Moral Hazard and Transparency in Peer-to-Peer Auto Insurance with Telematics

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Abstract

Peer-to-peer (P2P) insurance uses new technology to connect policyholders and brings about disruptive innovation. While P2P insurance serving people with relatively high degrees of social connection, like friends and relatives, has been theoretically and practically underpinned, there is a lack of understanding about its viability or efficiency in serving strangers with few to no social ties as moral hazard may be substantial. In this paper, we bridge the gap by empirically measuring moral hazard in a P2P auto insurance where the insured individuals are strangers. Our research findings remove an obstacle that may hinder a broad application of the P2P insurance model among large groups of individuals. Moreover, we investigate factors that mitigate moral hazard and study the impact of transparency in premium balance on driving safety. We show that the transparency allows people to learn vicariously from peers' lessons and lets them drive more safely.

Keywords: Insurtech, joint liability, group incentive, risk sharing network

Introduction

Many industries have been experiencing a reformatting of their business models due to the emergence of new technologies. Benefiting from digital technologies and social platforms, sharing economy can be one of the most significant and disruptive innovations, where consumers can easily share goods or services in a peer-to-peer manner with lower search and transaction costs (Benjaafar et al., 2019; Jiang and Tian, 2018). The peer-to-peer model has brought about a substantial change in the relationship between consumers and companies and that among consumers, and the insurance sector has not been exempted from this transformation. Peer-to-peer (P2P) insurance emerges as a risk-sharing network where a group of insured individuals pools their premiums together to insure against a risk (EIOPA, 2019).

P2P insurance uses money from the pool to cover the cost of a claim in the event of a loss. Premiums not paid out for claims are either refunded to the policyholders or donated to charitable causes if claims are lower than expected. In situations where losses from claims surpass the collected premiums, a reinsurance company typically provides coverage to compensate for the shortfall. The P2P insurance platform serves primarily as a mediator for the group of insured individuals, often levies a flat fee, and refrains from profiting off any surplus premiums. This P2P model helps to reduce conflicts that may arise in traditional centralized insurance structures where the interests of the insurer and the insured may not always align (Frankenfield, 2021).

Taking advantage of technology in social networking, crowdsourcing, machine learning, the Internet of things (IoT), and so on to assemble the insured at a low cost, improve the settlement process, and reduce fraud (Clemente and Marano, 2020), P2P insurance revives the mission of insurance by bringing it back to its roots of mutual aid and risk-sharing. In the past, people would form guilds or groups to share the risks of their profession or trade. For example, in Medieval Europe, the guild system emerged, and members paid into a pool that covered their losses (Foucault, 1991). In the 1600s, sailors would pool their resources together to insure against the loss of their ships or cargo (Williams, 2011). To restore insurance to its original purpose and its former excellence, the fundamental objective and essence of P2P insurance are to benefit the insured and enhance the well-being of the community (NAIC, 2022). Moreover, in stark contrast to traditional insurance with no disclosure of what proportion of the premiums turns into insurers' underwriting profit, P2P insurance is typically more transparent. It informs the insured of how much of the premiums are used to pay claims and how much are retained in the pool, strengthening their control (Braun and Schreiber, 2017; Clemente and Marano, 2020).

As documented by the European Insurance and Occupational Pensions Authority (EIOPA, 2019) and the U.S. National Association of Insurance Commissioners (NAIC, 2022), P2P insurance platforms group like-minded individuals with mutual interests or similar risk profiles, introducing a sense of trust to the business model. For example, founded in 2010 as the pioneer of P2P insurance, the German company Friendsurance utilizes social media, encourages users to invite family members and friends to form small mutual support groups, and refunds the insured at the end of a coverage period if there is a surplus (Abdikerimova and Feng, 2022). Lemonade, the first P2P insurance company in the U.S., creates peer groups centered on charitable and social causes; the premiums of people who choose the same charity are pooled, and unclaimed premium money will be donated to the charity (Pritzker, 2022). We refer the readers to Huckstep (2016) for more information on the business of other P2P insurance platforms worldwide. Overall, the mutual interests among the insured individuals of P2P insurance serve to deter inflated claims (Braun and Schreiber, 2017; Levantesi and Piscopo, 2022; MacMinn and Ren, 2011).

Motivation

Originating in the insurance literature, *moral hazard* describes loss-increasing behaviors that arise under insurance (Rowell and Connelly, 2012). Concretely, people may be more likely to engage in risky behaviors if they know that negative consequences will be covered by their insurance policy[1]. The increased risk-taking behaviors can result in higher costs for the insurer and ultimately higher premiums for all policyholders. Moral hazard is an important consideration in the insurance sector as it has significant financial implications. To mitigate its impacts, traditional insurance companies use partial risk-sharing strategies such as deductibles, copays, and coinsurance, which require the insured to bear some of the cost of any losses and thus discourage risk-taking behaviors.

The P2P insurance model holds the belief that the insured individuals within a group have a stronger sense of responsibility and are less likely to engage in risky behaviors, thereby reducing moral hazard (Denuit et al., 2022). Since the members of the group are typically friends, relatives, or individuals with a shared charitable cause, resulting in a strong social bond that creates accountability among each other within the group, they understand that their actions can directly impact others they may care for, and thus tend to spend precautionary efforts to minimize risk. The effort provision largely depends on the group members' prosocial tendencies (Biener et al., 2018), which means that they not only prioritize their own payoffs but also care about the well-being of others, or more broadly, they desire to "do the right thing" or to "make the moral choice" (Levitt and List, 2007). The effectiveness of prosociality in mitigating moral hazard is well supported both theoretically (Casadesus-Masanell, 2004; Englmaier and Leider, 2012; Englmaier and Wambach, 2010) and by experimental evidence (Biener et al., 2018; Fehr et al., 1997; Fehr and Schmidt,

[1] More specifically, this phenomenon is known as *ex ante* moral hazard, which we focus on in this paper and refer to as moral hazard for simplicity.

2007; Rubin and Sheremeta, 2016).

While affinity groups in current P2P insurance models help to curb moral hazard, they are often restricted to a small or moderate size. For instance, Friendsurance typically groups up to 10 family members or friends (Abdikerimova and Feng, 2022). But when the group size is small, risk pooling becomes less effective, and the distribution of risks and apportion of losses become more challenging as dictated by the law of large numbers (Smith and Kane, 1994). Specifically, the capacity to absorb deviations from the expected outcome is diminished, and higher premiums may be charged for the added risk due to the large variance. The demand for bigger groups of insured individuals necessitates the expansion of the P2P insurance model such that people with few to no social ties can enroll. However, to the best of our knowledge, there is no literature providing empirical evidence regarding the scalability of the P2P model, or more specifically, whether and to what degree moral hazard exists in P2P insurance with groups of strangers.

Prosociality among strangers can be less prominent than among those with a closer social connection, like friendship, kinship, a shared religious belief, or the commitment to donate to a charity (Ariely, 2017; Maner and Gailliot, 2007; Norenzayan and Shariff, 2008; Schlenker and Britt, 2001; Sydney Business Insights, 2018). This potentially escalates moral hazard in P2P insurance with groups of strangers. On the other hand, a refund of unclaimed premiums incentivizes the insured to regulate risky behaviors, such that moral hazard is mitigated. So, it is difficult to determine the extent to which or even whether moral hazard exists in such a P2P model. Therefore, we are motivated to measure the moral hazard in P2P insurance among strangers with a premium refund scheme, find the insured who may have higher degrees of moral hazard, and investigate the transparency of P2P insurance and peer effects that may mitigate or aggravate moral hazard.

Empirical research on moral hazard in the insurance sector, especially the behavior change due to insurance enrollment, is scant, likely because perfect observation of risk-taking is often difficult or prohibitively expensive (Arnott and Stiglitz, 1991; Holmström, 1979). Our research attempts to answer this question in the context of P2P collision car insurance, where users' driving data before and after enrollment are collected by telematics, a type of IoT technology. More importantly, unlike the commonly seen usage-based insurance (UBI), driving behavior tracking through telematics and the P2P insurance are independent in our study, and the actuarial pricing does not take into account driving behaviors. Instead, it is determined using some classical model that is widely applied in the auto insurance sector. Since customers have no idea about any connection between the telematics service and the P2P insurance, the monitoring effect (Jin and Vasserman, 2021; Pierce et al., 2015; Staats et al., 2017; Welsh and Farrington, 2009), by which safe driving is incentivized, is ruled out. In addition, we also have tracking data of those who are not enrolled in the insurance and use them as the control group, facilitating a causal analysis. To the best of our knowledge, this is the first empirical research in P2P insurance. We start the investigation of this realm from moral hazard, one of the most fundamental problems in the insurance sector, and transparency, which is unique in the P2P model.

Theoretical Background and Research Questions

In traditional centralized insurance, moral hazard has been examined both theoretically and empirically (e.g., Autor et al., 2014; Chiappori and Salanie, 2000; Dionne et al., 2013; Marshall, 1976; Pauly, 1968). In the P2P model, however, the presence or absence of moral hazard can be unclear due to effects in opposite directions, by each of which precautionary efforts are either discouraged or encouraged. So, it remains unknown whether the insured are more or less risk-taking after enrollment. In addition, some distinctive attributes of the P2P insurance model, such as peer influence and transparency, have the potential to alter an insured individual's inclination towards risk-taking in an indeterminate manner. In light of these, we introduce some relevant theoretical context and outline our research questions.

First of all, group incentives, or rewarding a group of individuals who collectively meet or surpass a pre-established level of performance, have proven effective in curbing moral hazard in microfinance markets (i.e., reduce defaults; see Hermes and Lensink, 2007) and workplaces (i.e., enhancing productivity; see Che and Yoo, 2001; Lim and Chen, 2014; Nalbantian and Schotter, 1997). In P2P insurance, unclaimed premiums will be refunded if a group experiences fewer losses than what the pooled premiums would cover. It is plausible that the refunding scheme serving as a form of group incentive encourages the insured to take more precautionary measures than they would without the scheme. On the other hand, the precautionary effort is essentially a public good since an individual's choice to reduce risk-taking directly increases the expected payoffs of the whole group. Strangers have a lower prosocial tendency compared to those with social ties, which discourages them from contributing to the public good and encourages free riding (Chaudhuri, 2011; Dur and Sol, 2010; Gong et al., 2009; Holmström, 1982; Rotemberg, 1994). So, it is unclear whether the increased precautionary effort incentivized by a potential premium refund offset a reduced effort provision due to free riding.

We raise the first research question (RQ1): *In light of the countervailing effects of the premium refunding incentive and the free-riding tendency, to what extent does moral hazard exist in a P2P insurance with groups of strangers?* Our empirical analysis confirms the presence of moral hazard in this context, as individuals tend to drive more recklessly due to insurance enrollment. Additionally, we provide a monetary assessment of this moral hazard and show that it is associated with an average loss of 60 Chinese yuan (8.3 U.S. dollars) per insured individual per year, which is a reasonably small amount, highlighting the feasibility and scalability of P2P collision insurance with the premium refunding scheme and groups of strangers. The result provides valuable insights into the potential challenges and benefits of implementing P2P insurance models and offers a starting point for future applications, particularly in the context of auto insurance.

Second, it has long been recognized in theory that moral hazard can be mitigated through actuarial pricing and imposing higher premiums to penalize risk taking (Ehrlich and Becker, 1972). So, it is crucial to identify individuals with high degrees of moral hazard and make insurance costs commensurate with each individual's level of risk. Insurance providers often base their pricing strategies on insured individuals' baseline risk, but there is mixed evidence regarding how the baseline risk correlates with moral hazard. Concretely, theoretical analyses suggest that moral hazard can increase (Chade and De Serio, 2002; Grossman and Hart, 1992) or decrease (Zheng et al., 2021) in the degree of risk aversion, depending on the form of the utility function. While literature with a UBI context (Choudhary et al., 2022; Soleymanian et al., 2019) has suggested a correlation between the baseline risk level and precautionary efforts in the coverage period, the conclusions may not be generalized to P2P insurance, because unlike in the UBI setting, the actuarial pricing of the P2P insurance does not incentivize the insured to drive more safely.

To address this, we try to answer the second research question (RQ2): *Do all insured individuals exhibit the same degree of moral hazard in P2P insurance? If not, what characteristics can one examine for quick identification of individuals with higher levels of moral hazard?* Our analysis results show that moral hazard is attributed to more reckless driving after insurance enrollment from the drivers with a lower baseline risk, and this behavioral change lasts for a long time. For drivers with a relatively high baseline risk, however, the driving safety is slightly improved or does not change significantly in the coverage period. These findings suggest that actuarial pricing should pay extra attention to the moral hazard of those with lower baseline risk, which may be overlooked by extant pricing models. Insurance providers may also take actions, like using promotion incentives, to encourage precautionary efforts, especially for those with low baseline risk.

Third, and more importantly, transparency is greatly enhanced in the P2P insurance model by allowing the insured to know their premium balances. An individual's balance change implies the claims and the overall driving safety of her group members because of their joint liability. So, the balance change may induce peer effects on the individual's provision of precautionary efforts. The peer effects can be either negative or positive on driving safety. On the one hand, a large decrease in the premium balance can upset an individual as her money was used to cover others' faults even if she did not make any mistakes. Consequently, the individual is likely to drive more recklessly. This is known as negative reciprocity, an individual's propensity to retaliate for unfair behaviors (Alfaro et al., 2022), which can be a strong motivator (Abbink et al., 2000; Offerman, 2002). On the other hand, according to the vicarious learning theory, people learn through others' successful or failed experiences (Gioia and Manz, 1985; Myers, 2018) using the medium of human emotion and imagination (Roberts, 2010). In our context, a large decrease in an individual's premium balance suggests more accidents and claims of the group, and through vicarious learning, the individual learns a lesson from others and is likely to drive more safely. Moreover, this positive effect attributed to vicarious learning can be more substantial among peers due to in-group empathy (De Dreu and Kret, 2016). So, the overall peer effect on driving safety is indefinite.

Considering negative reciprocity and vicarious learning together, we study the third research question (RQ3) about the transparency in P2P insurance: *To which direction and to what extent does a decrease in the premium balance affect an individual's driving safety?* In our study, a brief statement is sent to an insured individual every Friday evening showing her reduced amount in premium balance over the last seven days. We find that with every one-U.S.-dollar reduction in the premium balance, an insured individual drives more safely (with about a 0.6 point increase in her performance score) in the next seven days. This finding reveals implications for curbing moral hazard in P2P insurance and enhancing driving safety. For example, more transparency-related notifications can be released to invoke vicarious learning.

Our paper contributes to the literature by investigating moral hazard in P2P insurance, a fundamental problem in an emerging and insufficiently studied business model. To the best of our knowledge, this is the first empirical research in the realm. The paper proceeds as follows. In the next section, we review related literature and discuss our contribution, followed by introducing our research context and data. Then we present the empirical models for causal inference and the findings. Finally, we conclude the paper and provide managerial implications.

Literature Review

This study contributes to the literature in multiple domains, including but not limited to management information systems, insurtech, and business innovation. Our paper is closely related to three research streams, 1) telematics and usage-based insurance, 2) joint liability in risk management, and 3) transparency among peers and in operations. We highlight their importance and how our work contributes to each stream.

Telematics and Usage-Based Insurance

Telematics combines the technology of telecommunications and informatics and is widely used in the automotive industry for onboard services. A significant application of this technology is in usage-based insurance (UBI), which uses telematics and sensors to collect data about a car's speed and location, track driving behaviors, and calculate the insurance premium such that drivers who have good driving habits can get a discount. It is known that the UBI adoption helps improve driving safety (Jin and Vasserman, 2021; Soleymanian et al., 2019) and reduce fatal accidents (Reimers and Shiller, 2019). From the perspective of insurers, UBI improves underwriting performance by reducing their loss ratio (Che et al., 2022). In addition, feedback on driving safety via telematics can also affect driving behaviors (Choudhary et al., 2021; Choudhary et al., 2022). All these studies are in a UBI context, where the improved driving safety is primarily attributed to the monitoring effect, or more specifically, the premium discounts as an economic incentive.

Our paper contributes to the literature on telematics, but ours is unique in that the technology is not directly aimed at monitoring driving behaviors or incentivizing safe driving. We have a non-UBI research setting, where actuarial pricing is independent of driving safety. We identify moral hazard, which is the change in driving safety due to insurance enrollment and is not entangled with the effects of monitoring or feedback because they are controlled for by the presence of non-insured individuals and the driving data in the pre- and post-enrollment periods. Our unique research setting facilitates the measurement of moral hazard, which is a fundamental problem in the insurance sector. The study investigates the scalability of P2P insurance with groups of strangers and paves the way for future research on this business model.

Joint Liability in Risk Management

Joint liability denotes the obligation of two or more people being held responsible for paying back a debt or satisfying a liability. It has been extensively studied in the context of microfinance markets (Ahlin and Townsend, 2007; Bauer et al., 2012; Ghatak and Guinnane, 1999; Giné and Karlan, 2014; Hill, Sarangi, et al., 2012; Karlan, 2007) and proved to be effective in mitigating moral hazard (i.e., curbing loan defaults). Joint liability is also widespread in insurance-like organizations, such as self-help groups and community-based risk-sharing networks (Bhattamishra and Barrett, 2010; Fafchamps and Lund, 2003). The literature on joint liability in insurance is scant and largely makes theoretical contributions to actuarial science (Abdikerimova and Feng, 2022; Denuit et al., 2022; Denuit and Robert, 2021; Feng et al., 2023). A closely related work to ours is by Biener et al. (2018), who study the effects of prosociality through behavioral experiments and setting up a joint liability group. But they do not assess moral hazard when peers are strangers.

We contribute to the literature in this stream by the first empirical study in P2P insurance, a risk-sharing network with a joint liability of the insured. Specifically, we examine the moral hazard when insured individuals are strangers and address the scalability issue of this business model. We also emphasize the role of information technology, particularly telematics, in facilitating and evaluating insurance innovations. Without this technology, the driving behaviors would not have been observed. Overall, our study sheds light on the potential of P2P insurance as a viable alternative to traditional insurance and opens up new possibilities for insurtech development.

Transparency among Peers and Operational Transparency

Our research is closely aligned with the literature on transparency among peers, where a vast amount of research has been conducted in the workplace setting. Specifically, transparency in compensation (e.g., Card et al., 2012; Long and Nasiry, 2020; Ockenfels et al., 2015), effort (e.g., Gächter et al., 2013; Mas and Moretti, 2009), performance (e.g., Blanes i Vidal and Nossol, 2011; Lount Jr and Wilk, 2014), and work ethics (e.g., Beer et al., 2021) can affect employees' satisfaction and productivity due to various peer influences, like social pressure, mutual monitoring, social comparison, inequality aversion, and reciprocity. We contribute to the literature on transparency among peers in the insurance sector, where information disclosure to policyholders is often limited. Our work has circumvented a big obstacle in investigating peer effects. Specifically, individuals tend to act similarly for reasons unrelated to peer interactions when groups are formed endogenously (Manski, 1993). In our study, there is only one group for all the insured and the members are strangers, eliminating the endogeneity issue. Moreover, we find a positive effect of premium balance change on driving safety and explain the transparency-induced peer effect by vicarious learning, which, to our knowledge, has not been discussed in the extant literature on transparency.

Our work is also related to the literature on platform operational transparency, such as that of sharing economy and crowdfunding. In sharing economy, Cui et al. (2020) shows that positive reviews of guests help eliminate discrimination on Airbnb, whereas Mejia and Parker (2021) finds that revealing riders' profiles leads to gender and racial biases on a ridesharing platform. Research in crowdfunding has studied the effects of transparency in identity, contribution amount (Burtch et al., 2015; Burtch et al., 2016), and work-related updates (Mejia et al., 2019). Operational transparency is achieved by information sharing of an organization's workings. It can, for example, improve customers' perceived service value and employees' satisfaction (Buell et al., 2017), boost firm performance (Mohan et al., 2020), and increase trust and engagement (Buell et al., 2021). We contribute to the literature by studying the transparency of a P2P insurance platform that may have a broader impact. The improvement in driving safety attributed to transparency not only enhances the efficiency of the business model, but also brings benefits to society, like reducing traffic accidents and congestion and lowering emissions and other environmental impacts of driving.

Research Context and Data

Our analysis uses proprietary data from a Chinese company that offers P2P collision insurance to non-commercial car owners. If an insured driver is (partially) at fault in an accident, this insurance covers the cost of repairing her car. Customers must register and manage their insurance policy through a mobile app. The company asks customers to upload their current proof of insurance when they are trying to enroll in the P2P insurance, and they can enroll only if they do not have other collision insurance. To maximize the capacity of risk and loss apportion, there is only one insurance group, and all premiums are pooled together regardless of when an insured individual enrolls. The company employs a classical actuarial pricing model that considers factors such as a driver's age, gender, location, vehicle details, and accident and insurance claim history. The company charges a fixed proportion of the premiums as the administration fee.

When an insured individual files a claim, the payment is initially deducted from her premium account balance. If there is still an outstanding amount left on the claim, it will be shared among other insured individuals in proportion to their premium balances. To promote transparency in the P2P insurance system, an insured individual receives a brief statement every Friday around 7 PM documenting the reduced amount

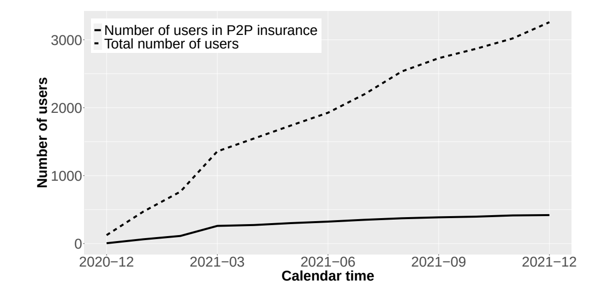


Figure 1. Number of Drivers

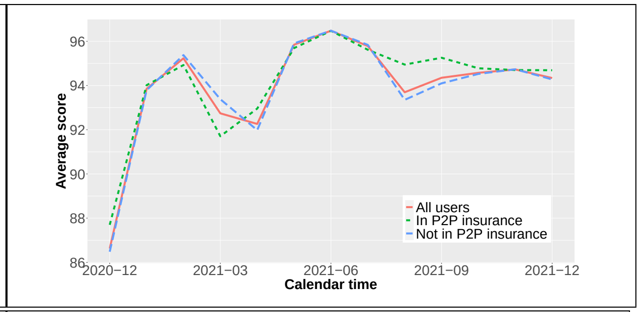


Figure 2. Average Score by Calendar Time

in her premium balance account over the last seven days. At the end of each one-year coverage period, any remaining balance in the premium account is either refunded to the insured individual or used to pay the premium for the following year. The P2P insurance program began in June 2019 and continued operating in December 2021, which is the end of our study period.

In December 2020, the company introduced to the app a telematics service that is independent of the P2P insurance, allowing the app to serve a broader range of customers. This service enables all app users, irrespective of insurance enrollment, to monitor their driving behaviors and gather information about their trips, including driving distance, speed, and dangerous events (harsh braking, harsh acceleration, and phone use while driving). Such information and a performance score reflecting the overall driving safety during the trip are available for user review after the trip. To encourage user engagement with the telematics service, the app offers rewards points for every tracked mile, which can be redeemed for gifts. The app uses a novel machine learning algorithm and confidential technical means to determine whether a tracked trip is indeed driven by the user. On the app, there is no information about whether the tracked driving behaviors are used for actuarial pricing, and the company did not do so. The P2P insurance and telematics are two independent services. Users of one service do not have to use the other.

Our data consist of $147,853$ trip records of $3,259$ random drivers between December 2020 and December 2021, who began to use the app after the telematics service was introduced. Among these drivers, 419 enrolled in the P2P insurance, and they had $34,855$ trips in the study period. The other $2,840$ drivers had not enrolled and had $112,998$ tracked trips. Drivers had their first tracked trip at different times. In December 2020 when the telematics feature was launched, our data record trips of 124 drivers, and only 5 of them enrolled in the insurance later in the same month. These numbers gradually increase in later months as shown in Figure 2. Table 1 shows the varying lengths of time that insured drivers had their trips tracked before enrolling in the insurance, with all of them having been tracked at least once prior to and after enrollment, respectively. For each insured individual, the data provide the insurance enrollment time.

Months	7	6	5	4	3	2	1
Number of users	1	1	6	8	14	42	347

Table 1. Months Being Tracked Before Enrollment

Upon completion of a trip, a performance score (ranging from 0 to 100) is available for review irrespective of insurance enrollment. This score represents a comprehensive evaluation of driving safety and is calculated by an undisclosed algorithm that considers various aspects of driving, such as time of day, speed, sharp turns, dangerous events, and so on. A higher score indicates better driving performance. Figure 1 reports the average performance scores in the study period for all drivers, the insured drivers, and drivers not enrolled in the insurance, respectively. It shows that their scores are highly correlated despite fluctuation over time.

For each tracked trip, the data contain the following variables, which are employed in our study. *Distance* is the total distance traveled in a trip. *Event* indicates whether or not dangerous events (harsh brake and acceleration and phone use) occur in a trip. *Trip_start_time* is the time when a trip starts. *Time_enrolled_P2P*

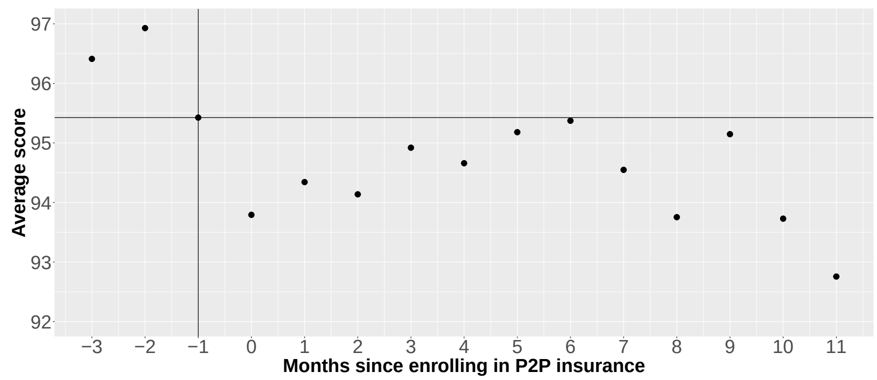


Figure 3. Average Score Before and After Joining P2P Insurance

is the time and date when a driver gets enrolled in the P2P insurance. It is only available for drivers enrolled in the insurance. *Pay* is the reduction in the premium balance in the last seven days, and it is released to the insured driver on Friday around 7 PM. Due to some unknown technical issues, this variable is missing a small proportion and is available for 377 of the insured drivers. In addition, 42 of the 377 drivers filed one claim, respectively, in our study period, and we know in which week the claims were filed but do not know the claim amount.

To better capture the characteristics of a trip, we create new variables using the existing ones. First, two binary variables, *rush_hour*, which indicates whether the trip starts between 7 AM and 9 AM or between 5 PM and 8 PM, and *weekend*, which indicates whether the trip is on the weekend, are created to account for the impacts of the trip time. Second, we calculate *months_since_tracking* for each trip, which is the elapsed time in months (30 days) since the first tracked trip, to capture the effect of learning from the feedback of trip information. This variable is used to measure the alteration in driving safety resulting from being exposed to telematics. Considering a potential nonlinear learning effect, we further generate multiple binary variables $monitor\_month_m$, which is equal to 1 if $months\_since\_tracking = m$ and 0 otherwise.

Estimation of Moral Hazard

In this section, we investigate moral hazard in the P2P collision insurance. First, we provide model-free evidence of how the insurance enrollment affects driving safety, as measured by the performance score. We then employ a staggered difference-in-differences (DID) model to formally examine the causal effect of insurance enrollment. Inverse probability of treatment weighting (IPTW) is used to address the imbalance between the treatment and control groups. Finally, we conduct heterogeneity analysis to explore how enrolling in the P2P insurance program results in moral hazard among drivers with different baseline risks.

Model-Free Evidence

We plot in Figure 3 the average score of all insured drivers prior to and after enrolling in the P2P insurance. The x-axis represents the number of months since enrollment, where a negative number represents the number of months prior to the enrollment, 0 is the month of enrollment, and a positive number indicates the number of months after the enrollment. Trips completed within one month prior to the enrollment (i.e., month "-1") are used as the baseline. We aggregate trips that are completed three months or more prior to the enrollment to month "-3" to account for the limited number of insured drivers and their trips long before enrollment.

It can be observed that the average performance score drops remarkably in the month of enrolling in the P2P insurance, illustrating the presence of moral hazard. In addition, all the average scores after enrollment are lower compared to the average scores prior to enrollment, indicating moral hazard may last for a long time. While Figure 1 shows the score drop, it can be unknown to what degree the safety degradation is attributed to the insurance enrollment, considering the existence of other influential factors, like the aforementioned trip characteristics. So, we investigate the causal effect of insurance enrollment on driving safety.

Difference-in-differences Estimation

Two-Way Fixed Effects model

We find the difference-in-differences (DID) estimation for the causal effect of enrolling in the P2P insurance on driving safety. We use a staggered DID setting since the drivers in the treatment group, i.e. those who had ever been insured, get enrolled at different times. Concretely,

$$\begin{aligned} score_{ij} =& \alpha_i + \eta_{M(t_{ij})} + \beta_{-3}\delta_i \mathbf{1}(\lfloor t_{ij} - E_i \rfloor \leq -3) + \beta_{-2}\delta_i \mathbf{1}(\lfloor t_{ij} - E_i \rfloor = -2) + \sum_{l=0}^{11} \beta_l \delta_i \mathbf{1}(\lfloor t_{ij} - E_i \rfloor = l) \\ &+ controls_{ij} + \varepsilon_{ij}, \end{aligned} \tag{1}$$

where $score_{ij}$ is the score of trip j from user i, t_{ij} is the calendar time of this trip, and $M(t_{ij})$ extracts the calendar month of t_{ij}. α_i is the fixed effect for driver i, and $\eta_{M(t_{ij})}$ is a fixed effect for the calendar month of the trip. δ_i is a binary indicator of treatment, which is equal to 1 if the driver ever enrolled in the P2P insurance and 0, otherwise. E_i represents the calendar time when driver i enrolls in the P2P insurance, and $\lfloor t_{ij} - E_i \rfloor$ indicates the elapsed time in months (30 days) from insurance enrollment to the trip at t_{ij}. So, the binary dummy $\mathbf{1}(\lfloor t_{ij} - E_i \rfloor \leq -3) = 1$ if the trip is 60 days or more before insurance enrollment, $\mathbf{1}(\lfloor t_{ij} - E_i \rfloor = -2) = 1$ if the trip is 30 to 60 days before enrollment, and for $l = 0, 1, \ldots, 11$, $\mathbf{1}(\lfloor t_{ij} - E_i \rfloor = l) = 1$ if a driver had been insured for l to $l + 1$ months until t_{ij}. We exclude $l = -1$ because the trips happening 30 days or less before enrollment serve as the baseline.

The coefficient β_l, $l = -3, -2, 0, 1, \ldots, 11$ measures the effect of pre- or post-enrollment on the driving score. For $l = -3$ or -2, β_l measures the driving behaviors of not-yet-insured drivers one month or more before their enrollment compared to one month or less. The estimation of β_{-3} and β_{-2} will be used to test the parallel trend assumption between the uninsured and the insured before enrollment. For $l = 0, 1, \ldots, 11$, β_l measures the change in driving behavior between day $30 \times l$ and day $30 \times (l + 1)$ in the coverage period compared to the baseline ($l = -1$) and is the effect of interest. We may also include control variables, *distance*, *rush_hour*, *weekend*, *months_since_tracking*, and *monitor_month*$_m$ (see the data section for details) of each trip j of driver i as $controls_{ij}$. ε_{ij} is the noise term.

Matching Estimator

The two-way fixed effects model in equation (1) compares the scores of drivers who enrolled in the P2P insurance with those of uninsured drivers. Since the treatment, or being insured or not, is determined by the drivers, we estimate the treatment effect by comparing the driving performance between the insured drivers with their matched sample of uninsured ones to address the self-selection bias. We use the driving information collected by telematics to construct a profile for each driver, which can well represent their driving habits and risk preference. Specifically, for the insured drivers, we use their driving information before insurance enrollment, and for uninsured drivers, we use their entire driving history. We calculate the following four variables, *average historical driving speed*, *average score*, *average driving distance per day*, and *average number of trips per day*, to construct a profile of risk and driving habits for each driver and match the insured with the uninsured. These variables quantify customers' driving intensity, frequency, and risk preference. Table 2 shows the distribution of the four variables for the treatment (insured) and control (uninsured) groups.

We combine inverse probability of treatment weighting (IPTW), a propensity score method, in the DID setting to strike a balance in the profile of risk and habits between the treatment and control groups. Given the large difference between the number of drivers in the treatment (429 drivers) and the control ($2,840$ drivers) groups, the IPTW is able to retain most individuals in the analysis and thus remains a large effective sample size. We first find the probability of a driver's enrolling in the insurance using a logistic regression with the four variables in Table 2 as the covariates. Then the weight for the driver is the inverse of the probability if she is insured and the inverse of one minus the probability otherwise.

		Score	Distance (in meters)	Number of trips	Average speed (km/h)
Treatment group	Mean	94.46	11880.03	1.68	23.44
(prior to enrollment)	Std.	12.42	19040.32	1.28	18.62
Control group	Mean	94.40	12430.81	1.98	25.67
	Std.	10.80	22758.74	1.53	18.11

Table 2. Driving Habits and Safety

	Dependent variable: score		
β_l	(1)	(2)	(3)
-3 months since joining P2P	0.76 (0.78)	0.72 (0.87)	0.42 (0.71)
-2 months since joining P2P	0.12 (0.45)	0.08 (0.47)	-0.21 (0.46)
0 month since joining P2P	-1.42 *** (0.53)	-1.44 *** (0.54)	-2.27 *** (0.67)
1 month since joining P2P	-0.35 (0.66)	-0.38 (0.65)	-1.54 * (0.74)
2 months since joining P2P	-0.34 (0.73)	-0.12 (0.72)	-1.34 (0.92)
3 months since joining P2P	-0.39 (0.88)	-0.05 (0.94)	-1.88 (1.04)
4 months since joining P2P	-0.61 (1.02)	-0.47 (1.04)	-2.02 (1.08)
5 months since joining P2P	0.09 (1.10)	-0.41 (1.10)	-2.24 (1.16)
6 months since joining P2P	-0.05 (1.34)	-0.26 (1.38)	-1.97 (1.19)
7 months since joining P2P	-0.68 (1.52)	0.00 (1.53)	-2.21 (1.93)
8 months since joining P2P	-1.24 (1.65)	-0.42 (1.64)	-1.71 (2.17)
9 months since joining P2P	0.74 (1.86)	1.02 (1.86)	0.44 (1.74)
10 months since joining P2P	-1.95 (1.32)	-2.75 (1.48)	-3.57 (1.43)
11 months since joining P2P	-2.92 (2.30)	-3.84 (2.44)	-4.84 (2.30)
N	147853	147853	147853
R^2	0.13	0.13	0.13
Adjusted R^2	0.11	0.11	0.11
Individual fixed effect	Yes	Yes	Yes
Time fixed effect (calendar month)	Yes	Yes	Yes
Control variables	No	Yes	Yes
Matching	No	No	IPTW

Note. *** $P \leq 0.001$, ** $P \leq 0.01$, * $P \leq 0.05$. Standard errors are in parentheses.

Table 3. Effects of Joining P2P Insurance

Estimation results

We estimate the effect of enrolling in the P2P insurance on driving safety by the two-way fixed effects model as in equation (1) excluding and including the control variables and by the IPTW estimation with the control viriables, and report the results in columns 1 to 3, respectively, of Table 3. As a result, the estimations from the three models are consistent. Specifically, the insignificant estimations of β_{-3} and β_{-2} imply that the insured drivers do not differ from the uninsured in driving safety before enrollment. So, we cannot reject the parallel trend assumption, and the treatment effect estimation by the DID approach is credible.

The change in driving due to enrolling in the P2P insurance is measured by β_l, $l = 0, 1, \ldots, 11$. We find that β_0 is significantly negative from the three models, implying that, on average, enrolling in the P2P insurance leads to a decrease of one point or two in the score in the following month, ascertaining the presence of moral hazard. When using IPTW matching (the last column of Table 3), β_1 is barely significant. We see that β_l with $l > 2$ are negative but insignificant with an exception in β_9, which is insignificantly positive. This implies that the drivers are remarkably more risk-taking immediately after enrolling in the P2P insurance, which diminishes after one month or two. The significant moral hazard only in the first couple of months of the coverage period possibly suggests heterogeneity in the insured drivers. Specifically, some drivers exhibit higher moral hazard than others. Distinguishing drivers with different moral hazards motivates us to examine the impacts of baseline risk preference as RQ2.

We further quantify how much loss the moral hazard is worth by measuring the monetary value of safe driving. We find by a simple linear regression that a one-point decrease in an insured driver's average score is associated with a loss of 181.9 Chinese yuan (about 26 U.S. dollars) in the premium. So, by the IPTW estimation, a 2.27- and 1.54-point decrease in the first two months are approximately associated with $189.1 \times (2.27+1.54)/12 = 60.0$ Chinese yuan (about 8.3 U.S. dollars). This answers RQ1, to what extent moral hazard exists in the P2P insurance with a group of strangers. The reasonably small amount of loss due to moral

	Insured		Uninsured	
	High-risk	Low-risk	High-risk	Low-risk
Number of drivers	170	249	1,460	1,380
Average score (before enrollment)	95.47	99.91	94.03	99.80

Table 4. Comparison of High- and Low-Risk Groups

hazard demonstrates the viability of this insurance model.

Moral Hazard by Baseline Risk

On average, enrolling in the P2P insurance has a significantly negative impact on driving safety, which can last for one month or two. To facilitate a more sophisticated actuarial pricing model that takes into account moral hazard, we are interested in studying RQ2, how drivers with various inherent risk preferences react differently to the insurance enrollment. The heterogeneity analysis of moral hazard is also crucial if the insurance provider seeks to provide personalized promotions and incentivize safe driving.

We categorize drivers into high- and low-risk groups based on their average score. For drivers in the control group, we use their entire driving records to calculate their average score, and for those in the treatment group, we use their driving records prior to enrollment to avoid the impact of moral hazard. We group drivers whose average scores are above the median into the low-risk group and others into the high-risk group. Table 4 shows the number of drivers and their average scores in the high- and low-risk groups.

To examine moral hazard of drivers with different risk preferences, we apply the DID model in equation (1) on both the high- and low-risk groups including all control variables and using IPTW. The estimated treatment effects are shown in Figure 4 together with the 95% confidence intervals (CIs). It shows that for the high-risk group, there is a slight improvement or no significant change in driving safety in the coverage period. In stark comparison, the moral hazard of the drivers with low risk is persistent in the one-year coverage. So, the moral hazard found among the insured drivers is primarily attributed to those with low baseline risk. This finding reveals an important implication that might have been long overlooked; actuarial pricing should consider the moral hazard of those who have low baseline risk but become more risk-taking after enrollment in this context, in addition to penalizing those with high baseline risk.

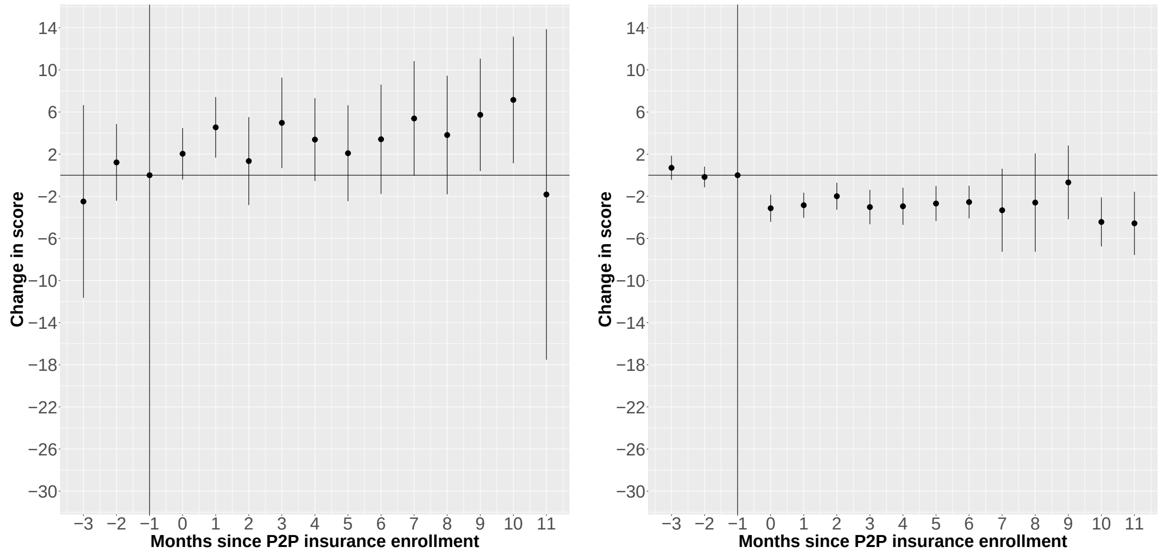
Transparency in Premium Balance

We have shown that enrolling in the P2P insurance, on average, leads to more reckless driving, and this impact is more severe and lasts longer among drivers with relatively low baseline risk. In this section, we investigate our RQ3, the effect of transparency in premium balance, which is unique in the P2P insurance, and try to understand in which direction and to what extent a drop in premium balance changes driving behaviors.

Difference-in-Differences Estimation with IPTW Matching

Every Friday around 7 PM, an insured driver receives a brief statement of her current premium account balance and the reduced amount that is used to pay her or others' claims in the last seven days. Since the exact value of the premium account balance is confidential and not provided, we use the weekly change in balance as a continuous treatment and study its impacts on driving safety. We are interested in the effect of a shared amount of an individual paying others' claims but only know the total amount reduced in the balance. So, we exclude from the analysis the trips of an individual in the next seven days if she filed a claim in the last seven-day statement period. Since there were only 42 claims, we only exclude a small proportion of the trips. Setting T to be Friday 7 PM, approximately when the statement is sent every week, we construct the following two-way fixed effects model to estimate the causal effect of premium balance reduction.

$$score_{ij} = \alpha_i + \sum_{l=0}^{6} \theta_l \mathbf{1}(\lfloor T_{ij} - T \rfloor = l) + \sum_{l=0}^{6} \gamma_l \delta_i \mathbf{1}(\lfloor T_{ij} - T \rfloor = l) \times pay_{ij} + claim_{ij} + controls_{ij} + \varepsilon_{ij}, \quad (2)$$



(a) High-Risk Group **(b) Low-Risk Group**

Figure 4. DID Estimation Using IPTW with 95% CIs for the High- and Low-Risk Groups

where $score_{ij}$ is the score for trip j of driver i, α_i is the fixed effect of driver i, T_{ij} indicates the day and time (e.g., Tuesday 8:30 AM) of the trip, δ_i is a binary indicator that is equal to 1 if the driver enrolled in the P2P insurance and 0 otherwise, pay_{ij} is the most recent amount reduced in the premium balance paying others' claims before the trip, and $claim_{ij}$ is equal to 1 if individual i had ever filed a claim before trip j and equal to 0 otherwise. The analysis includes the trips of the insured drivers in the coverage period and the trips of the uninsured. With $\lfloor T_{ij} - T \rfloor$ indicating the elapsed time in days (24 hours) from the last statement of the premium balance to the trip, θ_l, $l = 0, \ldots, 6$, are the fixed day effects of the trip that are the same across the insured and uninsured drivers. This is equivalent to setting 7 PM as the start of a day and estimating day effects in a week. Furthermore, γ_l, $l = 0, \ldots, 6$, are the coefficients of interest and represent how many points are increased in the driving score of an insured driver on the l-th day since the last statement of a unit amount reduced in the premium balance. Moreover, if an insured driver has claimed a loss from an accident, she may drive more cautiously in the future, and her claim may cause others' change in driving behaviors, which in turn, cause a reduction in her premium balance used to pay others' loss. Therefore, we control $claim_{ij}$, a confounder that affects both pay_{ij} and $score_{ij}$.

We also introduce $controls_{ij}$, including *distance*, *rush_hour*, *months_since_tracking*, and *monitor_month*$_m$ (see the data section) as the control variables. For model estimation, we use the trips of uninsured drivers and those of the insured after enrollment, where the uninsured trips serve as the control group and enable the identification of the day effects θ_l's. Table 5 reports the estimated effects of every one-U.S.-dollar reduction in premium balance on the driving score. As a result, γ_l, $l = 0, \ldots, 6$, are around 0.6 with γ_0, γ_1, γ_2, γ_4, and γ_6 significantly positive. This implies that a one-dollar reduction in the premium balance leads to a persistent improvement in driving safety in the next seven-day statement period.

The positive effect of transparency in premium balance reduction suggests that the insured drivers are vicariously learning from a peer's lesson, and their propensity to safe driving dominates that to reckless driving attributed to negative reciprocity. The finding suggests important managerial implications; to enhance transparency and maximize its positive effects, a P2P insurance platform may disclose more information, like incidents and near-misses, to induce peer empathy and facilitate vicarious learning. The result shows that the transparency in this business model not only serves to enhance trust, but also improves the operational efficiency, road safety, and thus the well-being of the whole society.

We have conducted multiple robustness checks, and our conclusions are qualitatively unchanged. First,

	Dependent variable: score
γ_0 (0 day after pay × pay)	0.60 * (0.29)
γ_1 (1 day after pay $\times pay$)	0.61 ** (0.22)
γ_2 (2 day after pay $\times pay$)	0.58 * (0.23)
γ_3 (3 day after pay $\times pay$)	0.53 (0.38)
γ_4 (4 day after pay $\times pay$)	0.67 ** (0.23)
γ_5 (5 day after pay $\times pay$)	0.34 (0.25)
γ_6 (6 day after pay $\times pay$)	0.63 ** (0.29)
Control variables	Yes
N	139804
R^2	0.13
Adjusted R^2	0.11
Individual fixed effect	Yes
Time fixed effect (Number of 24 hours after push)	Yes
Matching	IPTW

Note. *** $P \leq 0.001$, ** $P \leq 0.01$, * $P \leq 0.05$. Standard errors are in parentheses.

Table 5. Effects of Premium Balance Reduction

for the dependent variable quantifying driving safety in all the models, we replace the score with *event*, a binary indicator of whether a dangerous event occurs during a trip, and use a linear probability model, which allows easy implementation of IPTW matching. As a result, enrolling in the P2P insurance leads to an increased probability of a dangerous event. Second, since a statement of premium balance is sent on Friday at approximately instead of exactly 7 PM, and the app users may not immediately review it, we set T to be Friday 8 PM and 9 PM, respectively, and re-estimate the two-way fixed effects model in equation (2) when studying the effects of transparency in premium balance. Finally, we replace θ_l in equation (2), which is the effect of a day that is assumed to start from 7 PM, with the effect of a calendar day that starts from 12 AM. Our conclusion on the effects of transparency is robust to these changes.

Conclusion and Managerial Implications

We study moral hazard in P2P insurance by DID estimations and quantify to what extent the decrease in driving safety jeopardizes operational efficiency. Our estimation reveals insights into this emerging business model. First, we show the presence of moral hazard despite the refunding scheme of unclaimed premiums, and the moral hazard is associated with a reasonably small loss of the premium. This loss from moral hazard is acceptable, especially when considering the P2P insurance group is composed of strangers with little prosociality. So, our finding addresses the size limitation of the extant P2P insurance with affinity groups and proves the scalability of this business model, which can encompass a large number of strangers to enhance its risk-distribution capability.

Furthermore, we find that the moral hazard is primarily attributed to the behavior change from drivers with relatively low baseline risks. The converging driving safety of the high- and low-risk drivers indicates no need for grouping drivers based on pre-enrollment risk. Instead, a large group is further underpinned to better ensure against risks. This finding also suggests the necessity of accounting for moral hazard in actuarial pricing. Concretely, classical pricing models should not only prioritize the baseline risk, but also charge higher premiums to individuals with high degrees of moral hazard. This can ultimately lead to a more sustainable insurance system and lower premiums for everyone.

In addition, we find that transparency in the premium balance helps deter reckless driving, and we explain this phenomenon by peer influences, where vicarious learning that induces safer driving dominates negative reciprocity that leads to more dangerous actions. This is consistent with the idea that people conform to social norms of risk aversion. Overall, knowing that people drive more safely through learning vicariously from their peers suggests the importance of enhancing transparency and facilitating peer influence. The platform can foster a culture or incentive system of transparency by not only disclosing premium balance but also encouraging the insured to report incidents and near-misses without fear of retribution.

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