NO NEWS IS GOOD NEWS: MORAL HAZARD IN OLIGOPOLISTIC INSURANCE MARKETS

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ABSTRACT. I conduct inference on moral hazard in the Italian automobile insurance market. I disentangle moral hazard from adverse selection and state dependence by exploiting the non-linearities in the penalties across driving records and companies, and a discontinuity in the cost of accidents in the last 60 days of the contractual year. I employ a unique matched insurer-insuree panel dataset, containing rich information on 4,316,647 auto insurance contracts underwritten by all Italian insurers. The results demonstrate that moral hazard is a pervasive feature of the market, although its magnitude varies across companies.

Keywords: Moral hazard, Adverse Selection, Risk, Risk Aversion, Asymmetric Information, Self-Selection

JEL classification: D82, G22, J24

Economic analysis of the role of asymmetric information in determining market failures has been extremely influential (see Arrow (1963), Akerlof (1970) and Rothschild and Stiglitz (1976)). There are two main sources of asymmetric information: moral hazard–when someone takes more risks because someone else pays the cost of those risks–and adverse selection, when high-risk individuals self-select into more generous coverage. Within the context of the auto insurance market, Chiappori and Salanie (2012) say that “moral hazard occurs when the probability of a claim is not exogenous but depends on some decision

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made by the subscriber (e.g., effort of prevention)."

Recent literature has attempted to assess empirically whether asymmetric information exists. In a seminal paper, Chiappori and Salaniè (2000) exploited the well-known positive correlation property: if there are informational asymmetries, high-risk individuals purchase higher coverage than low-risk individuals. They find no evidence to corroborate the existence of asymmetric information in the French automobile insurance market. Unfortunately, the positive correlation property does not allow one to distinguish between moral hazard and adverse selection. Understanding which kind of asymmetric information is present is crucial because welfare implications and policy recommendations differ depending on whether moral hazard or adverse selection exist in a contractual relationship. In the auto insurance industry, if moral hazard is absent, changing the structure of penalties will not lead to reductions in the accident rate because the insured drivers do not respond to financial incentives. But if moral hazard is present in this industry, adjusting penalty structures could reduce car accidents.

The auto insurance market has traditionally been considered an ideal laboratory to study private information because of the standardized contracts—summarized by a limited number of variables—in contrast to employment contracts. However, empirical estimates on the importance of moral hazard vary, see Abbring, Chiappori, and Zavadil (2008), Abbring, Chiappori, and Pinquet (2003) and Dionne, Michaud, and Dahchour (2013). This puzzle typically is resolved by arguing that the “institutional” aspects of the market matter. Unfortunately, as researchers typically conduct inference using samples of contracts underwritten by only one or two companies, the available estimates are not necessarily robust to self-selection of drivers into companies. In fact, even in the highly regulated auto insurance market, insurers can choose discretionary penalty structures to incentivize safe driving and heterogenous premium-coverage menus, leading to possible sorting into companies.¹

¹A more careful examination of modern auto insurance markets reveals that contracts are increasingly differentiated—in Italy and in the United Kingdom, the so-called insurance telematics represents a notable manifestation of this phenomenon—but companies also provide a variety of services, such as assistance in the event of an accident, and differ in their intrinsic quality, e.g., efficiency in liquidating claims.
The primary goal of this article is to test for and measure moral hazard in the Italian automobile insurance market, while controlling for adverse selection and state dependence. I do so by exploiting newly collected representative matched insurer-insuree panel data, that are far more comprehensive and complete than data used in previous research.2

Disentangling moral hazard from adverse selection is often difficult. A prominent strategy for doing so is based on the idea that under adverse selection, the probability of accidents should be constant regardless of the incentives faced by the insured party. In contrast, in the presence of moral hazard, there are certain observable relationships between accident rates and incentives, relationships that are typically governed by experience rating systems. This approach, which originated in labor economics (see Heckman (1991)), characterizes several papers in the literature surveyed by Cohen and Siegelman (2010), under the label “dynamic properties” (DPA). Specifically, DPA exploits the non-linearity of the premium-driving record schedule: under moral hazard, the higher the penalty for having an accident—the slope of the premium schedule at a given point—the higher the effort exerted by the policyholder. To the extent that driving records are subject to exogenous time-variation, repeated observations of the same policyholder allow DPA to control for adverse selection. For example, exploiting the evolution of the French bonus-malus system, Abbring, Chiappori, and Pinquet (2003) and Abbring, Chiappori, Heckman, and Pinquet (2003) show that because the next accident will be costlier in terms of insurance rate increases, people who have an accident face a financial incentive to drive more carefully, and, as a result, they should be less likely to have another accident, the so-called negative contagion effect. As noted by Ceccarini (2007) and Israel (2004), a driver might respond to an accident by driving more carefully or giving up the car for a while, leading to state dependence. As these papers find evidence of negative state dependence, the authors argue that neglecting this channel leads the negative contagion approach to underestimate moral hazard.

I distinguish moral hazard from adverse selection and state dependence using two different methods. First, I apply DPA by implementing a two-step procedure. In the first step, I recover the slopes of the premium-driving record

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2I have been leading a two-person team in charge of designing the structure of the data, the sampling procedure, the technical documentation, the legal/administrative aspects, the interaction with the companies, and the organization/maintenance/quality check of the data.
schedules in the market. I document the presence of a large number of non-linearities in the penalties both within and across companies. Therefore, my data contain a richer source of identifying variations than previous research. In order to identify the effect of financial penalties on driving attentiveness, in a second step, I regress the event of one or more accidents on the driving record holding at each company. As my panel follows policyholders across change of companies, I can also control for state dependence by exploiting the changes in the penalties faced by switchers.

The second research design is based on a peculiar feature of the Italian bonus-malus experience rating system: accidents during the last 60 days of contractual year \( t \)–the grace period–cannot be used to update the driving record of year \( t+1 \) but, instead, only the one of year \( t+2 \). Thus, the monetary cost of accidents that occur during and outside the grace period of year \( t \) will be reflected on the premium of year \( t+2 \) and \( t+1 \), respectively. Moreover, accidents during the grace period of year \( t \) are likely to disappear from the driver’s record if the insured party switches to another company (see section 2). My striking descriptive evidence of moral hazard–the hazard rate increases during the grace period, and the peak is more marked in the sample of switchers–motivates an event history analysis to check whether policyholders are less careful during a time period in which accidents would be less costly. I also argue that the grace period-variation disentangles moral hazard from state dependence.

The results obtained from DPA are in accord with the moral hazard story: a higher penalty translates into a lower accident probability. The negative correlation is stronger in some companies than others. I also find evidence of negative state dependence.

The event history analysis also indicates that moral hazard is at play. I find that the baseline hazard rate of the last month with respect to the ninth month–my preferred measure of moral hazard–equals 21 percent. The estimated effect of moral hazard is larger when using the sample of switchers–about 116 percent–and heterogeneous across companies, ranging from 100 up 188 percent. A back of the envelope calculation suggests that heterogeneity in the preferences for risk play an important role in determining the different effects across companies. Taken together, my findings suggest data limitations, coupled with sorting into companies, as a novel explanation to rationalize the conflicting evidence in
The data I employ represent a notable advancement along several dimensions. Notably, my panel is a representative and large—4,316,667 contracts and related claims from 2013 to 2017:Q1—matched insurer-insuree dataset, following policyholders after changing companies. Moreover, the details on the contracts are richer than usual: along with the traditional variables, information on nine additional clauses shifting the premium and the expected indemnities are available.3

The relationships I examine empirically are interpreted within a duopoly model in which heterogenous drivers dynamically sort into companies, characterized by different premium-driving record schedules. I provide conditions under which, under moral hazard, a negative association between penalties and accident probabilities arises. The model allows me to cast the identification problem as one in which, given information on penalties and accidents, an average treatment effect—the average moral hazard in the market—has to be recovered. I also clarify the relationship between, and the external validity of, the parameters identifiable with representative and company-specific samples of contracts.

This paper is structured as follows. In section 1 I describe the duopoly model and discuss the identification problem. In sections 2 and 3 I describe the institutional features of the Italian insurance market and the data I employ in my analysis; the estimates of the slopes of the premium-driving record schedule are in section 4, and the estimates of their effect on the accident probability are in section 5. In section 6 I then carry an event history analysis, present the estimates from the conditional analysis, and address possible reverse causality bias; section 6.4 documents the variability of moral hazard across companies. Concluding remarks are in section 7. Sections 8 and 9 contain tables and figures.

3To put these features into perspective, the seminal paper by Chiappori and Salaniè (2000) employs a single cross-section of 20,716 contracts subscribed by a set of 21 companies accounting for 70 percent of the French auto insurance market. Abbring, Chiappori, and Zavadil (2008) and Jeziorskiy, Krasnokutskaya, and Ceccarini (2017) base their inference on 1,730,559/12,576 contracts subscribed by a single Dutch/Portuguese company, respectively; Dionne, Michaud, and Dahchour (2013) employ a rotating representative French panel of approximately 20,000 records with self-declared variables; Ceccarini (2007) employs data on 300,000 policyholders covered by a small Italian company.
respectively.

The online appendix is structured as follows: section 11 presents the results on the effect of the grace period on the size of the damage and a discussion on the importance of fraudulent claims and ex-post moral hazard. I discuss three confounding factors—seasonality effects, learning and misreporting—in section 11.1; in section 11.2 I document selective attrition effects in company-specific panel data. The online appendix also includes a description of the sampling procedure in section 12 and of the variables I use in my econometric analysis in section 12.1. Section 13 contains a number of omitted tables.

1. The Identification Problem

A risk-averse agent with intrinsic risk $\eta$—a shifter of the accident probability—initial wealth $w$, and observable individual and car characteristics $X$ lives for $T$ contractual years. At most one accident can occur within a year; i.e., $a_t = 1$ if an accident occurs and is zero otherwise. Let $n_t$ signify the driving record at the beginning of period $t$: $n_t = \sum_{i=1}^{t-1} a_i$. Two companies, $a$ and $b$, are active in the market; contracts are exclusive and cover one contractual year. The premium charged by company $j$ for year $t$ evolves according to a nonlinear pricing rule $h(\cdot)$ increasing in $n_t$

$$p^j_t = h^j(p_j, n_t, v^j_t) \text{ for } j \in \{a, b\}.$$  

The deterministic part of the base premium $p_j$ depends implicitly on $X$, $v^j_t \in R^+$ is an iid shock distributed according to a smooth distribution $G$. Let $\Delta_j(n)$ denote the “penalty”—the increase in the premium after an accident—at $n$ when covered by company $j$ and $P_t = (p^a_t, p^b_t)$ the vector containing the deterministic part of the base premium. Without loss of generality, let $\Delta^a(n) < \Delta^b(n)$ and $p_a > p_b$. These inequalities imply a dynamic tradeoff the policyholder faces when choosing the company: a low base premium versus a high marginal increase of the premium if an accident occurs.

The state space at the beginning of each period is represented by $s_t = (P_t, n_t, a_{t-1}, i_{t-1})$, where $i_t \in \{a, b\}$ provides information on the company chosen in the previous period. The timing of the events is as follows. At the beginning of period $t$, conditional on $s_t$, the driver decides to stay with the current company ($c_t = 0$) or switch ($c_t = 1$), and subsequently an effort level $e_t \in [0, \bar{e}]$ is selected. $a_t$ realizes and $n_t$ is updated. At the beginning of year $t+1$ the two random shocks $v^j_{t+1}$ are drawn and $P_{t+1}$ gets updated according to (1); the driver chooses $c_{t+1}$ and $e_{t+1}$ conditional on $s_{t+1}$, and so forth.
The flow utility for an insuree covered by $j$ reads

$$u(\epsilon_t, c_t; n_t) = u(w - h^j(p_j, n_t, v^j_t)) - \theta c_t - \lambda(\epsilon_t)$$  \hspace{1cm} (2)

where $\theta > 0$ captures a switching cost, and $u(\cdot)$ and $\lambda(\cdot)$ are utility and effort disutility functions, respectively. Moreover, $u(\cdot)$ and $\lambda(\cdot)$ are increasing and concave and convex, respectively. Let the accident production function be

$$a_t = f(e_t, a_{t-1}, \epsilon_t; X, \eta) \in \{0, 1\}$$  \hspace{1cm} (3)

where $f(\cdot)$ is decreasing in $e_t$ and increasing in the risk parameter $\eta$; $a_{t-1}$ captures state dependence (SD) and $\epsilon_t$ is a “structural” iid random variable distributed according to a cdf $F$. Let $\Pi(e_t, a_{t-1}) = Pr(a_t = 1|e_t, a_{t-1})$ denote the accident probability. Henceforth to ease notation I will omit the dependence on $(X, w, \eta)$.

To characterize the equilibrium it is useful to define two sequences of company-specific value functions $\langle V^j_t(v^j_t, n_t, a_{t-1}, j) \rangle_{t=1}^T$ for the insuree, where by company-specific value function I mean the value function in case the contractual relationship is renewed at each period ($c_t = 0$ for all $t$). Each sequence can be obtained by proceeding backwards At $t = T$ the value function reads

$$V^j_T(v^j_T, n_T, a_{T-1}, j) = -\lambda(0) + u(w - h^j(p_j, n_T, v^j_T))$$  \hspace{1cm} (4)

where the optimality condition $e_T = 0$ is incorporated in the problem. The generic $t$-period problem is

$$V_t(v^j_t, n_t, a_{t-1}, j) = \max_{e^j_t} \left\langle u(w - h^j(p_j, n_t, v^j_t)) - \lambda(e^j_t) + \beta \Pi(e^j_t, a_{t-1}) E[V_{t+1}(v^j_{t+1}, n_t + 1, 1, j) - V_{t+1}(v^j_{t+1}, n_t, 0, j)] + \beta E[V_{t+1}(v^j_{t+1}, n_t, 0, j)] \right\rangle$$  \hspace{1cm} (5)

where $\beta \in (0, 1)$ denotes the discount factor. Letting $e^j_t(n_t, a_{t-1})$ denote the optimal effort strategy of a policyholder covered by company $j$, the following proposition provides sufficient condition on $h^j$ such that the optimal effort is increasing in the penalty $\Delta^j(n)$.

**Lemma 1.** Let the pricing rule be specified as:

$$h^j(n_t, v^j_t) = p_j + \delta^j_n + v^j_t \ 	ext{for} \ j \in \langle a, b \rangle.$$  \hspace{1cm} (6)

If penalties are increasing in $n_t$ ($\delta_j > 1$), policyholders will drive more carefully as their driving record worsens.
Proof. Given that $\Pi$ is decreasing in $e$ and using the standard monotonicity arguments it is enough to show that

$$V_{t+1}(v_{t+1}^j, n_t + 1, 1, j) - V_{t+1}(v_{t+1}^j, n_t, 0, j)$$

is decreasing in $\delta_j$. Applying the envelope theorem and plugging (6) into the value functions,

$$\frac{\partial V(v^j, n + 1, 1, j)}{\partial \delta_j} < \frac{\partial V(v^j, n, 0, j)}{\partial \delta_j} \iff u'(w - p_j - \delta_j^n - v_j)\delta_j^{n-1} < (n + 1)\delta_j^n u'(w - p_j - \delta_j^{n+1} - v_j)$$

Given the concavity of $u$ the inequality holds if $\delta_j^{n-1} < \delta_j^n$. This condition holds if $\delta_j > 1$. □

The particular functional form in (6) is only assumed for convenience; nevertheless, it provides an acceptable approximation of the most common pricing strategies adopted by the market.\footnote{It can be verified that the lemma holds if the law of motion of the premium were to be specified as $p_t^j = h^j(n_t, v_t^j) = p_j + n_t^\delta + v_t^j$, or if the shock is multiplicative.} Notice that what drives moral hazard is the degree of convexity in $n$, indexed by $\delta$. There is little hope of deriving a testable implication under general conditions if the slope of the premium-driving record schedule is left unrestricted, see Ceccarini (2007).

Given the company-specific value functions, the optimal sequence of switching decisions can be characterized by proceeding backward. At $T$

$$c_T^j(s^j_T) = 1 \iff u(w - h^j(p_j, n_T, v_T^j)) - \theta > u(w - h^k(p_j, n_T, v_T^j)) \text{ with } j \neq k,$$

where $c_T^j(s_T)$ denotes the optimal switching choice; the value function at $T$ for an insuree covered by company $j$ at $T - 1$ can be written as

$$V_T(s_t) = \max_{c_T^j}((1 - c_T)u(w - h^j(p_j, n_T, v_T^j)) + c_T[u(w - h^j(p_j, n_T, v_T^j)) - \theta] - \lambda(0))$$

with $j \neq k$. The value function at $t$ for an insuree covered by company $j$ at $t - 1$ reads

$$V_t(s_t) = \max_{c_t^j}((1 - c_t)V_t^j(v_t^j, n_t, a_{t-1}, j) + c_t[V_t^k(v_t^k, n_t, a_{t-1}, k) - \theta])$$

Abusing notation let $c_t^j(s_t)$ denote the switching strategy of an insuree covered by $j$ at period $t - 1$. Given the monotonicity of $u$ it follows immediately that

$$c_t^j(s_t) = 1 \iff v_k < \tilde{v}_j(p_j, v_j, n_t, a_{t-1})$$

(7)
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where \( \tilde{v} \) is a company-specific critical cut-off. Intuitively, if the premium offered by \( k \) is small enough with respect to \( j \), switching from \( j \) to \( k \) will be profitable despite \( \theta \). This implication will motivate a placebo test I employ to address reverse causality when using the grace period research design.

Letting \( Z = (X, \eta, w) \) and omitting the time indexes, the equilibrium induces a company-specific conditional distribution \( g^j(Z|a,n) \) and a conditional effort strategy \( e^j(n,a|Z) \). Abusing notation, let \( \pi^j(n|a,Z) = \Pi(e^j(n,a|Z)) \) denote the realized, in equilibrium, accident probability for a type \( Z \), in driving category \( n \) and history of accidents \( a \).\(^5\)

The structure now allows me to interpret the behavioral responses observed in the data in terms of meaningful treatment effects resulting from the optimizing behavior of agents.\(^6\) Moral hazard at driving category \( n \) for a type \( Z \) covered by company \( j \) can be defined as

\[
MH^j(n|a,Z) = \pi^j(n+1|a,Z) - \pi^j(n|a,Z) \quad \text{with} \quad n \in \{1, \ldots, N\} \quad (8)
\]

Conceptually, this marginal effect can be thought as the response of a type-\( Z \) when the penalty goes from \( \Delta^j(n) \) to \( \Delta^j(n+1) \). In the absence of moral hazard \( \pi^j(n|a,Z) \) is constant at all \( n \). Thus, moral hazard depends on the individual “responsiveness” to incentives, a parameter determined in equilibrium by the optimal effort, which depends on the primitives—such as \( u(\cdot) \) and \( \lambda(\cdot) \)—and on \( Z \). A company-specific average effect, obtained by integrating over \( g^j(Z|a,n) \), can be defined as

\[
AMH^j(n) = \int \pi^j(n+1|a,Z)g^j(Z|n+1,a) - \int \pi^j(n|a,Z)g^j(Z|n,a) \quad (9)
\]

This expression highlights the nature of the identification problem when drivers sort into companies. For example, if the high-elasticity drivers all sort into company \( a \), having panel data only on company \( a \) may lead one to overestimate moral hazard.

In the presence of random switching this parameter can be identified by applying DPA to a company-specific panel dataset, made up of those who choose company \( j \) at time \( t \) and \( t+1 \). In the presence of non-random switching, a matched

\(^5\)This notation reflects the fact that the driving category \( n \) and the company \( j \) pin down the penalty \( \Delta^j(n) \), the variable on which drivers condition their effort.

\(^6\)Heckman and Vytlacil (2005) provide a bridge between the various treatment effect parameters analyzed in the program evaluation literature.
insurer-insuree panel also allows me to recover the behavioral responses of those who move from company $k$ to $j$, between $t$ and $t+1$

$$AMH^{jk}(n) = \int \pi^j(n+1|a,Z)g^j(Z|n+1,a) - \int \pi^k(n|a,Z)g^k(Z|n,a)$$

(10)

One can define an average treatment effect—the average moral hazard in the market—identifiable through a matched insurer-insuree panel by weighting $AMH^{jj}(n)$—the effect among stayers identified by company-specific panel data—and $AMH^{jk}(n)$:

$$AMH(n) = \sum_{j \in (a,b)} w_{jj} AMH^{jj}(n) + \sum_{j \neq k \in (a,b)} w_{jk}(n) AMH^{jk}(n)$$

(11)

where $w_{jj}$ and $w_{jk}$ represent the proportion of stayers and switchers in driving category $n$.

As it comprises the behavioral responses of all types, $AMH(n)$ measures more accurately how, on average, financial penalties in the market affect the accident probabilities. The formula shows that, in the presence of sorting, the average moral hazard in the market depends on a weighted average of the parameters that previous research identified using company-specific samples, the $AMH^{jj}$'s. It also clarifies that, in the presence of endogenous switching, previous research did not take into account the behavioral responses of policyholders changing companies. Notice that the distinction between average treatment effects among stayers and switchers is not immaterial; in section 11.2 I demonstrate that better types are overrepresented in company-specific panel data because policyholders with a poor driving record are more likely to switch companies.

Summing up, $AMH(n)$ and $AMH^{jj}(n)$ will coincide only if the following assumptions both hold:

**(RS):** $Z$ is randomly distributed across companies at each point in time

**(HP):** pricing is homogeneous in the market, e.g., $\delta_j = \delta$ for all $j$

I now argue that if (HP) does not hold and one is willing to assume that switching companies is partially random, applying DPA to a matched insurer-insuree database also allows me to distinguish moral hazard from state dependence.
State Dependence To distinguish moral hazard from state dependence, a variable shifting $a_{t-1}$ and not $\Delta(n_t)$, or vice versa, is needed. Unfortunately, as $\epsilon_t$ affects both, another source of identifying variation is needed.\(^7\) Now, if (HP) does not hold and drivers are followed over change of companies, the difference in the accident probabilities from $t$ to $t + 1$ among switchers with no change in accident histories can be attributed to moral hazard. Again, the heterogeneity in the slopes of the premium-accident schedules aids the identification problem. This argument rests on the existence of some randomness in the switching decisions. In the simple duopoly model, this randomness is achieved by allowing the base premium to be stochastic. Obviously, it is crucial to assume that $v_i^t$ is i.i.d., namely uncorrelated with $Z$.

2. Institutional Background

Italian law establishes that vehicles must be covered by basic rc auto insurance ("Responsabilità Civile Auto"), a mandatory motor third-party liability insurance contract. The rc auto contract covers damage to third parties’ health and property in accidents where one is not at fault. It is possible to purchase comprehensive insurance contracts to cover one’s own property damage; however, in practice, because of the high cost of insurance, the vast majority of contracts only feature the compulsory coverage.

Henceforth, by accident I mean an accident at fault. Both for historical reasons and because of a peculiar law—if a deductible exists, the insurer must initially refund the entire amount of damage and, subsequently, the policyholder must return it to the company—deductibles are almost always absent.\(^8\) On the other hand, contracts are often characterized by a number of clauses—see section 3—that alter the size of the indemnity and the premium. The law establishes a mandatory minimum of liability coverage ("massimali"): 1 and 6 million euros for property and health damage to third parties, respectively. The policyholder is responsible for any amount exceeding the liability limit. Section 3 shows that many policyholders choose higher coverage than the compulsory liability limits. The owner of the car and the subscriber of the contract typically are the same person and the default length of the policy is one year: contracts that cover

\(^7\) As an alternative, one could exploit unexpected changes over time of the pricing rule. Israel (2004) exploits an “insurance event” implied by the pricing rule of an American company.

\(^8\) Companies discourage deductibles because the legal disputes after drivers refuse to refund the company are costly.
more or less than 12 months are quite rare. Contracts are exclusive and are not automatically renewed at the end of the contractual year.

Each accident is characterized by a percentage of liability ("percentuale di responsabilità"), denoted by \( r \in [0, 100] \). For accidents involving two vehicles there exists “major” liability ("responsabilità principale") if \( r > 50 \) and “equal” liability ("responsabilità paritaria") if \( r < 50 \). A driver is at fault if \( r > 50 \), in which case no indemnity is received; if \( 0 \leq r < 50 \), the indemnity equals \( 1 - r \) times the own damage. For accidents involving more than two vehicles, a driver holds major responsibility if the percentage of fault is greater than that attributed to the other drivers combined. The indemnities in multiple vehicle accidents are also determined according to the proportional criterion.

In Italy, as in many other countries, a uniform experience rating system relates the history of accidents to class of risk, the so-called bonus-malus (bm) class. The bm class is specific to the pair subscriber-vehicle, so if the same individual underwrites multiple contracts to cover multiple vehicles, she may hold different bm classes.\(^9\)

The driving history at the beginning of a new contractual year is summarized by a public certificate, “attestato di rischio” (AR), a paper document that reports the bm class and the number of accidents over the previous five years with major and equal liability (with associated \( r \)). The AR also records the expiration date of the contract, vehicle information, and the level of deductible (if any); companies are free to establish their own system of penalties based on the driving history on the AR. The law prescribes that companies send the AR at least 30 days before the expiration date of the contract; if someone wants to insure a vehicle for the first time or change companies, the AR must be provided to get a quote. The AR is usually received during the last 60 days, when consumers can “shop around” for other contracts and companies.

There are 18 bm classes; class 1 is the best, and class 18 is the worst. New drivers are assigned to class 14. The bm class is updated using the information in the AR according to the rule in table 10: if the malus (bonus) is applied,

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\(^9\)This system is clearly inefficient because the multiple sources of information on individual risk are not aggregated.
the bm class increases (decreases) two (one) categories. The malus is applied if an additional accident with major liability or if multiple accidents with equal liability with cumulative $r > 50$ appear on the AR.

Accidents in the so-called period of observation ("periodo di osservazione") are used to update the bm class and number of accidents on the AR holding at the beginning of year $t$. For vehicles with a sufficiently long insurance history, such a period includes the contractual year $t - 1$ except the last 60 days and the last 60 days of year $t - 2$, about 12 months. For recently insured vehicles, the period of observation is from the first day of year $t - 1$ until 60 days before the expiration date, about 10 months. Therefore, accidents in the last 60 days of year $t - 1$–henceforth the grace period–are not reflected immediately on the AR and only increase the premium in year $t + 1$. As a result, the cost of accidents in the grace period is delayed.

**No news is good news** The delay-rule is enforced after a change of company if the new insurer checks that the AR provided at the beginning of year $t + 1$ reports the whole history of accidents, including those in the grace period of year $t - 1$, covered by a different company. Such scrutiny can be accomplished by consulting a database on claims held by the Italian association of insurers (ANIA). In practice, however, companies rarely do so. This glitch in the system—the “unpleasant” information can be endogenously eliminated by switching companies—generates a shift in the incentives during the contractual year I exploit to identify moral hazard.\(^{10}\)

### 3. Data

The central source of information for this study is a new administrative database—a matched “insurer-insuree” panel—denominated IPER ("Indagine sui prezzi effettivi per la garanzia rc auto"), collected by IVASS ("Istituto di Vigilanza per le Assicurazioni"), the Italian supervisory authority. The data contain information on basic rc auto contracts subscribed by a representative sample—the core sample—of 989,581 individuals, identified by their social security number.

\(^{10}\)IVASS recently implemented the “dematerialization of the AR”, establishing that all the information on the AR will become paperless and stored in a centralized database on claims that companies have to update. The new company will base the premium on the true history of accidents in the observation period.
(SSN), who had one or more auto insurance contracts in 2013. Contracts covering motorcycles and other types of vehicles are excluded. The stratification scheme is non-proportional, in that younger age groups are oversampled. However, the degree of oversampling is very mild: the weighted and unweighted average premiums over the period of observation are 457.7 and 470.2 euros, respectively. More details are in the online appendix.

The main innovation by IPER is in the representation of the “insurance histories” of the core sample. That is, information on the evolution of initial contracts underwritten in 2013 and of new ones subscribed afterward is available; IPER represents the Italian auto insurance market equivalent of the well-known matched employer-employee databases used in the labor literature. Because the unit of observation is the SSN, not the plate-number in the databases used insofar, a variety of dynamics typically absent are represented: switching from one company to another, multiple contracts subscribed by the same individual for the same contractual year, contracts covering new vehicles purchased after 2013, and suspensions in the coverage period of a given vehicle. The representativeness of the sample constitutes a notable advantage over all previous empirical papers on auto insurance; information on contracts underwritten by virtually all of the companies operating in the Italian market is available. The number of companies subscribing contracts varies over time because of mergers, ranging from 49 in 2014-2015 to 37 in 2017-2018. The estimating sample is large: there are 4,316,667 contracts identified by a pair SSN-plate number covering at most five years, from 2013 to 2017:Q1.

**Patterns** Table 1 shows the number of contracts and policyholders at each contractual year. For 2017 only contracts underwritten in the first quarter are available. As can be inferred by comparing the total number of contracts with the number of subscribers, about 11 to 15 percent of the core sample covers more than one car across the first four contractual years. Interestingly, about 30 percent of multiple subscribers purchase insurance from multiple companies.
Table 2. Availability of Contracts

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>527,468</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>❌</td>
</tr>
<tr>
<td>136,069</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>127,199</td>
<td>✓</td>
<td>❌</td>
<td>❌</td>
<td>❌</td>
<td>❌</td>
</tr>
<tr>
<td>16,533</td>
<td>✓</td>
<td>✓</td>
<td>❌</td>
<td>❌</td>
<td>❌</td>
</tr>
<tr>
<td>118,036</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>❌</td>
<td>❌</td>
</tr>
<tr>
<td>87,083</td>
<td>❌</td>
<td>❌</td>
<td>❌</td>
<td>✓</td>
<td>❌</td>
</tr>
<tr>
<td>75,466</td>
<td>❌</td>
<td>❌</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>38,573</td>
<td>❌</td>
<td>✓</td>
<td>✓</td>
<td>✓</td>
<td>❌</td>
</tr>
<tr>
<td>29,688</td>
<td>❌</td>
<td>❌</td>
<td>❌</td>
<td>✓</td>
<td>✓</td>
</tr>
<tr>
<td>16,375</td>
<td>other patterns</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. This table describes the dynamics of contracts in IPER.

There is some attrition, both as a consequence of the aging process of the individuals in the core sample and because of the economic cycle: during recessions car usage is reduced in favor of public transportation, and insurance contracts are less likely to be renewed.

Table 2 describes the most common histories in the data; 136,069 contracts are available for all five contractual years, and 527,468 contracts are available for the first four contractual years. 29,688 contracts are subscribed for the first time in 2016 and renewed in 2017, reflecting the coverage of new vehicles.

Driving record and other characteristics The data contain the typical variables used by insurers for pricing: age, gender, province of residence, and characteristics of the car, including the car’s age, power in KW, cubic cylinder, and type of power source (16 mutually exclusive categories). The information on the driving record–bonus-malus class and number of accidents at fault during the past five years–is also available. IPER also contains the altimeter zone group of the city of residence and variables related to its geomorphological classification.

Contracts IPER provides information on the yearly premium paid and, if the contract was not subscribed online or by phone, on the discount applied
by the agent. The number of installments in which the premium is divided—
anecdotal evidence suggests that such a variable is correlated with wealth—is also reported. Although, as explained in section 2, very few contracts feature a deductible, the data contain information on its presence and amount as well as detailed information on several common clauses, generating nine additional variables. Clauses play a major role in screening consumers—a second-degree price discrimination—in highly regulated insurance markets in which insurance is mandatory, such as the Italian market. In estimation, they act as a sufficient statistic for the unobserved component of risk.

Among the additional types of information on the contractual relationship, it is worth mentioning the upper limit on the amount the company will pay for accidents at fault (labeled coverage) and whether the coverage equals the minimum mandatory liability limit of 6 million (1 million for property damage and 5 million for health damage); in addition, there is information on whether the clause “risarcimento in forma specifica” exists (if an accident not at fault occurs, the vehicle has to be repaired by a specified list of body shops). Furthermore, information on the so-called driving clause is reported; in essence, this clause makes the indemnity a function of the identity of the driver. For example, the “free driving clause” does not condition the size of the indemnity on the person driving. Importantly, it is reported whether there are other clauses on the contract that increase the base premium beyond those explicitly asked about. This dummy variable helps to control for unobserved features of the contract. The interested reader can find a detailed description of the available clauses in the online appendix. These variables are new in the literature; typically, the data include only the premium and the deductible.

**Claims** The “Banca Data Sinistri” (BDS), containing information on the universe of claims filed in the market, has been used to complement the data on claims. Specifically, each pair SSN-plate number of the core sample has been matched with the BDS to gather information on the first three accidents (in chronological order) filed within a contractual year. Information on the date of the accident, when the claim has been filed, and the size of the damage

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11 About 88 percent of contracts are underwritten through an agent/broker. If this is not the case, the discount is, by definition, zero.

12 In an ongoing work with Gaurab Aryal, the role of the clauses in shaping the choice of the contract of the company is examined.
has been obtained. It is also known whether the refunding procedure has been terminated, e.g., the claim is not on-hold. Table 3 describes the distribution of claims per contractual year; the probability of being responsible for one or more claim in the first and second contractual year is 5.13 percent, and 5.27 and 4.65 in the third and fourth contractual year. Being responsible for more than one accident within the same year is a very low probability event.

Table 3. Distribution of the Number of Claims in IPER

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>0 claims</td>
<td>94.87</td>
<td>94.87</td>
<td>94.73</td>
<td>95.35</td>
<td>97.85</td>
</tr>
<tr>
<td>1 claim</td>
<td>4.80</td>
<td>4.81</td>
<td>4.97</td>
<td>4.41</td>
<td>2.09</td>
</tr>
<tr>
<td>2 claims</td>
<td>0.28</td>
<td>0.28</td>
<td>0.27</td>
<td>0.22</td>
<td>0.05</td>
</tr>
<tr>
<td>3 or more claims</td>
<td>0.04</td>
<td>0.03</td>
<td>0.03</td>
<td>0.02</td>
<td>0.00</td>
</tr>
<tr>
<td>Number of contracts</td>
<td>1,111,285</td>
<td>1,012,726</td>
<td>979,395</td>
<td>975,937</td>
<td>237,304</td>
</tr>
</tbody>
</table>

Note. In this table the proportion of contracts involving a given number of claims is reported. Sampling weights have not been used.

Given the time span covered by the BDS and the fact that accidents can be filed after the end of the contractual year, only the claiming history of the contracts covering the first three contractual years and the first quarter of the fourth year can be considered complete.

3.1. Descriptive Statistics. Figure 1 depicts the density of the premium in the Italian market from 2013 to 2017:Q1: it is right-skewed and unimodal. The mean premium—457 euros—is among the highest in Europe and is such that the compulsory insurance coverage is in the top 10 most expensive items purchased by Italian households. The statistics of the premium, in table 4, show that the mean and the median differ by about 48 euros, 5/50 percent of the policyholders pay less than 227/422 euros, and 5 percent are charged more than 876 euros. The standard deviation is about 216 euros. A simple OLS regression of the premium on the variables related to the expected cost of the insuree—section 4 describes the specification of a hedonic premium regression—yields an $R^2$ of about 0.5. Therefore, half of the variability is left unexplained.

As can be seen from figure 2, the Italian market is quite concentrated. The first five companies cover 24.59, 12.14, 10.9, 5.13, and 4.81 percent of the market, accounting for 57.5 percent of the market. The first 10 and 20 companies hold
Figure 1. Premium

Note. This graph depicts a histogram of the premium (in euros) reported on the contracts over the period 2013-2017:Q1. Contracts featuring a premium higher than 2000 euros–3,802 records–have been excluded from the sample used to graph the density. Sampling weights have not been used.

Table 4. Statistics of the Premium

<table>
<thead>
<tr>
<th>5th perc.</th>
<th>25th perc.</th>
<th>Median</th>
<th>75th perc.</th>
<th>95th perc.</th>
<th>Mean</th>
<th>St. dev</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>227.27</td>
<td>325.76</td>
<td>422.26</td>
<td>559.18</td>
<td>876</td>
<td>470.2</td>
<td>216.37</td>
<td>2.10</td>
<td>11.52</td>
<td>4,315,503</td>
</tr>
</tbody>
</table>

Note. This table reports statistics on the premium reported on the contracts over the period 2013-2017:Q1.

about 75 percent and 92 percent of the market, respectively. The Herfindahl-Hirschman index (HHI) over the period considered equals 994.73. The other companies hold negligible market shares ranging from 0.85 to 0.01 percent.\textsuperscript{13} An oligopoly seems the most appropriate model to approximate the market structure.

Tables 12 and 13 present weighted means of several characteristics of the contract, policyholder, and vehicle. Each statistic is available for the market, for the first five largest companies, for the set of medium companies–a company

\textsuperscript{13}These statistics are computed using the sampling weights. The unweighted market shares are very similar.
Note. This graph depicts the market share held by companies over the period 2013-2017:Q1. The market shares are computed without using the sampling weights. Companies are indexed in terms of their market shares from the largest (1) to the smallest.

belongs to this group if its ranking in terms of market share is greater than 5 and smaller than 20–and for the remaining companies, the small companies. For antitrust reasons, it is not possible to exactly rank companies according to their market shares; companies A-D and X-Z in the tables belong to the set of the five largest companies without any ordering.

The average policyholder is 52 years old, and 60 percent of insured drivers are male. The average bm class and number of accidents on record are 1.92 and 0.16, respectively. About 12 percent of policyholders switch companies at the end of the contractual year; the retention rate is higher than other auto insurance markets.\textsuperscript{14} The accident rate across the period—the probability of provoking one or more accidents in a year—is about 5 percent, and the average size of the damage—the indemnity perceived by the third parties—is about 2,145

\textsuperscript{14}Honka (2014) estimates a retention rate of 74 percent in the US market.
Table 5. Transitions in the BM Class and in the Number of Accidents on the AR

<table>
<thead>
<tr>
<th>bm class t</th>
<th>1</th>
<th>2-3</th>
<th>4-10</th>
<th>11-18</th>
<th>acc. on AR t + 1</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>&gt; 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>97.16</td>
<td>2.76</td>
<td>0.07</td>
<td>0.01</td>
<td>0</td>
<td>91.74</td>
<td>2.78</td>
<td>0.07</td>
<td>0</td>
</tr>
<tr>
<td>2-3</td>
<td>48.31</td>
<td>47.99</td>
<td>3.69</td>
<td>0.01</td>
<td>1</td>
<td>18.17</td>
<td>78.15</td>
<td>3.54</td>
<td>0.14</td>
</tr>
<tr>
<td>4-10</td>
<td>0.21</td>
<td>20.41</td>
<td>78.71</td>
<td>0.67</td>
<td>2</td>
<td>4.89</td>
<td>27.89</td>
<td>62.91</td>
<td>4.31</td>
</tr>
<tr>
<td>11-18</td>
<td>0.6</td>
<td>0.09</td>
<td>31.91</td>
<td>67.4</td>
<td>&gt; 2</td>
<td>2.17</td>
<td>9.17</td>
<td>28.91</td>
<td>59.75</td>
</tr>
</tbody>
</table>

Driving Record

To summarize the information on the driving record, I group bm classes in the following categories: class 1, classes 2-3, classes 4-10, and classes 11-18. The majority of drivers—77.84 percent—are assigned to bm class 1, 9.11/11.43 percent to classes 2-3/4-10, and very few—1.62 percent—are in classes 11-18; only 12.24/1.42 percent of policyholders have provoked one/two accidents in the past five years, while driving records with more than two accidents in the past five years are extremely rare. Table 3.1 contains the transitions matrix of the bm class and of the number of accidents on record. The persistence of the bm class—the diagonal—is non-monotonic in the class: those in class 1 at $t$ are very unlikely to move at $t + 1$, while those in class 2 have a 50-50 chance of staying or moving to class 1. For the accidents on record, the higher their number, the lower the persistence. Overall, these patterns indicate that except for the clean record policyholders—bm class 1 and no accidents on record—driving records fluctuate considerably over time.

Variations across companies

The premium varies considerably across companies; it ranges from 378 to 498, and there is no clear correlation with market shares. Age and other observable variables, such as the area of residence, display moderate dispersion in the market. The average number of accidents on record and bm class vary substantially, ranging from 0.18 to 0.12 and from 1.82 to 2.04, respectively. The switching rate varies too and is higher at small and medium companies. Interestingly, despite these differences, the accident rate is quite stable at around 5 percent (panel A of table 13); in contrast, the average size of the damage ranges from 2,014 to 2,308 euros, indicating that the average cost of a contract differs across companies. This aspect is reflected, at least partially, in the differences in vehicle characteristics (panel C of table
The data reveal considerable variability in the observable features of the contracts across companies. For example, 35 (15) percent of policyholders covered by \( X(\mathcal{Z}) \) choose a “black box” clause, while among companies \( W \), the medium companies, and small companies, the proportion is zero, 3, and 8 percent, respectively; analogously, the fraction of contracts in which the “free driving” clause is present ranges from 17 to 70 percent. The heterogeneity in the maximum liability ranges from 6.75 million to 29 million; the fraction of subscribers choosing the minimum mandatory coverage of 6 million varies from 39 to 75 percent. The other clauses also display a conspicuous volatility.

Product differentiation—some companies do not offer some clauses such as the black box—cannot fully rationalize these descriptive statistics. That is, one may argue that drivers sort randomly into companies and that the observed variability in the clauses reflects the different choice set faced by consumers. A counterexample to this narrative is provided by documented variability of the minimum liability coverage—“coverage” and “min coverage” in table 12—a mandatory feature of all contracts. Therefore, the differences in the features of the contracts also reflect the variation of the unobservable preferences for risk across companies, an indication that company-specific samples of contracts are non random.

4. The Effect of the Driving Record on Insurance Rates

Letting \( p_{ijt} \) denote the premium paid by consumer \( i \) for coverage of contractual year \( t \) if covered by company \( j \), consider the following specification of the hedonic premium function

\[
p_{ijt} = c_{jt} + \beta_{2}^{AR} X_{it}^{AR} + \beta_{3}^{BM} X_{it}^{BM} + \beta_{4}^{a} a_{it-1} + \beta_{5}^{Z} Z_{it} + \gamma_{t} + \eta_{i} + \epsilon_{it}
\]

where:

- \( X_{it}^{AR} \) contains oneaccAR and twoaccAR taking value one if one and two accidents are on record, respectively. The omitted category is an indicator taking value one if the insuree has zero accidents on the AR.\(^{15}\) Let \( \beta^{AR} = (\beta_{1}^{AR}, \beta_{2}^{AR}) \) be the vector containing the associated coefficients.

\(^{15}\) Recall that the AR reports accidents at fault over the previous five years. A negligible proportion of policyholders have three or more accidents on record.
• $X_{it}^{BM}$ contains the following indicators for the bm class group: $bmclass_1$ (class 1), $bmclass_{2or3}$, classes 2-3, $bmclass_{4to10}$, and classes 4-10. The omitted categories are classes 11-18. Let $\beta_j^{BM} = (\beta_1^{BM}, \beta_{2-3}^{BM}, \beta_{4-10}^{BM})$ be the vector containing the coefficients associated with the bm class indicator.

• $a_{i,t-1}$ is an indicator taking value one if the policyholder is responsible for one or more accidents in year $t-1$.

• $Z_{it}$ contains the individual and car characteristics, the contractual clauses, province and company dummies, characteristics of the city the subscriber lives in and the number of “installments”.\(^{16}\)

• $c_{jt}$ and $\gamma_t$ are company and contractual year fixed effects, respectively.

The aggregation of different bm classes in the same group is instrumental to precisely estimate the parameters of interest; in fact, a small proportion of drivers is assigned to classes higher than one.

I am interested in identifying $(\beta_j^{AR}, \beta_j^{BM})$, the effect of the driving record on the premium. If the accident does not alter the driving record, the entire effect is captured by $\beta^a$; if it does–section 2 describes when this happens–$\beta^a$ captures the residual effect.

**Penalties** In order to compute the penalties one has to take into account how much the premium increases after an accident—the effect of the malus—relative to the reward for having no accident, the effect of the bonus. For drivers in class one the penalty is computed as $\Delta p_{bm1}^j = \beta_{2-3}^{BM} - \beta_1^{BM}$. Notice that according to the rule in table 11 drivers assigned to class 1 are moved to class 3, if liable of an accident. As the premium monotonically increases in the bm class, $\Delta p_{bm1}^j$ underestimates the penalty because $\beta_{2-3,j} < \beta_{2,j}$. For what concern the penalties for those in classes 2-3,

I refer to the difference $\Delta p_{bm1}^j = \beta_{2-3,j}^{BM} - \beta_1^{BM}–how much the premium changes if one moves from bm 1 to bm classes 2-3—as to the penalty at bm class 1. $\Delta p_{bm2or3}^j = \beta_{4-10,j}^{BM} - \beta_{2-3,j}^{BM}$ and $\Delta p_{bm4to10}^j = -\beta_{4-10,j}^{BM}$ denote the penalty at classes 2-3 and 4-10, respectively. Analogously, $\Delta p_{oneaccAR}^j = \beta_{1,j}^{AR}$ and $\Delta p_{twoaccAR}^j = \beta_{2,j}^{AR} - \beta_{1,j}^{AR}$ measure the increase in the premium if the number of accidents on the AR increases from zero to one and from one to

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\(^{16}\)The greater the number of installments, the higher the premium. This variable is a proxy for wealth.
Table 6 assigns to the following combination bm class-number of accidents on record a driving category identifier.

**Table 6. Driving Record Categories**

<table>
<thead>
<tr>
<th># of Accidents on the AR</th>
<th>BM Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>zero</td>
<td>I</td>
</tr>
<tr>
<td></td>
<td>II</td>
</tr>
<tr>
<td></td>
<td>III</td>
</tr>
<tr>
<td>one</td>
<td>IV</td>
</tr>
<tr>
<td></td>
<td>V</td>
</tr>
<tr>
<td></td>
<td>VI</td>
</tr>
</tbody>
</table>

I construct indicators for each of the six combinations, which I use as controls. The omitted category—the combination of two or more accidents on record interacted with bm classes 11-18—includes the poorest driving records. Policyholders in category I have a clean record, as they have no accidents on the AR and are assigned to bm class 1. The occurrence of an accident moves those policyholders to V, with an increase in the premium equal to the penalty at bm class 1 plus the penalty for having one accident on record ($\Delta p_{bm1} + \Delta p_{oneaccAR}$).

If companies adopt a nonlinear pricing scheme—the amount the premium increases depends on the driving category—these coefficients are expected to be statistically different.

**Omitted Variables** One could think of $\eta_i$ in terms of unobservable vehicle characteristics, such as car value and the presence of an airbag, as well as individual characteristics such as marital status, occupation, zip code, and number of children over 18 living in the household used for pricing and absent in the data. While it is unlikely that any dataset could include all variables used for pricing, IPER contains a richer set of variables, such as the contractual clauses, than analogous datasets used insofar. $\eta_i$ could also be interpreted as the policyholder’s ability to negotiate good prices. This source of unobserved heterogeneity is relevant because agents enjoy a relative amount of discretion in applying discounts to reach sales targets. As the plain OLS estimator delivers downward (upward) biased estimates of $\beta^{AR}$ and $\beta^{BM}$, it is crucial to control for unobserved heterogeneity. Data limitations have prevented to do so in some previous work.

**Identifying variations** The longitudinal aspect of the data allows me to eliminate $\eta_i$ by means of the traditional fixed-effect transformations. Under the
assumption that $\eta_i$ is uncorrelated with the number of contracts subscribed, the cross-sectional variation among the multiple subscribers further allows me to net out $\eta_i$. Along the same lines, the company-specific parameters are identified by the information from the switchers and from the fraction (about 30 percent) of multiple subscribers purchasing insurance with different companies.

4.1. Results. Table 14 contains the estimates of the specification in (12), using as a dependent variable the premium in logs (panel A) and in levels (panel B). Column (1) presents the estimates of a restricted specification in which $\beta_j = \beta$ for all $j$, while columns (2)-(7) contain the estimates of the company-specific parameters of the unrestricted specification.

Having one and two accidents on record generates insurance rate increases of about 11 percentage points and 21 percentage points, respectively, which translates into increases of 56 and 121 euros. Relative to the omitted category—classes 11-18—being in bm class 1, 2-3, and 4-10 implies a discount of 23 percent, 16 percent, and 10 percent, respectively. The associated discounts are 186, 148, and 103 euros. Considering that the average premium over the four contractual years used for estimation is about 457 euros, these numbers suggest that the penalty for careless driving is large. Panels A and B in table 15 translate the estimates of the coefficients of the specification in logs and levels, respectively, into a penalty at each bm class category and number of accidents.

<table>
<thead>
<tr>
<th>Driving Category</th>
<th>Market</th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>Medium</th>
<th>Small</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>94.1</td>
<td>91.01</td>
<td>105.986</td>
<td>98.095</td>
<td>74.512</td>
<td>90.428</td>
<td>99.565</td>
</tr>
<tr>
<td>II</td>
<td>101.41</td>
<td>110.625</td>
<td>109.382</td>
<td>110.648</td>
<td>74.753</td>
<td>92.791</td>
<td>100.662</td>
</tr>
<tr>
<td>III</td>
<td>159.909</td>
<td>167.175</td>
<td>171.01</td>
<td>146.837</td>
<td>110.942</td>
<td>143.604</td>
<td>179.471</td>
</tr>
<tr>
<td>IV</td>
<td>103.047</td>
<td>126.1</td>
<td>88.31</td>
<td>98.317</td>
<td>82.848</td>
<td>93.359</td>
<td>99.249</td>
</tr>
<tr>
<td>V</td>
<td>110.357</td>
<td>145.715</td>
<td>91.706</td>
<td>110.87</td>
<td>83.089</td>
<td>95.722</td>
<td>100.346</td>
</tr>
<tr>
<td>VI</td>
<td>168.856</td>
<td>202.265</td>
<td>153.334</td>
<td>147.059</td>
<td>119.278</td>
<td>146.535</td>
<td>179.155</td>
</tr>
</tbody>
</table>

Note. This table shows the estimated increase in the premium after an accident—the penalties—for each driving category and company. These numbers are computed using the estimates of the penalties at each bm class and number of accidents on record reported in panel B of table 15.
Focusing on the effect on the premium in levels, table 7 translates the penalties at each bm class and number of accidents on record–panel A of table 15–into premium increases after an accident in driving categories I-VI of table 6.

For policyholders with a clean record, an accident implies, on average, a rate increase of $94.1 = 56.2 + 37.89$ euros, the result of the transition from bm class 1 to 2 and of the penalty for having one accident on record. Conditional on the number of accidents on record, the penalty is increasing, indicating that pricing is non-linear and convex in the bm class. The increases in the premium are quite heterogeneous across records, ranging from 94.1 (I) to 168.85 euros (VI).

Figure 7 shows how penalties differ across categories and companies. Companies A and D adopt the toughest/most lenient pricing strategy: the total penalties across driving categories are about 850 and 550 euros, respectively. Companies B and C are quite similar and adopt an intermediate strategy–the overall penalties are about 720 and 711 euros–while the small companies heavily penalize accidents: the sum of the penalties is roughly 760 euros. Conditional on the number of accidents, the higher the bm class, the higher the penalties across companies. This pattern indicates that the heterogeneity in the company’s cost structure plays a more important role when ex-ante risk is high. To further examine whether the differences in the premium-driving category schedules can be characterized by a mechanic company-specific intercept, or whether companies also choose different slopes, figure 8 shows how much the driving category’s penalty contributes to the overall company-specific penalty in percentage points.

Company A penalizes category I less than other companies–the penalty accounts for 11 percent of the total–while those in VI are subject to a rate increase that accounts for 24 percent of the total penalties. At B, the difference in the penalties between categories is more nuanced. Category III shows a marked variability in how much it contributes to the total penalty across categories. Small companies inflict a penalty of about 100 euros in three of six driving categories, a much flatter schedule than company B, for instance.

All in all, the data reveal a rather rich heterogeneity in the slopes, a rich source of identifying variations.
**Sticks and carrots** In an effort to characterize the heterogeneity of penalty structures, companies can be roughly divided in two groups: the “forgiving” companies—C, medium, and small—and the “tit-for-tat” companies, A, B, and D. The former group holds the penalty fairly constant as the number of accidents on record varies, delegating to the bm class the role of the “stick”. The tit-for-tat companies are less forgiving: prices are convex both in the bm class and in the number of accidents on record.

This heterogeneity leads one to expect that certain patterns would arise, such as high-risk types choosing the forgiving companies. These kinds of sorting behaviors are the ones researchers need to worry about when using company-specific samples.

To summarize, two main messages arise: 1) financial penalties are substantial, and 2) the “treatments” are quite heterogeneous. As a consequence, even if drivers sort randomly into companies having access to company-specific sample of contracts does not necessarily allow the researchers to conduct “valid” inference. I now examine the relationship between driving records and accident probabilities.

5. The Effect of the Driving Record on the Accident Probability

It is useful to apply the estimates of penalties in table 7 to illustrate how the DPA allows me to separate moral hazard from adverse selection and state dependence. Consider a driver with a clean record—bm class 1 and zero accidents on record—covered by company A at $t$ and by company D at $t+1$. If an accident is provoked, the insurance rate increases 91 euros at $t$ and 74 euros at $t+1$. Because the history of accidents and the driving record are left unchanged, under moral hazard, the incentives to drive safely are higher in period $t$ than in period $t+1$. To test these predictions, let $a_{ijkt}$ be a dummy taking value one if driver $i$ assigned to driving category $k$, with $k \in \{I, \ldots, VI\}$, is responsible for one or more accident during year $t$ while being covered by company $j$, and consider the following specification of the accident probability

$$
Pr(a_{ijkt} = 1) = \Phi(c_j + \alpha_{jk} d_{it}^k + \alpha^a a_{i,t-1} + \alpha^Z Z_{it} + \text{contr. year FE} + \theta_i) \quad (12)
$$

where $d_{it}^k$ is a dummy taking value one if driver $i$ is assigned to a given driving category $k$ at time $t$. The coefficients of interest are the $\alpha_{jk}$’s. Abusing notation, let $p_{jk}$ denote the penalty associated with driving category $k$ at company $j$. 
Under the null of no moral hazard, $\alpha_{jik} = 0$ for all $k$. That is, once risk is taken into account, the bm class should be inconsequential for the accident probability. On the contrary, lemma 1 implies that

$$
(1) \quad p_{jk} > p_{jh} \Rightarrow \alpha_{jik} < \alpha_{jhk} \quad \text{for all } k \neq h \\
(2) \quad p_{jk} > p_{hk} \Rightarrow \alpha_{jik} < \alpha_{hk} \quad \text{for all } j \neq h
$$

That is, (1) and (2) allow me to infer moral hazard from the behavioral responses across driving records within companies and from within driving records across companies, respectively. The within and across variations can be combined to examine whether the overall relationship in the market between penalties and accident probabilities is negative, evidence of “market” moral hazard.

**Results** My benchmark specification is a linear probability model, allowing for a direct computation of the marginal effect of the driving record. As the presence of the lagged outcome variable in the conditioning set is such that the standard within-group (WG) transformations do not eliminate the fixed effect when the covariates are only predetermined and not strictly exogenous, I also use the estimator proposed by Arellano and Bond (1991) (AB). Panels A and B of table 16 present the estimates obtained by the WG estimator and the AB estimator, respectively. The estimates obtained by the fixed-effect logit estimator are in table 17. The coefficients in column (1) of the two tables are obtained by setting $\alpha_{jik} = \alpha_{ik}$ for all $k$ and capturing the average effect in the market of the driving record, while the coefficients in columns (2)-(7) are the estimates of company-specific parameters of the full specification in (12).

The province and company dummies turned out not to be statistically significant across the various estimators, indicating that differences in risk across local markets and companies are fully captured by my controls. Importantly, the lagged outcome variable I control for—a dummy taking value one if the driver had an one or more accidents in the previous year—is statistically significant at the 1 percent level. The coefficients ($\alpha^a$) obtained by estimating the restricted specification with the Arellano-Bond, linear probability model fixed-effect estimator and the fixed-effect logit estimator are at -0.531, -0.378, -4.141, respectively. This evidence of negative state dependence—consistent with Ceccarini (2007)—indicates that neglecting this channel leads to misspecification bias.
Focusing on the average effect of the driving records in the market, all the coefficients of interest are statistically significant at the 1 percent level, regardless of the estimator employed. Thus, the null of no moral hazard can be rejected. Five out of six of the coefficients estimated by means of the WG estimator are higher than the ones I obtain with the AB estimator, my preferred estimator, indicating that the assumption of strict exogeneity is too restrictive. Table 18 contains in a more compact form the association between penalties and accident probability for each driving record and company, conditional on the estimator employed. From panel I, an overall negative association emerges, on average, consistent with moral hazard. Only driving category V–bm class 2-3 and one accident on record makes the pattern non-monotonic, as the associated accident probability (0.269) should be lower than the accident probability of category IV (0.235). However, the penalties of these two driving categories only differ by 7 euros. To better visualize the relationship of interest, figure 9 presents six scatter plots of the pairs’ penalty-accident probability at each driving record category, obtained by the AB estimator. A negative relationship emerges at all of the companies, consistent with implication (1). The scatter plot in figure 10 combines the within and across variations and shows the correlation between all of the estimated penalty-accident probability pairs. Not surprisingly, an overall negative association between penalties and accidents emerges.

Table 19 presents three standard measures of association between the accident probabilities and penalties: the Pearson correlation coefficient ($\rho$), the Spearman’s rank correlation coefficient ($r$), and the Kendall rank correlation coefficient ($\tau$). Panels A, B, and C contain the results using the AB, WG, and FE logit estimator, respectively. Column (1) shows the results using all of the pairs’ penalty-accident probability. Columns (2)-(7) contain the correlations obtained using each set of company-specific penalties; column (8) displays the correlations using the restricted specification (the effect of the driving record on prices is uniform across companies).

The association between the penalties and the accident probabilities is negative irrespective of the measure of correlation and the estimator, for all companies. Focusing on the AB estimator, $\rho$ is estimated to be $-0.408$, while $r$ and $\tau$ are $-0.397$ and $-0.308$ (column (1)). Therefore, unambiguously moral hazard
is at play.

The negative correlation is stronger at company A—\(\rho = -0.801\)—and weakest among the small companies, \(\rho = -0.372\). The variability in the strength of the association points to a certain amount of heterogeneity in the incidence of moral hazard across companies, as predicted by my model.

The validity of the results obtained by applying DPA and exploiting the documented non-linear pricing schemes rests on two main assumptions. First, the AB estimator allows me to fully control for unobserved heterogeneity. Second, policyholders fully optimize on the premium-driving record schedules enforced by companies, e.g., the pricing schemes are “salient”. Given the complexity in some of the schedules, the salience assumption is far from trivial.\(^{17}\) To address these issues, I now examine moral hazard within a research design stemming from an arguably salient mechanism, the grace period.

6. Grace Period

Descriptive Analysis Figure 3—showing the pattern of the hazard rate during the contractual year—provides clear descriptive evidence of moral hazard. The hazard rate at the beginning of the year experiences a 1.5-fold increase by the end of the year. Because some fraction of the population is presumably not aware of the change in the penalties in the last 60 days, the grace period effect actually understates moral hazard.

Because drivers can escape the penalty for accidents during the grace period by switching companies, it is natural to examine how such a decision is related to the pattern of the hazard rate. Figures 4 describes the pattern of the hazard rate for stayers and for switchers. Interestingly, the two curves nearly overlap before the grace period, indicating that switchers’ and stayers’ risk are roughly similar. However, the grace period effect is far more pronounced among switchers—a 3.5-fold increase—a clear sign of an association between the glitch in the system and the switching decisions.

\(^{17}\)The importance of salience has been extensively investigated in public finance. In particular, Chetty (2009) shows that taxes explicitly indicated in the posted prices—more salient taxes—have a larger effect on demand. Finkelstein (2009) examines the role of salience by exploiting the introduction of electronic toll collection.
Unfortunately, because the date on which the driver decided to change companies is not known, one may worry that this pattern is driven by self-insurance (see Elrich and Becker (1972)). In other words, it could be that having an accident during the grace period induces people to switch. This is a confounder because according to the moral hazard story, the casual relationship between the switching decision and accidents in the grace period goes into the opposite direction: anticipating that they can change companies, drivers are more careless. Although these two mechanisms are indistinguishable, notice that the hazard rate increases monotonically during the grace period. If only self-insurance were at play, the hazard rate would exhibit a jump after the grace period and stay flat, as the accident probability only reflects adverse selection. On the contrary, moral hazard can reasonably rationalize the monotonic increase observed in the data. Under the assumption that a roughly constant fraction of drivers decides to change companies at each date, the proportion of “actual” switchers gradually increases over time during the grace period. In the presence of moral hazard, this dynamic selection is such that the average driving effort monotonically decreases over time, consistent with the shape of the hazard rate in figure 4.\textsuperscript{18}

In addition to this informal argument, I will address the reverse causality problem by implementing a placebo test in section 6.3. I now describe my quasi-experimental research design and carry over an event history analysis.

\textbf{6.1. The research design.} Let $G \in \{0, 1\}$ take value one if an accident occurs during the grace period and zero if no accident occurs or if it occurs before the last 60 days; let $c \in \{0, 1\}$ take value one if the policyholder changes company and zero if she stays. Let $\Delta p^i(n)$ denote the penalty inflicted to those in driving category $n$ and covered by company $j$, if an accident occurs. The grace period generates the following research design:

\[
\Delta p^i(n) = \begin{cases} 
\Delta p^i(n), & \text{if } G = 0 \\
\beta \Delta p^i(n), & \text{if } G = 1 \text{ and } c = 0 \\
0, & \text{if } G = 1 \text{ and } c = 1
\end{cases}
\]  

\textsuperscript{18}The peak observed during the last 10 days is consistent with anecdotal evidence suggesting that much of the shopping around happens at the very end of the year.
Accidents during the grace period either cost less because of a discounting effect—if the policyholder stays with the current company—or imply no cost if she decides to change. Either way, in the absence of moral hazard and other time effects, the hazard rate should be constant along the contractual year. In contrast, if policyholders change their driving effort in response to the change in penalties, the hazard rate should increase in correspondence of the grace period.

**Figure 3. Hazard Rate During the Contractual Year**

*Note.* The hazard rate is bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rate. A PWP gap-time model has been adopted to take into account the correlation across multiple accidents.

**Figure 4. Hazard Rate and the Switching Decision**

Smoothed hazard estimates

<table>
<thead>
<tr>
<th>Days Elapsed Since the Beginning of the Contractual Year</th>
</tr>
</thead>
<tbody>
<tr>
<td>270</td>
</tr>
<tr>
<td>95% CI</td>
</tr>
<tr>
<td>stayers</td>
</tr>
</tbody>
</table>

**Note.** The hazard rates are bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rates. A PWP gap-time model has been adopted to take into account the correlation across multiple accidents.

Observe that:

(1) $G$ is uncorrelated with the history of accidents of the previous years and only changes the penalty for accidents within the same contractual year
(2) if $G = 1$ and $c = 1$, penalties for accidents are uniformly zero across insurers

Observation (1) is such that, as in Israel (2004), the grace period generates an “insurance event” that allows me to distinguish state dependence from moral hazard. The idea is that the variation in the penalties within the contractual year is exogenous to the history of accidents. As argued in section 1, variation in the penalties arising from a change in the experience rating class are instead, by definition, correlated with past accidents.

According to observation (2), the research design can be thought as an experiment eliminating all penalties across insurers for a subset of drivers, the switchers. While the argument will be clearer later, for now notice that because in the grace period the heterogeneity of penalties is exogenously removed, differences in the accident rates across companies in the last 60 days must reflect underlying heterogeneity.

6.2. Event history analysis. Let time, a given day of a contractual year, be indexed by $\tau$, with $\tau = 1, \ldots, 365$. Let the “structural” hazard rate of an accident for policyholder $i$, covered by company $k$ at day $\tau$ of a given contractual year be expressed in terms of a proportional Cox hazard model (Cox (1972))

$$
\lambda(\tau|X_{ik}) = \lambda_0(\tau) \exp(\beta X_{ik})
$$

where $X_{ik}$ includes a rich set of controls related to intrinsic risk: the driver and vehicle characteristics, the driving record, company and province dummies, a dummy for whether the driver had an accident the previous year, the features of the contract, and the number of installments. In the absence of confounding external time-effects, the pattern of $\lambda_0(\tau)$—the baseline hazard rate (bhr)—describes how driving effort changes along the contractual year.\footnote{This specification is consistent with a model in which policyholders choose their driving effort on a daily basis, as opposed to the model in section 1 in which the effort decisions are made on an annual basis.}

A natural way to conduct inference is to partition the duration along the contractual year into $J$ intervals with cut-points $0 = \tau_0 < \tau_1 < \cdots < \tau_J = 365,$
where the $j - \text{th}$ interval is defined as $[\tau_{j-1}, \tau_j)$ and to approximate $\lambda_0(\tau)$ by a step function. Operationally, I divide the year into 30-day intervals until day 270, and the remaining fraction of the contractual year as follows: $[270,305]$, $[305,335]$, and $[355,365]$, a total of 12 intervals. I denote by $\lambda_j$, with $j = 1, \ldots, 12$, the baseline hazard rate in the $j$-th interval and by $\Delta_j = (\lambda_j - \lambda_{j-1})/\lambda_{j-1}$ the percentage change of the $j$-th interval-specific baseline hazard rate with respect to the $j - 1$-th interval. The hazard rate in interval $j$ for a generic contractual year for policyholder $i$ covered by $k$ is as follows:

$$
\lambda_{ijk}(\tau | \tau_{j-1} \leq \tau \leq \tau_j) = \lambda_j \exp(\beta X_{ik})
$$

with $j = 1, \ldots, 12$. This model is known as the piecewise exponential model (PEM)–see Friedman (1982)–because the distribution of the survival time within any interval is exponential, implying an interval-specific constant hazard rate $\lambda_j$. The large number of contracts available is instrumental to precisely estimate the $\lambda_j$’s in 30-days intervals, allowing a flexible approximation of the baseline hazard rate. The jumps in the hazard rate are interpreted as the effect of the shift in incentives caused by the grace period. Later on, I will more formally define my test of moral hazard and how measure it.

**Multiple events** Although having more than one accident in a year is an extremely rare event (see table 3), the econometric model has to accommodate possible repeated events–multiple accidents in a year–and the possible state dependence between them. I do so by relying on variance correction methods. The idea underlying these models is to use the non-independence of the events to correct for the standard error of the estimates. The sequential nature of the events naturally falls into one of those models, the conditional risk set model, proposed by Prentice, Williams, and Peterson (1981) (PWP). The assumption

---

20 Using a finer grid would make the estimation computationally harder. In fact, to estimate PEM in STATA the original dataset needs to be transformed into a “derived” dataset through the command *stsplit*. The finer the grid, the larger such a dataset. Intuitively, each “subject” is associated with a number of rows proportional to the number of intervals. The derived dataset using the three contractual years and the 30-days grid is approximately 90 GB.

21 My approach is analogous to Meyer (1990), who studies the effect of unemployment benefits on the duration of unemployment, and to Finkelstein and Poterba (2004), who adopt a PEM to examine the annuitant survival rate after purchasing an annuity.

22 Cleves (2000) describes the various methods to model repeated events and how to implement them in Stata. Box-Steffensmeier and Zorn (1982) provides a survey on variance-correction models.
is that an observation is not at risk for a later event until all prior events have occurred. Thus, the conditional risk set at day $\tau$ for accident $k$, with $k = 1, 2, 3$, is made up of all drivers under observation at day $\tau$ that have had accident $k - 1$ or no accident. There are two variations to this approach: time from entry and time from previous event (the so-called gap time model). In the first variation, time to each event is measured from entry time, and in the second variation, the gap time model, the duration of the $k^{th}$ accidents is measured from the the date of the $k - 1^{th}$ accident (see section 3.2.3 of Cleves (2000)). I adopt the gap time approach; nevertheless, the shape of unconditional hazard arising from the two models turns out to be nearly identical.

My estimating sample is represented by all contracts covering the first three contractual years; I excluded contracts covering the fourth and fifth years to minimize the bias arising from the incompleteness of the history of accidents. As contracts covering different time periods are pooled together, the estimated $\lambda_j$'s are an average of the year-specific $\lambda_j$'s. By doing so, to the extent that they differ across contractual years, I minimize the bias from confounding external time effects, such as the trend of the aggregate accident rate.

To correctly interpret the results, it has to be taken into account that accidents that occur right before day 305—in the ninth month of the contractual year—are also less likely to appear after switching. This is because companies have little time to update the information and print and mail the driving record. To incorporate this aspect into the analysis, I define the average moral hazard as $AMH = (\lambda_{12} - \lambda_9)/\lambda_9$. The definition captures the “fixed-effect” idea underlying DPA: comparing the hazard rate at different points in time allows one to net out the time-invariant component of risk. The estimate of $\lambda_{12}$—the baseline hazard rate of the last month—captures the effect of moral hazard at a time in which incentives to drive safely are the weakest. $\lambda_9$—my reference point—reflects the average driving effort when the benchmark penalties are enforced. The relatively short time period—three months—allows me to further minimize

---23The grace period is not, stricto sensu, a regression discontinuity design, as there is no random assignment around the critical date. However, this aspect makes my identification strategy similar to a fuzzy regression discontinuity design in which the number of elapsed days represents the running variable and the outcome variable is the probability that an accident appears on record.
the bias arising from other confounding factors related to time, such as learning.

**Testing and Measuring** If one is interested only in checking for the presence of moral hazard, the null hypothesis $H_0: AMH > 0$ against $H_A: AMH = 0$ can be tested using the all sample, containing contracts underwritten by both stayers and switchers. However, if one wants to interpret $AMH$ as true measure of moral hazard, pursuing this strategy can be misleading because stayers and switchers face a different set of incentives. Arguably, switchers respond to a more sizable change in the monetary incentives. Furthermore, the interpretation of $AMH$ is more transparent: the percentage change in the hazard rate when the penalty drops from its baseline to zero. To the extent that stayers and switchers systematically differ in their characteristics, one may worry that focusing on switchers might generate sample selection bias.

To investigate the presence of selection on observables, I estimate the following specification:

$$\Pr(s_{ijt} = 1) = \Phi(\beta Z_{ijt}),$$  \hspace{1cm} (16)

where the dependent variable $s_{ijt}$ takes value one if driver $i$ covered by company $j$ during year $t$ changes company at the end of the year, and zero otherwise. $\Phi$ is the CDF of the normal distribution function, $Z_{ijt}$ is a large set of controls—all the covariates in the specification of the premium equation (12)—including the variables related to the driving record, individual and car characteristics, features of the contract, province and company dummies and time fixed effects. I then predict, using an estimating sample of 2,736,518 records, the switching probabilities, i.e., the individual propensity score $\hat{p}_i$. Figure 5 shows the density of the propensity scores for the two groups. It can be noted that the distribution of the propensity score for switchers has a fatter tail.

Table 8 contains some statistics of the distribution of $\hat{p}_i$ for stayers and switchers. The difference in the average propensity score is of 3 percent and is higher for switchers; overall, the percentiles of the distribution are not far from each other and are higher for switchers. Therefore, the differences in the statistics between the two distributions are modest.

Another valid concern is that relevant unobservable factors, such as risk and risk aversion, also differ in the two groups. If so, these factors affect both the
Figure 5. Density of the Propensity Score

Note. This graph shows the density of the predicted probabilities of changing companies for stayers and switchers, using the specification of the accident probability in equation (21).

decision to change companies and the event of an accident. As in Chiappori and Salaniè (2000), I estimate a pair of probits

\[ a_{ijt} = \mathbb{I}[Z_{ijt}\beta + u \geq 0] \]
\[ s_{ijt} = \mathbb{I}[Z_{ijt}\gamma + v_i \geq 0] \]

where \( \mathbb{I}[\cdot] \) is the indicator function and \( a_{ijt} \in \{0, 1\} \) is a dummy taking value one if one or more accidents occur during year \( t \), and zero otherwise. \( s_{ijt} \in \{0, 1\} \) takes value one if the policyholders switches companies, and zero otherwise. \( Z_{ijt} \) is a vector containing the same set controls I employ to estimate the Cox model specified in (15), and \( u \) and \( v \) are normally distributed random error terms with mean zero and variance of one. The coefficient of correlation \( \rho \) conveys information on the extent to which these two events are driven by a common component of the unobservables.

Using a sample of 2,538,093 contracts covering the first three contractual years, I obtain \( \hat{\rho} = 0.02 \), the standard error is 0.008 and the 95 percent confidence interval is \([0.001; 0.012]\). The statistically significant but nearly zero correlation between \( u \) and \( v \) suggests that stayers and switchers are roughly
### Table 8. Statistics of the Distribution of the Propensity Scores

<table>
<thead>
<tr>
<th></th>
<th>5th perc.</th>
<th>25th perc.</th>
<th>Median</th>
<th>75th perc.</th>
<th>95th perc.</th>
<th>Mean</th>
<th>St. dev</th>
<th>Skewness</th>
<th>Kurtosis</th>
<th>N</th>
</tr>
</thead>
<tbody>
<tr>
<td>Stayers</td>
<td>0.06</td>
<td>0.09</td>
<td>0.12</td>
<td>0.16</td>
<td>0.23</td>
<td>0.13</td>
<td>0.05</td>
<td>1.34</td>
<td>8.72</td>
<td>2,379,070</td>
</tr>
<tr>
<td>Switchers</td>
<td>0.07</td>
<td>0.11</td>
<td>0.14</td>
<td>0.19</td>
<td>0.28</td>
<td>0.16</td>
<td>0.08</td>
<td>3.36</td>
<td>27.15</td>
<td>357,448</td>
</tr>
</tbody>
</table>

*Note. This table reports descriptive statistics of the distributions of the propensity score for stayers and switchers, depicted in figure 5.*

...similar in terms of unobservables.

All in all, given this evidence and considering that the hazard rates before the grace period are nearly identical (see figure 4) I will the regard the estimate of AMH using the sample of switchers—a “valid” sample—as my preferred measure of moral hazard.

**Baseline Results** The estimates of the logarithm of interval-specific baseline hazard rates obtained by estimating a piecewise exponential model are in table 21. The parameters are precisely estimated, and all are statistically significant at the 1 percent level. Figure 6 shows the pattern of the estimated baseline hazard rates for stayers and switchers.

Table 20 provides more details on the pattern of the bhr and presents the estimates of the $\hat{\Delta}_j$’s. Columns (4)-(6) report the p-values of the test of the null hypothesis that each jump is equal to zero. Focusing on the all sample, the baseline hazard rate is quite flat until the last month—$\hat{\Delta}_{12}$ is statistically significant at the 1 percent level and is estimated at 16 percent. Therefore, driving effort mostly decreases during the last 30 days. AMH using the all sample is estimated to be 21 percent and is statistically significant at the 1 percent level. Therefore the hypothesis of moral hazard cannot be rejected.

Interestingly, the baseline hazard rate among stayers is higher than switchers in the first eight months: the percentage difference ranges from 7 percent (eighth month) to 33 percent (third month), and the two curves overlap at the ninth month—the bhr among stayers is only 4 percent higher—when the
expected penalties change. From the 10th month on, risk among switchers increases dramatically and the percentage differences becomes negative: $-15$, $-26$, and $-51$ percent in months 10, 11, and 12, respectively. As a result, $\hat{\Delta}_{10}$, $\hat{\Delta}_{11}$ and $\hat{\Delta}_{12}$ are statistically significant at the 1 percent level and are estimated to be 20, 14, and 57 percent. In contrast, the baseline hazard rate of stayers is roughly flat with an increase of 4.81 percent during the last month.

The AMH for stayers and switchers are estimated at 2.84 and 116 percent, respectively. Thus, when policyholders face no financial penalty, they dramatically lower their driving attentiveness.

6.3. Reverse Causality. To overcome the reverse causality problem—the increase in the hazard rate might be due to policyholders changing companies after an accident in the grace period (self-insurance) and not moral hazard—I hinge on the intuition of the switching rule in (7) of the model described in section 1 to construct a placebo test. The idea is that, from an ex-post prospective, policyholders who received the more attractive outside offers—the sample of “lucky” switchers—would have changed companies regardless of whether an accident occurred during the grace period. Evidence of a grace period effect even among this subset of people—for whom there is no causal effect of accidents in the grace period on the decision to switch—can be attributed to moral hazard.

The main identifying assumption is that the arrival rate of outside options is random. Clearly, if drivers who provoke an accident during the grace period search more intensely for outside options, it is also more likely that they obtain an attractive offer and switch companies. In this case, the change in the premium upon switching—my instrument to identify the lucky switchers—is correlated with the number of accidents in the grace period no matter what.

In order to identify the set of “self-insurance free” policyholders, I adopt the following procedure. First, I estimate by OLS, using the sample of switchers, the following specification:

$$\Delta \log(p_{ijt}) = \beta \Delta X_{ijt} + \epsilon_{i,t}$$  \hspace{1cm} (17)

where $\Delta$ denotes the first difference operator and $X_{ijt}$ is the set of variables I control for in my hedonic premium regressions specified in section 4. I then use the estimates to predict $\hat{\epsilon}_{i,t}$, the part of the percentage change in the price
Table 9. Average Moral Hazard Across Groups of Switchers

<table>
<thead>
<tr>
<th>AMH</th>
<th>All</th>
<th>G10</th>
<th>G20</th>
<th>G30</th>
<th>G50</th>
<th>G70</th>
<th>G80</th>
<th>G100</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>116.41</td>
<td>182.92</td>
<td>149.93</td>
<td>146.70</td>
<td>151.68</td>
<td>101.98</td>
<td>94.25</td>
<td>77.89</td>
</tr>
<tr>
<td>av. % ch. in cond. premium</td>
<td>0</td>
<td>-0.46</td>
<td>-0.24</td>
<td>-0.14</td>
<td>-0.04</td>
<td>0.06</td>
<td>0.15</td>
<td>0.33</td>
</tr>
<tr>
<td>average penalty</td>
<td>106.85</td>
<td>108.28</td>
<td>108.01</td>
<td>107.41</td>
<td>106.97</td>
<td>106.29</td>
<td>105.61</td>
<td>106.22</td>
</tr>
</tbody>
</table>

Note: The values of AMH are computed using the estimates of the interval-specific baseline hazard rates ($\lambda_j$) obtained by fitting the Cox model specified in equation (15) on each G-group. The estimates are presented in table 22. The last row is the mean of $\hat{\epsilon}_{it}$ in the group, the fitted residuals obtained after estimating the model specified in (17). The average penalty for each group is computed using the market (average) penalty at each driving category presented in panel A of table 7 (first column). Each penalty is weighted using the group-specific proportion of drivers in the corresponding driving category.

unexplained by changes in the risk factors, e.g. clauses and time varying variables, such as age or province of residence. Finally, I use the percentiles p10, p20, p30, p50, p70, and p80 of the distribution of $\hat{\epsilon}_{it}$ to identify the groups ($G_{10}, G_{20}, \ldots, G_{80}, G_{100}$): a switcher belongs to G10 if $\hat{\epsilon}_{it} \leq p_{10}$, to G20 if $p_{10} \leq \hat{\epsilon}_{it} < p_{20}$ and so forth, up to G100, in which case $\hat{\epsilon}_{it} > p_{80}$.

Policyholders in the group G10–characterized by the greatest percentage reduction in the premium are unlikely to have switched because of accidents in the grace period of year $t - 1$, according to my argument, and can be used to run my placebo test.

I fit the Cox model specified in (15) on each $G$-sample and recover the baseline hazard ratio for the different groups of switchers. The estimates are presented in table 22 in the online appendix. The estimates of AMH across the different groups are in table 9; the last two rows describe the average percentage change in the conditional premium—the average of $\hat{\epsilon}_{it}$ for each group—and the average penalties. This latter statistic is computed using the information on the penalty for each driving category–panel A of table 7–weighted by the fraction of policyholders in each driving category and G-group.

As one would expect, a positive relationship between AMH and the percentage reduction in the premium emerges: the grace period effect appears to be stronger when it is less likely to be due to self-insurance. For policyholders in
group G10, the elimination of the average penalty of 107 euros generates, on average, an increase in the hazard rate of 183 percent: a 1 euro decrease in the penalty roughly translates into a 2 percent increase in the hazard rate, a 2.8-fold increase of $\lambda_{12}$ with respect to $\lambda_9$. This rather large elasticity suggests that the estimate of AMH using all of the switchers—116.41 percent—is a lower bound of the actual effect. In other words, self-insurance attenuates my estimate of moral hazard.

6.4. Variations across companies. Consider the following specification for the hazard rate in the interval $j$ for a policyholder $i$ covered by company $k$:

$$
\lambda_{ijk}(\tau|\tau_{j-1} \leq \tau \leq \tau_j) = \lambda_{jk} \exp(\beta X_{ik})
$$

where the company-specific hazard rate captures the heterogeneity of moral hazard. The point estimates of the company-specific hazard rates using the all sample and the switchers are in tables 23 and 24, respectively, of section 13 of the online appendix. Figure 11 shows the estimates of the company-specific baseline hazard rates obtained using the sample of switchers.

Interestingly, the baseline hazard rate of the small companies is roughly three-fold that of the first four companies and the set of medium companies. The patterns appear quite similar in that the baseline hazard rate increases monotonically, with the notable exception of company D, for which the baseline hazard rate decreases between intervals 10 and 11. Table 10 presents the results on the magnitude of AMH across companies for the switchers (panel A) and the full sample (panel B). While the differences using the all sample are mild—AMH ranges from 18.06 to 28.92—there exists ample heterogeneity when the sample of

| Panel A: Switchers | | | | | | |
|---|---|---|---|---|---|
| AMH | 113.19 | 170.20 | 122.11 | 188.35 | 99.97 | 103.40 |
| $\lambda_{12}/\lambda_{12}^{\text{medium}}$ | 1.052 | 1.669 | 1.229 | 1.468 | 1 | 1.923 |

| Panel B: Full Sample | | | | | | |
|---|---|---|---|---|---|
| $100 \times [\lambda_{12} - \lambda_9]/\lambda_9$ | 21.29 | 28.92 | 21.17 | 19.24 | 20.68 | 18.06 |

Note: Panel A and B report the values of AMH among switchers and in the full sample. AMH is computed by fitting the Cox model specified in (15) using the two samples. The estimates of the baseline hazard rates for the all sample and for the sample of switchers are presented in tables 23 and 24, respectively.
switchers is employed. AMH ranges from 99.97 (medium companies) to 188.35 percent (company D).  

This empirical result—the magnitude of the moral hazard varies across companies—implies that having access to a representative sample is key to obtaining unbiased measures of the average effect of moral hazard. The econometric analysis supports the hypothesis that the conflicting evidence in the literature (see Cohen and Siegelman (2010)) is due to data limitations rather than to the “institutional” aspect of the market under examination.

**Heterogeneity or Incentives?** The differences in the estimated AMH across companies can result from two effects. The first effect is driven by heterogeneity; drivers sort into companies based on unobservable preferences for risk generating different behavioral responses to the grace period. The second one has to do with the different structure of penalties faced by drivers across companies, conditional on their type. A rigorous assessment of the relative importance of these two factors requires the estimation of a structural model. While this exercise is beyond the scope of the paper, it is still possible to provide a back of the envelope calculation of the importance of the first effect. Under the assumption that most policyholders have decided on the company before the last 30 days of the coverage period, observation 2) implies that $\hat{\lambda}_{12,j}$ is a sufficient statistics of the company-specific average risk ($\eta$). This is because, conditional on switching, effort level is at its minimum in response to the no-penalty regime. The second row of panel A of table 10 presents the company-specific $\hat{\lambda}_{12}$, normalized by the estimated value at the medium companies, the smallest one in the set. Differences are important—for example average risk at the small companies is nearly twice than at medium companies. The estimates suggest the following ranking of companies in terms of risk: Small Companies $> B > D > C > A >$ Medium. When compared to the ranking of companies in terms if AMH—the first row of table A of table 10—one can see that the correlation between moral hazard and unobservable risk preferences

---

24 I also estimated the model specified in equation 15 on each company-specific sample. The results coincided with those in table 10.

25 In an ongoing work with Gaurab Aryal, the self-selection mechanism into companies is examined from the theoretical and empirical point of view.

26 An additional mild assumption for this argument to be valid is that the effort level exerted for self-protection purposes is homogenous across agents.
is non-monotonic. Interestingly, the realized risk of policyholders covered by small companies is the highest, but AMH is the lowest. These patterns suggest that the company-specific average moral hazard is determined by a non-trivial interaction between selection and the structure of penalties.

7. Conclusions

The literature on the auto insurance market has suffered from severe data limitations, impeding comprehensive empirical assessments of its efficiency. Recognizing this gap, considerable effort and time has been dedicated to collect the data used in this article, a matched insurer-insuree panel. The data are novel along many dimensions, including the size and representativeness of the samples, the richness of the information on the contracts, and the opportunity to follow policyholders after change of companies.

I used the data in this first project, to examine moral hazard in the Italian auto insurance market. I implemented two identification strategies that allow me to distinguish moral hazard from adverse selection and state dependence. This latter confounding factor has typically been neglected by previous work.

The first strategy is inspired by some papers on moral hazard, and relies on the non-linearities—the slopes—of the premium-driving record schedules. The availability of data on premium and driving records reported on contracts subscribed by all the companies in the market allows to recover the financial penalties enforced in the market, a rich set of “treatments”. As a result, the identification power of the traditional strategy is greatly enhanced. I also argue that the information on the insurance histories of those who change companies allows me to control for dependence. Overall, consistent with moral hazard, a negative and heterogeneous—across companies—correlation between penalties and accident probabilities emerges.

The second strategy relies on a quasi-natural experimental research design, generated by a glitch in the Italian experience rating system. I document at the descriptive level a monotonic increase of the hazard rate at the end of the year, the grace period. Consistently with the incentives at stake, the peak is more marked among switchers. The results from the event history analysis confirm
that moral hazard is quantitatively important and heterogeneous across companies. My placebo test to take self-insurance into account—a confounding factor leading to reverse causality—implies that my estimates are likely to represent a lower bound of the overall effect.

The empirical results can be interpreted in light of the model I describe at the beginning of the paper. The model generates sorting within a duopolistic market in which two companies adopt different penalty structures. The self-selection mechanism—driven by the heterogeneity in the slopes of the premium-driving record schedules—generates differential behavioral responses across companies. This framework allows me to relate, using the concepts of the program evaluation literature, the parameter previously identified through company-specific samples to the one I can recover with my representative panel data.

I conclude by arguing that this work sets the stage for a promising and policy-relevant research agenda. Structurally estimating the model I use to specify my econometric relationships is a natural extension of this paper. Enriching the model would allow one to ascertain the importance of the various channels—product differentiation, heterogeneity in the slopes of the premium schedule—in generating the sorting patterns. The data used in this article are also well suited to address other important issues. Among these are the extent of adverse and advantageous selection, the effectiveness of contractual clauses in screening consumers and combating moral hazard, and the relationship between the intensity of competition and the efficiency of the market.
8. Tables

Table 11. Bonus-Malus Class at Year $t+1$ as a Function of the Number of Accidents at Year $t$.

<table>
<thead>
<tr>
<th>Bonus-Malus Class</th>
<th>Year $t$</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4 or more</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>3</td>
<td>6</td>
<td>9</td>
<td>12</td>
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<tr>
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<td>1</td>
<td>4</td>
<td>7</td>
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<tr>
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<td>2</td>
<td>5</td>
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<td>11</td>
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<tr>
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<td>5</td>
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<td>11</td>
<td>14</td>
<td>17</td>
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<td>7</td>
<td>6</td>
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<td>12</td>
<td>15</td>
<td>18</td>
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<tr>
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<td>7</td>
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TABLE 12. Observable Characteristics-I

<table>
<thead>
<tr>
<th></th>
<th>premium</th>
<th>discount</th>
<th>age</th>
<th>accidents on AR</th>
<th>bm class</th>
<th>man</th>
<th>switching rate</th>
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<tr>
<td>Market</td>
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<td>0.16</td>
<td>1.92</td>
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<td>0.12</td>
</tr>
<tr>
<td>A</td>
<td>473.75</td>
<td>115.45</td>
<td>53.15</td>
<td>0.17</td>
<td>1.86</td>
<td>0.59</td>
<td>0.12</td>
</tr>
<tr>
<td>B</td>
<td>498.07</td>
<td>70.55</td>
<td>53.00</td>
<td>0.12</td>
<td>1.82</td>
<td>0.61</td>
<td>0.12</td>
</tr>
<tr>
<td>C</td>
<td>461.16</td>
<td>73.48</td>
<td>52.56</td>
<td>0.16</td>
<td>1.90</td>
<td>0.58</td>
<td>0.09</td>
</tr>
<tr>
<td>D</td>
<td>378.54</td>
<td>106.37</td>
<td>49.61</td>
<td>0.18</td>
<td>1.88</td>
<td>0.63</td>
<td>0.09</td>
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<td>Medium</td>
<td>447.15</td>
<td>88.73</td>
<td>51.07</td>
<td>0.17</td>
<td>2.04</td>
<td>0.58</td>
<td>0.13</td>
</tr>
<tr>
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<td>88.99</td>
<td>51.34</td>
<td>0.16</td>
<td>1.91</td>
<td>0.59</td>
<td>0.15</td>
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Panel B: Clauses and Coverage

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<th></th>
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<th>exclusive dr.</th>
<th>expert dr.</th>
<th>free dr.</th>
<th>coverage</th>
<th>min coverage</th>
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<td>0.42</td>
<td>0.48</td>
<td>13.69</td>
<td>0.65</td>
</tr>
<tr>
<td>I</td>
<td>0.29</td>
<td>0.33</td>
<td>0.02</td>
<td>0.37</td>
<td>0.47</td>
<td>8.71</td>
<td>0.75</td>
</tr>
<tr>
<td>II</td>
<td>0.14</td>
<td>0.72</td>
<td>0.01</td>
<td>0.73</td>
<td>0.21</td>
<td>29.39</td>
<td>0.46</td>
</tr>
<tr>
<td>III</td>
<td>0.19</td>
<td>0.51</td>
<td>0.04</td>
<td>0.22</td>
<td>0.71</td>
<td>6.75</td>
<td>0.81</td>
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<tr>
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<td>0.00</td>
<td>0.00</td>
<td>0.83</td>
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<td>18.35</td>
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<td>0.11</td>
<td>0.39</td>
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<td>0.05</td>
<td>0.28</td>
<td>0.02</td>
<td>0.35</td>
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<th>black box</th>
<th>No. installments</th>
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<td>0.14</td>
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<tr>
<td>X</td>
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<td>0.35</td>
<td>1.46</td>
</tr>
<tr>
<td>Y</td>
<td>0.21</td>
<td>0.06</td>
<td>1.46</td>
</tr>
<tr>
<td>Z</td>
<td>0.02</td>
<td>0.15</td>
<td>1.53</td>
</tr>
<tr>
<td>W</td>
<td>0.28</td>
<td>0.00</td>
<td>1.52</td>
</tr>
<tr>
<td>Medium</td>
<td>0.08</td>
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<tr>
<td>Small</td>
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<td>0.08</td>
<td>1.37</td>
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</table>

Panel C: Car’s Characteristics

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<thead>
<tr>
<th></th>
<th>car age</th>
<th>power</th>
<th>diesel</th>
<th>petrol</th>
<th>cubic cylinder</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market</td>
<td>8.59</td>
<td>66.32</td>
<td>0.43</td>
<td>0.47</td>
<td>14.02</td>
</tr>
<tr>
<td>A</td>
<td>8.65</td>
<td>65.05</td>
<td>0.42</td>
<td>0.47</td>
<td>13.87</td>
</tr>
<tr>
<td>B</td>
<td>8.99</td>
<td>67.15</td>
<td>0.43</td>
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<td>14.23</td>
</tr>
<tr>
<td>C</td>
<td>8.61</td>
<td>65.17</td>
<td>0.39</td>
<td>0.50</td>
<td>13.81</td>
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<td>0.45</td>
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*Note:* This table reports the means of the variables using the sampling weights.
Table 13. Observable Characteristics-II

**Panel A: Accidents**

<table>
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<tr>
<th></th>
<th>size first accident</th>
<th>SOARF</th>
<th>SINDEN</th>
<th>acc. rate</th>
</tr>
</thead>
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<tr>
<td>Market</td>
<td>2145.96</td>
<td>0.04</td>
<td>0.05</td>
<td></td>
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<tr>
<td>X</td>
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<td>0.05</td>
<td></td>
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<tr>
<td>Y</td>
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<td>0.046</td>
<td></td>
</tr>
<tr>
<td>Z</td>
<td>2122.50</td>
<td>0.04</td>
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<td>W</td>
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<td>0.04</td>
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<td>Small</td>
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**Panel B: Local Markets**

<table>
<thead>
<tr>
<th></th>
<th>North-West</th>
<th>North-East</th>
<th>Center</th>
<th>South</th>
<th>Islands</th>
</tr>
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<tbody>
<tr>
<td>Market</td>
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<td>0.21</td>
<td>0.21</td>
<td>0.20</td>
<td>0.10</td>
</tr>
<tr>
<td>A</td>
<td>0.26</td>
<td>0.18</td>
<td>0.20</td>
<td>0.24</td>
<td>0.12</td>
</tr>
<tr>
<td>B</td>
<td>0.25</td>
<td>0.21</td>
<td>0.15</td>
<td>0.28</td>
<td>0.11</td>
</tr>
<tr>
<td>C</td>
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<td>0.23</td>
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<td>0.13</td>
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<td>0.21</td>
<td>0.17</td>
<td>0.10</td>
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<td>Small</td>
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<td>0.26</td>
<td>0.21</td>
<td>0.16</td>
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</table>

**Panel C: Subscriber’s Location Characteristics**

<table>
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<th>non-mountain</th>
<th>partially mountain</th>
<th>totally mountain</th>
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<tr>
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<td>1173.33</td>
<td>0.67</td>
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</tr>
<tr>
<td>Small</td>
<td>1243.17</td>
<td>0.65</td>
<td>0.20</td>
<td>0.15</td>
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</table>

**Panel D: Altimeter Zone**

<table>
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<tr>
<th></th>
<th>internal mountain</th>
<th>coastal mountain</th>
<th>internal hill</th>
<th>coastal hill</th>
<th>lowland</th>
</tr>
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<tbody>
<tr>
<td>Market</td>
<td>0.11</td>
<td>0.02</td>
<td>0.25</td>
<td>0.14</td>
<td>0.48</td>
</tr>
<tr>
<td>A</td>
<td>0.11</td>
<td>0.02</td>
<td>0.25</td>
<td>0.16</td>
<td>0.47</td>
</tr>
<tr>
<td>B</td>
<td>0.12</td>
<td>0.02</td>
<td>0.24</td>
<td>0.16</td>
<td>0.46</td>
</tr>
<tr>
<td>C</td>
<td>0.11</td>
<td>0.02</td>
<td>0.26</td>
<td>0.13</td>
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</tr>
<tr>
<td>D</td>
<td>0.11</td>
<td>0.02</td>
<td>0.29</td>
<td>0.19</td>
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<td>Medium</td>
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*Note: This table reports the means of the variables using the sampling weights.*
Table 14. The Effect of the Driving Record on the Premium

<table>
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<td>-------</td>
</tr>
<tr>
<td>oneaccAR</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>twoaccAR</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>bmclass1</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>bmclass2or3</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>bmclass4to10</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B–Dependent Variable: Yearly Premium</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>oneaccAR</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>twoaccAR</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>bmclass1</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>bmclass2or3</td>
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<tr>
<td>bmclass4to10</td>
</tr>
<tr>
<td></td>
</tr>
</tbody>
</table>

* *, **, and *** denote statistical significance at the 90%, 95% and 99% confidence levels, respectively.

Note: This table reports fixed-effect estimates of $\beta_{AR}^j$ and $\beta_{BM}^j$–the effect of the bm class and of the number of accidents on the AR on the premium—as specified in equation 12. Column (1) contains the estimates of a restricted specification in which $\beta_{AR}^j = \beta_{AR}^j$ and $\beta_{BM}^j = \beta_{BM}^j$ for all $j$. Columns (2)-(7) contain the estimates of the company-specific parameters.

## Table 15. Penalties Across Companies

### Panel A—Penalties in Percentage Points

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
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<tbody>
<tr>
<td>Market</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>Medium</td>
<td>Small</td>
<td></td>
</tr>
<tr>
<td>$\Delta p_{\text{oneaccAR}}$</td>
<td>11.5</td>
<td>10.2</td>
<td>13.2</td>
<td>11.9</td>
<td>6.4</td>
<td>11.9</td>
<td>12.5</td>
</tr>
<tr>
<td>$\Delta p_{\text{twoaccAR}}$</td>
<td>9.5</td>
<td>12.4</td>
<td>7.5</td>
<td>8.5</td>
<td>5.3</td>
<td>9.2</td>
<td>8.4</td>
</tr>
<tr>
<td>$\Delta p_{\text{bm}1}$</td>
<td>6.9</td>
<td>6.1</td>
<td>5.4</td>
<td>6.8</td>
<td>12.4</td>
<td>6.9</td>
<td>7.6</td>
</tr>
<tr>
<td>$\Delta p_{\text{bm}2or3}$</td>
<td>7.1</td>
<td>8.4</td>
<td>5.1</td>
<td>7.5</td>
<td>11.4</td>
<td>6.4</td>
<td>7.0</td>
</tr>
<tr>
<td>$\Delta p_{\text{bm}4to10}$</td>
<td>9.2</td>
<td>9.1</td>
<td>9.9</td>
<td>9.2</td>
<td>8.9</td>
<td>8.7</td>
<td>10.3</td>
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</table>

### Panel B—Penalties in Euros

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Market</td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>Medium</td>
<td>Small</td>
<td></td>
</tr>
<tr>
<td>$\Delta p_{\text{oneaccAR}}$</td>
<td>56.205</td>
<td>51.713</td>
<td>73.118</td>
<td>58.981</td>
<td>23.086</td>
<td>56.441</td>
<td>58.944</td>
</tr>
<tr>
<td>$\Delta p_{\text{twoaccAR}}$</td>
<td>65.152</td>
<td>86.803</td>
<td>55.442</td>
<td>59.203</td>
<td>31.422</td>
<td>59.372</td>
<td>58.628</td>
</tr>
<tr>
<td>$\Delta p_{\text{bm}1}$</td>
<td>37.895</td>
<td>39.297</td>
<td>32.868</td>
<td>39.114</td>
<td>51.426</td>
<td>33.987</td>
<td>40.621</td>
</tr>
<tr>
<td>$\Delta p_{\text{bm}2or3}$</td>
<td>45.205</td>
<td>58.912</td>
<td>36.264</td>
<td>51.96</td>
<td>51.667</td>
<td>36.35</td>
<td>41.718</td>
</tr>
<tr>
<td>$\Delta p_{\text{bm}4to10}$</td>
<td>103.704</td>
<td>115.462</td>
<td>97.892</td>
<td>112.307</td>
<td>87.856</td>
<td>87.163</td>
<td>120.527</td>
</tr>
</tbody>
</table>

*Note:* Panels A and B contain the increase in the premium in percentage points and in euros, as a function of the driving record. These estimates are obtained using the estimates in panels A and B of table 14. $\Delta p_{\text{oneaccAR}}$ and $\Delta p_{\text{twoaccAR}}$ measure the increase in the premium for having one and two accidents on record, respectively. $\Delta p_{\text{bm}1}$, $\Delta p_{\text{bm}2or3}$ and $\Delta p_{\text{bm}4to10}$ measure the increase of the premium after transitioning to the following bm class group, for policyholders in classes 1, 2-3, and 4-10.
Table 16. The Effect of the Driving Record on the Accident Probability

<table>
<thead>
<tr>
<th>Driving Category</th>
<th>Panel A–AB Estimator</th>
<th>Panel B–WG Estimator</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)  (2)  (3)  (4)  (5)  (6)  (7)</td>
<td>(1)  (2)  (3)  (4)  (5)  (6)  (7)</td>
</tr>
<tr>
<td></td>
<td>Market  A   B   C   D   Medium  Small</td>
<td>Market  A   B   C   D   Medium  Small</td>
</tr>
<tr>
<td>I</td>
<td>0.414***</td>
<td>0.423***</td>
</tr>
<tr>
<td></td>
<td>[0.004]</td>
<td>[0.007]</td>
</tr>
<tr>
<td>II</td>
<td>0.336***</td>
<td>0.346***</td>
</tr>
<tr>
<td></td>
<td>[0.004]</td>
<td>[0.007]</td>
</tr>
<tr>
<td>III</td>
<td>0.269***</td>
<td>0.278***</td>
</tr>
<tr>
<td></td>
<td>[0.004]</td>
<td>[0.007]</td>
</tr>
<tr>
<td>IV</td>
<td>0.235***</td>
<td>0.247***</td>
</tr>
<tr>
<td></td>
<td>[0.004]</td>
<td>[0.007]</td>
</tr>
<tr>
<td>V</td>
<td>0.058***</td>
<td>0.077***</td>
</tr>
<tr>
<td></td>
<td>[0.004]</td>
<td>[0.008]</td>
</tr>
<tr>
<td>VI</td>
<td>0.041***</td>
<td>0.055***</td>
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<td>[0.005]</td>
<td>[0.009]</td>
</tr>
<tr>
<td>N</td>
<td>1,142,797</td>
<td>1,142,797</td>
</tr>
</tbody>
</table>

Policyholder char.  Yes  Yes  Yes  Yes  Yes  Yes  Yes
Car char.          Yes  Yes  Yes  Yes  Yes  Yes  Yes
Clauses FE         Yes  Yes  Yes  Yes  Yes  Yes  Yes
City char.         Yes  Yes  Yes  Yes  Yes  Yes  Yes
Number of installments FE  Yes  Yes  Yes  Yes  Yes  Yes  Yes
Contr. year FE     Yes  Yes  Yes  Yes  Yes  Yes  Yes
Company FE         Yes  Yes  Yes  Yes  Yes  Yes  Yes
Province FE        Yes  Yes  Yes  Yes  Yes  Yes  Yes

Note: The dependent variable takes value one if one or more accidents are provoked during the year. The estimates in panels A and B are obtained by the WG and the AB estimator after assuming that the accident probability specified in equation (12) is linear—a linear probability model. In column (1), the estimates of a restricted specification—\( \alpha_{dr}^{jk} = \alpha_{dr}^{k} \) for all \( j \)—are presented. The estimates of the \( \alpha_{dr}^{jk} \)'s of the baseline specification are in columns (2)-(7). Standard errors are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95% and 99% confidence levels, respectively.

Table 17. The Effect of the Driving Record on the Accident Probability, Cont.

<table>
<thead>
<tr>
<th>Driving Category</th>
<th>Fixed Effect Logit Estimator</th>
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</thead>
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<tr>
<td></td>
<td>(1)</td>
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<td></td>
<td>Market</td>
</tr>
<tr>
<td></td>
<td>[0.074]</td>
</tr>
<tr>
<td>II</td>
<td>5.102***</td>
</tr>
<tr>
<td></td>
<td>[0.080]</td>
</tr>
<tr>
<td></td>
<td>[0.081]</td>
</tr>
<tr>
<td></td>
<td>[0.078]</td>
</tr>
<tr>
<td>V</td>
<td>2.542***</td>
</tr>
<tr>
<td></td>
<td>[0.066]</td>
</tr>
<tr>
<td>VI</td>
<td>1.504***</td>
</tr>
<tr>
<td></td>
<td>[0.076]</td>
</tr>
<tr>
<td>N</td>
<td>212,052</td>
</tr>
</tbody>
</table>

policyholder char. | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
car char. | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
clauses FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
city char. | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
number of installments FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
contr. year FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
company FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
province FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |

Note: The dependent variable takes value one if one or more accidents are provoked during the year. The estimates in panels A and B are obtained by the WG and the AB estimator after assuming that the accident probability specified in equation (12) is linear—a linear probability model. In column (1), the estimates of a restricted specification—\( \alpha_{dr_{jk}} = \alpha_{dr_k} \) for all \( j \)—are presented. The estimates of the \( \alpha_{dr_{jk}} \)'s of the baseline specification are in columns (2)-(7). Standard errors are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95% and 99% confidence levels, respectively.

Source: IPER (contracts starting in 2013, 2014, 2015 and in the first quarter of 2016.).
### Table 18. Penalties and Accident Probabilities

<table>
<thead>
<tr>
<th>Driving Category</th>
<th>MC</th>
<th>AB</th>
<th>WG</th>
<th>FE</th>
<th>Logit</th>
</tr>
</thead>
<tbody>
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<td><strong>Panel I: Market</strong></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>I</td>
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<td>0.414</td>
<td>0.313</td>
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<tr>
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<tr>
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<td>0.058</td>
<td>0.05</td>
<td>2.542</td>
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<tr>
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<td>0.197</td>
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<tr>
<td>VI</td>
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<td>0.038</td>
<td>1.504</td>
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<td><strong>Panel II: A</strong></td>
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<td></td>
<td></td>
<td></td>
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<td>I</td>
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<td>0.041</td>
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<td>0.024</td>
<td>1.701</td>
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<tr>
<td><strong>Panel IV: C</strong></td>
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<td></td>
<td></td>
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<tr>
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<td>0.036</td>
<td>0.03</td>
<td>1.817</td>
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<td>0.032</td>
<td>0.031</td>
<td>1.003</td>
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</tr>
<tr>
<td><strong>Panel V: D</strong></td>
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<td></td>
<td></td>
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<td>I</td>
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<td>0.047</td>
<td>0.035</td>
<td>1.677</td>
<td></td>
</tr>
<tr>
<td><strong>Panel VI: Medium</strong></td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>I</td>
<td>99.565</td>
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<td>0.297</td>
<td>6.061</td>
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<td>0.313</td>
<td>0.232</td>
<td>4.795</td>
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</tr>
<tr>
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<td>0.251</td>
<td>0.182</td>
<td>3.894</td>
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<tr>
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<td>179.155</td>
<td>0.019</td>
<td>0.026</td>
<td>1.428</td>
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</tr>
</tbody>
</table>

**Note:** The coefficients in columns (2)-(4) of each panel of the table report the corresponding coefficients of columns (2)-(7) of table 16. Column (1) reports the estimated penalties at each driving category and company reported in table 7.
### Table 19. The Association between Penalties and Accident Probabilities

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
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<td>Pearson</td>
<td></td>
<td>-0.408</td>
<td>-0.801</td>
<td>-0.141</td>
<td>-0.445</td>
<td>-0.524</td>
<td>-0.424</td>
<td>-0.372</td>
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<tr>
<td>Spearman</td>
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Note: This table reports measures of correlation between the penalties and the accident probabilities across driving categories. In column (1) the measures of correlations are computed using all the penalty-accident probability combinations across companies (36 pairs), reported in columns (1) and (2) of panels II-VII of table 18. Columns (2)-(7) report the measures using the penalty-accident probability combinations at each company (6 pairs), reported in columns (1) and (2) of each company-specific panel in table 18. Column (8) reports the measures of association using the pairs in panel I of the same table.
Table 20. Jumps the Baseline Hazard Rate

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$AMH$ 21.17 2.84 116.41

Note: Columns (1)-(3) reports the estimates jumps of the interval-specific baseline hazard rates—the $\Delta_j$’s defined in the main text—for each sample. Columns (4)-(6) contain the p-values of a $t$-test of the null hypothesis that $\Delta_j = 0$. 
Note. This graph shows the estimates of the hazard rates—\( \lambda_j \)—appearing in the Cox model specified in equation (15); the estimates of \( \log(\lambda_j) \) are in table 21. Each value on the \( x \)-axis represents the number indexing each interval. Intervals to the right of the vertical line belong to the “actual” grace period.
Figure 7. Premium Increase Across Driving Categories and Companies

Note. This graph depicts the estimates of the company-specific penalties at driving records I-VI, presented in table 7.

Figure 8. Premium Increase Across Driving Categories and Companies

Note. This graph presents for the market and for each company the contribution in percentage points of the driving record-specific penalty to the sum of the penalties across driving records I-VI. The estimates of the penalties are reported in table 7.
Figure 9. The Relationship Between Penalties and Accident Probabilities Within Companies

Note. These scatter plots depict the correlation between penalties and accident probabilities across companies estimated by the AB estimator, as reported in columns (1) and (2) of panels II-VII of table 18. The label “marginal cost” for the x-axis denotes the penalties.
Figure 10. The Relationship Between Penalties and Accident Probabilities in the Market

Note. This scatter plot depicts the correlation between all the penalties across driving categories and companies and the accident probabilities reported in columns (1) and (2) of panels II-VII of table 18. The label “marginal cost” for the x-axis denotes the penalties.
Figure 11. Estimates of the Baseline Hazard Rate Across Companies

Note. This graph shows the estimates of the baseline hazard rates $\lambda_{jk}$ appearing in the Cox model specified in equation (18); the estimates of $\log(\lambda_{jk})$ are in table 24. Each value on the $x$-axis represents the number indexing each interval. Intervals to the right of the vertical line belong to the “actual” grace period.


11. **The Effect of the Grace Period on the Severity of Accidents**

A common assumption in the literature is that careless driving only affects the frequency of accidents, not their severity. This assumption is for convenience, as it allows one to distinguish ex-ante from ex-post moral hazard. Recent evidence from insurance telematics data, however, suggests that driving style does play a role. For example, “distracted driving”—driving while doing another activity that takes your attention away from driving, such as talking on the phone or texting—contributes to both the number of accidents and their seriousness. Notice that because the size of the damage does not affect insurance rates—true in the data—the causal effect of the grace period on the severity of accidents cannot be rationalized by self-insurance and can be attributed to moral hazard.

I estimate by OLS the following specification:

$$\log(s_{ijt}) = \alpha_0 g_i + \alpha_1 res_{tg_i} + \alpha_2 res_{nug_i} + \beta X_{ijt} + \epsilon_{ijt}$$ (19)

where $s_{ijt}$ measures the total indemnity received by the parties not at fault as a consequence of the first accident driver $i$ covered by company $j$ is liable for during contractual year $t$. The indicator $g_i$ takes value one if the first accident happened during the grace period, $res_i$ measures the residual days left before the contracts expires from the day of the accident (if any), $res_{tg_i}(= res \times g_i)$ and $res_{nug_i}(= res \times (1 - g_i))$ are interaction terms. This specification allows me to flexibly capture the effect of the residual days left on the size of the damage. I restrict the sample to claims related to accidents of the first and second contractual years to minimize the proportion of claims whose final indemnity has not been liquidated. The vector $X_{ijt}$ contains a number of controls described at the bottom of table 25. In particular I control for car characteristics, province, company fixed effects and characteristics of the city. I also control for $SOARF\_SINDEN$—the proportion of claims over which, in a given province

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27 Insurance telematics allow the company to monitor the driving style of the insuree and condition the premium on a host of variables, such as miles driven, frequency of brakes, speed, and miles driven on the highway versus other types of roads.

28 I do not consider second and third accidents as there are few observations. The original distribution of the indemnity has been trimmed using the 99th-percentile of the contractual year-specific distribution.

29 About 96.5 percent and 96 percent of the claims of the first and second contractual year are not on-hold.
and year, an auditing procedure started—my proxy for province-level incidence of frauds.

Table 25 presents the estimates of the effect using the all sample (panel A1) and the sample of switchers (panel A2). Given the great dispersion of the size of the damage, I analyze the effect on various part of the distribution. I focus on the first (Q1), second (median), and third quartile (Q3) by means of quantile regression as well as on the conditional mean (OLS). Columns (1) and (5) present the estimates by OLS, columns (2) and (6) the effect on Q1, columns (3) and (7) on the median, and columns (4) and (8) on Q3. I find that, all else being equal, the grace period implies an increase of the conditional mean of about 10 percent; moreover, the closer the accident is to the expiration date within the grace period, the higher the associated damage (res.\_gi is statistically significant). The grace period effect on the mean/median is more pronounced across switchers: damage increases 19 percent, and the effect of the residual days left is also higher. The effects on the different quantiles are similar and slightly stronger on the higher quantiles, suggesting that the grace period implies a positive location-shift of the distribution. All in all, these findings reinforce the moral hazard story and understate the role of self-insurance.

To detect systematic variation across companies, I estimate the following specification:

$$\log(s_{ijt}) = \sum_j \alpha_{0j} g_i \times c_j + \sum_j \alpha_{1j} res.\_g_i \times c_j + \alpha_{2j} res.\_g_i \times c_j + \beta X_{ijt} + \epsilon_{it}$$

where $c_j$ is a company $j$ dummy, with $j \in \{A, B, C, D, Medium, Small\}$. The results, presented in table 27, indicate no statistically significant effect of the grace period on the conditional mean for companies A, B, C and D. The same is true for the effect on the median, with the exception of the sample of switchers covered by company A. The hypothesis that moral hazard is heterogeneous across companies is confirmed by these findings. There is no obvious explanation to reconcile this result—the bulk of the grace period effect comes from the set of medium and small companies—with the fact that AMH is lower in those companies (see table 10). One possible story is that effort is multidimensional: drivers choose speed and miles, say. Speed and miles have a different effect on the accident probability versus the severity of the accidents and they are
heterogeneous across companies.\footnote{Certainly, further analysis using actual data from insurance telematics—data on distance driven and driving styles—is in order to shed light on the actual mechanism through which the various forms of driving effort affect the likelihood of an accident.}

**Frauds** The positive effect of the grace period on the size of damage could be justified by fraudulent claims. There are two relevant types of frauds; the first is when the accident is real (not organized ex-ante) and the driver who is not responsible “simply” overreports the size of the damage. One reason there can be overreporting during the grace period of the contract subscribed by the liable driver has to do with possible “bargaining” on the individual percentage of fault. As the received indemnity is proportional to the percentage of fault, it is possible that liable drivers in the grace period are more prone to overstating their percentage of fault, thereby increasing the indemnity received by third parties. As for this type of fraud—parties agree to misreport their percentage of fault but not the occurrence of the accident—its presence still allows one to interpret the grace period effect on the hazard rate as true ex-ante moral hazard.\footnote{Recall that a driver is at fault if her percentage of fault is higher than 50 percent.}

The second type of fraud—two drivers set up a fake accident and agree to split the indemnity of the non “liable” party—is more problematic. Clearly, the incentive to arrange fake accidents is more pronounced during the grace period of one of the contracts, as the penalties are postponed or eliminated. As by law bodily injuries have to be certified at a public hospital to obtain an indemnity—this idea was first proposed by Chiappori and Salaniè (2000) to detect ex-post moral hazard—it is unlikely that fake accidents involve bodily injuries as they imply too-high non-monetary costs.\footnote{Chiappori and Salaniè (2000) argue that ex-post moral hazard should be absent in claims with bodily injuries, as filing the claim is mandatory, but they could not pursue this strategy to check for ex-post moral hazard because their sample was too small.} Thus, the absence of a statistically different effect of the grace period on the two types of claims makes the fake accident story less plausible.\footnote{Fraudulent claims with bodily injuries were thought to be pervasive among whiplash claims in Italy and elsewhere. To combat this type of fraud, a recent law (“decreto Monti”) establishes that to receive any indemnity, the bodily injuries of a small entity have to be documented by a clinical visual assessment (MRI)—the simple medical certificate does not suffice. There is evidence that the law drastically decreased the incidence of whiplash claims.}
In my sample, about 15 percent of claims involve bodily injury. I estimate the specification in (19) on the sample of claims with and without bodily injuries. The estimates for these two types of claims are presented in panels A and B of table 26. As can be seen from panel A, the effect among claims without bodily injuries both in terms of mean and median is similar to the one obtained using the sample with all types of claims, regardless of the switching decision. Interestingly, when I employ the sample of claims with bodily injuries, the effect on the conditional mean vanishes, but the effect on the median is analogous to the one obtained using all/the bodily injuries claims.

As the qualitative results using the two types of claims change little, the positive association damage-grace period is unlikely to be driven by a pure fraud effect. As a further robustness check, in figure 13 the hazard rates of claims with and without bodily injuries, conditional on being responsible for at least one accident, are shown. Both types of accidents are characterized by a very similar hazard rate, with a peak corresponding with the grace period.

Ex-post Moral Hazard In at-fault insurance regimes, ex-post moral hazard occurs when, after comparing the increase in the premium and the cost directly compensating the non-liable parties, the policyholder at fault persuades the third parties to not file the claim. The general idea, summarized by Chiappori and Salaniè (2000) is that these kind of “street” arrangements are unlikely to arise in accidents involving multiple drivers because parties cannot commit.34 However, under the assumption that the severity of the accidents does not depend on driving effort, in the presence of ex-post moral hazard one would expect a negative effect of the grace period on the size of the damage because also small claims are filed. This effect is contrary to the results I obtained by estimating specification 19. As much as for the possible presence of fraudulent claims, the comparison of the size of the claims with and without bodily injuries—as proposed by Chiappori and Salaniè (2000), though it could not be implemented because of the small sample size of their data—also indicates that ex-post moral is of second order.

34Jezioriskiy, Krasnokutskaya, and Ceccarini (2017) also abstract from ex-post moral hazard within the Portuguese auto insurance market.
11.1. Further Robustness Checks. I now analyze three confounding factors: misreporting, learning and seasonality effects.

Misreporting  As the identification comes from the date of the accident within a contractual year, one may worry that many accidents that are reported to have happened during the grace period in fact happened before. However, accidents at fault—the ones under examination in this study—always involve third parties. For misreporting to happen, drivers not at fault have to be persuaded to lie about the real date. In other words, a fraud has to be organized. It is reasonable that the expected cost of such a fraud—the expected legal sanctions—is increasing in the distance between the actual date of the accident and the reported one. If the cost is small enough, and accidents right before the grace period are inputted to a day right after, one should observe a decrease of the hazard rate right before the grace period. However, figure 6 shows a sharp increase before day 305. As an additional placebo test, it is comforting that the hazard rate is characterized by a grace period effect regardless of the presence of bodily injuries (see figure 13).

Learning  Although it is reasonable that drivers improve their driving skills over time, the following observations suggest that such a mechanism is of second order. First, if lower uncertainty leads to better driving, one would expect the hazard rate to decline over time, contrary to what we observe. Second, a grace period effect also exists among more experienced drivers (age $\geq 55$), a group typically characterized by little learning. Finally, if learning occurs smoothly over time, the rate at which the hazard rate increases should be constant. In the data, the second derivative of the hazard rate increases in correspondence of the grace period.

Seasonality  It is well known that accidents are more likely to occur in winter. At first blush, one may suspect that the grace period effect is an artifact of seasonality. Figure 12 depicts the pattern of the hazard rate, conditional on the starting quarter of contract. The grace period effects appear regardless of the season in which the contract ends.

11.2. The Effect of the Driving Record on the Switching Probability. To investigate the effect of the driving record on the decision to switch I specify
the following reduced-form regression:

$$\Pr(s_{ijkt} = 1) = \Lambda(c_{jt} + \beta_{dr}^k d_{rk} + \beta_{dr}^k d_{rk} + \beta^Z Z_{it} + \gamma_t + \eta_i)$$

(21)

where the dependent variable $s_{ijkt}$ takes value one if driver $i$ assigned to driving category $k$ is covered by company $j$ during year $t$ and zero otherwise, $\Lambda$ is the logistic function, $Z_{it}$ is a large set of controls included in the regression equation 12, $\gamma_t$ is a contractual year indicator, $\eta_i$ is an unobservable fixed-effect, and $c_{jt}$ is a company indicator. I am primarily interested in identifying $\beta_{dr}^k$, the average effect of the driving category, and $\beta_{dr}^j k$; this latter parameter captures the deviation from the mean of the driving record as a consequence of the specific pricing of the company. Panels A and B of table 28 show the results obtained using the simple logit estimator and the fixed effect logit, respectively. Column (1) and columns (2)-(7) contain the estimates of the $\beta_{dr}^k$’s and of the $\beta_{dr}^j k$ parameters, respectively. Focusing on the average effects, column (1) shows that the coefficients for driving categories I-V are statistically significant with a negative sign when using the plain logit model. Once $\eta_i$ is accounted for by the fixed effect logit the coefficients attached to I-III and VI are significant with a negative and positive sign, respectively. These results indicate that policyholders with a poor driving record are more likely to switch, and therefore company-specific samples are subject to non-random attrition. Columns (2)-(7) in panel B show that most of the company-specific coefficients are significant with a positive sign; this is true for policyholders of companies A-D and less so for those covered by a medium or small company. Overall, the slope of the premium-driving record schedule also contributes to the dynamic selection patterns.

12. Sampling the core sample

The core sample has been extracted from the universe of individuals subscribing one or more auto insurance contracts in 2013, the universe of subscribers in 2013. Contracts for motorcycles or car fleets are not considered. The survey design is stratified single-stage (see Cochran (1977)). The stratification variables are region (20), city size (small, medium, large) and age group (<25, [25,35), [35,45), [45,60), and ≥ 60). The combination of these variables generates 300 theoretical cells, of which only 240 contain some elements of the population. The sum of the survey weights reproduces the population size of the 2013 subscribers within each cell. The total sample size is divided among the cells according to the population distribution (proportional sampling), with
the exception of the age class, for which the younger classes are oversampled according to the following criterion:

- < 25: sampling probability is 5 percent, 1.78 in the population
- [25, 35): sampling probability is 20 percent, 11.62 in the population
- [35, 45): sampling probability is 25 percent, 21.88 in the population
- [45, 60): sampling probability is 30 percent, 34.18 in the population
- ≥ 60: sampling probability is 20 percent, 30.54 in the population

From the second year on, the sampling weights attached to each contract are updated dynamically by considering as a population of interest the universe of subscribers at each quarter of the calendar year.

12.1. **Description of the Variables.** I now describe in detail variables I use in the empirical analysis and whose means are shown in tables 12 and 13:

- premium (in euros): yearly premium paid for the third-party liability insurance
- discount (in euros): discount on the theoretical tariff applied by the agent/broker, if any. The theoretical tariff by definition equals premium + discount
- installments: number of chunks the premium is split in: 0 (the entire amount is paid when subscribing the contract), 2, 3, or 4 payments. Dummy variables have been constructed.
- age (in years): age of the subscriber at the time of underwriting date of the contract. Depending on the specification, I either use the variable as it is or dummies for the following age groups: [18;25), [25;34), [35;44), [45;60), and ≥ 60.
- accidents on AR: number of accident at fault (percentage of fault > 50) over the past five years reported on the AR (“Attestato di Rischio”)
- bm class: bonus-malus class (1-18)
- man: indicator for whether the subscriber is a male
- switching rate: mean of the indicator change, taking value one if the subscriber switches at the end of the contractual year and zero if she stays.
- clauses
  - repair: indicator taking value one if the clause “risarcimento in forma specifica” is active. The clause establishes that if an accident not at fault occurs, the vehicle has to be repaired by a specified list
of body shops. Typically, companies have agreements with those body shops to minimize expenses.

– black box: indicator for whether the so-called black box, a device able to record a variety of behaviors (e.g., km driven and whether there has been a “crash”), has been installed and guarantees a reduction of the base premium.

– driving clauses: this clause conditions the indemnity on the identity of the driver. In particular, if restrictions on the drivers are present, in case an accident is provoked and the restrictions are not met the company refunds whoever is not at fault and recoups the damage from the subscriber of the contract. There are four mutually exclusive alternatives generating the following dummies
  * free driving: indicator taking value one if there is no restriction on the driver’s identity
  * expert driving: indicator taking value one if only individuals with a certain driving experience can drive
  * exclusive driving: indicator taking value one if only individuals with a certain driving experience can drive
  * other: other types of driving clauses are present (the omitted category is “other”)

– protected bonus: indicator taking value one if the so-called “bonus protetto” clause is active on the contract. Such a clause allows me to eliminate/diminish the increase in the premium in case of an accident.

• increasing clause: indicator taking value one if there are other clauses that i) imply an increase in the premium, or ii) are different than the ones listed that are active on the contract

• coverage (in euros): upper limit on the amount the company will pay for accidents at fault. The insured driver is responsible if the damage exceeds the specified liability limit

• min coverage: indicator taking value one if the coverage equals the minimum mandatory liability limit of 6 million (1 million for property damage and 5 million for health damage)

• car’s characteristics:
- type of fuel supply. The categories are diesel, fuel, electric, gpl, hybrid diesel/electric, hybrid petrol/electric, methane, mixture, particulate filter, petrol, petrol/ethanol, petrol/lpg, petrol/wank, and petrol/methane.

I constructed two dummies, petrol and diesel—taking value one if the fuel supply is diesel or petrol, respectively, and zero otherwise. The omitted category is other types of fuel supply.

- car's age: year of registry of the vehicle
- cc: cubic cylinder of the vehicle, ranging from 1 to 100. I constructed dummies for the following groups: [10, 12), [12, 13), [13, 15), [15, 22), [22, 100]. The omitted category is [1, 10).

- power of the vehicle (in KW) ranging from 1 to 585

  • size first accident (in euros): total indemnity obtained by the third parties for the first accident the policyholder is responsible for
  
  • SOARF_SINDEN: fraction of claims in the province of residence of the subscriber over which an investigation for possible fraud has started. Available for years 2013 and 2014
  
  • acc rate: mean of the indicator ACC, taking value one if the driver is responsible for one or more accident during the year
  
  • 5 dummies taking value one if the subscriber resides in one of the five macroregions of Italy: North-East, North-West, Center, South, Islands
  
  • city density: number of people living in the province the subscriber lives in divided by the area (in square KM) of the province
  
  • type of city: non-mountain, partially mountain, totally mountain
  
  • altimeter zone: altitude of the province of residence of the subscriber according the classification provided by ISTAT, the Italian Institute of Statistics. There are five groups in descending order with respect to altitude: internal mountain, coastal mountain, internal hill, coastal hill, lowland
  
  • geomorphological classification: ISTAT divides location in three groups: non-mountain, partially mountain, totally mountain
### Table 21. Baseline Hazard Rate

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bm class: Yes Yes Yes
accidents on the AR: Yes Yes Yes
policyholder char.: Yes Yes Yes
car char.: Yes Yes Yes
clauses: Yes Yes Yes
city char.: Yes Yes Yes
clauses: Yes Yes Yes
no. of installments FE: Yes Yes Yes
contr. year FE: Yes Yes Yes
province FE: Yes Yes Yes
company FE: Yes Yes Yes
N: 37,208,804 26,514,671 4,050,172

Note: This table reports the estimates of the bhr’s—λ_j’s—obtained by estimating the Cox model specified in equation (15) on each sample. hr₁₀₂₀ denotes the logarithm of the bhr in the interval [1; 30); the other parameters are defined analogously. N denotes the total number of spells used in estimation. Standard errors, clustered at the province level, are reported in parentheses. *, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Table 22. Baseline Hazard Rate Among Different Groups of Switchers

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<td>(0.598)</td>
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<td>(0.331)</td>
<td>(0.473)</td>
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<td>(0.612)</td>
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<td>(0.295)</td>
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<td>Yes</td>
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<td>Yes</td>
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N = 4,050,172  432,378  432,308  425,985  828,194  774,995  379,016  777,296

Note: This table reports the estimates of the baseline hazard rates ($\lambda_j$), obtained by fitting the Cox model specified in equation (15) on the sample of groups G10-G10, as defined in the text. hr_1_30 denotes the logarithm of the baseline hazard rate function in the interval [1; 30). The other parameters are defined analogously. $N$ denotes the total number of spells used in estimation. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Table 23. Estimates of the Company-Specific BHR–All Sample

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<td>(Small)</td>
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<td>[0.074]</td>
<td>[0.071]</td>
<td>[0.097]</td>
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<td>[0.073]</td>
<td>[0.074]</td>
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<td>[0.081]</td>
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<td>[0.079]</td>
<td>[0.074]</td>
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</tr>
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</table>

bm class | Yes | Yes | Yes | Yes | Yes | Yes |
accidents on the AR | Yes | Yes | Yes | Yes | Yes | Yes |
policyholder char. | Yes | Yes | Yes | Yes | Yes | Yes |
car char | Yes | Yes | Yes | Yes | Yes | Yes |
clauses | Yes | Yes | Yes | Yes | Yes | Yes |
city char. | Yes | Yes | Yes | Yes | Yes | Yes |
clauses | Yes | Yes | Yes | Yes | Yes | Yes |
no. of installments FE | Yes | Yes | Yes | Yes | Yes | Yes |
contr. year FE | Yes | Yes | Yes | Yes | Yes | Yes |
province FE | Yes | Yes | Yes | Yes | Yes | Yes |
company FE | Yes | Yes | Yes | Yes | Yes | Yes |

\( N = 37,208,804 \)  

**Note:** This table reports the estimates of the company-specific baseline hazard rates (\( \lambda_{jk} \)), obtained by fitting the Cox model specified in equation (18) on the all sample. \( hr_{1,30} \) denotes the logarithm of the baseline hazard rate function in the interval [1; 30). The other parameters are defined analogously. \( N \) denotes the total number of spells used in estimation. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

**Source:** IPER (contractual years 2013-2014, 2014-2015, and 2015-2016).
Table 24. Estimates of the Company-Specific BHR–Switchers

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<tr>
<td>(A)</td>
<td>(B)</td>
<td>(C)</td>
<td>(D)</td>
<td>(Medium)</td>
<td>(Small)</td>
</tr>
<tr>
<td>[0.181]</td>
<td>[0.177]</td>
<td>[0.209]</td>
<td>[0.246]</td>
<td>[0.175]</td>
<td>[1.031]</td>
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| [0.174] | [0.226] | [0.180] | [0.251] | [0.187] | [1.069] |

| [0.173] | [0.196] | [0.198] | [0.253] | [0.192] | [1.036] |

| [0.181] | [0.236] | [0.184] | [0.215] | [0.179] | [1.033] |

| [0.176] | [0.207] | [0.193] | [0.225] | [0.177] | [1.032] |

| [0.158] | [0.168] | [0.196] | [0.236] | [0.168] | [1.046] |

| 7.244*** | -8.122*** | -8.099*** | -8.515*** | -7.735*** |
| [0.164] | [0.184] | [0.166] | [0.180] | [0.171] | [1.031] |

| 7.214*** | -8.175*** | -7.89*** | -8.31*** | -7.592*** |
| [0.152] | [0.197] | [0.183] | [0.164] | [0.180] | [1.027] |

| [0.159] | [0.164] | [0.152] | [0.218] | [0.179] | [1.045] |

| 7.988*** | -7.873*** | -7.538*** | -8.093*** | -7.44*** |
| [0.148] | [0.148] | [0.177] | [0.196] | [0.161] | [1.037] |

| [0.139] | [0.146] | [0.137] | [0.203] | [0.164] | [1.032] |

| 7.461*** | -7.00*** | -7.306*** | -7.128*** | -7.512*** | -6.858*** |
| [0.129] | [0.166] | [0.153] | [0.161] | [0.137] | [1.034] |

bm class: Yes Yes Yes Yes Yes Yes
accidents on the AR: Yes Yes Yes Yes Yes Yes
car char: Yes Yes Yes Yes Yes Yes
clauses: Yes Yes Yes Yes Yes Yes
city char: Yes Yes Yes Yes Yes Yes
no. of installments FE: Yes Yes Yes Yes Yes Yes
cor. year FE: Yes Yes Yes Yes Yes Yes
company FE: Yes Yes Yes Yes Yes Yes

N = 4,050,172 4,050,172 4,050,172 4,050,172 4,050,172 4,050,172

Note: This table reports the estimates of the company-specific baseline hazard rates ($\lambda_{jk}$), obtained by fitting the Cox model specified in equation (18) on the sample of switchers. $\text{hr}_{1,30}$ denotes the logarithm of the baseline hazard rate function in the interval $[1; 30)$. The other parameters are defined analogously. $N$ denotes the total number of spells used in estimation. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

### Table 25. The Effect of the Grace Period on the Size of Damage

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<td>87,847</td>
<td>9,813</td>
<td>9,813</td>
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<tr>
<td>$R^2$</td>
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<td>Yes</td>
<td>Yes</td>
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<td>bm class</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Yes</td>
<td>Yes</td>
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<tr>
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<td>Yes</td>
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<td>clauses</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Yes</td>
<td>Yes</td>
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</tr>
<tr>
<td>city’s char.</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>no. of installments FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>contr. year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>company FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>SOARF_SINDEN</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Note: The dependent variable is the logarithm of the total indemnity (in euros) received by the third parties involved in the first accident of the contractual year the driver is liable of. The sample is restricted to claims not on hold. The distribution of the indemnity has been trimmed using the 99\textsuperscript{th} percentile. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Table 26. The Effect of the Grace Period on the Size of Damage–Claims with and without Bodily Injuries

<table>
<thead>
<tr>
<th></th>
<th>Panel A: Claims Without Bodily Injuries</th>
<th></th>
<th>Panel B: Claims With Bodily Injuries</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>A1-All Sample</td>
<td>A2-Switchers</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$g$</td>
<td>0.130***</td>
<td>0.298***</td>
<td>0.315***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.052)</td>
<td>(0.036)</td>
</tr>
<tr>
<td>$res_g$</td>
<td>-0.003***</td>
<td>-0.006***</td>
<td>-0.008***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>$nores_g$</td>
<td>-0.000*</td>
<td>-0.000**</td>
<td>-0.000**</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
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<tr>
<td>$N$</td>
<td>74,953</td>
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<td>8,247</td>
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<tr>
<td>$R^2$</td>
<td>0.037</td>
<td>0.086</td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Claims With Bodily Injuries

|                  | B1-All Sample                          | B2-Switchers     |                                      |
|                  |                                        |                  |                                      |
| $g$              | 0.056*                                 | 0.157            | 0.192***                             |
|                  | (0.032)                                | (0.099)          | (0.061)                              |
| $res_g$          | -0.001                                 | -0.004**         | -0.004**                             |
|                  | (0.001)                                | (0.002)          | (0.001)                              |
| $nores_g$        | -0.000                                 | -0.001*          | -0.000                               |
|                  | (0.000)                                | (0.000)          | (0.000)                              |
| $N$              | 12,894                                 | 1,668            | 1,668                                |
| $R^2$            | 0.049                                  | 0.184            |                                      |

* driver char.    | Yes                                    | Yes              | Yes                                   |
| bm class         | Yes                                    | Yes              | Yes                                   |
| accidents on AR  | Yes                                    | Yes              | Yes                                   |
| car char.        | Yes                                    | Yes              | Yes                                   |
| clauses          | Yes                                    | Yes              | Yes                                   |
| city's char.     | Yes                                    | Yes              | Yes                                   |
| no. of installments FE | Yes                      | Yes              | Yes                                   |
| contr. year FE   | Yes                                    | Yes              | Yes                                   |
| province FE      | Yes                                    | Yes              | Yes                                   |
| company FE       | Yes                                    | Yes              | Yes                                   |
| SOARF_SINDEN     | Yes                                    | Yes              | Yes                                   |

Note: The dependent variable is the logarithm of the total indemnity (in euros) received by the third parties involved in the first accident of the contractual year the driver is liable of. The sample is restricted to claims not on hold. The distribution of the indemnity has been trimmed using the 99th percentile. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Table 27. OLS Regression on the Impact of the Grace Period on the Size of Damage Across Companies

<table>
<thead>
<tr>
<th></th>
<th>(1) OLS (Stayers)</th>
<th>(2) Median Regr. (Stayers)</th>
<th>(3) OLS (Switchers)</th>
<th>(4) Median Regr. (Switchers)</th>
</tr>
</thead>
<tbody>
<tr>
<td>G×A</td>
<td>0.041</td>
<td>0.042</td>
<td>0.137*</td>
<td>0.263***</td>
</tr>
<tr>
<td></td>
<td>(0.041)</td>
<td>(0.042)</td>
<td>(0.081)</td>
<td>(0.096)</td>
</tr>
<tr>
<td>G×B</td>
<td>0.143**</td>
<td>0.135***</td>
<td>0.133</td>
<td>0.161</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.051)</td>
<td>(0.110)</td>
<td>(0.148)</td>
</tr>
<tr>
<td>G×C</td>
<td>0.074</td>
<td>0.073</td>
<td>0.202</td>
<td>0.169*</td>
</tr>
<tr>
<td></td>
<td>(0.059)</td>
<td>(0.080)</td>
<td>(0.127)</td>
<td>(0.099)</td>
</tr>
<tr>
<td>G×D</td>
<td>0.072</td>
<td>0.041</td>
<td>0.076</td>
<td>0.088</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.092)</td>
<td>(0.203)</td>
<td>(0.284)</td>
</tr>
<tr>
<td>G×Medium</td>
<td>0.114***</td>
<td>0.123***</td>
<td>0.262***</td>
<td>0.247***</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.044)</td>
<td>(0.077)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>G×Small</td>
<td>0.151***</td>
<td>0.163***</td>
<td>0.253***</td>
<td>0.295***</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.038)</td>
<td>(0.083)</td>
<td>(0.062)</td>
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<tr>
<td>bm class</td>
<td>Yes</td>
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<td>Yes</td>
<td>Yes</td>
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<td>accidents on the AR</td>
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<td>Yes</td>
<td>Yes</td>
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<tr>
<td>policyholder char.</td>
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<td>Yes</td>
<td>Yes</td>
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<td>car’s char</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>clauses</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>clauses</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>contr. year FE</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>province FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>company FE</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>SOARF_SINDEN</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
</tbody>
</table>

N = 87,849 87,849 9,915 9,915
R² = 0.034 0.080

Note: The dependent variable is the logarithm of the total indemnity (in euros) received by the third parties involved in the first accident of the contractual year for which the driver is liable. The sample is restricted to claims not on hold. The distribution of the indemnity has been trimmed using the 99th percentile. Standard errors, clustered at the province level, are reported in parentheses.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Table 28. Switching Probability

<table>
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<tr>
<th>Driving Category</th>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tr>
<td></td>
<td>A</td>
<td>B</td>
<td>C</td>
<td>D</td>
<td>Medium</td>
<td>Small</td>
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</tr>
<tr>
<td>I</td>
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<td>0.155***</td>
<td>0.201***</td>
<td>0.048</td>
<td>0.092***</td>
<td>0.034</td>
<td>-0.129***</td>
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<td>[0.020]</td>
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<td>[0.030]</td>
<td>[0.034]</td>
<td>[0.033]</td>
<td>[0.039]</td>
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<tr>
<td>II</td>
<td>-0.129***</td>
<td>0.230***</td>
<td>0.111**</td>
<td>0.075**</td>
<td>0.292***</td>
<td>0.352***</td>
<td>0.155***</td>
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<td>[0.031]</td>
<td>[0.037]</td>
<td>[0.042]</td>
<td>[0.050]</td>
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<tr>
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<td>-0.109***</td>
<td>0.034</td>
<td>-0.148***</td>
<td>-0.93</td>
<td>-0.112**</td>
<td>-0.111**</td>
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<td>[0.045]</td>
<td>[0.046]</td>
<td>[0.050]</td>
<td>[0.051]</td>
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<tr>
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<td>0.139***</td>
<td>0.252***</td>
<td>0.292***</td>
<td>0.092*</td>
<td>-0.056</td>
<td>0.148**</td>
</tr>
<tr>
<td></td>
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<td>[0.038]</td>
<td>[0.058]</td>
<td>[0.048]</td>
<td>[0.054]</td>
<td>[0.064]</td>
<td>[0.073]</td>
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<tr>
<td>V</td>
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<td>0.107***</td>
<td>0.148***</td>
<td>0.077***</td>
<td>0.145***</td>
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Panel B: Fixed Effect Logit

<table>
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<tr>
<th></th>
<th>A</th>
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<th>C</th>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>I</td>
<td>-0.254***</td>
<td>0.207***</td>
<td>0.162***</td>
<td>0.078*</td>
<td>0.266***</td>
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</tr>
<tr>
<td></td>
<td>[0.026]</td>
<td>[0.035]</td>
<td>[0.052]</td>
<td>[0.044]</td>
<td>[0.052]</td>
<td>[0.057]</td>
</tr>
<tr>
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<td>0.367***</td>
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<td>0.074</td>
<td>0.244***</td>
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<tr>
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<td>[0.044]</td>
<td>[0.061]</td>
<td>[0.053]</td>
<td>[0.063]</td>
<td>[0.069]</td>
</tr>
<tr>
<td>III</td>
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<td>0.383***</td>
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<tr>
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<td>[0.045]</td>
<td>[0.067]</td>
<td>[0.056]</td>
<td>[0.069]</td>
<td>[0.072]</td>
</tr>
<tr>
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<td>0.199**</td>
<td>0.226***</td>
<td>-0.391***</td>
<td>-0.419***</td>
</tr>
<tr>
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<td>[0.086]</td>
<td>[0.073]</td>
<td>[0.085]</td>
<td>[0.095]</td>
</tr>
<tr>
<td>V</td>
<td>0.035</td>
<td>0.215***</td>
<td>0.335***</td>
<td>0.162***</td>
<td>0.261***</td>
<td>0.061</td>
</tr>
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<td>[0.032]</td>
<td>[0.046]</td>
<td>[0.039]</td>
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<td>VI</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

bm class Yes Yes Yes Yes Yes Yes Yes
accidents on the AR Yes Yes Yes Yes Yes Yes Yes
car’s char Yes Yes Yes Yes Yes Yes Yes
clauses Yes Yes Yes Yes Yes Yes Yes
city’s char Yes Yes Yes Yes Yes Yes Yes
clauses Yes Yes Yes Yes Yes Yes Yes
no. of installments FE Yes Yes Yes Yes Yes Yes Yes
contr. year FE Yes Yes Yes Yes Yes Yes Yes
province FE Yes Yes Yes Yes Yes Yes Yes
company FE Yes Yes Yes Yes Yes Yes Yes

Note: The dependent variable is a dummy taking value one if the policyholder switches at the end of the contractual year. Column (1) contains the estimates of $\beta_k^{dr}$ in the regression specified in (21)–the average effect of the driving record–while columns (2)-(7) are the estimates of $\beta_k^{dr}$–the company-specific penalties. Standard errors are reported in parentheses. Standard errors are clustered at the province level in panel A. $N = 2,736,518$ in panel A and $N = 745,651$ in panel B.

*, **, and *** denote statistical significance at the 90%, 95%, and 99% confidence levels, respectively.

Note. This graph depicts the hazard rate of accidents conditional on the starting quarter of the contract. The hazard rate is bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rate. A PWP gap-time model has been adopted to take into account the correlation across multiple accidents.

Figure 13. Hazard Rate During the Contractual Year Conditional on the Presence of Bodily Injuries

Smoothed hazard estimates

Note. The hazard rates are bounded by the 95 percent confidence interval. A gaussian kernel is used to smooth the hazard rates. The sample is restricted to contracts associated with one or more claims during the contractual year. The continuous (dotted) line represents the hazard rate of claims with (without) bodily injuries.