# Land development and frictions to housing supply over the business cycle<sup>\*</sup>

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#### Abstract

Using a novel dataset on U.S. residential land development, we document that the average time-to-develop (TTD) for residential properties—which includes both the time spent preparing land infrastructures and construction—is about three years, with significant geographic variation. Incorporating these lengthy and dispersed TTDs into a housing investment model, we find that short-run housing supply elasticities differ markedly from long-run elasticities, influencing housing market dynamics over the business cycle. Our empirical analysis reveals that short-run elasticities can account for local house price variations more effectively than long-run measures during the 2010s housing recovery and the COVID housing boom. Furthermore, we demonstrate through our model that regions with a wider gap between the short- and long-run elasticities via lengthy TTD experience delayed supply responses, limiting the immediate effectiveness of supply policies aimed at stabilizing house prices but enhancing their medium-term impact.

**Keywords:** Housing supply; house price dynamics; residential investment. **JEL Classification Numbers:** E22, E32, R31.

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## **1** Introduction

Researchers have long emphasized significant adjustment costs in standard investment models to account for the empirically observed lag in investment responses to economic shocks. Because ships and factories cannot be built in a day, these adjustment costs are typically motivated as stand-ins for the time it takes to produce new capital and the difficulties in adjusting investment plans once they are in train. A strand of literature on the housing market also highlights inelastic short-run housing supply as a sensible feature to explain the dynamic properties of the housing market, such as the difference in the short- and long-run housing market reactions to COVID-19 (Howard, Liebersohn and Ozimek, 2023).<sup>1</sup> Quantitatively, little is known, however, about the precise time it takes to develop residential properties and its implications for housing market adjustments over time.

In this paper, we document the time it takes to build a house from undeveloped piece of land across regions using a new dataset and study its aggregate and cross-regional implications using a model of investment dynamics. A desirable feature of our dataset is that we observe the time it takes not only to build structures on a developed lot but also to develop land in-frastructure on a vacant, undeveloped piece of land. Accordingly, we are able to analyze the *comprehensive* process of residential construction across major U.S. regions.

Empirically, we document two key patterns in land development. First, residential land development is indeed a lengthy process that takes more than three years, on average, after receiving a preliminary approval of the site plan from the local government, including more than a year, on average, to develop raw land with a subdivision map into a lot on which structures could be built. Second, the time it takes to develop land is highly dispersed across locations, even after controlling for an extensive list of variables that are likely to affect local construction demand. In turn, we find that a county's median time to develop (TTD) is associated not only with a measure of its long-run housing supply elasticity, but also with adverse local weather conditions that hinder construction activity in the short run. This information suggests that local factors that determine TTD are not fully aligned with the local factors that determine housing supply in the long run.

We then use the local variations in TTD to quantify the local housing supply elasticity, a measure that has taken center stage in the macro-housing literature. As housing wealth is about one-third of the total net worth of U.S. households, house price changes have significant spillover effects to the broader economy and estimates of the housing supply elasticity are

<sup>&</sup>lt;sup>1</sup>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).

frequently used to decipher the causal effect of house price changes to economic activity.<sup>2</sup> While the existing estimates of the housing supply elasticity mainly focus on the long-run determinants of housing supply, we show that TTD helps quantify the housing supply elasticity more relevant for the evolution of housing supply within the next five years. Towards that, we elaborate a housing investment model with TTD and derive analytical expressions that relate the short-run (up to five years) housing supply elasticity to TTD and the long-run housing supply elasticity. Combining the model and the data, we find that short-run housing supply elasticities vary significantly across counties and are indeed smaller than, and distinct from, corresponding long-run elasticities.

We show that the consideration of relatively long and dispersed TTD in an otherwise standard local general equilibrium model of housing investment helps rationalize two recent empirical facts on the housing market. 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, when the TTD friction is included, our model is capable of generating both a relative construction boom and a relative house price increase in an elastic supply region, in line with the recent housing market experience of the sunbelt compared to the coastal region. Intuitively, as the short-run elasticity is low in all regions with the introduction of TTD, the slope of the elasticity over time is steeper in the elastic supply region. As such, developers in the elastic supply region face a stronger intertemporal substitution motive for investment across different stages of construction, and when they face higher demand for housing, they bunch investment for new projects which crowds out investment for existing projects. This endogenous slowdown of the short-run housing supply in response to a positive housing demand shock puts an upward pressure for house prices in the elastic supply region.

Finally, we draw a policy implication by conducting a counterfactual exercise where the government aims to stabilize house prices by a discretionary housing supply policy. When

<sup>&</sup>lt;sup>2</sup>According to the 2022 financial accounts of the United States from the Federal Reserve Board's flow of funds statistics, the total real estate at market value for households and nonprofit organizations is 47.1 trillion dollars and the net worth of households and nonprofit organizations is 143.7 trillion dollars.

TTD is present, we find that government incentives to boost the housing supply affect house prices through the expectations channel of future housing supply. Therefore, the policy could be somewhat less effective in immediately stabilizing house prices for regions where land development takes a long time, but it could be more effective in stabilizing medium-run house prices for those regions.

Related literature. Studies on housing supply mainly focus on estimating its long-run determinants (Saiz, 2010; Lutz and Sand, 2022; Baum-Snow and Han, 2024), and these estimates are typically used to identify regional variations to economic shocks (Mian, Rao and Sufi, 2013; Mian and Sufi, 2014; Davis and Haltiwanger, 2019; Bhattarai, Schwartzman and Yang, 2021; Aastveit, Albuquerque and Anundsen, 2023). This approach could be problematic when the economic shock of interest does not persist in the long run and when the short-run determinants of housing supply differ from the long-run estimates. For example, Guren, McKay, Nakamura and Steinsson (2020) suggest that a puzzling feature of the cross-regional housing price and quantity correlation discussed in Davidoff (2016) could be potentially resolved by assuming a lower short-run housing supply elasticity in all regions. Not much is known, however, about the determinants of housing supply elasticity at business cycle frequencies, with notable exceptions such as Topel and Rosen (1988), who estimate short- and long-run housing supply elasticities and find that most of the long-run response occurs within a year, and Gorback and Keys (2020), who exploit variation in international capital flows to ethnic neighborhoods to estimate short-run supply elasticities across the largest 100 U.S. metro areas and find substantial spatial heterogeneity. We contribute to this literature by (i) quantifying frictions to housing supply at a business cycle frequency based on the observed duration of land development and (ii) studying the implications of our quantified frictions on the housing market through an equilibrium model of housing investment. By investigating the link between new housing supply data and the elasticity of housing supply, we also complement the literature that studies the sensitivity of local economic activity to house prices (Guren, McKay, Nakamura and Steinsson, 2021; Graham and Makridis, 2023). Research in this topic identifies plausibly exogenous house price variations by focusing on variables of the local economy or existing housing characteristics; 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 implica-

tions 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). 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 present the land development data and estimate a TTD measure that is comparable across regions by controlling for various factors. In Section 3, we develop a TTD model of housing investment and analytically derive housing supply elasticities in each horizon. 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 Duration of land development across regions

In this section, we use a unique dataset that tracks development activities for residential properties in the U.S. to measure the duration of land development across regions. The desirable feature of our dataset is that it includes the period of site development prior to building construction.

We show that the duration of land development that includes the period of site development

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

Table 1: New housing completions between 2003 and 2019

is lengthy and varies widely across regions. These variations persist even after controlling for a number of observable regional demand factors.

#### **2.1** Land development data and summary statistics

Our main source of data is Zonda, which provides data and analysis to the national residential home-building industry. The dataset 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 dataset displays the total number of housing units as well as other construction characteristics by sections. We have access to this dataset from 2000 to 2021.

As shown in Table 1, our dataset includes a large number of new housing supply across the U.S. Between 2003 and 2019, the dataset contains 222,868 developed sections with a total of 7.8 million units of new housing. 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 dataset. Our dataset is not biased toward multi-unit housing development, as the Census coverage of single-unit housing completion is also around 39 percent.<sup>3</sup> 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.<sup>4</sup>

Besides the high coverage ratio, a desirable feature of the dataset is that it continuously tracks the construction status of subdivisions and sections. Land development is a lengthy process, starting from the acquisition of land by developers and the design of a development

<sup>&</sup>lt;sup>3</sup>In our dataset, single-family housing units comprise 82.6 percent of the completions, followed by town-houses (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.

<sup>&</sup>lt;sup>4</sup>Of the top 20 CBSAs ranked by the 2020 Census population, only 2 CBSAs (Boston and Seattle) are not included in our dataset.

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 dataset 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, such as the site having survey stakes or equipment. 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 dataset 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 dataset 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. Our definition for the beginning quarter of TTD fully takes this feature on board; in the Appendix, we present results using an alternative definition for the beginning quarter of TTD.<sup>5</sup> 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.

<sup>&</sup>lt;sup>5</sup>Our baseline definition is also driven by data availability. In the dataset, the preliminary approval date is missing for many sections, which limits our sample size substantially. In the Appendix, we provide details on how we measure the beginning quarter of development.

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

Table 2: Summary statistics for section-level TTD

*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.

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.<sup>6</sup> We further dropped 16,133 observations without lot size information or demand controls, leaving us with 104,426 observations.

### 2.2 Stylized facts on the duration of housing development

The total time it takes for housing development (TTD) comprises two parts: time to develop infrastructure at the site (site TTD) and time spent on the construction of buildings (building TTD). Just by looking into the raw measures of TTD based on Table 2, we find two stylized facts on the duration of housing development that stand out.

First, housing development is a lengthy process with significant time spent on land development. As shown in the first row of the table, housing development takes a total of 1,274 days on average. While less emphasized in the literature because of limited data availability, we find that the duration between the land development plan approval and the finishing of

<sup>&</sup>lt;sup>6</sup>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 dataset. 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 dataset.

site development is substantially long, averaging 573 days. The mean construction time of buildings on these developed sites is 701 days.

Second, there is substantial heterogeneity in the duration of housing development. The standard deviation and the interquartile range of total TTD are both around three years (1, 082) days and 1,005 days, respectively). The significant heterogeneity is also pronounced in site TTD, as its standard deviation is more than two years.

Note that the distribution of TTD is skewed to the right, as the mean is larger than the median in all TTD measures. This finding is also evident from the lengthy TTD at the 90th percentile.

#### 2.3 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 dataset 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 0.14 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 economic 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 local controls potentially relevant for housing supply—such as a Bartik-type variable that measures the local demand pressure,

Variables	(1)	(2)	(3)
Log(number of units)	0.140***	$0.145^{***}$	0.142***
-	(0.00425)	(0.00429)	(0.00415)
Log(lot size)	$0.146^{***}$	0.153 ***	0.151 ***
	(0.00489)	(0.00506)	(0.00498)
Single family	_	_	_
Townhouse	0.208***	0.199***	0.190***
	(0.0113)	(0.0117)	(0.0116)
Condo	$0.181^{***}$	0.208 * * *	0.221***
	(0.0419)	(0.0423)	(0.0413)
Duplex	0.0343	0.0310	0.0331
	(0.0318)	(0.0319)	(0.0309)
Etc.	0.00885	0.0190	0.00804
	(0.0261)	(0.0260)	(0.0243)
Builder fixed effect	$\checkmark$	$\checkmark$	$\checkmark$
Year fixed effect	$\checkmark$	$\checkmark$	$\checkmark$
Local controls		$\checkmark$	
Local controls $\times$ Year			$\checkmark$
Constant	4.341***	4.455***	5.439***
	(0.0515)	(0.0846)	(0.172)
Observations	104, 426	104, 426	104, 426
R-squared	0.272	0.277	0.303

Table 3: Section TTD regression results

*Note:* Regression with 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. Robust standard errors are reported in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

population shares of immigrants and college-educated adults, and population density—as suggested in Davidoff (2016). We also include the annual county-level GDP in the regression to control for any country-level time-varying economic factors. 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

(unit: days)	Raw TTD	Reg. (1)	Reg. (2)	Reg. (3)
Mean	970	911	917	919
Std. dev.	425	302	305	293
IQR	365	376	363	342
P10	638	532	551	591
P25	731	719	732	741
P50	914	889	900	899
P75	1,096	1,095	1,095	1,083
P90	1,279	1,296	1,275	1,295
Observations	267	267	267	267

Table 4: Summary statistics for county-level TTD

*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.

independent role after taking into account the developer's choice of construction characteristics.

The third column of Table 3 allows for additional flexibility in the time-varying response of TTD to local economic factors by interacting the time-invariant local controls with year fixed effects. While the R-squared moderately improves to 30.3 percent, the regression coefficients on construction characteristics remain relatively robust across all three specifications.

#### 2.4 County-level TTD

Using the regression results in Table 3, we now construct the county-level TTD for the representative housing. That is, we normalize TTD for each section by assuming that the controlled observables are at their national average values and add the fitted residuals. We then take the median of this value for each county of interest. Note that we use the median instead of the mean, as the distribution of TTD is skewed to the right. Moreover, the median TTD should be relatively insensitive to any remaining time-varying demand factors of TTD, such as the fat right tail in construction time during the Great Recession (Oh and Yoon, 2020).

Table 4 presents some cross-county moments of each county's measure of TTD. In the first column ("Raw TTD"), we observe that the average of the county-level TTD using raw section TTD data is almost the same as the average of the section TTD itself. The standard deviation and the interquartile range are sizable at 425 days and 365 days, respectively. The second

to fourth columns present the same statistics using the controlled TTD estimates in Table 3. Controlling for construction characteristics and focusing on a nationally representative housing development, we find that the cross-county mean TTD is 911 days or about two and a half years. The standard deviation and the interquartile range are also sizable at around one year. Results for the third and fourth columns are similar to those of the second column, consistent with the R-squared results in Table 3, suggesting that after one controls for construction characteristics, the marginal contribution of local demand factors is limited.

### 2.5 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 significant degrees of crossregional variation even after controlling for construction characteristics and local economic factors. Based on the described process of land development, we then ask whether any observable geographic differences in engineering challenges could account for that variation. Some of the geographic differences could be highly correlated with factors that determine long-run housing supply described in Saiz (2010), but other geographic differences that do not play a major role in accounting for the long-run housing supply could nevertheless matter for the duration of land development. For example, each location is exposed to different weather conditions that might not materially affect the decision to develop land but might still matter for the cost and duration of land development. That is, locations with extreme storm and heat conditions could still be desirable for new construction, but severe weather will occasionally delay on-site construction activity and the developer's building design to tolerate extreme weather conditions might further lengthen the development process.

Table 5 displays the regression result using our controlled TTD measures and the observed

Variables	Reg. (1)	Reg. (2)	Reg. (3)
Saiz elasticity	$-0.172^{***}$	$-0.153^{***}$	$-0.134^{***}$
	(0.045)	(0.047)	(0.043)
Rainfall intensity	$0.135^{***}$	$0.125^{***}$	0.117***
	(0.025)	(0.025)	(0.024)
Heat	0.015	0.020	0.018
	(0.022)	(0.023)	(0.023)
Observations	224	224	224
R-squared	0.201	0.178	0.162

Table 5: County-level TTD regression results

*Note:* We use counties with at least 10 completed sections observed. "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). "Heat"—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). Robust standard errors are reported in parentheses. \*\*\* p < 0.01, \*\* p < 0.05, \* p < 0.1.

geographic determinants described in this section. Both the long-run housing supply elasticity and rainfall intensity affect TTD in a statistically significant sense. That is, the duration of land development is longer for locations where (i) the long-run housing supply is limited and (ii) rainfalls are more intense, more frequent, or both. Heat also delays TTD, but its statistical significance is not pronounced. A careful study of these engineering challenges is beyond the scope of this paper, but the significance of these geographic determinants in accounting for the variation in TTD across locations suggests the potential of our controlled TTD measure to reflect plausibly exogenous variations to economic shocks.

## **3** Time-to-develop model of housing investment

This section outlays the theoretical framework that ties our TTD data to the housing supply elasticity, which is a key measure of interest in the housing literature. In the model, the developer makes housing investment decisions under a TTD constraint. We analytically derive and characterize the short- to long-run housing supply elasticities as a function of several parameters, including TTD. As our focus is to analytically formulate housing supply elasticity based on TTD, it is important to note that our framework abstracts from the endogeneity of TTD or other potential short-run determinants of housing supply studied in the literature.

### **3.1** Model description

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

$$I_t = \left(\sum_{p=0}^P U_{t-p|t}^{\frac{\theta-1}{\theta}}\right)^{\frac{\theta}{\theta-1}}, \quad \theta > 0.$$
(3.1)

The parameter P is the number of periods it takes to complete a project from the beginning, and  $\theta$  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  $\theta \to 0.^7$ 

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  $p \in \{0, 1, \dots, P\}$ . These inputs are built based on a Cobb-Douglas production function:

$$U_{t|t+p} = M_{t+p-P|t+p}^{1-\alpha} N_{t|t+p}^{\alpha}, \quad \forall p \in \{0, 1, \cdots, P\},$$
(3.2)

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 (3.1) and (3.2) is

$$I_{t} = M_{t-P|t}^{1-\alpha} \left( \sum_{p=0}^{P} (N_{t-p|t}^{\alpha})^{\frac{\theta-1}{\theta}} \right)^{\frac{\theta}{\theta-1}},$$
(3.3)

which features three desirable properties. First, land inputs are fixed in period t - P and therefore not substitutable with variable inputs after the start of development. Second, variable inputs are substitutable across time based on parameter  $\theta$ . 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).<sup>8</sup>

<sup>&</sup>lt;sup>7</sup>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.

<sup>&</sup>lt;sup>8</sup>To be precise, if  $M_{t-P|t} = M$  and  $N_{t-p|t} = N$  for all  $p \in \{0, 1, \dots, P\}$ , 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,

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,  $\Phi_t$ , is

$$\Phi_{t} = q_{t}I_{t} - q_{M,t}M_{t|t+P} - w_{t}N_{t},$$
  
where  $N_{t} = \sum_{p=0}^{P} N_{t|t+p}.$  (3.4)

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

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

subject to the TTD equations (3.1), (3.2), and (3.4). 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, the permits are supplied by the local government and are elastic to the house price:

$$M_{t|t+P} = \bar{M}q_t^{\gamma}. \tag{3.5}$$

This assumption is common in the literature and is consistent with the long-run housing supply elasticity as a function of  $\gamma$  (Guren, McKay, Nakamura and Steinsson, 2020).

### 3.2 Developer's housing supply

We denote  $\mu_{t|t+p}$  as the period-*t* Lagrange multiplier of equation (3.2) 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:

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

consistent with our Cobb-Douglas specification.

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

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.

After log-linearizing the previous optimality conditions as well as equations (3.1) through (3.5), we derive the following lemma that summarizes the model's housing supply conditions.

**Lemma 1 (log-linearized dynamic housing supply equilibrium)** Let each hatted variable be the log deviation from its steady-state value. The following log-linearized equilibrium conditions summarize the TTD model of housing investment:

$$\begin{split} \hat{I}_t &= \frac{1}{B(P)} \sum_{p=0}^{P} \left( \tilde{\beta}^{\alpha(\theta-1)/\theta} \right)^p \hat{U}_{t-p|t}, \\ \left( \frac{1-\alpha}{\alpha} + \frac{1}{\theta} \right) \hat{U}_{t|t+p} &= \frac{1}{\theta} \mathbb{E}_t \hat{I}_{t+p} + \mathbb{E}_t \hat{q}_{t+p} + \frac{1-\alpha}{\alpha} \hat{M}_{t+p-P|t+p} - \hat{w}_t + \mathbb{E}_t (\hat{\lambda}_{t+p} - \hat{\lambda}_t), \\ \hat{U}_{t|t+p} &= (1-\alpha) \hat{M}_{t+p-P|t+p} + \alpha \hat{N}_{t|t+p}, \\ \hat{N}_t &= \left( \frac{1-\tilde{\beta}}{1-\tilde{\beta}^{1+P}} \right) \sum_{p=0}^{P} \tilde{\beta}^p \hat{N}_{t|t+p}, \\ \hat{M}_{t|t+P} &= \gamma \hat{q}_t, \end{split}$$

where

$$\Lambda_{t|t+p} = \beta^p \frac{\lambda_{t+p}}{\lambda_t}, \ \tilde{\beta} = \beta^{\frac{\theta}{\theta+\alpha(1-\theta)}}, \ and \ B(t) = \frac{\tilde{\beta}^{(\alpha(\theta-1)/\theta)(1+t)} - 1}{\tilde{\beta}^{\alpha(\theta-1)/\theta} - 1}$$

Note that in Lemma 1, we introduced the deterministic per-period discount factor parameter  $\beta < 1$ . As such, the stochastic discount factor between period t and t + p,  $\Lambda_{t|t+p}$ , is decomposed into the deterministic discount factor  $\beta^p$  and the net stochastic discount factor  $\lambda_{t+p}/\lambda_t$ .

Using Lemma 1, the following proposition derives the developer's period-by-period housing supply choice as a function of house prices and other general equilibrium forces.

**Proposition 2 (period-by-period housing supply curve)** *Based on the lemma and assuming a steady-state equilibrium before period* 0, *we derive the following period-by-period housing* 

supply curve:

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

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 2 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 before the TTD constraint (t < P) and the *P*-period lagged house price after the TTD constraint ( $t \ge P$ ). 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  $t \ge P$ . The following corollary provides us some useful comparative statics with regard to the derived static housing supply elasticities.

**Corollary 3 (comparative statics)** The static housing supply elasticity when t < P,  $\Upsilon_t(P)$ , has two properties. First,  $\Upsilon_t(P)$  is positive and an increasing function of time, 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:

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

Corollary 3 is visualized in Figure 1. As observed, the static housing supply elasticity is an



Figure 1: Theoretical static housing supply elasticities

increasing function up to the TTD constraint. Afterward, the static housing supply elasticity is determined by the parameter  $\alpha$ , 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  $\theta \rightarrow 0$ . 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.

#### **3.3** 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 4** (*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 2 and assuming  $\Upsilon_t(P) = \alpha/(1-\alpha)$  when  $t \ge P$  for simplicity of notation, we define the *T*-horizon housing supply elasticity with *P*-period *TTD*,  $\mathcal{E}_T(P)$ , as

$$\mathcal{E}_T(P) \equiv \frac{\Delta_{t=0}^T \hat{I}_t}{\Delta_{t=0}^T \hat{q}_t} \equiv \frac{1}{T+1} \sum_{t=0}^T \left[ \Upsilon_t(P) + \gamma (T-P+1) \times \mathbf{1}_{\{T \ge P\}} \right],$$
(3.6)

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

$$\mathcal{E}_{\infty} \equiv \lim_{T \to \infty} \mathcal{E}_T(P) = \frac{\alpha}{1 - \alpha} + \gamma.$$
(3.7)

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  $\gamma$  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  $\gamma$  and  $\alpha$ ; 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.

## 4 Quantifying housing supply elasticities in each horizon

Using the duration of land development statistics in Section 2 and our theoretical result in Section 3, this section presents regional housing supply elasticities in each horizon. We ask whether the significant TTD variations we find in the data translate to significant variations in the T-horizon housing supply elasticities by comparing those with the counterpart long-run elasticities. In this section, our main focus is on quantifying housing supply elasticities at

different horizons; their relevance in accounting for housing market dynamics will be studied in Section 5.

#### 4.1 Parameterization

Recall the *T*-horizon housing supply elasticity from Definition 4. In Equation (3.6), the elasticity  $\mathcal{E}_T(P)$  requires five structural parameters: P,  $\gamma$ ,  $\alpha$ ,  $\beta$ , and  $\theta$ . 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  $\gamma$  and  $\alpha$  follows Guren et al. (2020) in that (i) for each county, our long-run housing supply elasticity  $\mathcal{E}_{\infty}$  in Equation (3.7) is equal to Saiz's housing supply elasticity, (ii)  $\alpha$  is common across all counties, and (iii) the lowest value for  $\gamma$  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,  $\beta$ , is set at 0.99, consistent with a 2 percent annual real interest rate.

Fourth, we discuss the calibration strategy for the nonnegative parameter  $\theta$  that governs the substitutability of construction stages. When  $\theta \rightarrow 0$  as in Kydland and Prescott (1982), TTD investment is not substitutable and the initial amount of housing construction is sufficient information to predict the amount of housing completions that will be realized in the future. For higher values of  $\theta$ , however, TTD investment is substitutable and housing completions could differ significantly from what was expected at the beginning of development, especially if the housing market has shifted considerably since then. These insights suggest that both the deviation in housing completions from the initial plan and the change in housing market conditions are informative in calibrating  $\theta$ . The deviation in housing completions from the initial plan could be empirically measured by the percentage difference between the planned number of units when development was initiated and the actual number of units built later on. Our calculation indicates that there was at least a 5 percent deviation in housing completions from the initial plan for about 32.4 percent of the total number of sections in our sample. Using the



Figure 2: Supply elasticities in each horizon

*Note:* This figure shows the scatter plot comparing the Saiz supply elasticity and the T-year supply elasticities with T = 1, 5, 9 years.

time series for real house prices and real construction wages to simulate our TTD investment model in the previous section, we calibrate  $\theta$  to 0.334 at which the model-implied frequency with at least 5 percent absolute difference between planned and actual investment matches the empirical frequency.<sup>9</sup> Note that  $\theta$  is below one, which implies that TTD investments across stages are closer to complements. This is consistent with the observation that many on-site construction activities need to be conducted sequentially, which limits 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

<sup>&</sup>lt;sup>9</sup>Details of the calibration strategy in described in the Appendix.

supply elasticities tend to increase and converge to the 45 degree line that equates the longrun 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 5-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.<sup>10</sup> 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 starkly 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.

Alternative measure 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 dataset. Nevertheless, as we focus on quantifying the short-run housing 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 the measure of the long-run supply elasticity that we use. For example, Baum-Snow and Han (2024) measures a comprehensive medium-run housing

<sup>&</sup>lt;sup>10</sup>To be precise, counties with a centroid within 50 miles of either the Atlantic or the Pacific are defined as coastal, and counties with a centroid more than 50 miles from either coast and in states of the southern border between Florida and Arizona are classified as the sunbelt. The rest are classified as the interior.



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.

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 elasticities to the county average of their neighborhood track level elasticities. 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) but are lower on average because of the shorter time horizon of their data.

## 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 3 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 3. Below, we describe the households, the rest of the economy, and the equilibrium of



Figure 4: Housing supply and demand curves

the model.

#### 5.1.1 Households

The representative local household's expected lifetime utility is

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

where  $C_t$  is the household consumption of nondurable goods,  $H_t$  is the service flow of housing,  $N_{n,t}$  is the labor supply for the nondurable goods sector, and  $\varphi_t$  is an exogenous process for housing demand. The household's one-period subjective discount factor,  $\beta$ , is consistent with the housing developers' deterministic discount factor specified in Section 3.

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  $\delta$  is the depreciation rate of the housing stock.

The household flow budget constraint is given by

$$C_t + q_t I_t + \frac{B_{t+1}}{R_t} + \frac{\psi_b}{2} B_{t+1}^2 = w_{n,t} N_{n,t} + w_t N_t + B_t + \Phi_t + T_t,$$
(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,  $\Phi_t$  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  $\psi_b$  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,  $Y_t = \overline{Z}N_{n,t}$ , where  $Y_t$  is the output of the nondurable good and  $\overline{Z}$  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 (3.5), 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  $T_t$ :

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

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

**Exogenous housing demand.** The exogenous component of housing demand,  $\varphi_t$ , is attached to the household's preference over the housing stock  $H_t$  in the utility function (5.1) and follows a first-order autoregressive process in logs:

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

where  $\epsilon_{\varphi,t}$  is the exogenous housing demand shock and  $\rho_{\varphi}$  is the persistence of exogenous housing demand from its mean  $\bar{\varphi}$ .

#### 5.1.3 Equilibrium

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

- 1. Housing developers maximize their profit subject to (3.1) through (3.4).
- 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).



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

*Note:* The left panel plots the Spearman's 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.

### 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

To investigate the degree to which our short-run housing supply elasticities should influence house prices in theory, we solve our local general equilibrium model and compute each county's house price response to a common housing demand shock.

In the left panel of Figure 5, we plot the rank correlation for each horizon T between a county's T-horizon housing supply elasticity,  $\mathcal{E}_T$ , and its impact house price response to

a common housing demand shock,  $q_0$ . For each persistence parameter of interest for the housing demand shock, the rank correlation is negative as house prices tend to increase more in counties where housing supply elasticities are lower. The rank correlations are not exactly -1, however, because the county rankings of the *T*-horizon housing supply elasticity are not the same across the horizons, as discussed in Section 4. Moreover, the non-monotone rankings of the various horizons of housing supply elasticities suggest that the rank correlation should depend on the persistence of the housing demand shock. In the figure, we find that when the persistence is relatively high ( $\rho_{\varphi} = 0.92$ ), the rank correlation is close to -1 for housing supply elasticities at a horizon of 7 or more years. This near-perfect, negative alignment between the longer-run housing supply elasticities and the impact house price response no longer holds when the persistence is relatively low ( $\rho_{\varphi} = 0.88$ ), as the lowest rank correlation is above -0.6 at the long-run housing supply elasticity.

These results suggest that our short-run housing supply elasticities capture nuanced house price variations not accounted for by the long-run housing supply elasticity. That is, when the persistence of the common housing demand shock is relatively low, our shorter-run housing supply elasticities are more relevant in accounting for the sensitivity of house prices in terms of exhibiting the lowest rank correlation. In the right panel of Figure 5, we show the optimal horizon  $T^*$  at which the Spearman's rank correlation between the *T*-horizon housing supply elasticity and the impact house response is minimized, for each persistence parameter  $\rho_{\varphi}$  of the housing demand shock:

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

We find that the most relevant housing supply elasticity depends on the persistence of the housing demand shock. For example, when the housing demand shock of interest is highly persistent at or above 0.98, the optimal T-horizon housing supply elasticity is 15 years or higher, suggesting that the Saiz long-run elasticity is a relatively good benchmark to study house price responses. However, when the persistence of the housing demand shock of interest is less than 0.90, the optimal T-horizon housing supply elasticity is 7 years or lower and the relevance of the long-run elasticity is diminished.

In sum, we find that when the housing demand shock of interest has a relatively low persistence, housing supply elasticities with short horizons are more relevant than the long-run elasticity in accounting for the relative house price variations across counties. The performance of the long-run elasticity is limited because shocks with low persistence do not last long enough to affect housing supply in the long run. We also verify that when the housing demand shock of interest is highly persistent, the long-run housing supply elasticity dominates the short-run elasticity as variations in TTD matters less in this case.

These findings hold even when we allow for cross-regional spillovers. In the Appendix, we study a two-region general equilibrium model with asymmetric housing 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 two.

#### 5.2.2 Empirical exercise

To study 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). In each of these episodes, we estimate the following relative house price regression for each horizon  $T \in \{1, 2, 3, \dots\}$ :

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

The left hand side variable is the log change of county *i*'s house price index,  $P_i$ , relative to the national house price index,  $P_N$ , between the years of interest. The variable  $\tilde{\mathcal{E}}_T^i$  is county *i*'s *T*-horizon housing supply elasticity standardized to have the same cross-county variation across *T*. We allow for 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. Because a higher value of the housing supply elasticity should imply a lower sensitivity of the relative house price to shocks, a simple test to validate the empirical relevance of the *T*-horizon housing supply elasticity is to show that the estimated coefficient  $\kappa_T$  is significantly negative.

Figure 6 displays the estimation results of the relative house price regression in each of the four episodes. During the 2000s housing boom and bust periods, we find that the long-run elasticity is more relevant than the short-run elasticity in accounting for changes in a county's relative house price, in the sense that the estimated coefficients for the long-run elasticities are more negative than the coefficients for the short-run elasticities. In both the 2010s housing recovery and the COVID housing boom periods, however, the short-run elasticity outperforms the long-run elasticity. The estimated coefficients for the elasticities below the 6-year horizon



Figure 6: Relative house price regression coefficients

*Note:* Each figure shows the estimated coefficients for  $\kappa_T$  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 as controls and use robust standard errors for the confidence intervals.

are negative and the one standard deviation confidence intervals around the 2- and 3-year elasticities remain below zero. On the other hand, the estimated coefficients for longer horizon elasticities are positive and not distinguishable from zero.

Through the lens of our model, the 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.

#### 5.3 TTD and housing dynamics of the sunbelt

Existing measures of the housing supply elasticity such as Saiz (2010) suggest that housing supply tends to be more elastic in the sunbelt region relative to the coastal region. Then, conditional on a positive housing demand shock, the sunbelt region should experience a greater increase in construction activity and a smaller increase in house prices relative to the coastal region. However, this prediction has often been challenged when confronted with the data. For example, Davidoff (2016) argues that house prices are likely to rise more in counties where housing supply increases more. More recently, despite the relative surge in construction activity such as employment or number of establishments in the sunbelt during the COVID era, house price growth was also higher in the sunbelt than in the coastal region (Figure 7).

We use the rich dynamics of our local general equilibrium TTD model to discuss how TTD could help address the puzzling relative housing dynamics of the sunbelt. As a model exercise, we assume two regions that differ in their long-run housing supply elasticity but are identical otherwise. The two regions are labeled as elastic supply and inelastic supply and we set TTD to be the same 11 quarters in both regions. Solving the model by second-order approximation to the policy function to allow for state dependence, we conduct two experiments. First, assuming that both regions are at their respective steady states where the housing stocks are in balance, we hit both regions with a positive housing demand shock. Second, assuming that



Figure 7: Distribution of growth rate variables by region (2019–22)

*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.

both regions are below their respective steady states with regards to their housing stock and construction activity—i.e., a housing shortage state—we again hit both regions with the same positive housing demand shock. The two model experiments reveal how TTD could affect housing dynamics with regards to a housing demand shock in line with the recent housing market experience of the sunbelt.

Figure 8 shows the impulse responses of construction variables with respect to the positive housing demand shock, based on the first experiment where both regions are initially at their respective steady states. As shown on the top-left panel, local governments supply new permits when a positive demand shock hits the economy, and the region with elastic housing supply observes a larger increase in new permits compared to the region with inelastic housing supply. This response is the standard *level effect* of the supply elasticity—that is, permit supply is higher in locations with higher long-run elasticity. In turn, this is consistent with relatively higher total construction activity in the elastic supply region as shown on the top-right panel, where the increase in total construction variable inputs is higher in the elastic supply region for 12 quarters. Because of TTD, however, it is important to note that higher construction activity in the elastic supply region does not immediately increase new housing supply.



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.

The bottom panel breaks down the variable construction input into beginning and existing stage inputs  $(N_t = N_{t|t+P} + \sum_{p=0}^{P-1} N_{t|t+p})$ . With the introduction of TTD, a unique channel of our model is the *slope effect* of the supply elasticity—that is, TTD implies a positive slope between the short- and long-run supply elasticity which affects the developers' intertemporal investment decision as the marginal product of the variable input differs across time. As developers in each region deal with multiple projects under different stages of construction, they make the most out of their flexibility by optimally allocating variable inputs towards projects with higher gains. Because developers in the elastic supply region face a steeper slope, their intertemporal substitution motive for construction is stronger compared to developers in the inelastic supply region. In particular, the bottom-left panel shows that there is a surge of investment for new projects in the elastic supply region when a positive housing demand



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.

shock hits, as developers make the most out of the higher permit supply in that region. This crowds out investment for existing projects with lower permits in the elastic supply region. In contrast, developers in the inelastic supply region face a weaker intertemporal substitution motive as the higher housing demand is not accompanied by a large increase in permit supply. Therefore, the investment rate for existing stage inputs becomes higher in the inelastic supply region despite the higher investment rate for total inputs in the elastic supply region, as shown on the bottom-right panel.

Figure 9 shows the relative housing dynamics between the elastic and inelastic supply regions. The gray lines in the top panel plot the difference between the elastic and inelastic regions' housing permit and variable construction input responses shown in Figure 8. The gray lines in the bottom panel show the relative new housing supply  $(I_t)$  and the relative house price

 $q_t$  responses. As discussed above, despite the positive relative housing permit and relative total input, relative new housing supply stays negative for 10 quarters and moves positive only later on as investment for existing projects were crowded out in the elastic region. As new housing supply remains relatively low in the elastic region, there is an upward pressure to house prices compared to a model without TTD. However, the relative house price still remains negative, as the reversal effect of TTD itself is not enough to overcome the difference in the long-run elasticities between the two regions.

Turning to the second experiment where the positive housing demand shock occurs during a housing shortage state, the black lines in Figure 9 show the same impulse responses as the gray lines, but instead starting from a state where the existing housing stock as well as units under construction are below their respective steady state values.<sup>11</sup> The goal of this experiment is to observe the state-dependent response to a positive housing demand shock when there is already an ongoing housing shortage. In that case, we find that the effects are amplified, as the responses of the relative housing permit and the relative total inputs are even higher when there is an ongoing housing shortage in the model. That is, when housing demand suddenly increases in the midst of an ongoing housing shortage in both the elastic and inelastic regions, permits and construction activity in the elastic region increases even further than in the inelastic region. As the slope effect becomes amplified, the near-term relative new housing supply is even more negative and the relative house price becomes positive on impact.

**Discussion.** Our model experiments suggest that the assumption of TTD combined with housing shortage is capable of generating both a relative boom in construction activity and a temporary increase in the relative house price for the elastic region in response to a positive housing demand shock. The upward pressure to the relative house price in the elastic region comes from the following three channels. First, the level effect of TTD puts some upward pressure to the near-term relative house price in the elastic region, because elevated construction activity is no longer associated with an increase in new housing supply in the short run that lowers house prices, but is still associated with higher higher construction costs. Second, the TTD friction generates a slope effect where the elastic region faces a steeper slope between the short- and long-run housing supply elasticity. As such, construction activity in the elastic region surges for newer projects, crowding out resources for projects that are already under construction. This channel further widens the near-term gap between construction activity and new housing supply, putting an upward pressure to house prices especially in the elastic

<sup>&</sup>lt;sup>11</sup>We generate state-dependent impulse responses by solving the model by second-order approximation to the policy function.

region. Third, the TTD friction can also interact with the housing shortage state by amplifying the slope effect, putting a further upward pressure to the relative house price in the elastic region.

As the sunbelt region resembles the elastic region in the model experiments, we argue that TTD could be a key friction that helps rationalize the puzzling rise of house prices in the sunbelt region. The fact that TTD tends to be even longer in the sunbelt region relative to the coastal region corroborates with the three model channels discussed above in putting an upward pressure to the relative house price in response to a positive housing demand shock.

We note that the channels that we discuss in this section are qualitative and more studies are necessary to quantitatively match the relative house price dynamics. That is, our modeling of the housing demand side is stylized to clearly lay out the key effects that TTD brings to the discussion of house prices in the sunbelt region where construction activity is booming. However, we abstract from several frictions of the housing demand side, such as barriers to housing search and mortgage financing, that could amplify or smooth out the channels we discussed. Moreover, household expectations on house prices could be formed in a manner that departs from rationality. Empirically, quantifying the recent housing shortage would be important to understand the state dependence of the construction and house price responses. Nevertheless, with these caveats, our argument supports the view that housing supply elasticities could be consistent with a richer set of housing dynamics if short-run housing supply frictions in the form of TTD are also taken into account, related to a point raised 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,



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.

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 (3.5) 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 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.<sup>12</sup> 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 shortand long-run housing supply elasticities and analyze TTD for residential development across the U.S. using a unique dataset. We then quantify frictions to housing supply over the business cycle across 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 dataset 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 is still conducted on site, climate change and environmental regulation would also have a first-order effect on the construction sector. We hope that

<sup>&</sup>lt;sup>12</sup>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.

our modeling framework as well as our granular TTD data open up a new avenue of research along these lines.

## References

- Aastveit, Knut Are, Bruno Albuquerque, and André K. Anundsen, "Changing Supply Elasticities and Regional Housing Booms," *Journal of Money, Credit and Banking*, October 2023, 55 (7), 1749–1783.
- Baum-Snow, Nathaniel and Lu Han, "The Microgeography of Housing Supply," *Journal of Political Economy*, June 2024, *132* (6), 1897–1946.
- Bhattarai, Saroj, Felipe Schwartzman, and Choongryul Yang, "Local Scars of the US Housing Crisis," *Journal of Monetary Economics*, 2021, *119*, 40–57.
- Charoenwong, Ben, Yosuke Kiruma, Alan Kwan, and Eugene Tan, "Capital Budgeting, Uncertainty, and Misallocation," *Journal of Financial Economics*, 2024, *153*, 103779.
- **Davidoff, Thomas**, "Supply Constraints Are Not Valid Instrumental Variables for Home Prices Because They Are Correlated With Many Demand Factors," *Critical Finance Review*, 2016, *5*, 177–206.
- **Davis, Morris and Jonathan Heathcote**, "Housing and the Business Cycle," *International Economic Review*, 2005, *46* (3), 751–784.
- **Davis, Steven J and John C Haltiwanger**, "Dynamism Diminished: The Role of Housing Markets and Credit Conditions," Working Paper 25466, National Bureau of Economic Research January 2019.
- **Epple, Dennis, Brett Gordon, and Holger Sieg**, "A New Approach to Estimating the Production Function for Housing," *American Economic Review*, 2010, *100* (3), 905–924.
- Fernandes, Adriano and Rodolfo Rigato, "K Wasn't Built in a Day: Investment with Endogenous Time to Build," *working paper*, 2024.
- **Glaeser, Edward L. and Joseph Gyourko**, *Rethinking Federal Housing Policy*, The AEI Press, 2008.
- **Glaeser, Edward L, Joseph Gyourko, and Albert Saiz**, "Housing Supply and Housing Bubbles," *Journal of Urban Economics*, 2008, *64* (2), 198–217.
- \_, \_, Eduardo Morales, and Charles G Nathanson, "Housing Dynamics: An Urban Approach," *Journal of Urban Economics*, 2014, 81, 45–56.
- Goolsbee, Austan and Chad Syverson, "The Strange and Awful Path of Productivity in the U.S. Construction Sector," *NBER Working Paper*, 2023, *30845*.

- **Gorback, Caitlin S and Benjamin J Keys**, "Global Capital and Local Assets: House Prices, Quantities, and Elasticities," Working Paper 27370, National Bureau of Economic Research June 2020.
- Graham, James and Christos A. Makridis, "House Prices and Consumption: A New Instrumental Variables Approach," *American Economic Journal: Macroeconomics*, January 2023, *15* (1), 411–443.
- Green, Richard K, Stephen Malpezzi, and Stephen K Mayo, "Metropolitan-Specific Estimates of the Price Elasticity of Supply of Housing, and Their Sources," *American Economic Review*, 2005, 95 (2), 334–339.
- Guren, Adam, Alisdair McKay, Emi Nakamura, and Jon Steinsson, "What Do We Learn From Cross-Regional Empirical Estimates in Macroeconomics," *NBER Macroeconomics Annual*, 2020, pp. 175–223.
- \_, \_, \_, \_, and \_, "Housing Wealth Effects: The Long View," *Review of Economic Studies*, 2021, 88 (2), 669–707.
- Gyourko, Joseph, Jonathan S. Hartley, and Jacob Krimmel, "The Local Residential Land Use Regulatory Environment across U.S. Housing Markets: Evidence from a New Wharton Index," *Journal of Urban Economics*, July 2021, *124*, 103337.
- Haughwout, Andrew, Richard W. Peach, John Sporn, and Joseph Tracy, "The Supply Side of the Housing Boom and Bust of the 2000s," in Edward L. Glaeser and Todd Sinai, eds., *Housing and the Financial Crisis*, University of Chicago Press, 2013, chapter 2, pp. 69–104.
- Howard, Greg, Jack Liebersohn, and Adam Ozimek, "The Short- and Long-Run Effects of Remote Work on U.S. Housing Markets," *Journal of Financial Economics*, 2023, 150 (1), 166–184.
- **Iacoviello, Matteo and Stefano Neri**, "Housing Market Spillovers: Evidence from an Estimated DSGE Model," *American Economic Journal: Macroeconomics*, April 2010, 2 (2), 125–164.
- Kalouptsidi, Myrto, "Time to Build and Fluctuations in Bulk Shipping," *American Economic Review*, 2014, *104* (2), 564–608.
- Kaplan, Greg, Kurt Mitman, and Giovanni L. Violante, "The Housing Boom and Bust: Model Meets Evidence," *Journal of Political Economy*, 2020, *128* (9), 3285–3678.

- **Kiyotaki, Nobuhiro, Alexander Michaelides, and Kalin Nikolov**, "Winners and Losers in Housing Markets," *Journal of Money, Credit and Banking*, 2011, *43* (2–3), 255–296.
- Kone, D. Linda, Land Development, 10 ed., BuilderBooks.com, 2006.
- **Kydland, Finn E. and Edward C. Prescott**, "Time to Build and Aggregate Fluctuations," *Econometrica*, 1982, *50* (6), 1345–1370.
- \_\_, Peter Rupert, and Roman Šustek, "Housing Dynamics over the Business Cycle," International Economic Review, 2016, 57 (4), 1149–1177.
- Lucca, David O., "Resuscitating Time-to-Build," mimeo, 2007.
- Lutz, Chandler and Ben Sand, "Highly Disaggregated Land Unavailability," mimeo, 2022.
- Mayer, Christopher J. and C. Tsuriel Somerville, "Residential Construction: Using the Urban Growth Model to Estimate Housing Supply," *Journal of Urban Economics*, 2000, 48, 85–109.
- Meier, Matthias, "Supply Chain Disruptions, Time to Build, and the Business Cycle," *work-ing paper*, 2020.
- Mian, Atif and Amir Sufi, "What Explains the 2007-2009 Drop in Employment?," *Econometrica*, 2014, 82 (6), 2197–2223.
- \_, Kamalesh Rao, and Amir Sufi, "Household Balance Sheets, Consumption, and the Economic Slump," *Quarterly Journal of Economics*, 2013, *128* (4), 1687–1726.
- Millar, Jonathan N., Stephen D. Oliner, and Daniel E. Sichel, "Time-To-Plan Lags for Commercial Construction Projects," *Regional Science and Urban Economics*, 2016, 59, 75–89.
- Murphy, Alvin, "A Dynamic Model of Housing Supply," *American Economic Journal: Economic Policy*, November 2018, *10* (4), 243–267.
- Nathanson, Charles G. and Eric Zwick, "Arrested Development: Theory and Evidence of Supply-Side Speculation in the Housing Market," *Journal of Finance*, December 2018, 73 (6), 2587–2633.
- **Oh, Hyunseung and Chamna Yoon**, "Time to Build and the Real-Options Channel of Residential Investment," *Journal of Financial Economics*, 2020, *135* (1), 255–269.
- Paciorek, Andrew, "Supply Constraints and Housing Market Dynamics," *Journal of Urban Economics*, 2013, 77, 11–26.

- Saiz, Albert, "The Geographic Determinants of Housing Supply," *Quarterly Journal of Economics*, 2010, *125* (3), 1253–1296.
- Sarte, Pierre-Daniel, Felipe Schwartzman, and Thomas A. Lubik, "What Inventory Behavior Tells Us About How Business Cycles Have Changed," *Journal of Monetary Economics*, 2015, *76*, 264–283.
- **Topel, Robert and Sherwin Rosen**, "Housing Investment in the United States," *Journal of Political Economy*, 1988, *96* (4), 718–740.