A Value Evaluation Method of Traffic Data Assets with Data Element Transactions Based on Game Theory

Dan Zou, Mengjia Yan, Jianzhong Cao, and Jianqiang Wang

Abstract—**In the digital economy era, the value of data elements has grown significantly, especially in the transportation sector, which boasts an extensive repository of transportation data assets. This study proposes a Stackelberg game-theoretic pricing model to optimize the utilization of these data elements. The model delves into the complexities of trading transportation data assets, exploring unique market trading strategies and pricing mechanisms. Focusing on a marketplace with a single seller and multiple buyers, the seller preprocesses data for platform distribution while devising strategic actions, simultaneously aligning with buyers' acquisition strategies. Leveraging the interplay between buyers and sellers, the model employs backward induction to demonstrate the existence and uniqueness of the game solution, followed by a comprehensive numerical analysis. The results indicate that data quality and market risks significantly influence unit pricing, transaction volumes, and the profits of all stakeholders.**

This method seeks to improve the accuracy of transportation data asset valuation by integrating essential data elements pertinent to trading entities. It provides a robust theoretical foundation for the management and decision-making processes related to transportation data assets.

Index Terms—**data asset; data trading market; data pricing; Stackelberg game**

I. INTRODUCTION

WITH the swift progress in technologies like the Internet of Things (IoT) and artificial intelligence (AI), the generation of global data is increasing at an extraordinary pace[1]. Data has become a crucial resource, holding immense potential as a vast, untapped resource. Many industries, such as IoT platforms[2] and healthcare services[3, 4], generate vast data. In the transportation sector[5], data assets like train operation data and station passenger flow are generated daily. These data cover various aspects of railway transportation and are highly valuable. Furthermore, data is not free. Challenges such as data privacy[6, 7] and data silos[8] necessitate trading to unlock its total value. Consequently, accurately valuing transportation data assets has become essential for system optimization and service enhancement.

In the digital economy[9, 10], data has become a key driver of production and distribution as a novel factor of production[11]. However, assessing traffic data assets is difficult because of their complexity. Data sources are diverse and rapidly changing, making traditional approaches[12], quality assessments[13], and auctions[14] insufficient for addressing data complexities in production and distribution. Thus, understanding the dynamics of the traffic data market, valuing these assets across their lifecycle, and formulating sound pricing strategies are pressing concerns for both academic research and practical application.

Scholars have approached data asset pricing from two primary theoretical perspectives: algorithmic methodologies grounded in computer science and economic theory-based frameworks.

From the algorithmic perspective, Jiang et al.[15] developed an outsourced data classification platform model for service transactions. The model determines transaction prices by dynamically learning buyers' data valuations via an online pricing mechanism. Fernandez et al.[16] created a data marketplace platform for data sharing, where data owners earn currency and consumers pay to meet their data needs. Chen et al.[17] introduced a pricing structure utilizing machine learning models. Abdelhak et al.[18] introduced a document-oriented distributed data warehouse that securely stores data in databases, facilitating pricing and retrieval. Hao et al.[19] proposed a heterogeneous integrated pricing model (HCEG) based on clustering strategies and gravity weights to effectively improve the pricing accuracy of data assets and optimize pricing performance. Xu et al.[20] suggest a combined MCDM framework that integrates DEMATEL, BWM, and Fuzzy TOPSIS for evaluating and improving data asset quality. They offered an algorithmic solution enabling data sellers to price models across various market scenarios to maximize revenue.

From an economic perspective, Pei[21] explored the principles of data pricing through economics-based approaches and provided a comprehensive review of data and digital products. Xu et al.[22] analyzed issues related to data

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Dan Zou is a senior engineer at the Institute of Computing Technology, China Academy of Railway Sciences Corporation Limited, Beijing 100081, China (e-mail: zoudan06102024@126.com).

Mengjia Yan is a postgraduate student at the School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (e-mail: yanmj_lzjt@126.com).

Jianzhong Cao is a postgraduate student at the School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (e-mail: cc7804@126.com).

Jianqiang Wang is an associate professor at the School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China. (corresponding author to provide e-mail: xinxiwjq@126.com).

ownership, valuation, and privacy solutions. Zhang et al.[23] proposed a novel categorization system for data pricing approaches by considering the various factors influencing data prices. Xu et al.[24] introduced a blockchain-powered alliance data exchange framework to address pricing challenges in the ride-sharing data market. They developed a three-layer Stackelberg game model involving data proprietors, service vendors, and purchasers, solving it using backward induction. Liu et al.[25] developed a two-stage Stackelberg game model to tackle the pricing and acquisition issues between data consumers and market players. Li et al.[26] introduced a two-level income distribution model for roadway data assets, utilizing an enhanced Shapley value method that integrates entropy weight, rough set theory, and fuzzy evaluation to ensure equitable and precise profit distribution among stakeholders.

Despite these advances, challenges remain in data asset pricing. Algorithmic methods often require extensive datasets for real-time pricing, enabling sellers to adapt to market fluctuations but limiting their broad applicability. Additionally, these methods introduce complexity to data transactions. On the other hand, economic models effectively theorize market participant interactions but rarely consider replicability and context-specific circulation of data in specialized markets.

To address these gaps, this study focuses on a single-seller, multi-buyer market for traffic data circulation. Leveraging a Stackelberg game-based approach [25, 27, 28], we develop a trading market model and confirm the existence and uniqueness of its solution through backward induction. We then conduct numerical analysis to examine how traffic data quality and market risk affect pricing strategies, transaction volumes, and buyer-seller revenues. This study seeks to broaden perspectives on data asset transactions, provide fresh insights into pricing strategies in the traffic data market, and steer the monetization and value enhancement of traffic data.

The key contributions of this study are outlined as follows:

(1) Focusing on traffic data asset value, this study examines the dynamic interactions between a single seller and multiple buyers using the Stackelberg game model. The goal is to offer an analytical framework that reflects actual market conditions to address the complexities of data asset transactions.

(2) This study proposes a new pricing approach that clarifies the effects of data quality, market risk, and buyer numbers on pricing strategies, deepening our understanding of market dynamics.

(3) Theoretical analysis and numerical validation confirm the feasibility and effectiveness of this method, offering a new perspective for studying pricing mechanisms in the traffic data asset market.

The problem statement and hypotheses on this issue will be discussed in Section II. The construction and solution of the traffic data asset evaluation model are presented in section III. Section IV covers the numerical analysis and simulation of the model construction. The conclusion is provided in Section V.

II. Problem Formulation and Model Assumptions

In traffic data transactions, buyers interact freely with sellers on a data trading platform to purchase necessary traffic data, as shown in Fig. 1. A key challenge is determining the optimal unit price for traffic data to maximize profits for all market participants, leading to a competitive pricing issue.

This paper introduces the problem through a Stackelberg game framework, with the traffic data seller playing the role of the leader, responsible for tasks such as data collection, storage, quality enhancement, anonymization, and transmission. Through these processes, the seller sets the unit price for traffic data in the market. Meanwhile, buyers act as followers, deciding how much traffic data to buy based on the seller's price. The game model seeks to align the interests of sellers and buyers, foster the healthy growth of the data trading market, and ultimately optimize profits for all stakeholders involved.

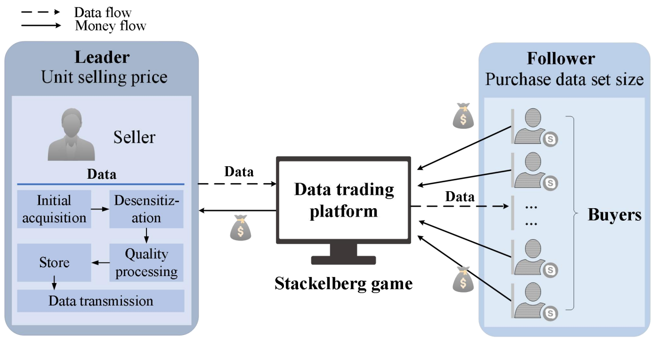


Fig. 1. Data Trading Scenario

To facilitate research on the pricing of traffic data assets during the circulation process, this paper makes the following assumptions:

Assumption 1: A complete traffic data asset trading market and platform have been established, where buyers and sellers have equal status and access to sufficient market information.

Assumption 2: The trading prices of traffic data assets on the platform are influenced by market conditions.

Assumption 3: Buyers do not resell traffic data, and its usage is restricted only to transacting parties.

Assumption 4: Traffic data assets are sold in units of data sets.

Assumption 5: The traffic data in the transaction is assumed to have been desensitized, and the entire transaction and circulation process complies with legal regulations.

III. Construction and Solution of Traffic Data Asset Valuation Model

A. Model Construction

Define s as the sole seller in the trading market, possessing the pricing authority for unit traffic data. Let A denote the set of buyers, $A=[1,2,\cdots,n]$, and n represent the established quantity of buyers in the market, and b_i means buyer i, $i\in A$. The market sales price of unit data set by seller s is represented as p, the buyer b_i decides to purchase is expressed as q_i. p^* and q_i^* represent the optimal market sales price of seller s unit data and the optimal traffic data set size of buyer b_i purchase, respectively. The model construction process is depicted in Fig. 2.

Once the data is collected, the traffic data seller must carry out initial processing on the raw traffic data to enhance the service provided to buyers. The quality of the traffic data is influenced by elements such as precision, comprehensiveness, consistency, validity, and distinctiveness.Therefore, we define the traffic data quality $\xi = f(\delta)$, where δ is a state vector encompassing precision, comprehensiveness, consistency, validity, and distinctiveness. $\xi \in [0,1]$, The greater the worth of ξ , the better the quality of the traffic data.

Traffic data buyers will decide on the volume of the traffic data set they purchase based on various factors, including the unit market price and their evaluation of future revenue. The traffic data set Q purchased by all buyers in the market is described as follows:

$$Q = \sum_i q_i, i \in A \tag{1}$$

The seller will incur certain fixed costs during the processing and maintenance of traffic data. Once the traffic data is transferred to the platform, transaction costs will be incurred based on the data sold, and the actual cost will vary depending on the buyer's specific quality requirements for the traffic data.Define the seller's actual cost of maintaining unit data as c, as described below :

$$c = \frac{C}{Q} + \xi \cdot t \tag{2}$$

where C is the fixed cost of packaging all traffic data uploaded to the platform, and t is the unit data transaction cost.

In this game, the seller as the leader independently sets the market price of unit data, and the seller aims to maximize the revenue. The mathematical model is constructed as follows:

$$\max Z = Q(p-c) \tag{3}$$

$$s.t.$$

$$c \le p \le p_{\max} \tag{4}$$

where $p_{\max}$ is the maximum market price of unit traffic data guided by the government.

The expenditure of the buyer b_i for purchasing traffic data is equivalent to the product of the size of the traffic data set sold to buyer b_i and the unit cost of the data in the market. The total cost for buyer b_i to acquire traffic data is denoted as k_i.

$$k_i = p \cdot q_i, i \in A \tag{5}$$

The income per unit of data for buyer b_i is related to the total volume of traffic data purchased by all buyers in the market, and the market's risk conditions. Consequently, the income per unit of data for buyer b_i , denoted as r , is expressed as follows:

$$r = \xi \cdot r_0 - \varphi \cdot Q \tag{6}$$

where r_0 is the baseline unit data revenue, representing the optimal revenue per unit data in a risk-free market, and φ is a parameter that models the market's risk conditions, $\varphi \in (0,1)$. A larger φ indicates higher market risk.

Each time buyer b_i purchases a traffic data set, the data set generates an estimated benefit. As the number of traffic data sets purchased increases, the estimated benefit from each additional data set decreases. To quantify this phenomenon, we define buyer's marginal revenue function $m(\tau)$ as follows:

$$m_i(\tau) = r - \eta_i \cdot \tau \tag{7}$$

where η measures the buyer's understanding or estimation of how valuable the data could be compared to its price, $\eta \sim N(\mu, \sigma^2)$, $\tau \in [0, q_i]$.

Therefore, the total revenue achieved by buyer b_i after deciding the size q_i of the purchased traffic data set is expressed as T_i.

$$T_i = \int_0^{q_i} m_i(t)\,dt - k_i \tag{8}$$

In this game, given the unit data market sales price p , buyer b_i , acting as the follower, decides on the amount of the traffic data set to purchase. The goal of buyer b_i is to maximize their overall revenue. The corresponding mathematical model can be represented by (9) to (11):

$$\max F = \sum_i \int_0^{q_i} T_i(\omega)\,d\omega \tag{9}$$

$s.t.$

$$\xi \cdot r_0 - \varphi \cdot Q - \eta_i \cdot q_i - p \ge 0, i \in A \tag{10}$$

$$q_i \ge 0, i \in A \tag{11}$$

where (9) represents the buyer's total revenue maximization objective, (10) ensures that the marginal revenue generated by the size of the purchased traffic data set is not less than the unit data market sales price, and (11) is the non-negativity constraint on the size of the purchased traffic data set.

B. Model Solution

The mathematical programming models of the leader and follower constitute a Stackelberg game pricing problem. The goal of this game is to identify the Stackelberg equilibrium, where the leader, leveraging their first-mover advantage, maximizes their profit through a strategic combination with the followers, who in turn make their optimal response decisions..

Definition 1: If condition $Z(q_i^*, p^*) \ge Z(q_i^*, p)$, and $F(q_i^*, p^*) \ge F(q_i, p^*)$, $\forall i \in A$, is satisfied, then point (q_i^*, p^*) exists and is the only equilibrium point for the Stackelberg game pricing problem.

Proof: Using backward induction.

This problem can be divided into a series of sub-games between the leader and each follower. Represent this non-cooperative game as $\Gamma = \{p, Z(q_i, p)\}$. The traffic data seller must set the unit sales price based on market conditions. For the traffic data seller, sub-games are independently played between the seller and each buyer. Therefore, the pricing problem can be solved by deriving the Stackelberg equilibrium for each sub-game.

Follower's Purchase Strategy: Given the unit data market price p , traffic data buyer b_i maximizes their total revenue by determining their optimal purchase strategy q_i . In (8), the first and second derivatives of the buyer's total income for the size q_i of the purchased traffic data set can be expressed as

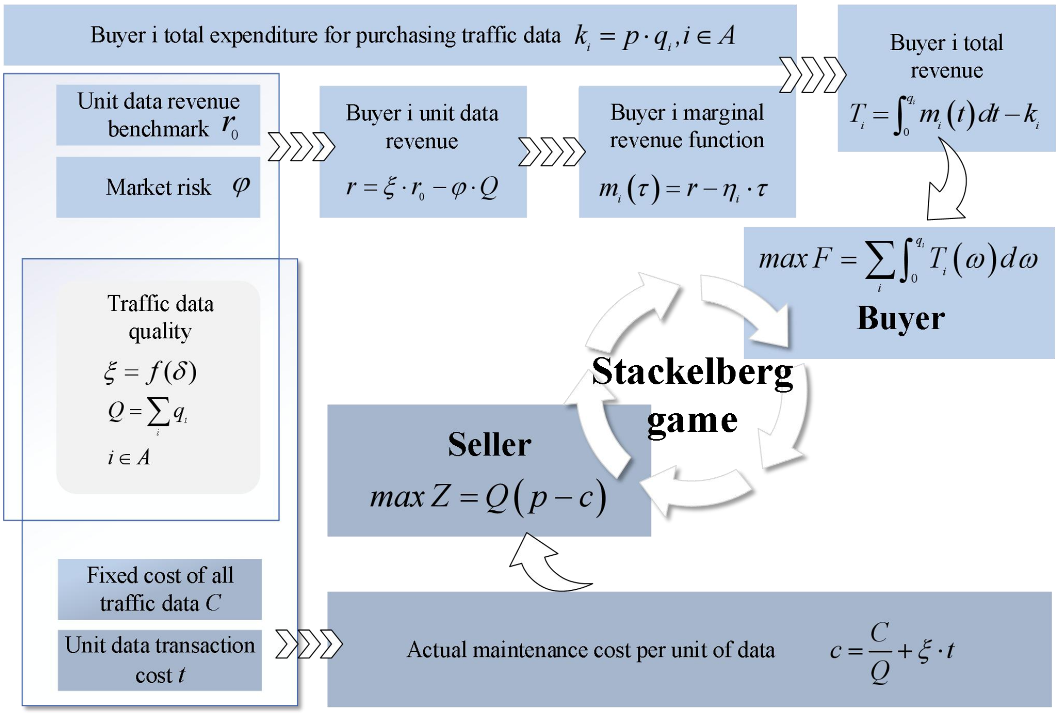


Fig. 2. Model Construction Process

(12) and (13):

$$\frac{\partial T_i}{\partial q_i} = m_i(q_i) - p = \xi \cdot r_0 - \varphi \cdot Q - \eta_i \cdot q_i - p \tag{12}$$

$$\frac{\partial^2 T_i}{\partial q_i^2} = -\varphi - \eta_i < 0 \tag{13}$$

These derivatives indicate that $T_i(q_i, p)$ is a strictly concave function. By solving $[(\partial T_i)/(\partial q_i)] = 0$, the optimal purchase strategy for the traffic data buyer can be obtained as follows:

$$q_i^* = \frac{\xi \cdot r_0 - \varphi \cdot Q^- - p}{\eta_i + \varphi} \tag{14}$$

Leader's Pricing Strategy: Based on the optimal purchase strategies decided by the buyers, the traffic data seller provides their pricing strategy to maximize their profit. By substituting (14) into (3), the traffic data seller's profit can be rewritten as (15):

$$\begin{aligned} Z(q_i^*, p) &= Q(p-c) \\ &= Q\left(p - \frac{C}{Q} - \xi \cdot t\right) \\ &= Q(p - \xi \cdot t) - C \\ &= \sum_i q_i^*(p - \xi \cdot t) - C \\ &= \sum_i \frac{\xi \cdot r_0 - \varphi Q^- - p}{\eta_i + \varphi}(p - \xi \cdot t) - C \end{aligned} \tag{15}$$

To derive the first and second derivatives of $Z(q_i^*, p)$ with respect to p, and simplify (15) into (16), and subsequently derive the first derivative (17) and the second derivative (18):

$$Z = n \cdot \frac{\xi \cdot r_0 - \varphi Q^- - p}{\mu + \varphi}(p - \xi \cdot t) - C \tag{16}$$

$$\frac{\partial Z}{\partial p} = n \cdot \frac{\xi \cdot r_0 - \varphi Q^- - 2p + \xi \cdot t}{\mu + \varphi} \tag{17}$$

$$\frac{\partial^2 Z}{\partial p^2} = -2 < 0 \tag{18}$$

Therefore, since $Z(q_i^*, p)$ is strictly concave with respect to p, we can find the optimal pricing strategy by solving for $[(\partial Z)/(\partial p)] = 0$ where the first derivative equals zero. The optimal pricing strategy is given by (19) :

$$p^* = \frac{\xi \cdot r_0 - \varphi Q^- + \xi \cdot t}{2} \tag{19}$$

where Q^- is the sum of the other accumulations of the inside and outside.

IV. Numerical Analysis

A. Model validity analysis

This paper investigates a traffic data trading market involving one seller and multiple buyers, simulates real-world trading scenarios, and provides numerical examples to assess the effectiveness of the proposed method. The relevant parameter values are adjusted to align with real-world application conditions. Table 1 lists the parameter values. s represents the only seller in the trading market, and the value is 1; the buyer set is defined as A, set $A = [1, 2, \cdots, n]$; n denotes the quantity of buyers in the market; for the numerical analysis, the scenario involves a single data seller and 10 data buyers, so the value is set to 10. The fixed cost C of all the traffic data packaged and uploaded to the platform is 3 million yuan, and the unit data transaction cost t is 10,000 yuan. η represents the buyer's perception of the ratio between the economic value potential of the data and the data cost and η follows a normal distribution with an average of μ and a variability of σ . Since the buyers are limited rational and most have a medium level of cognition, the mean is set to 1/2, and the standard deviation is 1/6. According to the 3 σ rules of normal distribution, the value of this set of data guarantees the non-negative and rational degree of cognition. r_0 is the benchmark value of unit data income, that is, the best income per unit data when there is no risk in the market; the value is 200,000. $P_{\max}$ is the maximum market price of unit traffic data guided by the government; that is, the market transaction unit price shall not exceed this value, set at 240,000 yuan. ξ is defined as the quality of traffic data and φ is defined as the fitting parameter of market risk status. In fact, at the same price, buyers are more inclined to buy data with high data quality and low market risk. The data quality parameter is set to 0.8, and the market risk is set to 0.05, which meets the purchase needs of most buyers.

TABLE I
PARAMETER VALUES

Parameter symbol	Parameter values	Parameter symbol	Parameter values
s	1	n	10
C	300	t	1
μ	1/2	σ	1/6
r_0	20	$P_{\max}$	24
ξ	0.8	φ	0.05

TABLE II
DATA PURCHASE RESULTS FOR TRAFFIC DATA BUYERS

Traffic data Buyer number	Traffic data transaction size	Buyer's income (thousand yuan)	Buyer's yield (thousand yuan)
1	7.85	653.3	196.8
2	5.74	475.1	141.0
3	37.45	3395.3	1216.6
4	7.19	597.2	179.1
5	8.36	697.4	210.9
6	16.4	1400.7	446.5
7	10.81	908.5	279.4
8	8.3	692.3	209.3
9	4.22	347.5	102.0
10	4.81	396.9	117.0

In the traffic data asset trading market with ten buyers, the unit price per transaction is 58,200 yuan, resulting in a total revenue of 3.0988 million yuan for the buyers and 2.5764 million yuan for the seller. Table 2 details the transaction volume, revenue, and profit for each buyer. It is evident from Table 2 that the transaction volume of traffic data buyers directly impacts their revenue, with a strong positive correlation between the two. This indicates buyer revenue follows a corresponding upward trend as transaction size increases. However, transaction volume and unit data price influence the buyer's profit. When the unit transaction price is fixed, buyers can increase profits by increasing transaction volume.

B. Analysis of how the number of traffic data buyers affects the market

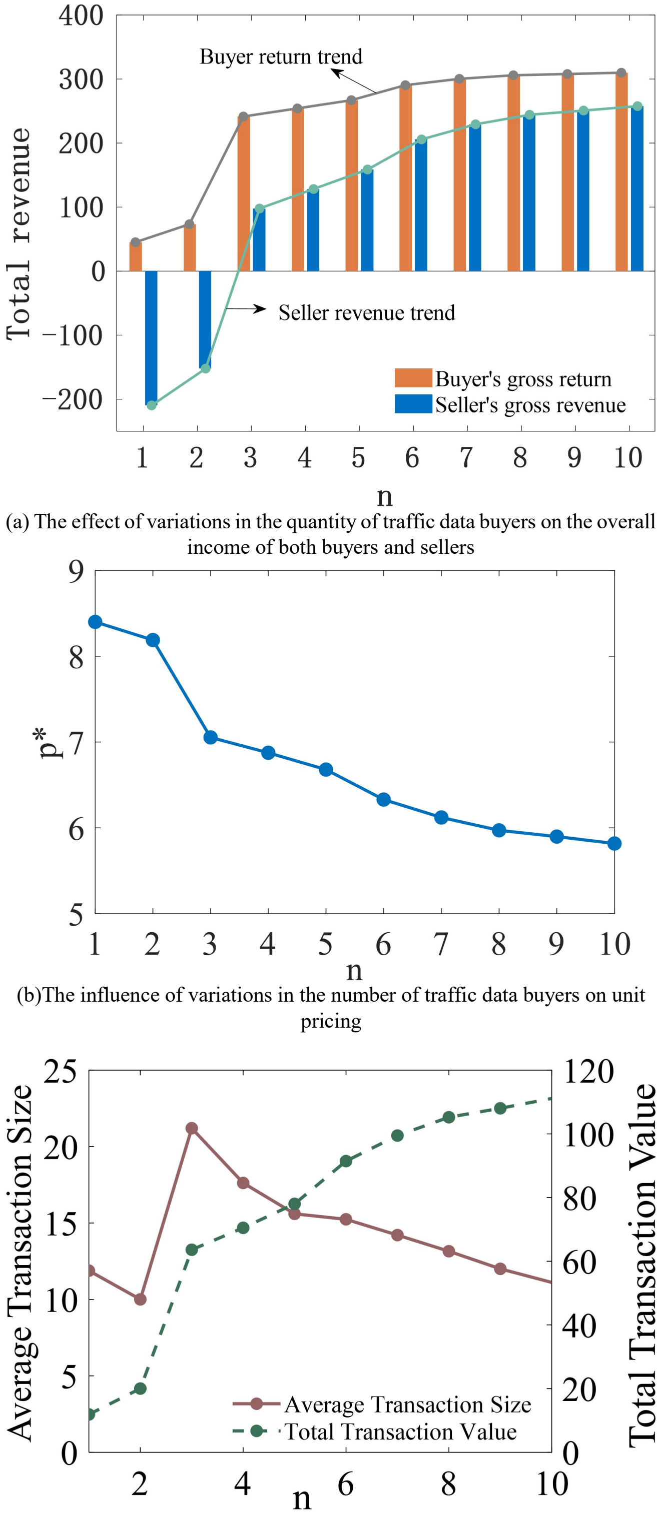
This study examines the market dynamics in a single-seller traffic data market by varying the number of buyers, aiming to understand how the number of buyers influences key factors in the trading process. Figure 3 illustrates the changes in total revenue for buyers and sellers, optimal market pricing, average transaction size, and total transaction volume as the number of buyers increases from 1 to 10.

As shown in Figure 3(a), both buyers’ and sellers’ total revenues increase as the number of buyers in the traffic data market rises. Notably, when the number of buyers reaches three or more ($n \geqslant 3$), buyers’ total revenue experiences a significant increase, while sellers' revenue shifts from negative to positive. This shift indicates that sellers do not generate profits when the number of buyers is small ($n < 3$), suggesting that a rise in the quantity of buyers significantly enhances market vitality and economic efficiency. Once the number of buyers surpasses a certain threshold, the potential for profit in market transactions is fully realized.

Figure 3(b) illustrates how the number of traffic data buyers correlates with the data unit cost. As the quantity of buyers increases, the price per unit of data tends to decrease. This effect is particularly pronounced when the number of buyers is small, especially when fewer than three buyers are involved. In such cases, sellers struggle to cover their costs, leading to higher initial prices. However, as the number of buyers increases beyond two, fluctuations in unit prices diminish and gradually stabilize, reflecting the influence of supply and demand dynamics on pricing.

Figure 3(c) illustrates the effect of the number of traffic data buyers on both the average transaction size and the total transaction volume. When the number of buyers is low ($n \leqslant 2$), there are only slight fluctuations in the average transaction size and overall transaction amount. However, a notable increase in both occurs when the number of buyers rises from 2 to 3. Although the total transaction volume continues to increase with more buyers, the average transaction size begins to decrease once the number of buyers exceeds three. Overall, the average transaction size initially decreases, then increases, and finally decreases again. Several factors contribute to this pattern: when the number of buyers is small, sellers may incur losses, leading to higher unit prices, which causes buyers to reduce their transaction sizes to maintain profitability. Once the number of buyers reaches three or more, sellers start to make a profit, which leads to lower unit prices. This signals a positive market environment, encouraging buyers to increase their transaction sizes and significantly boosting the total transaction volume. As the number of buyers continues to grow, sellers remain profitable, total transaction volume stabilizes, and the average transaction size gradually decreases.

These findings highlight the intricate relationship between the number of buyers and key market factors, underscoring the importance of buyer dynamics in determining pricing strategies, transaction sizes, and overall market efficiency.



(a) The effect of variations in the quantity of traffic data buyers on the overall income of both buyers and sellers

(b)The influence of variations in the number of traffic data buyers on unit pricing

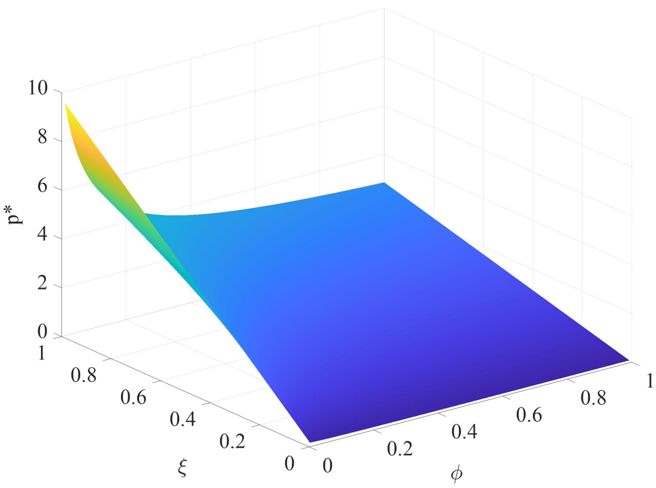
(c)The effect of fluctuations in the number of traffic data buyers on the average transaction size and the total amount of buyers

Fig. 3. Effects of Variations in the Number of Traffic Data Buyers on Outcomes

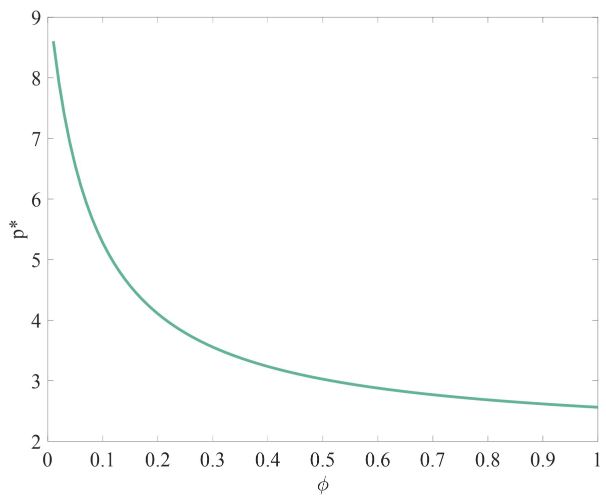
C. Analysis of the impact of data quality ξ and market risk status φ

This paper further analyzes the effects of the fitting parameters data quality ξ and market risk condition φ on the market, based on the scenario where the number of traffic data buyers is 10. Fig. 4 to Fig.7 illustrate the impact of these fitting parameters on the unit pricing of traffic data, the overall transaction volume in the market, the overall revenue of traffic data buyers, and the seller's total revenue. To further refine the understanding of the impact of the fitting parameters on the market, this study conducted a controlled variable numerical analysis. The three-dimensional graph clearly shows the combined impact of data quality and market risk on the results. However, the three-dimensional graph cannot directly observe the specific impact of one parameter on the results when the other parameter is determined. To show the diversity of results, in subfigures (b) of Fig.4 to Fig.7, we set $\xi = 0.9$ as constant to observe the effect of φ on the results. In subfigures (c) of Fig.4 and Fig.7, we set $\varphi = 0.1$ as constant to observe the impact of changes in ξ . Subfigures (a) in Fig. 4 to Fig.7 display the three-dimensional effects of both fitting parameters.

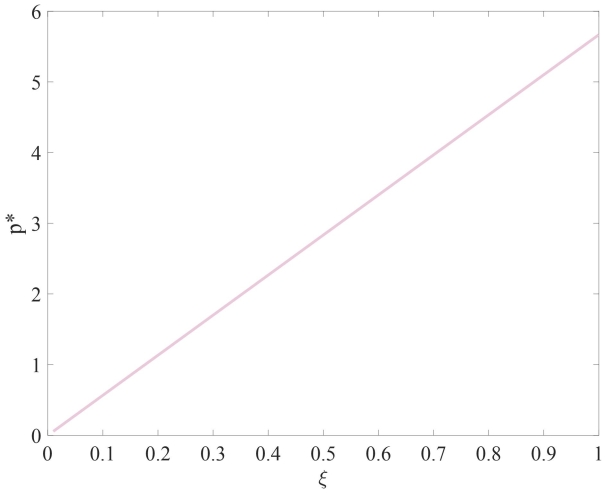
As shown in Fig.4 and Fig.5, when traffic data quality remains constant, unit prices and total market transaction volume decline as market risk increases. As market risk increases, buyers and sellers adopt a more pessimistic outlook, reducing buyer activity and declining unit prices and total transaction volume. Moreover, the decline in unit prices and transaction volume slows as market risk grows, indicating that after initial shocks, participants adjust their expectations, reducing volatility as risk accumulates.



(a) ξ , φ impact on unit pricing



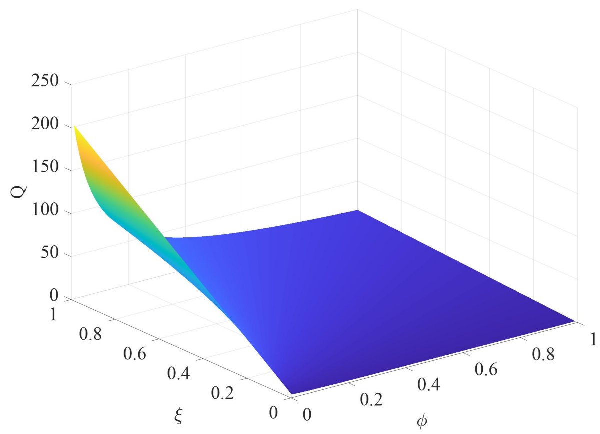
(b) $\xi = 0.9$, φ impact on unit pricing



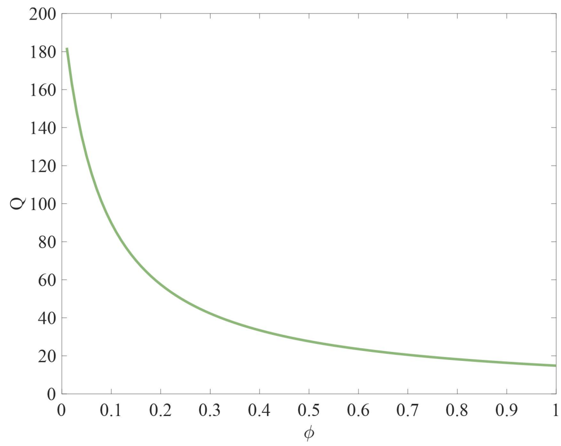
(c) $\varphi = 0.1$, ξ impact on unit pricing

Fig. 4. Impact of Parameters on Unit Pricing

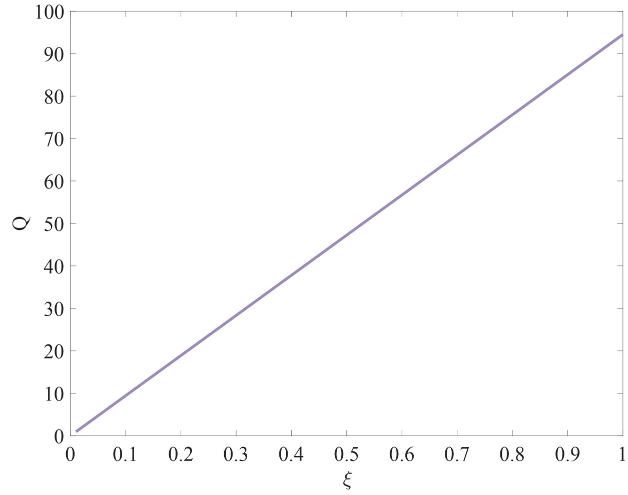
When market risk is stable, a positive linear relationship exists between unit prices and total transaction volume as traffic data quality improves. As buyers demand higher data quality, unit prices and total transaction volume rise. Higher quality demands from buyers increase sellers' maintenance costs, pushing up unit prices. Despite the higher prices, buyers are willing to increase transaction volumes because high-quality traffic data offers more value.



(a) ξ , φ influence the overall size of market transactions



(b) $\xi = 0.9$, φ affect the total volume of market transactions

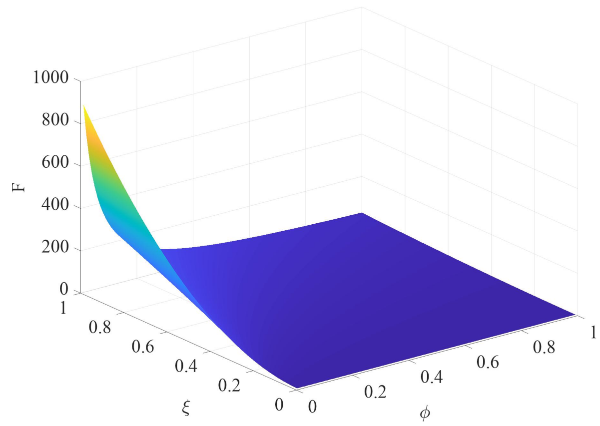


(c) $\varphi = 0.1$, ξ impact on the total size of market transactions

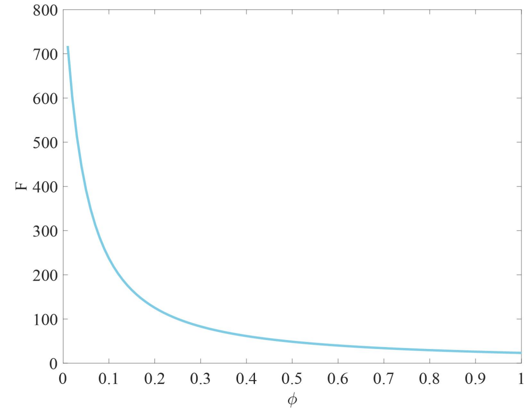
Fig. 5. Impact of Parameters on Total Market Transaction Size

Based on the analysis in Figures 6 and 7, when data quality remains constant, the total transaction revenue for both traffic data buyers and sellers declines as market risk rises. Similarly, the results from Figures 4 and 5 indicate that increased market risk leads to lower unit data prices and reduced total transaction volume, which in turn decreases the overall revenue for both buyers and sellers. Seller revenue is not always positive; at a data quality of 0.9, sellers fail to profit when market risk exceeds 0.15.

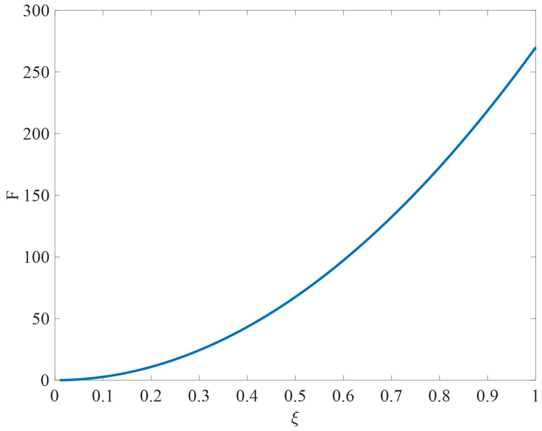
When market risk is constant, total transaction revenue for buyers and sellers rises significantly as data quality improves. The higher the quality, the more substantial the revenue growth for both parties. For example, sellers turn profitable at a market risk of 0.1 only when data quality surpasses 0.8. This indicates the market's strong demand for high-quality data and willingness to pay a premium. It highlights the crucial role of data quality in the data economy and its significant influence on economic behavior.



(a) ξ , φ impact on the total revenue of traffic data buyers

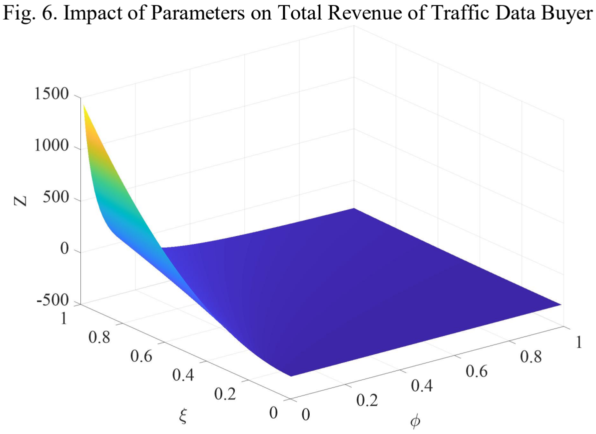


(b) $\xi = 0.9$, φ impact on the total revenue of traffic data buyers

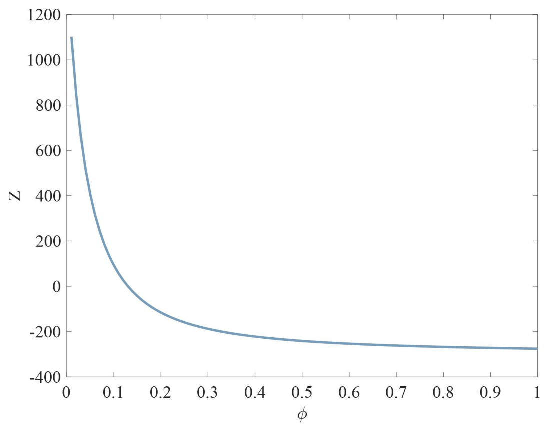


(c) $\varphi = 0.1$, ξ impact on the total revenue of traffic data buyers

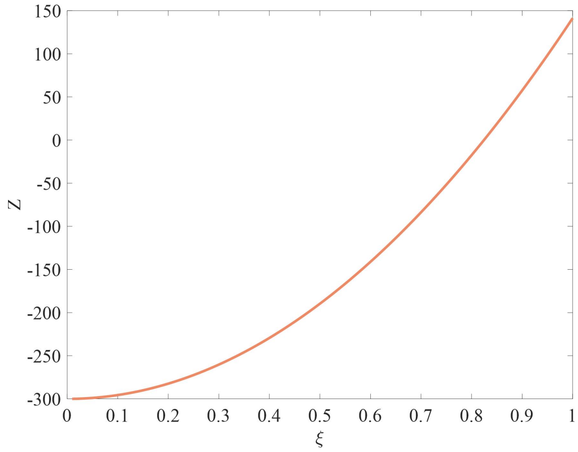
Fig. 6. Impact of Parameters on Total Revenue of Traffic Data Buyer



(a) ξ , φ impact on the total revenue of traffic data sellers



(b) $\xi = 0.9$, φ impact on the total revenue of traffic data sellers



(c) $\varphi = 0.1$, ξ impact on the total revenue of traffic data sellers

Fig. 7. Impact of Parameters on Total Revenue of Traffic Data Sellers

D. Simulation of large-scale

This section presents a numerical analysis involving 100 traffic data buyers and a single seller to further explore the effects of the number and size of buyers on the market. The data quality parameter is set at 0.95, with all other parameters consistent with those used in the small-scale simulation. Table 3 presents the purchase results of large-scale traffic data buyers. With 100 traffic data buyers and a unit price of 20.1 thousand yuan, the total revenue for buyers is 4.4845 million yuan, while sellers earn 398.5 thousand yuan. Compared to the scenario with 10 buyers, a tenfold increase in buyer numbers leads to a significant decrease in buyers' and sellers' per capita revenue. Due to the replicability of data, higher trading volumes of similar data reduce its inherent value, lowering the revenue it can generate.

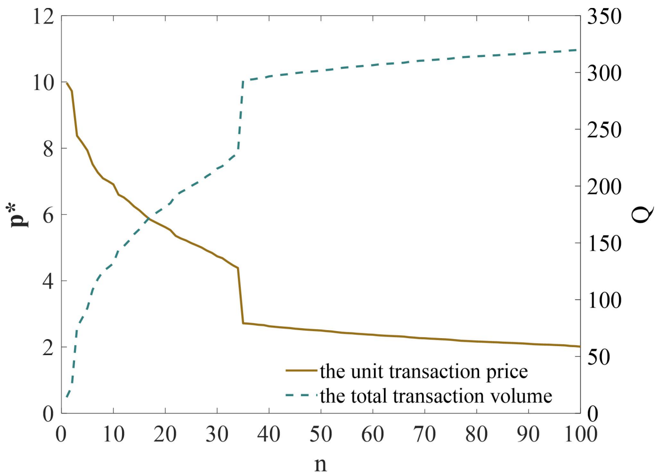


Fig. 8. The effect of fluctuations in the number of traffic data buyers on unit pricing and total transaction volume in transportation data

Fig. 8 illustrates the connection between the number of traffic data buyers and the trends in unit pricing and total transaction volume in the transportation data market. The unit transaction price gradually decreases as the quantity of buyers increases, while the total transaction volume rises accordingly. A significant shift occurs at 35 buyers, where the unit price drops sharply, and transaction volume increases

TABLE III
DATA PURCHASE RESULTS OF LARGE-SCALE TRAFFIC DATA BUYERS

Traffic data Buyer number	Traffic data transaction size	Buyer's income (thousand yuan)	Buyer's yield (thousand yuan)	Traffic data Buyer number	Traffic data transaction size	Buyer's income (thousand yuan)	Buyer's yield (thousand yuan)
1	1.66	42.2	8.8	51	2.75	70.6	15.3
2	1.21	30.7	6.3	52	1.91	48.6	10.2
3	7.92	213.7	54.4	53	3.29	84.9	18.8
4	1.52	38.6	8.0	54	3.11	80.2	17.6
5	1.77	45.0	9.4	55	1.96	50.0	10.6
6	3.47	89.7	20.0	56	1.30	32.8	6.8
7	2.29	58.5	12.5	57	2.63	67.5	14.6
8	1.76	44.7	9.4	58	1.74	44.3	9.3
9	0.89	22.5	4.6	59	2.12	54.0	11.5
10	1.02	25.7	5.2	60	1.43	36.2	7.5
11	3.56	92.1	20.6	61	3.07	79.2	17.4
12	0.97	24.6	5.0	62	1.94	49.3	10.4
13	1.58	40.0	8.3	63	1.65	42.0	8.8
14	2.00	51.0	10.8	64	1.43	36.3	7.5
15	1.58	40.1	8.4	65	1.29	32.7	6.7
16	2.10	53.6	11.4	66	1.90	48.5	10.2
17	2.04	52.1	11.0	67	3.89	101.1	22.8
18	1.31	33.1	6.8	68	2.60	66.7	14.4
19	1.33	33.7	7.0	69	3.03	78.0	17.1
20	1.33	33.7	6.9	70	1.10	27.7	5.7
21	1.60	40.6	8.5	71	2.46	63.1	13.6
22	3.27	84.6	18.7	72	1.57	39.8	8.3
23	1.58	40.1	8.3	73	2.09	53.4	11.3
24	1.27	32.1	6.6	74	1.51	38.3	8.0
25	1.68	42.8	8.9	75	2.63	67.4	14.6
26	1.45	36.9	7.6	76	3.67	95.2	21.3
27	1.58	40.0	8.3	77	3.72	96.5	21.7
28	2.18	55.6	11.8	78	1.68	42.8	8.9
29	1.78	45.4	9.5	79	2.08	53.1	11.3
30	2.65	68.1	14.7	80	2.09	53.4	11.3
31	1.51	38.3	8.0	81	1.33	33.7	6.9
32	3.17	81.7	18.0	82	1.78	45.4	9.5
33	3.04	78.3	17.2	83	1.84	46.7	9.8
34	2.68	68.8	14.9	84	1.28	32.4	6.7
35	105.36	5409.7	3290.6	85	2.67	68.6	14.9
36	1.32	33.5	6.9	86	1.59	40.3	8.4
37	1.77	44.9	9.4	87	1.53	38.9	8.1
38	2.61	67.1	14.5	88	2.13	54.4	11.6
39	1.34	34.0	7.0	89	1.83	46.5	9.8
40	4.56	119.1	27.5	90	3.20	82.6	18.2
41	2.03	51.7	10.9	91	3.17	81.8	18.0
42	2.13	54.3	11.5	92	1.89	48.2	10.1
43	1.77	45.0	9.4	93	1.58	40.1	8.3
44	1.77	45.1	9.5	94	1.05	26.6	5.4
45	2.75	70.6	15.3	95	2.52	64.5	13.9
46	1.98	50.4	10.6	96	1.84	46.9	9.9
47	2.07	52.8	11.2	97	2.01	51.3	10.9
48	1.62	41.1	8.6	98	5.50	145.1	34.5
49	1.43	36.4	7.5	99	2.29	58.6	12.5
50	1.43	36.2	7.5	100	4.87	127.7	29.8

dramatically. The number of buyers is a key factor driving market dynamics. Below the critical threshold, the increase in buyers consistently leads to a significant drop in unit prices and an expansion of total transaction volume. Beyond this point, changes in unit pricing and total transaction volume become more moderate, leading to stabilization. This trend highlights the market's sensitivity to buyer influx and the resulting pricing and transaction metrics adjustments.

V. CONCLUSION

The ongoing evolution of traffic data elements has transformed them into "assets" with distinct value realization characteristics, setting them apart from "general assets." During circulation, these assets demonstrate distinctive value appreciation features. Current research typically develops universal data asset pricing strategies tailored to various data scenarios or market roles. However, these universal pricing mechanisms are insufficient due to traffic data assets' vast, complex, and time-sensitive nature. This paper tackles the replicable nature of data in transactions by modeling traffic data asset pricing with Stackelberg game theory in the context of market trading scenarios during traffic data circulation. Using backward induction, we derive and verify the optimal purchasing strategy for traffic data buyers and the optimal pricing strategy for sellers. Numerical simulations were performed to comprehensively evaluate the proposed model, revealing phenomena and patterns arising from changes in specific market factors. The key insights from this study are presented as follows:

(1) The existence of multiple buyers ($n \geqslant 3$), rather than a single buyer, significantly stimulates market activity, increases total transaction volume, and aids in seller profitability. A strong positive correlation exists between the scale of traffic data transactions and buyer income, indicating that larger transaction scales accompany higher buyer income. However, with an increase in traffic data buyers, the unit price decreases, while the total transaction volume expands. At a critical threshold of buyer numbers, the unit price plummets, and the total transaction volume surges. Beyond this threshold, changes in the unit price and total transaction volume become more moderate, reaching an equilibrium state.

(2) In an environment with stable market risk, there is a clear, direct, linear positive correlation between unit pricing, total transaction volume, and the quality of traffic data transactions. Buyers are increasingly demanding high-quality traffic data. Improvements in data quality act as a catalyst, increasing buyer willingness to transact and stimulating market activity.

(3) When the quality of traffic data remains constant, market risk increases negatively with both unit pricing and total transaction volume. A rise in market risk diminishes the confidence of both buyers and sellers in the data market, causing a decrease in profits for both parties. Even minor fluctuations in market risk can significantly impact the data economy.

Although the proposed traffic data asset pricing method meets the basic pricing needs in traffic data asset trading, it still has some limitations. For instance, it does not fully examine the characteristics of the entire production and distribution process of traffic data assets and neglects the potential for secondary or multiple transactions by buyers. Future studies will further investigate these areas.

REFERENCES

[1] J. Hao, Z. Deng, and J. Li, “The evolution of data pricing: From economics to computational intelligence,” *Heliyon,* vol. 9, no. 9, 2023.

[2] Z. Cong, X. Luo, J. Pei, F. Zhu, and Y. Zhang, “Data pricing in machine learning pipelines,” *Knowledge and Information Systems,* vol. 64, no. 6, pp. 1417-1455, 2022.

[3] S. Shamshirband, M. Fathi, A. Dehzangi, A. T. Chronopoulos, and H. Alinejad-Rokny, “A review on deep learning approaches in healthcare systems: Taxonomies, challenges, and open issues,” *Journal of Biomedical Informatics,* vol. 113, 2021.

[4] R. Sangeetha, and T.N. Ravi, "Random Probit Regressive Decision Forest Classification based IoT aware Content Caching with Healthcare Data," IAENG International Journal of Computer Science, vol. 51, no. 6, pp582-593, 2024

[5] B. Tu, Y. Zhao, G. Yin, N. Jiang, G. Li, and Y. Zhang, “Research on intelligent calculation method of intelligent traffic flow index based on big data mining,” *International Journal of Intelligent Systems,* vol. 37, no. 2, pp. 1186-1203, 2022.

[6] Z. Lv, L. Qiao, M. S. Hossain, and B. J. Choi, “Analysis of Using Blockchain to Protect the Privacy of Drone Big Data,” *IEEE Network,* vol. 35, no. 1, pp. 44-49, 2021.

[7] Prabhavathi Krishnegowda, and Anandaraju M Boregowda, "Fully Homomorphic Encryption of Floating-Point Matrices for Privacy-Preserving Image Processing," IAENG International Journal of Computer Science, vol. 50, no.4, pp1460-1469, 2023

[8] L. Li, Y. Fan, M. Tse, and K.-Y. Lin, “A review of applications in federated learning,” *Computers & Industrial Engineering,* vol. 149, 2020.

[9] C. Li, H. Li, and C. Tao, “Evolutionary game of platform enterprises, government and consumers in the context of digital economy,” *Journal of Business Research,* vol. 167, pp. 113858, 2023.

[10] K. Rong, “Research agenda for the digital economy,” *Journal of Digital Economy,* vol. 1, no. 1, pp. 20-31, 2022.

[11] G. Sidorenko, A. Fedorov, J. Thunberg, and A. Vinel, “Towards a Complete Safety Framework for Longitudinal Driving,” *IEEE Transactions on Intelligent Vehicles,* vol. 7, no. 4, pp. 809-814, 2022.

[12] Y. Jiao, P. Wang, D. Niyato, M. Abu Alsheikh, S. Feng, and Ieee, "Profit Maximization Auction and Data Management in Big Data Markets," *IEEE Wireless Communications and Networking Conference*, 2017.

[13] H. Yu, and M. Zhang, “Data pricing strategy based on data quality,” *Computers & Industrial Engineering,* vol. 112, pp. 1-10, 2017.

[14] Q. Wu, M. Zhou, Q. Zhu, and Y. Xia, “VCG Auction-Based Dynamic Pricing for Multigranularity Service Composition,” *IEEE Transactions on Automation Science and Engineering,* vol. 15, no. 2, pp. 796-805, 2018.

[15] X. Jiang, N. N. Xiong, X. Wang, C. Ying, F. Wu, and Y. Luo, “DIVINE: A pricing mechanism for outsourcing data classification service in data market,” *Information Sciences,* vol. 636, pp. 118922, 2023.

[16] R. C. Fernandez, P. Subramaniam, and M. J. Franklin, “Data Market Platforms: Trading Data Assets to Solve Data Problems,” *Proceedings of the Vldb Endowment,* vol. 13, no. 11, pp. 1933-1947, 2020.

[17] L. Chen, P. Koutris, A. Kumar, and M. Assoc Comp, "Towards Model-based Pricing for Machine Learning in a Data Marketplace," *International Conference on Management of Data.* pp. 1535-1552, 2019.

[18] Abdelhak Khalil, Mustapha Belaissaoui, and Fouad Toufik, "A Data Placement Strategy for Distributed Document-oriented Data Warehouse," IAENG International Journal of Computer Science, vol. 50, no.4, pp1541-1549, 2023.

[19] J. Hao, J. Yuan, and J. Li, "HCEG: A heterogeneous clustering ensemble learning approach with gravity-based strategy for data assets intelligent pricing," Information Sciences, Article vol. 678, Sep 1 2024, Art no. 121082, doi: 10.1016/j.ins.2024.121082.

[20] W. Yang, Y. Fang, X. Zhou, Y. Shen, W. Zhang, and Y. Yao, "Networked Industrial Control Device Asset Identification Method Based on Improved Decision Tree," Journal of Network and Systems Management, Article vol. 32, no. 2, Apr 2024, Art no. 32, doi: 10.1007/s10922-024-09805-z.

[21] J. Pei, “A Survey on Data Pricing: From Economics to Data Science,” *IEEE Transactions on Knowledge and Data Engineering,* vol. 34, no. 10, pp. 4586-4608, 2022.

[22] J. Xu, N. Hong, Z. Xu, Z. Zhao, C. Wu, K. Kuang, J. Wang, M. Zhu, J. Zhou, K. Ren, X. Yang, C. Lu, J. Pei, and H. Shum, “Data-Driven Learning for Data Rights, Data Pricing, and Privacy Computing,” *Engineering,* vol. 25, pp. 66-76, 2023.

[23] M. Zhang, F. Beltran, and J. Liu, “A Survey of Data Pricing for Data Marketplaces,” *IEEE Transactions on Big Data,* vol. 9, no. 4, pp. 1038-1056, 2023.

[24] C. Xu, K. Zhu, C. Yi,and R. Wang, "Data Pricing for Blockchain-based Car Sharing: A Stackelberg Game Approach," *IEEE Global Communications Conference*, 2020.

[25] K. Liu, X. Qiu, W. Chen, X. Chen, and Z. Zheng, “Optimal Pricing Mechanism for Data Market in Blockchain-Enhanced Internet of Things,” *IEEE Internet of Things Journal,* vol. 6, no. 6, pp. 9748-9761, 2019.
[26] S. Li, L. Chu, J. Wang, and Y. Zhang, "A road data assets revenue allocation model based on a modified Shapley value approach considering contribution evaluation," Scientific Reports, Article vol. 14, no. 1, Mar 2 2024, Art no. 5179, doi: 10.1038/s41598-024-55819-7.
[27] Z. Xiao, D. He, and J. Du, “A Stackelberg Game Pricing Through Balancing Trilateral Profits in Big Data Market,” *IEEE Internet of Things Journal,* vol. 8, no. 16, pp. 12658-12668, 2021.
[28] S. WANG, “A Manufacturer Stackelberg Game in Price Competition Supply Chain under a Fuzzy Decision Environment,” IAENG International Journal of Applied Mathematics, vol. Vol.47, no. No.1, pp. 49-55, 2017.