Stochastic Productivity, Congestion, and Firm Location Choice

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1 Introduction

The factors that influence worker migration has been studied, explored, and modeled using a variety of mechanisms: workers may self-sort to locations according to their skills (Diamond, 2016), factor mobility frictions (Caliendo et al., 2019), wage prospects (Kennan and Walker, 2011), or location amenities (Desmet and Rossi-Hansberg, 2013). Looking to the labor demand side of this location choice is an interesting perspective to explore given the greater frictions firms face when relocating or establishing operations in new areas. It is significantly more costly for a firm to move to a different location due to having to not only incur direct financial expenses such as relocation fees, infrastructure investments, and potential downtime, but also bear substantial indirect costs, such as the disruption of established supply chains, the loss of local business relationships, the need to rebuild logistical networks, and the time and resources required to adapt to a new market environment. The operations literature has explored these location decisions as far back as 1909 with the Weber problem posing the problem of positioning a plant in a location at minimal cost (Weber, 1909) which was then generalized by Balinski (1965) and Stollsteimer (1961). Krugman (1991) posited that firms choose where to locate by balancing the tension between agglomeration (increasing returns to scale as firms bunch up in a location) and dispersion forces (transportation costs) to service consumers in other locations. Gaubert (2018) highlights the role of firm productivity since they observed that more productive firms locate in dense, high-rent areas while less productive firms do the opposite which Oberfield et al. (2024) echoes in the context of American firms. Lindenlaub et al. (2022) build on this by showing that firms sort across space by weighing local productivity gains against labor market competition, where more productive firms settle in high-productivity locations only if the benefits of better fundamentals outweigh the difficulty of hiring and retaining workers in competitive labor markets.

I aim to study firms' endogenous location choices in a simplified setting with only two locations. This abstraction allows me to set aside labor demand decisions and instead focus purely on location-specific productivities, which are subject to period-specific stochastic shocks and affected by congestion. These productivity shocks are stylized representations of real-world, short-term fluctuations (such as unusually heavy rainfall or a sudden improvement in internet speeds) that can influence a firm's output. The relative productivity levels of the two locations determine which city is more profitable in a given period, prompting firms to relocate based on expected returns, despite uncertainty about future shocks. However, firms cannot all relocate to the more productive city because congestion (arising from increased firm concentration) reduces individual productivity. This congestion may take the form of traffic delays, pollution, or strained infrastructure, ultimately hampering efficiency. To account for individual heterogeneity, firms also receive idiosyncratic taste shocks that influence their relocation decisions probabilistically. This model seeks to understand how firms choose where to locate when facing stochastic productivity and congestion forces. Specifically, it aims to answer the following questions:

- What is the steady-state fraction of firms in each city, and how is it determined by the congestion elasticity θ, moving cost m, and shock volatility σ_z?

- In the absence of taste shocks, what productivity threshold z^* triggers relocation?

- How quickly does the share of firms converge following a large disturbance to the initial distribution?

2 Model

Overview. A continuum of identical firms decide each period where to operate, choosing between two symmetric cities $i \in \{1, 2\}$. Symmetry keeps the equilibrium one-dimensional (only α_t matters) while still capturing congestion trade-offs. The only aggregate state is the share of firms located in city 1, $\alpha_t \in [0, 1]$. $1 - \alpha_t$ then represents the fraction of firms in city 2. Each period unfolds in five steps:

1. **Start of period firm concentration.** Firms observe current period's share of firms across locations α_t and $1 - \alpha_t$.

2. **Relative productivity shock.** A productivity shock that alters the relative productivity of the two cities $z_t \sim \mathcal{N}(0, \sigma_z^2)$ is realized, altering firms' relative profits earned between these locations.

3. **Firm profit.** Given crowding costs, firms realize their profits which are defined in city 1 and 2 respectively as:

$$\pi_1(z_t, \alpha_t) = e^{z_t}\, \alpha_t^{-\theta}, \qquad \pi_2(z_t, \alpha_t) = e^{-z_t}\, (1 - \alpha_t)^{-\theta},$$

   where $\theta > 0$ is the congestion elasticity.

4. **Idiosyncratic tastes.** Location-specific utility shocks $\eta_{\text{stay}}, \eta_{\text{move}} \overset{i.i.d.}{\sim} \text{EV}(0, \sigma_\eta)$ are drawn.

5. **Relocation decision.** Each firm can opt to pay a fixed cost $m > 0$ to switch locations in hopes of better productivity in the next period. Moves occur instantly and determine α_{t+1}.

2.1 Dynamic optimization

Let $V_i(z,\alpha)$ be the expected present value after observing (z,α) but before the taste shocks in step (iv). With discount factor $\beta \in (0,1)$ the Bellman equation is

$$\begin{aligned} V_i(z,\alpha) = \max\Big\{ & \pi_i(z,\alpha) + \beta\,\mathbb{E}_{z'|z}[V_i(z',\alpha')], \\ & \pi_j(z,\alpha) - m + \beta\,\mathbb{E}_{z'|z}[V_j(z',\alpha')]\Big\}, \qquad j \neq i. \end{aligned} \tag{1}$$

Here z' is next period's shock and α' the future congestion level determined by $\Phi(z,\alpha)$ in Equation 3 below.

2.2 Choice probabilities

Latent utilities. For a firm currently in city 1, the option–specific utilities after taste shocks realize are:

$$U_{\text{stay}} = \pi_1(z,\alpha) + \beta\mathbb{E}_{z'|z}[V_1(z',\alpha')] + \eta_{\text{stay}}, \qquad U_{\text{move}} = \pi_2(z,\alpha) - m + \beta\mathbb{E}_{z'|z}[V_2(z',\alpha')] + \eta_{\text{move}},$$

where $\eta_{\text{stay}}, \eta_{\text{move}} \overset{i.i.d.}{\sim} \text{EV}(0,\sigma_\eta)$. Relocation occurs whenever $U_{\text{move}} > U_{\text{stay}}$. The extreme-value distribution implies that $\eta_{\text{move}} - \eta_{\text{stay}}$ is logistic, which leads directly to the logit formula and allows the single scale parameter $\sigma_\eta$to capture taste heterogeneity (McFadden, 1974). The deterministic relocation surplus is defined to be the expected, forward-looking gains from moving (net of the moving cost m) before the taste shocks are drawn:

$$\Delta V(z,\alpha) \;=\; [V_2(z,\alpha) - m\,] - \; V_1(z,\alpha).$$

If $\Delta V > 0$, moving has higher deterministic utility making moving almost always the optimal choice unless it is overridden only when the taste-shock difference $\eta_{\text{move}} - \eta_{\text{stay}}$ is sufficiently negative. Conversely, if $\Delta V < 0$, staying is better and a firm would move only if this difference is sufficiently large.

With the relocation criteria $U_{\text{move}} > U_{\text{stay}}$, I can expand these latent utilities and rearrange them to observe $\Delta V(z,\alpha) > \eta_{\text{stay}} - \eta_{\text{move}} \sim \text{Logistic}(0, \sigma_\eta)$.

From this I directly get the probability that a firm in city 1 relocates to city 2 in the form of the logit:

$$P_{\text{move}}(z,\alpha) = \Pr[\text{Logistic}(0,\sigma_\eta) < \Delta V(z,\alpha)] = \frac{1}{1+\exp(\frac{-\Delta V(z,\alpha)}{\sigma_\eta})} \tag{2}$$

As $\sigma_\eta \to 0$, (2) collapses to the deterministic threshold rule $P_{\text{move}} = \mathbb{I}\{\Delta V > 0\}$.

2.3 Aggregation

These individual decisions by firms are aggregated by the expected share that will reside in city 1 next period, conditional on current relative productivity z. Because firms form a continuum, integrating (2) over the normal productivity shock z dictates the evolution for the city 1 share:

$$\alpha_{t+1} = \Phi(\alpha_t) := \int_{-\infty}^{\infty} \Big[\alpha_t\big(1 - P_{\text{move}}(z,\alpha_t)\big) + (1-\alpha_t)P_{\text{move}}(z,\alpha_t)\Big]\varphi(z)\,dz, \tag{3}$$

where $\varphi(\cdot)$ is the standard normal density.

2.4 Stationary spatial equilibrium

A stationary equilibrium is a fixed point

$$\alpha^* = \Phi(\alpha^*),$$

so that firms' relocation expectations are consistent with the congestion they subsequently generate.

3 Numerical methods

The state variable in this model is the share of firms in city 1 $\alpha \in [0,1]$ and there is the location productivity shock $z \sim \mathcal{N}(0, \sigma_z^2)$. I use the following methods:

1. **31-point Gauss–Hermite.** Expectations $E_{z'|z}$ are evaluated as

$$\sum_{i=1}^{31} \omega_i \, f(z_i), \qquad z_i = \sqrt{2}\, \sigma_z \, \xi_i,$$

where $\{\xi_i, \omega_i\}$ are the standard Hermite nodes and normalized weights. Thirty-one points suffices for machine-precision accuracy on smooth integrands.

2. **Value-function iteration.** For each trial share α, the firm's Bellman equation is solved on the 31-point grid by iterating $\|V_{t+1} - V_t\|_\infty < 10^{-8}$. Since the productivity shock is i.i.d., the continuation values collapse to scalars and VFI converges quickly.

3. **Cubic-spline interpolation.** Once the value functions $V_1(z, \alpha)$ and $V_2(z, \alpha)$ are obtained at the quadrature nodes, I build natural cubic splines for each. These splines allow the evaluation of the forward-looking surplus $\Delta V(z, \alpha) = V_2(z, \alpha) - m - V_1(z, \alpha)$ at arbitrary Monte-Carlo draws of z, preserving smoothness and avoiding bias from coarse grids.

4. **Brent's method (one-dimensional).** The map $\alpha \mapsto \Phi(\alpha) - \alpha$ is continuous on the search interval $[0.05, 0.95]$ and changes sign because

$$\Phi(0.05) - 0.05 \;=\; \underbrace{\Phi(0.05)}_{\approx 0.12} - 0.05 \;>\; 0, \qquad \Phi(0.95) - 0.95 \;=\; \underbrace{\Phi(0.95)}_{\approx 0.88} - 0.95 \;<\; 0.$$

So by the Intermediate Value Theorem, there exists a unique fixed point $\alpha^\star \in (0.05, 0.95)$. Thus, since the function can be evaluated within this interval, Brent's method is guaranteed to converge.

5. **Monte-Carlo simulation.**

   To visualize the model's transition dynamics, the code draws $N = 10,000$ independent productivity shocks for each period and evaluates $\Delta V(z, \alpha)$ via the cubic splines above, converts these to logit move probabilities (if $\sigma_\eta \neq 0$), and updates α_t. The large cross-section closely tracks the deterministic law of motion while preserving realistic noise as in real-world data.

4 Results

4.1 Baseline Parameters and Equilibrium

Table 1 lists the parameter values used in the baseline run. I set the congestion elasticity to $\theta = 0.40$, moving cost to $m = 0.25$, and the standard deviation of the productivity shock to $\sigma_z = 0.10$. The taste-shock scale $\sigma_\eta = 0.6$ smooths relocation decisions through a logit rule.

Parameter	β	θ	m	σ_z	σ_η
Value	0.95	0.40	0.25	0.10	0.60

Table 1: Baseline parameter values.

Steady state. Solving the fixed-point condition $\Phi(\alpha^\star) = \alpha^\star$ with Brent's method yields

$$\boxed{\alpha^\star = 0.5458}, \qquad \boxed{1 - \alpha^\star = 0.4541},$$

so roughly 55% of firms reside in city 1 at equilibrium. Expected per-period profits, computed by 31-point Gauss–Hermite quadrature, are

$$\mathbb{E}[\pi \mid \text{city } 1, \alpha^\star] = 1.2804 \quad \text{and} \quad \mathbb{E}[\pi \mid \text{city } 2, \alpha^\star] = 1.3781. \tag{4}$$

Under perfect mobility, firms would reallocate until expected profits would equalize in equilibrium, however Equation 4 shows a different story where city 2 has higher expected profits. Note also that the difference between these expected profits are not fully offset by the moving cost ($m = 0.25$). This gap is consistent with the location decision that firms make in the model, that it is not entirely dictated by profit differentials but rather on the full deterministic relocation surplus ($\Delta V(z, \alpha)$) which incorporates these expectations and moving costs on top of idiosyncratic taste shocks. The presence of this taste heterogeneity means that even when average profits are higher in one city, some firms will remain in the other due to their own preferences. In real life, these preferences may look like loyalty to local networks, attachment to a particular regional identity, or simply the inertia in decision-making. This probabilistic margin helps reconcile the realistic sluggishness in firm relocation with profit-based models. As $\sigma_\eta \to 0$, the logit probability becomes more of a threshold for a deterministic rule, and the profit gap converges to the moving cost in equilibrium. So in equilibrium, even though firm's preferences differ, congestion in the larger city caps its edge at just 10 percentage points. The model itself produces almost equal city sizes, mirroring the real-world "Zipf's Law" pattern of metropolitan areas.

I visualize this in Figure 1, which plots the fixed-point map $\Phi(\alpha)$ (solid curve) against the 45° identity line (dashed). The unique intersection of the two curves (marked by the red dot) is the steady-state share α^*. Points to the left of the crossing lie above the 45° line, indicating net inflows to city 1, whereas points to the right lie below it, indicating net outflows; hence the equilibrium is both unique and locally stable.

Intuitively, this means that if the share of firms in city 1 is too low, the expected relocation behavior will raise that share in the next period, and conversely if the share is too high, relocation incentives will push firms away, restoring balance. This self-correcting mechanism comes from the interplay between stochastic productivity shocks, congestion penalties, and individual relocation incentives shaped by the logit rule. The flattening of the $\Phi(\alpha)$ curve at the tails highlights the diminishing marginal impact of additional relocation as cities become either nearly empty or saturated which is consistent with the logit's asymptotic behavior

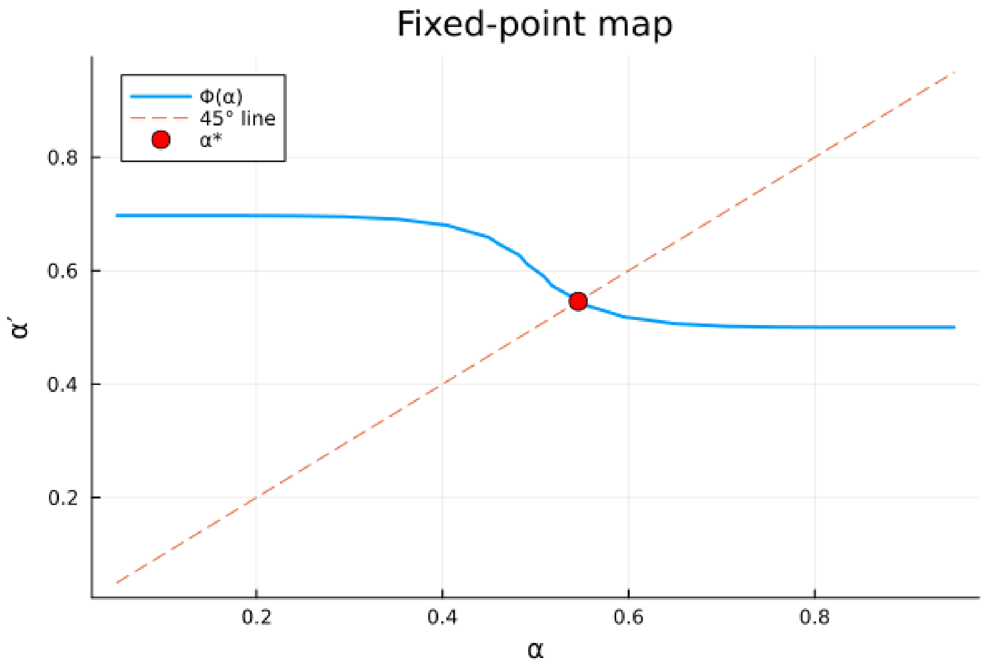

Figure 1: Fixed–point characterization of the baseline equilibrium

and congestion's nonlinear impact.

4.2 Dynamic adjustment

Starting from a large disturbance ($\alpha_0 = 0.20$) I simulate a cross-section of $N = 10,000$ firms for $T = 500$ periods with an initial distribution of firms where 20% lie in city 1 while 80% are in city 2. Figure 2 shows the resulting path, while Table 2 reports the speed of convergence.

Criterion	Periods to reach	Interpretation
$\lvert\alpha_t - \alpha^\star\rvert < 0.05$	3	90% of the gap closed
$\lvert\alpha_t - \alpha^\star\rvert < 0.01$	11	within 1 p.p. of steady state

Table 2: Speed of convergence after a 30-percentage-point shock.

Interpreting one model period as a year, the metropolitan system needs roughly a generation (two to three decades) to iron out a 30-percentage-point misallocation. Congestion therefore disciplines the long-run distribution, but frictions and idiosyncratic tastes keep transitional imbalances persistent.

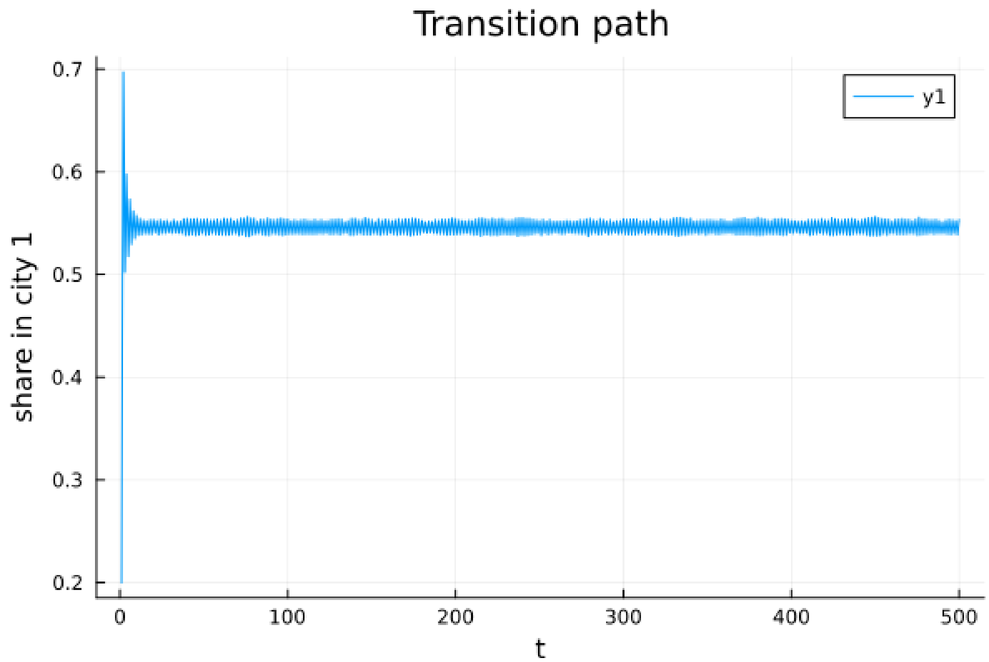

Figure 2: Monte-Carlo transition path for α_t ($\alpha_0 = 0.20$, $N = 10\,000$).

Granted the smoothness of the transition path, it reflects the forward-looking nature of firm's decision-making under uncertainty. Firms anticipate long-run benefits, even when immediate conditions are noisy. Although idiosyncratic taste shocks introduce some randomness at the individual level, the law of large numbers ensures that in the aggregate, α evolves in a stable and predictable manner.

The quick reversion to the mean in the early periods suggests that the economy has a strong stabilizer, that is, relocation incentives respond quickly and sharply to deviations from equilibrium. When α is far from $\alpha^\star$, the deterministic surplus becomes large in magnitude, greatly skewing relocation probabilities and accelerating the rate of convergence. As the system approached $\alpha^\star$, relocation incentives weaken and settles into a stable equilibrium.

This transition path captures a basic yet key pattern common in macroeconomics. How even without centralized coordination or ex-ante planning, independent actors can produce orderly adjustment through local, probabilistic rules. But persistence in individual-specific heterogeneity (taste) means that it there will still be some level of noise, which echoes real urban patterns.

4.3 Sensitivity of the steady-state share

Figure 3 varies each structural parameter by ±50% around their baseline and recalculates for $\alpha^\star$. The results show that:

- **Congestion elasticity θ.** Increasing θ intensifies the productivity penalty for large cities, pushing the steady-state share $\alpha^\star$ toward 0.5 (perfect symmetry). Halving θ to 0.20 raises $\alpha^\star$ to 0.5587, while raising it to 0.60 lowers $\alpha^\star$ to 0.5398.

- **Moving cost m.** Higher moving costs reduce the frequency of relocation in both directions, allowing whichever city happens to be larger to retain more firms. Doubling m to 0.375 increases $\alpha^\star$ to 0.5488, while halving it to 0.125 lowers the share to 0.5341.

- **Shock volatility σ_z.** Changes in σ_z yield the most pronounced effect on $\alpha^\star$. Lowering σ_z by 50% to 0.05 reduces $\alpha^\star$ to approximately 0.5255, while raising it to 0.15 boosts the share to around 0.5598. Greater volatility magnifies productivity differences across cities, inducing sharper relocation incentives.

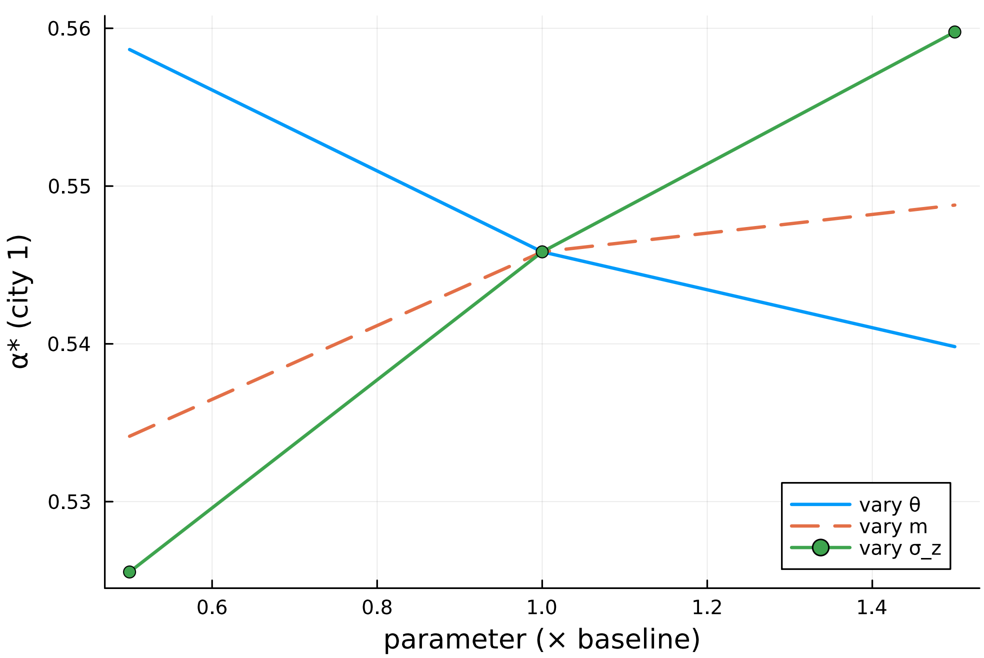

Figure 3: Comparative statics of the steady-state share $\alpha^\star$ around the baseline calibration.

These comparative statics shine a light on the roles of the model's parameters in shaping the spatial distribution of firms across locations.

The sensitive reaction of $\alpha^\star$ to σ_z reflects the influence of productivity volatility in long-run location choices. As firms become more and more volatile with a greater σ_z, cities experience larger relative swings in productivity, increasing their incentive to relocate. Consequently, the city that happens to be larger benefits more frequently from these productivity fluctuations, making the firms concentrate more there. In this way, volatility amplifies the concentration of activity, showing that uncertainty disproportionately benefits already dominant locations.

The congestion elasticity acts as a dispersion force that balances location's firms distribution, absent this parameter all firms would likely bunch up in one location. A higher θ penalizes firms crowding together and pushes the equilibrium toward a more even distribution between cities. The opposite is true for the case of lowering this elasticity. Overall, the relationship is intuitive, congestion disciplines growth by making agglomeration less profitable.

Mobility costs do not necessarily make one location more (as σ_z does) or less (as θ does) attractive. Instead, it constrains firms from perfectly responding to such differences in attractiveness/profitability. When m is relatively high, firms may be discouraged from relocating even if productivity shocks would induce them to move which illustrates the real inertia and persistence of some firms in particular locations. Again, lower m does the opposite and allows firms to avoid congestion or chase favorable shocks more easily. This aligns with most of the literature that reducing frictions can promote more efficient and welfare-maximizing spatial sorting.

All in all, this exercise emphasizes that equilibrium firm concentration in cities are not solely determined by fundamental differences (e.g. amenities) but are also very sensitive to volatility, congestion, and frictions. Even in this abstract symmetric environment, adjustments in parameters can magnify or dampen these firms' aggregate location decisions.

4.4 Sensitivity to the discount factor

To examine how firms' patience shapes their relocation choices, I fix the aggregate share at the steady-state value α^*, show the productivity shock up to 3 standard deviations away from z's mean, and vary the discount factor across:

$$\beta \in \{0.20,\ 0.50,\ 0.80,\ 0.90,\ 0.95,\ 0.99\}.$$

For each β, the Bellman equations are solved through value-function iteration, approximate a cubic spline for said value functions, and compute the deterministic relocation surplus $\Delta V(z, \alpha)$ before taste shocks. I then evaluate the logit relocation probability

$$P_{\text{move}} = \frac{1}{1 + \exp\bigl(-\Delta V(z, \alpha)/\sigma_\eta\bigr)}$$

on a fine grid of productivity shocks z. Figure 4 plots these curves.

Three main patterns stand out:

1. **Higher move propensity at neutral shocks.** At $z = 0$, more patient firms (higher β) have a larger relocation probability. This intuitively makes sense since more patient firms are willing to incur today's moving cost even when current productivity is unchanged granted their greater value for the future.

2. **Earlier and steeper drop for impatient firms.** While firms of all discount factors generally follow a similar pattern across all z, more impatient firms (low β) see their $P_{\text{move}}(z, \alpha)$ decline at smaller negative shocks and with a sharper slope than more patient firms. This implies that impatient firms require a larger immediate productivity boost to justify moving, so their relocation probability falls off sooner and more abruptly as z becomes positive (making them want to stay more). In contrast, more patient firms delay and smooth this decline, reflecting their willingness to wait for future gains before moving.

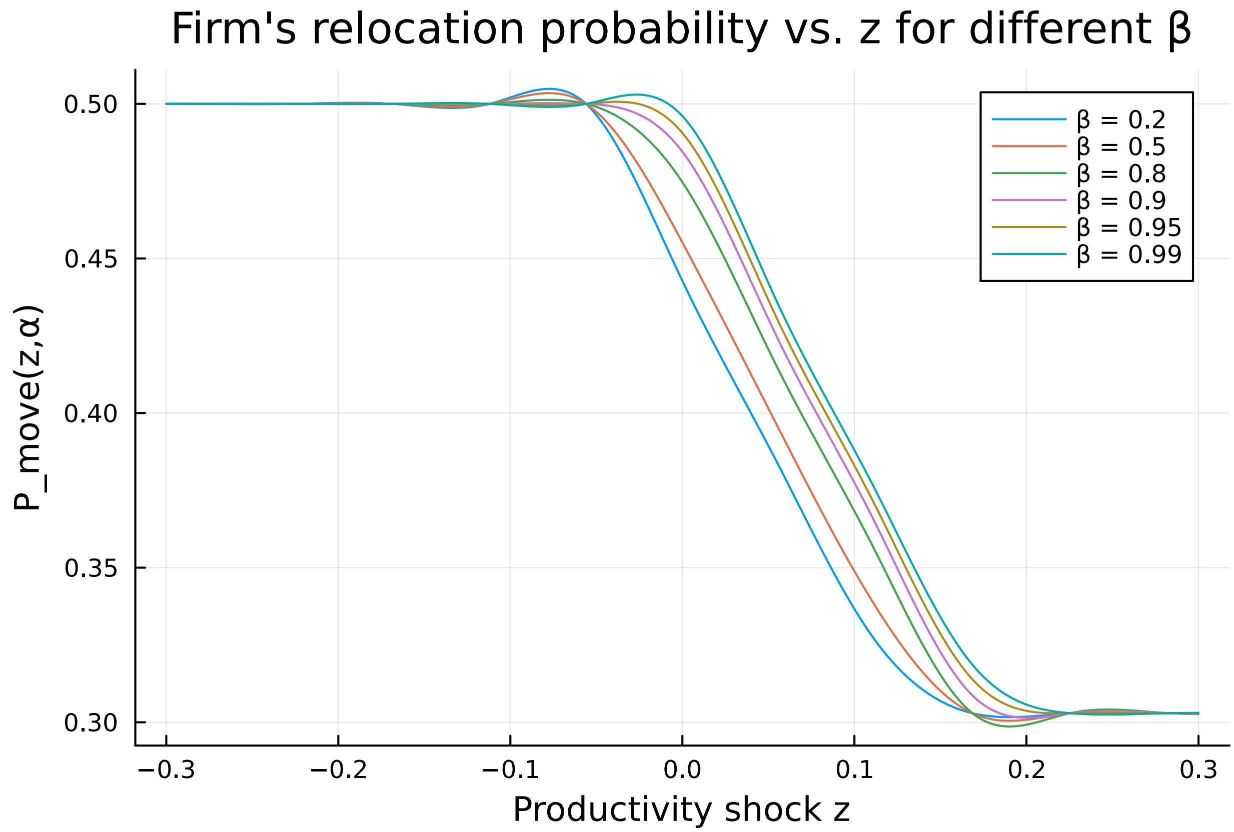

Figure 4: Relocation probability $P_{\text{move}}(z, \alpha)$ for a firm in city 1 as a function of the productivity shock z, for various discount factors β

3. **Common plateaus at extremes.** For very negative or very positive z, all six curves converge to nearly the same asymptotic levels. When a shock is strong enough, the immediate gain or loss dominates future considerations regardless of the firm's patience.

Overall, higher patience (β) makes firms more sensitive to smaller productivity differences and smooths their switching rule, but does not alter the fact that relocation probabilities remain pinned to roughly 0.5 or 0.3 once z is far from being a neutral shock. These qualitative patterns still hold true even if the horizontal axis is extended up to $\pm 5\sigma_z$.

4.5 Relocation threshold without taste shocks

Setting $\sigma_\eta = 0$ converts the logit rule to a step function. Solving $\Delta(z^\star, \alpha^\star) = 0$ on $[-2\sigma_z, 2\sigma_z]$ gives

$$\boxed{z^\star = -0.0577} \qquad \text{(baseline parameters except } \sigma_\eta = 0\text{)},$$

so firms in city 1 relocate to city 2 whenever their productivity draw satisfies $z < z^\star$. The cutoff moves inversely with m and one-for-one with θ: doubling the moving cost to $m = 0.50$ lowers the threshold to $z^\star = -0.1513$, whereas halving θ also lowers the threshold to $z^\star = -0.0901$.

Without idiosyncratic taste shocks, relocation is a deterministic choice for the firms, they would only move if their location's productivity draw falls below the cutoff $z^\star$. In the steady-state, this cutoff reflects the exact balance between expected profits/latent utility from swapping cities and the moving cost m. The intuition lies in the fact that if a firm draws $z < z^\star$, its current-period advantage from staying (even accounting for the adverse effect of congestion) is so small that the future benefit of relocating outweighs the fixed moving cost. Conversely, draws above this threshold means that the firm would be better off staying put despite the uncertainty.

Although this threshold rule is stark, it delivers an interesting micro-foundation for the observed "small" net flows in the full model with taste shocks. When $\sigma_\eta > 0$, the hard cutoff now becomes randomized, which ends up producing the smooth logit decision rules above. These decision rules are what enables some mass of near-threshold firms to switch in either direction.

5 Conclusion

I study firms' endogenous location decisions in a stylized two-city model where relocation behavior is shaped by stochastic productivity shocks, congestion effects, and moving costs. Idiosyncratic taste heterogeneity introduces probabilistic switching that smooths out the sharp thresholds of purely deterministic rules. Despite the abstraction, the model generates empirically plausible features of the spatial distribution of firms in space.

In the steady state, the equilibrium share is near symmetric, with congestion penalizing overcrowding and preventing firms from bunching in a single location. Comparative statics reveal that productivity volatility (σ_z) has the most pronounced influence on firm concentration, followed by congestion elasticity (θ) and moving costs (m). Volatility amplifies sorting by magnifying productivity differentials, while congestion acts as a dispersion force. Mobility frictions serve more as a dampener, slowing but not fully offsetting relocation incentives.

Monte Carlo simulations show rapid convergence after large shocks, with the system returning close to steady state within 10 time periods. This dynamic behavior arises from the forward-looking nature of firms, who anticipate long-run gains when making location choices, even in the presence of noise. While idiosyncratic tastes introduce randomness at the micro level, the aggregate share α_t evolves predictably.

Relocation probabilities also respond to firms' discount factors. More patient firms exhibit smoother and more frequent switching behavior, especially near neutral shocks. Without taste shocks ($\sigma_\eta = 0$), the model simplifies to a deterministic cutoff rule where firms relocate only when the productivity gap justifies paying the fixed cost.

Overall, this framework highlights how spatial firm distributions are not solely dictated by fundamental differences across locations but also depend on volatility, congestion, and frictions. Even under symmetry, small structural shifts can meaningfully affect equilibrium outcomes.

Appendix

The Julia code used for this analysis, including the generation of figures and tables, is contained in `final.jl`, which is supplemented by `spline.jl` for spline-related functions.

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