0.63 | 0.69 | 0.66 |
| | Avg. $\Delta$Welfare, All | -$3,876 | -$5,359 | -$9,732 | -$18,932 |
| | Avg. $\Delta$Welfare, Owner | -$3,552 | -$10,313 | -$8,687 | -$18,967 |
| | Avg. $\Delta$Welfare, Renter | -$14,290 | -$25,232 | -$62,417 | -$123,965 |
| | | Q1 | Q2 | Q3 | Q4 |
| **Panel (d)** | **Avg. share white (< 500 meters)** | 0.55 | 0.80 | 0.89 | 0.95 |
| | Share who dislike density | 0.65 | 0.68 | 0.68 | 0.61 |
| | Avg. $\Delta$Welfare, All | -$6,762 | -$12,991 | -$11,266 | -$6,830 |
| | Avg. $\Delta$Welfare, Owner | -$9,415 | -$17,454 | -$9,846 | -$4,748 |
| | Avg. $\Delta$Welfare, Renter | -$24,478 | -$52,476 | -$77,724 | -$70,896 |
| | | Q1 | Q2 | Q3 | Q4 |
| **Panel (e)** | **Share have children (< 500 meters)** | 0.17 | 0.23 | 0.27 | 0.33 |
| | Share who dislike density | 0.71 | 0.66 | 0.64 | 0.61 |
| | Avg. $\Delta$Welfare, All | -$10,486 | -$7,309 | -$9,890 | -$10,164 |
| | Avg. $\Delta$Welfare, Owner | -$8,168 | -$9,373 | -$9,432 | -$14,491 |
| | Avg. $\Delta$Welfare, Renter | -$30,044 | -$36,705 | -$58,577 | -$100,230 |

*Note: This table shows summary statistics on individual preference estimates by quartile subgroup using the baseline specification of Table 3. Panel (a) shows the share of individuals who dislike density (MWTP < 0) and the average welfare changes from increasing density exposure 1/2 unit per acre splitting the sample by quartile of density exposure. Panel (b) shows the same summary statistics but splitting the sample into quartiles by the median household income of a house's census block group. Panel (c) splits by quartile of the share of people aged 25 or more with a bachelor's degree or above. Panel (d) splits the sample by quartile of the share of people identifying as white in nearby census blocks. Panel (e) splits by quartile of the share of households with children.*

Table A5: Average $\Delta$Welfare estimates with household mobility

| Tenure | Avg. $\Delta$Welfare | % move | Avg. moving cost |
|---|---|---|---|
| **Panel (a): Baseline, no moving allowed** | | | |
| All housing units | -$9,462 | 0% | . |
| Owner occupied | -$10,366 | 0% | . |
| Renter occupied | -$56,392 | 0% | . |
| **Panel (b): Moving costs 10% of house value** | | | |
| All housing units | -$7,583 | 6% | -$28,276 |
| Owner occupied | -$8,540 | 7% | -$25,513 |
| Renter occupied | -$5,062 | 23% | -$37,308 |
| **Panel (c): Moving costs 15% of house value** | | | |
| All housing units | -$8,151 | 3% | -$40,995 |
| Owner occupied | -$9,147 | 4% | -$35,202 |
| Renter occupied | -$8,808 | 17% | -$55,582 |
| **Panel (d): Moving costs 20% of house value** | | | |
| All housing units | -$8,474 | 2% | -$53,228 |
| Owner occupied | -$9,469 | 2% | -$43,281 |
| Renter occupied | -$11,695 | 14% | -$75,035 |

*Note: This table presents estimates of the average welfare change for individual homeowners from increasing their density exposure by 1/2 unit per acre depending on how easily homeowners can avoid utility loss by moving. The first panel repeats the mean welfare change using the baseline specification with no moving allowed (Table 3). Panels (b)-(d) display the average welfare losses when homeowners can move by paying a price that is proportional to their home value. In panel (b) homeowners face movement costs that are 10% of house value. In panels (c) and (d) moving costs are 15% and 20% of house value respectively. The first column displays the average welfare change estimates. The second column shows the percent of homeowners that move under each counterfactual increase. The third column shows the average moving cost among the homeowners who move.*

## Appendix B. Negative product characteristics in the hedonic model

In this section we show that when the density exposure is not inverted and density is viewed as a disamenity then a log linear utility function will be convex and there is no hedonic equilibrium. Consider the hedonic model as in Section 5. Let $j \in J$ be a house consisting of $z_{j,k}$ housing characteristics and $\xi_j$ unobservable characteristics. Now instead of the inverted density exposure set to $z_{j,1} = D_j$ the non transformed measure of density. $p_j$ is the price of house $j$. $w_i$ is the wealth of individual $i$. Individuals take utility in the form:

$$u_{ij} = \beta_{i,D} \log(D_j) + \beta_{i,2} \log(z_{j,2}) + ... + \beta_{i,k} \log(z_{j,k}) + \beta_{i,\xi} \log(\xi_j) + c$$
$$\text{s.t. } p_j + c \leq w_i$$

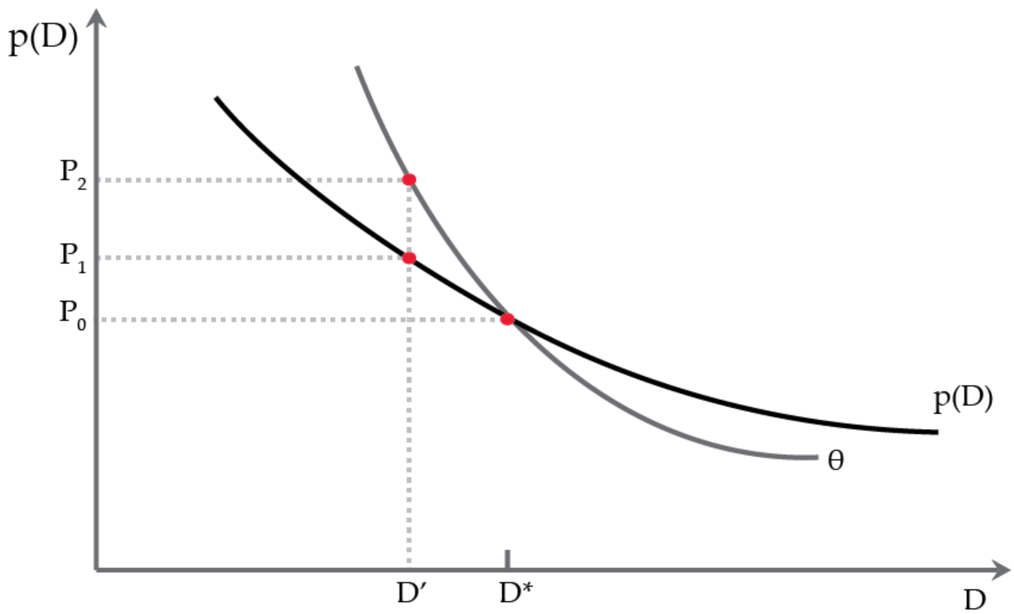
Assume for exposition that all individuals consider density exposure a disamenity. Then by assumption $\beta_{i,D} < 0$ for all $i$ and the hedonic price schedule will be monotonically decreasing in the density exposure. Similar algebra as in Section 5 reveals that an individual i's bid curve fixing the other product characteristics is given by

$$\theta_i(D; \boldsymbol{z^*_{-k}}, w, \tilde{u}) = \beta_{i,D} \log(D_j) + \beta_{i,2} \log(z^*_{j,2}) + ... + \beta_{i,k} \log(z^*_{j,k}) + \beta_{i,\xi} \log(\xi^*_j)$$
$$+ w_i - \tilde{u}_{ij}$$

Because $\beta_{i,D} < 0$ and the remaining terms are constant, the resulting bid curve $\theta_i(D; \boldsymbol{z^*_{-k}}, w, \tilde{u})$ is convex in the density exposure.

The figure below diagrams a convex bid curve $\theta$ tangent to the hedonic price schedule at $D^*$. However, this point does not represent an equilibrium. The individual's bid curve implies they would be indifferent between a house with exposure $D^*$ at the price $P_0$ and a house with exposure $D'$ at the price $P_2$. The prevailing price in the market for $D'$ according to the price function is only $P_1 < P_2$, implying the homeowner would be willing to pay more than the market price to live at a lower density exposure. The homeowner would have been better off paying any price in $[P_1, P_2)$ and getting a house with density exposure $D'$. Hence, this hedonic price schedule cannot represent an equilibrium.

Figure B1: A hedonic price schedule with convex bid curves.




*Note: Diagram of the hedonic price schedule as in Rosen (1974). For one consumer type, we plot her bid curve $\theta$ and its tangency point at the density exposure $D^*$ considering density exposure a negative product characteristic and a convex bid curve. The homeowner with bid curve $\theta$ would have been willing to pay a price higher than the market price ($P_2 > P_1$) to get a house with the lower density exposure $D'$.*

## Appendix C. Alternative approaches to utility parametrization

A well documented concern in the hedonic model is endogeneity coming from the correlation between the quantity of a product characteristic consumed and a consumer's idiosyncratic taste heterogeneity (Bartik, 1987, Epple, 1987). While Bajari and Benkard (2005) circumvent this issue by assuming the slope of the MWTP function is known, an alternative approach is considered in Bishop and Timmins (2019).

### *A. Model*

For transparency we consider a simple parametric specification of the hedonic price function as linear quadratic in the density exposure. This functional form is used as an example in Bishop and Timmins (2019) for exposition, and was the functional form studied by much of the early hedonic literature. An advantage of this specification is that it leads to a closed form solution. Formally, model the hedonic price function as

$$p_{j,l} = \gamma_1 D_{j,l} + \frac{\gamma_2}{2} {D_{j,l}}^2 + X'_{j,l}\theta + \epsilon_{j,l} \text{ for } l \in \{1, 2, \ldots, L\}$$

in which all terms are defined analogously to the main text. The hedonic price gradient for each market $l$ is then

$$\frac{\partial p_{j,l}}{\partial D_{j,l}} = \gamma_{1,l} + \gamma_{2,l} D_{j,l}$$

Furthermore, assume the following form for homeowners' indirect utility

$$u_{ij} = \alpha_{0,l} + \alpha_{1,l} D_{j,l} + \frac{\alpha_2}{2} {D_{j,l}}^2 + \nu_{i,l} D_{j,l} + w_i - p_j$$

in which $\nu_{i,l}$ are unobservable individual preference shocks. Then the homeowner's first order condition implies

$$\gamma_{1,l} + \gamma_{2,l} D_{j,l} = \alpha_{1,l} + \alpha_2 D_{j,l} + \nu_{i,l}$$

where the left hand side is the price derivative of the hedonic price function with respect to $D$ and the right hand side is the MWTP function. This equation represents the second stage suggested by Rosen (1974) and an estimate of $\alpha_{1,l}, \alpha_2$ could be retrieved by a standard regression. However, such estimates are likely to be biased without an instrumental variable, with Bartik (1987) and Epple (1987) analyzing why finding an appropriate instrumental variable typically is not feasible.

Bishop and Timmins (2019) suggest an alternative procedure that does not require an IV. Rearranging terms to solve for $D_{j,l}$

$$D_{j,l} = \frac{\alpha_{1,l} - \gamma_{1,l}}{\gamma_{2,l} - \alpha_2} + \frac{1}{\gamma_{2,l} - \alpha_2} \nu_{i,l}$$

Assuming $\nu_{i,l} \sim N(0, \sigma^2)$, then $D_{j,l}$ is normally distributed with mean $\frac{\alpha_{1,l} - \gamma_{1,l}}{\gamma_{2,l} - \alpha_2}$ and standard deviation $\frac{\sigma}{\gamma_{2,l} - \alpha_2}$. Taking $\hat{\gamma}$ from the estimates of the hedonic regressions, the individual parameters

$\alpha$ and variance $\sigma$ can be solved by maximum likelihood estimation with the likelihood function $L(\text{data}) = \prod_{i=1}^{N} l(D_{j,l}; \alpha, \sigma)$ in which

$$l(D_{j,l}; \alpha, \sigma) = \frac{1}{(\frac{\sigma}{\hat{\gamma}_{2,l} - \alpha_2})\sqrt{2\pi}} \exp\{-\frac{1}{2(\frac{\sigma}{\hat{\gamma}_{2,l} - \alpha_2})^2}(D_{j,l} - (\frac{\alpha_{1,l} - \hat{\gamma}_{1,l}}{\hat{\gamma}_{2,l} - \alpha_2}))^2\}$$

In practice, we solve for the likelihood maximizing parameter values following the suggestion in Bishop and Timmins (2019) to concentrate the likelihood function on $\alpha_2$. We run a grid search over possible values of $\alpha_2$. For each guess of $\alpha_2$, the likelihood-maximizing values of $\alpha_{1,l}$ can be recovered by regressing $P'(D; \hat{\gamma}) - \alpha_2 D$ on border area indicators, and the likelihood maximizing value of $\sigma$ can be recovered by $\frac{1}{N}\sum \nu_{i,l}^2$. We then choose $\hat{\alpha}_{1,l}$ and $\hat{\alpha_2}$ with the largest likelihood across the grid search.

After retrieving parameter estimates, we can characterize individuals' MWTP functions.

$$MWTP_i(D) = \hat{\alpha}_{1,l} + \hat{\alpha_2} D + \hat{\nu}_{i,l}$$

where

$$\hat{\nu}_{i,l} = \gamma_{1,l} + \gamma_{2,l} D_{j,l} - \hat{\alpha}_{1,l} D_{j,l} - \hat{\alpha_2} D_{j,l}$$

is a constant idiosyncratic preference shock calculated at the equilibrium value of $D_{j,l}$. Then utility changes can be estimated by integrating the MWTP function. Letting $D'$ be a counterfactual level of density exposure,

$$\int_{D_j}^{D'} MWTP_i(D) = \hat{\alpha}_{1,l} D + \frac{\hat{\alpha_2}}{2} D^2 + \hat{\nu}_{i,l} D \Bigg|_{D_{j,l}}^{D'} = (\hat{\alpha}_{1,l} D' + \frac{\hat{\alpha_2}}{2} D'^2 + \hat{\nu}_{i,l} D') - (\hat{\alpha}_{1,l} D_{j,l} + \frac{\hat{\alpha_2}}{2} D_{j,l}^2 + \hat{\nu}_{i,l} D_{j,l})$$

As in the main section of this paper, we model the homeowners as also bearing the price change from the counterfactual increase in housing density. Then the total welfare change can be estimated by

$$\begin{aligned} \Delta \hat{\text{Welfare}}_i = \hat{\Delta p} + \hat{\Delta u} = (\hat{\gamma}_1 D' + \frac{\hat{\gamma}_2}{2} D'^2) - (\hat{\gamma}_1 D_{j,l} + \frac{\hat{\gamma}_2}{2} {D_{j,l}}^2) \\ +(\hat{\alpha}_{1,l} D' + \frac{\hat{\alpha_2}}{2} D'^2 + \hat{\nu}_{i,l} D') - (\hat{\alpha}_{1,l} D_{j,l} + \frac{\hat{\alpha_2}}{2} D_{j,l}^2 + \hat{\nu}_{i,l} D_{j,l}) \end{aligned}$$

***B. Welfare change comparison***

In this section, we compare the welfare change estimate under three different approaches: (1) by simply assuming a constant MWTP function set at the observed price derivative, (2) by following Bajari and Benkard (2005) as is done in the main section of this paper, and (3) by following the maximum likelihood procedure of Bishop and Timmins (2019).

Table C1 shows the average welfare change by the form of utility function assumed. The left column shows the average welfare change estimate assuming a linear utility function, and therefore a constant MWTP function. The middle column follows the approach of Bajari and

Benkard (2005) as described in the main section of this paper. The right column shows the average welfare change estimate using the functional form and likelihood-maximizing parameters estimated following Bishop and Timmins (2019). The welfare change estimates under a linear utility function versus a log linear utility function are fairly similar with the log linear estimate being only moderately larger in magnitude (-$9,600 versus -$10,700).[1] On the other hand, the mean welfare change estimate following Bishop and Timmins (2019) is over three times the magnitude of the estimates for either of the other two utility parametrizations. The large discrepancy in magnitudes is because following Bishop and Timmins (2019) we estimate a steep downward slope of consumers' MWTP functions with a parameter value of $\hat{\alpha}_2 = -195{,}500$, whereas the linear utility function assumes a flat MTWP function. The approach of Bajari and Benkard (2005) also reflects a downward sloping MWTP function, however at least for a 1/2 unit per acre change, this slope is fairly flat as shown by the similarity between the estimates in the left and middle columns.

Table C1: Average $\Delta$Welfare estimate comparison

| | (1) Linear Utility | (2) Bajari and Benkard (2005) | (3) Bishop and Timmins (2019) |
|---|---|---|---|
| Avg. $\Delta$Welfare | -$9,609 | -$10,704 | -$33,984 |
| | ($1,404) | ($1,446) | ($3,858) |

*Note: This table presents average welfare change estimates from a 1/2 increase in total housing units per acre under different parametrizations of homeowners' utility functions. The left column shows the average welfare change estimate assuming a linear utility function, and therefore a constant MWTP function. The middle column follows the approach of Bajari and Benkard (2005) as described in the main section of this paper. The right column shows the average welfare change estimate using the parameters estimated by following the procedure of Bishop and Timmins (2019) as outlined directly above. All estimates are based on a linear quadratic hedonic specification including all controls in our baseline specification. Standard errors are calculated by cluster resampled bootstrap. The 217 border areas were resampled with replacement for 1,000 bootstrap replications. For the right column, bootstrap samples were drawn prior to maximum likelihood estimation.*

Qualitatively, our results are similar to those in Bishop and Timmins (2019)'s application estimating homeowners' willingness-to-pay for nonmarginal changes in the local crime rate. For homeowners WTP to avoid increases in crime, Bishop and Timmins (2019) find that estimates under a linear versus log linear utility function are very similar while estimates following their method are significantly larger in magnitude. That traditional models tend to underestimate the willingness to pay to avoid disamenities is consistent with the direction of the bias suggested by Bartik (1987) and Epple (1987). We take these results to indicate that the estimates presented in the main section of this paper should be considered conservative by allowing only moderate curvature away from the price derivatives observed in the data. Because there is currently no consensus in the literature for which approach is the best practice for nonmarginal hedonic demand estimation (Bishop et al., 2020), we use the more conservative approach of Bajari and

[1]The estimates using a linear quadratic specification for the hedonic regressions are also very similar to the average estimate of -$9,500 using the semiparametric model presented in the main section of this paper.

Benkard (2005) to generate our baseline results. We consider these results to constitute a valuable first-order approximation characterizing homeowners' demand for housing density. Further study of the curvature of consumers' demand in hedonic models generally and for housing density in particular presents an important direction for future research.

## Appendix D. Price gradient around a border

In this section we write out a more formal theoretical framework to describe house prices as a function of distance to the municipal boundary following Turner et al. (2014) and Kulka et al. (2024). In their frameworks the effects of zoning on house and land prices are decomposed into three components termed the own-lot, external, and supply effect. The own lot effect captures direct effects from changes to an individual house. This could be the option value for redeveloping the parcel or due to changes in the structural characteristics, e.g. more restrictive zoning induces larger houses with higher prices. The external effect captures effects on the local neighborhood, e.g. the change in the housing density of the surrounding area. Finally, the supply effect reflects changes in the number of units or share of land that is developed. Additionally, we discuss the issue of how supply effects might be relevant to our analysis in ways not discussed in Turner et al. (2014)'s context.

### *A. An equivalence result*

Returning to the simple model of a border, there is one border between two municipalities in 1-dimensional space $x$ where the boundary is at $x = 0$. The right side of the border is more highly regulated than the left side. On the left, all houses have lot size $\underline{l}$, while on the right a minimum lot size constraint $\bar{l}$ is binding so all houses have lot size $\bar{l} > \underline{l}$. Then, the density exposure measure as a function of $x$ is given by the following,

$$D(x) = \begin{cases} 2R/\underline{l} = \bar{D} & \text{if } x < -R, \\ 2R/\bar{l} = \underline{D} & \text{if } x > R, \\ 4R^2/[x(\bar{l} - \underline{l}) + R(\bar{l} + \underline{l})] & \text{if } x \in (-R, R). \end{cases}$$

Furthermore, we allow consumer heterogeneity. Let consumers have type $i$, which determines their preferences over housing characteristics $l$ and $D$, and the reservation value of their outside option $o_i$. To emphasize the connection between this model and the hedonic model in Section 5, let $\beta_i$ index homeowners' heterogenous preferences over housing characteristics. Homeowners preferences over large lots and housing density are likely to change at the municipal boundary as people sort into neighborhoods according to their preferences. Further, these may also change approaching the boundary. For exposition, make the strong assumption that lot size and density exposure are the only housing characteristics consumers care about.

Consumers choose a location $x$ by paying the house price $p(x)$ to maximize utility $u(x, l, D, \beta_i)$ subject to their wage $w$. Utility comes from nonhousing consumption $U(w - p(x))$ and housing utility $V(x, l, D, \beta_i)$. Diverging slightly from the Turner et al. (2014), assume that individuals' utility as a function of $x$ is additively separable rather than multiplicably separable. Then,

$$u(x, l, D, \beta_i) = U(w - p(x)) + V(x, l, D, \beta_i).$$

If we assume $U(w - p(x)) = w - p(x)$, then the bid curve for a consumer of type $i$ is

$$p^b(x) = w - o_i + V(x, l, D, \beta_i).$$

Turner et al. (2014) decompose the effect on utility $V$ into the own lot and external effect. In this context in which we have assumed the relevant housing characteristics are only the lot size and density exposure, we have the following

$$p^b(x) = w - o_i + V_{OWN}(x, l, \beta_i)) + V_{EXT}(x, D, \beta_i)).$$

Further, notice that if we assume log linear utility then this bid curve is exactly the same as that in Section 5.B. That is, if we set $V_{OWN}(x, l, \beta_i) = \beta_{i,l} \log(l(x))$ and $V_{EXT}(x, l, \beta_i) = \beta_{i,D} \log(\bar{D} - D(x))$, then

$$p^b(x) = w - o_i + \beta_{i,l} \log(l(x)) + \beta_{i,D} \log(\bar{D} - D(x)).$$

This result shows that if we make the same parametric assumptions on the utility function, the model of Turner et al. (2014) is equivalent to the standard hedonic model, although with the variation in housing characteristics varying through the distance to the boundary. Furthermore, the classic result from Rosen (1974) implies that heterogeneity in individuals' MWTP parameterized by $\beta_i$ according to distance to the boundary is identified by the price derivative.

In theory, this result suggests that an analysis based on the slope of the price with respect to the distance to the boundary $x$ (score-based) and an analysis based on the slope of the price with respect to density exposure (standard hedonic) would yield the same result. However, in practice many other housing characteristics, observable and unobservable, may vary with distance to the boundary, which leads us to rely on a more typical hedonic regression that can control for and/or decompose the effects from these other housing characteristics.

### *B. Supply effects*

In equilibrium, the pricing schedule $p(x)$ is determined by the marginal consumer at each $x$ according to their values of $o_i$ and $\beta_i$. In Turner et al. (2014), the outside reservation value $o_i$ generates non perfectly elastic demand elasticities and the possibility of supply effects. Following Turner et al. (2014), let individuals' outside options be in the range $o_i \in [0, \infty)$ and let $g(o_i)$ be the measure of consumers of type $o_i$. Let $G(o_i) = \int_0^{o_i} g(o')do'$ with type less than or equal to $o_i$. Define $o^*$ to be the type such that both municipalities fill up with consumers whose outside option is no better than $o^*$. In equilibrium, the pricing surface as a function of $x$ is

$$p(x) = w - o^* + \beta_{i,l} \log(l(x)) + \beta_{i,D} \log(\bar{D} - D(x)).$$

Supply effects change the price gradient by changing who the marginal homeowner is, i.e. by changing the value of $o^*$. Hence, following Turner et al. (2014) supply effects materialize as a parallel vertical shift in the entire pricing gradient along with a reduction in the share of land developed. That supply effects only enter as a parallel vertical shift implies that one can use the slope of the pricing gradient to identify the "external effects of regulation without regard to supply effects". (Turner et al., 2014, pg. 1354) And, given the equivalence result above, it seems likely that this also applies to the analysis based on standard hedonic regressions.

This suggests two things. First, a model following Turner et al. (2014) and Kulka et al. (2024) with house sales is a hedonic model, but the variation in housing characteristics is driven by distance to the municipal boundary and they remain agnostic about which characteristics these might be. Second, by the assumptions of Turner et al. (2014), supply effects are irrelevant in measuring external effects by the slope of the pricing gradient.

### *C. When could supply effects effect the slope of the pricing gradient?*

Supply effects could be an issue if the market conditions change at the boundary or if market conditions change across space. If demand and supply shifts at the boundary, this invalidates the law of one price for the hedonic model. Consider the following example. The left side of the border and the right side of the border are different markets. The left side is less regulated and has higher supply, and the right side is more regulated and has lower supply. As a result of the higher supply, prices are lower directly on the left side of the border and increase discontinuously at $x = 0$. Here the discontinuous increase is due to a supply effect from entering a new market rather than an own lot effect. Hence, an estimate of the own lot effect as described in Turner et al. (2014) is invalidated. Estimates of the external effect that pool both sides of the border may also be invalidated. However, splitting the border areas into the two distinct markets would then allow you to measure the external effects again (although measuring the own lot effect is still infeasible). In Appendix A3, we present results analogous to Table 3 only forming comparisons within the same municipality on each side of the boundaries.

What if supply conditions decay across space in the same way as a disamenity effect? This is the kind of local supply effect argued for in Hartley (2014), Anenberg and Kung (2014), Pennington (2021), Li (2022) and Asquith et al. (2023). In this case, it is difficult to disentangle supply effects from disamenity effects. In Section 7.C, we discuss the patterns in our results and argue it is hard to rationalize our estimates as coming primarily from a supply effect, while the patterns in the data are readily explained as coming from preferences.