The Microgeography of Housing Supply

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We perform a comprehensive neighborhood-level analysis of housing supply. Predictions of floor space and housing unit supply elasticities using our estimates average 0.5 and 0.3 across all urban neighborhoods in the United States, exhibiting greater variation within than between metro regions. New construction accounts for about 50% of unit supply responses, with important additional roles for teardowns and renovations. Supply responses grow with central business district distance mostly from the increasing availability of undeveloped land, flatter land, and less regulation. Identification comes from variation in labor demand shocks to commuting destinations, as aggregated using insights from a quantitative spatial equilibrium model.

I. Introduction

Quantification of housing supply elasticities at a microgeographic scale is required to analyze a wide range of phenomena that involve neighborhood-level variation in housing demand within cities and regions. Targeted

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neighborhood investment for economic development (Hanson 2009; Busso, Gregory, and Kline 2013), new transportation infrastructure (Severen 2019), changes in labor demand conditions (Fogli and Guerrieri 2019), and changes in local amenities and public goods (Calabrese, Epple, and Romano 2011; Couture et al. 2019; Baum-Snow and Hartley 2020) all induce shifts in housing demand that vary across neighborhoods. The extent to which these changes affect the welfare of renters versus owners depends crucially on neighborhood-level estimates of housing supply elasticities. In addition, such elasticities are central for evaluating the efficacy of housing affordability policies (Davis, Gregory, and Hartley 2019; Favilukis, Mabille, and Van Nieuwerburgh 2023), understanding spatial variation in booms and busts within metro areas (Glaeser, Gottlieb, and Tobio 2012; Genesove and Han 2013; Guerrieri, Hartley, and Hurst 2013), and determining the extent to which urban growth takes the form of densification or sprawl (Glaeser, Gyourko, and Saks 2005). While the existing literature documents large differences in housing supply elasticities between cities (Saiz 2010), little evidence exists on how housing supply elasticities differ within cities. In this paper, we provide the first comprehensive examination of housing supply at the neighborhood level, facilitating quantitative analysis of a wide range of neighborhood-level phenomena and place-based policies.

This paper conceptually and empirically examines housing supply and its components for all residential census tracts in US metropolitan areas. Our investigation delivers new evidence on how floor space supply and housing unit supply decompose into teardowns, renovation of existing buildings, and new construction on newly developed and redeveloped land. Moreover, we quantify how each of the associated supply elasticities differs within cities as functions of distance to the center, land availability, building density, and zoning restrictions. As in Severen (2019), we use Bartik-type variation (Bartik 1991) in labor demand shocks to commuting destinations within metro areas for identification. Insights from a quantitative spatial equilibrium model help to conceptualize this identification strategy. To account for differences between metro areas, our analysis incorporates a finite mixture model (FMM) empirical setup, in which parameters that govern tract supply elasticities are allowed to flexibly differ between metro areas as functions of metro land unavailable for development, regulation, and developed land. Central to our analysis are tract-level measures of housing supply components and price indexes for housing services that are newly constructed using the Zillow Transaction and Assessment Database (ZTRAX; Zillow 2017), married with newly organized information on land cover. Our analysis is carried out in changes for the 2000–2010 period.

Across urban census tracts in our estimation sample, we estimate an average floor space supply elasticity of 0.42, an average housing units supply elasticity of 0.35, and an average land development elasticity of 0.09. Within floor space and unit supply, we separate out responses to demand shocks due to new construction, reductions in teardowns, and renovation of existing buildings. We find that new construction accounts for 55% of unit supply and 69% of floor space supply responses, with the remainder split roughly evenly between reduced teardowns and expansion or reconfiguration of existing structures. Only a small fraction of this new construction response comes on parcels that are already developed.

We uncover striking differences within metro areas in neighborhood-level housing supply elasticities as functions of location, available land, topography, and regulation. Land development as well as unit and floor space supply responses all grow with distance from central business districts (CBDs), flatten out in suburban areas, and then grow again at urban fringes. At CBDs, new construction accounts for a smaller share of these unit and floor space elasticities than in the average tract. Corresponding suburban elasticities are similar to the overall average supply elasticities cited above. Positive CBD distance profiles for supply elasticities are mainly driven by the fact that the fraction of land that is initially developed decreases moving away from CBDs. Tracts with more flat land and less stringent regulations also exhibit more elastic supply. Teardowns and renovation of existing units are in general not significantly related to CBD distance and developed fraction, though price growth spurs more new construction to replace teardowns on flatter land.

Using parameters estimated with data from about 50% of census tracts nationwide in the United States, we predict supply elasticities for all 50,410 tracts in 306 metro regions. Looking across all urban census tracts nationwide and accommodating both tract and metro region variation in factors that influence supply elasticities, we find that predicted elasticities range from 0.14 to 0.44 for unit supply and 0.33 to 0.70 for floor space supply in 25th and 75th percentile neighborhoods, with means of 0.29 and 0.51, respectively. Among the predicted elasticities, variation within metro areas exceeds the corresponding variation between metro areas. We confirm evidence in Saiz (2010) that supply elasticities are decreasing in metro area land unavailable for development, existing development intensity, and regulation, even conditional on these tract-level influencers.

We approach recovery of neighborhood-level housing supply elasticities as the fundamentally reduced-form problem of identifying coefficients in regressions of changes in tract-level housing quantities on changes in a tract-level home price index. The reduced-form estimation is microfounded on a stylized model of neighborhood new construction supply that explicitly distinguishes between land development and intensity of construction conditional on development. The housing production literature, notably Ahlfeldt and McMillen (2014) and Combes, Duranton, and Gobillon (2021), mostly focuses on developers' choices of capital intensity conditional on land development, leaving out consideration of the parcel selection margin. Our reduced-form estimates imply new construction floor space relative to land development supply elasticities of between 2 and 4, consistent with recent land share estimates of less than 0.34 in the context of standard models of housing production. In our model, the extensive land development margin of supply also plays an important role and depends crucially on the availability of developable sites at sufficiently low fixed costs, as shaped by topography, existing development, and regulation. In complementary work, Murphy (2018) structurally estimates a dynamic model of housing supply that predicts the timing and intensity of single-family home construction on undeveloped lots as a function of the path of expected future prices for housing services. Like in our analysis, his model accommodates cross-sectional variation in construction costs to fit intensive and extensive margin price responses. We stress, however, that at least 30% of new unit and floor space supply in the average tract come from endogenous teardown and renovation responses to price shocks. These are forces not captured by standard housing production or supply models, suggesting an important role for model-agnostic estimates that incorporate all margins of supply response.

The central challenge in identifying housing supply elasticities is to find an exogenous source of variation that shifts neighborhood-level housing demand but not local construction costs, land use regulations, parcel size, or land availability. To achieve identification, we use Bartik-type labor demand shocks to commuting destinations from each residential location as the fundamental source of variation in housing demand shocks, which feed through the commute time matrix to generate exogenous variation in home price growth across residential locations. These labor demand shocks are built using 1990 industry shares in commuting destinations interacted with national industry-specific employment growth rates after 2000. We follow Tsivanidis (2022) and nest our reduced-form estimation problem into an urban quantitative spatial equilibrium model in which residential demand in neighborhood i depends on resident market access (RMA_i), a coherent measure of access to employment from tract i. RMA_i amounts to the commute time discounted sum of employment in each commuting destination from location i, adjusted for labor supply competition effects from other commuting origins. Labor demand shocks in each potential commuting destination are used to generate a simulated counterpart to the change in RMA_i that, conditional on appropriate controls, is purged of shocks to tract housing productivity or changes in other unobserved tract-level housing supply factors. Construction of this simulated instrument uses predicted employment and population growth in locations beyond 2 kilometers of tract i

using 1990 tract employment shares by industry, excluding construction interacted with post-2000 national employment growth by industry. Structural estimation of this demand model yields parameters of the neighborhood demand system.

We aggregate our neighborhood-level housing supply elasticity estimates to the metro area level, accounting for the fact that the aggregation scheme is specific to the nature of demand shocks and to the degree of housing demand substitutability across neighborhoods. Aggregation of broad-based neighborhood-level demand shocks delivers average metro area–level supply elasticities that are considerably smaller than those found in Saiz (2010). Allowing for a high amount of demand substitution across tracts implies an average of region-level unit elasticity of 0.41, with a standard deviation of 0.11 and a rank correlation of 0.49 with Saiz's estimates. We show that our smaller elasticities come mostly because of the later and shorter time period of study than Saiz's 1970–2000 analysis. In addition, the nature of demand shocks used for identification and aggregation may be important. As neighborhoods become stronger demand substitutes, a shock affecting labor market opportunities in one location affects housing demand in a wider range of areas, as households are more willing to substitute across residential options to take advantage of lower housing prices in some places, thereby opening up more opportunities for supply elastic neighborhoods to be included. However, we note that because of the limited flexibility of parameters to differ across metros, we are somewhat less confident about levels of supply elasticities calculated using our estimates than their within-metro dispersion.

As an example application, we use our supply elasticity estimates to explore the welfare consequences of the Opportunity Zone (OZ) provisions of the 2017 Tax Cuts and Jobs Act. The OZ program targets about one-quarter of low-income census tracts with reduced capital gains taxes on new real estate investments. The resulting lower cost of capital associated with new construction in these neighborhoods is reflected in reduced marginal costs and outward (downward) shifts in neighborhood supply functions. The OZ program may also spur improvements in local amenities, thereby boosting local residential demand. Our analysis reveals that because OZ neighborhoods have among the lowest local supply elasticities in their metro areas, welfare gains from the program are smaller than if the program were implemented in almost any other neighborhood. In particular, we show that the potential gains in consumer surplus from implementing the same tax incentive in non-OZ neighborhoods is greater by about $5 million per tract on average. Moreover, these OZ tract gains are overstated by 34% if calculated using regional rather than tract-level supply elasticity estimates. Gains in producer surplus from demand increases are also smaller in OZ tracts than they would be for the same percentage demand growth in quantity terms for other types of locations.

Our empirical work delivers magnitudes of regional supply elasticity that are in line with other recent evidence. Gorback and Keys (2020) uses variation in international capital flows to ethnic neighborhoods to identify short-run local unit supply elasticities that average 0.1 across the largest 100 US metro areas. Cosman, Davidoff, and Williams (2018) confirm our evidence with the help of a calibrated dynamic theory that housing supply elasticities are increasing in the availability of buildable land at each CBD distance. Using identifying variation from foreign-born residents and fertility rates across Swiss municipalities and cantons, von Ehrlich, Schöni, and Büchler (2018) show, like us, that housing supply elasticities depend on geography and regulatory constraints. While estimated Swiss owner-occupied housing supply elasticities are similar in magnitude to our evidence for the United States, rental supply elasticities are considerably higher. Finally, Orlando and Redfearn (2021) use a structural vector autoregression to nonparametrically measure housing supply elasticities in each county nationwide in the United States. They find elasticities that are quantitatively similar to those discussed in this paper and declining over time. Some of this work uses housing units, while other papers use housing starts as supply measures. The housing production literature uses floor space or latent housing services in new construction instead as supply measures. Our paper helps to unify these literatures by systematically characterizing all margins of response of supply to price shocks in a unified way. In addition, we introduce an identification strategy that can be employed in many settings to structurally estimate quantitative spatial models.

II. Data

We compile information on housing and labor markets at the census tract level for all metropolitan areas in the United States. Using the ZTRAX data files supplemented with aggregate census and American Community Survey (ACS) data from 1990, 2000, 2010, and 2008–12, we construct various housing price and quantity measures. We measure local labor demand conditions using the place of work and journey to work tabulations in the 1990 and 2000 US Census of Population and the 2006 and 2010 Longitudinal Employer-Household Dynamics (LEHD) Origin-Destination Employment Statistics (LODES) data. Finally, we use remote sensing information on land cover in 2001 to measure baseline tract development intensity and topography and 2011 to construct changes in tract developed land. All data are keyed to 2000 definition census tracts, covering 50,410 unique tracts and 63,897 observations across 306 metro areas (with some spatial overlap across metros). The use of census tract geography allows us to conceptualize a data-generating process with a uniform price per efficiency unit of housing services within each location while also having sufficient transaction information to be able to construct a price index covering a large set of locations. Appendix A (apps. A–D are available online) has further details.

A. *Housing Quantities and Prices*

We construct housing stock and flow measures to facilitate unified decompositions of tract residential floor space supply responses into components. The total residential floor space in census tract i, S_i, is the amount of developed land L_i times the average number of housing units per developed parcel H_i/L_i times the average floor space per housing unit S_i/H_i. We think of floor space per land, $A_i = S_i/L_i$, as a key choice variable for housing developers. Log differencing, we have

$$\Delta\ln S_i = \underbrace{\Delta\ln L_i + \Delta\ln\frac{H_i}{L_i}}_{\Delta\ln H_i} + \Delta\ln\frac{S_i}{H_i}. \qquad (1)$$

(In the printed equation, a second brace labelled $\Delta\ln A_i$ spans $\Delta\ln\frac{H_i}{L_i} + \Delta\ln\frac{S_i}{H_i}$.)

We further decompose changes in units and floor space into those from new construction, teardowns and, renovations. For units, $\Delta\ln H_i = H_i^{R}/H_i + H_i^{U}/H_i + H_i^{T}/H_i + H_i^{E}/H_i$, where H_i^{R} refers to new units developed on already developed land (redevelopment), H_i^{U} refers to new units developed on land that has not been developed before (new development), H_i^{T} refers to the combination of full depreciation and teardowns and is always negative, and H_i^{E} refers to the loss or the addition of units due to reconfiguration within existing buildings (renovation). Correspondingly, we decompose changes in floor space $\Delta\ln S_i$ into $S_i^{R}/S_i + S_i^{U}/S_i + S_i^{T}/S_i + S_i^{E}/S_i$. While total new construction responses include both redevelopment and new development, we distinguish the former from the latter as they may have different cost structures.

Annual tract-level stocks and flows of units and floor space are aggregated from ZTRAX assessment files, which contain residential parcel–level information. These are reported about every 3 years from around 2000 until 2016, with improved geographic coverage over time. Data for missing years are filled in using the reported year built.[1] As a secondary source, we construct analogous measures using 2008–12 ACS data on new construction flows (5% sample) in calendar years 2000–2009 and 100% count stocks of occupied units from the 2000 and 2010 censuses.

To build census tract–level price indexes, we use ZTRAX transaction information as transcribed from local recorders of deeds. We include only arm's length transactions for resale or new construction, excluding deed

[1] Some rental buildings report only total square footage and do not break out the number of units. In these cases, we impute the number of rental units using the average square footage of units in other rental and condominium buildings of similar size in the tract.

transfers such as bank foreclosures and quitclaim deeds. We include residential units of all kinds but consider only individual buyer transactions, excluding those involving institutional buyers. We also exclude homes that sell more than nine times over our sample period. To fill out property attributes, we merge in 2016 assessment data.

Using standard methods described in appendix A, we construct repeat sales and hedonic price indexes for each tract and year 2000–2010, excluding tract-year combinations with fewer than 10 sales. Sufficient transaction information exists for only about half of the tracts in our sample.[2] To fill out a measure of home prices for tracts with incomplete ZTRAX coverage and to facilitate a 1990–2000 pretrends analysis, we also build a lower-quality hedonic price index using self-reported data from the 1990 and 2000 housing censuses and the 2008–12 ACS aggregated to the census tract level.

B. Satellite Data and Regulation

We construct topographic information using the Scientific Investigations Map 3085, derived from the US Geological Survey's National Elevation Database. This dataset uses raster information on slope and elevation range for all 30×30-meter land pixels within a 0.56-kilometer radius (1 square kilometer) of each pixel to classify it into one of nine categories that describe how flat or hilly the surrounding area is. We focus on the fraction of land area surrounded by flat plains as our main topographic measure. Flat plains are defined to have a slope of less than 8% in more than half of these nearby pixels and an elevation range of less than 15 meters in this 1-square-kilometer region.

We construct tract developed fraction from the National Land Cover Database (NLCDB) for 2001 and 2011. In addition to reporting other classes of land coverage, the NLCDB provides four categories of development (0%–19%, 20%–49%, 50%–79%, 80%–100%) for each 30×30-meter cell nationwide. To impute average developed fraction, we aggregate to tracts after assigning pixels to category midpoints. Because the historical assessment data for 2000 is incomplete, we use the NLCDB and ZTRAX geocodes to impute whether each 2001–10 new construction property is redevelopment. We consider a given pixel developed as of 2001 if it was coded as high or medium development intensity in the 2001 NLCDB land cover data.

We spatially aggregate tract data to construct various metro area–level land unavailability measures. To be consistent with Saiz (2010), we calculate the fraction of area within 50 kilometers of the CBD of each region that is

[2] Most dropped tract years have zero transactions. As such, this count restriction drops only 8% of tract year observations in 2000 and 14% in 2010, with a minor impact on results.

undevelopable because of steep slopes, water, or wetlands. We also construct the fraction that is developed as of 2001.[3] To measure regulation, we use the 2005 Wharton Residential Land Use Regulatory Index (WRLURI), which is collected for a random sample of municipalities and aggregated to metro regions.

C. *Population, Employment, and Commutes*

The Census Transportation Planning Package (CTPP) reports tabulations of 1990 and 2000 census data by residential location, work location, and commuting flow. The 1990 CTPP assigns microgeographic units the size of census tracts or smaller to regions, which roughly correspond to metropolitan areas. These partially overlapping regions form our study area.

For 2006 and 2010, we use the LEHD origin-destination employment statistics (LODES) data to measure employment by industry and place of work. As this dataset does not have commute times, we maintain year 2000 commute times for these later years.

Census tract information for 1970–2010 from the Neighborhood Change Database is used to measure aggregate outcomes and to control for pretreatment trends in observables.

D. *Summary Statistics*

The estimation sample includes all tracts for which the 2000 Zillow unit stock is less than 25% below the occupied housing stock reported in the 2000 census and for which the repeat sales index can be calculated in 2000 and 2010. To reduce noise associated with using small quantity bases, we exclude 206 tracts that have fewer than 500 housing units in 2000. Because the CTPP and LODES fully cover our sample area, these datasets do not introduce any additional sample constraints.

Summary statistics for housing quantities are presented in panel A of table 1. The average 2000–2010 growth rate for units ($\Delta \ln H_i$), which incorporates teardowns, is 7% based on Zillow and 8% based on census data. Average construction rates of new units across tracts during the same sample period ($(H_i^{\mathrm{R}} + H_i^{\mathrm{U}})/H_i$) are 10% based on Zillow data and 12% based on the census/ACS data, with 80% of this new construction occurring in 2000–2006 in the average tract. An average of 3% of the housing stock was lost because of teardowns and depreciation. There was no average change in units from building renovations.

[3] Variants of these two measures for which we instead aggregate to the metro area level—from the CBD to within 50% or from the CBD to within 100% of the distance from the CBD to the furthest tract in each metro—yield similar results.

TABLE 1
Summary Statistics

	Mean	SD	Observations	Tracts
	A. Tract Housing Quantity Changes, Estimation Sample			
Stock of housing units, census, 2000–2010	.08	.22	30,840	24,532
New units, census/ACS, 2000–2009	.12	.20	30,829	24,521
Stock of housing units, Zillow, 2000–2010	.07	.19	30,840	24,532
New units, Zillow, 2000–2006	.08	.15	30,840	24,532
New units, Zillow, 2000–2010	.10	.18	30,840	24,532
New units on developed land, 2000–2010	.03	.06	30,840	24,532
Teardown + renovation units, Zillow, 2000–2010	−.03	.10	30,836	24,528
Renovation units, Zillow, 2000–2010	−.00	.06	30,380	24,095
Floor space, Zillow, 2000–2010	.14	.26	30,384	24,099
New floor space, Zillow, 2000–2010	.13	.22	30,395	24,110
Teardown/renovation floor space, Zillow, 2000–2010	.01	.16	30,379	24,094
Renovation floor space, Zillow, 2000–2010	.03	.13	30,380	24,095
Developed land, 2001–2011	.08	.12	30,840	24,532
	B. Tract Home Price Changes, Estimation Sample			
Repeat sales index, 2000–2006	.64	.35	30,502	24,233
Hedonic index, 2000–2006	.62	.34	29,274	23,239
Repeat sales index, 2000–2010	.25	.38	30,840	24,532
Hedonic index, 2000–2010	.25	.35	29,424	23,378
Census index, 2000–2010	.54	.28	30,694	24,417
	C. Tract-Level Supply Influencers, Estimation Sample			
Fraction of land area developed, 2001	.33	.21	30,840	24,532
Fraction of land area flat	.41	.43	30,840	24,532
Wharton real estate index (municipality-level variation)	.28	1.02	12,367	10,016
Residential FAR (eight cities)	1.76	1.50	2,128	1,714
Fraction of way from CBD to metro edge	.27	.21	30,840	24,532
	D. Tract Employment and Population Variables			
Tract employment, 2000–2010, regions in estimation sample	−.19	.87	56,043	42,755
Tract-level Bartik instrument, 2000–2006, regions in estimation sample	.08	.05	56,274	42,902
RMA, 2000–2010, estimation sample	.04	.05	30,840	24,532
Simulated RMA, 2000–2006, estimation sample	.04	.01	30,840	24,532

Note.—All changes are in percentage terms. The full study region includes the 50,410 unique census tracts in the 306 partially overlapping metro regions with 1990 information on tract employment. The estimation sample includes 24,532 equally weighted unique tracts in 169 regions with at least 10 housing market transactions in 2000 and 2010 in the ZTRAX data. It excludes tracts for which the 2000 ZTRAX housing unit counts are more than 25% below the 2000 census count or tracts with fewer than 500 ZTRAX housing units in 2000. Within estimation sample tracts, 2.6% experienced zero growth in developed land, and 6.1% experienced zero new construction.

The average 2000–2010 growth in floor space ($\Delta \ln S_i$) at the tract level is 14%. Out of this, the floor space added through new construction is about 13%. That is, new units are typically larger than existing units. Renovation of existing units expands total floor space by 3% on average. The loss of floor space due to teardowns and demolitions averages 2%.

Panel B in table 1 shows that average 2000–2006 repeat sales and hedonic price index growth rates are similar at about 0.63. For 2000–2010, average growth rates are 0.25 for each, reflecting the 2007–8 housing market crash. The correlation between the two Zillow indexes is 0.92 for the 2000–2010 period, but those with the census index are only about 0.43 for both Zillow-based indexes. Because of the slightly better coverage of the repeat sales index, we use this as our primary price measure throughout the analysis.

Figure 1*A* shows kernel densities of fraction flat and fraction developed. Both are bimodal. Fraction flat has modes near the extremes of 0 and 1, while fraction developed is a smoother distribution with modes near 0 and 0.4. Figure 1*B* shows that both decline on average with CBD distance, though fraction developed declines more rapidly. Figure 1*B* also shows that both floor area ratio (FAR) and the Wharton index fall with CBD distance out to about 15% of the way to the urban fringe. As the Wharton index is measured at the municipality level, its decline within this range of CBD distance is fully due to between-region variation from

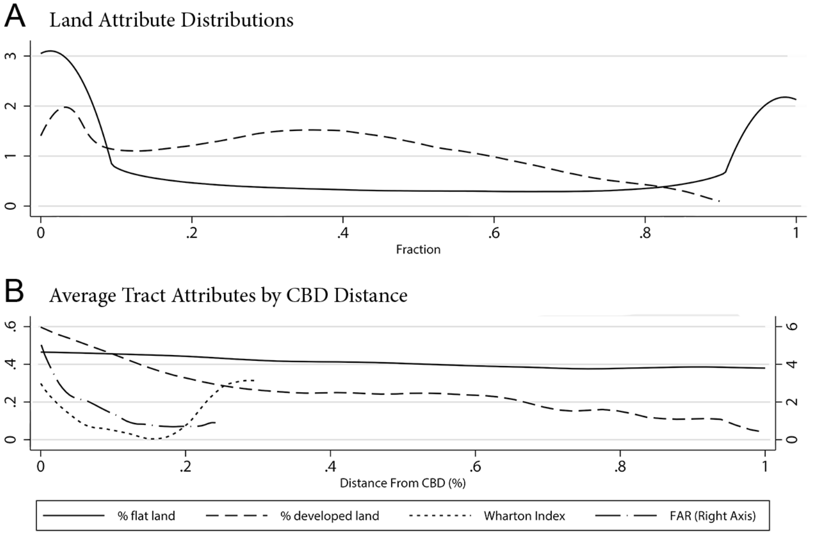

FIG. 1.—Development, topography, and regulation. Wharton index and FAR are shown for only CBD distances with good coverage.

increased representation of less dense central cities, which are typically less heavily regulated. The Wharton index rises steeply beyond that such that land use in municipalities 30% of the way to the urban fringe is on average more heavily regulated than at CBDs. Beyond 30%, we have no FAR data and we do not have sufficient Wharton index coverage to precisely measure regulation.

III. Conceptual Framework

We are interested in recovering estimates of γ_{ir} in the reduced-form expression below, where Q^s_{ir} denotes a measure of housing quantity in tract i of metropolitan area r, P_{ir} is the price per unit of housing services, and region fixed effects θ_r capture region-specific factors that influence construction costs:

$$\ln Q^s_{ir} = \theta_r + \gamma_{ir} \ln P_{ir} + u_{ir}, \tag{2}$$

where u_{ir} includes supply shifters within metro areas both observed and unobserved. We allow γ_{ir} to depend on tract i's observed heterogeneity, including initial building density, geographic features, and distance to the CBD in metropolitan area r. Because of the durability and immobility of housing, (2) is likely to hold with a greater γ_{ir} for price growth than for price declines (Glaeser and Gyourko 2005; Goodman 2005). For this reason, despite using price and quantity information for 2000–2010, we rely on the 2000–2006 period for demand shocks. During this time, price growth was positive in 98% of the tracts in our sample, more so than for any other period in our data.

In this section, we first sketch a simple model of neighborhood housing supply for new construction. While stylized, the model delivers a natural decomposition of the residential floor space supply elasticity into intensive (floor space per parcel) and extensive (parcel development) margins. It delivers a theoretical basis for the floor space and developed land supply elasticities we measure in the empirical work, provides rough calibrated quantification of the intensive margin component, and microfounds our empirical specifications. The drawback of this model is that its static formulation makes it easier to understand comparisons of new development across neighborhoods in the cross section, whereas the empirical work additionally compares changes over time for identification reasons. This requires some adjustments (developed in sec. V.E) to relate our empirical estimates to quantitative implications of the supply model.

We incorporate neighborhood housing supply functions into a spatial equilibrium model that links neighborhood housing and labor markets in an urban area. This part of the model theoretically justifies the instruments and helps guide the OZ application in section VII.

A. *Housing Supply*

We analyze an environment in which competitive developers with the same technology produce housing on some land parcels in each neighborhood. As the model is static, it is most natural to view it as describing comparisons of housing supply responses across different neighborhoods that are ex ante identical but experience different exogenous increases in the price of housing services. The key object delivered by the model that is relevant for the empirical work is a description of relationships between housing stocks and prices across these ex ante identical neighborhoods.

A representative developer only builds on land parcels with fixed development costs that are sufficiently low such that the variable profit minus fixed development cost is weakly positive. Conditional on development, the amount of floor space supplied on each parcel in neighborhood i is A_i. A_i is chosen on the basis of tract housing productivity, parcel size, and demand conditions summarized by the uniform price per unit of housing services P_i.

Developers combine land and capital to produce housing services. Each building lot l in neighborhood i has a fixed lot size, faces the same continuous variable cost function $C_i(A_i)$, and has the lot-specific fixed development cost g_{il}. The fixed lot size assumption reflects land assembly frictions that are likely to bind over the 5–10-year time horizon that is the focus of our empirical analysis (Brooks and Lutz 2016). The fixed cost g_{il} captures permitting and land preparation costs plus the potential opportunity cost associated with exercising the real option to develop. Each tract has its own continuous distribution of fixed development costs $F_i(x)$.

The profit associated with building on parcel l in neighborhood i is

$$\text{profit}_{il} = P_i A_i(P_i) - g_{il} - C_i(A_i) - p_{il},$$

where p_{il} is the endogenous parcel acquisition price. Imposing zero profits and perfect competition, we have

$$p_{il} = C_i(A_i(P_i))\left(\frac{d\ln C_i(A_i(P_i))}{d\ln A_i} - 1\right) - g_{il}.$$

This is the bid rent function for lot l in neighborhood i. The first term reflects the intuition that more development implies greater variable profits, which get capitalized into a higher parcel price. The second term reflects capitalization of the fixed development cost into the parcel price. Henceforth, consistent with Cobb-Douglas production, we assume that $(d\ln C/d\ln A) - 1 = \phi > 0$. If we normalize the opportunity cost per unit of land to 0, this means that the fraction of land developed in each tract is $F_i[\phi C_i(A_i(P_i))]$. Differentiating the developed land supply function yields

$$\gamma_i^{\text{land}} = \frac{f_i(\phi C_i[A_i(P_i)])}{F_i(\phi C[A_i(P_i)])}\frac{\Delta \ln A_i(P_i)}{\Delta \ln P_i}\phi P_i A_i(P_i). \tag{3}$$

(3) reveals that tracts with a greater density of parcels available for development at the fixed cost that equals marginal variable profit exhibit more elastic land supply. Details are in appendix B.

Though the reduced-form nature of the empirical work allows us to avoid imposing functional form assumptions, to get a sense of magnitudes we parameterize with an example that delivers a convenient form. Consistent with evidence in Combes et al. (2021), we use a Cobb-Douglas production technology with land share α and a tract-specific housing productivity, resulting in the parcel-level housing services supply function $A_i(P_i) = \rho_i P_i^{(1-\alpha)/\alpha}$. We assume that fixed costs follow the Frechet distribution $F_i(x) = \exp(-\Gamma_i x^{-\lambda})$, with the common dispersion parameter $\lambda > 1$ and the tract-specific scale parameter $\Gamma_i > 0$. The resulting floor space supply elasticity is

$$\frac{\Delta \ln S_i}{\Delta \ln P_i} = \underbrace{\frac{1-\alpha}{\alpha}}_{\Delta \ln A_i / \Delta \ln P_i} + \underbrace{\alpha^{-1-\lambda} \lambda \rho_i^{-\lambda} P_i^{-\lambda/\alpha} \Gamma_i}_{\Delta \ln L_i / \Delta \ln P_i}. \tag{4}$$

The first term reflects developers' responses in the quantity of housing services supplied per parcel. With α estimated to be 0.2–0.33 in the literature, $(1-\alpha)/\alpha$ is between 2 and 4. The second term reflects the extensive margin response, which is increasing in the scale parameter Γ_i and decreasing in the initial price level P_i. Fixed cost distributions in tracts with a higher Γ_i have higher means and variances and hence thicker right tails. This implies a higher density of land available for development at the marginal variable profit and hence higher γ_i^{land}. We expect that tracts with lower initial development density, more flat land, and less stringent regulation have fixed cost distributions with higher scale parameters, Γ_i, and hence more responsiveness along the extensive supply margin.[4] In addition, a higher initial price in tract i implies a thinner right tail of the fixed cost distribution and hence less land available for development at the marginal fixed cost, which in turn causes the extensive margin to be less responsive.[5,6]

B. Housing Demand

We incorporate housing supply conditions that differ across locations within cities into a variant of the quantitative urban model developed by Ahlfeldt et al. (2015). While tracing out housing supply functions is ultimately about estimating reduced-form impacts of housing demand

[4] In the empirical work, we recognize that Γ_i and ρ_i may additionally depend on unobserved tract characteristics. We also recognize that these same attributes may be supply shifters.

[5] If P_i is too low or the minimum of the support of $F_i(x)$ is too high, $\gamma_i^{\text{space}} = \gamma_i^{\text{land}} = 0$.

[6] The equilibrium split of $(A_i \equiv S_i/L_i)$ into floor space per unit (S_i/H_i) and units per parcel (H_i/L_i) depends on the composition of housing demand (e.g., families vs. singles), which neither our data nor our identification strategy is well suited to handle.

shocks on housing quantities and prices, this part of the theory is helpful in operationalizing this goal in three ways. First, the model shows how to leverage variation across space within cities in local labor demand shocks to isolate exogenous variation in housing demand shocks across census tracts. We show how housing demand conditions in each census tract i can be summarized through RMA_i, which is the sum of commute time discounted wages available to residents of tract i. This object can be calculated using data on counts of workers and residents in each tract. Shocks to wages in commuting destinations are reflected as shocks to RMA_i. Second, the model makes clear the conditions required for census tract–level Bartik shocks to represent a valid source of empirical identification. Finally, the model delivers enough structure to estimate parameters governing neighborhood demand conditions used to perform welfare analysis of place-based policies, as in section VII. Detailed derivations and further discussion of key model equations are in appendix C.

1. Setup

While the main empirical work uses data for over 150 metros, our focus is on within-metro variation in housing supply elasticities. As such, the model is of a single metro area.

A continuum of ex ante identical workers indexed by ω chooses residential tract i, work tract j, and industry of work k within the metro area. They receive productivity shocks $z_{ijk\omega}$ over commute origin-destination and industry triplets and preference shocks $v_{i\omega}$ over residential locations. The preference shocks are revealed first, leading agents to first choose residential locations and housing while anticipating the quality of accessible employment opportunities before productivity shocks are revealed. Productivity shocks are then revealed, and agents choose work locations.

The indirect utility of living in tract i, commuting to tract j, and working in industry k is

$$v_{ijk\omega} = \frac{v_{i\omega} B_i z_{ijk\omega} w_{jk}}{P_i^{1-\beta} e^{\kappa \tau_{ij}}}, \tag{5}$$

where B_i is a local amenity, w_{jk} is the price of a unit of skill in commuting destination j and industry k, P_i is the price of one unit of housing services in i, and $\kappa\tau_{ij}$ is the fraction of time spent commuting.

The productivity shock $z_{ij\omega}$ is drawn from the Frechet distribution with shape parameter ε. Following Couture et al. (2019) and Tsivanidis (2022), we incorporate a nested preference shock over residential locations $v_{i\omega}$. This shock is also distributed Frechet but with shape parameters η and ψ, where η is the elasticity of substitution in demand between neighborhoods in the same municipality and ψ is that between neighborhoods in different municipalities.

2. Resident Market Access

If we solve the model backward, conditional on living in residential location i, the probability that work location j provides the highest utility is

$$\pi_{ij|i} = \frac{\sum_k \left[w_{jk} e^{-\kappa\tau_{ij}}\right]^{\varepsilon}}{\sum_k \sum_j \left[w_{j'k} e^{-\kappa\tau_{ij'}}\right]^{\varepsilon}} \equiv \frac{\sum_k \left[w_{jk} e^{-\kappa\tau_{ij}}\right]^{\varepsilon}}{\mathrm{RMA}_i}, \tag{6}$$

where RMA_i summarizes access to employment opportunities from residential neighborhood i.

Before the productivity shock is revealed, individuals evaluate the expected wages net of commuting costs associated with residing in each tract. Solving for the expected maximum utility tract yields the population supply function to tract i:

$$\pi_i = \mu \left[\sum_{i' \in m(i)} \left(B_{i'} P_{i'}^{\beta-1} \mathrm{RMA}_{i'}^{1/\varepsilon}\right)^{\eta}\right]^{\psi/\eta - 1} \left(B_i P_i^{\beta-1} \mathrm{RMA}_i^{1/\varepsilon}\right)^{\eta}. \tag{7}$$

This expression reflects the attractiveness of neighborhood i's amenities and labor market opportunities as balanced against its housing cost. This attractiveness is relative to the attractiveness to other neighborhoods in tract i's municipality $m(i)$, captured by the object inside the summation. μ is an endogenous scalar that is set either to ensure everybody has a place to live (in a closed city with a fixed population) or to summarize the attractiveness of an outside option (in an open city).

Equilibrium commute flows follow a standard gravity equation in commute time τ_{ij}:

$$\ln \pi_{ij} = \ln(\pi_{ij|i}\pi_i) = a_i + b_j - (\kappa\varepsilon)\tau_{ij}. \tag{8}$$

That is, a regression of log commute probabilities between each origin-destination pair on origin and destination fixed effects plus commute time τ_{ij} recovers an estimate of the parameter bundle $\kappa\varepsilon$. We estimate $\kappa\varepsilon$ using separate flow-weighted commuting gravity regressions like (8) with origin and destination fixed effects in 2000 for each metropolitan region.[7]

Recognizing that the labor supply to tract j is $\Sigma_i \pi_{ij}$, we have

$$L_j = \mu \sum_k \left[w_{jk}^{\varepsilon}\right] \mathrm{FMA}_j, \tag{9}$$

[7] Across the 306 regions in our broad sample, the median estimated elasticity of commuting flow with respect to one-way commuting minutes in 2000 is −0.04, the minimum is −0.11, and the maximum is −0.01. Estimates of $\varepsilon\kappa$ are about half as large in absolute value in big cities like New York and Los Angeles relative to small cities like Bryan–College Station, Texas. This reflects the fact that households in bigger cities are willing to travel longer to reach work destinations.

where firm market access FMA_j is a measure of the access to workers experienced by firms in tract j. Plugging into the definition of RMA_i in (6) delivers the following system of equations:

$$\mathrm{FMA}_j = \sum_i \frac{e^{-\kappa\varepsilon\tau_{ij}}\pi_i}{\mathrm{RMA}_i}, \tag{10}$$

$$\mathrm{RMA}_i = \sum_j \frac{e^{-\kappa\varepsilon\tau_{ij}}L_j}{\mathrm{FMA}_j}. \tag{11}$$

Using data on employment L_j, residents π_i, the parameter cluster $\kappa\varepsilon$, and commute times τ_{ij}, we calculate FMA_j and RMA_i by solving this system in 2000, 2006, and 2010.

As individuals make housing consumption decisions before productivity shocks are revealed, residents of tract i have expected housing demand $(1-\beta)(\bar{y}_i/P_i)$, where $\bar{y}_i$ is the expected income associated with living in i. The resulting log aggregate residential floor space demand in tract i is

$$\ln S_i^d = \ln\rho_{\mathrm{HD}} + \frac{1}{\varepsilon}\ln(\mathrm{RMA}_i) + \ln\pi_i - \ln P_i. \tag{12}$$

This object is increasing in RMA_i conditional on population π_i because greater RMA_i is associated with greater income for tract residents. Conditional on P_i, equilibrium tract residential population π_i is also increasing in RMA_i, as seen in (7). Thus, shocks to RMA_i result in housing demand shocks. This is the key insight used for identification in the empirical work.

The reduced-form empirical work uses the housing supply equation (2) in tandem with the housing demand equation formed by substituting (7) into (12). Credible identifying variation in P_i must come from a component of RMA_i that is cleansed of variation in housing productivities and lot sizes. Section IV lays out how we isolate such variation using a simulated version of RMA_i based on Bartik-type labor demand shocks in commuting destinations for residents of tract i.

3. Equilibrium

Combining conditions governing population supply to residential tracts (7) and labor supply to work tracts (9) and imposing housing market clearing yields conditions describing equilibrium tract population and home prices. Differentiating the population condition yields

$$\Delta\ln\pi_i = \frac{\gamma_i+\beta}{\gamma_i+1+\eta(1-\beta)}\frac{\eta}{\varepsilon}\Delta\ln\mathrm{RMA}_i + v_m^{\pi} + u_i^{\pi}. \tag{13}$$

This equation incorporates an intuitive positive relationship between growth in employment opportunities and tract population. This relationship is stronger if housing supply in tract i is more elastic and/or if there is less dispersion in idiosyncratic preferences over locations (η is larger). In section VII, we use (13) as a basis for structural estimation of η and ψ, recognizing that identifying variation in $\Delta \ln \mathrm{RMA}_i$ must be uncorrelated with tract-level shocks to amenities and housing productivity for successful identification.

IV. Empirical Implementation

Our main estimation equation amounts to the time-differenced counterpart to the simple tract-level supply equation (2):

$$\Delta \ln Q_{ir}^{s} = \theta_r + X_{ir}\delta + \gamma_{ir}\Delta \ln P_{ir} + \tilde{\rho}_{ir}. \tag{14}$$

Observations are for tract i in metro region r. To allow for observed heterogeneity in supply elasticities, we parameterize $\gamma_{ir} = Z_{ir}\gamma$ to depend on tract observables.[8] As detailed in section II, the sources of observed heterogeneity are topography, developed fraction, land use regulation, and regulatory burden. Because we do not observe some relevant factors that may differ by CBD distance, we also include CBD distance interactions. As our empirical setting allows us to recover relationships only between observed tract attributes and supply elasticities, interaction coefficients also likely incorporate influences of unobserved factors. For example, if tract fraction developed is correlated with unobserved input costs, estimates of the coefficient on the interaction between fraction developed and price growth would in part capture impacts of input cost differences on supply elasticities. This means that while our estimates are well suited for characterizing tract-level housing supply elasticities for our study period, they are less appropriate for making causal predictions about impacts of changing one observed attribute, holding all else constant. Instead, our empirical implementation is primarily oriented toward ensuring that variation in price growth across tracts is uncorrelated with unobserved supply shifters.

Fundamental to our empirical strategy is inclusion of metro region fixed effects θ_r, ensuring that we compare different neighborhoods in the same labor market for identification. In tract characteristics X_{ir}, our main specification includes lagged demographic attributes, a cubic in CBD distance, 2001 tract developed fraction and share flat land, and controls for tract-specific labor demand shocks. Our controls for 1990 and

[8] In sec. V.C, we extend the empirical model to allow for unobserved heterogeneity. This allows us to additionally incorporate metro area–level predictors of tract supply elasticities.

2000 tract demographic characteristics account for potential influencers of the tract regulatory environment that may be correlated with the instrument for price growth laid out below. CBD distance controls hold constant any potential spatial trends in price growth that are related to costs and are useful given the stronger 2000–2010 labor demand growth in suburban areas. The 1990 and 2000 census rent and price indexes help to account for decadal mean reversion in home price growth. Controls for tract developed fraction and topography account for obvious potential housing supply shocks and are needed as main effects in interacted specifications. Finally, 1990 log tract employment and a 2000–2006 tract-specific Bartik labor demand shock (explained below) help ensure that our instrumental variable (IV) implementation is using only variation from outside of tract *ir* for identification.

Even when we include this long list of control variables, observed ordinary least squares (OLS) relationships between post-2000 quantity changes and contemporaneous price growth are implausibly small. Table A1 (tables A1–A8 are available online) shows that OLS estimates are at most 0.10 for housing units, 0.11 for floor space, and 0.03 for land development.[9] These small estimates point to several identification challenges in estimating housing supply. First, neighborhoods that experience stronger housing demand shocks may follow with unobserved changes in housing regulation in part in order to cope with these demand shocks, thereby maintaining open space and natural amenities. That is, negative supply shocks may be correlated with positive demand shocks. Similarly, Davidoff (2016) presents evidence that the magnitude of demand shocks may be correlated with supply elasticity, observing that more supply-constrained metro areas tend to have greater productivity and housing demand growth. Second, it is possible that positive productivity shocks outside of the construction sector may simultaneously boost local housing demand through higher household earnings and reduce housing supply through higher construction costs. This would further bias the OLS relationship between quantity and price growth downward. Moreover, our price index measure, while constructed as carefully as possible, is sure to be a noisy measure of the true price of housing services. Mechanical mean reversion in decadal house price growth that could reflect classical measurement error would lead to attenuation bias. A valid identification strategy must address the classic endogeneity concern of simultaneity in demand and supply by finding variation in local housing demand shocks across neighborhoods that are uncorrelated with local construction costs.

We develop an instrument that isolates variation in tract price growth that is plausibly uncorrelated with supply factors conditional on controls.

[9] Ouazad and Ranciere (2019) find similarly small OLS relationships between price growth and quantity growth for the San Francisco metro region.

Consider the tract-level inverse floor space demand equation from the model. This equation is derived by substituting for tract population π_i (7) in (12) and solving for price:

$$\begin{aligned}\ln P_i = \tilde{\rho}_{\mathrm{HD}} &+ \frac{1}{1+\eta(1-\beta)}\frac{1+\eta}{\varepsilon}\ln \mathrm{RMA}_i \\ &+ \frac{\psi/\eta - 1}{1+\eta(1-\beta)}\ln \sum_{i'\in m(i)}\left(B_{i'}P_{i'}^{\beta-1}\mathrm{RMA}_{i'}^{1/\varepsilon}\right)^{\eta} \\ &- \frac{1}{1+\eta(1-\beta)}\ln S_i^d + \frac{\eta}{1+\eta(1-\beta)}\ln B_i.\end{aligned} \tag{15}$$

The fact that the housing price in tract i is increasing in RMA_i through impacts on housing demand is intuitive. Labor demand conditions relevant to neighborhood i, as summarized in RMA_i, represent a useful source of variation in home prices. However, any component of RMA_i that is correlated with tract housing productivity or land parcel size is endogenous to housing supply. Indeed, through its codetermination with FMA_j, RMA_i depends structurally on tract population, which itself depends on tract housing productivity and parcel size. As such, our identification approach is to difference over time and pick out components of $\Delta\ln\mathrm{RMA}_i$ that are likely orthogonal to levels of and shocks to productivity or other factors that influence local construction costs.

Because supply elasticity varies at the tract level, there exists structural heterogeneity in relationships between price growth and $\Delta\ln\mathrm{RMA}_i$. For example, housing demand shocks in tracts with more land available for development may be expected to induce smaller price growth and greater quantity growth. Formally, substituting for $\ln S_i^d$ in (15) with the generic housing supply function $\ln S_i = \ln\rho_i + \gamma_i \ln P_i$ yields the equilibrium relationship $\partial \ln P_i/\partial \ln\mathrm{RMA}_i$ that is positive and with a negative cross derivative in the supply elasticity (see the discussion after eq. [34] in app. C). As a result, we also expect a heterogeneous first-stage relationship between housing price growth and our instrument providing exogenous variation in $\Delta\ln\mathrm{RMA}_i$.

A. *Instrument Construction*

We use (10) and (11) as a basis for calculating a simulated version of $\Delta\ln\mathrm{RMA}_i$, denoted $\Delta\ln\widetilde{\mathrm{RMA}}_i$, which excludes shocks to tract housing productivity and its correlates conditional on control variables. This simulated instrument is both a reduced-form housing demand shock that drives exogenous variation in tract-level house price growth and a predictor of the structural object $\Delta\ln\mathrm{RMA}_i$ that is unrelated to tract-level shocks to local amenities or housing productivities.

Calculation of $\Delta\ln\widetilde{\mathrm{RMA}}_i$ is analogous to that of $\Delta\ln\mathrm{RMA}_i$ except that it replaces actual tract employment with that predicted by 1990 tract industry compositions interacted with national industry growth rates. To solve jointly for $\widetilde{\mathrm{FMA}}_j$, we inflate the 1990 residential population of each tract by a constant to equalize counterfactual aggregate labor supply and demand in each region. The simulated instrument $\Delta\ln\widetilde{\mathrm{RMA}}_i$ is conceived in the spirit of shift-share identification strategies that go back to Bartik (1991).

Beyond fixing commute times to those from 1990, we incorporate three additional elements to reduce the likelihood that the instrument is correlated with trends in construction costs conditional on controls. First, we exclude construction from the set of industries used to build the instrument. This precludes the possibility that nearby changes in productivity in the construction sector may directly affect construction costs in tract i.[10] Second, we exclude all tracts with centroids within 2 kilometers of tract i. This exclusion mitigates the possibility that employment growth in or nearby tract i may influence the land available for residential development in tract i or that its construction labor costs change in a way that is correlated with the instrument. Finally, we always control for predicted employment growth in tract i itself.

Putting these elements together and following (10) and (11), we calculate the year 2000 component $\widetilde{\mathrm{RMA}}_i^{2000}$ of our main instrument as

$$\widetilde{\mathrm{RMA}}_i^{2000} = \sum_{j \subseteq R(i)} \frac{e^{-(\widehat{\varepsilon\kappa})_{r(i)}\tau_{ij}^{90}} 1(\mathrm{dis}_{ij} > 2\text{ km}) \sum_{k \neq \mathrm{cons}} L_{jk}^{90} [\mathrm{E}_{r'(j)k}^{2000}/\mathrm{E}_{r'(j)k}^{1990}]}{\widetilde{\mathrm{FMA}}_j^{2000}}, \tag{16}$$

$$\widetilde{\mathrm{FMA}}_j^{2000} = \sum_{i \subseteq R(j)} \frac{e^{-(\widehat{\varepsilon\kappa})_{r(i)}\tau_{ij}^{90}} 1(\mathrm{dis}_{ij} > 2\text{ km}) \pi_i^{90} \left[\left(\sum_{j \subseteq R(i)} \sum_{k \neq \mathrm{cons}} L_{jk}^{90} [\mathrm{E}_{r'(j)k}^{2000}/\mathrm{E}_{r'(j)k}^{1990}]\right) / \sum_{j \subseteq R(i)} L_j^{90}\right]}{\widetilde{\mathrm{RMA}}_i^{2000}}. \tag{17}$$

In these expressions, τ_{ij}^{90} is the reported or forecast commute time from i to j in the 1990 CTPP. $(\widehat{\varepsilon\kappa})_{r(i)}$ is estimated separately for each region r in year 2000, as explained in the context of (8). Distances from residential to work locations dis_{ij} are calculated using tract centroids. Employment in industry k and work location j, L_{jk}^{90}, is measured in the 1990 CTPP. $E_{r'(j)k}^{2000}$ and $E_{r'(j)k}^{1990}$ are 2000 and 1990 nationwide employment in industry k, excluding the region of tract j. That is, $\sum_{k \neq \mathrm{cons}} L_{jk}^{90} [E_{r'(j)k}^{2000}/E_{r'(j)k}^{1990}]$ captures the predicted amount of employment that would exist in tract j if 1990 employment by industry grows at national rates (excluding region r) to year 2000. $(\sum_{j \subseteq R(i)} \sum_{k \neq \mathrm{cons}} L_{jk}^{90} [E_{r'(j)k}^{2000}/E_{r'(j)k}^{1990}]) / \sum_{j \subseteq R(i)} L_j^{90}$ is a constant within each

[10] Failing to exclude the construction industry or additionally excluding finance, insurance and real estate deliver very similar estimates to our main ones, as seen by comparing results in tables 4 and A4.

region that captures the population growth rate needed to match the aggregate employment predicted by Bartik shocks in the region in year 2000. The 2006 component of the instrument is calculated analogously, with $E^{2000}_{r'(j)k}$ in (16) and (17) replaced by $E^{2006}_{r'(j)k}$.

The log difference in $\widetilde{\text{RMA}}_i$ for 2000–2006, $\widetilde{\text{RMA}}_i$, is our main instrument for $\Delta\ln P_i$, as measured for both the 2000–2006 and the 2000–2010 time periods. We build our instrument for the 2000–2006 period only, as this is the time period for which first-stage predictive power is strongest. Variation in 2006–10 employment changes are not well predicted by shift-share-type instruments.[11]

B. *Instrument Validity*

The fundamental sources of identifying variation used are tract-level Bartik-type shocks (Bartik 1991) in each employment location, which can be written as follows:

$$\text{Bartik}_j = \sum_{k \neq \text{cons}} \frac{L^{90}_{jk}}{\sum_k L^{90}_{jk}} [\ln E^{06}_{r'(j)k} - \ln E^{00}_{r'(j)k}]. \tag{18}$$

A prerequisite for the spatial aggregation of such shocks into $\Delta\ln\widetilde{\text{RMA}}_i$ to successfully predict $\Delta\ln\text{RMA}_i$ is for tract-level counterparts to successfully predict tract employment growth.

Panel A of table 2 presents evidence to this effect. It presents regressions of 2000–2006 or 2000–2010 employment growth in tract j on Bartik_j and controls for 1990 employment level, past demographic composition of tract residents, a cubic in CBD distance, and metro region fixed effects. All tracts in primary sample regions are included, as they all contribute to construction of $\widetilde{\text{RMA}}_i$ in tracts that contribute data to our main estimation exercises. We control for past employment to isolate employment growth due to only variation in industry composition. Lagged demographics and CBD distance controls account for potentially differing labor supply conditions. Results indicate that we can plausibly isolate labor demand shocks at the tract level. Each additional percentage point increase in the Bartik shock predicts 0.33 points greater 2000–2006 tract employment growth and 0.60 points greater 2000–2010 tract employment growth.[12]

One consideration we face when estimating the housing supply equation is accounting for serial correlation in home prices and quantities.

[11] Ferreira and Gyourko (2023) find that income growth is coincident with the beginning of local housing booms but has little predictive power for subsequent price dynamics.

[12] Results are robust to lagging the demographic tract controls by one additional decade and/or adding 2–2.5-kilometer CBD distance ring fixed effects interacted with metro region. Excluding demographic controls increases estimates to 0.69 and 1.04 in cols. 1 and 2, respectively (table A2, panel A).

TABLE 2
TRACT-LEVEL EMPLOYMENT AND HOUSING MARKET DYNAMICS

	(1)	(2)	(3)
	A. Tract-Level Regressions of Employment Growth on Bartik Shocks		
	Change in Log Employment		
	2000–2006	2000–2010	
Tract Bartik shock, 2000–2006	.33***	.60***	
	(.10)	(.10)	
No 1990 employment information	.13	.27	
	(.24)	(.23)	
Observations	51,900	56,043	
R^2	.06	.05	
Number of regions	158	169	
	B. Tract-Level Housing Market Dynamics		
	Δln House Price, 2000–2010	Δln House Quantity, 2000–2010	Δln Simulated RMA, 2000–2006
Δln house price, 1990–2000	−.25***	.01	.0000
	(.01)	(.01)	(.0001)
Δln house quantity, 1990–2000	−.02	.24***	−.0002
	(.03)	(.04)	(.0002)
	C. Analysis of Pretreatment Trends, 1990–2000		
	Δln House Price, 1990–2000	Δln House Quantity, 1990–2000	
Δln simulated RMA, 2000–2006	.26	−.31	
	(.52)	(.23)	

NOTE.—In panel A, regressions also include metro region fixed effects, fraction developed in 2001, fraction of tract land that is flat, a cubic in fraction of the way to region edge, log 1990 tract employment, and the following tract attributes from 1990 and 2000: census home price index, rent index, log population, log average household income, share black, share white, and share college. Sample includes all tracts in metro regions that are in the primary sample. Each tract receives equal weight. Robust standard errors are in parentheses. In panel B, each entry is from a separate regression of the variable in cols. 1–3 on the variable in the row header. Regressions include metro region fixed effects, a cubic in fraction of the way from the CBD to the metro edge, fraction of tract land that is flat, log 1990 tract employment, the 2000–2006 Bartik shock for the tract, and the following tract attributes measured in 1990 and 2000: log population, log average household income, share black, share white, and share college. In panel C, each coefficient is from a separate reduced-form regression of the variable in cols. 1 and 2 on the change in ln simulated RMA between 2000 and 2006 and region fixed effects. Controls are the same as in panel A, with the addition of a tract 2000–2006 Bartik shock. Standard errors are corrected for spatial autocorrelation up to 16 kilometers.

*** Significant at the 1% level.

Columns 1 and 2 of table 2, panel B, show that home price growth is negatively serially correlated across decades whereas unit quantity growth is positively serially correlated across decades.[13] These results may reflect supply shocks that respond to demand shocks with a lag and suggest that there could be local unobserved history that drives both relative price declines and more construction. A legitimate potential concern is thus that $\Delta\ln\widehat{\mathrm{RMA}}_i$ may be correlated with such unobserved history. However, results presented in column 3 of table 2, panel B, exhibit small and insignificant relationships between the instrument and pretreatment trends in key endogenous variables. $\Delta\ln\widehat{\mathrm{RMA}}_i$ is not correlated with 1990–2000 housing price or quantity growth for our main specification with region fixed effects and 1990 and 2000 demographic controls. Column 3 of table A2, panel B, shows that controls for year 2000 demographics are needed to generate the insignificant (and negative) relationship between the instrument and 1990–2000 housing quantity growth; these controls also attenuate the 1990–2000 price growth relationship, which remains statistically insignificant with and without demographic controls. Panel C of table 2 presents results of the reverse regressions with the same implication.[14] This pretrend evidence indicates that it is unlikely that our instrument is correlated with unobserved local history in a way that biases our supply elasticity estimates.

C. *First-Stage Estimates*

Table 3 presents the main first-stage estimates. Results in panel A show strong positive relationships between our primary measures of $\Delta\ln P$ and $\Delta\ln\widehat{\mathrm{RMA}}$. The slightly smaller first-stage coefficient for 2000–2010 relative to 2000–2006 reflects the fact that the 2007–10 period mostly saw housing market declines. Column 3 shows that we do not have strong first-stage power predicting the census hedonic index. For this reason, we use the census index only to account for pre-2000 price trends. Column 4 shows a significant estimated relationship between $\Delta\ln\widehat{\mathrm{RMA}}$ and $\Delta\ln\mathrm{RMA}$ for 2000–2010 of 0.74. According to the model, this is the mechanism through which $\Delta\ln\widehat{\mathrm{RMA}}$ predicts $\Delta\ln P$. Tracts that appear in multiple metro regions are weighted equally to tracts that appear in just one.[15]

[13] Results in panel B of table A2 show that these correlations are not sensitive to conditioning on demographic controls.

[14] Goldsmith-Pinkham, Sorkin, and Swift (2020) suggest this sort of pretrend test for evaluating the validity of Bartik instruments. Their other suggested validity tests use base year industry shares, which are not easily defined in our setting, as they are nonlinearly aggregated across all potential commuting destinations into $\Delta\ln\widehat{\mathrm{RMA}}_i$.

[15] First-stage predictions of our hedonic price index are similar to those reported in cols. 1 and 2 of table 3, panel A, for the repeat sales index. We also find significant positive reduced-form relationships between the instrument and 2000–2006 and 2000–2010 Zillow new construction.

TABLE 3
First-Stage Results for Baseline Specifications

	(1)	(2)	(3)	(4)
	A. Unified Specification			
	Repeat Sales Index		Census Index,	RMA,
	2000–2006	2000–2010	2000–2010	2000–2010
Δln simulated RMA, 2000–2006	5.94***	5.18***	.29	.74***
	(1.26)	(1.10)	(.96)	(.17)
Observations	30,500	30,838	30,692	30,838
R^2	.14	.23	.08	.04
Number of fixed effects	166	167	167	167
	B. Interacted Specification			
	$\Delta\ln P$	$\Delta\ln P \times$ CBD Distance	$\Delta\ln P \times$ % Developed	$\Delta\ln P \times$ % Flat
Δln simulated RMA	−2.04	−3.56***	−4.82***	−6.42***
	(1.76)	(.90)	(1.28)	(1.78)
Δln simulated RMA × CBD distance	2.92	11.12***	.55	5.12**
	(2.34)	(1.73)	(1.23)	(2.17)
Δln simulated RMA × % developed	19.44***	2.93**	20.01***	8.67***
	(4.13)	(1.34)	(3.44)	(2.81)
Δln simulated RMA × % flat	−.06	.48	.64	13.01***
	(1.58)	(.60)	(1.04)	(3.32)
Observations	30,838	30,838	30,838	30,838
R^2	.24	.38	.28	.25
Number of fixed effects	167	167	167	167

Note.—Regressions include metro region fixed effects and the same controls as in panel C of table 2. Tracts are equally weighted, even if they appear in multiple metro regions. Standard errors are corrected for spatial autocorrelation up to 16 kilometers using a Bartlett kernel. $\Delta\ln P$ in panel B refers to the 2000–2010 repeat sales index. Analogous estimates using the hedonic price index instead are very similar.

** Significant at the 5% level.

*** Significant at the 1% level.

Standard errors are adjusted for spatial autocorrelation out to 16 kilometers using a triangular kernel. The 16-kilometer cutoff was selected by inspecting the spatial correlogram of errors (fig. A2; figs. A1–A5 are available online) generated from a tract-level IV regression of the 2000–2010 growth rate in housing units on the 2000–2010 change in the repeat sales price index using the specification reported later in column 3 of table 4. The associated first-stage F-statistic is 22.2, which can be calculated from estimates in column 2 of the top row of table 3.

TABLE 4

UNIFIED IV RESULTS FOR HOUSING SUPPLY

	2000–2006		UNITS, 2000–2010					FLOOR SPACE, 2000–2010				TOTAL LAND, 2001–11
	Total Units (1)	Total Floor Space (2)	Total (3)	New (4)	Redevelopment (5)	Remainder (6)	Expansion (7)	Total (8)	New (9)	Remainder (10)	Expansion (11)	(12)
$\Delta \ln P$	.24***	.26**	.35***	.19**	.03	.16**	.08	.42***	.29**	.13	.09	.09
	(.09)	(.10)	(.12)	(.08)	(.03)	(.08)	(.06)	(.16)	(.12)	(.11)	(.09)	(.06)
Observations	30,500	30,048	30,838	30,838	30,838	30,834	30,377	30,381	30,392	30,376	30,377	30,838

NOTE.—Regressions include the same controls as those in panel C of table 2. The estimation sample uses data from 167 metro regions. The sample is reduced by one region for the floor space outcomes because of missing floor space information for some tracts. Entries in cols. 1 and 2 use 164–166 regions. All outcomes are measured using the ZTRAX data except developed land, which uses US Geological Survey land cover information. Standard errors are corrected for spatial autocorrelation to 16 kilometers. First-stage F-statistics can be determined from results in table 3.

** Significant at the 5% level.

*** Significant at the 1% level.

We undertake a number of checks to confirm that our instrument is sufficiently strong. Olea and Pflueger (2013) suggest that with dependent errors, the critical F-statistic for a strong first stage should be adjusted upward from the rule of thumb of 10 often used. In our context, the critical value of the F-statistic for the worst-case bias of 10% is 23.1. Lee et al. (2021) recommend that with a first-stage F-statistic of 22.2, second-stage standard errors should be multiplied by less than 1.3. Multiplying standard errors by this factor in table 4 maintains statistically significant estimates in almost all cases. Conservative Anderson-Rubin test statistics associated with regressions in table 4 using county-level clustering, which increases standard errors beyond our spatially corrected estimates in all cases, also reject that our instrument is weak.

Panel B of table 3 reports extended first-stage relationships between price growth and $\Delta\ln\widetilde{\text{RMA}}$ interacted with various factors that influence supply elasticity, which we demonstrate below. Inclusion of controls for CBD distance, fraction developed, and fraction of flat land is crucial for identification, as doing so forces all identifying variation to come from $\Delta\ln\widetilde{\text{RMA}}$ rather than the interacted observable. For supply elasticities to differ across tracts, it must be that we can predict different amounts of price growth for the same demand shock hitting different types of locations. Therefore, we see it as important that exogenous price responses induced by the instrument differ for tracts with different observable characteristics.

Interacted first-stage coefficients are of expected signs and significance. Results in column 1 indicate that tracts with a higher developed fraction experience larger price increases in response to a simulated RMA shock. The insignificant coefficient on uninteracted $\Delta\ln\widetilde{\text{RMA}}$ is as expected, as it applies to tracts with no developed land. Such locations are expected to have very elastic supply where positive demand shocks translate almost entirely into quantity rather than price responses. In other columns, estimates on the diagonal are positive and strongly significant, as expected. Anderson-Rubin test statistics assuming standard errors clustered at the county level (larger than the reported spatially corrected errors) yield evidence of strong first stages.

D. Sources of Identifying Variation

The unified supply elasticity estimates are identified by isolating comparisons between ex ante observationally identical tracts in the same metro area that receive different housing demand shocks because of variation in labor demand shocks in commuting destinations. Labor demand shocks in accessible locations are spatial aggregations of 1990 industry composition interacted with 2000–2006 industry growth. As changes over time become small, within any region we can express the instrument in a way that is somewhat analogous to the tract-level Bartik shocks in equation (18), as follows:[16]

$$\Delta\ln\widetilde{\mathrm{RMA}}_i = \sum_{k\neq\mathrm{cons}}\left[\sum_j \frac{e^{-\widehat{(\varepsilon\kappa)}\tau_{ij}^{90}}1(\mathrm{dis}_{ij}>2\ \mathrm{km})L_{jk}^{90}\left[E_{r'(j)k}^{2000}/E_{r'(j)k}^{1990}\right]}{\sum_{k\neq\mathrm{cons}}\sum_j e^{-\widehat{(\varepsilon\kappa)}\tau_{ij}^{90}}1(\mathrm{dis}_{ij}>2\ \mathrm{km})L_{jk}^{90}\left[E_{r'(j)k}^{2000}/E_{r'(j)k}^{1990}\right]}\right]\Delta\ln E_{r'(j)k}.$$

If we treat the quotient as endogenous and the industry growth rates $d\ln E_{r'(j)k}$ as exogenous, the instrument does not require recentering for clean identification because the shares sum to 1 (Borusyak and Hull 2020). However, it may alternatively (or additionally) be reasonable to treat the shares as exogenous, as they are predetermined. Our set of controls is oriented toward making these initial industry shares in commuting destinations uncorrelated with unobserved supply factors in tract i conditional on controls. The lack of pretrends seen in panel C of table 2 allays such potential concerns.

Of further interest is how average supply elasticities are built from aggregating impacts in tracts with different baseline attributes. Consider comparisons between tracts that receive the same demand shock and are ex ante identical except in one supply factor, like initial land developed fraction. This type of comparison cleanly applies for only the interacted specifications. The interacted first-stage results in panel B of table 3 show how the same shock affects their prices differently. The tract with a low developed fraction sees prices rise by less than that with the higher developed fraction. By contrast, inspection of results in table 5 shows that for a given demand shock–driven price rise in those tracts with a greater developed fraction, quantity rises by less.[17]

V. Main Results

A. *Unified Supply Elasticity Estimates*

While evidence below confirms that supply elasticities are heterogeneous across neighborhoods, we begin with unified estimates to provide a sense of magnitudes and of the relative importance of new construction versus other margins of response to positive demand shocks. Table 4 reports coefficients in regressions of various measures of housing quantity growth on home price growth. In all regressions, we instrument for $\Delta\ln P$ with

[16] We omit the multilateral resistance term, as $\Delta\ln\widetilde{\mathrm{RMA}}_i$ has a correlation of 0.98 with the reduced-form analog that leaves $\widetilde{\mathrm{FMA}}_j^Y$ out of the denominator.

[17] Identifying variation is not primarily from comparisons between neighboring or nearby tracts because such tracts typically have very similar shocks and attributes. Since we allow for spatial autocorrelation in errors out to 16 kilometers, adjacent tracts will be treated almost as identical observations.

TABLE 5

LINEAR IV MODEL: HETEROGENEITY IN SUPPLY ELASTICITIES BY CBD DISTANCE AND TRACT ATTRIBUTES

	Units						Floor Space				Land
	Total (1)	Total (2)	New (3)	Redevelopment (4)	Remainder (5)	Expansion (6)	Total (7)	New (8)	Remainder (9)	Expansion (10)	(11)
$\Delta \ln P$	.11	.94***	.62***	.07	.33**	.16	.91***	.70***	.15	.13	.30**
	(.12)	(.25)	(.20)	(.05)	(.14)	(.10)	(.31)	(.26)	(.20)	(.17)	(.13)
$\Delta \ln P \times$ CBD distance	1.89**	−.58**	−.43**	−.13**	−.17*	−.08	−.46*	−.50**	.12	.11	−.29**
	(.73)	(.24)	(.21)	(.05)	(.10)	(.08)	(.27)	(.25)	(.15)	(.12)	(.12)
$\Delta \ln P \times$ % developed		−1.54***	−1.33***	−.13	−.23	−.15	−1.39***	−1.32***	.08	−.06	−.61***
		(.40)	(.36)	(.09)	(.15)	(.11)	(.45)	(.40)	(.23)	(.18)	(.21)
$\Delta \ln P \times$ % flat		.30**	.37***	.08**	−.09**	−.01	.35**	.46***	−.15**	−.07*	.19***
		(.12)	(.12)	(.03)	(.05)	(.03)	(.14)	(.15)	(.07)	(.04)	(.07)
$\Delta \ln P \times$ (CBD distance)^2	−1.84**										
	(.78)										
Observations	30,838	30,838	30,838	30,838	30,834	30,377	30,381	30,392	30,376	30,377	30,838
Kleibergen-Paap F-statistic	17.49	11.01	11.01	11.01	11.01	10.18	10.22	10.13	10.17	10.18	11.01

NOTE.—Regressions are the same specification as in panel C of table 2, with the addition of indicated interaction terms. The repeat sales price index measure is used throughout. Standard errors are adjusted for spatial autocorrelation to 16 kilometers. If included where omitted, coefficients on $\Delta \ln P \times$ (CBD distance)^2 would be insignificant.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

$\Delta\ln\widetilde{\mathrm{RMA}}$ and control for region fixed effects and the same tract-level factors as in panel A of table 3.

Following our discussion in section II.B, we decompose 2000–2010 changes in housing units (col. 3) into that from new construction (col. 4) and from changes to existing buildings (col. 6). For the former, we further distinguish between new construction on developed land (col. 5) and that on undeveloped land (col. 4 minus col. 5). We decompose the latter into expansion and renovation of existing buildings (col. 7) and teardowns (col. 6 minus col. 7). Similarly, we decompose changes in floor space of existing buildings (col. 8) into additions through new construction (col. 9) and changes through teardowns and renovations (col. 10). We separate out renovations in existing buildings (col. 11) from fewer teardowns (col. 10 minus col. 11). We note that 2000–2010 supply responses in columns 3 and 8 are considerably larger than those for 2000–2006 in columns 1 and 2, even though both are identified using the same 2000–2006 labor demand shocks. Given the minimal number of 2007–10 housing starts, these gaps mostly reflect construction lags after 2000–2006 price shocks.[18]

Column 3 of table 4 shows that the estimated total unit supply elasticity during 2000–2010 is 0.35. That is, between two ex ante identical census tracts, if tract A experiences home price growth that is 10 percentage points higher than tract B, changes in total housing units in tract A would exceed that in tract B by 3.5 percentage points. Estimates in columns 4 and 6 show that out of these 3.5 points, 1.9 come from new construction and 1.6 come from fewer teardowns and reconfiguration of existing buildings into multiunit buildings. Out of the portion due to new construction, only a small and statistically insignificant portion is estimated to be redevelopment, as reported in column 5. This comes despite the fact that on average 36% of new construction in estimation sample tracts with some 2000–2010 new construction was through redevelopment. The portion due to teardowns and renovations is split about equally between these two mechanisms.[19]

Column 8 shows the estimated total floor space elasticity of 0.42. Of this, over two-thirds come from floor space in newly constructed units (col. 9); the remaining part comes from a combination of fewer teardowns and expansions of existing buildings (col. 10). Over two-thirds of this last component are through building renovation and expansion,

[18] Table A3 provides additional checks. Panel A shows robustness to using the hedonic price index. Columns 1–3 in panel B show robustness of unit elasticities to using census and ACS housing quantity measures. Column 5 shows robustness of the floor space elasticity to using the quantity index described in app. A.1.

[19] Rosenthal (2018) and Brueckner and Rosenthal (2009) also provide evidence on the contributions of teardowns and renovations to housing supply.

accounting for a noisily estimated 21% of the total floor space elasticity (col. 11 divided by col. 8).

Column 12 reports a statistically insignificant estimated elasticity of observed developed land of 0.09. In section V.E, we square this evidence with our supply model's predictions about the magnitude of land use intensification in response to price increases.

B. Tract-Level Heterogeneity

The local average treatment effect tract-level supply estimates in table 4 mask substantial variation across neighborhoods. To begin to unpack this heterogeneity, table 5 repeats the IV regressions in columns 3–12 of table 4, with the addition of a set of interactions between price growth and CBD distance, land availability, and topographical features. These factors may influence construction costs either directly or as proxies for land use regulations.[20]

Results in column 1 show that unit supply elasticity increases with CBD distance at a marginally decreasing rate. At the CBD, the implied average supply elasticity is estimated to be only 0.11, rising to 0.59 near halfway to the region edge. As only 18% of observations fall beyond the halfway point, the quadratic coefficient is mostly identified from variation near the CBD, and predicted elasticities using this specification are thus most accurate in that region. This positive CBD distance profile can be largely explained by neighborhood-level factors that affect development costs. The model predicts that the extensive margin of supply is more responsive in tracts where fixed cost distributions have fatter right tails. Such easier development conditions are associated with sparser initial development, flatter land, and looser regulation. Figure 1*B* shows that the average tract in our data is almost 60% developed at the CBD but less than 10% developed at the region edge. However, flat land declines from 45% to 38% from CBDs to region edges, and land use is more regulated at 30% of the way to region edges than at CBDs.

To quantify the importance of these factors, column 2 adds interactions between $\Delta\ln P$ and the 2001 fraction of land developed or the 2001 fraction of flat land in each tract.[21] Consistent with the model, we find that supply elasticity declines with developed fraction and increases with the fraction of flat land. Moreover, CBD distance coefficients turn

[20] CBD distance is measured as the fraction of the way from the CBD to the furthest census tract from the CBD in the same metropolitan region.

[21] As the CBD distance squared interaction is no longer significant, we drop this variable. Neither fraction flat squared nor fraction flat × fraction developed price interactions are significant, so we exclude these variables as well. Table A5 presents analogous parameter estimates for specifications that are quadratic in tract developed fraction.

negative, reflecting the negative correlation between the fraction of land developed and CBD distance seen in figure 1.

As in table 4, we decompose total unit supply responses in column 2 into components. Results in columns 3 and 4 show that the influences of tract-level factors on new construction elasticities for both all new development and redevelopment are attenuated versions of those for total unit supply in column 2. At CBDs, predicted supply elasticities using estimates in columns 2 and 3 and quantities in figure 1*B* show that the entire unit supply response to price growth is through fewer teardowns and renovations. Conditional on developed fraction and topography, the new construction elasticity declines with CBD distance, likely reflecting increasing regulation. However, the declining developed fraction in CBD distance outweighs this residual influence of CBD distance such that at 50% of the way to metro region edges, the predicted overall unit supply elasticity is 0.40 while that for new construction rises to 0.23. Developed fraction and topography affect the redevelopment supply elasticity in the same direction as the new construction elasticity, consistent with model predictions. Comparisons of results in columns 4–6 indicate that positive demand shocks precipitate more teardowns and redevelopment in neighborhoods with flatter land, possibly due to the fact that land assembly for demolition and rebuilding is easier in flatter areas (Dye and McMillen 2007).

Estimates in columns 7–10 for floor space supply mostly mirror those for unit supply in columns 2–6. In particular, developed land and CBD distance have negative effects on supply elasticities based on total changes and new construction but have no effects on teardowns and renovation of existing floor space. Similar to units, we observe a larger loss of existing floor space supply due to teardowns and full depreciation in flatter areas. Finally, column 11 of table 5 focuses on land development. These patterns are remarkably consistent with those for the unit supply (col. 2) and for the floor space supply (col. 7), though with attenuated coefficients.[22]

The negative CBD distance coefficients in table 5 likely reflect the impact of local regulations, as regulations increase on average with CBD distance within metro regions over the range well covered by our data (fig. 1*B*). Columns 1–8 of table A6 expand the quadratic specification in table A5 to include interactions of price changes with the WRLURI, measured at the municipality level, or tract-level residential FAR building restrictions. As expected, estimated impacts of regulation are if anything negative. Moreover, incorporating regulation moves coefficients on CBD distance from significantly negative to insignificantly negative or positive,

[22] Estimates analogous to those in table 5 using the Zillow hedonic price index instead are very similar (unreported).

depending on the outcome. These results corroborate the border discontinuity evidence in Shanks (2021) and Chiumenti, Kulka, and Sood (2022), finding that greater municipal regulation increases lot sizes and prices of single-family homes. As the WRLURI is observed for only 40% of our primary sample observations and FAR is observed for only six cities, table A6 estimates are not useful for predicting supply elasticities for most tracts.[23]

C. *Introducing Unobserved Heterogeneity*

To accommodate unobserved heterogeneity across metro areas, we now extend the environment to an FMM with two latent classes for coefficients on main and price interaction supply factors in the second-stage equation of the IV model described above. That is, we recover class-specific coefficients on price growth, developed fraction, fraction flat, CBD distance, and these three supply factors interacted with price growth. Coefficients on all other controls and region fixed effects are constrained to be the same across classes. To maintain statistical power, we also retain a single first-stage equation. Because estimation uses both generated and residualized regressors, we must bootstrap standard errors. We use a spatial block bootstrap in which blocks are constructed as 8×8-kilometer grid cells, with one centered on each CBD.[24]

Beyond adding additional parameter flexibility, the finite mixture formulation allows us to more closely connect our analysis to existing metropolitan area–level evidence on supply elasticities. To achieve this, we allow the probability of being assigned to each latent class to depend on three metro area–level attributes, following Saiz (2010). These are the fraction of land that is developed within 50 kilometers of the CBD; the fraction of area that is lost to hills, water, and wetland within the same radius; and the metropolitan area–level Wharton index. Conceptually, these metro area–level predictors may influence neighborhood supply elasticities through their impacts on initial prices and attributes of fixed development cost distributions that are common across tracts in a given metro area. We emphasize, however, that this is primarily a predictive

[23] We explore a number of plausible supply factors as additional price growth interactions. One of note is that supply elasticity is larger in tracts that are bordering or crossed by a highway (table A6). Better highway access may lower the cost of accessing construction materials and workers or lead to less land use regulation.

[24] We also experimented with specifications that index more parameters by class and with three class models. Adding the flexibility of indexing control variables and fixed effects by class increases standard errors and makes model convergence more difficult. Adding a third class results in key interaction parameter estimates that are very similar across two of the three classes, thereby providing little additional information about supply elasticities.

exercise. There may well be correlates of these three metro-level factors that are the true drivers of cross-metro variation in housing supply elasticities.[25,26]

Table 6 presents the FMM estimates. Panel A presents logit coefficients predicting membership in latent class 2, which is the less elastic class. Panel B presents class-specific coefficients. We show results for four key outcomes of interest.

Results in panel A echo evidence from Saiz (2010) that metro area–level factors matter for supply elasticities. For all supply components investigated, greater metro developed fraction increases the probability of being in the less elastic latent class. Conditional on initial development density, metros with a higher fraction lost to hills, water, and wetland also have a higher probability of belonging to the less elastic class in total unit and floor space supply elasticities, with insignificant positive estimates for new construction. Metro-level regulation is associated with less elastic new construction supply for both units and floor space. However, total floor space supply elasticities are positively related to regulation. This is evidence that building owners in more regulated areas are more likely to expand floor space through renovation. Overall, results in panel A show that natural and policy constraints at the metro level are key determinants of neighborhood supply elasticities.[27]

Results in panel B of table 6 are fully consistent with their IV counterparts reported in table 5. Class-specific coefficients replicate the patterns in table 5, though class 2 coefficients are muted. Across all supply measures, we find that the estimated effects of tract-level factors on supply elasticities conditional on being assigned to the more elastic class are 10–20 times larger than those conditional on being assigned to class 2. Metros with environments that are not conducive to development have much more similar supply elasticities across tracts than those with lots of developable land and low regulation.

The bottom three rows of table 6 provide summary statistics about the in-sample class-specific elasticities calculated with the FMM estimates. The average unit supply elasticity is 0.56 conditional on a tract being in the more elastic class and 0.21 conditional on a tract being in the less

[25] In the parametric example from the model, the land development component of the supply elasticity is $\alpha^{-1-\lambda}\lambda\rho_i^{-\lambda}P_i^{-\lambda/\alpha}\Gamma_i$. We imagine, e.g., that the Frechet shape parameter on the fixed development cost distribution λ may differ by metro area.

[26] An alternative (or complementary) approach would be to more flexibly allow the intercept to depend on metro area–level factors, identifying off of metro area–level variation in average price growth using Bartik-type instruments. Unfortunately in our sample of metros, first-stage power is not sufficient for this procedure to deliver precise estimates.

[27] For robustness, we also evaluate using the same metro region supply factors calculated for regions within 10 or 20 kilometers of CBDs; 10%, 50%, or 100% of maximum distances from CBDs to metro edges; or for entire metropolitan areas. These all deliver very similar results.

TABLE 6

Linear Finite Mixture IV Model Housing Supply Interacted Regressions

Outcome	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	A. Logit Parameters for Membership in Class 2 (More Inelastic Supply)							
	Units	New Units	Floor Space	New Floor Space				
Fraction developed within 50 km of CBD	5.34***	4.36***	4.37***	3.86***				
	(.61)	(.64)	(.60)	(.59)				
Fraction of land within 50 km of CBD unavailable	.52*	.29	1.11***	.40				
	(.29)	(.26)	(.31)	(.27)				
Metro Wharton index	.03	.12**	−.68***	.10**				
	(.06)	(.06)	(.09)	(.05)				
Constant	.60***	1.10***	.79***	1.20***				
	(.12)	(.11)	(.14)	(.11)				
	B. Second-Stage Estimates							
	Units		New Units		Floor Space		New Floor Space	
	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2	Class 1	Class 2
$\Delta \ln P$	1.79**	.29**	1.88**	.08	2.12**	.57***	1.43	.13
	(.71)	(.14)	(.81)	(.07)	(1.07)	(.22)	(1.21)	(.09)
$\Delta \ln P \times$ CBD distance	−1.14**	.03	−1.14**	.12**	−1.70**	.15	−.90	.10
	(.52)	(.11)	(.54)	(.06)	(.69)	(.21)	(.66)	(.08)
$\Delta \ln P \times$ % developed	−3.35***	−.30*	−4.14***	−.19**	−3.09***	−.71***	−3.09**	−.21*
	(.95)	(.17)	(1.14)	(.09)	(1.19)	(.26)	(1.46)	(.12)
$\Delta \ln P \times$ % flat	.47*	.03	.78**	.06	.75**	.09	1.03***	.08
	(.27)	(.05)	(.32)	(.04)	(.34)	(.08)	(.39)	(.05)
Mean class probability	.22	.78	.16	.84	.24	.76	.15	.85
Mean implied γ	.56	.21	.52	.08	.94	.41	.59	.11
SD implied γ	.59	.06	.74	.06	.56	.16	.59	.06

Note.—Sample sizes are the same as in table 5. Standard errors are bootstrapped with spatially clustered sampling with replacement. Clusters are defined as 8 × 8-kilometer grid squares with one grid square centered at each metro region's CBD.

* Significant at the 10% level.

** Significant at the 5% level.

*** Significant at the 1% level.

elastic class. Standard deviations of predicted supply elasticities are much greater in class 1 than class 2 for all outcomes.[28]

D. *Predicted Supply Elasticities*

Because the FMM-IV estimates in table 6 accommodate richer heterogeneity, we focus our discussion on predicted elasticities produced using these estimates. While the estimation sample is limited, we use coefficient estimates to predict supply elasticities for all 63,896 census tracts in the 306 metro regions in our data. We focus on supply responses for units, new construction units (new units), floor space, and floor space in new construction units (new floor space). Prediction standard errors are calculated using a parametric bootstrap of 100 draws from the joint normal distribution of FMM-IV estimated parameters. Recall that the new units and new floor space supply responses we calculate are not technically elasticities but instead are calculated as $d[Q_{ir}^{\mathrm{N}}/Q_{ir}^{2000}]/d\Delta \ln P_{ir}$, where Q_{ir}^{N} is the number of new units or amount of floor space in new units constructed in calendar years 2001–2010. d denotes cross-sectional differences, and Δ denotes differences over time. Figure 2 shows kernel density graphs of these four measures and their lower and upper 95% confidence bands. Average predicted units, new units, floor space, and new floor space supply elasticities are 0.29, 0.15, 0.51 and 0.19, respectively.

For comparison, we also make available predicted supply elasticities based on the FMM-IV model that is quadratic in developed fraction and the simple IV linear and quadratic in developed fraction models. Figure A3 depicts associated kernel densities. Compared with the FMM-IV estimates, distributions of tract IV estimates typically have longer left tails. IV estimates disproportionately weight large metros, which tend to have lower predicted elasticities, given their more intensely developed land. As such, the FMM-IV estimates are likely to apply more accurately in smaller metros. The quadratic estimates are somewhat wilder, as seen in their greater dispersion across tracts. The linear estimates are better powered but do not do as well at capturing nuanced differences between tracts.

Because our empirical setup is oriented toward exploiting variation within metros rather than between metros, we emphasize that our predicted supply elasticities may not fully capture variation in average tract elasticities between metros. For example, we identify the constant (uninteracted) impact of price changes on quantities by comparing tracts in the same metro at the same CBD distance, developed fraction, and topography with different exogenous price growth. The FMM-IV estimates show very different constants for the two latent classes and indicate that supply

[28] Table A7 presents analogous parameter estimates using specifications that are quadratic in tract developed fraction.

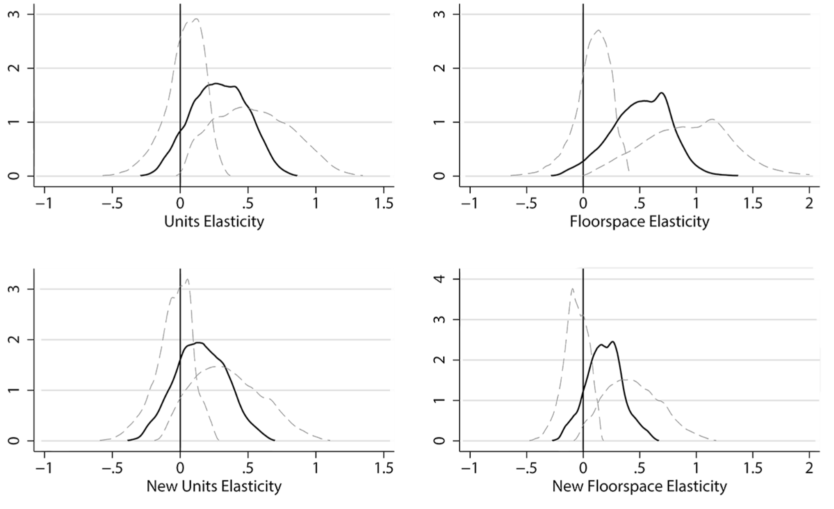

FIG. 2.—Kernel densities of predicted elasticities. Elasticities are predicted for all metro tracts nationwide using estimates in table 6. Dashed lines indicate 95% confidence intervals. Comparisons of estimates across all specifications are in figure A3.

parameters are likely to be different across different types of metro areas. Because of the necessarily limited flexibility of parameters to differ across metros, variation in levels of supply elasticities calculated using our estimates are less well identified than their within-metro dispersion. Nevertheless, in section VI, we demonstrate that the FMM-IV estimates are considerably more informative than the simple IV estimates about aggregate metro supply elasticities.

While we use empirical estimates to predict supply elasticities for each tract in our data, these elasticities should be viewed as averages across tracts with similar observables. Tracts with the same CBD distance, developed fraction, and topography in the same metro are assigned the same predicted elasticity even if they may be subject to different zoning restrictions. As a result, rather than being used to evaluate policies affecting specific tracts, our predicted supply elasticity estimates are more suitable in policy evaluation for a broad set of tracts, across which idiosyncratic differences in local regulation can average out.

Figure 3 shows how and why supply elasticities differ by CBD distance. Each panel shows local first-degree polynomial smoothed plots of actual predicted supply elasticities and three counterfactual elasticities holding certain tract attributes constant. Predicted supply elasticities (solid lines) are almost indistinguishable from supply elasticities that hold the fraction of flat land constant with CBD distance at metro means (long dash-dotted lines). Each supply elasticity increases with CBD distance, flattens in the

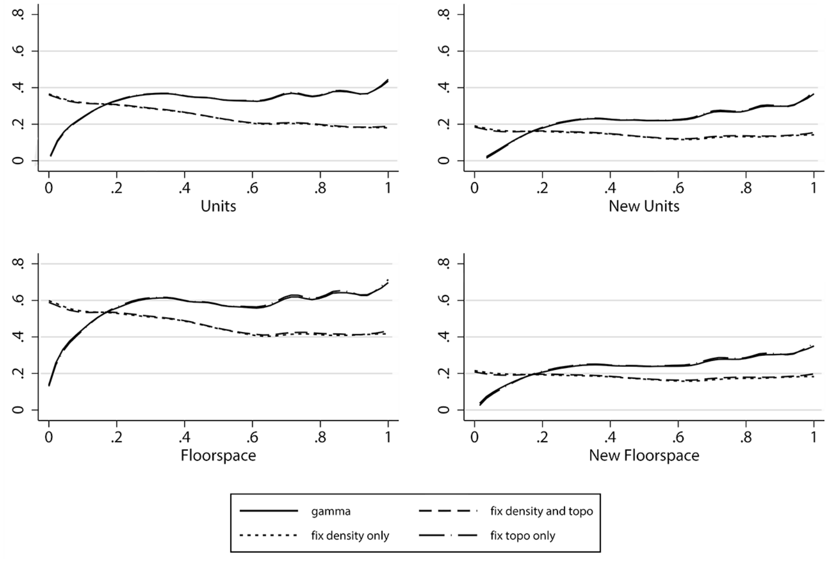

Fig. 3.—Supply elasticities by CBD distance.

suburbs, and then increases again toward the urban fringe. To understand this pattern, note our evidence from figure 1 that developed fraction declines monotonically in CBD distance, yet land use regulation is higher in suburbs than in central cities. These two forces offset to keep average supply elasticities constant in the suburbs from approximately 30%–90% of the way from CBDs to metro area edges, before the developed fraction effect again dominates, pushing supply elasticities up at metro edges.[29]

The remaining two lines in each panel represent predicted supply elasticities when holding the initial developed fraction at each metro region's mean and when holding both developed fraction and topography at the metro means. The two lines coincide, indicating that, on average, topography alone does not play a big role in explaining the CBD distance pattern in local supply elasticities. Under both counterfactuals, we see the supply elasticity falling over the full range of CBD distance for all quantity measures. Mechanically, this is because of the negative CBD distance coefficients in table 6, which likely capture increasing regulation with CBD distance. Figure A4 shows predicted unit and floor space supply elasticities by CBD distance in six select metros. It indicates marked divergence of these two objects with CBD distance in each city, reflecting the more floor space–intensive construction in suburban areas.

[29] Plots using predictions from the specification that is quadratic in developed fraction instead look similar except for sharper increases near the edge.

E. Relating Estimates to Model Predictions

Our parameterized supply model in section III.A predicts that the elasticity of floor space supply per parcel for new construction is $(1-\alpha)/\alpha$, where α is the land share in a Cobb-Douglas housing production function. The literature estimates α to be at most 0.35 (Combes et al. 2021), which implies that the elasticity of floor space per parcel in new construction should be at least 1.86.[30] Predicted floor space and unit elasticities reported in figure 2 do not map directly to the model, as they apply to changes in the total housing stock over time, not just changes due to new construction. The new units and new floor space plots in figure 2 are not elasticities but are built as components of total changes. As our focus is on calculating supply elasticities from all sources, we do not have the most appropriate empirical setting to estimate elasticities that apply to new construction flows only. These must come entirely from cross-sectional comparisons, whereas our empirical strategy exploits relative changes across tracts for identification. As such, our goal here is only to show that our estimates are roughly commensurate with evidence in the housing production literature.

To make such connections, we calibrate new construction elasticities using the new floor space, new units, and land development predictions reported in figures 2 and A3. We calculate $d\ln S_i^n/d\ln P_i$ as $(S_i/S_i^n)(d[\widehat{S_i^n/S_i}]/d\Delta\ln P_i)$ and $d\ln H_i^n/d\ln P_i$ as $(H_i/H_i^n)(d[\widehat{H_i^n/H_i}]/d\Delta\ln P_i)$, where $n = \mathrm{N}$ denotes new construction of all types and $n = \mathrm{U}$ denotes that on undeveloped land only. Given evidence in tables 4 and 5 that redevelopment supply elasticities are near 0, we assume $d[\widehat{S_i^{\mathrm{U}}/S_i}]/d\Delta\ln P_i = d[\widehat{S_i^{\mathrm{N}}/S_i}]/d\Delta\ln P_i$ and $d[\widehat{H_i^{\mathrm{U}}/H_i}]/d\Delta\ln P_i = d[\widehat{H_i^{\mathrm{N}}/H_i}]/d\Delta\ln P_i$ for the purpose of these calculations. For land, we can measure only $d\ln L_i^{\mathrm{U}}/d\ln P_i = (L_i/L_i^{\mathrm{U}})(d[\widehat{L_i^{\mathrm{U}}/L_i}]/d\Delta\ln P_i)$. Adjustments use 2000–2010 flows and 2000 stocks. Identification from comparison of ex ante observationally identical tracts prior to experiencing demand shock variation justifies equating $d\ln P_i$ with $d\Delta\ln P_i$ and allows 2000 stocks to cancel.

As there is wide dispersion across tracts in the ratio of stocks to new construction or land development flows, implied new construction elasticities vary quite sensitively across tracts. Nevertheless, our estimates for the median tract are sensible and in line with housing production function estimates. Calculated using the linear FMM-IV specification, medians of implied tract distributions of new construction floor space and units elasticities $d\ln S_i^{\mathrm{N}}/d\ln P_i$ and $d\ln H_i^{\mathrm{N}}/d\ln P_i$ are both 1.9. For new

[30] Other estimates of the land share range from 0.10 for Centre County, Pennsylvania (Yoshida 2016). to 0.14 for Allegheny County, Pennsylvania (Epple, Gordon, and Sieg 2010), to one-third for the average US housing market (ranging from 0.11 to 0.48 in low- to high-value areas; Albouy, Ehrlich, and Shin 2018). Ahlfeldt and McMillen (2014) provide empirical support for the Cobb-Douglas functional form as a reasonable approximation to the housing production function.

construction on undeveloped land ($d\ln S_i^{\mathrm{U}}/d\ln P_i$ and $d\ln H_i^{\mathrm{U}}/d\ln P_i$), these estimates are 3.2 and 2.8, respectively, with a corresponding new land development elasticity $d\ln L_i^{\mathrm{U}}/d\ln P_i$ of 0.2. Medians of the tract distributions of new construction floor space and units on undeveloped land relative to the new land development elasticity $((d\ln S_i^{\mathrm{U}}/d\ln P_i) - (d\ln L_i^{\mathrm{U}}/d\ln P_i)$ and $(d\ln H_i^{\mathrm{U}}/d\ln P_i) - (d\ln L_i^{\mathrm{U}}/d\ln P_i))$ are 3.0 and 2.8. Given Cobb-Douglas production, the floor space estimate thus implies a land share in housing production of 0.26.

VI. Aggregation

Much of the existing evidence on housing supply elasticities uses metro areas as the unit of analysis. To connect to metro-level estimates, in this section we explore the aggregation of tract-based supply elasticities to larger spatial units. As neighborhoods are linked in the residential demand system, metro-level demand shocks of the same size but aggregated from different combinations of changes in neighborhood fundamentals can imply different aggregate housing supply elasticities. Because of this sensitivity to setting, here we provide two examples of the macro supply elasticities implied from some simple broad-based shocks. Context matters and neighborhood-level supply elasticities must be aggregated as appropriate to the application at hand.[31]

The tract elasticity for supply measure Q, γ_{ir}^{Q}, generically aggregates to the metro region–level elasticity γ_r^Q as follows:

$$\Delta\ln Q_r = \sum_i \frac{Q_{ir}}{Q_r}\Delta\ln Q_{ir} = \sum_i \frac{Q_{ir}}{Q_r}\gamma_{ir}^{Q}\Delta\ln P_{ir} = \gamma_r^Q\Delta\ln P_r.$$

If we solve out, by definition the region-level elasticity is given by

$$\gamma_r^Q \equiv \left[\sum_i \frac{Q_{ir}}{Q_r}\gamma_{ir}^{Q}\Delta\ln P_{ir}\right] \Big/ \left[\sum_i \frac{Q_{ir}}{Q_r}\Delta\ln P_{ir}\right]. \tag{19}$$

In (19), we see that the metro-level elasticity depends on the mix of neighborhoods experiencing price growth that has been spurred by demand shocks. As neighborhoods are linked in spatial equilibrium, aggregation requires imposing the form of demand linkages across neighborhoods.

We first consider the special case in which all neighborhoods simultaneously experience identical housing demand shocks.[32] The resulting metro

[31] While our narrative is about aggregation from census tract to metro region levels, the same logic can be applied to recover elasticities for any aggregate spatial units.

[32] In the context of our model, a demand shock that changes aggregate expected income by the same percentage in every neighborhood makes $\Delta\ln S_{ir} + \Delta\ln P_{ir}$ a constant. This would happen if the outside option $\ln\mu$ in (7) changes, thereby leaving no scope for households to substitute across neighborhoods in response to this shock.

housing supply elasticity is a weighted average of tract-level elasticities, where the weight is the initial housing share adjusted for the neighborhood supply elasticity.[33] Using $\Delta\ln P_{ir} = x/(1 + \gamma_{ir})$ and (19) to aggregate over tracts, we have

$$\frac{\Delta\ln Q_r}{\Delta\ln P_r} = \gamma_r^1 = \sum_i \frac{H_{ir}/(1 + \gamma_{ir})}{\sum_i H_{ir}/(1 + \gamma_{ir})}\gamma_{ir}. \tag{20}$$

This expression reflects the fact that tracts with more elastic supply receive lower weight in aggregation because price growth is lower in these locations for a given demand shock. We apply this same expression to aggregate unit supply elasticities, recognizing that this requires tract per-unit price growth to match that for floor space.

As a second example, we consider the case in which aggregate housing demand shifts out in the city but agents get redistributed across neighborhoods in a way that maintains the same relative home prices across neighborhoods. This environment can be justified from the spatial equilibrium condition of a simpler model than that in section III.B, as in Roback (1982), in which neighborhoods differ in amenities but get hit with the same per capita potential income shock, thereby driving the same price growth rate but different tract population changes, depending on their supply elasticities. In this setting, conditional on amenities and wages net of commuting costs, neighborhoods are perfect substitutes. The resulting metro-level supply elasticity is

$$\frac{\Delta\ln Q_r}{\Delta\ln P_r} = \gamma_r^2 = \sum_i \left[\frac{H_{ir}}{H_r}\gamma_{ir}\right]. \tag{21}$$

Figure 4 presents the distributions of γ_r^1 and γ_r^2 for units and floor space. We report two versions of each, derived from linear FMM-IV and linear IV empirical specifications. Vertical lines show that the FMM-IV specification yields a mean unit supply elasticity across metro regions of 0.38 for γ_r^1 and 0.41 for γ_r^2. Analogous mean floor space elasticities are 0.61 and 0.63, respectively. As it accommodates more demand substitution across neighborhoods, γ_r^2 first-order stochastically dominates γ_r^1 in all cases. Comparison with Saiz (2010) elasticity estimates is in appendix D.[34]

Patterns in figure 4 highlight the advantages of using FMM-IV elasticities to capture cross-regional differences in supply elasticities. Because IV elasticities are constrained to be the same for tracts with the same observable supply factors in different regions, any cross-region differences

[33] To have complete coverage, we use housing units in the 2000 census for all weighting.

[34] Rather than using housing units as aggregation weights, it could also be reasonable to use tract land area. Doing so results in larger aggregate elasticities, with FMM-IV means of γ_r^1 at 0.52 for units and 0.77 for floor space.

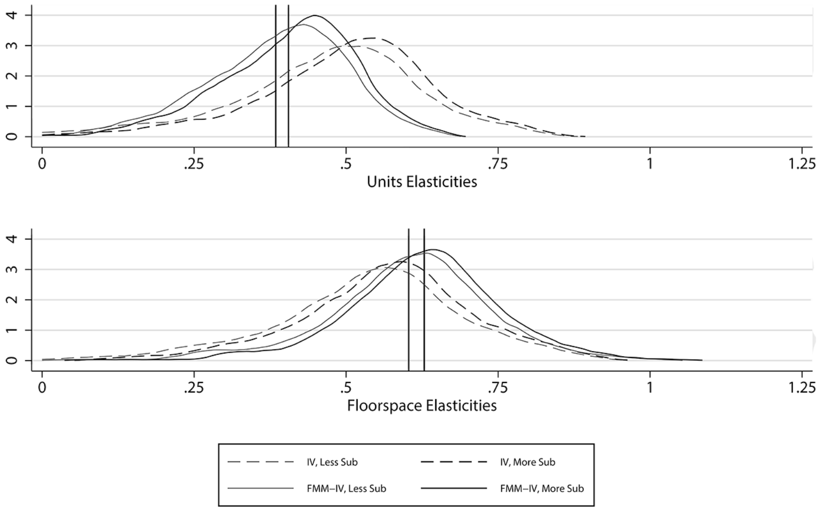

FIG. 4.—Kernel densities of region supply elasticities. Predicted elasticities in 306 metro regions contribute to all plots. Five regions have negative units IV elasticities, and one has negative space IV elasticities. Means of FMM-IV elasticities are indicated with vertical lines.

must be driven by variation in the distribution of tract-level supply factors. Moreover, as larger regions have more observations and more opportunity to provide the within-region identifying variation needed for estimation, IV estimated parameters are more heavily influenced by variation within larger regions and thus may not apply well to smaller regions. The result is more reasonable FMM-IV region supply elasticity estimates. For example, only Newark ($\gamma_r^1 = -0.04$ and $\gamma_r^2 = -0.02$) has negative FMM-IV unit elasticity estimates, whereas five regions have (more strongly negative) IV-based estimates. Moreover, the fact that floor space FMM-IV elasticities are typically greater than those for units is in line with model prediction.

Comparing the distributions of the metro-level elasticities in figure 4 with those of the tract-level elasticities in figure 2 reveals comparable or larger dispersion within than between regions. Both distributions of FMM-IV unit elasticities in figure 4 have a standard deviation of 0.11, while that for both distributions of floor space elasticity is 0.13. Analogous numbers for the full tract distributions in figure 2 are 0.20 and 0.26. Mechanical variance decompositions of the distributions in figure 2 reveals that 30% of the variation in tract unit elasticities and 24% of tract floor space elasticities are from cross-region variation. As such, use of metro-level supply elasticities is inadequate for evaluating economic consequences of neighborhood-level shocks.

VII. Opportunity Zone Application

Tract-level supply elasticities are essential to carry out welfare analysis of neighborhood-targeted place-based policies. In this section, we work through an example focusing on the census tracts designated for economic development as OZs under the auspices of the US federal Tax Cuts and Jobs Act of 2017.

A. Recovering the Neighborhood Demand System

Using the structure of our demand model, we estimate parameters governing demand substitution patterns across neighborhoods. Appendix C derives the floor space demand elasticity

$$\frac{\Delta \ln S_i^d}{\Delta \ln P_i} = [\eta(\beta - 1) - 1] + s_i\left[\frac{\psi}{\eta} - 1\right], \tag{22}$$

where s_i is the share of municipality $m(i)$'s population that is in tract i. The second term captures net migration with other municipalities. The implied elasticity of substitution between two neighborhoods in the same municipality is $1 + \eta(1 - \beta)$ and that between neighborhoods in different municipalities is $1 + \eta(1 - \beta) + (1 - (\psi/\eta))(s_i + s_{i'})$, where we expect $\psi < \eta$. The corresponding population and units elasticities of substitution are $\eta(1 - \beta)$ and $\eta(1 - \beta) + (1 - (\psi/\eta))(s_i + s_{i'})$, respectively.

Taking FMM-IV estimates of $\gamma_{ir}^{\text{space}}$, gravity regression estimates of $(\kappa\varepsilon)_r$, and calibrated values of 0.8 for β and 0.01 for κ as given,[35] we estimate using generalized method of moments, imposing that $\Delta\ln\widetilde{\text{RMA}}_i$ is orthogonal to the error term in (13). One specification includes metro region fixed effects, and a second conditions on five municipalities in each region: one for the central city and one each for suburbs to the north, south, east, and west. We use the same estimation sample and tract weights as in tables 4–6.

As identifying variation comes through labor demand shocks that lead to housing demand (rather than supply) shocks, recovery of neighborhood demand parameter estimates leans heavily on model structure. In particular, the model delivers how much neighborhood housing prices must change given exogenous shocks to holding population constant. Then, observations about population changes are informative about η and ψ because these parameters govern own and cross-price demand elasticities across neighborhoods.

With municipality fixed effects, the estimate of η is 8.5 (SE = 1.2). Without municipality fixed effects, we estimate it to be 3.9 (SE = 0.2). This

[35] $\kappa = 0.01$ implies that 2 minutes of commuting reduces full income by 1%. Attempts to estimate κ jointly with neighborhood demand parameters yield implied values of ε that were too low.

smaller estimate reflects less substitutability between neighborhoods in different municipalities than between neighborhoods in the same municipality. The resulting implied average elasticity of demand for floor space in each neighborhood is $-0.2 \times 3.9 - 1 = -1.8$, while that for units is -0.8. These estimates are similar to estimates in Hanushek and Quigley (1980) and Couture et al. (2019).

B. *Opportunity Zones*

The OZ program was created to incentivize investment in economically distressed communities. Among other incentives, the program provides preferential tax treatment of capital gains for new real estate investments within the census tracts designated by state governors to be in an OZ. Governors could designate 25% of eligible census tracts in their states for OZ status. Eligible tracts are those in low-income communities (LICs), which have an individual poverty rate of at least 20% and a median family income that is at most 80% of the area median, plus adjacent tracts that are sufficiently low income.

The OZ program may boost both the supply and demand for housing in OZ tracts. The reduction in the capital gains tax liability for investors reduces the financing costs of real estate development in these areas, which we model as a reduction in the marginal cost of building housing by Δs log points relative to other tracts. OZ status may additionally spur local governments to invest in tract amenities, which we treat as an outward shift in housing demand by Δd log points in terms of quantities. As the OZ program applies to 3,957 urban census tracts in our sample area, we see this treatment as broad-based enough such that our calculated impacts of the program can reasonably apply to an average OZ tract.

Following the model in section III, we assume that the demand and supply for floor space and housing units have constant elasticity forms. Generically, these equations are

$$\begin{aligned} \ln Q_i^d &= d_i + \varepsilon_{Di} \ln P_i, \\ \ln Q_i^s &= s_i \varepsilon_{Si} + \varepsilon_{Si} \ln P_i. \end{aligned}$$

Shocks of Δd to demand (in terms of $d\ln Q^d$) and Δs to supply (in terms of $d\ln P^s$) yield the equilibrium price change $\Delta \ln P_i = (\Delta d_i - \varepsilon_{Si}\Delta s_i)/(\varepsilon_{Si} - \varepsilon_{Di})$. Dollar changes in consumer surplus (CS) and producer surplus (PS) for small supply and demand shocks are

$$\begin{aligned} \Delta \mathrm{CS}_i &= -\Delta P_i H_i - \frac{1}{2} \Delta P_i \Delta H_i, \\ \Delta \mathrm{PS}_i &= \Delta P_i H_i + \frac{1}{2} \Delta P_i \Delta H_i. \end{aligned}$$

Associated percentage changes in CS and PS are $\Delta d_i + (1 + \varepsilon_{Di})\Delta \ln P_i$ and $\varepsilon_{Si}\Delta s_i + (1 + \varepsilon_{Si})\Delta \ln P_i$.

We measure base year prices using the 2016 repeat sales index and base year quantities of units and floor space in each tract using Zillow data from 2016. All values are in 2010 dollars. We use predicted linear FMM-IV tract supply elasticities based on results in table 6 and tract developed fraction from 2011. To get a sense of the importance of local heterogeneity, we compare results using predicted tract supply elasticities to those using region supply elasticities γ_r^2. Under these assumptions, we calculate changes in CS and PS for all census tracts for which we have repeat sales price index information in 2016, given either $\Delta s = 0.05$ or $\Delta d = 0.05$. If we assume a capital gain of 25% on an average property and savings of the 20% capital gains tax via the OZ program, $\Delta s = 0.05$ seems reasonable.[36]

Table 7 presents the results. Results in panel A show that our assumed supply shock would increase CS in the market for housing units by an estimated $3.3 million on average in OZ tracts, $3.7 million in other low-income tracts, $6.7 million in adjacent tracts, and $8.3 million in fully ineligible tracts. Imposing metro-level supply elasticities instead would imply much greater CS changes of $4.4 million in OZ tracts and smaller changes of $7.0 million in fully ineligible tracts, with smaller standard deviations for all types of locations. Increases in PS for 5% demand shocks are greater in magnitude than their CS counterparts, as housing demand is more elastic than housing supply. But as with CS, PS increases the least on average in OZ locations at $18.7 million, far below the $28.5 million average increase in fully ineligible tracts. Results for the floor space market in panel B exhibit similar patterns, though with smaller magnitudes because of the larger demand and supply elasticities for floor space than units.

Our OZ analysis concludes that because of relatively inelastic housing supply in OZ tracts, capital gains tax reductions impart lower average welfare gains than if the same policy were implemented in other neighborhoods. In addition, using metro level rather than tract supply elasticities would deliver misleading conclusions about the welfare consequences of the program.[37]

VIII. Conclusions

Since DiPasquale's (1999) lament about the limited amount of research on housing supply, large and distinct literatures on housing production

[36] Long-term capital gains are taxed at either 0%, 15%, or 20%, depending on the taxpayer's income.

[37] Other evidence on the efficacy of the OZ program is mixed. Comparing OZ to similar-looking non-OZ tracts, Chen, Glaeser, and Wessel (2022) find that the OZ program had little effect on home price growth, though Kennedy and Wheeler (2022) find effects on levels. Arefeva et al. (2020) find that the OZ program promoted job creation in OZ relative to non-OZ tracts. However, Freedman, Khanna, and Neumark (2023) find that OZ status had little effect on resident outcomes.

TABLE 7
WELFARE CONSEQUENCES OF OZ PROGRAM (millions of 2016)

OZ	Yes	No, LIC	No, Adjacent	No, Other
Sample size	2,580	8,776	3,704	15,939
	A. Market for Housing Units			
Tract supply elasticity	.20	.22	.31	.32
	(.17)	(.17)	(.19)	(.17)
Based on tract supply elasticities:				
CS ($\Delta s = .5$, $\Delta d = 0$)	3.28	3.74	6.69	8.28
	(4.63)	(4.66)	(7.41)	(8.68)
PS ($\Delta s = 0$, $\Delta d = .5$)	18.65	19.46	23.71	28.47
	(16.76)	(16.31)	(19.46)	(25.76)
Region supply elasticity	.28	.28	.29	.25
	(.12)	(.11)	(.12)	(.11)
Based on region supply elasticities:				
CS ($\Delta s = .5$, $\Delta d = 0$)	4.39	4.67	6.61	7.00
	(3.95)	(4.14)	(6.26)	(6.71)
PS ($\Delta s = 0$, $\Delta d = .5$)	17.30	18.33	23.81	30.03
	(15.82)	(15.36)	(19.37)	(26.86)
	B. Market for Floor Space			
Tract supply elasticity	.40	.43	.53	.56
	(.25)	(.24)	(.24)	(.23)
Based on tract supply elasticities:				
CS ($\Delta s = .5$, $\Delta d = 0$)	3.19	3.54	5.76	7.14
	(3.77)	(3.80)	(5.88)	(6.99)
PS ($\Delta s = 0$, $\Delta d = .5$)	8.35	8.77	11.06	13.30
	(7.43)	(7.24)	(8.97)	(11.74)
Region supply elasticity	.51	.51	.52	.47
	(.15)	(.15)	(.15)	(.14)
Based on region supply elasticities:				
CS ($\Delta s = .5$, $\Delta d = 0$)	3.90	4.14	5.70	6.28
	(3.37)	(3.55)	(5.20)	(5.70)
PS ($\Delta s = 0$, $\Delta d = .5$)	7.96	8.45	11.09	13.76
	(7.12)	(6.92)	(8.93)	(12.06)

NOTE.—The table shows tract means with standard deviations in parentheses. Entries are calculated using assumptions about demand and supply shocks. Estimates use a floor space demand elasticity of −1.8 and a units demand elasticity of −0.8. In the floor space market, indicated increases amount to 0.7% for OZs and LICs and 0.9% in other types of locations. PS increases by 3.2% in OZs and LICs and 3.3% in other locations. These percentages are undefined in the market for housing units because inelastic demand makes CS infinite.

and housing supply have developed. Evidence from the former finds support for a near Cobb-Douglas form of the production function in land and capital for newly constructed housing conditional on land development. Evidence from the latter shows that land use regulation and topographic conditions influence housing supply elasticities at the metro area level. This supply literature emphasizes how selection of land parcels into development influences overall supply elasticities.

This paper performs a comprehensive analysis of housing supply for the United States. We decompose total floor space supply responses to price shocks into eight margins. This aspect of the analysis includes separate consideration of land development, new construction, redevelopment, teardowns, renovation, and floor space per unit. While the new construction component of our analysis conforms quantitatively with evidence in the housing production literature, we demonstrate that new construction accounts for at most two-thirds of the supply response to price shocks in the average neighborhood. Because of housing's durability and variation in land development costs across locations, an understanding of the production function for housing is not sufficient to have a full picture of housing supply. Land availability matters, even at the neighborhood level. Maintenance and renovation margins matter as well, as they can reduce teardowns, thereby keeping vintage properties in the housing stock longer.

We recover variation in neighborhood housing supply elasticities as functions of both neighborhood and metro area topographic conditions, development intensity, and regulation. Using our FMM-IV estimates, we find that average predicted elasticities of floor space and housing unit supply with respect to price are 0.51 and 0.29 across 50,410 census tracts in 306 US metropolitan areas for the 2000–2010 period, with just over half of the unit supply response in the typical tract due to new construction. We find that each component of housing supply becomes more elastic moving out from urban centers and that there is more variation within than between metro areas in housing supply elasticities. This pattern is in part but not entirely due to the increasing fraction of land available for development with CBD distance. Initial development intensity, availability of flat land, and zoning regimes are all important determinants of local housing supply. Identification comes from variation in labor demand shocks to commuting destinations, as aggregated using insights from a quantitative spatial equilibrium model.

We hope this new evidence on housing supply informs housing affordability policies and aids in assessing the welfare consequences of place-based policies more generally. On affordability, our results indicate that intensive margin supply responses are important components of supply. Building renovations that add units and reduced teardown rates together account for about 40% of unit supply responses to price growth. As these segments of supply are more likely to serve lower-income households and are less sensitive to land availability constraints, policies that make them easier are likely to contribute to improved affordability, particularly in neighborhoods with low new construction supply elasticities because of limited land availability. On place-based policies, the OZ example shows the implicit costs of targeting inelastic supply neighborhoods with subsidies for housing construction. Our evidence of high within-metro variation in housing supply elasticities indicates the importance of considering neighborhood supply conditions in evaluations of the efficacy of neighborhood targeted policies.

Data Availability

Code for replicating the tables and figures in this article can be found in Baum-Snow and Han (2024) in the Harvard Dataverse, https://doi.org/10.7910/DVN/LFGAAW.

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