

Supplemental Appendix

“There Goes the Neighborhood? The Local Impacts of State Policies that Override Municipal Zoning”

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A Data Appendix

A.1 Linking 40B Developments to Infutor and Voter Records

We link address data on 40B developments to information about 40B beneficiaries and local residents from Infutor and the Massachusetts voter file in five steps. First, we standardize all linkage fields. Second, we identify 40B beneficiaries by linking 40B building addresses with individuals’ residential addresses in Infutor. Third, we create a dataset containing all Infutor individuals ever living within 0.6 miles of a 40B address, excluding 40B beneficiaries. Fourth, we link these individuals to voter records using a combination of individual’s names, birth dates, and addresses. Finally, we also link Infutor individuals to tax assessment and deed records from Zillow. We use probabilistic linkage methods for the second, fourth, and fifth steps.

Step 1. Standardizing Linkage Fields. We use the same protocol laid out by Sportiche (2023), which is based on the steps recommended in previous work (Winkler, 2014; Abramitzky et al., 2012; Enamorado and Imai, 2019) to standardize linkage fields.

These steps include removing all punctuation, converting all street suffixes to the USPS standard (e.g., ‘route’ becomes ‘route’ or ‘street’ becomes ‘st’), and parsing addresses into street number, street name, city, five-digit zip code, and—where applicable—unit numbers. We also standardize all Massachusetts municipalities to those listed in the 2010 census using a crosswalk of historical municipality and neighborhood names drawn from the Massachusetts Secretary of State’s database of archaic community and neighborhood names.²¹

We follow a similar protocol to standardize names and birth dates. First, we remove all punctuation. Then we split individuals’ full names into first name, middle initial (where applicable), and last name, removing all prefixes and suffixes (e.g., JR, junior, II, III) such that a name like James R. Jones III becomes James R Jones. Finally, we also remove all special characters from birth dates and convert them into a YYYYMM format.

Step 2. Identifying 40B Beneficiaries. We identify 40B beneficiaries by determining whether each address in Infutor is a 40B development address. We do so by linking the precise geocoded addresses of 5,288 buildings (1,209 developments) permitted under 40B in 1995 or after to addresses

²¹<https://www.sec.state.ma.us/cis/cisuno/unoidx.htm>

in Infutor based on street number, street name, city, and state. We use the `fastLink` package in R to complete this linkage using slightly more conservative parameters than those recommended in supplementary material provided by (Enamorado et al., 2019). Using this method, we are able to identify at least one address in Infutor for 93 percent of 40B developments. The vast majority of these are exact matches. In Infutor, this represents about 29,064 unique address IDs and 112,789 individuals.

Step 3. Identifying Non-Beneficiary Residents Living Within 0.6 Miles from a 40B Building.

We identify non-beneficiary residents living near 40B addresses in three steps. First, we create a dataset of all Infutor individuals who ever lived in Massachusetts excluding 40B beneficiaries as identified in the previous section. Second, we identify 1,067,388 unique address IDs in Infutor which are within 0.6 miles of the 5,288 buildings permitted under 40B. Third, we find 4,585,542 unique individuals included in the first step dataset who ever lived in an address identified in the second step ('40B non-beneficiary individuals').

We build our main dataset of *all local residents* by restricting this sample to 40B developments with a permit approval in 1995-2019. We are left with 768,137 unique address IDs and 3,456,180 unique individuals. Next, we discard individuals who started living in the address near a 40B development too late (12 or more years after the approval of the 40B) or finished living in that address too early (6 or more years before the approval of the 40B). This dataset of local residents contains 2,491,682 unique individuals.

We also build a separate dataset for *incumbent residents*. To do this, we only keep 40B non-beneficiary individuals who lived in the address neighboring the 40B building in years 8 and 7 before the year when the 40B permit was approved for that building. There are 605,004 such individuals. For these individuals, we create a panel dataset going from year 6 before approval to year 12 after approval or the year when the individual is last seen in Infutor, whichever takes place first.

Step 4. Linking Voter Records to Infutor Individuals. We link data on 40B non-beneficiary individuals to voter records based on first and last name, year of birth, street number, street name and municipality in Massachusetts. As described in the Step 2, we link individuals using slightly more conservative parameters via the `fastLink` package in R. We begin with about 5,185,067 million individuals registered to vote since 2012 and about 4.7 million 40B non-beneficiary individuals. Following recommendations from Abramitzky et al. (2020) and Winkler (2014), we block on fixed variables where mistakes are unlikely to expedite the matching process. Specifically, we restrict our comparisons to pairs of individuals who have last names starting with the same letter (e.g., we only compare records for people whose last names begin with "A" in both datasets). To maximize the matching rate, we include all addresses for each individual as observed in Infutor. In case of

multiple matches to different individual ids in the voter file, we keep the match with the highest probability. Using this method, we are able to match a total of 1,910,430 40B non-beneficiary individuals in the voter files.

Given that voter history records for general elections only start in 1996, we restrict our sample to 40Bs that were approved between 2000 and 2019 in the regressions involving voter turnout outcomes. With this in mind, we first match the linked dataset to the dataset of *all local residents* and restrict the sample to individual-address stays corresponding to Massachusetts. Out of 2,365,959 local residents, 1,073,152 of them show up in voter records (45.4% matching rate). We do the same for the dataset of *incumbent residents* (this time we do not discard addresses outside of MA): out of 605,004 incumbent residents, 358,565 of them show up in voter records (59.3% matching rate). In our empirical analysis, we further restrict the two samples to individuals who were registered to vote in year four or five before the 40B approval and lived near the 40B in year zero or one after its approval, which leaves a total of 319,049 local residents and 200,271 incumbent residents.

A potential concern for our analysis is that we may have a more incomplete coverage for earlier 40B developments because we only observe voter histories for individuals who are registered to vote in any year after 2012 (included). Figure A.1 shows the average 40B development-level matching rates by permit approval year for the sample of incumbent residents. Despite our data limitations, matching rates for this sample of individuals living within 0.6 miles of 40B developments is remarkably consistent during the entire study period.

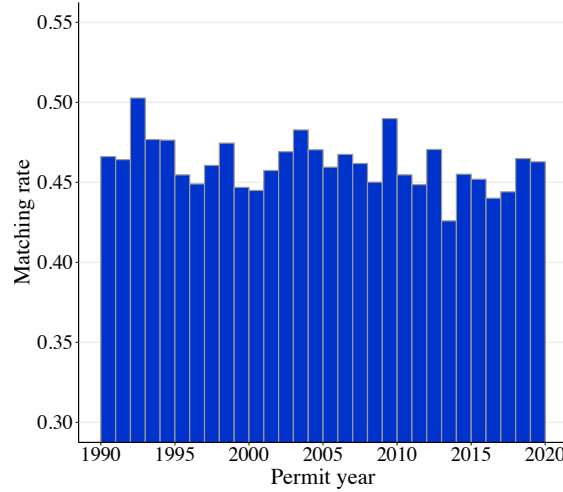
Step 5. Linking Zillow Assessment and Transaction Data to Infutor Individuals. We follow a similar approach to Step 4. We link data on 40B non-beneficiary individuals to tax assessment data in 2020 and residential transactions since 1987 based on first and last name, street number, street name and municipality in Massachusetts. Tax assessment records allows us to detect individuals that are homeowners in 2020, while residential transactions allow us to keep track of who used to be an owner before 2020 (using buyers' names) and when they become an owner (using sellers' names, if they bought a property after 1986). We also use the *fastLink* package in R and restrict comparisons to pairs of individuals who have last names starting with the same letter.

We are able to match 822,721 unique non-beneficiary individuals who own a property in 2020, 944,579 who bought a property before 2020, and 785,345 who sold a property before 2020. In total, these numbers capture 1,605,454 unique individuals. When we focus on the final sample of *all local residents* in Step 3, 21% of them show up in tax assessment records (529,861), 24% bought a home after 1986 (593,670) and 19% sold a home after 1986 (465,508). In total, these numbers cover 35% (870,242) of unique local residents.

When we focus on *incumbent residents*, 30% of them show up in tax assessment records (183,936), 28% bought a home after 1986 (171,466) and 28% sold a home after 1986 (170,672). In total, these

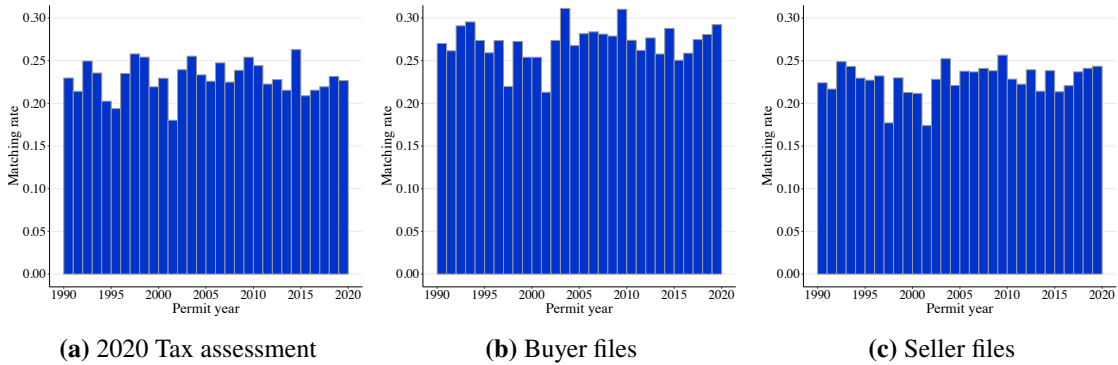
numbers cover 55% (334,855) of unique incumbent residents. As in the previous step, we test how consistent our matching rates are for 40B non-beneficiary individuals throughout our period in Figure A.2. The figure shows the share of residents that we can identify in each of the three files mentioned above. Matching rates are consistent across the three files and across all periods.

Figure A.1: Histogram of Infutor-voter file matching rates 40B permit approval



Note: The plot shows the average matching rate defined as the percentage of incumbent residents in Infutor who are present in the MA voter file by permit approval year.

Figure A.2: Histogram of Infutor-Zillow files matching rates 40B permit approval



Note: The plots show the average matching rate defined as the percentage of incumbent residents in Infutor who are present in three different Zillow datasets by permit approval year.

A.2 Local Elections

The first step to study the effect of Chapter 40B on local election outcomes is to build a dataset containing the list of dates when local elections were held in all 292 towns and 59 cities in Massachusetts. This task is challenging for two reasons. First, there is no such dataset that is publicly available. Second, the type and frequency of local elections held by towns and cities differ.²² For instance, most towns have town meetings, which is a term used both for an event that gathers all eligible voters and for the legislative body of a town. In contrast, cities are governed by the city council or a board of aldermen, i.e., citizens do not directly govern.

The paragraphs below describe how we overcome the issues above and how we build the main analysis sample to study turnout in local elections.

Identifying Local Election Dates. We adopt a data-driven approach to identify local election dates. L2 data’s information on local election turnout contains the list of individuals who *actually* voted in a local election starting in 2008. That is, we can observe the individuals who vote and the dates when they voted. Since L2 data also includes their addresses from 2012 to 2019, we can also infer the municipality where these individuals voted.²³

Using this information—and after standardizing municipality names as in Step 1 of the previous section—we generated a dataset that contains a list of municipality-election date pairs along with the number of individuals who show up as having voted in the corresponding municipality and election date. This process yields 34,906 municipality-election date pairs covering 347 municipalities. We further restrict this dataset as follows. First, we drop all municipality-election date pairs with less than 100 voters, which gets rid of irrelevant dates due to mistakes in allocating the right municipality where voters are actually voting in. Second, we drop municipality-election date pairs where the turnout was less than 25 percent of the turnout in the election date with the highest turnout within the same municipality. This second restriction should get rid of smaller elections that should not involve participation numbers that compare to most important local elections. We are left with 3,813 municipality-date pairs for 334 municipalities in the period 2008-2019.

To make sure that the identified election dates capture relevant local elections, we manually checked the nature of a subset of these elections. In the case of towns with town meetings, elections dates mostly refer to annual and special town meetings. In the case of cities, election dates mostly refer to mayoral and at-large elections.

²²By law, municipalities under 12,000 inhabitants cannot adopt a city form of government.

²³For years 2008-2011, we assume that the individual voted in the municipality corresponding to the first ever observed address for that individual.

Building the Final Sample of Residents for Local Elections. We start by obtaining the sample of 40B developments that were approved between 2010 and 2017. We impose this restriction because turnout data for local elections only starts in 2008. For this sample of 40Bs, we match voter records on local elections with the two Infutor datasets of non-beneficiary residents living within 0.6 miles of these 40B developments described in the previous section (*all local residents* and *incumbent residents*).

To do so, we follow the same steps as in Step 4 of that section with two differences. First, we restrict the Infutor sample to individual-address pairs that correspond to the municipality from which the 40B development they live near is located—hence, individual-address pairs outside of Massachusetts are dropped. Second, we do *not* restrict the sample to Infutor individuals who we are able to match to voter records and that were registered to vote in year four or five before the 40B approval: our sample contains any individual who lives within 0.6 miles of the 40B in the municipality where the 40B is located. These restrictions are motivated by the fact that we do not observe the municipality where individuals are registered to vote. Applying the restrictions, we end up with a sample of 153,805 local residents and 94,106 incumbent residents.

A.3 Identification of 40B Occupancy Dates

Our main dataset has limited information regarding the completion dates for developments permitted under 40B. This section explores the timing of completion by focusing on the sample of 40B developments that were approved between 1995 and 2012, which may have plausibly been completed by the end of our sample period. One option is using the date when the occupancy permit is issued as reported in the Subsidized Housing Inventory (SHI) as a proxy for completion. However, only 264 out of these 733 developments (36 percent) have a non-missing value for occupancy dates. Panel (a) of Figure A.3 shows a histogram of the difference between the reported occupancy permit date and the 40B permit approval date. On average, 40B buildings the occupancy permit is approved around 3.9 years after the 40B permit is approved.

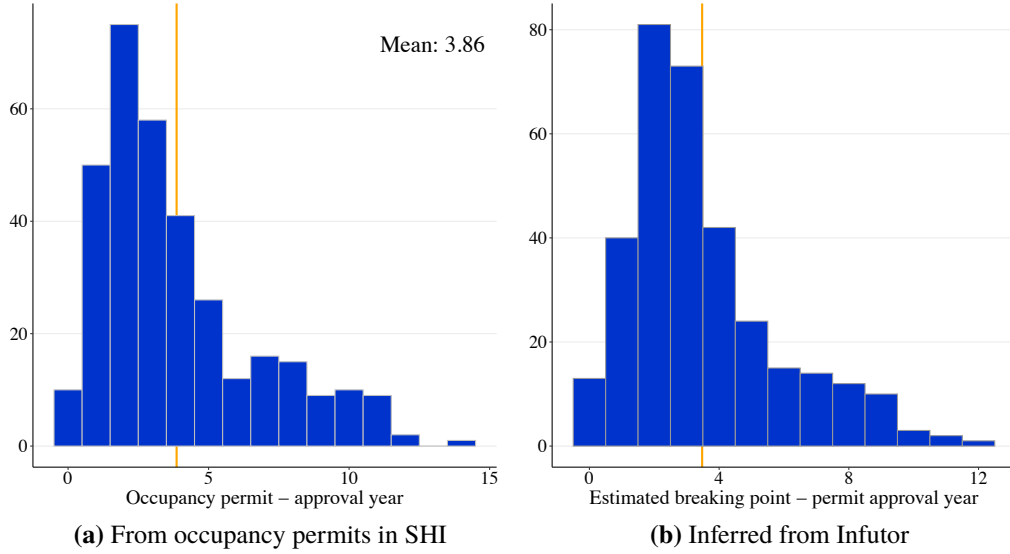
Given the incomplete data on occupancy dates, we also use Infutor data to better understand the timing of construction. Next, we describe the procedure to proxy occupancy dates from observed population inflows into 40B developments.

We identify all individuals who ever lived in a 40B development, as well as the time period during which they lived in that address, using Infutor data as described in the Step 2 of Section A.1. We restrict the sample to living spells that started in 1985 or later given that coverage in Infutor starts being meaningful around that year. Next, we create a dataset at the 40B development-year level indicating the number of individuals who we observe living in any 40B address belonging to that development in each year. In total, we find a positive number of individuals living in a 40B address for 684 developments approved between 1995 and 2012.

Next, we use a structural break detection algorithm to infer spikes in the number of individuals living in each 40B development. Intuitively, a discrete, big jump in the individual count of a development in a particular year should mean the start of occupancy. We follow several steps. First, we restrict the exercise to addresses in which we observe a minimum of 10 or more individuals to reduce noise in our estimation. This step decreases the number of developments to 355. Second, we follow the structural break detection literature to identify the shift in population counts (Bai, 1994, 1997a,b; Bai and Perron, 1998, 2003; Zeileis et al., 2003) using the package `strucchange` in R. For each 40B development, we implement this method for the regression of its population count over time on a constant limiting the number of structural breaks to one. This technique yields the year before the population count first jumps; hence, we add one year to this number to obtain the (start of) occupancy year.

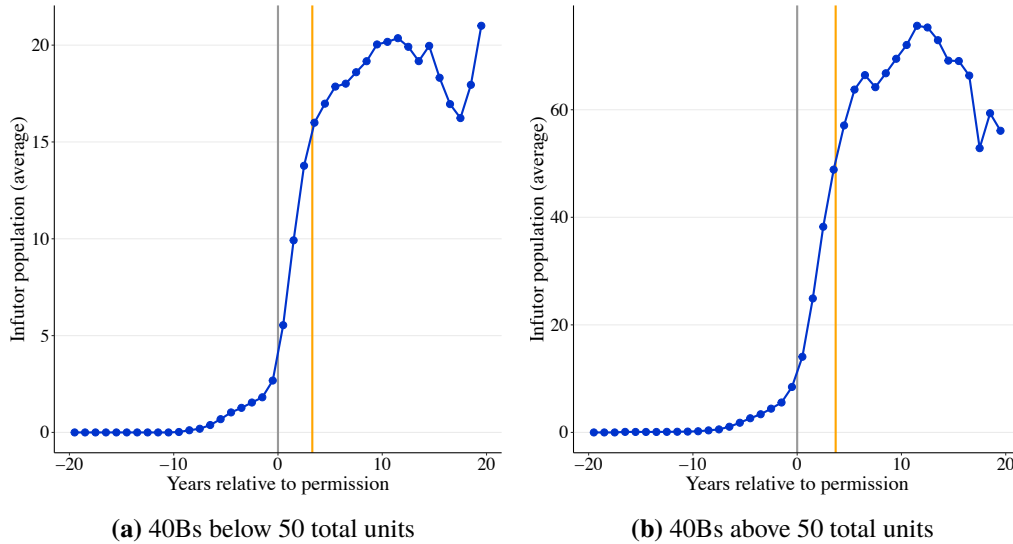
Using this method, we are able to estimate the start of occupancy year for 355 developments. However, the estimated occupancy year is lower than the 40B permit approval year for 25 developments. Panel (b) of Figure A.3 shows a histogram of the difference between our estimated occupancy year and 40B permit approval year for those with an estimated occupancy year greater than their approval year. There is some variation in the timing of occupancy: 40 percent are occupied within 2 years of approval and 75 percent within 4 years, while almost 20 percent take 6 or more years. Finally, Figure A.4 shows the evolution of Infutor population of the average 40B development for which we are able to apply the structural break algorithm around permit approval by development size. For small 40Bs, it takes an average of 3.29 years to go from approval to occupancy; for large 40Bs, it takes 3.69 years—closer to the average using occupancy permit dates from SHI.

Figure A.3: Histogram of estimated occupancy years relative to 40B permit approval



Note: The figure shows two histograms of the number of 40B developments by estimated occupancy year relative to 40B permit approval. Panel (a) uses occupancy permit dates from the SHI; panel (b) infers occupancy dates using population flows in Infutor. The vertical orange line indicates the mean. In panel (b), we drop 25 developments with an estimated breaking point taking place before permit approval year.

Figure A.4: Raw count of the average number of individuals living in a 40B development



Note: The plots show the average population count for 40B developments for which we are able to estimate occupancy years. The vertical gray line denotes the 40B permit approval year, the vertical orange line denotes the mean of the estimated occupancy year. Panel (a) focuses on the sample of 40Bs with less than 50 units, panel (b) reproduces the analysis for 40B developments with 50 units or more. We drop 19 developments with an estimated breaking point taking place before permit approval year.

A.4 Ownership near 40B Developments

This section provides a description of ownership around 40B developments and assesses the extent to which our imputed ownership measure is a good approximation. For this analysis, we use ownership rates in 2000 at the census block group level and limit our sample to 40B developments approved in 2000 or after. We impose this sample restriction to avoid counting 40B units towards ownership rates in the census.

Figure A.5 illustrates the variation in ownership rates in census block groups with 40B developments. Most areas surrounding 40Bs have high ownership rates. This finding is consistent with 40Bs being approved in areas restricted to single-family residences, which are more likely to be owned by their residents. However, there are still many other 40B areas with low ownership rates, as indicated by the histogram’s long right-tail. Given the potentially large population of renters, our heterogeneity analyses based on ownership status are less sensitive to error in the matching process (i.e., non-owners are less likely to be non-matched owners).

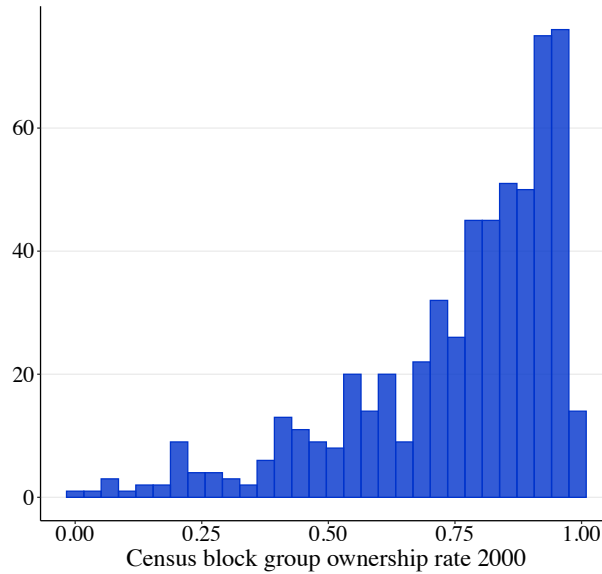
Next, we compare our imputed ownership measure to census ownership rates. Our measure is obtained by linking Infutor individuals that we observe living in 2000 in census block groups with 40Bs to Zillow tax assessment and transaction records. In particular, we consider that an individual is an ‘owner’ if they either (1) show up in 2020 tax assessment data and they did not buy the property after 2000, or (2) do not show up in 2020 tax assessment data and they sold the property after 2000. Then, we compute the average ownership rates for each block group.

Note that there are two main sources of error in our imputed measure—i.e., reasons why we would not be able to identify an individual as an owner. First, Infutor coverage is not complete. Diamond et al. (2019), which introduced this dataset to the economics literature, reports that Infutor has a 44% coverage in 1990 and increases to explain 90% of census tract variation in 2000 for the city of San Francisco. Second, households are usually composed of multiple adult individuals (Infutor only covers adults) but it is possible that only one of them is the owner of the household. In that case, individuals living in the same unit as an owner would count as non-owners.

Figure A.6 plots our imputed measure against the census measure. As expected, imputed rates are much lower than census ownership rates. However, there is a strong positive relationship between measures across block groups with 40Bs, suggesting that our fuzzy matching algorithm linking Infutor to Zillow records is a reasonable proxy for ownership status.

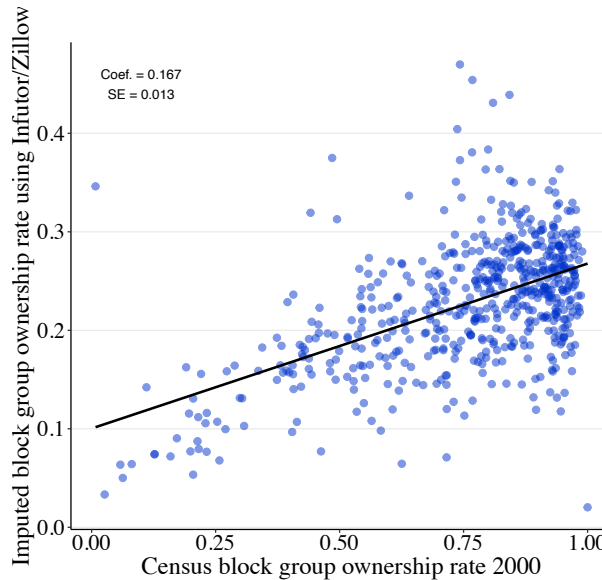
Finally, Figure A.7 uses imputed ownership status to calculate ownership rates for the rings used in our empirical specifications. The estimated ownership rates are around 23 percent beyond 0.2 miles away and seem to be slightly lower in areas closer to 40B developments, reaching a 20 percent ownership rate within 0.1 miles. The fact that we do not observe sharp changes across distances from 40Bs suggests that our heterogeneity estimates are not substantially biased by measurement error in closer distances.

Figure A.5: Histogram of 2000 ownership rates in census block groups with 40Bs



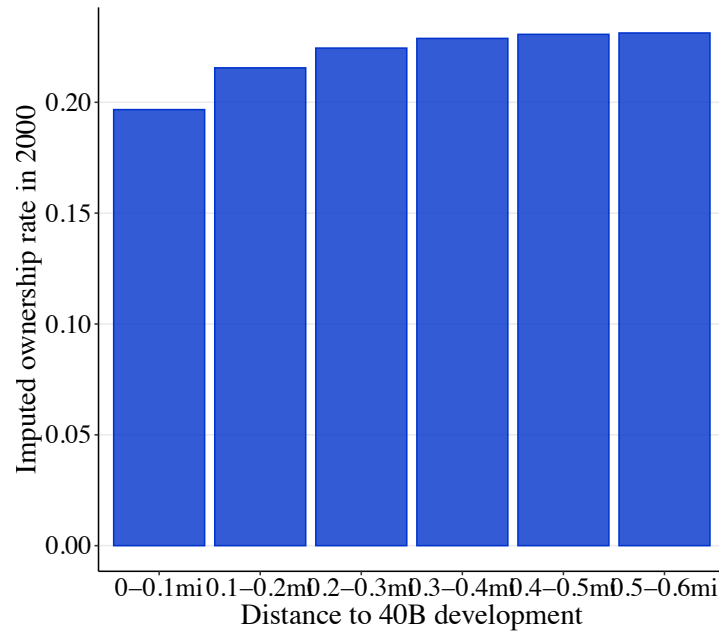
Note: The plot shows a histogram of ownership rates in 2000. The sample is census block groups with any 40B units that were approved in 2000 or after.

Figure A.6: Comparison of ownership rates: imputation (from Infutor/Zillow) vs census



Note: The figure is a scatter plot where every dot represents a 2000 census block group with any 40B units that were approved in 2000 or after. The y-axis is our imputed ownership rate calculated by matching Infutor individuals to Zillow's tax assessment and transaction records. The x-axis is the ownership rate as reported by the census. The line represents an ordinary least squares fit of the relationship between two variables. The coefficient and standard error of the regression are shown in the top left corner.

Figure A.7: Ownership rates by ring



Note: The plot shows ownership rates by 0.1 mile-wide rings around 40B developments using our imputed ownership measure. The sample includes 40B developments that were approved in 2000 or after.

B Comparison to Effects of Non-40B Large Developments

We compare the impact of 40B developments on housing prices and residents' responses with that of developments with similar characteristics and in similar locations that were not permitted under Chapter 40B ('non-40Bs'). This comparison should be informative of the impact of bypassing zoning laws given that, presumably, comparable non-40B developments should have been built in accordance to local zoning restrictions. Consistent with our main findings, we will focus on developments with 50 or more units.

We identify large developments built outside the scope of the 40B program using tax assessment data from Zillow. First, we identify and exclude all 40B developments in tax assessment records by using the fuzzy matching described in Section A.1 based on street number, street name, street type, and city. We block matches based on an exact match on street numbers and city names. Second, we restrict the sample to properties with 50 or more units and that were built between 1995 and 2012. Third, we exclude any buildings located in Boston to make our sample more comparable to 40B developments given that Chapter 40B is not binding in Boston. We are able to identify 295 non-40B developments. Note that approval dates for non-40B developments and completion dates for non-40B developments are not available: a comparison of the exact timing of the effects between both development types is not possible. However, the comparison is still informative, since the price effects of 40Bs only show up in the long run, when they are likely completed.

Despite Boston is excluded from the sample, non-40B developments are still slightly different from 40B developments approved during the same period. Figure B.1 shows that both types of developments are concentrated in the Greater Boston area. However, non-40Bs have a higher presence in municipalities closer to Boston, such as Cambridge, Somerville or Medford; while 40Bs have a greater presence in other areas such as Cape Cod. The first two columns of Table B.1 compare the two development types. Non-40Bs are slightly smaller and are located in census tracts that are denser, with lower white population and ownership shares, slightly higher housing prices and closer to the Central Business District (CBD). Despite this, census tracts where the two development types are located are remarkably similar along other dimensions, such as demographic composition, education, unemployment, and income.

We estimate the effects of non-40B developments using inverse probability weighting to deal with the selection problem. More specifically, we run a logistic regression of an indicator variable for whether the development is a 40B as the outcome variable on the number of units and census tract characteristics. We then construct a propensity score $\hat{p}_d$ for every non-40B development d . Column (3) of Table B.1 reports the same descriptive statistics for non-40Bs weighting each of them by $1/(1 - \hat{p})$. That is, non-40Bs that are more similar to 40Bs are weighted more. As a result, the (weighted) average non-40B development is more similar to 40Bs, though some differences

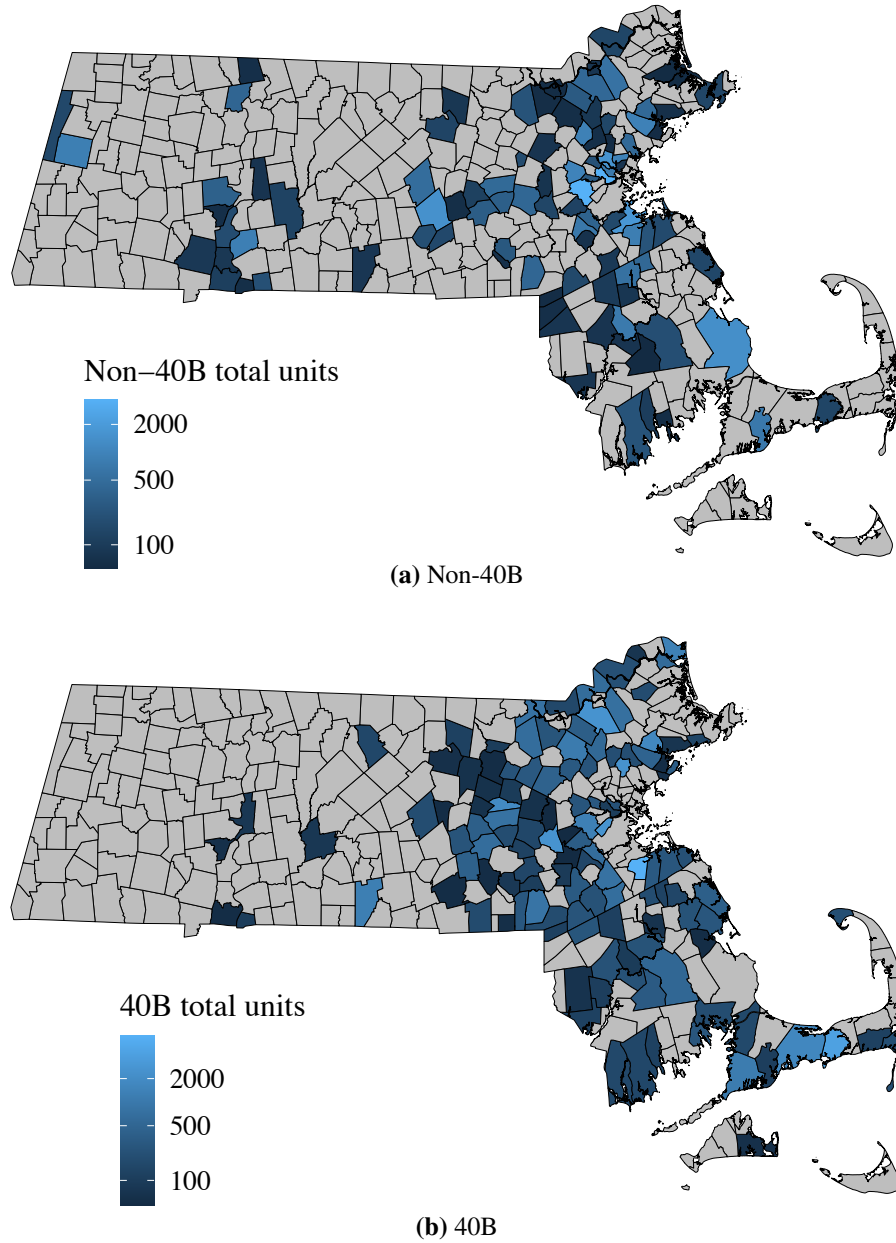
still persist. For instance, non-40B are still in denser census tracts and slightly closer to the CBD, consistent with the fact that they should be less likely to be in areas with stricter zoning laws.

Non-40B developments lead to negative effects on local housing prices beyond the distances where 40B lowers property values. To estimate these effects, we use the same methodology as in Section 3.3. Figure B.2 reports the event study and the pooled DID results for non-40Bs. The event study shows that sale prices temporarily go up around the completion year for preexisting housing located within 0.1 miles and then decrease by 20 percent in the long-run. This result must be interpreted with caution, given that pre-trends are relatively unstable—partly due to the fact that sale prices should react at the time when the building is approved and not when it is completed. However, there are no pre-treatment trends for distances beyond 0.1 miles. Overall, the pooled DID results show that sale prices go down by roughly 6-7 percent within 0.3 miles and by 3 percent within 0.3-0.4 miles after completion. There are no effects beyond 0.4 miles.

These findings contrast with the impact of large 40Bs on local housing prices. While 40B's negative price effects are restricted to the first 0.1 miles, non-40Bs negatively affects prices up to 0.4 miles away. Such result may be explained by a larger role of the supply effect in communities where non-40Bs is built, given that nearby existing housing may be more similar to units in the new building (as opposed to 40B neighborhoods, mostly composed of single-family residences). Another difference with our 40B findings is that non-40B developments seem to increase nearby sale prices in the very short run. A potential explanation is that non-40Bs may replace an eyesore, which is valued by local residents and prospective buyers, a result that has been previously linked to LIHTC developments Hankinson et al. (2022). Thus, the value of properties immediately adjacent to non-40Bs increases temporarily until the new units become available, when the new residents move in and the supply effect kicks in.

Non-40B developments trigger the outmigration of incumbent residents to a limited extent and does not generate responses in voter participation in general elections. Figure B.3 shows the event study results for move-out rates and voter turnout rates in general elections. Move-out rates increase within 0.1mi after completion, though the effect is smaller for the average local resident and more irregular for incumbent residents than that of 40Bs. Some of this variation may be due to the difference in the 'treatment event', given that in our 40B specification we use the approval year. Thus, the results for non-40Bs may be missing some of these effects. Furthermore, we do not observe a meaningful effect within 0.1-0.2mi for incumbent residents, even though 40Bs have a significant effect at these distances in the long run. These results suggest that move-out responses are not as strong as for 40Bs. This finding is consistent with a stronger negative preference of local residents for 40Bs in low-density neighborhoods. Finally, we do not observe a clear pattern of effects of non-40B developments on political behavior.

Figure B.1: Comparison of non-40B and 40B units in large developments between 1995 and 2012 by municipality (except Boston)



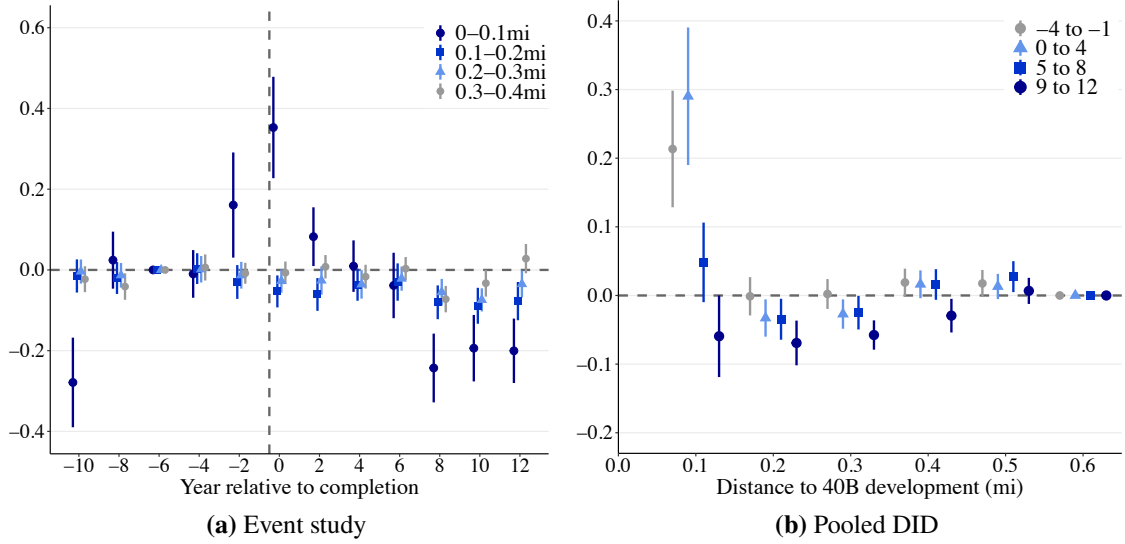
Note: The map shows the total number of units (includes both market and affordable units for 40B) in developments with 50 or more units by 40B status for each municipality. Panel (a) shows units completed in 1995-2012 without a 40B permit. We identify these developments using property tax assessments in the Zillow data. Panel (b) shows units approved under a 40B permit in the same period. We identify 40B units using the Subsidized Housing Inventory (SHI) from the Executive Office of Housing and Livable Communities (EOHLC) in Massachusetts. Each 40B address has been verified in the procedure detailed in Sportiche et al. (2025). Municipalities in gray did not approve any units except for Boston, which we exclude from our analysis. The legend coloring is log-transformed for visual purposes.

Table B.1: Summary statistics of non-40B developments

Characteristic	40B	No 40B	No 40B - IPW
<i>Panel A: Development</i>			
Total units	140	123	137
<i>Panel B: 2010 census tract</i>			
Population: total	5,530	5,273	5,379
Population: density (mi2)	2,027	3,810	2,989
Population: under 18	0.23	0.20	0.21
Population: 65 or more	0.15	0.17	0.16
Race: white	0.89	0.82	0.85
Race: black	0.025	0.04	0.035
Education: High school or less	0.07	0.07	0.07
Education: Bachelor or more	0.46	0.50	0.48
Unemployment rate	0.073	0.067	0.068
Household median income	89,746	86,663	86,491
Below poverty rate	0.06	0.08	0.07
Housing: owner-occupied	0.74	0.66	0.69
Housing: median year built	1,969	1,964	1,966
Housing: median rent	1,102	1,296	1,214
Housing: median home value	408,087	441,085	416,923
Distance to CBD (mi)	28	23	26
Number of developments	216	295	295

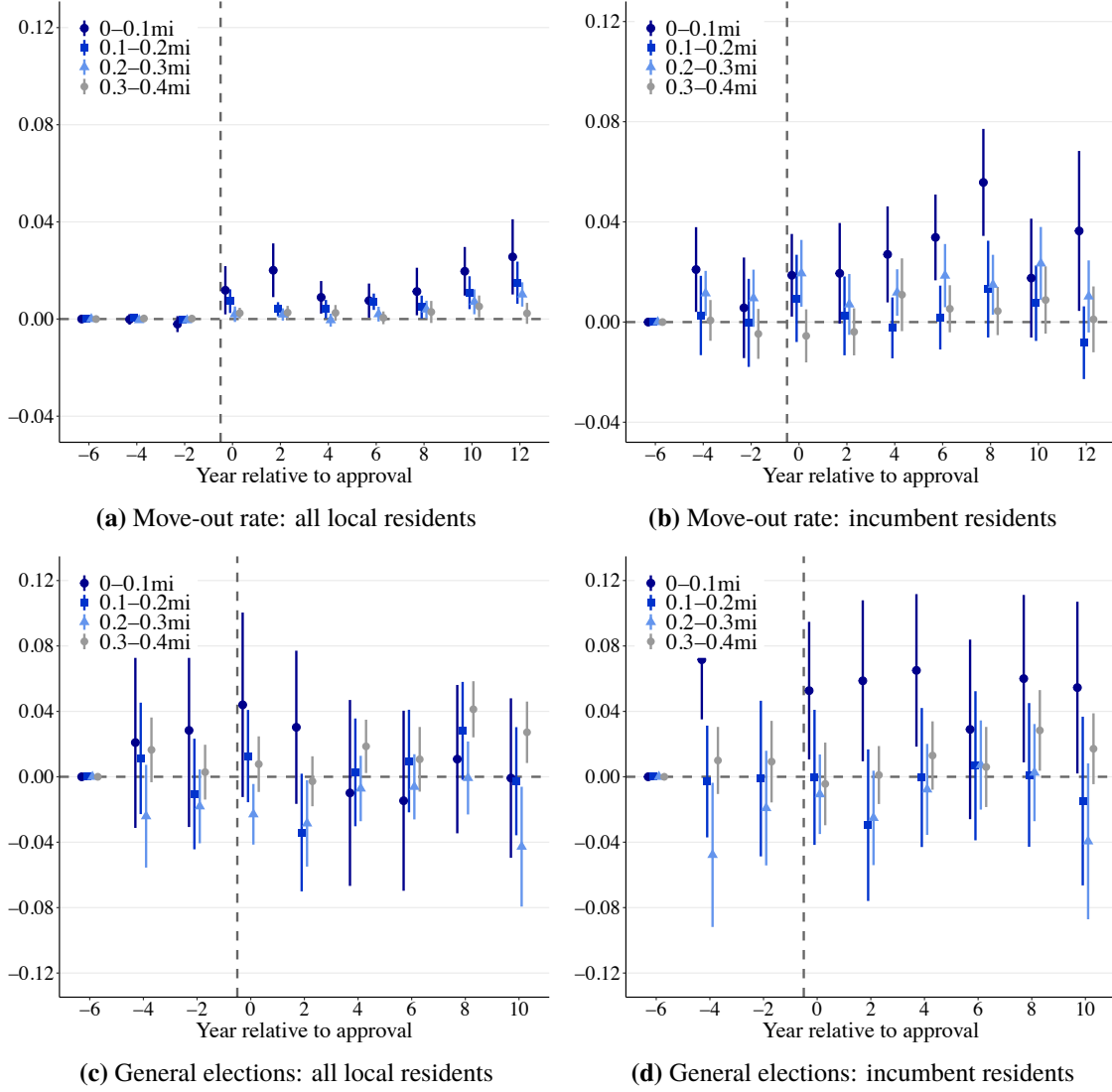
Note: Column (1) provides summary statistics for 40B developments with 50 or more units approved between 1995 and 2012, while columns (2) and (3) do the same for other non-40B developments with 50 or more units built anywhere in Massachusetts except for Boston. Column (3) weights each non-40B development by their propensity score as described in the text above. Panel A uses data from the Subsidized Housing Inventory processed as described in Sportiche et al. (2025) for column (1) and from property tax assessments in Zillow data for columns (2) and (3). Panel B uses 2010 census data.

Figure B.2: DID: sale prices of preexisting housing for large non-40Bs developments



Note: The figures plot estimated coefficients $\beta_{\tau,r}$ in Eq. (1) (panel a) and $\theta_{1,r}$, $\theta_{2,r}$ and $\theta_{3,r}$ (including one extra period, panel b) in Equation (2) using 0.1 mile-wide rings and the logarithm of sale prices as the outcome. The sample includes non-40B developments of 50 or more units that were completed in 1995-2012 and sales of old houses.

Figure B.3: Event study: move-out and turnout rates for large non-40B developments



Note: The figures show estimated coefficients $\beta_{\tau,r}$ in Eq. (1) using 0.1 mile-wide rings. The outcome variables are indicators of whether the individual moved out from the address neighboring a 40B (panels a and b) and whether they voted in a general election (panels c and d). We restrict the analysis to non-40B developments completed in 1995-2012 in panels (a) and (b) and in 2000-2012 in panels (c) and (d). Panels (a) and (c) run the analyses for the sample of all local residents, while panels (b) and (d) use the sample of incumbent residents of non-40B developments.

C Heterogeneity of the Price Effects of Chapter 40B

This section presents heterogeneity analyses of the price effects of 40B developments.

We start by focusing on *larger 40B developments*. There are several potential explanations for the negative price effect near larger 40B developments found on Section 4. One potential explanation is that by adding new units, 40B developments shift the housing supply curve outwards, which should put a downward pressure on prices. This supply channel may explain the highly localized results if there is strong market segmentation and new 40B housing is a close substitute to nearby housing, otherwise any supply effect should dissipate across the entire housing market (Kristof, 1965; Sweeney, 1974; Braid, 1981). 40B developments may also affect housing demand by introducing a disamenity. For example, nearby residents may view 40B housing as a negative physical externality (e.g., loss of ‘neighborhood character’) or they may negatively value the increase in low- and moderate-income residents moving into the new 40B units. Other potential explanations such as negative effects on the provision of public goods (e.g., congestion in public schools or traffic) are less plausible because the effect of larger 40B developments on prices that we estimate are highly localized rather than affecting the entire municipality.

To explore the relative importance of these supply and disamenity mechanisms, we conduct several sets of heterogeneity analyses based on development characteristics—such as tenure, monitoring agency, development size—and characteristics of the surrounding neighborhood such as local zoning and median household income. To do so, we begin by splitting our sample of larger 40B developments in two, converting any non-binary variables into indicators denoting whether a 40B development is above or below the median value in the sample. Table C.1 reports the results of this exercise.

Columns 1 and 2 in these results show that negative effects on property values are greater among ownership 40Bs. When compared to rentals, 40B ownership developments generate reductions in local sale prices that are roughly 3 percentage points larger for preexisting housing located within 0.1 miles of 40B housing. 40B ownership developments also decrease sale prices by 5 percent within 0.1-0.2 miles compared to rentals, which do not significantly affect prices at that distance. Since ownership 40B units compete directly with nearby for-sale houses, we interpret these results as suggestive evidence that the supply effect may be relevant in explaining negative effects.

We also find suggestive evidence that demand-side mechanisms play a role in our findings. Columns 5 and 6 show that the largest 40B developments (i.e., with 96 or more units) lead to larger price reductions within 0.1 miles than smaller large developments (i.e., between 50 and 95 units). These larger effect may be due either to a physical externality effect or to the more intense exposure to 40B residents. Two results suggest that the ‘neighborhood character’ argument may be an important factor explaining the results. In columns 7 and 8, we find that 40B developments

placed in single-family zoned areas concentrate most of the price decreases within 0.2 miles (12.4 and 4.6 percent decrease within 0.1 and 0.1-0.2 miles, respectively). In addition, the results from columns 11 and 12 showing that price reductions only affect the sale of single-family housing further supports this argument. Because we expect condos to be closer substitutes to new market-rate 40B units (and thus, the supply effect should be larger), these results for single-family houses indicate that households searching for single-family housing may negatively discount locations near such large developments, potentially due to the loss of neighborhood character or higher exposure to low- and moderate-income households.

Finally, we also explore the sources of the positive price effects associated with smaller 40B developments, as shown in Appendix Figure F.7. Table C.2 presents a heterogeneity analysis similar to the one above for this sample of smaller 40B developments. These results show that 40B developments with fewer units than the median smaller development (fewer than 12 units) and those built in areas not zoned for single-family residences largest actually lead to increases in sale prices for nearby housing beginning in years 5 to 8.²⁴ These results suggest that smaller 40B developments may generate positive spillovers, for example by replacing deteriorated buildings or vacant lots that previously imposed negative externalities on local residents. As prior literature shows, replacing these blighted spaces with new housing can raise nearby property values (Schwartz et al., 2006; Hankinson et al., 2022). Additionally, 40B developments may attract complementary public investments, such as repaved streets or new green spaces, which can further improve the neighborhood's appeal.

²⁴While most developments are in single-family zoned areas, about 5 percent of this sample are built in industrial areas.

Table C.1: Heterogeneity of price effects

Heterogeneity var.	Tenure		Agency		Development size		40B Zoning		Household income		Sale type	
	Ownership (1)	Rental (2)	MassHous. (3)	Others (4)	<median (5)	>median (6)	Other (7)	SFR (8)	<median (9)	>median (10)	Condo (11)	SFR (12)
Yrs. 0-4: 0-0.1mi	-0.022 (0.038)	0.043 (0.027)	0.061* (0.034)	-0.026 (0.034)	-0.034 (0.030)	0.097** (0.043)	0.002 (0.035)	0.012 (0.033)	0.027 (0.029)	-0.020 (0.042)	0.008 (0.026)	-0.004 (0.033)
Yrs. 0-4: 0.1-0.2mi	-0.034 (0.022)	0.011 (0.016)	-0.025 (0.020)	0.005 (0.018)	-0.011 (0.017)	-0.003 (0.021)	0.013 (0.019)	-0.023 (0.018)	-0.006 (0.019)	-0.010 (0.018)	0.018 (0.019)	-0.009 (0.016)
Yrs. 5-8: 0-0.1mi	-0.021 (0.034)	0.005 (0.033)	-0.032 (0.043)	0.017 (0.029)	-0.012 (0.027)	0.008 (0.048)	0.011 (0.040)	-0.018 (0.029)	0.006 (0.037)	-0.018 (0.030)	0.024 (0.039)	0.002 (0.033)
Yrs. 5-8: 0.1-0.2mi	-0.012 (0.023)	-0.008 (0.021)	0.002 (0.023)	-0.018 (0.021)	-0.013 (0.021)	-0.009 (0.023)	-0.021 (0.023)	-0.001 (0.021)	-0.009 (0.023)	-0.014 (0.021)	0.025 (0.032)	-0.021 (0.018)
Yrs. 9-12: 0-0.1mi	-0.104** (0.052)	-0.075** (0.035)	-0.093** (0.044)	-0.082* (0.045)	-0.067* (0.037)	-0.153*** (0.058)	-0.035 (0.044)	-0.124*** (0.043)	-0.099** (0.047)	-0.077* (0.043)	-0.010 (0.036)	-0.126* (0.067)
Yrs. 9-12: 0.1-0.2mi	-0.053* (0.028)	-0.020 (0.021)	-0.021 (0.023)	-0.045* (0.025)	-0.032 (0.023)	-0.040 (0.025)	-0.022 (0.029)	-0.046** (0.021)	-0.039 (0.025)	-0.030 (0.024)	0.033 (0.036)	-0.048** (0.022)
Developments	95	175	133	137	131	139	144	126	135	135	181	270
Observations	48,659	97,034	64,617	81,076	88,006	57,687	80,547	65,146	87,193	58,500	64,698	80,995
R ²	0.851	0.875	0.880	0.854	0.850	0.884	0.870	0.865	0.849	0.868	0.921	0.869

Note: The table reports estimates for coefficients $\theta_{1,r}$, $\theta_{2,r}$ and $\theta_{3,r}$ in Equation (2) using 0.1 mile-wide rings and the logarithm of house prices as an outcome. Each column uses a different sample depending on: tenure (ownership or rental 40Bs, columns 1-2), monitoring agency (MassHousing or other, columns 3-4), 40B development size (above or below the median in the sample, 5-6), whether the 40B development is in an area zoned as single-family residence (7-8), household income in the 40B's census tract in 1990 (above or below the median in the sample, 9-10), and whether the sold property is a condo or a SFR (11-12). Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table C.2: Heterogeneity of price effects

Heterogeneity var.	Tenure		Agency		Development size		40B SFR Zoning		40B Industrial		Household income		Sale type	
	Ownership (1)	Rental (2)	MassHous. (3)	Others (4)	<median (5)	>median (6)	Other (7)	SFR (8)	Other (9)	Industrial (10)	<median (11)	>median (12)	Condo (13)	SFR (14)
Yrs. 0-4: 0-0.1mi	0.005 (0.013)	0.011 (0.018)	0.023 (0.021)	0.0010 (0.013)	0.004 (0.015)	0.012 (0.017)	-0.002 (0.015)	0.007 (0.014)	0.007 (0.011)	0.010 (0.034)	-0.002 (0.017)	0.016 (0.014)	-0.013 (0.020)	0.0007 (0.014)
Yrs. 0-4: 0.1-0.2mi	-0.007 (0.009)	-0.013 (0.015)	-0.004 (0.016)	-0.009 (0.009)	-0.013 (0.011)	-0.002 (0.011)	-0.026* (0.013)	0.0008 (0.010)	-0.009 (0.008)	-0.0002 (0.029)	-0.014 (0.011)	-0.004 (0.011)	-0.011 (0.017)	-0.012 (0.009)
Yrs. 5-8: 0-0.1mi	0.0003 (0.014)	0.030 (0.028)	-0.0003 (0.024)	0.010 (0.015)	0.042*** (0.016)	-0.023 (0.019)	-0.010 (0.021)	0.012 (0.016)	0.007 (0.013)	0.081 (0.064)	-0.011 (0.020)	0.018 (0.017)	-0.004 (0.032)	0.018 (0.015)
Yrs. 5-8: 0.1-0.2mi	0.005 (0.011)	0.011 (0.018)	-0.014 (0.017)	0.014 (0.011)	0.017 (0.015)	-0.004 (0.012)	-0.014 (0.017)	0.014 (0.011)	0.005 (0.010)	0.028 (0.033)	-0.006 (0.013)	0.015 (0.013)	-0.029 (0.020)	0.002 (0.010)
Yrs. 9-12: 0-0.1mi	0.054*** (0.015)	0.051* (0.030)	0.042 (0.028)	0.061*** (0.015)	0.081*** (0.019)	0.033* (0.020)	0.080*** (0.021)	0.040** (0.017)	0.055*** (0.014)	0.078 (0.055)	0.056*** (0.019)	0.054*** (0.019)	-0.014 (0.028)	0.048*** (0.016)
Yrs. 9-12: 0.1-0.2mi	0.014 (0.011)	0.017 (0.021)	0.032* (0.016)	0.007 (0.012)	0.016 (0.015)	0.016 (0.013)	-0.009 (0.018)	0.026** (0.012)	0.012 (0.010)	0.059** (0.022)	-0.021 (0.014)	0.051*** (0.013)	-0.018 (0.024)	0.007 (0.010)
Developments	449	180	215	414	267	362	217	412	594	31	300	329	484	629
Observations	209,704	116,418	98,021	228,101	153,197	172,925	128,695	197,427	308,507	16,471	175,914	150,208	95,334	230,788
R ²	0.889	0.869	0.874	0.885	0.904	0.859	0.889	0.866	0.886	0.845	0.861	0.881	0.953	0.883

Note: The table reports estimates for coefficients $\theta_{1,r}$, $\theta_{2,r}$ and $\theta_{3,r}$ in Equation (2) using 0.1 mile-wide rings and the logarithm of house prices as an outcome. Each column uses a different sample depending on: tenure (ownership or rental 40Bs, columns 1-2), monitoring agency (MassHousing or other, columns 3-4), 40B development size (above or below the median in the sample, 5-6), whether the 40B development is in an area zoned as single-family residence (7-8), whether the 40B development is in an area zoned as industrial (9-10), household income in the 40B's census tract in 1990 (above or below the median in the sample, 11-12), and whether the sold property is a condo or a SFR (13-14). Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D The Aggregate Value of Chapter 40B

We estimate the housing value created by Chapter 40B and the property value losses borne by homes located near larger 40B developments using residential transactions and tax assessment data.

We compute the aggregate value of housing produced under Chapter 40B as follows. First, we identify 40B units in the 2020 tax assessment data as the sample of residential buildings located within 0.1 miles from 40B developments approved between 1995 and 2012 and constructed within twelve years of the approval year of the associated 40B development.²⁵ We limit the sample to developments approved by 2012 to ensure sufficient time for the 40B units to be constructed by the end of our sample. We identify at least one unit for 525 of the 733 40B developments approved in this period and further restrict the sample to developments for which we observe at least one-third of the units in the assessment records, yielding a final sample of 435 developments. Figure D.1 compares the number of 40B units identified in the assessment data with official unit counts for each 40B development. The close alignment with the 45-degree line suggests that our identification strategy is a reasonable proxy for actual 40B units.

Second, we estimate the market value of these units, acknowledging that assessment values may differ from market values. To do so, we generate year built-specific adjustment factors that convert assessment values to market values using transactions data on single-family residences. We start by converting sale prices in transaction data to 2019 dollars using FRED's All-Transactions House Price Index for Massachusetts.²⁶ Next, we regress sale prices in this dataset on their 2020 assessment value interacted with the year when the unit was built to obtain the built-year specific adjustment factors.²⁷ We apply these conversion factors to the assessment values of 40B units to obtain their estimated market value. For multifamily buildings, we divide the estimated building value by the number of units to obtain per-unit values.

Third, we estimate the aggregate value of Chapter 40B, shown in Table D.1. To do this, we compute the average market value of a 40B unit for each 40B development and then compute the average market value across all developments by tenure (rental, ownership, mix), weighting each development by their number of units. We then extrapolate this average market value by tenure to compute the aggregate value of two samples of 40B developments: all 40B developments (column 1) and those approved between 1995 and 2019 (column 2), which correspond to the main sample in our analysis. Columns 3 and 4 present the results for 40B developments with 50 or more units. The table shows aggregate values (in 2019 billions), average per-unit values, and the total number of 40B units in each sample.

²⁵ A caveat is that this approach may include non-40B units that were built near 40Bs around the same time.

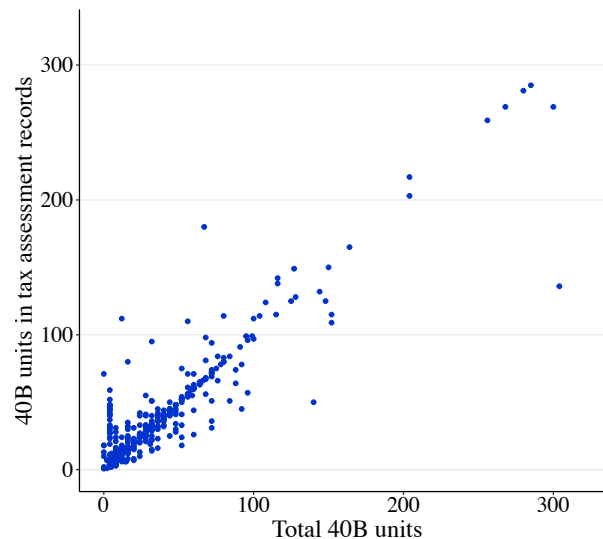
²⁶ <https://fred.stlouisfed.org/series/MASTHPI>.

²⁷ Properties built before 1899 are grouped into a single category due to small sample sizes, and we include a separate category for properties missing year-built information (1.7 percent of observations).

To estimate the property value losses for housing near larger 40B developments, columns 5–7 of Table D.1 focus on single-family residences located within 0.2 miles of such developments approved between 1995 and 2019. These are the properties for which we observe negative price effects, based on our heterogeneity analyses in Table C.1. As before, we use tax assessment records and apply our conversion methodology to estimate market values in 2019 dollars. We then multiply market values by the estimated price effects of larger 40B developments—12.6 percent for housing within 0.1 miles and 4.8 percent for housing between 0.1 and 0.2 miles—to calculate total property value losses. Column 5 reports the aggregate losses within 0.2 miles, while columns 6 and 7 separate the results for the 0.1 and 0.1–0.2 mile bands, respectively. The last row reports the number of affected single-family residences at each distance.

Overall, we estimate that Chapter 40B has produced approximately \$17.4 billion in housing value since its inception, with an average market value of \$248,055 per unit. Developments with 50 or more units, which represent 80 percent of 40B units, account for \$12.88 billion (74 percent) of this total. In contrast, the estimated property value losses for roughly 10,000 single-family residences located within 0.2 miles from these larger 40B developments approved between 1995 and 2019 total \$0.29 billion. These property value losses represent just 3.11 percent of the aggregate value generated by these larger 40B developments (\$9.31 billion).

Figure D.1: Comparison of 40B units in assessment data and official number of 40B units



Note: The x-axis represents the official number of units in a given 40B development as reported in the Subsidized Housing Inventory (SHI) and the y-axis shows the number of 40B units that we are able to identify in tax assessment records for that 40B development. The sample is restricted to 40B developments approved between 1995 and 2012 for which we find at least one third of the official number of 40B units in the development.

Table D.1: Aggregate value of Chapter 40B, by period and size

	Aggregate value of Chapter 40B housing				Property value losses		
	Full sample		50 units or more		50 units or more		
	All 40Bs	1995-2019	All 40Bs	1995-2019	0-0.2mi	0-0.1mi	0-0.2mi
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Total value (in 2019 billions of dollars)	17.40	12.77	12.88	9.31	0.29	0.11	0.17
Per unit value/loss (in 2019 dollars)	248,055	253,386	231,180	234,483	30,143	56,422	23,039
Number of units	70,149	50,407	55,733	39,719	9,634	2,082	7,552

Note: Columns 1-4 report the estimated aggregate value of 40B housing by sample (first two columns, full sample; last two columns, 40B developments with 50 units or more) and by approval period (in odd columns, all periods since the inception of the program; in even columns, 40B developments approved between 1995 and 2019). Columns 5-7 estimate property value losses for single-family residences near larger 40B developments approved between 1995 and 2019 by distance. The first two rows report the total value, which adds up the value across all units produced in the period, and the per-unit value added (columns 1-4) or lost (columns 5-7). The third row reports the total number of 40B units in Columns 1-4, and the total number of single-family residences within a given distance of the 40B as reported by tax assessment records in Columns 5-7.

E Robustness: An Alternative Estimator and an Alternative Identification Strategy

E.1 Estimator: Gardner (2022)

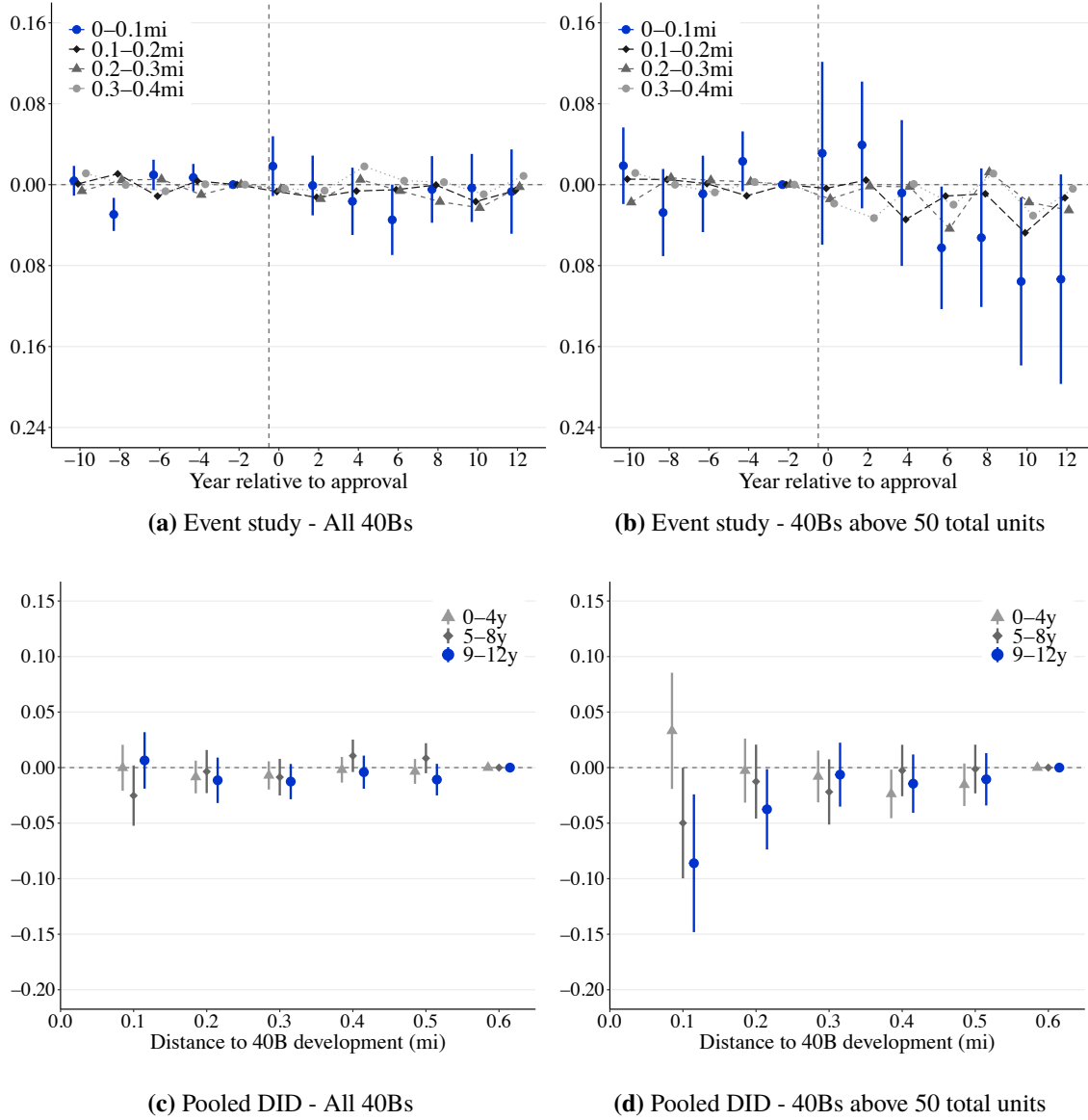
We estimate our main results using an alternative difference-in-differences estimation method proposed by Gardner (2022), which is also robust to treatment effect heterogeneity in staggered treatment adoption settings. This estimator proceeds in two steps. In the first step, it estimates group and time fixed effects using only untreated observations. In our case, we use observations belonging to either the pre-treatment period or the outermost ring as untreated observations. In the second step, the difference between the observed outcome and the predicted fixed effects is regressed on the treatment variables, which include interactions of event year-pair indicators with indicator variables for each treated ring. Importantly, this estimator allows us to accommodate several treatments (inner rings) in the same specification.

More specifically, we estimate the following regression using the R package `did2s`:

$$Y_{hdt} = \alpha_{dt} + \kappa_{r(h,d)} + \sum_{\tau=-10}^{12} \sum_{r \in R} \beta_{\tau,r} \mathbb{1}(t - E_d = \tau, r(h, d) = r) + \gamma' \mathbf{X}_{ht} + \epsilon_{hdt} \quad (4)$$

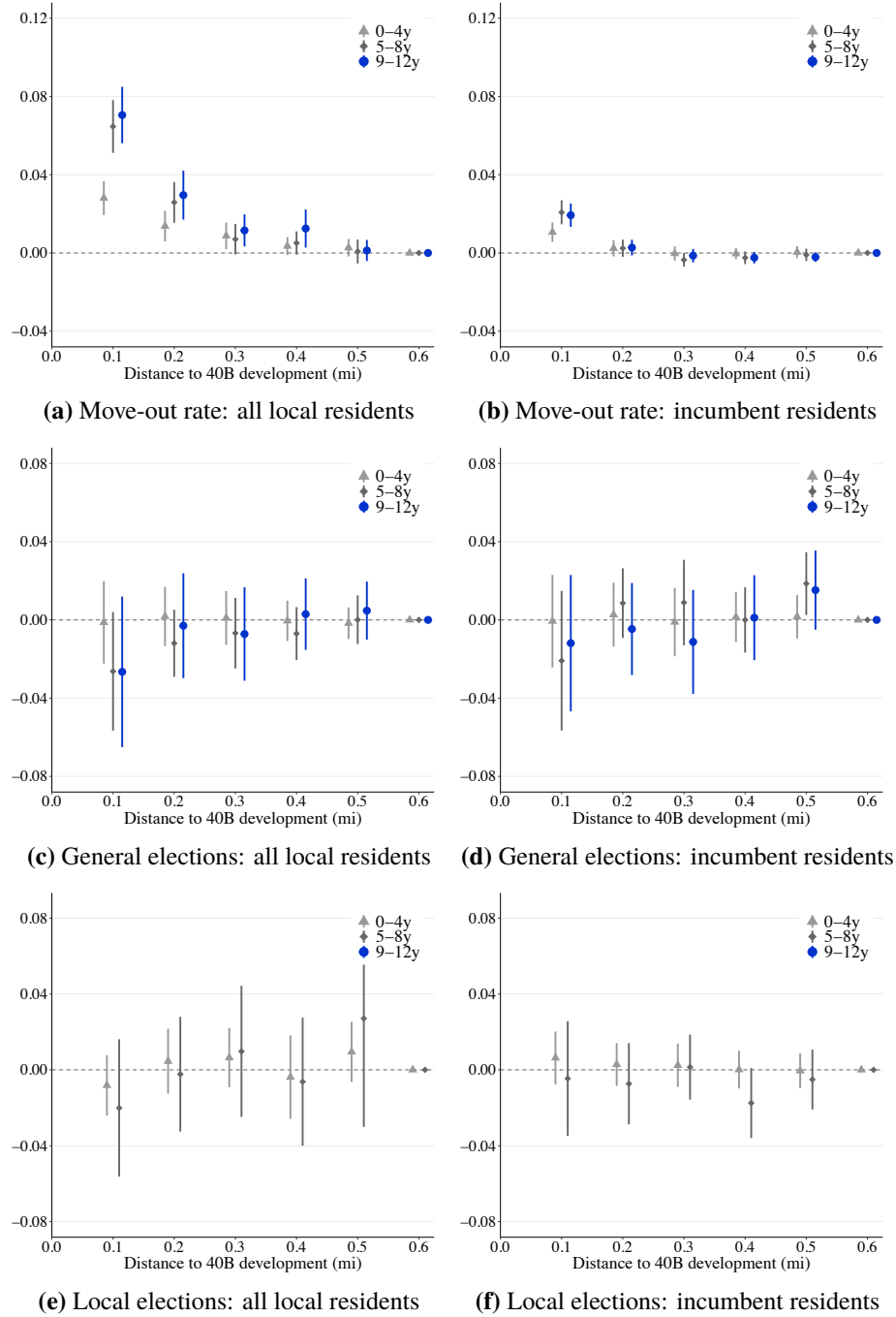
We weight every 40B development-ring-year combination equally, so that we can interpret the coefficients as the average of 40B development-specific treatment effects. Figures E.1 and E.2 show that our main results are robust to this alternative estimator.

Figure E.1: DID estimates of the impact of 40Bs on sale prices following Gardner (2022)



Note: The figures plot the estimated coefficients $\beta_{\tau,r}$ in Equation 4 (panels a and b) and $\theta_{1,r}$, $\theta_{2,r}$ and $\theta_{3,r}$ (panels c and d) in Equation (2) using 0.1 mile-wide rings and the logarithm of sale prices as the outcome, following Gardner (2022). We restrict the sample to 40B developments approved in 1995-2019 and sales of preexisting houses. Panels (a) and (c) include the entire sample of 40Bs in this period; panels (b) and (d) include only 40Bs with a total of 50 units or more.

Figure E.2: DID estimates for move-out and turnout rates for large 40Bs following Gardner (2022)



Note: The figures show estimated coefficients $\theta_{1,r}$, $\theta_{2,r}$ and $\theta_{3,r}$ in the version of Equation (4) that is analogous to Equation (2) using 0.1 mile-wide rings, following Gardner (2022). The outcome variables are indicators of whether the individual moved out from the address neighboring a 40B (panels a and b) and whether they voted in a general/local election (panels c to f). We restrict the analysis to 40B developments approved in 1995-2019 in panels (a) and (b) and in 2000-2019 in panels (c) to (f). Panels (a), (c) and (e) run the analyses for the sample of all local residents, while panels (b), (d) and (f) use the sample of incumbent residents. All panels only include 40Bs with a total of 50 units or more.

E.2 Identification Strategy: Quasi-Random Timing

Following prior literature (Asquith et al., 2023; Blanco and Neri, 2025), we implement an alternative empirical strategy leveraging quasi-exogenous variation in the timing of 40B development. The identifying assumption is that areas very close to different 40B developments should be similar and the reason why some areas build 40B developments earlier than others is as good as random. This randomness could result from idiosyncratic factors such as negotiations between local governments and developers or land assembly, as argued by prior research.

This ‘timing’ approach is complementary to our main specification in Section 3.3—which uses proximity to 40B developments to choose the comparison group—, though it has several limitations. The proximity approach assumes parallel trends between the inner and the outer ring, which offers two main advantages: (1) it controls for time patterns in the micro-neighborhood surrounding each 40B development by leveraging variation in the evolution of outcomes between near and farther away areas, and (2) it usually contains a positive number of observations in the comparison group (areas between 0.8 and 1 mile away) for each 40B development-year combination due to the larger area covered. In contrast, the timing approach cannot control for time patterns around each development and it may lack a valid control group within short distances for some developments due to the low number of sales in such small areas.

When we test for the ‘quasi-exogenous timing’ assumption, we find that the timing of 40B development correlates with certain 40B characteristics. Developments that are rental, located in more educated, lower-rent tracts tend to be built later. We show this by regressing the year of 40B permit approval on several development and neighborhood characteristics, with results shown in Figure E.3. The fact that some estimates are statistically significant at the 95% level supports the choice of the proximity approach as our main specification. Nonetheless, we will still estimate the timing approach controlling for such time-invariant characteristics by including development fixed effects.

We implement the timing approach using a stacked approach, similar to our main specification. We create a separate dataset s for each 40B development approved between 1995 and 2012, pairing each treated 40B development (which has $\text{Treated}_{ds} = 1$) with similar 40B developments to be built after 2012 ($\text{Treated}_{ds} = 0$) that meet four conditions: (1) they are built at least two years later than the treated development, (2) they are not in the same municipality, (3) they are the same tenure type (rental/ownership), and (4) the number of units in the control development is within 20 percent of the treated development. Next, we estimate the following equation, *separately for each ring*, following Gardner (2022):

$$Y_{hds} = \omega_{ts} + \phi_{ds} + \sum_{\tau=-6}^{10} \beta_{\tau} \mathbb{1}(t - E_s = \tau) \times \text{Treated}_{ds} + \gamma' \mathbf{X}_{hds} + \varepsilon_{hds} \quad (5)$$

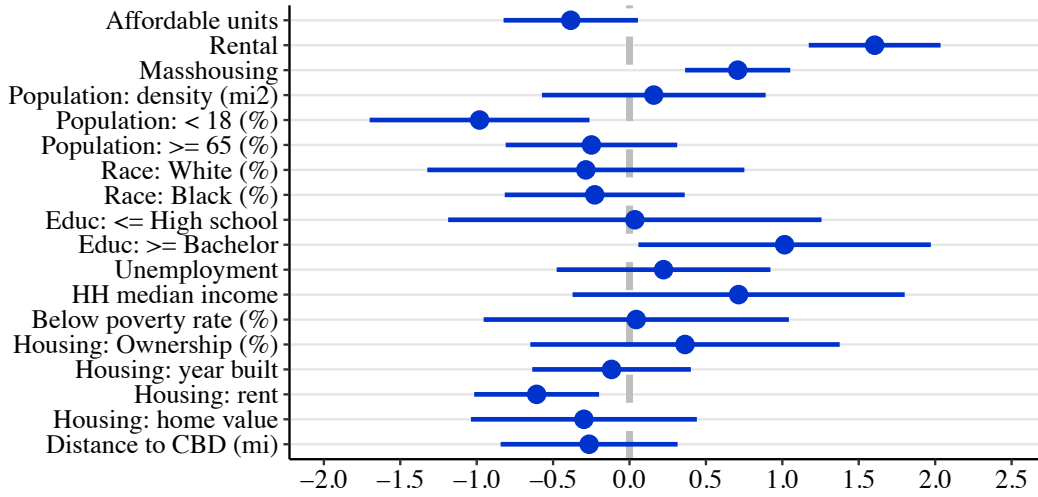
Here β_τ represents the effect of interest, i.e., evolution of the outcome for housing near current 40B developments compared to those near future 40B developments. ω_{ts} and ϕ_{ds} are calendar year-by-dataset and 40B development-by-dataset fixed effects, respectively. All fixed effects and control variables are interacted with indicator variables for each dataset s .²⁸ We weight each dataset-treated 40B development-year equally and each control 40B development equally within each dataset. Standard errors are clustered at the dataset level to account for 40B developments appearing in multiple comparison groups across datasets. In practice, we will estimate the pooled DID version that collapses relative years into three periods as in Equation (2).

Using this method, we obtain results that are consistent with our main specification. Figure E.4 plots the results for the pooled DID specification by ring. The average 40B development leads to moderate price decreases of about 4 percent within 0.1 miles (panel a). In contrast, there is a clear reduction in sale prices—of about 13 percent—for properties located within 0.1 miles of larger 40B developments in the long run (panel b), which is not present in farther away rings and aligns with our main results.

We also find similar results for move-out and voter turnout rates of residents around large 40B developments in Figure E.5. For these outcomes, we drop dataset-treated-year combinations with less than 10 observations to avoid over-weighting these combinations and obtaining noisier estimates. Effects on move-out rates within 0.2 miles align our main specification. However, estimates become unstable beyond 0.3 miles, possibly due to the identifying assumption being less plausible at these distances. Voter turnout is negatively affected but relatively constant within 0.6 miles, suggesting residents near earlier 40B developments experience a downward trend in voter turnout compared to those near later developments.

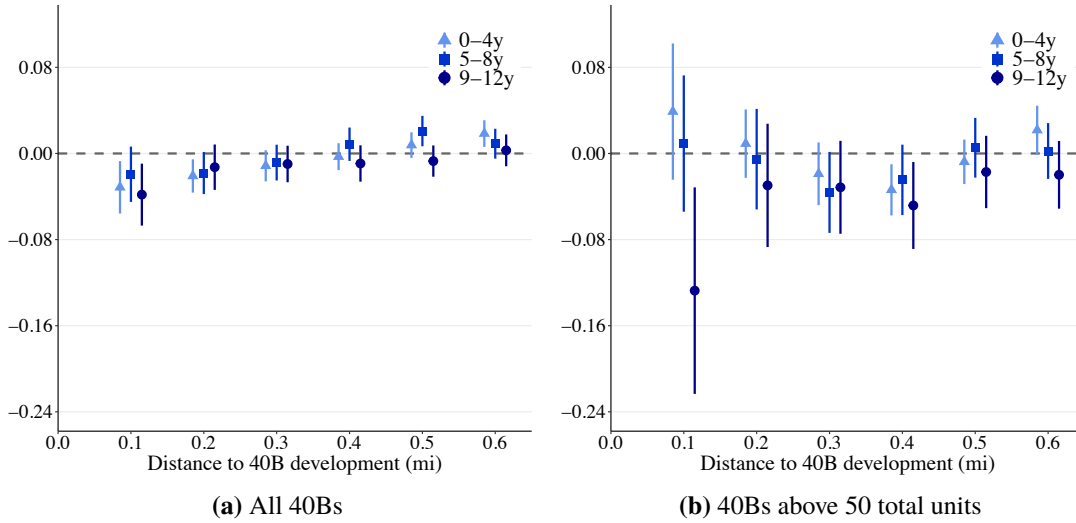
²⁸When using sale prices as the outcome, we cannot include calendar year-by-dataset fixed effects due to the low number of yearly sales in closer rings. Thus, we only include year fixed effects for this outcome. We also apply this strategy to voter turnout in general elections for incumbent residents, but only for the first ring.

Figure E.3: Coefficients of the regression of permit approval year on 40B characteristics



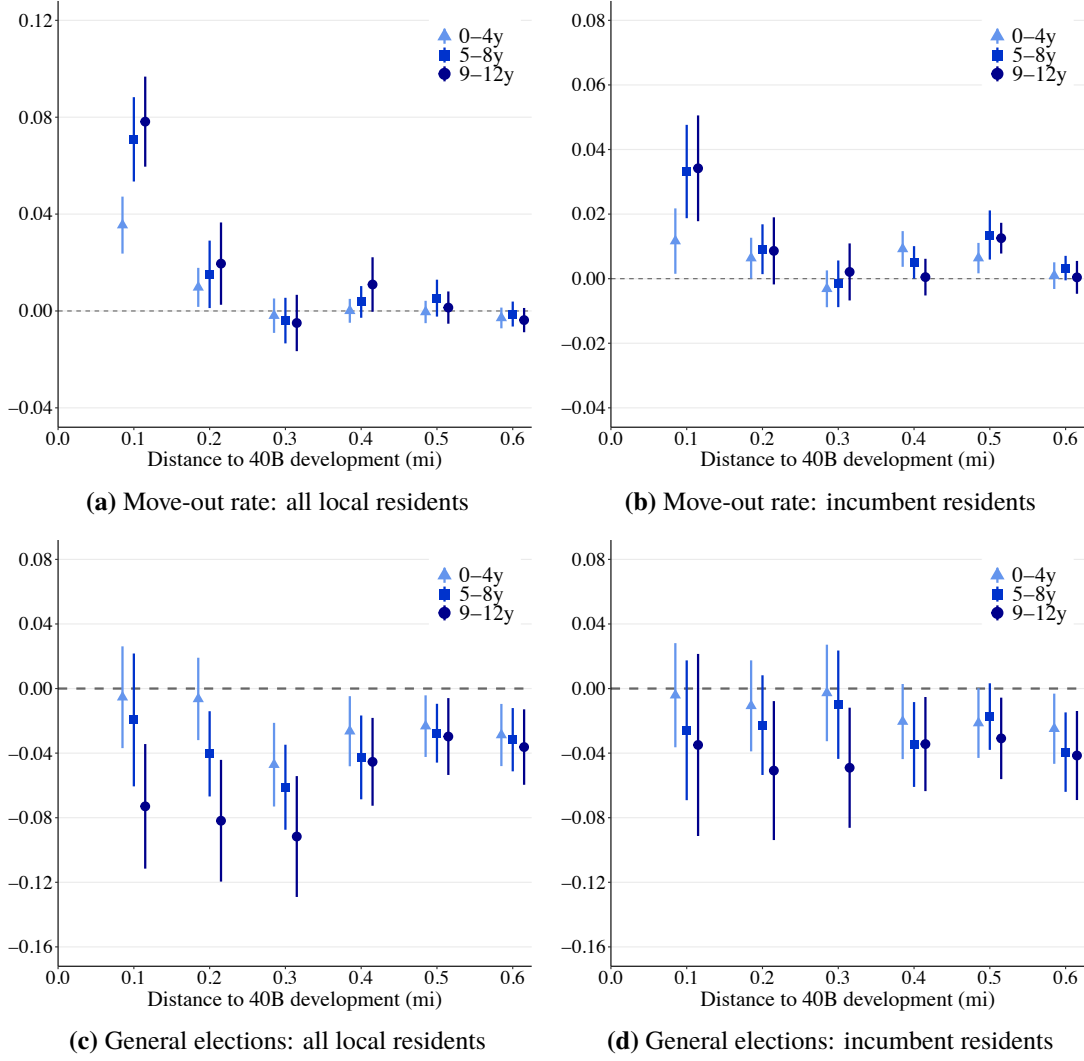
Note: The plot shows result of regressing the permit approval year on several 40B development and neighborhood characteristics. We use the sample of 40B developments approved between 1995 and 2019. All explanatory variables are standardized. Horizontal bars indicate 95% confidence intervals.

Figure E.4: DID estimates for sale prices of preexisting housing using quasi-exogenous timing



Note: The figures show estimated coefficients $\theta_{1,r}$, $\theta_{2,r}$ and $\theta_{3,r}$ in the version of Equation (5) that is analogous to Equation (2) using 0.1 mile-wide rings and the logarithm of sale prices as the outcome, following Gardner (2022). We restrict the analysis to 40B developments approved in 1995-2012 and sales of old houses. Panel (a) includes the entire sample of 40Bs; panel (b) includes only 40Bs with a total of 50 units or more.

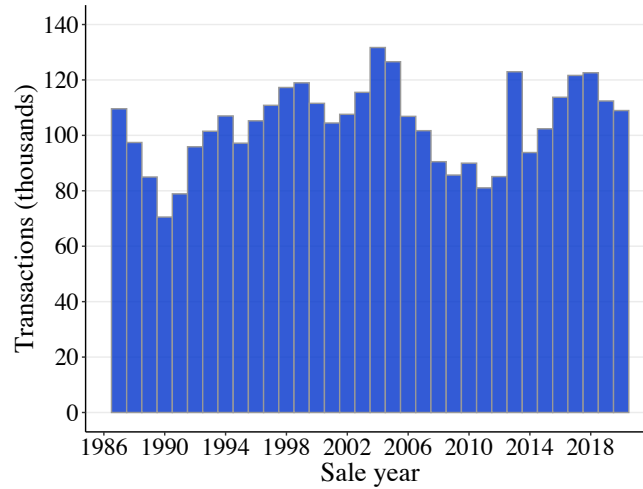
Figure E.5: DID estimates for move-out and turnout rates using quasi-exogenous timing for large 40Bs



Note: The figures show estimated coefficients $\theta_{1,r}$, $\theta_{2,r}$ and $\theta_{3,r}$ in the version of Equation (5) that is analogous to Equation (2) using 0.1 mile-wide rings, following Gardner (2022). The outcome variables are indicators of whether the individual moved out from the address neighboring a 40B (panels a and b) and whether they voted in a general election (panels c and d). We restrict the analysis to 40B developments approved in 1995-2012 in panels (a) and (b) and in 2000-2012 in panels (c) and (d). Panels (a) and (c) run the analyses for the sample of all local residents, while panels (b) and (d) use the sample of incumbent residents. All panels only include 40Bs with a total of 50 units or more.

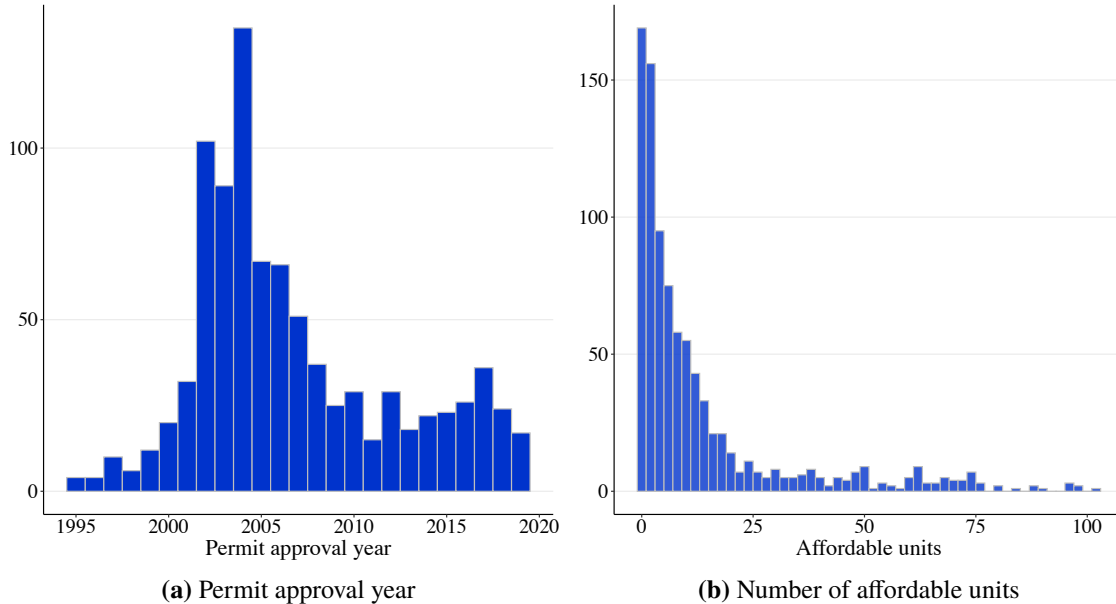
F Figures

Figure F.1: Histogram of Zillow ZTRAX transactions per year



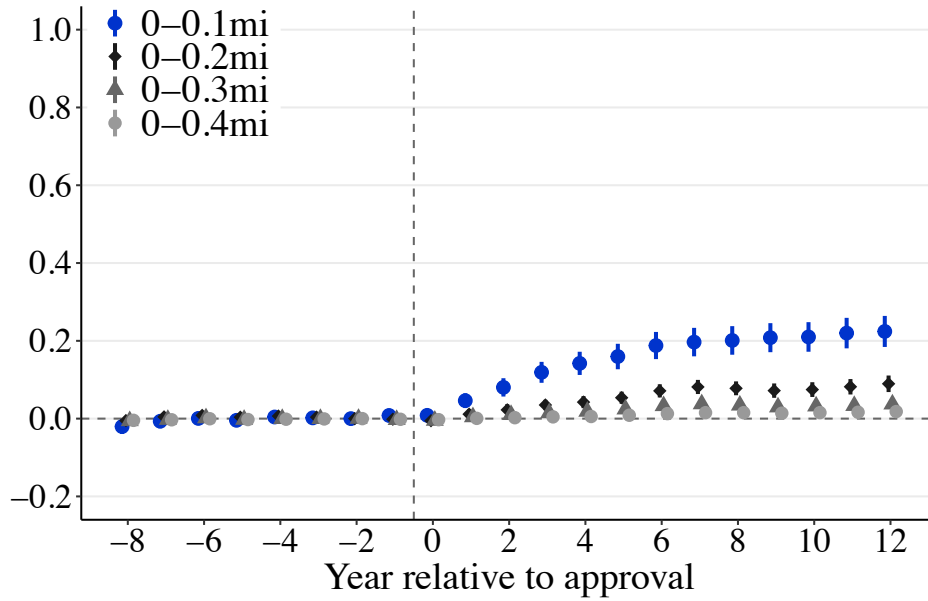
Note: The plot shows a histogram of the number of residential sales taking place each year between 1987 and 2020. Data was obtained from Zillow Ztrax.

Figure F.2: Histogram of permit approval year and number of affordable units

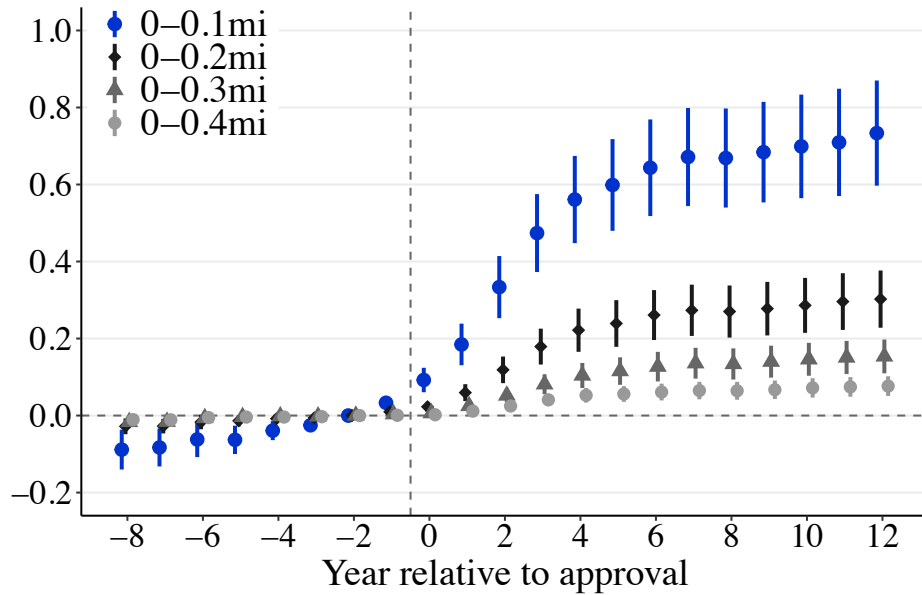


Note: Panel (a) plots the number of 40B developments by the year of permit approval. We define permit approval as the minimum of the following: Comprehensive 40B Permit year, building permit year, occupancy permit year, and year when 40B was added to the Subsidized Housing Inventory. Panel (b) plots a histogram of affordable units (25% of total units). In both panels, we use the sample of 40Bs approved between 1995 and 2019.

Figure F.3: Evolution of population density around 40B developments and characteristics of origin neighborhoods for residents of 40B units



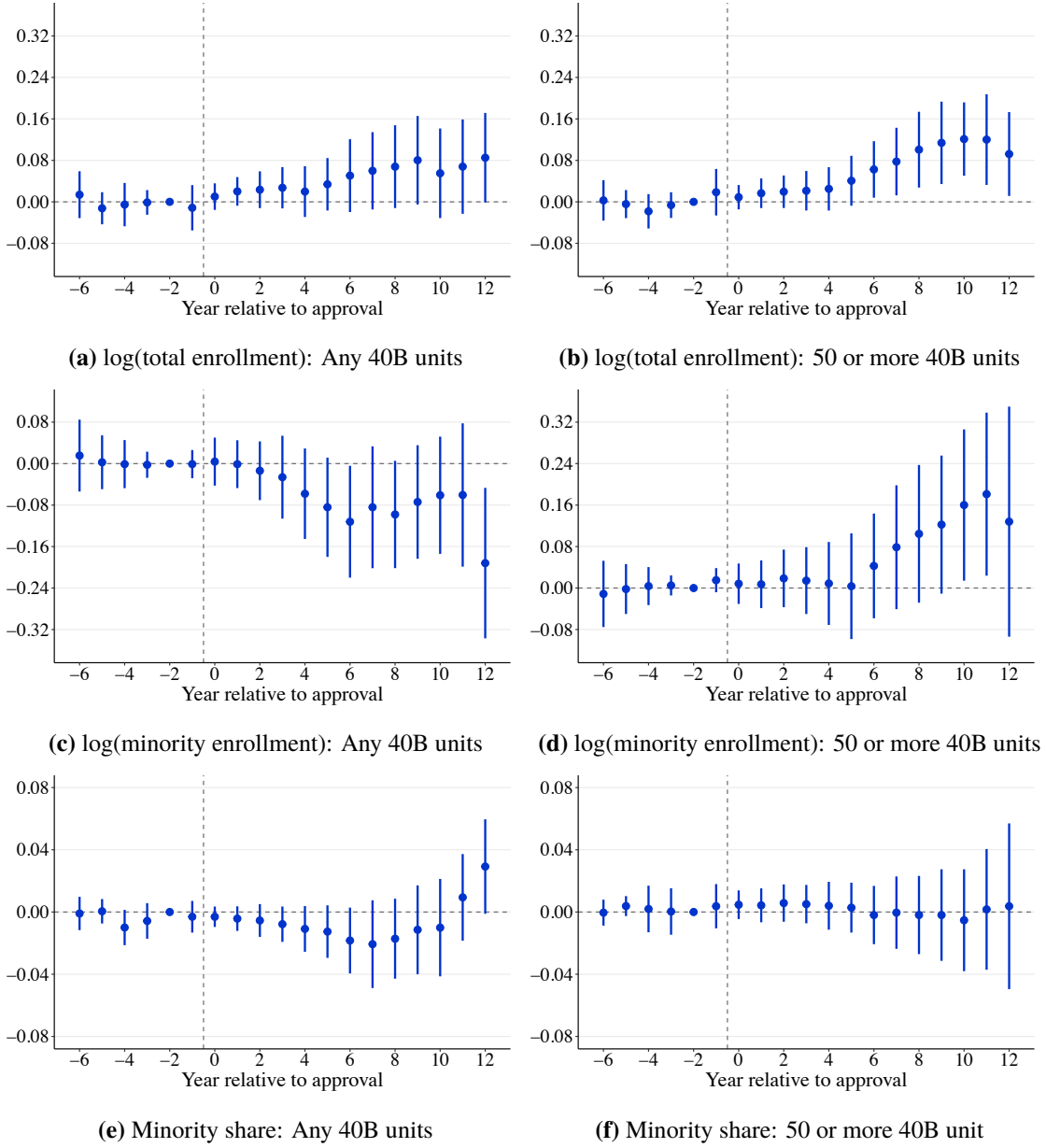
(a) 40Bs with less than 50 units



(b) 40Bs with 50 or more units

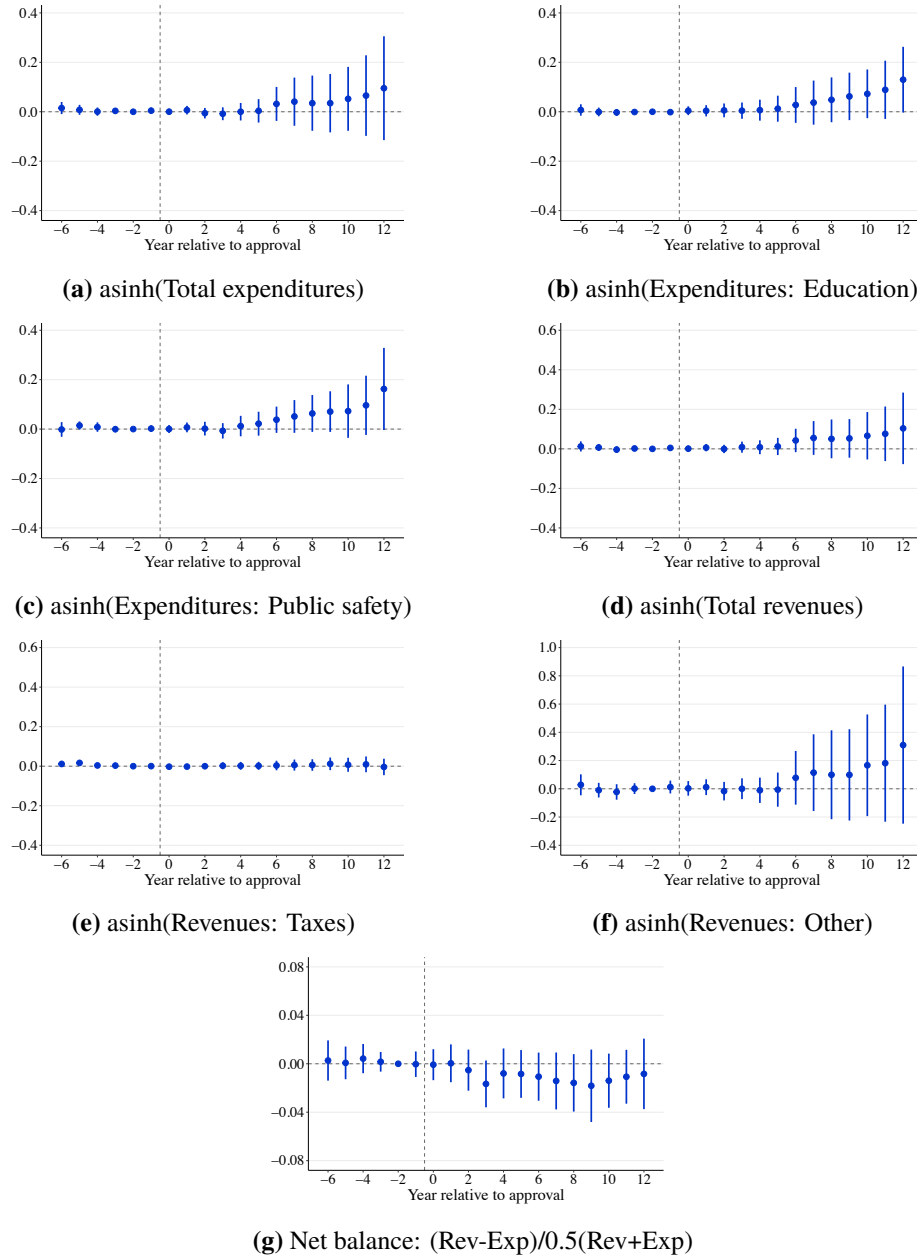
Note: Both panels plot the average number of individuals per square mile that Infutor reports as living within each of four cumulative rings around 40B developments. This population count includes 40B residents. The horizontal axis denotes years relative to the approval of the corresponding 40B development. Both panels use the sample of 40B developments that were approved between 1995 and 2019. Panel (a) restricts the sample to 40B developments with less than 50 units, panel (b) restricts the sample to 40B developments with 50 or more units.

Figure F.4: Event study of the impact of Chapter 40B on school district enrollment



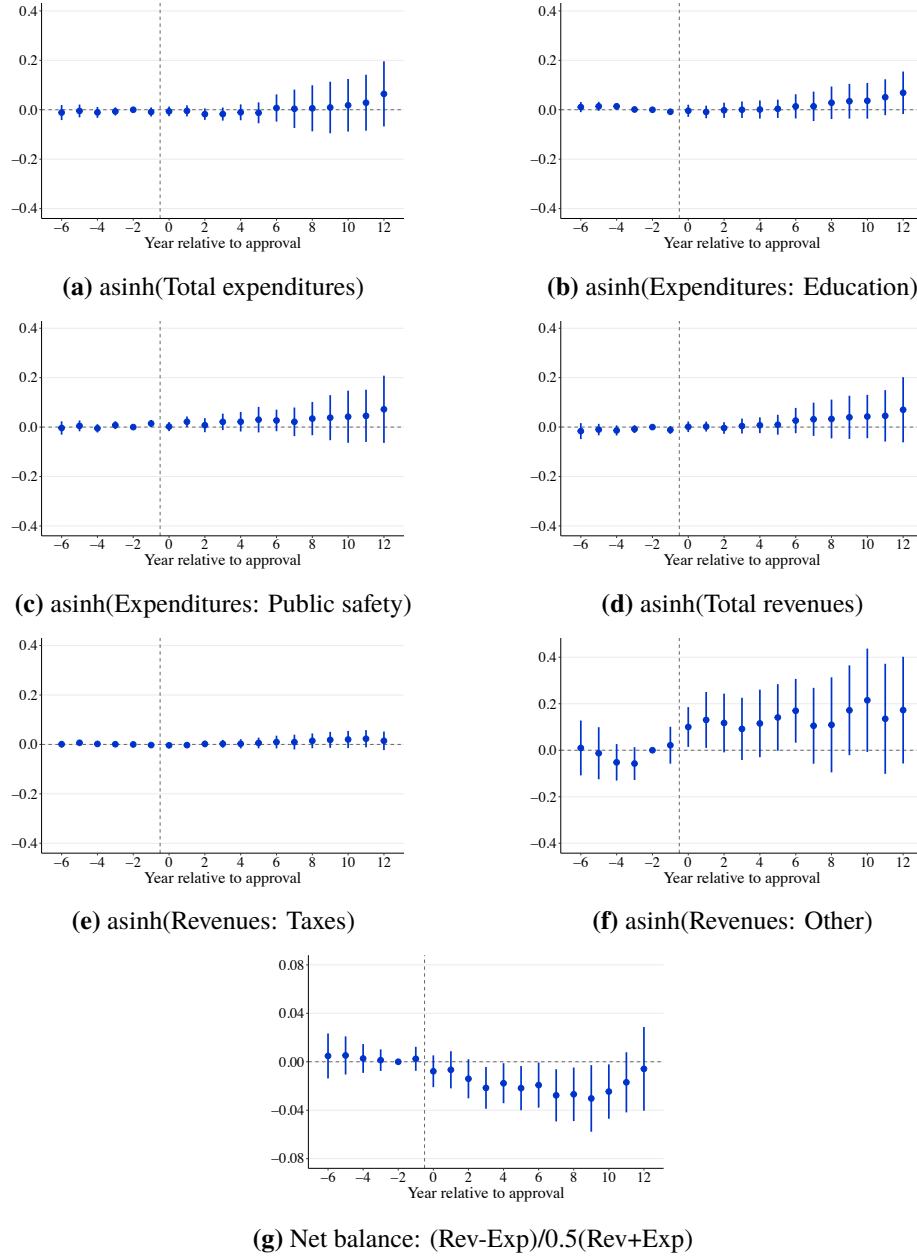
Note: The figures plot estimated coefficients of a staggered difference-in-differences regression following Callaway and Sant'Anna (2021) at the school district level using the logarithm of the total number of enrolled students (panels a, b), the logarithm of the number of minority enrolled students (panels c, d) and the share of minority students (panels e, f) as dependent variables. Minority students are defined as the total students minus non-Hispanic white students. The treatment period is defined as either the first year during which any 40B units were approved in the school district (left panels, including 169 districts) or during which 50 or more 40B units were approved (right panels, including 118 districts). We use publicly available data on school enrollment from 2002 to 2024 from the Massachusetts' Department of Elementary and Secondary Education (DESE). Vertical bars represent 95% confidence intervals. Standard errors are clustered at the school district level.

Figure F.5: Event study of the impact of Chapter 40B on local public finances (any 40B units)



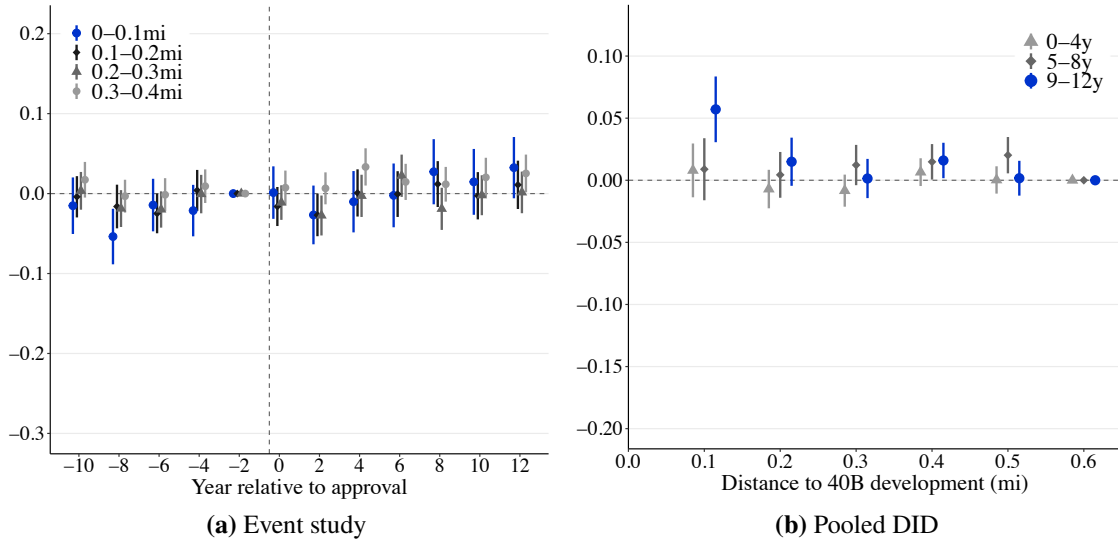
Note: The figures plot estimated coefficients of a staggered difference-in-differences regression following Callaway and Sant’Anna (2021) at the municipality level using the inverse hyperbolic sign—since a few municipality-years have zero values in the outcome—of several expenditure and revenue categories as dependent variables. The category “Revenue: Other” includes all other categories that are not taxes (e.g., federal/state transfers, permits and licensing, service charges). The net balance is computed as the difference between total revenues and expenditures divided by the average of the two. The treatment period is defined as the first year during which any 40B units were approved. We use publicly available data on local public finances from 2002 to 2024 from the Massachusetts’ Division of Local Services at the Department of Revenue. The number of treated municipalities throughout this period is 171. Vertical bars represent 95% confidence intervals. Standard errors are clustered at the municipality level.

Figure F.6: Event study of the impact of Chapter 40B on local public finances (≥ 50 40B units)



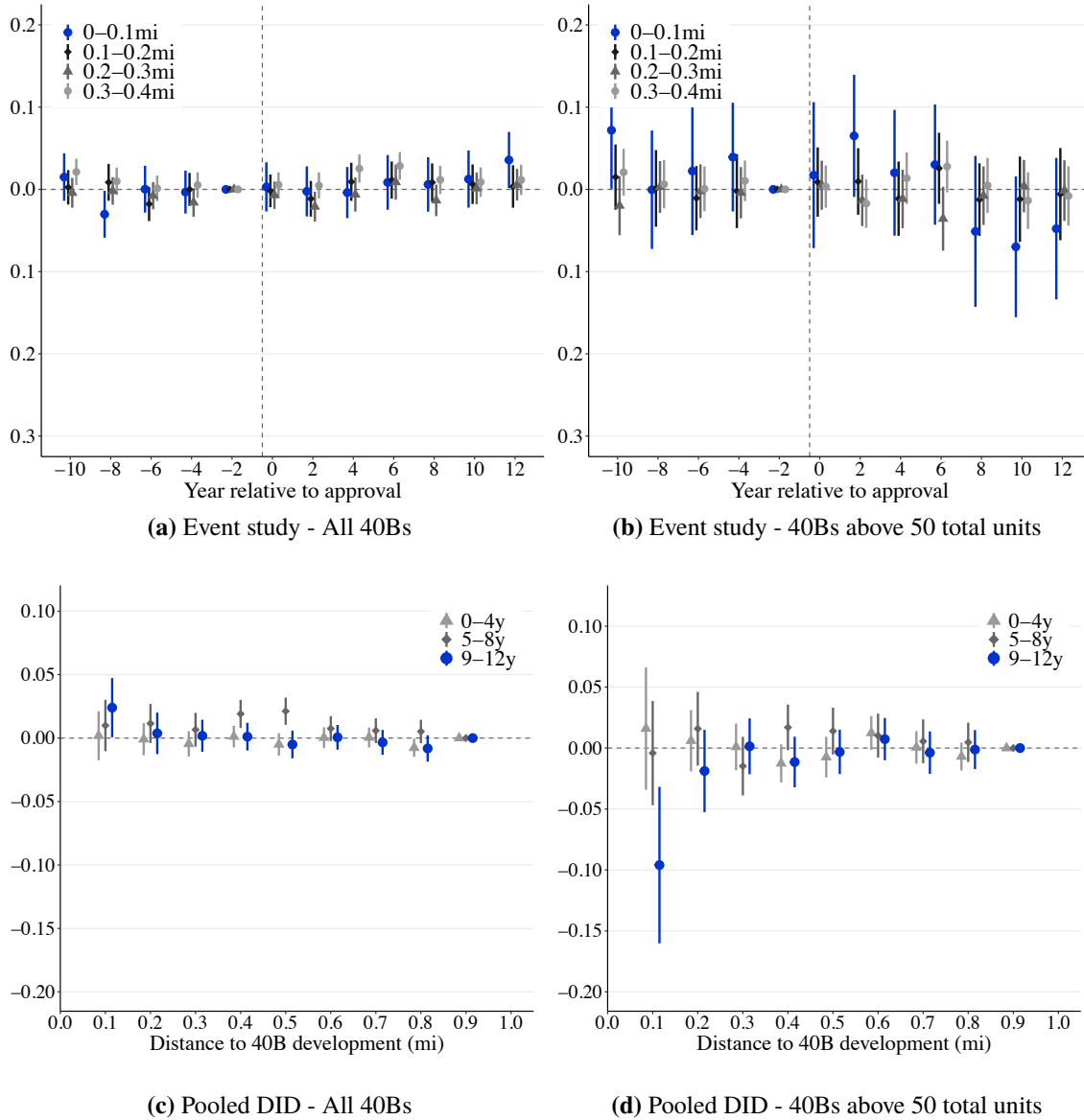
Note: The figures plot estimated coefficients of a staggered difference-in-differences regression following Callaway and Sant’Anna (2021) at the municipality level using the inverse hyperbolic sign—since a few municipality-years have zero values in the outcome—of several expenditure and revenue categories as dependent variables. The category “Revenue: Other” includes all other categories that are not taxes (e.g., federal/state transfers, permits and licensing, service charges). The net balance is computed as the difference between total revenues and expenditures divided by the average of the two. The treatment period is defined as the first year during which 50 or more 40B units were approved. We use publicly available data on local public finances from 2002 to 2024 from the Massachusetts’ Division of Local Services at the Department of Revenue. The number of treated municipalities throughout this period is 120. Vertical bars represent 95% confidence intervals. Standard errors are clustered at the municipality level.

Figure F.7: DID estimates of the impact of small 40Bs on sale prices of preexisting housing



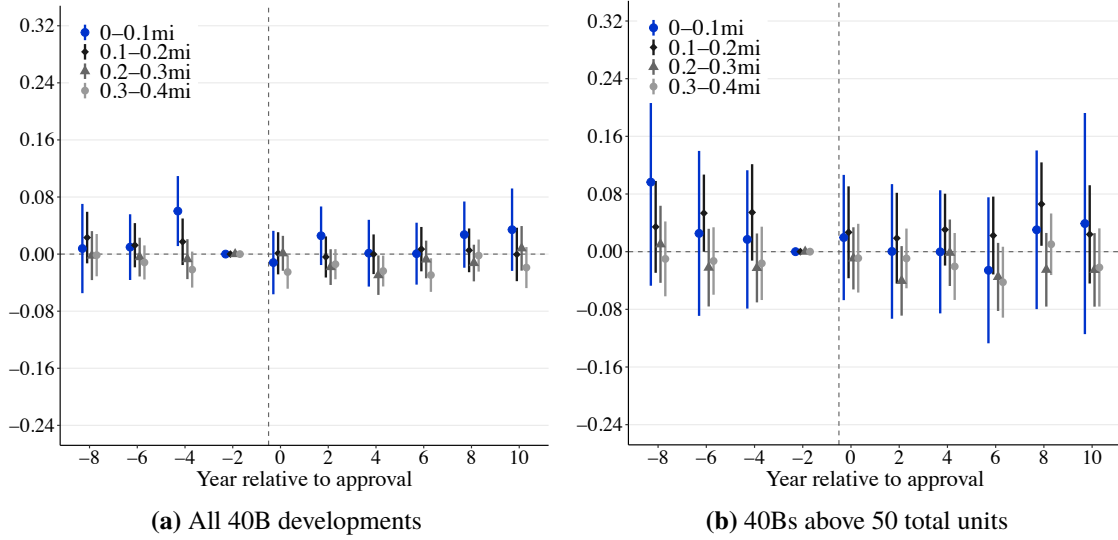
Note: This figure reproduces Figure 3 for the sample of 40B developments approved in 1995-2019 with less than 50 units.

Figure F.8: DID estimates of the impact of 40Bs on sale prices of preexisting housing within 1 mile



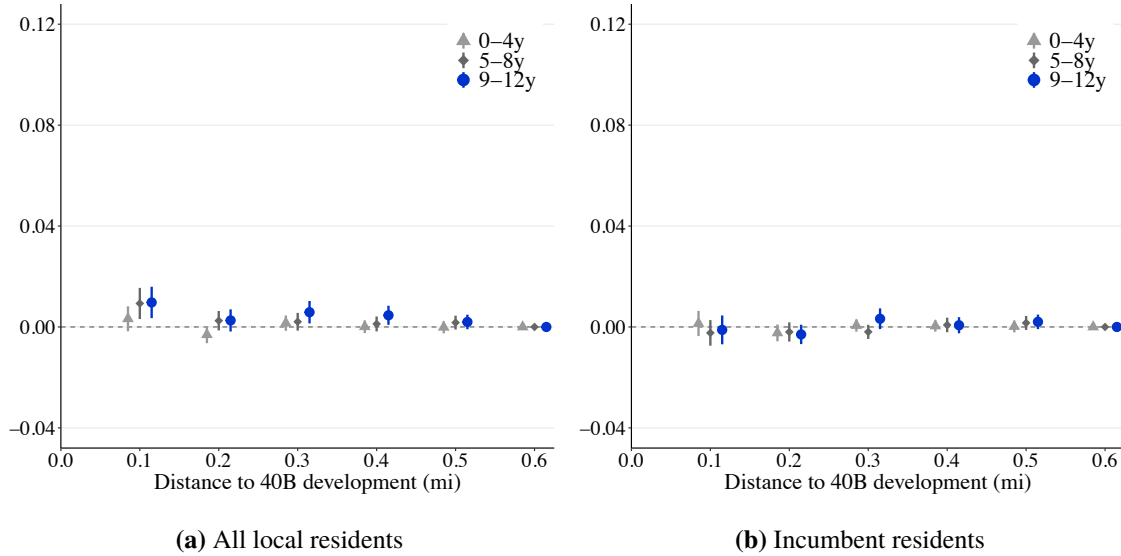
Note: This figure reproduces Figure 3 including all housing within 1 mile in the sample and using housing within 0.8 to 1 mile away as the comparison group.

Figure F.9: Placebo DID: impact of 40Bs on sale prices of preexisting housing



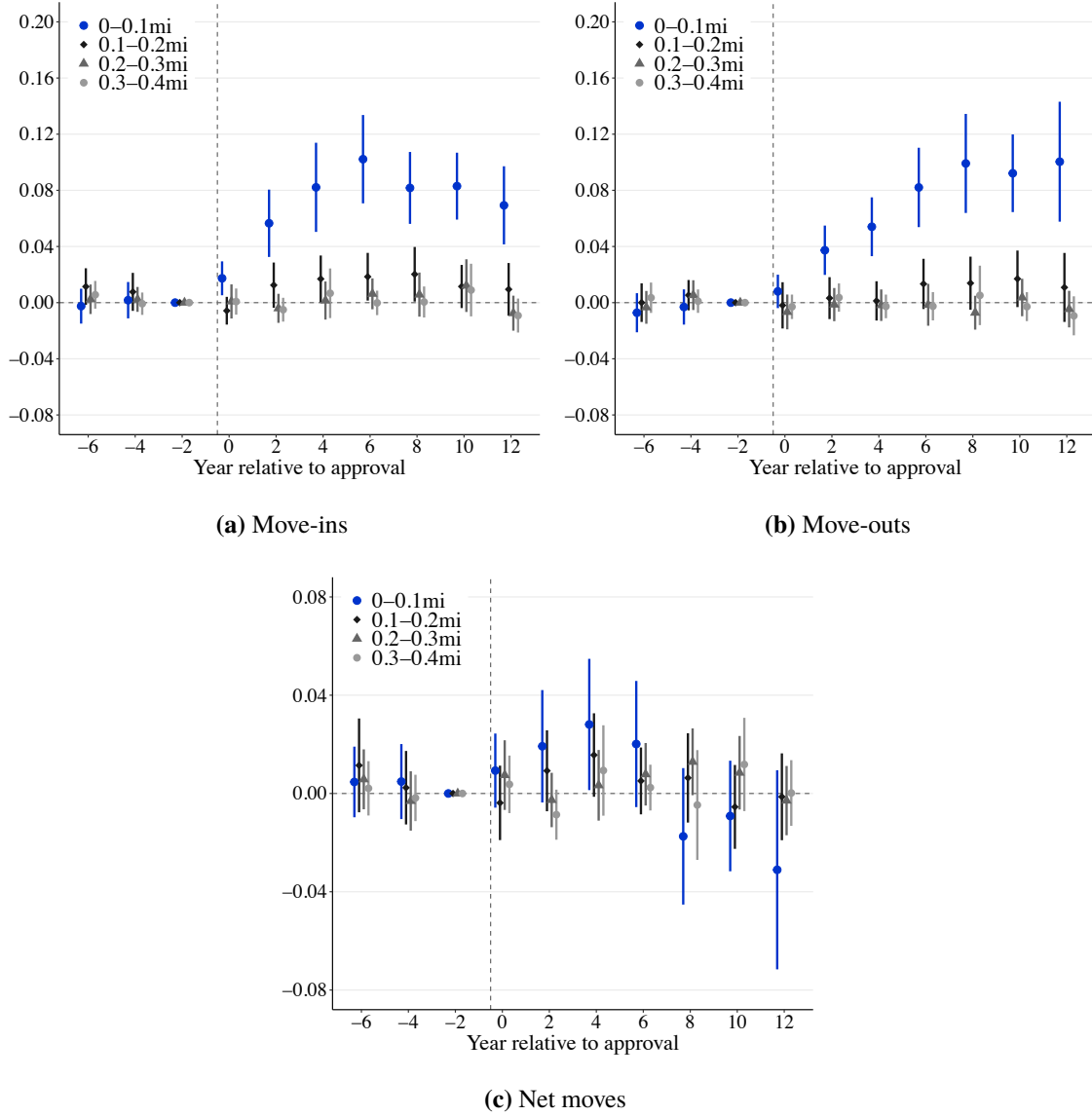
Note: The figures plot estimated coefficients $\beta_{\tau,r}$ in Equation (1) using 0.1 mile-wide rings and the logarithm of sale prices as the outcome. We define the 40B approval year as taking place nine years before announcement. We restrict the sample to all 40B developments (panel a) and 40B developments approved in 2002-2012 with 50 or more units (panel b); and sales of preexisting housing units.

Figure F.10: DID estimates of the impact of small 40Bs (less than 50 units) on residents' move-out rates



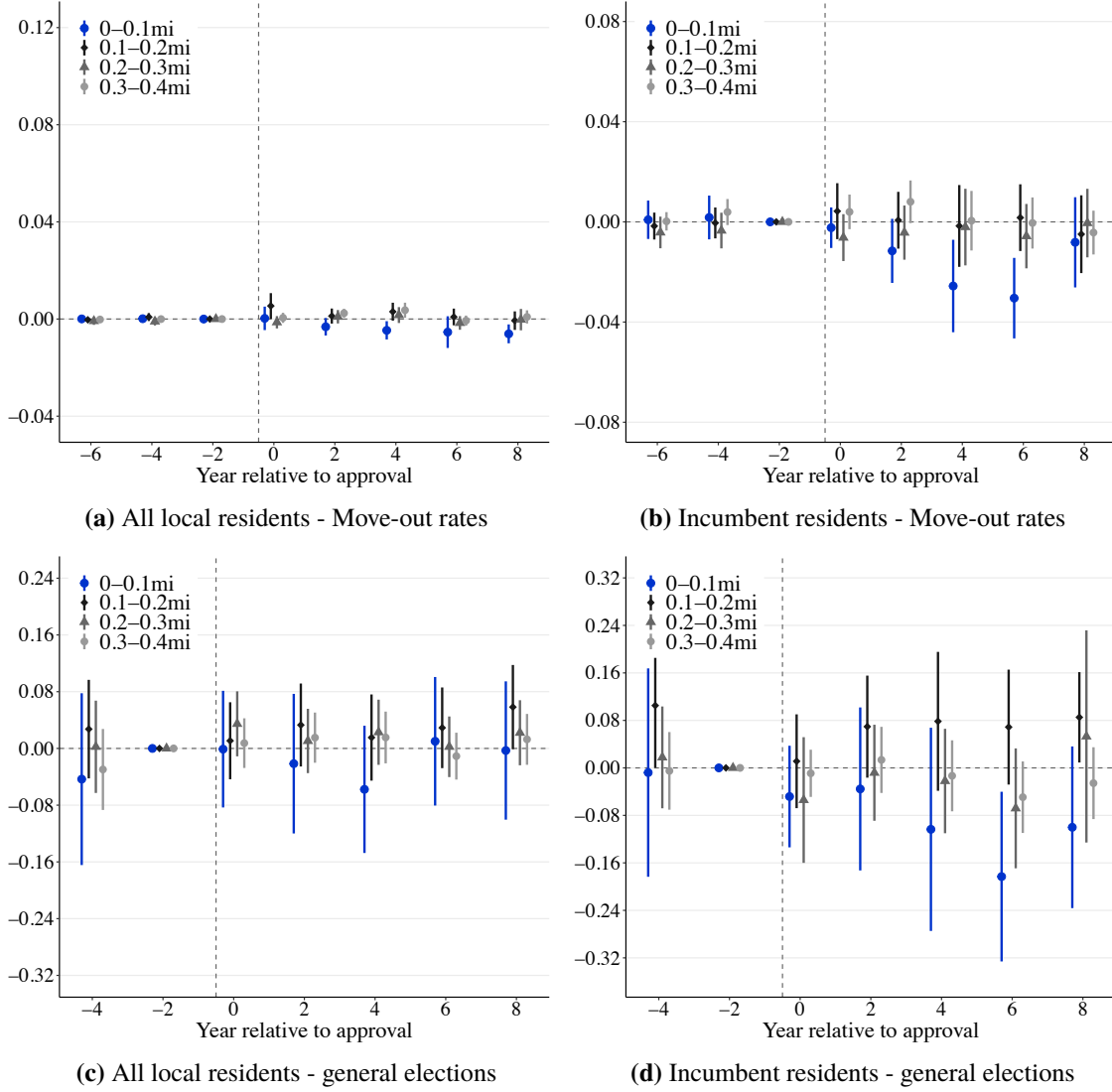
Note: The figure reproduces the pooled DID results in Figure 4 for 40B developments with less than 50 units.

Figure F.11: Event study for migration flows at incumbent residents' addresses for large 40Bs



Note: The figures show the estimated coefficients $\beta_{\tau,r}$ in Equation (1) using 0.1 mile-wide rings and incumbent residents' addresses within 0.5-0.6 miles from a 40B as a comparison group. All panels use the sample of individuals who ever lived at addresses where incumbent residents lived in year 7 before the corresponding 40B development is approved. The dependent variables are the number of residents moving into an incumbent address (panel a), moving out of an incumbent address (panel b), and the difference between these (panel c); all divided by the number of incumbent residents. The sample includes 40B developments with 50 or more units approved between 1995 and 2019. Vertical bars indicate 95% confidence intervals.

Figure F.12: Placebo DID: impact of 40Bs on move-out and turnout rates for large 40Bs



Note: The figures show estimated coefficients $\beta_{\tau,r}$ in Equation (1) using 0.1 mile-wide rings. The outcome variables are indicator variables for whether the individual moved out from the address neighboring a 40B as the outcome (panels a and b) and for whether an individual voted in a general election (panels c and d). We define the 40B approval year as taking place 9 years before announcement. We restrict the analysis to 40B developments approved in 2002-2012 with 50 or more units. Panels (a) and (c) uses the sample of ‘all local residents’, while panels (b) and (d) use the sample of ‘incumbent residents’ who were living near 40B developments in years 7 and 8 before permit approval—both of them are described in more detail in Section 3.1.

G Tables

Table G.1: Number of 40B developments by monitoring agency and municipality's Subsidized Housing Inventory (SHI)

	Above 10%	Below 10%
EOHLC	16	288
MassHousing	8	286
MassHousing and Other (non-EOHLC)	0	32
MassHousing Partnership	1	26
Other	45	197
Total	70	829

Note: This table shows counts of 40B developments approved between 1995 and 2019 based on a combination of their monitoring agency (rows) and whether the municipality where they are located is above or below the 10 percent affordable housing threshold. Data on municipalities' SHI percentages was obtained from EOHLC for years 1990, 1993, 1997, 2000, 2002-2014, 2017, 2020.

Table G.2: DID estimates of the quantity and quality of sold properties

Variable	Total numbers			All sales chars.				Old sales chars.			
	All (1)	New (2)	Old (3)	SFR (4)	Yr built (5)	Beds (6)	Baths (7)	SFR (8)	Yr built (9)	Beds (10)	Baths (11)
Yrs. 0-4: 0-0.1mi	42.3*** (3.37)	40.5*** (3.38)	-0.210 (0.732)	-0.134*** (0.012)	9.90*** (0.976)	-0.152*** (0.022)	0.038* (0.020)	-0.005 (0.006)	-0.492 (0.747)	-0.029 (0.023)	-0.024 (0.020)
Yrs. 0-4: 0.1-0.2mi	2.81*** (0.757)	1.23** (0.554)	0.660 (0.523)	-0.005 (0.006)	1.90*** (0.645)	0.024 (0.017)	0.047*** (0.015)	-0.002 (0.005)	-0.244 (0.565)	0.019 (0.017)	0.017 (0.015)
Yrs. 5-8: 0-0.1mi	22.5*** (2.69)	19.2*** (2.41)	-3.14*** (0.908)	-0.162*** (0.015)	11.4*** (1.10)	-0.145*** (0.029)	0.070*** (0.022)	0.012* (0.007)	-0.676 (0.836)	0.011 (0.031)	-0.006 (0.026)
Yrs. 5-8: 0.1-0.2mi	0.212 (0.978)	1.04 (0.758)	-1.93*** (0.632)	-0.0004 (0.008)	2.58*** (0.805)	0.018 (0.022)	0.057*** (0.021)	0.009 (0.006)	0.144 (0.731)	0.024 (0.021)	0.029 (0.020)
Yrs. 9-12: 0-0.1mi	24.6*** (2.96)	5.07** (2.17)	-2.24** (0.999)	-0.176*** (0.015)	10.9*** (1.12)	-0.169*** (0.028)	0.032 (0.023)	-0.005 (0.007)	-0.162 (0.823)	-0.010 (0.030)	-0.038 (0.025)
Yrs. 9-12: 0.1-0.2mi	1.41 (1.21)	0.121 (1.08)	-0.481 (0.568)	0.004 (0.008)	2.58*** (0.835)	0.037 (0.024)	0.027 (0.019)	0.009 (0.007)	-0.008 (0.725)	0.061** (0.025)	-0.002 (0.018)
Y mean (0-0.1mi)	34.3	8.43	26.4	0.772	1,957.4	2.96	1.98	0.785	1,950.2	2.93	1.89
Y mean (0.1-0.2mi)	30.0	6.00	24.2	0.810	1,957.1	3.03	2.02	0.830	1,950.5	3.00	1.93
Observations	166,108	166,108	166,108	142,677	141,637	140,385	141,610	133,174	133,174	131,407	132,721
R ²	0.649	0.287	0.850	0.777	0.682	0.542	0.609	0.828	0.709	0.545	0.602

Note: The table reports estimates for coefficients $\theta_{1,r}$, $\theta_{2,r}$ and $\theta_{3,r}$ in Equation (2) using 0.1 mile-wide rings for several outcomes. Columns 1-3 use the number of all sales, new house sales and old house sales per mi², respectively. Columns 4-7 use the following dependent variables for the sample of all sales: single-family residence indicator, year built, number of beds, and number of bathrooms. Columns 8-11 report these estimates restricting the sample to old houses. Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G.3: Long-differences regression of housing outcomes at the census tract level (1990-2019)

	Ln(units) (1)	Ownership (2)	Ln(home value) (3)	Ln(rent) (4)	Ln(units) (5)	Ownership (6)	Ln(home value) (7)	Ln(rent) (8)
40B	0.088*** (0.025)	-0.021** (0.009)	0.0008 (0.011)	0.045** (0.022)	0.064** (0.031)	-0.015 (0.011)	-0.012 (0.016)	0.0001 (0.029)
40B × 50 units or more					0.034 (0.030)	-0.009 (0.011)	0.017 (0.015)	0.063** (0.030)
Y mean (40B tracts, 1990)	1,864	0.730	188,655	578	1,864	0.730	188,655	578
Observations	1,376	1,376	1,376	1,376	1,376	1,376	1,376	1,376
R ²	0.317	0.263	0.642	0.493	0.318	0.263	0.642	0.495

Note: The table reports estimates of regressions at the census tract level where the dependent variable is the difference in the outcome between 2019 and 1990, as measured by 2015-2019 5-year ACS and 1990 decennial Census data. As an independent variable, Columns 1-4 use an indicator for whether there is any 40B approval within that period. Columns 5-8 also include an interaction of this indicator with another indicator for whether 50 or more 40B units were built. All regressions include municipality fixed effects. The third to last row shows the mean of the dependent variable in 1990 for census tracts that approve at least one 40B unit. Standard errors in parenthesis (clustered at the census tract level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G.4: Robustness of price effects in years 9-12

Sample	Full sample				50 units or more			
	Full	Bal	Comp year	Dups	Full	Bal	Comp year	Dups
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
0-0.1mi	0.027** (0.013)	0.029** (0.013)	0.022 (0.014)	-0.032 (0.019)	-0.092*** (0.033)	-0.075** (0.032)	-0.074** (0.031)	-0.100** (0.041)
0.1-0.2mi	0.002 (0.009)	0.004 (0.009)	-0.016* (0.009)	0.0003 (0.011)	-0.035** (0.017)	-0.015 (0.018)	-0.043** (0.018)	-0.012 (0.020)
0.2-0.3mi	-0.001 (0.007)	0.007 (0.007)	-0.013* (0.007)	-0.016 (0.011)	-0.008 (0.014)	0.002 (0.014)	-0.019 (0.014)	-0.030* (0.018)
0.3-0.4mi	0.005 (0.006)	0.011* (0.006)	-0.003 (0.007)	-0.018* (0.009)	-0.022* (0.012)	-0.007 (0.012)	-0.020 (0.012)	-0.032** (0.016)
0.4-0.5mi	-0.002 (0.006)	0.005 (0.006)	-0.008 (0.006)	-0.005 (0.008)	-0.010 (0.011)	0.003 (0.012)	-0.010 (0.012)	-0.004 (0.014)
Observations	471,815	296,629	449,224	242,358	145,693	94,165	136,132	92,533
R ²	0.881	0.873	0.881	0.894	0.868	0.856	0.866	0.888

Note: The table reports estimates for coefficient $\theta_{3,r}$ in Equation (2) using 0.1 mile-wide rings and the logarithm of house prices as an outcome. The first five columns includes all 40Bs regardless of size, the last five columns only include 40Bs with 50 or more units. Within each group, each column represents a different sample or design choice. In order: sample of 40Bs approved between 1995-2019 (full sample), sample of 40Bs approved between 1995-2007 (balanced sample), full sample using only Comprehensive 40B Permit as the treatment event (comprehensive year), and full sample dropping sales within 1 mile of more than one 40B (duplicates). Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G.5: Characteristics of destination census tracts of incumbent movers

	Out of state (1)	log(density) (2)	White (3)	HH income (4)	Ownership (5)	log(value) (6)	SFR zoning (7)
Yrs. 0-4: 0-0.1mi	-0.030 (0.024)	0.008 (0.082)	0.0005 (0.006)	0.006 (0.018)	0.009 (0.010)	0.003 (0.023)	0.007 (0.017)
Yrs. 0-4: 0.1-0.2mi	0.006 (0.019)	0.032 (0.057)	-0.007* (0.003)	-0.007 (0.011)	0.0004 (0.007)	-0.004 (0.016)	-0.003 (0.013)
Yrs. 5-8: 0-0.1mi	-0.009 (0.031)	-0.015 (0.101)	0.001 (0.008)	-0.011 (0.021)	0.009 (0.013)	-0.030 (0.027)	-0.001 (0.022)
Yrs. 5-8: 0.1-0.2mi	0.035 (0.023)	0.058 (0.072)	-0.007 (0.004)	-0.038** (0.016)	-0.009 (0.008)	-0.025 (0.017)	-0.024 (0.015)
Yrs. 9-12: 0-0.1mi	-0.015 (0.041)	-0.291** (0.127)	-0.004 (0.011)	0.038 (0.033)	0.025 (0.019)	0.013 (0.040)	0.045 (0.030)
Yrs. 9-12: 0.1-0.2mi	0.040 (0.032)	-0.123 (0.091)	-0.003 (0.005)	-0.005 (0.022)	0.003 (0.011)	-0.016 (0.029)	0.024 (0.023)
Y mean (0-0.1mi)	0.251	7,541.3	0.907	42,954.0	0.608	197,559.6	0.634
Y mean (0.1-0.2mi)	0.226	6,138.0	0.920	43,740.0	0.637	193,449.0	0.663
Observations	156,927	154,763	154,763	154,760	154,761	154,663	120,914
R ²	0.183	0.271	0.172	0.281	0.210	0.273	0.269

Note: The table reports estimates for coefficients $\theta_{1,r}$, $\theta_{2,r}$ and $\theta_{3,r}$ in Equation (2) using 0.1 mile-wide rings on the sample of incumbent residents moving out from housing within 0.6 miles of 40Bs. We use several characteristics of their destination tracts as an outcome. In order: out-of-state dummy (from Infutor), logarithm of density (population per square mile), share of white population, logarithm of household income, share of owner-occupied housing units, logarithm of median home value, and share of the tract zoned as single-family (from MassGIS). Data on columns 2-6 comes from the 1990 decennial census. Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G.6: Heterogeneity results: long-run price effects on sale prices, move-out and voter turnout rates of incumbent residents for large 40B developments

Heterogeneity var.	Tenure		Agency		Development size		40B Zoning		Household income		Age		Owner		Party	
	Ownership (1)	Rental (2)	Masshous. (3)	Others (4)	<median (5)	>median (6)	Other (7)	SFR (8)	<median (9)	>median (10)	<50 (11)	>=50 (12)	No (13)	Yes (14)	Other (15)	Rep (16)
<i>Panel A: Move-out rates - all local residents</i>																
0-0.1mi	0.047*** (0.008)	0.102*** (0.012)	0.093*** (0.012)	0.064*** (0.009)	0.044*** (0.008)	0.118*** (0.013)	0.093*** (0.010)	0.062*** (0.012)	0.067*** (0.009)	0.090*** (0.012)	0.073*** (0.008)	0.061*** (0.010)	0.066*** (0.007)	0.041*** (0.010)	0.030*** (0.009)	0.025** (0.012)
0.1-0.2mi	0.004 (0.005)	0.047*** (0.009)	0.036*** (0.009)	0.023*** (0.007)	0.009 (0.006)	0.053*** (0.010)	0.046*** (0.010)	0.011* (0.006)	0.034*** (0.009)	0.024*** (0.007)	0.024*** (0.007)	0.024*** (0.007)	0.021*** (0.006)	0.001 (0.006)	0.017** (0.007)	0.012 (0.008)
<i>Panel B: Move-out rates - incumbent residents</i>																
0-0.1mi	0.026*** (0.007)	0.051*** (0.010)	0.044*** (0.010)	0.035*** (0.008)	0.020*** (0.006)	0.064*** (0.012)	0.044*** (0.010)	0.036*** (0.009)	0.029*** (0.007)	0.052*** (0.011)	0.063*** (0.010)	0.033*** (0.006)	0.046*** (0.008)	0.009 (0.007)	0.040*** (0.010)	0.040*** (0.010)
0.1-0.2mi	0.008 (0.007)	0.022*** (0.006)	0.017*** (0.006)	0.015** (0.007)	-0.002 (0.005)	0.038*** (0.008)	0.030*** (0.007)	0.002 (0.005)	0.013** (0.006)	0.020*** (0.007)	0.022*** (0.006)	0.018*** (0.006)	0.015*** (0.005)	0.006 (0.004)	0.016** (0.007)	0.024*** (0.008)
<i>Panel C: Voter turnout in general elections - all local residents</i>																
0-0.1mi	-0.001 (0.029)	-0.057** (0.026)	-0.045 (0.029)	-0.013 (0.022)	-0.027 (0.023)	-0.039 (0.030)	-0.048* (0.027)	-0.009 (0.025)	-0.038 (0.029)	-0.020 (0.023)	-0.037 (0.026)	-0.010 (0.021)	-0.003 (0.021)	-0.006 (0.021)	-0.003 (0.023)	-0.073*** (0.026)
0.1-0.2mi	-0.022 (0.019)	-0.005 (0.019)	-0.015 (0.024)	-0.009 (0.014)	0.014 (0.017)	-0.033 (0.023)	-0.007 (0.022)	-0.011 (0.016)	0.007 (0.019)	-0.026 (0.021)	-0.040** (0.017)	0.026 (0.017)	0.012 (0.015)	-0.017 (0.015)	-0.023 (0.015)	-0.009 (0.019)
<i>Panel D: Voter turnout in general elections - incumbent residents</i>																
0-0.1mi	0.020 (0.034)	-0.030 (0.029)	-0.033 (0.034)	0.006 (0.027)	-0.007 (0.024)	-0.023 (0.037)	0.005 (0.031)	-0.030 (0.029)	-0.013 (0.030)	-0.009 (0.029)	0.024 (0.027)	-0.017 (0.025)	0.004 (0.025)	-0.015 (0.028)	0.0002 (0.026)	-0.040 (0.028)
0.1-0.2mi	0.028 (0.022)	-0.005 (0.019)	0.012 (0.027)	0.007 (0.014)	0.029* (0.016)	-0.016 (0.027)	0.006 (0.026)	0.014 (0.014)	0.009 (0.017)	0.010 (0.024)	-0.013 (0.019)	0.017 (0.018)	0.025 (0.017)	0.006 (0.019)	-0.008 (0.020)	-0.0002 (0.020)

Note: The table reports estimates for coefficient $\theta_{3,r}$ in Equation (2)—i.e., 9-12 years after 40B approval—using 0.1 mile-wide rings for several outcome variables in each panel. Each column uses a different sample depending on: tenure (ownership or rental 40Bs, columns 1-2), monitoring agency (Masshousing or other, columns 3-4), 40B development size (above or below median in the sample, 5-6), whether the 40B development is in an area zoned as single-family residence (7-8), median household income in the 40B's census tract in 1990 (above or below the median in the sample, 9-10), the individual's age (below or above 50, columns 11-12), whether the individual owns the unit near the associated 40B (13-14), and their political affiliation (15-16). Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G.7: Robustness of move-out rate estimates for all local residents in years 9-12

Sample	Full sample					50 units or more				
	Full (1)	Bal (2)	Comp year (3)	Dups (4)	Near (5)	Full (6)	Bal (7)	Comp year (8)	Dups (9)	Near (10)
0-0.1mi	0.029*** (0.003)	0.026*** (0.004)	0.034*** (0.004)	0.050*** (0.007)	0.029*** (0.003)	0.078*** (0.008)	0.075*** (0.008)	0.083*** (0.008)	0.078*** (0.013)	0.076*** (0.008)
0.1-0.2mi	0.010*** (0.002)	0.009*** (0.003)	0.013*** (0.003)	0.015** (0.006)	0.009*** (0.002)	0.029*** (0.006)	0.028*** (0.006)	0.032*** (0.006)	0.020* (0.012)	0.028*** (0.006)
0.2-0.3mi	0.008*** (0.002)	0.008*** (0.002)	0.010*** (0.002)	0.002 (0.005)	0.008*** (0.002)	0.014*** (0.004)	0.014*** (0.005)	0.015*** (0.005)	0.004 (0.009)	0.013*** (0.004)
0.3-0.4mi	0.008*** (0.002)	0.008*** (0.002)	0.008*** (0.002)	0.003 (0.005)	0.007*** (0.002)	0.014*** (0.005)	0.017*** (0.005)	0.017*** (0.006)	0.003 (0.010)	0.014*** (0.005)
0.4-0.5mi	0.003* (0.001)	0.003* (0.001)	0.003** (0.001)	0.002 (0.004)	0.003* (0.001)	0.004 (0.003)	0.003 (0.003)	0.006** (0.003)	-0.001 (0.009)	0.003 (0.003)
Observations	22,364,128	17,304,841	19,497,043	8,639,114	20,363,736	6,659,850	5,178,831	5,578,066	3,458,155	6,123,451
R ²	0.193	0.070	0.203	0.310	0.196	0.205	0.080	0.212	0.300	0.207

Note: The table reports estimates for coefficient $\theta_{3,r}$ in Equation (2) using 0.1 mile-wide rings and an indicator variable for whether the local resident moved out from an address within 0.6mi within a 40B development. The first five columns includes all 40Bs regardless of size, the last five columns only include 40Bs with 50 or more units. Within each group, each column represents a different sample or design choice. In order: sample of 40Bs approved between 1995-2019 (full sample), sample of 40Bs approved between 1995-2007 (balanced sample), full sample using only Comprehensive 40B Permit as the treatment event (comprehensive year), full sample dropping local residents who lived within 0.6 miles of more than one 40B (duplicates), and full sample only keeping the nearest address for those individuals who show up as local residents of multiple 40B addresses (near). Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G.8: Robustness of move-out rate estimates for incumbent residents in years 9-12

Sample	Full sample					50 units or more				
	Full (1)	Bal (2)	Comp year (3)	Dups (4)	Near (5)	Full (6)	Bal (7)	Comp year (8)	Dups (9)	Near (10)
0-0.1mi	0.011*** (0.003)	0.007** (0.003)	0.016*** (0.003)	0.022*** (0.004)	0.009*** (0.003)	0.040*** (0.007)	0.035*** (0.007)	0.047*** (0.007)	0.042*** (0.008)	0.038*** (0.007)
0.1-0.2mi	0.003 (0.002)	0.002 (0.002)	0.005** (0.002)	0.005 (0.003)	0.002 (0.002)	0.016*** (0.005)	0.018*** (0.005)	0.018*** (0.005)	0.014** (0.007)	0.014*** (0.005)
0.2-0.3mi	0.003 (0.002)	0.002 (0.002)	0.004* (0.002)	-0.0006 (0.003)	0.003 (0.002)	0.001 (0.004)	0.0004 (0.004)	0.003 (0.004)	-0.005 (0.005)	0.0004 (0.004)
0.3-0.4mi	0.0002 (0.001)	0.0005 (0.002)	0.002 (0.001)	-0.002 (0.002)	0.0004 (0.001)	-0.0009 (0.003)	0.000 (0.003)	0.001 (0.003)	-0.003 (0.003)	-0.002 (0.003)
0.4-0.5mi	0.001 (0.001)	0.0010 (0.001)	0.002* (0.001)	0.001 (0.002)	0.002 (0.001)	-0.0005 (0.002)	0.000 (0.003)	-0.0008 (0.002)	-0.002 (0.003)	-0.001 (0.002)
Observations	9,690,853	6,473,469	8,690,418	4,994,521	8,960,685	2,923,192	2,009,452	2,504,947	1,849,663	2,706,842
R ²	0.036	0.038	0.035	0.092	0.036	0.042	0.046	0.041	0.084	0.042

Note: The table reports estimates for coefficient $\theta_{3,r}$ in Equation (2) using 0.1 mile-wide rings and an indicator variable for whether the incumbent resident moved out from an address within 0.6mi within a 40B development. The first five columns includes all 40Bs regardless of size, the last five columns only include 40Bs with 50 or more units. Within each group, each column represents a different sample or design choice. In order: sample of 40Bs approved between 1995-2019 (full sample), sample of 40Bs approved between 1995-2007 (balanced sample), full sample using only Comprehensive 40B Permit as the treatment event (comprehensive year), full sample dropping incumbent residents who lived within 0.6 miles of more than one 40B (duplicates), and full sample only keeping the nearest address for those individuals who show up as incumbents of multiple 40B addresses (near). Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G.9: Robustness of general election turnout estimates for all local residents in years 9-12

Sample	Full sample					50 units or more				
	Full (1)	Bal (2)	Comp year (3)	Dups (4)	Near (5)	Full (6)	Bal (7)	Comp year (8)	Dups (9)	Near (10)
0-0.1mi	-0.0005 (0.008)	0.009 (0.009)	-0.009 (0.009)	-0.012 (0.012)	-0.0004 (0.009)	-0.029 (0.019)	-0.015 (0.020)	-0.035* (0.020)	-0.024 (0.024)	-0.031 (0.019)
0.1-0.2mi	0.009 (0.006)	0.019*** (0.006)	0.002 (0.006)	0.002 (0.010)	0.005 (0.006)	-0.009 (0.014)	-0.003 (0.015)	-0.011 (0.015)	-0.003 (0.016)	-0.013 (0.014)
0.2-0.3mi	-0.006 (0.006)	-0.002 (0.006)	-0.002 (0.006)	0.0002 (0.008)	-0.007 (0.006)	-0.011 (0.012)	-0.006 (0.013)	-0.010 (0.012)	-0.006 (0.014)	-0.013 (0.012)
0.3-0.4mi	0.000 (0.004)	0.0004 (0.005)	0.004 (0.004)	0.005 (0.007)	-0.001 (0.004)	0.0002 (0.009)	-0.004 (0.010)	-0.0006 (0.009)	0.002 (0.011)	-0.004 (0.009)
0.4-0.5mi	0.003 (0.004)	0.004 (0.004)	0.001 (0.004)	-0.007 (0.006)	0.002 (0.004)	-0.0002 (0.007)	0.006 (0.008)	-0.0002 (0.008)	-0.015 (0.012)	-0.002 (0.007)
Observations	3,350,176	2,279,497	3,047,650	1,705,325	2,999,788	974,710	687,759	846,425	631,379	878,374
R ²	0.496	0.488	0.498	0.504	0.495	0.479	0.467	0.480	0.486	0.480

Note: The table reports estimates for coefficient $\theta_{3,r}$ in Equation (2) using 0.1 mile-wide rings and an indicator variable for whether the local resident voted in a general election. The first five columns includes all 40Bs regardless of size, the last five columns only include 40Bs with 50 or more units. Within each group, each column represents a different sample or design choice. In order: sample of 40Bs approved between 1995-2019 (full sample), sample of 40Bs approved between 1995-2007 (balanced sample), full sample using only Comprehensive 40B Permit as the treatment event (comprehensive year), full sample dropping local residents who lived within 0.6 miles of more than one 40B (duplicates), and full sample only keeping the nearest address for those individuals who show up as local residents of multiple 40B addresses (near). Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table G.10: Robustness of general election turnout estimates for incumbent in years 9-12

Sample	Full sample					50 units or more				
	Full (1)	Bal (2)	Comp year (3)	Dups (4)	Near (5)	Full (6)	Bal (7)	Comp year (8)	Dups (9)	Near (10)
0-0.1mi	0.008 (0.010)	0.017 (0.010)	-0.004 (0.010)	0.006 (0.014)	0.007 (0.010)	-0.011 (0.021)	-0.001 (0.022)	-0.008 (0.022)	0.006 (0.025)	-0.020 (0.021)
0.1-0.2mi	0.004 (0.007)	0.009 (0.008)	-0.0003 (0.008)	0.004 (0.011)	0.002 (0.007)	0.009 (0.014)	0.018 (0.016)	0.005 (0.015)	0.026 (0.020)	0.005 (0.015)
0.2-0.3mi	-0.004 (0.006)	-0.004 (0.007)	0.003 (0.007)	0.007 (0.010)	-0.006 (0.007)	-0.010 (0.012)	-0.012 (0.013)	-0.011 (0.013)	0.011 (0.016)	-0.014 (0.013)
0.3-0.4mi	-0.004 (0.006)	-0.005 (0.007)	0.002 (0.006)	0.009 (0.009)	-0.006 (0.006)	0.004 (0.011)	0.003 (0.012)	0.007 (0.011)	0.023 (0.015)	-0.001 (0.011)
0.4-0.5mi	0.001 (0.005)	0.004 (0.006)	0.0005 (0.005)	-0.001 (0.008)	-0.001 (0.005)	0.010 (0.009)	0.021** (0.010)	0.013 (0.009)	0.005 (0.012)	0.006 (0.009)
Observations	2,084,395	1,321,169	1,899,663	1,156,401	1,910,805	605,179	404,279	526,779	409,186	555,254
R ²	0.496	0.488	0.498	0.505	0.496	0.488	0.480	0.486	0.495	0.490

Note: The table reports estimates for coefficient $\theta_{3,r}$ in Equation (2) using 0.1 mile-wide rings and an indicator variable for whether the incumbent resident voted in a general election. The first five columns includes all 40Bs regardless of size, the last five columns only include 40Bs with 50 or more units. Within each group, each column represents a different sample or design choice. In order: sample of 40Bs approved between 1995-2019 (full sample), sample of 40Bs approved between 1995-2007 (balanced sample), full sample using only Comprehensive 40B Permit as the treatment event (comprehensive year), full sample dropping incumbent residents who lived within 0.6 miles of more than one 40B (duplicates), and full sample only keeping the nearest address for those individuals who show up as incumbents of multiple 40B addresses (near). Standard errors in parenthesis (clustered at the 40B level). Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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