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Agent-based analysis of electricity contract switching considering multi-dimensional consumer satisfaction and social influence

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ABSTRACT

The widespread use of time-of-use (ToU) pricing tariffs in the liberalized retail electricity market has expanded households' opportunities to choose and switch among retail electricity contracts. Understanding why consumers switch contracts is crucial for energy policy and market design, yet the psychological and social drivers of switching behavior remain poorly quantified. This study develops an agent-based modeling framework in which consumers make contract switching decisions considering both personal multi-dimensional satisfaction and peer effects from their social network, governed by a social influence factor β. Simulations reveal pronounced nonlinear switching dynamics driven by heterogeneous consumer preferences. Economic rationality acts as a decision anchor that stabilizes market shares under moderate social influence, while strong peer effects give rise to distinct regime shifts in switching activity. Notably, a "social trap" emerges in which increased switching intensity coincides with declining average consumer satisfaction, despite individually rational decision-making. Under homogeneous preferences, switching exhibits a sharp phase transition around a tipping point separating stable and fluctuating market states. Under income-based heterogeneous preferences, switching thresholds become staggered across consumer groups: consumers with lower economic rationality transition at lower levels of social influence, whereas more economically rational consumers remain stable until substantially stronger peer effects prevail. These findings highlight how interaction-driven mechanisms shape consumer switching behavior and provide actionable insights for utilities and policymakers, including preference-specific contract design and interventions that strengthen the evaluability of contract attributes, to enhance consumer engagement in ToU pricing while maintaining market stability.

1. Introduction

1.1. Motivation

Over the past few decades, electricity markets worldwide have undergone significant liberalization, shifting from monopolistic utilities to more competitive retail systems [1]. This transition, together with the large-scale deployment of smart metering infrastructure, has enabled the implementation of dynamic retail pricing schemes such as time-of-use (ToU) and real-time tariffs. These tariffs are designed to incentivize consumers to adjust their demand, giving consumers the freedom to choose among multiple suppliers and contracts [2]. Under such schemes, consumers are expected to respond to time-varying price signals and can, in principle, choose among alternative suppliers and contract designs.

Dynamic pricing is often promoted for its potential to enhance consumer welfare and support system-level objectives by encouraging demand-side flexibility [3]. However, the realization of these benefits in practice critically depends on consumer engagement, most notably, whether consumers actively evaluate alternatives and switch contracts when advantageous. If consumers remain reluctant to switch providers or tariff plans, competitive pressure in liberalized retail markets may be substantially weakened, limiting both market efficiency and the effectiveness of pricing-based demand-side programs [4]. In practice, switching rates remain modest in many regions and vary widely across European countries. Evidence reported by the Centre on Regulation in Europe (CERRE) indicates that annual household switching rates were around 20% in a few liberalized markets, such as Norway, Belgium, Great Britain, and the Netherlands during 2019–2020, whereas switching activity was very low or negligible in several other countries

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with more tightly regulated retail markets [5]. This pronounced heterogeneity raises important questions about why consumers switch or stay, which factors shape switching decisions beyond price differences, and how policy and market design can better incentivize informed participation.

Despite extensive investigation of dynamic pricing and demand-side mechanisms, the dominant stream of energy management research largely concentrates on system-level optimization problems, including virtual power plant operation, network expansion planning, and storage system configuration [6–13]. These studies primarily address engineering and operational objectives. In contrast, the present study shifts the focus to the consumer level, investigating the behavioral and social dynamics underlying contract switching decisions. This behavioral dimension is critical for the real-world effectiveness of pricing-based demand-side mechanisms, yet remains underexplored in system-level analyses.

1.2. Literature review

Real-world electricity contract switching decision-making often departs from the fully rational, cost-minimizing benchmark due to behavioral frictions and psychological factors [14]. Classical economic frameworks typically model switching as the outcome of cost–benefit trade-offs under search and switching costs and assume a largely single-dimensional objective, most commonly expenditure minimization [15–18]. However, empirical evidence suggests that price considerations alone cannot fully explain observed switching patterns [19]. In particular, market-level studies point to supplier–customer relationship quality [20], local market characteristics and institutional context [21], and tariff complexity [22], as significant determinants of switching activity. At the individual level, behavioral biases, especially loss aversion and status-quo bias, can generate substantial inertia, discouraging switching even when expected monetary gains are positive [23–26].

To capture the richer structure of household decision-making, a growing stream of research has moved beyond single-utility models toward multi-dimensional consumer satisfaction and multi-criteria evaluation frameworks. These approaches recognize that households weigh multiple attributes (e.g., economic outcomes, convenience, perceived risk, service features, and environmental considerations) when assessing electricity contracts. For example, Parag emphasized the joint roles of socio-demographics, demand flexibility, convenience, and environmental motivations in ToU participation [27]. Similarly, Heinrich et al. adopted a consumer-satisfaction perspective and showed that contract attributes such as price, source regionality, and data privacy contribute differently to overall satisfaction [28]. Multi-criteria decision-making methods, including TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution), have also been applied to compare tariff designs under heterogeneous weighting schemes [29]. Together, these studies support the view that switching decisions are shaped by trade-offs across multiple dimensions rather than by cost alone.

Even when contract evaluation is modeled as multi-dimensional, decisions are embedded in social contexts where peer interactions can shape perceptions and choices [30]. Social influence has been shown to affect a wide range of energy behaviors through normative signals and peer comparisons [31]. Wolske et al. further indicated the importance of peer effects on the targeted energy behavior [32]. Choi et al. implemented an eye-tracking experiment and found that the electricity bills shared by neighbors can encourage the intention of a consumer with medium-size dwellings to conserve electricity [33]. Likewise, Moncada et al. demonstrated that peer effects may significantly accelerate the uptake of distributed energy resources in the short-term [34]. Although most of these studies focus on energy consumption or technology adoption, the underlying mechanisms of peer influence are equally relevant to contract evaluation and switching decisions. Modeling such influence commonly relies on explicit representations of social interactions on networks. For example, Du et al. constructed a mathematical model that describes the dynamic interactions of human behavior in social networks, representing how an individual's propensity for energy savings [35]. The results indicate that the strength of relationships between individuals has a greater impact on information dissemination than the number of connections an individual has. Since real-world social systems often exhibit both high clustering and short path lengths, small-world network is frequently used as a parsimonious representation of information diffusion processes [36,37].

The above literature has revealed two powerful forces shaping consumers' contract switching behavior, which are internal multi-dimensional satisfaction and external networked social influence. While current research offers profound insights into the mechanisms of these two dimensions individually, a significant gap remains in understanding their combined effects and dynamic interactions. Agent-based modeling (ABM) is well suited for such settings because it explicitly represents heterogeneous individuals and their non-linear interactions, enabling the study of emergent system-level outcomes [38,39]. ABMs have been widely applied in the energy domain, for instance, to analyze smart-meter diffusion [40,41], assess policy impacts [42], and model household adoption of energy-efficiency measures [43]. Nevertheless, ABM applications that explicitly target electricity contract switching and simultaneously integrate a multi-dimensional psychological satisfaction model with a dynamic social influence mechanism remain limited. Existing ABM studies related to dynamic tariffs, such as those by Kowalska-Pyzalska et al., largely focus on opinion dynamics and adoption tendencies rather than contract evaluation through multi-dimensional satisfaction coupled with evolving peer influence [44,45].

1.3. Research gaps

Based on the above literature review, several important gaps are identified in the current understanding of electricity contract switching dynamics, as summarized in Table 1.

First, existing contract switching models predominantly rely on single-dimensional or weakly behavioral utility-based representations, which are insufficient to capture the multi-dimensional psychological satisfaction underlying real consumer decisions. As a result, these models struggle to explain observed switching inertia and heterogeneous responses to identical pricing incentives.

Second, although social influence has been widely recognized as an important driver of energy-related behavior, it is often modeled in a static or simplified manner. In particular, dynamic mechanisms such as trust evolution are rarely incorporated into consumer contract switching behavior analysis.

Third, the interaction between heterogeneous consumer preferences and social influence has seldom been examined from a dynamic, system-level perspective. As a result, the emergence of collective phenomena remains poorly understood.

Finally, while ABM is well suited for representing heterogeneous

Table 1
Structured comparison of representative research works.

Ref.	Multi-dimensional satisfaction	Explicit contract switching modeling	Social influence modeling	Dynamic trust-based influence
[14–16]	×	Switching as outcome	×	×
[21–23]	✓	not modeled	×	×
[26–29]	×	not modeled	✓	×
[38,39]	×	Implicit adoption	✓	×
This work	✓	Switching as decision	✓	✓

agents and non-linear interactions, existing ABM applications to electricity contract switching remain limited and scattered, and rarely integrate multi-dimensional satisfaction with dynamic social networks in a unified framework.

1.4. Contributions

To address the above research gaps, this study proposes an ABM framework for electricity contract switching that explicitly integrates multi-dimensional consumer satisfaction and dynamic social influence. The framework operates through monthly cycles in which agents individually evaluate contracts, aggregate trust-weighted peer satisfaction through a small-world network, and execute switching decisions based on a composite decision rule, with detailed formulations presented in Section 2 and algorithmic implementation in Appendix B. The main contributions of this work are summarized as follows:

(1) Developing a multi-dimensional psychological satisfaction model that represents boundedly rational consumer decision-making, in which contract evaluation is based on multiple satisfaction dimensions, including electricity consumption, consumption habits, expenditure, electrification level, and switching payback.
(2) Modeling social interactions among consumers through a Watts–Strogatz small-world network (SWN) with trust-weighted information exchange. Trust relationships evolve over time based on realized satisfaction, enabling a realistic representation of peer influence dynamics.
(3) Integrating an ABM framework to capture individual behavioral heterogeneity and social interactions, enabling systematic analysis of emergent contract switching dynamics under different preference structures and social influence strengths.
(4) Revealing non-linear market dynamics, including phase transitions and socially induced inefficiencies, "social traps", as emergent outcomes of the interaction between heterogeneous preferences and social influence, providing insights into how contract design and social influence mechanisms may jointly shape market-level outcomes.

Fig. 1 provides a graphical overview of the proposed modeling framework, illustrating how the individual satisfaction model and social influence mechanism jointly shape consumer switching behavior.

1.5. Paper organization

Section 2 details the agent-based electricity contract switching model and simulation design. Section 3 presents simulation results under different scenarios. Section 4 provides behavioral interpretation and causal mechanism analysis of the simulation results, followed by discussions of limitations and future research directions. Section 5 concludes and discusses the policy implications.

2. Methodology

To reflect real-world diversity, consumers are modeled as heterogeneous, as empirical studies consistently show that socio-demographic differences and behavioral traits shape consumption patterns and preferences [46–48]. As illustrated in Fig. 1, the modeling framework is built around a trade-off between direct economic benefits and living comfort, which constitutes an immediate and tangible decision-making consideration for households. Accordingly, satisfaction is constructed from two complementary pillars: direct economic benefit, operationalized through monthly expenditure and switching cost payback time, and lifestyle comfort, expressed through consumption level, consumption habits, and household electrification. These perceptions are quantified via five dimension-specific indices (ECSI, ECHSI, EESI, ESI, and SPSI), defined in Section 2.2. In addition to self-evaluated satisfaction, the ABM features a peer interaction mechanism. Agents exchange contract satisfaction information with peers in a Watts–Strogatz small-world network (SWN).

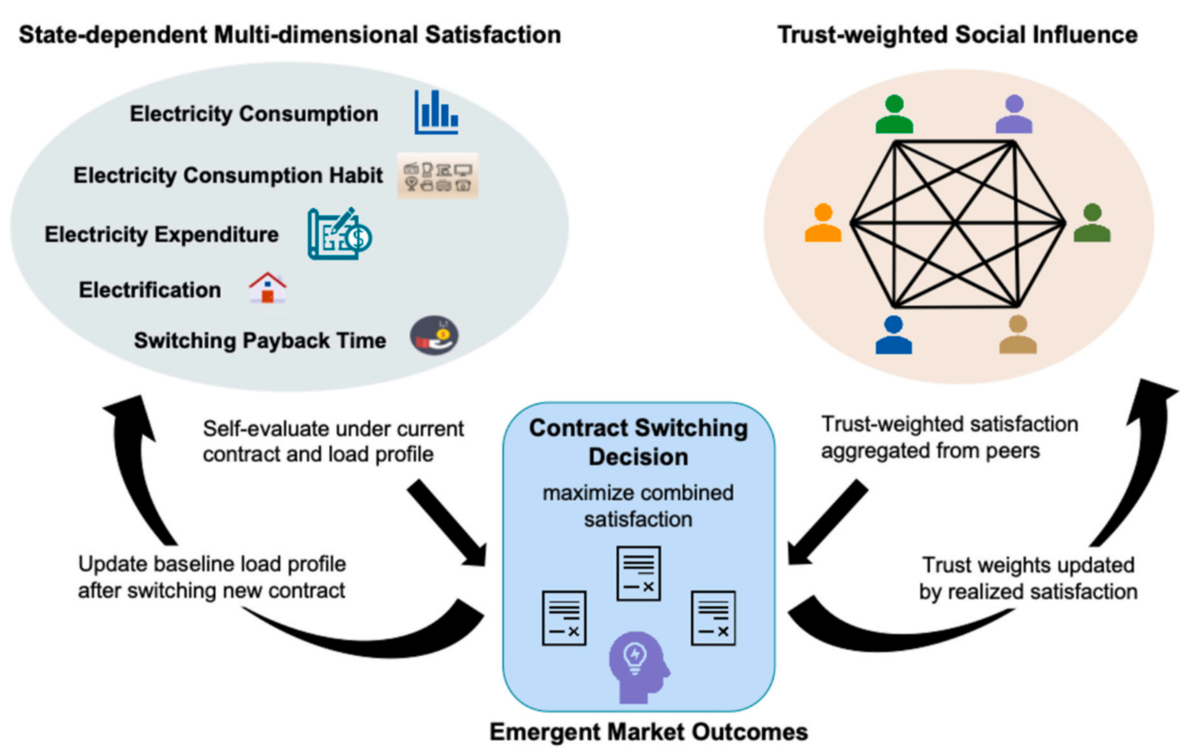


Fig. 1. Electricity contract switching framework.

2.1. Model assumptions

To realistically simulate electricity contract switching behavior, several key assumptions have been adopted based on empirical evidence and behavioral theory:

(a) **Agents:** Consumers are simulated as agents. Let $U = \{u_1, u_2, \ldots, u_N\}$ denote the set of agents and $C = \{c_1, c_2, \ldots, c_M\}$ the set of electricity contracts available in the retail market. At any time, each agent $u_k \in U$ is subscribed to exactly one contract $c_i \in C$.
(b) **Price-Adaptive Demand:** Each agent u_k is characterized by an electricity price elasticity coefficient ε_{u_k}, capturing short-run responsiveness of the agent's daily electricity load profile when evaluating alternative contracts with different price values. Elasticity values are specified within empirically reported ranges for residential demand response under ToU pricing $[-1.56, -0.33]$ [49].
(c) **Habit Inertia:** Agents experience disutility when their daily electricity load profile under the new contract deviates from their established baseline pattern. This habit disruption reduces satisfaction on electricity consumption habit dimension, reflecting empirically documented behavioral regularities such as status-quo bias and loss aversion [50–52].
(d) **Switching Costs and Payback:** Switching contracts entails a total switching cost, including a termination penalty proportional to the remaining contract duration, a fixed registration fee for the new contract, and unrecovered opportunity costs from the previous switch. These costs are amortized over expected monthly electricity bill savings. Agents derive switching payback satisfaction from the resulting payback time, with shorter payback periods yielding higher satisfaction and longer payback periods yielding lower or zero satisfaction. This assumption is consistent with behavioral evidence showing that consumers tend to overweight immediate losses relative to delayed gains, leading to switching inertia even when long-term benefits exist [53].
(e) **Information Sharing:** Agents interact with their peers within the SWN and exchange experience-based information monthly. During each interaction, agents only communicate the contract they are currently subscribed to together with their realized subjective satisfaction. The trust relationship between each pair of agents is quantified by a time-varying trust weight, initially assigned based on pairwise similarity. After each month, trust weights are gradually adjusted depending on whether following a peer's prior recommendation increased the agent's realized satisfaction.
(f) **Bounded-Rational Decision Rule:** Agents employ a maximum-satisfaction comparison rule when deciding whether to switch contracts. Bounded rationality is represented through a finite psychological satisfaction space, in which contract attributes are evaluated along a limited set of perceived dimensions under incomplete and experience-based information. At each decision step, agents compare the perceived overall satisfaction of the currently held contract with that of the available alternatives. If an alternative contract yields higher satisfaction, the agent switches immediately, reflecting proactive, satisfaction-maximizing behavior within this bounded cognitive representation.

Table 2 summarizes model entities and state variables, behavioral and network parameters, and scenario-dependent control variables.

Table 2
Model notation and parameter specification.

Symbol	Definition	Value/Reference
u_k	Consumer agent, $u_k \in U$	$U = \{u_1, \ldots, u_{1620}\}$
c_i, c_j	Index of current and alternative contract, $c_i, c_j \in C$	$C = \{A, B, C, D, E\}$
$C_{u_k}^{(n)}$	Perceived choice set of agent u_k in month n, including the current held contract and peer-recommended alternatives	-
n	Month index	$n = 1, \ldots, 24$
t	Intra-day time index, half-hourly resolution	$t = 1, \ldots, 48$
m	Satisfaction dimension index, $m \in \{1, 2, 3, 4, 5\}$ corresponds to electricity consumption satisfaction index (ECSI), electricity consumption habit satisfaction index (ECHSI), electricity expenditure satisfaction index (EESI), electrification satisfaction index (ESI), switching payback satisfaction index (SPSI), respectively.	-
$\mathcal{N}(u_k)$	Set of peers connected to agent u_k	-
$d_{u_k,c_i,t}^{(n)}$	Baseline daily electricity load of agent u_k at time t in month n under the currently held contract c_i	Initially constructed from Smart-meter data (Section 2.3.1)
$\widehat{d}_{u_k,c_i\to c_j,t}^{(n)}$	Price-adaptive daily electricity load of agent u_k at time t in month n when evaluating a switch from contract c_i to c_j	Calculated via price-adaptive demand rule in Section 2.2.1
$\widehat{s}_{u_k,c,m}^{(n)}$	Self-evaluated satisfaction of agent u_k with respect to dimension m for contract c in month n	Eqs. (2)–(6)
$\widehat{s}_{u_k,c}^{(n)}$	Self-evaluated overall satisfaction of agent u_k for contract c in month n, aggregated across all satisfaction dimensions	Eq. (1)
$s_{\mathcal{N}(u_k),c}^{(n)}$	Trust-weighted satisfaction aggregated from peers currently subscribed to contract c	Eq. (7)
$s_{u_k,c}^{(n+1)}$	Perceived satisfaction combining self-evaluated satisfaction $\widehat{s}_{u_k,c}^{(n)}$ and social influence from peers $s_{\mathcal{N}(u_k),c}^{(n)}$ in month n	Eq. (9)
λ_{m,u_k}	Behavioral sensitivity coefficient of u_k to satisfaction dimension m	Table 4
ε_{u_k}	Electricity price elasticity coefficient of agent u_k	Table 4
$\omega_{u_k,u_l,c_i}^{(n)}$	Trust weight between u_k and peer u_l under contract c_i in month n	Initialized at 0.9 for intra-cluster peers and 0.5 for inter-cluster peers, and updated via Eq. (8)
η	Trust learning rate	0.1
K	Mean degree of SWN	23
P	Rewiring probability of SWN	0.05
δ_{m,u_k}	Preference weight assigned by u_k to satisfaction dimension m	Scenario variable
β	Social influence factor	Scenario variable
seed	Fixed random seed	42

2.2. Electricity contract switching model

2.2.1. Satisfaction model

In month n, for each contract $c \in C_{u_k}^{(n)}$, agent u_k self-evaluates satisfaction by aggregating five dimension-specific indices:

$$\widehat{s}_{u_k,c}^{(n)} = \sum_{m=1}^{5} \delta_{m,u_k} \cdot \widehat{s}_{u_k,c,m}^{(n)}, \sum_{m=1}^{5} \delta_{m,u_k} = 1 \tag{1}$$

where, δ_{m,u_k} is the preference weight that u_k assigns to dimension m. Each dimension-specific index $\widehat{s}_{u_k,c,m}^{(n)}$ is evaluated using the daily electricity load profile under contract c. For the current held contract c_i, satisfaction is based on the baseline electricity load $d_{u_k,c_i,t}^{(n)}$. For an alternative contract c_j, satisfaction is evaluated using a price-adaptive load: $\widehat{d}_{u_k,c_i\to c_j,t}^{(n)} = d_{u_k,c_i,t}^{(n)} \cdot \left(1 + \Delta p_{c_i\to c_j,t} \cdot \varepsilon_{u_k}\right)$, where

$\Delta p_{c_i \to c_j,t} = \left(p_{c_j,t} - p_{c_i,t}\right)/p_{c_i,t}$ is the price difference at hour t between contract c_j and contract c_i. The electricity price elasticity coefficient ε_{u_k} is used to generate price-adaptive adjustments in the daily load profile under alternative contracts as mentioned in assumptions in section 2.1.

In the subsequent model description, for agent u_k considering a switch from contract c_i to c_j in month n, $\widehat{s}^{(n)}_{u_k,c_i \to c_j,m}$ denotes the self-evaluated satisfaction index under c_j, and when $c_j = c_i$ it reduces to the baseline self-evaluated satisfaction index under the current contract.

(1) Electricity Consumption Satisfaction Index (ECSI)

The ECSI reflects the direct satisfaction the agent derives from electricity usage itself. The exponential form is used to capture diminishing marginal utility of consumption [54,55]. Initially, small increases in consumption yield large gains in comfort or convenience (e.g. powering appliances, heating, EV charging), whereas further increases provide progressively smaller satisfaction increments. ECSI is defined as:

$$\widehat{s}^{(n)}_{u_k,c_i \to c_j,ECSI} = 1 - \exp\left(- \lambda_{1,u_k} \cdot \frac{\sum_{t=1}^{T} \widehat{d}^{(n)}_{u_k,c_i \to c_j,t}}{\sum_{t=1}^{T} d^{(n)}_{u_k,c_i,t}} \right) \tag{2}$$

where, $\lambda_{1,u_k} > 0$, is an electricity consumption sensitivity coefficient specific to agent u_k. Higher λ_{1,u_k} means the agent is more sensitive to changes and reaches satisfaction saturation with smaller increases in usage, whereas a smaller λ_{1,u_k} means the satisfaction grows more gradually with daily electricity consumption. Thus, if the new contract encourages higher daily electricity consumption, ECSI will increase with the rate of saturation controlled by λ_{1,u_k}, and vice versa.

(2) Electricity Consumption Habit Satisfaction Index (ECHSI)

The ECHSI measures the compatibility of the alternative contracts with the agent's established electricity consumption habits and captures the habit inertia psychology mentioned in assumptions. The Euclidean distance between the predicted daily electricity load profile under contract c_j and the baseline profile under current contract c_i is calculated as a lifestyle disruption metric [50], which is defined as $h^{(n)}_{u_k,c_i \to c_j} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\widehat{d}^{(n)}_{u_k,c_i \to c_j,t} - d^{(n)}_{u_k,c_i,t}\right)^2}$. To capture the decreasing marginal disutility of lifestyle disruption, ECHSI is then modeled as a decreasing exponential function of this distance:

$$\widehat{s}^{(n)}_{u_k,c_i \to c_j,ECHSI} = \exp\left(- \lambda_{2,u_k} \cdot h^{(n)}_{u_k,c_i \to c_j} \right) \tag{3}$$

where, $\lambda_{2,u_k} > 0$, is a habit sensitivity coefficient specific to agent u_k. Higher λ_{2,u_k} means agent u_k is more sensitive to habit changes, even small deviations cause a sharp drop in satisfaction, reflecting a stronger aversion to lifestyle disruption. Lower λ_{2,u_k} implies greater tolerance of change.

(3) Electricity Expenditure Satisfaction Index (EESI)

The EESI quantifies the agent's economic satisfaction by benchmarking the estimated monthly bill under a new contract against their current expenditure, consistent with expenditure-based utility formulations commonly used in household energy economics [56]. Denote the predicted monthly expenditure under contract c_j for agent u_k as $\widehat{C}^{(n)}_{u_k,c_i \to c_j} = Days \cdot \sum_{t=1}^{T} \widehat{d}^{(n)}_{u_k,c_i \to c_j,t} \cdot p_{c_j,t}$. Similarly, for the current contract c_i, $C^{(n)}_{u_k,c_i} = Days \cdot \sum_{t=1}^{T} d^{(n)}_{u_k,c_i,t} \cdot p_{c_i,t}$. So the monthly electricity expenditure ratio between the contract c_j and c_i is defined as $r^{(n)}_{u_k,c_i \to c_j} = \widehat{C}^{(n)}_{u_k,c_i \to c_j} / C^{(n)}_{u_k,c_i}$, and the EESI is defined as a decreasing function of $r^{(n)}_{u_k,c_i \to c_j}$:

$$\widehat{s}^{(n)}_{u_k,c_i \to c_j,EESI} = \exp\left(- \lambda_{3,u_k} \cdot \left(r^{(n)}_{u_k,c_i \to c_j} - 1 \right) \right) \tag{4}$$

where, $\lambda_{3,u_k} > 0$, is a cost sensitivity coefficient specific to agent u_k. Higher λ_{3,u_k} means the agent is highly price-sensitive, even a small bill increase causes a large drop in satisfaction. Lower λ_{3,u_k} implies the agent tolerates higher prices for other benefits more easily.

(4) Electrification Satisfaction Index (ESI)

The ESI represents satisfaction derived from the degree of household electrification. For agent u_k, an electrification degree is defined as the fraction of total household energy consumption that is electricity $q^{(n)}_{u_k,c_i \to c_j} = \widehat{Ele}^{(n)}_{u_k,c_i \to c_j} / E^{total}_{u_k}$, where $E^{total}_{u_k}$ is the assumed constant total monthly energy need (electricity and gas), $\widehat{Ele}^{(n)}_{u_k,c_i \to c_j} = Days \cdot \sum_{t=1}^{T} \widehat{d}^{(n)}_{u_k,c_i \to c_j,t}$ is the predicted monthly electricity consumption under contract c_j. Many modern energy services come from using electricity instead of other fuels, and greater electrification often means improved convenience, cleaner energy, and potentially higher quality of life [57]. Therefore, to reflect diminishing marginal utility, ESI is modeled as an increasing function of $q^{(n)}_{u_k,c_i \to c_j}$:

$$\widehat{s}^{(n)}_{u_k,c_i \to c_j,ESI} = 1 - \exp\left(- \lambda_{4,u_k} \cdot q^{(n)}_{u_k,c_i \to c_j} \right) \tag{5}$$

where, $\lambda_{4,u_k} > 0$, is an electrification sensitivity specific to agent u_k. Higher λ_{4,u_k} means the agent derives strong satisfaction from even modest increases in electrification, whereas lower λ_{4,u_k} means the agent's satisfaction grows gradually with electrification.

(5) Switching Payback Satisfaction Index (SPSI)

The SPSI quantifies agent satisfaction with the payback time of incurred switching costs when switching from contract c_i to c_j. Firstly, the estimated monthly expenditure savings is calculated: $\widehat{B}^{(n)}_{u_k,c_i \to c_j} = Days \cdot \left(C^{(n)}_{u_k,c_i} - \widehat{C}^{(n)}_{u_k,c_i \to c_j} \right)$. If $\widehat{B}^{(n)}_{u_k,c_i \to c_j} \le 0$, the new contract offers no savings or is more expensive, SPSI $= 0$. Otherwise, the payback time in months is $L^{(n)}_{u_k,c_i \to c_j} = \left\lceil SC^{(n)}_{u_k,c_i \to c_j} / \left| \widehat{B}^{(n)}_{u_k,c_i \to c_j} \right| \right\rceil$, where the total switching cost $SC^{(n)}_{u_k,c_i \to c_j} = F + P^{(n)}_{u_k,c_i \to c_j} + L^{(n)}_{u_k,c_m \to c_i} \cdot \left| B^{(n)}_{u_k,c_m \to c_i} \right|$ comprises the fixed registration fee $F = 30€$ of contract c_j, the prorated termination penalty $P^{(n)}_{u_k,c_i \to c_j} = P/12 \cdot D^{(n)}_{u_k,c_i}$ caused by the remaining months $D^{(n)}_{u_k,c_i}$ of contract c_i (with $P = 30€$, $D = 12\,months$), and uncovered residual opportunity cost $L^{(n)}_{u_k,c_m \to c_i} \cdot \left| B^{(n)}_{u_k,c_m \to c_i} \right|$ from the previous switching from contract c_m to c_i (with residual payback months $L^{(n)}_{u_k,c_m \to c_i}$, monthly expenditure savings $B^{(n)}_{u_k,c_m \to c_i}$). Then the payback time $L^{(n)}_{u_k,c_i \to c_j}$ is mapped to SPSI using a decreasing exponential function, reflecting that long payback periods drastically diminish the attractiveness of switching:

$$\widehat{s}^{(n)}_{u_k,c_i \to c_j,SPSI} = \exp\left(- \lambda_{5,u_k} \cdot L^{(n)}_{u_k,c_i \to c_j} \right) \tag{6}$$

where $\lambda_{5,u_k} > 0$ is a payback time sensitivity coefficient specific to agent u_k. This captures the agent's implicit discounting of future monetary benefits [58]. A high λ_{5,u_k} means the agent is very impatient or very cost-sensitive, they demand almost immediate payback and view multi-month recovery as unacceptable. A low λ_{5,u_k} means the agent is more patient or less cost-sensitive, they are willing to wait longer for payback.

2.2.2. *Social influence model*

In parallel with individual self-evaluation, agents form perceptions of contract alternatives through social interaction with peers embedded in the SWN. Let $\mathscr{N}(u_k)$ denote the set of peers connected to agent u_k. Social influence is modeled through peer-to-peer communication of realized satisfaction with currently subscribed contracts. At each month n, each peer $u_l \in \mathscr{N}(u_k)$ only recommends the contract c_i they currently subscribe to along with their realized satisfaction $s^{(n)}_{u_l,c_i}$, resulting in localized, subjective, and experience-based information exchange. The aggregated peer satisfaction perceived by agent u_k for contract c_i is computed as a trust-weighted average [59]:

$$s^{(n)}_{\mathscr{N}(u_k),c_i} = \frac{\sum\limits_{u_l \in \mathscr{N}(u_k), f(u_l)=c_i} s^{(n)}_{u_l,c_i} \cdot \omega^{(n)}_{u_k,u_l,c_i}}{\sum\limits_{u_l \in \mathscr{N}(u_k), f(u_l)=c_i} \omega^{(n)}_{u_k,u_l,c_i}} \tag{7}$$

where $\omega^{(n)}_{u_k,u_l,c_i} \in (0,1)$ represents the trust weight between agents u_k and u_l in month n under contract c_i. Initial trust weights are assigned based on agent similarity to capture homophily in social interactions. Agent similarity is identified using K-means clustering on observable household attributes. Higher initial trust is assigned to peers within the same cluster and lower trust to peers across clusters, as specified in Table 2. Trust weights evolve over time through a satisfaction-driven social learning process. If following a peer's prior recommendation results in higher realized satisfaction, trust in that peer increases; otherwise, trust decreases. The update rule is given by:

$$\omega^{(n+1)}_{u_k,u_l,c_i} = \begin{cases} \omega^{(n)}_{u_k,u_l,c_i} \cdot (1+\eta), \text{if } s^{(n)}_{u_k,c_i} < s^{(n)}_{u_l,c_i} \\ \omega^{(n)}_{u_k,u_l,c_i} \cdot (1-\eta), \text{if } s^{(n)}_{u_k,c_i} > s^{(n)}_{u_l,c_i} \\ \omega^{(n)}_{u_k,u_l,c_i}, \text{if } s^{(n)}_{u_k,c_i} = s^{(n)}_{u_l,c_i} \end{cases} \tag{8}$$

where $\eta = 0.1$ is the learning rate controlling the speed of trust adjustment over time, resulting in gradual changes of the responsiveness of peer effects on observed satisfaction outcomes.

2.2.3. Contract switching decision

In each month n, agent u_k evaluates the perceived choice set $C^{(n)}_{u_k}$ through a two-stage process that separates individual assessment from social influence. First, based on its own daily electricity load profile and the tariff structures of contracts, agent u_k computes self-evaluated satisfaction of available contracts using the multi-dimensional satisfaction model described in Section 2.2.1. In parallel, agent u_k receives experience-based recommendations from peers as described in Section 2.2.2. The final perceived satisfaction for each contract is then obtained by combining self-evaluated satisfaction and peer effects through a social influence factor $\beta \in [0,1]$:

$$s^{(n+1)}_{u_k,c} = (1-\beta)\widehat{s}^{(n)}_{u_k,c} + \beta s^{(n)}_{\mathscr{N}(u_k),c}, \forall c \epsilon C^{(n)}_{u_k} \tag{9}$$

Agent u_k then selects the contract with the highest perceived satisfaction:

$$f^{(n+1)}_{u_k} = \underset{c \in C^{(n)}_{u_k}}{argmax} s^{(n+1)}_{u_k,c} \tag{10}$$

when $\beta = 0$, decisions are driven solely by individual evaluation. As β increases, peer effects progressively shape contract choices, allowing the model to capture the transition from individually driven to socially driven switching behavior.

2.3. Simulation design

2.3.1. Agent initialization and parameterization

A population of household agents is initialized using the Irish CER Smart Metering Project dataset [60]. The dataset contains half-hourly electricity consumption records for 4232 households from July 2009 to December 2010, and includes survey data on socio-economic and dwelling characteristics.

(1) Data cleaning

To ensure data quality and completeness for model parameterization, first, 477 households that had not been allocated initial contracts are excluded. Then, 28 households with more than 5% missing smart meter readings during the observation period are excluded. Furthermore, 1951 households are excluded due to missing survey variables required for behavioral mapping. Based on a percentile screening method for electricity consumption, 156 households outside the 5th–95th percentile range are further excluded. After screening, 1620 households are retained to initialize the agent population.

(2) Initial contract assignment

The CER trial introduced five TOU electricity tariff contracts, characterized by different day, night, and peak prices, summarized in Table 3. Each household is initially assigned a contract originally allocated in the trial, which defines the agent's initial contract in the simulation.

(3) Behavioral parameterization

To reflect heterogeneity in household decision-making, each agent u_k is assigned five behavioral sensitivity coefficients $\lambda_{m,u_k} (m = 1, \dots, 5)$ and an electricity price elasticity coefficient ε_{u_k}, using a structured mapping from observable survey attributes, as summarized in Table 4. These coefficients govern agents' responsiveness to satisfaction changes in electricity consumption, habit disruption, expenditure, electrification level, and payback time.

Specifically, agents owning more appliances are assumed to exhibit higher comfort in electricity consumption and experience smaller disruptions in utility when their consumption patterns change. Accordingly, lower consumption λ_1 and habit λ_2 as well as higher electrification sensitivity λ_4 and a higher ε_{u_k} are assigned to reflect their enhanced flexibility and receptivity to new technologies. The cost sensitivity coefficient λ_3 and payback time sensitivity coefficient λ_5 have been linked to socio-economic characteristics. Lower-income agents, facing tighter budget constraints, are modeled with higher λ_3 and λ_5 values because any increase in their electricity bill more acutely affects their household finances. Conversely, higher-income agents are assigned lower λ_3 and λ_5, reflecting more gradual declines in their expenditure-related and payback-related satisfaction when faced with similar cost or payback changes. As a proxy for baseline gas demand and heating intensity, the number of bedrooms is used, reflecting the empirical association between dwelling size and gas consumption. A dedicated sensitivity analysis of the behavioral sensitivity coefficients is provided in Appendix A to assess the robustness of the results with respect to this parameterization.

(4) Baseline daily electricity load profile construction

For each agent, the initial baseline half-hourly daily load profile is constructed by averaging the cleaned smart-meter data over February. February is selected as the baseline month due to relatively stable winter demand and limited holiday-related disruptions, providing a representative reference profile for initialization.

2.3.2. Social network generation

Peer interactions are modeled using an SWN, which captures high clustering and short average path length commonly observed in social systems. The network is generated in two steps. First, a regular ring lattice is constructed where each agent is connected to K nearest neighbors. Second, each edge is rewired with probability P to a randomly selected node, avoiding self-loops and duplicate edges, following the standard Watts–Strogatz procedure.

Table 3
Contracts in Irish CER smart meter project and initial assignment.

	Time period	Contract-A	Contract-B	Contract-C	Contract-D	Contract-E
Day Rate (€/kWh)	08:00 – 17:00 19:00 – 23:00	0.14	0.135	0.13	0.125	0.14
Night Rate (€/kWh)	23:00 – 08:00	0.12	0.11	0.10	0.09	0.10
Peak Rate (€/kWh)	17:00 – 19:00	0.20	0.26	0.32	0.38	0.38
Consumer number of initial assignment		432	181	458	185	364

Table 4
Behavioral mapping and parameter settings.

Category	Class labels	Consumers number	Parameters mapping			
Appliances number			λ_{1,u_k}	λ_{2,u_k}	λ_{4,u_k}	ε_{u_k}
low ≤ 5	1	584	3	3	1	$[-0.74, -0.33]$
Middle >5 and ≤ 8	2	873	2	2	2	$[-1.15, -0.74]$
High >8	3	163	1	1	3	$[-1.56, -1.15]$
Income level (€/Year)			$\lambda_{3,u_k}, \lambda_{5,u_k}$			
$\geq$75,000	1	248	0.01			
50,000 - 75,000	2	419	0.02			
30,000 - 50,000	3	288	0.03			
15,000 - 30,000	4	621	0.04			
$\leq$15,000	5	44	0.05			
Bedrooms number			Annual gas consumption (kWh)			
1	1	19	5500			
2	2	140	8250			
3	3	695	11,000			
4	4	572	13,750			
5+	5	194	16,500			

The network parameters K and P are selected through a grid search, as illustrated in Fig. 2(b and c). The grid search aims to identify parameter combinations that jointly yield high clustering and short path length while remaining stable across random realizations. Specifically, K is varied from 20 to 30 while fixing $P = 0.05$, followed by fine-tuning P from 0.01 to 0.1. For each candidate setting, the clustering coefficient C and the average shortest path length L are computed over 10 independent realizations to account for stochastic variability in network realization. As an external reference for typical small-world properties, empirical statistics reported for large-scale online social networks (e.g., Facebook: $C = 0.605 \pm 0.015$, $L = 3.69 \pm 0.12$ [61]) are used to benchmark the order of magnitude of clustering and path length, rather than to replicate a specific platform structure. Based on this procedure, $K = 23$ and $P = 0.05$ are selected, yielding a network with C approximately 0.61 and L approximately 3.7. Fig. 2(a) visualizes the resulting initial network.

Following each monthly contract switching decision, the network topology is updated via the same probabilistic rewiring mechanism with probability P, such that agents' peer sets $\mathcal{N}(u_k)$ change across months. This dynamic rewiring preserves small-world characteristics in expectation while capturing evolving social contacts. In addition to network evolution, social ties are associated with time-varying trust weights that govern the strength of peer influence. The initialization and updating of trust weights follow the social influence model described in Section 2.2.2.

2.3.3. Iteration

The detailed algorithmic implementation of the simulation procedure is provided in Appendix B. All simulations are conducted using a fixed random seed. Each scenario is simulated over 24 monthly time steps. At each iteration n, a sequence of synchronized operations is performed for all agents, as shown in Fig. 3.

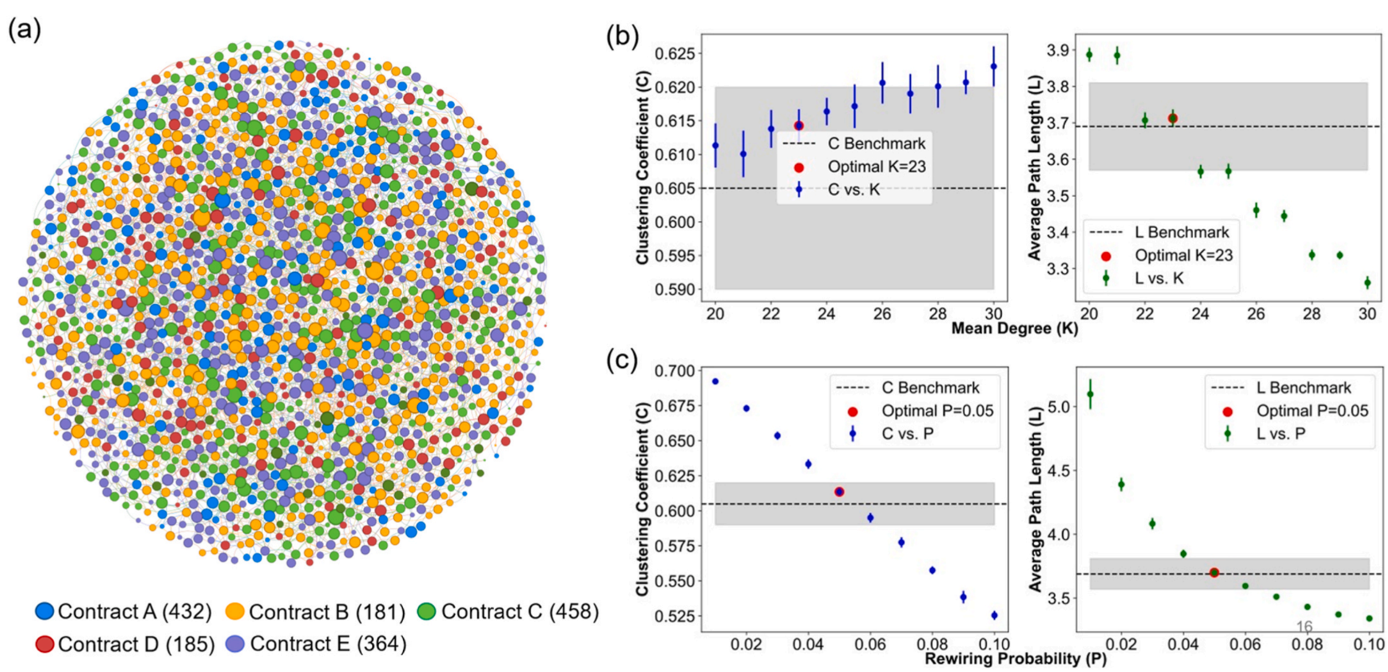


Fig. 2. Social network generation. (a) The initial connection between 1620 agents using SWN. Each node represents an agent with an initial contract assignment. (b) Grid search for optimal K while fixing $P = 0.05$. (c) Fine-tuning P between 0.01 and 0.1, while fixing $K = 23$.

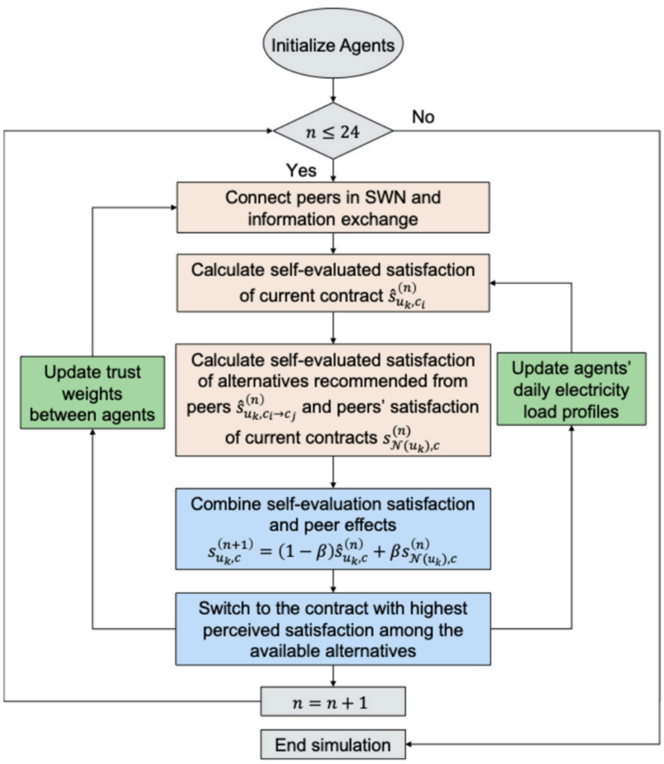


Fig. 3. Agent-based simulation of contract switching process.

(1) Information exchange:

Each agent u_k interacts with its peers in the SWN. During an interaction, peers communicate only the contract they are currently subscribed to and their realized satisfaction with that contract. Based on this localized and experience-based information, agents then form a self-evaluated satisfaction $\hat{s}^{(n)}_{u_k,c}$ and a peer-based satisfaction $s^{(n)}_{\mathcal{N}(u_k),c}$ over the perceived choice set $C^{(n)}_{u_k}$.

(2) Contract switching decision:

Agents combine self-evaluated satisfaction with peer effects and select the contract with maximum satisfaction among the perceived choice set. Contract choices are updated synchronously at the end of each month, based on information available within the current time step. In cases where multiple contracts yield identical satisfaction values, agents retain their current contract.

(3) Trust, load profile update and network rewiring:

Following contract switching, agents update trust weights on social ties based on realized satisfaction outcomes, according to the trust-learning mechanism defined in Section 2.2.2. Then they update daily electricity load profiles under the newly selected contracts, which serve as the baseline load profiles for satisfaction evaluation in the subsequent month. In SWN, each existing edge is rewired with probability P defined in Section 2.3.2, while preserving the mean degree K. This step allows agents' peer sets to evolve while maintaining small-world characteristics in expectation.

At each time step, key system-level metrics are recorded, including the number of agents switching contracts, contract market shares, and average satisfaction changes.

3. Results

3.1. Baseline switching dynamics

To distinguish the respective roles of intrinsic preferences and social influence in electricity contract switching, two baseline scenarios are examined: an individual-driven regime without social influence ($\beta = 0$) and a socially driven regime with maximal social influence ($\beta = 1$). In both regimes, five "one-hot" preference configurations are considered, in which each satisfaction dimension is activated independently ($\delta_m = 1$), allowing the effect of each dimension on contract selection to be isolated without preference mixing. Specifically, the analyzed cases correspond to preferences for (1) electricity consumption level, (2) consumption habits, (3) electricity expenditure, (4) electrification level, and (5) switching payback time.

3.1.1. Individual-driven decisions ($\beta = 0$)

Fig. 4 illustrates contract switching dynamics under purely individual-driven decision-making ($\beta = 0$). For comfort-oriented preferences, electricity consumption (case 1) and electrification (case 4), Contract D with the lowest off-peak rates rapidly attains about 1500 consumers, while other contracts diminish to near-zero market shares. Conversely, economically-driven preferences, electricity expenditure (case 3) and switching payback time (case 5) converge dominantly to Contract A, whose minimal peak rate optimizes cost satisfaction and payback efficiency, reflecting a clear economic optimum. A distinct pattern is observed for the consumption habit–preference case 2, where no switching occurs throughout the simulation horizon. This outcome reflects strong habit inertia, as agents avoid contract changes that disrupt established consumption routines.

3.1.2. Socially-driven decisions ($\beta = 1$)

Under maximal social influence ($\beta = 1$), switching dynamics change markedly, particularly for non-economic preference structures. As shown in Fig. 5(a1)–(a5), consumption-, electrification-, and habit-oriented cases (cases 1, 2, and 4) exhibit persistent volatility, with repeated switching driven by peer recommendations. These patterns are characteristic of socially amplified switching dynamics, in which peer-propagated satisfaction signals induce repeated contract changes that prevent convergence to a stable equilibrium. By contrast, economically driven preferences remain stable despite strong peer effects. For both electricity expenditure (case 3) and switching payback time (case 5), Contract A maintains a dominant market share exceeding 1000 agents. Box-plot results in Fig. 5(b1)–(b5) confirm this stability, showing high medians and narrow interquartile ranges for Contract A, whereas non-economic cases display low medians and overlapping distributions across contracts. These results indicate that social influence amplifies volatility only when consumer preferences lack objectively verifiable satisfaction anchors, whereas preferences grounded in economic attributes exhibit inherent resistance to socially induced switching.

3.2. Social influence dynamics

To investigate how the system transitions from individual-driven to socially-driven behavior, the social influence factor β is varied from 0.1 to 1.0 in increments of 0.1, considering two configurations for consumer preferences: (1) homogeneous preference weights and (2) heterogeneous preference weights based on income levels.

3.2.1. Homogeneous preferences

In this scenario, each consumer gives equal weights to all five dimensions $\delta_{m,u_k} = 0.2$, which provides a neutral benchmark in which behavioral heterogeneity arises solely from social interaction.

Fig. 6 illustrates the evolution of contract market shares as the social influence factor β increases. Two distinct behavioral regimes can be identified. When social influence is weak to moderate ($\beta \leq 0.6$), the

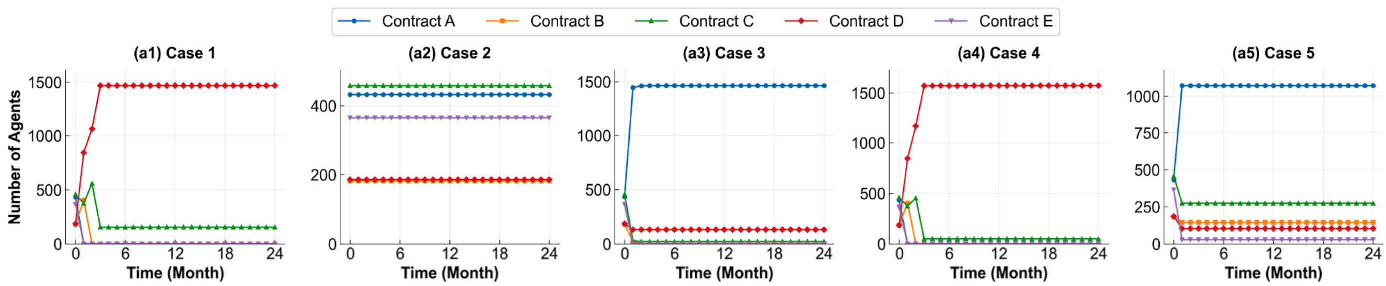


Fig. 4. Contract switching dynamics over 24 months under individual-driven decision-making (β = 0). (a1)–(a5) show the monthly consumer distributions across Contracts A–E for electricity consumption-preference, electricity consumption habit-preference, electricity expenditure-preference, electrification-preference, and payback time-preference, respectively. Results illustrate rapid convergence to a single dominant contract determined by the prioritized satisfaction dimension.

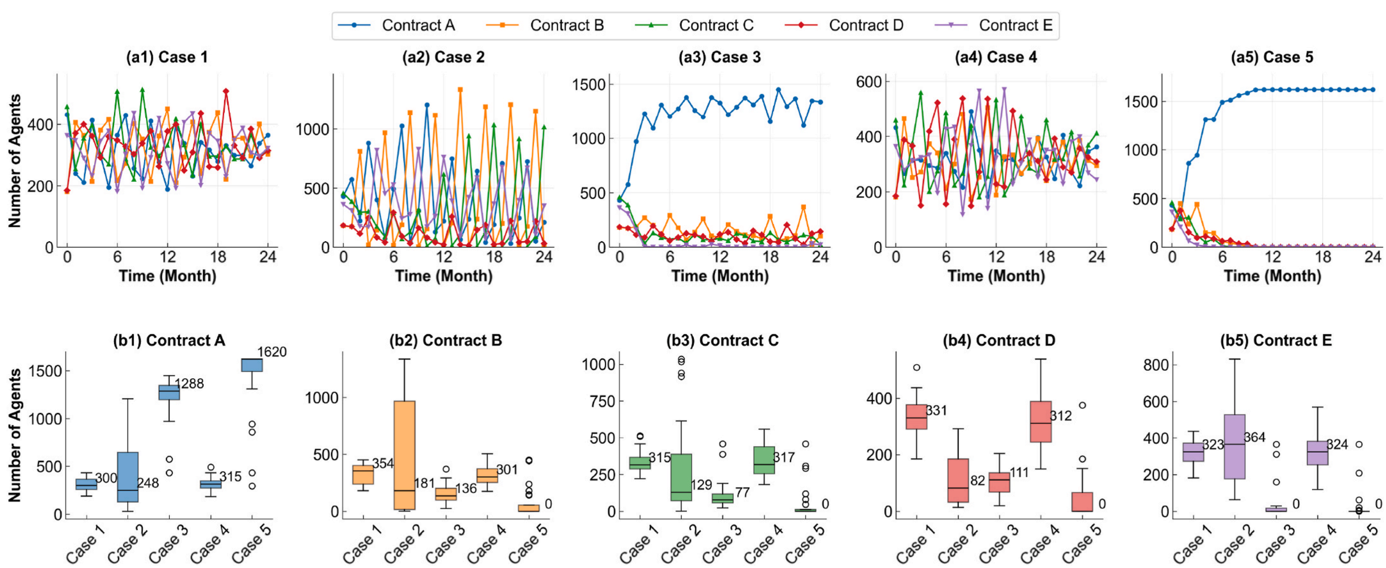


Fig. 5. Contract switching dynamics under maximal social influence (β = 1). (a1)–(a5) show monthly consumer distributions across contracts for the five one-hot preference cases. (b1)–(b5) report the distribution of contract adoption levels over the simulation horizon. Social influence induces persistent volatility for non-economic preferences, while economically-driven preferences remain relatively stable.

system rapidly converges to a stable market configuration. In this ordered regime, Contract A quickly emerges as the dominant option, and market shares stabilize within the first few months, indicating that switching behavior is primarily driven by individual satisfaction evaluation and early exploration. As β approaches 0.7 and above, the market dynamics undergo a phase transition. Contract adoption exhibits persistent adoption–abandonment cycles during the early and intermediate months, followed by eventual dominance of a single contract. This regime is characterized by prolonged instability and heightened sensitivity to peer influence, reflecting a shift from individual-driven to socially-driven dynamics.

The aggregate switching statistics in Fig. 7 further clarify this transition. As shown in Fig. 7(a), both the proportion of consumers who switch contracts and the average number of switches per consumer increase gradually with β up to approximately 0.6. Beyond this point, switching activity escalates sharply: the share of switching consumers rises to nearly 80%, and the average number of switches per consumer exceeds 2 within the 24-month horizon. Fig. 7(b) reveals a concurrent shift in satisfaction outcomes. For low to moderate levels of social influence, the average change in consumer satisfaction after switching remains positive and close to zero. However, once β exceeds approximately 0.6, the average satisfaction change becomes distinctly negative and declines rapidly with further increases in β. This divergence between intensified switching activity and declining satisfaction marks the emergence of a social trap. Although consumers continue to follow a satisfaction-maximizing decision rule based on locally available information, strong peer influence induces repeated switching that systematically undermines individual satisfaction at the aggregate level.

3.2.2. Income-based heterogeneous preferences

To examine how economic preference heterogeneity shapes contract switching dynamics, consumers with different income levels are assigned different preference weights, as summarized in Table 5. Lower-income groups place greater weight on electricity expenditure and payback time, whereas higher-income groups assign relatively more importance to comfort-related dimensions. This configuration introduces systematic heterogeneity in economic rationality while preserving the same decision structure.

Fig. 8 illustrates the switching dynamics under varying levels of social influence. Distinct phase-transition thresholds emerge across income groups. For the highest-income group (Fig. 8a1), switching activity increases sharply even under relatively weak social influence, with noticeable adoption dynamics appearing around β ≈ 0.1. In contrast, the middle-income group (Fig. 8a3) exhibits a more gradual response, with substantial switching behavior emerging only when β approaches 0.6. The lowest-income group shows the strongest resistance to social influence, maintaining stable contract choices until β exceeds approximately 0.7. These results indicate that stronger economic anchoring shifts the critical social-influence threshold required to trigger widespread switching.

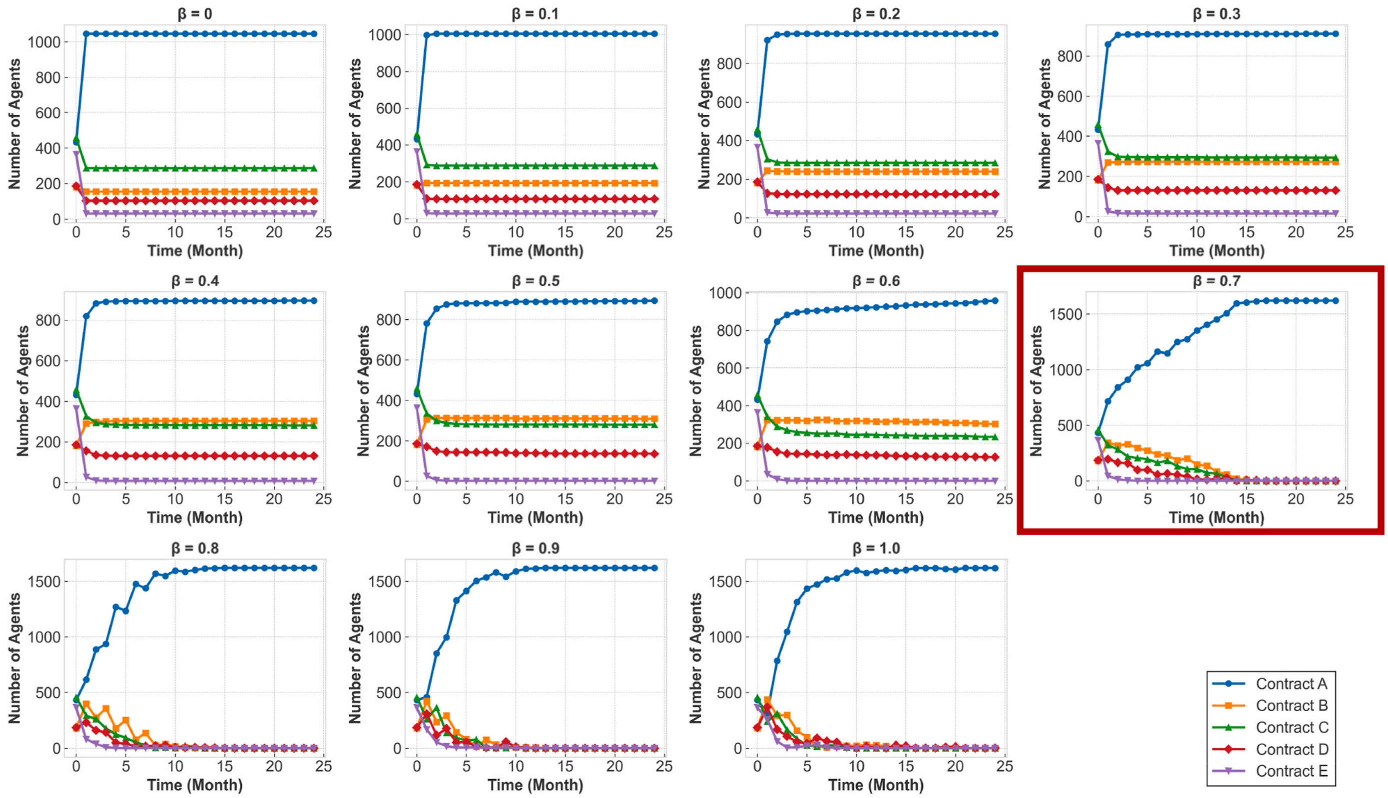


Fig. 6. Market share trajectories for homogeneous preferences under varying social influence. For β < 0.7, the system rapidly converges toward a single dominant contract, with market shares stabilizing within a few months. When β ≥ 0.7, contract adoption exhibits pronounced adoption–abandonment cycles, leading to a substantially prolonged convergence process.

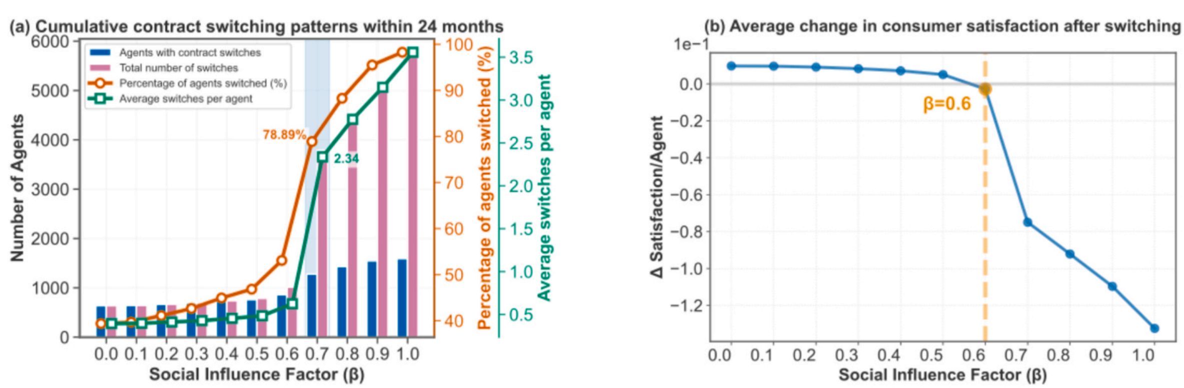


Fig. 7. Contract switching dynamics and satisfaction outcomes under homogeneous preferences under varying social influence. (a) Cumulative number of consumers who have switched at least once within 24 months, corresponding percentage of switching consumers and average number of switches per consumer. (b) Average change in consumer satisfaction following switching. A pronounced transition occurs around β ≈ 0.7, where switching intensity increases rapidly while average satisfaction outcomes decrease rapidly, indicating the emergence of a social trap driven by strong peer influence.

Table 5
Income-based heterogeneous preference weights configuration.

Income level	Description	δ_1	δ_2	δ_3	δ_4	δ_5
1	Hardly care about economic factors	0.33	0.33	0.005	0.33	0.005
2	Less care about economic factors	0.3	0.3	0.05	0.3	0.05
3	Same preference	0.2	0.2	0.2	0.2	0.2
4	More care about economic factors	0.1	0.1	0.35	0.1	0.35
5	Only care about economic factors	0	0	0.5	0	0.5

The same pattern is reflected in the cumulative switching statistics shown in Fig. 8(b1–b5). Under weak social influence (e.g., β ≈ 0.1), a large fraction of highest-income consumers switch at least once, whereas switching participation among lowest-income consumers remains limited. As β increases, switching participation and the average number of switches per consumer rise across all groups, but the increase is delayed and more abrupt for lower-income consumers. This confirms that economic-preference heterogeneity affects both the timing and intensity of switching transitions, while preserving the same qualitative regime structure.

Fig. 9 further reveals pronounced income-dependent differences in satisfaction outcomes following switching. For higher-income consumers, the average satisfaction change becomes negative at relatively

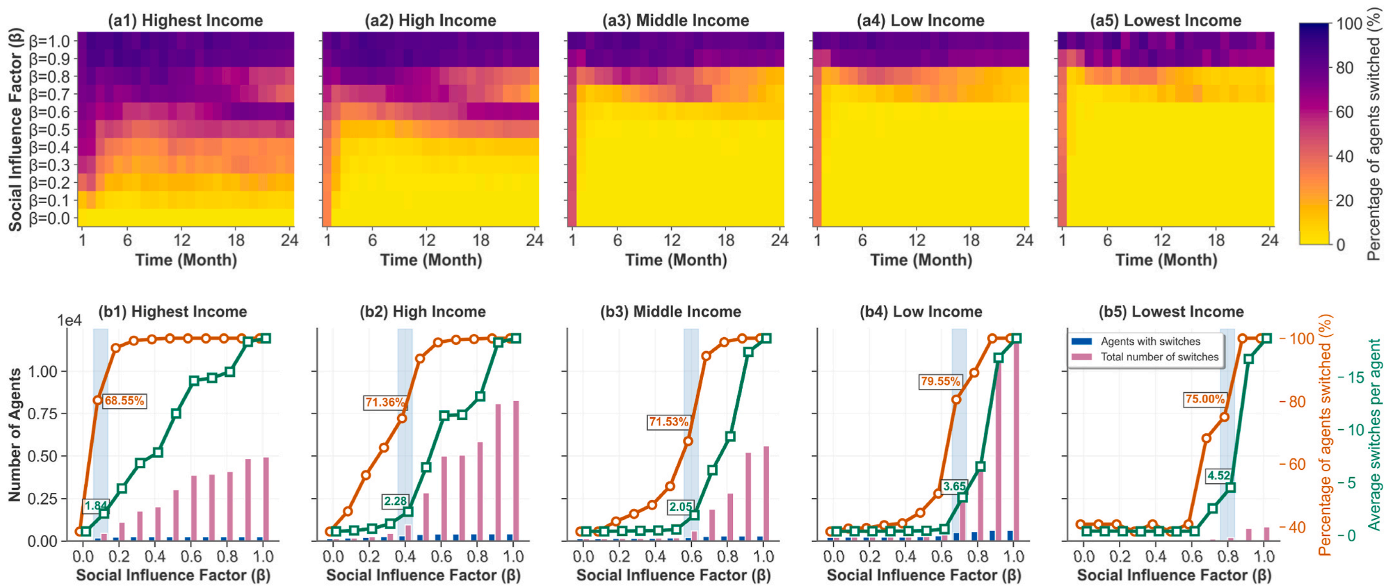


Fig. 8. Income-based heterogeneity in contract switching dynamics under varying social influence.
(a1–a5) The temporal evolution of the percentage of consumers switching contracts over 24 months for different income groups. (b1–b5) Cumulative number of consumers who have switched at least once within 24 months, corresponding percentage of switching consumers and average number of switches per consumer. Across all income groups, switching activity remains limited under weak social influence, with rapid stabilization of contract choices. As β increases, a pronounced transition emerges, characterized by a sharp rise in switching behavior. The location and sharpness of this transition vary systematically across income groups, indicating heterogeneous responses to strong peer influence while preserving the same qualitative switching regime structure.

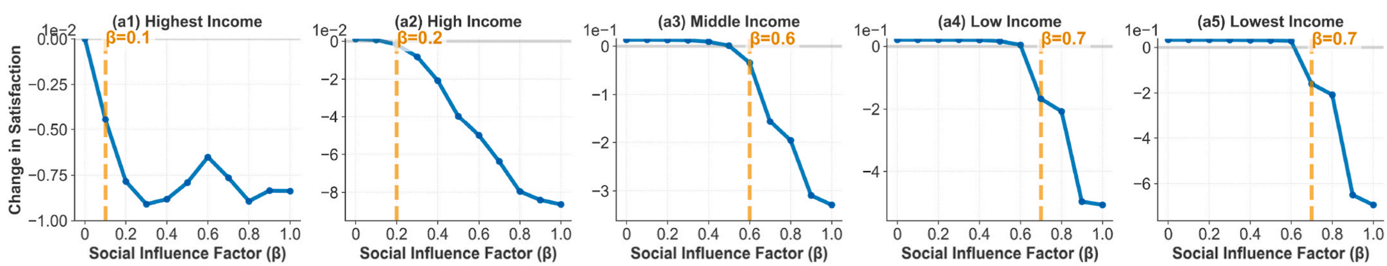


Fig. 9. (a1-a5) Average change in consumer satisfaction following switching across income groups. Under weak social influence, switching decisions are associated with mildly positive satisfaction outcomes across all income groups. Beyond income-specific critical levels of β, average satisfaction changes become negative, indicating the onset of satisfaction-reducing switching behavior. While higher-income groups experience earlier transitions with relatively moderate satisfaction losses, lower-income groups exhibit delayed but larger declines once the transition occurs, highlighting heterogeneous vulnerability to the social trap under strong peer influence.

low levels of social influence, indicating that satisfaction-reducing switching can arise early. Middle-income groups experience negative satisfaction returns at intermediate β values. In contrast, the lowest-income group maintains non-negative average satisfaction until β approaches 0.7, suggesting that strong economic preferences delay the onset of satisfaction losses. However, once this threshold is crossed, satisfaction declines sharply. At $\beta = 1$, the magnitude of satisfaction loss increases substantially as income decreases, indicating that lower-income consumers experience disproportionately larger satisfaction reductions under strong social influence.

Overall, income-based preference heterogeneity leads to systematic shifts in the critical social-influence threshold across consumer groups. Price-sensitive households enter high-switching regimes at higher levels of social influence and experience larger satisfaction declines once this transition occurs.

4. Discussion

The results presented in Section 3 reveal three salient patterns in consumer switching dynamics: (i) preference-driven market segmentation in the absence of social influence, (ii) a non-linear transition from stable convergence to persistent oscillatory dynamics as social influence strengthens, and (iii) the emergence of a social trap in which switching intensity and satisfaction losses increase concurrently. These patterns are jointly moderated by preference heterogeneity, particularly the relative weight assigned to economic dimensions. Sections 4.1 and 4.2 interpret these patterns at the behavioral level. Sections 4.3 and 4.4 then analyze the causal structure underlying the social trap and phase transition. Sections 4.5 and 4.6 address supply-side considerations and study limitations.

4.1. Preference-driven market segmentation

The individual-driven decisions scenario in Fig. 4 shows that consumers' satisfaction preference structure has a significant impact on electricity contract selection behavior, leading to systematic segmentation between comfort-oriented and price-oriented choices. This differentiated preference structure explains why a single type of electricity contract is difficult to meet all consumer needs and also reveals the need for diversified contract design in the electricity retail market. The strong preference for maintaining electricity consumption habits represents a behavioral tendency to avoid change due to loss aversion and habit inertia. Consumers who heavily weight habit satisfaction demonstrate no switching behavior, reflecting status quo bias commonly observed in behavioral economics. This result has significant implications for implementing dynamic pricing mechanisms, such as ToU or real-time pricing tariffs, where success depends not only on economic incentives but also on minimizing perceived deviation risks from established electricity consumption patterns.

4.2. Economic rationality as a decision anchor

Although social influence may introduce herd-like behavior and decision fluctuations, the results in the socially-driven decisions scenario in Fig. 5 show that consumers with strong economic preferences exhibit more stable decision-making patterns. These consumers have a stronger decision anchor and are able to maintain relatively rational judgments under the social influence, and ultimately form relatively stable group decisions. Income-based heterogeneous preference scenario in Fig. 8 also confirms this pattern. Higher-income consumers, who are assigned lower weights on economic factors, show pronounced decision fluctuations under low social influence. In contrast, lower-income consumers, who are assigned higher weights on economic factors, need stronger social influence to change their stable decision patterns. Economic rationality thus acts as a decision anchor that buffers social influence, stabilizing switching behavior until social pressure becomes sufficiently strong.

4.3. Social trap paradox

At high levels of social influence, the results in Fig. 7(b) reveal a regime in which switching frequency increases while average post-switch satisfaction declines, a pattern characteristic of a social trap where individually rational decision rules produce collectively suboptimal outcomes. This phenomenon originates from the interaction between the composite decision mechanism and the inherently idiosyncratic nature of electricity contract satisfaction.

The composite decision rule defined in Eq. (9) integrates two informational components: the agent's self-evaluated satisfaction, derived from individual load profiles and tariff responses, and the trust-weighted peer satisfaction aggregated through the social network. Because self-evaluated satisfaction is conditioned on agent-specific consumption characteristics, identical contracts may yield systematically different satisfaction levels across agents. Peer-propagated satisfaction, by contrast, reflects evaluations generated under heterogeneous consumption patterns and preference sensitivities. As the social influence factor β increases, the peer-derived component increasingly dominates the composite score, causing the decision criterion to reflect recommenders' satisfaction evaluation rather than the focal agent's own decision environment.

This misalignment has direct consequences for satisfaction outcomes under varying levels of social influence. When $\beta = 0$, agents select the contract maximizing self-evaluated satisfaction. Since self-evaluations for alternative contracts already incorporate price-adaptive load adjustments, switching decisions remain individually satisfaction improving, consistent with the positive satisfaction changes observed at low β. Under high β, however, composite rankings may reverse even when the agent's private evaluation favors the incumbent contract. Such reversals occur when the socially propagated satisfaction differential $\beta\left(s^{(n)}_{\mathcal{N}(u_k),c_j} - s^{(n)}_{\mathcal{N}(u_k),c_i}\right)$ exceeds the private differential $(1-\beta)\left(\widehat{s}^{(n)}_{u_k,c_j} - \widehat{s}^{(n)}_{u_k,c_i}\right)$, directing agents toward contracts better suited to peers' consumption contexts. The subsequent decline in post-switch satisfaction therefore arises from the composite decision rule assigning weight to socially propagated satisfaction signals that are inconsistent with the focal agent's satisfaction landscape.

Moreover, this mechanism is self-reinforcing. Satisfaction losses induced by mismatched switching propagate through the network and reshape subsequent composite evaluations, generating recursive switching distortions. Because agents continuously update satisfaction based on realized consumption, the persistence of these distortions reflects the dominance of socially amplified signals rather than informational rigidity. The simulation outcomes in Fig. 5 exhibit patterns consistent with this mechanism. When $\beta = 1$, economically anchored preference structures maintain stable contract choices, whereas comfort- and habit-oriented preferences display persistent switching volatility. This asymmetry reflects differences in cross-agent evaluability: economic satisfaction dimensions provide directionally consistent signals, while subjective dimensions generate heterogeneous satisfaction responses across agents. Income-based preference heterogeneity in Fig. 9 further reinforces this interpretation, as stronger economic weights widen private satisfaction differentials and systematically delay the onset of satisfaction-reducing switching regimes.

4.4. Emergent phase transitions

The simulations in Figs. 6 and 8a reveal a qualitative transition in market dynamics. Below a critical level of social influence, contract adoption converges toward a stable configuration, whereas beyond this threshold persistent adoption–abandonment cycles emerge. This behavioral shift can be understood through the ranking properties of the composite decision rule. In the low-β regime, self-evaluated satisfaction dominates the composite score, and contract rankings are primarily determined by agent-specific evaluations. Because these private evaluations are computed from stable consumption characteristics and preference structures, the resulting choice dynamics exhibit rapid convergence as agents settle on individually preferred contracts. As β increases, socially propagated satisfaction increasingly gains influence. At sufficiently high β, social satisfaction differentials may overturn private rankings for a non-trivial fraction of agents. These ranking reversals induce contract switches that modify the satisfaction signals circulating in the network, thereby generating further reversals and sustaining oscillatory adoption dynamics.

The location of this transition is governed by the magnitude of the private satisfaction differential between competing contracts, referred to here as private satisfaction discriminability. Larger private differentials require correspondingly stronger social differentials to alter composite rankings, shifting the regime boundary toward higher β values. The income-based heterogeneity experiments illustrate this relationship. Under homogeneous preferences ($\delta_m = 0.2$), moderate discriminability produces a transition at approximately $\beta \approx 0.7$ in Fig. 6. When economic preference weights are negligible ($\delta_3 = \delta_5 = 0.005$), private satisfaction differences compress and the transition threshold decreases markedly in Fig. 8a1. Conversely, when economic weights increase ($\delta_3 = \delta_5 = 0.5$), the cost-optimal contract becomes strongly differentiated in private satisfaction, restoring the transition to higher β levels in Fig. 8a5. These threshold shifts occur without modification of network structure or trust parameters, suggesting that preference-induced satisfaction structure is the dominant factor governing threshold location within the present model configuration.

Network topology and trust dynamics primarily modulate, rather than determine, the regime transition. Increased network density amplifies agents' exposure to peer satisfaction, while the trust learning rate governs the temporal accumulation of socially propagated signals. These factors influence the numerical position and sharpness of the threshold but do not alter the existence of distinct convergence and oscillation regimes, which arise from the structural interaction between private and socially propagated satisfaction. The results suggest that regime transitions reflect a structural property of socially influenced decision systems operating over heterogeneous satisfaction evaluations. The baseline value $\beta \approx 0.7$ reflects the satisfaction discriminability generated by the specific preference configuration and contract portfolio considered here. Alternative contract designs, preference distributions, or interaction structures may shift the numerical threshold, yet the underlying phase transition mechanism is likely to persist wherever socially propagated evaluations interact with individualized satisfaction criteria.

4.5. Supply-side dynamics

Within this framework, electricity tariffs are treated as exogenous and fixed to focus on demand-side decision-making, social interaction, and the emergence of collective switching dynamics. This modeling choice enables a clear identification of phase transitions and social traps driven by heterogeneous preferences and peer influence. In real retail electricity markets, however, suppliers may adapt contract design, pricing strategies, and marketing efforts in response to observed consumer behavior.

From a supply-side perspective, the phase transition highlights that switching behavior can change nonlinearly with social influence, which may have implications for how retailers perceive market responsiveness. In low-switching regimes, retailers may face limited competitive pressure and weak incentives to modify existing tariff structures. As switching activity increases, retailers may consider targeted promotions, tariff simplification, or measures that reduce perceived switching barriers. Heterogeneous consumer preferences further suggest the potential for tariff differentiation strategies, with contracts tailored to price-sensitive, habit-oriented, or electrification-focused consumers. Dynamic pricing or adaptive contract features may also interact with social influence, potentially mitigating or reinforcing collective inertia depending on how such adjustments affect perceived switching costs and uncertainty. These considerations highlight an important limitation of the present framework and point to promising directions for future research on the interaction between consumer dynamics and supplier behavior.

4.6. Limitations and future research

While the proposed agent-based framework captures key social dynamics in electricity retail markets, several methodological limitations merit consideration for future research.

First, bounded rationality is represented through deterministic mechanisms, including limited information availability, nonlinear satisfaction mappings, heterogeneous behavioral sensitivity parameters, and experience-based social influence. This choice allows the analysis to focus on interaction-driven mechanisms and emergent collective dynamics under controlled conditions. However, the absence of explicit stochastic noise or estimation errors in satisfaction calculations may understate idiosyncratic fluctuations in individual perceptions and short-term decision variability.

Second, social interactions are represented using an SWN to capture essential features of real social systems, while social influence may arise from multiple overlapping structures, e.g., geographical proximity or online communities, each with distinct interaction patterns. More complex or evolving network structures may influence diffusion intensity or timing.

Third, modeling parameters, including preference weights, sensitivity coefficients, and price elasticities, are treated as time-invariant and parameterized using survey attributes and behavioral rationale rather than statistically calibrated to observed switching trajectories. In practice, these parameters may evolve with changing income, accumulated experience, or external shocks.

Finally, this study is empirically grounded in the Irish retail electricity market during the CER trial. Although the market was already liberalized, retail electricity markets have evolved since then, with increased digitalization, higher electrification levels, and a wider range of tariff designs. Such developments are likely to affect model parameters, such as switching costs, electrification-related satisfaction, or demand flexibility. Accordingly, the timing, intensity, and threshold levels of the switching dynamics may differ, while the underlying decision and interaction mechanisms are expected to remain applicable across liberalized retail electricity markets.

Future research may extend this framework by examining different national market contexts, incorporating retailer-side strategic behavior, or exploring alternative social network structures. When transaction-level switching data or retail market records become available, the framework can be further developed through calibration to align model outputs with observed switching trajectories and to refine quantitative thresholds identified in the present study.

5. Conclusions and policy implications

This study develops an agent-based framework integrating multi-dimensional consumer satisfaction and social influence to examine electricity contract switching dynamics. The analysis identifies two structural mechanisms underlying the observed non-linear behaviors. First, the social trap emerges from systematic satisfaction signal misalignment between socially propagated evaluations and agent-specific assessments. Because contract suitability is inherently idiosyncratic, peer satisfaction reflects heterogeneous consumption contexts, allowing the composite decision rule to induce satisfaction-reducing switches. Second, the regime transition between convergence and persistent oscillation is governed by private satisfaction discriminability, defined as the magnitude of self-evaluated satisfaction differentials across contracts. This property is shaped by preference structure and contract differentiation. Together, these mechanisms provide a behavioral and informational explanation for emergent instability in socially influenced retail electricity markets.

A first implication concerns contract design and consumer heterogeneity. The results indicate that satisfaction-reducing dynamics arise when socially propagated evaluations are misaligned with individual decision contexts. This condition is more likely when contract performance depends on lifestyle-specific or comfort-related attributes rather than objectively assessable economic dimensions. Differentiated contract portfolios can mitigate this effect by strengthening private satisfaction discriminability, particularly for attributes anchored in measurable outcomes. Importantly, the preference dimensions represented in the framework correspond to observable behavioral and socioeconomic indicators routinely available to utilities, including consumption variability, peak-to-off-peak usage ratios, contract tenure, appliance ownership proxies, and income-linked tariff eligibility. Smart meter data, billing histories, and enrollment records therefore provide a feasible basis for constructing operational consumer segments aligned with preference-relevant characteristics.

A second implication relates to policy mechanisms influencing socially driven switching dynamics. Within the present framework, the social influence factor β represents the relative decision weight assigned to socially propagated satisfaction. In practical decision environments, analogous effects arise through institutional and informational structures shaping how consumers encounter and interpret peer information. Policy instruments that strengthen the salience and reliability of private evaluations, including standardized tariff disclosure formats, comparison benchmarks, personalized cost calculators, and decision deferral mechanisms, effectively increase the influence of agent-specific satisfaction relative to socially amplified signals. Interventions that alter the visibility or amplification of peer evaluations, such as public ranking systems, referral incentives, or collective switching campaigns, may conversely intensify socially coupled dynamics. Interpreting social influence through the lens of information structure highlights that policy can indirectly shape collective outcomes without constraining consumer interaction.

Finally, the results reveal distributional asymmetries in socially influenced markets. Consumers with stronger economic preference weights exhibit greater resistance to socially induced switching yet experience larger satisfaction losses once private evaluation anchors are displaced. This asymmetry implies that uniform social information policies may generate heterogeneous satisfaction effects across consumer groups. Protective mechanisms, including simplified tariff menus, income-appropriate default options, and decision aids emphasizing cost transparency, may therefore play a stabilizing role for economically sensitive consumers. More broadly, the findings indicate that market stability in socially interactive environments depends not only on price signals or contract structures but on the alignment between privately evaluated satisfaction and socially propagated evaluations.

CRediT authorship contribution statement

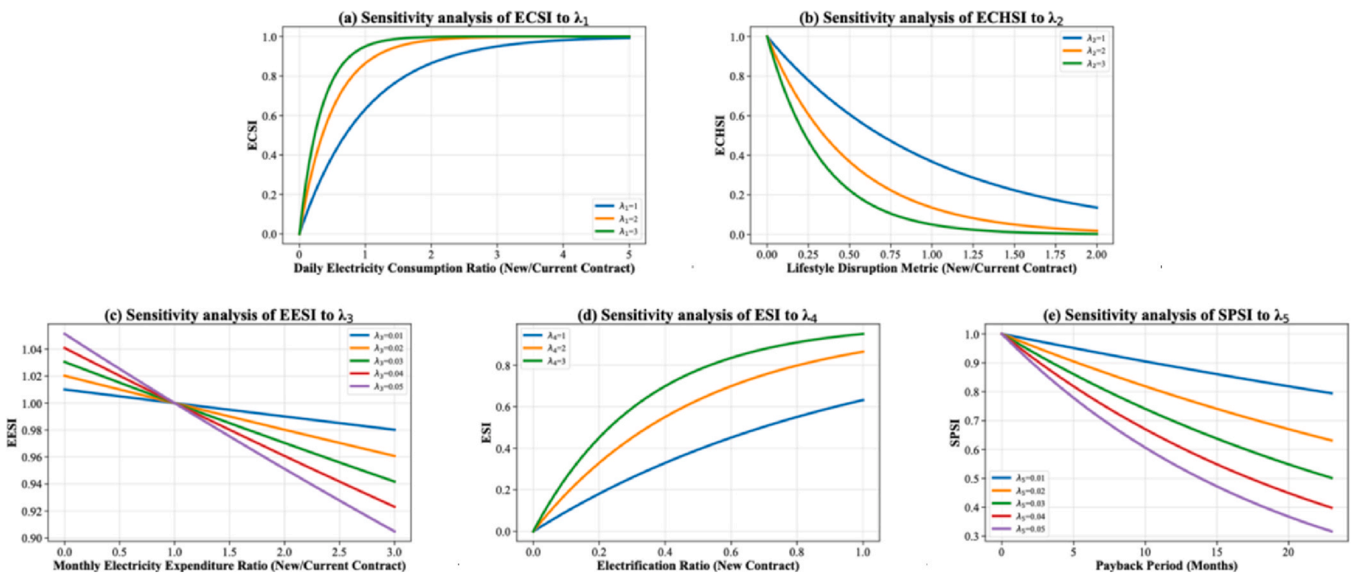
Jingsi Chen: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Conceptualization. **Jun Yin:** Writing – original draft, Visualization, Validation, Software, Data curation. **Michela Meo:** Writing – review & editing, Supervision, Resources, Project administration. **Tao Huang:** Writing – review & editing, Supervision, Resources, Project administration.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Sensitivity analysis of behavioral sensitivity coefficients

This appendix presents a sensitivity analysis of the behavioral sensitivity coefficients $\lambda_i (i = 1,\ldots,5)$, focusing on how variations in λ_i modulate the curvature and responsiveness of each satisfaction dimension.



A1. Sensitivity coefficients $\lambda_i (i = 1, 2, 3, 4, 5)$ analysis.

Fig.A1(a) illustrates the relationship between ECSI and the ratio of daily electricity consumption under new and current contract with different λ_1. Higher λ_1 rapid satisfaction saturation with minimal consumption increases, whereas lower λ_1 corresponds to gradual satisfaction growth. Fig. A1(b) depicts the sensitivity of λ_2 to the lifestyle disruption metric. A larger value of λ_2 reflects acute sensitivity to habitual pattern deviations, where minor changes trigger significant satisfaction losses. Lower λ_2 corresponds to a greater tolerance for changes in daily electricity habits. Fig.A1(c) shows the sensitivity of λ_3 to the monthly electricity expenditure ratio of new and current contracts. Consumers with higher λ_3 exhibit pronounced price sensitivity, such that marginal increases in the electricity bill precipitate declines in consumer satisfaction, whereas smaller λ_3 signify a greater tolerance for higher prices in exchange for other perceived benefits. Fig.A1(d) shows the sensitivity of λ_4 to the electrification ratio. Higher λ_4 indicates that consumer derives substantial satisfaction from even modest increases in electrification, whereas lower λ_4 imply that satisfaction accrues more gradually as electrification deepens. Fig.A1(e) shows the sensitivity of λ_5 to payback periods. Higher λ_5 indicates strict time-cost sensitivity with demand for immediate returns, whereas smaller λ_5 corresponds to greater patience or lower cost sensitivity, reflecting a willingness to accept longer payback time. Across all dimensions, variations in λ_i induce continuous and monotonic changes in satisfaction responsiveness, consistent with the data-informed behavioral parameterization described in Section 2.3.1.

Appendix B. Pseudo-code for monthly agent-based contract switching simulation

This appendix provides the detailed simulation logic. The agent-based model is implemented as a discrete-time iteration reflecting monthly decision-making cycles. All model parameters and their default values are consolidated in Table 2.

Input:

Agent set U (size $N = 1620$)
Contract set $C = \{A, B, C, D, E\}$

Scenario parameters (varied across cases):

Satisfaction weights δ_{m,u_k} for $m = 1, \dots, 5$
Social influence parameter $\beta \in [0, 1]$

Fixed parameters (fixed across cases):

Behavioral sensitivity coefficients λ_{m,u_k}
Electricity price elasticity coefficient ε_{u_k}
Initial trust weight $\omega^{(0)}_{u_k,u_l,c_i}$
Trust learning rate η
Network parameters: mean degree K, rewiring probability P
Simulation horizon T months
Fixed random seed *seed*

Output:

System-level metrics over T, including the number of agents switching contracts, contract market shares, and average satisfaction changes

Experimental design:

For each scenario defined by a given configuration of satisfaction weights δ_{m,u_k} and social influence factor β, the following simulation procedure is executed. Across scenarios, the agent population, behavioral parameters $(\lambda_{m,u_k}, \varepsilon_{u_k}, \eta)$, and network settings (K, P) are held fixed, so that outcome differences are attributable to δ_{m,u_k} and β. Each scenario corresponds to one deterministic simulation realization under the same random seed, ensuring full traceability and reproducibility of the mechanism-driven dynamics examined in this study.

Initialization

Set Random Seed (*seed*)
Initialize agent attributes and fixed behavioral parameters $\{\lambda_{m,u_k}, \varepsilon_{u_k}\}_{u_k \in U}$ (Table 2)
Generate SWN $G^{(0)}$ via Watts–Strogatz ring-lattice construction with parameters (K, P)
Assign initial trust weights $\omega^{(0)}_{u_k,u_l,c_i}$ based on agent similarity (Table 2)
Assign initial contracts $f^{(0)}(u_k)$ from CER dataset
Set scenario values $\{\delta_{m,u_k}\}$ and β

Monthly iteration (discrete time)

for $n = 1$ **to** T **do**
/*Information evaluation under current state*/
  for each agent $u_k \in U$ **do**
    Determine perceived choice set $C^{(n)}_{u_k}$ (from prior experience and peer effects)
    for each contract $c \in C^{(n)}_{u_k}$ **do**
      Construct the load profile used for evaluation:
      if $c = f^{(n)}(u_k)$, use baseline load $d^{(n)}_{u_k,c,t}$;
      else, generate price-adaptive load $\widehat{d}^{(n)}_{u_k,f^{(n)}(u_k)\to c,t}$ using ε_{u_k} (Section 2.2.1)
    Compute satisfaction components $\widehat{s}^{(n)}_{u_k,c,m}$ for $m = 1, \dots, 5$ using Eqs. (2)–(6)
      Aggregate self-evaluated satisfaction $\widehat{s}^{(n)}_{u_k,c}$ using Eq. (1)
      Compute peer-based satisfaction $s^{(n)}_{\mathcal{N}(u_k),c}$ using Eq. (7)
      Compute combined satisfaction $s^{(n+1)}_{u_k,c} \leftarrow (1-\beta)\widehat{s}^{(n)}_{u_k,c} + \beta s^{(n)}_{\mathcal{N}(u_k),c}$ (Eq. (9))
    end for
  end for
/*Synchronous switching decision*/
  for each agent $u_k \in U$ **do**
  $c^\star \leftarrow \underset{c \in C^{(n)}_{u_k}}{argmax} s^{(n+1)}_{u_k,c}$ (Eq. (10))
    if multiple maximizers exist **then** $f^{(n+1)}(u_k) \leftarrow f^{(n)}(u_k)$ /*status-quo tie-break*/
    else $f^{(n+1)}(u_k) \leftarrow c^\star$
  end for
/*State update*/
  Update each agent's baseline daily load profile under $f^{(n+1)}(u_k)$ (Section 2.2.1)
  Update trust weights $\omega^{(n)}_{u_k,u_l,c_i} \rightarrow \omega^{(n+1)}_{u_k,u_l,c_i}$ using Eq. (8)
  Rewire SWN edges with probability P while preserving mean degree K

31: Record system-level metrics for month n
32: **end for**

Data availability

The authors do not have permission to share data.

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