Land development and frictions to housing supply over the business cycle*

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Abstract

Using a novel dataset on U.S. residential land development, we document that the time required to develop housing—measured from initial site planning to substantial completion—averages over three years and varies widely across regions. We incorporate these time-to-develop frictions into a dynamic housing investment model to derive short- and long-run housing supply elasticities. Linking the model to the data, we show that short-run elasticities vary meaningfully across counties and differ from their long-run counterparts. We find that these frictions help explain recent regional housing market dynamics and reduce the short-run effectiveness of supply-side housing policies.

Keywords: Housing supply; house price dynamics; residential investment.
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1 Introduction

A central feature of investment dynamics is that new capital takes time to produce. In standard models, this is captured by adjustment costs that reflect both physical production lags and the difficulty of altering investment plans once underway. In the housing market, short-run inelastic supply is often invoked to explain the sluggish response of residential investment and house prices to shocks—such as the differing short- and long-run effects of the COVID-19 pandemic (Howard, Liebersohn and Ozimek, 2023).[1] Despite its importance, there is limited quantitative evidence on how long it takes to transform raw land into completed housing, or what that implies for the evolution of housing supply over time.

This paper provides both a theoretical framework and new empirical evidence to fill that gap. We begin by developing a housing investment model with an explicit time-to-develop (TTD) constraint, following the tradition of Kydland and Prescott (1982). The model yields analytical expressions for housing supply elasticities at different horizons—most notably over the short- to medium-run—as functions of both TTD and long-run supply fundamentals. These expressions clarify how even regions with "elastic" long-run supply can exhibit low responsiveness in the near term when development lags are long.

We then use a novel dataset that tracks residential land development across major U.S. metro areas to estimate TTD across counties. A key advantage of the data is that it covers the full development pipeline, from preliminary site plan approval through infrastructure installation and building completion. Using over 100,000 development sections from 2003 to 2019, we document two stylized facts. First, residential land development takes more than three years on average, including over a year for site preparation alone. Second, TTD varies widely across locations—even after controlling for construction characteristics and local demand factors—and is associated with both long-run supply constraints and short-run impediments, such as adverse weather, that hinder construction activity.

[1] Many models that account for residential investment and house price dynamics rely on the assumption of fixed land supply—for example, Davis and Heathcote (2005); Kiyotaki, Michaelides and Nikolov (2011); and Kaplan, Mitman and Violante (2020).

We use this variation in TTD, along with our model, to quantify county-level housing supply elasticities at different horizons. While existing estimates typically focus on long-run elasticity, we show that TTD plays a central role in shaping short-run responsiveness, particularly over business cycle horizons. Theoretically, our model clarifies how short-run elasticity depends on both the length of TTD and the substitutability of construction inputs across stages. Empirically, we find that short-run supply elasticities exhibit distinct cross-regional patterns and are indeed smaller and distinct from the corresponding long-run elasticities. These differences are especially pronounced in regions with long development pipelines, even if long-run supply is relatively unconstrained. For instance, we find that Sunbelt counties—commonly viewed as supply elastic in the long run—have some of the lowest short-run elasticities due to longer TTDs. This distinction matters: our estimates suggest that regions with similar long-run supply elasticities may respond very differently to business-cycle shocks.

We use these estimates to revisit the role of supply elasticity in explaining recent house price dynamics. First, our short-run housing supply elasticity restores the relevance of the housing supply elasticity in accounting for the post-2010 house price dynamics. Regressing a county's house price change (relative to the national house price change) on each of the short- to long-run housing supply elasticities, we find that our short-run supply elasticity is consistently relevant in accounting for the observed cross-county variation in house prices since the 2000s, whereas the long-run supply elasticity loses its relevance after the 2000s housing bust. Indeed, our model suggests that the short-run supply elasticity could be more relevant than the long-run supply elasticity if the autocorrelation of housing demand declined after the 2000s housing bust.

Second, the model also sheds light on a puzzling empirical pattern: many Sunbelt regions—typically viewed as having elastic supply—experienced both a construction boom and rapid house price growth in the 2010s. We show that this outcome can be reconciled by the presence of long but heterogeneous TTD. When TTD is introduced, short-run elasticity declines in all regions, but falls more in those with longer pipelines. In these areas, the slope of supply elasticity over time is steeper, creating stronger incentives for developers to shift investment toward new projects when demand rises. This behavior can crowd out in-progress developments and slow short-run completions, generating upward pressure on prices even in "elastic" regions.

Finally, we explore the implications for housing policy. In a counterfactual exercise, we consider a government intervention that boosts new construction in response to a demand increase. The model shows that when TTD frictions are present, the effect of such a policy operates primarily through the expectations channel—by increasing anticipated future supply rather than immediately expanding completions. As a result, the near-term price effects are muted in regions where land development takes longer, though the medium-run stabilization is more pronounced. This underscores the importance of accounting for development lags when designing or evaluating supply-side housing policies.

Related literature. Studies examining housing supply have primarily focused on estimating its long-run determinants (Saiz, 2010; Lutz and Sand, 2022; Baum-Snow and Han, 2024), using these estimates to identify regional differences in responses to economic shocks (Mian, Rao and Sufi, 2013; Mian and Sufi, 2014; Davis and Haltiwanger, 2024; Bhattarai, Schwartzman and Yang, 2021; Aastveit, Albuquerque and Anundsen, 2023). However, this long-run focus can be problematic when the shocks under study are transient, or when the determinants of housing supply elasticity differ significantly between the short and long run. For instance, Guren, McKay, Nakamura and Steinsson (2020) suggest that the puzzling correlation between regional housing prices and quantities documented by Davidoff (2016) could be reconciled by assuming uniformly lower short-run supply elasticities across regions. Despite this, relatively little is known about the determinants of housing supply elasticity at business-cycle frequencies. An early exception is Topel and Rosen (1988), who, using quarterly U.S. aggregate data for 1963–1983, estimate both short- and long-run housing supply elasticities based on a dynamic Tobin's q model of residential investment and find that most of the long-run adjustment occurs within a year, indicating that housing investment responded over relatively short horizons in their sample. Our paper contributes to this literature by (i) quantifying frictions in housing supply at business-cycle frequencies, using observed durations of land development processes in more recent decades, and (ii) examining the implications of these quantified frictions within an equilibrium model of housing investment. By linking new housing supply data to elasticity, we also add to the literature exploring the sensitivity of local economic activity to house price fluctuations. Recent studies in this area have identified plausibly exogenous variations in house prices based on local economic variables or existing housing characteristics (Guren, McKay, Nakamura and Steinsson, 2021; Graham and Makridis, 2023; Feng, Jaimovich, Rao, Terry and Vincent, 2023; Howard and Liebersohn, 2023; Chodorow-Reich, Guren and McQuade, 2023). We argue that data on the timing of new housing supply also capture an important source of local variation in house prices that could be used to estimate the sensitivity of local economic activity to house prices.

In the literature on business cycles, time to build has been noted as a key friction to investment dynamics at least since Kydland and Prescott (1982). Subsequently, several papers document the duration of building capital using newly available data or study its implications on investment behavior (Lucca, 2007; Kalouptsidi, 2014; Sarte, Schwartzman and Lubik, 2015; Millar, Oliner and Sichel, 2016; Kydland, Rupert and Šustek, 2016; Oh and Yoon, 2020; Meier, 2020; Charoenwong, Kiruma, Kwan and Tan, 2024; Fernandes and Rigato, 2024; Glancy, Loewenstein and Kurtzman, Forthcoming). Our paper contributes to this line of work, both by providing new stylized facts on the *comprehensive* construction process from undeveloped land to the completion of new structures and by delivering a number of housing market implications of the new stylized facts. Relatedly, our work contributes to existing studies of housing investment (Mayer and Somerville, 2000; Green, Malpezzi and Mayo, 2005; Haughwout, Peach, Sporn and Tracy, 2013; Paciorek, 2013; Murphy, 2018; Nathanson and Zwick, 2018). More broadly, our findings could also shed light on the importance of TTD frictions for nonresidential structures as both residential and nonresidential structures are likely to share some common hurdles from the site development stage.

As discussed earlier, the implications of these residential construction dynamics are less explored in the housing and macro literature. Most models that study the aggregate implications of the housing sector abstract from the dynamic aspect of land development (Davis and Heathcote, 2005; Iacoviello and Neri, 2010). Following the spirit of Glaeser, Gyourko and Saiz (2008), we explore the aggregate and regional implications of housing supply with a focus on the short-run dynamics.

Structure of the paper. In section 2, we develop a TTD model of housing investment and analytically derive the housing supply elasticity as a function of TTD and other variables. In section 3, we present the land development data and estimate a TTD measure that is comparable across regions by controlling for various factors. In section 4, we quantify local housing supply elasticities in the short to medium run by using the model derivations and the empirical TTD estimates. In section 5, we study three implications of our model for house prices and housing quantity. Section 6 concludes. The Online Appendix provides additional details and sensitivity analyses of our theoretical and empirical results.

2 Time-to-develop model of housing investment

This section presents the theoretical framework that connects our novel data on residential land development, introduced in Section 3, to housing supply elasticity—a central concept in the housing literature. The model incorporates a TTD constraint, following the approach of Kydland and Prescott (1982), and characterizes developers' investment decisions under this constraint. We derive expressions for both short- and long-run housing supply elasticities as functions of model parameters, including TTD.[2]

[2]The framework is designed to analytically capture the role of TTD in shaping supply elasticity. As such, it abstracts from the potential endogeneity of TTD and other short-run determinants emphasized in the literature. See Section 4.2.2 for a detailed discussion.

2.1 Model description

In period t, the developer produces housing units, I_t, using inputs built in current and previous periods, $\{U_{t-p|t}\}_{p=0,1,\cdots,P}$, based on the following TTD construction function:

$$I_t = \left(\sum_{p=0}^{P} U_{t-p|t}^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}, \quad \theta > 0. \tag{2.1}$$

The parameter P is the number of periods it takes to complete a project from the beginning, and θ governs the substitutability of the different stages of construction. This generalized TTD specification follows Sarte et al. (2015) and nests the investment assumption in Kydland and Prescott (1982) as a special case when $\theta \to 0$.[3] The variable $U_{t-p|t}$ indicates construction inputs built in period $t-p$ for houses that are scheduled to be completed in period t.

In turn, the developer builds construction inputs $U_{t|t+p}$ at a lot where housing completions are scheduled in period $t+p$ for each $p \in \{0, 1, \cdots, P\}$. These inputs are built based on a Cobb-Douglas production function:

$$U_{t|t+p} = M_{t+p-P|t+p}^{1-\alpha} N_{t|t+p}^{\alpha}, \quad \forall p \in \{0, 1, \cdots, P\}, \tag{2.2}$$

where $M_{t+p-P|t+p}$ is the amount of land input (or building permit) in the beginning period of development $t+p-P$ for the lot where new housing is scheduled to be completed in period $t+p$ and $N_{t|t+p}$ is the amount of variable construction input at that lot.

The dynamic housing production function that combines equations (2.1) and (2.2) is

$$I_t = M_{t-P|t}^{1-\alpha} \left(\sum_{p=0}^{P} (N_{t-p|t}^{\alpha})^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}}, \tag{2.3}$$

which features three desirable properties. First, land inputs are fixed in period $t-P$ and thus cannot be substituted with variable inputs once development begins. Second, variable inputs are intertem-

[3]Consistent with our TTD construction function when $\theta \to 1$, we assume that $I_t = \prod_{p=0}^{P} U_{t-p|t}$ when $\theta = 1$. To simplify the analysis without loss of generality, we assume $\theta \neq 1$ in this section.

porally substitutable according to parameter θ. This implies that while the entire development is completed over P periods based on an initially expected number of housing units, the developer retains some flexibility regarding the pace and intensity of construction over time, governed by θ. Third, our housing production function with equally distributed variable inputs renders a timeless Cobb-Douglas housing production function representation, consistent with existing estimates of the housing production function (Epple, Gordon and Sieg, 2010).[4]

In each period, the developer purchases building permits, $M_{t|t+P}$, from the local government at a price, $q_{M,t}$, for a lot that is at the beginning stage of development. Moreover, the developer hires variable construction inputs for each lot under development at a competitive cost, w_t. When a lot is fully developed, its completed new houses, I_t, are sold at a unit price, q_t. The developer's profit in period t, Φ_t, is

$$\Phi_t = q_t I_t - q_{M,t} M_{t|t+P} - w_t N_t,$$
$$\text{where} \quad N_t = \sum_{p=0}^{P} N_{t|t+p}. \tag{2.4}$$

The developer builds new houses at multiple lots by purchasing building permits and utilizing variable construction inputs to maximize its discounted sum of profits:

$$\max_{\{I_t, M_{t|t+P}, N_t, \{N_{t|t+p}, U_{t|t+p}\}_{p=0}^{P}\}} \quad \mathbb{E}_0 \sum_{t=0}^{\infty} \Lambda_{0|t}(q_t I_t - q_{M,t} M_{t|t+P} - w_t N_t),$$

subject to the TTD equations (2.1), (2.2), and (2.4). The variable $\Lambda_{0|t}$ is the stochastic discount factor between periods 0 and t, and $\mathbb{E}_t$ is the expectations operator conditional on information available in period t.

Finally, permits are supplied by the local government and are assumed to be elastic with respect

[4]To be precise, if $M_{t-P|t} = M$ and $N_{t-p|t} = N$ for all $p \in \{0, 1, \cdots, P\}$, then our housing production function can be writen as $I = (1+P)^{\frac{\theta}{\theta-1}} M^{1-\alpha} N^{\alpha}$. Epple et al. (2010) estimate a flexible housing production function and find that the elasticity of substitution between land and nonland factors is generally around 1, consistent with our Cobb-Douglas specification.

to the house price:

$$M_{t|t+P} = \bar{M} q_t^{\gamma}. \tag{2.5}$$

This specification follows a standard approach that facilitates the calibration of the long-run housing supply elasticity (Guren, McKay, Nakamura and Steinsson, 2020). In particular, the parameter γ directly governs the responsiveness of permit supply to prices, allowing the model's housing supply elasticity to align with empirical estimates in the literature.

2.2 Developer's housing supply

We denote $\mu_{t|t+p}$ as the period-t Lagrange multiplier of equation (2.2) for each p and express the respective optimality conditions of (i) construction at each stage, (ii) variable inputs at each stage, and (iii) building permits at the beginning stage of development as follows:

$$\mu_{t|t+p} = \mathbb{E}_t \left[\Lambda_{t|t+p} q_{t+p} \left(\frac{I_{t+p}}{U_{t|t+p}} \right)^{\frac{1}{\theta}} \right] \quad \text{for } p = 0, 1, \cdots, P,$$

$$w_t = \alpha \mu_{t|t+p} M_{t+p-P|t+p}^{1-\alpha} N_{t|t+p}^{\alpha-1} \quad \text{for } p = 0, 1, \cdots, P$$

$$q_{M,t} = (1-\alpha)\, \mathbb{E}_t \left[\sum_{p=0}^{P} \Lambda_{t|t+p} \mu_{t+p|t+P} \frac{U_{t+p|t+P}}{M_{t|t+P}} \right].$$

The first condition shows that construction at each stage is chosen such that its shadow value, $\mu_{t|t+p}$, is equal to its marginal contribution to the expected discounted value of the completed house in the future. The second and third conditions equate the costs of variable inputs and the building permit to the respective marginal products.

We introduce a deterministic per-period discount factor parameter $\beta < 1$, which allows us to decompose the stochastic discount factor between periods t and $t+p$ as

$$\Lambda_{t|t+p} = \beta^p \frac{\lambda_{t+p}}{\lambda_t},$$

where λ_{t+p}/λ_t represents the net stochastic discount factor between the two periods. We further define two auxiliary variables for the proposition below:

$$\tilde{\beta} = \beta^{\frac{\theta}{\theta+\alpha(1-\theta)}} \text{ and } B(t) = \frac{\tilde{\beta}^{(\alpha(\theta-1)/\theta)(1+t)} - 1}{\tilde{\beta}^{\alpha(\theta-1)/\theta} - 1}.$$

After log-linearizing the preceding optimality conditions as well as equations (2.1) through (2.5), the following proposition characterizes the developer's period-by-period housing supply choice as a function of house prices and other general equilibrium forces.

Proposition 1 (period-by-period housing supply curve) *Let each hatted variable be the log deviation from its steady-state value. Assuming the economy is in steady state prior to period* 0*, the developer's period-by-period housing supply curve implied by the log-linearized equilibrium conditions of the TTD model of housing investment is given by:*

$$\hat{I}_t = \begin{cases} \Upsilon_t(P)\hat{q}_t + \mathbf{GE}_t(P), & \forall t \in [0, P), \\ \frac{\alpha}{1-\alpha}\hat{q}_t + \gamma\hat{q}_{t-P} + \widetilde{\mathbf{GE}}_t(P), & \forall t \in [P, \infty), \end{cases}$$

where

$$\Upsilon_t(P) = \frac{B(t)}{\left(\frac{1-\alpha}{\alpha} + \frac{1}{\theta}\right) B(P) - \frac{1}{\theta}B(t)},$$

$$\mathbf{GE}_t(P) = -\frac{\Upsilon_t(P)}{B(t)} \sum_{j=0}^{t} (\tilde{\beta}^{\alpha(\theta-1)/\theta})^j \left(\hat{w}_{t-j} + (\hat{\lambda}_{t-j} - \hat{\lambda}_t)\right),$$

$$\widetilde{\mathbf{GE}}_t(P) = -\frac{\Upsilon_P(P)}{B(P)} \sum_{j=0}^{P} (\tilde{\beta}^{\alpha(\theta-1)/\theta})^j \left(\hat{w}_{t-j} + (\hat{\lambda}_{t-j} - \hat{\lambda}_t)\right).$$

All the proofs are available in the Appendix. Proposition 1 decomposes housing supply into its partial equilibrium and general equilibrium components. The general equilibrium component, denoted by $\mathbf{GE}_t(P)$ and $\widetilde{\mathbf{GE}}_t(P)$, depends on the current and past histories of construction wages and the stochastic discount factors. Our object of interest in this section is housing supply in partial equilibrium, and the general equilibrium forces that depend on the setup of the overall economy will be studied in section 5. The partial equilibrium component consists of the current housing price

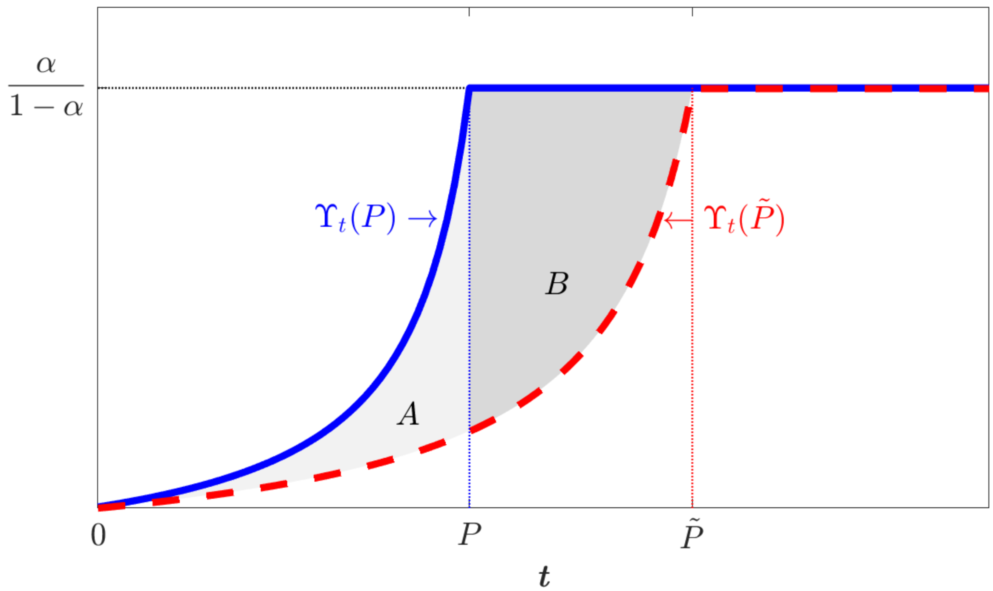

Figure 1: Theoretical static housing supply elasticities

Note: The figure illustrates how static housing supply elasticity, $\Upsilon_t(P)$, evolves over time, highlighting differences between regions with shorter and longer time-to-build (TTD) constraints. The elasticity increases up to the TTD threshold and then flattens based on the production elasticity parameter. Shaded areas represent the elasticity advantage of the shorter-TTD region.

before the TTD constraint ($t < P$) and the P-period lagged house price after the TTD constraint ($t \geq P$). The partial equilibrium component has a well-defined static housing supply elasticity, which is $\Upsilon_t(P)$ when $t < P$ and $\alpha/(1-\alpha)$ when $t \geq P$. The following corollary provides us some useful comparative statics with regard to the derived static housing supply elasticities.

Corollary 2 (comparative statics) *The static housing supply elasticity when $t < P$, $\Upsilon_t(P)$, has two properties. First, $\Upsilon_t(P)$ is positive and increasing in t, with an upper bound of $\alpha/(1-\alpha)$:*

$$0 < \Upsilon_{t-1}(P) < \Upsilon_t(P) < \frac{\alpha}{1-\alpha}.$$

Second, $\Upsilon_t(P)$ is larger when the TTD constraint P is shorter:

$$\Upsilon_t(P) > \Upsilon_t(\tilde{P}) \quad \textit{when } P < \tilde{P}.$$

Corollary 2 is visualized in Figure 1. As observed, the static housing supply elasticity is an increasing function up to the TTD constraint. Afterward, the static housing supply elasticity is determined by the parameter α, which represents the production elasticity to variable construction inputs. Comparing the housing supply elasticity between two regions with different TTD constraints, P and $\tilde{P}$, we find that the region with a shorter TTD constraint has a higher static housing supply elasticity for two reasons. First, housing supply is more flexible during periods under construction, represented by area A in the figure. Second, housing supply determined at the beginning period is completed earlier, represented by area B in the figure. In turn, area $A + B$ is the cumulative housing supply elasticity difference in the two regions. As noted earlier, our model nests the TTD assumption in Kydland and Prescott (1982) as a special case when $\theta \to 0$. In this case, the static housing supply elasticity becomes a step function: 0 before the TTD constraint is reached and $\alpha/(1-\alpha)$ afterward. As such, the difference in the static housing supply elasticity across regions in Kydland and Prescott (1982) arises only after the TTD constraint is reached in the more flexible region, which is area B.

2.3 The short- and long-run empirical housing supply elasticities

Using the proposition, we define the T-horizon housing supply elasticity that is consistent with existing empirical measures of the housing supply elasticity.

Definition 3 (T-horizon housing supply elasticity) *The T-horizon housing supply elasticity is defined as the average of the theoretical partial equilibrium period-by-period housing supply elasticities between periods 0 and T. Using Proposition 1 and assuming $\Upsilon_t(P) = \alpha/(1-\alpha)$ when $t \geq P$ for simplicity of notation, we define the T-horizon housing supply elasticity with P-period TTD, $\mathcal{E}_T(P)$, as*

$$\mathcal{E}_T(P) \equiv \frac{\Delta_{t=0}^{T}\hat{I}_t}{\Delta_{t=0}^{T}\hat{q}_t} \equiv \frac{1}{T+1}\sum_{t=0}^{T}\left[\Upsilon_t(P) + \gamma(T-P+1)\times\mathbf{1}_{\{T\geq P\}}\right], \tag{2.6}$$

where $\mathbf{1}_{\{T\geq P\}}$ is an indicator function equal to 1 when $T \geq P$. Moreover, the long-run housing *supply elasticity, $\mathcal{E}_\infty$, is defined as*

$$\mathcal{E}_\infty \equiv \lim_{T\to\infty} \mathcal{E}_T(P) = \frac{\alpha}{1-\alpha} + \gamma. \tag{2.7}$$

By taking an average of the period-by-period housing supply elasticities, our T-horizon housing supply elasticity summarizes the evolution of housing supply over time based on the supply-side behavior. In the short run when $T < P$, housing supply elasticity is not a function of γ but a function of TTD and other parameters of the housing construction function. In the long run, housing supply elasticity is purely a function of γ and α; TTD is no longer relevant. For $P \leq T < \infty$, housing supply elasticity is a weighted average of TTD and the long-run elasticity, where the latter matters more as $T \to \infty$.

Of note, this definition is not the only way to characterize the T-horizon housing supply elasticity. Depending on the endogenous forces that drive house prices, different weights on the period-by-period housing supply elasticities might better characterize the average housing supply elasticity over the horizon of interest. Indeed, our unweighted average of the period-by-period housing supply elasticities might be viewed as an agnostic measure to the various driving forces of the house price throughout the horizon.

3 Measuring the duration of land development

In this section, we use a unique data set that tracks residential development activities in the U.S. to measure the duration of land development across regions. A key feature of our data set is that it captures the period of site development prior to building construction, providing a more comprehensive view of land development by incorporating its early stages.

Our primary focus is on measuring TTD for each county in the data set, which is a key parameter in the model-implied local housing supply elasticity from the previous section. In line with this objective, we demonstrate that the duration of land development, including the site development phase, is substantial and varies significantly across counties. These variations persist even after controlling for a range of observable local demand factors.

3.1 Land development data and summary statistics

Our data set comes from Zonda, which provides data and analysis to the national residential home-building industry. The data set is constructed from Zonda's survey markets data, which cover many of the major metro areas with high residential construction activity in the U.S. The survey markets data put together a quarterly construction status survey in new home subdivisions, an area containing a large number of houses or apartments to be built close together at the same time. Large subdivisions are often broken down to multiple sections, each of which is typically built by a single-builder company. The data set displays the total number of housing units as well as other construction characteristics by sections. We have access to this data set from 2000 to 2021.

As shown in Table 1, our data set includes a large number of new housing supply across the U.S. Between 2003 and 2019, the data set contains 222,868 developed sections with a total of 7.8 million units of new housing.[5] For reference, the Census Bureau reports a sum of 20 million new housing completions in the same period, implying a 39 percent Census coverage ratio of our data set. Our data set is not biased toward multi-unit housing development, as the Census coverage of single-unit housing completion is also around 39 percent.[6] These completions are distributed over 318 counties in 113 core-based statistical areas (CBSAs) that represent 48 percent of the U.S. population. The average population size of those CBSAs is 1,590,428, which is 4.7 times larger than that of the U.S. average CBSA.[7]

Besides the high coverage ratio, a desirable feature of the data set is that it continuously tracks the construction status of subdivisions and sections. Land development is a lengthy process, start-

[5]Because many of the completed sections between 2000 and 2002 were already under development at the start of the sample, we are unable to trace their development origins. As such, we begin tracking completed sections from 2003. Additionally, we focus on the pre-COVID sample, as housing supply faced numerous shocks at the onset of the COVID pandemic, which may introduce noise into the analysis.

[6]In our data set, single-family housing units comprise 82.6 percent of the completions, followed by townhouses (10.2 percent), condos (2.3 percent), and duplexes (1.2 percent). We show in the Appendix that the Census coverage does not significantly fluctuate across years.

[7]Of the top 20 CBSAs ranked by the 2020 Census population, only 2 CBSAs (Boston and Seattle) are not included in our data set.

Table 1: New housing completions between 2003 and 2019

(unit: $1{,}000$ housing)	Zonda	Census	Coverage
Total housing	$7{,}790$	$20{,}020$	39%
Single-family housing	$5{,}939$	$15{,}314$	39%

Note: This table compares total and single-family new housing completions from 2003 to 2019 between Zonda and Census data, showing that the Zonda dataset covers approximately 39% of the Census-reported completions.

ing from the acquisition of land by developers and the design of a development plan. The plan is then submitted to the appropriate municipality for a preliminary review. The profile of the subdivision is first created and labeled as *future lots* in our data set when the municipality grants a preliminary approval as a first step in the process or, if the approval date is not available, after Zonda reviews and verifies the site plan submitted to the municipality. During each quarterly survey, the lot remains as future lots while there is ongoing land development. In detail, Zonda tracks the progression of future lots from vacant land, when the site remains untouched, through various stages such as the placement of survey flags and equipment, lot grading, street excavation, and utility work, to the paving of streets and their eventual accessibility to traffic. It follows that the final site plan is submitted and approved, and the necessary permits are processed. Thereafter, the infrastructure for the land is developed and the lot is now labeled as *active*. At this stage, separate homebuilders enter for construction projects in the active lots not pursued by the developer. When there is excavation activity with a slab or basement on these vacant developed lots, the units are classified as *under construction*, consistent with the Census Bureau's definition of housing starts. After the completion of home construction, each house is classified as either a *finished vacant* unit or an *occupied* unit, depending on its status of sales. Eventually, the subdivision is classified as *built out*, and it exits the data set when the number of occupied units equals its total units.

Based on this classification, we define a TTD measure for each new development section. TTD is defined as the duration between the quarter when the municipality likely approves a preliminary site plan and the quarter when the number of finished units (vacant or occupied) reaches at least half of the total number of units. The unique feature of our data set is that it captures the earliest stage of a completed development with a plan that is as concrete as a preliminary map submitted to the municipality. As such, we define the beginning quarter of TTD as the first quarter when we observe the total number of future lots to be the same as the total number of planned lots in the section.[8] The definition for the end quarter of TTD is consistent with the Census Bureau's definition of the completion of a multi-unit building, as it classifies the construction of a multi-unit building as complete when half of the units are finished. It is worth noting that the Census Bureau tracks construction time per building, whereas we can only track construction time per section. Therefore, our measure of the section's construction time could be longer than the construction time of an average building in that section if a developer decides to build structures sequentially rather than simultaneously. In the Appendix, we study the sensitivity of our empirical results when the end quarter of TTD is defined earlier than our baseline—that is, the date at which the number of finished units reaches a quarter of the total number of units in the section.

For the remaining analysis, we adopt the following sample selection criterion. Between 2003 and 2019, 223,499 sections were completed. We dropped 102,940 observations without information on TTD (for example, missing start dates), resulting in 120,559 observations.[9] We further dropped 16,133 observations without lot size information or demand controls, leaving us with 104,426 observations.

While our dataset provides novel information on project-level development timelines, it has limitations. Zonda's coverage of new housing activity is likely higher in regions with substantial development, and start dates are missing for a sizable share of completed sections. Missingness may arise when the data provider cannot precisely track the initial filing of subdivision maps, rather than from project attributes themselves. Nevertheless, the possibility of non-random selection implies that our estimates should be interpreted as representative of the subset of developments for which project timelines are accurately observed, rather than the full universe of U.S. residential

[8]For some sections, our data set also includes the preliminary approval date from the municipality. For that subsample, the quarter of the preliminary approval date mostly coincides with our definition of the beginning quarter of TTD, as shown in the Appendix.

[9]Specifically, we define the start date as the first quarter when the total number of planned units is equal to the total number of future lots, based on Zonda's quarterly review of newly submitted maps at the municipality. We find that our defined start date is close to the municipality approval date of the preliminary site plan, when the latter date is available in the data set. We dropped sections where their first observation already had positive active lots, as land development on these sections likely started (according to our definition) before they entered the data set.

Table 2: Section TTD statistics

(unit: days)	Total TTD	Site TTD	Building TTD
Mean	1,274	573	701
Std. dev.	1,082	765	789
IQR	1,005	458	458
P10	365	91	181
P25	548	181	273
P50	913	275	456
P75	1,553	639	731
P90	2,832	1,278	1,642
Observations	104,426	104,426	104,426

Note: Each observation is a subdivision or a section of a subdivision when there are multiple sections in a subdivision. IQR stands for the interquartile range (P75−P25). Five different percentiles of each TTD distribution are shown—for example, P50 referring to the median (50th percentile) of the distribution.

developments. In the Appendix, we present balance tests and construct an inverse-probability-weighted TTD measure to assess potential sample-selection bias. The reweighted estimates closely resemble our baseline results, suggesting that observable selection does not materially affect our findings.

3.2 Stylized facts on the duration of housing development

By examining the raw measures of TTD in Table 2, we find two stylized facts on the duration of housing development.

First, housing development is a lengthy process, with a significant portion of time spent on land development. As shown in the first row of the table, the average total duration of housing development is $1,274$ days. In particular, we find that the time between land development plan approval and the completion of site development (site TTD) is notably long, averaging 573 days, an aspect less emphasized in the literature due to limited data availability.[10]

Second, there is considerable heterogeneity in the duration of housing development. The stan-

[10]The total time for housing development consists of two components: time to develop infrastructure at the site (site TTD) and time spent on the construction of buildings (building TTD). In measuring site and building TTD, we define the completion of site infrastructure development (and the commencement of building construction) as the first quarter when future lots become zero, indicating that no further site infrastructure development is ongoing.

dard deviation and interquartile range of total TTD both span about three years ($1,082$ days and $1,005$ days, respectively). This substantial variation is also evident in site TTD, where the standard deviation exceeds two years.

It is important to note that the distribution of TTD is right-skewed, as the mean exceeds the median in all TTD measures. This skewness is further highlighted by the lengthy TTD at the 90th percentile.

3.3 Controlled measures of TTD

The lengthy and highly dispersed TTD across sections documented above could be driven by various factors. Our goal is to measure the developers' TTD constraint for housing development that is comparable across locations. Toward that goal, we need to first control for differences in construction characteristics that are likely to affect TTD. For each development section, the data set includes some of that information, such as the number of housing units, the average lot size, the type of housing, and the builder(s) of each section. Indeed, these construction characteristics have substantial variations. For example, there are an average of 42 housing units per each section, and the standard deviation is also 42 units.

The first column of Table 3 shows the regression result when the log of TTD is regressed on several construction characteristics in our sample. Builder fixed effects are included for the top 15 builders in our sample. Completion year fixed effects are also included to abstract from time variations in TTD. We find that both the number of units and the (average) lot size per housing unit are positively associated with TTD. One percent increases in the number of units and in the lot size per unit imply 0.140 percent and 0.146 percent increases in TTD, respectively. These results are highly significant and consistent with the findings in Oh and Yoon (2020), where the square footage of a single-family house under construction is shown to be positively associated with its time to build. In terms of the type of housing, townhouses and condos take a longer time to complete relative to single-family developments.

Even after we control for construction characteristics, TTD could also be driven by local eco-

Table 3: Section TTD regression results

Variables	(1)	(2)
Log(number of units)	0.140***	0.145***
	(0.00425)	(0.00429)
Log(lot size)	0.146***	0.153***
	(0.00489)	(0.00506)
Single family	–	–
Townhouse	0.208***	0.199***
	(0.0113)	(0.0117)
Condo	0.181***	0.208***
	(0.0419)	(0.0423)
Duplex	0.0343	0.0310
	(0.0318)	(0.0319)
Etc.	0.00885	0.0190
	(0.0261)	(0.0260)
Builder fixed effect	✓	✓
Year fixed effect	✓	✓
Local controls		✓
Constant	4.341***	4.455***
	(0.0515)	(0.0846)
Observations	104,426	104,426
R-squared	0.272	0.277

Note: The regression uses log(TTD) as the dependent variable. Local control variables include Bartik-type predicted industry employment growth, population share of immigrants, population share of college educated, population density, and county real GDP, all based on values from 1980. Year fixed effects are specified by the completion year of development. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

nomic factors that are linked to the developers' incentives in those locations. Because our model does not feature the developer's location choice, we would also need to control for these factors. The second column of Table 3 adds a number of time-invariant local controls potentially relevant for housing supply—such as a Bartik-type variable that measures the local demand pressure, population shares of immigrants and college-educated adults, and population density—as suggested in Davidoff (2016). The regression results show that several of these local economic factors are associated with TTD in a statistically significant manner. Counties with higher Bartik demand pressure, immigrant share, and population density experience longer duration in development, as shown in the Appendix. Even after we control for these local economic factors, however, the R-squared shows limited improvement over the regression in the first column, and the regression coefficients for construction characteristics remain robust. These results suggest that local economic factors might play a limited independent role after taking into account the developer's choice of construction characteristics.[11]

3.4 County-level TTD

Using the regression results from Table 3, we construct a county-level measure of TTD for a representative section. Specifically, for each section we normalize TTD by setting the controlled observables to their national mean values and then add the fitted residuals. We aggregate these normalized section-level values by taking the median within each county. Note that we use the median rather than the mean because the distribution of TTD right-skewed. In addition, the median TTD is less sensitive to remaining time-varying demand factors—such as the fat right tail in construction durations observed during the Great Recession (Oh and Yoon, 2020).

Table 4 reports cross-county moments of our county-level TTD measures. In the first column ("Raw TTD"), the average of county-level TTDs based on raw section-level data closely matches the average section-level TTD. The standard deviation and interquartile range are sizable—425 days and 365 days, respectively—indicating substantial heterogeneity in development duration across counties. The second and third columns present the same statistics using the controlled TTD estimates from Table 3. After controlling for construction characteristics and evaluating TTD for a nationally representative housing project, the cross-county mean TTD is 911 days, or roughly two and a half years. The dispersion remains large, with a standard deviation and interquartile range of approximately one year. Results in the third column are similar to those in the second, consistent with the R-squared patterns in Table 3, suggesting that once construction characteristics are accounted for, local demand factors add little explanatory power for TTD variation.

[11] As a robustness check, we also tried using start year fixed effects instead of completion year fixed effects. The main results remain, but the R-squared deteriorates, suggesting that completion year fixed effects provide a better control for understanding variations in TTD.

Table 4: County-level TTD statistics

(unit: days)	Raw TTD	Reg. (1)	Reg. (2)
Mean	970	911	917
Std. dev.	425	302	305
IQR	365	376	363
P10	638	532	551
P25	731	719	732
P50	914	889	900
P75	1,096	1,095	1,095
P90	1,279	1,296	1,275
Observations	267	267	267

Note: Each observation is a county's median TTD. We use counties with at least 10 completed sections observed. IQR stands for the interquartile range (P75−P25). Five different percentiles of each TTD distribution are shown—for example, P50 referring to the median (50th percentile) of the distribution.

3.5 The geographic determinants of the land development process

Land development is a major topic of interest in civil engineering, as each construction site poses unique engineering challenges based on soil characteristics, topography, weather, and other physical features (Kone, 2006). As such, developers create not only a master plan design that conceptualizes their new development at the location of interest, but also a site engineering plan that adapts the master plan design to the physical properties of the site. These site engineering plans include (i) a grading plan that shows the elevations of grounds and buildings, (ii) a storm water management plan that shows the volume and rate of storm water runoff, and (iii) an erosion and sediment control plan that shows the erosion control barriers and materials at the site. The local government regulation on development varies based on its transitory and permanent environmental effects, and this factor also plays an important role in shaping the engineering plans of each site.

As shown in Table 4, our county-level TTD measures exhibit substantial cross-regional variation even after controlling for construction characteristics and local economic factors. Based on the process of land development described above, we next ask whether observable geographic differences in engineering challenges can help account for this variation. Some geographic factors are

Table 5: County-level associations between TTD and geographic determinants

Bivariate regressions	Standardized β	Standard error	R-squared	Observations
TTD on Saiz elasticity	-0.086**	(0.039)	0.054	230
TTD on Heat exposure	0.074***	(0.021)	0.039	266
TTD on Rainfall intensity	0.108***	(0.020)	0.086	261

Note: County-level TTD is defined as the median section-level TTD among counties with at least ten completed sections. Section-level TTD is obtained from the residualized measure estimated in regression (2) of Table 3. "Heat exposure"—that is, cooling degree days—is a measure of the year's temperature hotness, calculated as the difference between the daily temperature mean (the sum of the high and low temperatures divided by two) and 65 degrees Fahrenheit, multiplied by the number of days with a positive value of this difference in a given year (Data source: National Centers for Environmental Information's Annual Climatological Data). "Rainfall intensity" measures the rainfall inches per hour on a storm of one-hour duration and a 100-year return period for each county (Data source: National Oceanic and Atmospheric Administration's Atlas 14 Precipitation Frequency Estimates). Right-hand-side variables are standardized to have mean zero and unit standard deviation. Robust standard errors are reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

closely related to long-run housing supply determinants emphasized by Saiz (2010), such as land availability and terrain constraints, while others—particularly those linked to weather conditions—may not play a major role in accounting for long-run housing supply but still matter for the *duration* of the development process. For example, each location is exposed to different climate conditions that might not materially affect the decision to develop land, but it can still affect how quickly developers and complete on-site work. Locations with extreme heat or intense rainfall can remain attractive for development, yet experience longer timelines due to weather-related construction delays or additional design requirements needed to meet local engineering standards.

Table 5 reports bivariate regressions of our controlled TTD measure on each geographic determinant. The results indicate that long-run supply elasticity, heat exposure, and rainfall intensity are all significantly associated with TTD. Specifically, land development takes longer in counties where (i) long-run supply elasticity is low, (ii) average heat exposure is high, and (iii) rainfall intensity is greater. A detailed investigation of these engineering mechanisms is beyond the scope of this paper, but the significance of these geographic determinants in accounting for cross-county variation in TTD suggests that our controlled TTD measure captures plausible sources of non-economic heterogeneity in land development. At the same time, we recognize that even weather variables can influence local economic activity through channels other than construction feasibility—for example, by affecting migration patterns, labor productivity, or sectoral composition. Accordingly, when we later instrument TTD with these weather variables to estimate the relationship between county-level house price changes and TTD, the results should be interpreted as reflecting variation in TTD that is plausibly exogenous to short-run housing demand, rather than as stemming from purely exogenous shocks to local economies.

4 Quantifying housing supply elasticities across different horizons

Using the theoretical framework from section 2 and the duration of land development statistics from section 3, this section presents local housing supply elasticities across different horizons. We explore whether the significant TTD variations observed in the data translate into significant variations in the $T-$horizon housing supply elasticities, by comparing these with the corresponding long-run elasticities. Our primary focus in this section is on quantifying housing supply elasticities at different horizons; their role in accounting for housing market dynamics will be examined in section 5.

4.1 Parameterization

Recall the T-horizon housing supply elasticity from Definition 3. In equation (2.6), the elasticity $\mathcal{E}_T(P)$ requires five structural parameters: P, γ, α, β, and θ. We discuss the calibration strategy for each of these parameters.

First, the parameter P for each county is set as the median value of its section TTD estimates. To be specific, the section TTD estimates we use are from the second regression specification in Table 3 that controls for both construction characteristics and local variables. Note that TTD is defined as the time span between approval of the preliminary site plan and completion of the project. As such, it is conceptually inclusive of the time span between submitting a project for final approval and receiving a decision, documented in Gyourko, Hartley and Krimmel (2021).

Second, calibration of the parameters γ and α follows Guren et al. (2020) in that (i) for each county, our long-run housing supply elasticity $\mathcal{E}_\infty$ in equation (2.7) is equal to Saiz's housing supply elasticity, (ii) α is common across all counties, and (iii) the lowest value for γ is zero at the county with the lowest Saiz elasticity. These conditions imply that $\alpha = 0.385$ and guarantee that $\gamma \geq 0$ for all counties.

Third, the quarterly time discount factor, β, is set at 0.995, consistent with a 2 percent annual real interest rate.

Fourth, we discuss the calibration strategy for the nonnegative parameter θ, which governs the degree of substitutability across construction stages. Because direct empirical measures of substitutability are unavailable, we infer plausible values of θ indirectly from the model's implications. When $\theta \to 0$ as in Kydland and Prescott (1982), TTD investment is not substitutable, and the initial amount of housing construction fully determines future housing completions. For higher values of θ, however, TTD investment becomes more substitutable, allowing realized housing completions to deviate from initial plans—particularly when housing market conditions shift significantly during the development process.

These insights suggest that both deviations in housing completions from the initial plan and changes in housing market conditions are informative for calibrating θ. Specifically, we exploit the model's prediction that θ and changes in housing market conditions jointly determine the *ex post* scale of completed development projects. The deviation in completions can be empirically measured as the percentage difference between the planned number of housing units planned at project initiation and the number ultimately completed.

Our data indicate that at least a 5-percent deviation in housing completions from the initial plan occurs for roughly 32.4 percent of all project sections in the sample. Using the time series for real house prices and real construction wages to simulate the TTD investment model described above, we calibrate $\theta = 0.334$, the value at which the model-implied frequency of projects with at least a 5-percent absolute deviation matches the empirical frequency.[12] The calibrated value of

[12]Details of the calibration procedure are provided in the Appendix.

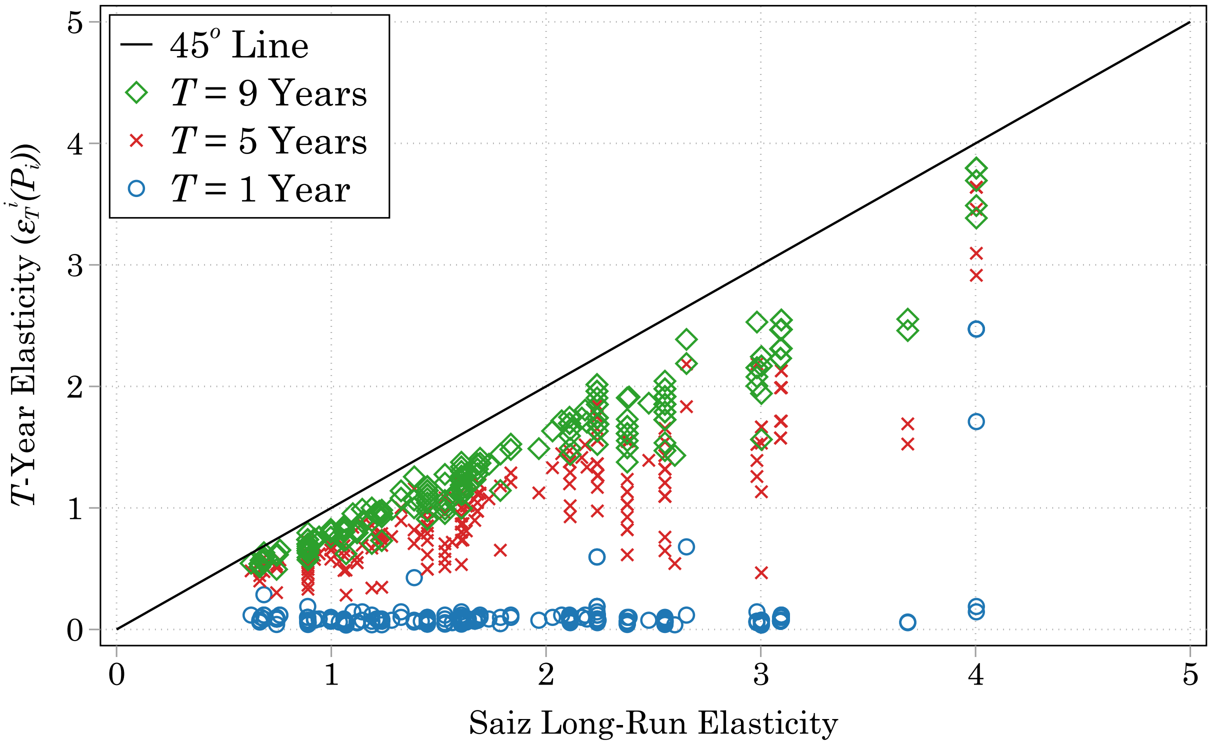

Figure 2: Supply elasticities in each horizon

Note: This figure shows a scatter plot comparing the Saiz supply elasticity and the $T-$year supply elasticities for $T = 1$ (blue circle), $T = 5$ (red cross), $T = 9$ (green diamond). The black line indicates the 45 degree line.

θ lies below one, implying that TTD investments across stages are closer to complements. This is consistent with the fact that many on-site construction activities must be carried out sequentially, limiting the degree of substitutability across different stages.

4.2 The $T-$horizon housing supply elasticity

Figure 2 compares our measure of horizon-specific elasticities with the Saiz long-run elasticities. Consistent with significant lags in land development, shorter horizon elasticities are much smaller than the long-run elasticities. In particular, one-year housing supply elasticities are close to zero and show little variability. As the horizon increases, the $T-$horizon housing supply elasticities tend to increase and converge to the 45 degree line that equates the long-run elasticities. At the same time, the shorter-run housing supply elasticities are not simply monotonically smaller versions of the long-run elasticities. For example, the five-year housing supply elasticities show significant variations apart from their long-run counterparts.

To investigate the regional patterns of our short-run housing supply elasticities, we broadly follow Glaeser, Gyourko, Morales and Nathanson (2014) in classifying the sample into three regions: Coastal, Sunbelt, and Interior.[13] Figure 3 displays the distributions of both the short- and long-run housing supply elasticities, for each of the three regions, where we find a stark contrast in the regional patterns. As is well documented in the literature, the right panel shows that the long-run housing supply elasticity in the Coastal region is lower than in the Sunbelt region. However, the left panel shows that the regional pattern is reversed for the short-run (3-year) housing supply elasticity, as the elasticity distribution for the Sunbelt region now appears to the left of that for the Coastal region.

To sum up, we find that long and variable TTD documented in the data translate to the low and variable short-run housing supply elasticities in our model. In particular, our short-run housing supply elasticity shows a starkingly different regional pattern compared to the long-run housing supply elasticity, in that the elasticity distribution of the Sunbelt shifts to the left of that of the Coastal region. This suggests that our short-run housing supply elasticities could provide a new perspective to the literature on housing dynamics. In the next section, we use both housing data and an equilibrium model of new housing supply to study the implications of the short-run housing supply elasticity on the cross-county and cross-region dynamics of house prices and construction.

4.2.1 Other measures of the long-run housing supply elasticity

Our benchmark long-run housing supply elasticity is taken from Saiz (2010). This measure is appropriate for us because a key metric that Saiz (2010) used to estimate the long-run housing supply elasticity is land availability which is directly related to the decision making of land developers observed in our data set. Nevertheless, as our focus is more on quantifying the short-run hous-

[13]To be precise, counties with a centroid within 50 miles of either the Atlantic or the Pacific are defined as the Coastal region, while counties with a centroid more than 50 miles from either coast and located in states along the southern border between Florida and Arizona are classified as the Sunbelt region. The remaining counties are classified as the Interior region.

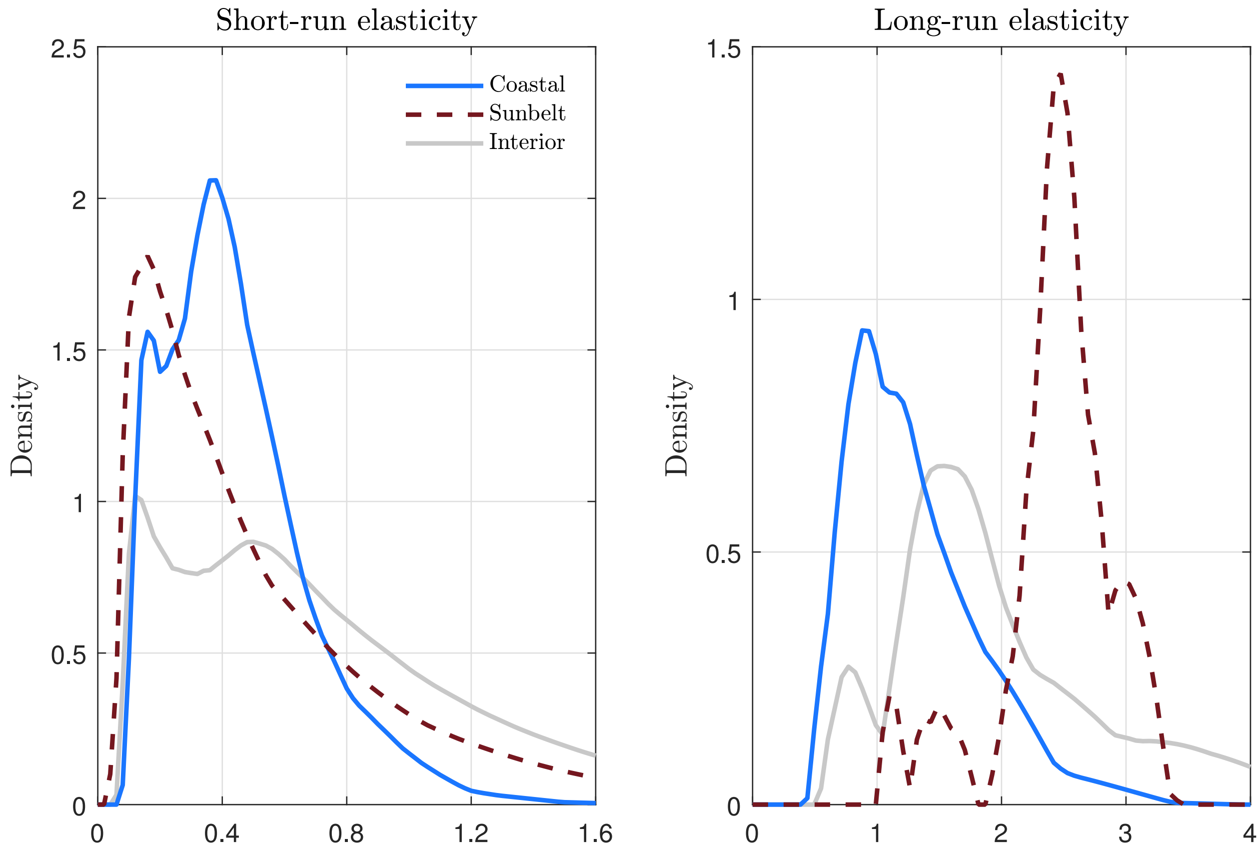

Figure 3: Distribution of housing supply elasticities by region

Note: The left panel shows the kernel density plots of the 3-year housing supply elasticities for the three regions. The right panel shows the kernel density plots of the Saiz housing supply elasticities for the three regions. The kernel densities for values above 1.6 in the left panel and above 4 in the right panel are not plotted for better visibility.

ing supply elasticity, and because our short-run housing supply elasticity is a weighted average of TTD and the long-run supply elasticity with higher weights on TTD when the horizon is shorter, the main message of our paper is not highly sensitive to measures of the long-run supply elasticity. For example, Baum-Snow and Han (2024) measures a comprehensive medium-run housing supply elasticity at the neighborhood track level using not only new construction data but also teardowns and renovations. For our purpose, we took a subset of their supply elasticity that targets new housing units and calibrated our long-run housing supply elasticity to the county average of this neighborhood track level data. In the Appendix, we plot the equivalent of Figure 3 using Baum-Snow and Han (2024) and find that our message stands, although the elasticities become much smaller for both the short and the long run as the average elasticity of Baum-Snow and Han

(2024) is smaller than that of Saiz (2010). Indeed, Baum-Snow and Han (2024) confirm that their supply elasticities have several similarities with Saiz (2010) and are lower on average because of the shorter time horizon of their data.

4.2.2 Endogenous TTD

Our model employs a fixed TTD parameter to capture regional variation in housing supply conditions. Although TTD is partly endogenous—responding to local demand factors—controls included in the previous section aim to mitigate these concerns. Moreover, to the extent that such endogeneity exists, it is unlikely to systematically distort the cross-regional ranking of TTD or the associated estimates of short-run housing supply elasticity. Nonetheless, a limitation of the fixed-TTD assumption is that it abstracts from the possibility that regions with shorter median TTDs may exhibit greater sensitivity to shocks, potentially altering the elasticity ranking. However, estimating regional differences in how TTD responds to national shocks is not feasible with available data and falls outside the scope of this study. Prior work, including Oh and Yoon (2020), has explored time-to-build endogeneity in the context of the 2002–2011 housing cycle, though only at the national level.

5 Theory and application of short- and long-run elasticities

Consider two regions with different housing supply elasticities. In Figure 4, the housing supply curves of the two regions are denoted as inelastic supply and elastic supply. Assume that the initial housing market equilibrium for both regions is at point A, where the demand curve is denoted as D. When there is positive housing demand that shifts the demand curve from D to D', the equilibrium price and quantity responses are different for the two regions. In the inelastic supply region, the equilibrium is formed at point C, where prices increase by a lot and quantities increase by little. By contrast, in the elastic supply region, the equilibrium is formed at point B, where prices increase by little and quantities increase by a lot. This implies that the differential house price dynamics across regions could be traced back to differences in the housing supply elasticity. As described earlier, the large literature that uses the housing supply elasticity to study the causal effect of house price changes on other variables relies on this intuition.

In this section, we revisit the above thought experiment after taking into account the dynamics of housing supply originating from TTD. Because TTD drives a wedge between the short- and long-run housing supply elasticities, it opens up a number of questions with regards to the link between house prices and housing supply. Specifically, we ask the following three questions. What is the relevant measure that drives house prices, the short-run housing supply elasticity or the long-run housing supply elasticity? Could the house price rise more at a region where construction is more active, such as the Sunbelt relative to the Coastal region? How effective is a government's discretionary housing supply policy in stabilizing house prices when construction takes a significant time? To address these questions, we extend the partial equilibrium model of developers in section 2 into a local general equilibrium model by incorporating a housing demand side. We hit the economy with a common housing demand shock and study the differential local house price and construction responses.

5.1 Local general equilibrium TTD model

The local economy consists of housing developers, households, nondurable goods producers, and a local government. Since the national central bank sets the interest rate, we assume that the local economy takes it as given. Therefore, the bond and nondurable goods markets do not clear locally, analogous to the assumptions in small open economy models in the international macro literature. Housing developers follow the same specification and notation as in section 2. Below, we describe the households, the rest of the economy, and the equilibrium of the model.

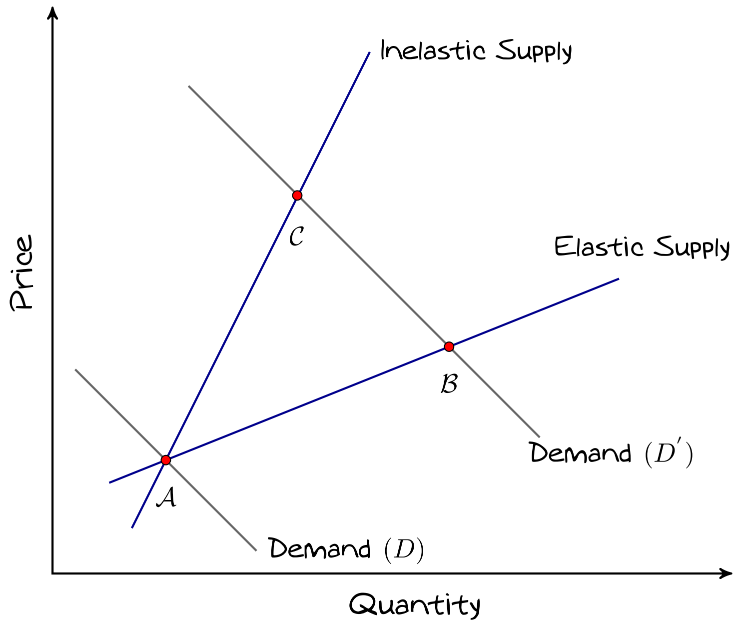

Figure 4: Housing supply and demand curves

Note: The figure illustrates housing market equilibria in regions with different supply elasticities. It compares equilibrium responses to an increase in housing demand ($\mathcal{D} \to \mathcal{D}'$), highlighting larger price increases and smaller quantity responses in regions with inelastic supply ($\mathcal{A} \to \mathcal{C}$), and smaller price increases but larger quantity responses in regions with elastic supply ($\mathcal{A} \to \mathcal{B}$).

5.1.1 Households

The representative local household's expected lifetime utility is

$$\mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_t, H_t, N_{n,t}, N_t; \varphi_t), \tag{5.1}$$

where C_t denotes nondurable consumption, H_t the flow of housing services, $N_{n,t}$ labor supplied to the nondurable-goods sector, N_t labor supplied to the housing (construction) sector, and φ_t an exogenous housing-demand shifter. The household's one-period subjective discount factor β is consistent with the housing developers' deterministic discount factor in section 2. Following Guren et al. (2020), we assume GHH preferences over nondurable consumption and leisure (Greenwood, Hercowitz and Huffman, 1988) and a Stone-Geary specification for housing demand:

$$U(C, H, N_n, N; \varphi) = \left[\frac{1}{1-\sigma}\left(C - \frac{\psi_n}{1+\nu}N_n^{1+\nu} - \frac{\psi}{1+\nu}N^{1+\nu}\right)^{\kappa}(H-\varphi)^{1-\kappa}\right]^{1-\sigma},$$

where σ is the confficient of relative risk aversion, ν is the inverse Frisch elasticity of labor supply, κ is the consumption-housing preference share parameter, and ψ_n and ψ are the disutility weights on nondurable-sector and housing-sector labor, respectively.

The household's service flow of housing is proportional to its housing stock. For simplicity of notation, the housing stock is also denoted as H_t. The housing stock evolves over time by

$$H_t = (1-\delta)H_{t-1} + I_t, \tag{5.2}$$

where δ is the depreciation rate of the housing stock.

The household flow budget constraint is given by

$$C_t + q_t I_t + \frac{B_{t+1}}{R_t} + \frac{\psi_b}{2}B_{t+1}^2 = w_{n,t}N_{n,t} + w_t N_t + B_t + \Phi_t + T_t, \tag{5.3}$$

where B_{t+1} is the household's one-period bond holdings that mature in period $t+1$, R_t is the gross bond interest rate between periods t and $t+1$, $w_{n,t}$ is the real wage for working in the nondurable goods sector, Φ_t is the period-t profit of developers because households are the final owners of the developers, and T_t is transfers from the local government. As is standard in small open economy models, the household is subject to the bond portfolio adjustment cost $\psi_b B_{t+1}^2/2$. The parameter ψ_b is calibrated to be positive for stability in solving the model but small enough to not materially affect the model dynamics.

5.1.2 The rest of the economy

As we will discuss next, the rest of the economy consists of the nondurable goods producers, the local government, and the market-clearing conditions. We also specify the exogenous process for housing demand that we use for later applications.

Nondurable goods producers. The representative nondurable goods producer operates with a linear production technology, $Y_t = \bar{Z}N_{n,t}$, where Y_t is the output of the nondurable good and $\bar{Z}$

captures its productivity. The profit of the producer is $Y_t - w_{n,t}N_{n,t}$, where both the input and output markets are perfectly competitive. The nondurable goods are tradable to other regions.

Local government. As specified in equation (2.5), the supply of housing permits is determined by its local government, which in turn is elastic to the region's equilibrium house price. For each housing permit, the local government collects a fee, $q_{M,t}$, from developers. The local government also collects the bond portfolio adjustment cost from households. The local government follows a balanced budget by rebating back its revenue to the households in the form of transfers T_t:

$$T_t = q_{M,t}M_t + \frac{\psi_b}{2}B_{t+1}^2. \tag{5.4}$$

Market clearing. The labor markets for the nondurable goods sector and the construction sector clear by equating the supply and demand of labor in each sector. The permit market clears by equating permit supply to permit demand. The market for new housing clears by equating the supply and demand of new housing investment. The bond and nondurable goods markets do not clear locally as we assume that the interest rate is exogenously determined by the national central bank. Finally, the following resource constraint of the local economy needs to be satisfied:

$$C_t + \frac{B_{t+1}}{R_t} = w_{n,t}N_{n,t} + B_t. \tag{5.5}$$

Exogenous housing demand. The exogenous component of housing demand, φ_t, enters the household's preference for housing services H_t in the utility function (5.1) and follows a first-order autoregressive process in logs:

$$\log \varphi_t = (1-\rho_\varphi)\bar{\varphi} + \rho_\varphi \log \varphi_{t-1} + \epsilon_{\varphi,t}, \tag{5.6}$$

where $\epsilon_{\varphi,t}$ is the exogenous housing-demand shock, and ρ_φ captures the persistence of housing demand around its steady-state level $\bar{\varphi}$.

5.1.3 Equilibrium

The local general equilibrium is a set of variables $\{U_{t|t+p}, N_{t|t+p}, \mu_{t|t+p}\}_{p=0}^{P}$, $M_{t|t+P}$, N_t, I_t, H_t, C_t, Y_t, $N_{n,t}$, B_{t+1}, w_t, $w_{n,t}$, q_t, R_t for $t \geq 0$ such that taking as given the endogenous prices w_t, $w_{n,t}$, and q_t, the exogenous processes R_t and φ_t, and the initial conditions B_0 and H_{-1}, the following conditions hold:

1. Housing developers maximize their profit subject to (2.1) through (2.4).

2. Households maximize their lifetime utility (5.1) subject to (5.2) and (5.3).

3. Nondurable goods producers maximize their profit.

4. The local government supplies permits and balances its budget according to (5.4).

5. Markets clear for nondurable goods labor, construction labor, permits, and housing investment, and the resource constraint (5.5) is satisfied.

We assume that the interest rate is fixed by the national central bank. The exogenous component of housing demand follows (5.6).

5.2 Housing supply elasticity and local house price variations

Section 4 finds that cross-county variations in the short-run housing supply elasticity are large and distinct from the variations in the long-run elasticity. Using both our model and the data, we now study the quantitative importance of these measured short-run housing supply elasticities in accounting for cross-county (i.e. local) house price variations. Our findings provide a potential explanation for the declining relevance of the long-run housing supply elasticity in accounting for local house price variations since the 2010s.

5.2.1 Model investigation

We illustrate how the persistence of housing demand shocks shapes which measure of housing supply elasticity is most relevant for local price dynamics. The key insight is straightforward:

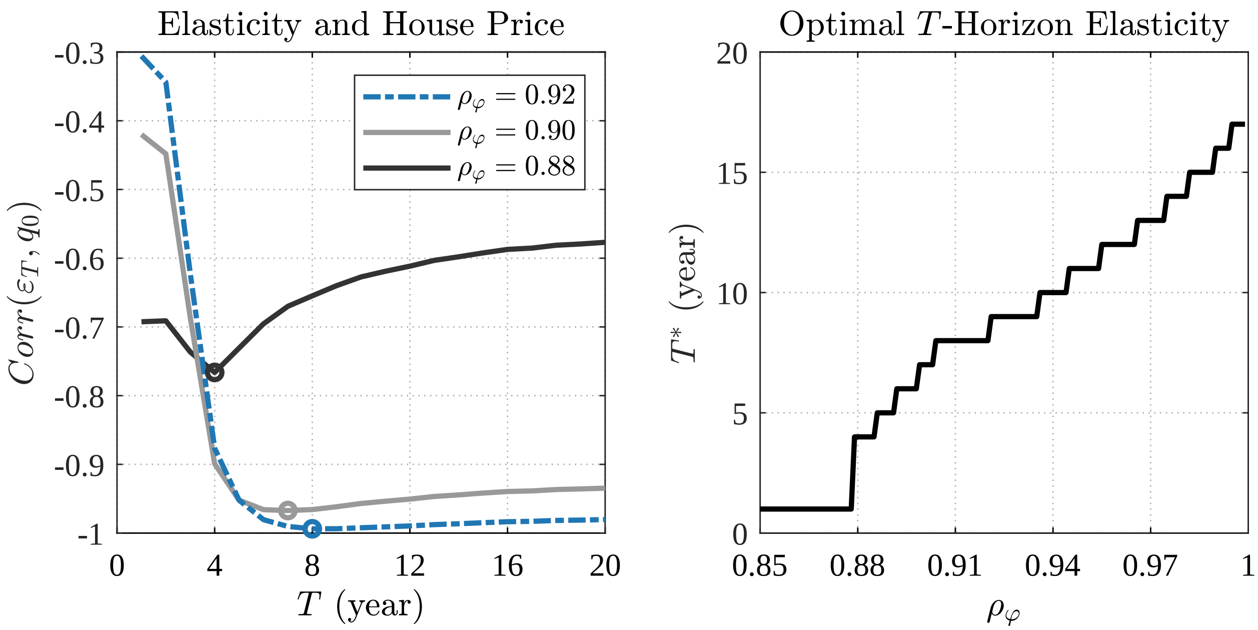

Figure 5: Short-run housing supply elasticities and house prices across counties

Note: The left panel plots the Spearman rank correlation coefficient (at each T) between a county's T-horizon housing supply elasticity and the size of its impact house price response, when each county is hit by a common housing demand shock subject to the three calibrated persistence parameters. The circle marker of each line indicates the lowest correlation coefficient for the given persistence parameter. The right panel plots the T value that is consistent with the lowest correlation between the T-horizon housing supply elasticity and the size of the impact house price response for each persistence parameter $\rho_\varphi \in (0.85, 1)$ of the common housing demand shock.

when housing demand shocks are highly persistent, long-run supply elasticities govern house price variation across counties; when shocks are transitory, short-run elasticities matter more.

Figure 5 formalizes this intuition using the local general equilibrium model's solution. For each county and each horizon T, we compute its T-horizon housing supply elasticity $\mathcal{E}_T$ and the impact house price response q_0 to a common demand shock $\epsilon_{\varphi,0}$ in equation (5.6). The left panel plots the Spearman rank correlation between $\mathcal{E}_T$ and q_0 for different persistence parameters ρ_φ. In all cases, the correlation is negative—counties with more elastic supply experience smaller price increases—but the magnitude of the correlation depends on shock persistence. When persistence is relatively high ($\rho_\varphi = 0.92$), the correlation approaches -1 for elasticities measured at horizons of seven years or more, implying that long-run elasticities capture nearly all the relevant cross-county variation. When persistence is lower ($\rho_\varphi = 0.88$), the minimum correlation occurs at shorter horizons (around four years), and the correlation with the long-run elasticity is generally weaker.

The right panel summarizes this relationship by plotting, for each ρ_φ, the optimal horizon T^* at which the correlation between $\mathcal{E}_T$ and q_0 is most negative:

$$T^*(\rho_\varphi) = \arg \min_{T\in[1,\infty)} Corr(\mathcal{E}_T, q_0(\rho_\varphi)).$$

As expected, T^* increases monotonically with persistence: highly persistent shocks correspond to long-run elasticities, while less persistent shocks are best explained by short-run elasticities.

In short, transitory shocks interact primarily with short-run frictions such as TTD, while persistent shocks engage the full long-run housing supply adjustment. In the Appendix, we confirm that this pattern remains even in a two-region general equilibrium extension with asymmetric supply conditions. Specifically, we assume that the short-run housing supply elasticity is larger in region one but that the long-run housing supply elasticity is larger in region two. Conditional on a positive common housing demand shock, we find that the impact house price response is larger in region two, but the response reverses eventually, and the medium-run house price response is larger in region one.

5.2.2 Empirical exercise

To assess the empirical relevance of our short-run housing supply elasticity in accounting for local house price variations, we focus on four episodes of the recent housing cycle: (i) the 2000s housing boom (2002–06), (ii) the 2000s housing bust (2006–09), (iii) the 2010s housing recovery (2012–19), and (iv) the COVID housing boom (2019–22). For each episode, we estimate the following relative house price regression for each horizon $T \in \{1, 2, 3, \cdots\}$:

$$\Delta \log \left(P_i/P_N\right) = \kappa_T \tilde{\mathcal{E}}_T^i + \Omega \mathbf{X_i} + u_i, \tag{5.7}$$

where the dependent variable is the log change in county i's house price index P_i relative to the national house price index P_N over the corresponding period. The regressor $\tilde{\mathcal{E}}_T^i$ is county i's $T-$horizon housing supply elasticity, standardized to have the same cross-county variation across

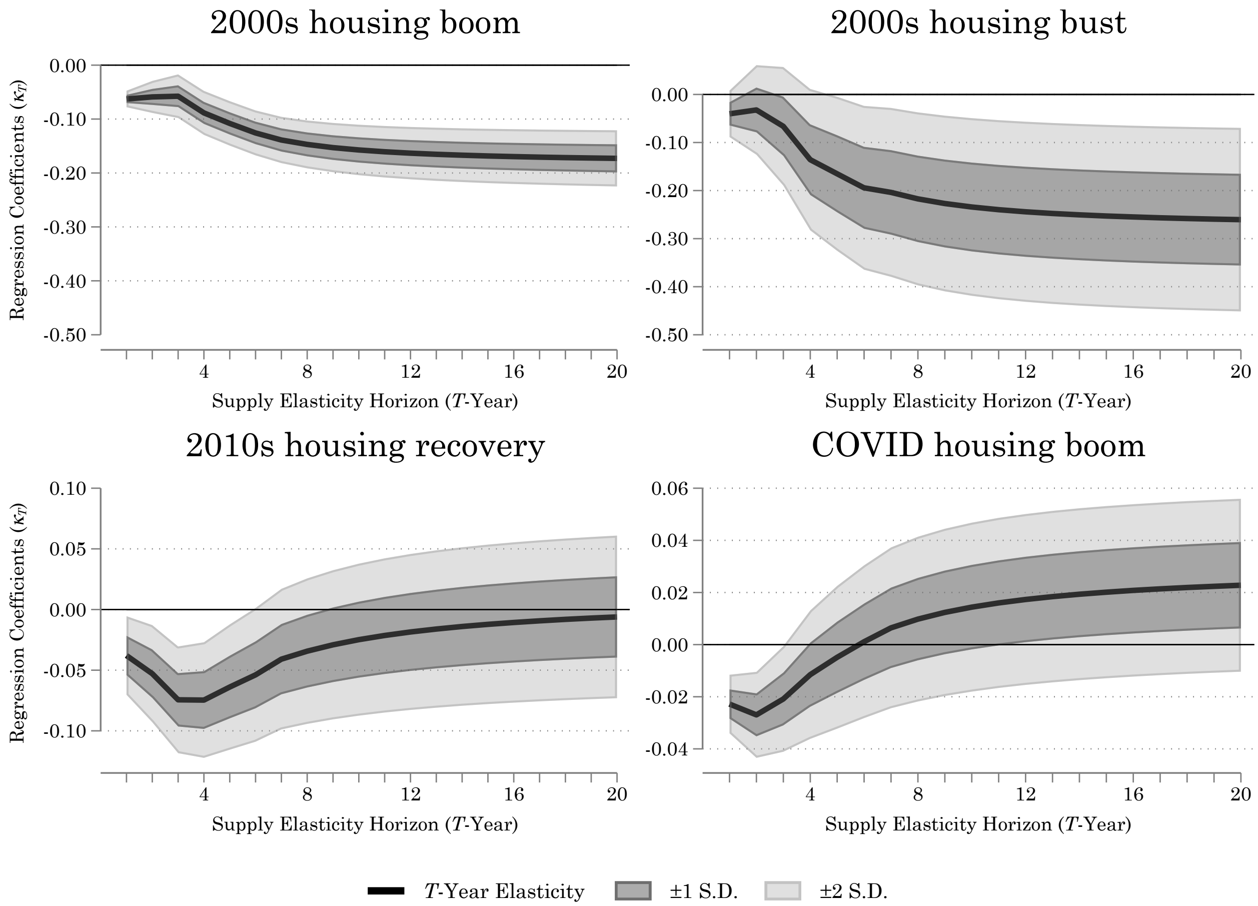

Figure 6: Relative house price regression coefficients

Note: Each figure shows the estimated coefficients for κ_T as a function of the standardized supply elasticity horizon T in equation (5.7). The confidence intervals for the 1 and 2 standard deviations of the estimates are shown as the dark gray and light gray areas, respectively. The four figures present the results using data for 2002–06 (top left panel), 2006–09 (top right panel), 2012–19 (bottom left panel), and 2019–22 (bottom right panel). We include indicators for sand states and coastal states, population density, and county-level real GDP growth as controls and use robust standard errors for the confidence intervals.

T. We allow for a set of control variables (including a constant), $\mathbf{X_i}$, as well as a residual term, u_i, that captures other unmodeled drivers of the relative house price. Since a higher elasticity should dampen price sensitivity to shocks, we expect $\kappa_T < 0$.

Figure 6 reports the estimation $\kappa_T < 0$ coefficients for each horizon and episode. During the 2000s housing boom and bust, the long-run elasticity has stronger predictive power for house price changes, with more negative coefficients than short-run elasticities. In contrast, during the 2010s housing recovery and the COVID housing boom, the short-run elasticity outperforms the long-

Table 6: Horse race between short- and long-run elasticities across housing cycles

Panel A. OLS	Dependent variable: House price change			
	2002–06	2006–09	2012–19	2019–22
Three-year elasticity	0.072	0.171	−0.194***	−0.069***
	(0.050)	(0.120)	(0.057)	(0.023)
Long-run elasticity	−0.262***	−0.425***	0.098*	0.066***
	(0.048)	(0.134)	(0.057)	(0.024)
Local controls	✓	✓	✓	✓
Observations	224	224	224	224
R-squared	0.626	0.673	0.482	0.550

Panel B. IV (Heat exposure)	Dependent variable: House price change			
	2002–06	2006–09	2012–19	2019–22
Three-year elasticity	0.024	1.517**	−0.298*	−0.560***
	(0.183)	(0.615)	(0.152)	(0.150)
Long-run elasticity	−0.243***	−1.012***	0.141*	0.280***
	(0.087)	(0.268)	(0.074)	(0.069)
Local controls	✓	✓	✓	✓
Observations	223	223	223	223
First-stage F-stat	20.48	23.23	23.64	20.49

Notes: Each column corresponds to a different subsample period. The dependent variable is the county-level house price change. Three-year and long-run housing supply elasticities are jointly included in each regression. Standard errors (in parentheses) are robust to heteroskedasticity. We include indicators for sand states and coastal states, population density, and county-level real GDP growth as controls. Panel A reports ordinary least squares (OLS) estimates, and Panel B reports two-stage least square (2SLS) estimates using heat exposure as the instrument for the three-year elasticity. *** p<0.01, ** p<0.05, * p<0.1.

run elasticity. The estimated coefficients on short-horizon elasticities (particularly at 3–4 years) are negative and statistically significant, while those on long-run elasticities are positive and not distinguishable from zero.

Table 6 formalizes this comparison. We conduct a "horse race" between the three-year (short-run) and long-run elasticities by including them jointly in the same regression. Panel A reports the results. Consistent with the findings above, the long-run elasticity is more relevant in the 2000s boom and bust, while the short-run elasticity becomes dominant in the 2010s recovery and the COVID boom. Panel B presents the two stage least squares results, where the three-year elasticity is instrumented with county-level heat exposure to mitigate endogeneity concerns.[14] The main findings remain robust.

Through the lens of our model, these results imply that both the positive housing demand shock in the 2000s boom and the negative housing demand shock in the 2000s bust were perceived as highly persistent, leading to the higher relevance of the long-run elasticity in accounting for house prices. After the 2000s housing cycle, however, agents might have expected the 2010s recovery to be less persistent, possibly reflecting on the recent housing boom experience, which then made the short-run elasticity more relevant to account for house prices. That is, even in a location where the long-run elasticity is high and buildable land is plentiful, residential developers in the 2010s might have thought that if TTD is too lengthy, pursuing new development is not as worthy as before due to concerns that the positive demand could quickly reverse course. The same goes with the COVID boom, where developers might have continued to believe that the higher housing demand induced by the greater flexibility of work-from-home would not last once the virus was under control.

We note some caveats to the empirical analysis. First, the estimated regression coefficients since the 2010s are smaller in absolute value compared to the 2000s. It is indeed likely that national housing shocks played a limited role since the 2010s amid location-specific shocks in the housing market. Second, TTD could have shifted especially during the COVID boom when there were known bottlenecks to construction, such as the shortage in lumber. While we think these bottlenecks were widespread across the country and did not meaningfully affect the *relative* TTD across locations, if TTD was disproportionately shifted in several locations to the extent that the overall TTD rankings were significantly changed, then our results should be taken with more caution.

[14]Identification relies on the assumption that, conditional on long-run elasticity and other county controls, variation in average heat exposure affects house price growth only through its impact on construction delays and the resulting short-run supply elasticity.

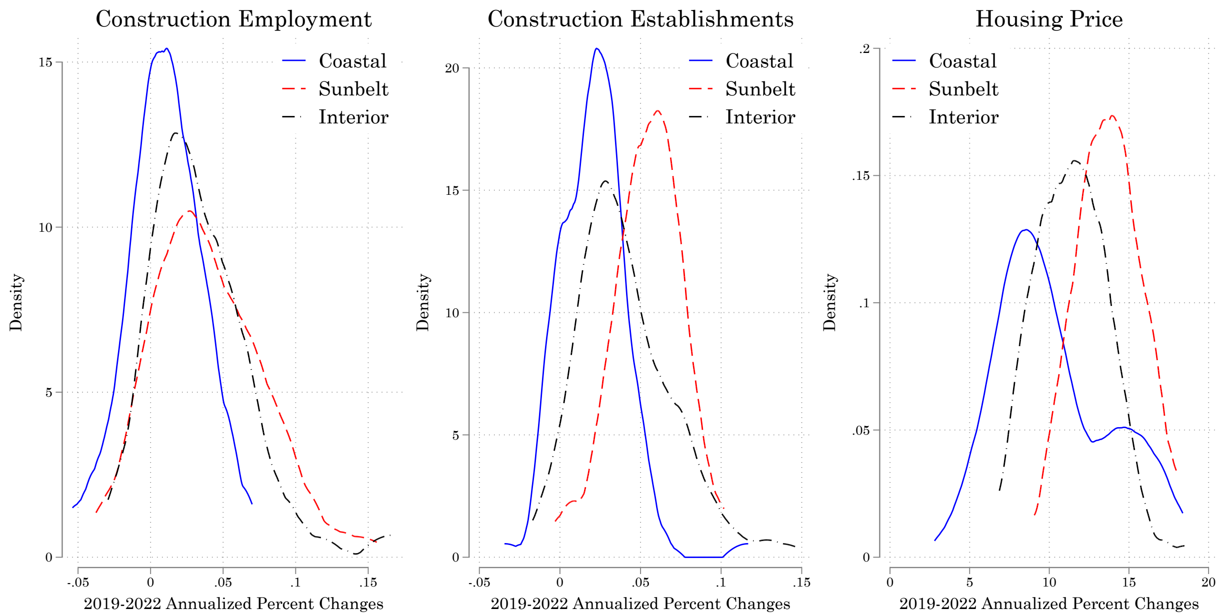

Figure 7: Distribution of growth rate variables by region

Note: The panels show the kernel density plots of the 2019-22 annualized growth rate of construction employment (left panel), construction establishments (middle panel), and house price (right panel) for the three regions. The total sample is 230 counties for which our TTD data exist. Construction employment and establishment data are taken from the quarterly census of employments and wages by the Bureau of Labor Statistics and house price data are taken from the Federal Housing Finance Agency.

5.3 TTD and housing dynamics of the Sunbelt

Existing measures of housing supply elasticity, such as Saiz (2010), suggest that supply is more elastic in Sunbelt markets than in coastal areas. Under this view, a positive housing demand shock should generate a larger increase in construction activity and a smaller increase in house prices in the Sunbelt relative to the coastal region. However, this prediction has been increasingly difficult to reconcile with recent data. For example, although the Sunbelt experienced a substantial rise in construction-related activity—such as employment and firm entry—during the COVID period, house price growth in the Sunbelt was also higher than in coastal markets (Figure 7). Consistent with this puzzle, Glaeser and Gyourko (2025) document unusually strong recent house price increases in major Sunbelt metros and argue that supply-side constraints, rather than elevated demand along, played a central role.

We use the rich dynamics of our local general equilibrium TTD model to illustrate how TTD can help explain the puzzling relative housing dynamics of the Sunbelt. As a stylized exercise, we consider two regions that differ only in their long-run housing supply elasticity—an elastic-supply region and an inelastic-supply region—while assuming the same TTD of 11 quarters in both. We solve the model using a second-order approximation to the policy functions and conduct two experiments.

First, we examine the response to a positive housing demand shock when both regions are initially at their respective steady states, with housing stocks in long-run balance. Second, we study the same shock when both regions begin from a state of housing shortage, with housing stocks and construction activity below steady-state levels. These two experiments reveal how TTD interacts with regional supply elasticities and how it can generate housing dynamics consistent with the recent experience of the Sunbelt in response to demand shocks.

Figure 8 reports the impulse responses of construction variables to a positive housing demand shock under the first experiment, in which both regions begin at their respective steady states. The top-left panel shows permit issuance, which rises immediately in both regions following the shock. As expected from the standard *level effect* of supply elasticity, the increase in new permits is larger in the elastic-supply region. This translates into higher total construction activity for roughly three years (top-right panel), reflecting the stronger long-run supply response in that region. Importantly, however, because of TTD, these increases in construction activity do not translate into housing supply on impact.

The introduction of TTD also generates what we call the *slope effect* of the supply elasticity: because TTD lowers the short-run elasticity relative to the long-run elasticity, it creates a positive slope of the supply elasticity over time. This, in turn, affects developers' intertemporal investment decisions, as the marginal return to allocating variable inputs differs across time. Developers in each region operate multiple projects at different stages, and they optimally allocate inputs across these projects depending on expected gains.

In the elastic-supply region, the positive demand shock leads to a much larger increase in permit supply. This implies a steeper intertemporal profile of marginal gains, strengthening developers'

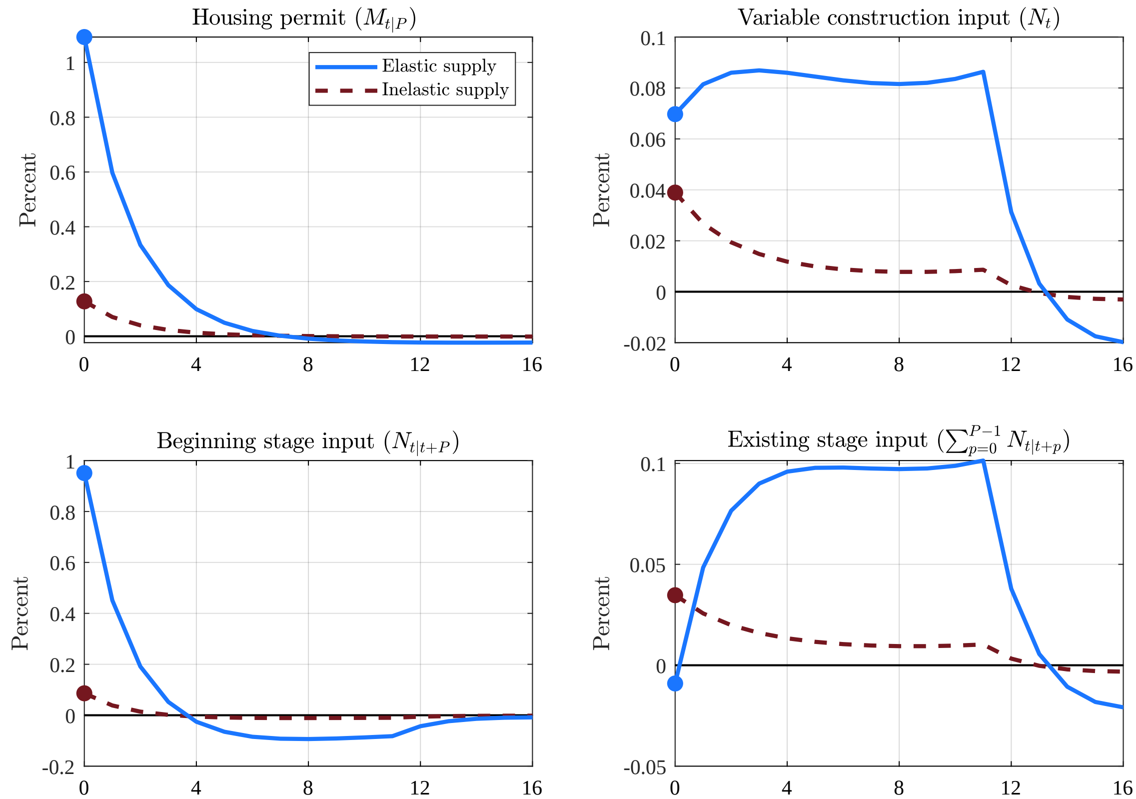

Figure 8: Impulse responses of construction variables to a positive demand shock

Note: This figure shows the generalized impulse responses of construction variables to a positive housing demand shock, for both the elastic supply (long-run elasticity: 3) and inelastic supply (long-run elasticity: 0.9) regions. The initial housing stock and construction variables are set at their respective steady state values and the housing demand shock is assumed to have a persistence of 0.6.

incentive to shift resources toward new projects that benefit from the higher permit availability. As shown in the bottom-left panel, investment in new projects rises sharply in the elastic-supply region, crowding out investment in existing projects with permits closer to steady-state levels.

In contrast, developers in the inelastic-supply region fact a much smaller increase in permit supply, and therefore a weaker intertemporal substitution motive. Because the marginal gains from investment in new projects rise only modestly, developers allocate relatively more inputs toward projects that are already underway. As shown in the bottom-right panel, the investment rate for existing-stage projects is higher in the inelastic-supply region even though total construction inputs rise more in the elastic-supply region.

These dynamics illustrate how TTD interacts with long-run supply elasticity to produce differ-

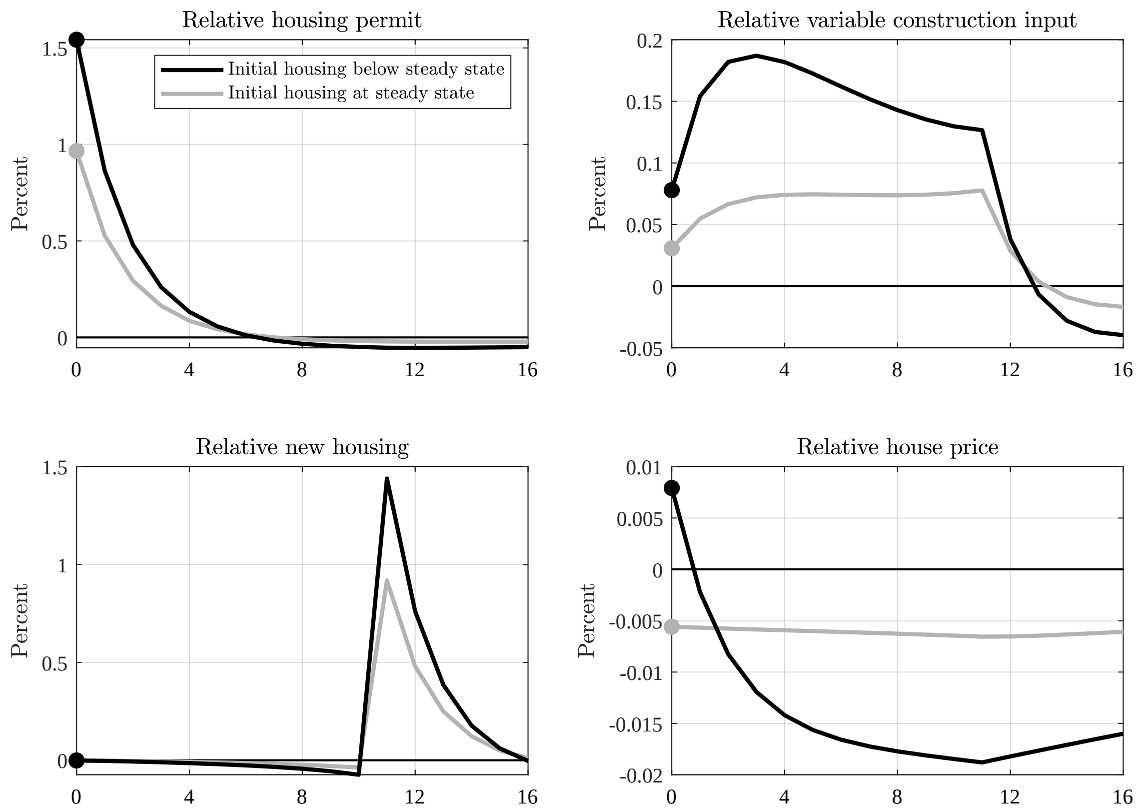

Figure 9: Impulse responses of elastic/inelastic housing variables to a positive demand shock

Note: This figure shows the generalized impulse responses of the relative housing variables between the elastic and inelastic supply regions to a positive housing demand shock. The initial housing stock and construction variables are set at their respective steady state values for the gray line and at 30 percent below their steady state values for the black line. The housing demand shock is assumed to have a persistence of 0.6.

ent short-run construction responses to an identical demand shock.

Figure 9 plots the relative housing dynamics between the elastic- and inelastic-supply regions. The gray lines in the top panel show the difference between the two regions' housing permit and variable input responses from Figure 8, while the gray lines in the bottom panel show the relative responses of new housing supply (I_t) and house prices (q_t). As discussed above, even though the elastic region experiences higher permit issuance and higher total construction inputs, relative new housing supply remains negative for roughly 10 quarters and turns positive only later as investment in existing projects has been crowded out in the elastic region. Because near-term new housing supply remains relatively low in the elastic region, there is an upward pressure on relative house prices compared to a model without TTD. However, the relative house price remains negative because the reversal effect generated by TTD is not sufficient to counteract the differential long-run supply responses implied by the regions' long-run elasticities.

Turning to the second experiment, in which the positive housing demand shock occurs during a housing-shortage state, the black lines in Figure 9 report the same relative impulse responses as the gray lines but starting from a state where both regions' existing housing stock and units under construction are below their steady-state levels.[15] This experiment allows us to examine how the response to a demand shock varies when the economy is already experiencing a shortage. In this case, the effects are amplified: the relative permit response and the relative increase in total inputs are even larger when the shock hits during a shortage. Intuitively, when demand surges in the midst of an ongoing shortage in both regions, the elastic region's permit issuance and construction activity rise even more strongly than in the inelastic region. As the slope effect strengthens, near-term relative housing supply becomes even more negative, and—unlike in the first experiment—the relative house price turns positive on impact.

Discussion. Our model experiments suggest that the combination of TTD and a housing-shortage environment can generate both a relative boom in construction activity and a temporary increase in the relative house price in the elastic region following a positive housing demand shock. The upward pressure on the relative house price in the elastic region operates through three channels.

First, the level effect of TTD raises near-term relative house prices because elevated construction activity in the elastic region is no longer associated with an immediate increase in new housing supply that would otherwise ease prices, while construction costs still rise. Second, the slope effect generated by TTD creates a steeper relationship between short-run and long-run supply elasticities in the elastic region. As a result, construction activity shifts more aggressively toward newly permitted projects, crowding out resources for projects already under way. This further widens the short-run gap between construction activity and new housing supply, putting additional upward pressure on relative house prices in the elastic region. Third, TTD interacts with the hosuing-

[15] We generate state-dependent impulse responses by solving the model using second-order approximation to the policy functions.

shortage stage by amplifying the slope effect: when the shock arrives during an ongoing shortage, developers' intertemporal substitution motive becomes even stronger, and the resulting gap between construction inputs and new supply becomes even larger, pushing relative house prices upward on impact.

Because the Sunbelt region closely resembles the elastic region in our model experiments, we argue that TTD provides a useful friction that can help rationalize the puzzling rise in house prices in the Sunbelt despite a construction boom. Moreover, TTD tends to be longer in the Sunbelt than in coastal areas, which reinforces the three mechanisms described above and strengthens the upward pressure on relative house prices in response to a demand shock.

We note that these channels are qualitative, and further work is needed to quantitatively match the observed relative house price dynamics. Our treatment of the housing demand side is intentionally stylized to make the mechanisms of TTD transparent. In richer environments, demand-side frictions—such as search costs, mortgage financing constraints, or deviations from rational expectations—may amplify or dampen the effects we highlight. With these caveats, our analysis provides a formal underpinning for the idea that long-run supply elasticities can be consistent with richer short-run housing dynamics once TTD-style frictions are incorporated, substantiating the argument in Guren et al. (2020).

5.4 The effectiveness of housing supply policy in stabilizing house prices

A rapid increase in house prices raises concerns of policymakers, as these developments could subsequently lead to outsized drops in those prices that amplify stress in the financial system and the broader economy. As such, stabilizing house prices is a key objective of policymakers, and various measures are discussed and implemented in practice. In this part, we study the effectiveness of the government's discretionary housing supply policy as a tool for house price stabilization when TTD is taken into account.

Before the analysis, we clarify what we mean by discretionary housing supply policy. As summarized in Glaeser and Gyourko (2008), new construction in the U.S. is regulated in terms of building codes and land-use rules. In particular, there are numerous examples of land-use regulations that directly limit housing supply across regions, such as minimum lot size requirements, height restrictions, or growth-control policies. The discretionary housing supply policy we have in mind is a temporary relaxation of these existing land-use regulations, as in practice, new development could receive a waiver to some of the regulations.

To be specific, we modify the local government's permit supply assumption in equation (2.5) to the following:

$$M_{t|t+P} = v_t \bar{M} q_t^{\gamma}, \qquad \log v_t = \rho_v \log v_{t-1} + \varepsilon_t^v,$$

where the variable v_t indicates the government's discretionary housing supply policy that follows a first-order autoregressive process in logs.

Figure 10 plots the impulse response functions of the house price, cumulative housing construction (as a percentage of the initial housing stock), and housing permits conditional on a discretionary permit supply shock that increases the 10-year (40-quarter) cumulative construction by 2 percent of the housing stock. Compared with the result when TTD is assumed to be zero, a positive discretionary housing supply policy is somewhat less effective in reducing house prices in the short run when TTD is set at the national median of 11 quarters. Note that the peak decline in house prices occurs at around two to three years with TTD, compared with the peak decline at around one year without TTD. This difference implies that a discretionary housing supply policy with TTD could be an effective tool to stabilize house prices in the medium run through its effects on forming expectations about future supply conditions. As the literature finds that house prices tend to show momentum in the short to medium run, these discretionary supply policies could be effective in countering that momentum by controlling the expectations of future supply under the TTD commitment.

In conclusion, setting aside the political constraints in implementing a discretionary housing supply policy, we find that lengthy TTD might also somewhat limit its effectiveness in stabilizing

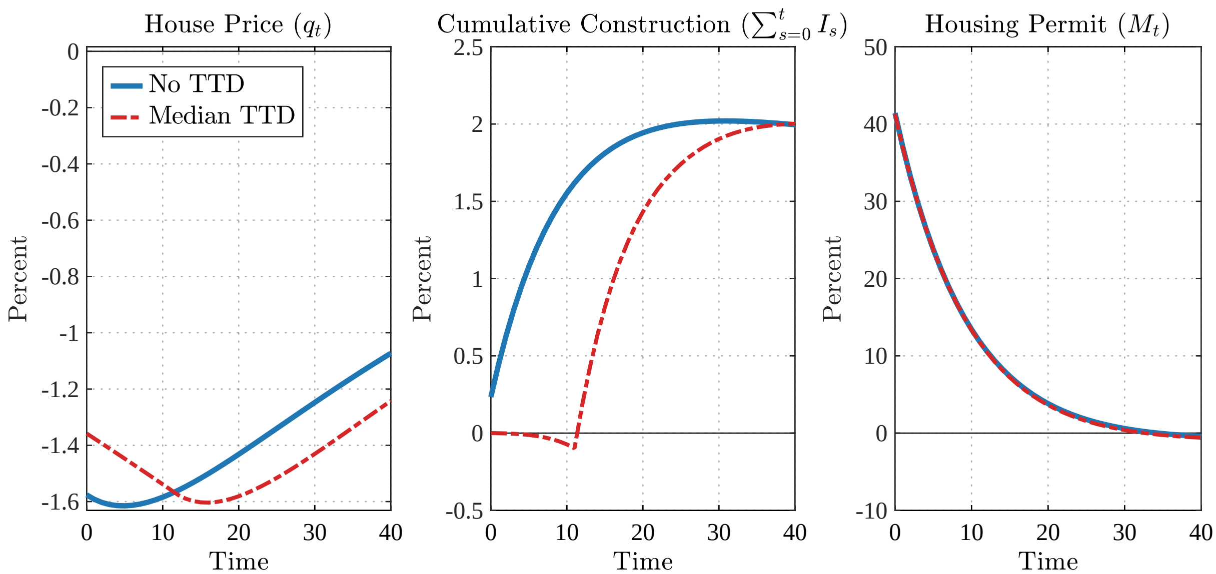

Figure 10: Model responses to a discretionary permit supply shock

Note: This figure shows the impulse responses of house price (left panel), cumulative housing construction as a percent of the initial housing stock (middle panel), and permit supply (right panel), to a discretionary permit supply shock with 0.9 persistence. We compare the model responses without TTD (blue solid lines) and those with the median TTD constraint (red dashed line). The size of the permit supply shocks in both models are scaled to have the same cumulative construction response at 40 quarters.

house prices in the short run. While a discretionary housing supply policy to stabilize house prices might not have been a discussion at the national level in the U.S., this policy was implemented in Korea to tackle surging house prices in early 2021.[16] Our analysis suggests the potential challenges of such a policy when TTD is lengthy. Of note, a nationwide housing supply policy is likely to interact with the interest rate, which is not allowed in the above experiment using a local general equilibrium model.

6 Conclusion

In this paper, we use a TTD model of housing investment to formulate a link between short- and long-run housing supply elasticities and analyze TTD for residential development across the U.S. using a unique data set. We then quantify frictions to housing supply over the business cycle across

[16]See Cynthia Kim (2021), "S. Korea to Boost Seoul Housing Supply by 10% to Calm Buying Frenzy," *Reuters*, February 4, https://news.trust.org/item/20210204030650-r2wji.

major counties and draw their implications for housing market dynamics through a local general equilibrium model.

As we stated, a comprehensive process for land development takes about three years, on average, in the U.S. This feature alone introduces a large difference between the short- and long-run housing supply elasticities. In this paper, we adopt insights from the investment adjustment cost literature to shed light on the role that lengthy and dispersed TTD could play on housing market dynamics. Toward that objective, we abstract from several features of the data set that might be useful for future research. First, one could explore the time-varying nature of TTD, especially during the recent periods. While Oh and Yoon (2020) study the cyclical pattern of time-to-build in the context of the 2002–2011 housing boom-bust cycle, its lower frequency trend could also be explored in the context of understanding the half century decline in construction-sector productivity (Goolsbee and Syverson, 2023). Second, our TTD regression results suggest that geographic determinants could play a key role in construction activity. As most construction activity is still conducted on site, climate change and environmental regulation would also have a first-order effect on the construction sector. We hope that our modeling framework as well as our granular TTD data open up a new avenue of research along these lines.

Declaration of generative AI and AI-assisted technologies in the manuscript preparation process

During the preparation of this work, the authors used Chatgpt in order to copyedit. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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