Unraveling the Causal Mechanisms behind Moral Hazard in China's Auto Industry

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Abstract

Moral hazard in auto insurance arises when greater coverage leads policyholders to drive less cautiously, increasing claim likelihood. While prior research has primarily examined the direct correlation between coverage and claims, limited attention has been paid to the underlying causal mechanisms, particularly the mediating role of driving behavior. This omission constrains insurers' ability to design effective risk mitigation strategies. To address this gap, we propose a novel approach that integrates mediation analysis with the residual inclusion method, explicitly accounting for the endogeneity of coverage selection. Simulation results demonstrate that our method surpasses the existing approach in both identifying moral hazard and uncovering its causal pathways. We apply the method to China's automobile insurance market, leveraging IoT devices that monitor driving behavior before and after policy acquisition. Empirical findings reveal no evidence of moral hazard. Instead, additional commercial coverage is associated with reduced driving risk compared to compulsory coverage.

Keywords: Moral hazard, Automobile insurance, Causal mechanisms, Mediation analysis, Driving behavior, IoT devices.

1 Introduction

Moral hazard, in economic terms, occurs when one party's behavior changes in a way that negatively impacts another party because the first party does not bear the full risks or costs of their actions. For example, in credit card markets, cardholders may be encouraged to spend beyond their financial capacity since credit cards allow for deferred payments. This, in turn, can lead financial institutions to take on excessive risks by extending credit without fully considering the consumer's ability to repay, thereby introducing a moral hazard (Akerlof, 1970; Chatterjee et al., 2007). Moral hazard is also a significant challenge in other sectors, such as the insurance industry. The literature identifies two main types of moral hazard: ex-ante and ex-post. Ex-post moral hazard refers to situations where the insured can influence the severity of a loss after it has occurred, often without the insurer's knowledge. This can lead to excessive use of insurance services, resulting in unexpected financial losses for the insurer. Health insurance is a typical example, with several studies showing that as insurance coverage increases, reducing the individual's out-of-pocket costs, there is often a corresponding increase in healthcare utilization

(Pauly, 1968; Finkelstein and McGarry, 2006).

On the ex-ante side, moral hazard (ex-ante moral hazard hereafter simply referred to as moral hazard, which is the focus of our study) has been widely studied in the car insurance market. It refers to the situation where the insured may engage in riskier driving behavior or be less cautious in driving given the amount of insurance cover. That is, the individual with higher coverage may have less incentive to avoid the occurrence of the risk and potentially increases the likelihood of claims. Thus, this phenomenon can be explained from an outcome-oriented perspective as follows: moral hazard exists if individuals who choose more coverage are more likely to file more claims than those with less coverage (Shavell, 1979). To assess the presence of moral hazard in auto-insurance markets, most researchers investigate the positive correlation between coverage choice and claim occurrence directly. For example, Greene (1998) employs a probit model, while Chiappori and Salanié (2000) suggest performing a correlation test between the residuals derived from the bivariate model of coverage and claims. Subsequent works that refine this approach suggest detecting moral hazard through a correlation test based on dynamic claims data, which tracks policyholders over multiple periods (Abbring et al., 2003; Israel, 2004; Wang et al., 2008; Dionne et al., 2013). This method enables the examination of whether coverage amounts influence claims in subsequent periods, while accounting for the potential impact of premium adjustments on the coverage-claim correlation.

However, these approaches do not differentiate between moral hazard and adverse selection, a critical challenge in this area of research, as both phenomena are characterized by a positive correlation between insurance choice and claims (Dionne and Gagné, 2002; Finkelstein and Poterba, 2004; Cohen and Siegelman, 2010). Unlike moral hazard, which arises when individuals alter their behavior after purchasing insurance, adverse selection occurs when individuals with higher risk are more likely to purchase insurance than those with lower risk. (Rothschild and Stiglitz, 1976; Puelz and Snow, 1994; Dionne et al., 2001). Since customer's private risk is typically unobservable to the insurer, adverse selection can be viewed as a self-selection problem, where the endogenous nature of the insured's coverage choice introduces bias into the estimation of the correlation between coverage and claims in the detection of moral hazard. Finkelstein and McGarry (2006) recommend using an instrumental variable for the coverage choice to control for the impact of adverse selection. This method captures the endogeneity but requires a strong assumption that the instrumental variable is relevant and exogenous (Weisburd, 2015). Additionally, the outcome variable, claims, is typically assumed to follow a normal distribution. An alternative approach to mitigating endogeneity bias is the Heckman procedure (Heckman, 1979; Tucker, 2010), which incorporates a function derived from an insurance choice model into a structural model of claims. Horowitz and Lichtenberg (1993) apply this methodology to detect moral hazard in crop insurance by analyzing the relationship between pesticide use and insurance selection. However, The Heckman procedure focuses on more correcting sample selection bias, which occurs when the outcome variable (e.g., insurance claims) is only observed for a non-randomly selected group, such as individuals who purchase insurance.

To the best of our knowledge, almost all existing methods do not further explore the causal mechanism of how coverage affects the insured's claim risk. Specifically, the amount of coverage purchased may influence a driver's level of caution in driving (e.g., reducing risk aversion), which in turn indirectly affects their likelihood of making a claim.

Our research question thus aims to identify moral hazard, taking into account the causal relationship between coverage and claims, as well as the endogeneity of the insured's decision-making process. At its core, moral hazard may arise when coverage influences claims through an increase in the policyholder's driving risk. Building upon this foundational understanding of moral hazard, we propose a novel method that directly incorporates the causal relationship between coverage and claims, while addressing the endogeneity inherent in the policyholder's coverage decision. Specifically, we hypothesize that moral hazard may manifest through an indirect effect of coverage selection on claims, mediated by driving behavior, which cannot be observed by simply examining the direct correlation between coverage and claims. To assess the causal mechanisms behind moral hazard, a mediation learning is employed along with the two-stage residual inclusion (2SRI) method. This approach, widely used in empirical research within health economics (Terza et al., 2008), addresses endogeneity concerns and allows for non-linear modeling of the outcome variable. To evaluate the performance of our proposed model, comprehensive simulations are conducted, where the data-generating process (DGP) uncovers the true causal mechanism behind moral hazard. The results demonstrate that failing to account for the indirect effect of coverage can bias the estimated coverage–claim relationship, and our proposed model outperforms alternative approaches in detecting this phenomenon with superior statistical power.

Building on our methodology, we empirically investigate the presence of moral hazard in China's auto-insurance industry. Our dataset originates from a Chinese insurance company and comprises 981 policyholders observed in 2017. It includes detailed information on each policyholder's age, vehicle value, coverage type, claim amounts, and driving behavior recorded by IoT devices. This rich dataset enables us to examine how insurance coverage influences driving behavior by observing drivers both before and after policy purchase.

Importantly, our method of collecting driving behavior data differs from that used in conventional usage-based insurance (UBI) studies. In typical UBI programs, customers are informed that their driving data will be collected after policy issuance through telematics devices or smartphone sensors (Holzapfel et al., 2024). Insurers then use these data to build predictive models and set personalized premiums based on driving behavior (Baecke and Bocca, 2017; Ma et al., 2018; Soleymanian et al., 2019; Henckaerts and Antonio, 2022; Li et al., 2023). In contrast, our IoT data are obtained from third-party sources using factory-installed OBD devices, entirely independent of insurer intervention. As a result, they capture genuine, unmonitored driving behavior, avoiding the behavioral distortions that often arise in insurer-led, telematics-based UBI programs (Li et al., 2022a).

Our results show that there is no direct effect and indirect effect of coverage amount on claims, showing no evidence of moral hazard in the China's automobile insurance market. Moreover, we observe that the coverage selection could influence policyholders tend to drive more cautiously after getting insured, particularly those who opt for more comprehensive coverage compared to those who only purchase compulsory coverage.

This study advances the theoretical understanding of ex-ante moral hazard by introducing a causal framework that explicitly models the indirect effect of insurance coverage on claims through driving behavior, addressing a key limitation of previous studies that overlooked this indirect pathway and focused solely on the direct coverage–claim correlation, which can lead to biased detection of moral hazard. Our proposed framework not only demonstrates superior statistical power in identifying moral hazard but also elucidates the behavioral mechanism linking insurance protection to risk-taking behavior. Practically, by applying this model to IoT-based driving data from the Chinese automobile insurance market collected independently of insurer intervention, our approach captures authentic, unmonitored driving behavior. The empirical findings reveal no evidence of moral hazard, offering insurers actionable insights for enhancing risk assessment, pricing strategies, and behavioral monitoring without introducing bias from observation effects.

The structure of this article is organized as follows. Section 2 provides a brief overview of the methodologies used in the study. Section 3 outlines the simulation procedure, including the data-generating process (DGP) and the simulation results. Section 4 presents the datasets utilized, along with their contents, and conducts the empirical analysis. Finally, Section 5 summarizes the key findings and discusses the study's limitations and potential directions for future research.

2 Methodology

2.1 Addressing Moral Hazard

Several studies have empirically assessed moral hazard in the auto-insurance industry by examining the correlation between coverage selection and claim risk, building on the framework established by Shavell (1979). In particular, if moral hazard exists in the insurance market, individuals with higher coverage may have a reduced incentive to avoid claims. As a result, the loss probability for individuals with higher coverage may exceed that of those with lower coverage. This relationship between coverage and claims is often modeled by coding individuals with insurance or more extensive coverage as 1, while those without insurance or with only compulsory coverage are coded as 0 (Horowitz and Lichtenberg, 1993; Wang et al., 2008). The variable Clm_i, representing the number of claims filed by individual i during the insurance period (Dionne et al., 2001; Cohen, 2005), is assumed to follow a Poisson distribution with parameter $\lambda_i = \mathbb{E}(Clm_i \mid Add_i, \boldsymbol{X}_i)$. This conditional expectation can be predicted by the regression model formulated as

$$\log(\lambda_i \mid Add_i, \boldsymbol{X}_i) = \alpha_0 + \alpha_1 Add_i + \boldsymbol{\alpha}_2' \boldsymbol{X}_i \quad (1)$$

where the variable Add_i indicates whether individual i purchases additional coverage, and $\boldsymbol{X}_i$ represents a vector of variables related to buyer characteristics. Moral hazard is present if the estimated coefficient $\hat{\alpha}_1$ from the regression in Eq. (1) is statistically significant and positive, suggesting that individuals with higher coverage tend to file more claims.

However, unobserved risk factors of the insured may simultaneously influence both their coverage choice and the likelihood of filing a claim, leading to endogeneity bias in the estimation of the coverage–claim correlation (coefficient α_1). Therefore, in model (1), it is essential to account for the endogenous nature of the insured's coverage selection in order to more accurately estimate this relationship. Terza et al. (2008) propose a straightforward estimation method, the two-stage residual inclusion (2SRI) approach, which addresses endogeneity bias and is applicable to a variety of nonlinear regression contexts. In the first stage of this estimation, the endogenous regressor, coverage selection Add_i, is modeled as a Bernoulli random variable with probability p_i, where $p_i = \Pr(Add_i \mid \boldsymbol{Z}_i)$. This relationship can be modeled using a logistic regression:

$$\Pr(Add_i = 1 \mid \boldsymbol{Z}_i) = \sigma\big(\beta_0 + \boldsymbol{\beta}_1' \boldsymbol{Z}_i\big) \quad (2)$$

where $\boldsymbol{\beta}_1$ represents the coefficient vector associated with the predictors $\boldsymbol{Z}_i$, and $\sigma(\cdot)$ denotes the standard logistic (sigmoid) function, defined as $\sigma(m) = \frac{1}{1+e^{-m}}$. From Eq. (2), the residuals are obtained as $\hat{u}_i = Add_i - \sigma\Big(\hat{\beta}_0 + \hat{\boldsymbol{\beta}}_1' \boldsymbol{Z}_i\Big)$, and are subsequently incorporated into model (1). This yields model (3), which captures the endogenous variation in Add_i that is not explained by $\boldsymbol{Z}_i$:

$$\begin{aligned}\log(\lambda_i \mid Add_i, \boldsymbol{X}_i, \hat{u}_i) = \alpha_0 + \alpha_1 Add_i \\ + \boldsymbol{\alpha}_2' \boldsymbol{X}_i + \alpha_3 \hat{u}_i\end{aligned} \quad (3)$$

If the estimated coefficient α_1 is no longer statistically significant, this suggests that the unobserved risk factors of the insured have been adequately accounted for, and that no residual moral hazard remains in the market.

2.2 Unraveling Underlying Mechanism behind Moral Hazard

In Section 2.1, we provide a brief overview of existing methods for identifying moral hazard. However, these approaches are limited in that they primarily focus on the direct correlation between coverage and claims, without accounting for the underlying causal mechanisms. According to Shavell's definition (Shavell, 1979), "the amount of insurance purchased may reduce the insured's incentive to avoid losses, thereby altering their behavior and potentially increasing the probability of loss." In the context of automobile insurance, this suggests that moral hazard can arise not only from the direct effect of coverage on claims but also from its indirect effects. Specifically, insurance coverage may affect the likelihood of a claim by influencing the insured's driving behavior during the policy period, denoted as Drv_{aft}, with driving behavior acting as a mediator in this causal relationship.

In this section, we propose a novel method to identify moral hazard by accounting for the causal relationship between coverage selection and claims, while also addressing the endogenous nature of the insured's coverage decision.

To examine the impact of insurance coverage on driving behavior, the following linear regression model is specified:

$$\mathbb{E}(Drv_{aft,i} \mid Add_i, \boldsymbol{\Psi}_i) = \gamma_0 + \gamma_1 Add_i + \boldsymbol{\gamma}_2' \boldsymbol{\Psi}_i \tag{4}$$

where $\boldsymbol{\Psi}_i$ represents a vector of control variables, which includes buyer characteristics $\boldsymbol{X}_i$ and $Drv_{bfr,i}$, the policyholder's driving behavior prior to purchasing insurance. The inclusion of pre-purchase driving behavior helps isolate the effect of insurance coverage from the influence of prior behavior, thereby leading to a more accurate and valid analysis. To further examine how the mediator ($Drv_{aft,i}$) influences the dependent variable (Clm_i) while controlling for the treatment variable of insurance coverage (Add_i), the relationship is expressed as follows:

$$\begin{aligned}\log\left(\lambda_i \mid Add_i, Drv_{aft,i}, \boldsymbol{X}_i, \hat{u}_i\right) &= \alpha_0 + \alpha_1 Add_i + \boldsymbol{\alpha}_2' \boldsymbol{X}_i \\ &\quad + \alpha_3 Drv_{aft,i} + \alpha_4 \hat{u}_i \end{aligned}\tag{5}$$

where the residuals $\hat{u}_i$ are computed from Eq. (2) and are included to account for endogeneity bias in coverage selection.

Under the model specification outlined in Eq. (4) and (5), there exists an indirect effect of insurance coverage on claims (denoted as ind), which quantifies the portion of the effect of insurance on claims mediated through changes in driving behavior, conditional on the hypothesis $H_1 : (\gamma_1 \times \alpha_3) > 0$. The direct effect of insurance coverage on claims (denoted as dir) is considered under the hypothesis $H_1 : \alpha_1 > 0$. Moral hazard is identified if the total effect of coverage on claims is statistically significant and greater than zero, which is tested by the hypothesis $H_1 \colon dir + ind > 0$. In other words, it is not only the direct effect of coverage on claims that matters; it is also crucial to consider whether there exists an indirect effect mediated by driving behavior.

The choice of candidate variable to describe the driving behavior of individuals depends on the data source available to researchers. One potential variable to measure the behavioral risk of an insured is the level of harsh driving (hereafter denoted as Hdl). This measure is widely used in road safety literature, such as in studies by Kamla et al. (2019); Li et al. (2022a) and Ziakopoulos (2021, 2024), to account for the risk of accidents. For simplicity, we incorporate this measure exclusively as a representation of driving behavior in the next section of the simulation study to streamline the data generation process.

3 Simulation Study

To assess the effectiveness of the proposed method for detecting moral hazard, it is essential to have access to ground truth data that reveals the true extent of moral hazard. However, obtaining such data is unlikely unless insurance buyers provide accurate disclosures. As an alternative, we rely on simulations, which allow us to control the data generation process (DGP). Through these simulations, we aim to evaluate how the new method performs in uncovering the causal mechanisms behind moral hazard and the endogeneity of decisions, while considering unobserved risk factors of the insured individuals.

3.1 Data Generating Process

Our data generation process is structured into three scenarios, each highlighting a different aspect of the relationship between insurance coverage and claims. In the first scenario (DGP1), insurance coverage has a direct effect on claims, influencing the outcome (Clm) without any intermediaries. The second scenario (DGP2) focuses on an entirely indirect effect, where coverage impacts claims through a mediator, specifically, harsh driving behavior (Hdl). The third scenario (DGP3) combines both effects, with coverage exerting a direct influence on claims and an indirect effect through harsh driving behavior, allowing us to capture a more nuanced relationship between these factors. Among all the data generation process scenarios, endogeneity in coverage selection is present.

3.1.1 DGP1: Direct Effect of Coverage on Claims

In this section, we analyze the baseline scenario characterized by endogeneity and the direct effect of insurance coverage on claims. Specifically, we assume that claims are directly influenced by the selection of insurance coverage, without the involvement of any intermediary factors.

For the selection of variables $\boldsymbol{Z}$, which represent consumers' self-assessed risk profiles influencing their insurance choices (Rothschild and Stiglitz, 1976; Puelz and Snow, 1994), we include the level of harsh driving behavior before purchasing insurance (Hdl_{bfr}) and the driver's ability to respond to sudden emergencies ($Emer$). These factors are frequently highlighted in studies on accident risk (Dilich et al., 2002; Li et al., 2022a,b) and are simulated using a standardized normal distribution, $N(0, 1)$. Additionally, the variable gender ($Gend$) is included. This is simulated as a Bernoulli distribution, $Ber(0.5)$, where $Gend = 0$ represents female and $Gend = 1$ represents male, following the framework proposed by Cohen (2005). For the predictors of the outcome variable, claims (Clm), in addition to $Emer$, we also include driving experience in years ($Exper$), simulated as a continuous uniform distribution $U(0, 34)$ following Cohen (2005), and the harsh driving level after insurance purchase, denoted as Hdl_{aft}. In DGP1, since the mediation effect of driving behavior is not considered, the harsh driving level after insurance purchase is generated based on pre-insurance behavior (Hdl_{bfr}) with an added random error $N(0, 1)$ to account for natural variation.

The decision-making process for insurance coverage (Eq. (2)) is represented by the treatment variable indicating the purchase of additional insurance, which is modeled as $p_i = \sigma(3 + 0.8\, Hdl_{bfr,i} - 1.5\, Gend_i + 0.8\, Emer_i)$. This specification yields an average probability of approximately 0.84, closely matching the observed rate of additional insurance purchases in the Chinese market (CBIT, 2018). To generate the outcome variable representing the number of claims, Clm_i, which follows a Poisson distribution (see Eq. (5)), the conditional mean is specified as $\log(\lambda_i \mid Add_i, Hdl_{aft,i}, \boldsymbol{X}_i, \boldsymbol{\Psi}_i) = 0.004 + \alpha_1 Add_i + 0.3\, Hdl_{aft,i} - 0.2\, Exper_i + Emer_i$, which produces an average claim frequency of approximately one. This is consistent with findings in the insurance literature, where most insureds experience between zero and two claims (Dionne et al., 2001; Cohen, 2005; Dionne and Liu, 2021).

The coverage–claim coefficient α_1 is evaluated at two levels, $\alpha_1 = 0.5$ and $\alpha_1 = 0$. These values correspond to different degrees of moral hazard. When $\alpha_1 = 0.5$, insurance coverage has a direct effect on claims, indicating the presence of moral hazard. When $\alpha_1 = 0$, neither a direct nor an indirect effect of coverage on claims exists, implying the absence of moral hazard.

Although no industry-specific studies exactly match our simulation setting, the parameter values are guided by the empirical and methodological literature on endogeneity between treatment and outcome variables and by standard practices in simulation design. In particular, moderate effect sizes and correlation levels around 0.5 are commonly employed in simulation studies to reflect realistic yet non-trivial endogeneity. Such parameter values create a meaningful dependence between treatment assignment and unobserved factors influencing the outcome, allowing the model to be sufficiently challenged while maintaining parameter identifiability (Dionne et al., 2001; Gao et al., 2009; Gan et al., 2015; Yang et al., 2025).

For each scenario, 500 iterations are conducted, with each iteration involving 1,000 simulated observations. In this process, the variable $Emer$, representing the driver's ability to respond to emergencies, is assumed to be unobservable. The analysis evaluates the performance of identifying moral hazard while accounting for the endogeneity caused by the omitted variable $Emer$. Two approaches are compared: the existing method (Eq. (5)), which considers only the correlation between insurance coverage and claims (α_1), where moral hazard is deemed present if $\alpha_1 > 0$; and the proposed method, which incorporates the underlying causal mechanisms associated with moral hazard (Eq. (4) and (5)). The proposed method decomposes the effect of coverage on claims into a direct effect (α_1) and an indirect effect ($\gamma_1 \times \alpha_3$). Moral hazard is verified as present if the total effect of coverage is greater than zero.

3.1.2 DGP2: Indirect Effect of Coverage on Claims through a Mediator

DGP2 differs from DGP1 primarily in that the manifestation of moral hazard, arising from the impact of insurance coverage on claim frequency, is fully mediated through driving behavior. This behavior is represented by variables such as the harsh driving level (Hdl), which serves as the intermediary linking coverage to claim outcomes. In this context, the harsh driving level is positively influenced by insurance coverage; individuals who purchase more coverage tend to drive with less caution, resulting in an increase in the harsh driving measure. Consequently, an insured individual's driving behavior after purchasing insurance is assumed to depend on their pre-insurance driving performance, the selected coverage type, and a random error term that accounts for natural variation. This relationship can be expressed as: $Hdl_{aft,i} = -1 + Hdl_{bfr,i} + 1.5\, Add_i + e_i, e_i \sim N(0, 1)$, where the coverage selection variable (Add) is modeled in the same way as in DGP1. Furthermore, since there is no direct effect of coverage on claims in this scenario, the coverage–claim coefficient (α_1 in DGP1) is set to zero in the simulation of the count of claims (Clm). As a result, the parameterization for the count of claims is given by $\log(\lambda_i \mid Add_i, Hdl_{aft,i}, \boldsymbol{X}_i, \boldsymbol{\Psi}_i) = 0.004 + 0 \cdot Add_i + 0.3\, Hdl_{aft,i} - 0.2\, Exper_i + Emer_i$, with an average claim frequency of about 1. Finally, the scenario representing the absence of moral hazard is simulated in the same way as DGP1, where neither direct nor indirect effects of coverage on claims are present in the market. For each iteration of the simulation, the variable *Emer* continues to be omitted. The performance of both the current model and the proposed model, as discussed in Section 2, is then assessed to evaluate the identification of moral hazard.

3.1.3 DGP3: Direct + Indirect Effect of Coverage on Claims

In DGP3, we introduce the scenario of moral hazard, where coverage exerts both a direct influence on claims and an indirect effect through driving behavior. This allows us to capture a more nuanced relationship between these factors. Post-insurance driving behavior remains the same as in DGP1, consisting of pre-insurance driving behavior and coverage type, and is adjusted to $Hdl_{aft,i} = -1 + Hdl_{bfr,i} + 0.7\, Add_i + e_i, e_i \sim N(0,1)$. This adjustment is incorporated into the outcome equation for claims, where the direct effect of coverage is considered, leading to the parametrization $\log(\lambda_i \mid Add_i, Hdl_{aft,i}, \boldsymbol{X}_i, \boldsymbol{\Psi}_i) = -0.5 + 0.5\, Add_i + 0.3\, Hdl_{aft,i} - 0.2\, Exper_i + Emer_i$, which maintains an average number of claims around 1. A total of 500 iterations of simulation is conducted to find a more accurate method, which demonstrates a greater power in identifying the presence of moral hazard in the market.

3.2 Simulation Results

To evaluate the performance of detecting moral hazard in a scenario where only the direct effect of coverage on claims exists (DGP1), we analyze the current method by assessing whether the estimate of α_1 in Eq. (5) is statistically greater than zero. Specifically, we test the alternative hypothesis $H_1 : \alpha_1 > 0$, considering the test's power $1 - \beta$, where $\beta = P(\text{Not reject } H_0 : \alpha_1 = 0 \mid H_1 : \alpha_1 > 0)$, while controlling for the Type I error rate α, defined as $\alpha = P(\text{Reject } H_0 : \alpha_1 = 0 \mid H_0 : \alpha_1 = 0)$. For the proposed model, we assess whether the total effect of coverage on claims exceeds zero by testing the hypothesis $H_1 : dir + ind > 0$. Similarly, we evaluate the power of the test, $1 - \beta$, where $\beta = P(\text{Not reject } H_0 : dir + ind = 0 \mid H_1 : dir + ind > 0)$, while controlling for the Type I error α, $\alpha = P(\text{Reject } H_0 : dir + ind = 0 \mid H_0 : dir + ind = 0)$. The results, shown in DGP1 in Figure 1, demonstrate that as the Type I error rate varies from 0 to 1, both methods exhibit similar power to detect moral hazard. This finding is reasonable, as there is no mediation effect of driving behavior in the relationship between coverage and claims.

We now extend our analysis to scenarios where the relationship between coverage and claims operates through distinct pathways. Specifically, in one scenario (DGP2), there is no direct influence of coverage on claims; instead, coverage affects claims indirectly by increasing harsh driving levels. In another scenario (DGP3), both the direct effect of coverage on claims and the indirect effect through harsh driving are present. The performance of the existing

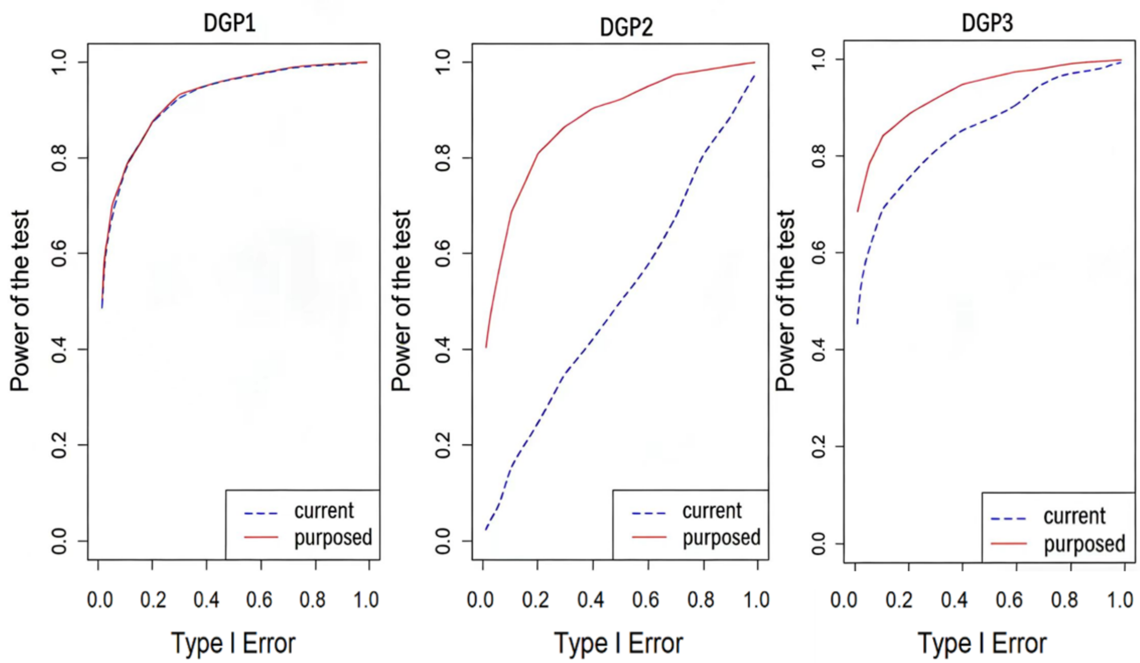

Figure 1 Evaluation of the Power to Detect Moral Hazard in the Current and Proposed Methods

and proposed models in detecting moral hazard is compared for both DGP2 and DGP3, as shown in Figure 1. The results reveal that, when controlling for the Type I error rate, the proposed model demonstrates superior power in identifying moral hazard within the insurance market.

3.3 Summary

We conducted a simulation study to develop a more reliable method for identifying moral hazard in insurance markets. The study considered various underlying mechanisms contributing to moral hazard, as well as the presence of endogeneity bias.

In the baseline scenario (DGP1), where only the direct effect of insurance coverage on claims exists, both the existing method and the proposed model demonstrated similar power in detecting moral hazard when controlling for the Type I error rate. This result is expected, as there is no mediation effect in this scenario. However, the innovation of the proposed model becomes evident in more complex settings, especially in scenarios involving indirect effects.

In DGP2, where coverage influences claims indirectly by increasing harsh driving behavior, and in DGP3, where both direct and indirect effects are present, the proposed model consistently outperformed the existing method. Notably, the performance gap between the two methods was especially pronounced in DGP2. As the share of the indirect effect in the total effect increases, the proposed model's ability to identify moral hazard improves substantially.

The primary innovation of the proposed model lies in its ability to decompose the effect of coverage into direct and indirect components, effectively capturing the causal mechanisms linking coverage, driving behavior, and claims. By explicitly accounting for these pathways, the proposed model provides a more nuanced and comprehensive understanding of moral hazard. This advantage highlights the model's robustness and its capability to uncover complex causal relationships within the insurance market, making it a valuable tool for more accurate detection and analysis of moral hazard.

4 Empirical Analysis

Our simulation study indicates that the proposed model, which accounts for the causal pathways through changes in driving behavior in ex-ante moral hazard detection, demonstrates superior performance compared with the existing approach that considers only the direct effect between coverage and claims. In this section, we conduct an empirical test of moral hazard in China's automobile insurance market.

4.1 Data Description

Our study utilizes data provided by a Chinese InsurTech start-up, which includes information on new policyholders who purchased domestic auto insurance in 2017. The dataset is divided into two components: personal policy information and driving behavior data. The policy data contains the effective date (January to December 2017), anonymized vehicle identification numbers and models, driver age, car value, selected coverage, and the number of claims recorded over a one-year insurance period.

Driving behavior data is accessed through the insurer's cooperation with other third parties using built-in On-Board Diagnostics (OBD) system, an automatic vehicle diagnostic monitoring system that is pre-installed in vehicles during manufacturing (Ho et al., 2020). This approach enables the recording of policyholders' driving behavior second-by-second for each trip since the vehicle's manufacture, both before and after their insurance purchase. Distinguishing between these two periods of driving data is essential for differentiating adverse selection effects from moral hazard. Pre-insurance driving data offers valuable insights into the endogenous self-selection process of insured individuals in their coverage decisions, where individuals hold private information about their driving risk prior to entering into an insurance contract. In contrast, post-insurance driving data enables the identification of behavioral changes in policyholders' driving patterns after acquiring insurance coverage (Dionne et al., 2013; Sharma and Goradia, 2023). It is noteworthy that the driving behavior data has been used exclusively for academic research and has not been incorporated into commercial insurance practices, as telematics-based insurance has not yet been implemented by the company. Therefore, it is reasonable to assume that there is no premium incentive effect in these data (Ma et al., 2018).

The OBD devices record trip-level variables, including mileage (km), travel date, travel time (h), speed (km/h), idle time (10ms), fuel consumption (L), the number of acceleration and braking events, coasting-neutral mileage (km), and the number of low-pressure events for each wheel (right rear, left rear, right front, and left front). Based on these trip-level data, we derive additional indicators, such as whether each trip occurred on a weekday or weekend. The dataset is subsequently preprocessed to remove noise, including duplicate entries and records with zero fuel consumption or zero speed. Following data cleaning, we aggregate the records into annual, policy-level metrics. Using the total number of trips, total mileage, and total driving time, we compute key performance indicators, including average speed (km/h), fuel consumption (L/10 km), average number of acceleration and braking events per kilometer, proportion of coasting-neutral mileage, average idle time (10ms/km), average number of low-pressure events per wheel (by wheel location), and the percentage of weekend driving. The final dataset consists of 981 vehicle policies.

4.2 Variable Definitions

In China's auto insurance market, liability insurance covering damage caused to other vehicles or drivers is mandatory by law. Another common optional coverage is business collision insurance, which covers the policyholder's own damages if they are deemed responsible for the incident, and is considered additional coverage. Therefore, the coverage selection variable, Add, can be defined as a dummy variable following the procedure outlined by Chiappori and Salanié (2000): it equals 0 if only compulsory insurance is purchased, and 1 if additional insurance is also purchased.

The *Clm* variable is a count variable representing the number of claims made by the insured during the insurance period. The *age* variable is categorized into three groups: *age1* (30 years or younger), considered the reference level; *age2* (between 31 and 40 years); and *age3* (older than 40 years). The value of the car, represented by *carprc*, is measured in units of ten thousand RMB. The *carmodel* variable is categorized into four types, from *model1* to *model4*, with model 1 serving as the reference level for data analysis.

Several driving behavior variables are included: $fuel$, representing fuel consumption in 10 km; *spd*, the average speed (km/h); *acc*, the average number of accelerations per km; *brk*, the average number of braking events per km; *idle*, the idle time (10 ms/km); *cst*, the fraction of coasting neutral mileage; *wkend*, the percentage of driving on weekends; *rrtl*, the average number of low-pressure events of the right rear wheel per km; *rltl*, the average number of low-pressure events of the left rear wheel per km; $frtl$, the average number of low-pressure events of the right front wheel per km; and $fltl$, the average number of low-pressure events of the left front wheel per km. A summary of the descriptive statistics for the main variables is provided in Table1 1.

To mitigate multicollinearity among the driving variables in the regression analysis (see Figure 2 in Appendix A), we perform a factor analysis (FA) to reduce the number of variables and identify latent factors that account for the correlations among them. FA summarizes correlated indicators into a smaller set of uncorrelated composite factors through orthogonal rotation, reducing dimensionality and information loss (Hair et al., 2014). This approach follows standard practice in economics (Bai and Ng, 2002; Stock and Watson, 2002) and behavioral research (e.g., investment, marketing, accident prevention), where latent dimensions are identified for theoretical interpretation (Chen et al., 2016; Bernstein and Calamia, 2019; Cao et al., 2021; Sharma, 2021).

Table 1 Descriptive Statistics of the Main Variables

Variable	Min	Mean	Max	Std.Dev
Main variables				
Clm	0	0.23	5	0.57
Add	0	0.87	1	0.33
carprc	10.68	14.95	19.98	2.51
Pre-insurance driving behavior				
fuel	0.002	0.88	1.99	0.69
spd	0.47	46.74	195	34.46
brk	0	7.20	27.5	3.78
acc	0	5.89	42	5.49
idle	85.85	14959.12	164558	18382.16
cst	0	0.01	0.5	0.06
wkend	0	0.26	1	0.32
rrtl	0	0	0.21	0.01
rltl	0	0	0.19	0.01
frtl	0	0	0.11	0.00
fltl	0	0	0.14	0.01
Post-insurance driving behavior				
fuel	0.01	0.62	4.98	0.49
spd	0.74	17.61	69.45	10.06
brk	0.11	4.33	14.35	2.21
acc	0.02	0.99	5.36	0.68
idle	73.04	2815.55	18416.91	1832.61
cst	0	0	0.07	0.003
wkend	0	0.29	0.8	0.07
rrtl	0	0	0.2	0.01
rltl	0	0	0.17	0.01
frtl	0	0	0.02	0.00
fltl	0	0	0.03	0.00

The Kaiser–Meyer–Olkin (KMO) value for the pre-insurance period is 0.79, exceeding the recommended threshold of 0.6 and confirming the suitability of the data for factor analysis. This result is further supported by Bartlett's test of sphericity ($\chi^2 = 9520$, $p < 0.001$). Based on the proportion of variance explained by the factors, three factors are extracted, with a cumulative variance proportion of 0.62, and their corresponding standardized loadings are presented in Table 2.

Table 2 Descriptive Statistics of the Main Variables

Variable	*fa_tire_bfr*	*fa_spd_bfr*	*fa_manual_bfr*
fuel	-0.04	0.89	0.24
spd	-0.00	0.86	-0.03
cst	0.00	-0.03	0.28
rrtl	0.99	-0.02	-0.04
frtl	0.99	-0.00	-0.03
fltl	0.94	-0.01	-0.03
rltl	0.97	-0.02	-0.05
wkend	0.01	0.01	-0.05
idle	-0.01	0.12	0.58
acc	-0.01	0.18	0.81
brk	0.00	0.11	0.58

The first factor, fa_tire_bfr, is positively associated with low tire pressure across tires, reflecting overall tire maintenance and condition. The second factor, fa_spd_bfr, shows a positive relationship between fuel consumption and vehicle speed, indicating frequent vehicle use, long-distance travel, or possibly aggressive driving (Peterson et al., 2021). A higher score on this factor suggests a tendency to drive at higher speeds, leading to greater fuel consumption. The third factor, fa_manual_bfr, captures the frequency of manual operations such as acceleration, braking, and idling. This factor likely reflects driving in stop-and-go traffic or aggressive driving patterns (Osafune et al., 2017; Li et al., 2018; Mase et al., 2020). A higher score indicates frequent acceleration and braking with

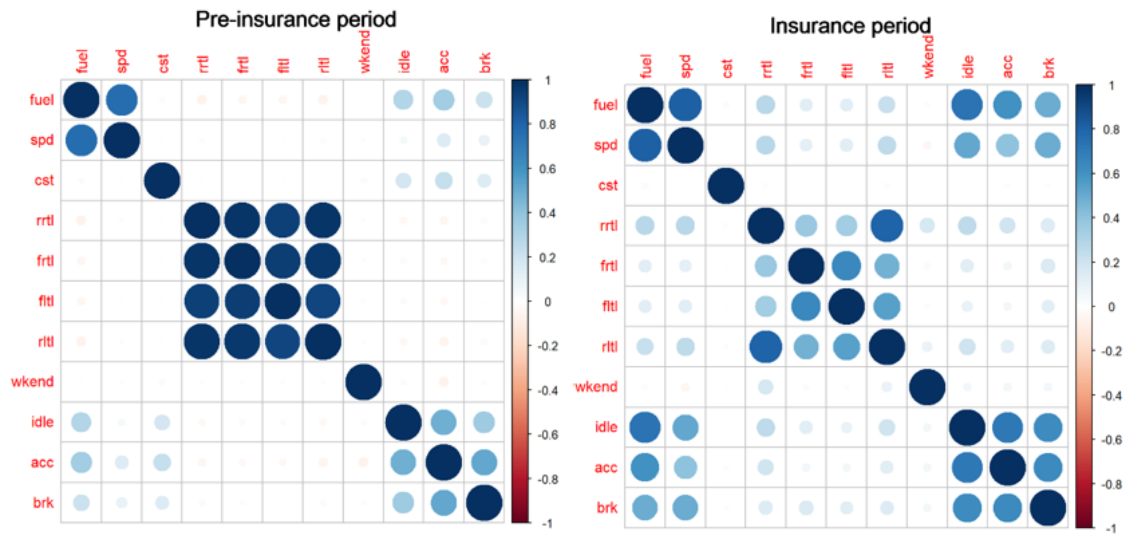

Figure 2 Correlation between the Driving Variables

longer idling times, behaviors often linked to erratic or aggressive driving that increase accident risk and vehicle wear.

For the post-insurance period, we derive the factors fa_tire_aft, fa_spd_aft, and fa_manual_aft based on the corresponding loadings from the pre-insurance period (see Table 2). This makes the interpretability of these driving factors remains logically consistent, while also guaranteeing that the latent constructs of driving behavior are measured in a comparable manner across both time periods.

4.3 Step 1: Examine the Coverage Decision Effect on driving behavior

In this study, we propose that the investigation of moral hazard should focus on uncovering the underlying mechanisms that drive it. Specifically, we aim to uncover the causal mechanism of moral hazard by examining how insurance coverage affects claim outcomes, both directly and indirectly through post-insurance driving behavior. The empirical framework proceeds in two steps.

The first step in this analysis involves assessing the impact of insurance coverage on post-policy driving behavior, as specified in Eq. (4). In particular, we test whether the selection of coverage levels affects drivers' driving patterns after purchasing insurance.

In Eq. (4), the term DRV_{aft}, which represents post-insurance driving behavior, is operationalized in our empirical analysis through three factors: tire condition (fa_tire_aft), speed and fuel efficiency (fa_spd_aft), and frequency of manual operations (fa_manual_aft). For each of these driving behavior measures, we estimate the effect of insurance coverage, captured by the significance of coefficient γ_1 in Eq. (4). Since there are three driving behavior measures, we estimate three separate models, denoted as Model 1, Model 2, and Model 3, and the corresponding results are presented in the first, second, and third columns of Table 3, respectively. The model also includes a set of control variables, $\boldsymbol{X}_i$, representing buyer characteristics such as driver's age (*age*), car model type (*model*), car price (*carprc*), and pre-insurance driving behaviors (*fa_tire_bfr*, *fa_spd_bfr*, and *fa_manual_bfr*).

Table 3 Main Results for the Impact of Coverage Decision on Driving Behavior Factors

Variable	*fa_tire_aft* **Model 1**	*fa_spd_aft* **Model 2**	*fa_manual_aft* **Model 3**
Add (γ_1)	-0.72**	-0.31*	-0.16
	(0.31)	(0.18)	(0.18)
model2	0.44	0.16	-0.24
	(1.18)	(0.71)	(0.70)
model3	1.65	-0.34	-1.03
	(1.28)	(0.76)	(0.76)
model4	0.11	0.12	-0.42
	(1.21)	(0.72)	(0.72)
carprc	-0.04	-0.20***	-0.16***
	(0.06)	(0.04)	(0.04)
age2	-0.26	-0.06	0.15
	(0.31)	(0.18)	(0.18)
age3	-0.39	-0.12	-0.08
	(0.33)	(0.19)	(0.19)
fa_tire_bfr	0.02		
	(0.03)		
fa_spd_bfr		0.05	
		(0.03)	
fa_manual_bfr			0.08**
			(0.03)
LR Statistic	20.70	73.26	62.28
N	981	981	981

Standard errors are reported in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

4.4 Step 2: Assess the Impact of Driving Behavior on Claim Outcomes

The second step in analyzing the causal mechanism between coverage and claims involves assessing the effect of post-insurance driving behavior on claim outcomes, as specified in Eq. (5). In this model, post-insurance driving behavior (DRV_{aft}) is represented by three factors: tire condition (*fa_tire_aft*), speed and fuel efficiency (*fa_spd_aft*), and frequency of manual operations (*fa_manual_aft*). For each factor, we estimate its effect on claims (Clm) through the coefficient α_3 in Eq. (5). The product of α_3 and γ_1 (from Eq. (4)) captures the indirect effect of coverage on claims, indicating whether insurance coverage influences claims through driving behavior. The significance of α_1 in Eq. (5) further reveals any direct effect of coverage on claims, after controlling for driving behavior and individual characteristics.

Since three behavioral factors are considered, we estimate three separate models (Models 4–6), with results presented in the first, second, and third columns of Table 4, respectively. Each model also includes control variables $\boldsymbol{X}_i$, representing driver characteristics such as age (*age*), car model (*model*), and car price (*carprc*). To address potential endogeneity in coverage decisions, we use the residuals ($\hat{u}_i$) from the regression specified in Eq. (2), with results reported in Table 5. This model estimates the determinants of coverage decisions using pre-insurance driving behavior factors (*fa_tire_bfr*, *fa_spd_bfr*, and *fa_manual_bfr*). The residuals from this model are incorporated into Eq. (5) as control variables to correct for endogeneity bias.

Table 4 Main Results for the Coverage Decision Effect on the Claim Outcome (Clm)

Variable	**Model 4**	**Model 5**	**Model 6**
Add (α_1)	0.19	0.20	0.19
	(0.57)	(0.56)	(0.57)
fa_tire_aft (α_3)	-0.01		
	(0.02)		
fa_spd_aft (α_3)		-0.04	
		(0.04)	
fa_manual_aft (α_3)			0.05
			(0.03)
model2	-1.50***	-1.50***	-1.49***
	(0.43)	(0.43)	(0.43)
model3	-0.94*	-0.98*	-0.89*
	(0.51)	(0.51)	(0.51)
model4	-1.09**	-1.09**	-1.07**
	(0.46)	(0.46)	(0.45)
carprc	0.00	-0.01	0.01
	(0.04)	(0.04)	(0.04)
*age*2	-0.06	-0.06	-0.07
	(0.20)	(0.20)	(0.20)
*age*3	-0.09	-0.09	-0.08
	(0.21)	(0.21)	(0.21)
$\hat{u}$	0.06	0.06	0.06
	(0.06)	(0.06)	(0.06)
LR Statistic	24.18	25.14	26.13
N	981	981	981

Standard errors are reported in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

From Model 4 in Table 4, no significant effect of the driving behavior factor *fa_tire_aft* on the number of claims is observed (Model 4, coefficient $\hat{\alpha_3} = -0.01$, $p > 0.1$). To evaluate the mediation effect of *fa_tire_aft*, specifically whether the effect of coverage on claims operates through the mediator *fa_tire_aft*, the significance of the indirect effect ($\gamma_1 \times \alpha_3$) is assessed using the bootstrap procedure. This method involves resampling the dataset across multiple iterations to generate a range of estimated values for the indirect effect ($\hat{\gamma_1} \times \hat{\alpha_3}$).

Table 5 Empirical Results for Coverage Selection (Add)

Variable	**Estimate**
fa_tire_bfr	-0.14
	(0.10)
fa_spd_bfr	0.19**
	(0.08)
fa_manual_bfr	0.16*
	(0.08)
model2	1.37
	(0.89)
model3	1.26
	(0.98)
model4	0.36
	(0.93)
carprc	0.05
	(0.06)
*age*2	0.16
	(0.30)
*age*3	0.51
	(0.33)
LR Statistic	41.37
N	981

Standard errors are reported in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

This approach does not rely on the distributional assumptions of $\gamma_1 \times \alpha_3$, and yields a mean estimated value of 0.02 for the indirect effect with a 95% confidence interval of $[-0.03; 0.14]$. As the confidence interval includes zero, there is no evidence of a mediation effect of tire-related driving behavior in the causal relationship between coverage and claims. Regarding the direct effect of coverage on claims, Model 4 also shows no significant result (Model 4, coefficient $\hat{\alpha_1} = 0.19$, $p > 0.1$). To ensure robust and reliable significance testing, the bootstrap procedure is applied, yielding a mean estimate of 0.13

with a 95% confidence interval of $[-1.23; 1.52]$. As the interval includes zero, there is no direct effect of coverage on claims. Finally, for the total effect ($\gamma_1 \times \alpha_3 + \alpha_1$), the bootstrap procedure provides a mean estimate of 0.15 with a confidence interval of $[-1.23; 1.51]$. Since the confidence interval also includes zero, we conclude that there is no overall effect of coverage on claims.

The same procedure was applied to verify the mediation effects of the driving behavior factors *fa_spd_aft* and *fa_manual_aft* in Models 5 and 6 (Table 4). For *fa_spd_aft*, the estimated coefficient $\hat{\alpha_3}$ is not significant (Model 5, coefficient $\hat{\alpha_3} = -0.04$, $p > 0.1$). The indirect effect of coverage on claims through the mediator *fa_spd_aft* ($\gamma_1 \times \alpha_3$) was estimated using the bootstrap method, resulting in a mean value close to zero (0.06) with a 95% confidence interval of $[-0.03; 0.18]$. This finding indicates the absence of an indirect effect of coverage on claims through *fa_spd_aft*. Similarly, the direct effect of coverage was not significant (Model 5, coefficient $\hat{\alpha_1} = 0.2$, $p > 0.1$), with a bootstrap-estimated mean of 0.13 and a confidence interval of $[-1.12; 1.47]$. To ensure robustness, the total effect of coverage on claims was also calculated, yielding no statistical significance (estimated mean: 0.19, CI: $[-1.07; 1.54]$).

For the mediator *fa_manual_aft*, which may be influenced by factors such as road congestion and aggressive driving behavior, the effect on the number of claims was not statistically significant (Model 6, coefficient $\hat{\alpha_3} = 0.05$, $p > 0.1$). When estimating the indirect effect ($\gamma_1 \times \alpha_3$) using the bootstrap procedure, the result was also non-significant, with a 95% confidence interval of $[-0.04, 0.02]$. Likewise, the direct effect of coverage on claims (Model 6, coefficient $\hat{\alpha_1} = 0.19$, $p > 0.1$) was insignificant, with a confidence interval of $[-1.14, 1.51]$. For robustness, the total effect was also examined and found to be non-significant, as its 95% confidence interval $[-1.14, 1.49]$ included zero.

The findings above collectively indicate no significant effect of coverage decisions on claims, either directly or through the driving behavior mediators *fa_tire_aft*, *fa_spd_aft*, and *fa_manual_aft*. Consequently, we find no evidence of moral hazard in the Chinese auto insurance market.

4.5 Robustness Check

To ensure the robustness of our empirical findings on ex-ante moral hazard, we conducted a series of supplementary analyses. First, Section 4.5.1 replaces the original continuous measure of claim frequency with a binary variable indicating whether a claim was made ($Clmornot$) to verify the consistency of the coverage–claim relationship under an alternative response specification. Second, Section 4.5.2 performs a heterogeneity analysis by separating drivers into high- and low-risk groups, allowing for a more detailed examination of moral hazard across different risk segments. Finally, Section 4.5.3 tests the robustness of the identified behavioral channel by employing the method of correlation coefficient to select driving behavior indicators, rather than relying solely on factor analysis. Collectively, these robustness checks confirm that the main conclusions remain stable across different model specifications, variable definitions, and analytical methods.

4.5.1 Alternative Response Variable: Binary Claim Indicator

Ex-ante moral hazard refers to a reduction in preventive effort before an accident, induced by insurance coverage. In this context, insured drivers may drive less cautiously, increasing accident risk. Both claim frequency and a binary indicator of whether a claim occurs capture this mechanism, as they reflect accident incidence arising from changes in preventive behavior (Zavadil et al., 2007; Wang et al., 2008). In the main analysis, the number of claims serves as the outcome variable, whereas this robustness check re-estimates the model using a binary claim indicator (*Clmornot*), coded as 1 if a claim was made during the insurance period and 0 otherwise.

Specifically, through three post-policy driving behavior factors (*fa_tire_aft*, *fa_spd_aft*, and *fa_manual_aft*), we examine the indirect effect of coverage (*Add*) on claim occurrence via driving behavior ($\gamma_1 \times \alpha_3$), along with the direct (α_1) and total effects ($\gamma_1 \times \alpha_3 + \alpha_1$). All effects are estimated using a nonparametric bootstrap procedure. The results (Table A1, Appendix A) show that neither the indirect, direct, nor total effects are statistically significant, as the 95% percentile bootstrap confidence intervals include zero. These findings confirm that the results are robust to alternative outcome specifications and reinforce the absence of ex-ante moral hazard in the market.

4.5.2 Heterogeneity Analysis: High- and Low-Risk Driver Groups

We further examine heterogeneity in China's automobile insurance market by analyzing drivers' pre-policy behavior, a perspective rarely explored due to limited access to such data. These behavioral indicators capture otherwise unobservable factors closely related to accident risk, including cautiousness, responsiveness to road events, and overall driving skills (Tao et al., 2017; Luo et al., 2023).

Driving risk can be defined via individual measures (e.g., speed, braking) or composite indices of broader behavior patterns (Lee et al., 2025; Ziakopoulos, 2021; Wan-Lin et al., 2025). Following the latter approach, we extract two latent pre-policy driving behavior factors, *fa_spd_bfr* and *fa_manual_bfr* (Table A2 in Appendix A), both positively and significantly associated with claim occurrence (*Clmornot* = 1 if a claim occurs). A synthetic risk indicator, *drv_rsk*, is constructed by weighting the two factors according to their explained variances, 0.23 and 0.22. Letting $w_1 + w_2 = 1$, the weights are defined as $w_1 = 0.23/(0.23 + 0.22)$ and $w_2 = 0.22/(0.22 + 0.23)$. Accordingly, the indicator is given by $drv\_rsk = w_1 \times fa\_spd\_bfr + w_2 \times fa\_manual\_bfr$.

Policyholders are classified into high- and low-risk groups based on the median *drv_rsk*, where *Group*=1 represents high-risk and *Group*=0 represents low-risk. High-risk drivers exhibit a significantly higher accident probability than low-risk drivers (0.21 vs. 0.15), consistent with rates reported in Ayuso et al. (2014) and Dionne and Liu (2021). Regression analysis (Table A3) further validates this classification, with the risk group positively associated with claim occurrence (coefficient = 0.45, $p < 0.05$).

Following Sections 4.3 and 4.4, we estimate the indirect effect of insurance coverage (Add) on claims (Clm) via post-policy driving behavior factors (*fa_tire_aft*, *fa_spd_aft*, *fa_manual_aft*), expressed as $\gamma_1 \times \alpha_3$, along with the direct effect (α_1) and total effect ($\gamma_1 \times \alpha_3 + \alpha_1$) within each risk group. Statistical inference uses a nonparametric bootstrap procedure.

Results show that for high-risk drivers, neither the indirect, direct, nor total effects are statistically significant, indicating they do not reduce driving caution or increase claim frequency after purchasing additional coverage (Table A4). The same holds for low-risk drivers (Table A5). These findings confirm that the absence of ex-ante moral hazard is robust across risk segments.

4.5.3 Alternative Behavioral Measure Selection

To test the robustness of the findings to the selection of driving behavior variables, we employed a correlation-based approach to mitigate multicollinearity by examining pairwise relationships among variables. This method enhances the interpretability of the regression results and clarifies their economic implications. As shown in the correlation matrix of driving behavior variables (Figure 2), several indicators are highly correlated, for example, average speed (*spd*) and fuel consumption (*fuel*) exhibit strong association, as do measures of low tire pressure across the four wheels. Similarly, idle time (*idle*), acceleration events (*acc*), and braking events (*brk*) are significantly correlated. These patterns are consistent with the factor analysis results reported in Table 2.

In the correlation coefficient analysis, higher correlation thresholds retain more variables by excluding fewer due to interdependence. With multicollinearity thresholds of 0.8 and 0.9, the retained variables include fuel consumption per 10 km (*fuel*), average speed (*spd*), fraction of coasting-neutral mileage (*cst*), average number of low-pressure events in the right front wheel per km (*frtl*), percentage of weekend driving (*wkend*), idle time per 10 ms/km (*idle*), number of accelerations (*acc*), and number of braking events (*brk*), reducing the dimensionality to eight key variables.

To assess the robustness of the moral hazard findings derived from the factor analysis in the main analysis, we re-estimated the indirect, direct, and total effects of insurance coverage (Add) on claims (Clm) using the variables selected via the correlation coefficient method. Specifically, for each post-policy driving behavior variable (*fuel_aft*, *spd_aft*, *cst_aft*, *frtl_aft*, *wkend_aft*, *acc_aft*, *idle_aft*, and *brk_aft*), we estimated the indirect effect of coverage on claims through driving behavior, expressed as $\gamma_1 \times \alpha_3$. We also estimated the direct effect (α_1) and the total effect ($\gamma_1 \times \alpha_3 + \alpha_1$), with all effects obtained using a nonparametric bootstrap procedure (Table A6). The results indicate that neither the indirect effects via driving behavior nor the direct and total effects of coverage on claims are statistically significant, as the 95% percentile bootstrap confidence intervals include zero. These findings confirm that the results are robust to alternative behavioral variable selection methods and further reinforce the absence of ex-ante moral hazard in the market.

4.6 Discussion

In our analysis, we find that individuals who purchase more extensive coverage exhibit safer driving behavior after the policy purchase (e.g., lower speeds and fewer tire pressure incidents; see Section 4.3). To further examine this relationship, we conducted a linear regression analysis comparing drivers' pre- and post-policy driving risks between those with additional coverage and those with only compulsory coverage. This model includes an interaction term between coverage and time ($time \times Add$), where $time = 0$ denotes the pre-insurance period and $time = 1$ denotes the post-insurance period, allowing us to assess whether coverage choice is associated with changes in driving behavior over time.

For the driving behavior factor *fa_tire*, which is positively associated with low tire pressure, the empirical results in column (1) of Table A7 in Appendix B show that before purchasing insurance, drivers who later opted for higher coverage had better tire conditions, as indicated by a significant negative coefficient of -3.02 ($p < 0.01$). However, the interaction term ($time \times Add$) is statistically insignificant, suggesting that the coverage amount did not significantly affect the change in tire condition over time.

In contrast, for the driving behavior factor *fa_spd*, which is positively associated with driving speed, the results in column (2) of Table A7) indicate that drivers who purchased additional coverage exhibited higher driving risk before insurance than those who did not, as shown by a significant coefficient of 1.90 ($p < 0.01$). This pattern reflects a self-selection effect, whereby riskier drivers tend to purchase more extensive coverage as a form of risk-averse protection. The interaction term between time and coverage is negative and significant (-1.00, $p < 0.01$), indicating a larger reduction in driving risk after policy purchase among drivers with higher coverage levels. This finding suggests behavioral adaptation following insurance acquisition, rather than evidence of moral hazard.

This finding can be explained by several institutional and technological factors specific to the Chinese automobile insurance market. First, the self-selection effect plays an important role: riskier drivers tend to purchase more extensive coverage as a form of risk-averse protection. Second, the rapid development of IoT-based monitoring technologies in China's automotive market has significantly altered traditional risk dynamics. According to the International Trade Administration (2021), the market for Intelligent and Connected Vehicles (ICVs) in China is expanding rapidly and is projected to reach a value of USD 2 trillion by 2040. IoT monitoring devices collect real-time data on driving behavior and conditions, enabling intelligent driving assistance and continuous feedback (Ho et al., 2020). These technologies increase drivers' self-awareness and allow them to make more informed coverage choices based on their individual risk profiles (Soleymanian et al., 2024).

Beyond self-selection, we observe behavioral adaptation driven by experience-based learning: drivers adjust their behavior over time in response to feedback and the outcomes of their past driving experiences. In particular, drivers who initially exhibit higher-risk driving but purchase additional coverage tend to improve their driving performance after obtaining insurance, suggesting that insurance can provide incentives for safer behavior.

The introduction of China's bonus–malus system (BMC) in 2022 has further strengthened these incentives. The BMC incorporates premium adjustments based on claim history and traffic violations, with a coefficient ranging from 0.5 to 2 (Dionne and Liu, 2021). By directly linking future premiums to past driving performance, this system discourages excessive claims and mitigates potential moral hazard (Ludkovski and Young, 2010). Drivers with higher initial risk, those who typically purchase more coverage are thus motivated to improve their driving behavior to avoid future premium increases.

Finally, IoT-based feedback mechanisms reinforce this process by providing real-time alerts during risky maneuvers and assisting in safer driving practices. Such feedback enhances drivers' experience-based learning and contributes to a sustained reduction in driving risk (Chen and Jiang, 2019; Choudhary et al., 2022; Holzapfel et al., 2024; Lee et al., 2025).

Taken together, these factors suggest that the absence of a moral hazard effect in our findings may stem from a combination of self-selection, regulatory incentives (the BMC reform), and IoT-enabled behavioral monitoring and learning, all of which jointly promote safer driving behavior after insurance purchase.

5 Conclusion and Future Study

In this paper, we propose a novel methodology for identifying ex-ante moral hazard by examining its underlying behavioral mechanisms, thereby addressing a key gap in the existing literature, which has largely focused on directly estimating the correlation between insurance coverage and claim frequency. Our approach provides insurers with deeper insights into the behavioral sources of information asymmetry, enabling the design of more effective risk management and pricing strategies. Thus, our study contributes to both the theoretical and practical understanding of ex-ante moral hazard in the automobile insurance market.

Ex-ante moral hazard in car insurance arises when insured drivers reduce their driving effort or take greater risks because they anticipate being financially protected by insurance (Dionne et al., 2013; Weisburd, 2015; Rowell et al., 2022). This behavioral adjustment increases the likelihood of a crash and leads to a positive correlation between coverage and claims, that is, individuals with higher coverage are more likely to file claims than those with lower or no coverage (Shavell, 1979). Although numerous studies have examined this correlation using various econometric frameworks, few have explored the causal mechanisms behind it, specifically, whether drivers actually change their driving behavior after obtaining insurance.

To address this limitation, we introduce a causal framework that incorporates the indirect effect of coverage on claims mediated by driving behavior, consistent with the conceptual foundation of ex-ante car crash moral hazard. In this framework, the insured's coverage choice can influence post-insurance driving behavior, making drivers less cautious, which, in turn, raises the probability of a claim. Through extensive simulation analyses, we demonstrate theoretically that omitting this indirect pathway can lead to biased estimates of the coverage–claim relationship and reduced power in detecting moral hazard. In contrast, our proposed method not only enhances the identification of moral hazard but also provides a causal explanation of its behavioral origins.

From a practical perspective, we apply this analytical framework to the Chinese automobile insurance market, utilizing IoT-based driving data collected before and after insurance purchase. Pre-insurance driving data capture individuals' inherent driving behavior and inform the self-selection process in coverage choice, while post-insurance data allow for the assessment of claim risk based on behavior during the policy period. This temporal distinction is crucial for detecting moral hazard, as it separates natural driving habits from behavioral changes induced by insurance coverage.

It is important to emphasize that our IoT data collection differs from conventional Usage-Based Insurance (UBI) systems. Unlike UBI programs in which insurers directly collect telematics data from policyholders, potentially prompting behavior changes due to awareness of monitoring, our data are obtained through third-party sources. These third parties collect vehicle data using factory-installed OBD devices, independent of insurers' pricing models. Consequently, the data reflect drivers' authentic, unmonitored behavior, free from bias caused by observation-induced behavioral adjustments.

Empirically, our results show that coverage influences driving behavior: higher coverage is associated with improved vehicle maintenance and safer driving patterns, such as fewer instances of low tire pressure and reduced speeding. We find no evidence of either a direct effect of coverage on claims or an indirect effect mediated through driving behavior. Given that the total effect of coverage on claims is statistically insignificant, we conclude that there is no observable moral hazard in the Chinese automobile insurance market.

The integration of IoT data with our proposed methodological framework not only enhances the identification of moral hazard but also deepens understanding of its causal structure. By linking insurance coverage, behavioral responses, and claim outcomes within a unified analytical model, our approach allows insurers to identify when and how insured drivers adjust their behavior after obtaining coverage. These insights offer a rigorous basis for developing targeted risk control strategies and adjusting premiums to reflect true individual risk levels, thereby mitigating potential moral hazard. Unlike UBI schemes that may induce temporary behavioral changes due to monitoring awareness (Li et al., 2022a), which can result in mispricing and reduced risk control effectiveness, our framework overcomes this limitation, offering a more accurate behavioral and actuarial assessment of risk.

This study also has several limitations that open avenues for future research. First, the use of claim frequency as a proxy for individual risk may not fully capture underlying risk behavior. A more precise measure could be the number of accidents in which an insured has been involved; however, obtaining reliable accident data is challenging, as incidents may be underreported. Second, incorporating data on past claims prior to insurance purchase could provide a more comprehensive understanding of individual risk profiles (Cohen, 2005), but access to such data requires information sharing across insurers, which poses practical barriers. From a methodological perspective, future research could examine moral hazard over multiple insurance periods, as its impact may evolve over time. As insureds accumulate claims history, premium adjustments may influence subsequent behavior (Wang et al., 2008). Incorporating longitudinal driving behavior data could provide a more robust framework for analyzing temporal changes in behavior, allowing for more precise identification of moral hazard and better accounting for drivers' responses to monitoring over time.

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Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

A Supplementary Analysis

Table A1 Robustness Test of Moral Hazard Findings Using the Binary Claim Indicator (*Clmornot*)

Driving Behavior Factor	Direct Effect	Indirect Effect	Total Effect
fa_tire_aft			
Mean	0.57	0.02	0.59
IC	[-0.82;1.89]	[-0.03;0.15]	[-0.80;1.93]
fa_spd_aft			
Mean	0.51	0.07	0.58
IC	[-0.72;1.82]	[-0.02;0.02]	[-0.67;1.89]
fa_manual_aft			
Mean	0.62	-0.01	0.61
IC	[-0.71;2.03]	[-0.06;0.02]	[-0.69;2.00]

Table A2 Logistic Regression Predicting *Clmornot* Using Latent Pre-Policy Driving Behavior Factors

Variable	Estimate
fa_tire_bfr	-0.85
	(0.92)
fa_manual_bfr	0.18^{**}
	(0.09)
fa_spd_bfr	0.21^{**}
	(0.09)
model2	-1.52^{*}
	(0.79)
model3	-0.41
	(0.87)
model4	-1.09
	(0.81)
carprc	-0.03
	(0.05)
age2	-0.07
	(0.26)
age3	-0.14
	(0.27)
LR Statistic	17.89
N	981

Standard errors are reported in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A3 Logistic Regression Predicting *Clmornot* Using Pre-Policy Risk Segments

Variable	**Estimate**
$Group = 1$	0.45^{***}
	(0.17)
model2	-1.47^{*}
	(0.78)
model3	-0.57
	(0.86)
model4	-1.01
	(0.81)
carprc	-0.03
	(0.05)
age2	-0.08
	(0.26)
age3	-0.14
	(0.27)
LR Statistic	14.15
N	981

Standard errors are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table A4 Analysis of Moral Hazard Within the High-Risk Group ($Group = 1$)

Driving Behavior Factor After Policy Purchase	**Direct Effect**	**Indirect Effect**	**Total Effect**
fa_tire_aft			
Mean	0.18	-0.23	0.16
IC	[-2.79;3.45]	[-0.19;0.32]	[-2.87;3.45]
fa_spd_aft			
Mean	0.14	0.03	0.16
IC	[-2.41;2.81]	[-0.04;0.16]	[-2.35;2.82]
fa_manual_aft			
Mean	0.27	-0.002	0.27
IC	[-2.47;3.34]	[-0.07;0.06]	[-2.48;3.32]

Table A5 Analysis of Moral Hazard Within the Low-Risk Group ($Group = 0$)

Driving Behavior Factor After Policy Purchase	Direct Effect	Indirect Effect	Total Effect
fa_tire_aft			
Mean	-0.62	0.02	-0.59
IC	[-2.73;1.91]	[-0.05;0.19]	[-2.7;1.93]
fa_spd_aft			
Mean	-0.70	-0.01	-0.71
IC	[-2.85;1.65]	[-0.07;0.05]	[-2.90;1.62]
fa_manual_aft			
Mean	-0.68	-0.02	-0.70
IC	[-3.07;1.82]	[-0.09;0.04]	[-3.08;1.80]

Table A6 Robustness Test of Moral Hazard Findings Based on Correlation Coefficient–Selected Driving Variables

Driving Behavior Variable	Direct Effect	Indirect Effect	Total Effect
fuel_aft			
Mean	0.19	0.01	0.20
IC	[-1.19;1.58]	[-0.02;0.06]	[-1.19;1.60]
spd_aft			
Mean	0.15	0.03	0.18
IC	[-1.23;1.64]	[-0.01;0.09]	[-1.22;1.64]
cst_aft			
Mean	0.17	0.00	0.18
IC	[-1.21;1.64]	[-0.02;0.05]	[-1.20;1.65]
frtl_aft			
Mean	0.20	0.01	0.20
IC	[-1.17;1.63]	[-0.03;0.09]	[-1.17;1.63]
wkend_aft			
Mean	0.17	-0.00	0.17
IC	[-1.19;1.64]	[-0.03;0.02]	[-1.18;1.63]
acc_aft			
Mean	0.17	-0.01	0.16
IC	[-1.26;1.61]	[-0.05;0.01]	[-1.27;1.60]
idle_aft			
Mean	0.16	-0.00	0.16
IC	[-1.39;1.64]	[-0.03;0.02]	[-1.38;1.64]
brk_aft			
Mean	0.20	-0.00	0.20
IC	[-1.34;1.68]	[-0.04;0.02]	[-1.34;1.65]

Table A7 Linear Regressions Evaluating the Effect of Coverage Incentives on Driving Behavior Factors *fa_tire* and *fa_spd*

Variable	**(1) *fa_tire***	**(2) *fa_spd***
Add	-3.02***	1.90***
	(0.53)	(0.27)
time	-0.40	0.89***
	(0.37)	(0.23)
time × *Add*	0.46	-1.00***
	(0.48)	(0.25)
model2	0.87	0.19
	(0.94)	(0.48)
model3	1.39	-1.14**
	(1.01)	(0.52)
model4	0.26	0.42
	(0.95)	(0.49)
age2	-0.15	-0.02
	(0.24)	(0.12)
age3	-0.09	-0.21
	(0.26)	(0.13)
carprc	0.02	-0.13***
	(0.05)	(0.02)
$\hat{u}$	0.18***	-0.12***
	(0.04)	(0.02)
LR Statistic	47.54	128.35
N	981	981

Standard errors are reported in parentheses: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

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