Remote Work and Real Estate Prices: A Tale of Two Markets

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Abstract

I study the effect of the remote work shock on the spatial distribution of U.S. residential and commercial real estate prices. To do so, I develop a dynamic quantitative spatial model featuring forward-looking migration and work-mode decisions, as well as investment in office capital. I analytically characterize residential real estate demand in terms of both current economic conditions and dynamic considerations, and show that the effect of increased remote work on commercial demand consists of two competing forces, yielding an overall ambiguous effect. I then quantify the impact of the remote shock and find heterogeneous effects on residential prices, with gains in some regions and losses in others, but widespread declines in commercial office values. Finally, I evaluate place-based policies targeting the drivers of these price shifts and show that welfare effects vary across locations and between the owners of residential and commercial real estate.

Keywords: remote work, real estate, spatial equilibrium, dynamics

JEL Classification: E2, G1, R2, R3, R5

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1 Introduction

During the COVID-19 pandemic, the share of the labor force working remotely increased approximately threefold as individuals transitioned from working in the office to working at home.[1] Notably, the remote work share has remained significantly elevated, even after the end of pandemic-related lockdowns. This persistent shift in working arrangements has reshaped the demand for real estate across the United States through two interconnected channels: (i) remote work decouples residential choice from job location, allowing workers to live far from their place of employment; and (ii) firms require less office space when employees work remotely. Regional exposure to these forces varied due to differences in local fundamentals, such as technologies and amenities, as well as the initial equilibrium distributions of labor and office capital.

In this paper, I study the effect of the remote work shock on the spatial distribution of residential and commercial office prices.[2] To do so, I develop a dynamic, quantitative spatial model of remote work to analyze how an exogenous increase in the preference for working remotely influences equilibrium prices of these two real estate assets. The model features forward-looking workers who make decisions over both migration and work mode (remote or non-remote), and purchase housing in distinct residential markets. In addition, the model includes endogenous investment in new office space by immobile, commercial owners, in response to evolving local market conditions. The distinction between residential and commercial office prices bridges a gap in the literature, as existing studies of remote work either treat these two asset classes as a single market or focus on one in isolation, ignoring general equilibrium interactions across space and property types.

This paper makes three main findings. First, the remote work shock led to a modest, short-run decline in average residential prices as remote workers relocated away from the most expensive regions. In contrast, it caused a larger and more persistent decline in average commercial office prices, reflecting the contraction in aggregate non-remote employment. In the long run, model dynamics show that the negative effect on residential prices reverses, while the decline in commercial values persists. Second, the shock generates substantial spatial heterogeneity. The effect on residential prices is roughly balanced across regions that experience gains and those that experience losses, whereas the impact on commercial space is negative in nearly all regions. Moreover, residential and commercial price effects are highly correlated across regions, producing "winner" locations, where housing values rise and office markets experience only modest losses, and "loser" locations which face large declines in

[1] See Appendix Figure 6.

[2] I focus on the office sector, which is likely more exposed to the remote shock than other commercial real estate classes (e.g., retail, industrial).

both markets. Third, the magnitude of these price effects depends crucially on differential migration patterns between remote and non-remote workers as well as the pre-shock spatial distribution of office capital. I consider two place-based policies, each of which targets one of these factors, and find they lead to mixed welfare outcomes for the owners of residential and commercial office space.

Building on existing static, spatial models of work-from-home (e.g., M. Davis et al., 2024; Delventhal and Parkhomenko, 2024), I model the home as an asset with which agents can transfer wealth across time. This introduces additional dynamic considerations into workers' optimization problems, linked to the future trajectory of residential prices. Following the remote shock, agents anticipate current and future price changes driven by differential migration patterns between remote and non-remote workers. These price changes affect agents' current housing wealth, as well as the option value associated with relocating to a particular region, leading to shifts in the spatial demand for housing.

On the production side, firms located in each labor market hire both non-remote workers (from their own region) and remote workers (from all regions), as well as rent office space in a local commercial office market. I show that the partial equilibrium response of office demand to a shift toward remote work can be decomposed into two opposing channels. The first is a positive complementarity effect, which arises from diminishing returns and the imperfect substitutability between remote and non-remote inputs, so that additional remote workers increase the marginal productivity of the non-remote input and thereby raise office demand. The second is a negative substitution effect, as the reallocation of labor away from non-remote work—an input complementary to office space—reduces office demand. Together, these forces imply an overall ambiguous effect of the remote shock on office rents. However, under a constant elasticity of substitution production framework, the relative magnitude of these effects depends crucially on the elasticity of substitution between remote and non-remote inputs. I estimate this elasticity using an instrumental variable strategy that exploits pre-pandemic variation in regional potential for remote work, measured by the share of jobs in each industry that could plausibly be done remotely, interacted with aggregate trends in remote work to instrument for local adoption. The resulting point estimate indicates strong substitutability between remote and non-remote work.

To quantify the price effects of the remote shock, I calibrate the full general equilibrium model to match key features of 234 U.S. metropolitan statistical areas (MSAs) prior to the pandemic. Region-specific productivities and the remote work share in production are calibrated to exactly match empirical mean wages and remote wage premiums in each MSA. Given the high computational cost of estimating local amenities and origin-destination-specific moving costs directly in a dynamic setting with hundreds of locations, I employ the dynamic exact-hat approach of Caliendo et al. (2019) and Kleinman et al. (2023) to solve the model in time-differences. This approach allows me to simulate model dynamics without knowledge of the underlying time-invariant fundamentals. The model is initialized using pre-pandemic data: population and migration rates from the American Community Survey, the residential price distribution from Zillow, and the commercial office price distribution from Attom Data. I then simulate the economy's dynamic response to an unexpected increase in the attractiveness of remote work, calibrated to match the observed post-pandemic rise in remote employment, and trace the resulting effects on residential and commercial real estate prices across U.S. MSAs.

The model predicts a small, immediate decline of 0.9% in average residential prices due to the remote shock, though this effect is temporary. In the long run, the sign reverses: residential prices rise by 1.3% after 50 years. In contrast, the average price of commercial office space falls persistently by 4.2%, reflecting the permanent loss of office workers. These aggregate patterns mask substantial spatial heterogeneity. Across the 50 largest MSAs, residential price effects of the remote shock range from −23% in San Francisco, CA to +27% in Austin, TX, while commercial price effects range from −9% in San Francisco to −1% in Orlando, FL. Across the full sample, 44% of MSAs experience an increase in residential prices, while the remaining regions experience a decline. In contrast, the value of commercial office space declines in 94% of regions, accounting for 99% of the pre-shock office stock. Further, residential and commercial price effects are highly correlated, such that regions experiencing large increases in residential demand tend to see only modest declines in office values, while others face large declines in both markets.

To isolate the mechanisms driving the price effects of the remote shock, I conduct a model decomposition based on seven counterfactual economies, each designed to capture the contribution of a specific factor. The exercise reveals that differential migration patterns between remote and non-remote workers and the initial (pre-shock) spatial distribution of office space play central roles in determining the magnitude of the remote shock's price effects for residential and commercial space respectively. When remote and non-remote workers migrate at the same rates, the residential price effect of the remote shock essentially disappears, indicating that differential migration patterns amplify the residential price effect of the remote shock. In contrast, the initial distribution of office space serves to dampen commercial price effects, which are 68% larger in an economy with a uniformly distributed office stock. Motivated by these findings, I evaluate two place-based policies that directly target remote migration and the spatial distribution of office space. The first is a remote work subsidy, financed by a labor tax on local residents, that incentivizes remote workers to relocate to a given region. The second is an office-to-residential conversion policy, which allows owners of office buildings to convert part of their stock into housing at a fixed per-unit cost. The remote work subsidy generates only modest price and welfare effects overall, though some regions including Seattle and Dallas experience notable (>2%) welfare gains for local workers. By contrast, the office conversion policy produces a 10% average decline in residential prices and a 0.63% average increase in commercial prices. These shifts are accompanied by a significant decline in average worker welfare (-7%) but an increase in the average welfare of office owners (0.64%).

Finally, I validate the quantitative model predictions by providing new reduced form estimates of the effect of remote work on commercial office prices. I employ a two-stage least square framework, to isolate the impact of exposure to local remote employment from other contemporaneous shifts in regional office demand. After controlling for observable characteristics of transacted buildings, the estimates show that higher rates of remote work lead to a statistically and economically significant decline in office prices. Moreover, the magnitude of the estimated effect closely matches that implied by the model.

1.1 Related Literature

This work contributes to several strands of the literature. First, a growing body of work explores the evolution of cities and regions in response to the increased prevalence of work-from-home, often using urban-style models. These include M. Davis et al. (2024), Monte et al. (2023), Delventhal et al. (2022), Howard et al. (2023), Gokan et al. (2022), Brueckner et al. (2023), Richard (2024), Bond-Smith and McCann (2024), and Behrens et al. (2024). Gupta, Mittal, and Van Nieuwerburgh (2022) study the impact of remote work on the commercial office market using a partial equilibrium asset pricing framework, focusing on the effect in New York City. In contrast, I emphasize the differential effects of the remote shock across U.S. markets in general equilibrium. As in this paper, Yoo (2024) considers the welfare effects of a subsidy for remote workers, finding small, positive effects when the subsidy is financed by local income taxes. I build on this analysis by considering welfare effects across U.S. MSAs, and study an additional policy response to the remote shock, office-to-residential conversions.

A closely related paper is Delventhal and Parkhomenko (2024), which also develops a spatial model of migration and remote work featuring many regions. However, their model assumes a single price for local floorspace. My model instead allows for differential effects on the demand for residential and commercial real estate, and, by incorporating forward-looking behavior, enables analysis of the dynamic equilibrium response of each real estate type.[3]

[3] In Section 5.6, I demonstrate the quantitative relevance of the residential-commercial distinction.

This paper also contributes to the literature which empirically documents the evolution of real estate prices post-pandemic. Ramani and Bloom (2021), Gupta, Mittal, Peeters, et al. (2022), Brueckner et al. (2023), and Liu and Su (2021) provide empirical evidence on the shifts in residential demand within cities, documenting an increase in demand in the suburbs relative to the urban core. Rosenthal et al. (2022) shows a similar pattern for commercial real estate. A subset of these also consider the residential price effect across cities differentially exposed to remote work (Liu and Su, 2021; Brueckner et al., 2023; as well as Mondragon and Wieland, 2022). I complement this literature by providing, to my knowledge, the first estimated effect of a city's remote work share on the price of commercial office real estate.

Finally, this paper contributes to the dynamic spatial literature (e.g., Bilal and Rossi-Hansberg, 2021; Desmet et al., 2018; Allen and Donaldson, 2020). Caliendo et al. (2019) develop the dynamic hat algebra approach to solve dynamic spatial models without knowledge of a set of economic fundamentals by conditioning on observed initial allocations. Kleinman et al. (2023) extends the approach to include endogenous capital accumulation by immobile landlords. I build on these by developing a two-stage discrete choice framework in which, after observing the aggregate state of the economy, agents first choose their work mode and then decide where to reside. This structure has the advantage of allowing the preference shocks for work mode and residential location to be drawn independently from two distinct distributions, rather than being represented by a single random variable.

In addition, while the solution methodology of Caliendo et al. (2019) and Kleinman et al. (2023) relies on an assumption of hand-to-mouth workers, I allow the intertemporal transfer of housing wealth by mobile workers.[4] This distinction implies that a worker's within-period consumption depends not only on their initial location, but also the destination region where they choose to migrate. To reflect this, I modify the timing of the worker's problem relative to these papers, such that consumption is determined by both their individual state (the origin region) and their choice variables (work mode and destination), and calibrate the model to match transitions across regions and work modes observed in the data.

The rest of this paper is organized as follows: Section 2 lays out the model, Section 3 analyzes the response of real estate demand to an increase in remote work, Section 4 describes the calibration, Section 5 presents the quantitative results, Section 6 characterizes the empirical response of real estate prices to remote work, and Section 7 concludes. Additional results are presented in the Appendix.

[4] Giannone et al. (2023) also allow workers to save, though their model features fewer locations (27), making it feasible to solve the model in levels. I instead apply the dynamic exact-hat approach of Caliendo et al. (2019) to a model with 234 locations and solve the model in time-differences.

2 Model

The economy consists of $\mathcal{L}$ discrete regions. Time is discrete and indexed by t. As in Kleinman et al. (2023), I assume the presence of two distinct types of households: (i) Workers who are mobile, purchase housing, and supply labor for production; and (ii) immobile owners of commercial real estate who invest in office development in response to local market conditions. In each region, firms produce a homogenous consumption good (traded nationally), as well as local supplies of new housing and office space. Throughout the paper, I use $r \in \{R, N\}$ to index work modes remote (R) and non-remote (N), and $l, k \in \{1, ..., \mathcal{L}\}$ to index regions.

2.1 Workers

A unit measure of infinitely lived workers is distributed across $\mathcal{L}$ regions. Workers are ex ante identical within each region. In each period t, workers receive idiosyncratic preference shocks over work modes, denoted $\zeta_{r,t}$ for $r \in \{R, N\}$, and over residential locations, denoted $\epsilon_{l,t}$ for $l \in \{1, \ldots, \mathcal{L}\}$. While location-specific shocks are standard in dynamic discrete choice models, the inclusion of preference shocks over remote status is intended to reflect the substantial heterogeneity in working arrangement preferences (M. Davis et al., 2024). As is standard in the literature, the preference shocks are independently drawn from type I extreme value distributions: $\zeta_{r,t} \sim \text{Gumbel}(0, \nu_r)$, $\epsilon_{l,t} \sim \text{Gumbel}(0, \nu_l)$. The worker's decision problem unfolds in two stages: first, the worker chooses a work mode; then, conditional on that choice, selects a new residential location.

At the beginning of each period, a worker observes their individual state—comprising their current location and idiosyncratic preference shocks over work modes—as well as the aggregate state of the economy. The worker first chooses a work mode. Specifically, a worker residing in region l and experiencing work mode preference shocks $\boldsymbol{\zeta}_t \equiv (\zeta_{R,t}, \zeta_{N,t})$ chooses $r \in \{R, N\}$ to maximize expected utility:

$$v_{l,t}^{w} = \max_{r \in \{R,N\}} E_{\boldsymbol{\epsilon}} \left[v_{r,l,t}^{w} \right] + \zeta_{r,t} + Z_{r,t}, \tag{1}$$

where $v_{r,l,t}^{w}$ is the conditional value function after the choice of work mode r, and the expectation is taken over the vector of location shocks $\boldsymbol{\epsilon}_t \equiv (\epsilon_{1,t}, \ldots, \epsilon_{\mathcal{L},t})$.[5] The term $Z_{r,t}$ captures

[5] In addition to fully remote work, hybrid working arrangements, in which a worker splits their time between the home and office, has emerged as an important feature of the post-pandemic economy (Barrero et al., 2021). However, as the focus of the quantitative exercise is on the differential effects of the remote shock across (rather than within) U.S. MSAs—which are often geographically isolated from one another—I instead emphasize the distinction between fully remote and fully in-person work.

an additional, deterministic amenity value associated with work mode r, such as stigma or flexibility, which is common across individuals, but may vary over time.

After choosing a work mode r, workers observe their idiosyncratic location preference shocks $\boldsymbol{\epsilon}_t$ and choose a new residential location k. Formally, they solve

$$v^w_{r,l,t} = \max_{k \in \Gamma(r,l)} \frac{c_t^{1-\gamma} - 1}{1-\gamma} + \beta E[v^w_{k,t+1}] + \epsilon_{k,t} + X_k - m_{l,k} \tag{2}$$
$$\text{s.t.} \qquad c_t = (1-\tau_k) w_{r,k,t} + p_{l,t}\bar{h}(1-\delta^h) - p_{k,t}\bar{h} + T_{k,r,l,t},$$

where X_k denotes the amenity value of location k, $m_{l,k}$ is a utility cost of relocating from l to k, and $\gamma \geq 1$ is the inverse elasticity of intertemporal substitution. The feasible set $\Gamma(r,l) \subseteq \{1, ..., \mathcal{L}\}$ captures the set of locations a worker in l can move to when selecting work mode r. This is motivated by the fact that, in the data, certain combinations of origin, destination, and work mode are never observed.[6] Consumption c_t is determined by the chosen work mode r, and destination k, as well as the worker's origin l. It is composed of after-tax wage income, net housing capital gains, and local government transfers. Extending the approach of Caliendo et al. (2019) and Kleinman et al. (2023) who model workers as hand-to-mouth, I allow workers to transfer wealth across periods via housing investment.

A worker relocating from l to k sells their existing housing stock net of deprecation, $\bar{h}(1-\delta^h)$, at price $p_{l,t}$, and purchases $\bar{h}$ units in k at price $p_{k,t}$, where the depreciation rate δ^h is used to capture the costs associated with homeownership (e.g., maintenance). As in Guren et al. (2021), I assume that all workers purchase fixed $\bar{h}$ units of housing.[7] In addition, the worker receives a wage income, $w_{r,k}$, which depends on work mode and location. Wages are taxed at rate τ_k based on the worker's physical residence. Remote workers supply labor to a national labor market, while non-remote workers supply labor only to firms in their physical location k.[8] Finally, workers receive local government transfer, $T_{k,r,l,t}$, which are allowed to vary by work mode r, as well as the worker's origin l and destination k.

Notice the worker's problem in (1) - (2) depends on not only the current individual and aggregate state of the economy, but also their expected future paths, making the agent's

[6] The properties of the Gumbel distribution imply that, for every initial location l and work mode r, the measure of agents relocating to a feasible region k is strictly positive. Thus, to be consistent with the observed initial migration rates needed to initialize the dynamic hat algebra approach (Section 4.2), I restrict the choice set to only those regions k with a positive number of movers in the data.

[7] Introducing an individual worker's housing stock as an additional state variable would require data on workers' beginning-of-period holdings of housing, which is unavailable. Given this abstraction from the intensive margin of housing choice, I assume flow utility depends only on consumption of the tradable good, c_t, and not on housing.

[8] The integration of the remote labor market across regions implies the equilibrium remote wage is the same across regions: $w_{R,l,t} = w_{R,t}$ for all l.

decision a dynamic one.[9] I discuss how agents form expectations concerning the aggregate state of the economy in Section 2.7.

2.1.1 Population flows

The properties of the Gumbel distribution imply that, conditional on an individual worker's initial location l, the probability that the worker chooses work mode r (before the realization of the work mode preference shocks $\boldsymbol{\zeta}$) is:[10]

$$\mu_{r,l,t} = \frac{\exp\left(\nu_r^{-1}\tilde{v}^w_{r,l,t}\right)}{\exp\left(\nu_r^{-1}\tilde{v}^w_{N,l,t}\right) + \exp\left(\nu_r^{-1}\tilde{v}^w_{R,l,t}\right)}, \tag{3}$$

where,

$$\tilde{v}^w_{r,l,t} \equiv E_{\boldsymbol{\epsilon}}\left[v^w_{r,l,t}\right] + Z_{r,t}.$$

By a law of large numbers, (3) also gives the share of workers who begin the period in region l, and choose work mode r after realization of the work mode preference shocks. Likewise, the share of workers who choose new residence k conditional on initial location l and work mode r is

$$\pi_{k,r,l,t} = \frac{\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k,r,l,t}\right)}{\sum_{k'\in\Gamma(r,l)}\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k',r,l,t}\right)}, \tag{4}$$

where

$$\tilde{\tilde{v}}^w_{k,r,l,t} \equiv u_{k,r,l,t} + \beta E[v^w_{k,t+1}] + X_k - m_{l,k},$$

and $u_{k,r,l,t}$ denotes the flow utility value of consumption subject to the worker's budget constraint in (2).

Taken together, (3) and (4) can be used to construct the laws of motion for workers. Using stars to denote the equilibrium residential population, one can write expressions for the measure of non-remote $N^*_{l,t}$ and remote $R^*_{l,t}$ workers residing in region l:

$$N^*_{l,t} = \sum_{k=1}^{\mathcal{L}} \mu_{N,k,t}\cdot\pi_{l,N,k,t}\cdot L^*_{k,t-1}, \tag{5}$$

$$R^*_{l,t} = \sum_{k=1}^{\mathcal{L}} \mu_{R,k,t}\cdot\pi_{l,R,k,t}\cdot L^*_{k,t-1}, \tag{6}$$

where $L^*_{k,t-1} = N^*_{k,t-1} + R^*_{k,t-1}$ is the residential population of region k in period $t-1$.

[9] I derive expressions for the expectations in (1) and (2) in Appendix E.

[10] See Appendix E for derivations of the choice probabilities.

2.2 Owners

Commercial office space is accumulated through investment by owners in response to local market conditions. Since most commercial real estate in the U.S. is directly owned by the firm that uses it as an input to production, I model each region as being populated by an immobile, representative owner who invests exclusively in local office capital, rather than interregional investors (e.g., real estate investment trusts), which constitute a small share of private, commercial ownership (Ghent et al., 2019). These infinitely-lived owners solve a standard consumption-savings problem, subject to a budget constraint and law of motion for office capital.

The commercial office owner in region l chooses consumption and investment in new office space to maximize the expected present discounted value of flow utility:

$$E_t \sum_{s=0}^{\infty} \beta^s \frac{(c^o_{l,t+s})^{1-\gamma} - 1}{1-\gamma}, \tag{7}$$

where $c^o_{l,t}$ denotes the owner's consumption of the numeraire tradable good. The owner faces a budget constraint equating rental income from the current stock of office space, $r_{l,t}b_{l,t}$, to consumption and investment expenditures:

$$c^o_{l,t} + q_{l,t}x_{l,t} = r_{l,t}b_{l,t}, \tag{8}$$

where $x_{l,t}$ denotes investment in new office space at per-unit price $q_{l,t}$.[11] The law of motion for office capital is:

$$b_{l,t+1} = x_{l,t} + (1-\delta^b)b_{l,t}, \tag{9}$$

where δ^b is the depreciation rate of office space. Office capital is region-specific and geographically immobile. To reflect the relatively long construction times for commercial (as opposed to residential) real estate, I model a one-period time-to-build lag for new office space.[12]

The first-order condition from the owner's problem yields the following asset pricing equation for office real estate:

$$q_{l,t} = E_t \left[M_{l,t+1} \left(r_{l,t+1} + (1-\delta^b) q_{l,t+1} \right) \right], \tag{10}$$

where $M_{l,t+1}$ is the stochastic discount factor. Iterating forward on equation (10), we ob-

[11]In principle, the owner could disinvest, resulting in negative investment ($x_{l,t} \leq 0$). However, market clearing in new office construction ensures that $x_{l,t} > 0$ in equilibrium.

[12]In Appendix C, I use the owner's first-order conditions to derive a recursive expression for the optimal savings rate $s_{l,t}$.

tain:[13]

$$q_{l,t} = E_t \left[\sum_{j=1}^{\infty} \left(\prod_{n=1}^{j} M_{l,t+n} \right) (1-\delta^b)^{j-1} r_{l,t+j} \right]. \tag{11}$$

That is, the price of a unit of office space in period t reflects the expected present discounted value of the stream of future rental income it generates, adjusted for depreciation. In Section 5, I examine how the remote work shock affects the regional distribution of office prices, $q_{l,t}$, in order to quantify its impact on commercial office real estate values.

2.3 Production

Regional firms operate in three sectors: (i) production of a tradable consumption good, (ii) construction of residential real estate, and (iii) construction of commercial office space. All sectors are perfectly competitive, and firms take prices as given. The consumption good is traded costlessly across regions, while newly constructed residential and commercial real estate are sold only in the local market.

Firms in the tradable goods sector produce a homogenous output $Y^C_{l,t}$ by combining remote ($Y^R_{l,t}$) and non-remote ($Y^N_{l,t}$) inputs using a region-specific production technology:

$$Y^C_{l,t} = F_l\left(Y^R_{l,t}, Y^N_{l,t}\right), \tag{12}$$

where $F_l(\cdot)$ is concave, with $\partial Y^C_{l,t}/\partial Y^Z_{l,t} > 0$, $\partial^2 Y^C_{l,t}/\partial (Y^Z_{l,t})^2 < 0$ for $Z \in \{R, N\}$, and the cross-partial is non-negative, $\partial^2 Y^C_{l,t}/\partial Y^N_{l,t}\partial Y^R_{l,t} \geq 0$.[14] The non-remote input $Y^N_{l,t}$ is produced using labor $N_{l,t}$ and office buildings $B_{l,t}$:

$$Y^N_{l,t} = F^N_l\left(N_{l,t}, B_{l,t}\right),$$

with $\partial Y^N_{l,t}/\partial Z_{l,t} > 0$, $\partial^2 Y^N_{l,t}/\partial Z^2_{l,t} < 0$ for $Z \in \{N, B\}$, and $\partial^2 Y^N_{l,t}/\partial N_{l,t}\partial B_{l,t} > 0$. The remote input $Y^R_{l,t}$ is produced using only remote labor $R_{l,t}$:

$$Y^R_{l,t} = F^R_l\left(R_{l,t}\right),$$

with $\partial Y^R_{l,t}/\partial R_{l,t} > 0$, and $\partial^2 Y^R_{l,t}/\partial R^2_{l,t} < 0$.[15] Note that the measure of remote labor employed in region l ($R_{l,t}$) may differ from that of remote labor living in l ($R^*_{l,t}$) since remote workers

[13] Equation (11) requires a (no-bubble) condition, $\lim_{n\to\infty} E_t[(\prod_{m=1}^{n} M_{t+m})(1-\delta^b)^n q_{t+n}] = 0$.

[14] The inputs $Y^N_{l,t}$ and $Y^R_{l,t}$ are q-complements if $\partial^2 Y^C_{l,t}/\partial Y^N_{l,t}\partial Y^R_{l,t} > 0$. This will be satisfied by the functional form used in the quantitative analysis.

[15] For simplicity, I do not model (non-office) capital explicitly. Alternatively, one could assume fixed stocks of remote and non-remote capital embedded in the production functions $F^R_l(\cdot)$ and $F^N_l(\cdot)$ respectively.

can be hired from any region. In contrast, non-remote labor employed in l must equal non-remote labor residing in l: $N_{l,t} = N^*_{l,t}$.

Taking the tradable good as the numeraire, firms maximize profits subject to their production technologies. The resulting first-order conditions for input demand are:

$$w_{N,l,t} = \frac{\partial Y^C_{l,t}}{\partial Y^N_{l,t}} \cdot \frac{\partial Y^N_{l,t}}{\partial N_{l,t}}, \tag{13}$$

$$r_{l,t} = \frac{\partial Y^C_{l,t}}{\partial Y^N_{l,t}} \cdot \frac{\partial Y^N_{l,t}}{\partial B_{l,t}}, \tag{14}$$

$$w_{R,t} = \frac{\partial Y^C_{l,t}}{\partial Y^R_{l,t}} \cdot \frac{\partial Y^R_{l,t}}{\partial R_{l,t}}. \tag{15}$$

Construction firms produce new local residential housing $Y^H_{l,t}$ and commercial office space $Y^B_{l,t}$ using materials (i.e., the tradable good) $M^H_{l,t}$, $M^B_{l,t}$, and land or permits $P^H_{l,t}$, $P^B_{l,t}$,

$$Y^Z_{l,t} = A^Z_l (M^Z_{l,t})^{\rho^Z_l} (P^Z_{l,t})^{1-\rho^Z_l}, \quad Z \in \{H, B\}.$$

Notice the material share ρ^Z_l, which governs the price elasticity of supply, is allowed to vary spatially, consistent with micro-level evidence on geographic heterogeneity in floorspace supply (Saiz, 2010; Baum-Snow and Han, 2024). Letting $r^H_{l,t}$ and $r^B_{l,t}$ denote the price paid for residential and commercial office permits, profit maximization implies,

$$r^H_{l,t} = \frac{\partial Y^H_{l,t}}{\partial P^H_{l,t}} \cdot p_{l,t}, \tag{16}$$

$$r^B_{l,t} = \frac{\partial Y^B_{l,t}}{\partial P^B_{l,t}} \cdot q_{l,t}, \tag{17}$$

where $p_{l,t}$ and $q_{l,t}$ are the prices of residential and commercial office space, respectively. Following Favilukis et al. (2017), I assume that a government supplies permits at a fixed rate, and uses the proceeds $r^H_{l,t}\bar{P}^H_l$ and $r^B_{l,t}\bar{P}^B_l$ to finance wasteful government spending. This ensures that construction firms receive zero profits in equilibrium.

2.4 Government

In each region, a local government taxes the labor income of residents and rebates the proceeds to them as lump-sum transfers. This mechanism enables redistribution across worker groups (remote and non-remote). The budget constraint of region l's government is given by:

$$\tau_{l,t}\left(w_{N,l,t}N^*_{l,t} + w_{R,t}R^*_{l,t}\right) = \sum_{k=1}^{\mathcal{L}} \sum_{r\in\{R,N\}} \left(T_{l,r,k,t}\cdot\mu_{r,k,t}\cdot\pi_{l,r,k,t}\cdot L_{k,t-1}\right), \tag{18}$$

where the left-hand side denotes labor tax revenue from both non-remote and remote workers, and the right-hand side is the sum of rebates to workers residing in l. The term $\mu_{r,k,t}\cdot\pi_{l,r,k,t}\cdot L_{k,t-1}$ denotes the measure of workers in region k who choose work mode r and new residence l, and who receive a rebate of $T_{l,r,k,t}$.

2.5 Market Clearing

There are $6\mathcal{L}+2$ markets that must clear in equilibrium. They are: (*i*) $\mathcal{L}$ residential real estate markets; (*ii*) $\mathcal{L}$ markets for newly constructed commercial office space; (*iii*) $\mathcal{L}$ markets for existing commercial office space; (*iv*) $\mathcal{L}$ markets for residential construction permits; (*v*) $\mathcal{L}$ markets for commercial office construction permits; (*vi*) $\mathcal{L}$ markets for non-remote labor; (*vii*) the (national) market for remote labor; and (*viii*) the (national) market for the tradable good.

In each region l, residential market clearing requires that housing demand equals total housing supply, which includes both newly constructed and existing residential units:

$$L^*_{l,t}\bar{h} = L^*_{l,t-1}(1-\delta^h)\bar{h} + Y^H_{l,t}, \qquad \forall l. \tag{19}$$

In the market for newly constructed commercial office space, investment by owners equals office space construction:

$$x_{l,t} = Y^B_{l,t}, \qquad \forall l. \tag{20}$$

The demand for office space by firms in the tradable goods sector equals the supply of existing office space provided by owners:

$$B_{l,t} = b_{l,t}, \qquad \forall l. \tag{21}$$

The market for home and office construction permits clears when demand equals the fixed regional supply set by the government:

$$P^H_{l,t} = \bar{P}^H_l, \qquad \forall l, \tag{22}$$

$$P^B_{l,t} = \bar{P}^B_l, \qquad \forall l. \tag{23}$$

Labor market clearing requires that demand equals supply for both non-remote and remote labor. For non-remote labor, this requires that the local demand for non-remote workers equals the supply:

$$N_{l,t} = N^*_{l,t}, \qquad \forall l. \tag{24}$$

Remote workers supply labor in an integrated national market, and market clearing for remote labor requires that the aggregate demand by firms equals the aggregate supply of remote labor across regions:

$$\sum_{l=1}^{\mathcal{L}} R_{l,t} = \sum_{l=1}^{\mathcal{L}} R^*_{l,t}. \tag{25}$$

By Walras's Law, if all markets for goods and labor except the final tradable good clear—that is, if equations (19)-(25) hold—then the market for the tradable good also clears.

2.6 Equilibrium

The endogenous state of the economy at time t is given by the distribution of labor across regions and work modes, as well as the distribution of office space, $\mathbf{S}_t = \{(N^*_{l,t}, R^*_{l,t}, B_{l,t})\}_{l=1}^{\mathcal{L}}$.[16] I follow Caliendo et al. (2019) and distinguish between time-varying and constant fundamentals of the economy. Specifically, let $\mathbf{\Theta}_t \equiv (Z_{N,t}, Z_{R,t})$ denote the time-varying amenities associated with non-remote and remote work. The remaining time-invariant fundamentals (which I refer to as parameters) are: moving costs, $\{m_{l,k}\}_{l=1,k=1}^{\mathcal{L},\mathcal{L}}$; tax rates, $\{\tau_l\}_{l=1}^{\mathcal{L}}$; productivities in the residential construction sector, $\{A_l^H\}_{l=1}^{\mathcal{L}}$; productivities in the commercial office construction sector, $\{A_l^B\}_{l=1}^{\mathcal{L}}$; residential permits, $\{\bar{P}_l^H\}_{l=1}^{\mathcal{L}}$; commercial office permits, $\{\bar{P}_l^B\}_{l=1}^{\mathcal{L}}$; the material share in residential construction, $\{\rho_l^H\}_{l=1}^{\mathcal{L}}$; the material share in commercial office construction, $\{\rho_l^B\}_{l=1}^{\mathcal{L}}$; the housing parameter, $\bar{h}$; housing deprecation, δ^h; office space deprecation, δ^b; the discount factor, β; regional amenities, $\{X_l\}_{l=1}^{\mathcal{L}}$; the dispersion of location shocks, ν_l; and the dispersion of work mode shocks, ν_r; as well as the functions characterizing production in the tradable sector $\{F_l(\cdot), F_l^N(\cdot), F_l^R(\cdot)\}_{l=1}^{\mathcal{L}}$. I collect these parameters in a vector $\bar{\mathbf{\Theta}}$. I now define a sequential equilibrium.

Definition 1: Given an initial allocation $\mathbf{S}_0$, a path for time-varying fundamentals $\{\mathbf{\Theta}_t\}_{t=0}^{\infty}$, and parameters $\bar{\mathbf{\Theta}}$, a sequential equilibrium is a time path for prices $\{(w_{N,l,t}, w_{R,t}, r_{l,t}, p_{l,t}, q_{l,t}, r^H_{l,t}, r^B_{l,t})\}_{l=1,t=0}^{\mathcal{L},\infty}$ worker and owner value functions $\{v^w_{l,t}\}_{l=1,t=0}^{\mathcal{L},\infty}$, and $\{v^o_{l,t}(\cdot)\}_{l=1,t=0}^{\mathcal{L},\infty}$, conditional choice probabilities associated with each work mode $\{(\mu_{N,l,t}, \mu_{R,l,t})\}_{l=1,t=0}^{\mathcal{L},\infty}$, and

[16] Recall $N_{l,t} = N^*_{l,t}$, while market clearing in the integrated market for remote labor implies a unique distribution $\{R_{l,t}\}_{l=1}^{\mathcal{L}}$ given aggregate remote labor supply $\sum_l R^*_{l,t}$. Thus, information on the distribution of residential populations and office buildings is sufficient to characterize the aggregate state of the economy.

location $\{(\pi_{k,N,l,t}, \pi_{k,R,l,t})\}_{k=1,l=1,t=0}^{\mathcal{L},\mathcal{L},\infty}$, and savings rates $\{s_{l,t}\}_{l=1,t=0}^{\mathcal{L},\infty}$ which solve the worker's problem (1) - (2), the owner's problem (7), satisfy firms' optimality conditions (13) - (17), the government budget constraint (18), the laws of motion for labor (5) - (6), and market clearing conditions (19) - (25).

Finally, I define a stationary equilibrium, for which all aggregates are constant. I use "ss" to denote a steady state value.

Definition 2: A stationary equilibrium is a sequential equilibrium for which all fundamentals $\mathbf{\Theta}_{ss}$, prices $\{(w_{N,l,ss}, w_{R,ss}, r_{l,ss}, p_{l,ss}, q_{l,ss}, r^H_{l,ss}, r^B_{l,ss})\}_{l=1}^{\mathcal{L}}$, value functions $\{v^w_{l,ss}\}_{l=1}^{\mathcal{L}}$ and $\{v^o_{l,ss}(\cdot)\}_{l=1}^{\mathcal{L}}$, choice probabilities $\{(\mu_{N,l,ss}, \mu_{R,l,ss})\}_{l=1}^{\mathcal{L}}$ and $\{(\pi_{k,N,l,ss}, \pi_{k,R,l,ss})\}_{k=1,l=1}^{\mathcal{L},\mathcal{L}}$, and savings rates $\{s_{l,ss}\}_{l=1}^{\mathcal{L}}$ are constant over time.

2.7 Remote Shock

In period $t = t^* > 0$, the economy is hit by a probability zero (MIT) shock that permanently increases the remote amenity by $\mathcal{Z}_R = Z_{R,t^*} - Z_{R,t^*-1} > 0$. Agents learn about the shock (as well as the new future path for aggregate variables) at the start of period $t = t^* - 1$.[17] The economy may or may not have been in steady state before the shock, but it begins transitioning toward a new steady state immediately after agents learn of the shock.

I model the remote shock as a preference shock, rather than a technology shock (as in M. Davis et al., 2024). I adopt this interpretation for two reasons. First, survey evidence indicates that workers are willing to accept meaningful pay cuts in exchange for the option to work remotely.[18] Importantly, Chen et al. (2023) document a post-pandemic shift in preferences toward remote work, with the largest changes occurring among those who experienced the greatest increases in remote work during the pandemic. This pattern suggests that positive experiences with remote work under pandemic-induced stay-at-home orders generated a lasting shift in worker preferences.[19] Second, because my object of analysis is the price of real estate, introducing a technology shock would confound the interpretation of the results. In particular, a remote-labor-augmenting technology shock would affect commercial real estate values both through the reallocation of labor toward remote work and through a direct productivity boost to the non-remote input via complementarity. My focus is on the former channel—the labor reallocation effect—and for this reason, I adopt a preference shock framework.

[17] The one-period delay between when agents learn about the shock and when preferences actually shift is introduced for consistency with the dynamic exact-hat solution methodology (see Section 4.2).

[18] Barrero et al. (2021) report that workers are, on average, willing to accept a 7% pay reduction in exchange for the ability to work from home two to three days per week.

[19] Bagga et al. (2025) summarize arguments in favor of a preference shock, rather than a technology shock.

3 Remote Work and Real Estate Demand

What is the effect of the remote shock on the demand for residential and commercial office real estate? In this section, I conduct a partial equilibrium analysis to study how an exogenous increase in the attractiveness of remote work affects demand in both real estate markets. I begin with the implications for commercial office space (Section 3.1) and then analyze residential housing demand (Section 3.2). All proofs are included in Appendix B.

3.1 Commercial Office Space

In classic models of urban economics (e.g., Rosen, 1979; Roback, 1982), workers sort across regions in response to differences in housing costs and wages, equalizing utility across space. In contrast, office buildings are fixed in place and depreciate slowly, making them vulnerable to becoming stranded assets in the wake of a shift toward remote work. Here, I use the production framework introduced previously to analyze how office rents respond to an exogenous increase in the supply of remote labor. To simplify the analysis, I focus on the demand response within a single region. I show that the effect on office rents is ambiguous, depending on the degree of substitutability between remote and non-remote inputs in production.

Suppose the stock of office space is fixed at $\bar{B}$, and the total supply of labor (remote and non-remote) is normalized to $\bar{L} = 1$. Within this setting, consider the effect on the office rental rate r—determined by the marginal product of office space as in equation (14)—of an exogenous increase in the relative supply of remote workers (e.g., due to health concerns that increase the attractiveness of remote work). That is, how does r change in response to a marginal increase in R?[20] The following proposition decomposes the total effect into a positive and a negative component.

Proposition 1. ***Effect of remote work on office rents:*** *The change in office rents resulting from a marginal increase in remote labor R is*

$$\frac{\partial r}{\partial R} = \underbrace{\left[\frac{\partial^2 Y^C}{\partial (Y^N)^2} \cdot \frac{\partial Y^N}{\partial N} \cdot \frac{\partial N}{\partial R} + \frac{\partial^2 Y^C}{\partial Y^N \partial Y^R} \cdot \frac{\partial Y^R}{\partial R}\right] \frac{\partial Y^N}{\partial B}}_{\textit{complementarity effect } (>0)} \quad + \underbrace{\frac{\partial Y^C}{\partial Y^N} \cdot \frac{\partial^2 Y^N}{\partial B \partial N} \cdot \frac{\partial N}{\partial R}}_{\textit{substitution effect } (<0)}. \tag{26}$$

The first term, which captures the complementarity effect of labor reallocation, is positive. A marginal increase in remote labor reduces the number of non-remote workers ($\partial N/\partial R <$

[20] In the special case of a single region with a fixed total labor supply, an increase in remote labor must be offset one-for-one by a reduction in non-remote labor: $dN/dR = -1$. In the full general equilibrium model with endogenous migration introduced in Section 2, this relationship no longer holds locally.

0), which lowers Y^N ($\partial Y^N/\partial N > 0$), and, due to diminishing returns ($\partial^2 Y^C/\partial(Y^N)^2 < 0$), raises the marginal product of the non-remote input. Likewise, the increase in remote labor output ($\partial Y^R/\partial R > 0$) further increases the marginal product of the non-remote input ($\partial^2 Y^C/\partial Y^N \partial Y^R \geq 0$). Conversely, the second term, which captures the substitution effect of labor reallocation, is negative. Fewer non-remote workers ($\partial N/\partial R < 0$) reduces the positive contribution of labor to the marginal product of office space in production of the non-remote input ($\partial^2 Y^N/\partial B \partial N > 0$), scaled by the non-remote input's contribution to total output ($\partial Y^C/\partial Y^N > 0$).

Thus, the overall sign of $\partial r/\partial R$ is ambiguous, as it depends on whether the increase in marginal productivity from complementarity outweighs the reduction due to input substitution away from non-remote production. This ambiguity holds under a general production process, and suggests that, in the short run when the stock of office space is fixed and labor is immobile, a decline in the demand for office space is not a necessary consequence of the remote work shock.

To further characterize the determinants of remote work's effect on office rents in (26), I adopt the functional form for production used in the quantitative analysis. Specifically, suppose output is produced using a constant elasticity of substitution (CES) aggregate of remote and non-remote inputs:[21]

$$Y^C = A^C \left[\alpha \left(Y^R\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left(Y^N\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{27}$$

where

$$Y^N = N^\eta B^{1-\eta},$$
$$Y^R = \phi R,$$

with $\phi \leq 1$ denoting the relative productivity of remote (vs. non-remote) work. This functional form is motivated by the observation that most regions utilized both remote and non-remote inputs in strictly positive quantities prior to the pandemic, suggesting some complementarity between the two ($\sigma < \infty$).[22]

Under the functional form in (27), the sign of $\partial r/\partial R$ depends on whether the initial share

[21] This specification is similar to the production functions employed by M. Davis et al. (2024) and Delventhal and Parkhomenko (2024) in their analyses of work-from-home. In Appendix M.4, I consider a model extension which includes agglomeration externalities in production.

[22] The joint use of remote and non-remote inputs may reflect task specialization, where certain tasks are better suited to remote work (e.g., those requiring sustained concentration) and others to in-person work (e.g., those requiring team coordination). Alternatively, firms may commit ex ante to a particular mix of remote and non-remote inputs, with relative prices adjusting ex post, as in a putty-clay model of investment.

of workers employed remotely is above a threshold value.

Lemma 1. *The change in office rents from a marginal increase in remote work is negative if and only if remote labor is not too low,*

$$\frac{\partial r}{\partial R} < 0 \Longleftrightarrow R \geq \tilde{R}, \tag{28}$$

for some $0 < \tilde{R} < \bar{L}$.

Lemma 1 highlights the non-monotonic effect of remote work on office rents. Intuitively, when the economy starts with a very low stock of remote workers, reallocating labor toward remote work significantly raises the marginal product of the non-remote composite via the complementarity effect in Proposition 1, increasing the value of office space. Conversely, once remote labor passes a threshold, the substitution effect dominates, and subsequent increases in remote work reduce office rents due to the lower supply of non-remote workers. Crucially, the relative strength of these opposing channels depends on the degree of substitutability between remote and non-remote inputs, as formalized in the following proposition.

Proposition 2. ***Remote substitutability and office rents:*** *The range of initial values of remote labor* $R \in (\tilde{R}, \bar{L})$ *for which a marginal increase in remote work reduces office rents (i.e., satisfies (28)) is increasing in the elasticity of substitution* σ*, if the following conditions hold: (i) the elasticity of substitution is greater than one; and (ii) the stock of office space is not too low that the complementary effect always dominates the substitution effect.*[23] *In this case, we have*

$$\frac{\partial \tilde{R}}{\partial \sigma} < 0.$$

Proposition 2 shows that, when the stock of office space is sufficiently large and remote and non-remote labor are imperfect substitutes (i.e., the elasticity of substitution satisfies $\sigma \geq 1$), greater substitutability increases the range of pre-shock equilibrium allocations that are associated with declines in office space demand following a shift toward remote work. Accordingly, the elasticity parameter σ plays a central role in determining how office prices respond to the remote shock. In Section 4.1.1, I estimate this key parameter. The results support the assumption of imperfect substitutability, with a point estimate $\hat{\sigma} > 1$. I then use this estimate to discipline the quantitative model's predictions. Furthermore, in Section 5.3, I examine the quantitative implications of complementarity between remote and non-remote inputs.

[23]A sufficient condition for Proposition 2 is $B \geq \exp(-\sigma/(1-\eta))(1-\tilde{R})^{-\eta/(1-\eta)}$. This condition holds for all regions in the initial period of the quantitative analysis.

3.2 Residential Real Estate

Next, I analyze the effect of remote work on residential housing prices. In contrast to commercial office demand, which is shaped by firms' input choices, residential housing demand is driven by migration and the resulting equilibrium distribution of the population across space.[24] To study this, I introduce a stylized two-region model.

Consider an economy with workers distributed across two regions: a "home" region (h) and a "foreign" region (f). For simplicity, I assume that the home region is sufficiently small relative to the foreign region that changes in market conditions at home do not affect prices in the foreign region. Further, I treat wages as exogenous and focus solely on the residential housing market. Under these assumptions, the analysis centers on how an increase in remote work influences equilibrium housing demand in the home region.

I begin with a static setting in which agents make one-time, permanent decisions about where to live and whether to engage in remote work. In this environment, an increase in housing demand in the home region arises if it successfully attracts the new remote workers. This relationship is formalized in the following proposition.

Proposition 3. ***Residential demand in a static model:*** *Suppose the continuation value in the worker's problem (2) is constant, $E[v^w_{l,t+1}] = \bar{v}$, so that the worker's problem becomes static. Given an initial distribution of agents across regions, (L^*_h, L^*_f), and a fixed residential price $\bar{p}_h$, the effect of a marginal increase in the remote amenity, Z_R, on the demand for housing in the home region, $D(p_h; Z_R)$, is:*

$$\left.\frac{\partial D(p_h; Z_R)}{\partial Z_R}\right|_{p_h=\bar{p}_h} = \sum_{k\in\{h,f\}} \Bigg(\underbrace{\frac{d\mu_{R,k}}{dZ_R}}_{\substack{\text{Change in region } k \text{ share} \\ \text{choosing remote } (>0)}} \times \underbrace{(\pi_{h,R,k} - \pi_{h,N,k})}_{\substack{\text{Difference in migration rate} \\ \text{between remote and non-remote}}} \Bigg) \bar{h} L^*_k. \tag{29}$$

If remote and non-remote workers migrate at the same rate, $\pi_{h,R,k} = \pi_{h,N,k}$, the demand effect of the remote shock is zero. If remote and non-remote workers migrate at different rates, $\pi_{h,R,k} \neq \pi_{h,N,k}$, and consumption associated with non-remote work in the home region is sufficiently small, then the home region sees an increase in residential demand following the remote shock.

Proposition 3 highlights the central mechanism underlying the effect of the remote shock

[24] While the rise of remote work may have increased overall housing demand by encouraging workers to seek larger homes (e.g., to accommodate a home office) as argued by Mondragon and Wieland (2022), this paper focuses on relative changes in real estate prices across regions. The model emphasizes the extensive margin of housing demand (i.e., the number of agents who choose to locate in a region), rather than the intensive margin (i.e., how much floorspace each agent demands), under the assumption that the intensive response is similar across regions.

on residential housing prices: differential migration rates between remote and non-remote workers. In particular, if remote workers are more likely to relocate to the home region, the remote shock leads to increased housing demand there. Empirically, I provide support for this mechanism in Appendix J, where I show that, conditional on observables, remote workers exhibit higher migration rates than their non-remote counterparts.

The sign of the residential demand effect in (29) hinges on the relative attractiveness of the home region to remote versus non-remote workers. This attractiveness, in turn, reflects differences in utility across worker types, shaped by spatial variation in residential prices. In Section 5, I quantitatively assess the relative contribution of the initial residential price distribution in shaping the price effect of the remote shock.

While the static setting helps clarify the link between migration and housing demand, it abstracts from a key element emphasized in the macro-housing literature: the asset value of housing. In reality, agents use their homes to transfer wealth over time and factor in expectations about future residential prices when making location decisions. To incorporate these dynamic considerations, I extend the analysis to a two-period model in which agents' migration choices in the first period reflect anticipated changes in residential prices caused by the remote shock. All other features of the economy remain as in the static framework of Proposition 3.

Proposition 4. ***Residential demand in a dynamic model:*** *Suppose the continuation value in the worker's problem (2) is constant in period two, $E[v^w_{l,2}] = \bar{v}$, such that the worker's problem becomes a dynamic two-period problem. Given an initial distribution of agents across regions, $(L^*_{h,0}, L^*_{f,0})$ and a fixed period-one residential price, $\bar{p}_{h,1}$, the effect of a permanent, marginal increase in the remote amenity on the period-one demand for housing in the home region, $D(p_{h,1}, p_{h,2}; Z_R)$, is*

$$\left.\frac{\partial D(p_{h,1}, p_{h,2}; Z_R)}{\partial Z_R}\right|_{p_{h,1}=\bar{p}_{h,1}} = \sum_{k\in\{h,f\}} \left(\underbrace{\frac{d\mu_{R,k,1}}{dZ_R}\left(\pi_{h,R,k,1} - \pi_{h,N,k,1}\right)}_{\textit{Direct effect}} + \underbrace{\Omega_k}_{\substack{\textit{Dynamic} \\ \textit{considerations}}} \right) \bar{h} L^*_{k,0}. \quad (30)$$

The term Ω_k is a linear transformation of the difference in weighted marginal utility benefits in period two between agents who choose home vs. foreign in period one, and with the weights given by the joint probability $(\mu_{r',l,2} \times \pi_{l',r',l,2})$ of choosing remote status r' and residential *location l' in period two, given period one residence l:*

$$\Omega_k = a_k + b_k \sum_{r' \in \{R,N\}} \sum_{l' \in \{h,f\}} \Bigg(\mu_{r',h,2} \times \pi_{l',r',h,2} \underbrace{\frac{du}{dc}\bigg|_{c=c(l',r',h;p_{h,2})} \frac{\partial c(l',r',h;p_{h,2})}{\partial p_{h,2}}}_{\textit{Home benefits}} \tag{31}$$

$$- \mu_{r',f,2} \times \pi_{l',r',f,2} \underbrace{\frac{du}{dc}\bigg|_{c=c(l',r',f;p_{h,2})} \frac{\partial c(l',r',f;p_{h,2})}{\partial p_{h,2}}}_{\textit{Foreign benefits}} \Bigg) \frac{dp_{h,2}}{dZ_R},$$

where $c(l', r', l; p_{h,2})$ denotes the consumption of an agent who migrates from location l to l' and works in mode r', given price $p_{h,2}$.

Due to agents' forward-looking behavior, current residential demand depends on the path of future residential prices. Equation (31) captures the trade-off that agents face when deciding where to live: they weigh the home benefits—the marginal utility gains from future consumption if residing in the home region today—against the foreign benefits, which capture the analogous gains from living in the foreign region. These benefits depend on how the remote shock alters future consumption opportunities through changes in prices and migration flows. When prices in the home region are expected to rise, the value of residing in the home region increases relative to the foreign region due to the option value of selling at a higher price tomorrow. This creates a feedback loop in which expectations of future appreciation raise current demand, reinforcing price momentum, consistent with empirical findings (e.g., Piazzesi and Schneider, 2009; Armona et al., 2019). Crucially, this dynamic behavior implies that the immediate impact of the remote work shock on real estate prices depends on the degree to which it shifts the economy off its pre-shock dynamic path, a feature missing from static models of real estate demand.

4 Calibration

This section lays out the calibration strategy for the model introduced in Section 2. The model is calibrated to match features of the pre-pandemic U.S. economy, where each region corresponds to a Metropolitan Statistical Area (MSA). It includes $\mathcal{L} = 234$ MSAs.[25] One period in the model corresponds to one year. I initialize the economy in period $t = 0$, corresponding to the U.S. economy in 2019, and assume that the remote preference shock occurs in 2021 ($t^* = 2$).

[25] Appendix K discusses the selection of the MSA sample.

Table 1: Parameter Values

Parameter	Value	Description	Source/Target
Externally Fixed Parameters			
τ_l	Varies	Tax rates	NBER Taxsim
ϕ	1	Remote Productivity	Fixed
σ	4.392	EOS between Remote and Non-remote	Estimated
$\bar{P}_l^H$	1	Housing Permits	Normalization
$\bar{P}_l^B$	1	Office Permits	Normalization
ρ_l^Z	Varies	Material Share in Construction	Saiz (2010) estimates
$\bar{h}$	1	Housing Parameter	Normalization
δ^b	0.024	Office Depreciation	BEA Fixed Assets
β	0.9615	Discount Factor	Fixed
ν_l	2.02	Dispersion of Location Shocks	Caliendo et al. (2019)
ν_r	0.0634	Dispersion of Work Mode Shocks	M. Davis et al. (2024)
γ	2	Inverse Elasticity of Intertemporal Substitution	Fixed
Internally Calibrated Parameters			
A_l^C	Varies	Tradable Sector TFP	Average wage (ACS)
A_l^H	Varies	Housing Sector TFP	Home prices (Zillow)
α_l	Varies	Remote Share in Production	Remote wage premium (ACS)
η_l	Varies	Labor's Share in Non-remote Input	Income shares in Valentinyi and Herrendorf (2008)
δ^h	0.058	Housing Depreciation	Housing Expenditure share (BLS)

A subset of parameters is fixed using standard values, estimates from the literature, or reduced-form estimates (Section 4.1). To avoid calibrating region-specific amenities and migration costs, I employ a dynamic exact-hat approach (Section 4.2). The remaining parameters are calibrated to match key moments of the pre-pandemic economy (Section 4.3). Table 1 summarizes parameter values used in the quantitative analysis.

4.1 Externally Fixed Parameters

I set the discount factor $\beta = 0.9615$, corresponding to an annual discount rate of 4%. As is standard in the macro literature, I assume utility has the constant relative risk aversion form, with inverse elasticity of intertemporal substitution $\gamma = 2$. The housing parameter is normalized to $\bar{h} = 1$, such that $p_{l,t}$ denotes the price of a typical house in MSA l. For the parameters controlling the dispersion of preference shocks, I borrow the location shock estimate from Caliendo et al. (2019), $\nu_l = 2.02$, and the work mode shock estimate from M. Davis et al. (2024), $\nu_r = 0.0634$. I take the depreciation rate for commercial office real estate from the 2018 Bureau of Economic Analysis (BEA) fixed assets tables, $\delta^b = 0.024$.[26]

For labor taxes τ_l, I use 2018 marginal tax rates from the National Bureau of Economic Research (NBER) Taxsim tables (Feenberg & Coutts, 1993), based on a household with a nominal income of \$75,000.[27] In the benchmark calibration, I assume that labor tax rebates are distributed uniformly to all residents of a region, such that $T_{l,r,k,t} = T_{l,t}$ for all l, r, k.

Empirical evidence on the relative productivity of remote work is mixed. For example, Bloom et al. (2015) find productivity gains associated with working remotely, while Gibbs et al. (2023) report productivity losses. To avoid taking a stand, I set the productivity of remote work $\phi = 1$, such that remote workers are as productive as their non-remote counterparts.

I choose the material shares in residential construction ρ_l^H to match each MSA's housing supply elasticity as estimated in Baum-Snow and Han (2024).[28] Due to limited empirical evidence on the elasticity of commercial real estate supply across geographies, I adopt the same values for the material share of office construction, ρ_l^B, as those used for housing, ρ_l^H. This choice reflects the fact that many local factors (natural or regulatory) affect both sectors in similar ways. Permits in the housing and office construction sectors are normalized to $\bar{P}_l^H = \bar{P}_l^B = 1$ for all l.

4.1.1 Estimating the Substitutability of Remote Work

Section 3 demonstrated that the elasticity of substitution between remote and non-remote inputs, σ, plays a central role in determining the impact of remote work on office demand. Here I provide a reduced-form estimate of σ by exploiting variation in pre-pandemic exposure to remote work.

Notice that the profit maximization problem of a firm facing the production function in (27) implies the following relationship between the remote wage and the firm's demand for remote labor,

$$\ln(w_R) = \bar{A}_l + \frac{1}{\sigma} \cdot \ln\left(\frac{Y_l^C}{R_l}\right),$$

where $\bar{A}_l \equiv \ln((A_l^C)^{\frac{\sigma-1}{\sigma}} \alpha_l)$ depends on fixed model parameters characterizing the production

[26] The depreciation rate is computed as the ratio of the 2018 depreciation for category "Office" relative to its stock.

[27] I use marginal tax rates (variable *mtr_wage*) from the nominal table (see link). For MSAs that cross state lines, I use the tax rate associated with the state where the largest principal city is located.

[28] Following the recommendation of Baum-Snow and Han (2024), I use the estimates from the FMM-IV model (*region_gamma111b_space_FMM*).

process in region l. This motivates the following estimating equation:

$$\ln\left(w_{R,l,t}\right) = \mu_l + \sigma^* \ln\left(\frac{Y_{l,t}^C}{R_{l,t}}\right) + \kappa_t + \varepsilon_{l,t}, \tag{32}$$

where μ_l is a region fixed effect and $\sigma = 1/\sigma^*$.[29] Additionally, I include year fixed effects, κ_t, to control for aggregate trends in remote work.[30]

I use data on remote wages and regional GDP to estimate σ. American Community Survey (ACS) data for the period 2015 - 2023 is used to compute the average remote wage among employed, civilian individuals, by region and year, $w_{R,l,t}$, as well as the number of remote workers $R_{l,t}$ (Ruggles et al., 2024).[31] Data on regional GDP $Y_{l,t}^C$ is collected from the BEA GDP by Metropolitan Area tables.[32]

Notice that unobserved changes to the productivity of remote work (e.g., the introduction of Zoom), which are correlated with the demand for remote labor, can lead to biased OLS estimates of the demand parameter σ^* in (32). To address this, I implement a two-stage least squares approach that exploits the pandemic-driven shift in the aggregate supply of remote workers. Specifically, I construct an instrument by interacting local pre-pandemic exposure to remote work with the national, time-varying share of workers employed remotely. For the former, I take the industry-level measure of exposure to remote work from Dingel and Neiman (2020), who assign to each industry the share of (pre-pandemic) jobs which could be done remotely (i.e., teleworkable jobs). I aggregate this measure to the MSA level, by combining it with the 2014 MSA-level share of total employment in each industry from the U.S. Census Business Patterns,

$$\mathrm{Exp}_l = \sum_j s_{j,l,2014} \cdot \mathrm{Exp}_j,$$

where $s_{j,l,2014}$ is the 2014 employment share of industry j in MSA l, and Exp_j is the share of teleworkable jobs in industry j. I then interact the log of the exposure measure with the

[29]While the model features a single market for remote labor, remote wages in the data differ by region due to differences in local industry makeup: remote jobs tend to be high paying and concentrated in certain industries (Barrero et al., 2023). Thus, I allow the remote wage to vary by region in the estimating equation (32).

[30]The remote share of the labor force grew at an average annual rate of approximately 3% from 2000 to 2019 (see Appendix A).

[31]As is standard in the work-from-home literature, remote workers are defined as those whose reported means of transportation to work in the ACS is "Worked at home".

[32]$Y_{l,t}^C$ denotes region l GDP less the contribution from residential and commercial office construction. Thus, I compute $Y_{l,t}^C$ as the total real GDP of MSA l minus the contribution from the construction industry in l.

Table 2: Estimates of the Elasticity of Substitution, σ

	(1)	(2)
First stage		
Log Exposure$_l$ $\times$ Remote$_t$	-9.996^{***}	-10.056^{***}
	(1.053)	(1.048)
Second stage		
Elasticity of Substitution, σ	4.392^{**}	4.423^{**}
	(2.169)	(2.184)
MSA FE	Yes	Yes
Year FE	Yes	Yes
Industry Control	No	Yes
Observations	1962	1962

Note: Standard errors are clustered at the MSA level, and are computed for σ using the delta method.

ACS's annual share of the U.S. workforce working remotely:

$$W_{l,t} = \ln\left(\text{Exp}_l\right) \cdot \text{Rem}_t. \tag{33}$$

The exogeneity of the instrument $W_{l,t}$ relies on the local pre-pandemic shares of teleworkable jobs being independent of other contemporaneous shocks to the regional demand for remote workers.

Column 1 of Table 2 reports the baseline estimation results. The first-stage results indicate that the instrument strongly predicts the ratio $Y^C_{l,t}/R_{l,t}$, with a first-stage F-statistic of 90.21. The second-stage results yield an estimated elasticity of substitution of $\hat{\sigma} = 4.392$. This estimate aligns with the values used in M. Davis et al. (2024) ($\sigma = 4.545$) and Delventhal and Parkhomenko (2024) ($\sigma \in [3.033, 4.355]$). I take this estimate as my preferred benchmark.

As noted by Barrero et al. (2023), remote work is concentrated in certain industries, which raises the possibility that industry-specific trends may confound the identification strategy. To address this, column 2 introduces a Bartik-style control that accounts for differential regional exposure to aggregate industry dynamics. Specifically, it uses the weighted average of national, industry-level employment growth, where the weights are based on region l's 2014 employment shares across industries. The results show that the estimated elasticity $\hat{\sigma}$ remains robust to the inclusion of this control.

4.2 Dynamic Exact-Hat Algebra

I adopt the dynamic exact-hat algebra methodology of Caliendo et al. (2019) and Kleinman et al. (2023) to solve the model in time differences rather than in levels. This approach allows me to simulate transition dynamics without estimating certain region-specific parameters.[33] The methodology requires data on the initial ($t = -1$) distribution of the population, office space, and office prices, $\{(L^{*data}_{l,-1}, B^{data}_{l,-1}, q^{data}_{l,-1})\}^{\mathcal{L}}_{l=1}$, $t = 0$ worker choices over work mode, $\{(\mu^{data}_{N,l,0}, \mu^{data}_{R,l,0})\}^{\mathcal{L}}_{l=1}$, and location, $\{(\pi^{data}_{k,N,l,0}, \pi^{data}_{k,R,l,0})\}^{\mathcal{L},\mathcal{L}}_{k=1,l=1}$, along with a sequence of changes in time-varying fundamentals (i.e., remote amenities $Z_{R,t}$).[34]

I use data from the 2018 ACS to measure the population distribution and from the 2019 ACS to compute conditional choice probabilities.[35] The values of $\mu^{data}_{r,l,0}$ and $\pi^{data}_{k,r,l,0}$ correspond to the share of individuals who resided in MSA l one year prior to the survey and live in MSA k with remote status r at the time of the survey.[36] For the distribution of office space, I use commercial building stock estimates from the U.S. Department of Energy.[37] Office price distributions are constructed using transaction data from Attom Data Solutions.[38]

To simulate the remote work shock requires the time-path of the remote amenity, $Z_{R,t}$, which determines the relative attractiveness of remote work. In the U.S., the share of remote employment rose from 5.8% in 2019 to a peak of 18.2% in 2021, before declining to 14.2% by 2023.[39] Survey evidence from Barrero et al. (2021) indicates that the remote share has stabilized in this range, with 12.5% of workers reporting remote work as of May 2025. To capture the long-run shift in real estate demand resulting from the remote shock, I calibrate the increase in the remote amenity $\mathcal{Z}_R = Z_{R,t^*} - Z_{R,t^*-1}$ such that the model-implied remote work share in 2023 matches the corresponding value in the 2023 ACS.

[33] Specifically, the dynamic exact-hat approach obviates the need to estimate moving costs $m_{l,k}$, office-sector TFP A^B_l, and regional amenities X_l.

[34] Appendix F provides derivations and further details of the exact-hat approach.

[35] The ACS sample is restricted to non-military, employed individuals. The ACS uses Public Use Microdata Areas (PUMAs) for geographic identifiers. I map an individual's residential or place of work PUMA to MSAs. Note that as PUMA and MSA boundaries do not align, the matching process may assign an individual to an MSA even if they live or work outside (but near) the MSA boundary. For residential PUMAs that span MSAs, I assign residents of the PUMA to the MSA which contains the largest share of the PUMA's population. For place of work PUMAs that span MSAs, I assign the PUMA to the largest MSA. I assume that non-remote workers are employed in the MSA where they live.

[36] In computing these choice probabilities, I exclude individuals who did not reside in one of the 234 MSAs either at the time of the survey or one year prior.

[37] Source: link. I include buildings classified as "Office" and constructed before 2019.

[38] Source: link. Appendix L describes the construction of the office price distribution in detail.

[39] See Appendix A.

4.3 Internally Calibrated Parameters

The remaining parameters are calibrated so that, when the model is initialized, key model-generated moments match their pre-pandemic empirical counterparts or estimates from the literature.

First, I calibrate the parameters governing production input shares: the remote share, α_l, and labor's share of the non-remote input, η_l. These are chosen to match two empirical targets: the remote wage premium and the income share of commercial office space. Given the distribution of labor and office space in period $t = -1$, the first-order conditions for tradable firms imply:[40]

$$\frac{w_{R,-1}}{w_{N,l,-1}} = \frac{\alpha_l}{(1-\alpha_l)} \cdot \frac{\phi^{\frac{\sigma-1}{\sigma}} R_{l,-1}^{-\frac{1}{\sigma}}}{B_{l,-1}^{\frac{(\sigma-1)(1-\eta_l)}{\sigma}} \eta_l N_{l,-1}^{\frac{(\sigma-1)\eta_l-\sigma}{\sigma}}}, \tag{34}$$

$$\frac{r_{l,-1}B_{l,-1}}{Y^C_{l,-1}} = \frac{(1-\alpha_l)(1-\eta_l)\left(N_{l,-1}^{\eta_l} B_{l,-1}^{1-\eta_l}\right)^{\frac{\sigma-1}{\sigma}}}{\alpha_l\left(\phi R_{l,-1}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha_l)\left(N_{l,-1}^{\eta_l} B_{l,-1}^{1-\eta_l}\right)^{\frac{\sigma-1}{\sigma}}}. \tag{35}$$

Equations (34) and (35) jointly determine α_l and η_l conditional on the wage ratio, $w_{R,-1}/w_{N,l,-1}$, and the office share of income, $r_{l,-1}B_{l,-1}/Y^C_{l,-1}$. The wage ratio is computed using 2018 ACS data on average wages by MSA.[41] I assign the commercial office share of income using factor income share estimates from Valentinyi and Herrendorf (2008).[42]

Next, the values for productivity in the tradable sector, A^C_l, are chosen so that the average income of workers employed in region l matches its empirical counterpart in the 2018 ACS, where the average wage income in the model is,

$$\frac{R_{l,-1}w_{R,-1} + N_{l,-1}w_{N,l,-1}}{L_{l,-1}}.$$

I calibrate the housing depreciation rate δ^h to match the 2019 average housing expenditure share from the BLS Consumer Expenditure Survey. The model-implied average housing

[40] Data from the 2018 ACS is used to generate the period $t = -1$ labor distribution, $\{(N^{data}_{l,-1}, R^{data}_{l,-1})\}_{l=1}^{\mathcal{L}}$.

[41] Since the model implies a single wage for remote workers, I use the average wage across all remote workers in the ACS sample to construct $w_{R,-1}$.

[42] Valentinyi and Herrendorf (2008) decompose capital income into land, structures, and equipment. Since the model abstracts from equipment, I reallocate its share to labor and office space: Office share = (Land share + Structure share)/(1 − Equipment share).

expenditure share is:

$$\sum_{l=1}^{\mathcal{L}} \sum_{r\in\{R,N\}} \sum_{k=1}^{\mathcal{L}} \mu_{r,l,0}\pi_{k,r,l,0}L^*_{l,-1} \left(\frac{p_{k,0}\bar{h} - (1-\delta^h)p_{l,0}\bar{h}}{(1-\tau_k)w_{r,k,0} + T_{r,k,0}} \right),$$

where $p_{l,0}$ is the average 2019 home price in region l, taken as the twelve-month average of the Zillow Home Value Index. Finally, productivity in the residential construction sector A^H_l is inferred from the housing market clearing condition and the first-order condition of construction firms:

$$A^H_l = \frac{\left(L^*_{l,0}\bar{h} - L^*_{l,-1}(1-\delta^h)\bar{h}\right)^{1-\rho^H_l}}{(p_{l,0}\rho^H_l)^{\rho^H_l} \left(\bar{P}^H_l\right)^{1-\rho^H_l}}, \tag{36}$$

where $L^*_{l,0}$ denotes the period zero population in region l, implied by the conditional choice probabilities $\mu^{data}_{r,l,0}$ and $\pi^{data}_{k,r,l,0}$.

5 Quantitative Analysis

In this section, I use the calibrated model to quantify the effect of remote work on residential and commercial real estate prices. Section 5.1 analyzes the impact of the remote work shock on aggregate price levels. Section 5.2 then turns to distributional consequences, examining how price changes vary across regions. Section 5.3 decomposes the overall price response into contributions from distinct underlying mechanisms. Section 5.4 explores price and welfare implications of place-based policies. Section 5.5 compares price dynamics predicted by the model with those observed in the data. Section 5.6 explains the importance of the residential-commercial real estate distinction.

5.1 Aggregate Effect of the Remote Shock

I begin by analyzing the aggregate effect of the remote shock on the evolution of residential and commercial real estate prices. To do so, I construct price indices for residential and commercial office real estate:

$$\bar{p}_t = \sum_{l=1}^{\mathcal{L}} \omega^h_{l,t} p_{l,t}, \tag{37}$$

$$\bar{q}_t = \sum_{l=1}^{\mathcal{L}} \omega^b_{l,t} q_{l,t}, \tag{38}$$

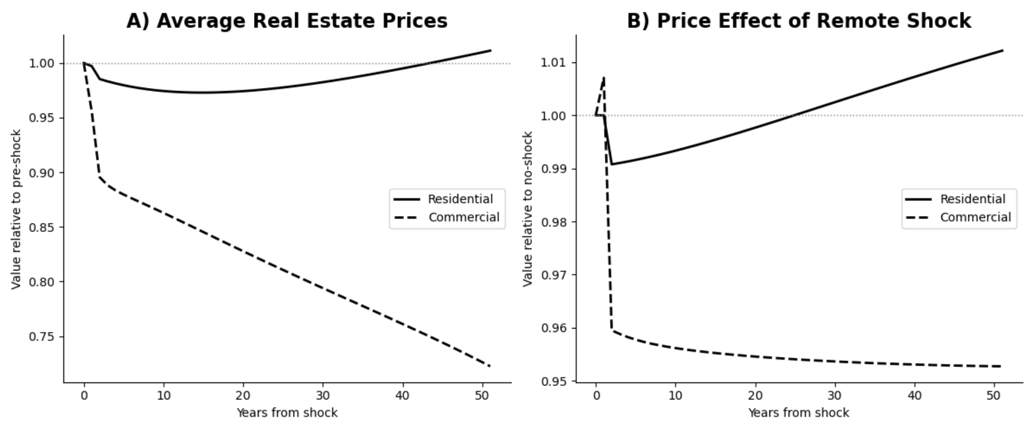

Figure 1: Evolution of real estate prices following the remote shock. A) Prices relative to pre-shock baseline. B) Prices under the baseline (remote shock) economy relative to a counterfactual economy absent the remote shock.

where the residential weights $\omega^h_{l,t}$ correspond to the period-t population share of region l, and the commercial weights $\omega^b_{l,t}$ reflect region l's share of the total office stock in period t. These aggregate measures, $\bar{p}_t$ and $\bar{q}_t$, capture both the direct effect of price changes across space, and the shifting spatial distribution of economic activity through reallocation of the population and office stock.[43]

Figure 1 displays the evolution of average real estate prices following the remote shock.[44] Panel A shows that the spatial reallocation of workers triggered by the remote shock coincides with an immediate, though modest, decline in average residential real estate prices. Over the long run, however, this trend reverses: residential prices gradually recover, returning to their pre-shock value after approximately 40 years. In contrast, commercial office prices see a sharper and more persistent decline. In the two years after agents learn of the shock, average office prices fall by 12% relative to their pre-shock value, followed by a continued decline over the subsequent decades (-0.6% per year, on average).

How much of the change in real estate prices is directly attributable to the remote shock, rather than pre-existing trends? Recall that the pre-shock economy is not in steady state, but is instead on the transition path towards some unobserved steady state when the remote shock hits. Thus, to isolate the effect of the remote shock from pre-shock trends, Panel B of Figure 1 plots the change in prices under the baseline economy that experiences the remote shock, relative to a counterfactual economy with constant fundamentals (i.e., absent

[43] Appendix M.1 decomposes the impact of the remote shock on the real estate price indices into contributions from price changes and from weight adjustments, and shows the aggregate effects of the remote shock are primarily driven by price changes.

[44] Throughout the quantitative analysis, the period immediately preceding agents' learning of the remote shock serves as the baseline for comparison.

the remote shock).[45] In what follows, I refer to this relative change in prices as the "price effect of the remote shock".

Panel B shows that residential real estate prices initially decline but eventually rise relative to the no-shock economy, mirroring the trajectory of the residential price index in Panel A. This confirms that the residential price dynamics in the model are primarily driven by the remote shock. Commercial office prices, by contrast, fall 4% in the two years following the shock, but then stabilize relative to the no-shock baseline. Two implications follow: (i) the long-run decline in office prices seen in Panel A is driven largely by pre-existing trends; and (ii) the remote shock induced an immediate and persistent drop in the average value of commercial office space.[46] These aggregate results, however, mask the degree to which the remote shock generates heterogeneous price effects across space, which I consider in the next subsection.

5.2 Distributional Effects of the Remote Shock

Turning to the distributional consequences of the remote shock, Figure 2 shows the long-run (steady state) real estate price effect of the remote shock across the 50 largest MSAs by 2019 population.[47] The figure underscores that the aggregate effects reported above conceal substantial regional variation. For example, Panel A shows the remote shock leads to a more than 20% *drop* in residential prices for San Francisco relative to the no-shock economy. In contrast, residential prices *rise* by over 20% in Austin due to the shock. Overall, the residential price response is mixed, with 20 MSAs experiencing price increases while 30 see declines. Thus, the small, aggregate residential effect seen in Figure 1 is due not to a quantitatively insignificant impact of the remote shock, but rather it arises from varying, and often large, price effects across space.

Figure 2 Panel B shows a price response for commercial office space that is more consistent with the aggregate results. In particular, the remote shock induces a decline in commercial office prices in each of the 50 largest MSAs. These declines vary in magnitude, ranging from modest (e.g., a -1% change in Orlando) to substantial (e.g., a -9% change in San Francisco).

Figure 3 extends the analysis by plotting changes in residential and commercial office

[45] In the counterfactual no-shock economy, the remote amenity remains constant ($\mathcal{Z}_R = 0$). This is the path agents anticipated prior to the shock's realization.

[46] The predicted long-run decline in office prices is smaller than that estimated by Gupta, Mittal, and Van Nieuwerburgh (2022) (41%). As discussed in Section 3, my model incorporates a complementarity effect that increases the marginal product of office space, partially offsetting the negative impact of remote work. These effects are absent in Gupta, Mittal, and Van Nieuwerburgh (2022). In Section 6, I show that my model's quantitative predictions are consistent with observed U.S. office prices through 2023.

[47] Results for all 234 MSAs are provided in Appendix M.3.

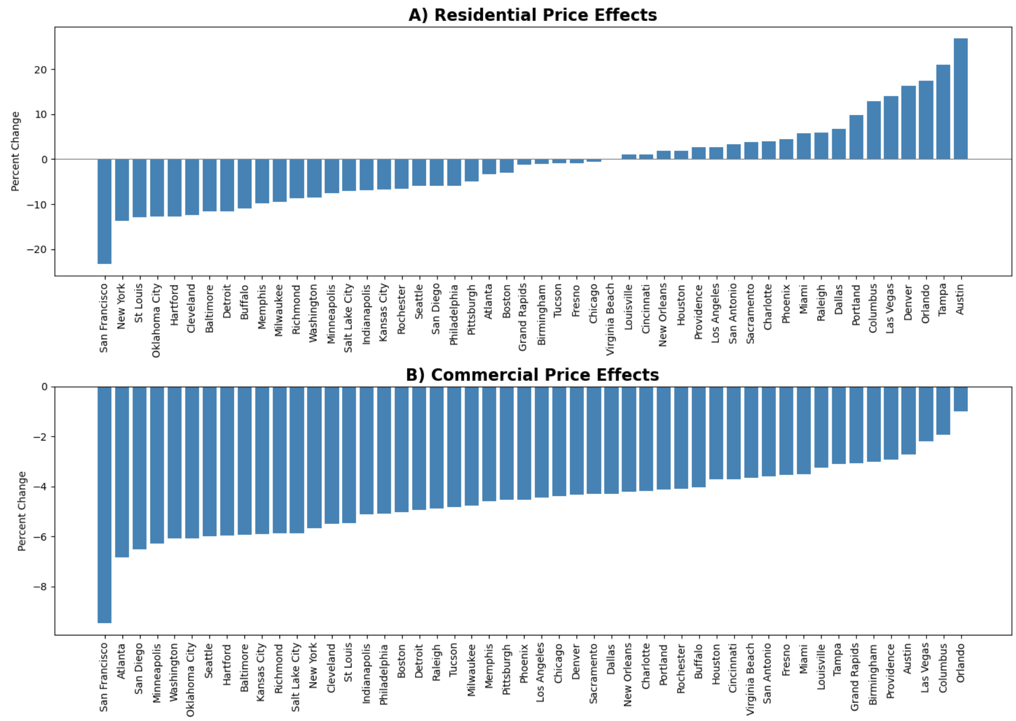

Figure 2: Long-run real estate price effects of the remote shock for the 50 largest MSAs by 2019 population.

prices across the full sample of MSAs, distinguishing between the total change in prices (Panel A) and the price effects of the remote shock (Panel B). The residential price effect of the remote shock is positive in 44% of MSAs, indicating a split between gains and losses consistent with that observed in the 50 largest MSAs. In contrast, the commercial office price effect is negative in most MSAs (219 of 234), with positive price effects limited to only a few small regions. Crucially, 99% of the pre-shock commercial office stock is located in MSAs that experience a price decline due to the remote shock. This indicates that most of the U.S. office real estate portfolio is at risk of becoming stranded following the rise of remote work.[48]

Figure 3 also shows a strong correlation between residential and commercial real estate markets in both total price changes (Panel A, correlation = 0.63) and in the price effects of the remote shock (Panel B, correlation = 0.83). Thus, regions experiencing price gains in one sector tend to gain, or lose less, in the other, producing "winners" (residential price gains with relatively modest commercial losses) and "losers" (residential price declines with large commercial losses) in the aftermath of the remote shock.

To summarize, the price effects of the remote work shock vary across MSAs and are

[48] Appendix M.2 provides a map of the price effects.

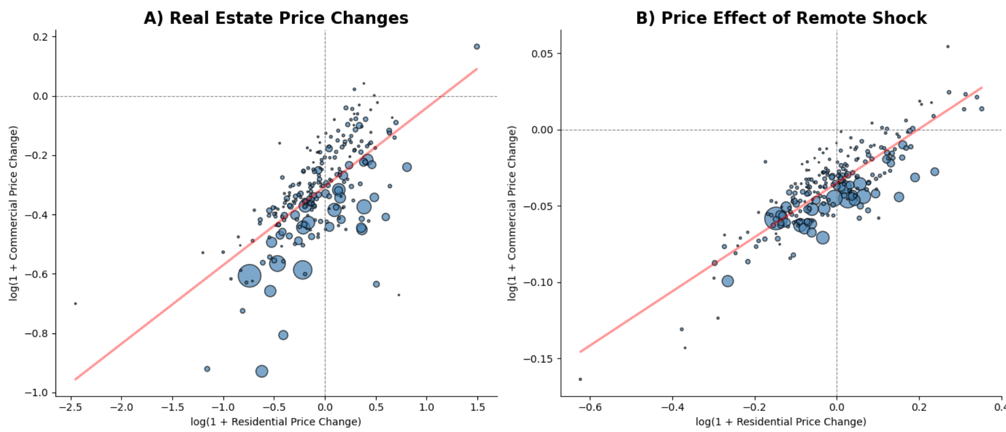

Figure 3: A) Long-run change in residential and commercial office prices relative to the pre-shock period. B) Long-run real estate price effects of the remote shock. Circle size reflects 2019 population.

strongly correlated between local residential and commercial office real estate markets. While residential markets exhibit a mix of positive and negative responses, all but a few small regions experience declines in commercial office prices due to the shock.

5.3 Inspecting the Mechanism

What drives the real estate price effects of the remote shock? In Section 3, I showed that the shift in residential demand induced by the remote shock is determined by differential migration rates between remote and non-remote workers as well as dynamic considerations (Proposition 4). In terms of commercial demand, I showed greater substitutability between remote and non-remote work in production increases the range of equilibria which lead to a negative commercial office price effect (Proposition 2). What is the quantitative relevance of each of these features vis-à-vis the economy's initial conditions? To answer, I consider seven model variations, each designed to isolate the contribution of a specific feature of the economy: (i) differential migration rates between remote and non-remote workers; (ii) dynamic considerations; (iii) the complementarity between remote and non-remote work; (iv) the initial population distribution; (v) the initial distribution of residential prices; (vi) the initial distribution of office space; and (vii) the initial distribution of office prices.[49] Each variation modifies only one feature of the baseline model at a time, holding all other features fixed. This approach allows for a clean decomposition of the mechanisms through which the

[49]For (i), I equalize migration rates for remote and non-remote workers. For (ii), I set the worker discount factor to zero. For (iii), I set the elasticity of substitution such that remote and non-remote work are (almost) perfect substitutes. For (iv)-(vii), I set the relevant variables equal to their initial-period weighted average across regions. See Appendix N for details.

remote work shock reshapes real estate markets.

To quantify the contribution of each factor to the total price effect of the remote shock, I compute the mean absolute change (MAC) in real estate prices between the baseline and the no-shock economy:

$$MAC^h = \frac{1}{(T+1)\mathcal{L}} \sum_{t=0}^{T} \sum_{l=1}^{\mathcal{L}} \left| p_{l,t}^{no\ shock} - p_{l,t}^{baseline} \right|,$$
$$MAC^b = \frac{1}{(T+1)\mathcal{L}} \sum_{t=0}^{T} \sum_{l=1}^{\mathcal{L}} \left| q_{l,t}^{no\ shock} - q_{l,t}^{baseline} \right|,$$

where MAC^h measures the average absolute change in residential real estate prices, and MAC^b captures the corresponding change in commercial office prices. Larger values of MAC^h and MAC^b indicate a stronger effect of the remote shock on prices. For each of the seven model variations (i)-(vii), I calculate the change in MAC^h and MAC^b relative to their values under the full model. This allows for a comparison of the relative importance of each factor in shaping the real estate price response to the remote shock. Table 3 reports the contribution of each mechanism to the residential price effect (Panel A) and the commercial price effect (Panel B). Negative values indicate a dampening of the remote shock's price effect (whether positive or negative), while positive values indicate an amplification. Additionally, Panel C shows the change, relative to the full model, in the correlation between the price effects of the remote shock in the residential and commercial office sectors.[50]

Column 1 reveals the residential price effect of the remote shock is almost entirely driven by differential migration patterns between remote and non-remote workers. When migration rates are equalized across worker types, the residential price response declines 99.97%, which also leads to a 0.65 (78%) drop in the correlation between residential and commercial price effects. In contrast, Column 2 shows no change in residential prices for the model with fully myopic workers. Thus, the residential price effect of the remote shock is driven by the direct effect—remote workers are more likely to move—as opposed to dynamic considerations.

Next, Column 3 evaluates the role of complementarities between remote and in-person work in shaping the value of office space. Consistent with Proposition 2, when the two are nearly perfect substitutes, the negative commercial price effect of the remote shock is

[50]The values reported in Table 3 Panel C correspond to the change in the correlation between long-run (i.e., steady-state) residential and commercial price effects, where the correlation is given by:

$$Corr\left(\frac{p_{l,ss}^{base.} - p_{l,ss}^{no\ shock}}{p_{l,ss}^{no\ shock}}, \frac{q_{l,ss}^{base.} - q_{l,ss}^{no\ shock}}{q_{l,ss}^{no\ shock}}\right).$$

Table 3: Sources of Remote Shock Price Effects

Amplification of price effects due to...						
Migration Rates	Dynamic Considerations	Complementarity Effect	Initial Pop. Dist.	Initial Res. Prices	Initial Com. Dist.	Initial Com. Prices
(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Residential Prices						
−99.97	0.00	0.13	86.85	34.79	−0.01	−0.01
Panel B: Commercial Prices						
−3.88	0.05	8.78	42.31	0.04	68.12	48.69
Panel C: Residential-Commercial Spread						
−0.65	0.00	−0.01	−0.46	−0.00	−0.34	−0.04

Note: Panel A reports the percent change in MAC^h from the full model to alternative specifications with: initial migration rates equalized between remote and non-remote workers, Column (1); fully myopic workers, Column (2); almost perfect substitutability between remote and non-remote inputs, Column (3); initial populations equalized across regions, Column (4); initial residential prices equalized across regions, Column (5); initial office space equalized across regions, Column (6); initial office prices equalized across regions, Column (7). Panel B reports similar statistics for MAC^b. Panel C reports the change in the correlation between residential and commercial price effects of the remote shock.

amplified 9%. On the other hand, the effect on residential prices is negligible.

Columns 4 - 7 explore the quantitative importance of the economy's initial conditions. Consider first the distribution of residential space (Column 4) and prices (Column 5). Imposing a uniform population across regions substantially increases the average effect of the remote shock on *both* residential (87%) and commercial (42%) real estate prices. Conversely, the correlation between the residential and commercial price effects falls by 0.46, or 56%. A uniform initial residential price distribution also increases the magnitude of the residential price effects, though to a lesser degree (35%). Instead, the initial population distribution plays the quantitatively larger role, by dampening the magnitude of the remote shock's impact and aligning its effects across the two real estate markets.

Finally, Columns 6 and 7 examine the role of the initial distribution of commercial office real estate, decomposed into contributions from floorspace (Column 6) and prices (Column 7). Both factors materially influence the commercial real estate response, but the spatial distribution of floorspace is especially important: the uniform distribution increases the magnitude of the commercial price effect by 68%, compared with a smaller 49% increase from the uniform price distribution. This highlights that the economy's initial allocation of office space is the key determinant of the commercial sector's sensitivity to the remote shock.

By contrast, the impact on residential prices is minimal.

To summarize, the residential price effect of the remote shock is determined by migration patterns of remote workers, who move at a higher rate than their non-remote counterparts.[51] The initial distribution of office space is the most important factor for the commercial price effect, and serves to dampen the impact of the remote shock. In the next section, I explore the price and welfare implications of place-based policies aimed at both remote worker migration and the local stock of office space.

5.4 Place-based Policies

A number of local policies have been implemented to address the regional impacts of the remote shock. This section examines the welfare implications of two such interventions which target the key drivers of the shock's price effects identified above: remote migration rates and the distribution of commercial office space. First, several locales have offered cash subsidies to attract remote workers.[52] Second, cities such as New York and San Francisco have sought to facilitate office-to-residential conversions by streamlining regulations and adjusting zoning restrictions.[53]

To study the local impact of these place-based policies, I consider counterfactual economies for which MSAs implement two types of interventions: a subsidy for remote workers and a policy allowing office-to-residential conversion.[54] I consider both price and welfare implications of each policy. Rather than taking a stand on the relative weight of workers and owners in a social welfare function, I separately report the welfare effects of each policy on each type of agent. The change in period-t welfare for a worker who begins the period in region l with remote status r (expressed in consumption-equivalent units) is given by,

$$\delta^w_{l,r,t} = \left(-1 + \left(\frac{\sum_{s=0}^{\infty} \beta^s \left(\frac{\left(c^{wC}_{l,r,l,t+s}\right)^{1-\gamma}}{1-\gamma} - \ln\left(\frac{(\mu^C_{r,l,t+s})^{\nu_r} (\pi^C_{l,r,l,t+s})^{\nu_l}}{(\mu^B_{r,l,t+s})^{\nu_r} (\pi^B_{l,r,l,t+s})^{\nu_l}} \right) \right)}{\sum_{s'=0}^{\infty} \beta^{s'} \frac{\left(c^{wB}_{l,r,l,t+s'}\right)^{1-\gamma}}{1-\gamma}} \right)^{1/(1-\gamma)} \right) \times 100, \quad (39)$$

where $c^{wB}_{l,r,l,t}$ and $c^{wC}_{l,r,l,t}$ denote consumption under the baseline (no-policy) and counterfactual

[51] In Appendix M.2, I show that pre-shock remote worker migration is positively correlated with residential price effects of the remote shock.

[52] Examples include Tulsa Remote in Tulsa, OK, and Ascend West Virginia.

[53] See the report from the New York City Comptroller, as well as this announcement from the City of San Francisco.

[54] I assume that policies are introduced in the period when agents first learn about the remote shock, and that they are unanticipated prior to implementation. For computational tractability, each counterfactual economy features only one region implementing a policy response to the remote shock.

(policy) economies, respectively.[55] Likewise, $\mu^B_{r,l,t+s}, \pi^B_{l,r,t+s}$ are baseline choice probabilities, and $\mu^C_{r,l,t+s}, \pi^C_{l,r,t+s}$ are the corresponding counterfactual probabilities. Notice worker welfare depends not only on consumption in the two policy regimes, but also on the relative option value of remaining in region l and work mode r, captured by the (log) shares of agents making those choices. These are scaled by the parameters ν_r and ν_l, which govern the variance of preference shocks. Analogously, the welfare effect of a policy for commercial office owners is given by

$$\delta^o_{l,t} = \left(-1 + \left(\frac{\sum_{s=0}^{\infty} \beta^s \frac{(c^{oC}_{l,s})^{1-\gamma}}{1-\gamma}}{\sum_{s'=0}^{\infty} \beta^{s'} \frac{(c^{oB}_{l,s'})^{1-\gamma}}{1-\gamma}} \right)^{1/(1-\gamma)} \right) \times 100, \tag{40}$$

where $c^{oB}_{l,t}$ and $c^{oC}_{l,t}$ denote the owner's consumption in the baseline and counterfactual economies, respectively. Table 4 summarizes the local welfare effects of each policy relative to an economy that experiences the remote shock in the absence of policy intervention for the twenty largest MSAs.[56]

5.4.1 Remote Subsidy

Consider a subsidy for remote workers that increases the transfer payment $T_{R,l,k,t}$ to a remote worker who migrates to region l from another region $k \neq l$. Motivated by the Tulsa Remote program, I model this policy as a one-time payment to remote workers who resided outside of l in the previous period, raising their rebate by $10,000 (in consumption units) relative to other residents of l.[57] This policy generates several competing effects on the welfare of workers in region l. First, the increase in housing demand from subsidized remote workers in period t raises the contemporaneous housing price $p_{l,t}$, boosting the consumption of current residents through higher housing wealth. Second, the permanent increase in remote workers' housing demand pushes up future housing prices $p_{l,t+j}$ for $j > 0$, raising the cost of remaining in region l. Third, the reallocation of labor across regions induced by the subsidy alters (current and future) equilibrium wages. Finally, the rebate, which is financed by labor taxes on region-l workers, reduces the rebate to other residents of l. The net welfare effect of the

[55]Equation 39 generalizes the welfare measure used by Caliendo et al. (2019) to the case of CRRA utility with a two-stage discrete choice structure. Full derivations are provided in Appendix G.

[56]Welfare is evaluated in the period the policy is implemented, $t = t^* - 1$. For worker welfare, I report the weighted average of δ^w_{l,r,t^*-1} across work modes $r \in R, N$, using the share of workers in each mode as weights.

[57]Unlike the Tulsa Remote program, which is funded by a non-profit organization, I assume the remote subsidy is financed by a labor tax.

Table 4: Welfare Effects of Place-based Policies

	Remote Subsidy		Office Conversion	
	Workers (1)	Owners (2)	Workers (3)	Owners (4)
New York	−0.031	0.001	0.404	0.037
Los Angeles	−0.251	0.001	−5.463	3.326
Chicago	−0.033	0.000	0.646	−0.000
Dallas	2.091	0.001	−18.467	0.819
Houston	1.939	−0.000	−18.236	0.461
Washington	−0.068	0.001	−18.410	2.049
Miami	−0.037	0.000	0.541	−0.000
Philadelphia	0.366	0.000	−2.302	0.085
Atlanta	0.805	0.000	−22.705	0.925
Phoenix	−0.096	0.001	−17.185	2.256
Boston	0.030	0.001	−57.834	0.910
San Francisco	−1.159	0.001	−60.270	2.571
Detroit	0.023	0.000	0.570	0.000
Seattle	13.265	−0.001	−30.724	2.744
Minneapolis	−0.037	0.000	−29.045	1.114
San Diego	−0.190	0.000	0.061	0.000
Tampa	0.411	0.001	−23.716	1.992
Denver	−0.341	0.001	−57.298	3.019
St. Louis	−0.038	0.000	0.013	0.000
Baltimore	0.595	0.001	1.034	0.000
Top 20	0.862	0.001	−17.919	1.115
All MSAs	0.918	0.000	−7.288	0.636

Note: The table reports the welfare effects for workers (Column 1) and owners (Column 2) of a remote-subsidy, and the welfare effects for workers (Column 3) and owners (Column 4) of an office-conversion policy. Welfare is expressed in consumption-equivalent percentage points for the twenty largest MSAs (by 2018 population), as well as the average across the twenty largest MSAs and the average across all MSAs.

subsidy on region-l workers depends on the relative strength of these forces.[58]

The first two columns of Table 4 report the welfare effects of the remote worker subsidy. Among the twenty largest MSAs, the effects on workers are mixed, with roughly as many regions experiencing gains as losses. Most effects are modest—generally less than one percent of annual consumption—though some cities (Dallas, Houston, Seattle) see larger positive gains. Across all MSAs, 48% experience positive worker welfare effects, with an average gain

[58] For regions with labor tax rate $\tau_l = 0$, I set τ_l under the policy counterfactual to the average across regions k for which $\tau_k > 0$.

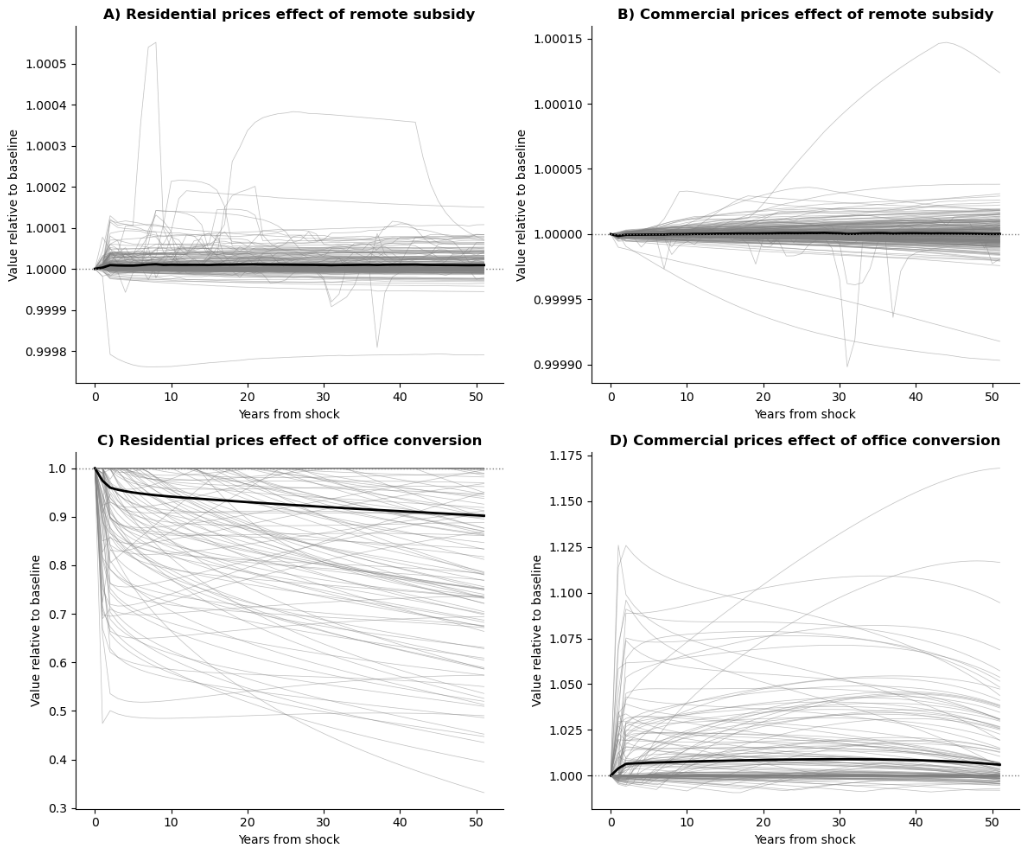

Figure 4: Change in real estate prices under place-based policies, relative to the no-policy baseline. Light gray lines show price effects for each region. Dark black lines show the average price effects across regions.

equivalent to 0.918% of annual consumption. By contrast, Column 2 shows that the welfare effect on owners is negligible.

What is the real estate price effect of the remote subsidy? Panels A and B of Figure 4 show the changes in residential and commercial office prices induced by the policy, relative to the no-policy baseline. The figure confirms that the demand shifts generated by the $10,000 subsidy are too small to produce meaningful changes in either residential or commercial office prices.

5.4.2 Office Conversion

I next consider an environment in which commercial office owners are free to convert part of the office stock into residential housing and sell it on the local housing market after the realization of the remote shock (e.g., following changes in zoning regulations prompted by the shock). Conversion is assumed to be one-directional: office space can be transformed into residential housing, but not vice versa. At the start of each period, the owner may choose to convert $a_{l,t} \in [0, \varphi b_{l,t}]$ units of office space into $\psi a_{l,t}$ units of residential housing at a constant marginal cost z, where φ is the share of office space eligible for conversion in period t. The owner's budget constraint in (8) is updated to reflect revenue received from office space net of conversion, $r_{l,t}(b_{l,t} - a_{l,t})$, as well as the revenue generated by the converted real estate, $(\psi p_{l,t} - z)a_{l,t}$:

$$c^o_{l,t} + q_{l,t}x_{l,t} = r_{l,t}(b_{l,t} - a_{l,t}) + (\psi p_{l,t} - z)a_{l,t}.$$

Conversion costs z represent all explicit (e.g., construction) and implicit (e.g., regulatory) expenses, and are destroyed during the conversion process.[59] The law of motion for office capital in (9) becomes

$$b_{l,t+1} = x_{l,t} + (1 - \delta^b)(b_{l,t} - a_{l,t}),$$

while the residential (equation (19)) and office (equation (21)) market-clearing conditions are modified to account for conversion:

$$\begin{aligned} L^*_{l,t}\bar{h} &= L^*_{l,t-1}(1 - \delta^h)\bar{h} + Y^H_{l,t} + \psi a_{l,t}, \\ B_{l,t} &= b_{l,t} - a_{l,t}. \end{aligned}$$

The owner's optimal conversion rule is straightforward: conversion occurs whenever the net return from converting exceeds the present value of keeping a unit of office space,

$$\psi p_{l,t} - z \geq r_{l,t} + q_{l,t}(1 - \delta^b).$$

Based on estimates from Gupta et al. (2023) of the share of office space suitable for conversion, I set $\varphi = 0.09$. To calibrate the conversion cost z and efficiency parameter ψ, I use evidence from recent office-to-residential projects documented in a 2023 Urban Land Institute report.[60] Among the fifteen projects for which cost data are reported, the average conversion cost was \$236 per square foot, with an average residential unit size of 1,152 square

[59]Alternatively, one could assume convex adjustment costs, in line with the macro literature on capital adjustment (e.g., Gould, 1968):

$$z_1 a_{l,t} + z_2 \left(\frac{a_{l,t}}{\varphi b_{l,t}}\right)^\kappa \varphi b_{l,t},$$

for $\kappa > 1$. However, since the share of office stock converted each year is small (0.04% annually pre-pandemic, according to a Goldman Sachs report), the linear term is likely to dominate.

[60]Source: link.

feet, which I use to calibrate z and ψ, respectively.[61] The results of the office conversion counterfactuals are reported in Table 4, Columns 3 and 4.

Among the twenty largest MSAs, owners in six regions choose not to convert any office space. In the remaining regions, an average of 0.4% of the office stock is converted to residential use annually in the decade following the remote shock. Column 3 shows that the office conversion policy generally results in substantial declines in worker welfare, with an average loss equivalent to 18% of annual worker consumption. Across all MSAs, the average welfare loss for workers is 7%.

Turning to commercial office owners, Column 4 shows the office conversion policy generates welfare gains for owners of office real estate. The policy allows them to participate in the residential market, effectively expanding their choice set from $a_{l,t} \in \{0\}$ to $a_{l,t} \in [0, \varphi b_{l,t}]$. This leads to average welfare gain for owners of 1.12% in the largest regions and 0.64% across all MSAs.

Figure 4 shows the residential and commercial price effects of the office conversion policy. The increase in residential supply generates persistent price declines, with average prices across markets falling by 10% relative to the baseline, 50 years after the remote shock. Combined with the worker welfare losses reported in Table 4, this suggests that the reduction in workers' housing wealth outweighs the benefit of lower housing costs. By contrast, commercial owners experience gains in the value of the office stock, with prices 0.63% higher after 50 years, partially offsetting the negative commercial office price effect of the remote shock reported in Section 5.1.

To summarize, the effects of place-based policies in response to the remote shock vary both by location and by policy type (remote subsidy vs. office conversion). Remote subsidies generally produce modest price and welfare effects, though some regions experience larger worker welfare gains. In contrast, the office conversion policies lead to substantial shifts in both residential and commercial prices, along with pronounced welfare effects, typically reducing worker welfare while benefiting owners.

[61] I set $\psi_l = 1/(1152 \times Pop_{2018})$, where Pop_{2018} is the 2018 residential population of the 234 MSAs. I choose z such that the model-implied cost of conversion relative to the average price of office space (from (38)) matches the corresponding ratio in the Attom data for model year 2018 ($t = -1$):

$$\frac{z}{\bar{q}_{-1}^{\,model}} = \frac{236}{\bar{q}_{-1}^{\,data}}.$$

Table 5: Price Growth in the Model and Data

	Residential (1)	Commercial (2)
Log Price Growth (model)	0.214***	1.379***
	(0.053)	(0.410)
Observations	234	225
R^2	0.066	0.048

Note: In Column (1), the dependent variable is the log change in real residential prices from the pre-shock period (2018) to the post-shock period (2023), based on Zillow data. In Column (2), the dependent variable is the log change in real commercial prices from the pre-shock period (2010-2018 average) to the post-shock period (2020-2023 average). Commercial price averages exclude the bottom and top deciles of the price distribution within each region and period. Column (2) includes fewer observations because some regions lack commercial price data in the post-shock period. Standard errors are reported in parentheses.

5.5 Model Validation

Do the model-predicted changes in real estate prices align with those observed in the data? Table 5 examines the relationship between model-predicted changes in real estate prices from the pre- to post-shock period and those observed in the data. Recall the quantitative model is initialized so that the initial price distributions exactly match their empirical counterparts.[62] Accordingly, the coefficient estimates capture the model's ability to replicate real estate price growth, conditional on starting from the same initial price distribution as in the data.

The coefficient estimates indicate a positive and statistically significant relationship between price growth predicted by the model and that observed in the data. A one-percent increase in residential price growth predicted by the model is associated with a 0.214% increase in residential prices in the data, while the corresponding effect for commercial prices is 1.379%. Hence, the model aligns reasonably well with observed price trends, particularly for commercial office space. Note that the estimates in Table 5 reflect the total change in real estate prices, not just the component directly attributable to the remote shock. Section 6 additionally presents empirical estimates of the effect of remote work on commercial office prices.

[62]Productivity in the residential construction sector is calibrated so that the residential price distribution in period $t = 0$ matches the 2019 Zillow Price Index (Section 4.3). For consistency with the commercial price distribution, which is initialized in period $t = -1$, I instead use the 2018 Zillow index as the pre-period in Table 5, which does not directly enter the model.

5.6 Why the Residential-Commercial Distinction Matters

Existing spatial models of remote work which explicitly incorporate the use of floorspace as both a residence and an input to production often treat all real estate as a single asset class, as opposed to distinguishing between residential and commercial space.[63] However, this treatment fails to capture either differences in their aggregate dynamics (Section 5.1), or the diverse distributional impacts on each real estate type (Section 5.2). Further, while real estate price effects are correlated across residential and commercial office markets, it is unclear to what extent demand shifts are driven by one market or the other without explicitly distinguishing between the two.

To illustrate these ideas, consider the quantitative implications of a model in which floorspace used for residential purposes is perfectly substitutable with that used in production of the consumption good. Namely, this implies that growth in the local price of unified (residential and commercial) floorspace, $p_{l,t}^{uni}$, is determined by changes in demand due to both migration by workers and investment by the local commercial owner:

$$\frac{p_{l,t}^{uni}}{p_{l,t-1}^{uni}} = \left(\frac{\left(L_{l,t}^* - L_{l,t-1}^*(1-\delta^h)\right)\bar{h} + \psi x_{l,t}}{\left(L_{l,t-1}^* - L_{l,t-2}^*(1-\delta^h)\right)\bar{h} + \psi x_{l,t-1}} \right)^{(1-\rho_l^{uni})/\rho_l^{uni}},$$

where $\rho_l^{uni}/(1-\rho_l^{uni})$ is the local elasticity of floorspace supply.[64] Figure 5 compares the price effects of the remote shock under the benchmark economy (x-axis) with that for a counterfactual economy in which floorspace is perfectly substitutable across local real estate markets (y-axis).[65] If price effects are identical under the two specifications—that is, if the distinction between residential and commercial office space is quantitatively irrelevant—each dot showing the price effects for a single MSA should lie on the red 45 degree line.

Panel A of Figure 5 shows that residential price effects are nearly identical whether or not one distinguishes between the sources of real estate demand. However, the distinction becomes quantitatively relevant when one considers the effect on commercial office space, as shown by Panel B. In particular, while the benchmark model predicts a negative price effect in most MSAs (most dots lie to the left of the vertical axis), the price effects in the counterfactual model without the residential-commercial distinction are approximately split between price gains and losses. Thus, one of the main quantitative predictions of the model of a decline in the value of most commercial office space due to the remote shock is absent

[63] Behrens et al. (2024) assume workers purchase homes and firms purchase office space in a single market. In Delventhal and Parkhomenko (2024), workers demand floorspace as both an input to production and for housing consumption.

[64] The parameter ψ converts commercial office into residential floorspace (see Section 5.4.2).

[65] Details regarding the calibration of the counterfactual economy are provided in Appendix O.

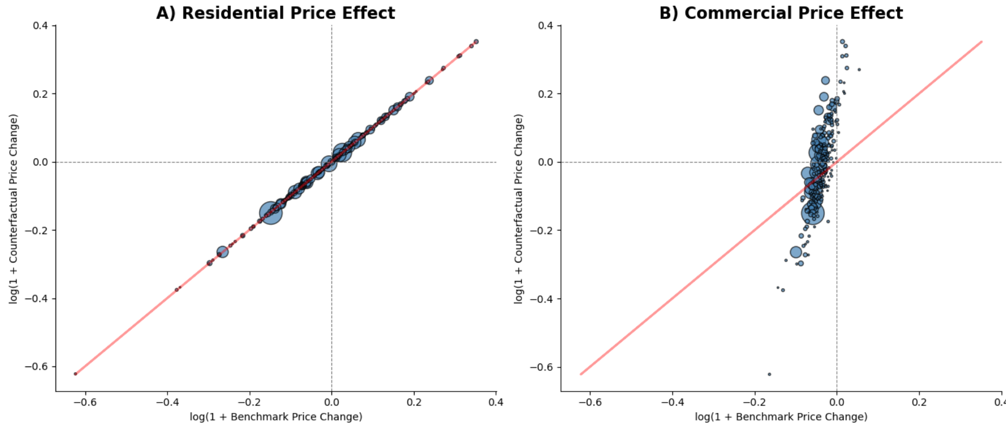

Figure 5: Price effects of the remote shock under both the benchmark economy and the counterfactual economy with perfectly substitutable real estate across sectors. Circle size reflects 2019 population.

without the explicit distinction between residential and commercial office markets.

6 Empirical Evidence

What is the effect of local exposure to remote work on the price of real estate? The effect on residential prices has been estimated in several previous studies (see Section 1.1), however the effect on commercial real estate has received considerably less attention. Unlike residential real estate, there is little publicly available data on commercial prices at the local level. To address this, I construct a regional commercial price index using office transaction data from Attom, and estimate the reduced form effect of remote work on average office prices.[66]

I adopt a similar approach to that used in estimating the elasticity of substitution (Section 4.1.1), employing a two-stage least squares strategy to isolate the effect of remote work on office prices. The identification leverages plausibly exogenous pre-pandemic variation in exposure to the remote shock. Specifically, I estimate the following system:

$$\text{First Stage:} \qquad Z_{l,t} = \delta W_{l,t} + \beta X_{l,t} + \zeta_l + \theta_t + \varepsilon_{l,t}, \tag{41}$$

$$\text{Second Stage:} \qquad Y_{l,t} = \pi \widehat{Z}_{l,t} + \gamma X_{l,t} + \mu_l + \kappa_t + \nu_{l,t}, \tag{42}$$

where $Z_{l,t}$ is the (log) remote share of employment in MSA l and year t, $Y_{l,t}$ is the (log) average real sale price of office space in MSA l and year t, and $X_{l,t}$ is a vector of controls, including both building characteristics of the properties sold in l and other economic attributes of MSA

[66]Appendix I shows that the Attom office data closely tracks an International Monetary Fund index for U.S. commercial real estate prices.

Table 6: IV Estimation Results

	OLS	*First Stage*	*Reduced Form*	*2SLS*	*Model*
Dependent Variable:	Log Price	Log Remote	Log Price	Log Price	Log Price
	(1)	(2)	(3)	(4)	(5)
Log Remote (Regional)	-0.385^{**}			-0.925^{***}	-1.826^{***}
	(0.156)			(0.283)	(0.176)
Log Exposure × Agg. Remote		14.286^{***}	-13.217^{***}		
		(1.388)	(3.822)		
Avg. Age (Decades)	-0.001	0.001	-0.002	-0.001	
	(0.003)	(0.001)	(0.003)	(0.003)	
Avg. Square Feet (1,000s)	0.017^{***}	0.001^{*}	0.016^{***}	0.016^{***}	
	(0.003)	(0.000)	(0.003)	(0.003)	
Labor Force (Millions)	-1.205^{*}	-0.174^{*}	-1.025^{*}	-1.186^{**}	16.202^{***}
	(0.627)	(0.106)	(0.573)	(0.594)	(4.995)
Industry	-7.794	3.009^{*}	-5.275	-2.491	
	(5.431)	(1.710)	(5.456)	(6.355)	
MSA FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
N	847	847	847	847	19,188

Note: Columns (1) through (4) show results of the estimation using the office transaction data. Controls include the average age of buildings being sold, their average square feet, the size of the labor force in the MSA, and a Bartik-style control for aggregate, industry-level employment trends. Column (5) shows results of an OLS regression using model-generated data. Standard errors are clustered at the MSA level.

l. The instrument $W_{l,t}$, given by equation (33), captures MSA-level exposure to the remote shock interacted with aggregate remote employment trends. I include MSA fixed effects (ζ_l, μ_l) and year fixed effects (θ_t, κ_t) to account for unobserved region-specific characteristics and aggregate shifts in demand for office space. Estimation results are reported in columns 1-4 of Table 6.

The OLS estimate in Column 1 indicates that higher rates of remote work are associated with lower average office prices, conditional on local economic and building characteristics. However, as with the estimation of remote work substitutability, the OLS estimate is likely biased by unobserved shocks to the demand for office space. To address this concern, Columns 2-4 present results from the IV specification. Column 2 shows that the instrument is strongly correlated with the local remote share (first-stage F-statistic = 106.04). The negative coefficient on the instrument in Column 3 implies that regions with greater exposure to the remote shock, driven by their industrial composition, experience larger declines in office values. Finally, Column 4 confirms a negative effect of remote work on office prices: a one percent increase in the remote share of employment in MSA l is estimated to reduce the average sale price of office space in that MSA by -0.925 percent, conditional on building characteristics and local labor force size.[67]

Do the model predictions align with this estimated effect of remote work on office prices? To answer, Column 5 of Table 6 provide an estimate of the relationship between remote work rates and office prices using model-generated data. The results show an elasticity of commercial prices with respect to the remote share of -1.826. To put this in perspective, the estimate implies a one standard deviation increase in the logarithm of the remote share reduces average commercial prices by 49%, compared to a 45% reduction in the data (Column 4).[68] Thus, the effect of remote work on commercial office prices predicted by the quantitative model closely aligns with that estimated from transaction data.

7 Conclusion

In this paper, I study the effect of the remote work shock on the spatial distribution of residential and commercial office real estate prices. To do so, I develop a quantitative spatial model featuring workers who migrate and choose whether to work remotely, endogenous investment by owners in new office space, and firms which hire labor and rent office space.

I highlight the competing effects on commercial office rents from remote work, as well as identify the substitutability of remote for non-remote work as driving the magnitude of these effects. Additionally, I show the residential demand effect of the remote shock depends on differential migration patterns between remote and non-remote workers, while house price dynamics introduce additional considertions into the workers' location problems. Quantitatively, I find the effect of the remote shock on residential prices is mixed, while most regions see a negative effect on commercial office prices. I then decompose the real estate price effects of the remote shock into the contributions from various model mechanisms, and identify differential migration rates as the driver for residential prices, while commercial office price effects are determined by the initial distributions of office space. The welfare effects of place-based policies are mixed: a remote subsidy tends to generate small welfare effects, while the office conversion policy leads to large welfare losses for workers and gains for commercial office owners. Finally, I empirically estimate the effect of remote work on commercial office prices, and show the magnitude of the estimated effect aligns with that predicted by the model.

[67] Appendix P.1 shows the results of an event study design, confirming the absence of pre-trends based on remote exposure.

[68] A one standard deviation increase in the log remote share corresponds to a $(\exp(s_Z \cdot \hat{\pi}) - 1) \cdot 100$ percent change in prices, where $\hat{\pi}$ corresponds to the coefficient estimate reported in Table 6, and s_Z is the standard deviation of the (log) remote share. I compute the product $s_Z \cdot \hat{\pi}$ separately using the standard deviation and coefficient estimates from the model, and those generated from the real estate data.

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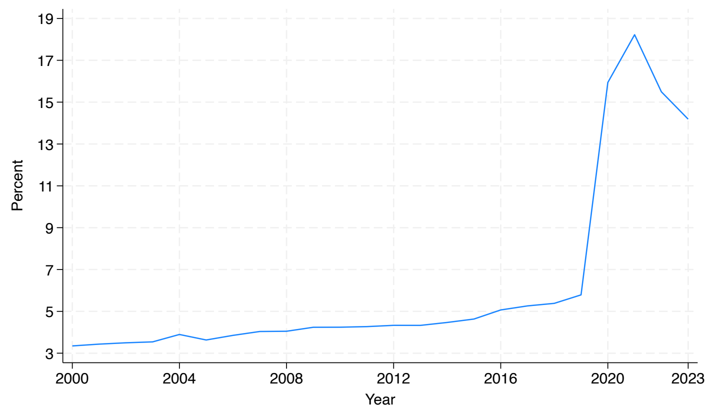
Appendix

A Remote Share Over Time

Figure 6: Remote share of employment



Note: Remote share of U.S. employed workers (excluding armed forces), 21 and over. *Source:* American Community Survery (Ruggles et al., 2024)

B Proofs of Propositions

B.1 Proof of Proposition 1

Holding the total supply of labor and the stock of office space fixed, one can express the rental rate of office space, r, given by the firm's first order condition (14), as a function of remote labor,

$$r(R) = \left.\frac{\partial Y^C(Y^R(R), Y^N(N(R), B))}{\partial Y^N}\right|_{B=\bar{B}} \times \left.\frac{\partial Y^N(N(R), B)}{\partial B}\right|_{B=\bar{B}}, \tag{43}$$

where $N(R) = \bar{L} - R$. Differentiating (43) with respect to R gives (26). Since $N'(R) = -1$, and by assumption, $\partial^2 Y^C/\partial(Y^N)^2 < 0$, $\partial Y^N/\partial N > 0$, $\partial^2 Y^C/\partial Y^N \partial Y^R \geq 0$, $\partial Y^R/\partial R > 0$, and $Y^N/\partial B > 0$, the first term on the right hand side of (26) (complementary effect) is positive. Further, since $\partial Y^C/\partial Y^N > 0$ and $\partial^2/\partial B \partial N > 0$ by assumption, the second term on the right hand side of (26) (substitution effect) is negative.

B.2 Proof of Lemma 1

Under the functional form in (27), the rental rate of office space is

$$r = A^C \left[\alpha\left(\phi R\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left(N^\eta B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} (1-\alpha)N^{\frac{(\sigma-1)\eta}{\sigma}}(1-\eta)B^{\frac{(\sigma-1)(1-\eta)-\sigma}{\sigma}}. \quad (44)$$

Setting $N = \bar{L} - R$, and differentiating (44) with respect to R gives

$$\begin{aligned}\frac{\partial r}{\partial R} &= A^C(1-\alpha)(1-\eta)B^{\frac{(\sigma-1)(1-\eta)-\sigma}{\sigma}}\left[\alpha\left(\phi R\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left((\bar{L}-R)^\eta B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} (\bar{L}-R)^{\frac{(\sigma-1)\eta}{\sigma}} \\ &\times \left\{\frac{1}{\sigma}\left[\alpha\left(\phi R\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left((\bar{L}-R)^\eta B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right]^{-1}\left(\alpha(\phi)^{\frac{\sigma-1}{\sigma}}R^{-1/\sigma}\right.\right. \\ &\left.\left. -(1-\alpha)\eta\left(\bar{L}-R\right)^{\frac{\eta(\sigma-1)-\sigma}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right) - \frac{(\sigma-1)\eta}{\sigma}\left(\bar{L}-R\right)^{-1}\right\}.\end{aligned}$$

This is negative if and only if

$$\frac{\alpha(\phi)^{\frac{\sigma-1}{\sigma}}R^{-\frac{1}{\sigma}} - (1-\alpha)\eta\left(\bar{L}-R\right)^{\frac{\eta(\sigma-1)-\sigma}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}}{\left[\alpha\left(\phi R\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left((\bar{L}-R)^\eta B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right]}\left(\bar{L}-R\right) - (\sigma-1)\eta \leq 0.$$

Let

$$\begin{aligned}F(R) &= \frac{\alpha(\phi)^{\frac{\sigma-1}{\sigma}}R^{-\frac{1}{\sigma}}\left(\bar{L}-R\right) - (1-\alpha)\eta\left(\bar{L}-R\right)^{\frac{\eta(\sigma-1)}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}}{\left[\alpha\left(\phi R\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left((\bar{L}-R)^\eta B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right]} - (\sigma-1)\eta \\ &= \frac{T_1(R) - T_2(R)}{T_3(R)} - (\sigma-1)\eta,\end{aligned}$$

defined for $R \in (0, \bar{L})$, so that the inequality holds for $F(R) \leq 0$. Consider the limit as R approaches $\bar{L}$. In this case, $T_1(R) \to 0$, while the behavior of $T_2(R)$ and $T_3(R)$ depend on the value of $\sigma > 0$.

- If $\sigma > 1$, then $T_2(R) \to 0$ and $T_3(R) \to$ *const.* which implies that $F(R) \to -(\sigma-1)\eta < 0$.
- If $\sigma = 1$, then $T_2(R) \to (1-\alpha)\eta$ and $T_3(R) \to 1$ which implies that $F(R) \to -(1-\alpha)\eta < 0$.
- If $\sigma < 1$, $T_3(R) \sim (1-\alpha)\left(\bar{L}-R\right)^{\frac{\eta(\sigma-1)}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}$ as $R \to \bar{L}$ and

$$\frac{T_2(R)}{T_3(R)} \to \frac{(1-\alpha)\eta\left(\bar{L}-R\right)^{\frac{\eta(\sigma-1)}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}}{(1-\alpha)\left(\bar{L}-R\right)^{\frac{\eta(\sigma-1)}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}} = \eta.$$

Thus $F(R) \to -\sigma\eta < 0$.

Next, consider the limit of $F(R)$ as R approaches 0. In this case, $T_1(R) \to +\infty$ and $T_2(R) \to const.$, while the behavior of $T_3(R)$ depend on the value of $\sigma > 0$.

- If $\sigma \geq 1$, then $T_3(R) \to const.$ which implies that $F(R) \to +\infty$.
- If $\sigma < 1$, $T_3(R) \sim \alpha(\phi R)^{\frac{\sigma-1}{\sigma}}$ as $R \to 0$ and

$$\frac{T_1(R)}{T_3(R)} \sim \frac{\alpha\phi^{\frac{\sigma-1}{\sigma}} R^{-\frac{1}{\sigma}} \left(\bar{L} - R\right)}{\alpha(\phi R)^{\frac{\sigma-1}{\sigma}}} = \frac{(\bar{L} - R)}{R} \to +\infty.$$

  Thus $F(R) \to +\infty$.

By continuity of $F(R)$ on $(0, \bar{L})$, there exists an $\tilde{R} \in (0, \bar{L})$ such that $F(R) \leq 0$ if $R \geq \tilde{R}$.

To show that the threshold is unique, consider any $\tilde{R}$ that satisfies $F(\tilde{R}) = 0$. That is,

$$\frac{\alpha\phi^{\frac{\sigma-1}{\sigma}}(\tilde{R})^{-\frac{1}{\sigma}}\left(\bar{L} - \tilde{R}\right) - (1-\alpha)\eta\left(\bar{L} - \tilde{R}\right)^{\frac{\eta(\sigma-1)}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}}{\left[\alpha\left(\phi\tilde{R}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha)\left((\bar{L} - \tilde{R})^{\eta}B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right]} - (\sigma - 1)\eta = 0,$$

which implies

$$\alpha\phi^{\frac{\sigma-1}{\sigma}}(\tilde{R})^{-\frac{1}{\sigma}}\left(\bar{L} - \tilde{R}\right) - (\sigma-1)\eta\alpha\left(\phi\tilde{R}\right)^{\frac{\sigma-1}{\sigma}} - \sigma\eta(1-\alpha)\left(\bar{L} - \tilde{R}\right)^{\frac{\eta(\sigma-1)}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}} = 0$$

Let

$$L(R) = \alpha\phi^{\frac{\sigma-1}{\sigma}}(R)^{-\frac{1}{\sigma}}\left(\bar{L} - R\right) - (\sigma-1)\eta\alpha\left(\phi R\right)^{\frac{\sigma-1}{\sigma}} - \sigma\eta(1-\alpha)\left(\bar{L} - R\right)^{\frac{\eta(\sigma-1)}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}$$

defined for $R \in (0, \bar{L})$, such that $L(\tilde{R}) = 0$. Notice,

$$L'(R) = \underbrace{\alpha\phi^{\frac{\sigma-1}{\sigma}}\left(-\frac{1}{\sigma}R^{\frac{-1}{\sigma}-1}\left(\bar{L} - R\right) - R^{-\frac{1}{\sigma}}\right)}_{<0} + \underbrace{(-1)(\sigma-1)\eta\alpha\phi^{\frac{\sigma-1}{\sigma}}\frac{\sigma-1}{\sigma}R^{-\frac{1}{\sigma}}}_{\leq 0}$$
$$+ \underbrace{\sigma\eta(1-\alpha)\frac{\eta(\sigma-1)}{\sigma}\left(\bar{L} - R\right)^{\frac{\eta(\sigma-1)}{\sigma}-1}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}}_{\leq 0 \text{ if } \sigma \leq 1}.$$

Thus, if $\sigma \leq 1$, $L(\cdot)$ is strictly decreasing and the solution $\tilde{R}$ to $L(\tilde{R})$ is unique. For the case

$\sigma > 1$, notice,

$$
\begin{aligned}
L''(R) = &\underbrace{\alpha\phi^{\frac{\sigma-1}{\sigma}}\left(\left(\frac{1}{\sigma}\right)\left(\frac{1}{\sigma}+1\right)R^{\frac{-1}{\sigma}-2}\left(\bar{L}-R\right)+\frac{1}{\sigma}R^{\frac{-1}{\sigma}-1}+\frac{1}{\sigma}R^{-\frac{1}{\sigma}-1}\right)}_{>0} \\
&+\underbrace{(\sigma-1)\eta\alpha\phi^{\frac{\sigma-1}{\sigma}}\frac{\sigma-1}{\sigma}\left(\frac{1}{\sigma}\right)R^{-\frac{1}{\sigma}-1}}_{>0} \\
&+\underbrace{(-1)\sigma\eta(1-\alpha)\frac{\eta(\sigma-1)}{\sigma}\left(\frac{\eta(\sigma-1)}{\sigma}-1\right)\left(\bar{L}-R\right)^{\frac{\eta(\sigma-1)}{\sigma}-2}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}}_{>0} > 0.
\end{aligned}
$$

Further,

$$
\begin{aligned}
&\lim_{R\to 0^+} L(R) = \infty, \\
&\lim_{R\to \bar{L}^-} L(R) = -(\sigma-1)\eta\alpha\left(\phi\bar{L}\right)^{\frac{\sigma-1}{\sigma}} < 0.
\end{aligned}
$$

Since $L(\cdot)$ is stricly convex and has a positive and a negative endpoint, it is single crossing, i.e. $\tilde{R}$ with $L(\tilde{R}) = 0$ is unique for $\sigma > 1$.

B.3 Proof of Proposition 2

As argued in the proof of Lemma 1, $\tilde{R}$ is given by the unique solution to

$$
\alpha\phi^{\frac{\sigma-1}{\sigma}}(\tilde{R})^{-\frac{1}{\sigma}}\left(1-\tilde{R}\right)-(\sigma-1)\eta\alpha\left(\phi\tilde{R}\right)^{\frac{\sigma-1}{\sigma}}-\sigma\eta(1-\alpha)\left(1-\tilde{R}\right)^{\frac{\eta(\sigma-1)}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}} = 0. \tag{45}
$$

Let

$$
L(R,\sigma) = \alpha\phi^{\frac{\sigma-1}{\sigma}}(R)^{-\frac{1}{\sigma}}(1-R)-(\sigma-1)\eta\alpha\left(\phi R\right)^{\frac{\sigma-1}{\sigma}}-\sigma\eta(1-\alpha)\left(1-R\right)^{\frac{\eta(\sigma-1)}{\sigma}}\left(B^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}.
$$

By the implicit function theorem,

$$
\frac{d\tilde{R}}{d\sigma} = -\frac{\frac{\partial L(\tilde{R},\sigma)}{\partial\sigma}}{\frac{\partial L(\tilde{R},\sigma)}{\partial R}}. \tag{46}
$$

I will show that both the numerator and the denominator of (46) are negative.

First recall from the proof of Lemma 1, $L(R,\sigma)$ is single-crossing in R, with $L(R,\sigma) > 0$ for $R < \tilde{R}$, and $L(R,\sigma) < 0$ for $R > \tilde{R}$. Thus, the partial derivative $\partial L(R,\sigma)/\partial R$ evaluated at $R = \tilde{R}$ is negative.

Next, consider the numerator of (46). This is given by

$$\begin{aligned}
\frac{\partial L(\tilde{R},\sigma)}{\partial \sigma} &= -(B^{1-\eta})^{\frac{\sigma-1}{\sigma}}\eta(1-\tilde{R})^{\eta\frac{\sigma-1}{\sigma}}(1-\alpha) - \alpha\eta(\phi\tilde{R})^{\frac{\sigma-1}{\sigma}} + \frac{\phi^{\frac{\sigma-1}{\sigma}}\alpha\ln(\phi)(1-\tilde{R})}{(\tilde{R})^{\frac{1}{\sigma}}\sigma^2} \\
&\quad - \frac{(B^{1-\eta})^{\frac{\sigma-1}{\sigma}}\eta\ln(B^{1-\eta})(1-\tilde{R})^{\eta\frac{\sigma-1}{\sigma}}(1-\alpha)}{\sigma} + \frac{\phi^{\frac{\sigma-1}{\sigma}}\alpha\ln(\tilde{R})(1-\tilde{R})}{(\tilde{R})^{\frac{1}{\sigma}}\sigma^2} \\
&\quad - \frac{(B^{1-\eta})^{\frac{\sigma-1}{\sigma}}\eta^2\ln(1-\tilde{R})(1-\tilde{R})^{\eta\frac{\sigma-1}{\sigma}}(1-\alpha)}{\sigma} - \frac{\phi^{\frac{\sigma-1}{\sigma}}\tilde{R}\alpha\eta\ln(\phi\tilde{R})(\sigma-1)}{\sigma^2(\tilde{R})^{\frac{1}{\sigma}}} \\
&= \frac{-\eta(1-\alpha)(1-\tilde{R})^{\eta\frac{\sigma-1}{\sigma}}(B^{1-\eta})^{\frac{\sigma-1}{\sigma}}\left(\sigma+\ln(B^{1-\eta})+\eta\ln(1-\tilde{R})\right)}{\sigma} \\
&\quad + \frac{-\sigma^2\alpha\eta\phi^{\frac{\sigma-1}{\sigma}}\tilde{R} + \phi^{\frac{\sigma-1}{\sigma}}\alpha\ln(\phi\tilde{R})(1-\tilde{R}) - \phi^{\frac{\sigma-1}{\sigma}}\tilde{R}\alpha\eta\ln(\phi\tilde{R})(\sigma-1)}{\sigma^2(\tilde{R})^{\frac{1}{\sigma}}}
\end{aligned}$$

The first fraction on the right side is negative since $B \geq \exp(-\sigma/(1-\eta))(1-\tilde{R})^{-\eta/(1-\eta)}$ by assumption, which implies $\sigma + \ln(B^{1-\eta} + \eta\ln(1-\tilde{R})) \geq 0$. As for the second, notice that (45) implies,

$$\begin{aligned}
\alpha\phi^{\frac{\sigma-1}{\sigma}}(\tilde{R})^{-\frac{1}{\sigma}}(1-\tilde{R}) &= (\sigma-1)\eta\alpha(\phi\tilde{R})^{\frac{\sigma-1}{\sigma}} + \underbrace{\sigma\eta(1-\alpha)(1-\tilde{R})^{\eta\frac{\sigma-1}{\sigma}}(B^{1-\eta})^{\frac{\sigma-1}{\sigma}}}_{>0} \\
&> (\sigma-1)\eta\alpha(\phi\tilde{R})^{\frac{\sigma-1}{\sigma}},
\end{aligned}$$

or equivalently,

$$\phi^{\frac{\sigma-1}{\sigma}}\alpha(1-\tilde{R}) - \phi^{\frac{\sigma-1}{\sigma}}\alpha\eta(\sigma-1)\tilde{R} > 0.$$

Thus,

$$\phi^{\frac{\sigma-1}{\sigma}}\alpha\ln(\phi\tilde{R})(1-\tilde{R}) - \phi^{\frac{\sigma-1}{\sigma}}\tilde{R}\alpha\eta\ln(\phi\tilde{R})(\sigma-1) = \ln(\phi\tilde{R})\left(\phi^{\frac{\sigma-1}{\sigma}}\alpha(1-\tilde{R}) - \phi^{\frac{\sigma-1}{\sigma}}\alpha\eta(\sigma-1)\tilde{R}\right) < 0,$$

since $\phi\tilde{R} \leq 1$. By extension,

$$-\sigma^2\alpha\eta\phi^{\frac{\sigma-1}{\sigma}}\tilde{R} + \phi^{\frac{\sigma-1}{\sigma}}\alpha\ln(\phi\tilde{R})(1-\tilde{R}) - \phi^{\frac{\sigma-1}{\sigma}}\tilde{R}\alpha\eta\ln(\phi\tilde{R})(\sigma-1) < 0,$$

and,

$$\frac{-\sigma^2\alpha\eta\phi^{\frac{\sigma-1}{\sigma}}\tilde{R} + \phi^{\frac{\sigma-1}{\sigma}}\alpha\ln(\phi\tilde{R})(1-\tilde{R}) - \phi^{\frac{\sigma-1}{\sigma}}\tilde{R}\alpha\eta\ln(\phi\tilde{R})(\sigma-1)}{\sigma^2(\tilde{R})^{\frac{1}{\sigma}}} < 0.$$

We can conclude that $\partial L(\tilde{R},\sigma)/\partial\sigma < 0$. Therefore, $d\tilde{R}/d\sigma < 0$.

B.4 Proof of Proposition 3

From (5)-(19), the demand for housing in the home region is

$$D(p_h; Z_R) = \sum_{k\in\{h,f\}} (\mu_{N,k}\pi_{h,N,k} + \mu_{R,k}\pi_{h,R,k})\,\bar{h}L_k^*$$
$$= \sum_{k\in\{h,f\}} (\pi_{h,N,k} + \mu_{R,k}(\pi_{h,R,k} - \pi_{h,N,k}))\,\bar{h}L_k^*$$

As $E[v_{l,t+1}^w] = \bar{v}$ by assumption, $d\pi_{h,r,k}/dZ_R = 0$ for all r, k, and

$$\frac{\partial D(p_h; Z_R)}{\partial Z_R} = \sum_{k\in\{h,f\}} \left(\frac{d\mu_{R,k}}{dZ_R}(\pi_{h,R,k} - \pi_{h,N,k})\right)\bar{h}L_k^*.$$

Notice that differentiating (3) with respect to Z_R evaluated at $r' = R$ yields,

$$\frac{d\mu_{R,k}}{dZ_R} = \frac{\exp\left(\nu_r^{-1}\left(\tilde{v}_{N,k}^w + \tilde{v}_{R,k}^w\right)\right)\nu_r^{-1}\frac{d\tilde{v}_{R,k}^w}{dZ_R}}{\left(\exp\left(\nu_r^{-1}\tilde{v}_{N,k}^w\right) + \exp\left(\nu_r^{-1}\tilde{v}_{R,k}^w\right)\right)^2} > 0,$$

since

$$\frac{d\tilde{v}_{R,k}^w}{dZ_R} = 1.$$

Thus, $\partial D(p_h, Z_R)/\partial Z_R \geq 0$ if $\pi_{h,R,k} - \pi_{h,N,k} \geq 0$ for all k. From (4), this condition is equivalent to:

$$\frac{\exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{h,R,k}^w\right)}{\sum_{k'\in\{h,f\}}\exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{k',R,k}^w\right)} \geq \frac{\exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{h,N,k}^w\right)}{\sum_{k'\in\{h,f\}}\exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{k',N,k}^w\right)}.$$

Rewriting the above,

$$\begin{aligned}
\exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{h,R,k}^w\right)\left(\exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{f,N,k}^w\right) + \exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{h,N,k}^w\right)\right) &\geq \exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{h,N,k}^w\right)\left(\exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{f,R,k}^w\right) + \exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{h,R,k}^w\right)\right)\\
\iff \exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{f,N,k}^w\right)\exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{h,R,k}^w\right) &\geq \exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{f,R,k}^w\right)\exp\left(\nu_l^{-1}\tilde{\tilde{v}}_{h,N,k}^w\right)\\
\iff \exp\left(\nu_l^{-1}\left(\tilde{\tilde{v}}_{h,R,k}^w - \tilde{\tilde{v}}_{h,N,k}^w\right)\right) &\geq \exp\left(\nu_l^{-1}\left(\tilde{\tilde{v}}_{f,R,k}^w - \tilde{\tilde{v}}_{f,N,k}^w\right)\right)\\
\iff \tilde{\tilde{v}}_{h,R,k}^w - \tilde{\tilde{v}}_{h,N,k}^w &\geq \tilde{\tilde{v}}_{f,R,k}^w - \tilde{\tilde{v}}_{f,N,k}^w\\
\iff u_{h,R,k} - u_{h,N,k} &\geq u_{f,R,k} - u_{f,N,k}.
\end{aligned}$$

As consumption associated with non-remote workers in the home region goes to zero, we have $c_{h,N,k} \to 0$ which implies

$$u_{h,N,k} = \frac{c_{h,N,k}^{1-\gamma} - 1}{1-\gamma} \longrightarrow -\infty,$$

for $\gamma \geq 1$, giving $u_{h,R,k} - u_{h,N,k} > u_{f,R,k} - u_{f,N,k}$ for all k.

B.5 Proof of Proposition 4

From equations (5) and (6), and noting that $L^*_{l,t} = N_{l,t} + R^*_{l,t}$, we have

$$\begin{aligned}
\frac{dL^*_{h,1}}{dZ_R} &= \sum_{k\in\{h,f\}} \left(\frac{d\mu_{R,k,1}}{dZ_R}\pi_{h,R,K,1} + \frac{d\mu_{N,k,1}}{dZ_R}\pi_{h,N,K,1} + \mu_{R,k,1}\frac{d\pi_{h,R,k,1}}{dZ_R} + \mu_{N,k,2}\frac{d\pi_{h,N,k,1}}{dZ_R} \right) L^*_{k,0} \\
&= \sum_{k\in\{h,f\}} \left(\frac{d\mu_{R,k,1}}{dZ_R}\left(\pi_{h,R,K,1} - \pi_{h,N,K,2}\right) + \mu_{R,k,1}\frac{d\pi_{h,R,k,1}}{dZ_R} + \mu_{N,k,1}\frac{d\pi_{h,N,k,1}}{dZ_R} \right) L^*_{k,0} \qquad (47)
\end{aligned}$$

where the second line follows since $\mu_{R,k,1} + \mu_{N,k,1} = 1$. Also,

$$\begin{aligned}
\frac{d\pi_{h,r,k,1}}{dZ_R} &= \frac{\nu_l^{-1}\exp\left(\nu_l^{-1}\left(\tilde{\tilde{v}}^w_{h,r,k,1} + \tilde{\tilde{v}}^w_{f,r,k,1}\right)\right)\left(\frac{d\tilde{\tilde{v}}^w_{h,r,k,1}}{dZ_R} - \frac{d\tilde{\tilde{v}}^w_{f,r,k,1}}{dZ_R}\right)}{\left(\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{h,r,k,1}\right) + \exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{f,r,k,1}\right)\right)^2} \\
&= \tilde{b}_{r,k}\left(\frac{d\tilde{\tilde{v}}^w_{h,r,k,1}}{dZ_R} - \frac{d\tilde{\tilde{v}}^w_{f,r,k,1}}{dZ_R}\right), \qquad (48)
\end{aligned}$$

where,

$$\tilde{b}_{r,k} \equiv \frac{\nu_l^{-1}\exp\left(\nu_l^{-1}\left(\tilde{\tilde{v}}^w_{h,r,k,1} + \tilde{\tilde{v}}^w_{f,r,k,1}\right)\right)}{\left(\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{h,r,k,1}\right) + \exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{f,r,k,1}\right)\right)^2}.$$

Since period 1 prices are assumed fixed, from (63) we have

$$\begin{aligned}
\frac{d\tilde{\tilde{v}}^w_{l,r,k,1}}{dZ_R} &= \beta\nu_r \frac{\sum_{r'\in\{R,N\}}\exp\left(\nu_r^{-1}\tilde{v}^w_{r',l,2}\right)\nu_r^{-1}\frac{d\tilde{v}^w_{r',l,2}}{dZ_R}}{\sum_{r'\in\{R,N\}}\exp\left(\nu_r^{-1}\tilde{v}^w_{r',l,2}\right)} \\
&= \beta \sum_{r'\in\{R,N\}} \frac{\exp\left(\nu_r^{-1}\tilde{v}^w_{r',l,2}\right)}{\sum_{r''\in\{R,N\}}\exp\left(\nu_r^{-1}\tilde{v}^w_{r'',l,2}\right)}\frac{d\tilde{v}^w_{r',l,2}}{dZ_R} \\
&= \beta \sum_{r'\in\{R,N\}} \mu_{r',l,2}\frac{d\tilde{v}^w_{r',l,2}}{dZ_R}. \qquad (49)
\end{aligned}$$

Also, from (62),

$$\begin{aligned}
\frac{d\tilde{v}^w_{r',l,2}}{dZ_R} &= \frac{dZ_{r'}}{dZ_R} + \nu_l \frac{\sum_{l' \in \{h,f\}} \exp\left(\nu_l^{-1} \tilde{\tilde{v}}^w_{l',r',l,2}\right) \nu_l^{-1} \frac{d\tilde{\tilde{v}}^w_{l',r',l,2}}{dZ_R}}{\sum_{l' \in \{h,f\}} \exp\left(\nu_l^{-1} \tilde{\tilde{v}}^w_{l',r',l,2}\right)} \\
&= \frac{dZ_{r'}}{dZ_R} + \sum_{l' \in \{h,f\}} \frac{\exp\left(\nu_l^{-1} \tilde{\tilde{v}}^w_{l',r',l,2}\right)}{\sum_{l'' \in \{h,f\}} \exp\left(\nu_l^{-1} \tilde{\tilde{v}}^w_{l'',r',l,2}\right)} \frac{d\tilde{\tilde{v}}^w_{l',r',l,2}}{dZ_R} \\
&= \frac{dZ_{r'}}{dZ_R} + \sum_{l' \in \{h,f\}} \pi_{l',r',l,2} \frac{d\tilde{\tilde{v}}^w_{l',r',l,2}}{dZ_R},
\end{aligned} \tag{50}$$

where $dZ_R/dZ_R = 1$ and $dZ_N/dZ_R = 0$. Since $E[v^w_{l,2}] = \bar{v}$,

$$\frac{d\tilde{\tilde{v}}^w_{l',r',l,2}}{dZ_R} = \left.\frac{du}{dc}\right|_{c=c(l',r',l;p_{h,2})} \frac{\partial c(l',r',l;p_{h,2})}{\partial p_{h,2}} \frac{dp_{h,2}}{dZ_R}, \tag{51}$$

where $c(l',r',l;p_{h,2}) \equiv (1-\tau_{l'})w_{r',l',2} + p_{l,2}\bar{h}(1-\delta^h) - p_{l',2}\bar{h} + T_{r',l',2}$. Combining (50) and (51) gives

$$\frac{d\tilde{v}^w_{r',l,2}}{dZ_R} = \frac{dZ_{r'}}{dZ_R} + \sum_{l' \in \{h,f\}} \pi_{l',r',l,2} \left.\frac{du}{dc}\right|_{c=c(l',r',l,2)} \frac{\partial c(l',r',l,2)}{\partial p_{h,2}} \frac{dp_{h,2}}{dZ_R}.$$

Plugging into (49),

$$\begin{aligned}
\frac{d\tilde{\tilde{v}}^w_{l,r,k,1}}{dZ_R} &= \beta \sum_{r' \in \{R,N\}} \mu_{r',l,2} \left(\frac{dZ_{r'}}{dZ_R} + \sum_{l' \in \{h,f\}} \pi_{l',r',l,2} \left.\frac{du}{dc}\right|_{c=c(l',r',l;p_{h,2})} \frac{\partial c(l',r',l;p_{h,2})}{\partial p_{h,2}} \frac{dp_{h,2}}{dZ_R} \right) \\
&= \beta \left(\mu_{R,l,2} + \sum_{r' \in \{R,N\}} \sum_{l' \in \{h,f\}} \mu_{r',l,2} \pi_{l',r',l,2} \left.\frac{du}{dc}\right|_{c=c(l',r',l,2)} \frac{\partial c(l',r',l,2)}{\partial p_{h,2}} \frac{dp_{h,2}}{dZ_R} \right),
\end{aligned}$$

and from (48),

$$\begin{aligned}
\frac{d\pi_{h,r,k,1}}{dZ_R} &= \tilde{b}_{r,k}\beta\left(\mu_{R,h,2} - \mu_{R,f,2}\right) + \tilde{b}_{r,k}\beta \sum_{r' \in \{R,N\}} \sum_{l' \in \{h,f\}} \Bigg(\mu_{r',h,2}\pi_{l',r',h,2} \left.\frac{du}{dc}\right|_{c=c(l',r',h;p_{h,2})} \\
&\qquad \frac{\partial c(l',r',h;p_{h,2})}{\partial p_{h,2}} \frac{dp_{h,2}}{dZ_R} - \mu_{r',f,2}\pi_{l',r',f,2} \left.\frac{du}{dc}\right|_{c=c(l',r',f;p_{h,2})} \frac{\partial c(l',r',f;p_{h,2})}{\partial p_{h,2}} \frac{dp_{h,2}}{dZ_R} \Bigg) \\
&= a_{r,k} + b_{r,k} \sum_{r' \in \{R,N\}} \sum_{l' \in \{h,f\}} \Bigg(\mu_{r',h,2}\pi_{l',r',h,2} \left.\frac{du}{dc}\right|_{c=c(l',r',h;p_{h,2})} \frac{\partial c(l',r',h;p_{h,2})}{\partial p_{h,2}} \frac{dp_{h,2}}{dZ_R} \\
&\qquad - \mu_{r',f,2}\pi_{l',r',f,2} \left.\frac{du}{dc}\right|_{c=c(l',r',f;p_{h,2})} \frac{\partial c(l',r',f;p_{h,2})}{\partial p_{h,2}} \frac{dp_{h,2}}{dZ_R} \Bigg).
\end{aligned}$$

where,

$$a_{r,k} = \tilde{b}_{r,k}\beta\left(\mu_{R,h,2} - \mu_{R,f,2}\right),$$
$$b_{r,k} = \tilde{b}_{r,k}\beta.$$

Finally,

$$\sum_{r\in\{R,N\}} \mu_{r,k,1}\frac{d\pi_{h,r,k,1}}{dZ_R} = \sum_{r\in\{R,N\}} \mu_{r,k,1}\Bigg(a_{r,k} + b_{r,k}\sum_{r'\in\{R,N\}}\sum_{l'\in\{h,f\}}(\mu_{r',h,2}\pi_{l',r',h,2}$$
$$\left.\frac{du}{dc}\right|_{c=c(l',r',h;p_{h,2})}\frac{\partial c(l',r',h;p_{h,2})}{\partial p_{h,2}}\frac{dp_{h,2}}{dZ_R} - \mu_{r',f,2}\pi_{l',r',f,2}\left.\frac{du}{dc}\right|_{c=c(l',r',f;p_{h,2})}\frac{\partial c(l',r',f;p_{h,2})}{\partial p_{h,2}}\frac{dp_{h,2}}{dZ_R}\Bigg)\Bigg)$$
$$= a_k + b_k\sum_{r'\in\{R,N\}}\sum_{l'\in\{h,f\}}\Bigg(\mu_{r',h,2}\pi_{l',r',h,2}\left.\frac{du}{dc}\right|_{c=c(l',r',h;p_{h,2})}\frac{\partial c(l',r',h;p_{h,2})}{\partial p_{h,2}}\frac{dp_{h,2}}{dZ_R}$$
$$-\mu_{r',f,2}\pi_{l',r',f,2}\left.\frac{du}{dc}\right|_{c=c(l',r',f;p_{h,2})}\frac{\partial c(l',r',f;p_{h,2})}{\partial p_{h,2}}\frac{dp_{h,2}}{dZ_R}\Bigg),$$

with

$$a_k = \sum_{r\in\{R,N\}}\mu_{r,k,1}a_{r,k},$$
$$b_k = \sum_{r\in\{R,N\}}\mu_{r,k,1}b_{r,k},$$

which, when combined with (47), gives (30).

C Owners' Problem

The owner's FOC is

$$(c^o_{l,t})^{-\gamma}q_{l,t} = \beta(c^o_{l,t+1})^{-\gamma}\left(r_{l,t+1} + q_{l,t+1}(1-\delta^b)\right).$$

Since $q_{l,t} > 0$, the development firm's FOC implies positive production of office space $Y^B_{l,t} > 0$.[69] Office market clearing then implies $x_{l,t} > 0$ for all t.

Denote by $s_{l,t} > 0$ the savings rate, $c^o_{l,t} = (1 - s_{l,t})r_{l,t}b_{l,t}$. Then, $b_{l,t+1} = (s_{l,t}r_{l,t}b_{l,t})/q_{l,t} + (1-\delta^b)b_{l,t}$. Also, let z^* denote the steady-state value of a variable z. Suppose the economy reaches a steady-state in period T, i.e. $x_{l,t} = x^*_l$ and $b_{l,t+1} = b_{l,t} = b^*_l$ for $t \geq T$. Then

[69] To see $q_{l,t} > 0$ must hold, consider the case $q_{l,t} = 0$. The owner's problem implies optimal investment $x_{l,t} = \infty$ for $r_{l,t+1} > 0$. Thus, $q_{l,t} > 0$.

(dropping the l subscripts for convenience),

$$\begin{aligned} q_{T-1}((1-s_{T-1})r_{T-1}b_{T-1})^{-\gamma} &= \beta((1-s^*)r^*)^{-\gamma}\left(\frac{b_{T-1}(s_{T-1}r_{T-1}+q_{T-1}(1-\delta^b))}{q_{T-1}}\right)^{-\gamma}(r^*+q^*(1-\delta^b)) \\ &= \beta(r^*-\delta^b q^*)^{-\gamma}\left(\frac{b_{T-1}(s_{T-1}r_{T-1}+q_{T-1}(1-\delta^b))}{q_{T-1}}\right)^{-\gamma}(r^*+q^*(1-\delta^b)), \end{aligned}$$

where the second line follows since, in steady-state, investment just covers deprecation, $s^*r^*/q^* = \delta^b$. Thus,

$$s_{T-1} = \frac{\left(\frac{\beta(r^*+q^*(1-\delta^b))}{q_{T-1}}\right)^{1/\gamma} - (r^*-\delta^b q^*)\frac{(1-\delta^b)}{r_{T-1}}}{\left(\frac{\beta(r^*+q^*(1-\delta^b))}{q_{T-1}}\right)^{1/\gamma} + (r^*-\delta^b q^*)\frac{1}{q_{T-1}}}.$$

Proceeding backwards, for $t < T-1$, we have

$$s_t = \frac{\left(\frac{\beta(r_{t+1}+q_{t+1}(1-\delta^b))}{q_t}\right)^{1/\gamma} - (1-s_{t+1})\frac{r_{t+1}(1-\delta^b)}{r_t}}{\left(\frac{\beta(r_{t+1}+q_{t+1}(1-\delta^b))}{q_t}\right)^{1/\gamma} + (1-s_{t+1})\frac{r_{t+1}}{q_t}}.$$

C.1 Office Conversion

Consider the case where the owner can convert commercial office space into residential. The owner's FOC is

$$(c^o_{l,t})^{-\gamma}q_{l,t} = \beta\left[(c^o_{l,t+1})^{-\gamma}\left(r_{l,t+1}+q_{l,t+1}(1-\delta^b)\right)+\mu_{l,t+1}\varphi\right],$$

where $\mu_{l,t}$ is the mulitplier on the upper bound conversion constraint. Since $q_{l,t} > 0$, the development firm's FOC implies positive production of office space $Y^B_{l,t} > 0$.[70] Office market clearing then implies $x_{l,t} > 0$ for all t.

Define $s_{l,t} > 0$ such that $q_{l,t}x_{l,t} = s_{l,t}r_{l,t}(b_{l,t}-a_{l,t})$ and $c^o_{l,t} = (1-s_{l,t})r_{l,t}(b_{l,t}-a_{l,t}) + (\psi_l p_{l,t} - z)a_{l,t}$. Then, $b_{l,t+1} = (s_{l,t}r_{l,t}(b_{l,t}-a_{l,t}))/q_{l,t} + (1-\delta^b)(b_{l,t}-a_{l,t})$. Also, let z^* denote the steady-state value of a variable z. Suppose the economy reaches a steady-state in period T, i.e. $x_{l,t} = x^*_l$ and $b_{l,t+1} = b_{l,t} = b^*_l$ for $t \geq T$. Then (dropping the l subscripts for

[70] To see $q_{l,t} > 0$ must hold, consider the case $q_{l,t} = 0$. The owner's problem implies optimal investment $x_{l,t} = \infty$ for $r_{l,t+1} > 0$. Thus, $q_{l,t} > 0$.

convenience),

$$
\begin{aligned}
&q_{T-1}((1-s_{T-1})r_{T-1}(b_{T-1}-a_{T-1})+(\psi p_{T-1}-z)a_{T-1})^{-\gamma} \\
&\quad = \beta\left(((1-s^*)r^*(b^*-a^*)+(\psi p^*-z)a^*)^{-\gamma}(r^*+q^*(1-\delta^b))+\mu^*\varphi\right) \\
&\quad = \beta\left(\left((1-s^*)r^*\left(\frac{(b_{T-1}-a_{T-1})(s_{T-1}r_{T-1}+q_{T-1}(1-\delta^b))}{q_{T-1}}-a^*\right)+(\psi p^*-z)a^*\right)^{-\gamma}(r^*+q^*(1-\delta^b))+\mu^*\varphi\right) \\
&\quad = \beta\left(\left(\left(r^*-q^*\left(\frac{a^*}{b^*-a^*}+\delta^b\right)\right)\left(\frac{(b_{T-1}-a_{T-1})(s_{T-1}r_{T-1}+q_{T-1}(1-\delta^b))}{q_{T-1}}-a^*\right)+(\psi p^*-z)a^*\right)^{-\gamma}\right. \\
&\qquad \left.(r^*+q^*(1-\delta^b))+\mu^*\varphi\right).
\end{aligned}
$$

In the case that $\mu^*=0$,

$$
\begin{aligned}
s_{T-1} = &\left[\left(\frac{\beta(r^*+q^*(1-\delta^b))}{q_{T-1}}\right)^{1/\gamma}(r_{T-1}(b_{T-1}-a_{T-1})+(\psi p_{T-1}-z)a_{T-1})-\left(r^*-q^*\left(\frac{a^*}{b^*-a^*}+\delta^b\right)\right)\right. \\
&\left.\left((b_{T-1}-a_{T-1})(1-\delta^b)-a^*\right)-(\psi p^*-z)a^*\right]\left[\left(r^*-q^*\left(\frac{a^*}{b^*-a^*}+\delta^b\right)\right)\left(\frac{(b_{T-1}-a_{T-1})r_{T-1}}{q_{T-1}}\right)\right. \\
&\left.+\left(\frac{\beta(r^*+q^*(1-\delta^b))}{q_{T-1}}\right)^{1/\gamma}r_{T-1}(b_{T-1}-a_{T-1})\right]^{-1}
\end{aligned}
$$

Proceeding backwards, for $t<T-1$, we have

$$
\begin{aligned}
&q_t((1-s_t)r_t(b_t-a_t)+(\psi p_t-z)a_t)^{-\gamma}= \\
&\beta\left(\left((1-s_{t+1})r_{t+1}\left(\frac{(b_t-a_t)(s_tr_t+q_t(1-\delta^b))}{q_t}-a_{t+1}\right)+(\psi p_{t+1}-z)a_{t+1}\right)^{-\gamma}(r_{t+1}+q_{t+1}(1-\delta^b))+\mu_{t+1}\varphi\right).
\end{aligned}
$$

When $\mu_{t+1}=0$,

$$
\begin{aligned}
s_t = &\left[\left(\frac{\beta(r_{t+1}+q_{t+1}(1-\delta^b))}{q_t}\right)^{1/\gamma}(r_t(b_t-a_t)+(\psi p_t-z)a_t)-(1-s_{t+1})r_{t+1}\right. \\
&\left.\left((b_t-a_t)(1-\delta^b)-a_{t+1}\right)-(\psi p_{t+1}-z)a_{t+1}\right]\left[(1-s_{t+1})r_{t+1}\left(\frac{(b_t-a_t)r_t}{q_t}\right)\right. \\
&\left.+\left(\frac{\beta(r_{t+1}+q_{t+1}(1-\delta^b))}{q_t}\right)^{1/\gamma}r_t(b_t-a_t)\right]^{-1}.
\end{aligned}
$$

D Firms' First Order Conditions

The firms FOCs yield the following pricing equations:

$$w_{R,t} = A_l^C \left[\alpha_l \left(\phi R_{l,t}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha_l)\left(\left(N_{l,t}\right)^{\eta} B_{l,t}^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} \alpha_l \phi^{\frac{\sigma-1}{\sigma}} \left(R_{l,t}\right)^{-\frac{1}{\sigma}} \tag{52}$$

$$w_{N,l,t} = A_l^C \left[\alpha_l \left(\phi R_{l,t}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha_l)\left(\left(N_{l,t}\right)^{\eta} B_{l,t}^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} (1-\alpha_l) B_{l,t}^{\frac{(\sigma-1)(1-\eta)}{\sigma}} \eta \left(N_{l,t}\right)^{\frac{(\sigma-1)\eta-\sigma}{\sigma}}, \tag{53}$$

$$r_{l,t} = A_l^C \left[\alpha_l \left(\phi R_{l,t}\right)^{\frac{\sigma-1}{\sigma}} + (1-\alpha_l)\left(\left(N_{l,t}\right)^{\eta} B_{l,t}^{1-\eta}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{1}{\sigma-1}} (1-\alpha_l) \left(N_{l,t}\right)^{\frac{(\sigma-1)\eta}{\sigma}} (1-\eta) B_{l,t}^{\frac{(\sigma-1)(1-\eta)-\sigma}{\sigma}}, \tag{54}$$

$$p_{l,t} = \frac{1}{A_l^H \rho_l^H \left(M_{l,t}^H\right)^{\rho_l^H - 1} \left(P_{l,t}^H\right)^{1-\rho_l^H}}, \tag{55}$$

$$q_{l,t} = \frac{1}{A_l^B \rho_l^B \left(M_{l,t}^B\right)^{\rho_l^B - 1} \left(P_{l,t}^B\right)^{1-\rho_l^B}}, \tag{56}$$

E Gumbel trick

Define

$$\tilde{v}_{r,l,t}^w \equiv E_{\boldsymbol{\epsilon}}\left[v_{r,l,t}^w\right] + Z_r. \tag{57}$$

Also, let

$$\mu_{s,l,t} \equiv \frac{\exp\left(\nu_r^{-1}\tilde{v}_{s,l,t}^w\right)}{\exp\left(\nu_r^{-1}\tilde{v}_{N,l,t}^w\right) + \exp\left(\nu_r^{-1}\tilde{v}_{R,l,t}^w\right)}. \tag{58}$$

I will show that this is the expression defines the share of agents living in l who choose remote status s conditional on the aggregate state $\mathbf{S}$.

$$\begin{aligned} Pr\left(r = s | l, \mathbf{S}_t\right) &= Pr\left(s = \arg\max_{r'}\{\tilde{v}_{r',l,t}^w + \zeta_{r'}\}\right) \\ &= \mu_{s,l,t}, \end{aligned} \tag{59}$$

where $\zeta_{r'}$ is the realization of the preference shock corresponding to remote status r'.

First note that the PDF and CDF for the Gumbel distribution with location parameter μ and shape parameter ψ are

$$\begin{aligned} f(x;\mu,\psi) &= \psi^{-1}\exp\left(\psi^{-1}(\mu - x) - \exp\left(\psi^{-1}(\mu-x)\right)\right), \\ F(x;\mu,\psi) &= \exp\left(-\exp\left(\psi^{-1}(\mu-x)\right)\right). \end{aligned}$$

Then, supressing the dependence on l and t in what follows for clarity, the probability that an individual chooses remote status s is[71]

$$
\begin{aligned}
Pr\left(r=s\right) &= E\left[Pr\left(\tilde{v}_y^w+\zeta_y \leq \tilde{v}_s^w+\zeta_s \;\; \forall y\neq s\right)\right]\\
&= E\left[\prod_{y\neq s} Pr\left(\tilde{v}_y^w+\zeta_y \leq \tilde{v}_s^w+\zeta_s\right)\right]\\
&= \int_{-\infty}^{\infty} f(m;\tilde{v}_s^w,\nu_r)\prod_{y\neq s} Pr\left(\tilde{v}_y^w+\zeta_y\leq m\right) dm\\
&= \int_{-\infty}^{\infty} f(m;\tilde{v}_s^w,\nu_r)\prod_{y\neq s}\exp\left(-\exp\left(\nu_r^{-1}(\tilde{v}_y^w-m)\right)\right) dm\\
&= \int_{-\infty}^{\infty} f(m;\tilde{v}_s^w,\nu_r)\exp\left(-\sum_{y\neq s}\exp\left(\nu_r^{-1}(\tilde{v}_y^w-m)\right)\right) dm\\
&= \int_{-\infty}^{\infty} \nu_r^{-1}\exp\left(\nu_r^{-1}(\tilde{v}_s^w-m)-\exp\left(\nu_r^{-1}(\tilde{v}_s^w-m)\right)\right)\\
&\exp\left(-\sum_{y\neq s}\exp\left(\nu_r^{-1}(\tilde{v}_y^w-m)\right)\right) dm\\
&= \int_{-\infty}^{\infty} \nu_r^{-1}\exp\left(\nu_r^{-1}(\tilde{v}_s^w-m)\right)\exp\left(-\sum_{y}\exp\left(\nu_r^{-1}(\tilde{v}_y^w-m)\right)\right) dm\\
&= \int_{-\infty}^{\infty} \nu_r^{-1}\exp\left(\nu_r^{-1}\tilde{v}_s^w\right)\exp\left(-\nu_r^{-1}m\right)\exp\left(-\exp\left(-\nu_r^{-1}m\right)\sum_{y}\exp\left(\nu_r^{-1}\tilde{v}_y^w\right)\right) dm,
\end{aligned}
$$

where the expectation is taken with respect to $\tilde{v}_s^w+\zeta_s$ and the second line follows by independence. Note that $\exp\left(\nu_r^{-1}\tilde{v}_s^w\right)=\mu_s\sum_y\exp\left(\nu_r^{-1}\tilde{v}_y^w\right)$ by definition. Thus,

$$
\begin{aligned}
Pr\left(r=s\right) = \nu_r^{-1}\mu_s\sum_y\exp\left(\nu_r^{-1}\tilde{v}_y^w\right)&\int_{-\infty}^{\infty}\exp\left(-\nu_r^{-1}m\right)\\
\exp&\left(-\exp\left(-\nu_r^{-1}m\right)\sum_y\exp\left(\nu_r^{-1}\tilde{v}_y^w\right)\right) dm\\
&= \nu_r^{-1}\mu_s\left[\sum_y\exp\left(\nu_r^{-1}\tilde{v}_y^w\right)\right]\frac{1}{\nu_r^{-1}\sum_y\exp\left(\nu_r^{-1}\tilde{v}_y^w\right)}\\
&= \mu_s,
\end{aligned}
$$

where the second equality follows because, for $a,b\in\mathbb{R}$, $\int\exp(-ax)\exp(-b\exp(-ax))dx=\frac{1}{ab}$. Thus, by a law of large numbers, we can conclude that $\mu_{s,l,t}$ is the share of agents living

[71] I prove the equality in 59 for the general case where the choice set $r\in\mathbb{R}$ satisfies $|\mathbb{R}|\geq 2$.

in l who choose remote status s.

In a similar way, it can be shown that conditional on choosing remote status r, the share of agents choosing new location k is

$$\pi_{k,r,l,t} = \frac{\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k,r,l,t}\right)}{\sum_{k'\in\Gamma(r,l)}\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k',r,l,t}\right)}, \tag{60}$$

where

$$\tilde{\tilde{v}}^w_{k,r,l,t} \equiv u(c) + \beta E[v^w_{k,t+1}] + X_k - m_{l,k}, \tag{61}$$

subject to the constraints in 2.

Note also that integrating with respect to the shocks's gives

$$\begin{aligned}\tilde{v}^w_{r,l,t} &= Z_r + E_{\boldsymbol{\epsilon}}\left[v^w_{r,l,t}\right] \\ &= Z_r + \nu_l \ln\left(\sum_{k\in\Gamma(r,l)}\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k,r,l,t}\right)\right) + \nu_l\gamma_{EM}\end{aligned} \tag{62}$$

and

$$E[v^w_{k,t+1}] = \nu_r \ln\left(\sum_{r'\in\{R,N\}}\exp\left(\nu_r^{-1}\tilde{v}^w_{r',k,t+1}\right)\right) + \nu_r\gamma_{EM}, \tag{63}$$

where γ_{EM} is the Euler-Mascheroni Constant. To see this, note that the CDF of $v^w_{r,l,t} = \max_{k\in\Gamma(r,l)}\{\epsilon_k + \tilde{\tilde{v}}^w_{k,r,l,t}\}$ is (again suppressing l, t),

$$F(x) = Pr\left(\max_{k\in\Gamma(r,l)}\{\epsilon_k + \tilde{\tilde{v}}^w_{k,r}\} \leq x\right) \tag{64}$$

$$= \prod_{k\in\Gamma(r,l)} Pr\left(\epsilon_k + \tilde{\tilde{v}}^w_{k,r} \leq x\right) \tag{65}$$

$$= \prod_{k\in\Gamma(r,l)} \exp\left(-\exp\left(\nu_l^{-1}(\tilde{\tilde{v}}^w_{k,r} - x)\right)\right) \tag{66}$$

$$= \exp\left(-\sum_{k\in\Gamma(r,l)}\exp\left(\nu_l^{-1}(\tilde{\tilde{v}}^w_{k,r} - x)\right)\right) \tag{67}$$

$$= \exp\left(-\exp(-\nu_l^{-1}x)\sum_{k\in\Gamma(r,l)}\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k,r}\right)\right), \tag{68}$$

and the corresponding PDF is

$$f(x) = \nu_l^{-1} \exp\left(-\nu_l^{-1}x\right) \left(\sum_{k\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\widetilde{\widetilde{v}}_{k,r}^{w}\right) \right) \tag{69}$$

$$\exp\left(-\exp(-\nu_l^{-1}x) \sum_{k\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\widetilde{\widetilde{v}}_{k,r}^{w}\right) \right).$$

Thus,

$$\begin{aligned}
E_{\boldsymbol{\epsilon}}\left[v_r^w\right] &= \int_{-\infty}^{\infty} x f(x) dx && (70)\\
&= \int_{\infty}^{0} -\nu_l \ln\left(\frac{y}{\sum_{k\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\widetilde{\widetilde{v}}_{k,r}^{w}\right)} \right) \nu_l^{-1} y \exp\left(-y\right) \left(-\nu_l/y\right) dy \\
&= \nu_l \int_{0}^{\infty} -\ln\left(\frac{y}{\sum_{k\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\widetilde{\widetilde{v}}_{k,r}^{w}\right)} \right) \exp\left(-y\right) dy \\
&= \nu_l \int_{0}^{\infty} \ln\left(\sum_{k\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\widetilde{\widetilde{v}}_{k,r}^{w}\right) \right) \exp(-y) dy + \nu_l \int_{0}^{\infty} -\ln(y)\exp(-y) dy \\
&= \nu_l \ln\left(\sum_{k\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\widetilde{\widetilde{v}}_{k,r}^{w}\right) \right) + \nu_l \gamma_{EM}, && (71)
\end{aligned}$$

where the second line follows from the substitution $y = \exp\left(-\nu_l^{-1}x\right) \sum_{k\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\widetilde{\widetilde{v}}_{k,r}^{w}\right)$ with $dy = -\nu_l^{-1} dx \exp\left(-\nu_l^{-1}x\right) \sum_{k\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\widetilde{\widetilde{v}}_{k,r}^{w}\right) = -\nu_l^{-1} dx y$, $\lim_{x\to\infty} y = 0$, and $\lim_{x\to-\infty} y = \infty$.

The proof for 63 follows similarly.

F Dynamic Exact-Hat Algebra

Let $\dot{x}_{t+1} \equiv x_{t+1}/x_t$ denote the change in a variable x. Assume constant fundamentals. Notice

$$\begin{aligned}
\dot{\pi}_{k,r,l,t+1} &= \frac{\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k,r,l,t+1}\right)}{\exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k,r,l,t}\right)} \cdot \frac{\sum_{k'\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k',r,l,t}\right)}{\sum_{k''\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k'',r,l,t+1}\right)} \\
&= \frac{\exp\left(\tilde{\tilde{v}}^w_{k,r,l,t+1} - \tilde{\tilde{v}}^w_{k,r,l,t}\right)^{1/\nu_l}}{\sum_{k''\in\Gamma(r,l)} \left(\sum_{k'\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k',r,l,t}\right)\right)^{-1} \exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k'',r,l,t+1}\right)} \\
&= \frac{\exp\left(\tilde{\tilde{v}}^w_{k,r,l,t+1} - \tilde{\tilde{v}}^w_{k,r,l,t}\right)^{1/\nu_l}}{\sum_{k''\in\Gamma(r,l)} \pi_{k'',r,l,t} \exp\left(\tilde{\tilde{v}}^w_{k'',r,l,t+1} - \tilde{\tilde{v}}^w_{k'',r,l,t}\right)^{1/\nu_l}} \\
&= \frac{\left(\dot{\tilde{\tilde{v}}}^w_{k,r,l,t+1}\right)^{1/\nu_l}}{\sum_{k''\in\Gamma(r,l)} \pi_{k'',r,l,t} \left(\dot{\tilde{\tilde{v}}}^w_{k'',r,l,t+1}\right)^{1/\nu_l}}.
\end{aligned}$$

where, with a slight abuse of notation, $\dot{\tilde{\tilde{v}}}^w_{k,r,l,t+1} \equiv \exp(\tilde{\tilde{v}}^w_{k,r,l,t+1} - \tilde{\tilde{v}}^w_{k,r,l,t})$. Likewise,

$$\begin{aligned}
\dot{\mu}_{r,l,t+1} &= \frac{\exp\left(\nu_r^{-1}\tilde{v}^w_{r,l,t+1}\right)}{\exp\left(\nu_r^{-1}\tilde{v}^w_{r,l,t}\right)} \cdot \frac{\sum_{r'} \exp\left(\nu_r^{-1}\tilde{v}^w_{r',l,t}\right)}{\sum_{r''} \exp\left(\nu_r^{-1}\tilde{v}^w_{r'',l,t+1}\right)} \\
&= \frac{\exp\left(\tilde{v}^w_{r,l,t+1} - \tilde{v}^w_{r,l,t}\right)^{1/\nu_r}}{\sum_{r''} \mu_{r'',l,t} \exp\left(\tilde{v}^w_{r'',l,t+1} - \tilde{v}^w_{r'',l,t}\right)^{1/\nu_r}} \\
&= \frac{\left(\dot{\tilde{v}}^w_{r,l,t+1}\right)^{1/\nu_r}}{\sum_{r''} \mu_{r'',l,t} \left(\dot{\tilde{v}}^w_{r'',l,t+1}\right)^{1/\nu_r}}.
\end{aligned}$$

where $\dot{\tilde{v}}^w_{r,l,t+1} \equiv \exp(\tilde{v}^w_{r,l,t+1} - \tilde{v}^w_{r,l,t})$. Notice,

$$\begin{aligned}
\dot{\tilde{v}}^w_{r,l,t+1} &= \left(\frac{\sum_{l''\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{l'',r,l,t+1}\right)}{\sum_{l'\in\Gamma(r,l)} \exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{l',r,l,t}\right)}\right)^{\nu_l} \exp\left(Z_{r,t+1} - Z_{r,t}\right) \\
&= \left(\sum_{l''\in\Gamma(r,l)} \pi_{l'',r,l,t} \exp\left(\tilde{\tilde{v}}^w_{l'',r,l,t+1} - \tilde{\tilde{v}}^w_{l'',r,l,t}\right)^{1/\nu_l}\right)^{\nu_l} \exp\left(Z_{r,t+1} - Z_{r,t}\right) \\
&= \left(\sum_{l''\in\Gamma(r,l)} \pi_{l'',r,l,t} \left(\dot{\tilde{\tilde{v}}}^w_{l'',r,l,t+1}\right)^{1/\nu_l}\right)^{\nu_l} \exp\left(Z_{r,t+1} - Z_{r,t}\right).
\end{aligned}$$

Thus,

$$
\begin{aligned}
\dot{\mu}_{r,l,t+1} &= \frac{\left(\dot{\tilde{v}}^{w}_{r,l,t+1}\right)^{1/\nu_r}}{\sum_{r''}\mu_{r'',l,t}\left(\dot{\tilde{v}}^{w}_{r'',l,t+1}\right)^{1/\nu_r}} \\
&= \left(\sum_{l'\in\Gamma(r,l)}\pi_{l',r,l,t}\left(\dot{\tilde{\tilde{v}}}^{w}_{l',r,l,t+1}\right)^{1/\nu_l}\right)^{\nu_l/\nu_r} \exp\left(Z_{r,t+1}-Z_{r,t}\right)^{1/\nu_r} \\
&\quad \left(\sum_{r''}\mu_{r'',l,t}\left(\sum_{l''\in\Gamma(r'',l)}\pi_{l'',r'',l,t}\left(\dot{\tilde{\tilde{v}}}^{w}_{l'',r'',l,t+1}\right)^{1/\nu_l}\right)^{\nu_l/\nu_r} \exp\left(Z_{r'',t+1}-Z_{r'',t}\right)^{1/\nu_r}\right)^{-1}
\end{aligned}
$$

Also,

$$
\begin{aligned}
\dot{\tilde{\tilde{v}}}^{w}_{k,r,l,t+1} &= \exp\left(u_{k,r,l,t+1}+\beta E_{t+1}[v^{w}_{k,t+2}]-u_{k,r,l,t}-\beta E_t[v^{w}_{k,t+1}]\right) \\
&= \exp\left(u_{k,r,l,t+1}-u_{k,r,l,t}\right)\exp\left(E_{t+1}[v^{w}_{k,t+2}]-E_t[v^{w}_{k,t+1}]\right)^{\beta} \\
&= \exp\left(u_{k,r,l,t+1}-u_{k,r,l,t}\right)\left(\frac{\sum_{r''}\exp\left(\nu_r^{-1}\tilde{v}^{w}_{r'',k,t+2}\right)}{\sum_{r'}\exp\left(\nu_r^{-1}\tilde{v}^{w}_{r',k,t+1}\right)}\right)^{\beta\nu_r} \\
&= \exp\left(u_{k,r,l,t+1}-u_{k,r,l,t}\right)\left(\sum_{r''}\mu_{r'',k,t+1}\exp\left(\tilde{v}^{w}_{r'',k,t+2}-\tilde{v}^{w}_{r'',k,t+1}\right)^{1/\nu_r}\right)^{\beta\nu_r} \\
&= \exp\left(u_{k,r,l,t+1}-u_{k,r,l,t}\right)\left(\sum_{r''}\mu_{r'',k,t+1}\left(\dot{\tilde{v}}^{w}_{r'',k,t+2}\right)^{1/\nu_r}\right)^{\beta\nu_r} \\
&= \exp\left(u_{k,r,l,t+1}-u_{k,r,l,t}\right)\left(\sum_{r''}\mu_{r'',k,t+1}\left(\sum_{l''\in\Gamma(r'',k)}\pi_{l'',r'',k,t+1}\left(\dot{\tilde{\tilde{v}}}^{w}_{l'',r'',k,t+2}\right)^{1/\nu_l}\right)^{\nu_l/\nu_r}\right. \\
&\quad \left.\exp\left(Z_{r'',t+2}-Z_{r'',t+1}\right)^{1/\nu_r}\right)^{\beta\nu_r}.
\end{aligned}
$$

F.1 Remote Shock

Suppose in period $t = t^* > 0$, the economy is hit with an exogenous shock to the remote amenity Z_{r,t^*}. Agents learn about the shock and the future path of $Z_{r,t}$ in period t^*-1. I compare the baseline economy which experiences the remote shock, to a no-shock economy with constant fundamentals. Define $\mathcal{Z}_{r,t+1} \equiv Z^{baseline}_{r,t+1} - Z^{baseline}_{r,t}$ the change in remote amenities under the remote shock regime. Let $\{\dot{\tilde{\tilde{v}}}^{w,no\ shock}_{k,r,l,t}\}_{t=1}^{T}$ denote the path in the absence of the remote shock, while $\{\dot{\tilde{\tilde{v}}}^{w,baseline}_{k,r,l,t}\}_{t=1}^{T}$ is the path under the remote shock. Notice, $\dot{\tilde{\tilde{v}}}^{w,baseline}_{k,r,l,t} = \dot{\tilde{\tilde{v}}}^{w,no\ shock}_{k,r,l,t}$ for $t < t^* - 1$. Define $\hat{x}_{t+1} \equiv \dot{x}^{baseline}_{t+1}/\dot{x}^{no\ shock}_{t+1}$ the relative change between the remote-shock economy and the economy with constant fundamentals for variable x. Then,

$$\frac{\dot{\pi}^{baseline}_{k,r,l,t+1}}{\dot{\pi}^{no\ shock}_{k,r,l,t+1}} = \frac{\dfrac{\left(\dot{\tilde{\tilde{v}}}^{w,baseline}_{k,r,l,t+1}\right)^{1/\nu_l}}{\left(\dot{\tilde{\tilde{v}}}^{w,no\ shock}_{k,r,l,t+1}\right)^{1/\nu_l}}}{\dfrac{\sum_{k''\in\Gamma(r,l)} \pi^{baseline}_{k'',r,l,t}\left(\dot{\tilde{\tilde{v}}}^{baseline}_{k'',r,l,t+1}\right)^{1/\nu_l}}{\sum_{k'\in\Gamma(r,l)} \pi^{no\ shock}_{k',r,l,t}\left(\dot{\tilde{\tilde{v}}}^{no\ shock}_{k',r,l,t+1}\right)^{1/\nu_l}}}$$

which implies

$$\begin{aligned}
\hat{\pi}_{k,r,l,t+1} &= \frac{\left(\hat{\tilde{\tilde{v}}}^{w}_{k,r,l,t+1}\right)^{1/\nu_l}}{\sum_{k''\in\Gamma(r,l)} \dfrac{\pi^{baseline}_{k'',r,l,t}\left(\dot{\tilde{\tilde{v}}}^{w,baseline}_{k'',r,l,t+1}\right)^{1/\nu_l}}{\sum_{k'\in\Gamma(r,l)} \pi^{no\ shock}_{k',r,l,t}\left(\dot{\tilde{\tilde{v}}}^{w,no\ shock}_{k',r,l,t+1}\right)^{1/\nu_l}}} \\
&= \frac{\left(\hat{\tilde{\tilde{v}}}^{w}_{k,r,l,t+1}\right)^{1/\nu_l}}{\sum_{k''\in\Gamma(r,l)} \dfrac{\pi^{baseline}_{k'',r,l,t}\left(\hat{\tilde{\tilde{v}}}^{w}_{k'',r,l,t+1}\right)^{1/\nu_l}}{\sum_{k'\in\Gamma(r,l)} \pi^{no\ shock}_{k',r,l,t}\left(\dot{\tilde{\tilde{v}}}^{w,no\ shock}_{k',r,l,t+1}\right)^{1/\nu_l}} \left(\dot{\tilde{\tilde{v}}}^{w,no\ shock}_{k'',r,l,t+1}\right)^{1/\nu_l}}.
\end{aligned} \tag{72}$$

Likewise,

$$\hat{\mu}_{r,l,t+1} = \frac{\left(\hat{\tilde{v}}^{w}_{r,l,t+1}\right)^{1/\nu_r}}{\sum_{r''} \dfrac{\mu^{baseline}_{r'',l,t}\left(\hat{\tilde{v}}^{w}_{r'',l,t+1}\right)^{1/\nu_r}}{\sum_{r'} \mu^{no\ shock}_{r',l,t}\left(\dot{\tilde{v}}^{w,no\ shock}_{r',l,t+1}\right)^{1/\nu_r}} \left(\dot{\tilde{v}}^{w,no\ shock}_{r'',l,t+1}\right)^{1/\nu_r}}, \tag{73}$$

where,

$$\begin{aligned}
\hat{\tilde{v}}^{w}_{r,l,t+1} &= \exp(\mathcal{Z}_{r,t+1}) \left(\frac{\sum_{l''\in\Gamma(r,l)} \pi^{baseline}_{l'',r,l,t} \left(\dot{\tilde{\tilde{v}}}^{w,baseline}_{l'',r,l,t+1}\right)^{1/\nu_l}}{\sum_{l'\in\Gamma(r,l)} \pi^{no\ shock}_{l',r,l,t} \left(\dot{\tilde{\tilde{v}}}^{w,no\ shock}_{l',r,l,t+1}\right)^{1/\nu_l}} \right)^{\nu_l} \\
&= \exp(\mathcal{Z}_{r,t+1}) \left(\sum_{l''\in\Gamma(r,l)} \frac{\pi^{baseline}_{l'',r,l,t} \left(\hat{\tilde{\tilde{v}}}^{w}_{l'',r,l,t+1}\right)^{1/\nu_l}}{\sum_{l'\in\Gamma(r,l)} \pi^{no\ shock}_{l',r,l,t} \left(\dot{\tilde{\tilde{v}}}^{w,no\ shock}_{l',r,l,t+1}\right)^{1/\nu_l}} \left(\dot{\tilde{\tilde{v}}}^{w,no\ shock}_{l'',r,l,t+1}\right)^{1/\nu_l} \right)^{\nu_l}
\end{aligned}$$

Furthermore,

$$\tilde{\tilde{\hat{v}}}^w_{k,r,l,t+1} = \frac{\exp\left(u^{baseline}_{k,r,l,t+1} - u^{baseline}_{k,r,l,t}\right)}{\exp\left(u^{no\ shock}_{k,r,l,t+1} - u^{no\ shock}_{k,r,l,t}\right)} \frac{\left(\sum_{r''} \mu^{baseline}_{r'',k,t+1} \left(\dot{\tilde{v}}^{w,baseline}_{r'',k,t+2}\right)^{1/\nu_r}\right)^{\beta\nu_r}}{\left(\sum_{r'} \mu^{no\ shock}_{r',k,t+1} \left(\dot{\tilde{v}}^{w,no\ shock}_{r',k,t+2}\right)^{1/\nu_r}\right)^{\beta\nu_r}}$$

$$= \frac{\exp\left(u^{baseline}_{k,r,l,t+1} - u^{baseline}_{k,r,l,t}\right)}{\exp\left(u^{no\ shock}_{k,r,l,t+1} - u^{no\ shock}_{k,r,l,t}\right)} \left(\sum_{r''} \frac{\mu^{baseline}_{r'',k,t+1} \left(\dot{\tilde{v}}^{w,baseline}_{r'',k,t+2}\right)^{1/\nu_r}}{\sum_{r'} \mu^{no\ shock}_{r',k,t+1} \left(\dot{\tilde{v}}^{w,no\ shock}_{r',k,t+2}\right)^{1/\nu_r}}\right)^{\beta\nu_r}$$

$$= \frac{\exp\left(u^{baseline}_{k,r,l,t+1} - u^{baseline}_{k,r,l,t}\right)}{\exp\left(u^{no\ shock}_{k,r,l,t+1} - u^{no\ shock}_{k,r,l,t}\right)} \left(\sum_{r''} \frac{\mu^{baseline}_{r'',k,t+1} \left(\hat{\tilde{v}}^{w}_{r'',k,t+2}\right)^{1/\nu_r}}{\sum_{r'} \mu^{no\ shock}_{r',k,t+1} \left(\dot{\tilde{v}}^{w,no\ shock}_{r',k,t+2}\right)^{1/\nu_r}} \left(\dot{\tilde{v}}^{w,no\ shock}_{r'',k,t+2}\right)^{1/\nu_r}\right)^{\beta\nu_r} \tag{74}$$

G Welfare

G.1 Workers

Let $V^w_{l,t} \equiv E[v^w_{l,t}]$. This can be viewed as the expected value of living in l before realization of the preference shocks, or the average value of agents living in l. Then,

$$\begin{aligned}
V^w_{l,t} &= \nu_r \ln\left(\sum_{j\in\{R,N\}} \exp\left(\nu_r^{-1}\tilde{v}^w_{j,l,t}\right)\right) + \nu_r\gamma_{EM} \\
&= \nu_r \ln\left(\frac{\exp\left(\nu_r^{-1}\tilde{v}^w_{r',l,t}\right)}{\mu_{r',l,t}}\right) + \nu_r\gamma_{EM} \\
&= \tilde{v}^w_{r',l,t} - \nu_r\ln\left(\mu_{r',l,t}\right) + \nu_r\gamma_{EM} \\
&= \nu_l \ln\left(\sum_{k\in\Gamma(r',l)} \exp\left(\nu_l^{-1}\tilde{\tilde{v}}^w_{k,r',l,t}\right)\right) + Z_{r',t} - \nu_r\ln\left(\mu_{r',l,t}\right) + \nu_r\gamma_{EM} + \nu_l\gamma_{EM} \\
&= \tilde{\tilde{v}}^w_{l',r',l,t} + Z_{r',t} - \nu_r\ln\left(\mu_{r',l,t}\right) - \nu_l\ln\left(\pi_{l',r',l,t}\right) + \nu_r\gamma_{EM} + \nu_l\gamma_{EM} \\
&= u_{l',r',l,t} + X_{l'} - m_{l,l'} + \beta V_{l',t+1} + Z_{r',t} - \nu_r\ln\left(\mu_{r',l,t}\right) - \nu_l\ln\left(\pi_{l',r',l,t}\right) + \nu_r\gamma_{EM} + \nu_l\gamma_{EM},
\end{aligned}$$

which holds for all l', r'. Take $l' = l$. Then, we have

$$V^w_{l,t} = \sum_{s=0}^{\infty} \beta^s \left(u_{l,r,l,t+s} + X_l - m_{l,l} + Z_{r,t+s} - \nu_r\ln\left(\mu_{r,l,t+s}\right) - \nu_l\ln\left(\pi_{l,r,l,t+s}\right) + (\nu_r + \nu_l)\gamma_{EM}\right).$$

Next, consider the change in worker welfare between a baseline and a counterfactual economy, $V_{l,t}^{wC} - V_{l,t}^{wB}$. Let $\delta_{l,r,t}^{w}$ be defined as the change in lifetime consumption (beginning in t) under the baseline economy such that welfare in the baseline is equal to that under the counterfactual:

$$
\begin{aligned}
V_{l,t}^{wC} &= \sum_{s=0}^{\infty} \beta^s \left(\frac{\left(c_{l,r,l,t+s}^{wC}\right)^{1-\gamma} - 1}{1-\gamma} + X_l^C - m_{l,l}^C + Z_{r,t+s}^C - \nu_r \ln\left(\mu_{r,l,t+s}^C\right) - \nu_l \ln\left(\pi_{l,r,l,t+s}^C\right) + (\nu_r + \nu_l)\gamma_{EM} \right) \\
&= \sum_{s=0}^{\infty} \beta^s \left(\frac{\left((1+\delta_{l,r,t}^w) c_{l,r,l,t+s}^{wB}\right)^{1-\gamma} - 1}{1-\gamma} + X_l^B - m_{l,l}^B + Z_{r,t+s}^B - \nu_r \ln\left(\mu_{r,l,t+s}^B\right) - \nu_l \ln\left(\pi_{l,r,l,t+s}^B\right) + (\nu_r + \nu_l)\gamma_{EM} \right).
\end{aligned}
$$

Then,

$$
\begin{aligned}
1 + \delta_{l,r,t}^w = & \left[\sum_{s=0}^{\infty} \beta^s \left(\frac{\left(c_{l,r,l,t+s}^{wC}\right)^{1-\gamma}}{1-\gamma} + X_l^C - X_l^B - m_{l,l}^C + m_{l,l}^B + Z_{r,t+s}^C - Z_{r,t+s}^B + \nu_r \ln\left(\frac{\mu_{r,l,t+s}^B}{\mu_{r,l,t+s}^C}\right) \right.\right. \\
& \left.\left. + \nu_l \ln\left(\frac{\pi_{l,r,l,t+s}^B}{\pi_{l,r,l,t+s}^C}\right)\right)\right]^{1/(1-\gamma)} \left(\sum_{s'=0}^{\infty} \beta^{s'} \frac{\left(c_{l,r,l,t+s'}^{wB}\right)^{1-\gamma}}{1-\gamma} \right)^{-1/(1-\gamma)}.
\end{aligned}
$$

In the special case where $X_l^C = X_l^B$, $m_{l,l}^C = m_{l,l}^B$, and $Z_{r,t+s}^C - Z_{r,t+s}^B$, we have

$$
1 + \delta_{l,r,t}^w = \left(\frac{\sum_{s=0}^{\infty} \beta^s \left(\frac{\left(c_{l,r,l,t+s}^{wC}\right)^{1-\gamma}}{1-\gamma} - \ln\left(\frac{(\mu_{r,l,t+s}^C)^{\nu_r} (\pi_{l,r,l,t+s}^C)^{\nu_l}}{(\mu_{r,l,t+s}^B)^{\nu_r} (\pi_{l,r,l,t+s}^B)^{\nu_l}} \right)\right)}{\sum_{s'=0}^{\infty} \beta^{s'} \frac{\left(c_{l,r,l,t+s'}^{wB}\right)^{1-\gamma}}{1-\gamma}} \right)^{1/(1-\gamma)}.
$$

That is, the change in welfare consists of a term that depends on consumption under both economies, as well as a term that depend on the option value of staying in region l with work status r. Notice that, while $V_{l,t}^{wC}, V_{l,t}^{wB}$ depend only on region l and period t, $\delta_{l,r,t}^w$ depends additionally on remote status r since consumption of remote workers will generally differ from that of non-remote. To provide a region-level measure of welfare, I take the weighted average across work modes,

$$
\delta_{l,t}^w \equiv \frac{\delta_{l,R,t}^w R_{l,t}^* + \delta_{l,N,t}^w N_{l,t}^*}{L_{l,t}^*}.
$$

I use δ_{l,t^*-1}^w as my measure of worker welfare, where a value $\delta_{l,t^*-1}^w > 0$ indicates a welfare gain under the counterfactual relative to the baseline economy.

G.2 Owners

Given b_t, the lifetime value of the owner is

$$v_{l,t}^{o} = \sum_{s=0}^{\infty} \beta^s \frac{(c_{l,s}^{o*})^{1-\gamma} - 1}{1-\gamma},$$

where $c_{l,s}^{o*}$ denotes the owner's optimal consumption, subject to their budget constraint and the law of motion for office capital. Consider the change in owner welfare between a baseline and a counterfactual economy, $v_{l,t}^{oC} - v_{l,t}^{oB}$. Let $\delta_{l,t}^{o}$ be defined as the change in lifetime consumption (beginning in t) under the baseline economy such that welfare in the baseline is equal to that under the counterfactual.

$$\begin{aligned} v_{l,t}^{oC} &= \sum_{s=0}^{\infty} \beta^s \frac{(c_{l,s}^{o*C})^{1-\gamma} - 1}{1-\gamma} \\ &= \sum_{s=0}^{\infty} \beta^s \frac{((1+\delta_{l,t}^{o})c_{l,s}^{o*B})^{1-\gamma} - 1}{1-\gamma}. \end{aligned}$$

Then,

$$1 + \delta_{l,t}^{o} = \left(\frac{\sum_{s=0}^{\infty} \beta^s \frac{(c_{l,s}^{o*C})^{1-\gamma}}{1-\gamma}}{\sum_{s'=0}^{\infty} \beta^{s'} \frac{(c_{l,s'}^{o*B})^{1-\gamma}}{1-\gamma}} \right)^{1/(1-\gamma)}.$$

I use $\delta_{l,t}^{o}$ as my measure of owner welfare, where a value $\delta_{l,t}^{o} > 0$ indicates a welfare gain under the counterfactual relative to the baseline economy.

H Solution Algorithm

Algorithm 1: Solving the sequential equilibrium with constant fundamentals

1. Guess a sequence of changes in utility $\{\dot{\tilde{\tilde{v}}}_{k,r,l,t+1}^{w}\}_{t=0}^{T-1}$ and a path of savings rates $\{s_{l,t}\}_{t=-1}^{T}$ for a large T (in the steady state, we have $\dot{\tilde{\tilde{v}}}_{k,r,l,t+1}^{w} = 1$ for $t \geq T$.).[72]

2. For each $t \in \{0, ..., T\}$:

[72] I assume the economy reaches steady state in model-year 2100.

(i) Construct the distribution of labor across regions and work modes:

$$\begin{aligned}
N_{l,t} &= \sum_{k=1}^{\mathcal{L}} \mu_{N,k,t}\pi_{l,N,k,t}L^*_{k,t-1}, \\
R^*_{l,t} &= \sum_{k=1}^{\mathcal{L}} \mu_{R,k,t}\pi_{l,R,k,t}L^*_{k,t-1}, \\
R_t &= \sum_{k=1}^{\mathcal{L}} \mu_{R,k,t}L^*_{k,t-1}, \\
R_{l,t} &= f(R_t) \\
L^*_{l,t} &= N_{l,t} + R^*_{l,t},
\end{aligned}$$

where $f(\cdot)$ returns the unique distribution of remote labor that equalizes remote wages.

(ii) Compute the stock of buildings,

$$B_{l,t} = \frac{B_{l,t-1}\left(s_{l,t-1}r_{l,t-1} + q_{l,t-1}(1-\delta^b)\right)}{q_{l,t-1}}$$

(iii) Compute wages and the rental rate of office space $w_{R,t}, w_{N,l,t}, r_{l,t}$ from the firms' FOCs.

(iv) Compute home prices $p_{l,t}$ from

$$p_{l,t} = \frac{1}{A_l^H \rho_l^H M_{t,l}^{\rho_l^H - 1}},$$

where,

$$M_{l,t} = \left(\frac{L^*_{t,l}\bar{h} - L^*_{t-1,l}(1-\delta^h)\bar{h}}{A_l^H}\right)^{1/\rho_l^H}$$

(v) Compute the price of new office space $q_{l,t} = \dot{q}_{l,t}q_{l,t-1}$, where $\dot{q}_{l,t}$ is given by

$$\dot{q}_{l,t} = \left(\dot{s}_{l,t}\dot{r}_{l,t}\dot{B}_{l,t}\right)^{1-\rho_l^B}.$$

To see this, note that from the office construction firm's FOCs,

$$\begin{aligned}
\dot{q}_{l,t} &= \frac{q_{l,t}}{q_{l,t-1}} \\
&= \frac{A_l^B \rho_l^B \left(M_{l,t-1}^B\right)^{\rho_l^B - 1} \left(P_l^B\right)^{1-\rho_l^B}}{A_l^B \rho_l^B \left(M_{l,t}^B\right)^{\rho_l^B - 1} \left(P_l^B\right)^{1-\rho_l^B}} \\
&= \left(\dot{M}_{l,t}^B\right)^{1-\rho_l^B},
\end{aligned}$$

and, since investment in new office space equals production of office space in each period,

$$\begin{aligned}
\frac{s_{l,t} r_{l,t} B_{l,t}}{q_{l,t}} &= A_l^B \left(M_{l,t}^B\right)^{\rho_l^B} \left(P_l^B\right)^{1-\rho_l^B} \\
\implies \dot{M}_{l,t}^B &= \left(\frac{\dot{s}_{l,t} \dot{r}_{l,t} \dot{B}_{l,t}}{\dot{q}_{l,t}}\right)^{1/\rho_l^B}.
\end{aligned}$$

(vi) Compute flow utility $u_{k,r,l,t} \equiv u(c_{k,r,l,t})$ associated with each choice of residence k and remote status r, given initial residence l.[73]

(vii) Compute $\pi_{k,r,l,t+1} = \dot{\pi}_{k,r,l,t+1} \pi_{k,r,l,t}$ and $\mu_{r,l,t+1} = \dot{\mu}_{r,l,t+1} \mu_{r,l,t}$ where

$$\begin{aligned}
\dot{\pi}_{k,r,l,t+1} &= \frac{\left(\dot{\tilde{\tilde{v}}}_{k,1,l,t+1}^w\right)^{1/\nu_l}}{\sum_{k'=1}^L \pi_{k',r,l,t} \left(\dot{\tilde{\tilde{v}}}_{k',1,l,t+1}^w\right)^{1/\nu_l}}, \\
\dot{\mu}_{r,l,t+1} &= \frac{\left(\dot{\tilde{v}}_{r,l,t+1}^w\right)^{1/\nu_r}}{\sum_{(r')} \mu_{r',l,t} \left(\dot{\tilde{v}}_{r',l,t+1}^w\right)^{1/\nu_r}},
\end{aligned}$$

and

$$\dot{\tilde{v}}_{r,l,t+1}^w = \left(\sum_k \pi_{k,r,l,t} \left(\dot{\tilde{\tilde{v}}}_{k,r,l,t+1}^w\right)^{1/\nu_l}\right)^{\nu_l} \exp\left(\hat{\mathcal{Z}}_{t+1}\right)$$

3. Proceeding backwards from $t = T-1$ to $t = 0$, solve for the changes in utility $\dot{\tilde{\tilde{v}}}_{k,r,l,t+1}^w$

[73] The properties of the Gumbel distribution imply that $\mu_{r,l,t}, \pi_{k,r,l,t} > 0$ for all feasible k, r. However, from the workers budget constraint (2), it is possible that $c_{k,r,l,t} < 0$ for some $k \in \Gamma(r,l)$. Thus, I set $c_{k,r,l,t} = \max\{c_{k,r,l,t}^{BC}, 0.01 \times ((1-\tau_k) w_{r,k,t} + T_{r,k,t})\}$, where $c_{k,r,l,t}^{BC}$ is consumption implied by (2).

according to:

$$\dot{\tilde{\tilde{v}}}^{w}_{k,r,l,t+1} = \exp\left(u_{k,r,l,t+1} - u_{k,r,l,t}\right)\left(\sum_{r'} \mu_{r',k,t+1}\left(\sum_{l'} \pi_{l',r',k,t+1}\left(\dot{\tilde{\tilde{v}}}_{l',r',k,t+2}\right)^{1/\nu_l}\right)^{\nu_l/\nu_r}\right)^{\beta\nu_r},$$

4. Set $s_{l,T} = (\delta^b q_{l,T})/r_{l,T}$. Proceeding backwards from $t = T-1$ to $t = -1$, solve for the savings rates $s_{l,t}$ according to:

$$s_{l,t} = \frac{\left(\frac{\beta(r_{l,t+1}+q_{l,t+1}(1-\delta^b))}{q_{l,t}}\right)^{1/\gamma} - (1-s_{l,t+1})\frac{r_{l,t+1}(1-\delta^b)}{r_{l,t}}}{\left(\frac{\beta(r_{l,t+1}+q_{l,t+1}(1-\delta^b))}{q_{l,t}}\right)^{1/\gamma} + (1-s_{l,t+1})\frac{r_{l,t+1}}{q_{l,t}}}. \tag{75}$$

5. Use the constructed sequences to update the guesses for $\{\dot{\tilde{\tilde{v}}}^{w}_{k,r,l,t+1}\}_{t=0}^{T-1}$ and $\{s_{l,t}\}_{t=-1}^{T}$ in step 1.

6. Repeat steps 1-5 until convergence.

Algorithm 2: Solving the sequential equilibrium under the remote shock

1. Guess a sequence $\{\dot{\tilde{\tilde{v}}}^{w}_{k,r,l,t}\}_{t=t^*-1}^{T}$ and $\{s_{l,t}\}_{t=t^*-1}^{T}$

2. For each $t \in \{t^*-1, ..., T\}$:

   (i) Compute $\pi^{baseline}_{k,r,l,t}$ and $\mu^{baseline}_{r,l,t}$ implied by (72) and (73) and where $\pi^{baseline}_{k,r,l,t^*-2} = \pi^{no\ shock}_{k,r,l,t^*-2}$ and $\mu^{baseline}_{r,l,t^*-2} = \mu^{no\ shock}_{r,l,t^*-2}$

   (ii) Construct the distribution of labor across regions and work modes:

$$\begin{aligned} N_{l,t} &= \sum_{k=1}^{\mathcal{L}} \mu^{baseline}_{N,k,t}\pi^{baseline}_{l,N,k,t} L^*_{k,t-1}, \\ R^*_{l,t} &= \sum_{k=1}^{\mathcal{L}} \mu^{baseline}_{R,k,t}\pi^{baseline}_{l,R,k,t} L^*_{k,t-1}, \\ R_t &= \sum_{k=1}^{\mathcal{L}} \mu^{baseline}_{R,k,t} L^*_{k,t-1}, \\ R_{l,t} &= f(R_t) \\ L^*_{l,t} &= N_{l,t} + R^*_{l,t}, \end{aligned}$$

   where $f(\cdot)$ returns the unique distribution of remote labor that equalizes remote wages.

(iii) Compute the stock of buildings,

$$B_{l,t} = \frac{B_{l,t-1}\left(s_{l,t-1}r_{l,t-1} + q_{l,t-1}(1-\delta^b)\right)}{q_{l,t-1}}$$

(iv) Compute wages and the rental rate of office space $w_{R,t}, w_{N,l,t}, r_{l,t}$ from the firms' FOCs.

(v) Compute home prices $p_{l,t}$ from

$$p_{l,t} = \frac{1}{A_l^H \rho_l^H M_{t,l}^{\rho_l^H - 1}},$$

where,

$$M_{l,t} = \left(\frac{L_{t,l}^* \bar{h} - L_{t-1,l}^*(1-\delta^h)\bar{h}}{A_l^H}\right)^{1/\rho_l^H}$$

(vi) Compute the price of new office space $q_{l,t} = \dot{q}_{l,t} q_{l,t-1}$, where $\dot{q}_{l,t}$ is given by

$$\dot{q}_{l,t} = \left(\dot{s}_{l,t}\dot{r}_{l,t}\dot{B}_{l,t}\right)^{1-\rho_l^B}.$$

(vii) Compute flow utility $u_{k,r,l,t} \equiv u(c_{k,r,l,t})$ associated with each choice of residence k and remote status r given initial residence l.

3. Proceeding backwards from $t = T$ to $t = t^* - 1$, solve $\hat{\tilde{\tilde{v}}}^w_{k,r,l,t}$ according to (74) where $u^{baseline}_{k,r,l,t^*-2} = u^{no\ shock}_{k,r,l,t^*-2}$.

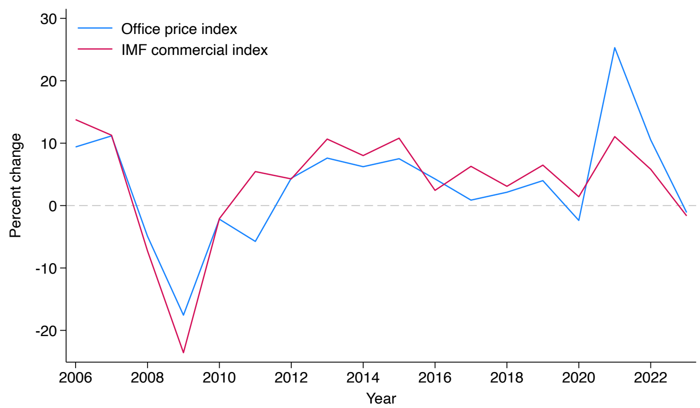
4. Set $s_{l,T} = (\delta^b q_{l,T})/r_{l,T}$. Proceeding backwards from $t = T-1$ to $t = t^* - 1$, solve for the savings rates $s_{l,t}$ according to (75).

5. Use the constructed sequences to update the guesses for $\{\hat{\tilde{\tilde{v}}}^w_{k,r,l,t}\}_{t=t^*-1}^T$ and $\{s_{l,t}\}_{t=t^*-1}^T$ in step 1.

6. Repeat steps 1-5 until convergence.

I Evolution of Office Prices

Figure 7: Change in Commercial Real Estate Prices



Note: Percent change from year prior for the office price index constructed from the Attom data (blue line) and the commercial real estate price index from the International Monetary Fund Financial Soundness Indicators International Monetary Fund (2025) (red line). The Attom series is constructed by averaging the sale price per square foot across observations in the 25th to 75th percentile in a given year.

J Migration by Remote Workers

In this section, I characterize the migration rate by remote (relative to non-remote) workers. Using data from the 2023 5-year ACS (Ruggles et al., 2024), I estimate the following regression:

$$y_i = \beta x_i + \delta X_i + \epsilon_i,$$

where y_i is an indicator equal to one if individual i moved across MSAs in the previous year, x_i is an indicator equal to one if individual i is a remote worker, and X_i is a vector of controls.[74] Controls include the average home price in the year prior to the survey in both the origin and destination MSA from the Zillow Home Value Index, the 2018 marginal tax rate in both the origin and destination MSA from the NBER Taxsim tables, individual i's age, sex, and income, as well as dummies for whether individual i is married, has children, graduated college, lived in their state of birth one year ago, was married in the last year, was divorced or widowed in the last year, had children in the last year, and owned their home. Additionally, I control for the individual's race, their MSA of residence one year before the

[74] I assume an individual moves MSAs if they report having moved houses, their MSA at the time of the survey is different from their MSA the year prior, and both their present and previous MSA are identifiable.

Table 7: Migration by remote workers

Remote	0.011^{***}	College	0.015^{***}
	(0.000)		(0.000)
log Homeprice (origin)	0.117^{***}	Tax (origin)	0.004^{***}
	(0.000)		(0.000)
log Homeprice (destination)	-0.113^{***}	Tax (destination)	-0.004^{***}
	(0.000)		(0.000)
Age	-0.001^{***}	Birthplace	-0.017^{***}
	(0.000)		(0.000)
Female	-0.002^{***}	Married in year	0.015^{***}
	(0.000)		(0.000)
log Income	0.000	Divorced/widowed in year	0.010^{***}
	(0.000)		(0.000)
Married	-0.001^{***}	Owns home	-0.026^{***}
	(0.000)		(0.000)
Children	-0.014^{***}	Child in year	0.001^{**}
	(0.000)		(0.000)
Race controls			Yes
Origin controls			Yes
Desination controls			Yes
Year controls			Yes
N			10980892

Note: Controls include the average home price in the year prior to the survey in both the origin and destination MSA, the tax rate in both the origin and destination MSA, the individual's age, sex, and income, as well as dummies for whether the individual is married, has children, graduated college, lived in their state of birth one year ago, was married in the last year, was divorced or widowed in the last year, had children in the last year, and owned their home. Additional controls include the individual's race, their MSA of residence one year before the survey, their MSA of residence at the time of the survey, and the year of the survey. Standard errors account for clustering at the primary sampling unit, stratification, and person weights, following the ACS survey design.

survey, their MSA of residence at the time of the survey, and the year of the survey. Table 7 shows the estimation results.

The estimated coefficient $\hat{\beta}$ indicates that, conditional on demographic characteristics as well as origin and destination attributes, remote workers are 1.1% more likely to move between MSAs than their non-remote counterparts. Given that the unconditional average share of movers in the sample is 2.4%, this estimate represents a meaningful increase in the likelihood of moving.

K MSA Sample

The quantitative model features 234 of the over 300 MSAs in the U.S. To select this sample, I start with the full set of MSAs. From this, I drop those MSAs which are missing supply elasticity estimates from Baum-Snow and Han (2024) (114 MSAs), those which are not included in the 2018 or 2019 ACS (2 MSAs), those which report zero remote workers in the 2018 ACS (5 MSAs), those missing from the Attom commercial office data (27 MSAs), and those missing from the Zillow data (1 MSA). In addition, I require that regions satisfy the following condition:

$$L^*_{l,0} - L^*_{l,-1}(1 - \delta^h) > 0, \tag{76}$$

where $L^*_{l,0}$ and $L^*_{l,-1}$ are constructed using ACS data on regional populations and individuals' migration decisions (see discussion in Section 4.2). This ensures that the housing market clearing condition in (19) is satisfied. One MSA fails condition (76) and is dropped from the analysis. Table 9 lists the MSAs included in the analysis.

L Office Price Distribution

To construct the initial office price distribution $\{q_{l,-1}\}_{l=1}^{\mathcal{L}}$, I first take the average real sale price per square foot for transactions involving an office building in a region, excluding the bottom and top 10 percent of transactions in each region, for the period 2010 to 2018. I classify a building in the Attom data as an office building if Attom assigns it to one of the following categories: "Commercial Office (General)", "Office Building", "Office Building (Multi-Story)", "Professional Building (Legal, Insurance, Real Estate, Business)", "Professional Building (Multi-Story)", "Skyscraper/High-Rise (Commercial Offices)", or "Store/Office (Mixed Use)". Office prices in the model are then chosen such that the average price of real estate in a region scaled by the region's (non-construction) GDP in the model matches its counterpart in the data,

$$\frac{q^{data}_{l,-1}}{Y^{Cdata}_{l,-1}} = \frac{q^{model}_{l,-1}}{Y^{Cmodel}_{l,-1}},$$

where $Y^{Cdata}_{l,-1}$ is collected from local GDP estimates from the BEA, and computed as the difference between total GDP in region l and the region l contribution to GDP from the construction sector.[75]

[75] For MSAs missing construction industry GDP, I substitute the construction share of total GDP for the U.S. as a whole.

M Additional Results

M.1 Price Effect Decomposition

The aggregate residential and commercial price effects of the remote shock reported in Section 5.1 are

$$\frac{\bar{p}_t^{baseline}}{\bar{p}_t^{no\ shock}}, \qquad \frac{\bar{q}_t^{baseline}}{\bar{q}_t^{no\ shock}}.$$

Notice,

$$\bar{p}_t^{baseline} - \bar{p}_t^{no\ shock} = \sum_{l=1}^{\mathcal{L}} \omega_{l,t}^{h,baseline}(p_{l,t}^{baseline} - p_{l,t}^{no\ shock}) + \sum_{l=1}^{\mathcal{L}} (\omega_{l,t}^{h,baseline} - \omega_{l,t}^{h,no\ shock}) p_{l,t}^{no\ shock},$$

and

$$\begin{aligned} \frac{\bar{p}_t^{baseline}}{\bar{p}_t^{no\ shock}} &= 1 + \frac{\bar{p}_t^{baseline} - \bar{p}_t^{no\ shock}}{\bar{p}_t^{no\ shock}} \\ &= 1 + \underbrace{\frac{\sum_{l=1}^{\mathcal{L}} \omega_{l,t}^{h,baseline}(p_{l,t}^{baseline} - p_{l,t}^{no\ shock})}{\bar{p}_t^{no\ shock}}}_{\text{Price contribution}} + \underbrace{\frac{\sum_{l=1}^{\mathcal{L}} (\omega_{l,t}^{h,baseline} - \omega_{l,t}^{h,no\ shock}) p_{l,t}^{no\ shock}}{\bar{p}_t^{no\ shock}}}_{\text{Weight contribution}}. \end{aligned}$$

A similar decomposition holds for the commercial office price index:

$$\frac{\bar{q}_t^{baseline}}{\bar{q}_t^{no\ shock}} = \quad = 1 + \underbrace{\frac{\sum_{l=1}^{\mathcal{L}} \omega_{l,t}^{b,baseline}(q_{l,t}^{baseline} - q_{l,t}^{no\ shock})}{\bar{q}_t^{no\ shock}}}_{\text{Price contribution}} + \underbrace{\frac{\sum_{l=1}^{\mathcal{L}} (\omega_{l,t}^{b,baseline} - \omega_{l,t}^{b,no\ shock}) q_{l,t}^{no\ shock}}{\bar{q}_t^{no\ shock}}}_{\text{Weight contribution}}.$$

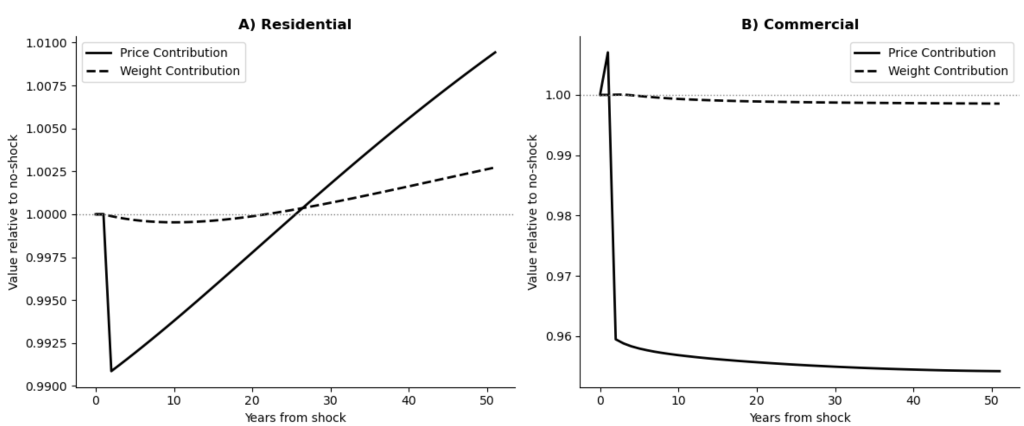


Figure 8: Decomposition of remote shock effect into contribution from price and weight changes.

Figure 8 shows the decomposition of the effect of the remote shock (Figure 1, Panel B) into its contributions from prices and weights. The figure reveals that the aggregate effects of the remote shock are driven primarily by shifts in prices rather than weights.

M.2 Geography of Price Effects

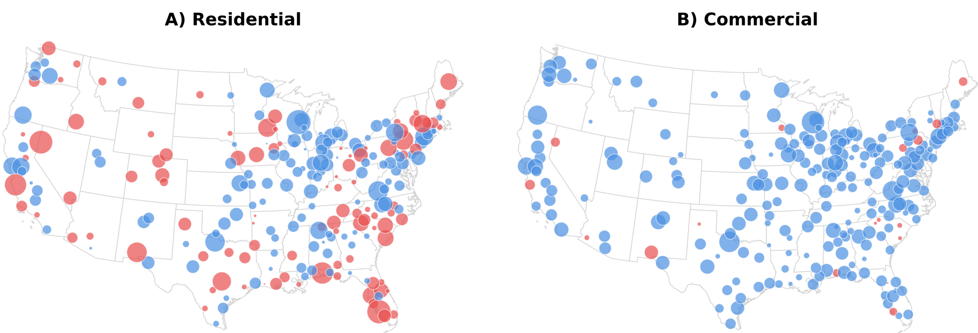


Figure 9: Price effect of remote shock, with red indicating a positive effect, blue indicating a negative effect, and circle size indicating the magnitude of the effect.

Figure 9 shows the price effect of the remote shock, with blue indicating a negative effect, red indicating a positive effect, and circle size reflecting the magnitude of the change. Panel A shows some regional patterns emerge in the residential real estate market. Negative effects dominate in several Midwestern states, particularly Illinois, Indiana, Michigan, and Wisconsin. By contrast, positive effects are more common across the South (e.g., Florida, the Carolinas) and the Mountain West (e.g., Colorado, Nevada). Cities along the West Coast and in the Northeast exhibit a more mixed response, with large positive and negative effects present in both regions. Panel B shows that positive effects in the commercial office sector are much rarer, with only a handful of small MSAs showing positive effects (average 2018 population = 175,489).

Table 8 shows the relationship between pre-shock conditions, and the real estate price effects of the remote shock. Column 1 of Panel A shows that, after controlling for period 0 residential and commercial prices, those regions which saw greater population growth before the remote shock tend to see positive residential price effects of the remote shock. Column 2 seperates this growth into remote and non-remote population growth. This reveals that the positive correlation arises from remote migration, while the effect of non-remote migration is insignificant.

Panel B considers the commercial price effect. It shows that growth in the commercial office stock pre-shock is positively correlated with the commercial price effect of the remote shock, though the effect is small.

Table 8: Initial Conditions and Price Effects of Remote Shock

	(1)	(2)
Panel A: Log Residential Price Effect		
Log Population Growth	0.938*	
	(0.558)	
Log Rem. Population Growth		0.090**
		(0.039)
Log Non-Rem. Population Growth		0.244
		(0.489)
Log Office Growth	0.003	0.003
	(0.018)	(0.017)
Log Initial Res. Prices	0.046	0.054
	(0.033)	(0.033)
Log Initial Com. Prices	0.005	0.004
	(0.021)	(0.021)
Panel B: Log Com. Price Effect	(1)	(2)
Log Labor Force Growth	−0.026	
	(0.086)	
Log Rem. Labor Force Growth		−0.000
		(0.005)
Log Non-Rem. Labor Force Growth		−0.074
		(0.082)
Log Office Growth	0.008*	0.007*
	(0.004)	(0.004)
Log Initial Res. Prices	−0.006	−0.006
	(0.007)	(0.007)
Log Initial Com. Prices	0.006	0.006
	(0.005)	(0.005)
Observations	234	234

Note: Effect of pre-shock factors on the price effects of the remote shock. All growth rates are for the period $t = -1$ to $t = 0$, while the price distributions correspond to $t = 0$. Robust standard errors are in parantheses.

M.3 Change in Real Estate Prices

Table 9: Price effect of the remote shock

MSA	Residential Price Effect (%)	Commercial Price Effect (%)
Abilene	9%	−1%
Akron	−16%	−7%
Albany	13%	−1%
Albany GA	5%	−1%
Albuquerque	−13%	−7%
Alexandria LA	−2%	−2%
Allentown	0%	−3%
Amarillo	13%	0%
Anniston	−7%	−3%
Appleton	−46%	−15%
Asheville	8%	−4%
Athens GA	−2%	−5%
Atlanta	−3%	−7%
Atlantic City	−16%	−2%
Augusta	−3%	−3%
Austin	27%	−3%
Bakersfield	−10%	−4%
Baltimore	−12%	−6%
Bangor	23%	2%
Baton Rouge	8%	−2%
Battle Creek	−7%	−3%
Beaumont	−10%	−4%
Bellingham	16%	−0%
Billings	11%	−3%
Binghamton	18%	1%
Birmingham	−1%	−3%
Bismarck	5%	−2%
Bloomington IN	−7%	−3%
Boise	20%	−1%
Boston	−3%	−5%
Bridgeport	−26%	−8%
Buffalo	−11%	−4%
Burlington NC	−17%	−5%
Canton	15%	−1%
Cape Coral	42%	1%
Casper	3%	−4%
Cedar Rapids	9%	−3%
Champaign	−2%	−3%
Charleston SC	20%	0%

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Table 9 – continued from previous page

MSA	Residential Price Effect (%)	Commercial Price Effect (%)
Charlotte	4%	−4%
Charlottesville	−3%	−5%
Chattanooga	15%	−2%
Cheyenne	14%	−2%
Chicago	−1%	−4%
Chico	−9%	−6%
Cincinnati	1%	−4%
Clarksville	−4%	−4%
Cleveland	−12%	−5%
Colorado Springs	6%	−6%
Columbia	1%	−3%
Columbia MO	−10%	−6%
Columbus	13%	−2%
Corpus Christi	−10%	−6%
Cumberland	−5%	−2%
Dallas	7%	−4%
Davenport	−11%	−5%
Daytona Beach	3%	−4%
Decatur AL	−24%	−7%
Decatur IL	−8%	−2%
Denver	16%	−4%
Des Moines	18%	−1%
Destin	−6%	−6%
Detroit	−12%	−5%
Dothan	5%	−2%
Dubuque	2%	−3%
Duluth	−18%	−7%
Eau Claire	16%	−0%
El Paso	−14%	−6%
Elkhart	−10%	−5%
Elmira	−26%	−9%
Erie	−3%	−3%
Evansville	−15%	−5%
Fargo	−4%	−4%
Fayetteville AR	1%	−3%
Fayetteville NC	5%	−1%
Flint	−10%	−4%
Florence SC	19%	−0%
Fort Collins	14%	−3%
Fort Smith	1%	−1%

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Table 9 – continued from previous page

MSA	Residential Price Effect (%)	Commercial Price Effect (%)
Fort Wayne	−10%	−5%
Fresno	−1%	−4%
Gadsden	−4%	−2%
Gainesville	−3%	−4%
Glens Falls	3%	−1%
Goldsboro	−7%	−4%
Grand Junction	11%	−6%
Grand Rapids	−1%	−3%
Great Falls	−7%	−5%
Green Bay	−15%	−5%
Greensboro	−19%	−8%
Greenville	19%	−0%
Gulfport	−5%	−3%
Hagerstown	−11%	−6%
Harrisburg	−3%	−5%
Hartford	−13%	−6%
Hattiesburg	−8%	−3%
Hickory	2%	−2%
Houston	2%	−4%
Huntington	2%	−2%
Huntsville	6%	−1%
Indianapolis	−7%	−5%
Iowa City	−11%	−8%
Jackson MI	−2%	−1%
Jackson MS	8%	−1%
Jackson TN	−6%	−4%
Janesville	−14%	−5%
Joplin	−4%	−3%
Kalamazoo	−22%	−8%
Kansas City	−7%	−6%
Kennewick	3%	−1%
Kingsport	−2%	−3%
Knoxville	14%	−2%
Kokomo	−21%	−7%
La Crosse	3%	−4%
Lafayette IN	−15%	−5%
Lafayette LA	11%	−1%
Lake Charles	0%	−2%
Lakeland	−6%	−5%
Lancaster	7%	−2%

Continued on next page

Table 9 – continued from previous page

MSA	Residential Price Effect (%)	Commercial Price Effect (%)
Lansing	−17%	−7%
Laredo	2%	−3%
Las Cruces	31%	6%
Las Vegas	14%	−2%
Lawrence	−6%	−5%
Lawton	−5%	−4%
Lexington	5%	−3%
Lima	−0%	−1%
Lincoln	−11%	−5%
Little Rock	−7%	−4%
Longview WA	−13%	−7%
Los Angeles	3%	−4%
Louisville	1%	−3%
Lubbock	−4%	−4%
Lynchburg	−7%	−3%
Macon	−5%	−4%
Madison	−0%	−3%
Mansfield	0%	−3%
McAllen	−3%	−4%
Medford	−25%	−12%
Memphis	−10%	−5%
Miami	6%	−3%
Milwaukee	−9%	−5%
Minneapolis	−8%	−6%
Missoula	5%	−3%
Mobile	−9%	−6%
Modesto	−6%	−3%
Monroe	−4%	−1%
Montgomery	−9%	−5%
Muncie	−13%	−5%
Naples	13%	−2%
New Haven	−8%	−4%
New London	−3%	−3%
New Orleans	2%	−4%
New York	−14%	−6%
North Port	8%	−3%
Ocala	13%	−0%
Oklahoma City	−13%	−6%
Olympia	−9%	−6%
Omaha	17%	−2%

Continued on next page

Table 9 – continued from previous page

MSA	Residential Price Effect (%)	Commercial Price Effect (%)
Orlando	17%	−1%
Palm Bay	2%	−4%
Panama City	5%	−4%
Parkersburg	−11%	−5%
Pensacola	36%	1%
Peoria	−7%	−3%
Philadelphia	−6%	−5%
Phoenix	4%	−5%
Pine Bluff	−3%	−2%
Pittsburgh	−5%	−5%
Pittsfield	26%	2%
Portland	10%	−4%
Portland ME	8%	−3%
Providence	3%	−3%
Provo	−10%	−8%
Raleigh	6%	−5%
Reading	0%	−3%
Redding	2%	−3%
Reno	41%	2%
Richmond	−9%	−6%
Roanoke	−31%	−12%
Rochester	−7%	−4%
Rochester MN	27%	1%
Rockford	−3%	−3%
Rome	3%	−2%
Sacramento	4%	−4%
Salinas	37%	2%
Salt Lake City	−7%	−6%
San Angelo	−14%	−7%
San Antonio	3%	−4%
San Diego	−6%	−7%
San Francisco	−23%	−9%
Santa Barbara	10%	−3%
Santa Fe	−9%	−6%
Savannah	1%	−3%
Scranton	31%	2%
Seattle	−6%	−6%
Sheboygan	1%	−0%
Sioux City	−2%	−3%
Sioux Falls	2%	−3%

Continued on next page

Table 9 – continued from previous page

MSA	Residential Price Effect (%)	Commercial Price Effect (%)
Spartanburg	12%	0%
Spokane	5%	−4%
Springfield MA	9%	−2%
Springfield MO	−3%	−3%
St. Joseph	−5%	−3%
St. Louis	−13%	−5%
State College	22%	2%
Stockton	−24%	−7%
Syracuse	4%	−3%
Tallahassee	−2%	−5%
Tampa	21%	−3%
Terre Haute	−7%	−2%
Texarkana	10%	−1%
Toledo	1%	−2%
Topeka	−21%	−7%
Trenton	12%	−1%
Tucson	−1%	−5%
Tulsa	−14%	−6%
Tuscaloosa	−10%	−3%
Tyler	10%	−4%
Victoria	−3%	−4%
Virginia Beach	−0%	−4%
Visalia	−9%	−4%
Washington DC	−9%	−6%
Waterloo	−1%	−5%
Wheeling	−7%	−4%
Wichita	−6%	−4%
Wichita Falls	−31%	−13%
Williamsport	−3%	−3%
Wilmington NC	12%	−3%
Worcester	8%	−5%
Yakima	−19%	−7%
York	−9%	−5%
Youngstown	2%	−3%
Yuma	9%	0%

M.4 Model Extension: Regional Externalities

The benchmark model abstracts from regional externalities tied to local population size. However, the urban literature has highlighted their quantitative importance.[76] In this section, I assess the robustness of the model's quantitative predictions when incorporating externalities in both local productivity and amenities.

Consider an environment where TFP in the tradable sector, $A^C_{l,t}$, depends on both an exogenous component a_l and an endogenous component determined by the size of the local labor force:

$$A^C_{l,t} = a_l L^{\lambda}_{l,t}, \tag{77}$$

where $\lambda \geq 0$ captures the elasticity of productivity with respect to local labor force size, $L_{l,t} = N_{l,t} + R_{l,t}$. This specification reflects agglomeration forces arising from mechanisms such as knowledge spillovers or collaborative interactions among workers.[77] I also allow amenities to depend on population. Specifically, the amenity value of residing in region l is given by $X_{l,t} = \ln(\tilde{X}_{l,t})$, where $\tilde{X}_{l,t}$ is a function of an exogenous shifter x_l and a population-dependent term:

$$\tilde{X}_{l,t} = x_l \left(L^*_{l,t}\right)^{\kappa}. \tag{78}$$

A value $\kappa \geq 0$ implies that a larger population increases the amenity value of l (e.g., via greater consumer variety or improved public goods provision), while $\kappa \leq 0$ implies negative effects (e.g., congestion, pollution, or traffic). When $\lambda = \kappa = 0$, the model collapses to the benchmark specification above. Following Ahlfeldt and Pietrostefani (2019), I set $\lambda = 0.06$ and $\kappa = 0.03$, which correspond to the average values reported in their meta-analysis.[78] I then recalibrate the remaining parameters following the procedure described in Section 4.3 to ensure internal model consistency with these values.

Table 10 reports the real estate price effects of the remote shock under both the benchmark model and the model with local productivity and amenity spillovers. Across all MSAs, the average residential price effect decreases from -0.75 to -7.38. Similarly, the average

[76] Notably, Allen and Donaldson (2020) show that in a dynamic model with forward-looking agents, even small and temporary shocks can generate permanent effects when agglomeration externalities are present. In a model of remote work, Monte et al. (2023) show that the interaction between agglomeration forces and remote productivity can lead to multiple stationary equilibria.

[77] Equation (77) implies that both remote and non-remote workers contribute equally to agglomeration in production. While one might argue that remote workers contribute less—due to fewer opportunities for face-to-face interaction—there is limited empirical evidence on their relative impact. Given this uncertainty, I adopt (77) as a plausible benchmark.

[78] See Table 3 in Ahlfeldt and Pietrostefani (2019). Larger values of λ have been used in the literature (e.g., Allen and Donaldson 2020; Ahlfeldt et al. 2015; Heblich et al. 2020), but I adopt a smaller value given that the unit of analysis is the MSA, rather than neighborhoods or counties. M. A. Davis et al. (2014) estimate a smaller elasticity (0.04) at the city level.

Table 10: Real Estate Price Effects with Regional Externalities

	Benchmark	Externalities	Difference
Residential Price Effect			
All MSAs	−0.75	−7.38	−6.64
Top 25%	−1.19	−1.07	0.12
Middle 50%	0.31	−7.56	−7.86
Bottom 25%	−2.40	−13.25	−10.85
Commercial Price Effect			
All MSAs	−3.68	−5.18	−1.50
Top 25%	−4.53	−4.54	−0.02
Middle 50%	−3.42	−5.13	−1.71
Bottom 25%	−3.38	−5.90	−2.53
Correlation			
All MSAs	0.83	0.81	−0.02
Top 25%	0.80	0.83	0.03
Middle 50%	0.89	0.85	−0.04
Bottom 25%	0.80	0.81	0.01

Note: Long-run real estate price effects of the remote shock under the benchmark model, and the model with regional externalities. The correlation between residential and commercial office price effects is also shown. Statistics are reported for both the (unweighted) average across all regions, and separately for the top 25%, middle 50%, and bottom 25% of regions by 2019 residential population.

commercial office price effect declines from −3.68 to −5.18. The impact of the externalities, however, varies across regions. In the top 25% of MSAs by 2019 population, the inclusion of the externalities leads to only modest changes in the remote shock's price effects. By contrast, the middle 50% and bottom 25% of MSAs experience substantially larger changes. For residential real estate, the average effect falls from 0.31 to −7.56 in the middle group and from −2.40 to −13.25 in the smallest MSAs. Commercial office prices show a similar pattern, declining from −3.42 to −5.13 in the middle group and from −3.38 to −5.90 in the smallest MSAs. Despite these heterogeneous effects, the strong correlation between residential and commercial office price responses remains intact. Overall, the results indicate that the benchmark model's implications are robust for the largest regions, while in mid-sized and small MSAs, the remote shock's impact on real estate prices becomes more negative once local productivity and amenity spillovers are taken into account.

N Inspecting the Mechanism

This section details the seven counterfactual exercises used in Section 5.3.

(i) Set period $t = 0$ remote migration rates equal to their non-remote counterpart:

$$\pi_{k,R,l,0} = \pi_{k,N,l,0}, \qquad \forall k, l.$$

(ii) Set the worker discount factor $\beta = 0$.[79]

(iii) Set the elasticity of substition $\sigma = 100$.

(iv) Set period $t = -1$ populations to their average:

$$L^*_{l,-1} = \frac{1}{\mathcal{L}}, \qquad \forall l.$$

(v) Set period $t = 0$ residential prices equal to their weighted average, with weights given by the $t = -1$ residential population distribution:

$$p_{l,0} = \sum_{k=1}^{\mathcal{L}} L^*_{k,-1} p_{k,0}, \qquad \forall l.$$

Update residential contruction productivity A^H_l according to (36).

(vi) Set period $t = -1$ commercial office space equal to its average:

$$B_{l,-1} = \frac{1}{\mathcal{L}} \sum_{k=1}^{\mathcal{L}} B_{k,-1}, \qquad \forall l.$$

(vii) Set period $t = -1$ commercial office prices equal to their weighted average, with weights given by the $t = -1$ office distribution:

$$q_{l,-1} = \sum_{k=1}^{\mathcal{L}} \frac{B_{k,-1}}{\sum_{j=1}^{\mathcal{L}} B_{j,-1}} q_{k,-1}, \qquad \forall l.$$

O Unified Real Estate Markets

Suppose real estate used by workers for a residence is perfectly substitutable with that used by firms for production. Market clearing in the local real estate market then becomes:

$$(L^*_{l,t} - L^*_{l,t-1}(1 - \delta^h))\bar{h} + \psi x_{l,t} = Y^{uni}_{l,t},$$

[79] I leave the discount factor for commercial owners unchanged.

where $Y^{uni}_{l,t}$ is production of the unified floorspace,

$$Y^{uni}_{l,t} = A^{uni}_l (M^{uni}_{l,t})^{\rho^{uni}_l} (P^{uni}_{l,t})^{1-\rho^{uni}_l}.$$

In addition, the local owner's budget constraint (8) is updated to reflect the new price of floorspace:

$$c^o_{l,t} + p^{uni}_{l,t} \psi x_{l,t} = r_{l,t} b_{l,t}.$$

The change in real estate prices from period $t-1$ to t is given by

$$\begin{aligned}
\dot{p}^{uni}_{l,t} &= \frac{p^{uni}_{l,t}}{p^{uni}_{l,t-1}} \\
&= \left(\dot{M}^{uni}_{l,t}\right)^{1-\rho^{uni}_l} \\
&= \left(\frac{(L^*_{l,t} - L^*_{l,t-1}(1-\delta^h))\bar{h} + \psi x_{l,t}}{(L^*_{l,t-1} - L^*_{l,t-2}(1-\delta^h))\bar{h} + \psi x_{l,t-1}}\right)^{(1-\rho^{uni}_l)/\rho^{uni}_l} \\
&= \left(\frac{(L^*_{l,t} - L^*_{l,t-1}(1-\delta^h))\bar{h} + \frac{\psi s_{l,t} r_{l,t} B_{l,t}}{p^{uni}_{l,t}}}{(L^*_{l,t-1} - L^*_{l,t-2}(1-\delta^h))\bar{h} + \frac{\psi s_{l,t-1} r_{l,t-1} B_{l,t-1}}{p^{uni}_{l,t-1}}}\right)^{(1-\rho^{uni}_l)/\rho^{uni}_l}.
\end{aligned}$$

As in the benchmark model, I set $P^{uni}_{l,t} = \bar{P}^{uni}_{l,t} = 1$. Further, I set ρ^{uni}_l to their values used in the benchmark analysis, and solve the model in time-differences to avoid estimating productivities A^{uni}_l. All other parameters are identical to their counterparts in the benchmark model calibration. To initialize the economy, I assume the $t = -1$ price of local real estate is a weighted average of 2018 residential price from Zillow and the 2018 commercial office price from Attom, with weights given by the stock of each floorspace type:

$$p^{uni}_{l,-1} = \frac{L^{*data}_{l,-1} \bar{h} p^{data}_{l,-1} + B^{data}_{l,-1} q^{data}_{l,-1}}{L^{*data}_{l,-1} \bar{h} + \psi B^{data}_{l,-1}}.$$

P Empirical Evidence

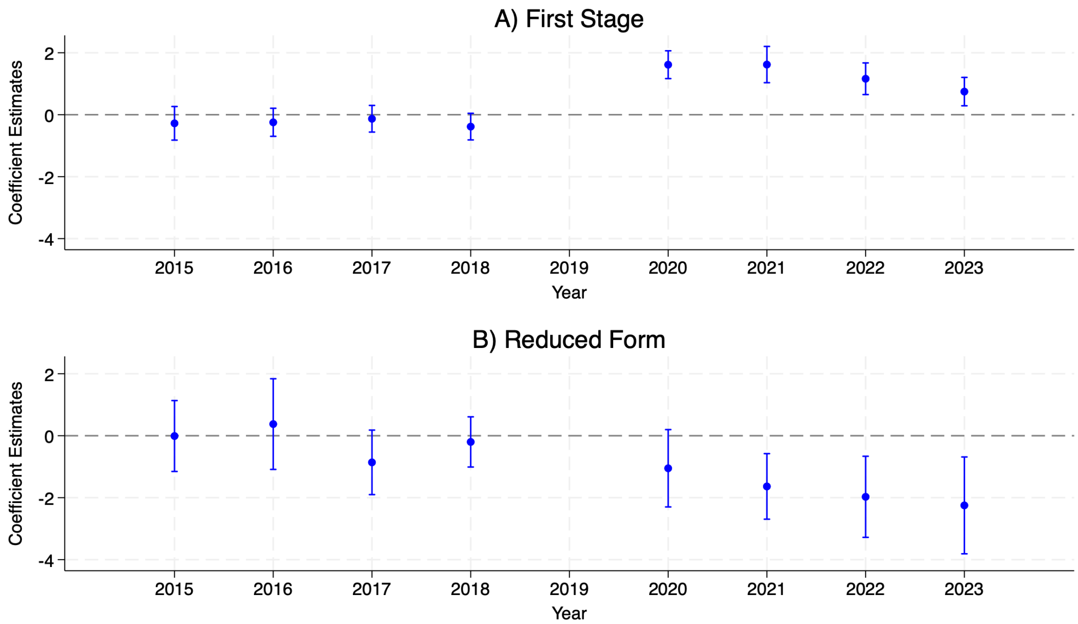

Figure 10: Event Study

P.1 Event Study

I estimate the effect of exposure to the remote shock using an event study design. Each regression takes the form:

$$Y_{l,t} = \sum_{\tau=2015}^{2023} \delta_\tau \ln(\text{Exp}_l) \cdot \mathbb{I}\,(t = \tau) + \beta X_{l,t} + \theta_t + \zeta_l + \epsilon_{l,t},$$

where $Y_{l,t}$ is an outcome, Exp_l is the MSA exposure to the remote shock, $X_{l,t}$ is a vector of controls, $zeta_l$ are region fixed effects, and θ_t are time fixed effects. Figure 10 shows results, where, in Panel A the outcome is the log remote share of employment, and in Panel B the outcome is the log average sale price of commercial office space. The figure confirms no significant effect of the remote exposure pre remote shock (2020).