Urban Parking Decisions Under Emotion:
A Rank-Dependent Expected Utility (RDEU) Game-Theoretic Approach

Shipei Huang; Advisor: Professor Quan Wen
Econ Honors Program, Department of Economics, University of Washington, Seattle, WA

Background

Parking compliance plays a critical role in urban systems—impacting traffic flow, fair access to public space, and public confidence in enforcement [1]. Drivers face the recurring choice of whether to pay for parking, and their decisions are shaped not only by the cost of parking or the threat of fines, but also by emotional factors, past experiences, and how likely they believe enforcement is at that moment.

At the same time, enforcement officers operate with limited resources and must decide where to patrol, balancing risk, incentives, and efficiency. Traditional economic models assume rational decision-making, but real-world behaviors often defy this logic. Some drivers comply even without visible enforcement, while others continue to evade fees despite steep penalties. These patterns suggest the presence of emotional decision-making—such as distorted risk perception—which this study investigates using behavioral game theory.

Research Goals

- To explore how emotional risk preferences affect parking behavior and enforcement strategy
- To study what equilibrium behaviors emerge from repeated interactions under emotional distortion

Model Framework

Players

- Vehicle Owner: Chooses to Pay or Not Pay
  (p: probability that the vehicle owner pays)
- Enforcement Officer: Chooses to Patrol or Not Patrol
  (q: Probability that the officer patrols the lot)

Payoff Matrix

- Vehicle Owner: $a > b > c > d$; Enforcement Officer: $A > B > C > D$
- Each outcome reflects costs, penalties, and opportunity losses depending on the strategy combination

		Enforcement Officer	
		Patrols (q)	Does Not Patrol ($1-q$)
Vehicle Owner	Pays (p)	b, C	c, B
	Does Not Pay ($1-p$)	d, A	a, D

Table 1. Payoff Matrix of Vehicle Owner and Enforcement Officer

Behavioral Modeling:

- Applies Rank-Dependent Expected Utility (RDEU) to reflect emotional weighting of risk and distorted probability perception [2]
- Game dynamics and strategy evolution are modeled using replicator dynamic equations

Risk Perception / Emotional Distortion Parameters:

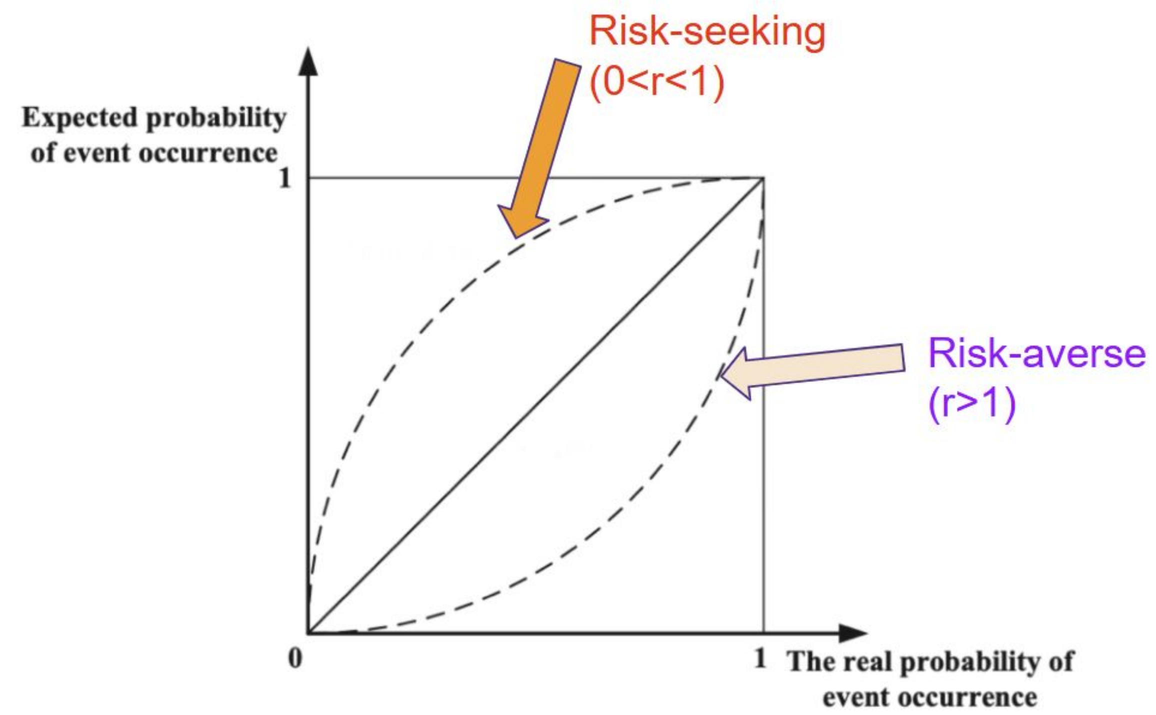

Figure 1. Emotional Distortion on The Real Probability of Event Occurrence

The parameters r_1 and r_2 model how players emotionally distorted probabilities when making decisions. Integrated via the RDEU framework, they adjust how risk is perceived: players overweight (r_1< 1, optimism) or underweight (r_1> 1, pessimism) the favorable outcomes based on emotional bias.

$$\omega(p) = p^{r_i}, \quad r_i > 0, \quad i = 1, 2$$

Evolutionary Game Model with Emotional Weighting:

Vehicle owner strategic benefits x_i	Probability p_i	Grade R_{p_i}	Decision weight π_i
a	$(1-p)(1-q)$	1	$\omega(1-p-q+pq)$
b	pq	$q+p-pq$	$\omega((1-q)(1-p)+pq) - \omega(1-p-q+pq)$
c	$p(1-q)$	$q+p-2pq$	$\omega(1-q+pq) - \omega((1-q)(1-p)+pq)$
d	$(1-p)q$	$(1-p)q$	$1-\omega(1-q+pq)$

Table 2. Strategy Evaluation and Weighted Utilities of Vehicle Owner (Player 1)

Enforcement officer strategic benefits x_i	Probability p_i	Grade R_{p_i}	Decision weight π_i
A	$(1-p)q$	1	$\omega(q-pq)$
B	$(1-q)p$	$1-q+pq$	$\omega(p+q-2pq) - \omega(q-pq)$
C	pq	$1-p-q+2pq$	$\omega(p+q-pq) - \omega(p+q-2pq)$
D	$(1-p)(1-q)$	$(1-p)(1-q)$	$1-\omega(p+q-pq)$

Table 3. Strategy Evaluation and Weighted Utilities of Enforcement Officer (Player 2)

Building on the expected utility framework above, evolutionary dynamics are introduced to capture how the strategies of both the vehicle owner and the enforcement officer adapt over time under emotional influence.

Replicator dynamics equation:

$$\frac{dp}{dt} = p^{r_1} \cdot (U_p - EU_p) \qquad \frac{dq}{dt} = q^{r_2} \cdot (U_q - EU_q)$$

The replicator dynamics equation models how strategies evolve over time based on their relative performance. In this study, it captures how the probability of paying or patrolling changes depending on whether that strategy yields higher utility compared to the average. Strategies that perform better than average grow more common, while less effective ones decline—reflecting a learning process driven by payoff feedback.

Numerical Simulation

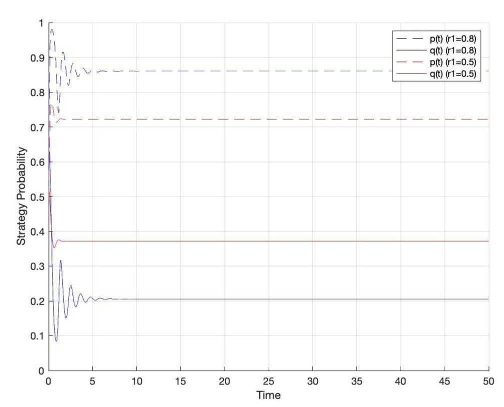

Figure (a)

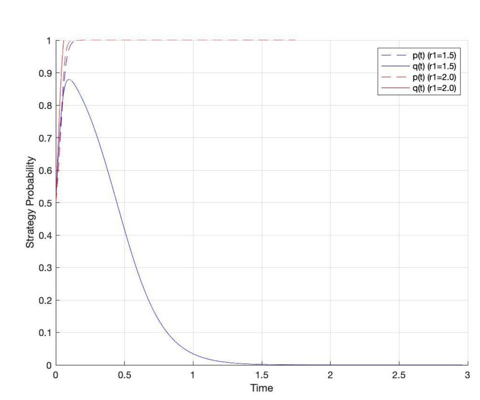

Figure (b)

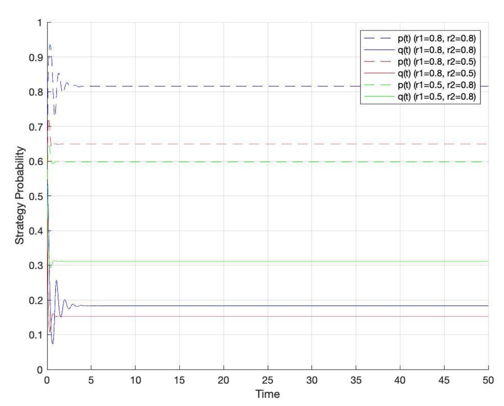

Figure (c)

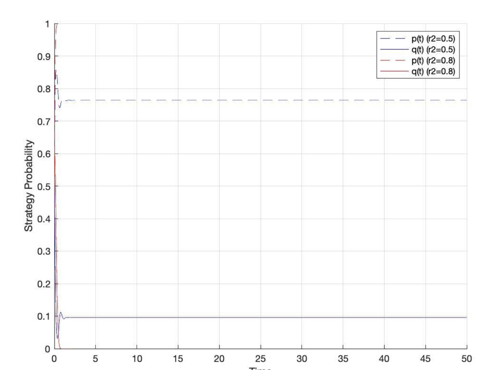

Figure (d)

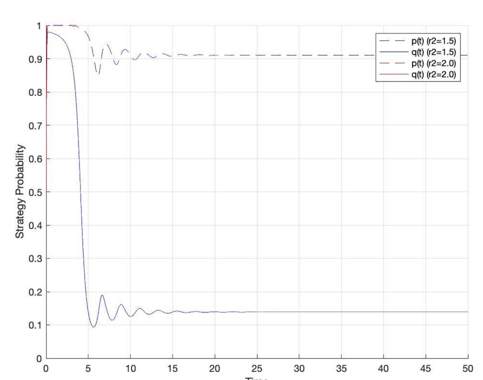

Figure (e)

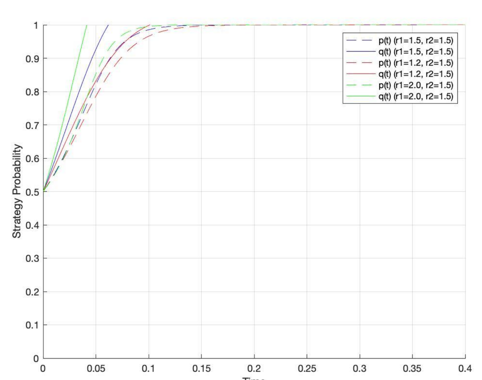

Figure (f)

This section presents six simulation plots (Figures a–f), each illustrating how strategy probabilities evolve over time under different combinations of emotional parameters.

Reference:

[1] Đorđević, A., Živojinović, T., & Kaplanović, S. (2023). Parking systems within the concept of smart mobility: Review and evaluation. Tehnika, 78, 464–471.

[2] Quiggin, J. (1982). A theory of anticipated utility. Journal of Economic Behavior & Organization, 3(4), 323–343.

Results

Emotional states strongly shape strategic behavior.

- Negative emotions lead to proactive strategies—more enforcement and higher compliance—with faster convergence. Positive emotions, reflecting optimism, lead to passivity, slower adjustment, and potential instability.
- The enforcement officer's emotions influence outcomes more significantly than the driver's: pessimistic officers over-enforce, while overly optimistic ones under-enforce.
- When both players are optimistic, strategy evolution is slow and gradual; when both are pessimistic, the system quickly locks into full compliance and enforcement.

Nash equilibrium occurs under rational expectations and full rationality. When neither party is affected by emotional bias, the vehicle owner adopts a fixed probability of paying the parking fee, while the enforcement officer similarly chooses to patrol with a fixed probability.

Future Work

Study cities that implement policy changes (e.g., increased fines, new enforcement technology) to assess how compliance and enforcement strategies evolve in response, which may potentially indicate shifts in perceived risk or emotional distortion.

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