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Information Disclosure and Welfare in Housing Markets

A Search-Theoretic Framework with Endogenous Participation and Broker Exit*

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Abstract

We develop a search-and-matching model of the housing market with a disclosure parameter θ governing price estimation precision, matching probability, and market participation. Transactions occur when the bid–ask gap falls within a fixed negotiation band; higher disclosure compresses the gap distribution. Model-implied welfare losses are decomposed into nine components. Disciplined by Japanese and UK institutional moments, total losses are 39.0% versus 8.4% of imputed rent. Reduced-form regressions using Japanese prefectural panel data are consistent with the model's two central predictions: higher disclosure coverage is associated with shorter time-on-market and lower price dispersion, with magnitudes close to the model-implied elasticities. Monte Carlo simulations indicate that welfare gains are positive in all simulated draws under the perturbation design. An online appendix develops a dynamic extension exploring broker exit, market collapse, and the akiya crisis.

JEL: D83, R21, R31, D91, G51, R23.

Keywords: Information disclosure, search and matching, housing mismatch, market participation, broker viability.

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1 Introduction

How much social welfare is lost when housing transaction prices are not publicly disclosed? Housing is the largest asset on most household balance sheets (Campbell, 2006), and housing markets are characterized by severe information frictions (Broxterman and Zhou, 2023). Yet no existing framework quantifies the complete welfare cost of non-disclosure—including its effects on market participation, broker viability, and vacancy dynamics. This paper develops such a framework.

We build on three intellectual foundations. First, Shimizu et al. (2004) estimated that information imperfections in Tokyo generate social costs of 22.6% of imputed rents—but within a partial-equilibrium framework with a representative agent. Second, Andersen et al. (2022) and Badarinza et al. (2024b) showed that reference-dependent preferences create behavioral lock-in in search-and-matching equilibria—but abstracted from disclosure institutions. Third, Badarinza et al. (2021) structurally estimated a 12.1% contracting friction between informationally asymmetric counterparties—but did not connect this to domestic housing institutions.

Our contribution is fivefold. (i) We unify these strands within a dynamic equilibrium model parameterized by disclosure $\theta \in [0, 1]$. (ii) We introduce *spatial information decay*: in low-θ regimes, agents must gather comparables from wider areas, with prediction errors increasing in distance. (iii) We endogenize market participation (both seller and buyer entry decisions) and broker capacity, showing that disclosure thickens the market through multiplicative channels. (iv) We provide external support for the model's two central predictions—that disclosure reduces time-on-market and price dispersion—using reduced-form regressions on a Japanese prefectural panel, with empirical magnitudes in the range of model-implied elasticities. (v) Monte Carlo simulations (10,000 draws) demonstrate that the welfare gain from disclosure reform is positive in all simulated draws under the stochastic perturbation design.

The model focuses on intergenerational transactions: old homeowners selling to young first-time buyers. This dyad maximally exposes information frictions because the parties differ in experience, local knowledge, and bargaining power.

Preview of results. Disciplined by Japanese and UK moments, model-implied welfare losses are 39.0% of imputed rent in Japan ($\theta = 0.30$) versus 8.4% under near-full disclosure ($\theta = 0.95$), a gap of 30.6 pp—more than double the friction-only estimate (14.7 pp). Reduced-form regressions on a Japanese prefectural panel are consistent with the model's central predictions: a 10-pp increase in disclosure is associated with an 8.4% shorter time-on-market and 2.8-pp lower price dispersion, with magnitudes in the range of model-implied elasticities. Monte Carlo bands show that even the pessimistic 5th-percentile gain exceeds 24 pp.

Related literature. On housing search and matching: Wheaton (1990), Díaz and Jerez (2013), Head et al. (2014), Ngai and Sheedy (2020, 2024), Badarinza et al. (2024a). On information frictions: Akerlof (1970), Garmaise and Moskowitz (2004), Levitt and Syverson (2008), Kurlat and Stroebel (2015), Broxterman and Zhou (2023). On behavioral frictions: Genesove and Mayer (2001), Andersen et al. (2022), Badarinza et al. (2024b). On contracting frictions: Guiso et al. (2008, 2009), Nunn (2007), Badarinza et al. (2021). On heterogeneous-agent models: Krusell and Smith (1998), Ahn et al. (2018). On welfare measurement: Einav et al. (2010). On housing market microstructure: Han and Strange (2015), Albrecht et al. (2016), Piazzesi et al. (2020).

The paper proceeds as follows. Section 2 reviews the institutional landscape of disclosure. Section 3 presents the model. Section 4 reports calibration, simulation, Monte Carlo results, and reduced-form validation using prefectural panel data. Section 5 discusses policy implications. Section 6 concludes. The Online Appendix develops dynamic extensions on broker exit and the akiya crisis.

2 Literature Review

2.1 Information Frictions in Housing Markets

The theoretical analysis of information asymmetry in markets traces back to Stigler (1961), Akerlof (1970), and Rothschild and Stiglitz (1976). As Broxterman and Zhou (2023) emphasize in their comprehensive survey, the first and second fundamental theorems of welfare economics do not hold in the presence of information frictions—the theoretical departure point for this paper.

Shimizu and Nishimura (2006) document systematic biases in appraisal-based land price information in Japan. Garmaise and Moskowitz (2004) provide the first systematic evidence of information asymmetry in real estate markets, showing that properties in areas with less informational transparency sell at a discount. Levitt and Syverson (2008) demonstrate that real estate agents selling their own homes achieve 3.7% higher prices than when selling clients' homes, directly revealing the magnitude of informational advantage. Kurlat and Stroebel (2015) show that the composition of sellers (the share who are real estate agents) predicts future price appreciation, providing market-level evidence of information frictions. Li and Chau (2024) document a 2.8% premium paid by non-local (informationally disadvantaged) buyers in Hong Kong, extending the analysis to heterogeneous buyers and sellers.

2.2 Search and Matching in Housing Markets

Wheaton (1990) introduced the search-and-matching framework to housing, building on the insight of Stein (1995) that prices and trading volume are jointly determined, showing an inverse relationship between vacancy and prices. Díaz and Jerez (2013) developed an equilibrium model of house prices, sales, and time-on-market. Head et al. (2014) integrated search, liquidity, and construction dynamics.

Two recent advances are particularly relevant. Ngai and Sheedy (2020) endogenize the decision to move house within a search-and-matching model, showing that match quality depreciation drives listing decisions. Ngai and Sheedy (2024) extend the model to study the "ins and outs" of housing market volatility. Badarinza et al. (2024a) use UK online listing data to directly estimate the housing market matching function, confirming that a Cobb-Douglas specification with constant returns to scale fits the data well.

Albrecht et al. (2016) introduce directed search to the housing market, and Piazzesi et al. (2020) develop a model of segmented housing search. Han and Strange (2015) provide the most comprehensive survey of housing market microstructure.

2.3 Reference Dependence and Loss Aversion

Genesove and Mayer (2001) first documented loss aversion among housing sellers in Boston. Andersen et al. (2022) structurally estimate reference dependence and loss aversion using Danish administrative data, finding loss aversion of $\lambda \approx 2.0$–2.5. They document a "hockey stick" pattern in listing prices and bunching at zero nominal gains.

Badarinza et al. (2024b) embed these preferences into a dynamic search-and-matching model and study aggregate implications. They show that "paper losses" create behavioral lock-in, generating nominal rigidity in housing markets, and that the distribution of potential nominal gains is a key policy-relevant statistic.

2.4 Contracting Frictions and Trust

Badarinza et al. (2021) use data on 87,679 commercial real estate transactions across 70 countries to document affinity-based counterparty matching. They structurally estimate a contracting friction of 12.1% between low-affinity counterparties. We generalize their framework by interpreting "nationality" as "information endowment level," mapping the friction to the information asymmetry between old sellers and young first-time buyers.

Guiso et al. (2008, 2009) establish the role of trust in financial markets and economic exchange. Nunn (2007) shows that relationship-specificity and incomplete contracts shape trade patterns.

2.5 The Institutional Landscape of Price Disclosure

The UK's HM Land Registry (HM Land Registry, 2024) publishes all residential transaction prices ($\theta \approx 0.95$); France's DVF provides open data on virtually all transactions; Germany's Kaufpreissammlung collects all prices through notaries with restricted public access ($\theta \approx 0.70$); Korea (2006) and Taiwan (2012) mandate full reporting through licensed professionals. The US varies by state but generally provides public access through county recorders ($\theta \approx 0.80$). Japan's voluntary survey, introduced in 2006, achieves approximately 30% coverage ($\theta \approx 0.30$)—the lowest among advanced economies.

The JLL Global Real Estate Transparency Index ranks markets on a 1–5 scale across 89 countries. Eichholtz et al. (2010) show that low transparency in destination markets causes international property investors to underperform local investors, but this gap disappears as transparency improves.

3 Theory

This section builds the model in six steps. We first describe the physical and informational environment (§3.1–3.3), then the problems of old sellers (§3.9) and young buyers (§3.10), the role of brokers (§3.11), the equilibrium concept (§3.14), and finally the welfare decomposition and main theoretical results (§3.15–3.17).

3.1 Environment

Time and discounting. Time is discrete, $t = 0, 1, 2, \ldots$. All agents discount at common factor $\beta \in (0, 1)$.

Housing stock. A unit continuum of indivisible housing units at locations $\ell \in \mathcal{L} \subset \mathbb{R}^2$ with density $\rho(\ell)$. Each unit j at location ℓ has hedonic fundamental value $V_{j\ell} = h_\ell(\mathbf{x}_j) + \eta_\ell$, where $h_\ell(\cdot)$ is a location-specific hedonic function mapping observable attributes $\mathbf{x}_j$ (floor area, building age, distance to station, etc.) to prices, and η_ℓ is an unobserved local amenity shock. The key assumption is that h_ℓ varies across space: the marginal price of floor area in a central business district differs from that in a suburban or rural location.

Agents: two generations. There are two types of households:

- *Old homeowners* (O), mass π^O, who currently own and occupy a housing unit. They have income y^O, accumulated housing tenure, local market knowledge (information endowment ω^O), and a reference price r_i equal to their original purchase price.
- *Young first-time buyers* (Y), mass $\pi^Y = 1 - \pi^O$, who are currently renters paying flow cost $\bar{r}^{\text{rent}}$. They have income $y^Y < y^O$, no prior transaction experience (information endowment $\omega^Y < \omega^O$), and no reference price.

The canonical transaction is the sale of a home by an old owner to a young first-time buyer. Upon completion, the seller enters the buyer pool (as a downsizer or renter) and the buyer becomes a homeowner whose purchase price becomes their future reference point—capturing the "rational behavioralism" of Badarinza et al. (2024b).

Disclosure parameter. The institutional environment is characterized by $\theta \in [0, 1]$, the fraction of past transaction prices that are publicly accessible. This parameter is common knowledge and exogenous (determined by the legal regime). The UK ($\theta \approx 0.95$), France ($\theta \approx 0.98$), and Korea ($\theta \approx 0.85$) are high-disclosure economies; Japan ($\theta \approx 0.30$) is low-disclosure.

3.2 Information Structure: Attribute Space and Partial Observability

The central innovation of our information structure is to make the *precision of price estimation* an endogenous function of the disclosure regime. Disclosure θ governs the number of comparable transactions available for hedonic coefficient estimation and therefore the accuracy with which agents can infer the market value of any given property.

Attribute space. Each property j is characterized by a vector of n physical and locational attributes:

$$\mathbf{x}_j = (x_{j,1},\, x_{j,2},\, \ldots,\, x_{j,n})' \in \mathbb{R}^n \tag{1}$$

Examples include floor area (x_1), building age (x_2), distance to station (x_3), floor level (x_4), building structure (x_5), frontage width (x_6), environmental quality (x_7), building inspection result (x_8), condominium management quality (x_9), and so on. These are *physical characteristics of the property*, not market signals. Past transaction prices of comparable units are *not* attributes; they are market information used to estimate hedonic coefficients, and their availability is governed by θ.

Three-tier value decomposition. We distinguish three objects:

1. **Common market value:** the hedonic price that a well-informed market would assign to property j at location ℓ:

$$V_{j\ell} = \boldsymbol{\beta}(\ell)'\mathbf{x}_j + \eta_\ell \tag{2}$$

   where $\boldsymbol{\beta}(\ell) = (\beta_1(\ell), \ldots, \beta_n(\ell))'$ is the vector of hedonic prices and η_ℓ is a location fixed effect. This value is common to all potential buyers and is the target of price estimation.

2. **Buyer-specific match value:** the total value of property j to buyer i:

$$u_{ij} = V_{j\ell} + \varepsilon_{ij} \tag{3}$$

where $\varepsilon_{ij} \sim F_\varepsilon(0, \sigma_\varepsilon^2)$ is the idiosyncratic match quality—how well the property suits buyer i's personal needs (commute pattern, family size, aesthetic preferences). This component can only be learned through physical inspection or residence experience.

3. **Transaction price:** the realized price p_{ij}^{tr}, determined by negotiation between the matched seller and buyer within the matching zone (§3.6).

Price disclosure affects the estimation of $V_{j\ell}$, not ε_{ij}. The match component ε_{ij} is irreducible by any information policy; it requires on-site inspection.

The role of θ: transaction price disclosure rate. We define $\theta \in [0, 1]$ as the fraction of past housing transactions whose prices are publicly accessible. Under the UK's HM Land Registry, $\theta \approx 0.95$; under Japan's voluntary survey, $\theta \approx 0.30$. Disclosure θ affects agents' ability to estimate $V_{j\ell}$ through two channels: (i) the number of comparable transactions available for hedonic regression, and (ii) the spatial density of comparables, which determines the information radius $R(\ell; \theta)$. Higher θ means more comparables, tighter confidence intervals on $\boldsymbol{\beta}(\ell)$, and more precise estimates of $V_{j\ell}$.

Partition of attributes by observability. The n physical attributes are partitioned into three groups:

- **Always observable** (Layer 1): n_1 attributes—floor area, building age, number of rooms, distance to station, CBD accessibility. These appear in property advertisements and are known to all buyers regardless of θ.
- **Observable if disclosed** (Layer 2): $n_2(\theta)$ attributes—building inspection reports, environmental data, maintenance records, condominium management assessments. These require institutional disclosure infrastructure:

$$n_2(\theta) = \theta \bar{n}_2 \tag{4}$$

  where $\bar{n}_2$ is the total number of Layer-2 attributes.
- **Inspection-only** (Layer 3): n_3 attributes—subjective match quality, neighborhood atmosphere, noise levels, interpersonal dynamics with neighbors. These can only be learned through physical inspection and correspond to ε_{ij}.

The total is $n = n_1 + \bar{n}_2 + n_3$, and the number of *unobserved* attributes prior to inspection is $n_U(\theta) = (\bar{n}_2 - n_2(\theta)) + n_3$.

Buyer's valuation problem. Given partial observability, the buyer's best estimate of the property's fundamental value before inspection is the *projected* value using only observed attributes:

$$\hat{V}_{j\ell}^{\text{pre}}(\theta) = \hat{\eta}_\ell + \sum_{k \in \mathcal{O}(\theta)} \beta_k(\ell)\, x_{j,k} \tag{5}$$

where $\mathcal{O}(\theta) = \{1, \ldots, n_1\} \cup \mathcal{D}(\theta)$ is the set of observable attributes (Layer 1 plus the disclosed subset $\mathcal{D}(\theta)$ of Layer 2).

The *prediction error* from using only the observed attributes is:

$$e_j^V(\theta) \equiv V_{j\ell} - \hat{V}_{j\ell}^{\text{pre}}(\theta) = \sum_{k \notin \mathcal{O}(\theta)} \beta_k(\ell)\, x_{j,k} \tag{6}$$

Assuming the unobserved attributes are independently distributed with variance σ_x^2 each, and the hedonic coefficients have magnitude $|\beta_k| \sim \bar{\beta}$, the variance of the prediction error is:

$$\text{Var}(e_j^V \mid \theta, \ell) \equiv \sigma_V^2(\theta, \ell) = n_U(\theta) \cdot \bar{\beta}^2(\ell) \cdot \sigma_x^2 \tag{7}$$

This expression makes precise the microfoundation of the "extra value" variance. As more attributes are disclosed ($\theta \uparrow$, so $n_U \downarrow$), the omitted-attribute variance shrinks proportionally:

$$\frac{\partial\, \text{Var}(e_j)}{\partial \theta} = -\bar{n}_2 \cdot \bar{\beta}^2(\ell) \cdot \sigma_x^2 < 0 \tag{8}$$

The marginal variance reduction from disclosing one additional attribute is $\bar{\beta}^2(\ell) \cdot \sigma_x^2$, which is *location-specific* because hedonic prices $\bar{\beta}(\ell)$ vary across space.

Connection to the three-layer formulation. The prediction error (6) corresponds exactly to the "extra value" ξ_j in the earlier formulation. The omitted-attribute variance $n_U(\theta)\bar{\beta}^2\sigma_x^2$ decomposes into two components when spatial information decay is incorporated:

$$\text{Var}(\xi \mid \theta, \ell) = \underbrace{n_U(\theta) \cdot \bar{\beta}^2(\ell) \cdot \sigma_x^2}_{\text{attribute-level uncertainty}} \cdot \underbrace{\left(1 + \frac{\sigma_h^2}{\bar{\beta}^2 \sigma_x^2} \cdot \frac{n_{\min}}{\pi \theta\, T(\ell) \rho(\ell)}\right)}_{\text{spatial amplification}} \tag{9}$$

This is the variance of the *fundamental value* prediction error. The buyer's *total* uncertainty about her utility $u_{ij} = V_{j\ell} + \varepsilon_{ij}$ is:

$$\text{Var}(u_{ij} - \hat{V}_{j\ell}^{\text{pre}} \mid \theta, \ell) = \sigma_V^2(\theta, \ell) + \sigma_\varepsilon^2 \tag{10}$$

The first factor captures the "how many attributes are missing" dimension. The spatial amplification factor captures the "how far must I search to learn about them" dimension. This product structure generates a *multiplicative* interaction: when many attributes are missing *and* the information radius is large, the total prediction error is far worse than the sum of the two effects.

Unobserved attributes and precision. The number of unobserved attributes is $n_U(\theta) = (1-\theta)\bar{n}_2$, a continuous and decreasing function of disclosure. As θ rises, σ_V^2 falls smoothly, the gap distribution g_{ij} compresses, and $\tilde{\alpha}$ rises through the Φ function. No threshold or indicator assumption is needed: the S-shaped response arises endogenously from the concavity of the normal CDF.

Deal completion probability. The conditional deal probability given a meeting is:

$$\tilde{\alpha}(\theta, \ell) = \Phi\left(\frac{\Delta - \mu_g}{\sigma_g(\theta, \ell)}\right) - \Phi\left(\frac{-\Delta - \mu_g}{\sigma_g(\theta, \ell)}\right) \tag{11}$$

The deal completion probability $\tilde{\alpha}$ varies smoothly with θ through the precision channel: higher θ reduces σ_V^2, compresses the gap distribution g_{ij}, and raises $\Pr(|g_{ij}| \leq \Delta)$. The resulting S-shaped pattern in $\tilde{\alpha}(\theta)$ is a consequence of the normal CDF, not of any threshold assumption.

Implications for search cost. When some attributes are unobserved, each inspection is less informative. The buyer must inspect more properties to learn the same amount about the distribution of extra values. Formally, the effective per-inspection information gain is:

$$\mathcal{I}(\theta) = \frac{n_1 + n_2(\theta)}{n} \tag{12}$$

which is the fraction of total attributes observed per inspection. The augmented per-inspection cost, adjusting for the reduced informativeness, is:

$$\tilde{s}^Y(\ell; \theta) = \frac{s^Y_{\text{physical}}(\theta) + C^{\text{info}}(\ell; \theta)}{\mathcal{I}(\theta)} \tag{13}$$

The denominator $\mathcal{I}(\theta) < 1$ inflates the effective search cost: each inspection reveals less, so more inspections are needed. In the limit $\theta \to 0$, $\mathcal{I} \to n_1/n$ (only Layer-1 attributes are revealed), and the effective cost is multiplied by $n/(n_1)$. Under full disclosure, $\mathcal{I}(1) = (n_1 + \bar{n}_2)/n$ and the inflation factor is $n/(n_1 + \bar{n}_2)$, reflecting only the irreducible Layer-3 uncertainty.

Numerical example. With $n = 15$ total attributes, $n_1 = 7$ (always observable), $\bar{n}_2 = 5$ (disclosable), $n_3 = 3$ (inspection-only):

Table 1: Attribute Observability and Search Cost Inflation

Regime	θ	$n_2(\theta)$	$n_U(\theta)$	$\mathcal{I}(\theta)$	Cost multiplier	$E[N^Y]$
Full disclosure	1.00	5	3	0.80	1.25×	3.8
UK (PPD)	0.95	4	4	0.73	1.37×	3.8
Korea	0.85	4	4	0.73	1.37×	3.9
Germany	0.70	3	5	0.67	1.50×	4.2
Japan	0.30	1	7	0.53	1.88×	7.1
No disclosure	0.00	0	8	0.47	2.14×	14.2

Under Japan's regime, only 1 of the 5 disclosable attributes (past transaction prices at district-level granularity, with incomplete coverage) is available. The cost multiplier of 1.88× relative to full disclosure combines with the spatial information decay to produce the expected 7.1 inspections estimated in Shimizu et al. (2004).

Key result: attribute–price bundling. The condition formalizes the intuition that *attributes and price must be jointly available for matching to occur.* A buyer who knows the price but not the attributes cannot assess whether the price is fair. A buyer who knows the attributes but not the price cannot formulate an offer. The hedonic model (2) makes this bundling precise: the price is a weighted sum of attributes, and the buyer must observe enough attributes (plus the price of comparable properties) to "solve" for the unobserved components.

This structural insight explains why partial disclosure (e.g., publishing prices without attribute details, or publishing attributes without prices) has limited welfare impact: it is the *joint* availability of attribute-price bundles for a sufficient number of comparables that enables matching. This is precisely the design principle embodied in the UK's Price Paid Data (which publishes price, address, and property type together) and France's DVF (which includes price, area, and location). Japan's system, which publishes anonymized prices at district-level with minimal attribute detail, provides neither component at sufficient granularity.

3.3 Spatial Information Decay

Definition 1 (Information Radius)**.** *The* information radius $R(\ell;\theta)$ *is the minimum distance from location ℓ within which an agent can find $n_{\min}$ disclosed comparable transactions:*

$$R(\ell;\theta) = \sqrt{\frac{n_{\min}}{\pi\theta\, T(\ell)\, \rho(\ell)}} \tag{14}$$

Derivation. Within a disk of radius R centered on ℓ, the area is πR^2. The number of properties is $\pi R^2 \rho(\ell)$. The fraction that transacted in the past year is $T(\ell)$. The fraction of those transactions whose prices are disclosed is θ. Setting $\pi R^2 \rho(\ell) T(\ell)\theta = n_{\min}$ and solving for R yields (14).

Comparative statics.

$$\frac{\partial R}{\partial \theta} = -\frac{R}{2\theta} < 0, \qquad \frac{\partial R}{\partial T} = -\frac{R}{2T} < 0, \qquad \frac{\partial R}{\partial \rho} = -\frac{R}{2\rho} < 0 \tag{15}$$

Higher disclosure, more transactions, and denser populations all shrink the information radius.

Information acquisition cost. When an agent at ℓ gathers comparables from within radius R, the cost of accessing each comparable depends on its distance d. We assume a linear cost $c(d) = c_0 + c_1 d$, where c_0 is the base cost (accessing a public record or calling a broker) and c_1 is the marginal cost of spatial reach. Integrating over the disk:

$$C^{\text{info}}(\ell;\theta) = n_{\min}\left[c_0 + \tfrac{2}{3}c_1\, R(\ell;\theta)\right] \tag{16}$$

Under full disclosure, c_0 is small (free online database) and R is small, so $C^{\text{info}} \approx n_{\min}c_0$, which is negligible. Under non-disclosure, both c_0 (records are not public) and R (comparables are scarce) are large, making C^{info} substantial.

3.4 Market Equilibrium Price and Signal Extraction

The market equilibrium price. Each property j at location ℓ has a *market equilibrium price* p_j^* determined by the intersection of supply and demand given the property's full attribute vector $\mathbf{x}_j$. This price is identical to the fundamental value defined in (2):

$$p_j^* \equiv V_{j\ell} = \boldsymbol{\beta}(\ell)'\mathbf{x}_j + \eta_\ell \tag{17}$$

We use p_j^* in the signal-extraction and matching-zone analysis to emphasize that agents are estimating a *price*; the notation $V_{j\ell}$ is used elsewhere when the focus is on welfare. The equilibrium price is "known only to God"—no agent observes p_j^* directly. Each agent must *estimate* it using whatever attributes and comparables are available to them.

Signal extraction. An agent of type $g \in \{O, Y, B\}$ (old seller, young buyer, broker) who observes attributes in the set $\mathcal{O}^g(\theta)$ forms an estimate:

$$\hat{p}_j^g(\theta,\ell) = \sum_{k\in\mathcal{O}^g(\theta)} \hat{\beta}_k(\ell)\, x_{j,k} \tag{18}$$

where $\hat{\beta}_k(\ell)$ are estimated hedonic coefficients (from the agent's experience and from disclosed comparables). The estimation error is:

$$\zeta_j^g \equiv p_j^* - \hat{p}_j^g \sim \mathcal{N}\big(0,\ \sigma_g^2(\theta,\ell)\big) \tag{19}$$

with precision (inverse variance) $\tau_g(\theta,\ell) \equiv 1/\sigma_g^2(\theta,\ell)$ that depends on the agent's information:

$$\sigma_g^2(\theta,\ell) = \underbrace{n_U^g(\theta)\cdot\bar{\beta}^2(\ell)\cdot\sigma_x^2}_{\text{unobserved attributes}} + \underbrace{\frac{\sigma_\beta^2}{n_{\text{comp}}^g(\theta,\ell)}}_{\text{hedonic coef. estimation}} + \underbrace{\sigma_h^2\cdot R^2(\ell;\theta)}_{\text{spatial extrapolation}} \tag{20}$$

The three terms are: (i) omitted-variable bias from unobserved attributes (n_U^g is the number of unobserved attributes for agent g, decreasing in θ); (ii) sampling error in estimating hedonic coefficients, decreasing in the number of available comparables n_{comp}^g; (iii) spatial extrapolation error from using distant comparables.

Information ordering. The seller has the highest precision, the broker intermediate, and the young buyer the lowest:

$$\sigma_O^2(\theta,\ell) < \sigma_B^2(\theta,\ell) < \sigma_Y^2(\theta,\ell) \quad \forall\, \theta < 1 \tag{21}$$

because the seller has local knowledge and residence experience ($n_U^O < n_U^Y$), while the broker has professional expertise but not property-specific knowledge. Under $\theta = 1$, $\sigma_O^2 = \sigma_B^2 = \sigma_Y^2 = \sigma_\varepsilon^2$ (only irreducible match quality remains).

3.5 Valuation Intermediaries: AI and Broker Appraisals

Even under full disclosure, individual sellers and buyers cannot instantly translate attribute data into a precise market price. A seller who knows the floor area, building age, and past transaction prices of comparable units still cannot compute $p_j^* = \boldsymbol{\beta}(\ell)'\mathbf{x}_j$ without estimating the hedonic coefficient vector $\boldsymbol{\beta}(\ell)$—a nontrivial statistical exercise. In practice, this estimation is performed by *valuation intermediaries*: licensed appraisers, real estate brokers providing "comparative market analyses" (CMA), or automated valuation models (AVMs) powered by machine learning.

The valuation technology. A valuation intermediary $\mathcal{V}$ of type $v \in \{\text{AI}, \text{broker}, \text{self}\}$ produces an estimate:

$$\hat{p}_j^{\mathcal{V}}(\theta,\ell) = \hat{\boldsymbol{\beta}}^{\mathcal{V}}(\ell;\theta)'\,\mathbf{x}_j^{\mathcal{O}(\theta)} \tag{22}$$

where $\hat{\boldsymbol{\beta}}^{\mathcal{V}}$ is the intermediary's estimated hedonic vector (using only the $|\mathcal{O}(\theta)|$ observed attributes) and the superscript denotes the subset of attributes available under disclosure

θ.

The quality of this estimate depends on two factors: the *quality of the algorithm* (denoted $q^{\mathcal{V}} \in (0,1]$) and the *quality of the input data* (determined by θ):

$$\sigma^2_{\mathcal{V}}(\theta,\ell) = \underbrace{\frac{1-q^{\mathcal{V}}}{q^{\mathcal{V}}} \cdot \sigma^2_\beta}_{\substack{\text{algorithm}\\ \text{error}}} + \underbrace{n_U(\theta) \cdot \bar{\beta}^2(\ell) \cdot \sigma^2_x}_{\substack{\text{missing}\\ \text{attributes}}} + \underbrace{\frac{\sigma^2_\beta}{n_{\text{comp}}(\theta,\ell)}}_{\substack{\text{estimation}\\ \text{error}}} + \underbrace{\sigma^2_h \cdot R^2(\ell;\theta)}_{\substack{\text{spatial}\\ \text{extrapolation}}} \tag{23}$$

The first term is new: it captures the intrinsic error of the valuation algorithm, decreasing in $q^{\mathcal{V}}$. An AI with access to millions of transactions and advanced non-parametric methods has q^{AI} close to 1; a seller performing "self-valuation" by browsing a few listings has q^{self} much lower; a professional broker falls in between.

The complementarity of algorithm and data. The key structural insight is that the valuation error (23) exhibits *complementarity* between algorithm quality $q^{\mathcal{V}}$ and data quality θ. Even the most sophisticated AI ($q^{\text{AI}} \to 1$) cannot overcome missing attributes ($n_U(\theta)$ large) or spatial extrapolation (R^2 large): the second, third, and fourth terms in (23) are irreducible by algorithm alone. Conversely, even with complete data ($\theta = 1$), a naive self-valuation (q^{self} small) retains a large first-term error.

Formally, define the *precision gain* from deploying an AI of quality q as $\Delta\sigma^2(q;\theta) \equiv \sigma^2_{\text{self}}(\theta) - \sigma^2_{\text{AI}}(q;\theta)$. Since $\sigma^2_{\text{self}} = \sigma^2_\beta + f(\theta)$ and $\sigma^2_{\text{AI}} = \frac{1-q}{q}\sigma^2_\beta + f(\theta)$, the gain is $\Delta\sigma^2 = \frac{2q-1}{q}\sigma^2_\beta$, which is independent of θ. However, the *marginal welfare value* of this precision gain—measured by $\partial\alpha/\partial\sigma^2$—is larger when the remaining (data-dependent) variance $f(\theta)$ is small, i.e., when θ is high:

$$\frac{\partial^2\alpha}{\partial q^{\mathcal{V}}\partial\theta} > 0 \tag{24}$$

meaning that the marginal return to better algorithms (in terms of matching probability) is *higher* when more data is disclosed, and vice versa. This is complementarity in the sense of Milgrom and Roberts (1990).

Effective precision available to each agent. Each agent g chooses the best available valuation intermediary. The seller can use self-assessment (leveraging local knowledge ω^O) or hire a broker. The buyer can use an AVM, hire a broker, or rely on self-assessment. The effective precision of agent g's price estimate is:

$$\sigma^2_g(\theta,\ell) = \min_{v\in\mathcal{V}^g} \; \sigma^2_v(\theta,\ell) + \underbrace{c^{\text{val}}_v}_{\text{valuation fee}} \cdot\gamma_c \tag{25}$$

where $\mathcal{V}^g$ is the set of valuation intermediaries available to agent g, c^{val}_v is the fee charged by intermediary v, and γ_c converts monetary cost into precision-equivalent units (reflecting the budget constraint of the agent). Young buyers with low income y^Y may be unable to afford a professional appraisal, forcing them to rely on free but imprecise AVMs or self-assessment.

Three valuation regimes. The model generates three distinct valuation regimes depending on θ:

Table 2: Valuation Intermediaries across Disclosure Regimes

θ range	Dominant technology	Precision	Market implication
$\theta > 0.80$ (UK, France)	AI/AVM with rich data	$\sigma^2 \approx \sigma_\varepsilon^2 + \sigma_{\text{algo}}^2$; narrow price bands	High $\tilde{\alpha}$; fast matching
$0.40 < \theta \leq 0.80$ (Germany, US)	Broker CMA + partial AVM	Moderate σ^2; wider bands	Moderate $\tilde{\alpha}$
$\theta \leq 0.40$ (Japan)	Broker judgment + self-valuation	Large σ^2; wide bands, seller–buyer gap systematic	Low $\tilde{\alpha}$; slow matching; cherry-picking

Implications for matching. Substituting into (37), the matching probability with valuation intermediaries is:

$$\tilde{\alpha}(\theta, \ell) = \Phi\left(\frac{\Delta - \mu_g}{\sigma_{\mathcal{V}}}\right) - \Phi\left(\frac{-\Delta - \mu_g}{\sigma_{\mathcal{V}}}\right) \tag{26}$$

where $\sigma_{\mathcal{V}O}^2$ and $\sigma_{\mathcal{V}Y}^2$ are the effective precisions of the seller's and buyer's best available valuation intermediaries.

Proposition 1 (Valuation Intermediaries Amplify Disclosure Effects)**.** *The marginal effect of disclosure on matching probability is amplified by the presence of valuation intermediaries:*

$$\left.\frac{\partial \alpha}{\partial \theta}\right|_{q^{\text{AI}}>0} > \left.\frac{\partial \alpha}{\partial \theta}\right|_{q^{\text{AI}}=0} \tag{27}$$

That is, the welfare gain from disclosure is larger in economies with better valuation technology.

Proof. See Appendix B.

The AI paradox in low-disclosure regimes. A counterintuitive implication: deploying sophisticated AI in a low-θ economy yields *smaller* gains than deploying the same AI in a high-θ economy. In Japan ($\theta = 0.30$), even a state-of-the-art AVM with $q^{\text{AI}} = 0.95$ faces $n_U(\theta) = 7$ missing attributes and $R(\ell) = 0.58$ km of spatial extrapolation error. The missing-attribute and spatial terms dominate, and the AI's algorithm quality q^{AI} has little scope to reduce total error. In the UK ($\theta = 0.95$), $n_U = 3$ and $R = 0.32$ km, so the

AI's high q^{AI} can bring total error close to the irreducible σ_ε^2. This is the formal content of the complementarity (24): *AI is most effective where data is most abundant.*

This result has direct policy implications: Japan cannot "leapfrog" to an AI-driven market without first establishing a data infrastructure through disclosure reform. Technology and institutions are complements, not substitutes.

3.6 Price Formation and the Matching Zone

Reference-dependent preferences. The seller's gain–loss utility from selling at price p relative to reference price r is:

$$W(p,r) = \begin{cases} \eta(p-r) & \text{if } p \geq r \\ \lambda\eta(p-r) & \text{if } p < r \end{cases} \tag{28}$$

with $\eta \geq 0$ (reference dependence) and $\lambda > 1$ (loss aversion; Andersen et al. 2022 estimate $\lambda \approx 2.0$–2.5). The behavioral markup in (30) is derived from the seller's first-order condition: loss-averse sellers with $\hat{p}^O < r$ add a price-unit premium $\mu^{\mathrm{ref}} = \kappa_1(r - \hat{p}^O)$ to compensate for the utility kink at $p = r$.

The seller's asking price. The seller forms an estimate $\hat{p}_j^O$ and sets an asking price incorporating a behavioral markup and a strategic component:

$$p_j^{\mathrm{ask}} = \hat{p}_j^O + \underbrace{\mu_j^{\mathrm{ref}}}_{\substack{\text{behavioral}\\ \text{markup}}} + \underbrace{m_j^O}_{\substack{\text{strategic}\\ \text{markup}}} \tag{29}$$

We adopt a *posted-price* protocol: the seller posts p^{ask}, and the buyer accepts or rejects. The transaction price is $p^{\mathrm{tr}} = p^{\mathrm{ask}}$ conditional on deal completion. The behavioral markup μ_j^{ref} is derived from the seller's first-order condition (see §3.9) and captures the price-unit effect of reference dependence:

$$\mu_j^{\mathrm{ref}} = \kappa_1 \max\{r_j - \hat{p}_j^O,\ 0\} \tag{30}$$

where r_j is the seller's reference (purchase) price and $\kappa_1 > 0$ governs the strength of loss aversion. When $\hat{p}_j^O \geq r_j$ (the seller expects a gain), $\mu^{\mathrm{ref}} = 0$. When $\hat{p}_j^O < r_j$ (a paper loss), the seller "fishes" for a higher price, adding a markup proportional to the perceived loss. The asking price is a noisy signal of $V_{j\ell}$:

$$p_j^{\mathrm{ask}} = V_{j\ell} + \zeta_j^O + \mu_j^{\mathrm{ref}} + m_j^O \tag{31}$$

The buyer's bid price. The buyer forms an estimate $\hat{p}_j^Y$ and determines a maximum willingness to pay:

$$p_j^{\text{bid}} = \hat{p}_j^Y - \underbrace{\lambda_{OY}(\theta) \cdot \hat{p}_j^Y}_{\text{contracting discount}} - \underbrace{r_j^Y}_{\substack{\text{risk} \\ \text{premium}}} \tag{32}$$

where the contracting discount reflects the BRS friction and $r_j^Y = \gamma_r \cdot \sigma_Y^2(\theta, \ell)$ is a risk premium proportional to the buyer's estimation uncertainty. The bid price is:

$$p_j^{\text{bid}} = V_{j\ell} + \zeta_j^Y - \lambda_{OY}\hat{p}_j^Y - r_j^Y \tag{33}$$

The matching zone. Define the *bid–ask gap*:

$$g_{ij} \equiv p_j^{\text{bid}} - p_j^{\text{ask}} \tag{34}$$

A transaction occurs if and only if the gap falls within a symmetric negotiation band $\Delta > 0$:

$$\boxed{|g_{ij}| \leq \Delta} \tag{35}$$

The two-sided condition requires that neither party's price is too far from the other's: the buyer does not drastically underbid, and the seller does not drastically overprice.

Substituting (31) and (33), the gap is:

$$g_{ij} = \underbrace{(\zeta_j^Y - \zeta_j^O)}_{\substack{\text{differential} \\ \text{estimation error}}} - \underbrace{(\lambda_{OY}\hat{p}_j^Y + r_j^Y)}_{\substack{\text{buyer's} \\ \text{discounts}}} - \underbrace{(\mu_j^{\text{ref}} + m_j^O)}_{\substack{\text{seller's} \\ \text{markups}}} \tag{36}$$

Let $\mu_g \equiv (\lambda_{OY}\bar{p} + r^Y) + (\mu^{\text{ref}} + m^O)$ denote the systematic (negative) drift and $\sigma_g \equiv \sqrt{\sigma_O^2(\theta, \ell) + \sigma_Y^2(\theta, \ell)}$ the volatility. Then $g_{ij} \sim \mathcal{N}(-\mu_g, \sigma_g^2)$, and the matching probability is:

$$\tilde{\alpha}(\theta, \ell) = \Phi\left(\frac{\Delta - \mu_g}{\sigma_g}\right) - \Phi\left(\frac{-\Delta - \mu_g}{\sigma_g}\right) \tag{37}$$

where Φ is the standard normal CDF. When valuation intermediaries are available (§3.5), the effective precisions $\sigma_{\mathcal{V}O}^2$ and $\sigma_{\mathcal{V}Y}^2$ from (26) replace σ_O^2 and σ_Y^2.

This two-sided formula has two essential properties. First, as $\sigma_g \to \infty$ (no information), both Φ terms converge to the same value, so $\tilde{\alpha} \to 0$—confirming that the market dies when price estimation becomes impossible. Second, as $\sigma_g \to 0$ (perfect information), $\alpha \to 1$ if $\mu_g < \Delta$ (the systematic wedge is within the negotiation band).

Proposition 2 (Information Increases Matching Probability)**.** *The matching probability $\tilde{\alpha}(\theta, \ell)$ is strictly increasing in disclosure θ:*

$$\frac{\partial \alpha}{\partial \theta} > 0 \tag{38}$$

through three channels: (i) both σ_O^2 and σ_Y^2 decrease, narrowing the gap distribution; (ii) $\lambda_{OY}(\theta)$ and r^Y decrease, reducing the systematic drift μ_g; (iii) μ^{ref} decreases as better-informed sellers moderate behavioral markups.

Proof. See Appendix B.

Intuition. When both seller and buyer have precise estimates of p_j^* (high θ), the asking and bid prices cluster tightly around the true equilibrium price. The bid–ask gap is small, and most encounters fall within the matching zone Δ. When estimates are noisy (low θ), asking and bid prices are dispersed, many encounters produce gaps exceeding Δ, and transactions fail.

Perfect information limit. As $\theta \to 1$, $\sigma_O^2, \sigma_Y^2 \to \sigma_\varepsilon^2$ (irreducible match quality only), $\lambda_{OY} \to 0$, $\mu^{\text{ref}} \to 0$, and $r^Y \to \gamma_r \sigma_\varepsilon^2$. The matching probability approaches:

$$\tilde{\alpha}^{FB} = \Phi\left(\frac{\Delta - \gamma_r \sigma_\varepsilon^2 - m^{O,FB}}{\sqrt{2\sigma_\varepsilon^2}}\right) \tag{39}$$

which is the "first-best" matching rate—positive but less than one, reflecting the irreducible heterogeneity in match quality.

3.7 Expected Search Duration and Time-to-Sale

The aggregate matching function follows Badarinza et al. (2024a):

$$m(B, S) = A_0\, B^\nu S^{1-\nu} \tag{40}$$

where $B = b(\theta)\bar{B}$ and $S = s(\theta)\bar{S}$ are the endogenous masses of active buyers and sellers (from §3.8), and A_0 is a constant matching-efficiency parameter. Market tightness is $q \equiv B/S$. The seller contact rate is $\chi^S(q) = A_0 q^\nu$; the buyer contact rate is $\chi^B(q) = A_0 q^{-(1-\nu)}$. Neither depends on θ: disclosure affects deal completion, not meeting technology. We define the *sale hazard*—the probability per period that a listed seller completes a sale—as:

$$h^S(\theta, \ell) \equiv \chi^S(q) \cdot \tilde{\alpha}(\theta, \ell) \tag{41}$$

This composite object governs time-on-market, withdrawal, and akiya dynamics throughout the model.

Seller's time-on-market. Given sale hazard h^S (contact rate times deal probability) (from (37)), the expected time-on-market is:

$$E[T^O(\theta, \ell)] = \frac{1}{h^S(\theta, \ell)} = \frac{1}{\chi^S(q) \cdot \tilde{\alpha}(\theta, \ell)} \tag{42}$$

Under complete information, $E[T^{O,FB}]$ is minimized. The excess time-on-market due to information friction is:

$$\Delta T^O(\theta, \ell) = E[T^O(\theta, \ell)] - E[T^{O,FB}] = \frac{1}{h^S(\theta, \ell)} - \frac{1}{h^{S,FB}} \tag{43}$$

If the seller could perfectly predict p_j^*, the asking price would equal $p_j^* + m^{O,FB}$ (a small rational markup), and the time-on-market would approach $1/h^{S,FB}$. The information deficit creates excess waiting time $\Delta T^O > 0$ whose opportunity cost is $R_j \cdot \Delta T^O$ (imputed rent times excess duration).

Buyer's search duration. The buyer must visit multiple properties before finding one where the matching condition (35) is satisfied. The expected number of inspections is:

$$E[N^Y(\theta, \ell)] = \frac{1}{\tilde{\alpha}(\theta, \ell)} \tag{44}$$

and the expected search duration in time periods is $E[N^Y]/\chi^B(q; \theta)$.

Key result: information reduces duration for both sides. Since $\partial\tilde{\alpha}/\partial\theta > 0$ (Proposition 2):

$$\frac{\partial E[T^O]}{\partial \theta} < 0, \qquad \frac{\partial E[N^Y]}{\partial \theta} < 0 \tag{45}$$

Higher disclosure simultaneously reduces the seller's time-on-market and the buyer's number of inspections.

3.8 Endogenous Market Participation

The preceding analysis takes the pools of active sellers S and active buyers B as given. In practice, these pools are *endogenous*: only a fraction of potential sellers and potential buyers choose to enter the market. We now model this participation decision, showing that disclosure increases market thickness on both sides.

Potential sellers. Let $\bar{S}(\ell)$ denote the mass of *potential sellers* at location ℓ: homeowners who have received a mobility shock ($\mu_i \geq \mu^{*,O}$) and wish to sell. Not all enter the market. Before listing, the seller estimates the likely sale price $\hat{p}_j^O$ and compares it with a *reservation price*:

$$\underline{p}_j^O = \max\{m_j, \;\; r_j - \mu_j^{\text{ref}}/\kappa_1, \;\; \bar{u}/r + \tau^{\text{sell}}\} \tag{46}$$

where m_j is the mortgage balance (the seller cannot sell below the outstanding debt without a short sale), $p_j^{\text{ref}} - \mu^{\text{ref}}/(\lambda\eta)$ is the minimum acceptable price given reference dependence, and $\bar{u}/r + \tau^{\text{sell}}$ is the capitalized flow utility of staying plus transaction costs.

Seller entry decision. The potential seller enters the market if the expected sale price exceeds the reservation price by a margin sufficient to cover the listing cost φ and the expected vacancy duration:

$$E[\hat{p}_j^O \mid \theta, \ell] - \underline{p}_j^O \geq \varphi + R_j \cdot E[T^O(\theta, \ell)] \tag{47}$$

The left-hand side is the expected net gain from selling. The right-hand side is the expected cost of the selling process (listing fee plus opportunity cost of vacancy). Both the expected price estimate and the expected duration depend on θ.

Under low disclosure, the seller faces two problems. First, the estimated sale price $\hat{p}_j^O$ has high variance $\sigma_O^2(\theta, \ell)$, creating *uncertainty about whether selling is worthwhile.* Risk-averse sellers facing this uncertainty choose inaction—the option value of waiting dominates. Second, $E[T^O]$ is large (from (42)), raising the right-hand side. Both effects reduce the probability of entry.

Seller participation rate. The fraction of potential sellers who enter the market is:

$$s(\ell; \theta) \equiv \frac{S(\ell)}{\bar{S}(\ell)} = \Pr\Big(E[\hat{p}_j^O] - \underline{p}_j^O \geq \varphi + R_j E[T^O(\theta, \ell)]\Big) \tag{48}$$

Since $E[\hat{p}_j^O]$ has variance $\sigma_O^2(\theta, \ell)$ (which is decreasing in θ) and $E[T^O]$ is decreasing in θ:

$$\frac{\partial s}{\partial \theta} > 0 \tag{49}$$

Higher disclosure raises the seller participation rate through two channels: (i) *uncertainty reduction*—sellers can more precisely assess whether their property will sell above reservation, reducing the option value of inaction; (ii) *duration reduction*—the expected vacancy cost falls, lowering the entry hurdle.

Potential buyers. Let $\bar{B}(\ell)$ denote the mass of *potential buyers*—renters who could afford to purchase in the price range available at ℓ. Each potential buyer has a budget constraint $\bar{p}_j^Y$ (determined by income y_j^Y, savings, and mortgage capacity). Before searching, the buyer must assess whether properties within their budget exist at acceptable quality levels.

Buyer entry decision. The potential buyer enters the market if the expected net surplus from purchasing exceeds the expected search cost:

$$E\big[(1-\lambda_{OY}(\theta))V_{ij} - p_j^* \mid p_j^* \le \bar{p}_j^Y\big] \ge \tilde{s}^Y(\ell;\theta)\cdot E[N^Y(\theta,\ell)] \tag{50}$$

Under low disclosure, the buyer faces two barriers. First, the buyer cannot assess whether affordable properties exist at acceptable quality—V_{ij} is highly uncertain, and the buyer may fear overpaying for a "lemon" (the Akerlof problem). Second, the expected total search cost $\tilde{s}^Y \cdot E[N^Y]$ is large, potentially exceeding the expected surplus. Young first-time buyers are especially deterred because their budget constraint $\bar{p}^Y$ is tight and their search cost is high (from (63)).

Buyer participation rate.

$$b(\ell;\theta) \equiv \frac{B(\ell)}{\bar{B}(\ell)} = \Pr\big(E[(1-\lambda_{OY})V_{ij} - p_j^*] \ge \tilde{s}^Y(\theta,\ell)\cdot E[N^Y(\theta,\ell)]\big) \tag{51}$$

Since λ_{OY} is decreasing in θ, $\tilde{s}^Y$ is decreasing in θ, and $E[N^Y]$ is decreasing in θ:

$$\frac{\partial b}{\partial \theta} > 0 \tag{52}$$

Active market size. The masses of active sellers and buyers are:

$$S(\ell;\theta) = s(\ell;\theta)\cdot \bar{S}(\ell), \qquad B(\ell;\theta) = b(\ell;\theta)\cdot \bar{B}(\ell) \tag{53}$$

Market tightness $q = B/S$ and the matching function $m = A_0 B^\nu S^{1-\nu}$ now depend on θ through *two* channels: the buyer pool $B(\theta)$ and the seller pool $S(\theta)$. Total transactions are:

$$\mathcal{T}(\ell;\theta) = A_0 \cdot \big[b(\theta)\bar{B}\big]^\nu \cdot \big[s(\theta)\bar{S}\big]^{1-\nu} \cdot \tilde{\alpha}(\theta,\ell) \tag{54}$$

Proposition 3 (Disclosure Thickens the Market)**.** *Total transactions $\mathcal{T}$ are increasing in θ through three multiplicative channels (Proposition 3):*

$$\frac{d\ln \mathcal{T}}{d\theta} = \underbrace{\nu\frac{b'}{b}}_{\substack{\text{buyer}\\ \text{entry}}} + \underbrace{(1-\nu)\frac{s'}{s}}_{\substack{\text{seller}\\ \text{entry}}} + \underbrace{\frac{\tilde{\alpha}'}{\tilde{\alpha}}}_{\substack{\text{deal}\\ \text{probability}}} > 0 \tag{55}$$

where primes denote derivatives with respect to θ. Each term is strictly positive.

This decomposition shows that previous analyses capturing only the deal-probability channel (as in SNA 2004) underestimate the total effect of disclosure by a factor of approximately three, because they miss the buyer-entry and seller-entry channels.

Participation–information feedback. Market participation and information quality are mutually reinforcing. Higher participation ($s\uparrow, b\uparrow$) increases transaction volume $T(\ell)$, which shrinks the information radius $R(\ell;\theta)$ and improves the precision of all agents' price estimates, which in turn encourages further participation:

$$\theta\uparrow\rightarrow\ s\uparrow, b\uparrow\rightarrow\ T\uparrow\rightarrow\ R\downarrow\rightarrow\ \sigma^2\downarrow\rightarrow\ s\uparrow, b\uparrow\rightarrow\ \cdots \tag{56}$$

This is the *participation–information feedback*—a positive externality: each agent's entry improves information for all. Under low disclosure, the loop reverses: low participation, few transactions, poor information, and even lower participation.

Implications for brokers. The broker's annual deal count is now:

$$D(\ell;\theta) = K(\theta,\ell)\cdot\tilde{\alpha}(\theta,\ell)\cdot\underbrace{\frac{s(\theta)\bar{S}(\ell)}{A^*(\ell;\theta)}}_{\text{listings per broker}}\cdot 12 \tag{57}$$

The term $s(\theta)\bar{S}/A^*$ is the number of active listings per broker, which is increasing in θ (more sellers enter, and the listing pool per broker grows before congestion drives entry of new brokers). This creates a *third channel* through which disclosure benefits brokers—beyond investigation efficiency and deal acceleration:

$$\frac{\partial D}{\partial\theta} = \underbrace{\frac{\partial K}{\partial\theta}\cdot\tilde{\alpha}\cdot\frac{s\bar{S}}{A^*}\cdot 12}_{\text{capacity}} + \underbrace{K\cdot\frac{\partial\tilde{\alpha}}{\partial\theta}\cdot\frac{s\bar{S}}{A^*}\cdot 12}_{\text{matching}} + \underbrace{K\cdot\tilde{\alpha}\cdot\frac{\partial}{\partial\theta}\left(\frac{s\bar{S}}{A^*}\right)\cdot 12}_{\text{market thickness}} > 0 \tag{58}$$

All three terms are positive: disclosure simultaneously expands the broker's capacity, raises the matching probability, and thickens the market.

Table 3: Market Participation Rates by Location and Disclosure

	Tokyo CBD	Suburbs	Regional	Rural
Seller participation rate $s(\ell;\theta)$				
$\theta = 0.30$	0.72	0.58	0.41	0.18
$\theta = 0.95$	0.89	0.82	0.71	0.45
Δs	+0.17	+0.24	+0.30	+0.27
Buyer participation rate $b(\ell;\theta)$				
$\theta = 0.30$	0.68	0.52	0.34	0.11
$\theta = 0.95$	0.86	0.78	0.63	0.38
Δb	+0.18	+0.26	+0.29	+0.27
Total transactions (index, $\theta{=}0.30$ *CBD = 100)*				
$\theta = 0.30$	100	42	14	1.2
$\theta = 0.95$	198	128	68	15.8
Growth factor	2.0×	3.0×	4.9×	13.2×

The results are striking. In rural areas under $\theta = 0.30$, only 18% of potential sellers and 11% of potential buyers enter the market. Under full disclosure, these rates rise to 45% and 38%—still below urban levels, but sufficient to generate 13.2 times more transactions. The participation channel is the largest contributor to the rural transaction increase: of the 13.2× growth factor, approximately 4× comes from participation expansion, 3× from matching probability improvement, and the remainder from matching efficiency and capacity gains.

3.9 The Old Seller's Problem (Refined)

An old homeowner i with reference price r_i, mortgage m_i, and match quality ϵ_i receives flow utility $\bar{u} + \epsilon_i$. Upon mobility shock $\mu_i \sim F_\mu$, they decide whether to list.

Bellman equation.

$$V_t^{h,O}(r_i, m_i, \epsilon_i) = \bar{u} + \epsilon_i - \tau^h + \beta E_\mu\Big[\max\Big\{\Omega_t^{\text{list}} - \varphi,\ \beta E_t[V_{t+1}^{h,O}]\Big\}\Big] \tag{59}$$

where the listing payoff, now incorporating the signal-extraction matching probability, is:

$$\Omega_t^{\text{list}} = \max_{p^{\text{ask}}} \tilde{\alpha}(\theta,\ell)\Big[U^O(p^{\text{ask}}, r_i, m_i) + \mu_i + \beta E_t[V_{t+1}^{b,O}]\Big] + (1 - \tilde{\alpha}(\theta,\ell))\,\beta E_t[V_{t+1}^{h,O}] \tag{60}$$

The seller's optimal asking price trades off the benefit of a higher price (more utility if sold) against the cost of lower matching probability (longer time on market):

$$\tilde{\alpha} \cdot U_p^O = 0 \tag{61}$$

Under the posted-price protocol, $p^{\text{tr}} = p^{\text{ask}}$. Following the standard search-theoretic approach, the deal completion probability $\tilde{\alpha}(\theta, \ell)$ is evaluated at the equilibrium asking price and treated as locally independent of the individual seller's price choice. This yields the standard result that the seller prices to maximize U^O conditional on sale.

Listing threshold.

$$\mu_i \geq \mu^{*,O}(r_i, m_i; \theta, \ell) \equiv \frac{\varphi}{\tilde{\alpha}(\theta, \ell)} - \left[U^O(p^{*,\text{ask}}, r_i, m_i) + \beta E[V^{b,O}] - \beta E[V^{h,O}]\right] \tag{62}$$

3.10 The Young First-Time Buyer's Problem (Refined)

A young buyer j renting at $\bar{r}^{\text{rent}}$ searches sequentially, inspecting properties at augmented cost:

$$\tilde{s}^Y(\ell; \theta) = \frac{c + w^Y \bar{h}^Y (1 - \gamma_h \theta) + C^{\text{info}}(\ell; \theta)}{\mathcal{I}(\theta)} \tag{63}$$

where $\mathcal{I}(\theta) = (n_1 + n_2(\theta))/n$ is the per-inspection information gain from (12), inflating the effective cost when few attributes are observable.

Bellman equation.

$$V_t^{b,Y} = -\bar{r}^{\text{rent}} + (1 - \chi_t^B)\,\beta E_t[V_{t+1}^{b,Y}] + \chi_t^B \cdot \tilde{\alpha}(\theta, \ell) \cdot E\left[\Gamma^Y \mid \text{match}\right] \tag{64}$$

where $\Gamma^Y = (1 - \lambda_{OY})V_{ij} - p^{\text{tr}} - \tau^b + \bar{r}^{\text{rent}} + \beta E[V_{t+1}^{h,Y}(p^{\text{tr}}, m^Y)]$ is the surplus, and p^{tr} is the negotiated transaction price within the matching zone.

Contracting friction.

$$\lambda_{OY}(\theta) = \bar{\lambda}_{OY}(1 - \theta)^{\kappa_\lambda} \tag{65}$$

3.11 The Broker's Problem: Capacity and Market Exclusion

Brokers are the third class of agents in the model. They are profit-maximizing intermediaries who select which properties to list, investigate their attributes, and facilitate matching. The broker's problem is central to understanding why low-price and rural properties are systematically excluded from the market.

Broker population and time budget. There is a continuum of brokers, each with a fixed time budget of $\bar{H}^B$ hours per period (e.g., $\bar{H}^B = 480$ hours/month for a two-person team). A listing consumes broker time in two phases: investigation (pre-listing) and marketing (post-listing until sale or withdrawal). The total time per listing is:

$$t_j^B(\theta, \ell_j) = \underbrace{t_j^{\text{inv}}(\theta, \ell_j)}_{\text{investigation time}} + \underbrace{E[T^O(\theta, \ell_j)] \cdot t^{\text{mkt}}}_{\text{marketing time}} \tag{66}$$

where $t_j^{\text{inv}} = c_j^B / w^B$ is the investigation time (cost divided by the broker's hourly wage w^B), and $E[T^O(\theta, \ell)]$ is the expected time-on-market from (42) multiplied by the per-period marketing effort t^{mkt} (showings, negotiations, follow-ups).

Endogenous capacity. The broker's effective capacity—the maximum number of simultaneous listings—is:

$$K(\theta, \ell) = \frac{\bar{H}^B}{t^B(\theta, \ell)} \tag{67}$$

This capacity is *increasing in* θ through two channels:

1. **Investigation channel**: higher θ reduces $n_U(\theta)$ and C^{info}, lowering t^{inv}.
2. **Duration channel**: higher θ raises $\tilde{\alpha}(\theta, \ell)$ (from Proposition 2), reducing $E[T^O]$ and hence t^{mkt}.

Under Japan's current regime ($\theta = 0.30$), with long investigation times and high expected time-on-market, the effective capacity is approximately $K \approx 3$ listings per month. Under full disclosure ($\theta = 0.95$), investigation is faster and deals close sooner, expanding capacity to $K \approx 5$–6. This is the *productivity effect* of disclosure on brokerage.

Investigation cost. To list a property, the broker must investigate its attributes, perform due diligence (title search, building inspection, neighborhood assessment), and prepare the legally mandated *jūyō jikou setsumeisho* (important matters explanation). The investigation cost for a property at location ℓ_j, given the broker's office location ℓ^B, is:

$$c_j^B(\ell_j, \ell^B; \theta) = \underbrace{\bar{c}_{\text{fixed}}^B}_{\substack{\text{title search,} \\ \text{legal docs}}} + \underbrace{c_{\text{dist}}^B \cdot d(\ell_j, \ell^B)}_{\substack{\text{travel to} \\ \text{property}}} + \underbrace{c_{\text{info}}^B(\theta, \ell_j)}_{\substack{\text{attribute} \\ \text{investigation}}} \tag{68}$$

The three components are:

- $\bar{c}_{\text{fixed}}^B$: the fixed cost of legal and administrative tasks (title search, document preparation). This is *independent of property price*—a critical feature.
- $c_{\text{dist}}^B \cdot d(\ell_j, \ell^B)$: the cost of physical travel to the property site, proportional to the distance $d(\ell_j, \ell^B)$ between the broker's office and the property. This generates a spatial gradient in brokerage costs.
- $c_{\text{info}}^B(\theta, \ell_j)$: the cost of investigating the property's attributes to produce a reliable valuation. This depends on θ and on the local information environment:

$$c_{\text{info}}^B(\theta, \ell_j) = n_U(\theta) \cdot \bar{c}_{\text{attr}} + C^{\text{info}}(\ell_j; \theta) \tag{69}$$

where $n_U(\theta)$ is the number of unobserved attributes (from §3.2), $\bar{c}_{\text{attr}}$ is the per-attribute investigation cost, and $C^{\text{info}}(\ell_j;\theta)$ is the spatial information acquisition cost from (16). Under full disclosure, many attributes are already public, reducing n_U and hence c^B_{info}.

Revenue. The broker's commission is a fixed fraction τ of the transaction price (in Japan, $\tau = 0.03 + 60{,}000/p \approx 0.03$ for typical prices). The expected revenue from listing property j at price p_j is:

$$\text{Rev}_j(\theta, \ell_j) = \tilde{\alpha}(\theta, \ell_j) \cdot \tau \cdot p_j \tag{70}$$

where $\tilde{\alpha}$ is the deal completion probability. Revenue is proportional to price p_j. For the broker's portfolio choice, we evaluate $\tilde{\alpha}$ at the equilibrium asking price, treating the deal probability as locally independent of the individual listing price (since the matching zone is centered on the market-clearing asking price).

Per-listing profit. The expected profit from accepting listing j is:

$$\pi_j(\theta, \ell_j) = \tilde{\alpha}(\theta, \ell_j) \cdot \tau \cdot p_j - c^B_j(\ell_j, \ell^B; \theta) \tag{71}$$

The broker's portfolio choice. Given endogenous capacity $K(\theta, \ell)$ and a set $\mathcal{J}_t$ of available listings, the broker solves:

$$\max_{\mathcal{S} \subseteq \mathcal{J}_t,\ |\mathcal{S}| \leq K(\theta,\ell)} \sum_{j \in \mathcal{S}} \pi_j(\theta, \ell_j) \tag{72}$$

The broker ranks all available listings by expected profit π_j and selects the top $K(\theta, \ell)$.

Time-cost amplification. The broker's effective cost per listing includes not only the investigation cost c^B_j but also the *opportunity cost of time* tied up during the marketing period. While a property remains unsold, it occupies one of the broker's K slots, preventing the broker from accepting another (potentially more profitable) listing. The opportunity cost of time for listing j is:

$$c^B_{\text{time},j} = E[T^O_j(\theta, \ell)] \cdot t^{\text{mkt}} \cdot \bar{\pi}^{\text{alt}} \tag{73}$$

where $\bar{\pi}^{\text{alt}}$ is the expected profit from an alternative listing that could have been accepted instead. The total cost becomes:

$$c^B_{\text{total},j} = c^B_j + c^B_{\text{time},j} = c^B_j + E[T^O_j] \cdot t^{\text{mkt}} \cdot \bar{\pi}^{\text{alt}} \tag{74}$$

This creates a *time-cost amplification*: low θ not only raises investigation costs but also extends marketing duration, locking the broker's capacity for longer and increasing the opportunity cost per slot. The total cost is convex in $(1-\theta)$.

Updated per-listing profit. Incorporating the time cost:

$$\pi_j = \tilde{\alpha}(\theta,\ell)\cdot\tau\cdot p_j - c_j^B(\theta,\ell) - E[T_j^O(\theta,\ell)]\cdot t^{\text{mkt}}\cdot\bar{\pi}^{\text{alt}} \tag{75}$$

Updated minimum viable price.

$$p^{\min}(\ell;\theta) = \frac{c_j^B(\theta,\ell) + E[T^O(\theta,\ell)]\cdot t^{\text{mkt}}\cdot\bar{\pi}^{\text{alt}}}{\tilde{\alpha}(\theta,\ell)\cdot\tau} \tag{76}$$

The time-cost term in the numerator is the key addition: it is proportional to $E[T^O] = 1/h^S$, which is large when θ is low. This *doubles the sensitivity* of $p^{\min}$ to disclosure: θ now enters both through c_j^B in the numerator (investigation cost) and through $1/h^S$ in the numerator (time cost) and through $\tilde{\alpha}$ in the denominator (deal completion).

Proposition 4 (Broker Productivity)**.** *Information disclosure increases broker productivity through three reinforcing channels:*

(i) ***Investigation efficiency**: $\partial t^{\text{inv}}/\partial\theta < 0$ (fewer attributes to investigate).*

(ii) ***Deal acceleration**: $\partial E[T^O]/\partial\theta < 0$ (higher matching probability shortens marketing).*

(iii) ***Capacity expansion**: $\partial K/\partial\theta > 0$ (faster turnover frees slots for additional listings).*

The broker's annual transaction volume $V^B = K(\theta)\cdot\tilde{\alpha}(\theta)\cdot 12$ is increasing in θ, and the elasticity of V^B with respect to θ exceeds unity in low-disclosure regimes.

Proof. See Appendix B.

Table 4: Broker Productivity by Disclosure Regime (suburban Japan)

	$\theta = 0.30$	$\theta = 0.50$	$\theta = 0.70$	$\theta = 0.95$
Investigation time (hrs/listing)	68	52	40	28
$E[T^O]$ (weeks)	11.8	8.5	6.8	5.2
Marketing time (hrs/listing)	94	68	54	42
Total time per listing (hrs)	162	120	94	70
Effective capacity K	3.0	4.0	5.1	6.9
Deal prob. $\tilde{\alpha}$	0.116	0.135	0.141	0.144
Annual deals	4.2	6.5	8.6	11.9
Annual revenue (¥M)	4.0	6.2	8.2	11.4
Revenue per hour (¥)	8,300	10,800	14,500	19,700
Productivity index	**100**	**130**	**175**	**237**

Quantitative illustration. Moving from $\theta = 0.30$ to $\theta = 0.95$ more than doubles broker productivity: annual completed deals rise from 4.2 to 11.9, and revenue per hour increases from ¥8,300 to ¥19,700. The capacity expansion from 3 to 6.9 listings accounts for approximately 60% of the productivity gain; the deal-acceleration channel (higher $\tilde{\alpha}$) accounts for the remaining 40%.

Cherry-picking: the price-sorting mechanism. Because revenue is proportional to p_j while the cost c_j^B is largely independent of p_j (the fixed and distance components dominate), the profit margin π_j is steeply increasing in price:

$$\frac{\partial \pi_j}{\partial p_j} = \tau\tilde{\alpha} + \tau p_j \frac{\partial \tilde{\alpha}}{\partial p_j} \approx \tau\tilde{\alpha} > 0 \tag{77}$$

This means the broker *always prefers high-price listings to low-price ones*, given equal completion probability and cost. With $K(\theta) \approx 3$ under Japan's current regime, a broker who receives requests from five sellers—two at ¥50M, one at ¥30M, one at ¥15M, and one at ¥5M—will accept the three highest-priced listings and reject the two lowest. The ¥5M property, despite being a perfectly viable housing unit, is *never intermediated.* Under full disclosure ($K \approx 7$), the broker could handle all five requests, potentially intermediating the low-price property. This is the *cherry-picking* mechanism, and disclosure mitigates it through the capacity channel.

The broker viability threshold. A property is intermediated if and only if its expected profit exceeds zero:

$$\pi_j \geq 0 \iff p_j \geq \frac{c_j^B(\ell_j, \ell^B; \theta)}{\tilde{\alpha}(\theta, \ell_j) \cdot \tau} \equiv p^{\min}(\ell_j; \theta) \tag{78}$$

The minimum viable price $p^{\min}$ depends on *both* location and disclosure:

$$p^{\min}(\ell; \theta) = \frac{\bar{c}^B_{\text{fixed}} + c^B_{\text{dist}} \cdot d(\ell, \ell^B) + n_U(\theta) \cdot \bar{c}_{\text{attr}} + C^{\text{info}}(\ell; \theta)}{\tilde{\alpha}(\theta, \ell) \cdot \tau} \tag{79}$$

This expression reveals four mechanisms through which low-disclosure regimes raise the minimum viable price:

1. Higher $n_U(\theta)$ raises c^B_{info} (more attributes to investigate).
2. Higher $C^{\text{info}}(\ell; \theta)$ from larger information radius (spatial decay).
3. Lower $\tilde{\alpha}(\theta)$ from buyer search frictions (fewer deals close).
4. All three operate through the denominator and numerator simultaneously.

Capacity constraint and intensive margin. Even when $p_j > p^{\min}$, the property may still be excluded if the broker's capacity is binding. Define the *marginal listing*—the lowest-profit listing in the broker's optimal portfolio—with profit π^{cut}. A property is listed if and only if:

$$\pi_j \geq \max\{0,\ \pi^{\text{cut}}\} \tag{80}$$

The cutoff π^{cut} depends on the distribution of available listings and is higher in urban markets where many high-price properties compete for the broker's limited capacity. This generates an additional channel of exclusion: in Tokyo, a ¥15M suburban condominium may have $\pi_j > 0$ but still be rejected because the broker's three slots are occupied by ¥50M+ properties.

Spatial equilibrium of brokerage. We can now characterize which properties are intermediated in equilibrium. Define the *brokered set* $\mathcal{B}(\ell;\theta)$ as the set of property prices that are actively intermediated at location ℓ:

$$\mathcal{B}(\ell;\theta) = \left\{ p \;\middle|\; p \geq p^{\min}(\ell;\theta) \text{ and } \pi(p,\ell;\theta) \geq \pi^{\text{cut}}(\ell;\theta) \right\} \tag{81}$$

The *unserved fraction*—the share of properties at ℓ that are not intermediated—is:

$$u(\ell;\theta) = F_p\big(\max\left\{p^{\min}(\ell;\theta),\ p^{\text{cut}}(\ell;\theta)\right\}\big) \tag{82}$$

where F_p is the local price distribution and p^{cut} is the price corresponding to π^{cut}.

Spatial gradient of market exclusion. The model generates a sharp spatial gradient:

Table 5: Broker Viability and Market Exclusion by Location (Japan, $\theta = 0.30$)

	Tokyo CBD	Suburbs	Regional	Rural
$d(\ell, \ell^B)$ (km)	2	15	50	120
c_j^B (¥000)	420	530	780	1,250
$\tilde{\alpha}$	0.142	0.116	0.078	0.031
$p^{\min}$ (¥M)	9.9	15.2	33.3	134.4
Median price (¥M)	65.0	33.4	18.0	5.0
$u(\ell)$: unserved (%)	8.2	24.1	68.5	98.7
Counterfactual: $\theta = 0.95$				
c_j^B (¥000)	320	380	490	720
$\tilde{\alpha}$	0.165	0.144	0.112	0.068
$p^{\min}$ (¥M)	6.5	8.8	14.6	35.3
$u(\ell)$: unserved (%)	3.1	10.8	38.2	87.4
Δu (pp)	−5.1	−13.3	−30.3	−11.3

The results reveal three layers of market exclusion:

(i) Rural collapse. In rural areas, $p^{\min} = ¥134.4\text{M}$ under $\theta = 0.30$—far exceeding the median price of ¥5M. This means 98.7% of rural properties are below the broker viability threshold. The broker simply *cannot* profitably serve these markets. Even under full disclosure, $p^{\min}$ drops to ¥35.3M, which still excludes 87.4% of rural properties. This is the *structural* component of the akiya crisis that requires commission reform beyond disclosure.

(ii) Regional squeeze. In regional cities, the median price (¥18M) sits close to $p^{\min}$ (¥33.3M at $\theta = 0.30$). Over two-thirds of properties are unserved. Disclosure reform alone ($\theta \to 0.95$) brings $p^{\min}$ down to ¥14.6M, pulling the median property into the brokered set and reducing the unserved fraction from 68.5% to 38.2%—the largest absolute improvement.

(iii) Urban cherry-picking. In Tokyo suburbs, $p^{\min}$ is below the median, but the capacity constraint $\bar{K} = 3$ creates a secondary exclusion mechanism. When brokers fill their slots with high-value CBD properties, suburban listings below ¥20–25M are crowded out despite being individually viable. This explains why low-price urban condominiums—perfectly habitable units in the ¥10–20M range—languish unsold.

Proposition 5 (Endogenous Market Segmentation)**.** *In the equilibrium with capacity-constrained brokers, the housing market endogenously segments into three tiers:*

(i) ***Premium tier*** *($p \gg p^{\min}$): fully intermediated, high transaction rate, low akiya rate.*

(ii) ***Marginal tier*** *($p \approx p^{\min}$): intermittently intermediated, moderate transaction rate, rising akiya rate.*

(iii) ***Excluded tier*** *($p < p^{\min}$ or crowded out by capacity): not intermediated, near-zero transaction rate, high akiya rate.*

The boundaries between tiers depend on θ: higher disclosure shifts properties from the excluded to the marginal tier and from the marginal to the premium tier.

Connection to akiya dynamics. The unserved fraction $u(\ell;\theta)$ feeds directly into the akiya formation model of §3.13. Properties that cannot be listed (because $p < p^{\min}$ or because the broker's capacity is full) proceed immediately to the "temporarily vacant" state, bypassing the "listed for sale" state entirely. This accelerates the transition to permanent vacancy:

$$\Psi^{\text{total}}(\ell;\theta) = \underbrace{(1-u)\cdot \pi^{\text{withdraw}}}_{\text{Pathway 1: listed but unsold}} + \underbrace{u \cdot (1-\pi^{\text{relist}})^{\bar{T}_{\text{akiya}}}}_{\text{Pathway 2: never listed}} \tag{83}$$

Pathway 2 (never listed) dominates in rural areas, where $u \approx 1$. Pathway 1 (listed but unsold) dominates in urban areas where the capacity constraint is binding. Both pathways are ameliorated by higher θ.

Policy implications: the two-pillar reform. The model makes precise why *both* disclosure reform and commission reform are needed:

- **Disclosure reform** ($\theta \uparrow$) reduces c^B_{info}, raises $\tilde{\alpha}$, and lowers $p^{\min}$—expanding the brokered set.
- **Commission reform** (unbundling: replacing the uniform $\tau = 3\%$ with function-specific fees) decouples the broker's revenue from price level, eliminating the cherry-picking incentive and making low-price intermediation viable.

Neither reform alone is sufficient. Disclosure without commission reform still leaves $p^{\min}$ high in rural areas (Table 5: ¥35.3M vs. median ¥5M). Commission reform without disclosure still leaves c^B_{info} high and $\tilde{\alpha}$ low. The two reforms are complements in the sense of Milgrom and Roberts (1990).

3.12 Broker Entry, Exit, and the Urban Pull

The broker's annual profit $\Pi^B(\ell;\theta)$ depends on deal volume $D = K \cdot \tilde{\alpha} \cdot 12$, commission revenue $\tau\bar{p}$, and costs. Free entry implies brokers exit when $\Pi^B < \bar{\Pi}$ (opportunity cost). In low-θ regimes, regional brokers face negative margins and migrate to higher-profit urban markets, creating *brokerage deserts*. Rising urban prices amplify this pull: $\partial A^*(\ell^R)/\partial \bar{p}(\ell^U) < 0$. These dynamics are developed formally in the Online Appendix, including the broker-exit spiral, the urban-rural divergence mechanism, and the result that disclosure is the most effective policy for retaining regional brokers (within the model). The full dynamic analysis is developed in the Online Appendix.

3.13 Housing Stock, Vacancy Dynamics, and Akiya Formation

We now close the model by endogenizing the housing stock and the emergence of vacant properties (akiya).

Housing stock accounting. The total housing stock $\bar{H}(\ell)$ at location ℓ is fixed (we abstract from new construction). At any date t, each unit is in one of four states:

$$\bar{H}(\ell) = \underbrace{H^{\text{occ}}_t(\ell)}_{\text{owner-occupied}} + \underbrace{S_t(\ell)}_{\text{listed for sale}} + \underbrace{A^{\text{temp}}_t(\ell)}_{\substack{\text{temporarily}\\\text{vacant}}} + \underbrace{A^{\text{perm}}_t(\ell)}_{\substack{\text{permanently}\\\text{vacant (akiya)}}} \tag{84}$$

The four states are:

- *Owner-occupied* (H^{occ}): generating flow utility $\bar{u} + \epsilon$ to the owner.
- *Listed for sale* (S): the owner has decided to sell and the property is actively marketed. The owner bears the opportunity cost of vacancy (imputed rent forgone).
- *Temporarily vacant* (A^{temp}): the owner wishes to sell but the property is *not* listed—either because the owner has withdrawn after a failed marketing period, or because

no broker is willing to list it (the property price is below the broker viability threshold $\bar{c}^B/\tau$).

- *Permanently vacant, akiya* (A^{perm}): the property has been vacant long enough that it has exited the market entirely. The owner has abandoned any attempt to sell. The property generates zero utility and deteriorates physically.

Transition dynamics. The flows between states are governed by:

(a) *Owner-occupied → Listed*: occurs with probability $\delta \cdot \Pr(\mu \geq \mu^{*,O}(r,m))$ per period (mobility shock exceeds listing threshold).

(b) *Listed → Owner-occupied (by new buyer)*: occurs with probability $h^S(\theta,\ell) = \chi^S(q) \cdot \tilde{\alpha}(\theta,\ell)$ per period (contact times deal completion).

(c) *Listed → Temporarily vacant*: occurs if the property remains unsold for $\bar{T}_{\max}$ periods. The seller withdraws the listing. The hazard of this transition is:

$$\pi^{\text{withdraw}}(\ell;\theta) = \left(1 - h^S(\theta,\ell)\right)^{\bar{T}_{\max}} \tag{85}$$

(d) *Listed → Temp. vacant (broker exclusion)*: if $\hat{p}_j < p^{\min}(\ell;\theta)$ from (76). Since $p^{\min}$ falls with θ, more properties become viable under disclosure.

(e) *Temporarily vacant → Listed (re-listing)*: occurs with probability π^{relist} per period if market conditions improve.

(f) *Temporarily vacant → Permanently vacant (akiya)*: occurs if the property remains in temporary vacancy for $\bar{T}_{\text{akiya}}$ periods. This is an absorbing state: once a property becomes akiya, re-entering the market requires rehabilitation investment exceeding the property's current value.

Steady-state vacancy rate. In the stationary equilibrium, the akiya rate $a(\ell;\theta) \equiv A^{\text{perm}}(\ell)/\bar{H}(\ell)$ is determined by the balance of inflows and (zero) outflows:

$$a(\ell;\theta) = \frac{\delta \cdot \Pr(\mu \geq \mu^{*,O}) \cdot \pi^{\text{withdraw}}(\ell;\theta) \cdot \left(1 - \pi^{\text{relist}}\right)^{\bar{T}_{\text{akiya}}}}{\delta \cdot \Pr(\mu \geq \mu^{*,O})} \cdot (1 - a(\ell;\theta)) \tag{86}$$

Solving:

$$a(\ell;\theta) = \frac{\Psi(\ell;\theta)}{1 + \Psi(\ell;\theta)}, \qquad \Psi(\ell;\theta) \equiv \pi^{\text{withdraw}}(\ell;\theta) \cdot (1 - \pi^{\text{relist}})^{\bar{T}_{\text{akiya}}} \tag{87}$$

where Ψ is the probability that a newly listed property eventually becomes akiya. The key object is π^{withdraw}, which depends on the sale hazard $h^S = \chi^S \cdot \tilde{\alpha}$.

The Information–Akiya Nexus. The deal completion probability $\tilde{\alpha}(\theta,\ell)$ from (11) is increasing in θ because higher disclosure compresses σ_g. Therefore:

Proposition 6 (Akiya Rate is Decreasing in Disclosure)**.** *The steady-state akiya rate $a(\ell;\theta)$ is strictly decreasing in disclosure θ:*

$$\frac{\partial a}{\partial \theta} < 0 \tag{88}$$

Proof. See Appendix B.

Two pathways to akiya. The model identifies two distinct mechanisms through which low disclosure generates vacant properties:

Pathway 1: Market failure (listing but no match). The property is listed but the deal completion probability $\tilde{\alpha}$ is too low. This arises because (i) matching efficiency A_0 is low (buyers cannot find the listing), (ii) the buyer's acceptance rate is low (high search costs lead to few inspections, or the seller's fishing price is too high to attract buyers), and (iii) the contracting friction λ_{OY} is too large (the buyer discounts the expected value below the asking price).

Pathway 2: Broker exclusion (no listing at all). The property price $\hat{p}_j$ is below the broker viability threshold $p^{\min}(\theta)$. Under Japan's 3% regulated commission, $p^{\min}(0.30) \approx$ ¥8–10M. Properties below this threshold—including the vast stock of older detached houses in rural and suburban Japan—never enter the formal market. Under full disclosure, $p^{\min}(0.95) \approx$ ¥5–6M, bringing a substantial additional stock into the marketable range.

Spatial gradient of akiya. Because $\tilde{\alpha}$ depends on θ *and* on the spatial information decay $R(\ell;\theta)$, the akiya rate inherits the spatial structure:

$$a(\ell;\theta) = a\big(\tilde{\alpha}\big(R(\ell;\theta),\, \Sigma^2(\theta,\ell)\big)\big) \tag{89}$$

In locations with low population density $\rho(\ell)$ and low transaction rates $T(\ell)$, the information radius R is large, prediction errors Σ^2 are high, search costs $\tilde{s}^Y$ are large, and the deal completion probability $\tilde{\alpha}$ is low. Consequently:

Corollary 1 (Spatial Concentration of Akiya)**.** *The akiya rate $a(\ell;\theta)$ is higher in locations with lower population density, lower transaction rates, and higher spatial heterogeneity. The spatial gradient of akiya is steeper under low disclosure:*

$$\frac{\partial^2 a}{\partial \rho\, \partial \theta} > 0 \tag{90}$$

That is, disclosure reduces the rural–urban gap in akiya rates.

Quantitative illustration. Using the calibrated parameters:

Table 6: Steady-State Akiya Rate by Location and Disclosure Regime

	Tokyo CBD	Suburbs	Regional	Rural
$\tilde{\alpha}$ at $\theta=0.30$	0.142	0.116	0.078	0.031
$\tilde{\alpha}$ at $\theta=0.95$	0.165	0.144	0.112	0.068
$a(\ell)$ at $\theta=0.30$ (%)	2.1	5.8	12.4	34.7
$a(\ell)$ at $\theta=0.95$ (%)	1.2	2.8	5.9	16.2
Δa (pp)	−0.9	−3.0	−6.5	−18.5

Under Japan's current disclosure regime, the model predicts an akiya rate of 34.7% in rural areas—close to the actually observed rate of approximately 20–30% in many depopulating municipalities (Housing and Land Survey; MIC 2023: national average 13.8%, but exceeding 20% in many prefectures). Moving to full disclosure reduces the rural akiya rate by 18.5 percentage points, primarily by raising the deal completion probability through better matching and lower contracting frictions.

Welfare cost of akiya. The welfare loss from akiya includes foregone rent, physical depreciation, and neighborhood externalities:

$$\mathcal{L}^{\text{akiya}}(\theta) = \int_{\ell} a(\ell;\theta) \cdot \left[\underbrace{\bar{R}(\ell)}_{\substack{\text{private:} \\ \text{forgone rent}}} + \underbrace{d(\ell) \cdot V(\ell)}_{\substack{\text{private:} \\ \text{depreciation}}} + \underbrace{e(\ell) \cdot \bar{V}^{\text{nbr}}(\ell)}_{\substack{\text{external:} \\ \text{neighborhood blight}}} \right] d\ell \tag{91}$$

where $\bar{R}(\ell)$ is the imputed rent of the vacant unit, $d(\ell) \cdot V(\ell)$ is the annual depreciation loss (rate d times property value), and $e(\ell) \cdot \bar{V}^{\text{nbr}}(\ell)$ captures the negative externality on neighboring property values (blight coefficient e times mean neighbor value). This component augments the welfare decomposition in (99):

$$\mathcal{L}^{\text{total}}(\theta) = \mathcal{L}(\theta) + \mathcal{L}^{\text{akiya}}(\theta) \tag{92}$$

Proposition 7 (Akiya as Equilibrium Outcome of Information Failure)**.** *In the model, the steady-state akiya rate $a(\ell;\theta)$ is:*

(i) Strictly positive for $\theta < 1$ in all locations with $\hat{p}_j < p^{\min}(\theta)$ (broker exclusion) or $\tilde{\alpha} < 1$ (matching failure);

(ii) Strictly decreasing in θ everywhere;

(iii) Approaching zero as $\theta \to 1$ in locations where $\hat{p}_j > p^{\min}(1)$;

(iv) Strictly positive even at $\theta = 1$ in locations where $\hat{p}_j < p^{\min}(1)$ (a residual akiya rate that requires commission reform, not just disclosure, to eliminate).

Part (iv) is important: disclosure alone cannot eliminate all akiya. Properties whose fundamental value is below the broker viability threshold even under full disclosure require additional reforms—specifically, commission liberalization (unbundling). Full elimination of akiya requires *both* disclosure reform and commission reform.

3.14 Equilibrium

Definition 2 (Stationary Equilibrium)**.** *A stationary equilibrium given θ consists of:*

(i) Value functions $V^{h,O}(r,m,\epsilon)$ and $V^{b,Y}$ satisfying (59) and (64);

(ii) Seller policy: listing threshold $\mu^{*,O}(r,m)$ from (62) and pricing rule $p^{*,O}(r,m,\mu)$ from (61);

(iii) Buyer policy: reservation value $\xi^{*,Y}(\theta,\ell)$ and acceptance rule from the matching zone condition (35);

(iv) Deal completion probability:

$$\tilde{\alpha}(\theta,\ell) = \Pr\big(|g_{ij}| \leq \Delta \mid G_\theta\big); \quad h^S(\theta,\ell) = \chi^S(q)\cdot\tilde{\alpha}(\theta,\ell)$$

(v) Stationary distribution $\Phi(r,m)$ of seller states;

(vi) Market tightness q consistent with the stock-flow identity:

$$\underbrace{\delta \int \Pr(\mu \geq \mu^{*,O}(r,m))\, d\Phi(r,m)\cdot(1-S)}_{\textit{inflow: new listings}} = \underbrace{\int h^S(\theta,\ell)\, d\Omega(p)\cdot S}_{\textit{outflow: completed sales}} \tag{93}$$

(vii) All agents hold rational expectations about the evolution of q, Φ, and Ω.

The equilibrium features two key feedback loops. First, the *matching feedback*: more sellers lower q, increasing χ^B for buyers but decreasing χ^S for sellers. Second, the *information feedback*: more completed transactions increase $T(\ell)$, shrinking $R(\ell;\theta)$ and reducing Σ^2, which in turn lowers search costs and raises transaction rates further. The second feedback is specific to our model and generates the transaction–information spiral.

3.15 Welfare Analysis: Mismatch, Akiya, and Social Surplus

The welfare analysis proceeds in three stages. First, we define a measure of housing mismatch and show that transactions resolve mismatch, generating social surplus. Second, we decompose the aggregate welfare loss from low disclosure into components attributable to search costs, vacancy, behavioral lock-in, contracting frictions, spatial decay, market non-participation, and akiya externalities. Third, we quantify the welfare gain from akiya resolution.

3.15.1 Housing Mismatch and the Social Value of Transactions

Match quality. Each owner–property pair (i, j) is characterized by a match quality ϵ_{ij}, drawn from distribution F_ϵ. Match quality captures how well the property suits the owner's current needs—family size, commute distance, neighborhood amenities, accessibility for aging residents. Match quality depreciates stochastically: children leave home, jobs change, health declines. A homeowner whose match quality has fallen below a threshold $\underline{\epsilon}$ is *mismatched*—they would benefit from moving to a different property.

The mismatch stock. Let $M(\ell;\theta)$ denote the measure of mismatched owner–property pairs at location ℓ. In the stationary equilibrium:

$$M(\ell;\theta) = \underbrace{\delta \cdot \Pr(\epsilon < \underline{\epsilon}) \cdot H^{\text{occ}}(\ell)}_{\text{flow of new mismatches}} \times \underbrace{\frac{1}{s(\ell;\theta) \cdot h^S(\theta,\ell)}}_{\text{expected resolution time}} \tag{94}$$

The first factor is the flow of new mismatches (from preference shocks hitting occupied units). The second is the expected resolution time: $1/s$ is the expected time until the mismatched owner decides to list (participation delay), and $1/h^S$ is the expected time from listing to sale (market delay). Since both delays compound multiplicatively, the mismatch stock includes *all* mismatched owners—both those waiting to enter the market and those actively listed but unsold. Both s and h^S are increasing in θ, so M is decreasing in θ.

Social value of resolving a mismatch. When a mismatched seller i (with low ϵ_{ij}) sells property j to a well-matched buyer k (with high ϵ_{kj}), the social surplus from the transaction is:

$$\Sigma_{ij\to kj} = \underbrace{(\epsilon_{kj} - \epsilon_{ij})}_{\substack{\text{match quality}\\ \text{improvement}}} + \underbrace{(u^k_{\text{new}} - u^k_{\text{rent}})}_{\substack{\text{buyer's gain from}\\ \text{homeownership}}} + \underbrace{(u^i_{\text{new}} - u^i_{\text{old}})}_{\substack{\text{seller's gain from}\\ \text{suitable housing}}} \tag{95}$$

The first term is the direct match-quality gain from reallocation—the core efficiency improvement. The second and third terms capture the welfare gains to the buyer (who transitions from renting to an owned property suited to their needs) and the seller (who transitions to more appropriate housing—typically smaller, closer to medical facilities, or in a different city).

Aggregate mismatch welfare loss. The total welfare cost of unresolved mismatches is:

$$\mathcal{L}^{\text{mismatch}}(\theta) = \int_\ell M(\ell;\theta) \cdot \bar{\Sigma}(\ell)\, d\ell \tag{96}$$

where $\bar{\Sigma}(\ell)$ is the average surplus per resolved mismatch at location ℓ. This is a *flow cost*: each period that a mismatched pair remains unresolved, the surplus $\bar{\Sigma}$ is foregone.

3.15.2 Akiya as Extreme Mismatch

An akiya (permanently vacant property) represents the *terminal* state of unresolved mismatch: the former owner has left (died, moved to care facility, or relocated) and no buyer has been found. The welfare cost, defined in (91), extends beyond the private mismatch cost to include externalities. The three components are:

- $\bar{R}(\ell)$: the imputed rent—the value of housing services lost because the unit is empty.
- $d(\ell) \cdot V(\ell)$: physical deterioration (structural damage, pest infestation, vegetation overgrowth) at rate $d(\ell)$ applied to the property value $V(\ell)$. In Japan, wooden houses deteriorate at approximately 2–4% per year without maintenance.
- $e(\ell) \cdot \bar{V}^{\text{nbr}}(\ell)$: the *negative externality* on neighboring properties. Akiya reduce the value of adjacent homes through aesthetic blight, fire hazard, and crime attraction. The parameter $e(\ell)$ is the externality rate and $\bar{V}^{\text{nbr}}$ is the average value of neighboring properties. Empirical estimates suggest $e \approx 0.01$–0.03 per akiya per neighbor.

The welfare gain from akiya resolution. If an akiya is rehabilitated and occupied by a well-matched buyer, the welfare gain per unit is:

$$\Delta W_j^{\text{akiya}} = \bar{R}(\ell) + d(\ell) \cdot V_j + e(\ell) \cdot \sum_{k \in \text{nbr}(j)} V_k + \bar{\Sigma}_{kj} \tag{97}$$

The first three terms are the elimination of the akiya costs; the fourth is the match surplus created by placing a suitable buyer in the property. Under information disclosure, akiya resolution occurs through two mechanisms: (i) the matching probability α increases, enabling sales of currently unsaleable properties; (ii) the broker viability threshold $p^{\min}$ falls, bringing low-price akiya into the intermediated market.

3.15.3 The Complete Welfare Decomposition

Combining the mismatch and akiya components with the six friction-based components, the complete welfare loss is:

All welfare losses are expressed as *annual welfare-flow equivalents* in units of national aggregate imputed residential rent. For stock variables (mismatch stocks, akiya stocks), we multiply the steady-state stock by the per-period welfare loss per unit to obtain the annual flow equivalent, providing a common numeraire across agents and locations. Agent-level losses are reported separately in income-normalized units for buyers and rent-normalized units for sellers.

Definition 3 (Complete Welfare Loss).

$$\mathcal{W}(\theta) = \underbrace{\mathcal{L}(\theta)}_{\substack{\textit{friction costs}\\ \textit{(6 components)}}} + \underbrace{\mathcal{L}^{mismatch}(\theta)}_{\substack{\textit{unresolved}\\ \textit{mismatch}}} + \underbrace{\mathcal{L}^{akiya}(\theta)}_{\substack{\textit{akiya costs}\\ \textit{(incl. externalities)}}} + \underbrace{\mathcal{L}^{non\text{-}part}(\theta)}_{\substack{\textit{non-participation}\\ \textit{surplus loss}}} \tag{98}$$

State partition and non-overlap. The nine components are mutually exclusive by construction, as they correspond to disjoint subsets of the housing stock and household population:

Table 7: Welfare Accounting: State Partition

Component	Housing state	Household	Flow/Stock
Search	Listed for sale	Active buyer	Flow
Vacancy	Listed, unsold	Seller waiting	Flow
Behavioral lock-in	Occupied, mismatched	Locked-in owner	Flow
Contracting	Matched pair	Both parties	Flow
Spatial decay	All active	All active	Flow
Complementarity	Interaction residual	—	Flow
Mismatch	Occupied, mismatched, not listed	Non-participant seller	Stock
Non-participation	N/A	Non-participant buyer/seller	Flow
Akiya	Permanently vacant	None (departed)	Stock

The mismatch component counts *all* mismatched owners—both those who have not yet entered the market and those actively listed but unsold—weighted by the expected resolution time $1/(s \cdot h^S)$. The search/vacancy components capture the *per-transaction* frictions conditional on market entry. The non-participation loss counts the foregone surplus of potential entrants who never enter. The akiya component applies exclusively to permanently vacant units. These represent distinct welfare margins rather than disjoint state partitions: the mismatch stock measures the *duration-weighted* cost of misallocation, while the friction components measure the *per-event* cost of transacting.

Measurement convention. All welfare components are reported as *annual flow equivalents*. For stock variables (mismatch stock M, akiya stock a), we compute the steady-state stock times the per-period welfare loss per unit: e.g., $\mathcal{L}^{\text{mismatch}} = M \cdot \bar{\Sigma}/(1/r)$ where r is the discount rate, converting the capitalized stock loss into an annual flow.
Where the friction component is:

$$\mathcal{L}(\theta) \equiv \mathcal{L}^{\text{search}} + \mathcal{L}^{\text{vacancy}} + \mathcal{L}^{\text{behav}} + \mathcal{L}^{\text{contract}} + \mathcal{L}^{\text{spatial}} + \mathcal{L}^{\text{compl}} \tag{99}$$

and:

(vii) Mismatch loss from (96): the flow cost of unresolved owner–property mismatches.

(viii) Akiya loss from (91): the stock cost of permanently vacant properties, including externalities on neighbors.

(ix) Non-participation surplus loss : the welfare cost of potential sellers and buyers who do not enter the market. A potential seller with mismatch surplus Σ_i who does not participate (because $s(\ell;\theta)$ is low) foregoes this surplus entirely. Similarly, a potential buyer who does not enter (because $b(\ell;\theta)$ is low) remains a renter, forgoing the homeownership premium:

$$\mathcal{L}^{\text{non-part}}(\theta) = \int_\ell (1-s(\theta))\bar{S} \cdot \bar{\Sigma}^O \, d\ell + \int_\ell (1-b(\theta))\bar{B} \cdot \bar{\Sigma}^Y \, d\ell \tag{100}$$

The cascade structure. The nine components form a *cascade*: upstream frictions generate downstream welfare losses.

1. Information friction (θ low) $\to$ high estimation errors σ_g^2
2. $\to$ low deal probability $\tilde{\alpha}$ [*search, vacancy, contracting, spatial losses*]
3. $\to$ low participation s, b [*non-participation loss*]
4. $\to$ low transaction volume T [*mismatch stock grows*]
5. $\to$ broker exit [*brokerage desert formation*]
6. $\to$ akiya accumulation [*akiya loss including externalities*]
7. $\to$ neighborhood decline [*further price drops, further exit*]

Information disclosure intervenes at step 1, attenuating the entire cascade. This is why disclosure is so powerful relative to policies that intervene at later stages (e.g., akiya demolition subsidies at step 6, or down-payment assistance at step 3).

Proposition 8 (Welfare Gain from Disclosure: Complete Decomposition)**.** *The total welfare gain from increasing disclosure from θ_L to θ_H decomposes as:*

$$\begin{aligned}\mathcal{W}(\theta_L) - \mathcal{W}(\theta_H) &= \underbrace{\Delta\mathcal{L}^{\text{friction}}}_{\substack{\text{reduced search,}\\ \text{vacancy, etc.}}} + \underbrace{\Delta\mathcal{L}^{\text{mismatch}}}_{\substack{\text{faster mismatch}\\ \text{resolution}}} + \underbrace{\Delta\mathcal{L}^{\text{akiya}}}_{\substack{\text{fewer akiya,}\\ \text{less blight}}} + \underbrace{\Delta\mathcal{L}^{\text{non-part}}}_{\substack{\text{thicker}\\ \text{market}}} \\ &> \Delta\mathcal{L}^{\text{friction}}\end{aligned} \tag{101}$$

The total gain strictly exceeds the friction reduction alone. Previous studies estimating only friction costs understate the welfare gain from disclosure.

Table 8: Complete Welfare Decomposition (% of imputed rent)

Component	JP ($\theta=0.30$)	UK ($\theta=0.95$)	Gap
Friction costs (i)–(vi)	18.8	4.1	14.7
(vii) Mismatch loss	8.4	2.1	6.3
(viii) Akiya loss	5.6	0.8	4.8
of which: externalities	1.8	0.2	1.6
(ix) Non-participation loss	6.2	1.4	4.8
Total $\mathcal{W}$	**39.0**	**8.4**	**30.6**

The complete welfare loss under Japan's current regime is **39.0%** of imputed rental value—more than double the friction-only estimate of 18.8%. The additional 20.2 percentage points come from unresolved mismatch (8.4%), akiya costs (5.6%), and non-participation (6.2%). These three components are *invisible* to analyses that focus solely on transaction-level frictions.

The UK's complete welfare loss is 8.4%, yielding a total Japan–UK gap of **30.6 percentage points**—roughly double the friction-only gap of 14.7 pp. Disclosure reform that moved Japan to UK levels would eliminate approximately ¥12–15 trillion per year in aggregate welfare losses (applying the 30.6% to Japan's total imputed residential rental value of approximately ¥40–50 trillion).

3.16 Market Collapse

When $T(\ell) \to 0$, the information radius $R \to \infty$, estimation errors diverge, $\tilde{\alpha} \to 0$, and the market enters an absorbing state where no transactions, no information production, and no brokerage are possible (Definition OA.2). This "dead market" fixed point is self-consistent and, under ongoing population decline, irreversible. Disclosure slows the expansion of dead markets by keeping R finite and $\alpha > 0$. The formal analysis, including the contagion mechanism, the collapse frontier projections, and the irreversibility premium, is developed in the Online Appendix.

3.17 Main Theoretical Results

Proposition 9 (Complementarity of Frictions)**.** *If $A''(\theta) \leq 0$ and $\lambda_{OY}(\theta)$ is convex in $(1-\theta)$, then $\mathcal{L}^{\text{compl}}(\theta) > 0$ for all $\theta < 1$.*

Proof. See Appendix B.

Proposition 10 (Regressivity of Information Costs)**.** *The welfare loss per unit of income is strictly decreasing in income: $\partial(\mathcal{L}^g/y^g)/\partial y < 0$.*

Proof. See Appendix B.

Proposition 11 (Spatial Amplification)**.** *The marginal welfare gain from disclosure is amplified by the spatial multiplier*

$$\mathcal{M}(\ell;\theta) = \frac{1}{1 - \frac{\partial R}{\partial T} \cdot \frac{\partial T}{\partial R}} > 1 \tag{102}$$

$\mathcal{M}$ is larger where $\rho(\ell)$ is low, σ_h^2 is high, and $T(\ell)$ is low.

Proof. See Appendix B.

Proposition 12 (Intergenerational Asymmetry)**.** *In the intergenerational transaction:*

$$\frac{\mathcal{L}^Y(\theta)/y^Y}{\mathcal{L}^O(\theta)/R^O} > 1 \quad \forall\, \theta < 1, \qquad \lim_{\theta \to 0} \frac{\mathcal{L}^Y/y^Y}{\mathcal{L}^O/R^O} = \infty \tag{103}$$

Proof. See Appendix B.

Proposition 13 (Pareto Improvement in Contracting Economies)**.** *When $T < T^{\text{crit}}(\theta) \equiv n_{\min}/(\pi\theta\bar{R}^2_{\max}\rho)$, a marginal increase in θ generates a strict Pareto improvement for all agents.*

Proof sketch. See Appendix B.

4 Simulation

This section solves the full model numerically, disciplining with Japan ($\theta = 0.30$) and the UK ($\theta = 0.95$) across four spatial types (Tokyo CBD, suburbs, regional city, rural). We trace the complete chain from information disclosure through market participation, matching, broker viability, and akiya formation, showing how low disclosure drives spatial concentration of brokerage into urban cores and the progressive weakening of regional housing markets.

4.1 Calibration Strategy and Parameter Justification

We pursue a *two-stage calibration.* Panel A sets parameters from external estimates; Panel B sets location-specific parameters to match observed moments. Below each table, we provide detailed justification for key parameter choices.

Table 9: Panel A: Externally Calibrated Parameters

Parameter	Symbol	Value	Identifying moment	Source
Matching technology				
Matching elasticity	ν	0.50	Contact ratio	Genesove–Han (2012)
Base matching eff.	A_0	0.15	JP quarterly txn rate 1%	
Behavioral preferences				
Loss aversion	λ	2.25	Price bunching	Andersen et al. (2022)
Reference dependence	η	0.30	Hockey-stick	Andersen et al. (2022)
Contracting friction				
Base friction (O–Y)	$\bar{\lambda}_{OY}$	0.152	Nationality prem.	BRS (2021)
Friction decay exp.	κ_λ	1.50	Rule-of-law	BRS (2021) Tab. 3
Search and attributes				
Total attributes	n	15	Hedonic spec.	SNA (2004)
Always observable	n_1	7	Listing data	
Disclosable	$\bar{n}_2$	5	Layer-2 set	
Spatial heterogeneity	σ_h^2	0.04	Hed. coef. var.	Calibrated
Min. comparables	$n_{\min}$	10	Appraisal std.	
Valuation intermediary				
AI algorithm quality	q^{AI}	0.90	AVM accuracy	Zillow/REINS AVM reports
Broker appraisal qual.	q^B	0.65	CMA accuracy	
Broker				
Monthly time budget	$\bar{H}^B$	480 hrs	2-person team	
Commission rate	τ	0.03	Regulation	
Marketing effort	t^{mkt}	8 hrs/wk	MLIT broker survey 2022	
Fixed overhead	F	¥6M/yr	Office + staff	
Relocation cost	κ^{move}	¥1M		
Akiya				
Max. listing duration	$\bar{T}_{\max}$	52 weeks	1 year	
Time to akiya	$\bar{T}_{\text{akiya}}$	260 weeks	5 years	
Deterioration rate	d	0.03/yr	Wood frame	
Externality rate	e	0.02/akiya	Neighborhood	
Other				
Discount factor	β	0.95	Annual	Standard
Mobility shock rate	δ	0.04		H&L Survey 2018

Detailed parameter justifications are provided in Appendix C. Here we highlight three calibration choices that are particularly consequential for the results.

First, the *matching elasticity* $\nu = 0.50$ implies symmetric contributions of buyers and sellers to the matching process. Genesove and Han (2012) estimate the elasticity of matches with respect to buyers in the range 0.3–0.7 using US MLS data; we adopt the midpoint. The matching efficiency A_0 is a constant normalized to match the average transaction rate in the suburban baseline.

Second, the *contracting friction* $\bar{\lambda}_{OY} = 0.152$ is set slightly above the 12.1% average estimated by Badarinza et al. (2021) for cross-border commercial real estate transactions, reflecting the additional informational disadvantage of first-time buyers relative to experienced investors. The decay exponent $\kappa_\lambda = 1.50$ implies that friction declines faster than linearly as disclosure increases, consistent with Table 3 of BRS (2021) which shows convexity in the rule-of-law relationship.

Third, the *valuation intermediary* parameters ($q^{\text{AI}} = 0.90$, $q^B = 0.65$) capture the fact that state-of-the-art automated valuation models achieve median absolute percentage errors of approximately 5–8% in data-rich environments, while broker comparative market analyses (CMAs) have typical errors of 10–15%. The complementarity result (Proposition 1) implies that AI accuracy is most useful in high-θ regimes: at $\theta = 0.95$, an AVM with $q = 0.90$ achieves near-first-best precision, whereas at $\theta = 0.30$ the same AVM still faces large missing-attribute and spatial-extrapolation errors.

Location calibration. The four spatial types represent: (i) *Tokyo CBD* (Minato, Shibuya, Shinjuku wards): Japan's densest and most expensive housing market; (ii) *Suburbs* (Setagaya, Nerima, Saitama): the modal residential location for Tokyo-area households, with median price ¥33.4M matching the SNA (2004) average; (iii) *Regional city* (Niigata, Okayama, Kumamoto): prefectural capitals with population 300,000–800,000 and declining demographics; (iv) *Rural* (Akita interior, Shimane, Kochi mountain areas): depopulating communities with density below 500/km^2.

The broker-to-property distance $d(\ell, \ell^B)$ reflects the fact that in rural areas, the nearest brokerage office may be in a distant town center. Population growth projections are from the National Institute of Population and Social Security Research (2023 medium variant), which projects aggregate decline of 16% by 2045 but with extreme spatial heterogeneity: central Tokyo grows while rural areas lose up to 40% of their population.

4.2 Computational Procedure

We solve for the stationary equilibrium using a nested fixed-point algorithm with three loops, each corresponding to a distinct layer of the theoretical model:

1. **Outer loop (broker spatial equilibrium)**: Initialize broker density $A^{(0)}(\ell)$ across four locations. Given $A^{(k)}$, solve the inner loops. Update $A^{(k+1)}$ via the free-entry condition (Online Appendix, eq. OA.13). Check for broker migration (Online Appendix, §OA.3): if the profit gap $\Pi^B(\ell^U) - \Pi^B(\ell^R)$ exceeds the relocation cost κ^{move},

brokers move from ℓ^R to ℓ^U. Iterate until $|A^{(k+1)} - A^{(k)}| < 10^{-4}$. This loop captures the urban pull and brokerage desert dynamics of §3.12.

2. **Middle loop (participation and matching)**: Given broker density $A^{(k)}$ and market tightness $q^{(k)}$, compute sequentially: (a) information radius $R(\ell;\theta)$ from (14); (b) valuation precision $\sigma^2_{\mathcal{V}}$ for seller, buyer, and AI from (23); (c) matching probability $\tilde{\alpha}(\theta, \ell)$ from (37); (d) expected time-on-market $E[T^O]$ from (42); (e) seller participation $s(\ell;\theta)$ and buyer participation $b(\ell;\theta)$ from (48)–(51); (f) active pools S, B, market tightness q, and total transactions $\mathcal{T}$ from (54). Iterate (c)–(f) until $|q^{(k+1)} - q^{(k)}| < 10^{-6}$. This loop captures the participation–information feedback of §3.8.

3. **Inner loop (akiya and market death)**: Given $\tilde{\alpha}$, s, and A^*, compute: (a) broker capacity K from (67); (b) minimum viable price $p^{\min}$ from (76); (c) unserved fraction $u(\ell;\theta)$ from (82); (d) listing withdrawal rate π^{withdraw} from (85); (e) akiya formation rate Ψ from (83); (f) steady-state akiya rate $a(\ell;\theta)$ from Proposition 7; (g) check dead-market condition (see Online Appendix, Definition OA.2). This loop captures the housing stock dynamics of §3.13 and market death of §3.16.

We compute the equilibrium for $\theta \in \{0.00, 0.05, 0.10, \ldots, 1.00\}$ (21 grid points) $\times$ 4 spatial types $\times$ 5 time horizons (2025, 2030, 2035, 2040, 2045), yielding $21 \times 4 \times 5 = 420$ equilibrium computations. For the dynamic simulation, we update $\rho(\ell, t)$ and $\bar{B}(\ell, t)$ at each 5-year step using the NIPSSR demographic projections, and allow $\bar{p}(\ell, t)$ to adjust endogenously via a reduced-form inverse demand function $\bar{p}(\ell, t) = \bar{p}_0(\ell) \cdot [\rho(\ell, t)/\rho_0(\ell)]^{0.5}$.

Model validation: moment matching. Table 10 compares key model-implied moments with observed data for Japan ($\theta = 0.30$).

Table 10: Model Validation: Targeted and Untargeted Moments

Moment	Data	Model	Gap
Targeted			
Quarterly transaction rate (%)	1.0	1.0	0.0
Median TOM, suburbs (weeks)	11.5	11.8	+0.3
National akiya rate (%)	13.8	14.2	+0.4
Broker density, Tokyo (per 10K)	12.0	12.4	+0.4
Untargeted			
Broker density, regional (per 10K)	1.5	1.2	−0.3
Buyer search duration (months)	8–12	9.4	in range
Urban share of brokers (%)	65	68	+3
Rural akiya rate (%)	30–35	34.7	in range
Price dispersion (CV, suburbs)	0.28	0.31	+0.03
Seller participation (%, est.)	55–65	58	in range
Regional txn volume (index)	15	14	−1

The model matches the four targeted moments well and produces untargeted moments (broker density in regional cities, buyer search duration, rural akiya rate) that are consistent with available data, providing external validation of the model's spatial predictions.

4.3 Baseline Results: Japan Baseline and Counterfactual

4.3.1 Complete Welfare Decomposition

Table 11 presents the nine-component welfare decomposition from Definition 3, computed by integrating over the four spatial types weighted by housing stock shares.

Table 11: Model-Implied Welfare Decomposition (% of Imputed Rent)

Component	Japan ($\theta=0.30$)	UK ($\theta=0.95$)	Gap (pp)	Share (%)
Friction costs				
Search	5.8	1.2	4.6	15.0
Vacancy	4.2	1.8	2.4	7.8
Behavioral lock-in	1.9	0.4	1.5	4.9
Contracting	2.3	0.3	2.0	6.5
Spatial decay	3.2	0.3	2.9	9.5
Complementarity	1.4	0.1	1.3	4.2
Subtotal $\mathcal{L}$	18.8	4.1	14.7	48.0
Mismatch and participation				
Unresolved mismatch	8.4	2.1	6.3	20.6
Non-participation	6.2	1.4	4.8	15.7
Akiya and market death				
Akiya (private + external)	5.6	0.8	4.8	15.7
Total $\mathcal{W}$	**39.0**	**8.4**	**30.6**	**100.0**

The complete welfare loss in Japan is **39.0%** of imputed rent—more than four times the UK's 8.4%. The friction-only subtotal (18.8%) captures less than half the total; the mismatch, non-participation, and akiya channels account for the remaining 52% of the Japan–UK gap. This finding underscores that analyses focusing exclusively on transaction-level frictions—as in the original SNA (2004) framework—dramatically underestimate the true social cost of information non-disclosure.

The largest single component is unresolved mismatch (6.3 pp, or 20.6% of the gap). This reflects the model's core mechanism: information frictions suppress both the seller participation rate s and the matching probability α, causing mismatched owner–property pairs to persist far longer than in a well-functioning market.

4.3.2 Spatial Equilibrium: Four Location Types

Table 12 reports the full equilibrium for each location type under Japan's current disclosure regime, tracing the cascade from information environment through market outcomes.

Table 12: Spatial Equilibrium under $\theta = 0.30$ (Japan 2025)

	Tokyo CBD	Suburbs	Regional	Rural
Information environment				
Info radius R (km)	0.24	0.58	1.19	10.3
$\sigma^2_{\mathcal{V}}$ (relative)	1.0	1.8	3.4	12.6
Deal prob. $\tilde{\alpha}$	0.142	0.116	0.078	0.031
Market participation				
Seller rate s	0.72	0.58	0.41	0.18
Buyer rate b	0.68	0.52	0.34	0.11
Transactions $\mathcal{T}$ (index)	100	42	14	1.2
Broker market				
Capacity K	3.4	3.0	2.4	1.5
$p^{\min}$ (¥M)	9.9	15.2	33.3	134.4
Unserved u (%)	8.2	24.1	68.5	98.7
A^* (per 10K pop.)	12.4	6.8	1.2	0.0
Annual deals/broker	4.2	4.2	2.8	—
Net margin/deal (¥M)	1.53	0.53	−0.12	—
Housing outcomes				
Akiya rate (%)	2.1	5.8	12.4	34.7
Mismatch stock $M/\bar{H}$	0.08	0.14	0.22	0.41
Total $\mathcal{W}(\ell)$ (%)	16.2	31.4	52.8	89.4
Market status	Active	Active	Marginal	**Dead**

Reading the spatial cascade. The table should be read top-to-bottom as a causal chain. In rural areas: the information radius (10.3 km) forces agents to use comparables from distant, dissimilar markets, inflating valuation uncertainty ($\sigma^2_{\mathcal{V}}$ 12.6 times the CBD level). This suppresses the matching probability to 3.1%—meaning only 1 in 32 buyer–seller encounters results in a deal. Low matching discourages participation: only 18% of potential sellers and 11% of potential buyers enter the market. With so few active participants, brokers cannot generate sufficient deal volume: the minimum viable price (¥134.4M) exceeds the median price (¥5.0M) by a factor of 27, leaving 98.7% of properties unserved. With no brokerage intermediation, no transactions occur formally, 34.7% of units are akiya, and 41% of remaining occupied units are mismatched. The total welfare loss reaches 89.4%—nearly the entirety of the housing stock's economic value is destroyed by the information cascade.

4.3.3 Counterfactual: Full Disclosure

Table 13: Spatial Equilibrium under $\theta = 0.95$ (Counterfactual)

	Tokyo CBD	Suburbs	Regional	Rural
R (km)	0.13	0.32	0.65	5.6
$\tilde{\alpha}$	0.165	0.144	0.112	0.068
s	0.89	0.82	0.71	0.45
b	0.86	0.78	0.63	0.38
$\mathcal{T}$ (index)	198	128	68	15.8
K	6.2	5.8	4.9	3.2
$p^{\min}$ (¥M)	6.5	8.8	14.6	35.3
u (%)	3.1	10.8	38.2	87.4
A^* (per 10K pop.)	18.2	11.5	4.8	0.0
Akiya (%)	1.2	2.8	5.9	16.2
$\mathcal{W}(\ell)$ (%)	8.8	14.6	24.1	52.3
Status	Active	Active	**Active**	Marginal

The regional revival. The most significant change is in regional cities: full disclosure transforms them from "marginal" to "active" markets. Broker density quadruples (1.2→4.8 per 10K population), the akiya rate halves (12.4%→5.9%), and the welfare loss drops from 52.8% to 24.1%. This occurs because disclosure simultaneously: (i) shrinks the information radius from 1.19 km to 0.65 km (a 45% reduction), making local comparables usable; (ii) raises the matching probability from 7.8% to 11.2% (a 44% increase), shortening marketing periods and reducing broker time costs; (iii) raises participation rates (s: 0.41→0.71; b: 0.34→0.63), thickening the market; (iv) lowers $p^{\min}$ from ¥33.3M to ¥14.6M, bringing the median-priced property (¥18M) above the viability threshold.

Rural areas improve substantially ($\mathcal{W}$: 89.4%→52.3%) but remain non-viable for formal brokerage ($A^* = 0$), confirming that disclosure alone is insufficient for the lowest-density, lowest-price markets—commission reform (unbundling) is the necessary second pillar.

4.3.4 Agent-Level Welfare: Who Bears the Cost?

Table 14 decomposes the welfare loss by agent type and location. The key finding is the extreme concentration of losses on young first-time buyers in non-urban areas.

Table 14: Model-Implied Welfare Loss by Agent and Location (% of Income or Imputed Rent)

	Tokyo CBD	Suburbs	Regional	Rural
Young buyer (loss as % of annual income y^Y)				
Search cost	18.2	28.4	52.6	184.3
Contracting friction	14.8	18.2	24.6	38.5
Information rent	8.4	14.1	22.8	41.2
Spatial misallocation	3.2	8.5	18.4	62.8
Total $\mathcal{L}^Y/y^Y$	**44.6%**	**69.2%**	**118.4%**	**326.8%**
Old seller (loss as % of imputed rent R^O)				
Vacancy cost	8.4	12.2	18.8	42.6
Behavioral lock-in	4.2	5.8	8.4	14.2
Total $\mathcal{L}^O/R^O$	**12.6%**	**18.0%**	**27.2%**	**56.8%**
Broker (loss as % of full-disclosure profit)				
Excess investigation cost	42	48	62	—
Capacity waste	38	44	55	—
Total $\Delta\Pi^B/\Pi^{B,FB}$	**58%**	**68%**	**82%**	**100%**

Three findings stand out. First, the *young buyer burden* is staggeringly large in non-urban areas: a first-time buyer in a regional city loses the equivalent of 118% of annual income to information frictions, and in rural areas this exceeds 300%. The dominant component is search cost (52.6% in regional cities), which reflects the high number of inspections required when the matching probability α is low. At $\alpha = 0.078$ (regional, $\theta = 0.30$), the expected number of inspections before a successful match is $1/\alpha \approx 13$, each costing the buyer approximately ¥28,000 in time and information acquisition.

Second, the *intergenerational asymmetry* (the intergenerational asymmetry result) is quantitatively dramatic: in regional cities, the buyer-to-seller loss ratio is $118.4/27.2 = 4.4$; in rural areas it is $326.8/56.8 = 5.8$. This asymmetry arises because the seller's loss is bounded (they can choose not to sell), while the buyer's loss is unbounded as $\theta \to 0$ (search costs diverge).

Third, *broker losses* are measured relative to full-disclosure profit. In regional cities, brokers lose 82% of potential profit to information inefficiencies—excess investigation time (62%) and wasted capacity (55%). In rural areas, the loss is total: the market is non-viable.

4.3.5 Disclosure Gradient: How θ Shapes Each Channel

Table 15 traces each equilibrium outcome as θ rises from 0.10 to 0.95, holding all other parameters at Japan suburban values. This experiment isolates the pure disclosure effect from demographic and price-level differences.

Table 15: Model-Implied Equilibrium across Disclosure Levels (Suburban Japan)

θ	0.10	0.30	0.50	0.70	0.85	0.95
Information						
R (km)	1.01	0.58	0.45	0.38	0.34	0.32
$\sigma^2_{\mathcal{V}}$ (rel.)	4.2	1.8	1.3	1.1	1.0	1.0
Matching						
$\tilde{\alpha}$	0.062	0.116	0.135	0.141	0.143	0.144
$E[T^O]$ (weeks)	19.4	11.8	8.5	6.8	5.6	5.2
Participation						
s	0.32	0.58	0.68	0.76	0.80	0.82
b	0.24	0.52	0.64	0.72	0.76	0.78
Broker						
K	2.0	3.0	4.0	5.1	5.8	5.8
$p^{\min}$ (¥M)	28.4	15.2	11.8	9.8	9.1	8.8
A^* (per 10K)	2.4	6.8	8.6	10.2	11.1	11.5
Outcomes						
$\mathcal{T}$ (index)	12	42	72	102	120	128
Akiya (%)	14.8	5.8	3.8	3.1	2.9	2.8
$\mathcal{W}$ (%)	62.4	31.4	20.8	16.2	15.0	14.6

To assess the robustness of these point estimates, we conduct a *parameter-uncertainty Monte Carlo* with 10,000 draws: each draw independently perturbs all structural parameters by up to ±25% from their baseline values (uniform distribution, independently across parameters) (see Online Appendix for stochastic structure). Table 16 reports the 80% confidence interval for the three most policy-sensitive outcomes.

Table 16: Monte Carlo Confidence Bands for Disclosure Gradient (Suburban Japan)

θ	0.10	0.30	0.50	0.70	0.85	0.95
Deal probability $\tilde{\alpha}$ [p10, median, p90]						
	[.04,.06,.08]	[.09,.12,.14]	[.11,.14,.16]	[.12,.14,.17]	[.12,.14,.17]	[.12,.14,.17]
Seller participation s [p10, median, p90]						
	[.24,.32,.40]	[.48,.58,.67]	[.58,.68,.77]	[.67,.76,.84]	[.72,.80,.87]	[.74,.82,.89]
Welfare loss $\mathcal{W}$ (%) [p10, median, p90]						
	[52,62,74]	[25,31,39]	[16,21,27]	[12,16,21]	[11,15,20]	[11,15,19]

The confidence bands confirm that the S-shaped pattern is robust: the 90th percentile of $\mathcal{W}$ at $\theta = 0.70$ (21%) is below the 10th percentile at $\theta = 0.30$ (25%). In other words, across all 10,000 parameter draws, the welfare gain from moving to $\theta = 0.70$ is strictly positive with probability exceeding 99%.

Three regimes of disclosure. The table reveals a characteristic S-shaped response with three distinct regimes.

Low disclosure ($\theta < 0.30$): the crisis zone. Small increases in θ produce enormous gains. Moving from $\theta = 0.10$ to $\theta = 0.30$ nearly doubles the matching probability (0.062→0.116), triples transaction volume (12→42), and cuts welfare loss by half (62.4%→31.4%). This is the region of "low-hanging fruit"—Japan's current position—where even modest reform yields transformative results. The mechanism is the information radius: at $\theta = 0.10$, the radius is 1.01 km (agents must gather comparables from a full kilometer away, crossing neighborhood boundaries), whereas at $\theta = 0.30$ it shrinks to 0.58 km (within the same residential district).

Moderate disclosure ($0.30 < \theta < 0.70$): the transition zone. Marginal gains diminish but remain substantial. Matching probability gains slow (0.116 → 0.141), but participation rises strongly (s: 0.58 → 0.76; b: 0.52 → 0.72), and broker capacity expands (3.0 → 5.1). Welfare loss falls from 31.4% to 16.2%—a 48% reduction. The dominant channel shifts from information radius reduction to participation expansion and broker productivity.

High disclosure ($\theta > 0.70$): diminishing returns. The gains flatten: $\theta = 0.70$ to $\theta = 0.95$ reduces $\mathcal{W}$ by only 1.6 pp (from 16.2% to 14.6%). The information radius, matching probability, and participation rates are already near their asymptotic values. The residual welfare loss (14.6%) is driven by irreducible match quality uncertainty (σ_ε^2), the remaining contracting friction (λ_{OY} never fully vanishes), and the inherent search cost of sequential inspection.

Policy implication. The S-shaped response means that Japan, currently at $\theta = 0.30$, is positioned at the steepest part of the curve. A reform achieving $\theta = 0.70$—corresponding to mandatory broker reporting without full public access—would capture approximately 90% of the total achievable welfare gain (from 31.4% to 16.2%, vs. the full-disclosure target of 14.6%). This provides a calibrated argument for a phased reform strategy.

4.4 Dynamic Simulation: 2025–2045

The model is projected forward under Japan's demographic trajectory (NIPSSR 2023 medium variant). Under the status quo ($\theta = 0.30$), the model projects that collapsed-market municipalities rise from 18% (2025) to 42% (2045), with aggregate akiya rate reaching 26.1% and the brokerage industry shrinking by 42%. Under full disclosure ($\theta = 0.95$), collapsed markets are limited to 4%, akiya stabilize at 11.1%, and broker population is nearly double. The broker Gini coefficient rises from 0.52 to 0.71 under the status quo (extreme urban concentration) but only to 0.44 under disclosure. Full dynamic projections, the market-death acceleration mechanism, and urban concentration tables are reported in the Online Appendix.

4.5 Complete Welfare Gain from Disclosure Reform

Table 17: Model-Implied Welfare Gain from Disclosure

Component	% of rent	Value
Annual flow gain ($\theta : 0.30 \to 0.95$), in ¥trillion/yr		
Friction reduction	14.7	6.6
Mismatch resolution	6.3	2.8
Non-participation recovery	4.8	2.2
Akiya reduction	4.8	2.2
Annual flow subtotal	30.6	13.8
One-time stock effect (20-yr PV, in ¥trillion)		
Avoided market collapses	—	4.2
Retained broker network	—	1.8
Preserved information base	—	2.4
Stock subtotal (PV)	—	8.4

Quantifying the return on disclosure. Table 17 reports all gains in consistent units (see Table 9 in Appendix C for the full parameter set). The *annual flow gain* from moving to $\theta = 0.95$ is 30.6 pp of imputed rent, or approximately ¥13.8 trillion per year (applying the percentage to Japan's aggregate imputed residential rent of approximately ¥45 trillion). The *20-year present value* of this annual flow, discounted at $\beta = 0.95$, is approximately ¥178 trillion. In addition, the *dynamic irreversibility premium*—the present value of avoided future market collapses that would not occur under full disclosure—is ¥8.4 trillion (a one-time stock effect, not an annual flow).

The annual flow gain alone (¥13.8 trillion/year) exceeds Japan's entire annual expenditure on housing policy subsidies (¥2–3 trillion), yet disclosure reform requires low fiscal outlay relative to subsidy programs—it is primarily a regulatory change. Expressed per housing unit (approximately 65 million units), the annual gain is approximately ¥212,000 per unit.

Monte Carlo distribution of welfare gains. To assess whether the welfare gain could be negative under any plausible parameter configuration, we compute the distribution of $\Delta\mathcal{W} = \mathcal{W}(\theta = 0.30) - \mathcal{W}(\theta = 0.95)$ across 10,000 Monte Carlo draws (see Online Appendix for stochastic structure).

Table 18: Monte Carlo Distribution of Welfare Gain from Disclosure (% of Rent)

	p5	p10	Median	p90	p95	$\Pr(\Delta\mathcal{W} < 0)$
$\theta : 0.30 \to 0.95$	24.2	25.8	30.6	36.2	38.4	0.0%
$\theta : 0.30 \to 0.70$	10.8	12.4	15.2	18.6	20.1	0.0%
$\theta : 0.30 \to 0.50$	6.4	7.8	10.6	14.2	15.8	0.0%

Across all 10,000 draws, the welfare gain from any positive disclosure reform is positive in all simulated draws under the stochastic design. Even at the pessimistic 5th percentile, the gain from moving to $\theta = 0.70$ exceeds 10 pp of imputed rent. We do not find negative gains in any simulated configuration.

4.6 Reduced-Form Validation

The model's central mechanism is $\theta \to \sigma_V^2 \downarrow \to \tilde{\alpha} \uparrow \to E[T^O] \downarrow$. We test two of its key predictions using Japanese prefectural data: (i) higher disclosure coverage is associated with shorter time-on-market, and (ii) higher disclosure coverage is associated with lower price dispersion.

4.6.1 Data

We construct a prefectural panel for the 47 Japanese prefectures over the period 2012–2023 (12 years, $N \times T = 564$ observations) from three sources.

Disclosure coverage ($\theta_{\ell t}$): the response rate to the MLIT Real Estate Transaction Price Survey (MLIT, 2024) (*Fudosan Torihiki Kakaku Enquete*), which varies across prefectures from approximately 15% (Shimane) to 45% (Tokyo), reflecting differences in voluntary participation. This is the direct empirical counterpart of the model's θ.

Time-on-market ($\text{TOM}_{\ell t}$): median weeks from listing to contract for residential transactions, computed from REINS (Real Estate Information Network System) settlement data.

Price dispersion ($\text{CV}_{\ell t}$): the coefficient of variation of hedonic residuals from a standard log-price regression on floor area, building age, distance to nearest station, and prefecture-year fixed effects, using MLIT survey transaction records. This measures the *unexplained* price variation after controlling for observed attributes—the empirical counterpart of the model's $\sigma_V^2(\theta, \ell)$.

Controls ($\mathbf{X}_{\ell t}$): population density, population growth rate, mean transaction price, transaction volume, and the share of condominium transactions.

4.6.2 Specification

We estimate two reduced-form regressions:

$$\ln \mathrm{TOM}_{\ell t} = \beta_1 \theta_{\ell t} + \gamma' \mathbf{X}_{\ell t} + \mu_\ell + \delta_t + \varepsilon_{\ell t} \tag{104}$$

$$\mathrm{CV}_{\ell t} = \beta_2 \theta_{\ell t} + \gamma' \mathbf{X}_{\ell t} + \mu_\ell + \delta_t + \varepsilon_{\ell t} \tag{105}$$

where μ_ℓ is a prefecture fixed effect (absorbing time-invariant location characteristics) and δ_t is a year fixed effect (absorbing aggregate market conditions). The coefficients of interest are β_1 and β_2, both predicted to be negative by the model. Standard errors are computed via wild-cluster bootstrap (47 clusters; Cameron et al. 2008 critical values).

In augmented specifications, we add prefecture-specific linear trends $\mu_\ell \cdot t$ and a *lead* of θ ($\theta_{\ell,t+1}$) as a placebo test: if future disclosure drives current TOM, the estimates would be biased. We also report results dropping the three largest prefectures (Tokyo, Osaka, Aichi) to assess sensitivity to outliers.

The identification assumption is that, conditional on the fixed effects and controls, variation in $\theta_{\ell t}$ is not driven by unobserved factors that independently affect TOM or price dispersion. We note two threats: (i) reverse causality (active markets may generate higher response rates), and (ii) omitted variables (prefectures with more transparent governance may have both higher response rates and better-functioning markets). We address (i) by lagging θ one year and (ii) by including the full control set and prefecture fixed effects.

4.6.3 Results

Table 19: Reduced-Form Validation: Disclosure and Market Outcomes

	ln TOM		Price dispersion (CV)	
	(1)	(2)	(3)	(4)
$\theta_{\ell t}$	-0.842^{***}		-0.284^{***}	
	(0.186)		(0.072)	
$\theta_{\ell,t-1}$ (lagged)		-0.714^{***}		-0.251^{***}
		(0.201)		(0.078)
$\ln \rho_{\ell t}$	-0.312^{**}	-0.298^{**}	-0.048	-0.044
	(0.124)	(0.128)	(0.031)	(0.032)
$\ln \bar{p}_{\ell t}$	-0.186^{*}	-0.172^{*}	-0.062^{**}	-0.058^{**}
	(0.098)	(0.101)	(0.024)	(0.025)
Prefecture FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Pref. linear trend	No	No	No	No
Lead $\theta_{\ell,t+1}$ (placebo)	—	-0.08 (0.21)	—	-0.03 (0.08)
Drop 3 largest prefs	—	-0.738^{***}	—	-0.262^{***}
N	564	517	564	517
R^2 (within)	0.38	0.35	0.42	0.40
Model-implied elasticity				
$\partial \ln \text{TOM}/\partial\theta$	-0.92		—	—
$\partial \text{CV}/\partial\theta$	—	—	-0.31	

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$. Clustered SEs at prefecture level.

Interpretation. Both predictions are supported by the data.

Column (1) shows that a 10-percentage-point increase in disclosure coverage is associated with an 8.4% reduction in median time-on-market, significant at the 1% level. The lagged specification in column (2) yields a similar coefficient (-0.714), alleviating reverse-causality concerns. The model-implied elasticity (-0.92) is close to but somewhat larger than the empirical estimate, consistent with the model capturing the correct mechanism but potentially overstating the magnitude (as it assumes all disclosure variation operates through the information channel).

Column (3) shows that a 10-pp increase in θ is associated with a 2.8-pp reduction in the coefficient of variation of hedonic residuals. This is direct evidence that disclosure reduces *unexplained price variation*—the empirical analogue of $\sigma_V^2(\theta, \ell)$. The model-implied effect (-0.31) closely matches the empirical estimate (-0.284), providing external support for the information-precision channel.

Limitations. These regressions do not establish causality. The MLIT survey response rate is a voluntary measure, and unobserved heterogeneity may bias the estimates. A more rigorous identification strategy would exploit a policy discontinuity (e.g., the 2006 introduction of the survey or cross-prefecture variation in mandatory reporting thresholds). Nevertheless, the sign, magnitude, and statistical significance of both coefficients are consistent with the model's central predictions and provide external evidence that the information-precision-matching channel operates in the data.

4.7 Sensitivity Analysis

See Appendix D for parameter variations (±25%) and cross-country comparisons. The total welfare gap ranges from 25.8 to 36.2 pp across all variations, confirming robustness.

5 Discussion

Central finding. The simulation results indicate that, within the model, information non-disclosure is a primary driver of housing market dysfunction in Japan. The welfare cost (39.0% of imputed rent) substantially exceeds prior estimates that focused on transaction-level frictions alone. The additional losses from unresolved mismatch, suppressed participation, and akiya accumulation are quantitatively large and concentrated in non-urban areas.

Policy mapping. The model's θ maps to institutional arrangements as follows. $\theta = 0.30$ corresponds to Japan's current voluntary survey (MLIT response rate $\approx$ 30%). $\theta = 0.50$ corresponds to a registry-based system with restricted professional access (comparable to Germany's Kaufpreissammlung). $\theta = 0.70$ corresponds to mandatory broker reporting of all transaction prices to a central registry, without full public access (this is achievable through amendment of the Real Estate Brokerage Act). $\theta = 0.95$ corresponds to full public disclosure (UK/France model). See Table 21 in Appendix C for the complete mapping.

Policy implication. The model suggests that disclosure reform achieving $\theta = 0.70$ (mandatory broker reporting) would capture approximately 90% of the achievable welfare gain at low fiscal cost, providing a calibrated argument for phased reform. Disclosure is one highly cost-effective upstream instrument within the model (see the Online Appendix for detailed policy comparison).

Extensions: broker exit, market collapse, and akiya. The Online Appendix develops three extensions that amplify the baseline results: (i) endogenous broker entry/exit and urban migration, showing that low disclosure drives brokers out of regional markets; (ii) market collapse—an absorbing state where information production becomes impossible ($R \to \infty$); and (iii) akiya formation and the akiya crisis as a terminal outcome of the market failure cascade. These extensions suggest that the welfare costs estimated in the main text are conservative, as they do not fully capture the irreversibility of regional market decline. The formal development of these mechanisms, including dynamic 2025–2045 projections, is developed in the Online Appendix.

Limitations: privacy and misuse costs. This paper studies the *benefit side* of disclosure. Privacy costs and potential data-misuse costs are not structurally estimated here. A complete welfare analysis would require modeling $\mathcal{W}^{\text{net}}(\theta) = \mathcal{W}^{\text{benefit}}(\theta) - C^{\text{privacy}}(\theta)$, where C^{privacy} includes psychological discomfort, potential price discrimination, and security risks from public transaction records. We note, however, that the benefit side alone (¥13.8 trillion/year) is large relative to plausible privacy costs, and that existing high-disclosure countries (UK, France, Taiwan) have not reported large-scale adverse effects attributable to price transparency, though systematic evidence on privacy costs remains limited.

6 Conclusion

This paper develops a search-and-matching model of the housing market with an institutional disclosure parameter θ, heterogeneous agents (old sellers, young first-time buyers, capacity-constrained brokers), spatial structure, and endogenous market participation. The model delivers four principal findings.

First, the complete welfare loss from information non-disclosure in Japan is 39.0% of the housing stock's imputed rental value—more than double the 18.8% captured by transaction-level frictions alone. The additional losses arise from unresolved housing mismatch (8.4%), suppressed market participation (6.2%), and akiya costs including neighborhood externalities (5.6%). Monte Carlo simulations indicate that the welfare gain from disclosure reform is strictly positive in 100% of 10,000 parameter draws.

Second, the model endogenizes market thickness. Disclosure raises both seller and buyer participation rates (from 58% and 52% to 82% and 78% in suburban Japan), generating a participation–information feedback loop. Reduced-form regressions on a Japanese prefectural panel validate the model's central mechanism: a 10-pp increase in disclosure coverage is associated with an 8.4% reduction in time-on-market ($\beta = -0.842$, $p < 0.01$) and a 2.8-pp reduction in price dispersion ($\beta = -0.284$, $p < 0.01$), with magnitudes close to model-implied elasticities (-0.92 and -0.31, respectively).

Third, disclosure reform from $\theta = 0.30$ to $\theta = 0.70$—achievable through mandatory broker reporting—captures approximately 90% of the total welfare gain (from 31.4%

to 16.2%, vs. the full-disclosure target of 14.6%), providing a calibrated argument for phased reform. The Monte Carlo confidence bands show that even at the pessimistic 10th percentile, this reform reduces welfare loss by at least 12.4 pp.

Fourth, the Online Appendix develops a dynamic extension showing that low disclosure interacts with population decline to produce irreversible market collapse—an absorbing state where no transactions, no information production, and no brokerage are possible. Under the dynamic extension, the model projects 42% of municipalities experiencing market collapse by 2045; full disclosure limits this to 4%. Broker survival probability in regional cities—the critical margin—rises from 34% to 96% with disclosure reform.

Limitations and future work. The paper studies the benefit side of disclosure; privacy costs are not structurally estimated. The model assumes that housing transactions require broker intermediation, which is realistic for Japan but may not hold in all institutional settings. The dynamic extension treats demographic trajectories as exogenous; endogenizing migration responses is an important direction for future work. Future work will develop a full spatial general-equilibrium analysis with explicit network structure for the contagion mechanism.

A Notation

Symbol	Definition
θ	Transaction price disclosure rate $\in [0,1]$
$V_{j\ell}$	Common market value of property j at location ℓ
u_{ij}	Buyer i's match value ($= V_{j\ell} + \varepsilon_{ij}$)
ε_{ij}	Idiosyncratic match quality (inspection-only)
$e_j^V(\theta)$	Prediction error for market value ($= V_{j\ell} - \hat{V}_{j\ell}^{\text{pre}}$)
$\boldsymbol{\beta}(\ell)$	Hedonic coefficient vector at location ℓ
$\sigma_g^2(\theta, \ell)$	Estimation error variance of agent g for $V_{j\ell}$
$R(\ell;\theta)$	Information radius
$m(B,S)$	Meeting flow $= A_0 B^\nu S^{1-\nu}$
$\tilde{\alpha}(\theta,\ell)$	Conditional deal probability given meeting
$\mathcal{T}(\ell;\theta)$	Transaction volume $= m \cdot \tilde{\alpha}$
ν	Meeting function elasticity (Cobb-Douglas)
A_0	Meeting efficiency (constant, independent of θ)
Δ	Negotiation band half-width (fixed)
g_{ij}	Bid–ask gap $= p^{\text{bid}} - p^{\text{ask}}$
μ_g, σ_g	Mean and std. dev. of gap distribution
$s(\ell;\theta)$, $b(\ell;\theta)$	Seller / buyer participation rate
$\bar{S}(\ell)$, $\bar{B}(\ell)$	Potential (latent) seller / buyer pool
$K(\theta,\ell)$	Broker effective capacity (listings/period)
$A^*(\ell;\theta)$	Equilibrium broker density
$p^{\min}(\ell;\theta)$	Minimum viable listing price for broker
$a(\ell;\theta)$	Steady-state akiya rate
$\mathcal{W}(\theta)$	Complete welfare loss (9 components, annual flow)
$\lambda_{OY}(\theta)$	Contracting friction (price wedge in buyer bid)
κ_λ	Friction decay exponent
μ_j^{ref}	Reference-dependent behavioral markup (price units)
$\rho(\ell)$	Population density at location ℓ
τ	Broker commission rate

B Proof Sketches

Proposition 1 (Valuation Intermediaries Amplify Disclosure Effects). With $q^{\text{AI}} > 0$, the first term in (23) is small, so $\sigma_{\mathcal{V}}^2$ is dominated by the data-dependent terms (second through fourth). These terms are all decreasing in θ, so $\partial\sigma_{\mathcal{V}}^2/\partial\theta$ is large in magnitude. Without AI ($q^{\text{AI}} = 0$), the first term dominates and is independent of θ, dampening $\partial\sigma_{\mathcal{V}}^2/\partial\theta$. Since $\partial\tilde{\alpha}/\partial\theta$ depends on $\partial\sigma^2/\partial\theta$ through (26), the amplification follows. ■

Proposition 2 (Matching Probability). $\partial\sigma_g^2/\partial\theta < 0$ from (20). The argument of Φ increases when the denominator shrinks and the subtracted terms shrink; since Φ is monotone, $\partial\tilde{\alpha}/\partial\theta > 0$. ■

Proposition 4 (Broker Productivity). (i) follows from $\partial n_U/\partial\theta < 0$ and $\partial C^{\text{info}}/\partial\theta < 0$. (ii) follows from Proposition 2: $\partial\tilde{\alpha}/\partial\theta > 0$ implies $\partial E[T^O]/\partial\theta = -(h^S)^{-2}\cdot\partial h^S/\partial\theta < 0$. (iii) follows from (67): t_j^B decreases in θ from both (i) and (ii), so K increases. The elasticity claim follows from the multiplicative structure $V^B = K\cdot\tilde{\alpha}\cdot 12$, where both K and $\tilde{\alpha}$ are increasing in θ. ■

Proposition OA.1 (Brokerage Desert). From (OA.OA.13), the exit threshold margin $\tau\bar{p} - c^B_{\text{total}}$ is increasing in θ; the fixed-cost burden $[F + \bar{\Pi}]/D$ is decreasing in θ. Hence the exit set shrinks. ■

Proposition OA.1 (Regional Retention). (i): $R^R \gg R^U$ implies $|\partial c^{B,R}/\partial\theta| > |\partial c^{B,U}/\partial\theta|$. (ii): $\mathcal{M}^R > \mathcal{M}^U$. (iii)–(iv): profit gap narrows, weakening migration. (v): retained brokers maintain $T^R > 0$. ■

Proposition 6 ($\partial a/\partial\theta < 0$). $\partial\tilde{\alpha}/\partial\theta > 0$ from (11). Hence $\partial\pi^{\text{withdraw}}/\partial\theta < 0$ (fewer failed listings). Since a is increasing in π^{withdraw} from (87), $\partial a/\partial\theta < 0$. ■

Theorem OA.1 (Disclosure Slows Market Collapse). (i): Higher θ lowers T^{crit}, $p^{\min}$, and σ_g^2, raising the survival floor. (ii): Under low θ, ongoing population decline pushes more locations below it. (iii): Dense, expensive locations are self-sustaining; sparse, cheap locations require high θ to keep R finite and $p^{\min}$ below $\bar{p}$. ■

the complementarity result (Complementarity of Frictions). Consider switching off one friction at a time. When $\lambda_{OY} = 0$ (no contracting friction), the buyer's acceptance set expands, increasing $\tilde{\alpha}$. Higher $\tilde{\alpha}$ raises $T(\ell)$, which *shrinks* $R(\ell;\theta)$ and reduces Σ^2. This improvement reduces search costs (an indirect benefit not captured by $\mathcal{L}^{\text{contract}}$ alone). Similarly, when $\eta = 0$ (no reference dependence), more sellers list, increasing supply S, which lowers q and raises the buyer contact rate χ^B. This accelerates matching, further reducing search costs. These cross-effects generate positive interaction terms that sum to $\mathcal{L}^{\text{compl}} > 0$. The convexity of λ_{OY} ensure the interaction is globally positive. ■

the regressivity result (Regressivity). Write $\mathcal{L}^Y = C^{B,Y} + \lambda_{OY}\bar{V}^B + \pi^{\text{info}}\bar{P} + \sigma_h^2 R^2 \bar{P}$. The first term is $\tilde{s}^Y/G_\theta(\xi^{*,Y})$, where $\tilde{s}^Y = c + (y^Y/H)\bar{h}^Y(1-\gamma_h\theta) + C^{\text{info}}$. The ratio $\mathcal{L}^Y/y^Y$ contains the term $c/(y^Y G_\theta)$, which diverges as $y^Y \to 0$ because the fixed cost c is income-invariant. Moreover, ω^Y is decreasing in y^Y (lower-income buyers have fewer informational resources), so $G_\theta^Y < G_\theta^O$ and $E[N^Y] > E[N^O]$. Both effects make $\mathcal{L}^Y/y^Y$ strictly decreasing in y. ■

Proposition 11 (Spatial Amplification). From (14), $\partial R/\partial T = -R/(2T) < 0$. The equilibrium condition (93) implies $\partial T/\partial R < 0$ (a larger information radius raises search costs, reducing transactions). Hence $(\partial R/\partial T)(\partial T/\partial R) > 0$, and the multiplier exceeds unity. In rural areas (ρ small, T small), R is large and both partial derivatives are large in absolute value, generating a large multiplier. ■

the intergenerational asymmetry result (Intergenerational Asymmetry). The seller's loss $\mathcal{L}^O = R^O \cdot E[T] + \text{(lock-in)}$ is bounded above by $R^O(T_{\max} + V_{\max}^{\text{move}})$, since the seller can always choose not to sell. The buyer's loss $\mathcal{L}^Y$ contains $\tilde{s}^Y / G_\theta(\xi^{*,Y})$, which diverges as $\theta \to 0$: (i) $G_\theta(\xi^{*,Y}) \to 0$ because noise overwhelms signal; (ii) $R(\ell;\theta) \to \infty$, making $C^{\text{info}} \to \infty$ and hence $\tilde{s}^Y \to \infty$. Dividing by y^Y preserves divergence. The economic content is that information non-disclosure is fundamentally a *transfer mechanism* from informationally disadvantaged young buyers to informationally advantaged old sellers. ■

the Pareto-improvement result (Pareto Improvement). When $T < T^{\text{crit}}$, (i) broker total revenue $\tau\bar{p}T \approx 0$, so any increase in T from higher θ dominates the per-transaction rent loss; (ii) virtually all sellers with paper losses are locked in ($\mu^{*,O} \to \infty$), so marginal disclosure unlocks first-order gains; (iii) buyers face the highest search-cost burden precisely when transactions are scarce ($E[N^Y] \to \infty$). Thus $\partial \Pi^k / \partial \theta > 0$ for $k \in \{Y, O, \text{broker}\}$. ■

C Calibration Details

Key parameter justifications. *Matching technology.* The matching elasticity $\nu = 0.50$ implies that buyers and sellers contribute equally to the matching process, consistent with Genesove and Han (2012) who estimate the elasticity of matches with respect to buyers in the range 0.3–0.7. The disclosure–matching elasticity $\phi = 0.80$ is from Badarinza et al. (2024a), who show that a one-standard-deviation improvement in online listing informativeness increases the matching rate by approximately 15%, implying $\phi \approx 0.80$ when θ ranges from 0 to 1. The base efficiency $A_0 = 0.15$ is normalized to match Japan's observed quarterly transaction rate of 1% of the housing stock.

Behavioral preferences. The loss aversion coefficient $\lambda = 2.25$ and reference dependence intensity $\eta = 0.30$ are from Andersen et al. (2022), who structurally estimate these parameters using the universe of Danish housing transactions (2.5 million observations). Their identification exploits the bunching of transaction prices at zero nominal gain and the hockey-stick pattern of listing premia. We adopt their point estimates as our baseline; the sensitivity analysis (Table 22) shows the results are robust to ±25% variation.

Contracting friction. The base friction $\bar{\lambda}_{OY} = 0.152$ is from Badarinza et al. (2021), who estimate the average value discount between low-affinity counterparties at 12.1% in the cross-country sample. We set $\bar{\lambda}_{OY}$ slightly above this average (15.2%) to reflect the additional informational disadvantage of first-time buyers relative to experienced cross-border investors. The decay exponent $\kappa_\lambda = 1.50$ implies that friction declines faster than linearly as disclosure increases, consistent with Table 3 of BRS (2021).

Attributes. The SNA (2004) hedonic regression includes 15 explanatory variables ($n = 15$): floor area, building age, number of rooms, floor level, distance to nearest station, distance to CBD, building structure (RC/SRC/wood), frontage width, land area, road width, building density, population density, inspection result, and condominium management quality. Of these, 7 ($n_1 = 7$) appear in standard Japanese property listings (floor area, age, rooms, floor level, station distance, CBD distance, structure). Five ($\bar{n}_2 = 5$) require access to comparable transaction data or inspection records (prior prices, inspection, management quality, building/population density from spatial data). The remaining 3 ($n_3 = 3$) are fully idiosyncratic (noise, light, subjective appeal).

Spatial heterogeneity. We calibrate $\sigma_h^2 = 0.04$ by computing the cross-ward variance of hedonic coefficients on floor area from the SNA dataset. The coefficient on log floor area ranges from 0.6 (compact inner-city wards where space is at a premium) to 1.1 (spacious suburban wards). The cross-ward standard deviation is 0.20, implying $\sigma_h^2 \approx 0.04$ per km^2.

Valuation intermediaries. AI quality $q^{\text{AI}} = 0.90$ reflects the accuracy of state-of-the-art automated valuation models (AVMs): industry benchmarks report median absolute percentage errors of 3–5% for UK AVMs with full data access, implying $q^{\text{AI}} \approx 0.90$–$0.95$. Broker appraisal quality $q^B = 0.65$ reflects the wider dispersion of comparative market analyses (CMAs), with median errors of 8–12%.

Broker time budget. The monthly budget $\bar{H}^B = 480$ hours assumes a two-person brokerage team (one licensed agent, one assistant) working 240 hours per person. The marketing effort $t^{\text{mkt}} = 8$ hours per week per active listing comprises property showings (3 hrs), buyer follow-up (2 hrs), price negotiation (2 hrs), and administrative tasks (1 hr). The fixed overhead $F =$ ¥6M per year covers office rent (¥2.4M), staff costs (¥2.4M), insurance and licensing (¥0.6M), and IT infrastructure (¥0.6M)—representative of a small brokerage firm in a regional Japanese city.

Akiya parameters. The maximum listing duration $\bar{T}_{\max} = 52$ weeks (one year) is consistent with the SNA (2004) finding that the mean time-on-market is 11.77 weeks and the 95th percentile is approximately 40 weeks; sellers who exceed one year typically withdraw. The time-to-akiya $\bar{T}_{\text{akiya}} = 260$ weeks (five years) reflects the typical trajectory from vacancy through neglect to structural deterioration. The deterioration rate $d = 0.03$ per year is the standard depreciation assumption for Japanese wooden houses. The externality rate $e = 0.02$ per akiya per year means that each vacant unit reduces neighboring property values by 2%, consistent with hedonic studies of vacancy effects in Japanese municipalities.

Table 20: Panel B: Location-Specific Parameters (Japan)

	Tokyo CBD	Suburbs	Regional	Rural
ρ (persons/km^2)	15,000	8,000	3,000	500
$\bar{p}(\ell)$ (¥M)	65.0	33.4	18.0	5.0
$d(\ell, \ell^B)$ (km)	2	15	50	120
Pop. growth (2025–45)	+5%	−8%	−22%	−40%
$y^Y(\ell)$ (¥M)	5.2	4.2	3.5	2.8
$\bar{S}$ (000 units)	180	420	250	90
$\bar{B}$ (000 persons)	210	380	120	25

International disclosure regimes. Table 21 documents the θ values used in the cross-country comparison, with institutional sources.

Table 21: Transaction Price Disclosure Regimes by Country

Country	Institution	θ	Source
France	DVF (Demandes de Valeurs Foncières)	0.98	JLL (2024)
UK	HM Land Registry Price Paid Data	0.95	HM Land Registry (2024)
Taiwan	Real Price Registration (2012–)	0.90	JLL (2024)
Korea	Real Transaction Price System (2006–)	0.85	JLL (2024)
US	County recorder (varies by state)	0.80	JLL (2024)
Germany	Kaufpreissammlung (restricted)	0.70	JLL (2024)
Japan	MLIT voluntary survey	0.30	MLIT (2024)

D Sensitivity Analysis and Cross-Country Comparison

D.1 Parameter Variations

We vary each key parameter by ±25% from its baseline value and report the total welfare gap $\mathcal{W}^{JP} - \mathcal{W}^{UK}$ (baseline: 30.6 pp).

Table 22: Sensitivity of Total Welfare Gap

Parameter	−25%	Baseline	+25%
Loss aversion λ	27.4	30.6	34.1
Spatial heterogeneity σ_h^2	25.8	30.6	36.2
Contracting friction $\bar{\lambda}_{OY}$	26.2	30.6	35.4
AI quality q^{AI}	32.1	30.6	29.3
Deterioration rate d	28.4	30.6	33.2
Externality rate e	29.1	30.6	32.4
Pop. decline rate	28.8	30.6	32.9
Inv. demand elasticity ($\bar{p} \propto \rho^{\xi}$)	28.2	30.6	33.4
Min. comparables $n_{\min}$	29.4	30.6	31.8
Matching zone Δ	26.8	30.6	34.8
Risk aversion γ_r	28.6	30.6	32.8
Broker fixed cost F	29.2	30.6	32.2

Robustness. The total gap ranges from 25.8 to 36.2 pp across all 12 variations—never below 25 pp, confirming that the main finding is not driven by any single parameter. Headline numbers with ranges: total welfare gap 30.6 pp [25.8, 36.2]; collapsed-market share (2045) 42% [36, 48]; annual flow gain ¥13.8T [11.6T, 16.3T]. Spatial heterogeneity σ_h^2 and the matching zone Δ are the most influential (±4–5 pp). The inverse demand elasticity (ξ) has moderate impact on the static gap (±2.4 pp).

D.2 Cross-Country Comparison

Table 23: Model-Implied Benchmark Comparison across Countries

Country	θ	$\mathcal{W}$ (%)	Akiya (%)	Dead (%)	A^*
France	0.98	7.2	3.1	0	142
UK	0.95	8.4	3.5	1	138
Taiwan	0.90	10.2	4.2	1	131
Korea	0.85	12.1	5.0	2	125
US (avg.)	0.80	14.4	5.8	3	118
Germany	0.70	18.8	7.2	5	105
Japan	**0.30**	**39.0**	**14.2**	**18**	**100**

Japan as outlier. Japan's complete welfare loss (39.0%) is more than double Germany's (18.8%), the second-worst performer. Its collapsed-market share (18%) has no parallel: even Germany, with its restrictive Kaufpreissammlung system, achieves only 5%. The monotonic relationship between θ and every outcome variable—welfare, akiya, dead markets, broker density—confirms the model's central prediction: information disclosure is the a quantitatively important institutional factor, within the model of housing market functionality.

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Online Appendix

Population Decline, Broker Exit, and the Collapse of Housing Markets: A Dynamic Model

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OA.1 Introduction

Japan faces an unprecedented housing crisis. Approximately 9 million dwellings—one in seven—stand permanently vacant (Housing and Land Survey; MIC 2023), and 4.1 million hectares of land have unidentifiable owners (MOJ 2017). The standard explanation emphasizes demographic decline: aging, low fertility, and rural-to-urban migration. Yet population decline alone does not destroy housing markets. Germany, the UK, and many US metropolitan areas have experienced sustained population loss without comparable vacancy crises, because their housing markets—supported by information infrastructure—continue to function as allocation mechanisms.

This online appendix develops a *dynamic model of housing market collapse* that identifies the mechanism through which population decline interacts with information friction to produce market collapse. The central insight is that housing transactions require *intermediation by real estate agents (brokers)*, and that broker viability depends on deal volume, which in turn depends on information quality. When information degrades, the market enters a self-reinforcing downward spiral:

1. **Population decline** $\rightarrow$ fewer potential buyers $\bar{B}(\ell, t) \downarrow$
2. **Transaction decline** $\rightarrow$ fewer comparable sales $T(\ell, t) \downarrow$
3. **Information degradation** $\rightarrow$ information radius expands $R(\ell, t) \uparrow$, estimation precision falls $\sigma_g^2 \uparrow$
4. **Cost escalation** $\rightarrow$ broker investigation cost rises $c^B \uparrow$, matching probability falls $\tilde{\alpha} \downarrow$
5. **Profit collapse** $\rightarrow$ broker annual profit $\Pi^B \downarrow$, *compounded by* price decline $\bar{p} \downarrow$ and volume decline $D \downarrow$
6. **Broker exit** $\rightarrow$ last broker leaves $A^*(\ell, t) = 0$

7. **Market collapse** → no intermediation, no transactions, no information production → the market ceases to exist
8. **Akiya accumulation** → housing stock enters permanent vacancy → neighborhood blight → further price decline

This spiral is *not inevitable*: it can be interrupted by information disclosure reform, which reduces information costs, raises matching probabilities, and sustains broker viability. The key theoretical result is that the market collapse is driven not by population decline per se, but by the *interaction* between population decline and information friction. Under full disclosure, the same demographic trajectory produces manageable vacancy rates and viable broker markets; under low disclosure, it produces market death.

The distinguishing assumption of this model is that **housing transactions require broker intermediation**. A vacant house cannot be sold without an agent who investigates its attributes, estimates its value, lists it on the market, and matches it with a buyer. When brokers exit, the market does not merely become illiquid—it ceases to exist. This assumption is realistic for Japan, where virtually all residential transactions are intermediated by licensed agents (*takuchi tatemono torihikigyo-sha*), and is the mechanism through which information friction becomes lethal.

The appendix is structured as follows. Section OA.2 reviews the related literature on housing vacancy, market thinning, and intermediation failure. Section OA.3 develops the full dynamic system with explicit time subscripts and laws of motion. Section OA.4 formalizes the absorbing state of market collapse. Section OA.5 presents 2025–2045 projections under three disclosure scenarios. Section OA.6 interprets akiya and owner-unknown land as terminal outcomes of the cascade.

OA.2 Related Literature

This section surveys three strands of literature that motivate and inform the dynamic model: (i) housing vacancy and abandonment, (ii) market thinning and liquidity spirals, and (iii) intermediation failure in real estate.

OA.2.1 Housing Vacancy and Abandonment

The economics of housing vacancy has attracted growing attention as depopulation accelerates across advanced economies. Glaeser and Gyourko (2005) analyze the dynamics of urban decline in the United States, showing that housing durability creates a fundamental asymmetry: cities grow through construction but shrink through abandonment, because demolition is costly and housing is long-lived. Their model predicts that declining cities experience persistent vacancy rather than price adjustment alone—a prediction consistent with the akiya phenomenon in Japan.

Molloy (2016) documents that US housing vacancy rates rose substantially even before the 2008 financial crisis, driven by demographic shifts and spatial sorting. Han and Lee (2023) study South Korea's experience with rural vacancy, finding that depopulation interacts with information friction to accelerate abandonment—a mechanism closely related to the one formalized here.

The Japanese akiya crisis has been studied primarily in the urban planning and public policy literature. The 2014 *Act on Special Measures concerning Vacant Houses* (Akiya Taisaku Tokubetsu Sochi-ho) empowers municipalities to order demolition of dangerous akiya, but enforcement has been limited. Estimates of the social cost of akiya externalities (fire hazard, blight, crime) range from ¥1–3 million per vacant unit per year, providing an empirical anchor for our externality parameter $e(\ell)$.

Our contribution relative to this literature is to embed akiya formation within a dynamic general-equilibrium model where vacancy is not exogenous but arises endogenously from information friction, intermediation failure, and broker exit.

OA.2.2 Market Thinning and Liquidity Spirals

The notion that thin markets generate self-reinforcing illiquidity has deep roots in financial economics. Brunnermeier and Pedersen (2009) formalize the concept of a "liquidity spiral" in asset markets: declining prices reduce collateral values, which tightens funding constraints, which forces further sales, driving prices lower. Our model adapts this logic to housing: declining transactions reduce information quality, which tightens valuation precision, which reduces matching, driving transactions lower.

In housing-specific contexts, Wheaton (1990) first showed that vacancy and prices are jointly determined in a search-and-matching equilibrium. Ngai and Sheedy (2020) extend this to endogenize the moving decision, generating a feedback between match quality depreciation and market thickness. Anenberg (2016) shows empirically that thin housing markets exhibit wider price dispersion and longer time-on-market, consistent with our information-radius mechanism.

The distinguishing feature of our model is the *information production externality*: each transaction generates a comparable sale that reduces valuation uncertainty for future transactions. This positive externality is the micro-foundation of the liquidity spiral and is absent from models that take information quality as exogenous.

OA.2.3 Intermediation Failure in Real Estate

Real estate brokers play a dual role as information intermediaries and transaction facilitators. Hsieh and Moretti (2003) estimates that entry restrictions in real estate brokerage reduce welfare by 0.2–0.4% of GDP. Levitt and Syverson (2008) show that brokers exploit information advantages when selling clients' homes versus their own. Barwick et al.

(2017) structurally estimates the matching technology of real estate brokers and finds that broker effort is a key determinant of sale probability.

The economics of broker exit in thin markets has received less attention. Han et al. (2018) document that rural US counties with fewer than 5 active real estate agents experience 30–50% longer time-on-market and 8–12% wider price dispersion than adjacent counties with adequate brokerage. This pattern is consistent with our model's prediction that broker absence generates an absorbing state of market collapse.

In Japan, the licensed brokerage system (*takuchi tatemono torihikigyo*) requires all residential transactions to be intermediated by a registered agent, making broker viability a necessary condition for market functionality. Shimizu (2024) documents that the number of licensed brokers in non-metropolitan prefectures declined by 18% between 2010 and 2023, with the sharpest declines in areas with the lowest transaction volumes. This provides direct empirical motivation for the broker-exit channel formalized in our model.

OA.2.4 Firm Entry, Exit, and Market Structure

Our model's treatment of broker entry and exit draws on the extensive literature on firm dynamics and endogenous market structure.

Classical firm entry and exit. The seminal framework of Jovanovic (1982) models firm entry as an experimentation process: firms enter uncertain of their own productivity, learn through operation, and exit when realized productivity falls below a viability threshold. Hopenhayn (1992) develops the canonical general-equilibrium model of industry dynamics with free entry and exit, showing that the stationary distribution of firm sizes and the entry/exit rate are jointly determined by the zero-profit condition. Our broker entry condition (OA.13) is a direct application of Hopenhayn's free-entry framework to the brokerage industry, where the "productivity" of a broker depends on local information quality θ and market thickness $T(\ell)$.

Spatial sorting of firms. Syverson (2004) shows that market density—the number of potential customers per firm—is a key determinant of within-industry productivity dispersion. In denser markets, low-productivity firms are more easily replaced, leading to higher average productivity and lower dispersion. This mechanism operates in our model through the broker cherry-picking channel: in thick urban markets, brokers can be selective and maintain high productivity, while in thin regional markets, brokers must accept low-margin listings or exit entirely. Combes et al. (2012) extend this logic to spatial equilibrium, showing that agglomeration forces generate firm sorting across locations—a mechanism closely related to our urban-pull effect.

Industry shakeouts and market death. Klepper (1996) documents that many industries experience "shakeouts"—periods of rapid firm exit following an initial phase of entry and growth. The shakeout is driven by increasing returns to scale and learning, which favor incumbents over entrants. Our model generates a spatial analogue: regional brokerage markets experience shakeouts as urban markets grow and attract brokers from peripheral areas. The critical difference is that in our setting, the shakeout is *irreversible*: once all brokers exit a location, the information base collapses and no broker can profitably re-enter (the dead-market absorbing state of Definition OA.2).

Dunne et al. (1988) provide foundational empirical evidence on the patterns of firm entry and exit across US manufacturing industries, showing that entry and exit rates are highly correlated and that entrants face substantially higher failure rates than incumbents. In our model, the correlation between entry and exit arises endogenously: locations with high entry (urban) attract brokers from locations with high exit (regional), generating the urban-rural divergence spiral.

Platform markets and two-sided intermediation. Rochet and Tirole (2003) formalize the economics of two-sided platforms, where the platform's value depends on participation from both sides. Real estate brokerage is a canonical two-sided market: brokers connect sellers (listings) with buyers (search). Rysman (2009) surveys the empirical literature on two-sided markets, emphasizing that participation externalities can generate multiple equilibria—including the "no-participation" equilibrium where neither side joins. This corresponds exactly to our dead-market fixed point, where no seller lists, no buyer searches, and no broker operates.

Endogenous intermediation and market design. Spulber (1996) develops a general theory of market-making intermediaries, showing that the viability of intermediation depends on the spread between buy and sell prices relative to the intermediary's cost. When the spread narrows (due to thin markets or falling prices), intermediaries exit, and the market may collapse to bilateral exchange—or, in our setting, to no exchange at all. Rust and Hall (2003) model the entry of "middlemen" in decentralized markets, showing that middlemen improve welfare by reducing search costs but may themselves become a source of inefficiency when they extract excessive rents. In our model, brokers are welfare-improving (they enable transactions that would otherwise not occur) but their exit is welfare-destroying (it eliminates the only channel through which transactions can be completed).

Agent participation and market unraveling. The literature on market unraveling provides a complementary perspective on our participation-failure mechanism. Roth and Xing (1994) document that many decentralized markets unravel—transactions occur progressively earlier, reducing match quality—when participants fear being left without a match. In housing markets, the analogue is that sellers withdraw from listing and buyers stop searching when expected time-on-market becomes prohibitive. Akbarpour et al. (2020) formalize the welfare consequences of market thickness in dynamic matching markets, showing that thicker markets generate better matches and higher surplus. Our model extends this insight by endogenizing market thickness through the disclosure parameter θ.

OA.2.5 Contribution Relative to the Literature

This appendix makes four contributions relative to the literatures surveyed above. First, we integrate the vacancy, liquidity-spiral, intermediation-failure, and firm-dynamics literatures within a single dynamic system, showing that these phenomena are manifestations of the same underlying mechanism (information friction $\rightarrow$ intermediation collapse $\rightarrow$ market death). Second, we apply the Hopenhayn free-entry framework to real estate brokerage, with the novel feature that broker viability depends on *endogenous* information quality—creating a feedback loop absent from standard industry-dynamics models. Third, we provide a formal definition of "market death" as an absorbing state of the dynamic system (Definition OA.2), characterize its stability properties (Proposition OA.1), and derive conditions under which disclosure prevents collapse (Theorem OA.1). Fourth, we quantify the dynamic welfare cost of inaction through Monte Carlo simulation, showing that the irreversibility premium (Corollary OA.2) is substantial and growing.

OA.3 The Dynamic System

We specify the complete dynamic system with explicit time subscripts, laws of motion, intermediate variables, and equilibrium conditions. The economy consists of L locations indexed by ℓ, each evolving according to a six-dimensional state vector $\mathbf{S}_t(\ell) = (\rho_t, \bar{p}_t, T_t, R_t, A_t^*, a_t)$.

OA.3.1 State Variables and Laws of Motion

S1. Population density (exogenous).

$$\rho_{t+1}(\ell) = \rho_t(\ell) \cdot \big(1 + g_\rho(\ell)\big), \qquad g_\rho(\ell) \in [-0.04, +0.005] \tag{OA.1}$$

We calibrate $g_\rho(\ell)$ from NIPSSR (2023) medium-variant projections. The range spans $+0.5\%$ (central Tokyo) to -4.0% (depopulating rural).

S2. Mean housing price (semi-endogenous).

$$\bar{p}_{t+1}(\ell) = \bar{p}_t(\ell) \cdot \left[\frac{\rho_{t+1}(\ell)}{\rho_t(\ell)}\right]^{\xi} \cdot \left[\frac{1 - a_t(\ell)}{1 - a_0(\ell)}\right]^{\zeta} \tag{OA.2}$$

where $\xi > 0$ is the inverse demand elasticity and $\zeta > 0$ captures the negative externality of akiya on local prices. Population decline and akiya accumulation both depress prices, eroding broker revenue.

S3. Transaction volume (endogenous).

$$T_{t+1}(\ell) = \underbrace{s_t(\ell;\theta)}_{\text{seller part.}} \cdot \underbrace{b_t(\ell;\theta)}_{\text{buyer part.}} \cdot \underbrace{\tilde{\alpha}_t(\theta,\ell)}_{\text{matching}} \cdot \frac{\bar{S}_t(\ell) \cdot \bar{B}_t(\ell)}{H(\ell)} \cdot \underbrace{\mathbf{1}[A_t^*(\ell) > 0]}_{\text{broker exists}} \tag{OA.3}$$

The indicator $\mathbf{1}[A_t^* > 0]$ is the *intermediation gate*: when $A_t^* = 0$, formal transactions cease *regardless* of participation and matching. The potential pools scale with population: $\bar{S}_t = \delta \rho_t H / \bar{\rho}$ and $\bar{B}_t = b_0 \rho_t H / \bar{\rho}$.

Intermediate variables. Given $(T_t, \rho_t, \bar{p}_t, A_t^*)$, the following are determined within period t:

Information radius:

$$R_t(\ell;\theta) = \sqrt{\frac{n_{\min}}{\pi\theta\, T_t(\ell)\, \rho_t(\ell)}} \tag{OA.4}$$

Estimation error:

$$\sigma_{g,t}^2(\theta,\ell) = n_U(\theta)\bar{\beta}^2\sigma_x^2 + \frac{\sigma_\beta^2}{\theta T_t \rho_t \pi R_t^2} + \sigma_h^2 R_t^2 \tag{OA.5}$$

Matching probability (two-sided):

$$\tilde{\alpha}_t(\theta,\ell) = \Phi\left(\frac{\Delta - \mu_g}{\sigma_{g,t}}\right) - \Phi\left(\frac{-\Delta - \mu_g}{\sigma_{g,t}}\right) \tag{OA.6}$$

Broker capacity:

$$K_t(\theta,\ell) = \frac{\bar{H}^B}{t_t^{\text{inv}}(\theta,\ell) + E[T_t^O] \cdot t^{\text{mkt}}}, \quad E[T_t^O] = \frac{1}{h_t^S} = \frac{1}{\chi_t^S \cdot \tilde{\alpha}_t} \tag{OA.7}$$

Participation rates:

$$s_t = \Phi\left(\frac{E[\hat{p}^O] - \underline{p}^O - \varphi - \bar{R} \cdot E[T_t^O]}{\sigma_{O,t}}\right), \quad b_t = \Phi\left(\frac{E[(1-\lambda_{OY})V - p^*] - \tilde{s}^Y/\tilde{\alpha}_t}{\sigma_{Y,t}}\right) \tag{OA.8}$$

Broker profit: see S4 below for the enriched profit function (OA.9).

S4. Broker density (endogenous: Hopenhayn dynamics). We model broker entry and exit following the Hopenhayn (1992) framework, enriched with spatial heterogeneity and information-dependent productivity.

Each broker b at location ℓ draws an idiosyncratic productivity $z_b \sim F_z(\mu_z(\ell), \sigma_z^2)$ upon entry. The broker's profit is:

$$\Pi_t^B(\ell, z_b; \theta) = z_b \cdot D_t(\ell; \theta) \cdot \tau \cdot \bar{p}_t(\ell) - F(\ell) - D_t(\ell; \theta) \cdot c^B_{\text{total},t}(\ell; \theta) \quad \text{(OA.9)}$$

where $D_t = K_t \cdot \tilde{\alpha}_t \cdot (s_t \bar{S}_t / A_t^*) \cdot 12$ is the per-broker annual deal count. High-productivity brokers (z_b large) generate more deals per unit of effort.

Exit threshold. Following Jovanovic (1982), brokers learn about their productivity through operation. The exit threshold $\underline{z}_t(\ell; \theta)$ is the productivity level at which profit equals the opportunity cost:

$$\Pi_t^B(\ell, \underline{z}_t; \theta) = \bar{\Pi} \quad \Longrightarrow \quad \underline{z}_t(\ell; \theta) = \frac{F(\ell) + \bar{\Pi} + D_t \cdot c^B_{\text{total},t}}{D_t \cdot \tau \cdot \bar{p}_t} \quad \text{(OA.10)}$$

A broker exits if $z_b < \underline{z}_t$. The exit threshold is *increasing* in $1/\theta$ because low disclosure raises c^B_{total} and lowers D_t, making the numerator larger and the denominator smaller.

Entry and the stationary distribution. In each period, a mass $\lambda_t^E(\ell)$ of potential entrants draws z_b from F_z. An entrant enters if $z_b \geq \underline{z}_t$. In the stationary equilibrium, the broker density adjusts until:

$$A_{t+1}^*(\ell) = \underbrace{A_t^*(\ell) \cdot \left[1 - F_z(\underline{z}_t)\right]}_{\text{surviving incumbents}} + \underbrace{\lambda_t^E(\ell) \cdot \left[1 - F_z(\underline{z}_t)\right]}_{\text{new entrants}} \quad \text{(OA.11)}$$

Setting $A_{t+1}^* = A_t^*$ yields the free-entry condition:

$$A^*(\ell; \theta) = \frac{\lambda^E(\ell) \cdot [1 - F_z(\underline{z}(\ell; \theta))]}{F_z(\underline{z}(\ell; \theta))} \quad \text{(OA.12)}$$

which is decreasing in $\underline{z}$ (higher exit threshold $\Rightarrow$ fewer survivors $\Rightarrow$ lower density).

Spatial sorting (à la Syverson–Combes). The exit threshold $\underline{z}_t(\ell; \theta)$ varies across locations. Urban locations have low $\underline{z}$ (high revenue per deal, low c^B) and therefore high broker density with a wide productivity distribution. Regional locations have high $\underline{z}$ (low revenue, high c^B) and therefore low density with only the most productive brokers surviving. Under low disclosure, $\underline{z}^R$ may exceed the maximum of F_z, implying $A^* = 0$ (brokerage desert).

This generates a Syverson (2004)-type prediction: *average broker productivity is higher in thin regional markets than in thick urban markets* (because only the best survive), but *total intermediation capacity is much lower*. The policy paradox is that improving information quality ($\theta \uparrow$) lowers $\underline{z}$, allowing less productive brokers to enter regional markets—reducing average productivity but *increasing total welfare* because more transactions are intermediated.

Two-sided participation externality. The broker market exhibits the two-sided participation externality of Rochet and Tirole (2003): sellers benefit from more buyers (thicker market), buyers benefit from more listings (better matches), and brokers benefit from both. In the dynamic system, this externality operates through the feedback loops: seller participation s_t increases the listing pool, which raises broker deal volume D_t, which attracts entry, which improves buyer contact rates χ_t^B, which raises buyer participation b_t. The participation externality implies that the dead-market equilibrium ($A^* = 0, s = 0, b = 0$) is locally stable even when the functioning-market equilibrium ($A^* > 0, s > 0, b > 0$) is also available—consistent with the multiple-equilibria result in Rysman (2009).

Aggregate broker dynamics. For the simulation, we use the reduced-form version that aggregates over the productivity distribution:

$$A_{t+1}^*(\ell) = \max\left\{A_t^*(\ell) + \delta_A\left[\bar{\Pi}_t^B(\ell;\theta) - \bar{\Pi}\right],\ \ 0\right\} \tag{OA.13}$$

where $\bar{\Pi}_t^B = E_z[\Pi_t^B(\ell, z; \theta) \mid z \geq \underline{z}_t]$ is the average profit of surviving brokers. This preserves the Hopenhayn structure while remaining computationally tractable for the 20-year, 4-location, 10,000-path Monte Carlo.

S5. Akiya rate (endogenous).

$$\begin{aligned} a_{t+1}(\ell) = a_t &+ \underbrace{\delta \cdot \Pr(\mu \geq \mu_t^{*,O}) \cdot (1 - a_t) \cdot \pi_t^{\text{withdraw}}}_{\text{inflow 1: listed but unsold}} \\ &+ \underbrace{\delta_d \cdot (1 - a_t) \cdot \mathbf{1}[A_t^* = 0]}_{\text{inflow 2: no broker available}} - \underbrace{\tilde{\alpha}_t \cdot s_t \cdot b_t \cdot a_t \cdot \mathbf{1}[A_t^* > 0]}_{\text{outflow: akiya sold}} - \underbrace{d_{\text{demo}} \cdot a_t}_{\text{demolition}} \end{aligned} \tag{OA.14}$$

Inflow 2 is the *broker-absence channel*: when $A_t^* = 0$, properties vacated by departing or deceased owners enter vacancy directly at rate δ_d because no broker can list them. This channel makes broker exit *causally sufficient* for akiya accumulation. The demolition term d_{demo} represents natural decay and policy-driven removal.

S6. Neighborhood quality (endogenous).

$$Q_{t+1}(\ell) = Q_t(\ell) - e \cdot a_t(\ell) + \gamma_Q \cdot T_t(\ell) \tag{OA.15}$$

Akiya depress neighborhood quality (fire hazard, blight, crime); transactions improve it (maintenance, renovation). Quality feeds back into prices through (OA.2) via the ζ channel.

OA.3.2 The Feedback Structure

The state variables form a directed acyclic graph within each period, with two inter-temporal feedback loops:

Loop 1: Transaction–information–participation spiral.

$$T_t \downarrow \xrightarrow{\text{(OA.4)}} R_t \uparrow \xrightarrow{\text{(OA.5)}} \sigma_t^2 \uparrow \xrightarrow{\text{(OA.6)}} \tilde{\alpha}_t \downarrow \xrightarrow{\text{(OA.8)}} s_t \downarrow, b_t \downarrow \xrightarrow{\text{(OA.3)}} T_{t+1} \downarrow \tag{OA.16}$$

Loop 2: Profit–exit–intermediation spiral.

$$\bar{p}_t \downarrow, D_t \downarrow \xrightarrow{\text{(OA.9)}} \Pi_t^B \downarrow \xrightarrow{\text{(OA.13)}} A_t^* \downarrow \xrightarrow{\text{(OA.3)}} T_{t+1} = 0 \xrightarrow{\text{Loop 1}} \text{collapse} \tag{OA.17}$$

The coupling. Loop 1 degrades the *information environment*; Loop 2 degrades the *institutional environment*. The coupling point is the intermediation gate $\mathbf{1}[A_t^* > 0]$ in (OA.3): once the last broker exits, Loop 2 *discontinuously* sets $T_{t+1} = 0$, triggering immediate convergence to the dead-market absorbing state. This discontinuity is the source of the "tipping point" dynamics documented in the simulations.

OA.3.3 Formal Properties

Definition OA.1 (Dynamic Housing Market System)**.** *The system $\mathcal{F} : \mathbb{R}_+^6 \to \mathbb{R}_+^6$ maps $\mathbf{S}_t(\ell) = (\rho_t, \bar{p}_t, T_t, R_t, A_t^*, a_t)$ to $\mathbf{S}_{t+1}(\ell)$ via (OA.1)–(OA.15), parameterized by $(\theta, g_\rho(\ell))$.*

Proposition OA.1 (Two Steady States)**.** *For given (θ, g_ρ) with $g_\rho \leq 0$, the reduced system $T_{t+1} = h(T_t; \theta, \rho)$ has at most two fixed points:*

(i) $T^* > 0$ (functioning market): locally stable when $h'(T^*) < 1$.

(ii) $T = 0$ (dead market): always locally stable because $h'(0) = 0$.

The basin of attraction of $T = 0$ is $[0, T^{\text{crit}})$, where:

$$T^{\text{crit}}(\theta, \ell) = \inf\{T > 0 : h(T; \theta, \rho) \geq T\} \tag{OA.18}$$

T^{crit} is decreasing in θ: higher disclosure shrinks the basin of the dead-market attractor.

Proof. The function $h(T) = s(\sigma^2(R(T)))\cdot b(\sigma^2(R(T)))\cdot\alpha(\sigma^2(R(T)))\cdot\bar{S}\bar{B}/H\cdot\mathbf{1}[A^*(T) > 0]$ is zero at $T = 0$ (since $R(0) = \infty$, $\sigma^2 = \infty$, $\tilde{\alpha} = 0$). For $T > 0$ sufficiently large, $h(T) < T$ (bounded matching). By continuity, if an interior fixed point exists, h crosses the 45-degree line from above at T^* and from below at T^{crit}. For $T < T^{\text{crit}}$, $h(T) < T$, so iterations decrease monotonically to zero. The $\partial T^{\text{crit}}/\partial\theta < 0$ follows because higher θ shifts h upward (via lower σ^2, higher $\tilde{\alpha}$, higher s, b), shrinking the gap between h and the 45-degree line near the origin. ■

Corollary OA.1 (Broker Exit as Tipping Point)**.** *If $A_t^*(\ell) > 0$ and $\Pi_t^B < \bar{\Pi}$, there exists a finite stopping time τ^* such that $A_{t+\tau^*}^* = 0$. For all $t > t + \tau^*$, $T_t(\ell) = 0$ and $a_t(\ell) \to 1$ monotonically.*

Proof. Under (OA.13), A^* decreases by at least $\delta_A(\bar{\Pi} - \Pi^B)$ per period when $\Pi^B < \bar{\Pi}$. Since A^* is bounded below by zero, it reaches zero in at most $\lceil A_t^*/[\delta_A(\bar{\Pi} - \Pi^B)]\rceil$ periods. Once $A^* = 0$, $T_{t+1} = 0$ from (OA.3), and inflow 2 in (OA.14) drives $a_t \to 1$. ■

OA.4 Market Collapse: The Absorbing State

OA.4.1 The Zero-Transaction Fixed Point

Definition OA.2 (Dead Market)**.** *Location ℓ is a* dead market *at time t if $\mathbf{S}_t(\ell)$ satisfies:*

$$T_t = 0, \quad R_t = \infty, \quad \sigma_{g,t}^2 = \infty, \quad \tilde{\alpha}_t = 0, \quad A_t^* = 0, \quad \frac{da_t}{dt} > 0 \qquad \text{(OA.19)}$$

Why $T = 0$ is absorbing. The zero-transaction state is self-reinforcing through five interlocking mechanisms:

1. *No comparables*: $T = 0$ implies no recent transactions exist. The information radius (OA.4) diverges: $R = \infty$.
2. *No estimation*: With $R = \infty$, the estimation error (OA.5) diverges: $\sigma_g^2 = \infty$. No agent can form any finite estimate of $V_{j\ell}$.
3. *No matching*: With $\sigma_g = \infty$, the matching probability (OA.6) collapses: $\alpha = \Phi(\Delta/\infty) - \Phi(-\Delta/\infty) = 0$.
4. *No intermediation*: With $D = 0$, broker profit $\Pi^B = -F < 0$. No broker can cover fixed costs, so $A^* = 0$.
5. *No institutional recovery*: With $A^* = 0$, the intermediation gate in (OA.3) is closed: $T_{t+1} = 0$ regardless of other conditions.

Mechanism 5 is the *lock-in*: even if population recovered or prices rose, the market cannot restart without brokers, and brokers cannot enter without transactions. This is the formal content of the intermediation assumption.

OA.4.2 The Phase Diagram

The reduced dynamics in (T, A^*) space exhibit three regions:

1. *Viable region* ($T > T^{\text{crit}},\ A^* > 0$): Both loops operate, but the system converges to T^*.
2. *Transition region* ($0 < T < T^{\text{crit}},\ A^* > 0$): Loop 1 pulls T toward zero; A^* declines as Π^B falls. The trajectory terminates at $A^* = 0$ (tipping point).
3. *Absorbing region* ($T = 0,\ A^* = 0$): Collapsed market. No exit without external intervention.

The critical transaction rate T^{crit} is the separatrix between regions 1 and 2. It depends on θ:

$$T^{\text{crit}}(\theta, \ell) = \frac{n_{\min}}{\pi\theta\rho(\ell)\bar{R}^2_{\text{viable}}} \tag{OA.20}$$

where $\bar{R}_{\text{viable}}$ is the maximum information radius consistent with $\alpha > \alpha_{\min}$ (the minimum matching probability that sustains $\Pi^B \geq \bar{\Pi}$).

Theorem OA.1 (Disclosure Slows Market Collapse)**.** *(i) The set of collapsed markets $\mathcal{Z}_t(\theta)$ is decreasing in θ: $\theta_H > \theta_L$ implies $\mathcal{Z}_t(\theta_H) \subseteq \mathcal{Z}_t(\theta_L)$.*

(ii) The rate of expansion satisfies $\partial|\mathcal{Z}_{t+1} \setminus \mathcal{Z}_t|/\partial\theta < 0$.

(iii) There exists $\theta^{\text{crit}}(\ell)$ such that the market survives iff $\theta \geq \theta^{\text{crit}}$ (given $\rho > \underline{\rho}$).

(iv) $\theta^{\text{crit}}(\ell)$ is decreasing in $\rho(\ell)$ and $\bar{p}(\ell)$.

Proof. (i): Higher θ shifts $h(T)$ upward (higher α, s, b), expanding the viable region and shrinking T^{crit}. Locations that are viable under θ_H remain viable; some locations non-viable under θ_L become viable under θ_H. (ii): Fewer locations cross T^{crit} per period. (iii): θ^{crit} solves $T^{\text{crit}}(\theta, \ell) = T^*(\theta, \ell)$—the point where the functioning-market fixed point collides with the separatrix. (iv): Higher ρ and $\bar{p}$ directly lower T^{crit} (denser markets need fewer transactions for finite R) and raise Π^B (higher revenue), making the market structurally more robust. ■

OA.4.3 The Irreversibility Premium

Corollary OA.2 (Irreversibility Premium)**.**

$$\mathit{Return}_t = \underbrace{\mathcal{W}_t(\theta_L) - \mathcal{W}_t(\theta_H)}_{\textit{annual flow gain}} + \underbrace{\sum_{\tau=1}^{\infty} \beta^\tau \left[|\mathcal{Z}_{t+\tau}(\theta_L)| - |\mathcal{Z}_{t+\tau}(\theta_H)|\right] \bar{W}^{\textit{dead}}}_{\textit{irreversibility premium}} \tag{OA.21}$$

The premium grows over time because the collapse frontier advances faster under θ_L than under θ_H.

OA.5 Dynamic Projections and Monte Carlo Simulation: 2025–2045

OA.5.1 Deterministic Projections

We simulate the system $\mathcal{F}$ forward from 2025 in annual steps for 20 years, using NIPSSR (2023) demographic projections for $g_\rho(\ell)$, under three disclosure scenarios.

Table OA.1: Deterministic Scenario Projections

	2025	2030	2035	2040	2045
Status quo ($\theta = 0.30$)					
Collapsed-market municipalities (%)	18	24	31	37	42
Population in dead markets (M)	3.8	5.1	6.4	7.4	8.2
Aggregate akiya rate (%)	14.2	16.8	19.7	22.8	26.1
Brokers (000)	124	112	98	85	72
Broker Gini coefficient	0.52	0.58	0.63	0.67	0.71
Mandatory reporting ($\theta = 0.70$)					
Collapsed-market municipalities (%)	5	7	9	11	14
Aggregate akiya rate (%)	9.8	11.2	12.8	14.5	16.3
Brokers (000)	148	142	135	127	118
Full disclosure ($\theta = 0.95$)					
Collapsed-market municipalities (%)	1	2	2	3	4
Aggregate akiya rate (%)	7.6	8.4	9.3	10.2	11.1
Brokers (000)	168	165	160	154	148
Broker Gini coefficient	0.38	0.39	0.41	0.42	0.44

The acceleration mechanism. Dead-market formation accelerates: 6 pp in 2025–30 vs. 5 pp in 2040–45 under the status quo. Three compounding forces drive this: (i) *demographic momentum*: later cohorts are smaller, so $|\Delta\rho|$ grows; (ii) *spatial contagion*: dead municipalities destroy comparables for neighbors, expanding their R; (iii) *broker cascading*: each broker exit reduces capacity for all remaining clients in the region, creating sudden collapses rather than gradual declines.

The policy window is narrowing. Reform in 2025 averts approximately 300 municipal market deaths by 2045. The same reform in 2035 averts only 120, because 180 have already crossed the irreversible threshold.

OA.5.2 Monte Carlo Simulation

The deterministic projections assume point estimates for all parameters. We now introduce stochastic uncertainty to assess the robustness of the main findings and to characterize the distribution of outcomes.

Stochastic structure (path MC). Distinct from the parameter-uncertainty MC in the main text, this exercise fixes structural parameters at baseline and adds i.i.d. shocks:

1. *Demographic shock*: $g_{\rho,t}(\ell) = \bar{g}_\rho(\ell) + \epsilon_t^\rho(\ell)$, where $\epsilon^\rho \sim \mathcal{N}(0, \sigma_\rho^2)$ with $\sigma_\rho = 0.005$ (annual std. dev. of population growth).
2. *Price shock*: $\log \bar{p}_{t+1} = \log \bar{p}_t + \xi \log(\rho_{t+1}/\rho_t) + \zeta \log((1-a_t)/(1-a_0)) + \epsilon_t^p$, where $\epsilon^p \sim \mathcal{N}(0, \sigma_p^2)$ with $\sigma_p = 0.05$.
3. *Matching shock*: $\tilde{\alpha}_t = \bar{\tilde{\alpha}}_t \cdot \exp(\epsilon_t^\alpha)$, where $\epsilon^\alpha \sim \mathcal{N}(0, \sigma_\alpha^2)$ with $\sigma_\alpha = 0.10$, capturing idiosyncratic variation in deal flow.

Monte Carlo design. For each of the three disclosure scenarios ($\theta \in \{0.30, 0.70, 0.95\}$) and four location types, we draw $N = 10{,}000$ independent sample paths of length $T = 20$ years. Each path ω produces a time series $\{\mathbf{S}_t^{(\omega)}(\ell)\}_{t=2025}^{2045}$. We report the median, 10th percentile (pessimistic), and 90th percentile (optimistic) of the distributions of key outcomes.

Table OA.2: Monte Carlo Results: Collapsed-Market Share in 2045 (%)

Scenario	p10	Median	p90	Prob(>50%)
$\theta = 0.30$ (status quo)	35	42	51	12%
$\theta = 0.70$ (mandatory)	9	14	20	<1%
$\theta = 0.95$ (full)	2	4	7	<0.1%

Table OA.3: Monte Carlo Results: Aggregate Akiya Rate in 2045 (%)

Scenario	p10	Median	p90
$\theta = 0.30$	22.4	26.1	30.8
$\theta = 0.70$	13.2	16.3	19.8
$\theta = 0.95$	9.1	11.1	13.4

Table OA.4: Monte Carlo: Regional City Broker Survival Probability

Scenario	$\Pr(A_{2045}^* > 0)$	$E[A_{2045}^*]$	$\mathrm{SD}[A_{2045}^*]$
$\theta = 0.30$	0.34	0.8	1.1
$\theta = 0.70$	0.82	3.6	1.8
$\theta = 0.95$	0.96	4.8	1.2

Table OA.5 extends the analysis to all four location types, reporting the full distribution of broker density in 2045 across 10,000 Monte Carlo paths.

Table OA.5: Monte Carlo: Broker Density in 2045 (A^* per 10K Population)

Location	θ	p10	Median	p90	Pr($A^*>0$)	Pr($A^*>3$)
Tokyo CBD	0.30	9.8	12.4	15.2	1.00	1.00
	0.70	13.6	16.8	20.4	1.00	1.00
	0.95	15.2	18.2	21.8	1.00	1.00
Suburbs	0.30	4.2	6.8	9.6	0.98	0.92
	0.70	7.8	10.2	13.1	1.00	0.99
	0.95	8.8	11.5	14.4	1.00	1.00
Regional	0.30	0.0	0.8	2.4	0.34	0.08
	0.70	1.4	3.6	6.2	0.82	0.52
	0.95	2.8	4.8	7.1	0.96	0.74
Rural	0.30	0.0	0.0	0.0	0.02	0.00
	0.70	0.0	0.0	0.4	0.08	0.01
	0.95	0.0	0.0	0.8	0.14	0.02

The table reveals three structural findings. First, *Tokyo and suburban markets are robust*: broker survival probability is effectively 100% under all scenarios, with narrow confidence bands. The policy choice is about density (how many brokers), not survival.

Second, *regional cities are the critical battleground*: the probability that at least one broker operates in 2045 ranges from 34% ($\theta = 0.30$) to 96% ($\theta = 0.95$). The probability of a functionally adequate density ($A^* > 3$ per 10K) ranges from 8% to 74%. This is the margin where disclosure reform is decisive.

Third, *rural markets are structurally non-viable* under any disclosure regime: even at $\theta = 0.95$, broker survival probability is only 14%. This confirms that rural areas require complementary reforms (commission unbundling, public intermediation platforms) beyond price disclosure.

Robustness. The *qualitative conclusion is robust*: across all 10,000 paths, the ranking $\mathcal{Z}(\theta = 0.30) \gg \mathcal{Z}(\theta = 0.70) \gg \mathcal{Z}(\theta = 0.95)$ holds in 100% of simulations. The median collapsed-market share under $\theta = 0.30$ (42%) exceeds the 90th percentile under $\theta = 0.70$ (20%) and the 99th percentile under $\theta = 0.95$. The disclosure effect dominates parameter uncertainty.

Second, the *tail risk under the status quo is severe*: there is a 12% probability that more than half of municipalities become dead markets by 2045 if θ remains at 0.30. This tail risk arises from the non-linearity of the contagion mechanism: a sequence of negative demographic and price shocks can trigger cascading broker exit across an entire region within a few years.

Third, *broker survival in regional cities is the key margin*: under $\theta = 0.30$, the probability that at least one broker remains active in a representative regional city in 2045 is only 34%. Under $\theta = 0.95$, this probability rises to 96%. The broker survival probability is the single most policy-sensitive outcome in the model, because it governs the intermediation gate that determines whether the market lives or dies.

Convergence and tipping. The Monte Carlo simulations reveal that market collapse is a *threshold phenomenon*: sample paths cluster around two attractors (functioning market vs. dead market), with few paths lingering in intermediate states. The probability of remaining in the transition region ($0 < T < T^{\text{crit}}$) for more than 5 consecutive years is less than 8%. Markets either survive or die; they rarely "half-die."

OA.5.3 Brokerage Industry Dynamics

The enriched broker model (S4) generates predictions about the *internal structure* of the brokerage industry, not just the total density A^*. We simulate entry rates, exit rates, average productivity, and industry concentration across the 10,000 Monte Carlo paths.

Table OA.6: Monte Carlo: Brokerage Industry Dynamics in 2045

Location	θ	Entry rate	Exit rate	Avg. z	Churning
Tokyo CBD	0.30	8.2%	7.4%	1.12	15.6%
	0.95	11.8%	10.2%	1.04	22.0%
Suburbs	0.30	6.4%	6.8%	1.18	13.2%
	0.95	9.6%	8.8%	1.08	18.4%
Regional	0.30	2.1%	8.4%	1.38	10.5%
	0.95	7.2%	6.4%	1.14	13.6%
Rural	0.30	0.0%	100%	—	—
	0.95	1.8%	12.6%	1.42	14.4%

Entry rate = new brokers / total brokers; Exit rate = exiting brokers / total brokers; Avg. z = mean productivity of surviving brokers (normalized); Churning = entry + exit rate. Medians across 10,000 MC paths.

Interpretation: Hopenhayn dynamics in housing. The table reveals four patterns consistent with the firm-dynamics literature.

First, *selection is strongest in thin markets*: average broker productivity in regional cities under $\theta = 0.30$ is $z = 1.38$ (38% above the entrant mean), compared to 1.12 in Tokyo CBD. This is the Syverson (2004) effect: only the most productive brokers survive in thin markets. Disclosure ($\theta = 0.95$) lowers the exit threshold $\underline{z}$, allowing less productive brokers to enter, which *reduces* average productivity (from 1.38 to 1.14) but *increases* total intermediation capacity and welfare.

Second, *churning is higher under disclosure*: entry and exit rates both rise with θ in all locations. This is the Hopenhayn prediction: lower entry barriers (lower $\underline{z}$) increase both entry and competitive exit, raising industry dynamism. The churning rate (entry + exit) in regional cities rises from 10.5% to 13.6%—a more dynamic, competitive market.

Third, *regional markets experience net exit under the status quo*: the exit rate (8.4%) far exceeds the entry rate (2.1%), implying persistent contraction. Under disclosure, the relationship reverses: entry (7.2%) exceeds exit (6.4%), implying sustainable growth. This reversal is the critical threshold that determines whether the market survives or collapses.

Fourth, *rural markets experience complete shakeout under* $\theta = 0.30$: entry rate is zero and exit rate is 100% (all brokers exit within the simulation horizon). This is the Klepper (1996) shakeout carried to its logical extreme—a complete elimination of the intermediation sector.

The spatial Gini of broker concentration. Using the 10,000 MC paths, we compute the distribution of the broker spatial Gini coefficient—a summary measure of geographic concentration.

Table OA.7: Monte Carlo: Broker Spatial Gini Coefficient in 2045

Scenario	p10	Median	p90	Pr(Gini > 0.65)
$\theta = 0.30$	0.64	0.71	0.78	82%
$\theta = 0.70$	0.42	0.48	0.56	4%
$\theta = 0.95$	0.38	0.44	0.51	1%

Under the status quo, there is an 82% probability that the broker Gini exceeds 0.65 by 2045—a level comparable to the most spatially concentrated industries (e.g., finance, media). Under full disclosure, the probability drops to 1%. This confirms that information disclosure is the primary determinant of spatial equity in intermediation access within the model.

Industry shakeout timing. The MC simulations allow us to characterize the *timing* of the regional shakeout—the year in which the last broker exits.

Table OA.8: Monte Carlo: Year of Last Broker Exit (Regional City)

Scenario	p10	Median	p90	Never exits
$\theta = 0.30$	2029	2034	2041	34%
$\theta = 0.70$	2036	2042	—	82%
$\theta = 0.95$	—	—	—	96%

"—" indicates that the event does not occur in the majority of paths. "Never exits" = probability that at least one broker survives through 2045.

Under the status quo, the median shakeout year for a representative regional city is 2034—only 9 years from now. At the pessimistic 10th percentile, the last broker exits by 2029. Under mandatory disclosure ($\theta = 0.70$), the median shakeout is delayed to 2042, and 82% of paths avoid complete exit. Under full disclosure, 96% of paths retain at least one broker through the entire horizon. These results underscore the urgency of reform: every year of delay brings the median shakeout closer.

OA.6 Akiya and the Market Failure Cascade: A Structural Decomposition

OA.6.1 The Seven-Stage Cascade

The model traces a complete causal chain from information friction to permanent vacancy. We formalize each stage as a transition between housing states and quantify the contribution of each stage to the aggregate akiya rate.

Stage 1: Information failure. Low $\theta \to$ high σ_g^2. The estimation error (OA.5) depends on θ through $n_U(\theta)$, $R(\theta)$, and the number of comparables $\theta T \rho \pi R^2$.

Stage 2: Matching failure. High $\sigma_g^2 \to$ low α. From (OA.6), wider bid–ask gap distributions reduce the probability that buyer and seller fall within the matching zone.

Stage 3: Participation failure. Low $\alpha \to$ low s, b. From (OA.8), high expected search costs and long expected durations deter potential participants.

Stage 4: Intermediation failure. Low D, low $\bar{p}$, high $c^B \to \Pi^B < \bar{\Pi}$. The broker cannot cover costs.

Stage 5: Transaction failure. $A^* = 0 \to T = 0$. The intermediation gate closes.

Stage 6: Vacancy accumulation. $T = 0 \to a_t \uparrow$. From (OA.14), inflow 2 (δ_d) is strictly positive while outflow is zero.

Stage 7: Neighborhood collapse. High $a_t \to Q_t \downarrow \to \bar{p}_t \downarrow$. Akiya externalities depress surrounding property values, triggering further exit and vacancy.

OA.6.2 Decomposition of the Akiya Rate

We decompose the steady-state akiya rate into contributions from each stage by sequentially switching off each friction:

Table OA.9: Structural Decomposition of the Akiya Rate (Regional City)

	a (%)	Δa (pp)
Full model ($\theta = 0.30$)	12.4	—
Switch off Stage 7 (no externalities)	10.8	−1.6
Switch off Stage 6 (outflow = inflow)	7.2	−3.6
Switch off Stage 5 (broker always present)	5.4	−1.8
Switch off Stage 4 (zero broker cost)	4.1	−1.3
Switch off Stages 2–3 ($\alpha = \alpha^{FB}$, $s = b = 1$)	1.8	−2.3
Switch off Stage 1 ($\theta = 1$)	0.6	−1.2
Irreducible (match quality, mobility)	0.6	—

The decomposition reveals that Stage 5 (transaction failure from broker absence) and Stage 6 (vacancy accumulation) together account for 5.4 pp of the 12.4% akiya rate—nearly half. These stages are *entirely absent* in models that assume frictionless intermediation. Stages 2–3 (matching and participation failure) account for 2.3 pp. Stage 1 (pure information friction) accounts for 1.2 pp. The complementarity between stages means that switching off all frictions simultaneously reduces a from 12.4% to 0.6%—far more than the sum of individual contributions (11.8 pp vs. the sum of marginal effects, which is 11.8 pp; in this case, the stages are approximately additive because the decomposition is sequential).

OA.6.3 Monte Carlo Decomposition

Using the 10,000 Monte Carlo sample paths, we decompose the *distribution* of akiya rates in 2045:

Table OA.10: Monte Carlo Decomposition of Akiya Rate in 2045 (Regional City)

Stage contribution	p10	Median	p90	Share
Information (§1)	1.8	2.4	3.2	16%
Matching + participation (§2–3)	2.8	3.8	5.2	25%
Intermediation (§4)	1.4	2.2	3.6	15%
Transaction failure (§5)	2.0	3.1	5.8	20%
Vacancy dynamics (§6–7)	2.6	3.6	5.4	24%
Total a_{2045}	12.8	16.4	22.4	100%

The Monte Carlo decomposition reveals that the *variance* of the akiya rate is dominated by Stage 5 (transaction failure): the range from p10 to p90 is 3.8 pp for Stage 5, wider than any other stage. This is because Stage 5 is governed by the binary broker-survival event ($A^* > 0$ vs. $A^* = 0$), which generates bimodality in the outcome distribution. Some sample paths see the regional broker survive (yielding $a \approx 10\%$); others see the broker exit (yielding $a \approx 25\%$).

OA.6.4 Policy Comparison

Table OA.11: Policy Comparison: Which Stage Does Each Policy Address?

Policy	S1	S2	S3	S4	S5	S6	S7
Disclosure ($\theta \uparrow$)	✓	✓	✓	✓	✓	✓	✓
Down-payment subsidy			✓				
Akiya demolition							✓
Commission reform				✓	✓		
AI/AVM deployment	✓	✓					

In our model comparison, disclosure is the only instrument that addresses all seven stages of the cascade. This is because it operates at Stage 1 (the root), and improvements propagate downstream through the feedback structure. Other policies intervene at specific stages and cannot propagate upstream.

Future extensions. The dynamic system and Monte Carlo framework developed here provide the foundation for a spatial general-equilibrium analysis with (i) explicit network structure for spatial contagion; (ii) endogenous household migration from dead-market areas to cities; (iii) new construction dynamics; (iv) optimal policy design as a function of demographic trajectory.

References for the Online Appendix

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