Nomadic Theory in the AI-driven Economy and Its Evolutionary Analysis

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Abstract. The rapid integration of artificial intelligence and information technology has transformed the feasibility of cross-regional remote work. Yet, as these mobile professionals migrate, they inevitably precipitate competition over local social resources that are strictly bound by capacity limits. To capture the friction and behavioral shifts inherent in these remote-work ecosystems, we formulate a continuous-time nomadic game model. We find that the trajectory of this system is jointly dictated by resource limits, the efficacy of institutional rules, and the agents' own experiential learning. This model elucidates the underlying mechanisms required to sustain cooperation and navigate structural transitions within the contemporary AI-driven economy.

Keywords: Nomadic Game, Digital Nomadism, Remote Work.

1 Introduction

Driven by advancements in artificial intelligence and remote-work technologies, digital nomadism has emerged as a novel economic model characterized by location independence and online collaboration[1]. The work flexibility of digital nomads is continuously increasing, but remote collaboration is still influenced by knowledge sharing mechanisms and local labor market conditions[2]. The remote work model has not completely eliminated spatial constraints; it has changed the way people access shared resources, such as office space, digital infrastructure, platform opportunities, local services, and community support[3].

Recent studies further show that digital nomadism is not determined solely by a preference for travel. Rather, it emerges from the joint effects of mobility, local environments, and infrastructure conditions[4]. Coworking spaces have become important organizational sites not only because they provide desks and internet access, but also because they offer social proximity, community governance, and opportunities for knowledge sharing, all of which influence collaboration and work–life balance[5]. However, as digital nomads migrate across regions, their varying digital capabilities and demands for local opportunities inevitably generate new forms of resource competition.

This influx of mobile workers frames the allocation of remote-work resources as a complex governance problem involving capacity constraints, congestion, and rule en-

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forcement. Research on common-pool resources shows that environmental feedback can lead to multiple long-run outcomes. For example, Tu et al. introduce the Allee effect into a common-resource game and find that the resource system may exhibit bistability between sustainable and unsustainable states[6]. These frameworks are rarely applied to the context of digital nomadism. Specifically, the literature lacks an analysis of the frictions and bargaining processes that occur when mobile nomads attempt to access resources governed by local communities.

To address this gap, this paper models digital nomadism as a dynamic resource-allocation game. Unlike traditional common-pool resource studies that assume a static population, our original contribution lies in integrating spatial mobility and search frictions into an evolutionary framework. First, we propose an analytical nomadic game that embeds group social resources and mobile agents into a unified continuous-time system. Second, rather than assuming open access, we formalize resource sharing as a bargaining process constrained by capacity, institutional rules, and cooperative history. Third, by developing a mechanism of behavioral evolution, we use numerical simulations to examine the system's collaborative dynamics, showing how resource thresholds and experiential memory drive structural transitions in the AI-driven economy.

2 System and Model

2.1 Population Structure and State Variables

Within a continuous-time framework with $t \geq 0$, the economy contains a population of size N divided into three bounded-rational groups: stayers $x_S(t)$, movers $x_M(t)$, and waiters $x_W(t)$. In the context of the remote-work economy, stayers represent local resource incumbents, such as long-term members of a coworking space or resident remote workers who maintain the local ecosystem. Movers represent traveling digital nomads or cross-regional freelancers actively seeking new workspaces and collaboration opportunities. Waiters are inactive agents evaluating the market, such as traditional office workers observing the remote work trend or nomads temporarily exiting the market due to high competition. These shares satisfy:

$$x_S(t) + x_M(t) + x_W(t) = 1, \qquad x_S, x_M, x_W \in [0,1]. \tag{1}$$

Let $R(t) \in [0,1]$ denote the quality of the resource environment, i.e., the stock of composite digital work resources available to digital nomads within a location, platform, or coworking community, including project access and community support. Stayers choose the local occupation intensity $u(t)$ and maintenance effort $m_S(t)$, whereas movers choose the bargaining-preparation investment $v(t)$ and mobility level $m_M(t)$. The system is also subject to an exogenous institutional constraint $I \in [0,1]$, capturing macro-level conditions such as digital labor-market regulation and local support policies.

The resource state evolves through endogenous recovery, maintenance-based improvement, and depletion caused by resource use:

$$R(t) = rR(t)(1-R(t)) + \omega m_S(t)(1-R(t)) - \chi_S x_S(t)u(t)R(t) - \chi_M g_M(t)R(t) \tag{2}$$

Here, $r, \omega, \chi_S, \chi_M > 0$ denote, respectively, the intrinsic growth rate of the resource, the efficiency of maintenance-based recovery, and the per-unit occupation coefficients of the two groups. Rather than biological regeneration, this recovery process reflects the restoration of local capacity through infrastructure upgrading, platform governance, and the rebuilding of community trust. The term $g_M(t)$ represents the effective pressure exerted by movers on local resources:

$$g_M(t) = x_M(t)\left(P_{\text{succ}}(t)q^*(t) + (1-P_{\text{succ}}(t))q\right) \tag{3}$$

Here, $P_{\text{succ}}(t)$ denotes the probability that bargaining succeeds and the contract is enforced, and $q^*(t)$ is the bargained resource quota. If bargaining fails or enforcement breaks down, movers enter in a disorderly manner and generate an equivalent grazing intensity $q \in [0,1]$, which is typically higher than under the contracted arrangement.

2.2 Contact and Bargaining Mechanism

Movers and stayers are not instantaneously matched under complete information. Instead, they face search frictions across both space and time. The effective rate at which movers contact stayers and attempt to initiate bargaining is specified as:

$$\lambda_{\text{eff}}(t) = \lambda\phi_M(m_M(t)), \quad \lambda > 0, \quad \phi_M(m) = m^{\eta_M}, \quad \eta_M \ge 1. \tag{4}$$

The baseline contact rate λ is nonlinearly amplified by the mobility level $m_M(t)$. Accordingly, the expected number of contacts per unit time is $\lambda_{\text{eff}}(t)x_M(t)$ for each stayer and $\lambda_{\text{eff}}(t)x_S(t)$ for each mover.

In each effective contact, the two parties bargain over an access contract (q, Γ). Here, q denotes the resource quota granted to the mover, which practically represents time-limited workspace access or local project opportunities. The term $\Gamma \ge 0$ is a compensatory transfer paid by the mover to the stayer, typically taking the form of membership fees, revenue sharing, or service payments. Given the carrying capacity of the digital ecosystem, the quota is subject to a strict ecological upper bound:

$$\bar{q}(R) = \bar{q}_0 R, \quad \bar{q}_0 \in (0,1]. \tag{5}$$

Whether a contract is reached depends on the benefits and costs associated with quota q. The mover's instantaneous payoff is:

$$B(q,R) = aRq - \frac{b}{2}q^2, \quad a > 0, \quad b > 0. \tag{6}$$

This quadratic form captures diminishing marginal returns, with payoff increasing in the current resource quality R.The cost borne by stayers when opening quota to movers is:

$$D(q,R) = d(1-R)q + \frac{e}{2}q^2,\ d \geq 0,\ e \geq 0\ . \tag{7}$$

Hence, scarcer resources imply a higher marginal cost of granting additional quota.

2.3 Payoff Functions of the Nomadic Populations

Reaching a contract does not guarantee compliance. The enforcement probability $s(t)$ reflects the joint effects of institutional quality, governance effort, and past cooperative experience:

$$s(t) = s_0 + (1-s_0)\frac{I + \chi_E(E_S(t)+E_M(t)) + \chi_m m_S(t)}{1 + I + \chi_E(E_S(t)+E_M(t)) + \chi_m m_S(t)}\ . \tag{8}$$

Here, $s_0 \in (0,1)$ is the baseline enforcement probability, and $\chi_E, \chi_m \geq 0$ are sensitivity parameters. Higher I , E_S , and E_M increase the likelihood that a contract is enforced.

Bargaining also involves transaction frictions. The net costs borne by stayers and movers in each round are:

$$\begin{cases} k_S(m_S;I) = (1-I)k_{S0} + k_{S1}m_S^2, \quad k_{S0}, k_{S1} \geq 0 \\ k_M(v, m_M;I) = (1-I)k_{M0} + k_{M1}m_M^2 + \dfrac{k_{M2}}{1+v}, \quad k_{M0}, k_{M1}, k_{M2} \geq 0 \end{cases}, \tag{9}$$

An improvement in institutional quality I reduces baseline frictions, while movers' bargaining-preparation investment v lowers the term $k_{M2}/(1+v)$. In a real world setting, a higher I reflects more predictable rules, stronger dispute resolution mechanisms, and clearer membership criteria.

When transferable payment Γ is feasible, the optimal quota q^* follows the Nash bargaining logic and is obtained by maximizing the usable resource surplus of both parties:

$$\begin{aligned} q^*(t) \in \arg\max\nolimits_{q\in[0,\bar{q}(R(t))]} \{ & s(t)(B(q,R(t)) - D(q,R(t))) \\ & - k_S\left(m_S(t);I\right) - k_M\left(v(t), m_M(t);I\right)\} \end{aligned}\ . \tag{10}$$

Because k_S and k_M are independent of q and $s(t) > 0$, this problem is equivalent to maximizing $B(q,R) - D(q,R)$ over the feasible set. Substituting the optimal quota yields the optimal net resource surplus:

$$\begin{aligned} S^*_{\text{net}}(t) &= s(t)\Big(B\big(q^*(t),R(t)\big)-D\big(q^*(t),R(t)\big)\Big) \\ &\quad -k_S\left(m_S(t);I\right)-k_M\left(v(t),m_M(t);I;I\right) \end{aligned}. \tag{11}$$

To allow for heterogeneous matching and possible bargaining breakdown, the agreement probability is specified by a Logistic function[7]:

$$P_{\text{agr}}(t)=\frac{1}{1+\exp(-\zeta S^*_{\text{net}}(t))}, \quad \zeta>0. \tag{12}$$

Higher expected surplus therefore raises the probability that bargaining leads to agreement. The overall success probability is:

$$P_{\text{succ}}(t)=P_{\text{agr}}(t)s(t). \tag{13}$$

Based on this bargaining structure, we define the payoff functions of the two groups. For stayers, the local return from remote work is:

$$Y_S(t)=b_S R(t)u(t), \quad b_S>0. \tag{14}$$

Their total cost includes convex effort costs and a penalty for violating the sustainability constraint through excessive use of shared resources:

$$C_S(u,m_S;R)=c_{Su}u^2+c_{Sm}m_S^2+c_{S0}+\psi_S[x_S u-\bar{u}(R)]_+^2, \quad \bar{u}(R)=\bar{u}_0+\bar{u}_1 R. \tag{15}$$

Here, $\bar{u}(R)$ denotes the upper bound on the sustainable occupation intensity of local stayers under a given level of resource-environment quality. Similarly, the movers' cost structure is:

$$C_M(v,m_M)=c_{Mv}v^2+c_{Mm}m_M^2+c_{M0}+\psi_M[v-\bar{v}]_+^2. \tag{16}$$

Here, $\bar{v}$ denotes the experience-based benchmark for acceptable preparation investment by movers.

After contact and bargaining, a successful match allocates the net common surplus according to the bargaining-power parameter $\theta\in(0,1)$; otherwise both parties incur losses. The expected per-capita net payoffs per unit time are thus:

$$\begin{cases} \pi_S(t)=Y_S(t)-C_S(u(t),m_S(t);R(t))+\lambda_{\text{eff}}(t)x_M(t)\Big(P_{\text{agr}}(t)\theta S^*_{\text{net}}(t)-\big(1-P_{\text{agr}}(t)\big)L_0\Big) \\ \pi_M(t)=-C_M(v(t),m_M(t))+\lambda_{\text{eff}}(t)x_S(t)(P_{\text{agr}}(t)(1-\theta)S^*_{\text{net}}(t)-(1-P_{\text{agr}}(t))F_0) \end{cases} \tag{17}$$

2.4 Evolutionary Mechanism of Nomadic Behavior

The model assumes bounded rationality at the population level. Strategy adjustment and status switching are driven by learning from past experience and by the evaluation of recent payoffs. Successful cooperation accumulates positive experience, though part of that experience is gradually lost through a forgetting mechanism:

$$\begin{cases} E_S(t) = \rho_S \lambda_{\text{eff}}(t) x_M(t) P_{\text{succ}}(t) - \mu_S E_S(t) \\ E_M(t) = \rho_M \lambda_{\text{eff}}(t) x_S(t) P_{\text{succ}}(t) - \mu_M E_M(t) \end{cases}. \tag{18}$$

Here, $\rho_S, \rho_M \geq 0$ denote the rates at which experience is converted and accumulated, while $\mu_S, \mu_M > 0$ are the forgetting rates. The attractiveness of a given strategy is updated through exponential smoothing of recent payoffs. The smoothing speed α_i depends on the accumulated level of experience:

$$M_S(t) = \alpha_S(E_S(t))(\pi_S(t) - M_S(t)), \quad M_M(t) = \alpha_M(E_M(t))(\pi_M(t) - M_M(t)), \tag{19}$$

$$\alpha_i(E) = \alpha_{i0} + \alpha_{i1}\frac{E}{1+E}, \quad \alpha_{i0} > 0, \alpha_{i1} \geq 0, \quad i \in \{S, M\}. \tag{20}$$

The waiters determine whether to join the stayers or the movers according to the relative attractiveness of the two strategies, following a discrete-choice rule:

$$\sigma(t) = 1/(1 + \exp(-\beta(M_S(t) - M_M(t)))), \quad \beta > 0. \tag{21}$$

The waiting population becomes active at the constant rate $p > 0$. When active agents face resource deterioration or a high risk of bargaining failure, part of the active population exits and returns to the waiting state. The resulting population dynamics are:

$$x_S(t) = p x_W(t)\sigma(t) - h_S(t) x_S(t), \quad x_M(t) = p x_W(t)(1 - \sigma(t)) - h_M(t) x_M(t). \tag{22}$$

3 Simulations and Discussion

To further examine the performance of the nomadic game model developed in this paper under dynamic conditions, this section builds a virtual simulation environment in MATLAB on the basis of the model specification and parameter restrictions introduced above. Numerical simulations are conducted over the time interval $t \in [0, 400]$ to trace the evolutionary path of the system. Under the benchmark parameter setting, our primary focus lies in tracking how resource quality, bargaining outcomes, and demographic distributions evolve over time. Table 1 reports the baseline parameter choices used in the numerical simulations.

Table 1. Baseline Parameter Choices and Justifications.

Symbol	Value	Economic Justification	Symbol	Value	Economic Justification
r	0.4	Fast recovery of digital resources	β	2.5	Choice sensitivity to payoff differences

ω	0.2	Efficiency of stayers' maintenance	s_0	0.2	Baseline contract execution probability
χ_S,χ_M	0.25,0.45	Higher per-unit pressure from movers	θ	0.5	Symmetric bargaining power
ρ_S,ρ_M	0.4,0.4	Experience accumulation rate	λ	0.5	Baseline matching friction
μ_S,μ_M	0.08,0.08	Decay rate of cooperative memory	I	0.4	Partial regulatory enforcement

The impact of resource quality and historical cooperation on bargaining success is illustrated in Figure 1. Under conditions of severe resource scarcity (low R), the feasible quota shrinks, leading to a low probability of agreement and a negative net surplus. Conversely, a robust history of cooperation shifts these curves upward. This dynamic lowers the resource threshold required to achieve a positive surplus, demonstrating that accumulated experience can sustain cooperation even when underlying capacity constraints remain tight.

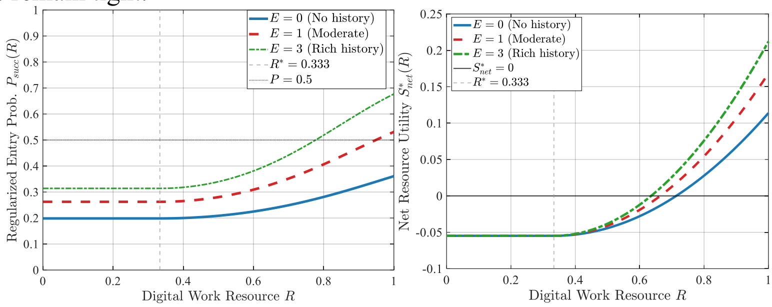

Figure 1. Success probability and net surplus under different levels of cooperation history.

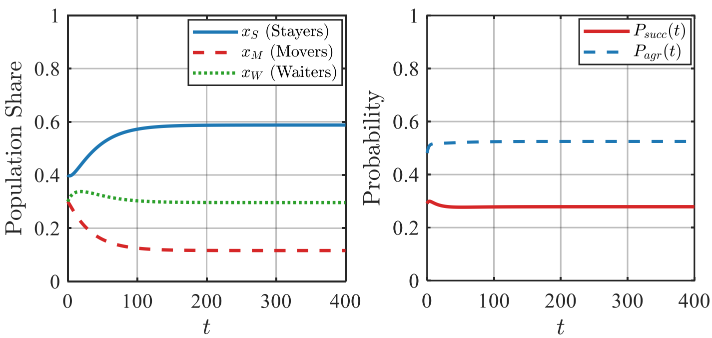

Figure 2. Evolutionary dynamics of population groups over time.

As observed in Figure 2, the system eventually converges from its initial state toward a stable demographic structure. Applying our benchmark parameters, the proportion of stayers increases while the mover population shrinks, ultimately settling into a steady state characterized by moderate agreement rates but diminished enforcement. This pattern implies that post-bargaining implementation—rather than the initial contact phase itself—acts as the primary bottleneck within the system.

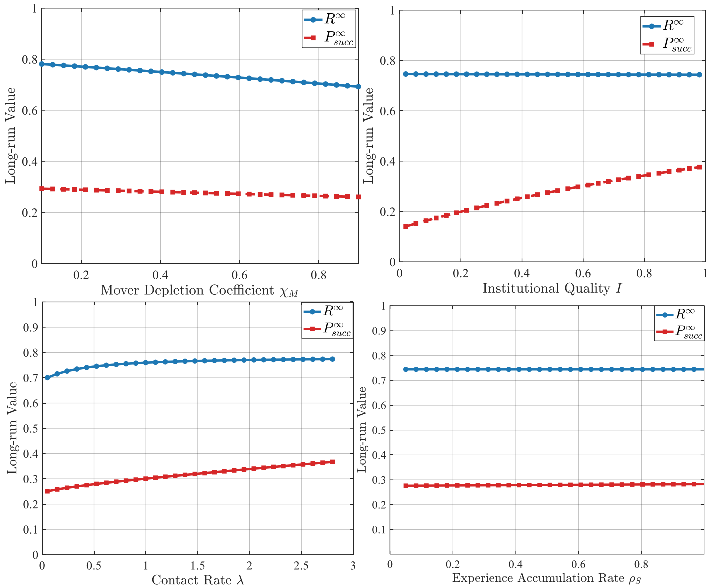

Figure 3. Sensitivity of long-run outcomes to key parameters.

To test the robustness of our numerical findings, Figure 3 evaluates the sensitivity of four key parameters against long-run resource quality R^∞ and cooperation success rate P^∞_{succ}. The contact rate λ initially facilitates cooperation by easing the search frictions nomads face when locating coworking opportunities, yet its marginal benefit diminishes as local work spaces approach congestion. Raising the mover depletion coefficient χ_M tends to degrade both metrics, reflecting the pressure that an influx of mobile workers places on shared community resources. In contrast, strengthening institutional quality I steadily raises bargaining success with little adverse effect on resource quality, suggesting that clearer platform rules and stronger dispute-resolution mechanisms are among the more effective levers for reducing transaction frictions. The experience accumulation rate primarily influences convergence speed rather than the steady-state values, indicating that cooperative memory shapes the evolutionary path but not the long-run equilibrium. Overall, these results suggest that sustaining cooperation among digital nomads depends more on sound institutional design than on simply accelerating spatial mobility.

4 Conclusion

This paper develops a continuous-time nomadic game model to study how mobile remote workers compete for capacity-constrained digital work resources. By integrating stayers, movers, and waiters into a unified framework, the model captures the interplay among resource dynamics, contact matching, quota bargaining, contract enforcement, and cooperative memory. Unlike traditional common-pool resource games that assume static local populations, our contribution lies in embedding spatial mobility and search frictions into an evolutionary setting, revealing that sustaining cooperation in digital nomadism depends not only on resource abundance but critically on overcoming bargaining frictions through institutional design and accumulated cooperative experience. Future research may extend the model by incorporating platform-level micro data, coworking-space samples, and multi-regional network structures.

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