

Where Is Housing Slow to Build,
And Is It Getting Slower?

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Abstract

We estimate the time durations of permitting and development for standardized new housing projects across 60 U.S. cities from 2000 to 2025. We report three new facts. First, the fastest cities complete projects in the time the slowest cities take to merely approve them. Second, across cities, permitting duration is positively associated with housing prices and negatively associated with production. The strength of these relationships rivals that of other measures of land-use regulation and suggests a high cost of delay. Third, permitting duration has risen steadily over time, whereas total project duration has fluctuated cyclically.

Keywords: building permit, housing development, time-to-build

JEL Codes: H73, R31, R38

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1 Introduction

In 2024, for the first time in at least a decade, housing was the second most commonly-cited priority of large-city U.S. mayors, according to an analysis of speeches by the National League of Cities.¹ This mayoral attention follows a sustained rise in housing costs in many U.S. cities, and with it, a wave of policy reforms seeking to reduce regulatory burdens on housing development. A premise for many of these reforms is that the process of regulatory approval for new development (“permitting”) has become slow and costly, as distinct from more-familiar concerns about regulations that constrain allowed land uses or that impose costly requirements on construction.²

Despite this policy focus, there is little systematic evidence on the amount of time required to approve new housing or to complete it. Across U.S. cities, where can new homes be built most quickly? How do permitting and construction times correlate with housing costs? What other city-level factors predict the durations of permitting and construction? Is housing development getting faster or slower? Are these changes mostly attributable to permitting or construction? None of these questions have conclusive answers, as there are no representative estimates of permitting and development durations for new housing, either across cities or over time.

This paper produces these estimates by collecting comprehensive permit records for applications to build new housing across 60 U.S. cities from 2000 to 2025, recording the dates at which permits are submitted, issued, and completed. Using these data, we separately estimate the time required to obtain regulatory approval and the total time from permit submission to completion. We then compare these outcomes across cities and over time, adjusting for differences in observed project characteristics and for right-censoring among incomplete projects. The result is a set of standardized measures of where housing development is slow, whether it is getting slower, and at what point observed delays arise in the development process.

We report three main findings. First, average project duration varies greatly across cities, even when comparing observably similar projects. In coastal cities like Los Angeles, New York, and San Francisco, a typical 20-unit apartment building takes on average 4.6 years to complete. By comparison, such a structure requires two years in Sunbelt cities like Raleigh, Orlando, and Phoenix. We attribute 30 to 43 percent of the difference between the slowest and fastest cities is due to differences in the time to receive a permit, rather than in the time to actually build.

Second, across cities, permitting duration is positively associated with housing costs and negatively associated with housing production and estimates of housing supply elasticities. An additional

¹National League of Cities (NLC), “Appendix B: Mayoral Priorities Over the Last Decade” in *2025 State of the Cities*. NLC’s data begins in 2014.

²Among such permitting-reform policies are categorical exemptions from discretionary or environmental reviews, “shot clock” triggers on processing timelines, and “one-stop-shop” bureaucratic reorganizations so that reviews are performed by one government agency—or at least concurrently, rather than sequentially, across agencies.

year of permitting time for multi-family housing is associated with a 39-percent increase in median rent. The strength of this relationship with housing costs rivals that of prior measures of land-use regulation. Furthermore, it survives controls for neighborhood characteristics that are associated with housing costs, such as per-capita income and population density. Relationships with production are less robust to controls. Permitting duration is also positively associated with land prices, a result which suggests a more complex, and possibly endogenous, relationship between local amenities and regulatory hurdles lengthening the permitting process.³

Third, permitting duration approximately doubled from 2000 to 2023, holding fixed observed project characteristics and adjusting for censoring due to incomplete projects. We estimate that, in 2000, our standardized multi-family project had a 71-percent probability of approval within six months of applying for a permit. In 2025, that project had a 44-percent approval probability within six months. For single-family housing, the probability of approval within two months fell from 88 to 70 percent over the same period. For total project duration, by comparison, we see strong fluctuations over the business cycle, obscuring secular trends over time.

This paper contributes to three strands of the literature. First, while we think we are the first to measure our objects of interest, other papers consider related objects, such as construction durations once permits are issued, permitting durations of commercial development, or permitting durations for housing in individual cities. In commercial development, [Millar et al. \(2016\)](#) estimate the time from project announcement to regulatory approval, and [Glancy et al. \(2026\)](#) show these lags affect the business cycle in commercial development. In the U.S. and U.K. respectively, [Oh and Yoon \(2020\)](#) and [Ball et al. \(2025\)](#) estimate the extent to which developers endogenously adjust (post-permitting) construction durations in response to demand, and [Oh et al. \(2024\)](#) estimates variation across cities in construction duration for larger (subdivision-scale) single-family development. Finally, several papers ([Manville et al., 2023](#); [Lyons and Sweeney, 2025](#); [Kestelman, 2025](#); [Gabriel and Kung, 2026](#)) have studied durations in individual cities, all highlighting the link between regulatory institutions and project duration.⁴ We extend this work by measuring permitting and project durations separately, for standardized housing, across many U.S. cities over 25 years.⁵

³In theory, a slow permitting process should reduce land prices, all else equal. Land prices capitalize profits from development, which are reduced by permitting costs. Political economy can generate an opposite-signed relationship, if for instance, local incumbents in attractive cities impose barriers to new construction ([Duranton and Puga, 2023](#)).

⁴More broadly, urban economists have used permitting and construction delays to understand the dynamic responses of cities to housing-market shocks, with a focus on variation in responses across cities and on asymmetries between booms and busts ([Glaeser and Gyourko, 2005](#); [Saks, 2008](#); [Paciorek, 2013](#); [Notowidigdo, 2020](#); [Saiz, 2024](#)).

⁵Governments have made several efforts to record project durations. The California Department of Housing and Community Development requires jurisdictions to submit Annual Progress Reports with such information, but it does not standardize or otherwise process the submissions. The Survey of Construction of the U.S. Census Bureau includes national and regional “length-of-time” measures of post-permitting construction durations for new private residential construction, without adjustment for project characteristics and only for completed projects. Our data allow us to replicate the Census approach to construction duration (see Appendix Figure A1).

Our motivation to isolate permitting from overall project duration follows from a broader interest in the link between land-use regulation and housing supply (see., e.g., [Glaeser and Gyourko, 2018](#); [Ellickson, 2022](#)). Of all the potential mechanisms, one of the most direct and intuitive is how quickly and smoothly a government reviews permit applications ([Mayer and Somerville, 2000](#)), although public policy also affects construction duration after permitting. The seminal measurement contribution on this topic is the Wharton Residential Land Use Regulatory Index ([Gyourko et al., 2008, 2021](#)), which has surveyed thousands of officials about regulatory practices. Yet the costs and limitations of this survey approach (as discussed in [Gyourko and Molloy, 2015](#); [Lewis and Marantz, 2019](#); [O’Neill et al., 2019](#)) have spurred several efforts to simplify or automate regulatory measurement ([Cui, 2024](#); [Bartik et al., 2025](#); [Song, 2025](#)).⁶ Our outcomes-based measure of regulation—with its project-level granularity, spatiotemporal variation, and low cost to collect—has potential appeal as a new tool to study the role of regulation in housing markets.

Finally, these durations and their evolution over time relate to recent work that sheds light on the productivity decline in the construction sector ([Brooks and Liscow, 2023](#); [Goolsbee and Syverson, 2023](#); [D’Amico et al., 2024](#); [Garcia and Molloy, 2025](#); [Potter and Syverson, 2025](#)). Slow development ties up capital to projects for longer, in principle raising developers’ breakeven sale prices for new homes through higher effective construction costs. Duration-based measures of regulation have also been used in other policy contexts, most notably by [Djankov et al. \(2002\)](#).

The remainder of the paper proceeds as follows. Section 2 describes the data and our duration measures. Section 3 presents the paper’s three main empirical facts. Section 4 provides some economic interpretation of these facts. Section 5 concludes.

2 Data and Measurement

2.1 Data

Permits. We compiled permit applications for new single- and multi-family housing. Our primary sources were municipal open-data websites and developer-facing online permit portals, which we supplemented with public-records requests to city buildings departments.

For each permit, we collected the following fields: official permit and parcel identifiers; street address; geographic coordinates; construction type (e.g., single-family residential); dates of permit submission, issuance, and completion or finalization, often indicated by certificate of occupancy or equivalent final approval; number of units; floorspace (in square feet); attached/detached structure status; and site type (single-structure infill, small cluster, or large subdivision).

Additional Data. We linked permits to several other data sources. First, we recorded lot sizes

⁶Other research measuring land-use regulation includes [Evenson and Wheaton \(2003\)](#), [Quigley and Rosenthal \(2005\)](#), [Glaeser and Ward \(2009\)](#), [Zabel and Dalton \(2011\)](#), [Xu et al. \(2023\)](#), and [Gallagher et al. \(2026\)](#).

from property tax assessments (obtained via Cotality, and supplemented on an ad-hoc basis from localities). Linkages to assessments were performed using parcel numbers or, as a fallback, via a spatial join to parcel maps, which first required that we geocode addresses on permits. We also use assessments to fill in missing values for floor area, attachment status, and site type.

Second, we mapped permits to census tracts and obtained neighborhood attributes from the 2015–2019 (five-year) tabulation of American Community Survey data. Third, for use in robustness checks, we link to other parcel covariates, including measures of terrain, natural-disaster risk, and lot shape (see Appendix B). Finally, we obtain city-level data on housing production from the Census Building Permits Survey.

2.2 Measurement

Our objects of interest are the potential time durations of permitting and construction to build the “same” new housing development across cities and over time. To make projects more comparable, we adjust durations for differences in observed project characteristics and, where relevant, for right-censoring among incomplete projects.

We implement these adjustments using log-linear duration models with covariates. For a project stage i (for example, permitting), let T_i denote the realized duration when the stage is completed, and let T_i^* denote the potential duration but for censoring. Let c_i denote the elapsed time from project start to the end of observation. We observe the completed duration when $T_i^* \leq c_i$, and we define completion as $D_i = 1[T_i^* \leq c_i]$.

Estimation. We use two complementary approaches to adjust for project characteristics and censoring. The first is a series of covariate-adjusted Poisson pseudo-maximum-likelihood models (Correia et al., 2020) estimated on completed projects:

$$E[T_i | X_i, t(i), D_i = 1] = \exp\{\alpha_{t(i)} + X_i' \beta\}, \quad (1)$$

where X_i contains observed project attributes, $t(i)$ denotes the submission cohort (in five-year bins), and $\alpha_{t(i)}$ is a cohort effect. These estimates adjust for observed characteristics but not censoring.

The second approach is a series of covariate-adjusted accelerated failure time (AFT) models:

$$\log T_i^* = \gamma_{t(i)} + X_i' \delta + \sigma \varepsilon_i, \quad (2)$$

where σ is a scale parameter and ε_i is an error term with a parametric distribution. In our main specification, we assume that ε_i is Gaussian, yielding a lognormal AFT model. These estimates adjust for both observed project heterogeneity and censoring.

We note several implementation details. First, in the cross-sectional analysis, we always estimate

Table 1: Definitions for Single-Family and Multi-Family Project Archetypes

	Single-Family	Multi-Family
Parcel Characteristics		
Units	1	20
Floor Area Per Unit (sq. ft.)	2,800	1,200
Lot Size (Acres)	0.15	n.a.
Site Type	One-Off Infill	n.a.
Structure Type	Detached	n.a.
Census Tract Characteristics		
Population Density (per sq. mi.)	2,400	4,100
Median Household Income (2019 dollars)	\$79,000	\$66,000

Notes: This table reports the characteristics used to standardize city-level predictions. Entries marked “n.a.” indicate characteristics not used in that archetype’s definition.

Equations 1 and 2 on a city-by-city basis. This approach allows the relationship between duration and observed project characteristics to vary across cities, without imposing a single covariate adjustment for all cities. Second, we lack data on non-issued permit applications in a third of cities, and so permitting durations can only be observed there conditional on eventual issuance, which we argue imparts a downward bias in levels (see Appendix Table A1). Third, throughout the paper we cluster standard errors at the project level, which accounts for a small share of projects with multiple, separately-permitted structures that share administrative identifiers.

Project Archetypes. We estimate durations for standardized projects (“archetypes”) across cities and over time, adjusting for differences in observed project characteristics. As some cities surely lack projects which exactly match our archetypes, we view this approach as yielding index measures, and we consider the extent of extrapolation in Section 3.

Our archetypes are for a single-family project and a medium-sized multi-family project (see Table 1). With respect to project characteristics, the single-family project is standardized on lot size and floor area. Furthermore, the archetype is specified to be a detached home built as “one-off” infill, as opposed to part of a subdivision. The multi-family archetype fixes the unit count (20 units) and floor area. We have also implemented a duplex archetype (see Appendix Figure A2).

Estimation involves both sample restrictions and covariate adjustments. For the single-family archetype, we limit the sample to one-unit projects. Attachment and subdivision statuses are included as covariates. For multi-family, we keep only projects with between five and 200 units. Unit count (in logarithms) is included as a covariate.

For both archetypes, we fix census-tract covariates at common reference values, using rounded national medians. For single-family, population density is 2,400 people per square mile, and median household income is \$79,000 (in 2019 dollars). For multi-family, population density is

4,100 people per square mile, and median household income is \$66,000.

National medians are also used to standardize on floor area and lot size. Both variables enter in logarithms as controls. For single-family, we obtain a floor area of 2,800 square feet and a lot size of 0.15 acres (6,500 square feet). For multi-family, we proceed on per-unit basis, take medians, and then multiply by 20 units. We obtain a median per-unit area of 1,200 square feet.

Cross-Sectional Comparisons. We estimate expected permitting and construction durations across cities using the archetype values $\bar{X}$:

$$E[T_i \mid X_i = \bar{X}, t(i) = s^*, D_i = 1] = \exp\{ \hat{\alpha}_{s^*} + \bar{X}'\hat{\beta} \} \quad (3)$$

$$E[T_i \mid X_i = \bar{X}, t(i) = s^*] = \exp\{ \hat{\gamma}_{s^*} + \bar{X}'\hat{\delta} + \hat{\sigma}^2/2 \}. \quad (4)$$

We report these quantities for the archetypes described above, holding characteristics $\bar{X}$ and cohort s^* fixed at 2015–19 across cities, and obtaining standard errors by the delta method.

Due to data limitations, we cannot estimate all archetypes in all cities where we collect data. All reported city-level estimates respect a minimum sample size of 20 permits.

Over-Time Comparisons. We also estimate time series of permitting and total project duration for each archetype. For all archetypes and durations, we pool data across cities, and we include fixed effects for both city and annual submission-year cohort. We include the same covariates as in the cross-sectional analysis when estimating both PPML and AFT specifications.

In the PPML specification, for instance, we estimate

$$E[T_i \mid X_i, t(i), c(i), D_i = 1] = \exp\{ \alpha_{t(i)} + \lambda_{c(i)} + X_i'\beta \}, \quad (5)$$

where λ_c is a city fixed effect and α_t is an annual submission-cohort fixed effect. We obtain a duration estimate for cohort s by $\hat{T}_s = \sum_c \omega_c \exp\{ \hat{\alpha}_s + \hat{\lambda}_c + \bar{X}'\hat{\beta} \}$, where ω_c are proper city weights based on the composition of the estimation sample. This specification compares similar projects submitted across years, while absorbing time-invariant differences across cities.

2.3 Discussion of Data

Data Coverage and Summary Statistics. Our data covers a broad set of U.S. cities, with variation in geography, income, density, and housing mix (see Table 2). For some cities, coverage begins in the early 2000s, though many cities enter later.⁷ Permit counts vary substantially across cities,

⁷Appendix Table A2 reports data coverage by variable and city. Appendix Figure A3 maps the covered cities. Our data covers jurisdictions containing around 14 percent of the U.S. population as of 2019. It includes, in total, approximately 1.1 million permits for 2.7 million units, which represents roughly one in 13 of all units permitted nationally from 2000 to 2025, according to U.S. Census totals.

from several hundred in smaller or supply-constrained markets to tens of thousands in others. The table also previews our first empirical facts before adjusting for project characteristics or censoring, approval and completion durations differ greatly across cities.

Some Context and Limitations. Although a canonical example of U.S. open data, permit microdata have rarely been analyzed across cities, and only then in limited ways. One reason is that cities produce these records independently, and primarily for municipal operations rather than statistical reporting. Basic fields such as unit counts and completion dates thus require substantial effort to collect and harmonize (e.g., [Wheeler, 2022](#)). In this respect, one contribution of our study is a richer consistent dataset for housing research.⁸

Nevertheless, our data have several limitations. First, projects may complete additional stages of review before applying to their local buildings department (see, e.g., [Kestelman, 2025](#)). The nature of these reviews, and the agencies responsible for them, varies across cities. Our baseline definition of project duration inevitably omits some pre-permit stages.

Second, some variables are not measured identically across cities. In the case of completion dates, for example, some cities do not issue certificates of occupancy for all project types. We thus sometimes use the date at which a permit is “finalized.” The distinction is between the dates at which construction is completed and at which occupancy may legally begin.

Third, there is a tail of very complex projects that our approach is likely to measure imperfectly. Some projects may receive multiple permit identifiers, proceed in stages that cannot be linked reliably over time, or have permits expired and later resumed. Our approach is thus best suited to the “bulk” of the distribution of housing development, and more research is required before applying it confidently to the largest and most complex projects.

3 Facts About Permitting and Total Project Durations

Fact 1: Cities vary substantially in both permitting and total project duration, holding fixed the observed characteristics of projects.

Figure 1 presents our preferred estimates of permitting and total project durations across cities for single- and multi-family housing (Equation 3).⁹

In Sunbelt cities like Raleigh, Orlando, and Phoenix, we estimate that our standardized new single-family home would proceed from permit submission to completion in approximately one year. Such cities also typically complete our standardized multi-family project in around two years.

⁸Combining open data, web scraping, and public records requests also allows us to patch missing fields, both when individual records have missing values and when a city’s open-data products omit variables entirely.

⁹On average across cities, permitting duration for our multi-family archetype is 0.7 years and total project duration is 2.4 years. For our single-family archetype, permitting duration is 0.2 years, and total project duration is 0.9 years.

Table 2: Permit Coverage and Sample Characteristics Across U.S. Cities

Census Region	City	Years of Coverage		Count by Stage		Annual Permits Per 10,000 People	Mean Duration in Yrs. (Unadj., Completed)	
		Start	End	Issued	Completed		To Issuance	To Completion
Northeast	Boston, MA	2009	2025	2,307	2,001	1.95	1.32	2.85
	Buffalo, NY	2012	2025	278	161	0.78	0.52	1.65
	Jersey City, NJ	2013	2023	417	259	1.45	0.24	1.95
	New York, NY	2000	2025	54,701	50,520	2.59	0.56	2.78
	Philadelphia, PA	2015	2025	8,581	7,454	4.92	0.33	2.24
	Pittsburgh, PA	2016	2025	618	455	2.06	0.66	2.30
	Providence, RI	2016	2025	898	713	5.40	0.24	1.42
Midwest	Ann Arbor, MI	2008	2025	1,503	1,338	7.08	0.33	1.33
	Cincinnati, OH	2010	2025	2,157	1,846	4.98	0.30	1.55
	Cleveland, OH	2015	2025	1,644	1,459	4.70	0.64	1.80
	Columbus, OH	2009	2025	14,143	12,707	9.22	0.10	0.93
	Grand Rapids, MI	2015	2020	395	359	3.43	0.14	1.17
	Indianapolis, IN	2000	2025	20,860	20,821	9.23	0.05	0.55
	Kansas City, MO	2000	2025	6,128	5,651	4.76	0.10	1.24
	Omaha, NE	2011	2025	12,995	6,951	18.29	0.18	1.06
	Sioux Falls, SD	2014	2025	10,945	10,329	49.79	0.06	1.07
South	St. Paul, MN	2014	2025	924	721	2.51	0.27	1.98
	Atlanta, GA	2017	2024	10,998	10,210	27.71	0.44	1.42
	Austin, TX	2000	2025	82,405	78,850	32.37	0.15	0.92
	Baltimore, MD	2018	2025	569	230	1.21	0.46	1.00
	Baton Rouge, LA	2011	2025	11,384	10,970	34.46	0.15	0.77
	Charleston, SC	2010	2024	10,033	9,980	46.72	0.08	0.69
	Durham, NC	2010	2025	27,206	24,781	62.17	0.08	0.72
	El Paso, TX	2011	2025	15,649	15,202	15.55	0.09	0.58
	Fort Lauderdale, FL	2000	2025	4,582	3,984	9.66	0.59	2.30
	Fort Worth, TX	2001	2025	89,416	85,901	39.99	0.08	0.63
	Houston, TX	2010	2025	25,519	11,888	14.86	0.40	1.68
	Jacksonville, FL	2000	2025	101,063	100,788	42.64	0.11	0.75
	Little Rock, AR	2018	2025	2,760	2,338	17.61	0.04	0.89
	Louisville, KY	2008	2025	16,524	16,326	15.23	0.17	0.94
	Miami, FL	2012	2025	1,898	1,239	2.90	1.38	3.44
	Nashville, TN	2016	2025	24,244	24,244	38.21	0.14	1.11
	New Orleans, LA	2004	2025	11,737	10,694	14.77	0.23	1.19
	Norfolk, VA	2016	2025	2,491	2,317	10.28	0.24	0.90
	Oklahoma City, OK	2007	2025	41,389	40,711	34.13	0.04	0.75
	Orlando, FL	2000	2025	24,710	23,952	33.52	0.18	0.86
	Raleigh, NC	2000	2025	51,522	42,669	41.89	0.11	0.69
	San Antonio, TX	2010	2025	38,566	33,359	15.58	0.10	0.90
	Tampa, FL	2000	2025	15,899	14,826	15.71	0.26	1.11
	Tulsa, OK	2014	2025	3,887	3,619	8.14	0.15	1.06
	Washington, DC	2012	2025	2,800	832	2.83	0.69	2.68
West	Albuquerque, NM	2016	2024	3,797	3,529	7.53	0.15	1.28
	Anaheim, CA	2000	2025	2,046	1,982	2.28	0.65	1.44
	Boise, ID	2004	2025	9,638	9,225	19.13	0.20	0.86
	Boulder, CO	2007	2025	712	625	3.95	0.63	2.18
	Colorado Springs, CO	2000	2025	39,704	39,106	31.93	0.26	0.84
	Denver, CO	2010	2025	20,995	17,468	18.04	0.30	1.17
	Honolulu, HI	2000	2025	23,306	21,972	27.06	0.48	2.06
	Los Angeles, CA	2000	2024	40,961	37,436	4.12	0.83	2.49
	Mesa, AZ	2003	2025	31,101	29,816	26.11	0.07	0.68
	Oakland, CA	2003	2025	1,523	1,325	1.65	0.53	2.30
	Phoenix, AZ	2000	2024	63,246	60,106	15.08	0.11	0.80
	Portland, OR	2000	2021	19,151	18,393	14.11	0.45	1.31
	Reno, NV	2010	2025	15,034	14,030	37.67	0.15	0.80
	Sacramento, CA	2015	2025	9,143	8,698	16.80	0.23	0.98
	San Diego, CA	2003	2025	4,452	4,092	1.44	0.61	2.19
	San Francisco, CA	2000	2025	2,272	1,997	1.10	1.47	3.42
	San Jose, CA	2000	2025	710	622	0.27	0.21	1.24
	Seattle, WA	2000	2025	17,368	14,350	9.41	0.69	2.07
	Spokane, WA	2007	2025	4,814	4,750	11.42	0.14	1.05

Notes: This table summarizes our permit data. Coverage indicates the first and last years of submitted permits. Annual permits per 10,000 people, durations, and unit counts are calculated from our data. Tract characteristics are for the median permit. See Appendix A for data details.

Yet in coastal cities like New York, Los Angeles, and San Francisco, our estimates of average total project durations are higher: around 2.6 years for single-family and 4.6 years for multi-family.

Another implication of Figure 1 is that, across cities, variation in total project duration is partly explained by variation in permitting duration. Ranked by total project duration, the slowest cities often take longer to approve developments than the fastest cities take to complete them.

Comparing slower and faster cities, differences in permitting duration can account for 30 to 43 percent of differences in total project duration (see Appendix Table A3). Total duration rises more than one-for-one in permitting duration (see Panel A of Appendix Figure A4), implying that cities that are slower to permit are also slower to complete housing once permits are issued.¹⁰

These patterns are similar for duplexes (see Appendix Figure A2). Cities that are slower with single-family projects are also slower with multi-family projects (see Panel B of Appendix Figure A4), suggesting permitting speed is a systematic city-level object.

We explore the sensitivity of Fact 1 in three ways. First, we examine the role of our base covariates and the extent of extrapolation beyond the support of the data. Second, given our estimand—same project, different cities—we try controlling for additional covariates. Third, we account for incomplete projects via duration models.

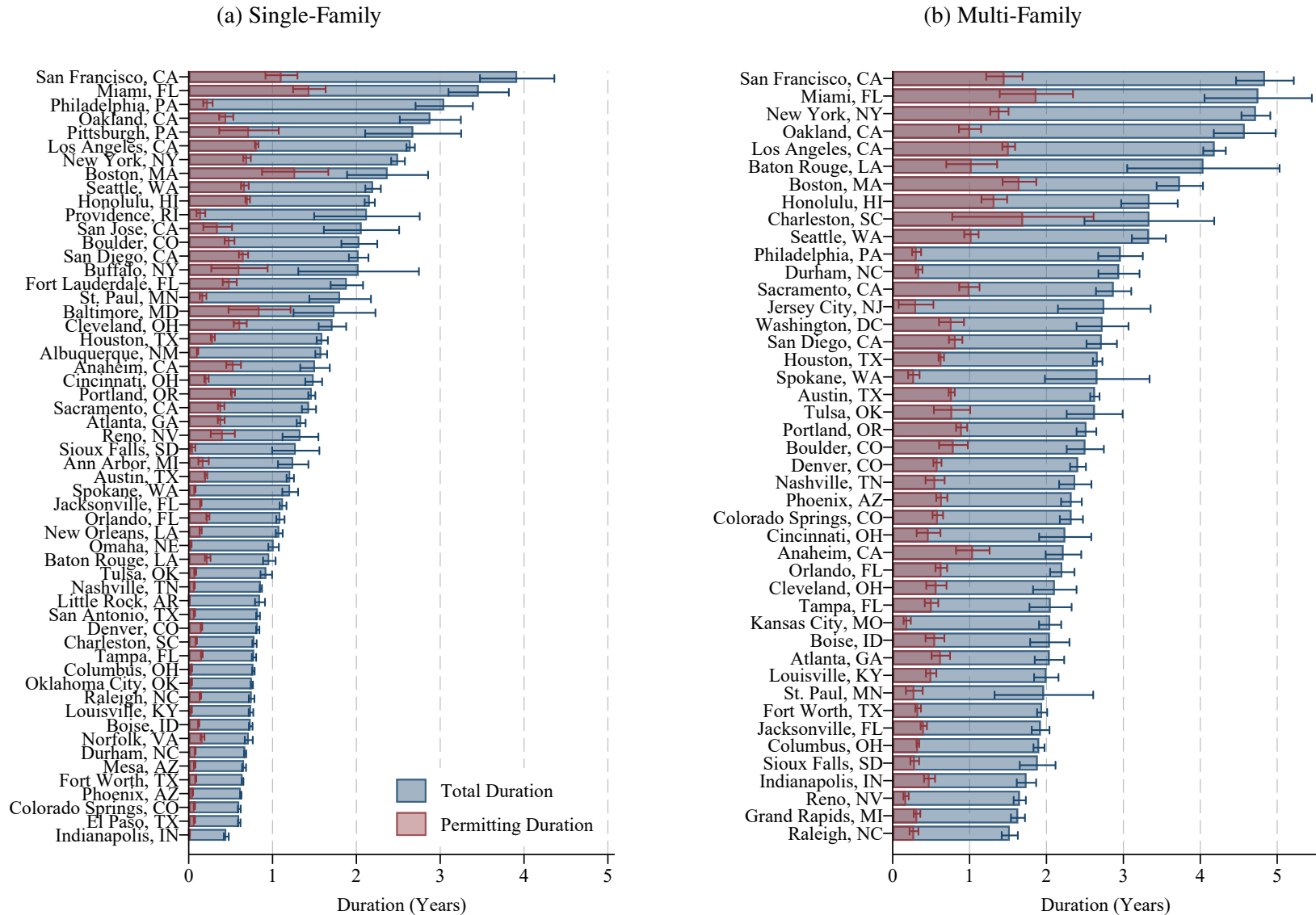
Extrapolation. A key concern is that some cities may have few actual projects that resemble our archetypes, making our estimates extrapolative and sensitive to functional form. For instance, smaller cities may lack dense neighborhoods in which multi-family housing is often built.

Two further analyses assuage this concern. First, across cities, estimated durations for our archetypes are strongly associated with the respective simple median durations restricted to single-family detached housing and to multi-family housing with more than 10 units (R^2 ranges from 0.85 to 0.95, see Appendix Figure A5). That is, for both levels and ranking across cities the raw data resemble our baseline estimates. Second, Nadaraya–Watson kernel estimates, which do not extrapolate through covariates, also align closely with our results (see Appendix Figure A6).

More broadly, we summarize the covariate adjustments with Appendix Table A5, which reports the distributions of control-coefficient estimates across cities. In multi-family projects, higher unit counts and floor areas generally mean longer durations. For single-family projects, durations also rise in floor area. Durations are longer for attached units (i.e., townhomes) and infill development, versus detached units and subdivision development. For both project types, durations are not very sensitive to neighborhood characteristics, but relatively denser and higher-income areas, within each respective city, tend to permit and to build more slowly.

¹⁰For another perspective, we have also considered an across-city variance decomposition: $\text{Var}(T_i) = \text{Var}(T_i^P) + \text{Var}(T_i^C) + 2 \cdot \text{Cov}(T_i^P, T_i^C)$, where i indexes cities and total project duration is $T_i = T_i^P + T_i^C$, the sum of permitting and construction durations. We find that permitting explains between 17 and 25 percent of across-city variance, including after adjustments for sampling variation following Kline et al. (2020) (see Appendix Table A4).

Figure 1: Permitting and Total Project Durations by City and Project Type



Notes: This figure presents city-level estimates of permitting and total project duration, in red and blue bars respectively, for the single- and multi-family housing archetypes, for the 2015-19 submission cohort. The single-family archetype is a 2,800-square-foot detached one-off infill home, and the multi-family archetype is a 20-unit building with an average floor area per unit of 1,200 square feet, in neighborhoods of median density and household income for such structures (see Table 1). We apply a minimum sample of 20 permits for reporting any estimate of single-family and multi-family durations. Confidence intervals are at the 95-percent level and reflect delta-method standard errors.

Additional Covariates. We include further covariates related to the natural environment (terrain, disaster risk), lot shape (dimensions, irregularity), and additional census-tract characteristics. This analysis addresses the concern that our main controls may not exhaust relevant differences in projects across cities. Yet, on net, introducing such controls increases the estimated across-city variance in duration (see Appendix Table A6). Taken by group, the sets of additional controls have varied and offsetting impacts on these variances, as we show through a Gelbach (2016) decomposition.

Incomplete Projects. The censoring-adjusted estimates of duration, obtained via Equation 4, order cities similarly to estimates without this adjustment (see Appendix Figure A7). A thornier problem arises from expired, voided, or canceled permits, as these terminal statuses are competing risks with project completion. Reassuringly, our ranking of cities is robust to including (versus dropping) terminations in the data and treating them as incomplete (see Appendix Figure A8).

Fact 2. Across cities, higher permitting and project duration is positively associated with housing costs and negatively associated with rates of housing production.

Panel A of Figure 2 presents scatter plots of median rents at the city level on permitting and total project durations.¹¹ The left figure shows the strong statistical fit (R^2) and slope of the association with permitting. Permitting duration explains 51 percent of the variance in rents, and one year longer in permitting duration is associated with 39 percent higher rents.

These associations are also present for total project duration and for single-family projects (see Appendix Figure A9). Furthermore, durations are positively associated with city-level home prices ($R^2 = 0.65$, see Panel A of Appendix Figure A10) and construction costs as measured by R.S. Means (see Appendix Figure A11). These results are robust to controls such as population density, college-graduate share, and median income (see Panels A–C of Appendix Table A7).

Panel B of Figure 2 then shows that, consistent with permitting acting as a burden on supply, durations are negatively associated with rates of housing production across cities. For an additional year in permitting duration, a city permits 3.8 fewer new homes per 10,000 city residents per year, which is near the average rate of permitting in our sample. However, this association is sensitive to some of our city-level controls (see Panel D of Appendix Table A7).

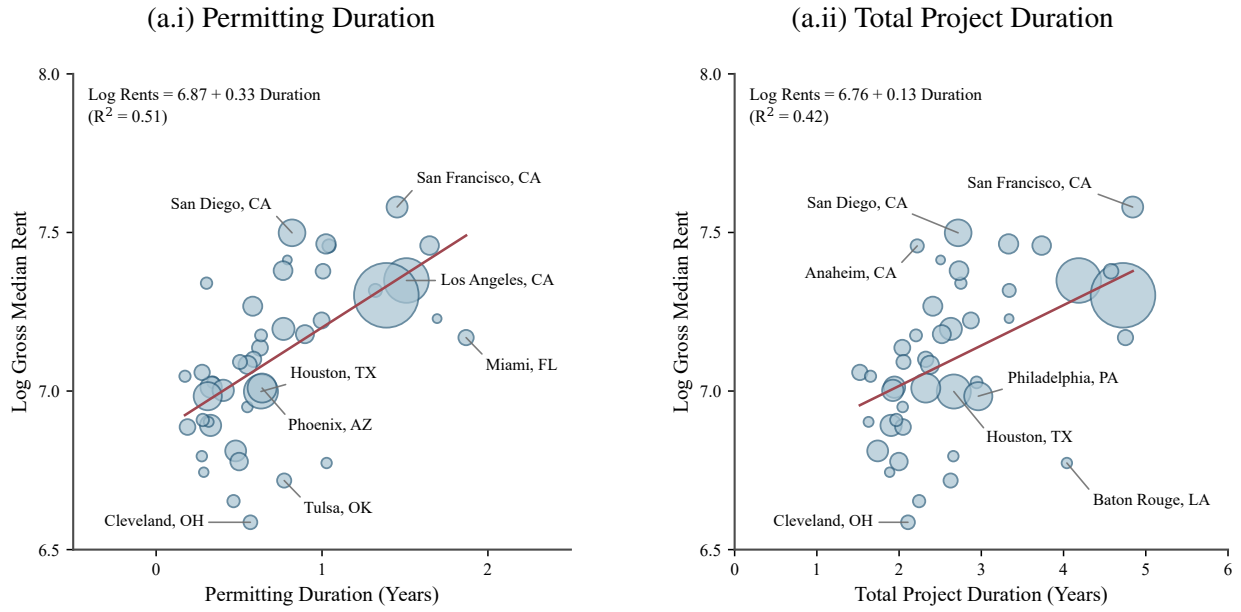
Furthering this connection to housing supply, durations are also strongly negatively associated with the elasticities estimated by Saiz (2010). Permitting duration alone explains roughly half of the variance across cities in his metro-level elasticities (R^2 of 0.47–0.54, see Appendix Figure A12), a relationship that is robust to all controls listed above (see Appendix Table A8).

One might have naively predicted the relationship between permitting durations and housing costs to have a slope closer to the marginal cost of capital for housing development. That is,

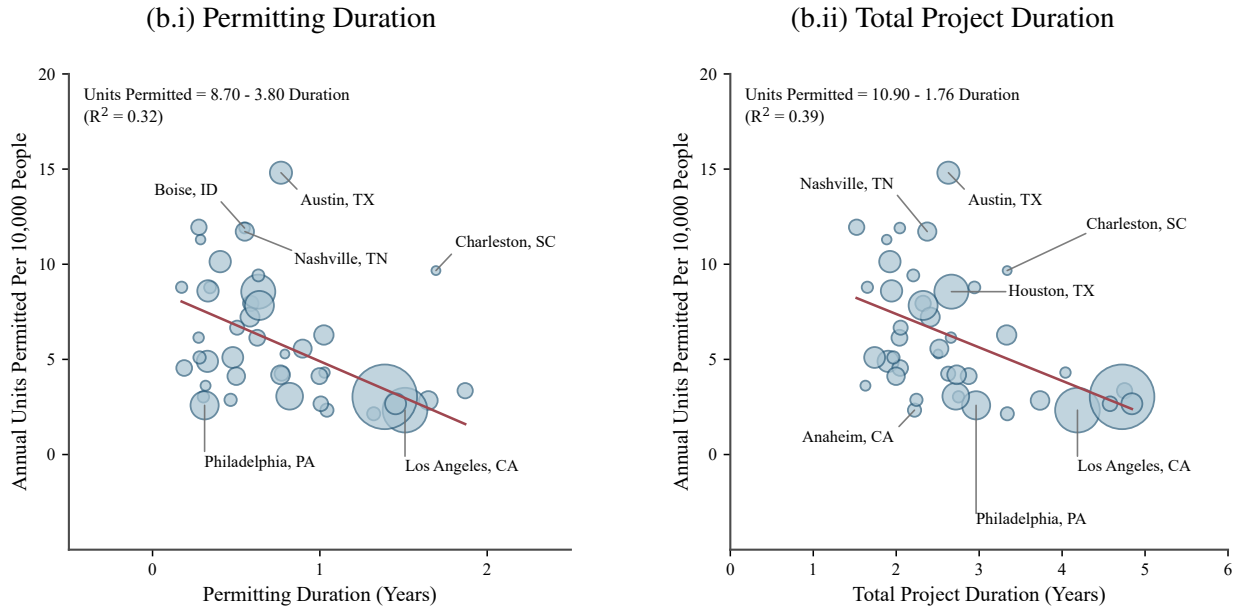
¹¹We emphasize that projects are standardized on neighborhood characteristics within city, not across, leaving us free to consider such across-city patterns.

Figure 2: Durations Versus Housing Prices and Production Across Cities

(a) Gross Median Rent



(b) Annual Units Permitted Per 10,000 People



Notes: This figure plots city-level estimated durations for new multi-family projects against city-level log rents and housing production. Estimated durations are for a standardized multi-family project, evaluated at common reference covariate values. Point sizes are proportional to city population. The solid line shows the population-weighted linear fit across cities. Select cities are labeled.

developers should be compensated for a one-year delay with an approximately eight-percent increase in the annuity value of rents. We instead find a slope roughly five times larger than this. Three further results help us interpret this surprising finding.

Variance in Duration. If developers are risk-averse, or if uncertainty in approval times leads them to hold labor or equipment idle, they should be compensated in equilibrium for both average duration and duration risk. We proxy for true ex-ante risk using the residual variance of log permitting duration conditional on observed characteristics.

Using “ridgeline” plots, we show that cities with longer average durations have more dispersion in durations among observably similar projects (see Appendix Figures A13–A16). Yet in “horse-race” regressions, mean duration—and not log-duration variance—drives the relationship with home prices and rents (see Appendix Table A9). This evidence cautions against interpreting the high apparent “rate of return” on permitting duration as a risk premium.

Endogenous Regulation. Next, there may be two-way causality between amenities and regulation. Places that are intrinsically more desirable to live may limit development more tightly (Duranton and Puga, 2023), and these limitations may manifest as slower permitting. If present, such patterns would generate a relationship between permitting and housing costs that is stronger than the true causal effect, consistent with our findings.

Furthermore, this endogenous-regulation story implies a sign test in land prices. If the sole equilibrium linkage between permitting and housing costs was through housing supply, then permitting burdens should reduce land prices, as all else equal, higher construction costs reduce land demand. Instead, we find land prices are higher in cities with slower permitting (see Panel B of Appendix Figure A10), bolstering this interpretation.

Benchmarking Against Other Measures. We compare our duration measures to existing measures of land-use regulation: the Wharton Residential Land Use Regulatory Index (WRLURI; Gyourko et al., 2008, 2021) and the “generative regulatory measurement” index of Bartik et al. (2025).

Permitting duration is positively associated with the WRLURI’s Approval Delay Index component (Appendix Figure A17). It also rivals the WRLURI and the Bartik et al. measure in explaining variation in rents, home values, land values, and housing production (see Appendix Tables A10 and A11). In horse-race specifications, permitting duration typically remains significant.

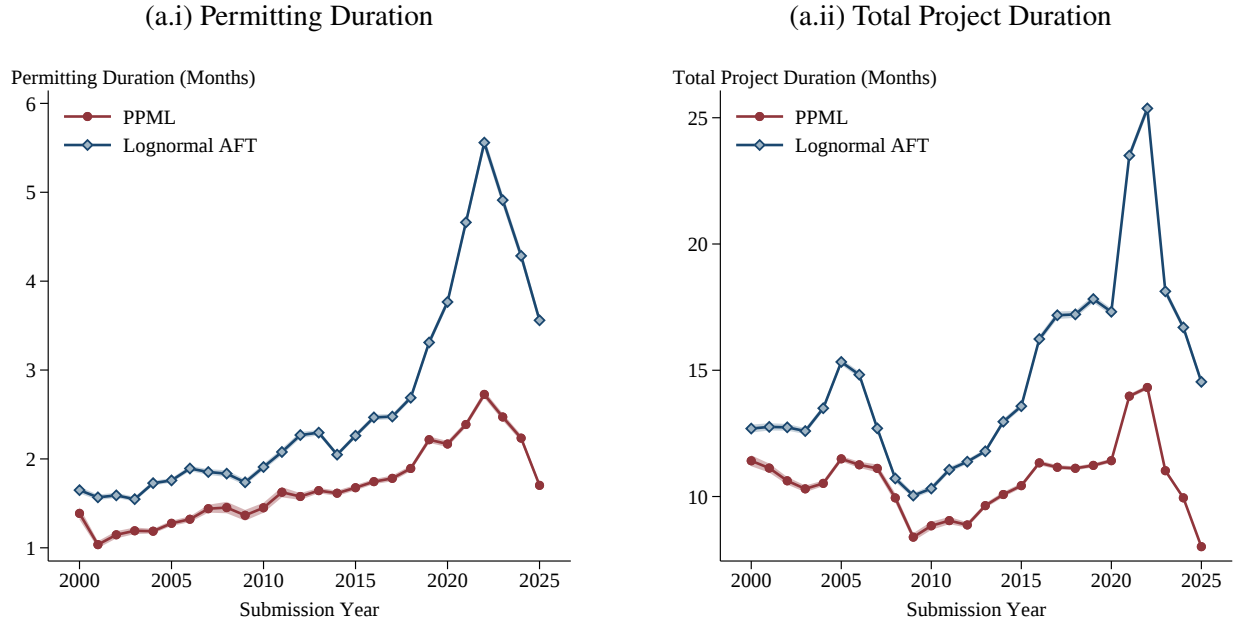
Fact 3: Permitting for new housing takes substantially more time in 2025 than it did in 2000.

Figure 3 shows our preferred time series for permitting and total project durations (Equation 5).

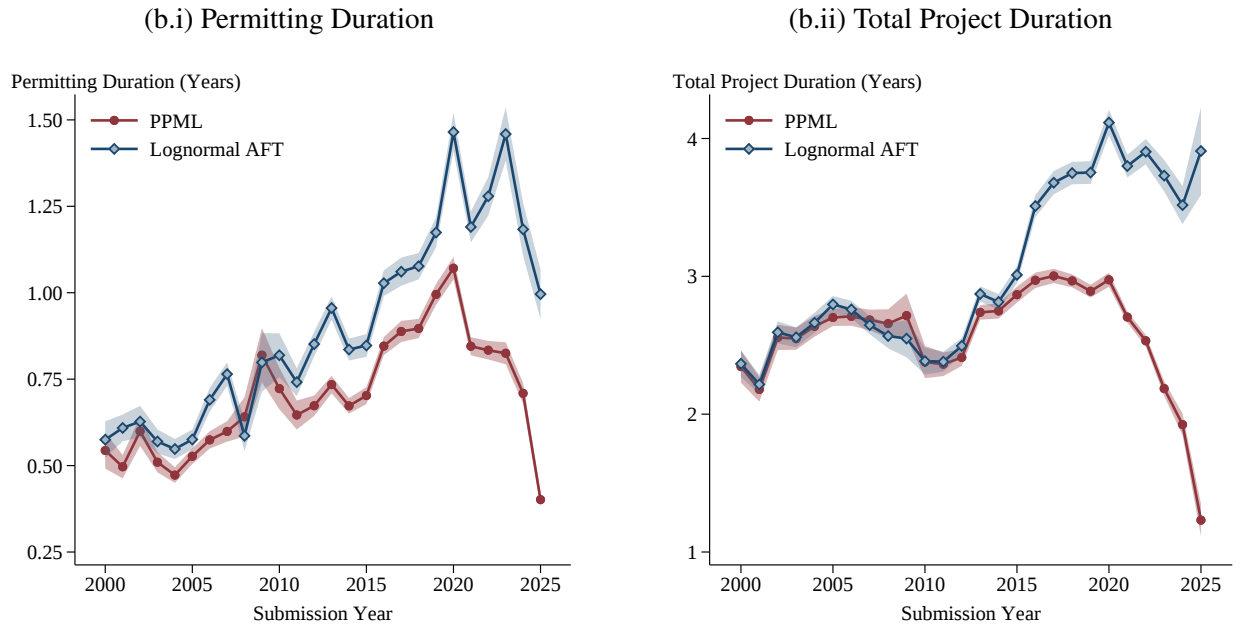
Adjusting for observed characteristics and censoring, multi-family permitting duration rose from 0.6 years to 1.5 years from 2000 to 2023, accounting for much of the contemporaneous increase in total project duration. Single-family housing shows similar trends, with a threefold rise

Figure 3: Permitting and Total Project Durations Over Time

(a) Single-Family



(b) Multi-Family



Notes: This figure plots estimated permitting and total project durations by submission-year cohort from 2000 to 2025 for single- and multi-family projects. The PPML series (maroon lines and circles; see Equation 3) adjust for project characteristics but not right-censoring. The AFT series (navy lines and diamonds; see Equation 4) use the same covariates while accounting for incomplete projects. Both specifications include fixed effects for city and submission year, as well as controls for project and tract characteristics. For each submission year, estimated duration is evaluated at common reference covariate values and averaged over the estimation-sample city composition. Shaded bands show pointwise 95-percent confidence intervals with standard errors clustered by project.

in permitting duration: 1.6 months in 2000 to 4.9 months in 2023.

The increase in permitting durations over time has been steady for both single- and multi-family projects. By contrast, total project durations appear highly cyclical, to a degree that obscures secular trends. For all duration outcomes, there is some indication of declines since 2023. While recent-year estimates are inherently most sensitive to censoring adjustments, and thus must be interpreted with caution, the recent improvements in permitting and total project duration for single-family housing appear real, as we examine below.¹²

We now review our sensitivity checks for three threats to these conclusions: censoring of incomplete projects, changes over time in unobserved project attributes, and finally staggered entry of cities into the sample. We then briefly describe heterogeneity in these time trends.

Censoring. Figure 3 already shows censoring adjustments are consequential. They increase the estimated permitting slowdown, and for multi-family housing, they also undo the extreme apparent decline in total project duration in recent years. The misleading appearance of declines before censoring adjustment is inevitable given long durations in multi-family development. As there is intense interest in recent trends, we carefully assess sensitivity to censoring.

First, we estimate the covariate-adjusted shares of projects by cohort that reach issuance or completion by fixed horizons after submission, as these outcomes have trivial censoring patterns. We find rates of “timely” issuance and completion declined markedly over time from 2000 to 2023 (see Appendix Figures A18 and A19). Importantly, these measures also show that recent improvements in permitting durations since 2023 are not artifacts of censoring adjustments.

Second, we show our results depend little on the specific parametric assumptions underlying the censoring adjustment (see Appendix Figures A20 and A21).¹³ Third, after adjustment for project covariates, the survival curves for permit issuance and project completion clearly differ across permit-submission cohorts (see Appendix Figure A24), with recent cohorts showing lower completion rates at fixed time horizons after submission. Taken together, these exercises give us substantial confidence in the estimated time trends.

Unobserved Attributes. It is possible that, conditional on covariates, the composition of projects has shifted over time to be faster or slower to approve and complete. First, we re-estimate the time series with an expanded set of covariates, finding only limited changes (Appendix Figure A25).

Second, we estimate Cox hazard models that include both cohort and calendar time indicator variables. These specifications are identified by “overlapping generations” of projects under per-

¹²Additional data, such as high-frequency satellite photography or stage-specific permit records (e.g., grading versus electrical), can potentially improve duration estimation for recent-submission cohorts.

¹³We find only slight distinctions between the survival curves produced by the parametric models. All fail to capture a tail of projects that appear abandoned and incomplete many years after issuance (see Appendix Figure A22). Furthermore, we observe only issued permits in one third of cities, our censoring corrections for permitting durations are inherently conservative (see Appendix Figure A23).

mitting or construction. Holding constant the cohort fixed effects, and varying only the calendar fixed effects, we still find large increases in expected duration like those in models that do not separate cohort and calendar effects (see Appendix Figure A26). This comparison suggests that trends over time in unobserved project composition cannot fully explain the estimated slowdown.

Imbalanced Panel. A final concern arises because cities enter the data on a staggered basis. Specifically, this data structure could create misleading time trends if earlier-entering cities have different trends than later-entering cities. Re-estimating the time series using only cities observed before selected years, however, yields similar results (Appendix Figures A27 and A28).

Regional Heterogeneity in Time Trends. We also estimate time series for each Census region (see Appendix Figure A29). These series are noisier than our national results but show some interesting patterns. First, the rise in permitting duration extends to the South, where U.S. housing production has recently been concentrated (Glaeser and Gyourko, 2025). Second, the high cyclicalality of total project duration is most prominent in the South and West.

4 Interpretation as Proxies for Regulatory Cost

This section considers two conceptual distinctions between exogenous regulatory costs and our permitting and total project durations. First, observed projects are selected among potential projects, possibly on the basis of expected duration. Second, observed durations are equilibrium outcomes, reflecting both the supply of and demand for project speed. These distinctions matter for whether researchers can treat our duration measures as supply-side primitives. We provide evidence on the likely importance of both concerns.

Self-Selection on Potential Duration. A first concern is that developers may select projects based on potential durations, while we observe durations only for actually selected projects. The resulting selection bias has ambiguous implications for cross-sectional comparisons: observed duration differences may either overstate or understate the dispersion in potential duration across cities.

To examine this concern, we treat the value of a site’s existing use as a selection instrument, inspired by Rollet (2025). Sites with more valuable existing uses face a higher redevelopment hurdle, screening out marginally viable potential projects.¹⁴ We use this variation to ask whether projects that enter our sample appear selected on ease of permitting or construction.

Conditional on our other project and neighborhood controls, sites with less-valuable existing uses have modestly longer permitting and construction durations than sites with more-valuable uses in the same city (Appendix Table A12). This pattern is consistent with downward selection in observed durations: projects that proceed despite more valuable existing uses appear, if anything,

¹⁴Excludability would entail that the existing use must not directly affect permitting or construction durations.

faster to permit and complete. Under this interpretation, our observed durations may understate the potential durations relevant for marginal redevelopment decisions.

Equilibrium Duration. A second concern is that observed durations are equilibrium outcomes rather than primitive regulatory parameters. The time required to obtain a permit depends both on the capacity and procedures of the permitting office and on developers’ demand for speedy approvals. Post-issuance construction duration may similarly reflect both construction-sector capacity and developers’ incentives to complete projects quickly (Oh and Yoon, 2020; Ball et al., 2025).

This equilibrium view has ambiguous implications for our analysis. If permitting offices or construction sectors are congestible, lower housing demand should reduce applications and shorten queues. But if developer effort, project readiness, or administrative attention also fall when demand falls, durations could instead rise. Differences in equilibrium durations may therefore understate or overstate differences in primitive regulatory frictions.

We assess this channel using city-level variation in the intensity of the Great Recession as a shock to housing demand, in the spirit of Yagan (2019) and Hershbein and Stuart (2024). In cities with larger peak-to-trough declines in home prices, permit volumes fell more, whereas durations fell only slightly (Appendix Figure A30). These results argue against a simple congestion model in which overloaded bureaucracy is the primary cause of slow permitting in high-cost cities.

5 Conclusion

Accelerating the permitting and development of new housing is a key focus of ongoing policy efforts to reduce housing costs in U.S. cities. Yet this policy activity has proceeded, to a striking degree, without basic facts about the typical durations of permitting and development, their variation across cities, and their evolution over time.

This paper assembles permit data across cities and uses them to estimate these durations for standardized single- and multi-family housing. We find: (1) substantial variation in project duration across cities, partly explained by variation in permitting; (2) across cities, permitting duration is positively associated with housing costs and negatively associated with production; and (3) permitting duration has risen steadily over time, whereas project duration is cyclical.

Finally, our work suggests an extension of U.S. official statistics. Permit records are widely available but reported inconsistently across cities. Standardized reporting, such as through the Census Building Permits Survey or Survey of Construction, could facilitate data collection. In harmonizing such data at scale, our contribution is not only to document new facts but also to demonstrate the feasibility of measuring these relevant housing outcomes.

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Appendices for Online Publication

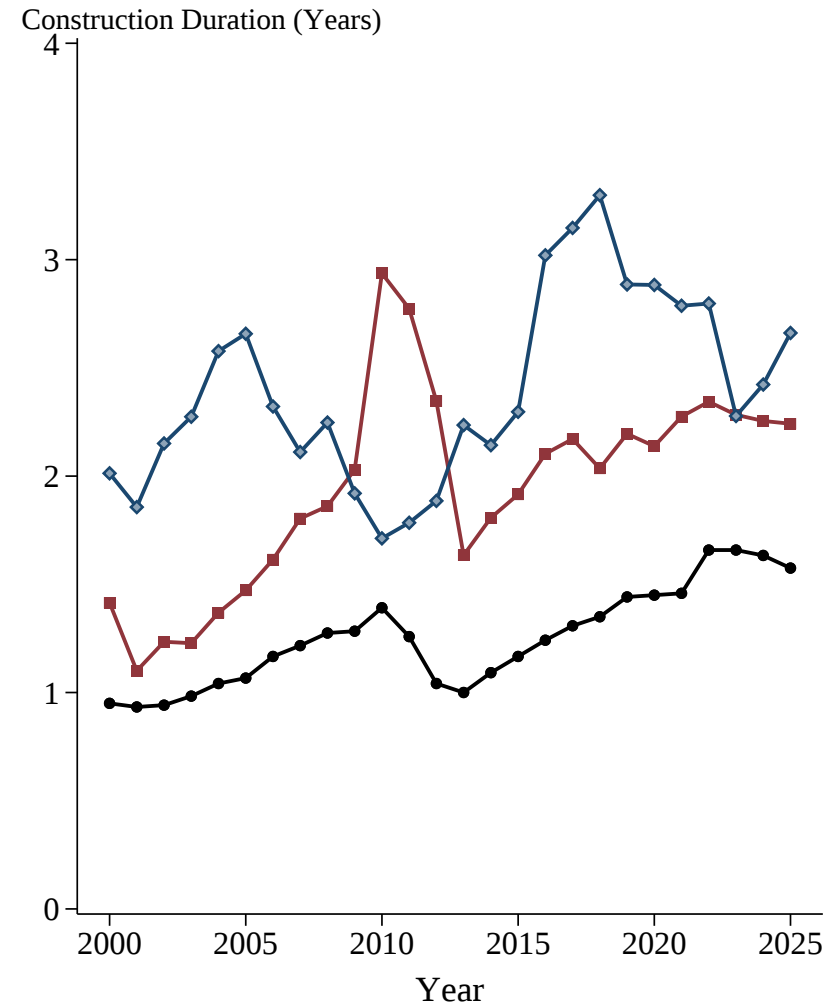
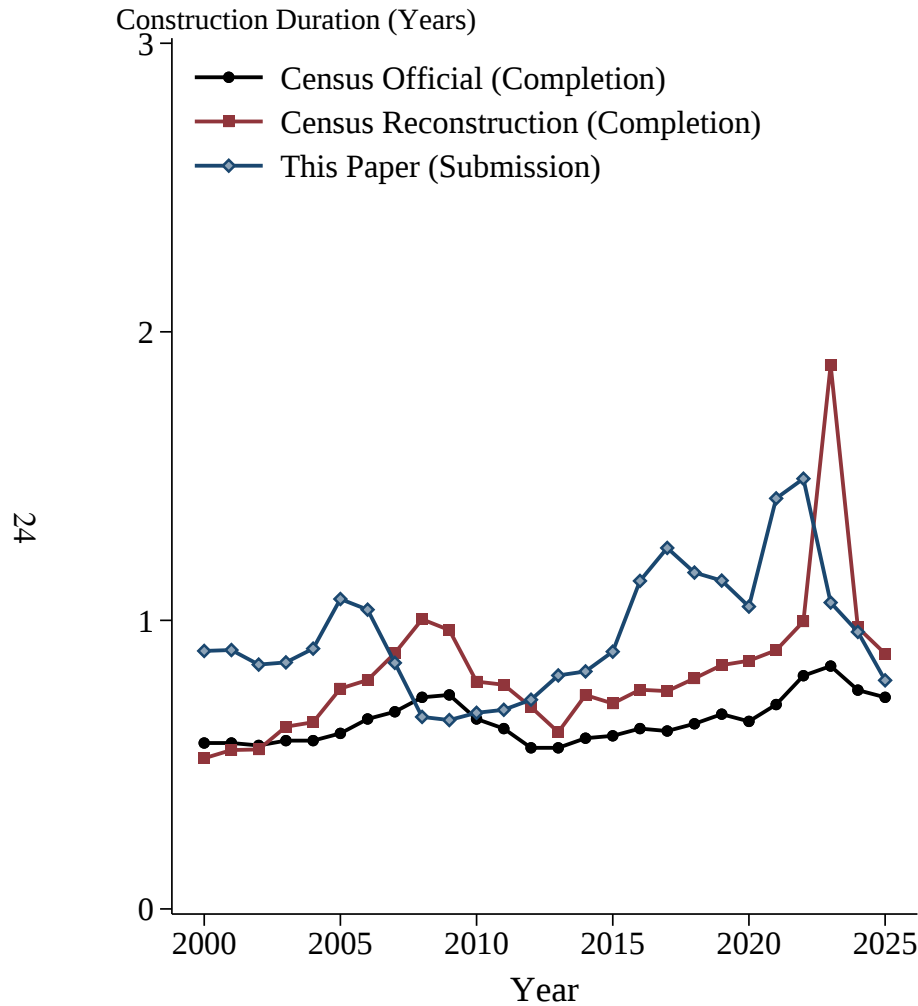
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A Additional Tables and Figures

Figure A1: Comparing Measures of Construction Duration Over Time

(a) Single-Family

(b) Multi-Family



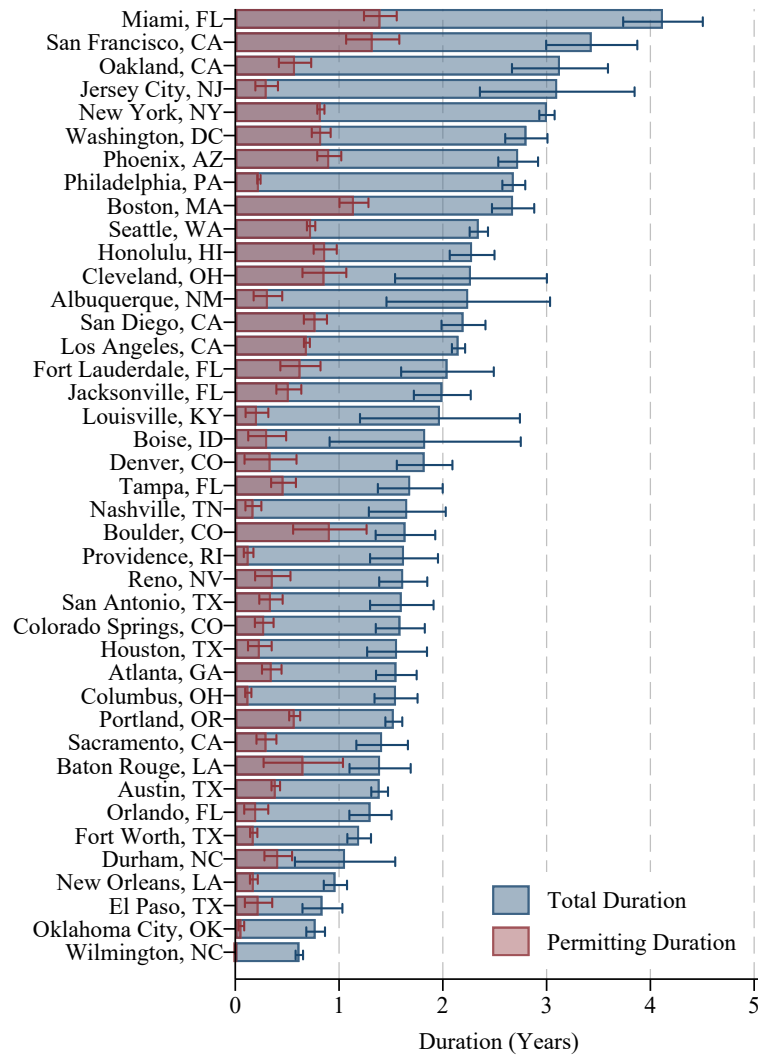
Notes: This figure compares three measures of post-permit duration over time for single-family and multi-family residential projects. The black series is the official Census completion-year measure, constructed as authorization-to-start plus start-to-completion duration. The maroon series is the analogous completion-year measure constructed from our permit data using raw mean issue-to-certificate-of-occupancy duration. The blue series is our preferred lognormal AFT submission-year index for issue-to-certificate-of-occupancy duration. All series are normalized to zero in 2002 and plotted as cumulative log changes thereafter.

Table A1: Permitting Durations by Data Coverage and Issuance Outcome

	Duration by Outcome (Years)		Data Coverage		
	Issued	Non-Issued	Cities	Applications	Share Issued (%)
<i>Panel A: Single-Family</i>					
Issued-Only Cities	0.39 (0.03)	n.d.	22	205,421	n.d.
All-Submissions Cities	0.34 (0.00)	3.16 (0.10)	39	652,606	97.1
<i>Panel B: Multi-Family</i>					
Issued-Only Cities	0.75 (0.14)	n.d.	21	10,601	n.d.
All-Submissions Cities	0.72 (0.02)	2.56 (0.21)	40	36,571	93.3

Notes: This table compares permitting durations across cities with different application-data coverage. Data for “issued-only” covers only issued permits, whereas data for “all-submissions” cities covers both issued and non-issued permit submissions. Issued durations are covariate-adjusted estimates evaluated at the common reference covariate values. Durations for non-issued permits are measured from submission to the most recent status date. Parentheses report standard errors of the estimated durations and are computed via the delta method. The issued share is a fraction of submissions. “N.d.” indicates a quantity not observed for issued-only cities.

Figure A2: Permitting and Total Project Duration (Duplex Archetype)



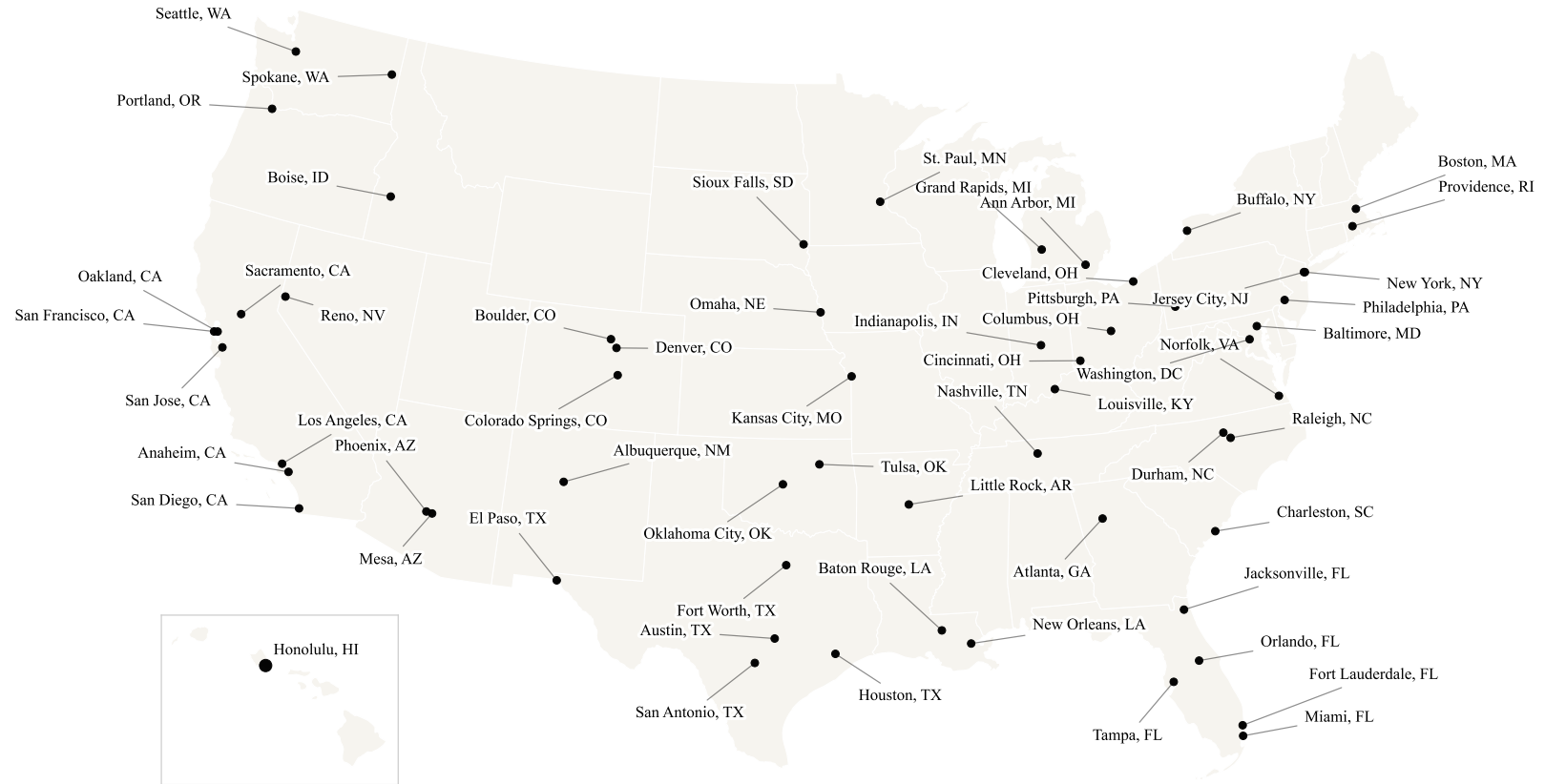
Notes: This figure presents city-level estimates of permitting and total project duration, in red and blue bars respectively for the duplex archetype, for the 2015-19 submission cohort. The duplex archetype is a 3,000-square-foot two-unit residential building, in neighborhoods of median density and household income for 2–3 unit structures. We apply a minimum sample of 20 permits for reporting any estimate of durations. Confidence intervals are at the 95-percent level and reflect delta-method standard errors.

Table A2: Variable Coverage Across U.S. Cities

City	Coverage Rate (Percent)							Permits
	Submit Date	Issued Date	Complete Date	Unit Count	Sq. Ft.	Lot Size	APN	
Albuquerque, NM	100.0	100.0	92.9	100.0	100.0	99.9	94.9	3,797
Anaheim, CA	100.0	98.7	95.6	100.0	93.4	100.0	99.9	2,073
Ann Arbor, MI	100.0	98.4	87.6	100.0	43.4	99.9	99.9	1,528
Atlanta, GA	100.0	97.9	90.9	100.0	97.8	99.8	68.3	11,236
Austin, TX	100.0	100.0	95.7	100.0	83.1	100.0	99.5	82,405
Baltimore, MD	100.0	99.0	40.0	100.0	79.5	98.4	100.0	575
Baton Rouge, LA	100.0	100.0	96.4	100.0	98.4	99.9	86.0	11,384
Boise, ID	100.0	100.0	95.7	100.0	95.2	100.0	97.7	9,638
Boston, MA	100.0	100.0	86.7	100.0	76.3	100.0	98.6	2,307
Boulder, CO	100.0	89.8	78.8	100.0	99.4	100.0	100.0	793
Buffalo, NY	100.0	99.3	57.5	100.0	97.5	100.0	100.0	280
Charleston, SC	100.0	100.0	99.5	100.0	87.6	99.9	100.0	10,033
Cincinnati, OH	100.0	89.1	76.2	100.0	53.0	100.0	99.3	2,421
Cleveland, OH	100.0	83.4	74.0	100.0	97.5	99.3	99.1	1,971
Colorado Springs, CO	100.0	100.0	98.5	100.0	99.9	99.8	99.8	39,704
Columbus, OH	100.0	100.0	89.8	100.0	99.6	99.9	100.0	14,143
Denver, CO	100.0	100.0	83.2	100.0	97.6	100.0	97.8	20,995
Durham, NC	100.0	97.9	89.2	100.0	99.4	100.0	99.7	27,796
El Paso, TX	100.0	98.4	95.6	100.0	97.0	99.9	96.7	15,901
Fort Lauderdale, FL	100.0	100.0	86.9	100.0	18.6	100.0	100.0	4,582
Fort Worth, TX	100.0	97.9	94.0	100.0	98.3	100.0	89.7	91,339
Grand Rapids, MI	100.0	95.4	86.7	100.0	25.1	97.3	99.3	414
Honolulu, HI	100.0	96.0	90.5	100.0	97.9	99.8	100.0	24,279
Houston, TX	100.0	46.3	21.6	100.0	83.1	99.9	28.7	55,081
Indianapolis, IN	100.0	99.9	99.7	100.0	99.9	100.0	100.0	20,891
Jacksonville, FL	100.0	100.0	99.7	100.0	99.9	100.0	100.0	101,066
Jersey City, NJ	100.0	99.5	61.8	100.0	99.0	100.0	100.0	419
Kansas City, MO	100.0	100.0	92.2	100.0	88.5	99.8	100.0	6,128
Little Rock, AR	100.0	99.3	84.1	100.0	100.0	99.9	88.6	2,780
Los Angeles, CA	100.0	100.0	91.4	100.0	100.0	99.6	96.1	40,961
Louisville, KY	100.0	97.6	96.4	100.0	99.5	100.0	99.9	16,936
Mesa, AZ	100.0	100.0	95.9	100.0	98.2	100.0	99.2	31,101
Miami, FL	100.0	100.0	65.3	100.0	100.0	99.0	100.0	1,898
Nashville, TN	100.0	94.9	94.9	100.0	98.1	99.8	54.2	25,547
New Orleans, LA	100.0	92.6	84.3	100.0	89.8	100.0	77.9	12,679
New York, NY	100.0	97.4	90.0	100.0	99.2	94.6	100.0	56,133
Norfolk, VA	100.0	99.8	92.9	100.0	99.9	100.0	100.0	2,495
Oakland, CA	100.0	92.6	80.5	100.0	96.0	100.0	73.6	1,645
Oklahoma City, OK	100.0	97.4	95.8	100.0	66.7	99.9	0.0	42,491
Omaha, NE	100.0	99.1	53.0	100.0	68.5	100.0	99.9	13,116
Orlando, FL	100.0	98.6	95.6	100.0	99.0	100.0	99.5	25,053
Philadelphia, PA	100.0	100.0	86.9	100.0	100.0	99.4	99.4	8,581
Phoenix, AZ	100.0	99.8	94.8	100.0	100.0	100.0	100.0	63,374
Pittsburgh, PA	100.0	100.0	73.6	100.0	52.9	100.0	100.0	618
Portland, OR	100.0	94.4	90.7	100.0	74.2	99.4	99.7	20,283
Providence, RI	100.0	92.4	73.4	100.0	95.1	99.9	99.8	972
Raleigh, NC	100.0	99.6	82.5	100.0	90.8	100.0	81.6	51,703
Reno, NV	100.0	97.6	91.1	100.0	99.8	99.6	99.6	15,409
Sacramento, CA	100.0	96.3	91.6	100.0	99.6	99.3	100.0	9,493
San Antonio, TX	100.0	100.0	86.5	100.0	100.0	99.8	99.4	38,566
San Diego, CA	100.0	94.5	86.9	100.0	96.9	100.0	90.2	4,710
San Francisco, CA	100.0	90.1	79.2	100.0	99.5	100.0	100.0	2,521
San Jose, CA	100.0	100.0	87.6	100.0	98.9	100.0	97.9	710
Seattle, WA	100.0	94.2	77.8	100.0	82.2	99.8	91.6	18,446
Sioux Falls, SD	100.0	99.7	94.1	100.0	98.3	100.0	99.9	10,982
Spokane, WA	100.0	99.9	98.6	100.0	95.0	100.0	32.8	4,818
St. Paul, MN	100.0	99.5	77.6	100.0	94.6	100.0	99.6	929
Tampa, FL	100.0	97.4	90.8	100.0	82.1	99.9	98.7	16,326
Tulsa, OK	100.0	99.0	92.2	100.0	98.3	99.9	91.6	3,926
Washington, DC	100.0	100.0	29.7	100.0	63.6	100.0	99.6	2,800

Notes: This table reports city-level coverage rates in the residential analysis sample. Coverage rates are the share of permit records in each city with a nonmissing value for the indicated variable. For unit count, square footage, and lot size, coverage requires a positive value. APN coverage is the share with a nonmissing parcel identifier in the permit application. Permits reports the number of records in the analysis sample for that city.

Figure A3: City Coverage



Notes: This figure shows the geographic locations of all cities in our data.

Table A3: Accounting for Differences in Total Project Duration Across Cities

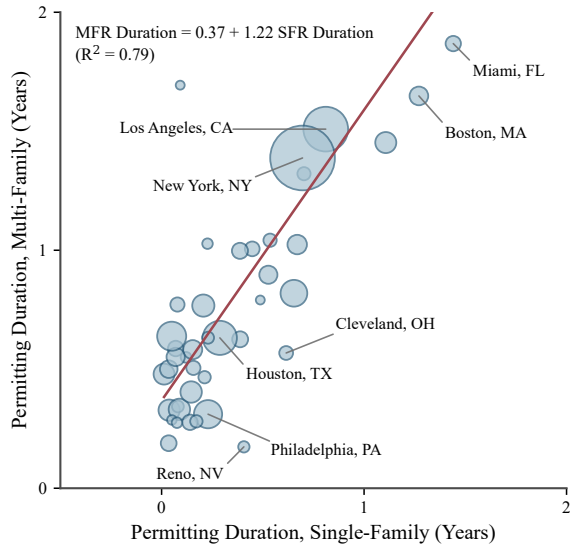
	Gaps by Percentiles of Total Project Duration	
	75–25 (1)	90–10 (2)
<i>Panel A: Single-Family</i>		
Difference in Total Project Duration (years)	1.90	2.51
Permitting (years)	0.61	0.73
Construction (years)	1.29	1.78
Permitting Share (%)	32.3	29.2
Construction Share (%)	67.7	70.8
<i>Panel B: Multi-Family</i>		
Difference in Total Project Duration (years)	2.15	2.93
Permitting (years)	0.93	1.14
Construction (years)	1.22	1.79
Permitting Share (%)	43.4	38.8
Construction Share (%)	56.6	61.2

Notes: Cities are sorted within archetype by predicted total project duration in the non-pooled PPML city sample used for the bar charts. Each column reports the difference in mean duration between cities in the upper and lower tails of the total-duration distribution. Post-permit time is defined as predicted total duration minus predicted permitting duration. The percentage rows divide the permitting and post-permit gaps by the total duration gap.

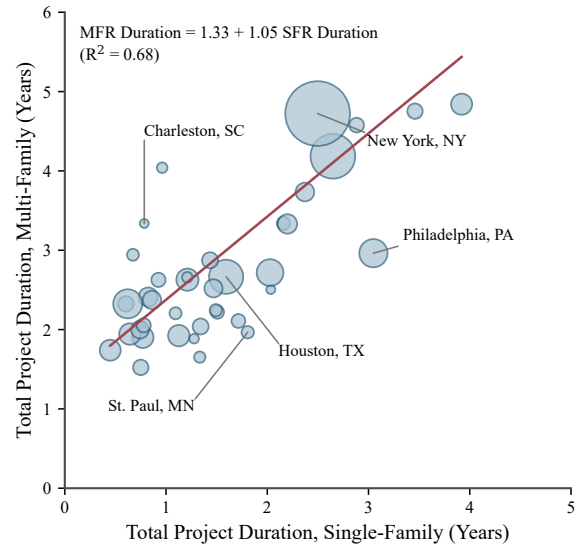
Figure A4: Across-City Comparisons of Permitting and Project Durations

(a) Multi-Family versus Single-Family

(a.i) Permitting Duration

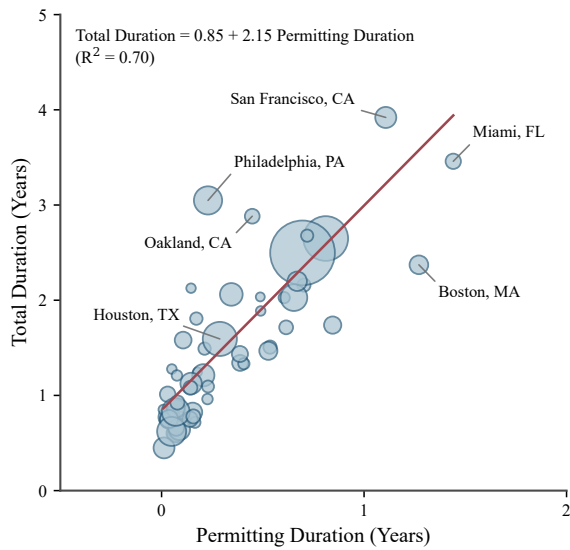


(a.ii) Total Project Duration

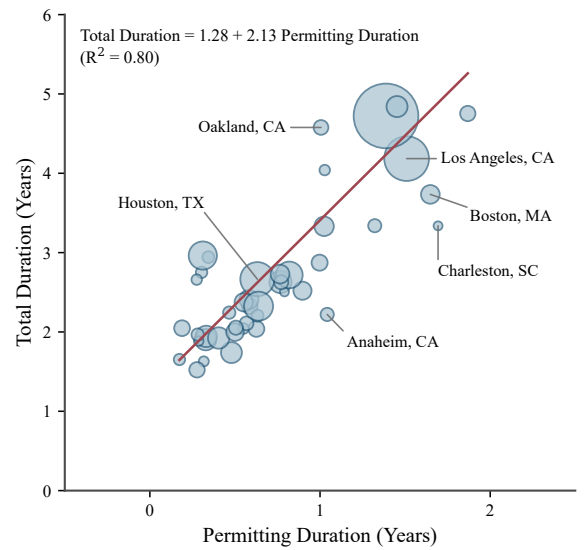


(b) Total Project Duration versus Permitting Duration

(b.i) Single-Family



(b.ii) Multi-Family



Notes: This figure summarizes two cross-city comparisons of estimated project durations. Panel A compares city-level estimated durations for new multi-family housing against the corresponding estimated durations for new single-family housing; subpanels (a.i) and (a.ii) report permitting and total project durations, respectively. Panel B compares city-level estimated total project durations against permitting durations within each housing archetype; subpanels (b.i) and (b.ii) report single-family and multi-family residential projects, respectively. Dots are sized in proportion to city population. The solid line shows the population-weighted linear fit across cities. Select cities are labeled.

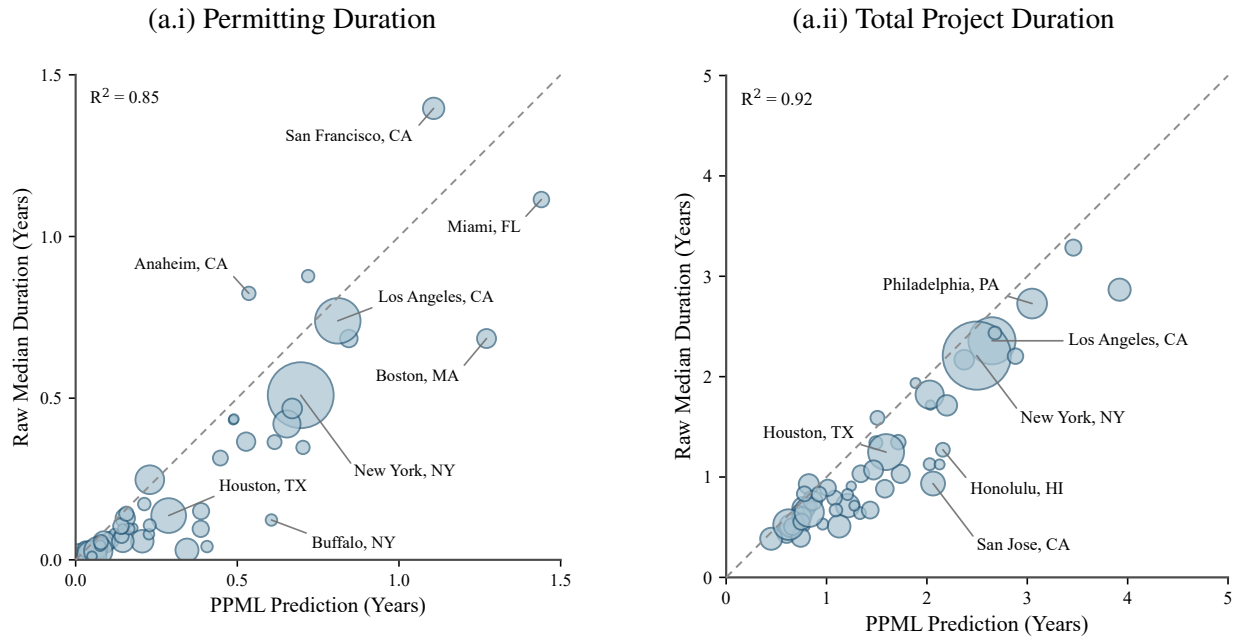
Table A4: Across-City Variance Decomposition of Total Project Duration

	Single-Family	Multi-Family
<i>Panel A: Share of Observed Across-City Variance (Percent)</i>		
Permitting	17.2	24.5
Construction	50.1	44.2
Covariance	32.8	31.3
Total Variance (Years ²)	0.63	0.80
No. of Cities	56	44
<i>Panel B: Share of Signal Variance (Percent)</i>		
Permitting	17.0	23.5
Construction	49.5	42.5
Covariance	33.5	34.1
Signal Variance (Years ²)	0.62	0.76
No. of Cities	56	44
Average Estimation Variance Removed (Years ²)		
Permitting	0.004	0.016
Construction	0.010	0.028
Covariance	0.001	-0.011

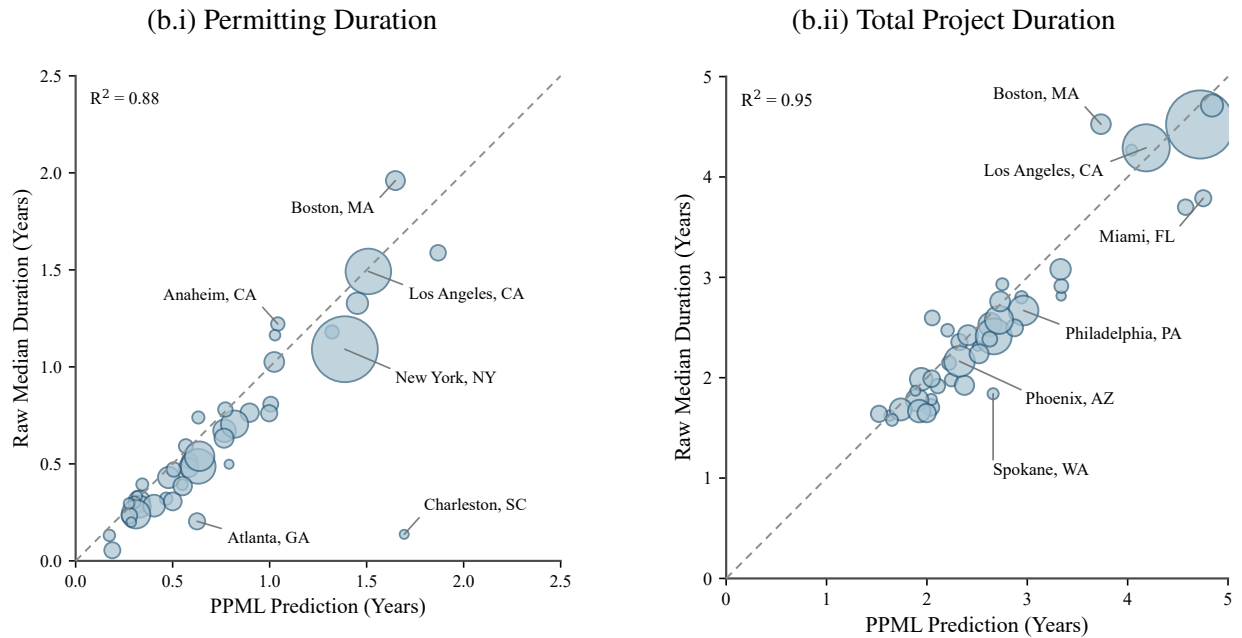
Notes: Panel A reports the decomposition of the observed across-city variance of total project duration into permitting duration, construction duration (defined as post-permit residual), and their covariance, where total project duration is measured from application to completion. Panel B subtracts the bootstrap-estimated sampling variance-covariance matrix of the city-level permitting and total-duration estimates before recomputing the decomposition. Both panels are reported on the same city sample within each project type.

Figure A5: Raw Median Versus PPML Duration Estimates

(a) Single-Family



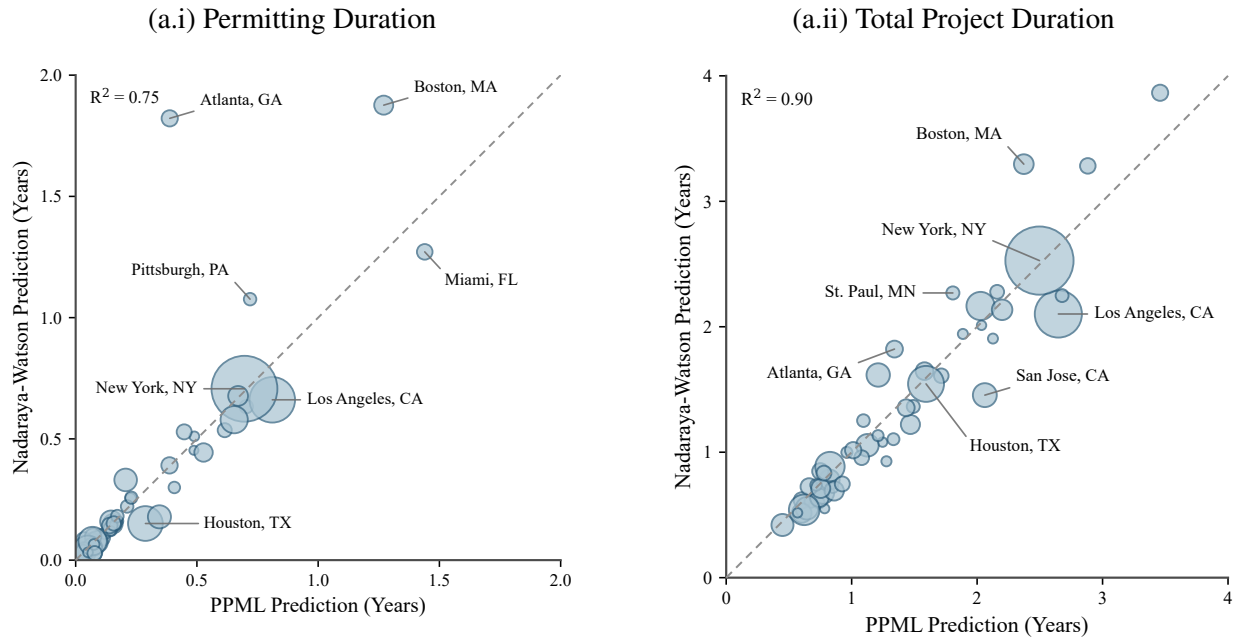
(b) Multi-Family



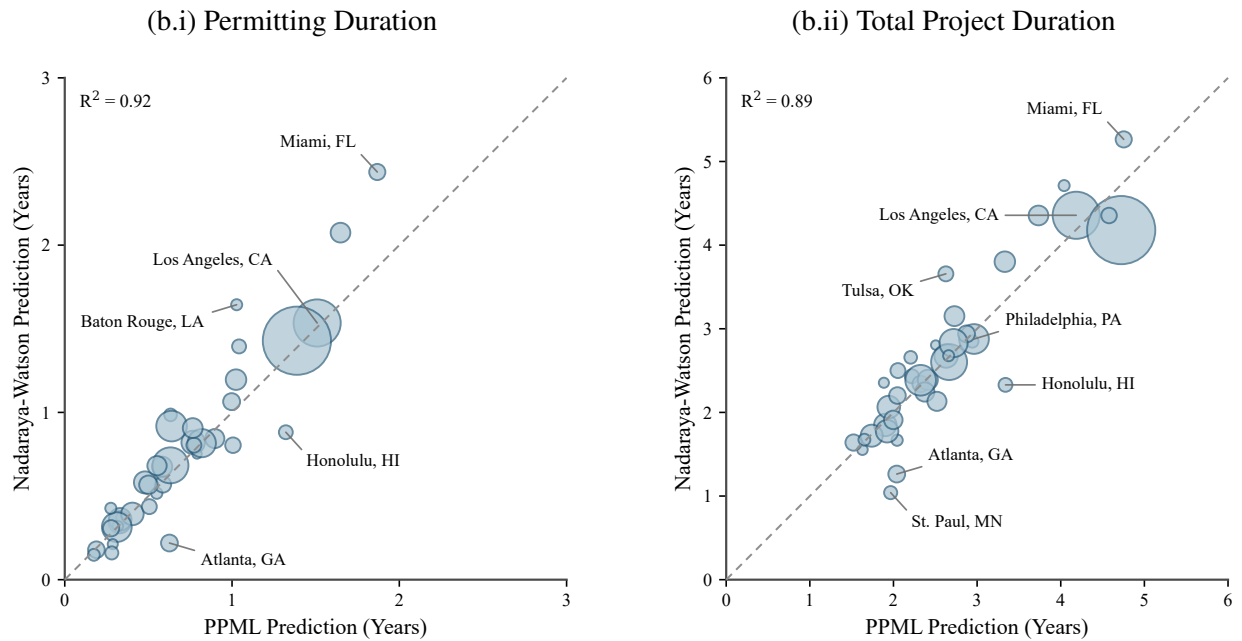
Notes: This figure compares city-level duration estimates from the PPML archetype specification to raw city-level median durations. By row, Panels A and B report single- and multi-family projects. By column, the left and right subpanels respectively show permitting and total project durations. Point sizes are proportional to city population. The dashed 45-degree line indicates equality between the two estimates. Select cities are labeled.

Figure A6: Nadaraya–Watson Versus PPML Duration Estimates

(a) Single-Family



(b) Multi-Family



Notes: This figure compares city-level duration estimates from the PPML archetype specification to Nadaraya-Watson local-mean estimates. Points represent cities, with marker sizes proportional to city population. The dashed 45-degree line indicates equality between the two estimates. Select cities are labeled.

Table A5: Effects of Baseline Covariates on Predicted Durations

	Permitting Duration				Total Project Duration			
	Pooled	City-Specific			Pooled	City-Specific		
		Median	P25	P75		Median	P25	P75
Panel A: Single-Family								
Log Floor Area	-0.009	0.016	-0.001	0.034	0.057	0.214	0.095	0.331
Log Lot Size	0.004	0.003	-0.008	0.012	0.024	0.026	-0.040	0.076
Log Population Density	0.076	0.006	-0.006	0.018	0.198	0.045	-0.007	0.103
Log Median Income	0.041	-0.023	-0.061	-0.000	0.170	-0.043	-0.118	0.115
Attached (vs. Detached)	0.110	0.021	-0.013	0.106	0.327	0.160	0.032	0.467
Infill (vs. Subdivision)	0.024	0.010	-0.038	0.054	0.192	0.062	-0.160	0.290
Panel B: Multi-Family								
Log Unit Count	-0.036	-0.020	-0.081	0.052	0.077	-0.043	-0.276	0.226
Log Floor Area	0.054	0.031	-0.029	0.114	0.145	0.209	0.021	0.376
Log Population Density	0.147	-0.006	-0.071	0.048	0.343	0.023	-0.083	0.114
Log Median Income	0.128	-0.032	-0.109	0.067	0.301	0.012	-0.114	0.182

Notes: This table summarizes city-specific marginal effects of baseline covariates on permitting and total project duration. For each city, we estimate Equation 1 and compute marginal effects at the standardized covariate values. Entries report the mean, median, 25th percentile, and 75th percentile of these city-specific marginal effects across cities, expressed in years. City-specific estimates are winsorized at the 1st and 99th percentiles in computing means. Panel A reports results for single-family projects and Panel B for multi-family projects.

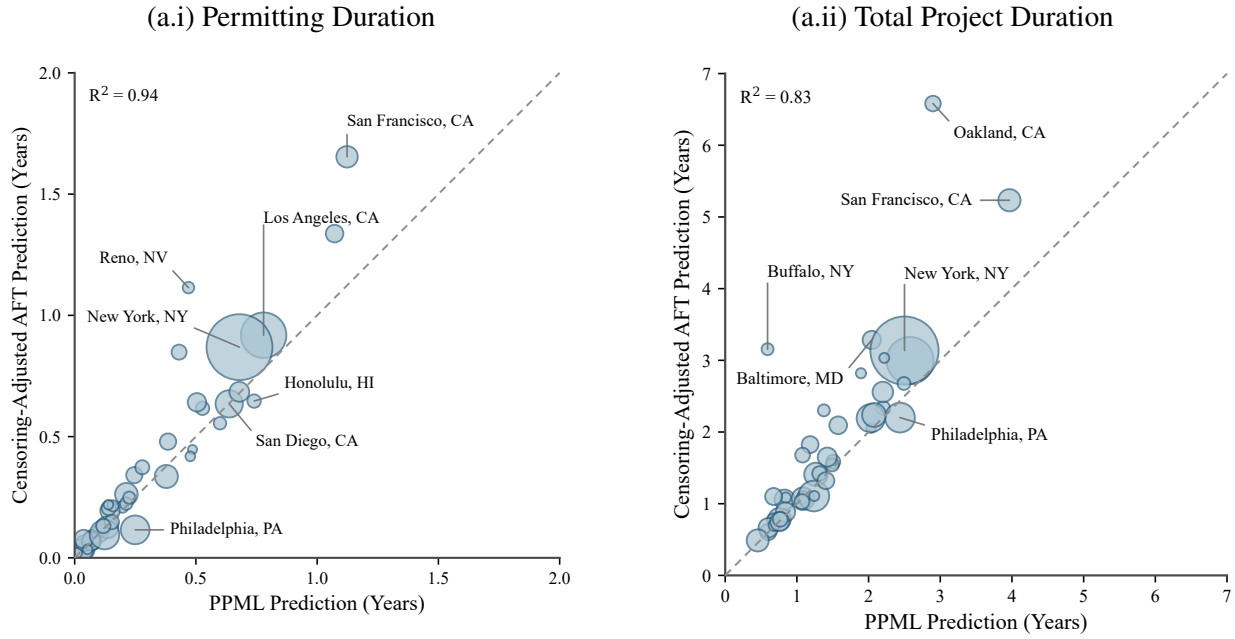
Table A6: Across-City Implications of Additional Controls

	Single-Family		Multi-Family	
	Permitting	Total Project	Permitting	Total Project
SD of Estimated City Effects				
Baseline	0.411	0.884	0.471	0.990
Additional Controls	0.527	0.877	0.720	1.166
Percent Difference in SD	28.2	-0.9	52.8	17.8
Variance Difference (Full - Base)	0.109	-0.014	0.296	0.380
Gelbach Contributions to Variance Difference				
Flood Risk / Terrain	-0.014	0.020	-0.103	0.323
Shape Regularity	-0.002	0.019	-0.008	-0.124
ACS Neighborhood	0.125	-0.052	0.407	0.181
Number of Cities	52	51	45	41

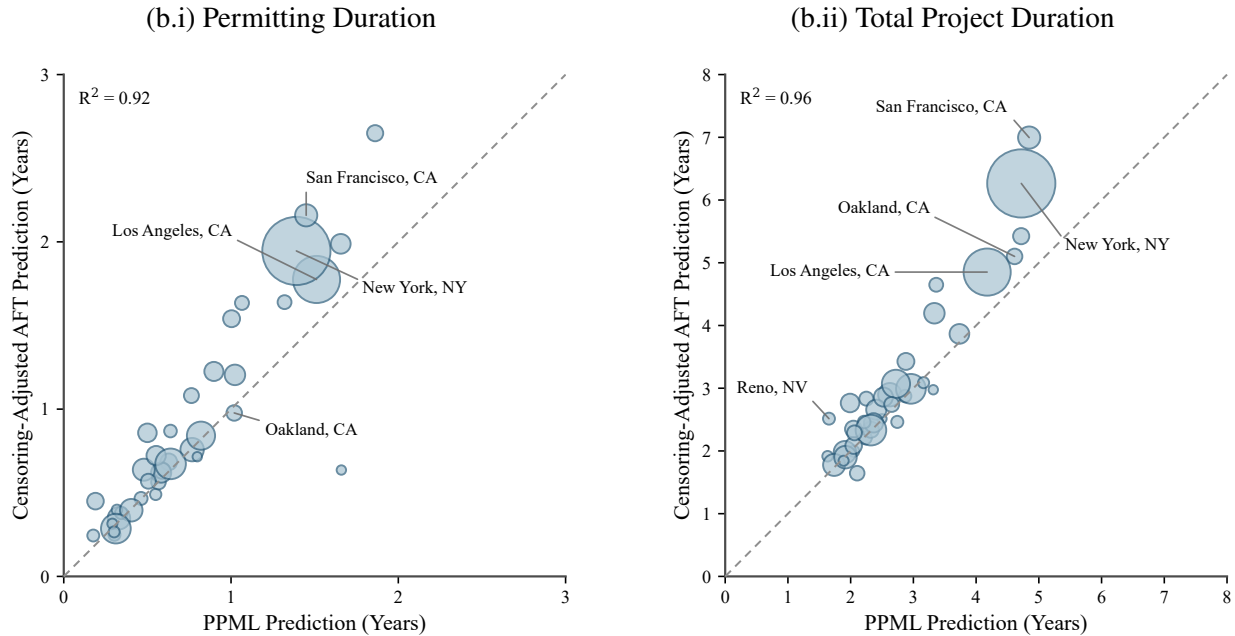
Notes: This table reports the impact of including additional controls on the across-city standard deviation of estimated durations by outcome (permitting or total project duration) and archetype (single- or multi-family). The table also reports the results of a [Gelbach \(2016\)](#) decomposition which shows the effect on estimated variance from each set of controls. See Appendix B for control-variable definitions.

Figure A7: Importance of Censoring Adjustment (AFT Versus PPML Duration Estimates)

(a) Single-Family



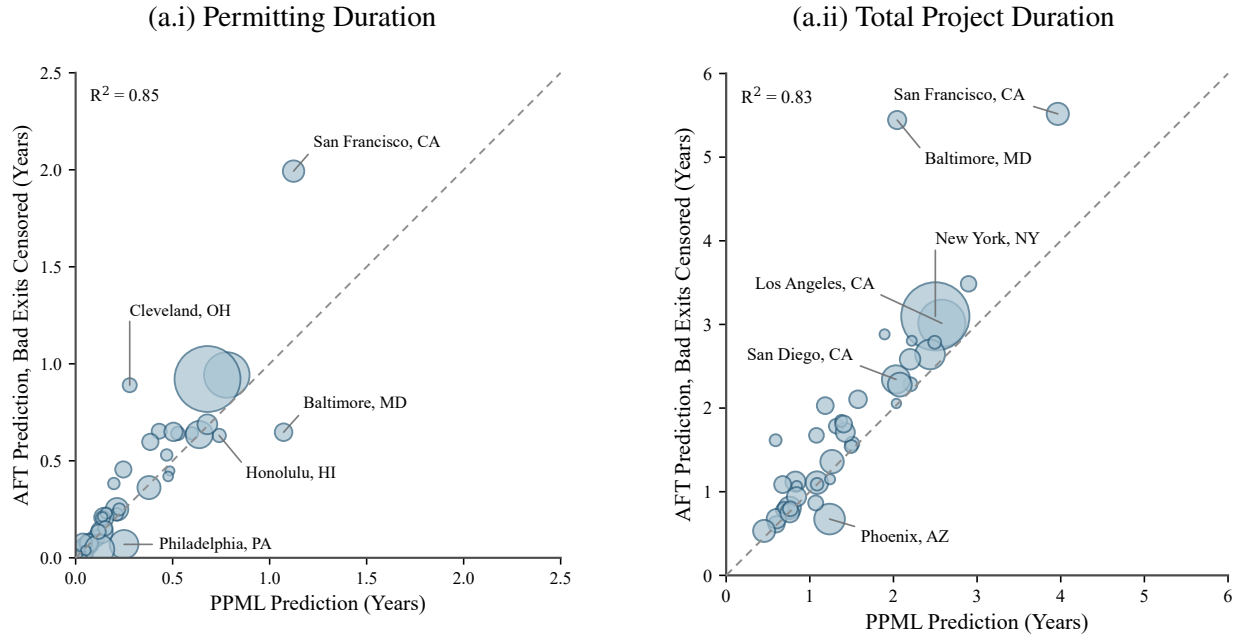
(b) Multi-Family



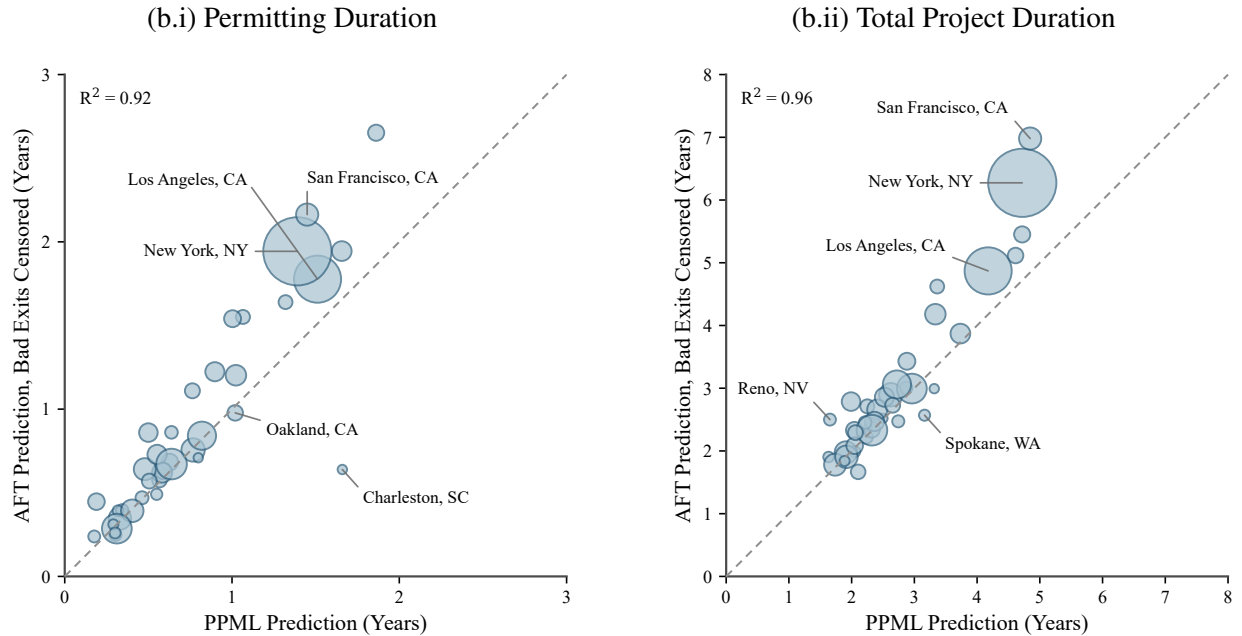
Notes: This figure compares city-level duration estimates from the PPML archetype specification to censoring-adjusted lognormal AFT estimates. By row, Panels A and B report single- and multi-family projects. By column, the left and right subpanels respectively show permitting and total project durations. Point sizes are proportional to city population. The dashed 45-degree line indicates equality between the two estimates. Select cities are labeled.

Figure A8: Importance of Censoring Adjustment
(AFT Versus PPML, Treating Bad Exits as Incomplete)

(a) Single-Family



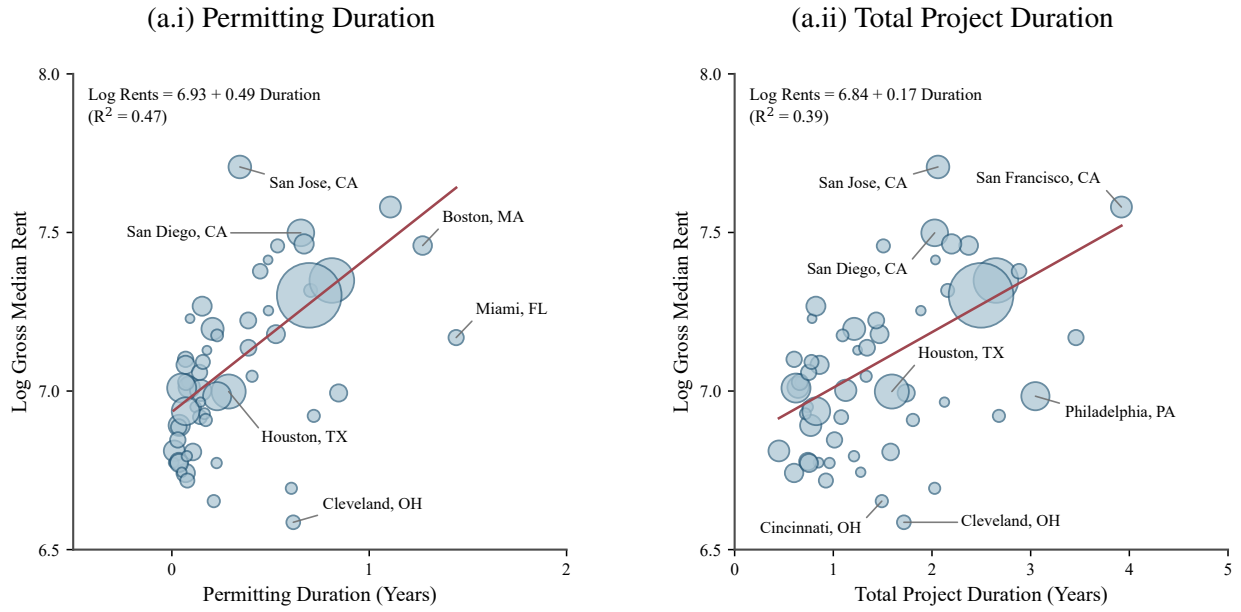
(b) Multi-Family



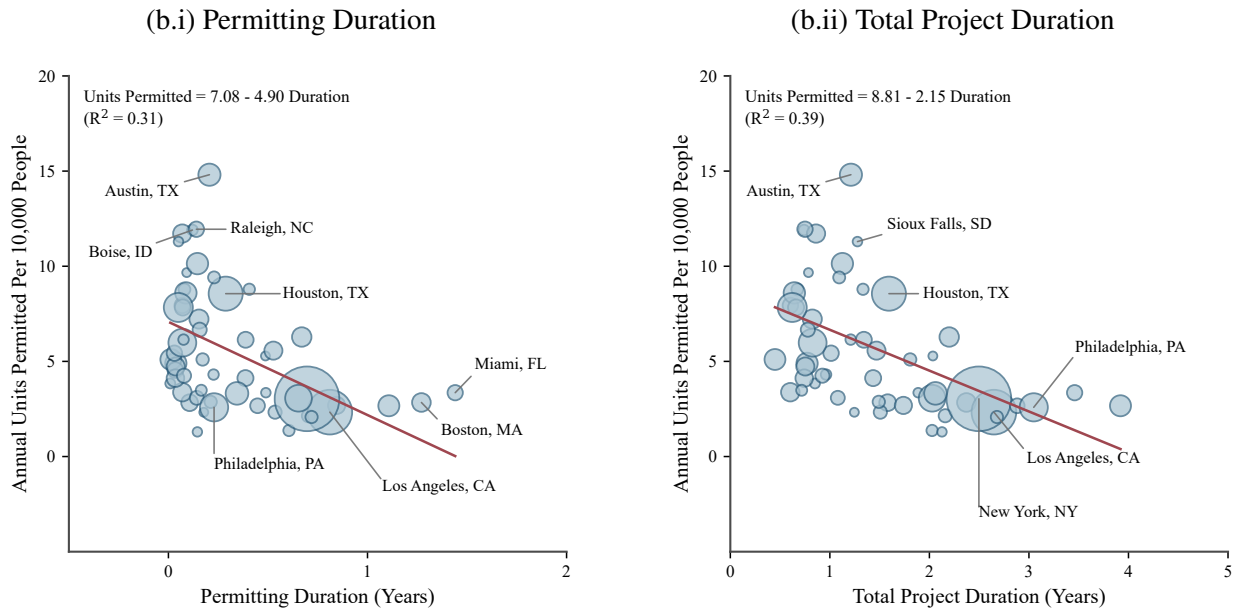
Notes: This figure compares city-level duration estimates from the PPML archetype specification to lognormal AFT estimates that treat bad-exit permits as censored incomplete projects. By row, Panels A and B report single- and multi-family projects. By column, the left and right subpanels respectively show permitting and total project durations. Point sizes are proportional to city population. The dashed 45-degree line indicates equality between the two estimates. Select cities are labeled.

Figure A9: Durations Versus Housing Costs and Production Across Cities (Single-Family)

(a) Gross Median Rent



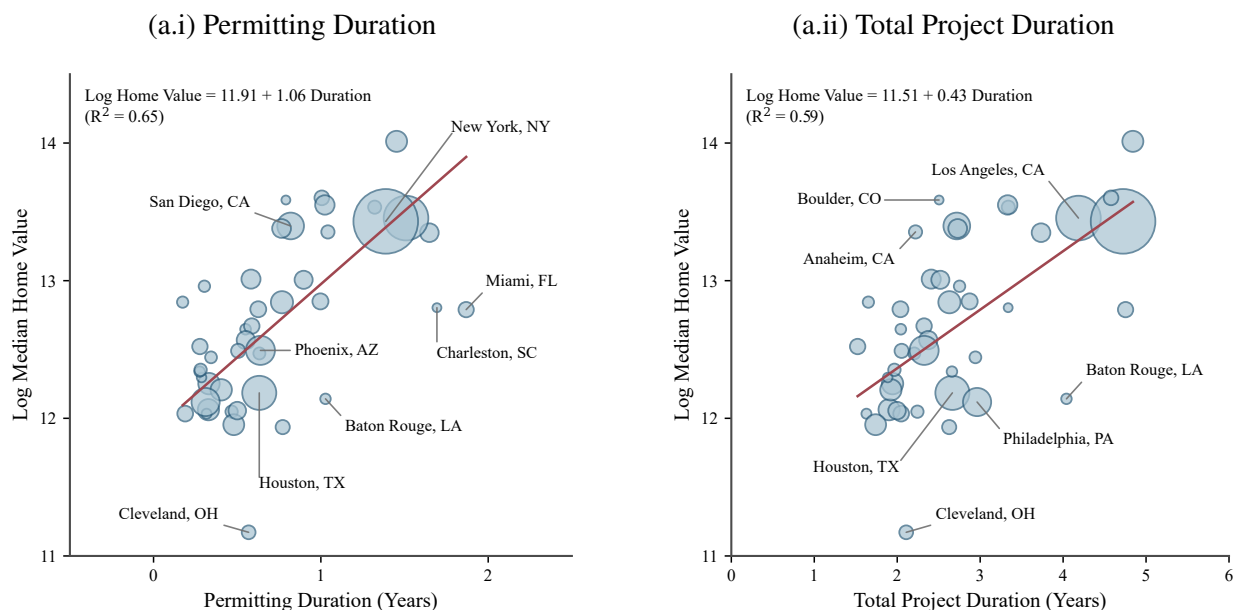
(b) Annual Units Permitted Per 10,000 People



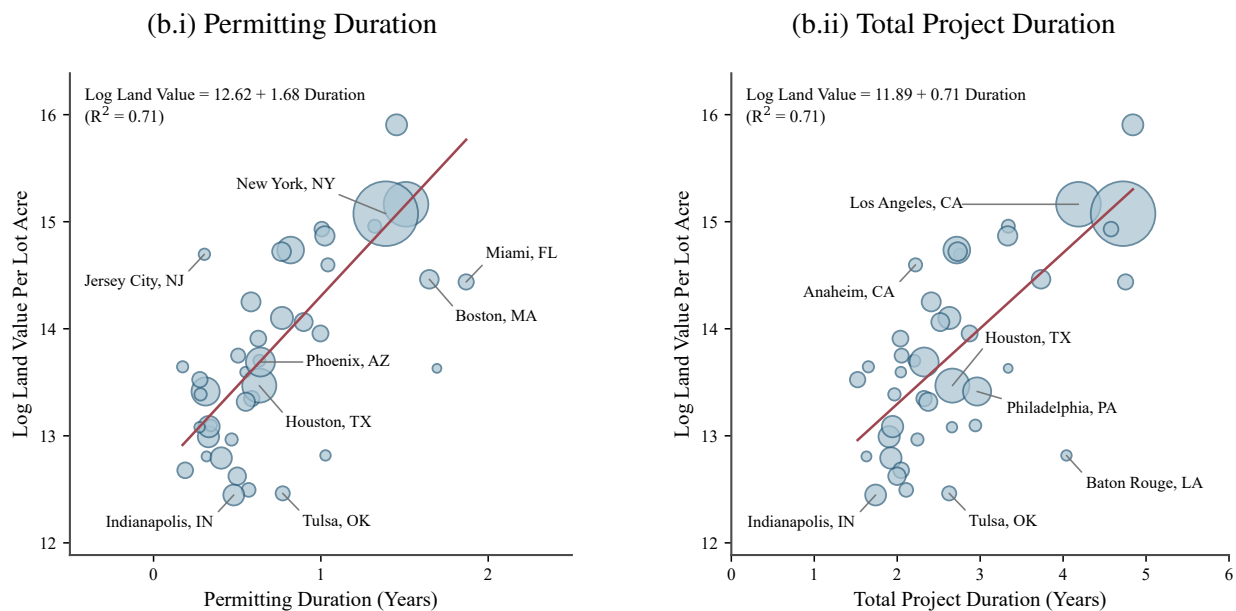
Notes: This figure plots city-level estimated durations for new single-family projects against corresponding city-level rents and housing production. Estimated durations are for a standardized single-family project, evaluated at common reference covariate values. Point sizes are proportional to city population. The solid line shows the population-weighted linear fit across cities. Select cities are labeled.

Figure A10: Durations Versus Other Measures of Housing Costs Across Cities (Multi-Family)

(a) Median Home Value

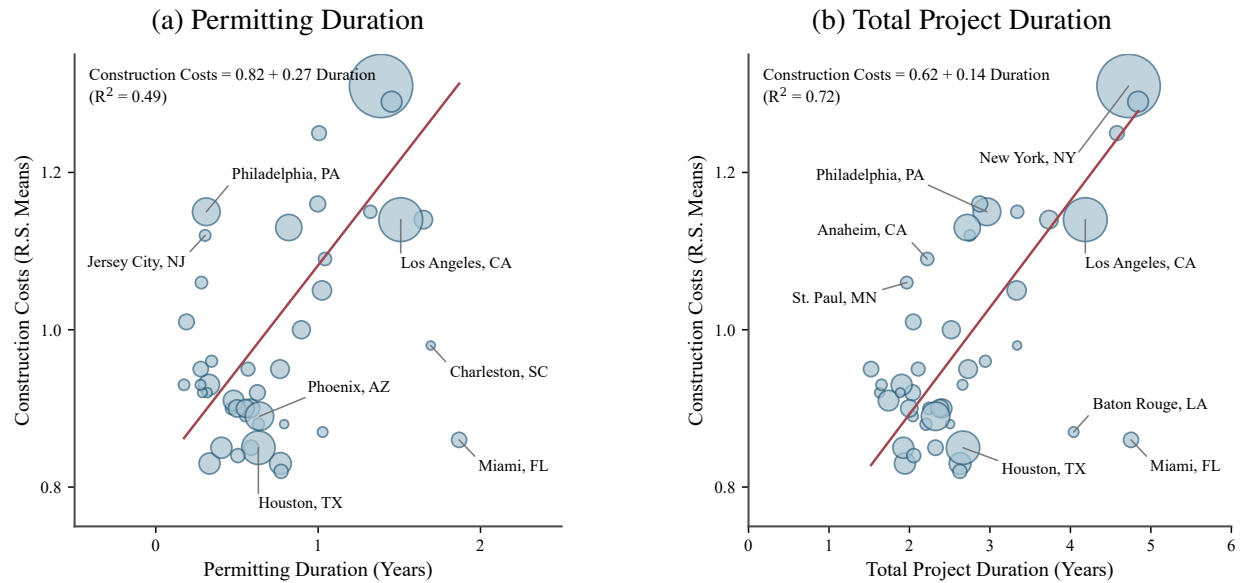


(b) Land Value Per Lot Quarter-Acre



Notes: This figure plots city-level estimated durations for multi-family housing against corresponding city-level housing-cost outcomes. By row, Panel A reports durations against home values, while Panel B reports durations against land values. By column, the left and right subpanels respectively show permitting and total project durations. Point sizes are proportional to city population. The solid line shows the population-weighted linear fit across cities. Select cities are labeled.

Figure A11: Durations Versus Construction Costs Across Cities (Multi-Family)



Notes: This figure plots city-level estimated durations for new multi-family projects against corresponding city-level construction costs (R.S. Means location factors for residential construction). Panels A and B respectively report permitting and total project durations. Point sizes are proportional to city population. The solid line shows the population-weighted linear fit across cities. Select cities are labeled.

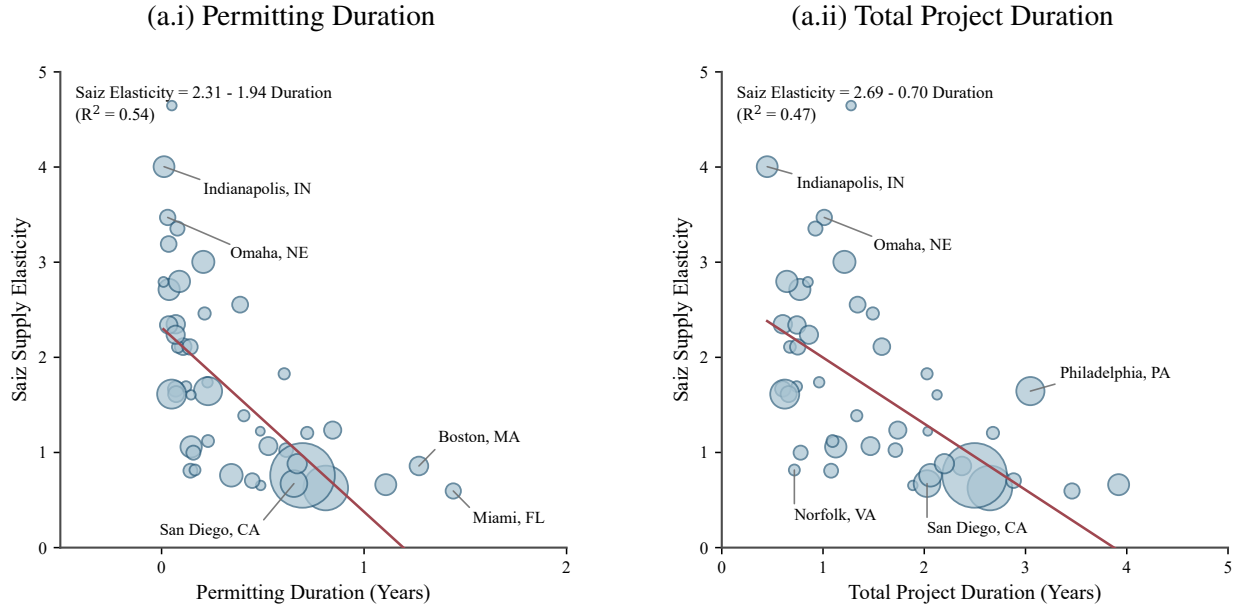
Table A7: Permitting Duration, Prices, and Units Permitted

	Single-Family					Multi-Family				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Panel A: Dependent Variable = Log Gross Median Rent (SF N = 54, MF N = 42)</i>										
Permitting Duration	0.520*** (0.125)	0.348** (0.170)	0.436*** (0.094)	0.349*** (0.057)	0.299*** (0.084)	0.571*** (0.118)	0.405*** (0.122)	0.475*** (0.109)	0.336*** (0.082)	0.259*** (0.063)
Population Density		0.233 (0.141)			0.073 (0.079)		0.370*** (0.115)			0.191*** (0.065)
College Grad Share			0.475*** (0.104)		-0.109 (0.071)			0.494*** (0.121)		-0.084 (0.090)
Median Income				0.783*** (0.069)	0.853*** (0.096)				0.748*** (0.079)	0.771*** (0.121)
R^2	0.270	0.295	0.488	0.854	0.864	0.326	0.436	0.561	0.831	0.863
<i>Panel B: Dependent Variable = Log Median Home Value (SF N = 54, MF N = 42)</i>										
Permitting Duration	0.494*** (0.142)	0.283 (0.192)	0.404*** (0.111)	0.319*** (0.070)	0.225** (0.094)	0.609*** (0.136)	0.443*** (0.128)	0.513*** (0.130)	0.374*** (0.090)	0.297*** (0.080)
Population Density		0.286* (0.156)			0.133** (0.064)		0.370*** (0.098)			0.191*** (0.069)
College Grad Share			0.506*** (0.113)		-0.060 (0.071)			0.490*** (0.122)		-0.090 (0.076)
Median Income				0.800*** (0.062)	0.830*** (0.091)				0.748*** (0.053)	0.776*** (0.094)
R^2	0.244	0.281	0.492	0.853	0.864	0.371	0.480	0.602	0.875	0.908
<i>Panel C: Dependent Variable = Log Land Value Per Lot Acre (SF N = 54, MF N = 42)</i>										
Permitting Duration	0.644*** (0.134)	0.316* (0.158)	0.575*** (0.115)	0.512*** (0.081)	0.265** (0.099)	0.628*** (0.138)	0.376*** (0.107)	0.551*** (0.141)	0.433*** (0.127)	0.267*** (0.076)
Population Density		0.445*** (0.129)			0.343*** (0.067)		0.561*** (0.091)			0.428*** (0.055)
College Grad Share			0.388*** (0.088)		0.005 (0.076)			0.397*** (0.111)		-0.066 (0.074)
Median Income				0.606*** (0.052)	0.573*** (0.079)				0.620*** (0.084)	0.579*** (0.077)
R^2	0.415	0.505	0.561	0.765	0.817	0.394	0.646	0.546	0.741	0.884
<i>Panel D: Dependent Variable = Annual Units Permitted Per 10,000 People (SF N = 53, MF N = 41)</i>										
Permitting Duration	-0.417*** (0.091)	-0.105 (0.120)	-0.515*** (0.124)	-0.504*** (0.146)	-0.228 (0.166)	-0.334** (0.143)	-0.079 (0.096)	-0.389*** (0.130)	-0.371** (0.145)	-0.124 (0.093)
Population Density		-0.422*** (0.151)			-0.402*** (0.149)		-0.564*** (0.107)			-0.627*** (0.111)
College Grad Share			0.431*** (0.120)		0.344** (0.156)			0.298** (0.145)		0.371** (0.158)
Median Income				0.303** (0.148)	0.107 (0.154)				0.116 (0.129)	0.013 (0.162)
R^2	0.174	0.255	0.351	0.259	0.421	0.111	0.365	0.197	0.123	0.501

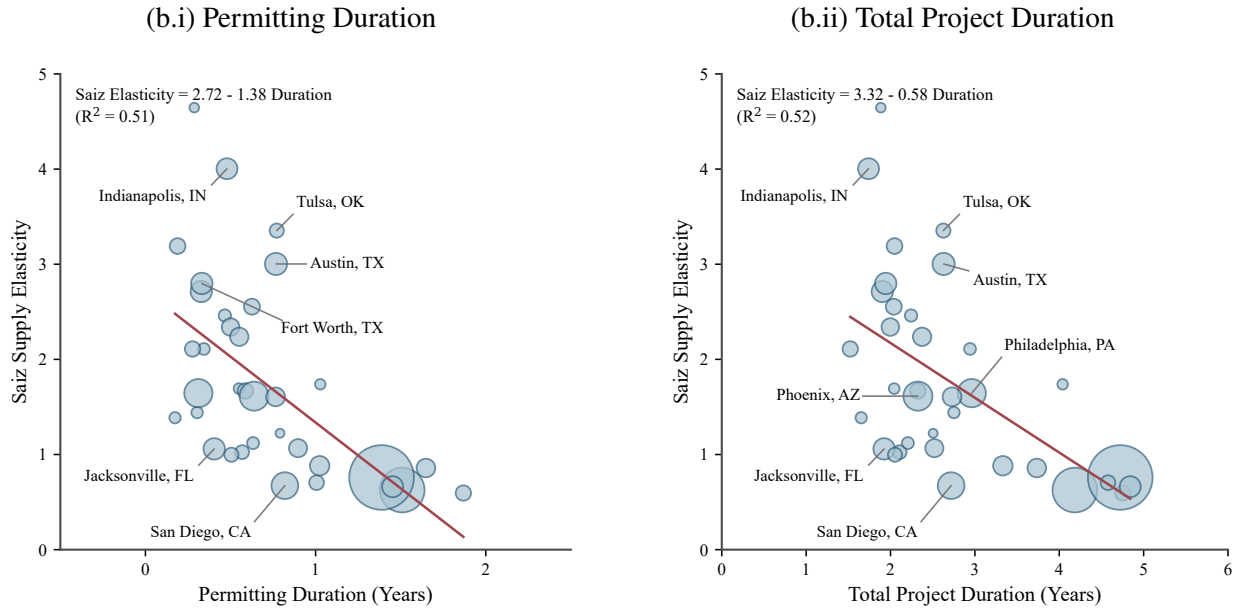
Notes: This table reports standardized coefficients from unweighted city-level regressions of rents (Panel A), home values (Panel B), land values (Panel C), and annual units permitted per 10,000 people (Panel D) on single- and multi-family permitting duration. Column 1 and 6 report the bivariate regression for single-family and multi-family archetypes' permitting durations, respectively. Columns 2–5 adds controls to the single-family archetype, while columns 7–10 add the same controls for the multi-family archetype: population density, the college graduate share of adults, and median household income. Observation counts (N) reflect the number of cities. Heteroskedasticity-robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A12: Durations Versus Housing Supply Elasticities Across Cities

(a) Single-Family



(b) Multi-Family



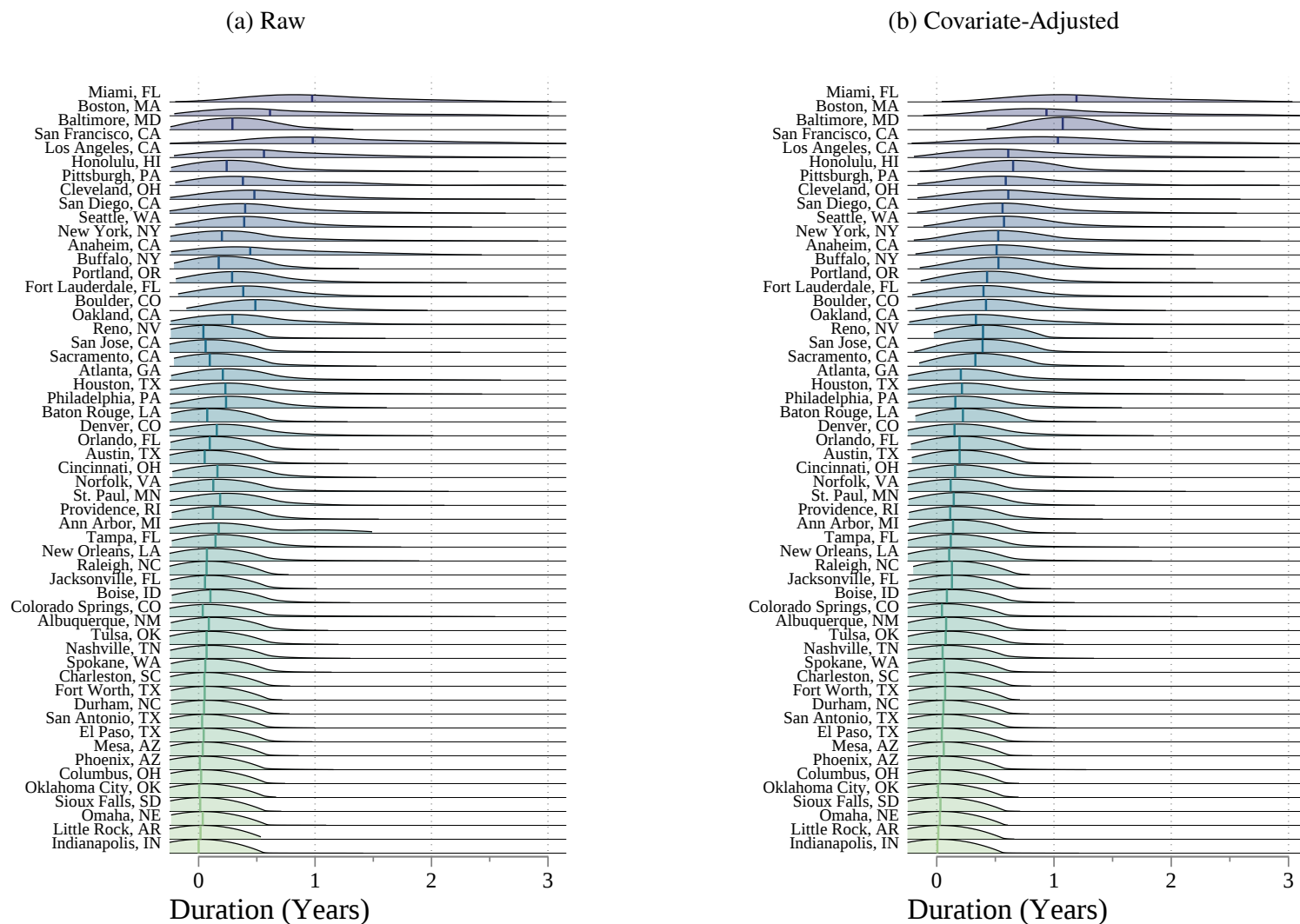
Notes: This figure plots city-level estimated durations for new single-family (Panel A) and multi-family (Panel B) projects against the metro-level housing supply elasticities of [Saiz \(2010\)](#), with each permitting jurisdiction assigned the elasticity of its surrounding metropolitan area under 1999 definitions. Estimated durations are for standardized projects, evaluated at common reference covariate values. Point sizes are proportional to city population. The solid line shows the population-weighted linear fit across cities. Select cities are labeled.

Table A8: Permitting Duration Versus Housing Supply Elasticity

	Dependent Variable: City-Level Housing Supply Elasticity									
	Single-Family (N = 46)					Multi-Family (N = 35)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Permitting Duration	-0.733*** (0.119)	-0.589*** (0.140)	-0.747*** (0.119)	-0.682*** (0.119)	-0.585*** (0.115)	-0.716*** (0.104)	-0.534*** (0.112)	-0.715*** (0.104)	-0.670*** (0.097)	-0.458*** (0.135)
Population Density		-0.197* (0.116)			-0.124 (0.113)		-0.246 (0.157)			-0.231 (0.165)
% College Educated			0.062 (0.096)		0.259* (0.136)			-0.020 (0.123)		0.181 (0.184)
Median Income				-0.139 (0.104)	-0.321** (0.131)				-0.123 (0.132)	-0.267 (0.201)
R^2	0.537	0.555	0.541	0.554	0.602	0.513	0.540	0.513	0.526	0.563

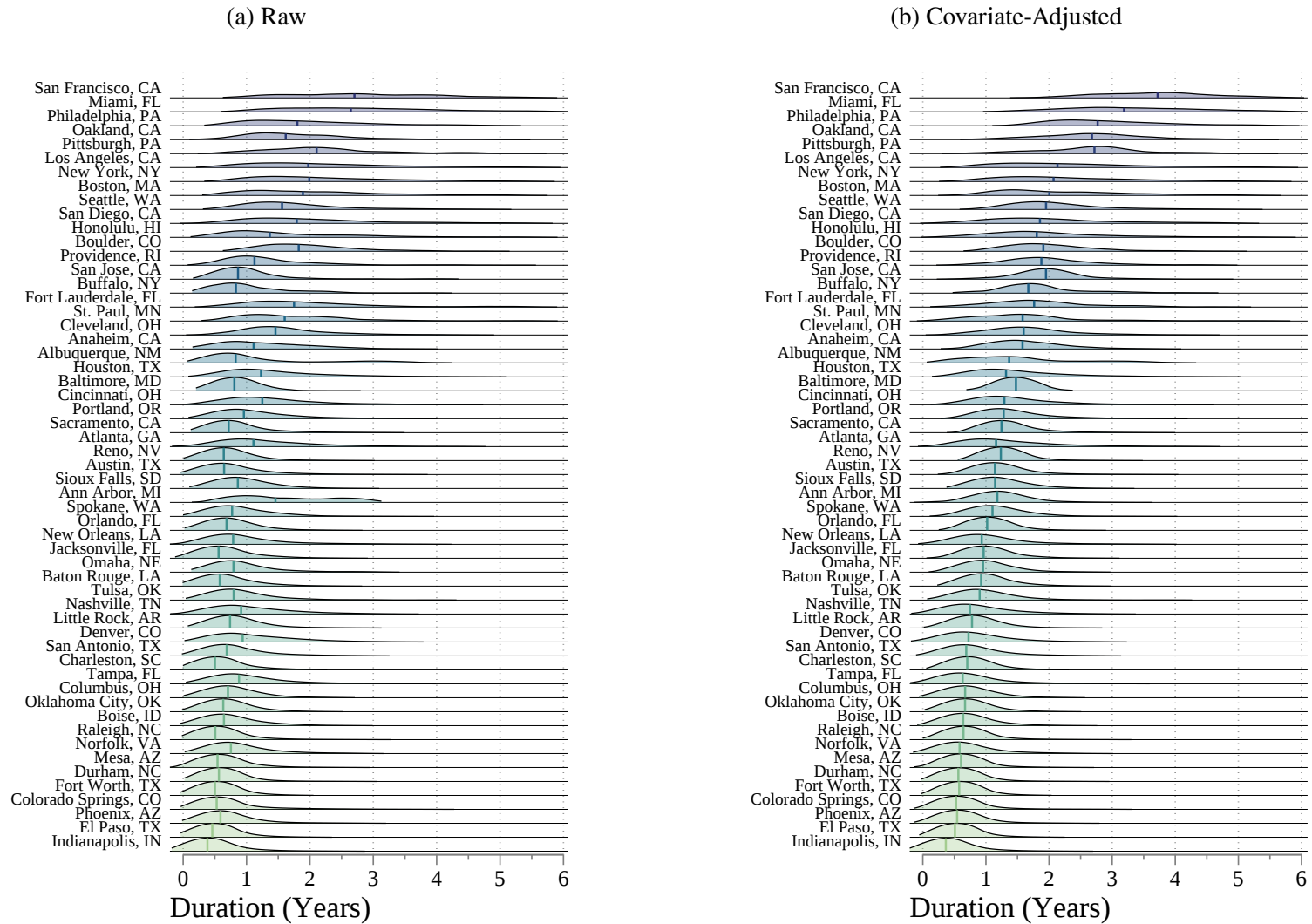
Notes: This table reports standardized coefficients from city-level regressions of the [Saiz \(2010\)](#) metro housing supply elasticity on permitting duration for single-family (Columns 1–5) and multi-family (Columns 6–10) projects. Each permitting jurisdiction is assigned the elasticity of its surrounding metropolitan area under 1999 definitions. Columns 1 and 6 report bivariate regressions; the remaining columns add controls: population density, the college graduate share of adults, and median household income. Observation counts reflect the number of cities. All regressions are weighted by city population. Heteroskedasticity-robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A13: Raw and Covariate-Adjusted Distributions of Permitting Duration (Single-Family)



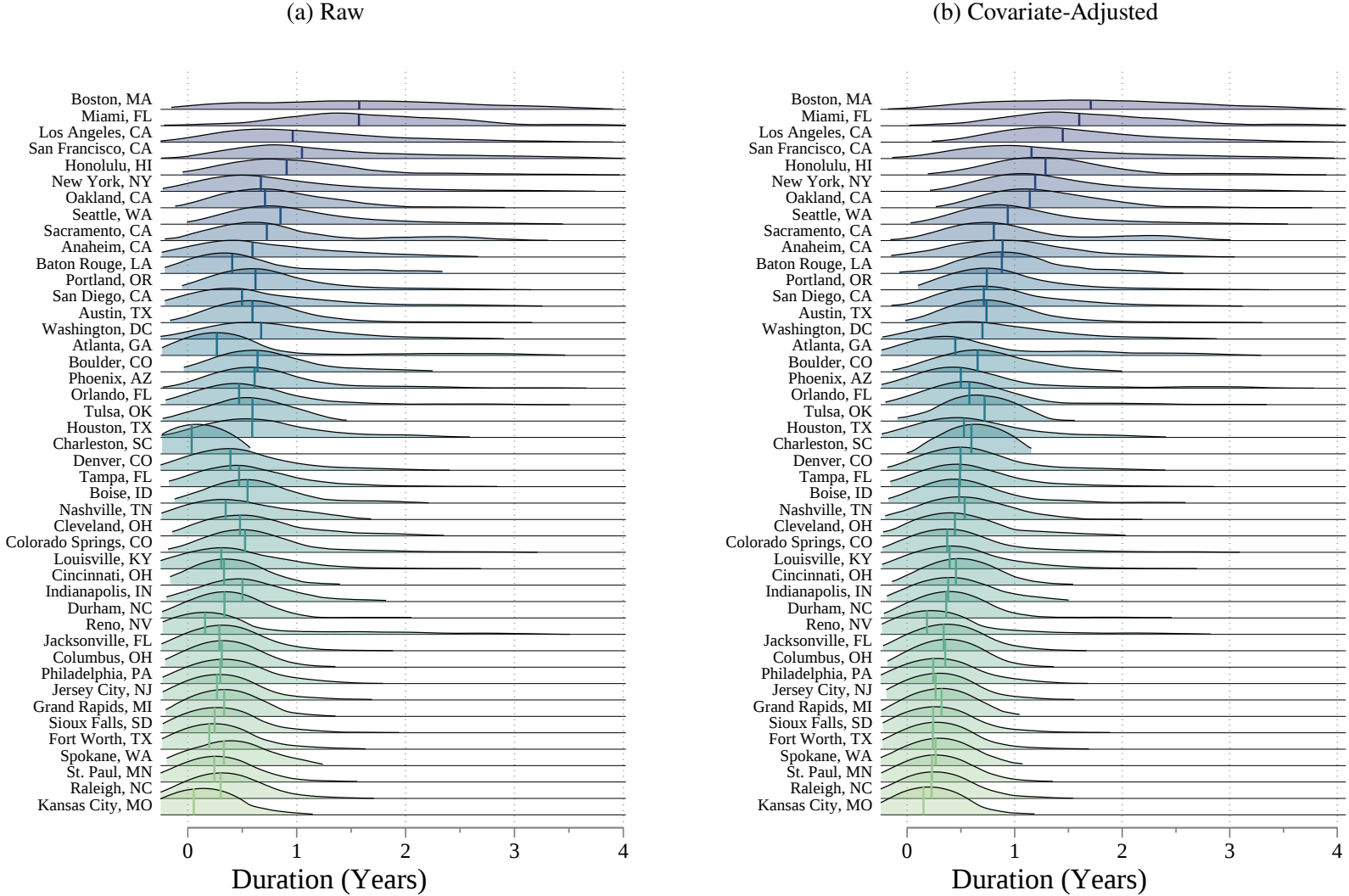
Notes: This figure displays kernel density estimates of the distribution of permitting duration by city for single-family projects. Panel A presents raw durations, while Panel B presents covariate-adjusted durations. Vertical lines indicate city-level medians. Section 2 discusses covariate adjustments; no adjustment is made for right-censoring.

Figure A14: Raw and Covariate-Adjusted Distributions of Total Project Duration (Single-Family)



Notes: This figure displays kernel density estimates of the distribution of total project duration by city for single-family projects. Panel A presents raw durations, while Panel B presents covariate-adjusted durations. Vertical lines indicate city-level medians. Section 2 discusses covariate adjustments; no adjustment is made for right-censoring.

Figure A15: Raw and Covariate-Adjusted Distributions of Permitting Duration (Multi-Family)



Notes: This figure displays kernel density estimates of the distribution of permitting duration by city for multi-family projects. Panel A presents raw durations, while Panel B presents covariate-adjusted durations. Vertical lines indicate city-level medians. Section 2 discusses covariate adjustments; no adjustment is made for right-censoring.

Figure A16: Raw and Covariate-Adjusted Distributions of Total Project Duration (Multi-Family)

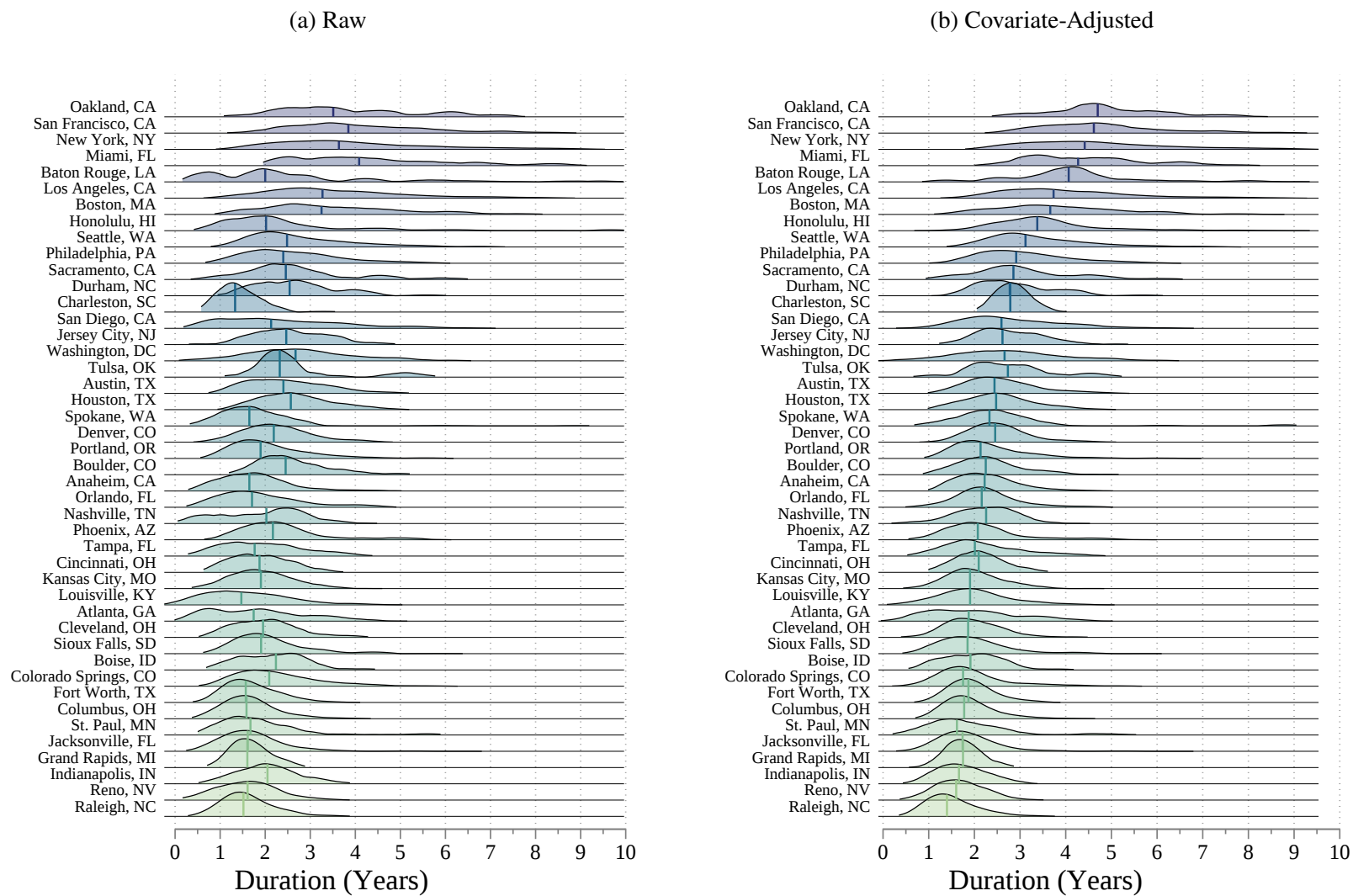


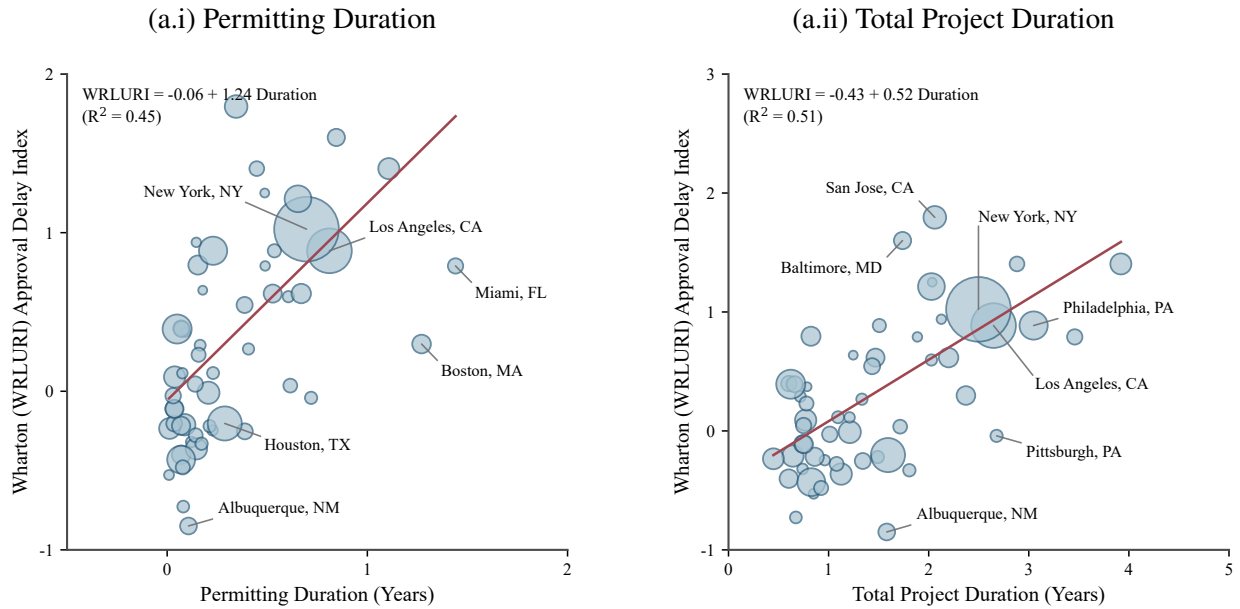
Table A9: Associations of the Mean and Variance of Duration With Housing and Construction Costs

	Single-Family						Multi-Family					
	Permitting			Total Project			Permitting			Total Project		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
<i>Panel A: Dependent Variable = Log Gross Median Rent</i>												
Average Duration	0.491*** (0.068)		0.499*** (0.069)	0.175** (0.037)		0.175** (0.038)	0.334*** (0.038)		0.332*** (0.039)	0.127*** (0.022)		0.128*** (0.023)
Variance of Log Duration		-0.031 (0.068)	0.030 (0.037)		0.124 (0.285)	0.003 (0.196)		-0.073 (0.127)	-0.040 (0.064)		0.120 (0.470)	0.129 (0.346)
R^2	0.468	0.004	0.472	0.391	0.003	0.391	0.508	0.013	0.512	0.419	0.004	0.424
N	57	57	57	56	56	56	44	44	44	44	44	44
<i>Panel B: Dependent Variable = Log Home Value</i>												
Average Duration	1.373*** (0.227)		1.409*** (0.223)	0.494* (0.125)		0.491* (0.127)	1.065*** (0.095)		1.060*** (0.102)	0.425*** (0.043)		0.426*** (0.044)
Variance of Log Duration		-0.041 (0.229)	0.131 (0.150)		0.613 (0.732)	0.271 (0.583)		-0.195 (0.385)	-0.091 (0.155)		0.604 (1.223)	0.633 (0.747)
R^2	0.511	0.001	0.521	0.437	0.009	0.438	0.654	0.011	0.656	0.592	0.012	0.605
N	57	57	57	56	56	56	44	44	44	44	44	44
<i>Panel C: Dependent Variable = Log Land Value Per Lot Acre</i>												
Average Duration	2.340*** (0.381)		2.422*** (0.374)	0.886*** (0.172)		0.882** (0.174)	1.682*** (0.142)		1.673*** (0.151)	0.706*** (0.059)		0.706*** (0.060)
Variance of Log Duration		-0.002 (0.365)	0.296* (0.177)		1.053 (1.295)	0.459 (0.825)		-0.347 (0.593)	-0.178 (0.202)		0.400 (1.804)	0.477 (1.044)
R^2	0.616	0.000	0.637	0.587	0.011	0.589	0.709	0.016	0.714	0.710	0.002	0.713
N	54	54	54	53	53	53	42	42	42	42	42	42
<i>Panel D: Dependent Variable = Construction Costs (R.S. Means)</i>												
Average Duration	0.363*** (0.103)		0.383*** (0.098)	0.166*** (0.034)		0.165*** (0.034)	0.266*** (0.077)		0.268*** (0.077)	0.136*** (0.018)		0.136*** (0.018)
Variance of Log Duration		0.026 (0.076)	0.073 (0.062)		0.175 (0.197)	0.060 (0.145)		0.022 (0.107)	0.048 (0.059)		0.133 (0.296)	0.142 (0.135)
R^2	0.460	0.005	0.501	0.626	0.009	0.627	0.488	0.002	0.496	0.720	0.007	0.728
N	57	57	57	56	56	56	44	44	44	44	44	44

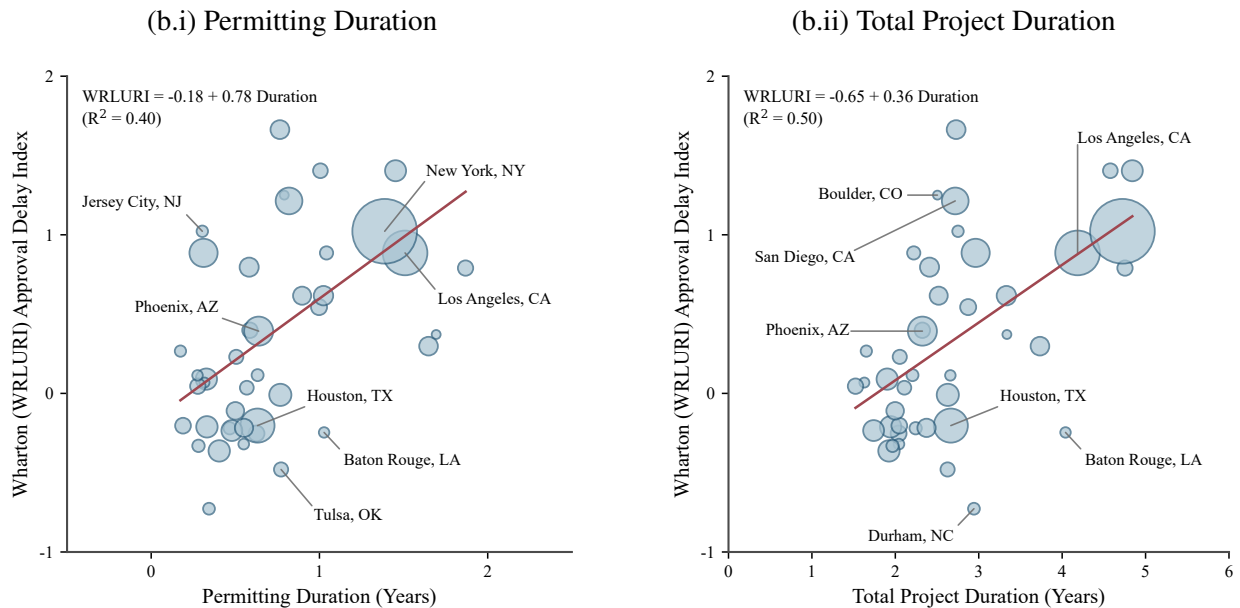
Notes: This table reports estimated coefficients from city-level regressions of four outcomes (rent, home value, land value, construction cost) on the mean and variance of permitting or total project duration for single- or multi-family housing projects. Each set of three columns shows the outcome of interest on mean duration only, then the log-duration variance only, and finally mean and log-variance jointly. Rents and home values are from the ACS, land values are from [Davis et al. \(2021\)](#), and construction costs are the location indexes from R.S. Means. All regressions are weighted by city population. Heteroskedasticity-robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A17: Relationship Between Permitting Duration and the Wharton Index

(a) Single-Family



(b) Multi-Family



Notes: This figure displays scatter plots of the Approval Delay Index (ADI) component of the Wharton Residential Land Use Regulation Index (WRLURI) versus our measures of permitting and total project duration for multi- and single-family housing. Dots are sized in proportion to city population. The solid line shows the population-weighted linear fit across cities. Select cities are labeled.

Table A10: Permitting Duration Versus Other Measures of Regulation (Multi-Family)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A: Dependent Variable = Log Gross Median Rent (N = 31)</i>								
Permitting Duration	0.750*** (0.090)						0.360* (0.183)	0.355* (0.199)
WRLURI		0.771*** (0.115)					0.467*** (0.161)	
WRLURI ADI			0.777*** (0.100)		0.592*** (0.207)			0.376* (0.204)
WRLURI ex-ADI				0.699*** (0.114)	0.237 (0.200)			0.139 (0.165)
Bartik, Gupta & Milo						0.454*** (0.151)	0.195 (0.125)	0.168 (0.120)
R^2	0.563	0.595	0.603	0.489	0.625	0.206	0.720	0.732
<i>Panel B: Dependent Variable = Log Median Home Value (N = 31)</i>								
Permitting Duration	0.849*** (0.073)						0.507*** (0.106)	0.498*** (0.139)
WRLURI		0.816*** (0.084)					0.429*** (0.115)	
WRLURI ADI			0.805*** (0.087)		0.548** (0.200)			0.305* (0.171)
WRLURI ex-ADI				0.757*** (0.090)	0.329* (0.186)			0.172 (0.127)
Bartik, Gupta & Milo						0.431*** (0.143)	0.131 (0.083)	0.113 (0.084)
R^2	0.720	0.666	0.648	0.573	0.690	0.185	0.837	0.846
<i>Panel C: Dependent Variable = Log Land Value Per Lot Acre (N = 30)</i>								
Permitting Duration	0.867*** (0.079)						0.474*** (0.062)	0.461*** (0.079)
WRLURI		0.851*** (0.074)					0.462*** (0.074)	
WRLURI ADI			0.848*** (0.099)		0.594** (0.215)			0.319*** (0.090)
WRLURI ex-ADI				0.794*** (0.074)	0.321* (0.179)			0.196** (0.075)
Bartik, Gupta & Milo						0.513*** (0.120)	0.215*** (0.059)	0.198*** (0.046)
R^2	0.754	0.724	0.719	0.627	0.757	0.264	0.916	0.928
<i>Panel D: Dependent Variable = Units Permitted per 10,000 People (N = 30)</i>								
Permitting Duration	-0.493*** (0.165)						-0.252 (0.241)	-0.173 (0.150)
WRLURI		-0.543*** (0.112)					-0.380** (0.184)	
WRLURI ADI			-0.704*** (0.139)		-0.867** (0.316)			-0.900** (0.324)
WRLURI ex-ADI				-0.472*** (0.119)	0.212 (0.274)			0.322 (0.317)
Bartik, Gupta & Milo						-0.132 (0.166)	0.051 (0.127)	0.192 (0.164)
R^2	0.243	0.288	0.496	0.217	0.513	0.016	0.320	0.549

Notes: This table reports estimated coefficients from city-level regressions of four outcomes (rent, home value, land value, units permitted) on several measures of land-use regulation, all of which are standardized to unit variance. Column 1 projects the outcome on our measure of multi-family permitting duration. Columns 2–5 use the Wharton Residential Land Use Regulation Index (WRLURI), first the overall index, next its Approval Delay Index (ADI) component, then the index without the ADI, and finally the ADI and non-ADI components jointly. Column 6 uses the measure of [Bartik et al. \(2025\)](#). Columns 7 and 8 are the “horse races” of our measure, WRLURI, and [Bartik et al. \(2025\)](#). All regressions are weighted by city population. Each panel limits the sample to a consistent set of cities across columns. Heteroskedasticity-robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Permitting Duration Versus Other Measures of Regulation (Single-Family)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>Panel A: Dependent Variable = Log Gross Median Rent (N = 42)</i>								
Permitting Duration	0.731*** (0.072)						0.406*** (0.143)	0.297 (0.188)
WRLURI		0.684*** (0.101)					0.389** (0.158)	
WRLURI ADI			0.797*** (0.094)		0.759*** (0.117)			0.526** (0.239)
WRLURI ex-ADI				0.539*** (0.104)	0.061 (0.108)			0.033 (0.128)
Bartik, Gupta & Milo						0.406*** (0.133)	0.229** (0.103)	0.172 (0.119)
R^2	0.535	0.467	0.635	0.290	0.637	0.164	0.655	0.724
<i>Panel B: Dependent Variable = Log Median Home Value (N = 42)</i>								
Permitting Duration	0.766*** (0.100)						0.423*** (0.113)	0.349** (0.147)
WRLURI		0.723*** (0.108)					0.417*** (0.135)	
WRLURI ADI			0.781*** (0.106)		0.663*** (0.109)			0.395* (0.195)
WRLURI ex-ADI				0.605*** (0.124)	0.187* (0.111)			0.152 (0.115)
Bartik, Gupta & Milo						0.408*** (0.136)	0.223** (0.101)	0.189 (0.114)
R^2	0.587	0.522	0.610	0.366	0.631	0.167	0.717	0.745
<i>Panel C: Dependent Variable = Log Land Value Per Lot Acre (N = 41)</i>								
Permitting Duration	0.822*** (0.118)						0.470*** (0.078)	0.403*** (0.081)
WRLURI		0.750*** (0.109)					0.404*** (0.096)	
WRLURI ADI			0.807*** (0.115)		0.676*** (0.113)			0.351** (0.138)
WRLURI ex-ADI				0.638*** (0.129)	0.205* (0.110)			0.173* (0.086)
Bartik, Gupta & Milo						0.480*** (0.123)	0.280*** (0.076)	0.255*** (0.083)
R^2	0.679	0.562	0.651	0.405	0.676	0.231	0.826	0.848
<i>Panel D: Dependent Variable = Units Permitted per 10,000 People (N = 41)</i>								
Permitting Duration	-0.512*** (0.122)						-0.399* (0.212)	-0.298* (0.171)
WRLURI		-0.499*** (0.105)					-0.241 (0.169)	
WRLURI ADI			-0.554*** (0.140)		-0.468** (0.211)			-0.386* (0.202)
WRLURI ex-ADI				-0.436*** (0.111)	-0.138 (0.186)			-0.013 (0.212)
Bartik, Gupta & Milo						-0.014 (0.165)	0.145 (0.134)	0.189 (0.156)
R^2	0.264	0.245	0.308	0.187	0.320	0.000	0.322	0.372

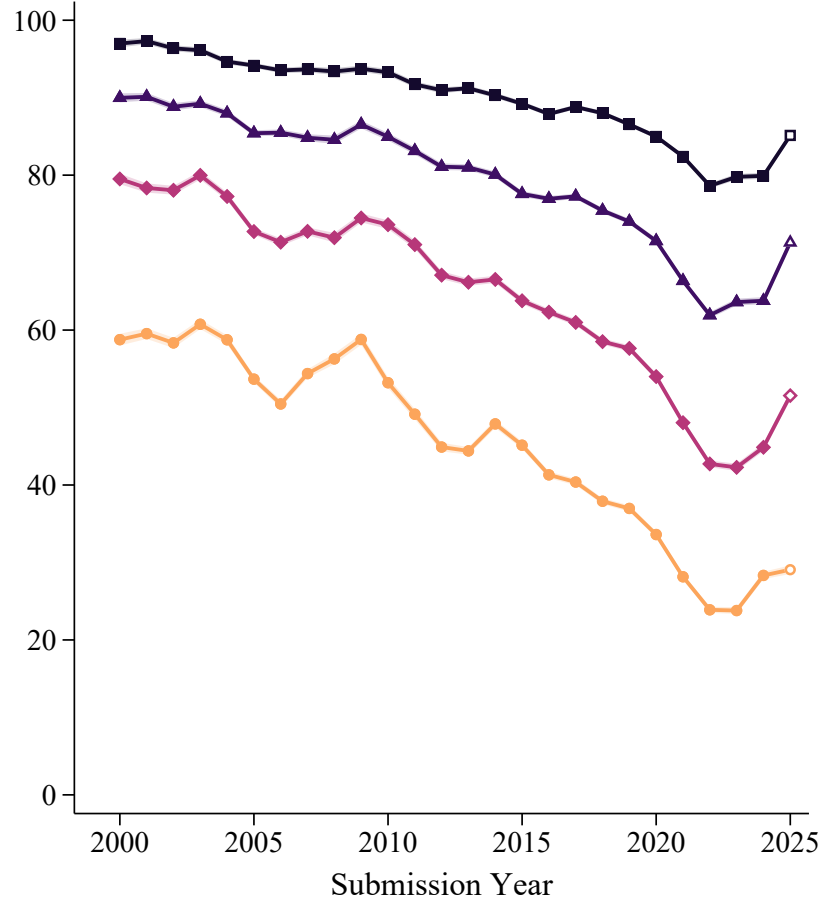
Notes: This table reports estimated coefficients from city-level regressions of four outcomes (rent, home value, land value, units permitted) on several measures of land-use regulation, all of which are standardized to unit variance. Column 1 projects the outcome on our measure of single-family permitting duration. Columns 2–5 use the Wharton Residential Land Use Regulation Index (WRLURI), first the overall index, next its Approval Delay Index (ADI) component, then the index without the ADI, and finally the ADI and non-ADI components jointly. Column 6 uses the measure of [Bartik et al. \(2025\)](#). Columns 7 and 8 are the “horse races” of our measure, WRLURI, and [Bartik et al. \(2025\)](#). All regressions are weighted by city population. Each panel limits the sample to a consistent set of cities across columns. Heteroskedasticity-robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A18: Project Shares Issued and Completed by Time Horizon (Single-Family)

(a) Permitting Duration

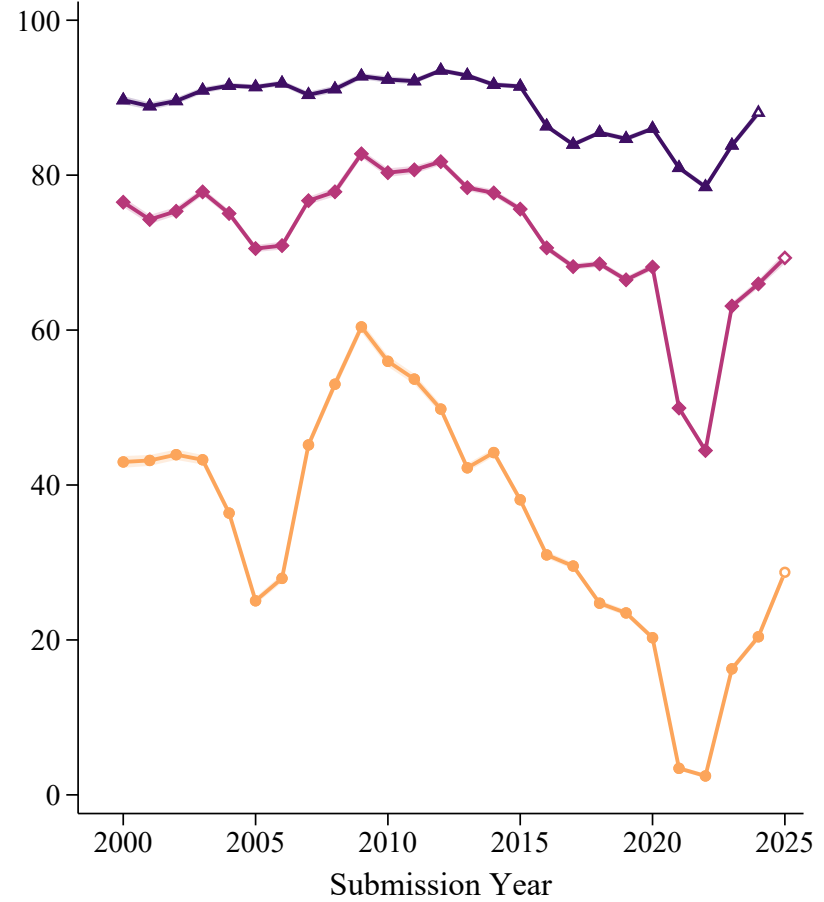
(b) Total Project Duration

Adjusted Share Among Issued Permits (Percent)



● ≤ 2 Weeks ◆ ≤ 1 Month ▲ ≤ 2 Months ■ ≤ 4 Months

Adjusted Share Among Issued Permits (Percent)



● ≤ 6 Months ◆ ≤ 12 Months ▲ ≤ 24 Months

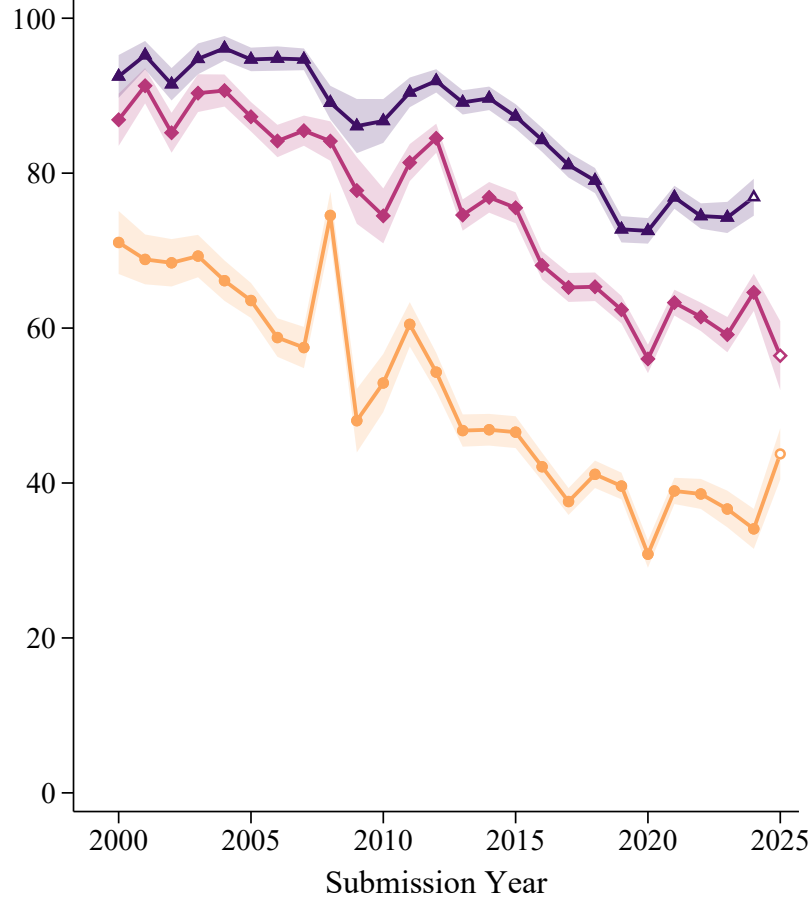
Notes: This figure presents covariate-adjusted time series of the shares of single-family projects that have issued permits (Panel A) or are completed (Panel B) within a given time horizon from permit submission. The estimating equation is $Y_{icy} = \alpha_c + \alpha_y + X_i' \beta_c + \varepsilon_{icy}$, where the outcome $Y_{icy} = 1[T_{icy} \leq t]$ is an indicator for whether the relevant duration is less than some amount t . The terms α_c and α_y denote city and submission cohort-year fixed effects, and X_i includes our benchmark controls. Series stop when the outcome is no longer observed at the horizon of interest. Hollow markers identify when outcomes are only partially observed for a submission-year cohort. Confidence bands are pointwise at the 95-percent level and reflect standard errors clustered by project.

Figure A19: Project Shares Issued and Completed by Time Horizon (Multi-Family)

(a) Permitting Duration

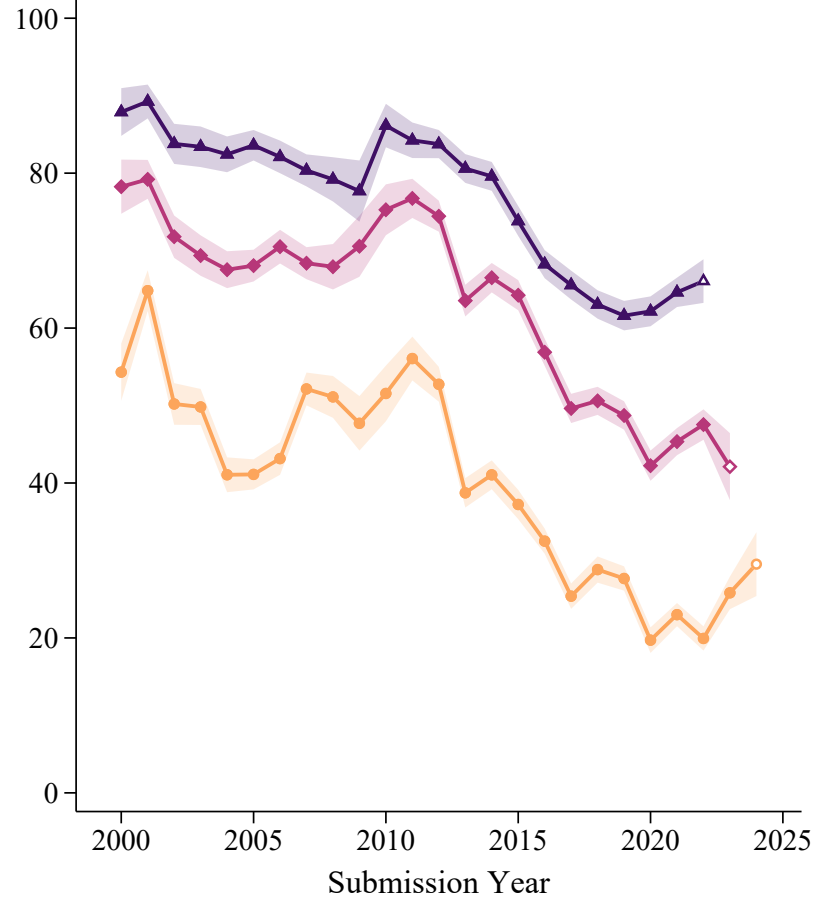
(b) Total Project Duration

Adjusted Share Among Issued Permits (Percent)



● ≤ 6 Months ◆ ≤ 12 Months ▲ ≤ 18 Months

Adjusted Share Among Issued Permits (Percent)



● ≤ 24 Months ◆ ≤ 36 Months ▲ ≤ 48 Months

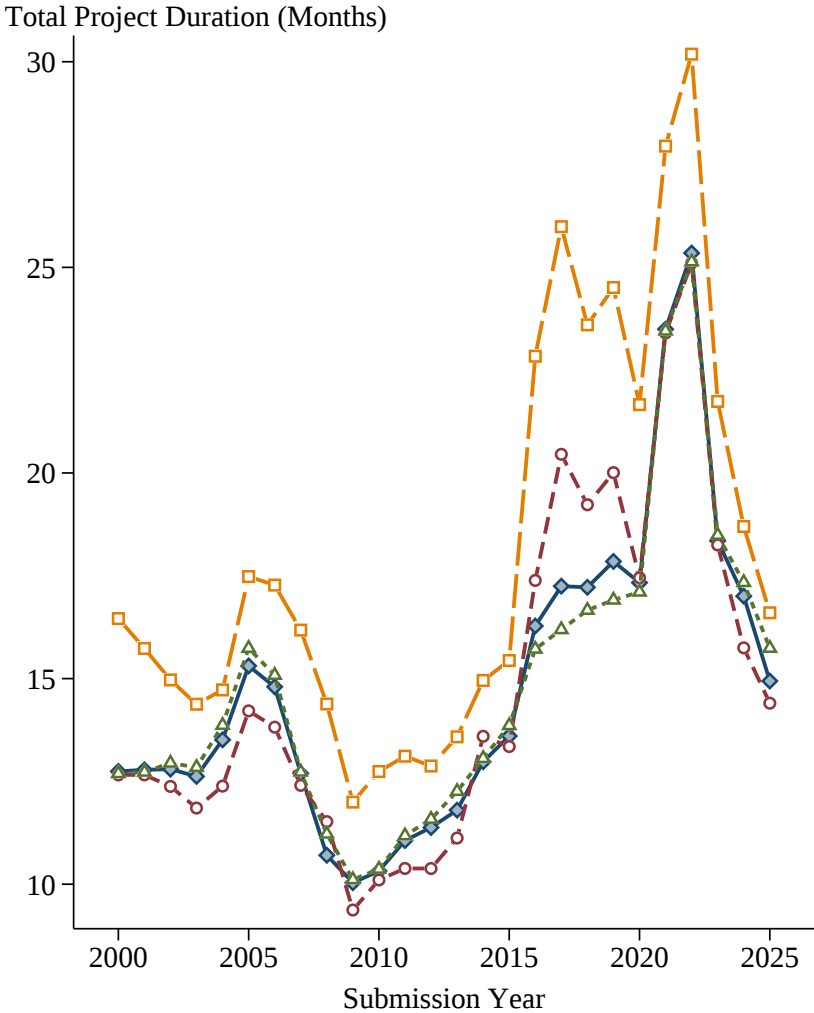
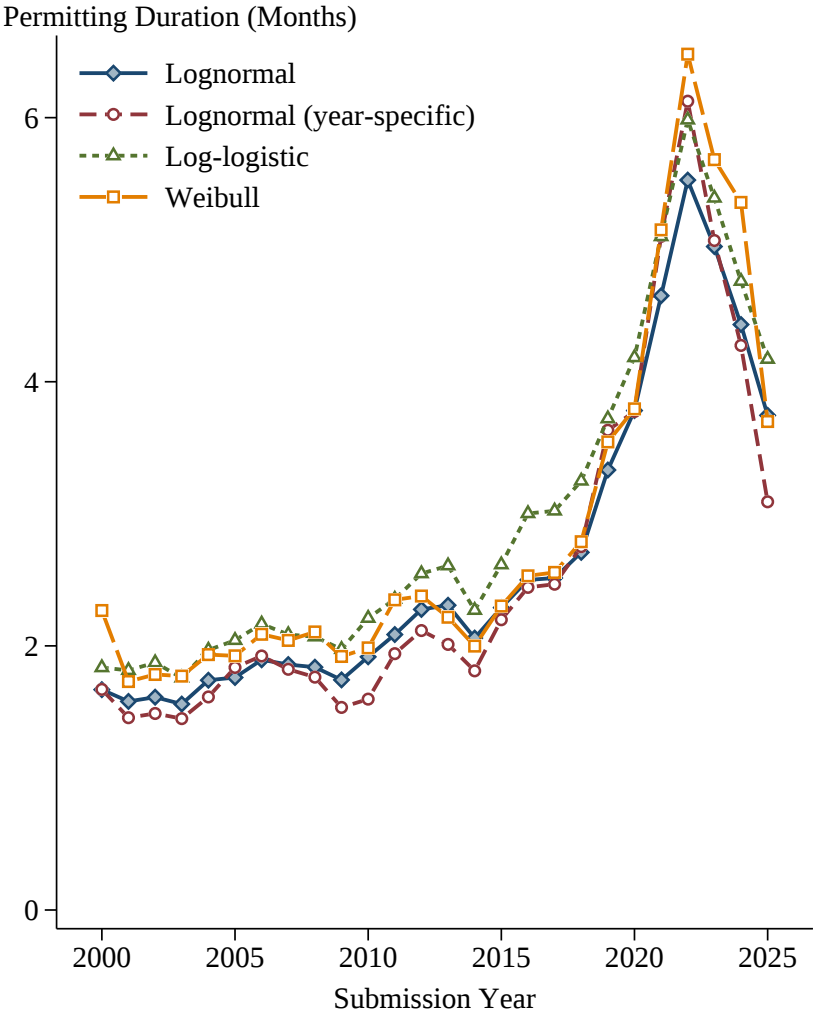
Notes: This figure presents covariate-adjusted time series of the shares of multi-family projects that have issued permits (Panel A) or are completed (Panel B) within a given time horizon from permit submission. The estimating equation is $Y_{icy} = \alpha_c + \alpha_y + X_i' \beta_c + \varepsilon_{icy}$, where the outcome $Y_{icy} = 1[T_{icy} \leq t]$ is an indicator for whether the relevant duration is less than some amount t . The terms α_c and α_y denote city and submission cohort-year fixed effects, and X_i includes our benchmark controls. Series stop when the outcome is no longer observed at the horizon of interest. Hollow markers identify when outcomes are only partially observed for a submission-year cohort. Confidence bands are pointwise at the 95-percent level and reflect standard errors clustered by project.

Figure A20: Robustness of Censoring Adjustment to Parametric Assumptions (Single-Family)

(a) Permitting Duration

(b) Total Project Duration

54



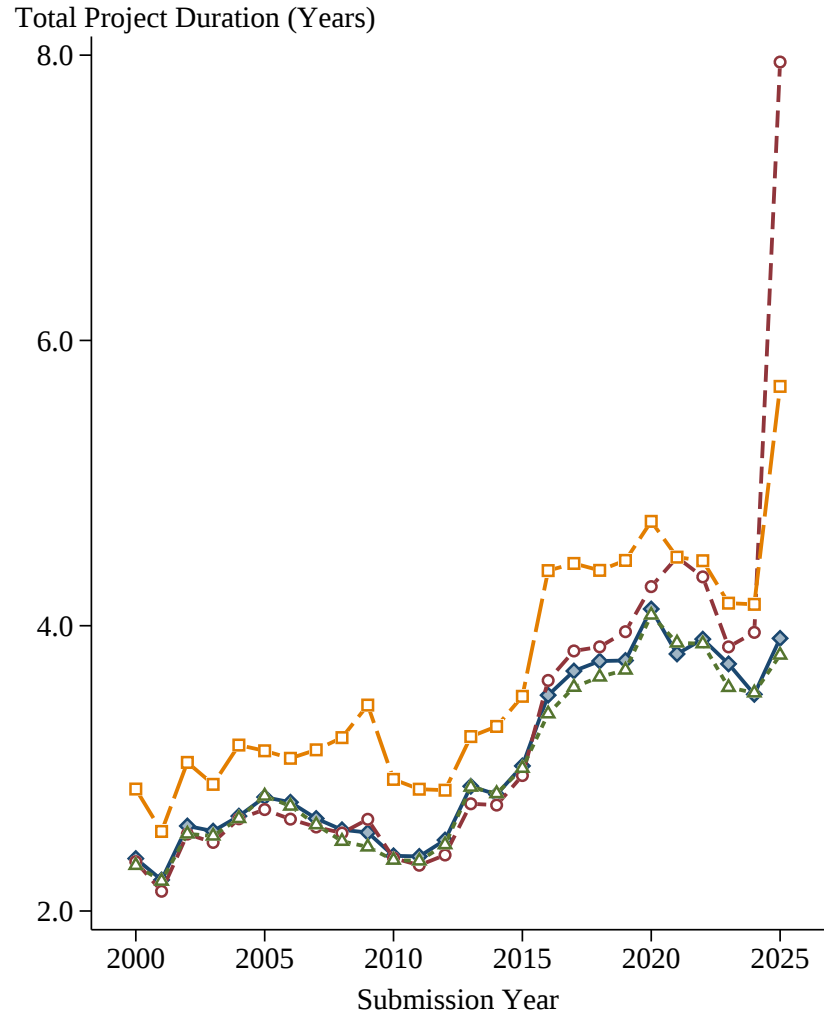
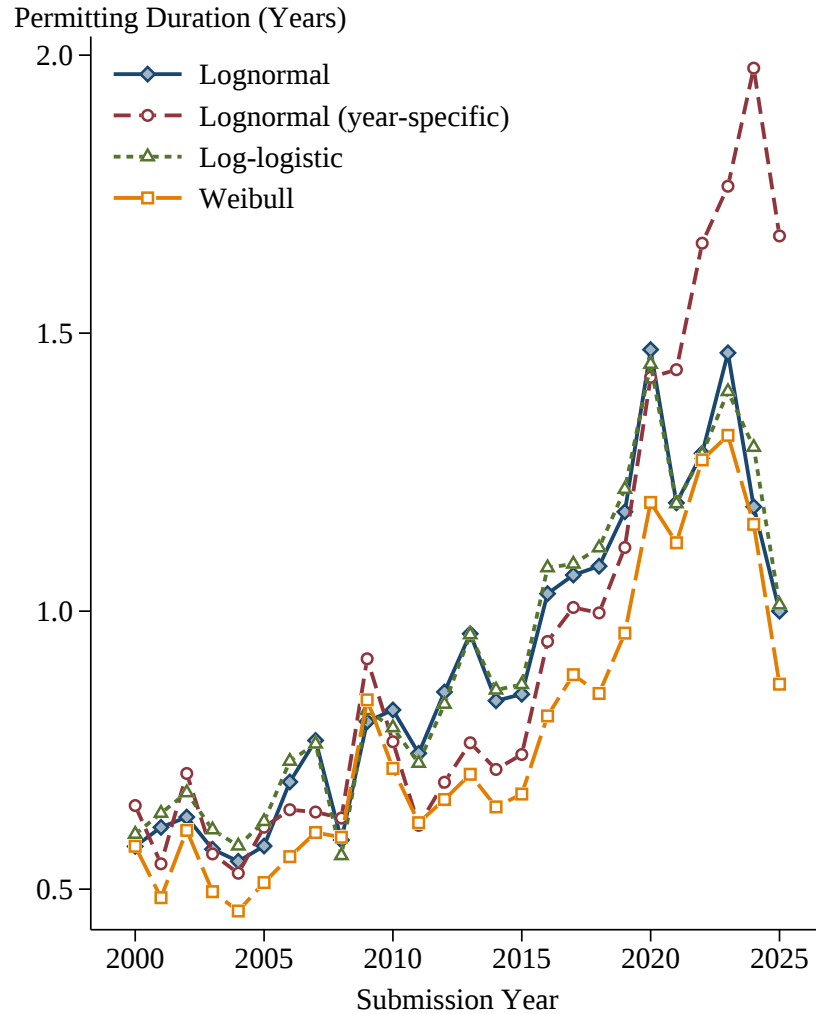
Notes: This figure presents our time series for permitting and total project durations under alternative parametric assumptions. All durations are for the standardized single-family project. “Lognormal” is our benchmark from Figure 3, and we further allow for year-specific heterogeneity in variance of the error term in the year-specific variant. “Log-logistic” and “Weibull” impose the indicated parametric distributions on the error.

Figure A21: Robustness of Censoring Adjustment to Parametric Assumptions (Multi-Family)

(a) Permitting Duration

(b) Total Project Duration

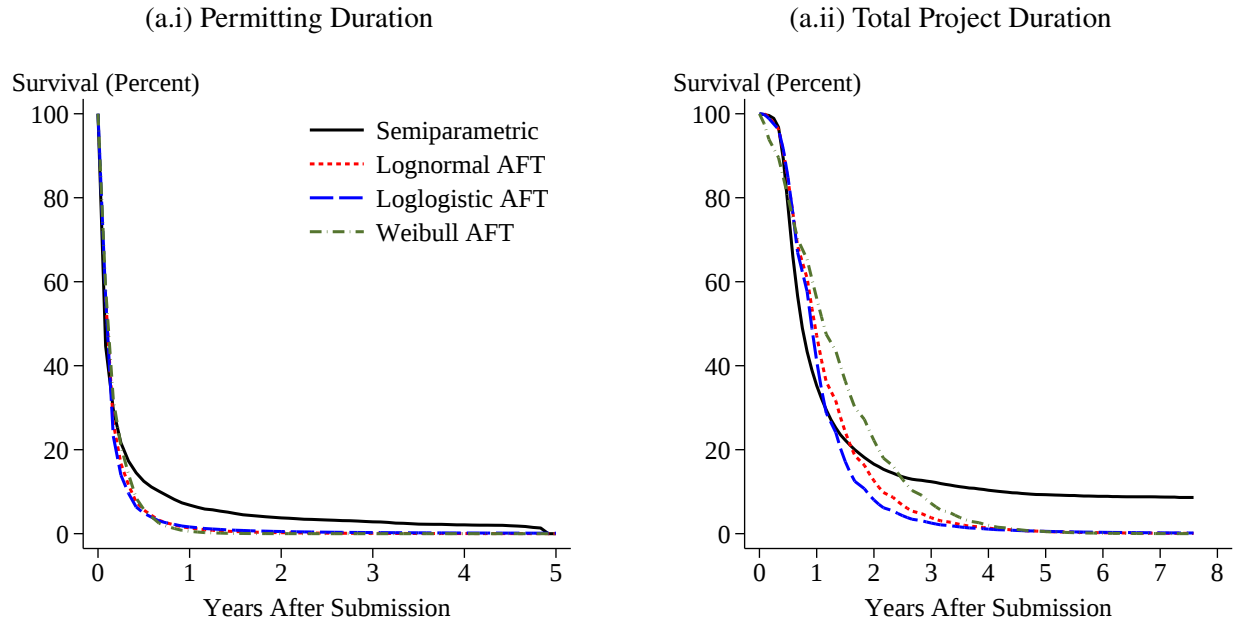
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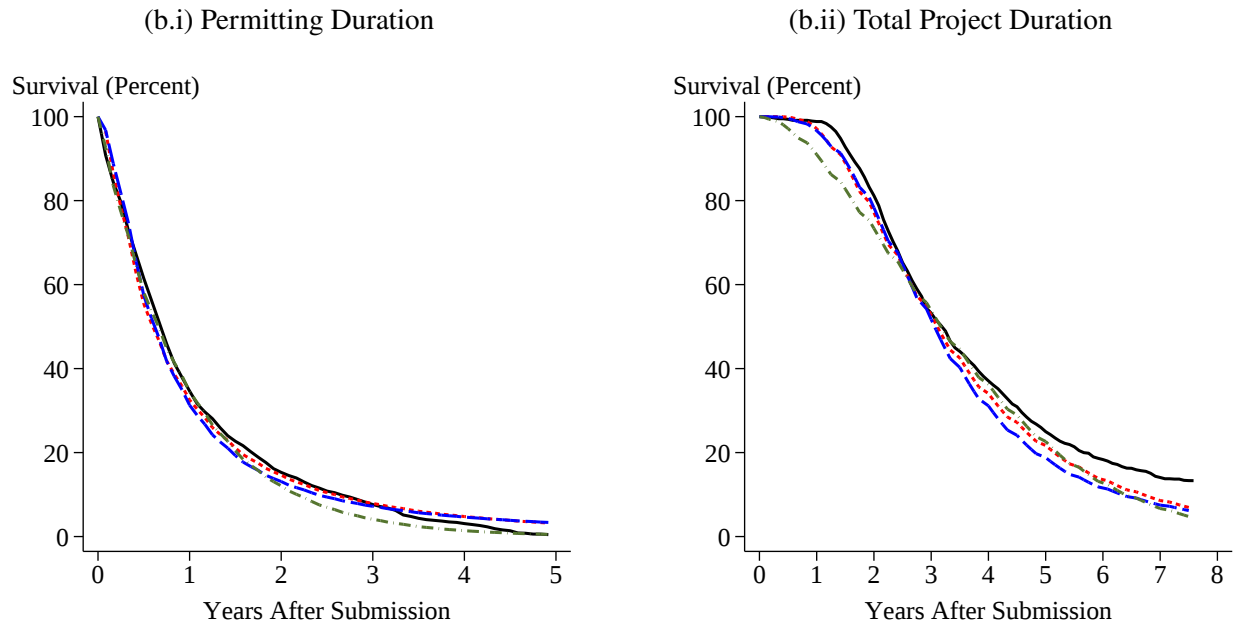
Notes: This figure presents our time series for permitting and total project durations under alternative parametric assumptions. All durations are for the standardized multi-family project. “Lognormal” is our benchmark from Figure 3, and we further allow for year-specific heterogeneity in variance of the error term in the year-specific variant. “Log-logistic” and “Weibull” impose the indicated parametric distributions on the error. In Panel B, estimates for the 2025 cohort’s total project duration appear sensitive to specification due to relatively high right-censoring.

Figure A22: Fit of Parametric Models to Survival Curves

(a) Single-Family



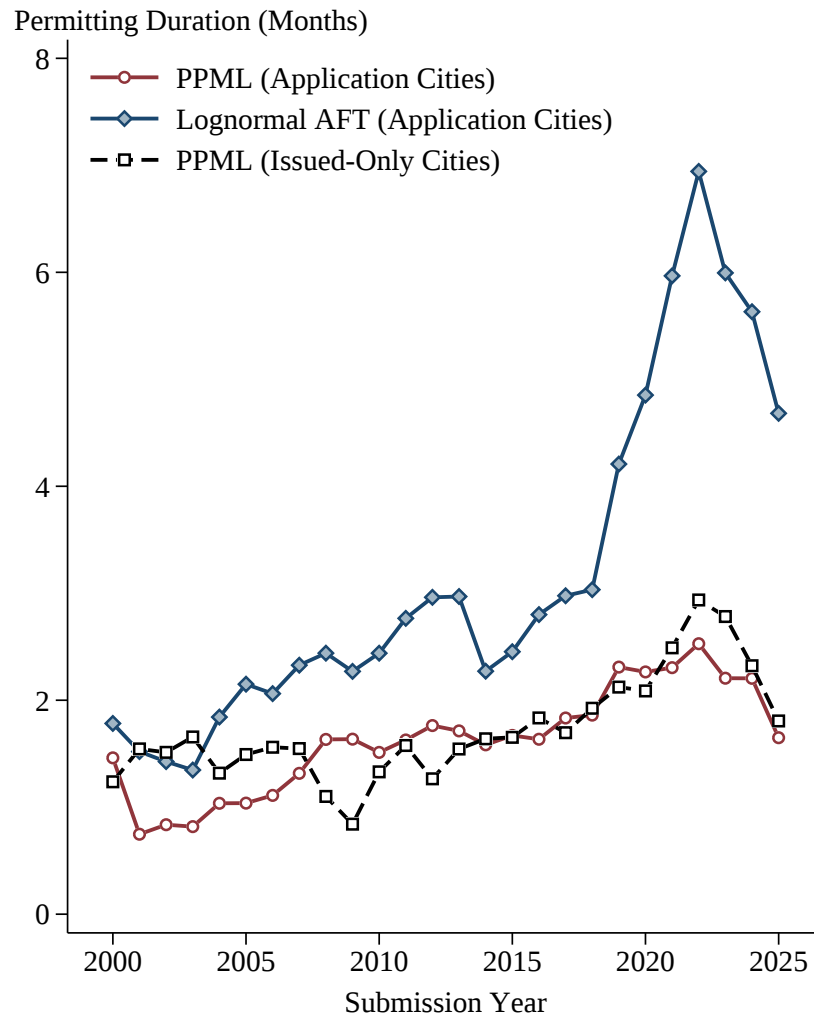
(b) Multi-Family



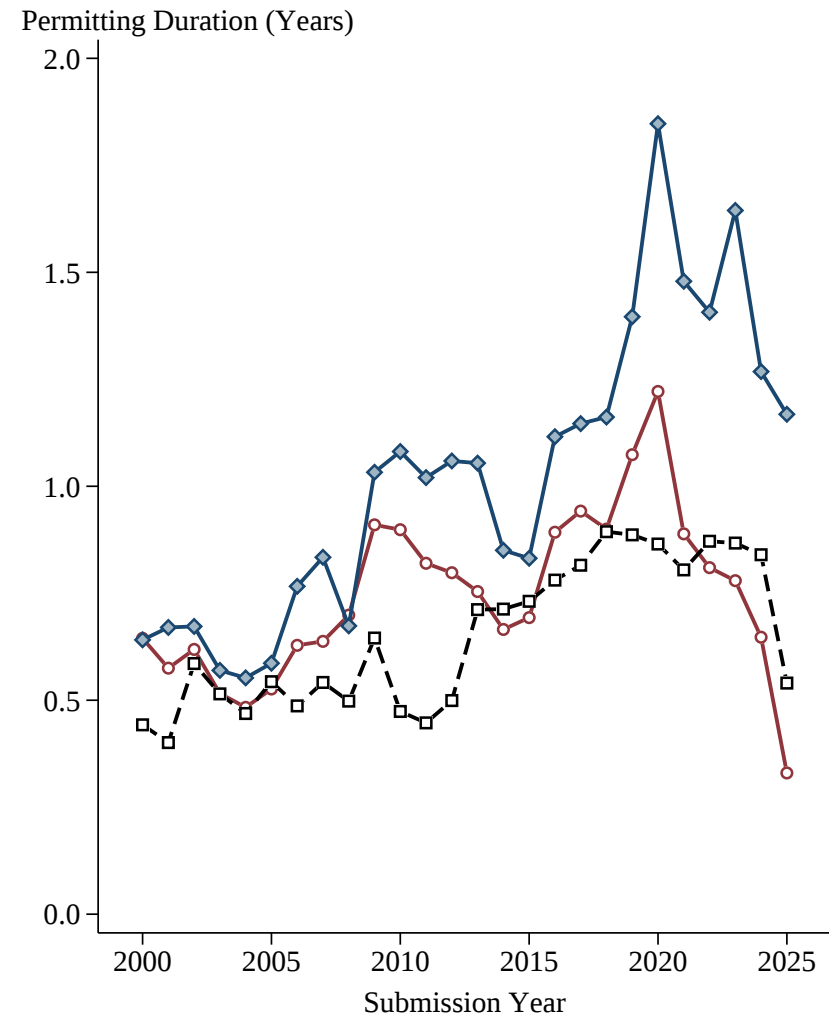
Notes: This figure contrasts the estimated parametric survival curves implied by our accelerated failure time (AFT) models to semiparametric estimates of survival curves. The semiparametric comparison is constructed by estimating month-specific completion hazards on the pooled sample of projects still at risk, conditioning on the same project characteristics, year effects, and city fixed effects used in the AFT specification, evaluating those hazards at a common reference project profile, and then cumulating them into a survival curve.

Figure A23: Permitting Duration by Data Coverage and Estimator

(a) Single-Family



(b) Multi-Family



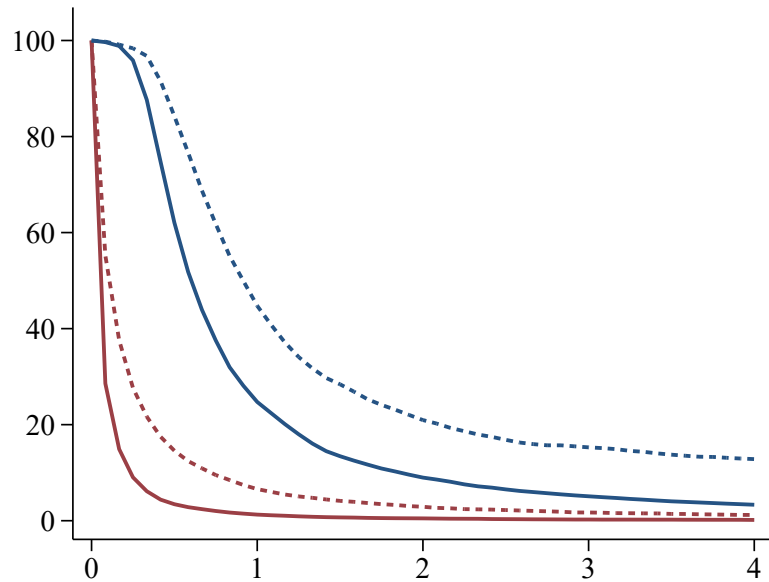
Notes: This figure presents permitting-duration indexes from 2000 to 2025 under alternative assumptions about data coverage and selection into issuance. “Application Cities: Issued-Only PPML” restricts the sample to permits that are observed to issue in cities where both issued and non-issued applications are observed. “Application Cities: Full-Sample Lognormal AFT” uses the full application sample in those same cities and adjusts for both observed project heterogeneity and right-censoring. “Issued-Only Cities: PPML” uses cities where only issued permits are observed. All series are estimated from pooled models with city and submission-year fixed effects, evaluated at common reference covariates, and averaged over the estimation-sample city composition.

Figure A24: Semiparametric Survival Curves for Issuance and Completion, by Project Type

(a) Single-Family

(b) Multi-Family

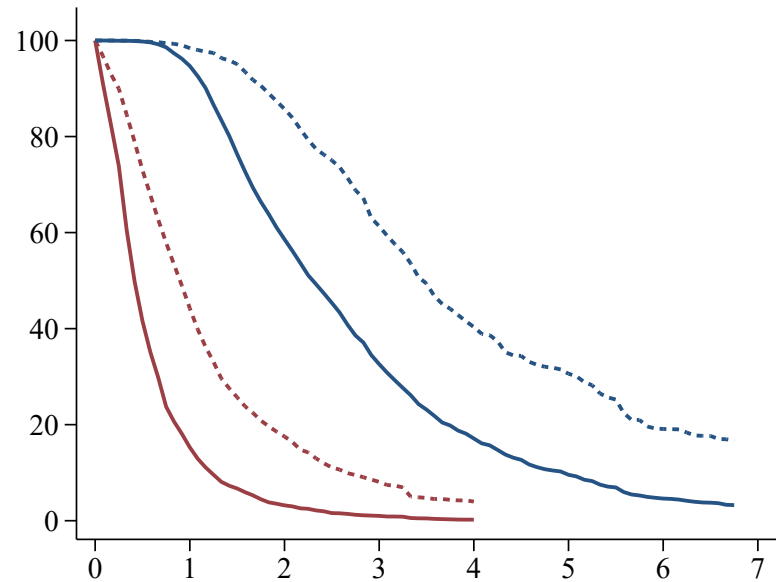
Survival (Percent)



Years After Submission

— Issuance, 2000-2005 - - - Issuance, 2019-2024
— Completion, 2000-2005 - - - Completion, 2019-2024

Survival (Percent)



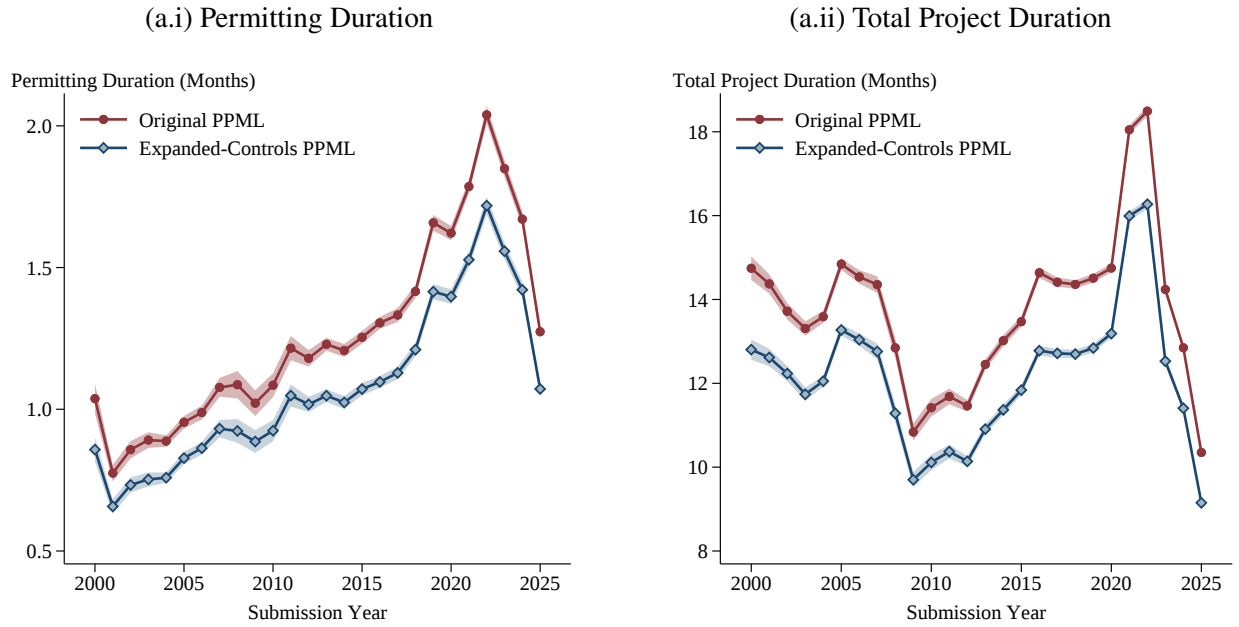
Years After Submission

— Issuance, 2000-2005 - - - Issuance, 2019-2024
— Completion, 2000-2005 - - - Completion, 2019-2024

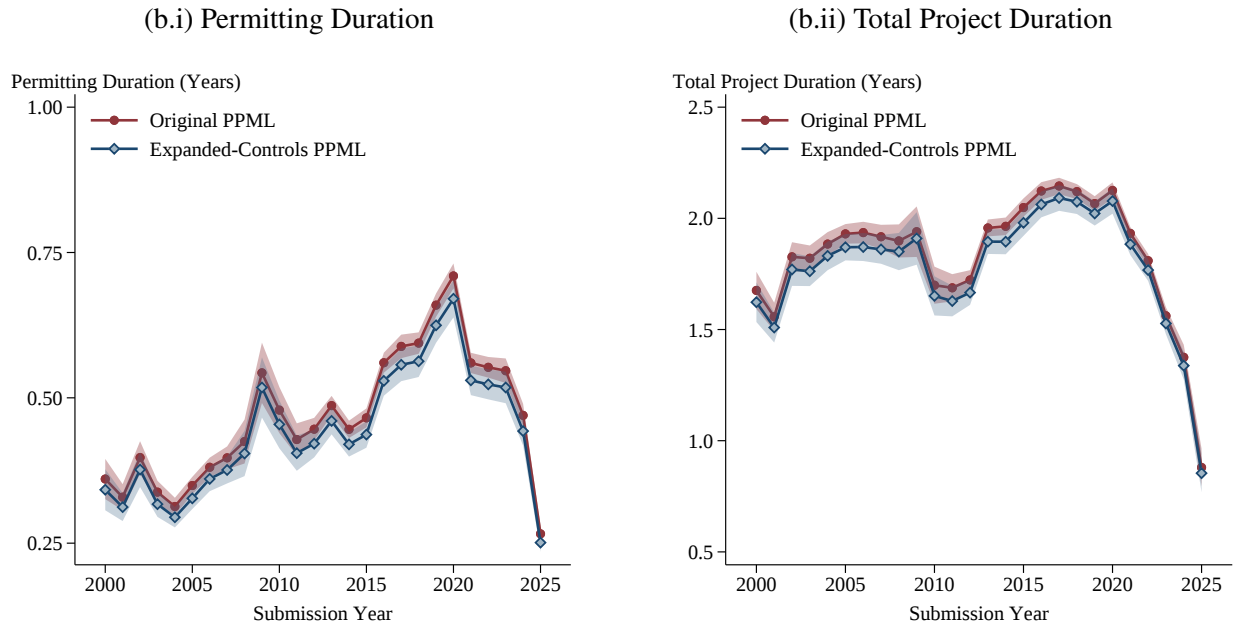
Notes: This figure plots covariate-adjusted survival curves from submission to permit issuance and from submission to project completion for single-family housing projects (Panel A) and multi-family housing projects (Panel B). Solid lines report submissions in 2000–2005, and dashed lines report submissions in 2019–2024. At each monthly horizon m , among projects still at risk, the underlying monthly hazards are estimated from regressions $Y_{im} = \alpha_{cm} + \delta_m 1[2019-2024]_i + X_i' \beta_c + \varepsilon_{im}$, where Y_{im} is an indicator for whether project i experiences issuance or completion at m months since submission, α_c denotes city fixed effects, and X_i includes observed project characteristics with pooled slopes (due to data limitations with monthly hazards). The predicted monthly hazards are then chained into survival curves. The sample is restricted to a balanced panel of cities observed in both 2000–2005 and 2019–2024. Curves are evaluated at common reference covariate values, and shaded bands depict pointwise 95-percent confidence intervals based on project-level bootstrap standard errors.

Figure A25: Duration Index Robustness to Additional Controls

(a) Single-Family



(b) Multi-Family

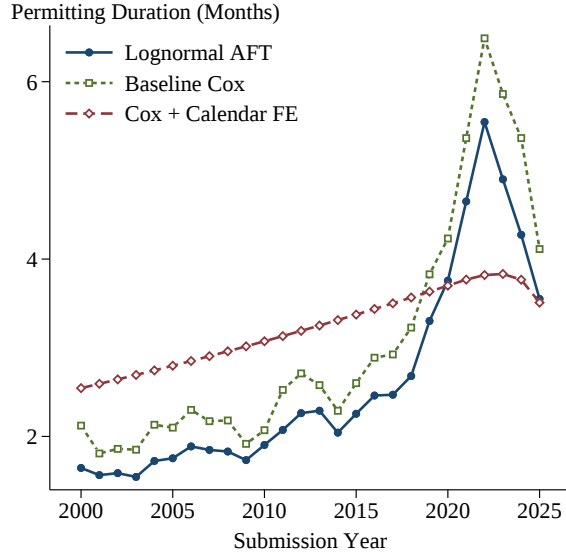


Notes: This figure compares estimated permitting and total project durations by submission-year cohort from 2000 to 2025 using different sets of controls. “Original PPML” uses our baseline controls, and “Expanded-Controls PPML” uses additional controls (namely, flood risk/terrain, shape regularity, and ACS neighborhood characteristics). Both specifications include fixed effects for city and submission year. For each submission year, estimated duration is evaluated at common reference covariate values and averaged over the estimation-sample city composition. Shaded bands show pointwise 95-percent confidence intervals with standard errors clustered by project. We limit to a consistent set of permits across specifications.

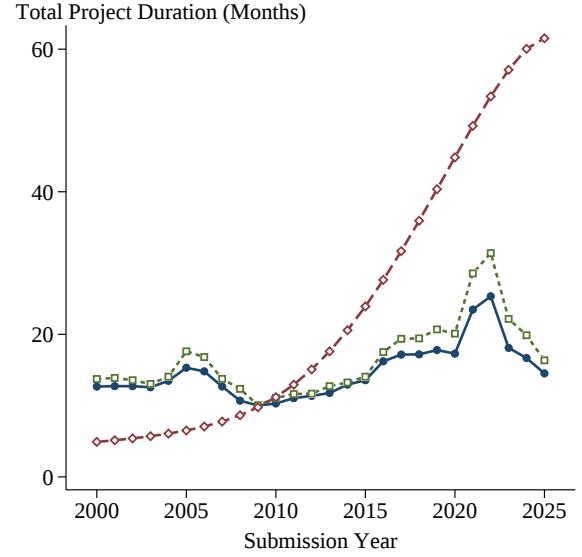
Figure A26: Duration Index Decompositions from Cox Models

(a) Single-Family

(a.i) Permitting Duration

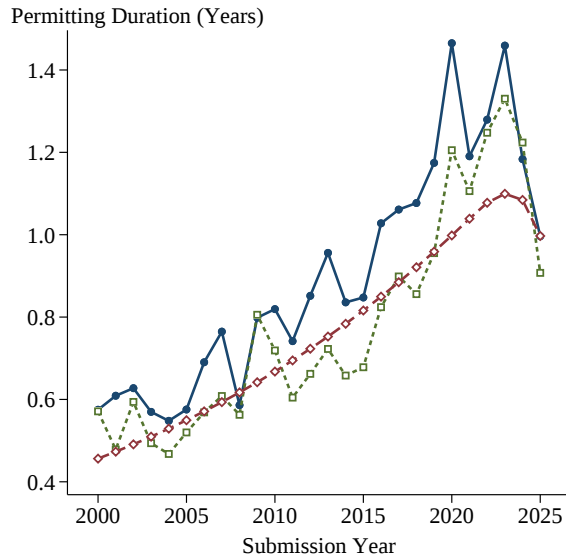


(a.ii) Total Project Duration

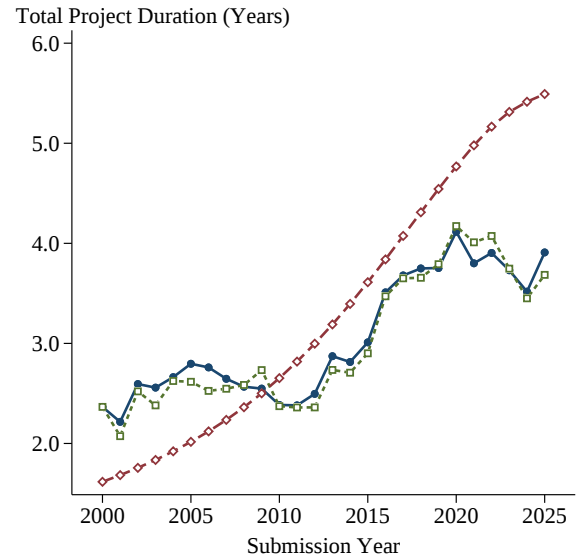


(b) Multi-Family

(b.i) Permitting Duration



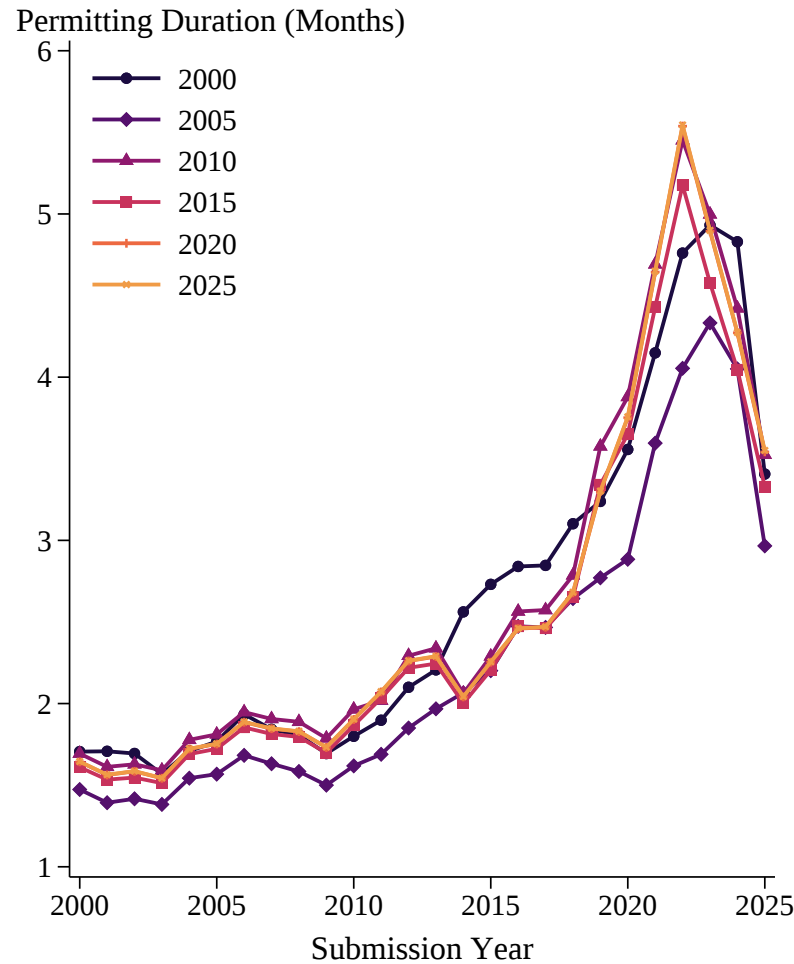
(b.ii) Total Project Duration



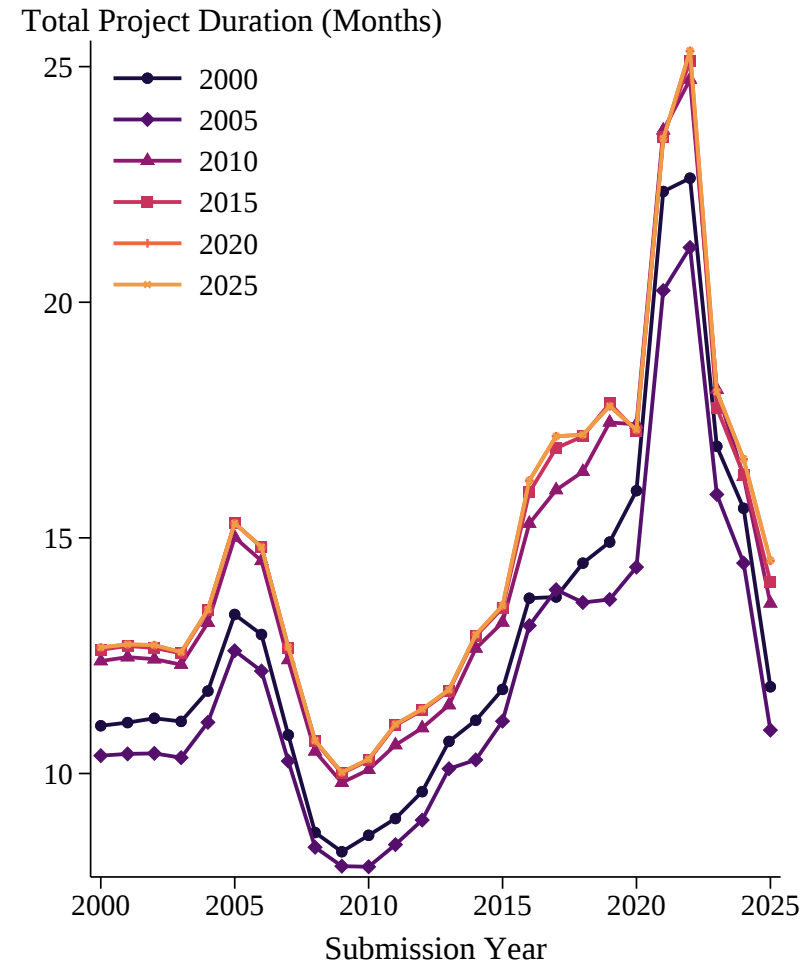
Notes: This figure compares our preferred lognormal AFT duration index to two Cox-model decompositions. The baseline-Cox series varies submission cohorts while holding fixed observed project characteristics. The “Cox-plus-calendar-FE” series is estimated with calendar-year fixed effects and then constructed to isolate the contribution of changing calendar-time conditions, holding fixed the cohort effect. For calendar years beyond the observed estimation support, fixed effects are extrapolated using a linear trend fit through the observed calendar-year fixed-effect series. All series are estimated from pooled models with city fixed effects. Predicted durations are computed for a common reference project and averaged over the estimation-sample city composition using observation-count weights. The vertical axis reports predicted duration.

Figure A27: Comparing Entry Cohorts (Single-Family)

(a) Permitting Duration



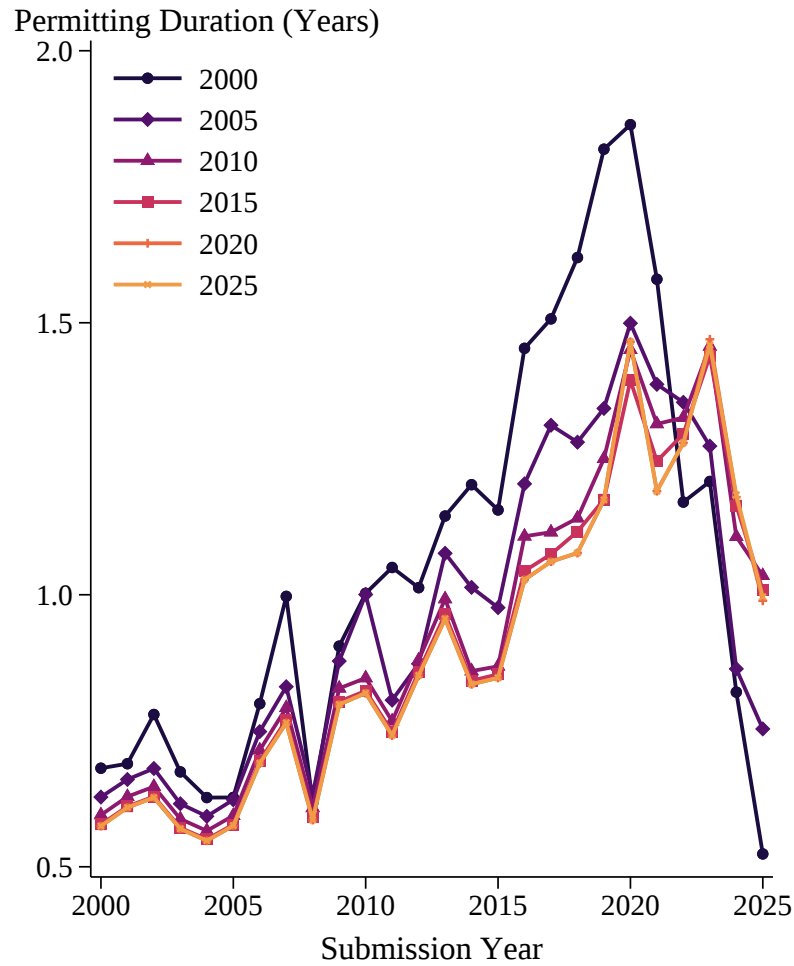
(b) Total Project Duration



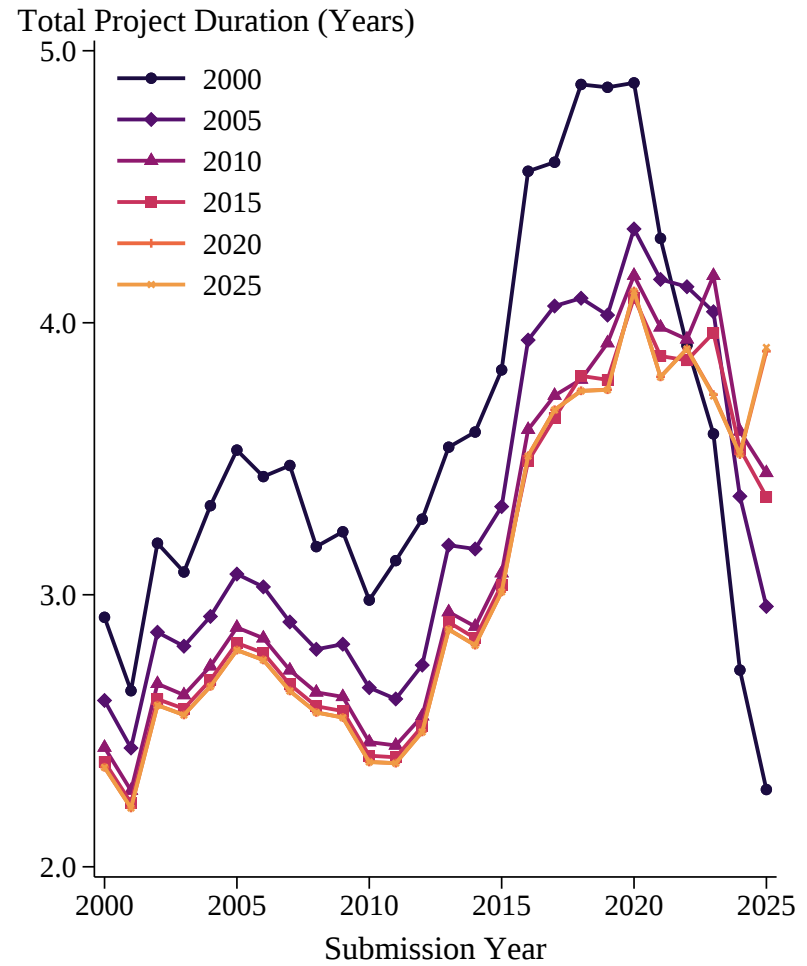
Notes: This figure explores the robustness of time trends in single-family durations to the staggered entry of cities into the sample. Panels A and B respectively show predicted permitting and total project durations from pooled lognormal accelerated failure time models (as in Equation 2). Each series is estimated using only cities that enter the sample in or before the indicated year, with estimated durations then predicted by submission year at common reference covariates. The year-2000 series thus reflects a balanced panel of cities.

Figure A28: Comparing Entry Cohorts (Multi-Family)

(a) Permitting Duration



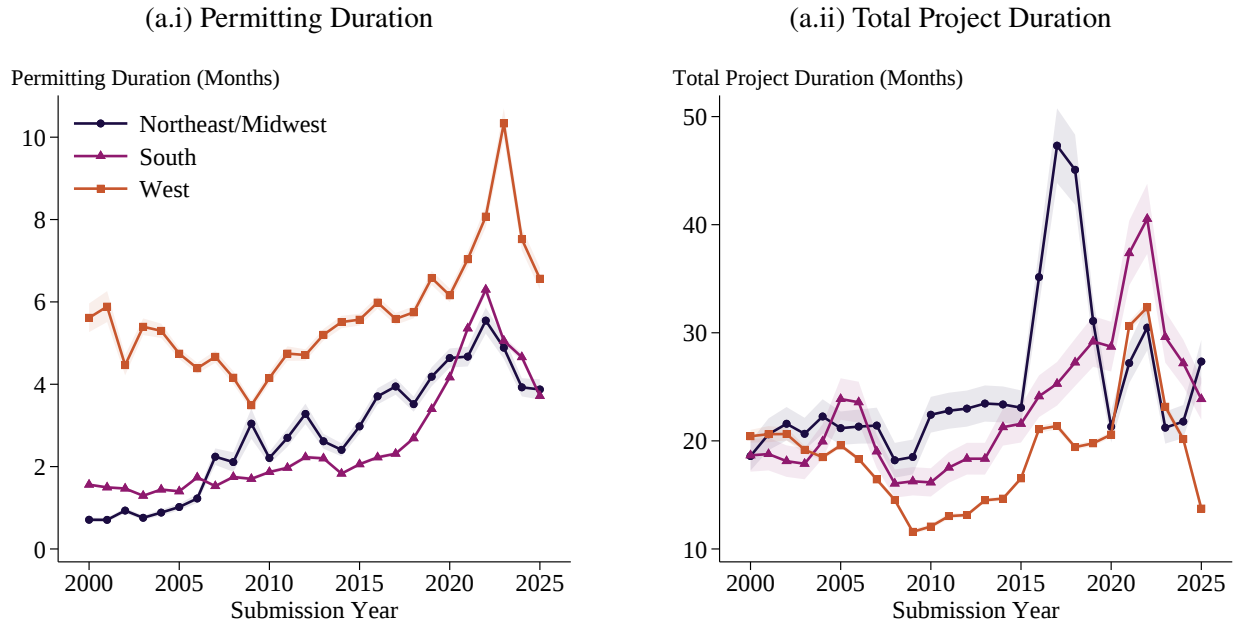
(b) Total Project Duration



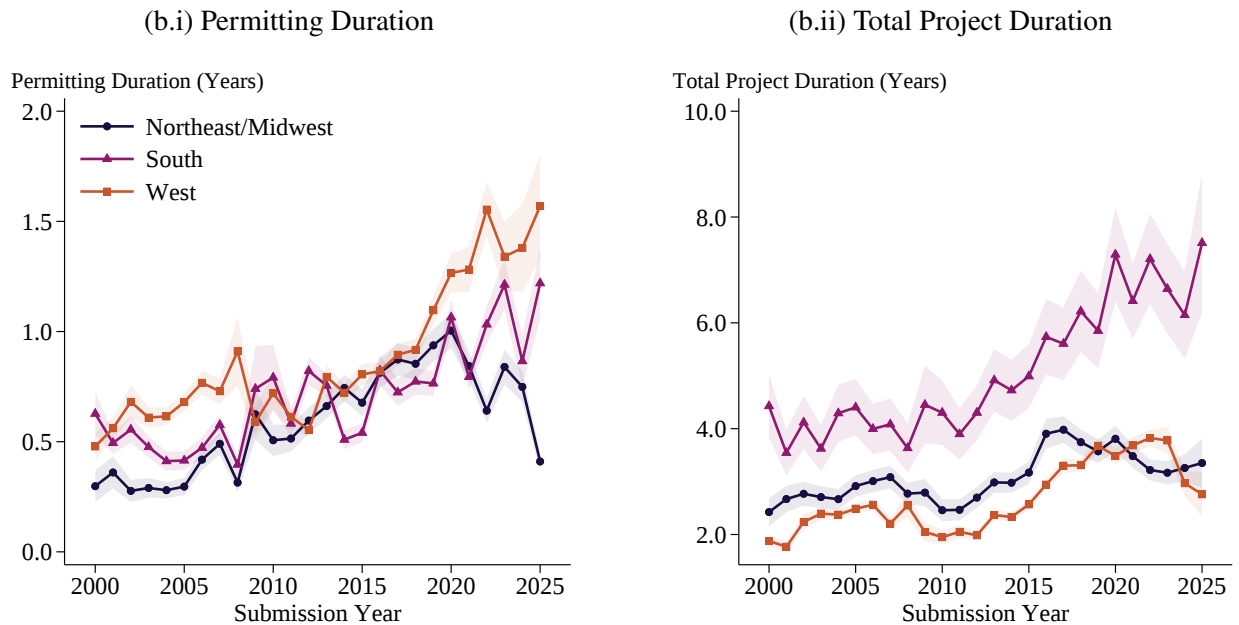
Notes: This figure explores the robustness of time trends in multi-family durations to the staggered entry of cities into the sample. Panels A and B respectively show predicted permitting and total project durations from pooled lognormal accelerated failure time models (as in Equation 2). Each series is estimated using only cities that enter the sample in or before the indicated year, with estimated durations then predicted by submission year at common reference covariates. The year-2000 series thus reflects a balanced panel of cities.

Figure A29: Regional Heterogeneity in Time Trends in Duration

(a) Single-Family



(b) Multi-Family



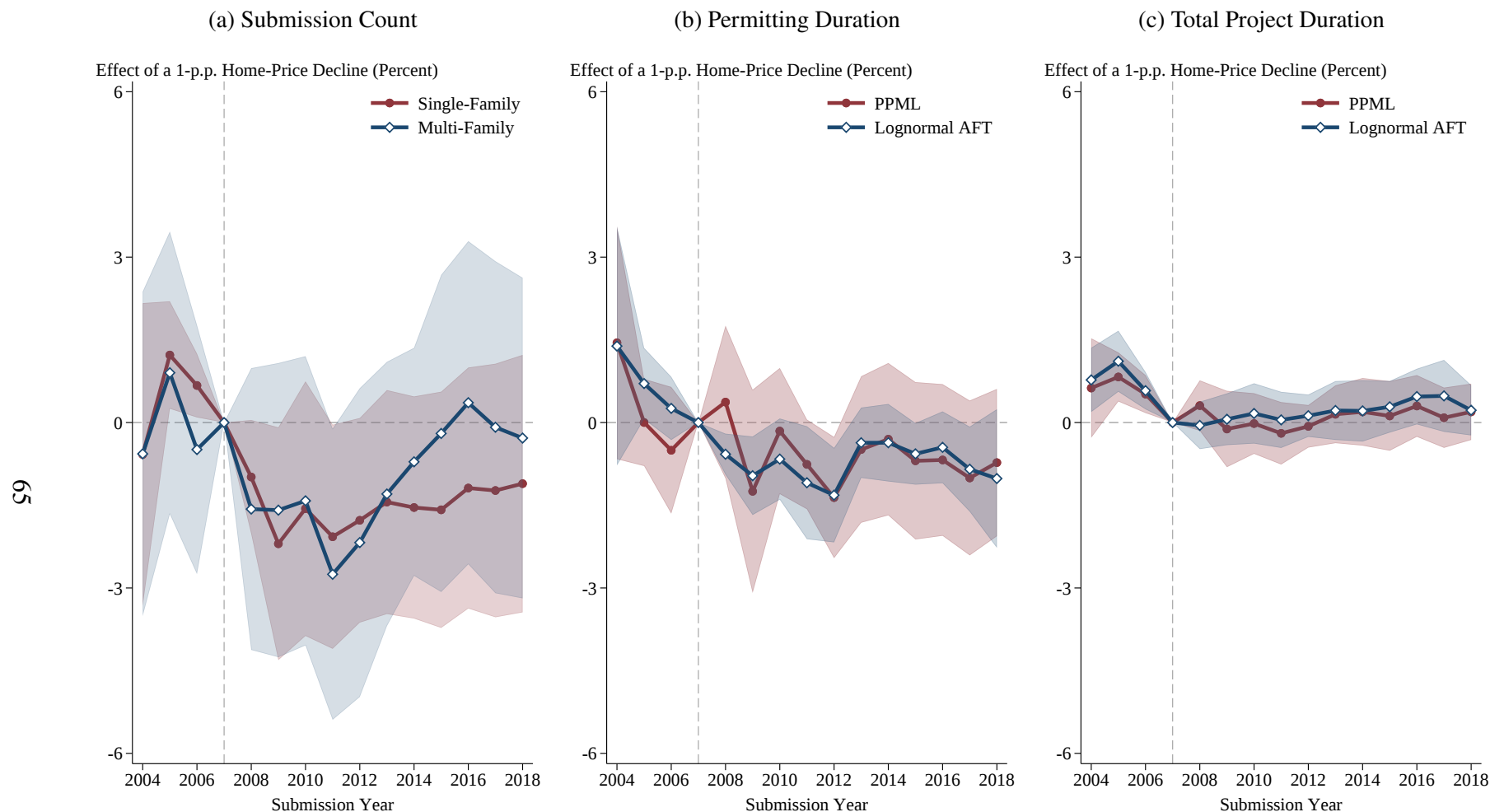
Notes: This figure shows regional heterogeneity in predicted permitting and total project duration. Series are estimated using lognormal AFT models with city and submission-year fixed effects, evaluated at common archetype-level reference covariates, and averaged equally across cities within each region group. Regions are grouped into Northeast/Midwest, South, and West. Shaded regions show 95 percent confidence intervals.

Table A12: Self-Selection on Potential Durations

	Single-Family		Multi-Family	
	Permitting Duration (1)	Total Project Duration (2)	Permitting Duration (3)	Total Project Duration (4)
Improvements Share of AV	-0.222*** (0.029)	-0.084*** (0.015)	-0.038 (0.046)	-0.066** (0.026)
Effect in Months	-0.047*** (0.007)	-0.096*** (0.018)	-0.033 (0.041)	-0.200** (0.079)
Number of Permits	56,377	56,377	3,104	3,104
Number of Cities	22	22	22	22
R^2	0.168	0.133	0.101	0.078

Notes: This table estimates a variant of Equation 1 in which we also include a measure of the intensity of the parcel's prior use. We perform this analysis by matching permits to property tax assessment data for cities in five states: California, Florida, North Carolina, Ohio, and Texas. Our measure of prior-use intensity is the improvements share of assessed value as recorded five years before the year of permit submission. Standard errors clustered by permit are reported in parentheses. "Effect in months" reports the average marginal effect of a one-unit increase in the improvements share on predicted duration, with standard errors calculated by the delta method. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A30: Effects of Great Recession Shock on Duration Outcomes



Notes: This figure shows event-study estimates relating local Great Recession house-price shocks to permit outcomes. Panel A shows submitted permit counts, separately for single-family and multi-family permits. Panels B and C show permitting and total project duration for the pooled unweighted sample of single-family and multi-family housing permits. In the duration panels, the maroon series reports PPML estimates and the navy series reports lognormal AFT estimates that account for right-censoring. Each point gives the estimated percent change associated with a 1-p.p. larger local peak-to-trough decline in home prices, relative to 2007. Duration estimates come from pooled unweighted project-level regressions with city and year fixed effects, controls for tract density, tract income, project size, unit count, and attached status, plus year interactions with these controls; the pooled specification also includes a multi-family indicator and its interaction with year effects. Submitted-count estimates come from city-year PPML regressions with city and year fixed effects, using the same event-study shock specification. Shaded regions show 95-percent confidence intervals, with standard errors clustered by city.

B Data Appendix

B.1 Construction and Harmonization

This appendix provides additional detail on construction and harmonization across cities. Data assembly proceeds with two goals in mind. First, we aim to improve the row- and variable-wise coverage of municipal open data through augmentation across other sources. Second, we aim to measure concepts as consistently as possible across cities.

Constructing the Data Universe. In most cities, we begin from municipal open data on building permits. However, several cities do not post such data. In those cities, our data assembly begins by scraping their user-facing permit portals.

For each city, a data-cleaning script restricts the raw data to records that are plausibly valid new-construction permits for primary dwelling units. That is, we limit the sample to the city’s official categories for residential and commercial new buildings. We also explicitly drop records that appear to include only ancillary non-dwelling structures (e.g., accessory dwelling units, club-houses, maintenance out-buildings), which are sometimes filed under the permit categories we identified.¹⁵ In addition, we drop records with statuses corresponding to cancellation, denial, revocation, expiration, or other inactive administrative states.

In some cities, project records appear in multiple stages, such as an initial case for a subdivision, plat or master plan followed by “child” building permits. We handled these records conservatively. First, we detect and collapse duplicates. Next, we search for explicit links between these initial cases and child permits using permit numbers, APNs, addresses, project names, or similar information in workflow histories in permit portals. Whenever these upstream records clearly serve as the first filing, we use these as an application date. However, we do not treat distant platting or addressing-only records as the start of permitting timelines.

We further define our data universe using project dates. First, we drop records with apparently invalid event sequences (e.g., issue dates after completion dates). Second, we drop records with reported durations of zero, as their dates likely reflect administrative imputations rather than true events. Third, we drop records missing submission or issuance dates.

We then trim the right tail of durations. We drop records if the observed permitting duration exceeds five years, or if the observed total project duration exceeds ten years. For incomplete projects, observed permitting and total project durations are measured through the end of the observation period if the permit has not yet been issued or the project has not yet been completed, respectively. Even with trimming, Appendix Figure A22 shows parametric duration models do not match a tail of projects which appear abandoned, based on being years after submission but not yet issued or not yet completed.

Harmonization. We record three event dates: application submission, issuance, and completion date. These concepts are not recorded with exact uniformity across cities. We sought to recover the closest available administrative concepts to our intended sequence.

In most cities, the application date comes directly from a filing, submission, receipt, or opening field. For some projects, the appropriate application date was instead tied to another permit (e.g., a zoning/planning review, a subdivision plat, or a master permit). We collected these whenever such records were found. In several cities, we discovered this measurement issue from implausibly fast

¹⁵Our sample does include submissions to build both primary dwellings and such ancillary non-dwellings.

permitting durations (e.g., two days for a single-family residence).

Issuance dates were the easiest and most nearly uniform dates to collect across cities. In most cities, we take the issuance date from the administrative data. However, we must occasionally infer it. For example, we have used latest-status dates on permits whose latest status is issued, or parsed workflow histories for permit approval dates.

Completion dates require significant harmonization. First, we preferred the date at which a final certificate of occupancy or completion was issued. Next, as a fallback, we accepted the date at which a new-building permit was finalized, signed-off, or closed (but not expired or any closure status that did not clearly indicate completion).

B.2 Additional Sources

- *Median rent and median home value*: Collected from the 2019 American Community Survey, and spatially merged using the same method as Neighborhood Population Density and Income above.
- *Elevation*: Elevation values (in meters) from the SRTM 30m Global 1 arc second V003, produced by NASA and NGA and hosted on Amazon S3 ([NASA JPL, 2013](#)).
- *Risk of natural hazards*: Spatially merged with the FEMA National Risk Index, December 2025 release ([Federal Emergency Management Agency, 2025](#)).
- *R.S. Means residential and commercial location factors*: [Gordian \(2024\)](#) records the national averages for the costs of building materials and installation. The residential and commercial location factors measure how construction costs in a given city differ from the national average. When a city in our dataset was not available in the source data, we assigned the location factors for the nearest available city. Specifically, we use Boston, MA's location factors for Cambridge, MA, the City of Los Angeles' location factors for Los Angeles County.
- *Land prices*: We use AEI-adjusted land price and land share indicators, which build on county-, ZIP code-, and tract-level estimates from [Davis et al. \(2021\)](#). Because the underlying data are anchored to tax assessments and limited to GSE appraisals, raw land price estimates may understate home price appreciation and, by extension, land price growth. To address this, the AEI adjusts the [Davis et al. \(2021\)](#) estimates using a constant-quality home price appreciation index. We geocode parcels to 2024 Census tracts and use 2019 values.
- *Land use regulation*: We merge the Wharton Residential Land Use Regulatory Index ([Gyourko et al., 2021](#)) using place, county subdivision, and county shapefiles from the 2023 TIGER/Line files. We also spatially merged permits to 2022 Census shapefiles and attached measures estimated in [Bartik et al. \(2025\)](#).
- *Population*: Intercensal estimates of the resident population for incorporated places, April 1, 2010 to April 1, 2020 ([U.S. Census Bureau, 2020](#)).
- *Lot size and shape regularity*: We obtain parcel boundaries from municipal open-data sources and spatially merge them to permits, then compute lot area directly from the parcel geometries.

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