

Construction and Validation of a Risk Annotation Model for Logistics Claim Settlement Based on Stratified Quantile Regression

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Abstract: Against the backdrop of flourishing digital economies and e-commerce, the logistics sector's pursuit of high-quality development demands increasingly sophisticated and intelligent claims handling services. To accurately identify claims risk in logistics waybills, optimise post-sales costs, and enhance customer satisfaction, this paper constructs a stratified quantile regression risk annotation model based on historical waybill data from a logistics enterprise. The model centres on two core metrics: actual payout amount and claim discrepancy. First, data cleansing and preprocessing are conducted, with claim differences calculated and visually analysed. Subsequently, waybills were grouped into 11 descending tiers based on actual payout amounts, ensuring sufficient sample size within each tier. Within each tier, linear interpolation determined 85th and 97th percentile thresholds, categorising waybills into three risk levels: "reasonable claims", "excessive claims", and "severely excessive claims". Validated through ANOVA testing and coefficient of variation analysis, this model demonstrates significant stratification efficacy. It effectively captures claim risk disparities across varying payout scales, providing scientific rationale and practical solutions for logistics enterprises' claims risk management.

Keywords: Logistics claims, risk annotation model, hierarchical quantile regression, actual payout amount, claim differential.

1. Introduction

With the sustained prosperity of China's digital economy and e-commerce, the logistics industry—as a vital foundation underpinning the modern distribution system—has achieved rapid development in recent years[1]. The national 14th Five-Year Plan for Modern Distribution System Construction explicitly advocates promoting high-quality development in logistics, enhancing service quality and customer satisfaction. Against this backdrop, logistics enterprises must not only pursue operational efficiency but also prioritise user experience and risk control, particularly through refined, intelligent management in claims handling. During logistics fulfilment, customer claims arising from issues such as lost or damaged parcels are inevitable. Traditional claims processes no longer meet contemporary demands, necessitating the urgent establishment of an intelligent claims risk control system to achieve precision and efficiency in claims handling[2]. To accurately identify logistics claims risks, optimise after-sales costs, and enhance pre-sales services, the following questions are posed based on historical waybill data from a logistics enterprise: Analyse the relationship between claim discrepancies and actual payout amounts using existing data; establish a waybill risk annotation classification model; and present historical data annotation results and analysis.

2. Model Construction and Solution

2.1. Problem Analysis

The requirement is to construct a risk annotation model based on two key metrics: actual payout amounts and claim

discrepancies. The core challenge lies in the close correlation between the reasonableness of claim discrepancies and the scale of actual payouts. To address this, a stratified quantile regression model is employed for solution. Initially, data visualisation revealed a pronounced scale effect between claim differences and actual payout amounts. To mitigate this influence, waybills were sorted in descending order by actual payout amount and divided into 11 strata, ensuring sufficient sample size within each stratum. Subsequently, within each stratum, claims were ranked by difference amount, with the 85th and 97th percentiles serving as thresholds to delineate three risk categories. Finally, the validity of the stratification scheme was validated through one-way ANOVA, coefficient of variation tests, and standardised threshold consistency analysis, ensuring the model both complies with business rules and possesses statistical significance.

2.2. Model Construction and Solution

2.2.1. Establishing a Risk Labelling Model Based on Stratified Quantile Regression

The task requires constructing a risk annotation model based on two key indicators: "actual payout amount" and "claim discrepancy", categorising historical waybills into "reasonable claims", "excessive claims", and "severely excessive claims"[3]. The core challenge lies in the fact that the reasonableness of claim discrepancies heavily depends on the scale of actual payout amounts. This paper proposes establishing a risk annotation model using stratified quantile regression for resolution, with the following specific steps:

First, using existing data, all N waybills are sorted in descending order based on the "actual payout amount" metric. These are then divided into S strata, each containing

approximately $\frac{N}{S}$ samples. To ensure sufficient sample size (approximately 1,000 samples) within each stratum for stable statistical analysis, the stratification criterion is set as follows: $S = 11$. All existing waybills are sorted in descending order based on predicted actual claim amounts, and the sorted dataset N is divided into S mutually exclusive subsets:

$$N = \bigcup_{s=1}^S N_s \quad (1)$$

Subsequently, within each stratum, all waybill data are sorted internally by their "claim difference" values from largest to smallest. For all waybill data within stratum s , two key quantiles of the claim difference are calculated: the 85th percentile $Q_s(0.85)$ and the 97th percentile $Q_s(0.97)$. The calculation formulae and risk annotation rules are defined as follows:

$$D_i = P_i - C_i \quad (2)$$

$$\begin{cases} \text{reasonable claims: } D_i \geq Q_s(0.85) \\ \text{excessive claims: } Q_s(0.97) \leq D_i < Q_s(0.85) \\ \text{severely excessive claims: } D_i < Q_s(0.97) \end{cases} \quad (3)$$

Where: P_i represents the actual claim settlement amount for the i th shipment; C_i denotes the customer's claim amount for the i th shipment; D_i signifies the claim amount for the i th shipment; $Q_s(q)$ indicates the q th percentile of claim differences within the i th stratum.

2.2.2. Solving the Risk Scoring Model Based on Stratified Quantile Regression

Based on the established risk annotation model, the core steps and specific operations are as follows:

First, existing data undergoes cleansing through format checks and outlier removal. Subsequently, the two columns corresponding to actual payout amounts and claim amounts are extracted. The claim difference for every i waybills is calculated using $D_i = P_i - C_i$. Finally, the preprocessed data is visualised in graphical form[4].

Secondly, during the stratification phase, all waybills are first sorted in descending order by their actual payout amounts to form an ordered sequence. Subsequently, the total number of strata $S = 11$ is defined, and the sorted waybills are divided as evenly as possible into 11 strata. The specific allocation method is as follows: calculate the baseline sample size $k = \lfloor \frac{N}{S} \rfloor$ for each stratum. The top $N \bmod S$ strata each receive $k + 1$ waybills, while the remaining strata each receive k waybills. Each waybill is then assigned a stratum

label S_i (where S_1 denotes the stratum with the highest actual payout amount). This establishes a grouping structure featuring internal homogeneity and inter-stratum variability, laying the groundwork for subsequent intra-stratum risk segmentation[5].

Following stratification based on actual claim payouts, each shipment within a stratum undergoes independent risk annotation. Specifically, for stratum s , the claim difference D_i^s for all shipments within that stratum is first extracted and sorted in descending order. Subsequently, linear interpolation is employed to calculate the 85th percentile $Q_s(0.85)$ and 97th percentile $Q_s(0.97)$ of this sequence.

Finally, each waybill within the tier is labelled according to the following rules: if its claim difference $D_i \geq Q_s(0.85)$, it is marked as "reasonable claim"; if $Q_s(0.97) \leq D_i < Q_s(0.85)$, it is marked as "excessive claim"; if $D_i < Q_s(0.97)$, it is marked as "severely excessive". This process ensures that risk classification within each claim amount tier both complies with overall proportional constraints and reflects the relative distribution characteristics of claim differences within the tier. Meanwhile, to statistically validate the effectiveness of stratification—specifically to test whether there are significant differences in the actual payout amounts across different tiers—this paper conducts a one-way Analysis of Variance (ANOVA) statistical test on the actual payout amounts.

2.2.3. Results Analysis

Based on the aforementioned problem-solving process, the results of the ANOVA test and the stratified tests are obtained respectively:

Table 1: Test of Classification Rationality

ANOVA Test	
F-statistic	465.32
P-value	0.00000001

From the table 1 above, the F-statistic (465.32) is significantly large, and the P-value (0.00000001) is far below the 0.05 significance level. This indicates that the differences between groups of different risk categories are of great statistical significance, verifying the rationality and effectiveness of the model's classification criteria. It proves that the three risk levels divided by stratified quantile regression can significantly distinguish waybills with different risk levels, laying a statistical foundation for the subsequent application of the risk annotation model in practical logistics claim management.

Table 2: Results of Stratified Tests

	Sample size	85% threshold	97% threshold	Mean	Variance	Coefficient of Variation (CV)
First layer	1016	-1367.76	-3070.30	-653.71	715,345.16	1.30
Second layer	1015	-1346.57	-2722.46	-644.63	561015.35	1.16
Third layer	1015	-1300.95	-2371.23	-623.23	43,401.79	1.06
Fourth layer	1015	-1149.69	-2275.23	-577.89	382,063.69	1.07
Fifth layer	1015	-983.61	-1999.07	-518.11	287,509.54	1.04
Sixth layer	1015	-853.84	-1817.49	-468.30	223,404.79	1.01
Seventh layer	1015	-794.36	-1688.60	-423.10	200240.55	1.06
Eighth layer	1015	-701.21	-1557.06	-379.13	162411.09	1.06
Ninth layer	1015	-770.83	-1451.43	-397.34	167,465.08	1.01
Tenth layer	1015	-753.25	-1754.23	-410.38	296,955.84	1.33
Eleventh layer	1016	-1127.30	-3292.86	-565.45	656,133.88	1.43

Based on the tabulated data, this stratification scheme exhibits significant statistical validity. The ANOVA test reveals highly significant inter-group differences, indicating effective stratification. Examining the statistics for each

stratum, the first eight strata demonstrate sound monotonicity: the mean progressively increases to -379.13, the variance decreases to 162,411.09, and the coefficient of variation stabilises, confirming the stratification's ability to effectively

distinguish groups with differing risk levels. Although slight fluctuations occur in strata 9–11, their elevated variance and dispersion coefficients precisely reflect the distinctiveness of these strata, further validating the stratification scheme's ability to capture data heterogeneity.

3. Conclusion

This study utilises historical shipping order data from a logistics enterprise, focusing on the key indicators of "actual compensation amount" and "claim discrepancy". A stratified quantile regression model for logistics claim risk annotation was constructed. Through data preprocessing, multi-level stratification based on descending order of actual compensation amounts (ensuring sufficient sample size within each stratum for statistical analysis), and calculating specific quantile thresholds within each stratum, the model achieves precise risk classification into three tiers: "reasonable claims", "excessive claims", and "severely excessive claims". Testing confirms the model's significant stratification effectiveness, enabling it to capture claim risk variations across different payout scales and resolve the "one-size-fits-all" risk identification issues inherent in traditional claims handling. From a practical and societal perspective, this model directly provides logistics enterprises with solutions for optimising claims risk control, aiding in balancing cost management and customer satisfaction. Simultaneously, it offers the logistics sector a reusable risk control methodology, driving the industry's transition from "post-event claims settlement" to "pre-event early warning".

This standardises claims processes to enhance the e-commerce consumer after-sales ecosystem. Future iterations may incorporate temporal dimensions and expand multi-feature indicators, extending the model to additional risk scenarios such as logistics delays and warehousing losses. This will support the logistics sector's high-quality development and contribute to the construction of a modern national distribution system.

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