Working Papers

FEDERAL RESERVE BANK OF BOSTON

No. 26-7

The Effect of Land Supply for New Homes on Residential Investment and House Prices

Justin Katz and Paul S. Willen

Abstract:
We use parcel-level data to provide new facts on the amount and distribution of land available for residential development, focusing on New England housing markets from 2007 to 2021. Most buildable parcels are small, and large buildable parcels are scarce in most geographic markets. Large buildable parcels are less available in more populous markets, become scarcer as populations grow, and have become scarcer over time. Markets with fewer large parcels experience higher house price growth and residential development that is lower relative to house price growth. We present evidence consistent with developer returns to scale in parcel size, meaning that fragmentation of buildable land across small, disjoint parcels increases house prices by reducing construction productivity and making development less responsive to demand. In counterfactual simulations from a simple calibrated model, we show that recombining small buildable parcels into larger ones while holding the total amount of buildable land fixed would increase supply, increase construction productivity, and slow house price growth.

JEL Classifications: R31, R52, R14
Keywords: Housing supply, land fragmentation, construction productivity, land-use constraints

Justin Katz (jkatz@g.harvard.edu) is a PhD student in the business economics program at Harvard Business School. In July 2026, he will join the Boston College Carroll School of Management as an assistant professor of finance. Paul S. Willen (paul.willen@bos.frb.org) is a principal economist and policy advisor in the Federal Reserve Bank of Boston Research Department.

For valuable comments and discussions, the authors thank Joe Gyourko, Ed Glaeser, Tobias Peter, and participants at the CRIW/NBER preconference on Measurement of Housing and the Housing Sector. They thank Max Worth for excellent research assistance. Justin Katz gratefully acknowledges support from the Institute of Consumer Money Management Pre-doctoral Fellowship on Consumer Financial Management, awarded through the National Bureau of Economic Research, and from the John Meyer Dissertation Fellowship of the Harvard Joint Center for Housing Studies.

This version: May 2026 **https://doi.org/10.29412/res.wp.2026.07**

In recent years, the United States has experienced house price growth that has outpaced income growth, a low supply of new housing units, and flat to negative growth in construction productivity (Molloy *et al.* 2020, Goolsbee and Syverson 2023, Garcia and Molloy 2023). Policymakers concerned about housing affordability have devoted increasing attention to these trends. A large body of academic research argues that land-use regulations play a central role in explaining these patterns by constraining housing supply (for example, Gyourko and Molloy 2015, Glaeser and Gyourko 2018, D'Amico *et al.* 2024).

In this paper, we explore a hypothesis that *complements* the regulatory explanation: In many high-cost markets, large plots of buildable land are scarce, constraining the amount and efficiency of residential construction. This hypothesis is consistent with some patterns in "superstar" cities (Duranton and Puga 2023) and, if it is quantitatively important, implies that land fragmentation creates supply constraints that operate alongside—and interact with—regulatory barriers. Despite its importance for evaluating housing policy, little comprehensive research has studied this alternative explanation (Baum-Snow and Duranton 2025).[1] This is partly because there is limited detailed historical parcel-level data on land available for residential development.

We provide new facts on the buildable-land distribution and study its impact on housing supply. We address the data challenge using a parcel-level data set maintained by the Federal Reserve Bank of Boston to measure the buildable-land distribution in New England and track its development since 2007. We show that in areas with high house prices, the supply of buildable land is fragmented across many small, disjoint parcels. This could impose a technological limit on the scale of new construction projects,[2] which potentially reduces efficiency, raises the unit cost of development, and makes construction less responsive to economic fluctuations. While fragmented land supply could result from population density or past land-use restrictions, it represents a distinct physical constraint that regulatory reform would not directly address. Our results thus suggest that both regulatory reform and policies targeting land fragmentation may be needed to meaningfully expand housing supply in built-up markets.

Housing market analysts have long emphasized the importance of scale in residential construction. As Baily and Solow (2001) summarize in a McKinsey Global Institute report on construction productivity,

[1] "Rather than institutional factors, it may have been available land that became scarce and limited new constructions.... More systematic evidence on land scarcity, including the lack of large parcels to develop new subdivisions, is greatly needed" (Baum-Snow and Duranton 2025, p. 389).

[2] In Section 3.1, we argue that small parcels are hard to combine into larger ones because (1) buildable parcels are usually isolated from others, and (2) adjacent parcels are subject to meaningful "land assembly" frictions due to holdouts, asymmetric information, and positive externalities from recombination (Brooks and Lutz 2016). Separate from these issues, land-use restrictions also limit parcel size (see Baum-Snow and Duranton (2025) for a review).

> "Scale matters.... Where large plots of land are zoned for residential housing, developers ... exploit the benefits of scale by building large numbers of similar houses at the same time. Elsewhere ... plots ... accommodate only a few houses and the result is lower productivity."

Across housing markets, differences in the size of available parcels are stark, meaning that construction must occur at very different scales. Figure 1 illustrates an example that compares typical buildable plots within a 15-minute drive of the city centers in Charleston, South Carolina, and Boston, Massachusetts, based on July 2025 sales listings. On a 4,600-acre greenfield plot available for residential development in Charleston, a builder could simultaneously construct many single-family homes. On a 0.1-acre plot available for infill construction in Boston, a developer could build a single townhome.

We first build a parcel-level data set to track the development of buildable land in New England. Our primary data come from a panel of public tax assessor records collected by the Warren Group, a real estate data firm, and maintained by the Boston Fed. The Boston Fed has archived the Warren Group's New England data feed each month since 2007 and applied harmonized data cleaning over time, so the data have consistent historical coverage.

Because the Warren Group specializes in the New England market, it better standardizes records across different municipalities that often have inconsistent reporting standards. Compared with other sources that offer similar products, the Warren Group provides data that cover a greater share of total land area and have more detailed information on land use. The data have sufficient detail to identify vacant parcels available for residential development, and for each year, they track the buildable acreage developed into residential units within arbitrarily granular geographic markets. To illustrate these advantages, we compare overall coverage and the supply of buildable land in the Warren Group data with similar information from CoreLogic, a data source commonly used to analyze housing markets.[3] The Warren Group covers many buildable parcels that CoreLogic misses, especially in urban areas. For example, in the average Zip code, buildable land comprises 6.7 percent of total acreage in the Warren Group data compared with 2.6 percent in the CoreLogic data.

We use the Warren Group data to document five facts about buildable land in New England. First, most buildable parcels in New England are small and surrounded by developed land, making scale difficult to achieve. As a result, most of the region's housing markets have few large buildable parcels—both in absolute terms and relative to housing markets in the southern United States. Second, large buildable parcels have become scarcer over time. Third, large buildable parcels are less available in more populous markets, and they become scarcer

[3] The American Real Estate and Urban Economics Association's data set catalogue describes the CoreLogic data as "probably the most complete housing transaction and assessment source" (AREUEA Data Insights 2026).

as populations grow. Fourth, markets where large buildable parcels are scarcer experience more rapid price growth. Fifth, markets where large buildable parcels are scarcer have lower development relative to price growth.

These facts indicate that housing development is more efficient on larger plots, and the price elasticity of supply is higher where available land is concentrated on larger parcels. To more precisely characterize how the size distribution of buildable land impacts development, we present a simple empirical model of housing supply with returns to scale in parcel size. In the model, developers decide whether to develop parcels of variable size. They face fixed development costs to prepare parcels for construction so that larger parcels are developed at a lower price per housing unit. This implies increasing returns to scale in parcel size and connects the size distribution of available parcels to aggregate housing supply. The theory implies that, holding fixed the total land supply and house prices, housing supply is increasing in average parcel size.

We calibrate the model using parcel-level data and conduct counterfactuals under a range of assumptions about returns to scale in parcel size. While we lack clean exogenous variation to identify the causal effect of parcel size on builder productivity, we present suggestive evidence of meaningful returns to scale. Using the calibrated model, we quantify how house prices, housing supply, supply elasticities, and construction productivity vary with the distribution of buildable land. Across counterfactual simulations with different returns-to-scale assumptions, both the *amount* and *distribution* of buildable land matter: Recombining fragmented parcels into larger lots lowers house prices, increases supply, and raises productivity, even when total acreage is held fixed.

Our results complement findings of the literature on how the supply of buildable land impacts construction. Saiz (2010) argues that physical constraints imposed by local terrain limit the supply of buildable land in many US cities and can help explain differences in metro-level housing supply elasticities. In their study of neighborhood-level housing supply elasticities, Baum-Snow and Han (2024) similarly find that metro-level terrain correlates with supply elasticities.

While these papers focus on the overall amount of buildable land available across housing markets, we emphasize measuring the *distribution* of land. Our data allow us to observe buildable parcels directly, unlike Saiz (2010) and Baum-Snow and Han (2024), who rely on remote sensing data to identify buildable land. This allows us to take a stance on project *scale* imposed by the land-supply distribution and to show how a scarcity of large plots reduces the efficiency of new development by reducing project scale.[4] D'Amico *et al.* (2024) also empha-

[4]Baum-Snow and Duranton (2025) also study project size but use the size distribution of *developed* parcels to make inferences about the size of buildable parcels.

size returns to scale in development but focus on a different mechanism, arguing that project scale is limited by local control and zoning regulations rather than by the availability of large parcels.

Sections 1 through 5, respectively, describe our data and our approach to measuring buildable land and tracking development; our five empirical facts; the model of developer returns to scale in parcel size; model calibration and counterfactuals; and the policy implications of our analysis.

1 Measuring the Supply of Buildable Land

This section describes our data sources and approach to measuring the distribution of buildable land. We combine parcel-level data from multiple administrative sources maintained by the Federal Reserve System to develop a comprehensive view of available land and development activity. Our analysis focuses on New England, for which the Boston Fed maintains relatively more detailed data on residential development; however, for comparison, we supplement our New England data with information on other markets.

1.1 Data sources

1.1.1 Warren Group tax assessor data

Our primary data source is a parcel-level panel of public tax assessor records collected by the Warren Group, a real estate data firm. The data contain the universe of tax parcels in covered municipalities, with information on parcel longitude and latitude, assessed value, parcel size in acres, land-use codes, and the characteristics of improvements such as the number of beds and baths in residential structures.

The Boston Fed has received monthly data updates from the Warren Group since 2007 covering Massachusetts, Connecticut, and Rhode Island.[5] Using repeated observations of individual parcels over time, we can track parcel-level development. By aggregating to arbitrarily granular geographic units, we can also track development at the level of local housing markets over time.

The Warren Group data are similar to real estate data products from other companies such as CoreLogic. We use Warren Group data in our analysis because it offers two advantages over other sources. First, the Boston Fed has maintained repeated snapshots based on monthly

[5] The Warren Group has traditionally focused on real estate intelligence in the New England region. The Boston Fed has focused on coverage of New England states due to its mandate to monitor economic activity in the region.

Warren Group data feeds, ensuring data coverage is consistent over time. Second, because the Warren Group has historically focused on a small set of New England municipalities, land-use designations in the data are granular and reliable. This is particularly true for parcels that fall outside the single-family residential land-use category. Section 1.3 presents a detailed comparison of coverage in both data sets.

1.1.2 CoreLogic tax assessor data

To expand our analysis outside southern New England, we use parcel-level assessor data from CoreLogic, which collects these data from local property tax authorities across the United States. We use the historical archive of this data set provided by CoreLogic to the Federal Reserve System. This data set reports fields similar to those in the Warren Group data. In addition to the southern New England states covered in the Warren Group data (Massachusetts, Connecticut, and Rhode Island), we pull data from the rest of the region (Vermont, New Hampshire, and Maine) and from the South (Virginia, North Carolina, South Carolina, Georgia, Tennessee, Mississippi, Louisiana, and Arkansas).

1.1.3 CoStar listings

For cross-regional comparisons, we supplement assessor records with commercial real estate listings from CoStar, a service that lists properties for sale, including vacant land available for residential construction. We download all listings of buildable land for sale in July 2025 within the New England states and South Carolina. This allows us to compare the size distribution of sites available for purchase by developers across high- and low-cost markets.

1.1.4 Public data

We supplement these administrative sources with several public data sets.

Federal Housing Finance Agency repeat sales indexes To estimate price growth by county and Zip code, we use house-price indexes published by the Federal Housing Finance Agency (FHFA). The indexes use repeated sales or appraisals for single-family properties covered by conforming mortgages. We use the annual series reported by the FHFA.

American Community Survey demographics We download local housing market demographic characteristics from the American Community Survey (ACS) 5-year estimates, accessed via the US Census Bureau API. We obtain estimates of the number of local households, household income, rents, and self-reported home values. These variables are used to examine heterogeneity across housing market types.

1.2 Buildable land data set construction

This section describes how we use Warren Group data to form a parcel-level panel to track the development of buildable land in New England. We follow similar steps in processing CoreLogic data, detailed in the Online Appendix A.

Warren Group data processing We start with the Boston Fed's historical records of Warren Group data and clean the data as follows. First, we retain the most recent observation for each parcel–fiscal-year combination. We then remove duplicate records arising from mid-year reassessments or data entry errors by keeping the observation with the latest entry date within each parcel–year. We next create a balanced panel by forward filling and backward filling missing observations for parcels that appear in at least two consecutive years. This procedure ensures that temporary gaps in reporting are not misclassified as development. Lastly, we drop the 11 parcels that are larger than 10,000 acres, which appear to reflect data entry errors.[6]

Land-use classifications We classify each parcel–year observation into one of the following mutually exclusive land-use categories:

(i) *Residential Vacant*: parcels with residential zoning and no occupied structures. These parcels represent the stock of readily buildable land for housing development.

(ii) *Single-family Residential*: parcels with one to three single-family units. These include single-family detached homes as well as townhouses and condominiums with as many as three units.

(iii) *Multifamily Residential*: parcels with structures containing four or more units. These include both multi-unit condominiums, rented apartments, and group dwellings.

(iv) *Nonresidential Vacant*: parcels designated for commercial, industrial, institutional, or other nonresidential uses with no structures present.

(v) *Nonresidential Developed*: Nonresidential parcels with structures.

(vi) *Mixed-use/Unclassified*: Parcels with mixed-use designations or land-use codes that do not fit cleanly into the preceding categories.

This classification scheme enables us to track the flow of land from vacant to developed status and to distinguish between single-family and multifamily development.

[6] Using the land-use classifications in the following subsection, nine of these parcels are nonresidential developed, two are mixed use/unclassified, and one is residential vacant.

We apply this classification scheme using land-use codes reported by the Warren Group. Our sample includes 284 land-use codes designed to correspond to Massachusetts Board of Assessors land-use designations prepared by the Department of Revenue (Massachusetts Department of Revenue 2019). In some cases, the Warren Group reports codes that do not correspond to the most recent guidelines, perhaps due to outdated codes used by recorders in local areas. In each of these cases, we manually classify the land-use code using a combination of the code's digit structure and a visual review of the parcel using Google Street View.[7]

Defining buildable land Our primary analysis considers only residential vacant parcels as buildable. It is theoretically possible for a developer to use any parcel for residential development, tearing down any existing structures and petitioning for a land-use re-designation if needed. In practice, such steps are costly and legally difficult, meaning much development occurs on land that is already vacant and designated for residential use.

This approach is maximally conservative, as it avoids inappropriately classifying nonbuildable parcels as buildable. However, it might miss opportunities to build residential units on farmland, vacant commercial land, or commercial land with structures that are not presently in use (for example, redevelopment of urban warehouse districts).

We therefore consider two additional definitions in robustness exercises that are less restrictive. The first, intermediately restrictive definition includes all vacant nonresidential land. The second, least restrictive definition includes all land with no residential structures.

Measuring the development rate with aggregate transitions. It is challenging to systematically identify how vacant land is developed. If development does not change how a parcel's classification with the county assessor's office, then we can identify residential vacant-parcel development using year-over-year changes in parcel-level land use. However, for large projects, developers often subdivide large parcels into smaller ones or combine smaller parcels, a process which often produces new parcel identifiers. Granular information on such re-parceling is typically unavailable.

To overcome this challenge, rather than tracking development at the parcel level, we aggregate to the level of local housing markets and track changes in the total acreage within each of the land-use categories described above. We track how residential vacant land transitions into developed single-family and multifamily residential properties by estimating changes in overall acreage within each of these categories.

Our approach to measuring land development avoids the need to track parcel-level changes.

[7]Land-use codes follow a three-digit hierarchy, with the first digit signifying major classification and the second digit signifying minor classification. For example, the land-use code "120" does not have a Board of Assessors designation, but it is close to "12" (non-transient group quarters), and Street View inspection shows that properties with code 120 appear to be boarding houses, so these parcels are categorized as multifamily residential.

Because we have parcel-level data, we can apply the approach to arbitrarily granular local housing markets. In practice, in most of our analysis, we aggregate to the Zip-code level; most of the results that follow hold if we aggregate to counties or census tracts instead. The downside of this approach is that we can only observe net changes across land-use categories, rather than gross flows between those categories. For example, we cannot separately measure teardowns that result in the conversion of developed single-family residential land to residential vacant land and the development of residential vacant land into single-family residential land.

Formally, we estimate the *development rate* in market m and year t as:

$$\text{Development Rate}_{mt,t-k} := \frac{\Delta\ \text{Residential Developed}_{mt}}{\text{Buildable Land}_{m,t-k}}. \tag{1}$$

This represents the share of buildable land available in $t-k$ developed into residential units between year $t-k$ and year t. In this expression, $\text{Buildable Land}_{m,t-k}$ is the total acreage of buildable land in $t-k$, and $\Delta\text{Residential Developed}_{mt,t-k}$ is the change in the acreage of developed residential land between t and $t-k$, measured as:

$$\begin{aligned}\Delta\ \text{Residential Developed}_{mt,t-k} := &\left(\text{Single-fam Residential}_{mt} + \text{Multi-fam Residential}_{mt}\right)\\ &-\left(\text{Single-fam Residential}_{m,t-k} + \text{Multi-fam Residential}_{m,t-k}\right)\\ &+\text{Residential Developed Exit}_{mt,t-k},\end{aligned} \tag{2}$$

where $\text{Residential Developed Exit}_{mt,t-k}$ is the acreage of single-family and multifamily developed parcels that appear to exit the sample between $t-k$ and t. Accounting for the exit of parcels from the sample captures depreciation, teardowns, or conversions into other land use for property currently used for residential units.

1.3 Coverage in CoreLogic versus Warren Group

To illustrate the strengths of the Warren Group data, Figure 2 compares the coverage of Warren Group and CoreLogic tax assessor records for Massachusetts, Connecticut, and Rhode Island from 2007 to 2021. We restrict each data set to year-end snapshots of parcels with nonmissing land-use information and remove duplicate entries. We then calculate total acreage across covered parcels for each year in each data set and plot the ratio of total covered acreage to total acreage in each state.[8]

Figure 2 shows that from 2011 to 2021, the Warren Group data cover about 80 percent of the total area of Massachusetts, 85 percent of the total area of Connecticut, and 67 percent

[8] We calculate total acreage using 2010 census estimates and subtract coastal area from total area.

of the total area of Rhode Island.[9] By comparison, CoreLogic coverage is poor before 2015. Thereafter, CoreLogic's coverage is typically about 10 percentage points lower than the Warren Group's, and coverage varies significantly year to year, especially in Connecticut and Rhode Island. This variable coverage indicates that parceled acreage drops out of the data before reappearing in a way that could give a distorted view of development activity.

Due to these coverage differences, the Warren Group data report information on many more buildable parcels compared with the CoreLogic data. Figure 3 focuses on Massachusetts and plots the residential vacant share of total acreage in each Zip code in 2019 for the CoreLogic and Warren Group data. Panel (a) shows the full state, and Panel (b) displays the Boston Metro area. The third column shows that in almost all Zip codes, the Warren Group data identify much more residential vacant acreage. As Panel (b) demonstrates, the difference is particularly stark in Boston's urban core. In the near suburbs around southern Boston, the Warren Group data show many Zip codes where 5 to 6 percent of the total acreage is residential vacant, whereas the CoreLogic data imply that only about 1 to 2 percent of the total acreage in these Zip codes is vacant. This suggests that the CoreLogic data do a poor job of identifying smaller buildable plots around cities that are more suitable for infill, rather than greenfield, development.

Outside southern New England, the CoreLogic data appear to exhibit similar coverage issues, although we cannot determine the implications for buildable land supply by using the Warren Group data for benchmarking. Online Appendix Table C.3 shows the fraction of noncoastal area reported by the census that is covered by parcels in the CoreLogic data for each state. Coverage is especially low in Maine, New Hampshire, Louisiana, and Mississippi while higher in South Carolina, Tennessee, and Vermont. We caution that apparently high coverage does not necessarily make the CoreLogic data a quality source of information about the buildable-land distribution: For example, although CoreLogic covers 87.5 percent of Vermont's noncoastal area, *none* of the parcels in Vermont parcels is classified as residential vacant.[10]

[9] Our approach yields a lower bound on coverage because it includes all noncoastal state area, including water area. Some water area (for example, navigable waterways) is public land that is not parceled and not reported in assessor public records. This is especially relevant for Rhode Island, where the US Census Bureau reports that 30 percent of the state's area is inland water.

[10] We suspect this is because local authorities in Vermont do not use residential vacant land-use codes to classify residential vacant land; rather, they use `land_use_code=100`, a "placeholder" for an unspecified residential developed property. In Vermont, parcels with `land_use_code=100` often eventually change to a more specific residential land-use code in the same year that the appraised value of structures increases and year-built fields are filled. However, any algorithm that identifies `land_use_code=100` using these patterns would produce many false positives because year-built and appraised-value fields are frequently missing and variable across years, and many parcels with `land_use_code=100` appear developed based on appraised-value fields.

2 Summary Statistics

Warren Group data Table 1 presents summary statistics for the Warren Group data.

Panel (a) presents summary statistics in which the parcel is the unit of observation. The typical parcel is small, with a median size of 0.29 acre. This belies considerable dispersion: The standard deviation of parcel size is 22 acres, and the 99th percentile parcel has 31 acres. The parcel-size distribution is right-skewed, as the mean parcel size of 2 acres lies above the median parcel size.

The average residential developed parcel is small, at 0.8 acre for single-family properties and 1.6 acres for multifamily properties. Residential developed parcels are smaller than residential vacant parcels, with an average size of 3.3 acres. This shows the limitations of using the size distribution of developed parcels to infer the distribution of buildable land, as in Baum-Snow and Duranton (2025).

Most buildable parcels are small. The median residential vacant parcel is 0.5 acre, which could produce only three single-family homes with 25th percentile lot sizes. Even the 90th percentile residential vacant parcel, with 6.5 acres, could produce only about 40 single-family homes with 25th percentile lot sizes. Large buildable parcels become more available using less conservative definitions of buildable land: For example, the 90th percentile nonresidential vacant parcel has 22.5 acres, and the 90th percentile nonresidential developed parcel has 16 acres.

Panel (b) presents summary statistics in which the Zip code is the unit of observation. We show the fraction of land in each Zip code in each land-use category and annual development rates using our most, intermediately, and least restrictive definitions of buildable land. About 84 percent of land in the average Zip code is developed, evenly split between residential and nonresidential land. Of the remaining 16 percent, about 13 percent is vacant, again evenly split between residential and nonresidential land.[11]

In the average Zip code, 7 percent of land is residential vacant—the most conservative definition of buildable land. This belies significant heterogeneity across markets. In the 25th percentile Zip code, only 2.5 percent of land is residential vacant, while in the 90th percentile Zip code, 14.3 percent of land is residential vacant.

In the average Zip code, about 8 percent of residential vacant land was developed into residential units during the 2018–2019 period. There is again significant heterogeneity, with development rates of 1.2 percent in the 25th percentile Zip code and 17.1 percent in the 90th percentile Zip code.[12] Development rates are generally lower when the more generous defini-

[11] The remaining 3 percent of land is undevelopable (for example, underwater land or marshes).

[12] The table shows development rates for Zip codes where development rates lie between 0 and 1. Develop-

tions of buildable land is used because the denominator in the development rate increases as a larger share of local land is considered buildable.

Panel (c) shows results in which the county is the unit of observation. Many of the qualitative patterns are similar to those of the Zip-code case.

CoreLogic data The Warren Group data cover only southern New England. To compare buildable land in southern New England with other markets, Table 2 presents summary statistics for residential vacant parcels identified in the CoreLogic data. We separately report statistics for southern New England, northern New England, and the South.

Panel (a) presents statistics in which the residential vacant parcel is the unit of observation. Buildable parcels are smaller in southern New England (median = 0.8 acre) compared with the South (median = 1.0 acre) and northern New England (median = 2.9 acres).[13] Differences are more pronounced at the upper end of the parcel-size distribution: For example, the 99th percentile residential vacant parcel in southern New England is 57 acres compared with 160 acres in the South.

Panel (b) presents statistics in which the Zip code is the unit of observation. Buildable land is much more abundant in the average Zip code in the South: The average residential vacant share of total acreage is about 60 percent higher in the South than in southern New England. Notably, buildable land appears more concentrated across space in the South than in New England: While the median Southern Zip code has lower residential vacant shares than in New England shares in the 90th and 99th percentile Southern Zip code are much higher. This could reflect that buildable parcels in southern New England are more fragmented, whereas buildable parcels in the South are often large greenfield plots.

The CoreLogic data present a very different picture of the buildable-land distribution compared with the Warren Group data for southern New England, meaning the coverage issues identified in Section 1.3 matter. The CoreLogic data identify many fewer residential vacant parcels ($\sim$ 115,000 versus $\sim$ 190,000). The median residential vacant parcel is 60 percent larger in the CoreLogic data (0.8 acre versus 0.5 acre), possibly reflecting the especially poor CoreLogic coverage in urban areas. For the average Zip code, the residential vacant share of total acreage is much smaller: 2.6 percent in the CoreLogic data compared with 6.7 percent in the Warren Group data.

ment rates could be outside that range if (i) there was no buildable land in 2018 (in which case the fraction of buildable land developed is undefined); (ii) there was a net decrease in acreage of residential land (for example, many vacant units were demolished); or (iii) the increase in residential acreage exceeded the lagged acreage of developed land (for example, because of new acreage covered in county assessors' offices).

[13] Results for northern New England should be interpreted with extreme caution. Recall that the CoreLogic data cover only 20 percent of Maine's land area and identify no buildable parcels in Vermont.

3 Empirical Facts about the Supply of Buildable Land

Using our parcel-level panel, we document five empirical facts about the supply of buildable land. Throughout, we consider primarily local housing markets defined by Zip code, although we find similar results if we aggregate more coarsely (with counties) or with more granularity (with census tracts). We also focus our analysis on housing markets from 2013 to 2019, the period after the housing crisis but before housing market disruption related to the COVID-19 pandemic. Unless otherwise noted, we use Warren Group data.

Facts 1 through 3 document basic summary statistics and trends about the buildable-land distribution in New England. Facts 4 and 5 show how the buildable-land distribution relates to house-price growth and investment.

3.1 Fact 1. The typical buildable parcel is small and isolated

New England buildable parcels are small Buildable parcels are small in most New England housing markets. To illustrate, for parcels observed in 2019, we first calculate the size in acres of the 90th percentile buildable parcel within each Zip code to show the size of a typical large plot. We then rank Zip codes by the size of their 90th percentile buildable plot. Figure 4 plots the size of the 90th percentile parcel against the fraction of Zip codes with a larger 90th percentile parcel (equal to one minus the Zip code's percentile rank). The vertical axis gives the fraction of Zip codes with a 90th percentile plot that is larger than the size on the horizontal axis. The solid black series shows results for the most restrictive buildable land definition (only residential vacant parcels), while the gray dashed series shows results for the least restrictive definition (all vacant and nonresidential developed parcels).

The figure shows that large plots are scarce in most housing markets. Using the restrictive buildable land definition, only about 10 percent of New England Zip codes have a 90th percentile buildable plot larger than 10 acres. This result is robust to the definition of buildable land, rising to only 12.5 percent using the less restrictive definition.

The low availability of large buildable plots in most housing markets would matter less for aggregate development if large plots were abundant in some markets. However, using the CoStar data, we find that large buildable plots for purchase are scarce in absolute terms. Figure 5 plots in solid black on the vertical axis the share of buildable parcels in New England that were available for sale in July 2025 with acreage exceeding the acreage indicated on the horizontal axis. About 2 percent of the buildable parcels for sale are larger than 100 acres, constituting 30 percent of buildable acres for sale. To put this in context, the gray dashed line shows comparable figures for South Carolina, where construction activity is more robust and property prices are much lower. A much greater share of buildable land is within large parcels: 4 percent of buildable parcels for sale are larger than 100 acres, constituting 60 percent of buildable acres.

New England buildable parcels are isolated Parcel size does not necessarily impede development scale if there are many adjacent buildable parcels that developers can easily combine. However, we find that most buildable parcels are surrounded by developed land, making such recombination difficult. Even on adjacent parcels, as previous empirical work shows, changing parcel boundaries is challenging (Brooks and Lutz 2016) due to holdouts extracting monopoly rents (Merrill 1986), asymmetric information (Strange 1995), and positive externalities not internalized by parcel owners (O'Flaherty 1994). Therefore, buildable parcel size imposes a meaningful technological limit on scale.

While the Warren Group data lack parcel boundaries, we have parcel latitude and longitude for most residential vacant parcels. For each residential vacant parcel, we calculate the fraction of the K nearest neighbors that are residential vacant or developed for $K = 1, 2, 5, 10$. Furthermore, for each Zip code, we calculate the fraction of residential vacant acreage on parcels with *no* K nearest neighbors that are also residential vacant.

Table 3 shows the results. Panel (a) shows that most residential vacant parcels are surrounded by developed parcels. Of the 10 nearest parcels, only 18 percent are residential vacant, and 77 percent are explicitly developed. This covers a 92-meter radius around each parcel on average, a land area of about 6.6 acres. Panel (b) demonstrates that in most markets, a large share of buildable acreage is on parcels with no nearby buildable parcels. In the median Zip code, about 73 percent of buildable acreage has no residential vacant parcel among its two nearest neighbors, and 47 percent of buildable acreage has no residential vacant parcel among its 10 nearest neighbors.

Large buildable parcels are more abundant in the South Large buildable parcels are relatively more scarce in southern New England than in the South. Figure 6 replicates Figure 4 using CoreLogic data, comparing southern New England, the South, and northern New England. Given the coverage issues in the CoreLogic data, the figure should be interpreted with caution. In the South, about 38 percent of Zip codes have a 90th percentile buildable parcel of at least 10 acres; only 25 percent of Zip codes in southern New England have a 90th percentile buildable parcel that large.[14]

[14]Large buildable parcels appear to be even more abundant in northern New England than in the South, but as discussed in Section 1.3, severe data coverage issues in that region require us to interpret the results with caution.

3.2 Fact 2. Large buildable parcels have become scarcer over time

In New England, large parcels have become less available over time. Figure 7 shows the average acreage of the median, 75th percentile, and 90th percentile buildable parcel across Zip codes in each year from 2012 through 2021. The size of buildable plots has shrunk appreciably over time, with the 50th, 75th, and 90th percentile plots declining by about 23 percent, 33 percent, and 26 percent, respectively.

3.3 Fact 3. Buildable parcels are smaller in more populous markets

Large parcels are scarcer in more populous markets. Figure 8a groups Zip codes into quintiles by the 2019 population and, within each quintile, plots the average size of the median, 75th percentile, and 90th percentile buildable parcel in 2019. The median, 75th percentile, and 90th percentile parcels are much smaller in more populous markets. For example, for Zip codes in the smallest population quintile, a buildable parcel must have more than 12 acres to be in the largest 10 percent, while for Zip codes in the largest population quintile, a buildable parcel needs only about 2.5 acres to be in the largest 10 percent.

Furthermore, areas with greater population growth experience a decline in the availability of large plots. Figure 8b groups Zip codes into quintiles based on population growth from 2013 to 2019 and, for Zip codes within each quintile, plots the average change in size of the median, 75th percentile, and 90th percentile buildable plot. Across the buildable-land distribution, areas with greater population growth saw a decrease in parcel size at each percentile rank, indicating increased scarcity of large parcels. The decrease is especially pronounced for 90th percentile buildable plots.

These patterns suggest two mechanisms that could explain the availability of large parcels. First, as people move into an area, dispersed settlements break up large contiguous parcels—for example, a subdivision that breaks a large farm into two parcels. Second, developers could selectively develop large parcels first so that areas with greater population growth have a depleted stock of large plots available for subsequent development.

3.4 Fact 4. House-price growth is greater in markets with fewer large parcels

Areas with low initial availability of large buildable plots experience greater house-price growth in subsequent years. This is consistent with small buildable plots constraining the amount and efficiency of new development. Figure 9 groups Zip codes into quintiles by the acreage of the median, 75th percentile, and 90th percentile buildable parcel in 2013 and, within each quintile, plots average price growth from 2013 to 2019 in solid black. Markets where large parcels are scarce show much larger price growth during this period. For example, areas where the 90th percentile buildable plot was less than 1 acre in 2013 saw nearly 50 percent nominal price growth, while areas where the 90th percentile buildable plot was 25 acres saw about 20 percent price growth.

The relationship between price growth and parcel size is convex. Price growth is much lower in areas where the 90th percentile buildable parcel is 10 acres compared with areas where the 90th percentile buildable parcel is 1 acre, but there is little difference in price growth compared with an area where the 90th percentile buildable parcel is 25 acres. This is consistent with developer scale efficiencies for projects of a certain size, after which point the benefits of incremental scale decline.

Of course, price growth reflects many factors, some of which may correlate with the buildable-parcel-size distribution. However, we find that the availability of large buildable parcels incrementally explains price growth above basic housing market demographic characteristics. Where m indexes Zip code, we run cross-sectional regressions of the form:

$$\%\Delta\text{Price}_m = \beta_0 + \beta_1 \cdot \text{Acres90}_m + X_m' \cdot \delta + \gamma_{g(m)} + \epsilon_m, \tag{3}$$

where $\%\Delta\text{Price}_m$ is 2013–2019 price growth, Acres90_m is the acreage of the 90th percentile buildable parcel, X_m is a vector of housing market characteristics, and $\gamma_{g(m)}$ is a set of fixed effects for group m.

Table 4 shows coefficient estimates. Column (1) estimates equation (3) without Acres90_m using the 2013 population, 2013 log income, 2013–2019 log income growth, and the 2013 price-to-rent ratio as explanatory demographic variables. The predictors have expected signs. For example, greater price growth predicts greater income growth, consistent with positive demand shocks, and a higher price-to-rent ratio predicts greater price growth, consistent with price-to-rent ratios capitalizing (partially) correct expectations about future price growth. These demographics explain 21 percent of the cross-sectional variation in price growth.

Column (2) regresses price growth on Acres90_m and confirms that areas with smaller 90th percentile buildable parcels—and hence fewer available large buildable plots—experienced greater price growth from 2013 to 2019. Variation in the 90th percentile buildable parcel size explains 9.7 percent of the price-growth variation. Column (3) shows that the availability of large buildable plots retains explanatory power in a specification including other control variables. The coefficient on Acres90_m is similar, and the R-squared increases 17 percent (3.5 percentage points) relative to column (1), with only demographic predictors.

Columns (4) through (6) of Table 4 repeat the analysis but include state fixed effects. The results are similar and, if anything, imply that the availability of large parcels, proxied with

Acres90_m, has *greater* incremental explanatory power for price growth relative to basic demographic predictors. Online Appendix Table C.2 shows similar results with even more granular county fixed effects.

3.5 Fact 5. Development rates correlate less with buildable parcel size than house-price growth does

The relationship between buildable parcel size in 2013 and development rates from 2013 to 2019 is much weaker than the relationship between buildable parcel size in 2013 and house-price growth from 2013 to 2019. The gray dashed series in Figure 9 plots the average fraction of 2013 buildable land developed from 2013 to 2019 (given by $\text{Development Rate}_{m,2019,2019-2013}$). Areas with smaller buildable parcels in 2013 saw more development.

However, the proportional differences in development by buildable plot size are *much* lower than the proportional differences in price growth by buildable plot size shown in solid black. This suggests that supply is less price-elastic in areas with smaller buildable plots. Focusing on the 90th percentile plot-size cut, about 25 percent of 2013 buildable land was developed from 2013 to 2019 in areas with the smallest plots. Figure 9 shows that house prices grew in those areas by 50 percent, an elasticity of 0.5. The equivalent elasticity was nearly double in areas with the largest buildable plots in 2013—in areas with the largest 90th percentile buildable parcels, from 2013 to 2019, prices grew by 18 percent, and 17 percent of buildable land was developed .

4 Returns to Scale and the Supply of Buildable Land

Facts 4 and 5 in Section 3 suggest that development is more efficient on larger plots. However, quantifying the impact of plot size on developer efficiency requires a more precise model of the developer production process. In this section, we introduce a simple model of returns to scale in residential housing development that reproduces the empirical patterns in Section 3. We present suggestive evidence that development exhibits returns to scale in parcel size, and we show how varying returns to scale and the buildable-land distribution impacts house prices and the efficiency of development. However, because we lack exogenous variation in parcel size, we do not view this suggestive evidence as causal and show our results under a wide range of plausible assumptions on the degree of returns to scale. Online Appendix B provides derivations.

4.1 Empirical model of developer returns to scale

A region has housing market segments indexed by m with floorspace Q_{mt} in year t. Each market segment has a fixed mass N_m of developers that use land and capital to meet the demand for new floorspace from homeowners. Buildable parcels in market m and year t have a_{mt} acres of land, where a_{mt} has time-varying distribution described by the cumulative distribution function (CDF) A_t. House prices equate regional floorspace demand and supply.

Developers Developers indexed by j are endowed with one parcel of buildable land. They choose the amount of floorspace per acre H_{jt} to build to maximize static profits, given a price per unit of floorspace P_{mt}.

Developers face both fixed and variable costs in parcel development. Fixed costs f_{jmt} include administrative costs from permitting, unit design, and procurement as well the costs of infrastructure used by all units (for example, roads in a subdevelopment and communal facilities). Variable costs $C_{mt}(H)$ include the costs of material and labor. Developers face an identical problem conditional on developing their parcel. Floorspace per acre satisfies:

$$\pi_{jmt} = \pi_{mt} := \max_{H} P_{mt} \cdot H - C_{mt}(H) \implies C'_{mt}(H^*) = P_{mt}. \tag{4}$$

Developer j builds if total variable profits exceed fixed costs: $\pi_{mt}(P_{mt}) \cdot a_{mt} \geq f_{jmt}$.

We parameterize variable costs as log-linear in floorspace: $C_{mt}(H) := c_{mt} \cdot \frac{\alpha-1}{\alpha} \cdot H^{\frac{\alpha}{\alpha-1}}$. Given this parameterization and equation (4), variable profits are $\pi_{0mt} \cdot P_{mt}^{\alpha} \cdot a_{mt}$, where π_{0mt} is a constant that depends on α and the constant c_{mt}. We parameterize fixed costs as: $f_{jmt} := f_{mt} \cdot a_{mt}^{1-\rho} \cdot \exp\left(\epsilon_{jmt}\right)$, where ϵ_{jmt} follows a logistic distribution. Developer j then builds if:

$$\underbrace{\pi_{0mt} \cdot P_{mt}^{\alpha} \cdot a_{mt}}_{\text{variable profits}} - \underbrace{f_{mt} \cdot \overbrace{a_{mt}^{1-\rho} \cdot \exp\left(\epsilon_{jmt}\right)}^{\text{returns to scale}}}_{\text{fixed costs}} \geq 0. \tag{5}$$

The parameter ρ determines returns to scale in parcel size. If $\rho = 0$, then parcel size a_{mt} has no impact on the development decision, and there are no returns to parcel size in development. If $\rho > 0$, then variable profits increase faster than fixed costs for larger parcels, meaning development exhibits *increasing* returns to scale. If $\rho < 0$, then variable profits increase more slowly than fixed costs for larger parcels, and development exhibits *decreasing* returns to scale.

In our model, under increasing returns to scale in parcel size, it is more efficient to develop a given amount of floorspace as part of one large project rather than to split that floorspace across many large projects. The model of returns to scale in housing development in D'Amico *et al.* (2024) also has this feature but emphasizes different mechanisms. In our model, project scale is constrained by the buildable-land distribution, and project consolidation is efficient because it reduces duplication of fixed lot-preparation costs. In D'Amico *et al.* (2024), project scale is constrained by local regulation, and project consolidation is efficient because developers have a limited span of control: It is costly to effectively monitor many projects simultaneously.

Integrating across developers j in year t, the development probability of an individual parcel is:

$$q_{mt} := \frac{\exp(\rho \cdot \ln a_{mt} + \alpha \ln P_{mt} + \ln(\pi_{0mt}/f_{mt}))}{1 + \exp(\rho \cdot \ln a_{mt} + \alpha \ln P_{mt} + \ln(\pi_{0mt}/f_{mt}))}. \tag{6}$$

The total supply of floorspace in market m and year t is $Q^S_{mt}(P_{mt}) := N_m \cdot a_{mt} \cdot q_{mt}(a_{mt}, P_{mt}; \cdot)$.

Housing demand A representative regional household has demand for new total regional floorspace ΔQ^D_t. Total floorspace demand depends on a regional price index P_t. The representative household pays price $P_{mt} := \mu_{mt} \cdot P_t$ per unit of floorspace. The coefficients μ_{mt} normalize quality differences across markets and over time due to unit characteristics or local amenities.

We parameterize regional demand for floorspace as log-linear:

$$\Delta \ln Q^D_t(P) := \eta_0 + \eta_1 \cdot (\ln P - \ln P_{t-1}). \tag{7}$$

Equilibrium The regional price of floorspace equates new floorspace supply and demand:

$$\Delta Q^D_t(P_t) = \sum_m Q^S_{mt}(\mu_{mt} \cdot P_t). \tag{8}$$

4.2 Estimating developer returns to scale

We next take the model to the data. The empirical counterpart of the modeled development probability q_{mt} is the development rate, given by Development Rate$_{m,t+1,t}$ in equation (1). Rearranging equation (6) and defining $\ln(\pi_{0mt}/f_{mt}) := \delta_m + \nu_t + \varepsilon_{mt}$ yields an estimating equation that is log-linear in development odds $q_{mt}/(1 - q_{mt})$:

$$\begin{aligned} \ln \frac{q_{mt}}{1 - q_{mt}} &= \rho \cdot \ln a_{mt} + \alpha \cdot \ln P_{mt} + \delta_m + \nu_t + \varepsilon_{mt} \implies \\ \Delta \ln \frac{q_{mt}}{1 - q_{mt}} &= \rho \cdot \Delta \ln a_{mt} + \alpha \cdot \Delta \ln P_{mt} + \Delta \delta_t + \Delta \varepsilon_{mt}, \end{aligned} \tag{9}$$

where the second line takes first differences to eliminate the time-invariant market-specific component of fixed costs and variable profits.

The coefficient of interest in equation (9) is ρ, which controls returns to scale. Ideally, we would estimate coefficients in equation (9) with an instrument for average parcel size a_{mt}. This would avoid bias arising from correlation between unobserved local factors that lead to changes in both the development rate and parcel size. For example, if developers expect an increase in relative demand for multi-unit condos in urban areas, they may develop places with small plots suitable for multi-unit buildings more rapidly than larger plots suitable for efficient single-family development. This would create downward bias in our coefficient estimates.

Absent an instrument, we present suggestive results that add increasingly restrictive control variables and show that coefficient estimates are stable across specifications. Throughout, we show how our conclusions would differ with different estimates of the returns-to-scale parameter ρ. To mitigate downward simultaneity bias in our estimate of the price coefficient α, we instrument for contemporaneous price growth $\Delta \ln P_{mt}$ with three lags of price growth with slopes that vary by county.

Table 5 shows coefficient estimates for equation (9). The first column has only calendar-year effects, which consistently estimate ρ assuming that $\Delta\varepsilon_{mt} + \Delta\delta_t$ is mean-independent of $\Delta \ln a_{mt}$, conditional on the calendar year and the instruments for price growth ΔP_{mt}. The second column adds county fixed effects. This avoids bias from, for example, developers expecting a regional increase in demand for multi-unit housing. The third column controls flexibly for separate county-level impacts of local demographics.

The coefficient on parcel size is stable and positive across specifications. This indicates increasing returns to scale in residential construction. In the third column, with the most stringent specification, a 1 percent increase in parcel size implies a 0.6 increase in log development odds.

The instrumental variable (IV) coefficient on price growth, while imprecise, is fairly stable and implies a price elasticity of per-acre floorspace supply of 3.5. This aligns with existing estimates in the literature that range from 1 to 16 in the United States.[15] The first stage of the IV is strong, with Olea and Pflueger (2013) effective F-stats above 10.[16]

What do these results imply about the price elasticity of housing supply? We calibrate A_t using the CDF of buildable plot sizes in New England and calculate a modeled price elasticity of supply as $\Delta Q^S/\Delta P$ for a 1 percent increase in house prices relative to 2018 levels.

Figure 10, panel (a), plots the modeled price elasticity of supply against the returns-to-scale parameter ρ. Based on the estimate of ρ in Column (4) of Table 5, the New England price elasticity of supply is 0.2. Despite the model's simplicity, this is remarkably close to the average supply elasticity of 0.2 reported in Baum-Snow and Han (2024) for census tracts in

[15] Baum-Snow and Duranton (2025) argue that in a model where housing is produced using a Cobb–Douglas aggregator in land and capital, conditional on building, the price elasticity of housing supply is $\frac{1-s}{s}$, where s is the land value share in construction. Albouy and Ehrlich (2018) find that the US land share ranges from 0.06 to 0.5, with an average of 0.35, implying an elasticity ranging from 1 to 16, with an average of 1.9.

[16] Andrews *et al.* (2019) recommends that in heteroskedastic settings with one endogenous regressor and multiple instruments, the Olea and Pflueger (2013) is appropriate to compare against a rule-of-thumb value of 10 to test for weak instruments.

Massachusetts, Connecticut, and Rhode Island during the 2000–2010.[17] The modeled supply elasticity is increasing in ρ. As ρ increases, fixed development costs grow more slowly with parcel size. This means larger parcels are more efficient to develop, making large developments more responsive to changes in prices, which increase variable profits.

4.3 The impacts of changing the buildable-land distribution

The results in the previous section suggest that parcel development exhibits returns to scale in parcel size. This implies that, holding fixed the total amount of buildable land, making more large parcels available—for example, by recombining smaller disjoint parcels—could increase development rates and reduce house prices.

We investigate the importance of the parcel-size distribution by conducting two counterfactual exercises using our model calibrated to the New England housing market in 2018.[18] First, we simulate price growth from 2018 to 2019 if the buildable-parcel-size distribution in New England matched the buildable-parcel-size distribution in South Carolina, holding fixed the total amount of buildable land. To do so, we assume that a_{mt} in New England followed the parcel size CDF in South Carolina and adjust N_m so that $\sum_m N_m a_{mt}$ is unchanged. This captures the incremental impact of increasing the share of land on large parcels, holding fixed total buildable land supply. Second, we simulate price growth from 2018 to 2019, assuming that the New England buildable-land distribution followed the land distribution in South Carolina, allowing the total amount of land to expand as well. This captures the joint impact of changing the amount and distribution of available land.

Figure 10, Panel (b), shows the impacts on house-price growth from 2018 to 2019, the supply of new floorspace, and developer productivity, defined as the ratio of floorspace produced to fixed and variable construction costs. Changing the land distribution impacts productivity through two channels: first, by changing costs on infra-marginal development and, second, by changing the amount of land developed and floorspace produced. To highlight the impact of the land distribution on the production process, we focus on the first channel and calculate changes in productivity while fixing prices and the set of developed parcels at baseline levels.[19]

[17] Baum-Snow and Han (2024) also reports a total floorspace elasticity that is higher (0.4 for southern New England) and a new floorspace elasticity that is lower (0.1 for southern New England). Neither is directly comparable: The total floorspace elasticity includes expanded floorspace in existing buildings, which is not included in the model, and the new floorspace elasticity excludes development on teardown construction, which will be to the extent teardowns show up as residential vacant for at least one year.

[18] See Online Appendix section B.2 for calibration details.

[19] Accounting for equilibrium impacts on prices and the set of developed parcels would have an ambiguous impact on modeled productivity. On the one hand, lower prices following land distribution would reduce variable construction costs, as builders reduce floorspace per acre. On the other hand, more acres per parcel cause developers with higher fixed costs to build, increasing fixed construction costs.

The dark solid bars show the results of the "land reorganization" counterfactual, in which we increase the share of buildable land on large parcels but hold the total supply of buildable land fixed. The light dashed bars show the results of the "land supply expansion" counterfactual, in which the amount and distribution of buildable land increases.

In the "land reorganization" counterfactual, price growth decreases by 3.4 percentage points. This wipes out the 2.9 percent increase in prices from 2018 to 2019 that was actually observed. Price growth is weaker because an increase in developer productivity expands housing supply.

Land reorganization alone, with no land supply expansion, achieves a large share of the total price decrease from a land supply expansion. In the land supply expansion counterfactual, price growth declines by 8.4 percentage points, meaning that land reorganization explains 40 percent of the price impacts of greater buildable land supply.

Because our estimates of the returns-to-scale parameter ρ are only suggestive, we do not view our main counterfactual results as definitive. To show the range of possible outcomes in our model, Panels (c) and (d) of Figure 10 illustrate how counterfactual price and productivity results vary for different estimates of the returns-to-scale parameter ρ. A higher value of ρ implies lower prices and greater productivity. Land reorganization and land supply expansion would still have a significant impact on housing supply and house-price growth under a wide range of estimates of the returns-to-scale parameter ρ.

5 Policy Implications and Conclusions

Our results have three implications for housing policy debates.

First, both regulatory constraints and physical land fragmentation contribute to housing supply constraints in built-up markets. A large body of research documents how land-use regulations limit housing supply. Our findings suggest that even in a counterfactual world with fewer regulatory barriers, the fragmentation of buildable land across small, disjoint parcels would still constrain construction productivity and housing supply. The two factors of regulation and land fragmentation are complementary explanations for housing supply constraints, not substitutes.

Second, policies that increase the availability of large development sites may have greater impact per acre than policies focused solely on infill development of small plots. Our counterfactual simulations suggest that reorganizing the same total acreage of buildable land into larger parcels meaningfully increases housing supply and construction productivity. This is consistent with the potential benefits of initiatives that redevelop large underused government, commercial, or industrial sites. For example, the Massachusetts State Lands for Homes initiative has proposed redeveloping the Erich Lindemann and Charles F. Hurley Buildings, which occupy 6.5 acres adjacent to Boston's Beacon Hill—acreage at the 90th percentile of the New England buildable-parcel distribution (Division of Capital Asset Management and Maintenance 2024).

Third, our results suggest path dependence in the development of growing areas. As incremental development proceeds, it can fragment large parcels into smaller ones, potentially reducing the efficiency of future development. This dynamic implies that the sequencing and spatial pattern of development may have long-run consequences for housing supply elasticity.

References

ALBOUY, D. and EHRLICH, G. (2018). Housing productivity and the social cost of land-use restrictions. *Journal of Urban Economics*, **107**, 101–120.

ANDREWS, I., STOCK, J. H. and SUN, L. (2019). Weak instruments in instrumental variables regression: Theory and practice. *Annual Review of Economics*, **11** (1), 727–753.

AREUEA DATA INSIGHTS (2026). Cotality (CoreLogic) public records. https://airtable.com/appJBlcF6hodW3YgH/shrRgGbsyWIRj2Td9, data tracker. Accessed: April 17, 2026.

BAILY, M. N. and SOLOW, R. M. (2001). International productivity comparisons built from the firm level. *Journal of Economic Perspectives*, **15** (3), 151–172.

BAUM-SNOW, N. and DURANTON, G. (2025). Housing supply and housing affordability. In D. Donaldson and S. J. Redding (eds.), *Handbook of Regional and Urban Economics, Handbook of Regional and Urban Economics*, vol. 6, Elsevier, pp. 353–461.

— and HAN, L. (2024). The microgeography of housing supply. *Journal of Political Economy*, **132** (6), 1897–1946.

BROOKS, L. and LUTZ, B. (2016). From today's city to tomorrow's city: An empirical investigation of urban land assembly. *American Economic Journal: Economic Policy*, **8** (3), 69–105.

CHODOROW-REICH, G., GUREN, A. M. and MCQUADE, T. J. (2024). The 2000s housing cycle with 2020 hindsight: A neo-kindlebergerian view. *Review of Economic Studies*, **91** (2), 785–816.

D'AMICO, L., GLAESER, E. L., GYOURKO, J., KERR, W. R. and PONZETTO, G. A. (2024). *Why has construction productivity stagnated? The role of land-use regulation*. Tech. rep., National Bureau of Economic Research.

DIVISION OF CAPITAL ASSET MANAGEMENT AND MAINTENANCE (2024). Healey-driscoll administration announces new redevelopment vision for hurley, lindemann buildings. https://www.mass.gov/news/healey-driscoll-administration-announces-new-redevelopment-vision-for-hurley-lindemann-buildings, accessed: 2026-03-01.

DURANTON, G. and PUGA, D. (2023). Urban growth and its aggregate implications. *Econometrica*, **91** (6), 2219–2259.

GARCIA, D. and MOLLOY, R. (2023). Can measurement error explain slow productivity growth in construction?

GLAESER, E. and GYOURKO, J. (2018). The economic implications of housing supply. *Journal of economic perspectives*, **32** (1), 3–30.

GOOLSBEE, A. and SYVERSON, C. (2023). The strange and awful path of productivity in the us construction sector.

GYOURKO, J. and MOLLOY, R. (2015). Regulation and housing supply. In *Handbook of regional and urban economics*, vol. 5, Elsevier, pp. 1289–1337.

MASSACHUSETTS DEPARTMENT OF REVENUE (2019). *Property Type Classification Codes, Non-Arms Length Codes and Sales Report Spreadsheet Specifications*. Massachusetts Department of Revenue, Division of Local Services, revised April 2019.

MERRILL, T. W. (1986). Economics of public use. *Cornell L. Rev.*, **72**, 61.

MOLLOY, R. *et al.* (2020). The effect of housing supply regulation on housing affordability: A review. *Regional science and urban economics*, **80** (C), 1–5.

O'FLAHERTY, B. (1994). Land assembly and urban renewal. *Regional Science and Urban Economics*, **24** (3), 287–300.

OLEA, J. L. M. and PFLUEGER, C. (2013). A robust test for weak instruments. *Journal of Business & Economic Statistics*, **31** (3), 358–369.

SAIZ, A. (2010). The geographic determinants of housing supply. *The Quarterly Journal of Economics*, **125** (3), 1253–1296.

STRANGE, W. C. (1995). Information, holdouts, and land assembly. *Journal of urban Economics*, **38** (3), 317–332.

Figures.

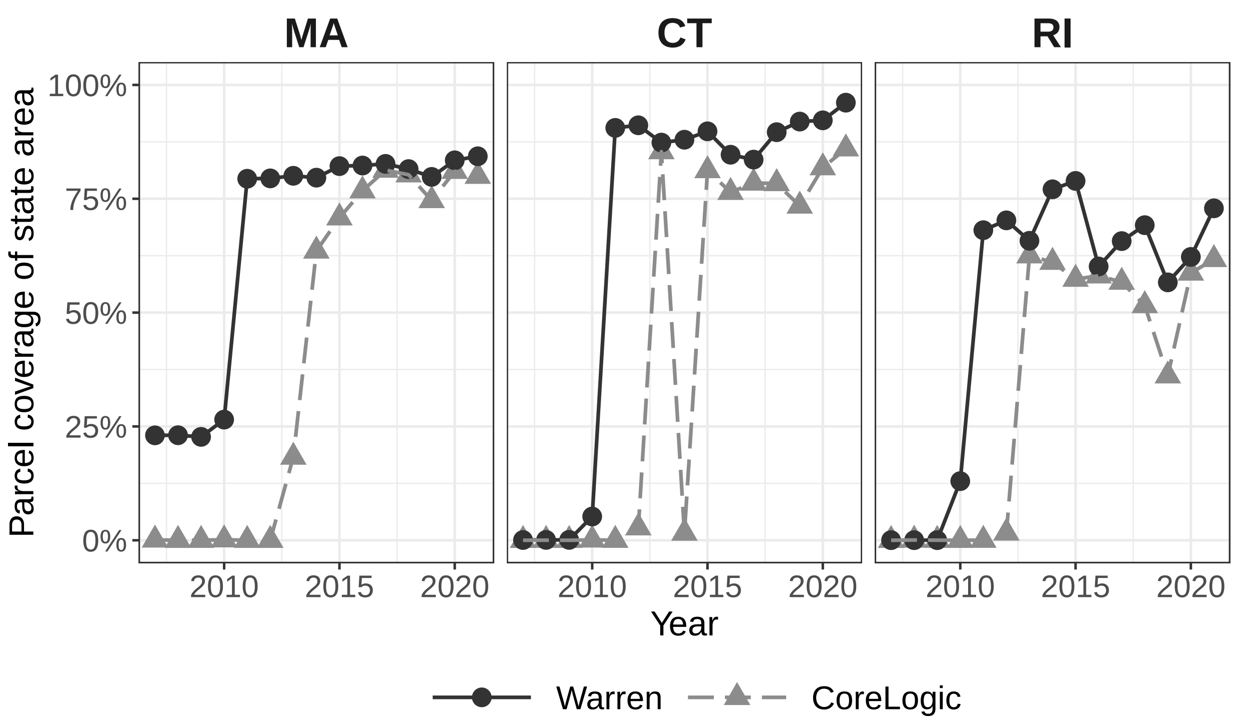
Figure 1: Examples of Buildable Plots across Housing Markets

(a) 4,600-acre buildable plot in Charleston, SC

(b) 0.1-acre buildable plot in Boston, MA

Source: CoStar. The panels show examples from CoStar listings of buildable plots for sale in Charleston, South Carolina, and Boston, Massachusetts, in July 2025. Both plots are a 15-minute drive from the centers of their respective cities.

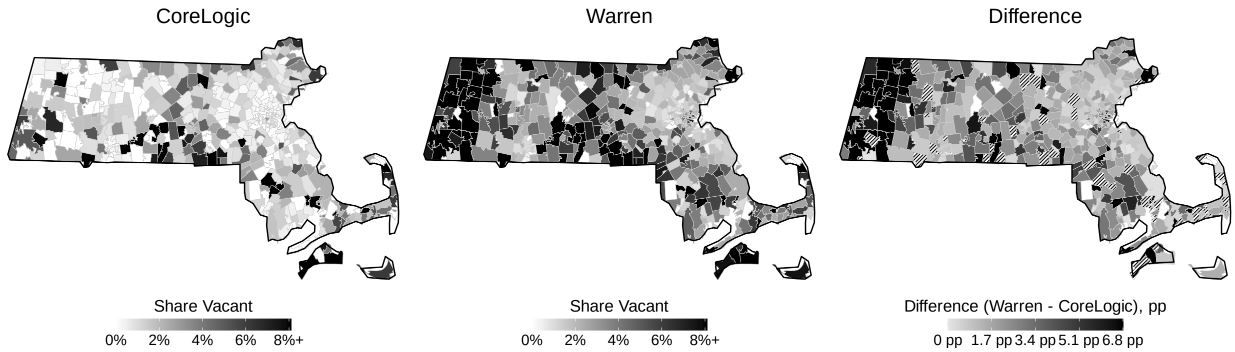
Figure 2: Data Coverage, Warren Group versus CoreLogic



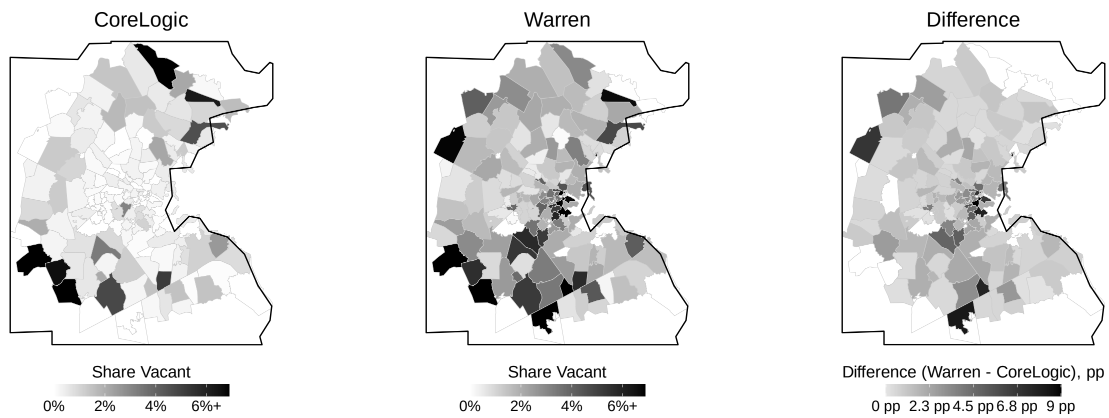
Sources: Warren Group and CoreLogic. The figure plots the fraction of total land area in each state covered by parcel-level annual assessor records in the Warren Group and CoreLogic public records data. Acreage covered by parcel-level records is calculated by summing the acreage of parcels with nonmissing land-use designations in each assessed year. Total acreage equals noncoastal land area estimated from 2010 census boundaries.

Figure 3: Buildable Land Availability in Massachusetts, Warren Group versus CoreLogic

(a) All Massachusetts Zip codes, 2019

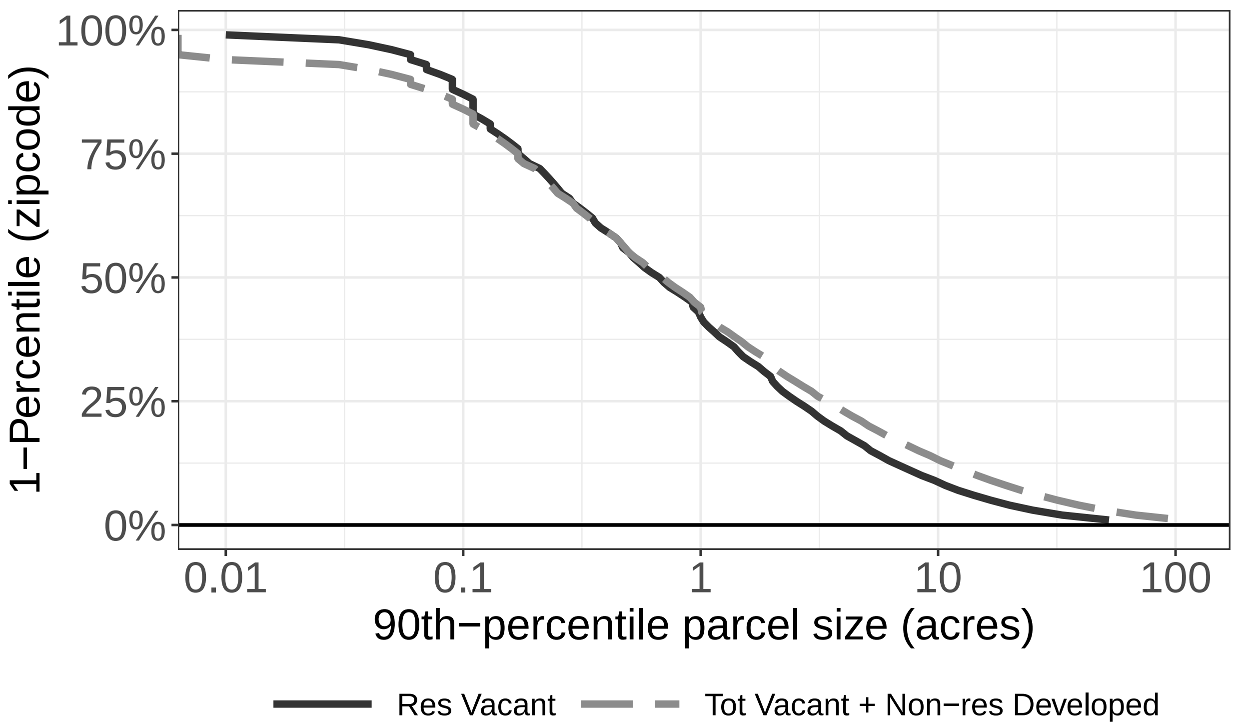


(b) Boston Metro Zip codes, 2019



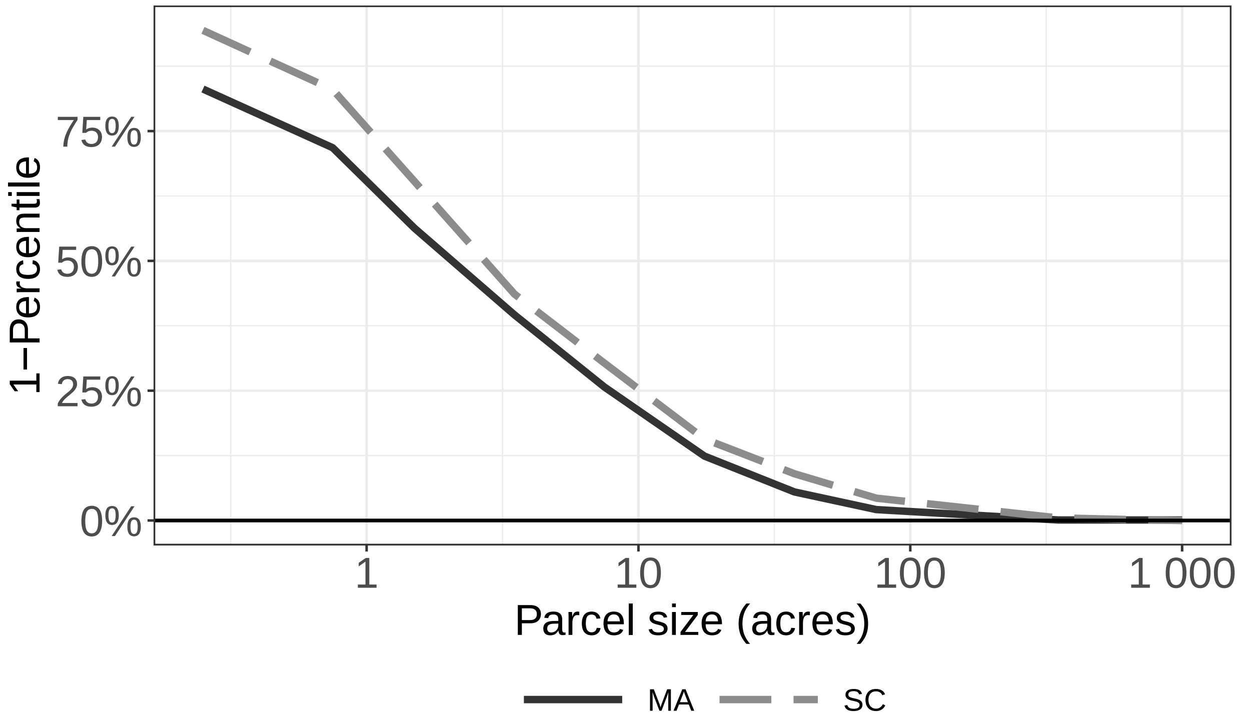
Sources: Warren Group and CoreLogic. Each panel plots residential vacant acreage in each Massachusetts Zip code as a fraction of total acreage in 2019. Panel (a) shows results for all of Massachusetts, and Panel (b) focuses on Zip codes within a 20-mile radius of the Boston city center. The first column shows results for CoreLogic. The second column shows results for Warren. The third column takes the percentage point difference between the Warren and CoreLogic columns. In the third column, color intensity indicates the magnitude of the difference, with positive differences plotted with solid fill and negative differences plotted as dashed fill.

Figure 4: Buildable-land Distribution by Zip code



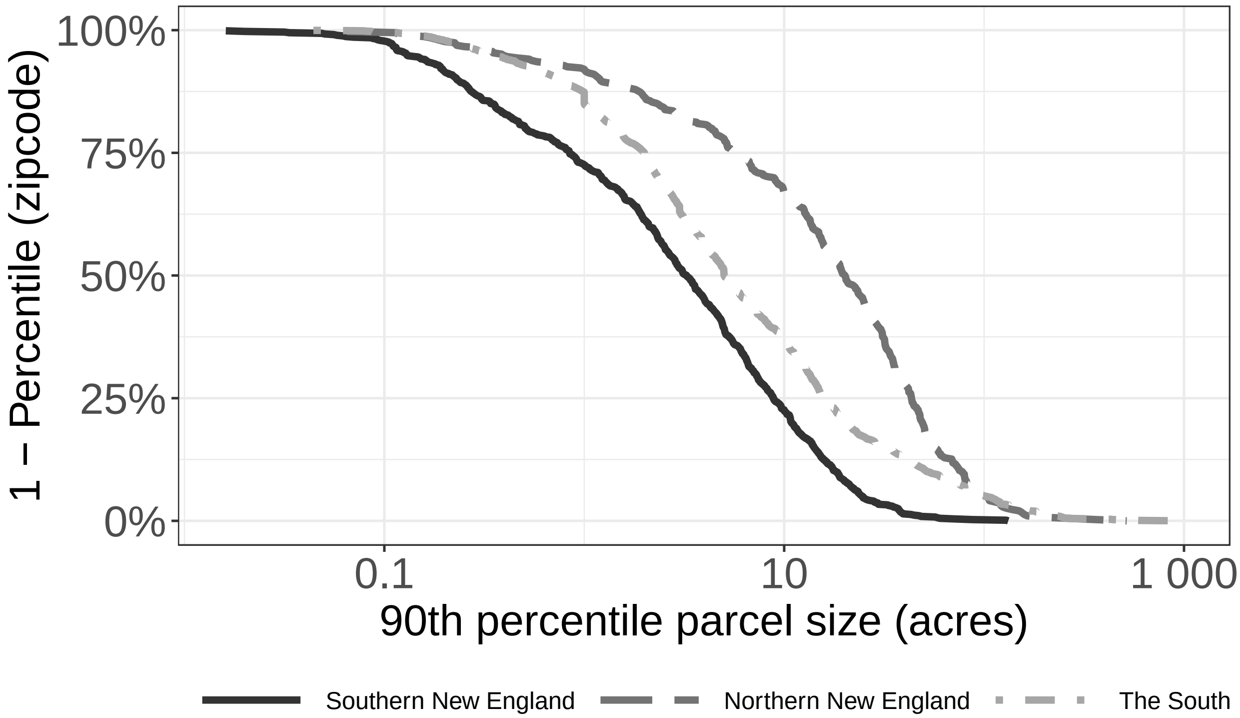
Source: Warren Group. In this figure, we rank Zip codes by the size in acres of the 90th percentile parcel within the Zip code and plot the size of the 90th percentile parcel against one minus the Zip code's percentile. The solid black series shows results using the most restrictive definition of buildable land (only including residential vacant land), while the gray dashed series shows results using the least restrictive definition (including all vacant and nonresidential developed land).

Figure 5: Buildable Land Distribution for Sale: Massachusetts versus South Carolina



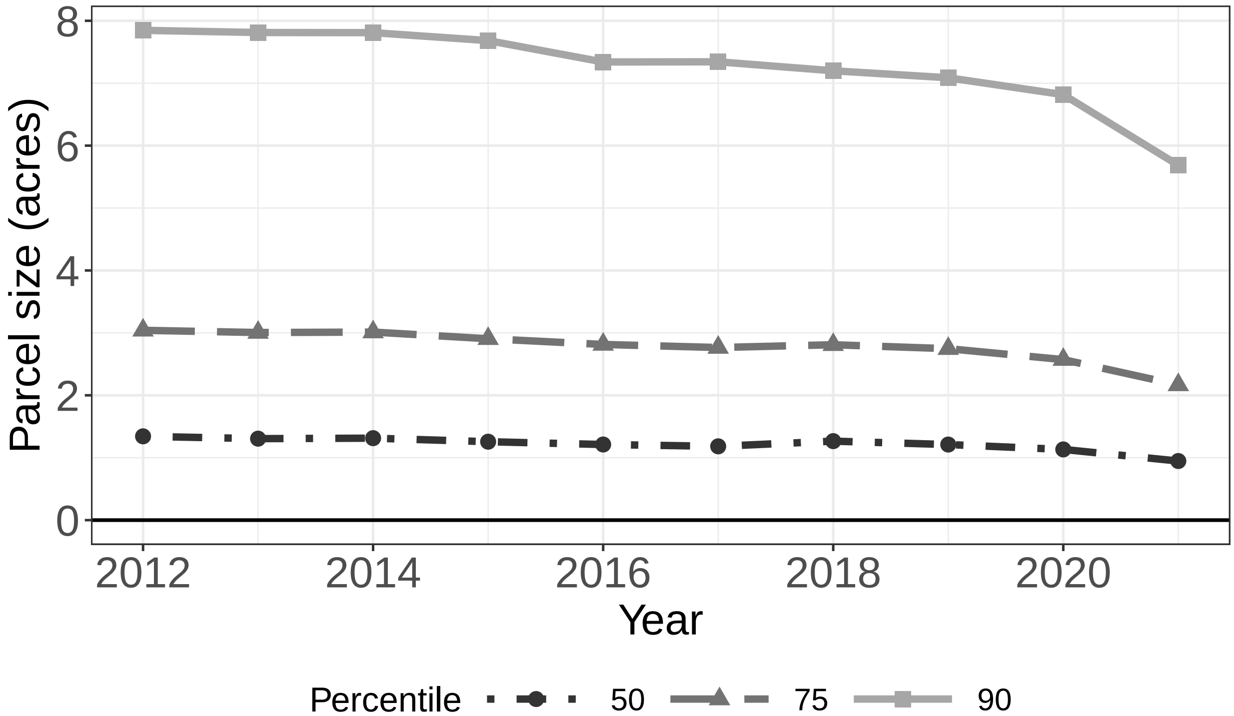
Source: CoStar. This figure plots the size in acres of buildable parcels for sale in July 2025 on the horizontal axis against one minus the percentile rank on the vertical axis. The solid black series shows results for Massachusetts, and the gray dashed series shows results for South Carolina.

Figure 6: Buildable Land Distribution by Zip code and Region



Source: CoreLogic. In this figure, we rank Zip codes by the size in acres of the 90th percentile parcel within the Zip code and plot the size of the 90th percentile parcel against one minus the Zip code's percentile. The solid black series shows results for southern New England (Massachusetts, Connecticut, and Rhode Island); the dark gray long-dash series shows results for northern New England (Vermont, Maine, and New Hampshire); and the light gray dot-dash series shows results for the South (Arkansas, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, and Virginia).

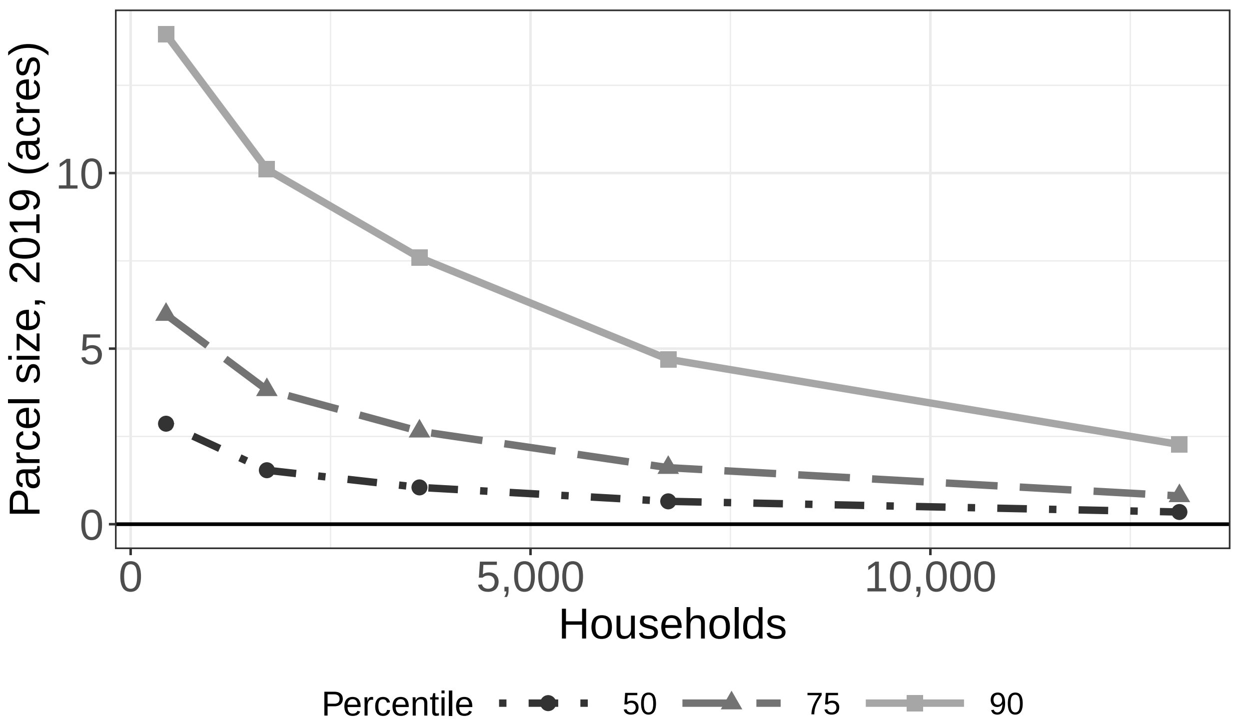
Figure 7: Buildable Land Distribution over Time



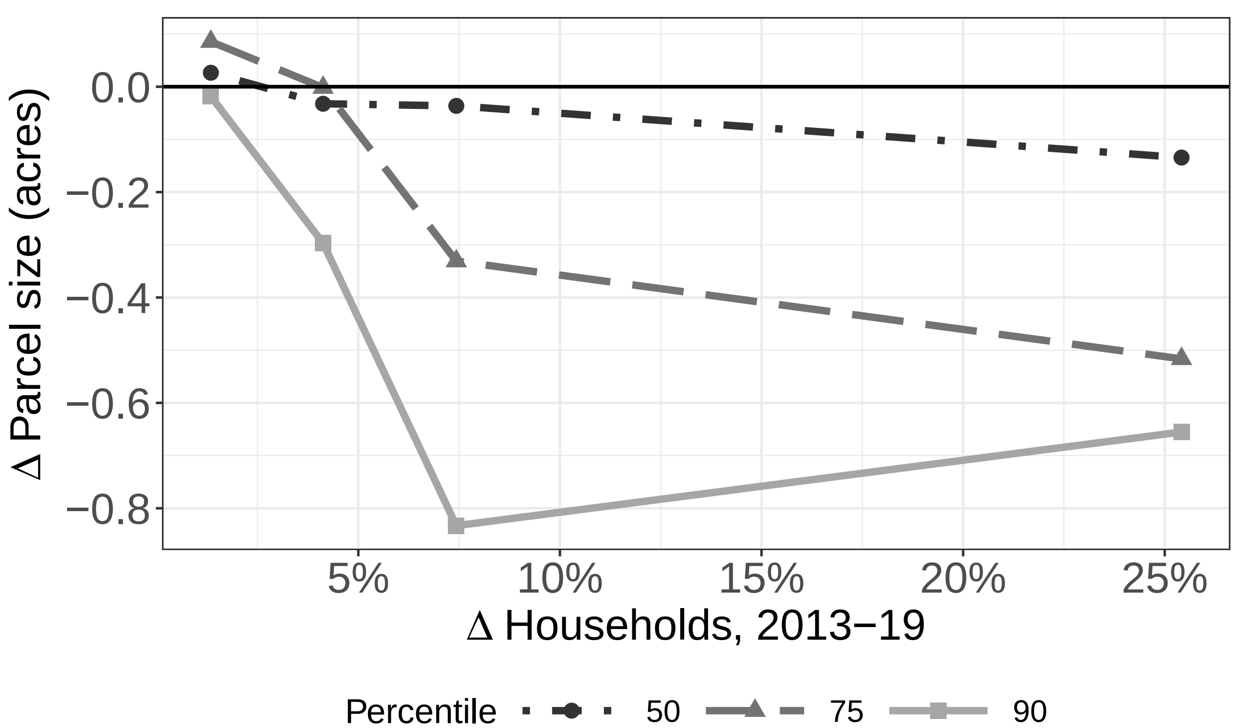
Source: Warren Group. The figure calculates the acreage of the median, 75th percentile, and 90th percentile buildable parcel for each Zip code and year from 2012 to 2021 and plots the average quantile across Zip codes for each year.

Figure 8: Buildable Land Distribution by Population

(a) Levels, 2019

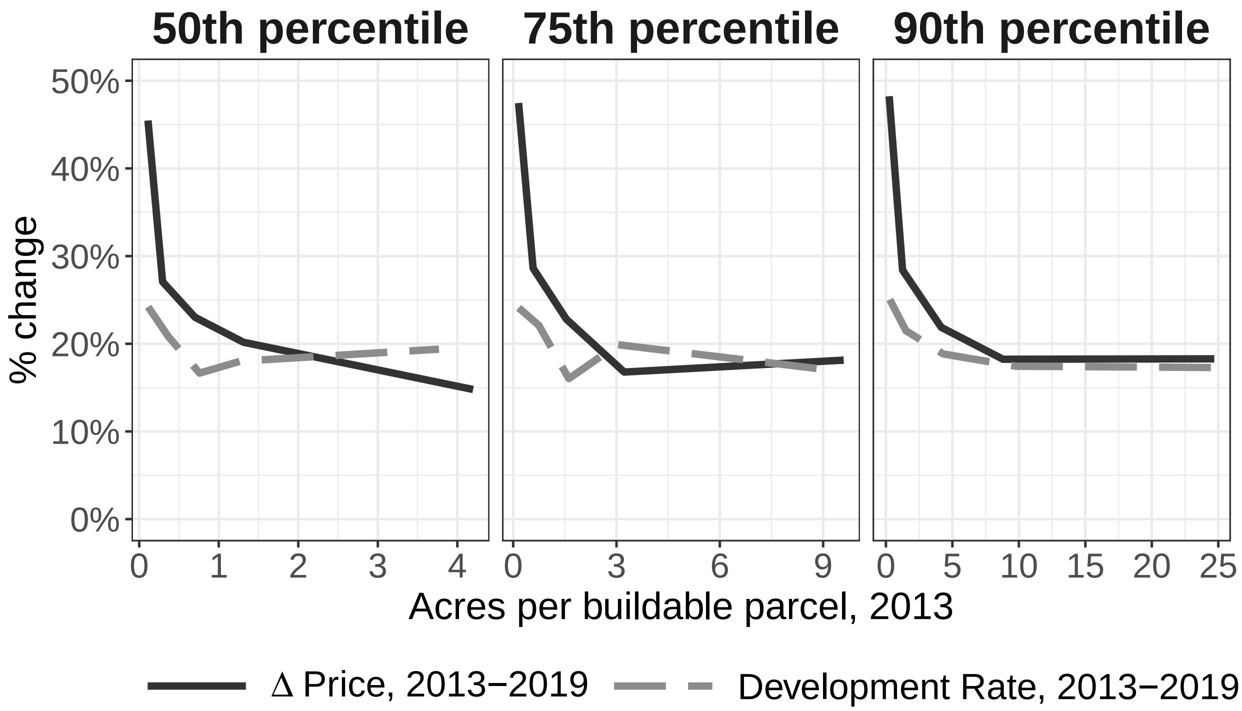


(b) Changes, 2013–2019



Source: Warren Group. The figure groups Zip codes into quintiles based on the acreage of the median, 75th percentile, and 90th percentile buildable parcel in 2013 and plots average house-price growth within each parcel between 2013 and 2019. Each panel shows results for a different quantile.

Figure 9: Price Growth and Development Rates by Availability of Large Buildable Parcels.



Source: Warren Group. The figure groups Zip codes into quintiles based on the acreage of the median, 75th percentile, and 90th percentile buildable parcel for each Zip code in 2013 and within each quintile calculates: (i) average price growth from 2013 to 2019 (solid black series) and (ii) the average fraction of buildable land developed between 2013 and 2019 (gray dashed series). The average fraction of buildable land developed between 2013 and 2019 is given by Development Rate$_{m,2019,2019-2013}$, as defined in equation (1).

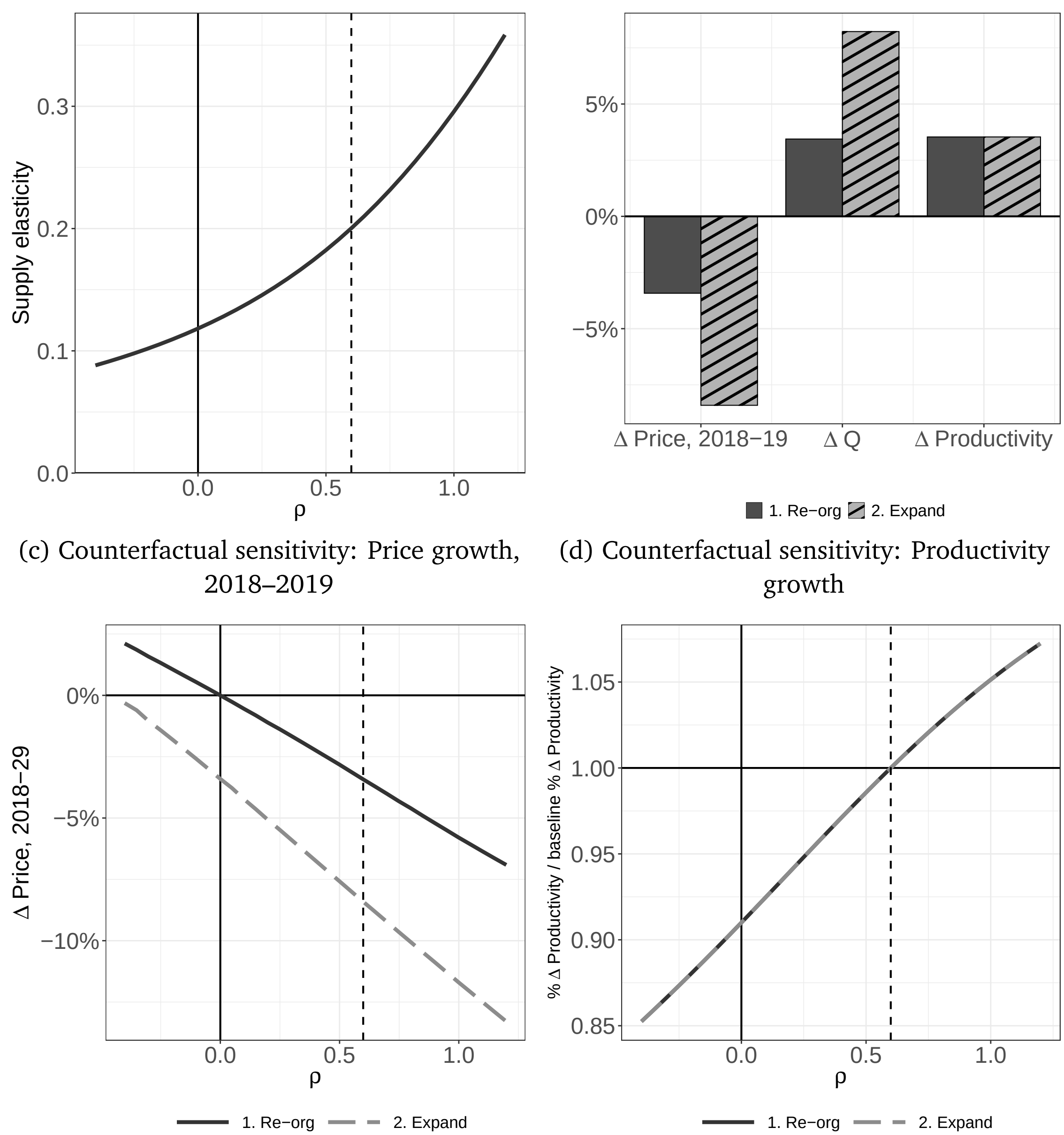
Figure 10: Model Results and Counterfactual Analysis

(a) Supply elasticity versus returns to scale

(b) Counterfactual results

(c) Counterfactual sensitivity: Price growth, 2018–2019

(d) Counterfactual sensitivity: Productivity growth



Sources: Authors' calculations and Warren Group. Panel (a) plots the modeled price elasticity of housing supply as a function of the returns-to-scale parameter ρ. A higher value of ρ indicates greater returns to scale in parcel size. The supply elasticity is calculated as $\Delta \ln Q^S / \Delta \ln P$, where ΔQ^S is the modeled increase in housing supply due to a 1 percent increase in house prices relative to 2018, and $\Delta \ln P = \ln(1.01)$. Panel (b) plots results of the land reorganization counterfactual (solid) and land supply expansion counterfactuals (dashed). The first column shows percentage point changes in house-price growth from 2018 to 2019. The second column shows percent changes in the quantity of floorspace produced. The third column shows percent changes in modeled developer productivity, measured as the ratio of floorspace produced to total (fixed + variable) costs and holding fixed baseline prices and the set of developed parcels. Panels (c) and (d) plot results from the land reorganization and land supply expansion counterfactuals for different values of ρ. Panel (c) shows the impact on house-price growth from 2018 to 2019 in percentage points. Panel (d) shows the impact on the percent change in productivity. The vertical dashed line in Panels (a), (c), and (d) shows the estimate from Column (4) in Table 5.

Tables.

Table 1: Summary Statistics: Warren Group Data

Variable	N	Mean	SD	p25	p50	p75	p90	p99
Panel A: Parcels.								
Parcel size (acres)	4,263,371	1.988	21.799	0.120	0.290	0.900	2.340	31.460
Residential vacant (acres)	193,278	3.328	15.130	0.150	0.520	2.020	6.533	48.000
SF residential (acres)	3,421,580	0.818	5.629	0.120	0.270	0.690	1.600	8.510
MF residential (acres)	49,468	1.564	11.294	0.120	0.190	0.390	1.320	30.180
Non-res vacant (acres)	65,854	9.276	31.729	0.090	0.870	6.910	22.547	119.000
Non-res developed (acres)	388,855	7.637	45.109	0.150	0.680	3.710	16.010	107.000
Panel B: Zipcodes.								
Residential vacant (share)	728	0.067	0.057	0.025	0.053	0.092	0.143	0.265
SF residential (share)	728	0.441	0.166	0.328	0.428	0.542	0.668	0.879
MF residential (share)	728	0.016	0.021	0.003	0.008	0.020	0.042	0.096
Non-res vacant (share)	728	0.064	0.075	0.016	0.042	0.081	0.153	0.399
Non-res developed (share)	728	0.383	0.136	0.289	0.387	0.468	0.553	0.723
All vacant (share)	728	0.131	0.098	0.058	0.108	0.184	0.260	0.464
All non-res (share)	728	0.514	0.158	0.412	0.522	0.621	0.701	0.856
Development rate, res vacant	654	0.077	0.129	0.012	0.031	0.084	0.171	0.716
Development rate, all vacant	665	0.051	0.102	0.008	0.018	0.044	0.113	0.561
Development rate, all nonres	666	0.016	0.053	0.002	0.005	0.012	0.029	0.209
House price (thous), 2013	728	322.734	159.355	227.155	283.613	363.332	497.400	986.476
% Δ Price, 2013-2019	728	24.711	16.991	10.521	25.642	34.036	43.979	80.010
Avg family income (thous), 2013	728	115.209	47.614	87.408	106.300	129.029	170.851	306.016
% Δ Income, 2013-2019	728	20.464	14.842	11.527	18.567	27.154	36.977	69.569
N hhlds (thous), 2013	728	5.683	4.759	1.903	4.274	8.253	12.199	21.124
% Δ N hhlds, 2013-2019	728	2.683	9.186	-1.715	2.194	6.205	11.268	36.438
Price/rent ratio, 2013	728	25.835	9.294	20.038	23.723	28.920	36.710	60.016
Panel C: Counties.								
Residential vacant (share)	24	0.039	0.017	0.024	0.045	0.048	0.057	0.067
SF residential (share)	24	0.585	0.191	0.529	0.616	0.720	0.772	0.793
MF residential (share)	24	0.013	0.019	0.004	0.009	0.014	0.020	0.083
Non-res vacant (share)	24	0.034	0.038	0.011	0.018	0.048	0.084	0.143
Non-res developed (share)	24	0.323	0.194	0.218	0.282	0.356	0.425	0.910
All vacant (share)	24	0.072	0.044	0.044	0.064	0.095	0.138	0.174
All non-res (share)	24	0.395	0.192	0.276	0.349	0.451	0.492	0.968
Development rate, res vacant	24	0.141	0.190	0.033	0.063	0.169	0.306	0.768
Development rate, all vacant	24	0.068	0.059	0.022	0.039	0.119	0.159	0.170
Development rate, all nonres	24	0.024	0.039	0.005	0.008	0.018	0.055	0.144

Sources: Warren Group, FHFA, and ACS. The table presents summary statistics for the Warren Group panel for parcels in Massachusetts, Rhode Island, and Connecticut. Unless otherwise noted, the summary statistics are for the 2019 cross section. Each row presents observation count, mean, standard deviation, and 25th, 50th, 75th, 90th, and 99th percentiles for the variable indicated in the first column. The unit of observation in Panel (a) is a parcel. The unit of observation in Panel (b) is a Zip code. The unit of observation in Panel (c) is a county. Variables are defined in Section 1. For development-rate calculations in Panels (b)and (c), we condition on markets where the development rate lies between zero and one.

Table 2: Summary Statistics: CoreLogic Data

Variable	N	Mean	SD	p25	p50	p75	p90	p99
Panel A: Residential vacant parcel size (acres)								
Southern New England	115,252	4.18	17.19	0.21	0.80	2.77	9.10	56.83
Northern New England	86,476	17.31	81.44	0.76	2.89	12.05	42.14	189.01
The South	1,204,853	10.32	49.25	0.29	0.97	4.00	21.00	160.00
Panel B: Residential vacant share (zipcode)								
Southern New England	859	0.026	0.059	0.003	0.011	0.032	0.061	0.169
Northern New England	586	0.020	0.039	0.000	0.004	0.025	0.058	0.204
The South	4,454	0.042	0.119	0.000	0.000	0.025	0.090	0.677

Source: CoreLogic. The table presents summary statistics for the CoreLogic data. Southern New England corresponds to Massachusetts, Connecticut, and Rhode Island; northern New England to Maine, New Hampshire, and Vermont; and the South to Arkansas, Georgia, Louisiana, Mississippi, North Carolina, South Carolina, Tennessee, and Virginia. Summary statistics are for the 2019 cross section. Each row presents observation count, mean, standard deviation, and 25th, 50th, 75th, 90th, and 99th percentiles for the variable indicated in the first column. The unit of observation in Panel (a) is a parcel. The unit of observation in Panel (b) is a Zip code.

Table 3: Buildable-land Isolation

Variable	N	k=1 Mean	k=1 Median	k=2 Mean	k=2 Median	k=5 Mean	k=5 Median	k=10 Mean	k=10 Median
Panel A: Parcels									
Distance to kth neighbor (meters)	103826	13.916	6.737	24.310	15.127	51.542	30.848	92.202	59.113
Share of neighbors: Residential vacant	103826	0.296	0.000	0.251	0.000	0.219	0.200	0.184	0.100
Share of neighbors: Developed	103826	0.650	1.000	0.697	1.000	0.733	0.800	0.768	0.900
Panel B: Zipcodes									
Frac. Isolated Acreage	721	0.788	0.818	0.705	0.728	0.589	0.594	0.491	0.467

Source: Warren Group. The sample restricts to parcels with nonmissing longitude and latitude data. Panel (a) takes parcels as the unit of analysis and shows the distance in meters and share of K nearest neighbors land-use type indicated in the row title. Panel (b) takes Zip codes as the unit of analysis and calculates the Zip-code-level share of residential vacant acreage on parcels with no other residential vacant parcels within the k nearest neighbors.

Table 4: House-price Growth by Buildable-land Distribution

	% Δ Price, 2013-2019					
	(1)	(2)	(3)	(4)	(5)	(6)
Variables						
N hhlds (thous), 2013	0.0109**		0.0075**	0.0103***		0.0065***
	(0.0040)		(0.0032)	(0.0027)		(0.0022)
Ln(Income), 2013	-0.1393**		-0.1467**	-0.0478		-0.0552
	(0.0619)		(0.0601)	(0.0380)		(0.0358)
Δ Ln(Income), 2013-2019	0.2197**		0.1975**	0.1310**		0.1039**
	(0.0828)		(0.0771)	(0.0505)		(0.0430)
Price / rent, 2013	0.0047***		0.0045***	0.0002		-3.03×10^{-5}
	(0.0015)		(0.0016)	(0.0008)		(0.0008)
Acres, p90 residential vacant		-0.0057***	-0.0038***		-0.0058***	-0.0042***
		(0.0018)	(0.0010)		(0.0014)	(0.0011)
Fixed-effects						
State				Yes	Yes	Yes
Observations	728	728	728	728	728	728
R^2	0.21283	0.09728	0.24721	0.55151	0.53222	0.59302
Within R^2				0.20945	0.17544	0.28262

SEs clustered by county
****: 0.01, **: 0.05, *: 0.1*

Source: Warren Group. The table shows results from estimating versions of equation (3) without fixed effects (Columns 1–3) and with state fixed effects (Columns 4–6). Columns (1) and (4) show results without Acres90_m as an explanatory variable, Columns (2) and (5) show results with only Acres90_m as an explanatory variable, and Columns (3) and (6) show results with all regressors.

Table 5: Developer Returns to Scale in Parcel Size

	Δ Ln(Development odds)		
	(1)	(2)	(3)
Variables			
Δ ln(Parcel size)	0.5751**	0.5824**	0.5991**
	(0.2747)	(0.2794)	(0.2816)
Δ ln(Price)	3.083	3.585	3.649
	(2.527)	(4.739)	(4.668)
Fixed-effects			
Year	Yes	Yes	Yes
County		Yes	Yes
Demo x County			Yes
Observations	4,931	4,931	4,931
F-test (1st stage), Δ ln(Price)	215.03	127.33	132.75
Effective F-test (1st stage), Δ ln(Price)	63.41	16.88	17.01

SEs clustered by county
****: 0.01, **: 0.05, *: 0.1*

Source: Warren Group. The table shows first difference estimates of coefficients in equation (9) for Zip codes from 2012 to 2021. The outcome variable is the change in log development odds, estimated as $\Delta \ln q_{mt}/(1-q_{mt})$. The explanatory variables are the change in the log average plot size in acres and the change in the log FHFA house-price index. Both the outcome variable and the log average plot size in acres are winsorized at the 1st and 99th percentiles. Column (1) has no fixed effects. Column (2) includes year fixed effects. Column (3) includes year-by-state fixed effects. Column (4) includes both year-by-state fixed effects and demographic controls that vary by year–state.

Online Appendix to "The Effect of Land Supply for New Homes on Residential Investment and House Prices"

Justin Katz and Paul Willen

April 2026

Table of Contents

A CoreLogic Data Cleaning

We start with the Boston Fed's maintained version of the CoreLogic Historical Property Basic data set for Massachusetts, Connecticut, Rhode Island, Vermont, New Hampshire, Maine, Virginia, North Carolina, South Carolina, Georgia, Tennessee, Mississippi, Louisiana, and Arkansas. We follow steps similar to our processing of the Warren Group data.

Data cleaning We drop rows with missing parcel identifiers and parcels larger than 10,000 acres and de-duplicate on parcel ID, assessed year, tax year, acres, and land-use codes. This forms the data set used to compare coverage over time in southern New England states.

2019 sample selection We then filter to parcels with nonmissing 2019 data. Assessors update parcel information as of the year given in the `assessed_year` field. Since we want information from 2019, we select one observation per parcel as follows. We keep the first tax year observation with the 2019 assessed year. If a parcel was not assessed in 2019, we keep the tax year observation with the 2019 tax year. If a parcel was not assessed in 2019 and has no 2019 tax year observation, we keep the earliest post-2019 tax year observation with a pre-2019 assessed year.

Land-use classifications We do not fully classify all land-use codes as we do with the Warren Group data because we only use CoreLogic data for select analyses. We do, however, classify parcels as residential vacant or not residential vacant. We do so with CoreLogic's harmonized `land_use_code` field. We classify a parcel as residential vacant if it falls into one of the following categories:

- 450: multifamily acreage
- 452: multifamily lot
- 453: residential open space
- 454: vacant mobile home
- 460: residential acreage
- 465: residential lot

Parcels with these land-use codes have de minimus assessed structure value, consistent with vacant land.

B Model Details

B.1 Derivation of equation (5)

From the FOC $C'_{mt}(H^*) = P_{mt}$ and the parameteriation of $C_{mt}(\cdot)$:

$$c_{mt} \cdot H^{\frac{1}{\alpha-1}} = P_{mt} \implies H^* = c_{mt}^{1-\alpha} \cdot P^{\alpha-1}. \tag{B.1}$$

Hence:

$$\pi_{mt}(P) = \alpha^{-1} \cdot c_{mt}^{1-\alpha} \cdot P^{\alpha} \tag{B.2}$$

$$= \pi_{0mt} \cdot P^{\alpha}, \tag{B.3}$$

where $\pi_{0mt} := \alpha^{-1} \cdot c_{mt}^{1-\alpha}$. Multiplying variable profits from floorspace per acre by parcel acreage and subtracting parameterized fixed costs yields equation (5).

B.2 Calibration details

This subsection provides additional details on our model calibration. Table B.1 summarizes results.

House prices and quantities We normalize 2018 house prices to one. We estimate real house-price growth of 2.9 percent from 2018 to 2019 using the FHFA repeat-sales price index for New England, deflated with the CPI-U. We normalize the total mass of buildable land to one. We calibrate the 2018 housing stock to 4.5, which matches the acreage-weighted ratio of residential developed land to residential vacant land in 2018 in the estimation sample for Table 5. We define housing markets as Zip codes and calculate the average parcel size in acres of residential vacant parcels to form the baseline distribution A_t.

Developers We calculate N_m as the ratio of total residential vacant acreage in Zip code m and average parcel size in Zip code m divided by the total residential acreage across all markets m. This ensures that $\sum_m N_m \cdot a_{mt} = 1$. We take $\rho = 0.60$ and $\alpha = 3.65$ from Column (3) of Table 5. We calculate $\ln(\pi_{0mt}/f_{mt})$ as the residuals in equation (9) winsorized at the 2.5th and 97.5th percentiles. By construction, residuals are mean zero across all markets; we shift the mean by a factor $\beta = -3.33$ so that the modeled 2019 development rate matches the average empirical development rate in the estimation sample for Table 5.

Housing demand We calibrate the price elasticity of housing demand as $\eta_1 = 1.0$, roughly the average demand elasticity estimated in Chodorow-Reich *et al.* (2024) (given in Table 2 of the published paper). We set the demand intercept $\eta_0 = -2.54$ so that the modeled 2018 equilibrium price equals 1.

Table B.1: Calibrated Parameters

Variable	Symbol	Value	Source
Prices and quantities			
2018 house price	P_{2018}	1	Normalization
Real price growth, 2018–2019	ΔP_{2019}	2.9%	FHFA repeat-sales index, CPI-U
Total mass of buildable land, 2019	$\sum_m N_m a_{m,2019}$	1	Normalization
2018 housing stock	Q_{2018}	4.5	Warren Group
Parcel size distribution	$\{a_{m,2019}\}_m$	3.2 (2.9)	Warren Group
Developer mass	$\{N_m\}_m$	4.9×10^{-4} (6.6×10^{-4})	Warren Group
Developers			
Supply elasticity	ρ	0.60	Table 5, Col. (3)
Supply curvature	α	3.65	Table 5, Col. (3)
Log profit–cost residual	$\{\ln(\pi_{0m,2019}/f_{m,2019})\}_m$	-2.6 (2.8)	Warren Group
Mean-shift factor	β	-3.33	Warren Group
Housing demand			
Price elasticity of housing demand	η_1	1.0	Calibrated
Demand intercept	η_0	-2.54	Calibrated

The table summarizes calibrated parameters. For rows with multiple parameter values (for example, the parcel size distribution), the Value column reports the mean and standard deviation across the parcels in the estimation sample.

B.3 Productivity calculations

We define productivity as total fixed and variable costs per unit of floorspace.

Variable costs per developed acre are:

$$c_{mt} \cdot \frac{\alpha - 1}{\alpha} \cdot (H^*)^{\frac{\alpha}{\alpha-1}} = c_{mt}^{1-\alpha} \cdot \frac{\alpha - 1}{\alpha} \cdot P^{\alpha}. \tag{B.4}$$

Fixed costs per developed acre are:

$$f_{mt} \cdot a_{mt}^{-\rho} \cdot \exp\big(\epsilon_{jmt}\big). \tag{B.5}$$

Taking expectations over j yields:

$$f_{mt} \cdot a_{mt}^{-\rho} \cdot E\Big[\exp\big(\epsilon_{jmt}\big) | \epsilon_{jmt} \leq \ln(\pi_{0mt}/f_{mt}) + \alpha \ln P_{mt}\Big]. \tag{B.6}$$

Note that for x distributed logistic with CDF F:

$$E\left[\exp(x)|x\leq c\right]=F(c)^{-1}\cdot\int_{-\infty}^{c}\exp(x)dF(x) \tag{B.7}$$

$$=F(c)^{-1}\cdot\int_{-\infty}^{c}\frac{\exp(x)\exp(-x)}{(1+\exp(-x))^2}dx \tag{B.8}$$

$$=F(c)^{-1}\cdot\int_{-\infty}^{c}\frac{1}{(1+\exp(-x))^2}dx. \tag{B.9}$$

Substituting $u=\frac{1}{1+\exp(-x)}$, meaning $\frac{du}{u(1-u)}=dx$:

$$\int_{-\infty}^{c}\frac{1}{(1+\exp(-x))^2}dx=\int_{u(-\infty)}^{u(c)}\frac{u}{1-u}du \tag{B.10}$$

$$=[-u-\ln(1-u)]_0^{u(c)} \tag{B.11}$$

$$=-u(c)-\ln(1-u(c)) \tag{B.12}$$

$$=\ln(1+\exp(c))-F(c). \tag{B.13}$$

Hence:

$$E\left[\exp\left(\epsilon_{jmt}\right)|\epsilon_{jmt}\leq\ln(\pi_{0mt}/f_{mt})+\alpha\ln P_{mt}\right]=\frac{\ln\left(1+\pi_{0mt}/f_{mt}+P_{mt}^{\alpha}\right)}{q_{mt}}-1. \tag{B.14}$$

Thus, productivity is:

$$\frac{c_{mt}^{1-\alpha}\cdot P^{\alpha-1}}{f_{mt}a_{mt}^{-\rho}E[\epsilon_{jmt}|\cdot]+\frac{\alpha-1}{\alpha}c_{mt}^{1-\alpha}P^{\alpha}}=\frac{P^{\alpha-1}}{(\alpha\pi_{0mt}/f_{mt})^{-1}a_{mt}^{-\rho}E[\epsilon_{jmt}|\cdot]+\frac{\alpha-1}{\alpha}P^{\alpha}}. \tag{B.15}$$

We have calibrated $\alpha, P, a_{mt}, q_{mt}$, and π_{0mt}/f_{mt} so we can calculate productivity using the formula in equation (B.15). As explained in the main text, all our productivity calculations hold P and q fixed at their 2018 baseline levels.

C Additional Tables

Table C.2: House-price Growth by Buildable-land Distribution: County Fixed Effects

	% Δ Price, 2013-2019		
	(1)	(2)	(3)
Variables			
nthou_hhlds_2013	0.0037**		0.0027**
	(0.0014)		(0.0011)
Ln(Income), 2013	-0.1122***		-0.1085***
	(0.0206)		(0.0208)
Δ Ln(Income), 2013-2019	0.0239		0.0221
	(0.0346)		(0.0327)
Price / rent, 2013	-0.0007		-0.0007
	(0.0005)		(0.0005)
Acres, p90 residential vacant		-0.0033***	-0.0019**
		(0.0010)	(0.0008)
Fixed-effects			
County	Yes	Yes	Yes
Observations	728	728	728
R^2	0.78254	0.72642	0.78861
Within R^2	0.26498	0.07531	0.28550

SEs clustered by county
****: 0.01, **: 0.05, *: 0.1*

Source: Warren Group. This table replicates Table 4, except that it includes county, rather than state, fixed effects. See the notes for Table 4 for details.

Table C.3: CoreLogic Coverage by State

State	**Coverage**
Southern New England	
CT	0.732
MA	0.694
RI	0.360
Northern New England	
ME	0.200
NH	0.636
VT	0.875
The South	
AR	0.834
GA	0.832
LA	0.381
MS	0.688
NC	0.744
SC	0.892
TN	0.849
VA	0.835

Source(s): CoreLogic. This table displays the fraction of total noncoastal area in each state covered by parcels in the CoreLogic data in 2019.