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THE RED QUEEN IN THE DASHBOARD: CO-EVOLUTIONARY DYNAMICS OF ALGORITHMIC CONTROL AND WORKER RESISTANCE

Gösterge Panelindeki Kırmızı Kraliçe: Algoritmik Kontrol ile İşçi Direnişinin Eş-Evrimsel Dinamikleri

Aras YOLUSEVER*

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Abstract

As gig economy platforms increasingly rely on algorithmic management to optimize labor supply, workers are developing sophisticated counter-strategies to regain autonomy. Conventional microeconomic models often treat these interactions as static principal–agent problems. This paper adopts an Evolutionary Game Theory framework to analyze the relationship between algorithmic control and worker behavior as a "Red Queen" dynamic—a co-evolutionary arms race in which the system does not converge to a stable static equilibrium. We model a population of workers choosing between compliance and algorithmic gaming (e.g., coordinated log-offs) against a platform that adjusts its surveillance strictness. Within a Lotka–Volterra–type replicator structure, the interior equilibrium is characterized as a center, generating path-dependent, non-convergent cyclical trajectories. We show that strict algorithmic control can increase the evolutionary fitness of coordinated resistance, producing persistent, neutrally stable oscillatory dynamics in the form of families of closed orbits around an interior center. These findings suggest that "algorithmic unions" may emerge organically as adaptive responses within ongoing, non-convergent platform–worker interactions.

Anahtar Kelimeler:
Evrimsel Oyun Teorisi,
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Öz

Gig ekonomisi platformları işgücü arzını optimize etmek için giderek daha fazla algoritmik yönetime başvurdukça, işçiler de özerkliklerini yeniden kazanmak amacıyla daha sofistike karşı-stratejiler geliştirmektedir. Geleneksel mikroekonomik modeller bu etkileşimleri çoğu zaman statik vekil–asil (principal–agent) problemleri olarak ele almaktadır. Bu çalışma, algoritmik kontrol ile işçi davranışı arasındaki ilişkiyi, hiçbir tarafın statik ve kararlı bir dengeye yakınsamadığı bir eş-evrimsel "Kızıl Kraliçe" dinamiği çerçevesinde incelemek üzere Evrimsel Oyun Teorisini (EOT) kullanmaktadır. Modelde, işçiler uyum (compliance) ile algoritmik manipülasyon arasında seçim yaparken, platform gözetim katılığını ayarlamaktadır. Lotka–Volterra tipi bir replikatör yapısı altında iç denge noktası bir merkez (center) olarak karakterize edilmekte ve başlangıç koşullarına bağlı, yakınsamayan döngüsel yörüngeler ortaya çıkmaktadır. Bulgular, katı algoritmik kontrolün koordineli direnişin evrimsel uyumunu artırabildiğini ve iç merkez etrafında kapalı yörüngelerden oluşan kalıcı, nötr kararlı salınımsal dinamikler ürettiğini göstermektedir. Bu sonuçlar, "algoritmik sendikaların" aşırı optimize edilmiş yönetim sistemlerine karşı süregelen ve yakınsamayan platform–işçi etkileşimleri içinde uyum sağlayıcı bir tepki olarak kendiliğinden ortaya çıkabileceğine işaret etmektedir.

* Asst. Prof. Dr., Istanbul Kültür University, Faculty of Economics and Administrative Sciences, Department of Economics, Türkiye, a.yolusever@iku.edu.tr

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1. Introduction

The rise of the gig economy has fundamentally restructured the labor market, shifting the paradigm from long-term relational contracts to short-term, task-based transactionalism. Initially heralded as a triumph of flexibility and entrepreneurship (Hall and Krueger, 2018), this ecosystem is increasingly defined by what sociologists' term algorithmic management—the use of opaque algorithms to assign tasks, set prices, and discipline workers (Rosenblat and Stark, 2016). While the technological substrate of these platforms is novel, the underlying economic tension is classical: A Principal-Agent problem characterized by information asymmetry and moral hazard.

However, traditional microeconomic modeling of this relationship exhibits a critical limitation. Standard Principal-Agent models typically solve for a static equilibrium in which the Principal (the platform) designs an optimal contract that satisfies the Agent's (the worker's) participation and incentive-compatibility constraints (Holmström, 1979). These models assume a fixed information structure. In reality, the gig economy is characterized by dynamic adaptivity. Platforms utilize machine learning to continuously refine pricing and allocation mechanisms to extract maximum surplus. Simultaneously, workers—despite lacking formal coordination channels—engage in algorithmic gaming, learning heuristics to manipulate demand signals, trigger surge pricing, or bypass monitoring systems (Möhlmann, 2015; Cameron, 2021).

Recent years have witnessed the rapid expansion of algorithmically managed labor platforms such as Uber, Lyft, Deliveroo, Glovo, DoorDash, and Amazon Flex, where managerial decisions are increasingly delegated to opaque algorithmic systems. These platforms regulate worker behavior through dynamic pricing, performance scoring, automated deactivation mechanisms, and real-time surveillance metrics. Workers frequently report adapting strategically to these systems through practices such as coordinated log-offs to trigger surge pricing, multi-apping across platforms to diversify risk, and selective acceptance of tasks to influence algorithmic rankings. Empirical studies document how such algorithmic governance reshapes autonomy, bargaining power, and temporal control over labor, often producing new forms of digital precarity alongside opportunities for flexible income generation (Rosenblat and Stark, 2016; Wood et al., 2019; Kellogg et al., 2020). These real-world dynamics motivate the need for a dynamic evolutionary framework capable of capturing continuous strategic adaptation between platforms and workers rather than static contractual relationships.

This paper argues that the interaction between algorithmic control and worker autonomy cannot be adequately understood through static Nash Equilibrium analysis. Instead, it represents a co-evolutionary "arms race." When platforms tighten control to mitigate gaming, they inadvertently alter the selection pressure on the worker population, increasing the evolutionary fitness of sophisticated resistance strategies. Conversely, successful resistance compels the platform to further increase algorithmic complexity.

This phenomenon is modelled through the lens of Evolutionary Game Theory (EGT), specifically by invoking Red Queen Dynamics (Van Valen, 1973). In evolutionary biology, the red queen hypothesis posits that organisms must constantly adapt merely to survive against co-evolving predators. Within the platform economy, this logic suggests that efficiency does not constitute a stable state; rather, it represents a transient moment embedded in ongoing, non-convergent oscillatory interactions between algorithmic control and worker evasion.

The contribution of the study is threefold. First, the analysis formalizes the algorithmic boss dilemma by extending the discussion beyond qualitative sociological accounts and situating it within a rigorous game-theoretic framework. Second, it is shown that under specific parameter values, particularly when heightened algorithmic strictness generates diminishing returns due to worker alienation, the system does not converge to a stable compliant equilibrium and instead exhibits persistent, neutrally stable oscillatory dynamics characterized by non-convergent cyclical trajectories and families of closed orbits around an interior center, rather than a stable limit cycle. Third, the results indicate that “algorithmic unions” emerge endogenously from these ongoing center dynamics: explicit communication or collective decision-making among workers is not required, as strategic coordination arises whenever workers update their strategies based on payoff differentials at a faster rate than the algorithm can repair its vulnerabilities.

2. The Model

The analysis considers an evolutionary game unfolding in continuous time within a large, well-mixed population. The interaction is structured between two distinct populations: Platforms (P) and Workers (W).

2.1. Strategy Spaces

The platform functions as the principal in a principal-agent relationship, seeking to maximize the extraction of labor surplus while ensuring market liquidity. The central strategic lever available to the platform is the design of the information architecture—specifically, how much information is revealed to the worker ex-ante and how strictly behavior is constrained ex-post. Platforms select a level of algorithmic rigidity to maximize surplus extraction and minimize service variance. For analytical clarity, the action space is reduced to two pure strategies:

i. *Loose Control (L):* Under this strategy, the algorithm prioritizes liquidity and low friction. Full information (destination, pay) is disclosed ex-ante, and penalties for task rejection remain minimal.

ii. *Strict Control (S):* Here, the algorithm emphasizes efficiency and control. It employs blind dispatching, assigns algorithmic penalties for rejection, and uses GPS monitoring to restrict multi-apping and unauthorized route deviations.

Let $x(t) \in [0,1]$ denote the frequency of the strict control strategy in the platform population at time t.

The worker is the agent, seeking to maximize a utility function composed of pecuniary wages and non-pecuniary autonomy. Workers act under bounded rationality; they do not know the full algorithmic code but learn heuristics to exploit it. They seek to maximize their utility, which is a function of pecuniary wage and non-pecuniary autonomy. Their strategy space consists of:

i. *Compliance (C):* The worker accepts the algorithmic dictates, maximizing utilization rate but surrendering autonomy.

ii. *Resistance (R):* The worker engages in strategic behavior to game the algorithm. This includes coordinated log-offs to induce surges, rejecting low-value rides to train the algorithm, or utilizing third-party apps to transparency-hack the interface.

Let $y(t) \in [0,1]$ denote the frequency of the resistance strategy in the platform population at time t .

2.2. Payoff Structure

The payoff matrices are defined in accordance with the economic incentives that characterize the gig economy.

i. V: The total economic value generated by a completed task.
ii. α: The platform's commission rate $(0 < \alpha < 1)$.
iii. β: The efficiency gains from strict control (e.g., lower latency, higher matching rate), where $\beta > 0$.
iv. c_m: The cost of monitoring and maintaining strict control algorithms (computational and R&D cost).
v. c_r: The friction cost of worker resistance to the platform (e.g., unfulfilled rides, refund requests).
vi. k: The cognitive or coordination cost for a worker to engage in resistance.
vii. γ: The psychological cost of loss of autonomy under strict control.
viii. δ: The wage premium gained by successful resistance (e.g., surge price multiplier).

The platform seeks to maximize revenue minus monitoring costs. Platform payoff matrix A can be defined as

$$A = \begin{pmatrix} \pi_P(S,C) & \pi_P(S,R) \\ \pi_P(L,C) & \pi_P(L,R) \end{pmatrix} = \begin{pmatrix} \alpha V(1+\beta) - c_m & \alpha V(1+\beta) - c_m - c_r \\ \alpha V & \alpha V \end{pmatrix} \quad (1)$$

Assumption I

$$\pi_P(S,C) > \pi_P(L,C) \quad (2)$$

Strict control yields higher profitability when confronting a predominantly compliant worker population, a result that aligns with the underlying economic logic of platform optimization. If algorithmic rigidity did not generate superior returns under conditions of high compliance, platforms would lack any incentive to invest in increasingly sophisticated monitoring technologies or dispatch mechanisms. The sustained adoption, and continuous refinement, of such systems therefore presupposes that strict control produces measurable gains in surplus extraction relative to more permissive governance structures, at least when worker compliance remains sufficiently high.

Assumption II

$$\pi_P(L,R) > \pi_P(S,R) \quad (3)$$

If workers resist effectively, strict control becomes suboptimal due to the high cost c_m and the damage c_r.

Workers also seek to maximize $(1-\alpha)V$ plus autonomy/gaming bonuses, minus costs. Worker payoff matrix B can be defined as

$$B = \begin{pmatrix} \pi_W(S,C) & \pi_W(S,R) \\ \pi_W(L,C) & \pi_W(L,R) \end{pmatrix} = \begin{pmatrix} (1-\alpha)V-\gamma & (1-\alpha)V(1+\delta)-k-\gamma' \\ (1-\alpha)V & (1-\alpha)V-k \end{pmatrix} \tag{4}$$

γ' represents autonomy cost under resistance, likely

$$\gamma' < \gamma \tag{5}$$

as resistance reclaims some agency.

Assumption III

$$\pi_W(L,C) > \pi_W(L,R) \tag{6}$$

Under loose control, there is no need to incur cost k; compliance is rational.

Assumption IV

$$\pi_W(S,R) > \pi_W(S,C) \tag{7}$$

Under strict control, the utility gain from gaming (δ) outweighs the coordination cost (k). This is the resistance condition.

2.2.1. Interpretation and Sensitivity of Payoff Assumptions

The payoff structure adopted in the model is intended to capture relative strategic incentives rather than precise monetary magnitudes. Algorithmic strictness increases platform efficiency but generates diminishing marginal returns as worker alienation intensifies, while resistance strategies provide individual adaptive benefits when strict control becomes excessively costly. Importantly, the qualitative dynamics do not depend on the exact numerical values of the payoffs but on the ordering of incentives and the existence of strategic trade-offs between control intensity and worker adaptation. The most critical assumptions for generating center-type oscillatory dynamics are (i) the presence of mutual strategic feedback between platform strictness and worker resistance payoffs, (ii) diminishing marginal returns to excessive algorithmic enforcement, and (iii) positive but bounded adaptive gains from resistance strategies. Variations in payoff magnitudes primarily affect the amplitude and speed of the trajectories rather than the qualitative structure of the evolutionary dynamics. These assumptions therefore represent structural conditions rather than empirical calibrations, and the results should be interpreted as illustrating general strategic tendencies rather than platform-specific numerical predictions.

3. Evolutionary Dynamics

Having established the static payoff matrices, the analysis proceeds to examine the system's dynamic evolution. In contrast to classical game theory—which presumes hyper-rational agents capable of instantaneously computing a Nash Equilibrium—the present framework adopts the tools of EGT.

Within this setting, both platform and worker populations are assumed to operate under bounded rationality. Agents do not engage in complex optimization or forward-looking equilibrium reasoning. Instead, their behaviour is governed by mechanisms of social learning (imitation) and reinforcement learning. Strategies that generate higher-than-average payoffs disseminate within the population, whereas strategies associated with inferior payoffs diminish in prevalence.

This adaptive adjustment process is formally characterized by the replicator dynamics, the canonical equation of motion in evolutionary games (Taylor and Jonker, 1978; Weibull, 1995). Through these dynamics, the distribution of strategies evolves endogenously, allowing the system to exhibit convergence, oscillatory motion, or instability depending on the underlying payoff structure and learning speeds.

The system of non-linear differential equations is defined as:

$$\dot{x} = x(1-x)[\pi_P(S) - \pi_P(L)] \tag{8}$$

$$\dot{y} = y(1-y)[\pi_W(R) - \pi_W(C)] \tag{9}$$

where the expected payoffs are:

$$\pi_P(S) = y\pi_P(S,R) + (1-y)\pi_P(S,C) \tag{10}$$

$$\pi_P(L) = y\pi_P(L,R) + (1-y)\pi_P(L,C) \tag{11}$$

$$\pi_W(R) = x\pi_W(S,R) + (1-x)\pi_W(L,R) \tag{12}$$

$$\pi_W(C) = x\pi_W(S,C) + (1-x)\pi_W(L,C) \tag{13}$$

Substituting the payoff parameters, the expanded form dynamics be derived. Let ΔP be the gain from strictness and ΔW be the gain from resistance.

$$\dot{x} = x(1-x)[\alpha V\beta - c_m - y(c_r)] \tag{14}$$

$$\dot{y} = y(1-y)\big[-k + x\big(\delta(1-\alpha)V + (\gamma' - \gamma)\big)\big] \tag{15}$$

To enable a more tractable stability analysis in Section 3.1, the system of differential equations is reformulated by consolidating the underlying structural parameters into four composite coefficients. These coefficients encapsulate the fundamental incentive forces embedded in the game and allow the dynamic interactions between platforms and workers to be expressed in a more compact and analytically transparent form. By reducing the dimensional complexity of the model in this way, the subsequent phase-plane examination, equilibrium characterization, and eigenvalue evaluation become considerably more straightforward, without altering the strategic content or economic interpretation of the original system.

For the platform

$$A = \alpha V\beta - c_m \tag{16}$$

$$B = c_r \tag{17}$$

For the workers

$$C = k \tag{18}$$

$$D = \delta(1-\alpha)V + (\gamma - \gamma') \tag{19}$$

A is the net efficiency rent generated by strict control and B is the vulnerability of the platform to worker sabotage. C is the explicit cost of coordination required to resist and D is the marginal utility gained by resisting a strict platform (comprising both the gaming premium δ and the recovered autonomy $\gamma - \gamma'$).

3.1. Stability Analysis of the Interior Fixed Point

Having established the system of non-linear differential equations governing the co-evolution of platform strictness (x) and worker resistance (y), it is now turned to the stability analysis of the system's equilibria.

The system is defined on the state space

$$\Omega = [0,1] \times [0,1] \tag{20}$$

which represents the unit square of possible population frequencies. The boundaries of Ω are invariants sets (if $x = 0$, $\dot{x} = 0$, and similarly for y).

The system possesses four trivial boundary equilibria at the vertices of the unit square: $(0,0), (0,1), (1,0), (1,1)$. Given the assumptions it is trivial to show that none of these vertices are Nash equilibria (and thus are not evolutionarily stable strategies). Each vertex is a saddle point, meaning the system is repelled from the corners and forced into the interior of the state space.

The paper focuses the analysis on the unique interior fixed point, denoted as

$$Q^* = (x^*, y^*) \tag{21}$$

where the populations of strategies effectively counterbalance one another.

The interior fixed point is found by setting the fitness differentials to zero.

$$A - By^* = 0 \rightarrow y^* = \frac{\alpha V\beta - c_m}{c_r} \tag{22}$$

$$-C + Dx^* = 0 \rightarrow x^* = \frac{k}{\delta(1-\alpha)V + \Delta\gamma} \tag{23}$$

Proposition I (Existence Condition)

A unique interior equilibrium Q^* exists if and only if

$$0 < x^* < 1 \tag{24}$$

$$0 < y^* < 1 \tag{25}$$

Economically, this implies two necessary conditions.

i. The cost of resistance (k) must be strictly less than the maximum possible gain from gaming the system (D). If coordination costs are prohibitive $(C > D)$, resistance never evolves, and the platform converges to $x = 1$.

ii. The net profit from strictness (A) must be less than the potential damage caused by universal resistance (B). If the platform is robust enough to ignore resistance $(A > B)$, it ignores the workers' reaction, and the system converges to $(1,1)$.

Assuming these conditions hold, the gig economy operates in a "contest regime" rather than a domination regime.

3.1.1. Local Stability Analysis (Linearization)

To determine the local stability of Q^* , the Jacobian matrix J of the linearized system evaluated should be computed at the fixed point.

Let

$$f(x,y) = \dot{x} \tag{26}$$

$$g(x,y) = \dot{y} \tag{27}$$

The Jacobian is defined as

$$J(x,y) = \begin{pmatrix} \frac{\partial f}{\partial x} & \frac{\partial f}{\partial y} \\ \frac{\partial g}{\partial x} & \frac{\partial g}{\partial y} \end{pmatrix} \tag{28}$$

Evaluating the partial derivatives

$$\frac{\partial f}{\partial x} = (1-2x)(A-By) + x(1-x) \tag{29}$$

$$\frac{\partial f}{\partial y} = x(1-x)(-B) \tag{30}$$

$$\frac{\partial g}{\partial x} = y(1-y)(D) \tag{31}$$

$$\frac{\partial g}{\partial y} = (1-2y)(-C+Dx) + y(1-y) \tag{32}$$

At the equilibrium point Q^* the payoff differentials vanish. Consequently, the diagonal elements of the Jacobian (the trace components) become zero.

$$J(Q^*) = \begin{pmatrix} 0 & -Bx^*(1-x^*) \\ Dy^*(1-y^*) & 0 \end{pmatrix} \tag{33}$$

Let

$$\omega_x = x^*(1-x^*) \tag{34}$$

$$\omega_y = y^*(1-y^*) \tag{35}$$

Since Q^* is in the interior

$$\omega_x, \omega_y > 0 \tag{36}$$

The simplified Jacobian is

$$J(Q^*) = \begin{pmatrix} 0 & -B\omega_x \\ D\omega_y & 0 \end{pmatrix} \tag{37}$$

The characteristic equation is given by

$$\det(J-\lambda I) = \lambda^2 - Tr(J)\lambda + Det(J) = 0 \tag{38}$$

Since

$$B, D, \omega_x, \omega_y > 0 \tag{39}$$

the determinant is strictly positive($\Delta > 0$). The eigenvalues are purely imaginary. According to the Hartman-Grobman theorem, the fixed point Q^* is a linear center. In the immediate vicinity of the equilibrium, the system exhibits non-decaying harmonic oscillations. The interior equilibrium constitutes a linear center rather than an asymptotically stable limit cycle. Consequently, the system exhibits a continuum of closed trajectories whose amplitude depends on initial conditions. These oscillations are neutrally stable and structurally sensitive to perturbations.

The mathematical analysis presented above may be interpreted in intuitive terms as a continuous strategic adjustment process rather than a mechanical equilibrium mechanism. When platforms increase algorithmic strictness to extract higher efficiency, workers gradually experiment with alternative behavioral responses, such as selective task acceptance, multi-platform participation, or temporary withdrawal, to restore autonomy and income stability. These adaptive responses do not permanently overturn platform control, but they alter the payoff landscape sufficiently to reduce the effectiveness of strict governance. Platforms then adjust their algorithms in response to emerging worker behaviors, initiating a new phase of strategic interaction. The resulting dynamics resemble a persistent strategic race in which both sides continuously adapt without reaching a final stable outcome. Rather than predicting precise behavioral trajectories, the model highlights a structural tendency toward ongoing mutual adjustment between algorithmic management and worker strategy.

3.1.2. Global Dynamics: The Constant of Motion

The existence of a constant of motion implies that the replicator system possesses a conservative structure. As a consequence, trajectories evolve along invariant level sets of the potential function rather than converging toward an isolated attractor. While these level sets form closed periodic trajectories surrounding the interior equilibrium, they do not constitute an asymptotically stable limit cycle. Instead, the system exhibits a continuum of neutrally stable closed orbits whose amplitude is determined by initial conditions. This conservative property implies the absence of dissipative forces that would otherwise generate convergence to a unique periodic attractor. Accordingly, the oscillatory behavior identified in this study should be interpreted as persistent but non-convergent evolutionary cycling rather than stable limit-cycle dynamics in the classical sense.

Although linearization around the interior equilibrium yields purely imaginary eigenvalues, suggesting a center in the phase plane, this information alone is insufficient to determine the global behaviour of the system. In nonlinear dynamical systems, equilibria with purely imaginary eigenvalues can correspond not only to true centers but also to weakly stable or weakly unstable spirals, depending on the influence of higher-order nonlinear terms that are not captured by local linear analysis. Consequently, linear techniques cannot definitively establish whether trajectories remain bounded, diverge slowly over time, or converge toward the equilibrium.

To demonstrate that the evolutionary trajectories form genuine closed orbits on a global scale, it becomes necessary to identify a Lyapunov function, a constant of motion, or an equivalent Hamiltonian structure for the replicator system. The existence of such a function implies that the dynamical flow is confined to level sets of the conserved quantity, thereby ruling out asymptotic convergence or divergence and confirming that the system evolves along neutral orbital motion. Establishing this invariant structure is therefore essential for proving that the interaction between Platforms and Workers generates persistent, endogenous oscillations rather than merely local rotational behaviour.

The replicator dynamics for asymmetric bimatrix games possess a known Hamiltonian structure (Hofbauer and Sigmund, 1998). The logarithmic potential function is

$$H(x,y) = Dln(x) + Cln(1-x) + Bln(y) + Aln(1-y) \tag{40}$$

Remark

Standard replicator equations possess the structural property that their trajectories maximize (or conserve) the product of strategy shares under appropriate payoff symmetries. In such systems, the constant of motion $\mathrm{V(x,y)}$ is typically obtained by separating the variables associated with each population and integrating them along the flow of the dynamics. This procedure yields an invariant function whose level sets define the closed orbits of the system.

To confirm that the proposed invariant truly functions as a constant of motion, the time derivative of the candidate function must be evaluated along the system's trajectories. A valid Hamiltonian or Lyapunov-like invariant requires that

$$\frac{\partial H}{\partial t} = \frac{\partial H}{\partial x}\dot{x} + \frac{\partial H}{\partial y}\dot{y} \tag{41}$$

$$= \left(\frac{D}{x} - \frac{C}{1-x}\right)\dot{x} + \left(\frac{B}{y} - \frac{A}{1-y}\right)\dot{y} \tag{42}$$

Substituting

$$\dot{x} = x(1-x)(A-By) \tag{43}$$

$$\dot{y} = y(1-y)(Dx-C) \tag{44}$$

$$\left(\frac{D(1-x)-Cx}{x(1-x)}\right)[x(1-x)(A-By)] + \left(\frac{B(1-y)-Ay}{y(1-y)}\right)[y(1-y)(Dx-C)] \tag{45}$$

Substituting the equilibrium definitions

$$C = Dx^* \tag{46}$$

$$A = By^* \tag{47}$$

$$= D(x^*-x)(A-By) + B(y^*-y)(Dx-C) \tag{48}$$

$$= BD(x^*-x)(y^*-y) + BD(y^*-y)(x-x^*) \tag{49}$$

$$= BD(x^*-x)(y^*-y) - BD(x^*-x)(y^*-y) = 0 \tag{50}$$

Theorem 1 (Global Neutral Stability and Conservation of Motion)

Since $\frac{\partial H}{\partial t} = 0$ for all $(x,y) \in \text{int}\ \Omega$ establishes that scalar field $H(x,y)$ is a strict constant of motion for the dynamical system. Consequently, the system is conservative; it exhibits neither asymptotic stability (dissipation of energy) nor instability (explosion of energy). The solution trajectories are confined to the level sets defined by the manifold

$$\mathcal{L}_h = \{(x,y) \in int\ \Omega | H(x,y) = h\} \tag{51}$$

where h is determined by the initial conditions (x_0, y_0).

Proof of Periodicity and Hessian Analysis

To confirm that these level sets $\mathcal{L}_h$ form closed, periodic orbits surrounding the equilibrium Q^*, the curvatore of the potential function $H(x,y)$ should be analyzed.

The Hessian matrix of second-order partial derivatives

$$\mathcal{H} = \begin{pmatrix} -\frac{D}{x^2} - \frac{C}{(1-x)^2} & 0 \\ 0 & -\frac{B}{y^2} - \frac{A}{(1-y)^2} \end{pmatrix} \tag{52}$$

Since parameters are positive, the diagonal entries are strictly negative for all $(x,y) \in int\ \Omega$, and the determinant det $(\mathcal{H}) > 0$. Thus $\mathcal{H}$ is negative definite everywhere in the interior domain.

This implies that $H(x,y)$ is a strictly concave function with a unique global maximum at the critical point $Q^* = (x^*, y^*)$. Furthermore, as the state variables approach the boundaries of the unit square the (i.e., $x \to 0{,}1$ or $y \to 0{,}1$) the logarithmic terms in $H(x,y)$ drive the function value to $-\infty$.

Corollary (Topological Structure of Orbits)

Since $H(x,y)$ is continuous, strictly concave, and approaches to $-\infty$ at the boundaries, the level sets $\mathcal{L}_h$near the maximum Q^* are topologically homeomorphic to circles (closed loops). This proves that for any initial condition $(x_0, y_0) \neq Q^*$ the system follows non-convergent closed trajectories consistent with a neutrally stable center, generating a path-dependent adjustment process rather than a self-sustaining attractor.

3.1.3. Economic Interpretation

The mathematical characterization of the interior fixed point Q^* is a linear center surrounded by closed orbits, with profound implications for the political economy of digital platforms. Contrary to standard neoclassical models where markets clear at a static equilibrium price and quantity, our results suggest that the gig economy is intrinsically characterized by persistent but non-convergent non-equilibrium dynamics. The economic implications of the model are organized into four analytically distinct dimensions.

3.1.3.1. The Fallacy of Algorithmic Optimization (The Red Queen Effect)

Standard management science assumes that for any production function, there exists an optimal control strategy that maximizes the principal's utility. The model demonstrates that in an evolutionary context, this assumption is false. The system exhibits Red Queen Dynamics (Van Valen, 1973), where the platform's attempt to optimize labor extraction through strict control (S) endogenously increases the evolutionary payoff of resistance (R). Consequently, the platform cannot solve the labor problem.

Every increment of algorithmic efficiency ($x \to 1$) effectively subsidizes the development of worker counter-strategies. The platform is forced to run faster, updating algorithms, patching loopholes, and increasing surveillance, simply to maintain the same level of surplus extraction, as the landscape of worker behavior shifts beneath it.

3.1.3.2. Phases Along the Closed Evolutionary Trajectories

The closed orbits predicted by the replicator dynamics correspond to observable "regimes" in the lifecycle of platform markets. The trajectory of the neutrally stable oscillations can be mapped to four distinct economic phases.

1. Phase I: Extraction (High x, Low y): The platform successfully deploys strict algorithms against a compliant workforce. Profits are maximized ($A > 0$), and the platform appears efficient.
2. Phase II: The Resistance Lag (High x, Rising y): The sustained pressure of strictness creates a high differential payoff for resistance ($Dx > C$). Gaming behaviors spread via social learning. The platform's metrics begin to degrade, but control remains strict.
3. Phase III: Algorithmic Retreat (Falling x, High y): The prevalence of resistance renders strict control unprofitable ($By > A$). The platform is forced to pivot back to loosen control (L)—for example, restoring destination transparency or reducing rejection penalties—to liquidity-constrained markets.
4. Phase IV: The Reset (Low x, Falling y): With the relaxation of control, the costly coordination of resistance is no longer incentivized. The workforce drifts back to atomized Compliance (C), setting the stage for a new cycle of extraction.

3.1.3.3. Emergent Coordination (Algorithmic Unions)

A central finding of this model is that coordinated behavioral responses can arise endogenously from payoff geometry rather than from formal institutions. To avoid overstating this mechanism, earlier language suggesting "mathematical inevitability" is replaced with a more circumspect formulation: the model demonstrates a mathematical possibility for endogenous coordination under the specified payoff ordering and parameter constraints (notably when the payoff advantage of resistance exceeds coordination and cognitive costs). Importantly, these emergent clusters of correlated behavior differ from institutionalized unions in two critical respects. First, they are behavioral and decentralized: strategy adoption occurs via imitation and reinforcement learning rather than through legal recognition, elected representation, or formal bargaining structures. Second, they are potentially ephemeral and path-dependent: their persistence depends on the underlying parameter regime and initial conditions rather than on durable organizational capacity or legal protections. Accordingly, the term "algorithmic unions" denotes endogenously emergent, decentralized coordination that can produce union-like effects (collective withholding, coordinated log-offs) without implying the presence of formal union institutions, statutory recognition, or established collective-bargaining mechanisms.

3.1.3.4. Path Dependence and Hysteresis

The topological finding that the system is neutrally stable (a center) rather than asymptotically stable (a sink) implies strong path dependence. In a stable system, a shock (e.g., a temporary regulatory fine, a pandemic) would eventually fade as the system returns to equilibrium. In the conservative system (x, y), a shock that displaces the state moves the economy to a new orbit with a different amplitude of conflict. This suggests a property of hysteresis: a temporary spike in platform aggression can permanently increase the volatility of the labor pool. Once the workforce learns high-level resistance (moving to an outer orbit), the system oscillates more violently, even if the initial cause of the conflict is removed. The "-memory of the conflict is encoded in the amplitude of the cycle.

3.1.3.5. Limitations and Structural Fragility of Center Dynamics

The identification of the interior fixed point as a linear center and the existence of a conservative constant of motion are derived under the model's specific payoff symmetries and deterministic replicator specification. It is important to note that center-type behavior is not structurally robust: small perturbations of the payoff structure (breaking exact symmetries), the introduction of heterogenous learning or revision rates across populations, stochastic shocks, mutation terms, or additional nonlinearities can alter the local linearization and lead to qualitatively different dynamics (for example, weakly stable or unstable foci, damped oscillations, or emergence of attracting limit cycles). Therefore, the center result should be interpreted as a formally valid outcome within the stated assumptions rather than as a universal prediction for all enrichments of the platform–worker interaction. Subsequent robustness checks (noise, asymmetric payoffs, different revision speeds) are recommended to determine how readily center behavior persists under plausible departures from the baseline specification.

4. Discussion: Policy Implications

The evolutionary dynamics presented in the preceding sections challenge the static assumptions underpinning current labor regulation. Traditional policy frameworks often view the gig economy through a binary lens, classifying workers as either independent contractors or employees, and assume that regulatory intervention moves the market from one stable equilibrium to another (Harris and Krueger, 2015). However, the results demonstrate that the ecosystem is characterized by structural sensitive center dynamics.

This red queen nature of the platform-worker conflict implies that static interventions may yield unintended dynamic consequences. By analyzing the sensitivity of the interior fixed point $Q^* = (x^*, y^*)$ to structural parameter changes, it can be derived specific policy implications for stabilizing the digital labor market.

4.1. Political and Institutional Constraints of the Model

While the policy implications derived above emphasize the dynamic sensitivity of the platform–worker interaction, it is equally important to clarify the institutional and market structure within which these dynamics unfold. The analytical framework employed in this study model's strategic adaptation at the population level in order to isolate the endogenous feedback mechanisms between algorithmic control and worker response. However, real-world digital labor markets are embedded in oligopolistic platform structures characterized by concentrated market power, asymmetric information, and significant entry barriers. Recognizing these structural features is essential for interpreting the model's scope, its abstraction choices, and the political economy constraints shaping strategic behavior. This sub-section therefore first situates the evolutionary dynamics within their broader institutional and market power context.

The analytical framework developed in this study adopts an intentionally atomized representation of platform actors in order to isolate the endogenous evolutionary interaction between algorithmic control and worker resistance. This modeling choice should be interpreted strictly as a methodological simplification rather than as an empirical claim about the industrial organization of digital platform markets. In reality, many platform-based sectors, such as ride-hailing, food delivery, and digital logistics, exhibit oligopolistic or highly concentrated structures characterized by strong network effects, data accumulation advantages, and significant barriers to entry (Rochet and Tirole, 2003; Parker et al., 2016; Khan, 2017). These structural features confer substantial strategic power upon dominant platforms and shape the institutional environment in which labor interactions unfold.

Within this context, the apparent symmetry between workers and platforms in the formal model does not imply an empirical symmetry of bargaining power or market influence. Rather, the symmetric evolutionary game formulation serves as a parsimonious baseline that enables tractable analysis of strategic adaptation dynamics without embedding exogenously imposed hierarchical structures directly into the payoff matrix. By abstracting from firm concentration and regulatory asymmetries, the model isolates the co-evolutionary feedback loop between worker resistance strategies and algorithmic enforcement intensity, thereby allowing the emergence of cyclical or non-convergent dynamics to be studied in a controlled theoretical environment. Similar abstraction strategies are common in evolutionary economics and replicator-based modeling, where simplified population assumptions facilitate the identification of dynamic mechanisms prior to institutional enrichment (Weibull, 1995; Samuelson, 1998).

Nevertheless, the institutional reality of oligopolistic platform capitalism introduces asymmetries that may significantly reshape the evolutionary landscape. Dominant platforms benefit from economies of scale, control over algorithmic information flows, and the ability to influence regulatory frameworks, which collectively enhance their capacity to discipline labor markets and shape strategic incentives (Srnicek, 2016; Acemoglu and Restrepo, 2020). Such structural power may alter payoff gradients, compress worker strategy diversity, and potentially transform the stability properties of equilibria identified under atomized assumptions. For instance, increased concentration could shift the system from neutral cyclical dynamics toward more asymmetric attractor structures or amplify the speed of strategic convergence through intensified monitoring technologies.

Moreover, the political economy of platform governance further complicates the interpretation of the model's outcomes. Labor classification regimes, antitrust enforcement intensity, and national regulatory institutions play a critical role in determining the feasible strategy space available to both platforms and workers. The atomized framework therefore abstracts from collective bargaining institutions, labor unions, and regulatory constraints that may introduce coordination effects or alter replicator dynamics at the population level. As highlighted in institutional and labor market literature, the evolution of strategic behavior cannot be fully understood without reference to broader governance structures that shape incentives and enforcement capacities (North, 1990; Ostrom, 2005; Acemoglu and Robinson, 2012).

Accordingly, the policy implications derived from this model should be interpreted as conditional on an abstract strategic environment rather than as direct empirical predictions for concentrated digital markets. The results illuminate the internal logic of evolutionary conflict between algorithmic governance and human strategic adaptation, but they do not negate the importance of structural power asymmetries in real-world settings. Future research could extend the framework by introducing asymmetric payoff matrices reflecting market concentration, hierarchical multi-population evolutionary games distinguishing dominant platforms from fringe competitors, or network-based interaction structures capturing platform ecosystems. Incorporating institutional constraints endogenously would allow researchers to evaluate how antitrust policy, labor regulation, and collective organization mechanisms reshape long-run strategic equilibria.

By explicitly recognizing the political and institutional limitations, this analysis clarifies the contextual boundaries within which its theoretical claims should be understood. The atomized modeling strategy serves as a foundational analytical framework that uncovers the micro-dynamic logic of resistance and control, while also acknowledging that the actual functioning of platform capitalism exists within a structurally asymmetric and politically mediated economic landscape.

4.2. The Paradox of Compliance Costs

A primary objective of modern labor regulation is to reduce the precarity and friction of the gig economy (i.e., minimize conflict). Standard intuition suggests that to protect workers, regulators should police worker behavior less or penalize platforms more. This paper offers a more nuanced view through the equilibrium condition derived as

$$y^* = \frac{\alpha V \beta - c_m}{c_r} \tag{53}$$

Here, y^* represents the equilibrium prevalence of worker resistance. Surprisingly, this level is determined solely by the platform's incentive structure, not the workers.

If regulators impose a transparency tax or strict data audit requirements on platforms (effectively increasing the monitoring cost, c_m), the numerator decreases. Consequently, the equilibrium level of resistance y^* falls.

Mechanism: When the cost of maintaining a strict algorithm (S) rises, the platform is evolutionarily pressured to adopt loose control (L) more frequently. As the platform relaxes control, the grievance triggering resistance dissipates, and the workforce naturally drifts toward compliance.

Implication: Paradoxically, the most effective way to reduce worker misbehavior (gaming/resistance) is not to police workers, but to tax the opacity of the platform. High compliance costs for black box algorithms function as a stabilizing friction, dampening the incentive for the platform to engage in the aggressive surveillance that triggers resistance cycles (Pasquale, 2015).

4.3. Empowering Collective Action to Tame the Algorithm

Conversely, the equilibrium level of platform strictness (x^*) is determined largely by the worker's cost structure

$$x^* = \frac{k}{\delta(1-\alpha)V + \Delta\gamma} \tag{54}$$

This equation reveals that the strictness of the algorithmic boss is proportional to the coordination cost (k) faced by workers.

If policy interventions lower the barrier to collective action (k) —for example, by legalizing digital unions or protecting the right to organize via app-based forums—the numerator decreases, leading to a lower equilibrium strictness x^*.

Mechanism: When workers can coordinate easily (low k), resistance becomes a viable threat even at lower levels of provocation. Anticipating this sensitivity, the platform's evolutionary trajectory shifts away from maximum strictness $(x \to 1)$ to avoid triggering a revolt. Thus, strong unions function as a "governor" on algorithmic over-optimization.

Implications: The persistent failure to implement meaningful antitrust exemptions for gig workers—most visibly reflected in the protracted political disputes surrounding the U.S. PRO Act—effectively keeps the parameter k at an artificially elevated level. In the context of the present model, such institutional rigidity functions as a structural constraint that suppresses workers' ability to coordinate, organize, or engage in collective bargaining. As a result, platforms face minimal risk of coordinated retaliation or strategic counter-mobilization, thereby granting them an extended evolutionary runway within which strict algorithmic control can be intensified without facing immediate or proportionate resistance. This dynamic reinforces the argument in Dubal (2017), which highlights how legal classifications and regulatory gaps systematically weaken workers' collective agency. By insulating platforms from the short-term repercussions of worker opposition, the absence of antitrust protections alters the payoff structure of the game in favour of increasingly rigid algorithmic governance.

4.4. Beyond the Classification Binary

Current legal battles focus on classifying workers as employees (which implies $x = 1$ via fiat) or contractors (which assumes $x = 0$). The model of red queen dynamics suggests that this binary is insufficient because the market naturally oscillates between these states.

Since the system tends toward neutral stable oscillations, rigid classification may be brittle. A more robust regulatory framework would recognize algorithmic due process (Crawford, 2016). Rather than forcing a classification, policy should target the amplitude of the center dynamics. By capping the maximum allowable penalty for task rejection or mandating minimum transparency standards, regulators effectively place a ceiling on (the efficiency gain from strictness). This shrinks the center dynamics, confining the market fluctuations to a narrower, more predictable band of behavior, reducing the systemic volatility.

4.5. The Technological Exit: Automation

The model also provides insight into the platform's long-run strategic orientation toward automation. Because the interior equilibrium of the system constitutes a center—that is, a neutrally stable point around which the dynamics follow non-convergent closed trajectories—the platform cannot secure a definitive or permanent advantage over human workers within the baseline conservative specification. The evolutionary interaction does not converge to a compliant steady state but instead exhibits persistent, path-dependent oscillatory dynamics, implying that algorithmic interventions can at best manage, but not fully eliminate, the recurring adjustment patterns between resistance and control.

This structural feature creates a strong incentive for what may be termed technological exit or technological decoupling. If the platform is unable to push the share of resisting workers toward zero through incremental increases in algorithmic strictness, the only remaining mechanism for eliminating the disruptive force of y is the removal of the human worker population altogether. In practical terms, this corresponds to replacing workers with autonomous systems—such as self-driving vehicles, delivery robots, or drone fleets—that can be interpreted as approximating a regime in which the effective resistance parameter becomes prohibitively large ($k \rightarrow$ very large), rendering strategic opposition negligible. Under such conditions, the co-evolutionary interaction is substantially attenuated, and the platform transitions from a dynamic, co-evolutionary game into a static optimization environment where strictness and productivity can be fine-tuned without endogenous strategic feedback.

The model therefore suggests that the platform's turn toward automation is not driven solely by the pursuit of lower marginal labor costs, as is often assumed in the technological change literature. Rather, automation serves a deeper strategic purpose: it offers a means of attenuating the volatility associated with the Red Queen dynamic. The recurrent, path-dependent fluctuations in worker strategy impose considerable uncertainty on future throughput, service reliability, and ultimately on the platform's financial valuation. In this sense, the adoption of autonomous technologies can function as a mechanism for stabilizing control by reducing a major source of co-evolutionary uncertainty. This aligns with the broader argument advanced by Acemoglu and Restrepo (2018), who emphasize that automation decisions are shaped not only by productivity gains but also by the desire to restructure the bargaining environment between capital and labor.

5. Conclusion

This study has examined the platform economy through an explicitly evolutionary lens, demonstrating that the interaction between algorithmic management and worker behavior constitutes a structurally nonequilibrium system. Contrary to the prevailing assumptions embedded in neoclassical labor models and contract theory, the labor process within gig platforms cannot be reduced to a static principal–agent problem or resolved through an optimal contract. Instead, the analysis reveals that platform–worker relations evolve as a coupled dynamical system governed by asymmetric replicator equations, generating persistent, path-dependent neutrally stable oscillatory dynamics consistent with a Red Queen process. Platforms and workers do not converge to a stable equilibrium; they co-evolve in a continuous arms race in which each side's adaptation reshapes the other's incentive structure.

The core theoretical contribution of the model lies in identifying the interior equilibrium as a neutrally stable center associated with a local conserved quantity consistent with center-type conservative dynamics. This structural property implies that algorithmic interventions designed to optimize labor extraction does not generate asymptotically stable compliance under the baseline conservative specification. Every incremental increase in platform strictness expands the evolutionary payoff to resistance, thereby catalyzing the diffusion of gaming strategies among workers. Conversely, sustained resistance erodes the profitability of strict control, forcing platforms to revert toward more permissive governance structures. The economic system thus follows non-convergent closed trajectories across phases of extraction, resistance escalation, algorithmic retreat, and reset, generating recurrent but path-dependent patterns of adjustment. In this context, algorithmic optimization functions not as a stabilizing force but as an endogenous source of persistent non-convergent dynamics.

The findings also challenge dominant narratives surrounding labor power in the digital economy. Rather than viewing coordination failures as intrinsic to decentralized gig workforces, the analysis demonstrates that algorithmic control can inadvertently create conditions for emergent collective action. When the payoff to resistance surpasses the cognitive and coordination costs faced by workers, resistance strategies propagate autonomously through reinforcement learning and imitation, forming what may be interpreted as algorithmic unions. These decentralized, non-institutional forms of collective action arise not from ideological commitment but from the geometry of the payoff landscape itself.

The emergence of so-called "algorithmic unions" in this framework does not presuppose explicit coordination, collective bargaining institutions, or fully rational collective action. Instead, it arises from decentralized evolutionary adaptation under heterogeneous learning speeds and observable payoff differentials. Individual workers update strategies through imitation, reinforcement learning, and local information signals rather than through centralized agreement. As a result, classical free-rider problems do not disappear but are partially mitigated when resistance strategies generate immediate individual payoffs, such as surge pricing manipulation or reduced algorithmic penalties, that are directly observable within the worker population. Coordination costs, therefore, remain present; however, when the marginal payoff advantage of resistance exceeds cognitive and switching costs, strategies diffuse endogenously without requiring formal organization. In this sense, "algorithmic unions" should be interpreted not as institutional unions but as emergent clusters of correlated strategic behavior generated by evolutionary selection dynamics.

The model further uncovers important policy implications. First, interventions that increase the cost of algorithmic opacity, such as transparency mandates, audit requirements, or constraints on data-driven penalization, reduce the evolutionary profitability of strict control and thereby diminish the long-run prevalence of resistance along the system's closed adjustment trajectories. Second, policies that reduce workers' coordination costs, including legal protections for digital organizing and antitrust exemptions for collective bargaining, constrain the platform's incentive to escalate surveillance intensity. These mechanisms reveal that effective labor regulation in digital markets must target structural parameters shaping the dynamic game rather than attempting to enforce a static classification of workers as employees or independent contractors. Regulatory frameworks must therefore be reoriented from equilibrium design toward the management of non-convergent adjustment patterns, with an emphasis on reducing the amplitude of recurring conflict dynamics.

Finally, the analysis provides an evolutionary explanation for the platform economy's strategic turn toward automation. Because human labor inherently reintroduces co-evolutionary non-convergence, platforms face continual uncertainty in throughput, service quality, and valuation. Automation, whether through autonomous vehicles, delivery robots, or hybrid reinforcement-learning systems, functions not merely as a source of marginal cost reduction but as a mechanism for transforming the underlying dynamic interaction. By eliminating the adaptive capacity of workers, automation converts a co-evolutionary antagonistic process into a static optimization environment largely devoid of endogenous resistance. This perspective situates automation within a broader political economy of control, aligning with theoretical accounts that emphasize its role in restructuring bargaining power rather than solely in enhancing productivity.

Collectively, these insights demonstrate that algorithmic management systems cannot be understood in isolation from the behavioral ecology they generate. The gig economy is not an equilibrium market but an evolving conflict system whose stability properties depend critically on endogenous learning processes, institutional frictions, and technological design choices. Future research would benefit from extending this framework to stochastic shocks, multi-platform ecosystems, and heterogeneous worker learning rules, as well as integrating empirical data on platform micro-behavior into parameter estimation. By foregrounding the evolutionary dynamics of control and resistance, this study underscores the need for a more dynamic, interdisciplinary political economy of digital labor—one that recognizes that in algorithmic markets, equilibrium is not a convergent endpoint but an ongoing co-evolutionary process.

Declaration of Research and Publication Ethics
This study which does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher's Contribution Rate Statement
I am a single author of this paper. My contribution is 100%.

Declaration of Researcher's Conflict of Interest
There are no potential conflicts of interest in this study.

Declaration of Artificial Intelligence Usage
The author(s) did not use any artificial intelligence tools during the preparation of this manuscript.

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