Identifying Moral Hazard in Car Insurance Contracts[1]

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September 12, 2010

[1]I would like to thank Yehuda Shavit for his thoughtful advice on the nature of insurance data and its research potential. Without his help this work would not have been possible. I would like to thank my advisor Professor Saul Lach for his guidance and support. Additionally, I would like to thank Motti Mor for providing insight and information on car insurance in Israel. Finally, I want to express my appreciation to participants in the Seventh CEPR School on Applied Industrial Organization as well as Professor Josh Angrist, Professor David Genesove, and Professor Daniel Nagin for their helpful comments and suggestions on an earlier draft. I gratefully acknowledge financial support from the Israel National Road Safety Authority Doctoral Fellowship. E-mail: <sarit.weisburd@mail.huji.ac.il>.

Abstract

This paper capitalizes on a unique situation in Israel where car insurance coverage is often distributed as a benefit by employers. Employer-determined coverage creates an environment where individuals are "as if" randomly allocated to different insurance contracts regardless of their preferences. In this situation, the confounding effects of adverse selection are removed, and the effect of car insurance on driving behavior and on car accidents reflects moral hazard. Using data provided by an insurance firm in Israel (2001-2008) and controlling for state dependence and unobserved heterogeneity, I find that employees benefiting from company insurance – holding higher insurance coverage at a lower cost – are 3.6 percentage points more likely to have an accident. This estimate increases when considering a subsample of newly insured employees. These results can be interpreted as the effect of moral hazard on car accidents.

1 Introduction

A positive correlation between the occurrence of an accident and insurance coverage is often observed in empirical research.[1] One explanation for this positive correlation is that insurance alters individuals' behavior by decreasing their motivation to prevent loss. This change in behavior, often attributed to the presence of "moral hazard", suggests that access to insurance coverage leads to increases in the rate of accidents.[2] There is, however, another explanation for the observed positive correlation: adverse selection. Adverse selection means that people with a higher risk of accidents self-select into insurance coverage. In this context, the possession of insurance does not change individuals' behavior. Rather, adverse selection implies that those who are insured are more "risky" in the first place and therefore disproportionately more likely to suffer accidents irrespective of the insurance they hold. Thus, the observed positive correlation between insurance coverage and accidents can be the result of both moral hazard and adverse selection and it is very difficult to empirically disentangle the contribution of each factor. Yet, identification of the channels through which this correlation arises is important as it gives insight into the effect of monetary incentives on risk-taking behavior. In the context of driving, identifying moral hazard has important policy implication in terms of the design of insurance contracts aimed at reducing auto accidents. For example, the existence of a significant moral hazard effect would suggest that increasing the penalty or deductible charged when involved in an accident could significantly decrease the accident rate.

This paper capitalizes on a unique situation in Israel where car insurance coverage is often included as a fringe benefit distributed by employer. Employer-dependent car

[1] See works by Abbring, Chiappori and Zavadil (2008), Ceccarini (2009), Cohen and Dehejia (2004), and Schneider (2008).

[2] The term "moral hazard" was first introduced in 18$^{\text{th}}$ century England to describe how insurance could result in lower incentives to protect oneself against the risk of accidents (Dembe & Boden, 2000). Arrow (1963) was among the first economists to describe the change in incentives caused by insurance.

insurance generates variation in the expected cost of accidents for individuals regardless of their preferences or private knowledge of accident risks. This alleviates much of the confounding influences of adverse selection so that the estimated effect of the change in insurance coverage on car accidents can be associated with a change in behavior induced by the possession of insurance, i.e., with moral hazard.

I analyze data on 1,046 employees of a large company in Israel holding car insurance policies from a single insurance firm (which provided the data) during 2001-2008. 291 of these employees pay for their insurance policies while the remaining 755 employees receive coverage free of charge as a benefit from their employer.[3] Both types of employees face, on average, a $160 deductible when reporting an accident while those with private insurance face an additional penalty ranging between $80 and $400 per accident upon policy renewal.[4] Importantly, for those holding company coverage, $160 per accident is the total annual cost of insurance coverage; these drivers do not pay the annual insurance premium – their employer does – and therefore do not face the risk of future premium increases (nor the possibility of being denied coverage) as a result of past accident history. In this context, some individuals face lower out-of-pocket costs resulting from auto accidents than others, allowing us to identify an "insurance effect" on the probability of a car accident. I will argue that this insurance effect is less confounded by pre-existing characteristics of drivers than in other studies in this area, because receiving company coverage is largely determined by the employer rather than by personal preferences.[5] That is, an estimated positive insurance effect in this study would reflect moral hazard and not adverse selection.

[3] The average cost of a policy for those who purchased insurance privately was $803.

[4] The size of the penalty is dependent on the driver's accident history and can be as high as $400 if this is the second reported accident in a given year. This penalty is expected to remain even if the private client transfers to a different insurance firm (clients are required by law to submit an accident history from their previous insurer).

[5] While employees can choose where they work, all employees in this dataset belong to the same large company. Thus, the two groups being compared in this study are not a product of self-selection but of employer delegation.

I develop an empirical model linking driving behavior to post-insurance accident costs and show how the introduction of company coverage presents an opportunity to identify moral hazard. Using this framework, I estimate a dynamic probit model of the probability of an accident. The main finding is that controlling for a variety of personal characteristics and for unobserved heterogeneity among individuals, having company insurance increases the likelihood of an accident by 3.6 percentage points relative to employees who paid for their insurance privately. This represents a 22 percent increase in auto accidents as a result of moral hazard since the mean accident rate for people in these data is 16.3 percent. These results highlight an unintended consequence of the widespread use of company-subsidized car insurance in Israel, namely, the increase in car accidents.

Using a subset of 350 privately insured and company insured employees who began their insurance policies after 2001, I also estimate a moral hazard effect using a differencing approach. This approach is feasible if drivers do not adjust to higher level coverage immediately in the first year of company coverage. This may occur if drivers are initially unclear about the ramifications of company coverage or have not yet internalized changes in driving behavior. I show that if we treat the first period of insurance with the provider as a transition period where driving behavior is still determined largely by previous habits, we can use a fixed effect approach to estimate the moral hazard effect. In this context, I estimate a moral hazard effect that increases the accident rate for those receiving company insurance by 12 percentage points. One explanation for this larger estimate is that this subgroup is especially susceptible to the moral hazard effect because newer employees tend to be younger than long-serving employees.

This paper is organized as follows. The next section reviews relevant research on insurance and its effects on behavior. Section 3 outlines the model relating driving behavior to insurance and shows how it distinguishes between moral hazard and adverse selection. Section 4 describes the institutional setup and the data used in the empirical analysis while Section 5 reports the empirical results for both the dynamic probit model and differencing approach. Section 6 concludes.

2 Research on Moral Hazard and Adverse Selection

The New York Times magazine described the issue of moral hazard using the following questions: "Does protection against risk tempt a person to do ever-riskier things? Does it endanger your moral sense to reduce the severe consequences of foolish action?"(Saffire, 2008). While the term moral hazard first appeared in the late 1800's, whether it manifests in reality and how its effect can be estimated remains unresolved.

In theoretical insurance models, moral hazard exists due to a principal-agent problem where the person insured does not have the same incentives as the insurance provider to prevent loss. Most of these models examining optimal insurance contracts are based on the assumption that, other things equal, those with high accident probabilities will demand more insurance than those who are less accident prone.[6] Rothschild and Stiglitz (1976) develop a model incorporating this "adverse selection" and show that when an insurer has incomplete information regarding accident risk levels, an efficient insurance equilibrium does not exist. Numerous authors, including Harris and Raviv (1978) and Shavell (1979), analyze alternative insurance contracts that incorporate incomplete coverage and performance contingency in order to arrive at an efficient equilibrium.

The first empirical studies examining the role of moral hazard in auto accidents focused not on the effect of insurance but, rather, on how automobile safety features affect driving behavior. Peltzman (1975) concluded that moral hazard exists in automobile safety components, finding that safety regulation did not lower the highway death toll

[6] The assumption that those with higher accident probabilities purchase more insurance was challenged by Mezza and Web (2001). They introduce a model where more risk-averse people are both more inclined to buy insurance and more cautious, resulting in a lower probability of an accident. If more cautious people purchase more insurance then observing a correlation between high coverage insurance and increased accidents is a clear sign of moral hazard. Thus, this model allows moral hazard to be tested simply by a positive correlation between accident rates and insurance coverage.

and that regulation could have increased the total number of accidents. Cohen and Einav (2003) reach a different conclusion when evaluating the effect of seat belt laws on driver behavior and fatalities. Using an instrumental variables technique, they find no evidence that higher seat belt usage affects driver behavior.

Empirical work on automobile insurance is also unable to provide a clear answer to the question of whether or not moral hazard exists in car insurance. Cohen and Dehejia (2004) use state-level data to investigate the effects of compulsory auto insurance and no fault liability laws on driver behavior and conclude that moral hazard exists in automobile insurance and leads to an increase in traffic fatalities. While state level comparisons allow an exogenous change such as legislation to differentially affect accident coverage, it is difficult to control for other between-state differences that could affect accidents (such as changes in police surveillance). One alternative method is to use individual level data and control for differences in observed characteristics that could affect the accident rate. Using a French survey of automobile insurance contracts, Chiappori and Salanie (2000) find no evidence of adverse selection or moral hazard on a sample of young drivers. Their data do not allow them to differentiate between adverse selection and moral hazard, only to assess whether there is unobserved information affecting both the insurance choice and the accident outcome.

Abbring et. al. (2003) expand on this research by presenting a model that differentiates between adverse selection and moral hazard. They identify adverse selection as unobserved heterogeneity that does not change over time, while moral hazard changes with accident occurrence. Abbring et.al. (2003) claim that if moral hazard exists in this scenario then each accident decreases the chance of a future accident, as the additional cost of a future accident has increased.[7] They find no evidence of moral hazard. In

[7] In the French system the premium level each year is determined by the premium in the previous year multiplied by a bonus-malus coefficient. Each year without an accident decreases the size of this coefficient, while having an accident increases it. Thus, the cost of an accident is higher for drivers who have been involved in an accident in the past.

a more recent study, Abbring et. al. (2008) do find evidence of moral hazard using Dutch longitudinal micro data. Their model assumes that if moral hazard does not exist, claim rates remain constant over time and a person's accident rate is a function of only his/her personal characteristics and preferences. Their technique for estimating this effect with unobserved personal preferences is comparing accident timing for people with the same number of total accidents in a given year who face different costs due to their bonus-malus class.[8] Dionne et. al. (2010) also find evidence of moral hazard, but only for a subset of drivers with under 15 years of driving experience. They use the Sofres survey, a French longitudinal microdataset which provides self-reported information on insurance and car accidents. They identify moral hazard by examining both the effects of the previous year's insurance contract as well as the driver's bonus-malus class on car accidents.

Past accidents, however, can affect the probability of an accident independently of moral hazard. Individuals may alter their driving behavior after being involved in an accident because of physical injuries, a reassessment of their driving capabilities, fear of future accidents, etc., even if there are no changes in the future cost of insurance.[9] In other words, car accidents may exhibit negative "state dependence" which does not necessarily reflect moral hazard. In studies where past accidents increase current accident costs the moral hazard effect and state dependence effects are often combined. Ceccarini (2007) attempts to account for state dependence separately from moral hazard by using a longitudinal dataset on Italian car insurance policies and finds that both moral hazard and negative state dependence exist. Similar to research by Abbring et. al. (2003),

[8] The bonus-malus class is determined at each annual contract renewal date and is based on accident history. This class defines the premium paid by the insured.

[9] This fear of a future accident can be explained by the "availability heuristic" where people classify the probability of an event by the "ease of which instances of occurrence come to mind" (Tversky and Kahneman, 1974). Thus, a person who was recently involved in an accident may consider the probability of a future accident more likely and drive more carefully. Abbring et. al. (2003) classify this as a "learning effect" where someone involved in accident understands he/she may not be a good driver and thus drives more cautiously.

Ceccarini (2007) measures moral hazard by comparing accident probabilities of people grouped into different experience classes and thus facing different accident costs. State dependence is addressed by comparing people in the same experience class with different recent accident histories.

Another approach to identifying moral hazard is comparing driving patterns between people holding different types of insurance contracts as a result of vehicle ownership or leasing. This can remove some of the issues of adverse selection if the choice to lease/own a vehicle is not correlated with insurance preferences. Dunham (2003) examines differences in vehicle depreciation of corporate owned fleet and rental versus private vehicles. He estimates an upper bound for moral hazard since there remain significant differences between fleet and private vehicles that provide alternative explanations for the increased depreciation rate. Schneider (2008) investigates differences in driving behavior between taxi owners and leasers in New York City. His dataset allows him to control for a wide range of observable differences in driver characteristics of those who choose to lease versus those who choose to own taxis and examine changes in driver behavior due to moral hazard. Schneider finds that taxi drivers who lease their car have 62 percent more accidents and that 46 percent of this difference can be attributed to moral hazard.

As can be assessed from this review of the literature, much of the difficulty in identifying adverse selection and moral hazard is that in most situations insurance coverage is a direct result of personal choice and driving behavior. Since complete information on accident risk level for each person is unavailable, alternative methods of risk classification can result in different evaluations of insurance outcomes. Ideally, to estimate a moral hazard effect we would like to eliminate the adverse selection aspect of insurance. That is, we would want to have a sample of individuals that are "as if" randomly allocated to different insurance contracts regardless of their preferences. Section 3 illustrates how the insurance situation in Israel provides a unique opportunity to move in this direction.

3 An Empirical Framework

In this section I model the relationship between driver behavior and insurance that will guide the empirical work. The model highlights the problem of separately identifying moral hazard parameters from adverse selection parameters. It also clarifies why the unique features of the car insurance market in Israel help to neutralize the adverse selection channel.

Dangerous driver behavior (d) measures how recklessly an individual drives. Higher values of d are therefore associated with more accidents. d is determined by personal and car characteristics (x), the expected out-of-pocket cost of an accident (C_A) and involvement in an accident last period (y_{-1}),

$$d = x\beta_x + \beta_1 C_A + \beta_2 y_{-1} + v \tag{1}$$

Previous research has shown that personal characteristics such as age, gender, and driving experience as well as car characteristics can affect driver behavior (Cohen and Einav (2005), Peltzman (1975)). These factors are captured by x. The presence of y_{-1} captures negative state dependence (see Ceccarini (2007)). If the occurrence of an accident prompts individuals to drive better then $\beta_2 < 0$.

The variable C_A represents the out-of-pocket cost of an accident. This cost is determined by the driver's insurance package due to deductibles and expected penalties if involved in an accident. For example, a driver with higher deductibles and/or penalties will face a larger C_A. This implies higher financial risks if involved in an accident and is therefore considered a lower level of insurance coverage. The effect of this expected out-of-pocket cost on driving behavior depends on the existence and strength of moral hazard. If there is no moral hazard then the expected cost of an accident should not affect behavior, $\beta_1 = 0$, but if moral hazard exists then the expected cost of an accident will reduce dangerous driving behavior because the driver now bears larger consequence for his/her actions, i.e., $\beta_1 < 0$. The zero-mean error term v is the individual effect capturing time-invariant unobservable personal characteristics that affect dangerous driving behavior.

We are interested in estimating β_1, the moral hazard effect of insurance coverage. Consistent estimation of β_1 requires the regressors to be uncorrelated with the error term in equation (1). However, even if we were to assume that dangerous driver behavior (d), the out-of-pocket cost of an accident (C_A), and involvement in an accident last period (y_{-1}) are observed by the econometrician, the presence of the unobserved individual effect v creates two problems. First, the lagged variable y_{-1} is positively correlated with v since more dangerous drivers are more likely to be involved in an accident in all periods. The second problem is that drivers have the ability to decrease the out-of-pocket cost of an accident (C_A) by paying a higher premium. If adverse selection exists, more dangerous drivers will choose higher premiums and lower out-of-pocket costs of accidents so that d will have a negative effect on C_A. This is a classic simultaneity problem: adverse selection implies that C_A is partly determined by d, while moral hazard implies that d is partly determined by C_A. The out-of-pocket cost of an accident is therefore endogenous in equation (1) and an OLS estimator of β_1, the moral hazard effect, will be biased downward. It is the presence of adverse selection that confounds the effect of moral hazard on driver behavior.

Car characteristics and accident history play a significant role in determining the types of insurance packages available to the individual. In general, individuals select insurance packages based on their driving behavior and personal characteristics and thus directly affect their out-of-pocket accident costs (C_A). This is what makes C_A generally endogeneous in (1). Fortunately, unique features in the allocation of car insurance benefits in Israel result in out-of-pocket accident costs, C_A, that are not completely determined by the driver. In Israel, car insurance coverage is often part of the fringe benefits offered by employers to their employees. Thus, in these data, drivers receiving company coverage face no post-accident penalty and the size of their deductible is independent of their preferences or previous accident occurrence (y_{-1}). Individuals without company coverage incur a post-accident penalty and their deductibles depends on accident history. Thus, individuals who receive these fringe benefits face lower out-of-pocket accident costs than identical individuals who are privately insured.[10]

Let $z = 1$ denote receiving company coverage, while $z = 0$ denotes private coverage. Accident costs can then be expressed,

$$C_A = \begin{cases} x\delta_x + \delta_2 y_{-1} + \delta_3 d + u \text{ if } z = 0 \\ \\ x\delta_x + \delta_1 + u \text{ if } z = 1 \end{cases} \tag{2}$$

The zero-mean error term u includes time-invariant unobservable personal characteristics that affect the insurance outcome in the presence of adverse selection such as general preferences regarding financial risks. More specifically, individuals with higher u who are more risk-seeking in personality will prefer higher expected accident costs and lower base premiums. u and v could be positively correlated if people who are more risk-seeking in personality have more dangerous driving patterns.

The beneficial aspects of company coverage mean that $\delta_1 < 0$ and $\delta_2 > 0$ since the occurrence of an accident increases the cost of a future accident. As explained above we expect $\delta_3 < 0$ since more dangerous drivers will prefer lower costs per accident in the presence of adverse selection. Because C_A is not observed (in our data) we can use equation (2) to relate driving behavior to an observed company coverage indicator, personal and car characteristics, and accident history,

[10] In addition, the annual cost of the insurance policy is paid by the employer. This large benefit, however, may not be relevant to moral hazard since these expenses are sunk at the beginning of the contract period.

$$d = \pi_1 z + x\pi_x + (z \times x)\pi_z + \pi_2 y_{-1} + \pi_3(z \times y_{-1}) + e \quad (3)$$

$$\pi_1 = \beta_1\delta_1, \quad \pi_x = \frac{\beta_x + \beta_1\delta_x}{1-\beta_1\delta_3}, \quad \pi_z = -\beta_1\delta_3\pi_x$$

$$\pi_2 = \frac{\beta_2 + \beta_1\delta_2}{1-\beta_1\delta_3}, \quad \pi_3 = \frac{-\beta_1(\beta_2\delta_3 + \delta_2)}{1-\beta_1\delta_3}, \quad e = \begin{cases} \frac{v+\beta_1 u}{1-\beta_1\delta_3} \text{ if } z = 0 \\ v + \beta_1 u \text{ if } z = 1 \end{cases}$$

When moral hazard exists we expect a positive estimate of π_1 since $\beta_1 < 0$ (the moral hazard effect) and $\delta_1 < 0$ because the company fringe benefit reduces out-of-pocket accident costs. Thus, even though we cannot estimate β_1 directly, we can estimate π_1, the moral hazard effect of increased company coverage. Importantly, due to the differential allocation of insurance we can infer the presence of moral hazard even if adverse selection is present for those purchasing private coverage, as specified in equation (2). In our model we identify the increase in dangerous driving behavior induced by the differential coverage of those receiving company insurance ($z = 1$).

The allocation of company coverage is plausibly exogenous because the insurance benefit is allocated by the employer and not decided upon by the individual. It could still be argued that the employer's decision is based on the employee's personal characteristics (gender, age, motivation, etc.) which could be correlated with his or her risk preferences which are included in $(v + \beta_1 u)$. We control, however, for some of these characteristics while remaining unobserved personal characteristics are likely to be, if anything, associated with better driving behavior and lower riskiness levels.[11] Thus, individuals receiving company coverage ($z = 1$) are also likely to be less dangerous drivers for reasons unrelated to moral hazard. This implies that our estimate of π_1 could be biased downwards and may therefore be viewed as an underestimate of the moral haz-

[11] Higher ranking employees tend to be older and better educated. These characteristics are associated with lower accident rates. See Cohen and Einav (2005) who find a negative relationship between age, education and accident claims.

ard effect of car insurance. This result should be contrasted to the usual positive bias resulting from presence of adverse selection in car insurance.

Abbring et. al. (2003) argue that a negative effect of past accidents identifies a moral hazard effect. In our framework, following the argument in Section 2, if there is negative state dependence ($\beta_2 < 0$), a negative effect of past car accidents will not necessarily imply the existence of moral hazard. Yet, since previous accidents affect only the post-insurance cost of an accident for those with private coverage we can separately identify state dependence by $\pi_2 + \pi_3 = \beta_2$.

Absent random allocation of insurance among individuals, these data provide a promising opportunity for identifying moral hazard. To my knowledge, this is the first attempt to study moral hazard in a case where insurance is determined by an external decision-maker and not by direct personal preferences.

4 The Data

In Israel, all car owners are required by law to hold a minimal level of insurance coverage. This mandatory insurance covers claims on injuries incurred by people in the insured vehicle and pedestrians injured in an accident. Most drivers purchase additional coverage against damage to their vehicle and other vehicles in the case of an accident.[12] This additional coverage usually includes a deductible averaging $200 if involved in an accident and using an in-policy garage. In cases where the driver is under age 24, or has his/her license for less than a year, the deductible increases by 50% at most insurance companies. There is also the opportunity to purchase additional legal and third party coverage as well as windshield damage coverage, towing, and temporary vehicle replacement. Some insurance providers give options with lower premium costs and higher deductibles, or alternatively offer policies with higher premiums and no deductible. Despite these

[12] Alternatively, drivers can purchase third party insurance which covers damage to other vehicles but does not cover damages to their own vehicle.

alternative options, the majority of drivers purchase a standard package insuring them against damage to their own vehicle and other vehicles.

Data for this study come from a private insurance firm and from Israel's Central Bureau of Statistics. Under a confidentiality agreement with the insurance firm I received data on 6,813 policies activated between 2001 and 2008. These policies belong to employees of a single, large Israeli company. 4,590 of the policies were paid for by the employer as a benefit, while 2,223 were paid for privately by the employees.

Some insurance policies lasted for a short period of time because the insurance firm attempts to set a uniform starting month (September). Thus, clients who started their policy mid-year often had short first year policy lengths. Since we will be interested in analyzing the number of car accidents per policy it is important to maintain a uniform policy duration and to control for systematic differences, if any, in the contract duration of company and privately paid clients. If the client did not switch vehicles I combined consecutive insurance contracts when the duration of one of them was under six months. This reduced the number of company paid policies to 4,372. Additionally, I excluded 140 policies that were not renewed and therefore do not allow for panel data analysis.[13] This resulted in 4,232 company paid policies. The same procedure was applied to the 2,223 private policies. In addition, I excluded private policies with only mandatory and/or third-party insurance so that the remaining private policies are standard insurance packages against damage to the client's own vehicle and other vehicles. This ensures that private and company-paid policies are the same homogeneous product. Details of the data cleaning process and variable definitions are in Appendix B.

The final sample consists of 5,477 policies corresponding to 1,046 employees of a large Israeli company. 4,232 policies (77 percent) belonging to 755 individuals were paid by the employer, while 1,245 policies (23 percent) belong to 291 employees who privately

[13] I find no evidence that this would create selection bias in this sample since the accident rates of those employees with private coverage who leave after 1 year are lower (though not statistically significant) than those who remain in the sample.

paid for their car insurance and chose to be insured through the same firm as those receiving company coverage.[14]

This insurance provider sold a standard policy without the option of paying a higher annual premium in order to decrease deductible costs. Most policies last for a year and therefore each individual in the sample holds, on average, 6 policies. The 291 privately insured employees included in the data faced a penalty ranging between \$80 and \$400 per accident after being involved in an accident. Both types of employees faced on average a \$160 deductible when reporting an accident, but for the 755 employees with company insurance this was the only cost of auto insurance. The annual cost of insurance (averaging \$803) was covered directly by the company and was not affected by driver behavior. Not only were their insurance costs paid by their employer, these drivers were guaranteed coverage regardless of accident history.

All policies included in the data are full-coverage insurance policies (insured against damage to their vehicle and other vehicles in the case of an accident). For each policy we have information on city of residence, car model, car year, engine size, gender of policy holder, opening and closing date of policy, accident date, accident damage, accident description, and accident location. In order to allow for further controls between employees receiving company coverage and those purchasing private insurance, I expanded the dataset to include socioeconomic and geographical information corresponding to the cities where the 1,046 policy holders live. The Central Bureau of Statistics provides economic and geographical data through its GEOBASE program. I use data on average family income and percentage of students passing their matriculation exams by city in Israel. These data will help to control for differences in the populations between those

[14] The privately insured employees therefore constitute only a subset of the employees with private insurance. The insurance firm estimated, however, that they insure about fifty percent of the employees not covered by company insurance. The average \$160 accident deductible offered by the insurance firm to those privately insured is significantly lower than the average deductible offered by other insurance firms (\$200). Thus, I expect that most employees who were aware of the company insurance provider chose to insure through them.

with private or employer paid insurance contracts.[15]

I exploit the fact that all drivers work at the same location to control for different driving patterns. I group the 60 cities in the sample into 4 groups according to their location relative to that of the employer. This information allows me to control for the different roads drivers travel to work. In addition, I calculated distances between the employees' city and their employer's location as well as the distance between the latter and each accident's location. I will use these distances to control for different driving patterns which could be correlated with the type of insurance they hold. In essence, it is important to understand whether increased accidents can be explained simply by increased time spent on the road or by the types of roads traveled on.

Table 1 provides summary statistics for key variables used in this study. These statistics highlight the initial differences between characteristics of the two insurance groups. One of the most significant differences between insurance groups is the number of years people remain insured: people with company insurance start their policies earlier and continue for longer periods. This is not surprising given that the insurance firm secures all employees with the company insurance benefit directly, but must advertise for those purchasing private insurance. Additionally, company insured drivers do not have the flexibility to switch to a difference insurance provider.

Company policy holders are 76 percent male while those with private insurance are 84 percent male. Because men have been shown to have a higher probability of accidents this means that we would expect more collisions from those with private insurance (Cohen & Einav, 2005). While the relatively small 7.6 kilometer difference in commute distance is statistically significant, if there is any effect on car accidents we would expect those with private insurance to have more collisions due to their longer commute to work. Additionally, Table 2 shows that the collisions of drivers with company insurance occur

[15] Because the company-paid insurance indicator does not change during the sample period, I cannot use fixed residence effects to capture all unobserved socio-economic differences.

significantly closer to work. These findings are reassuring because they suggest that company-insured drivers may not be using their cars significantly more than privately-insured drivers (and actual car usage is not observed).

Unfortunately we do not have data on drivers' age and driving experience (defined as the number of years elapsed since receipt of first driving license) except for those drivers that were involved in an accident in 2004-2005. We find no significant difference in age and driving experience across types of insurance.

One important issue when examining the number of accidents reported to the insurance company is that this number is a fraction of the total number of accidents that occurred. Private policy holders face higher reporting costs than those holding company insurance and are therefore less likely to report smaller accidents when only their car is involved. Thus, the effect of company coverage would include the effect of increased reporting and thus overestimate the effect of increased coverage on driving behavior. A solution to this identification problem is to focus on specific types of accidents such as collisions where the correlation between accident occurrence and reporting is expected to be high. Therefore, despite having data on all accidents reported to the insurance firm, I only include collision accidents where at least two cars were involved in my analysis, as done by Chiappori & Salanie (2000). The probability of reporting is much higher in accidents involving other cars (for both types of insurance holders) and therefore restricting the analysis to this subset of the sample is less affected by selective reporting and achieves a more accurate comparison of accident rates. Indeed when comparing the median damage estimates for both groups, we find no evidence that those with company coverage have a higher frequency of reporting small collisions.

Each policy contains information on the number of accidents occurring during each period of coverage. For the majority of policies (83.7 percent) there is no accident reported, 14.4 percent report having one accident, and 1.9 percent report having more than one accident per period. In principle, the number of accidents should be treated as a count variable, but in practice I treat it as a binary variable because having 2 or more accidents per period is such a rare event. I assign the value $y = 1$ to those policies reporting at least one accident in the given period.

In Table 2 we compare mean accident rates across all years and find that on average company insurance holders are 1.5 percent more likely to be involved in an accident than those privately insured. While this difference is not statistically significant its direction is the opposite of what we would predict based on mean characteristics of drivers in both groups. Examining the accident rate by years of coverage with the provider allows a closer look at differences between those with private and company insurance. In the first year of insurance, drivers with private coverage are six percent more likely than those with company coverage to be involved in an accident. The significantly lower initial accident rate of drivers' holding company coverage could reflect the negative correlation between individuals who receive the fringe benefit and unobserved characteristics resulting in more dangerous driving. Remarkably, while the collision rate remains relatively constant across periods for those with private insurance, it increases significantly between period 1 and 2 for those with company coverage, and remains relatively constant in periods 3 and onwards. One possibility is that moral hazard does not affect people's driving behavior immediately and thus the consequences of increased coverage appear with a one-year delay. We explore this issue further in Section 5.1.

5 Empirical Results

We estimate equation (3) using a binary indicator of involvement in an accident (y) as a measure of dangerous driving behavior (d). This step is necessary because d is not observed directly. Nevertheless, this is interesting in its own right as well as relevant to policy.

In our data, there is no role for driving behavior affecting the type of coverage a driver holds (the combination of deductibles, penalties and premium) because these are pre-determined by the insurance provided and the employer. Thus, even for privately-insured drivers, their out-of-pocket accident costs depend only on their car and observed driver characteristics x, as well as on their accident history. In short, all drivers were offered a standard policy without the option of paying a higher annual premium in order to decrease deductible costs. That is, in our data it is the case that $\delta_3 = 0$ for both types of drivers.[16] Under this assumption, equation (3) simplifies to

$$y = \pi_1 z + x\pi_x + \pi_2 y_{-1} + \pi_3 (z \times y_{-1}) + \eta \tag{4}$$

$$\begin{aligned} \pi_1 &= \beta_1 \delta_1, \qquad \pi_x = \beta_x + \beta_1 \delta_x, \qquad \pi_2 = \beta_2 + \beta_1 \delta_2 \\ \pi_3 &= -\beta_1 \delta_2, \qquad \eta = v + \beta_1 u + \varepsilon \end{aligned}$$

The use of car accidents (y) as an indicator for driving behavior introduces a random error ε which we assume is unpredictable – white noise– and reflects the randomness associated with the occurrence of an accident involving other automobiles and unexpected road hazards.

In addition to the moral hazard effect π_1 we can also estimate the moral hazard effect driven by an increase in the cost of future accidents induced by the occurrence of an accident as in Abbring et. al. (2003). The coefficient π_3 captures the moral hazard effect (β_1) of higher future accident costs resulting from involvement in an accident last period for those drivers with private coverage (δ_2).

The presence of unobserved individual effects in the composite error η complicates the estimation of dynamic models because it implies a correlation between y_{-1} and η

[16] We tested for the presence of the interaction effects ($z \times x$) and could not reject the null hypothesis of no effects using a linear probability model. The probit procedure failed to converge when all interactions were included. Omitting some of these interactions solved this problem and also resulted in non-significant estimates of the interaction effects. Moreover, the point estimates of π_1 were nonsensical when the interactions were included.

(as mentioned in Section 3). The usual technique to deal with unobserved heterogeneity in panel data is by differencing out the unobserved individual effect. This, however, is not a feasible approach in nonlinear probability models. Moreover, the variable of interest – receiving company insurance – does not change over time and therefore cannot be estimated with a differencing method (even if we were to specify a linear probability model). Instead, following Blundell (1999) and Wooldridge (2002), I model the unobserved individual effect $(v+\beta_1 u)$ as a function of accident involvement in the first period y_0, observed characteristics during the entire period of insurance summarized by their time average for each component of x, and an unobserved random variable a.

$$v + \beta_1 u = \tau_0 + \tau_1 y_0 + \overline{x}\tau_2 + a \tag{5}$$

Assuming that a is normally distributed conditional on y_0 and $\overline{x}$, we can integrate a out of the likelihood function, to obtain a likelihood function for accidents $(y_1, .., y_T)$ that is a function of only the observed explanatory variables $(x, z, y_{-1}, y_0, \overline{x})$. Details appear in Appendix A. This methodology allows first period accidents to predict future accidents. In essence, whether a driver had an accident in his/her first period of insurance can give us added information on his/her general level of driving care. This is especially relevant given the collision rates in Table 2 since the first period of insurance may provide information on driving behavior prior to changes invoked by differential coverage. The resulting model is a random effects dynamic probit model that controls for unobserved time invariant heterogeneity.

I report the estimated coefficients from the probit model for a number of specifications in Table 3. All of these specifications control for available individual and car characteristics, as described in the table notes. Column (i) uses only those regressors that would be available in the absence of panel data. We find no significant difference in the probability of an accident between those holding company and private policies. Since we do not control for the negative correlation between z and unobserved heterogeneity the estimated moral hazard effect is biased downwards resulting in a small coefficient which is not significantly different from zero. Note that drivers who commute with traffic and hold longer histories with the insurance provider are more likely to have an accident.[17]

Column (ii) uses the same specification as in (i) except that it deletes the first period of insurance for each client. Recall from Table 2 that company-insured individuals have significantly fewer car accidents in the first period. Omitting the initial observation for each individual should therefore increase the estimated coefficient of z. This is indeed what happens as the estimated coefficient of z increases five-fold and is significant. This is consistent with a strong correlation between unobserved heterogeneity and receiving company insurance which is not mitigated by moral hazard during the first period of insurance coverage perhaps because people do not change their behavior immediately, as mentioned at the end of Section 4. In Section 5.1 I develop this idea further into a difference-in-differences estimator of the moral hazard effect.

Specification (iii) controls for state-dependence by adding past driving behavior to the regression. If state dependence in accidents acts as a negative shock to dangerous driving behavior that fades quickly over time it is possible that its effect is no longer significant by the time the next observation is observed because of the annual frequency of the data. In order to capture this effect, I consider larger accidents that occurred less than 6 months prior to the beginning of the current policy.[18] Under this classification, the estimated coefficient of past accidents is negative, as expected, but not statistically significant. Specification (iv) includes an interaction term between lagged accidents and company coverage. While this coefficient has the expected positive sign it is not

[17] If the policies of bad drivers were not renewed the observed sample would include disproportionately "better" drivers. If this were the case then we would expect a negative coefficient on "total years insured". Since the estimated coefficient is positive this type of selection bias is not likely to be important in our data.

[18] I classsify larger accidents as those with damage estimates over \$1,034 (the median reported damage estimate in the data), implicitly assuming there is a correlation between accident damage cost and its severity.

statistically significant. Thus, we do not find a significant effect of involvement in an accident on driving behavior neither via negative state dependence ($\widehat{\pi}_2 + \widehat{\pi}_3 = \widehat{\beta}_2 = -0.154$, $s.e. = 0.157$) nor via the moral hazard effect of increased insurance costs due to past accidents ($\widehat{\beta}_1\widehat{\delta}_2 = -0.104$, $s.e. = 0.423$). Using a shorter time-window may indicate that involvement in an accidents plays a larger role in driving behavior than that estimated in this specification.[19]

The last specification in Table 3 controls for both unobserved heterogeneity and state dependence. The coefficient on company insurance remains positive and statistically significant at the five percent level when controlling for involvement in an accident in the first period, as well as mean car and driver characteristics. The coefficient on accident first period is also positive, as we would expect since this controls for an initial tendency towards dangerous driving. Overall, however, controlling for unobserved heterogeneity via first period accidents does not essentially alter the estimated moral hazard effect, suggesting that the correlation between receiving company insurance and unobserved individual characteristics affecting driving behavior may not be that important in these data.

To assess the quantitative impact of moral hazard on car accidents it is important to estimate not only whether an effect exists but how substantial it is. The first column of Table 4 reports average partial effects with standard errors calculated by bootstrapping.[20] Average partial effects were computed by calculating the expected effect of each regressor on the probability of an accident, holding all else constant, for each observation in the sample and averaging across all observations. For example, the average partial effect of receiving company coverage is computed as: $\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T_i}\Phi\left(\frac{\widehat{\pi}_1+x_{it}\widehat{\pi}_x+(\widehat{\pi}_2+\widehat{\pi}_3)y_{it-1}}{\sqrt{\widehat{\sigma}_a^2+1}}\right) -$

[19] However, shorter time-windows imply zero accidents for almost all observations.

[20] The estimated standard errors were not significantly different from the asymptotic standard errors estimated via the delta method. I report results for the probit specification with bootstrapped standard errors following Wooldridge's estimation approach (see Appendix A).

$\Phi\left(\frac{x_{it}\widehat{\pi}_x+\widehat{\pi}_2 y_{it-1}}{\sqrt{\widehat{\sigma}_a^2+1}}\right)$ where $T=\sum_{i=1}^{N} T_i$ and $\widehat{\sigma}_a$ is an estimate of the standard deviation of a (See Appendix A for additional details). For comparison, the second column reports the estimated effects from a linear probability random effects specification. The results are very similar except for a change in sign in the estimate of π_2 in the linear model (although in both the probit and linear model the estimate is not statistically different from zero). Moral hazard is estimated to increase the accident rate for those with company insurance by 3.6 percentage points.[21] This represents a 22 percent increase in the mean probability of being involved in an accident (16.3 percent).

5.1 A Driver's First Introduction to Company Coverage

Table 2 illustrates a distinct change in accident rates that occurs between the first and later periods of insurance for those with company coverage (an increase from a 9 to a 19 percent annual accident rate). This phenomenon appears only for drivers with company coverage as opposed to drivers holding private coverage who keep a fairly constant annual accident rate of 14 percent throughout all periods. Drivers receiving employer-paid insurance may not adjust their driving behavior immediately because, initially at least, they may not understand and/or internalize the changes in insurance coverage. As time elapses and information becomes available, drivers with employer-paid coverage may change their driving behavior with the knowledge that they will not face a post accident penalty. If we take the first year of insurance as the initial period when moral hazard does not yet play a role, we can then compute the change in accident rates between the first year of insurance and later years for both groups of drivers. Comparing this change in accident rates between those drivers receiving company-paid insurance and those paying privately estimates the moral hazard effect of insurance. In this Section we

[21] It is interesting to note that when including all reported accidents (as opposed to only collision accidents) we find a much larger estimate of 4.5 percentage points. This finding is consistent with the idea that including all accidents measures a reporting effect which overestimates the effect of coverage on driving behavior.

implement this using a differencing approach.

The first year of the sample data, 2001, is not necessarily the first year an individual receives employer-paid insurance. The first year of coverage is the relevant year for calculating the difference in car accidents but, unfortunately, we do not have this information. However, for drivers whose first observed year in the sample is 2002 or later we can assume that their initial year is also the first year of receiving employer-paid insurance.[22]

Using this subset of 350 newly insured employees holding 1,225 policies, I estimate the following linear probability model,

$$y_{it} = x_{it}\pi_x + \psi_1 z_i + \psi_2 post_{it} + \pi_1 (z_i \times post_{it}) + \eta_{it}$$

where $post_{it}$ takes the value of 0 for the first year of insurance and 1 for later years.

Note that in this specification ψ_1 no longer measures the moral hazard effect. In fact, $\psi_1 = E(y|z = 1, x, post = 0) - E(y|z = 0, x, post = 0)$ so that it reflects pretreatment differences in unobserved heterogeneity between those receiving company insurance and those who do not. We therefore expect ψ_1 to be negative when those receiving company coverage are also better drivers. Note that $z's$ coefficient now has the opposite sign of that in the previous section.

The coefficient on the interaction term $\pi_1 = E(y_{post} - y_{pre}|z = 1, x) - E(y_{post} - y_{pre}|z = 0, x)$ estimates the moral hazard effect. In essence, we compare the change in accidents between the first period of insurance – when, by assumption, there is no moral hazard – and future periods for individuals with company coverage – $E(y_{post} - y_{pre}|z = 1, x) = \psi_2 + \pi_1 -$ and for individuals with private insurance coverage $-E(y_{post} - y_{pre}|z = 0, x) = \psi_2$. We cannot identify a state dependence effect in this specification because

[22] If some of these drivers are new to the company as well as to the insurance provider they may have received higher level insurance coverage at their previous company. In this case they may have already altered their driving behavior due to moral hazard and a differencing technique will underestimate the moral hazard effect.

including a lag of the dependent variable would necessitate dropping the first observation for each client.[23]

Table 5 presents estimates of the moral hazard effect of company provided insurance on accidents using this approach. We find that providing company insurance increases the accident rate for those employees new to company coverage by about 12 percentage points. This effect is robust to controlling for different background characteristics as well as for fixed effects at the individual level. While the interpretation of a "difference-in-differences" estimate is more straightforward in a linear framework, I include the average partial effects from a probit regression in column (iii). The average partial effects were computed using the same method applied to the dynamic probit model in the previous section, with standard errors calculated via the bootstrap method. Since the dependent variable is binary it is important to ensure that the linear framework is providing interpretable results.[24]

Columns (i)-(iii) include a control for receiving company coverage. As mentioned above, this coefficient estimates the level of unobserved heterogeneity in accident outcomes between those receiving company insurance and those who do not. We estimate that without differential coverage, employees allocated to company insurance were 10 percent less likely than those in the private group to be involved in an accident.

The last column in Table 5 estimates the moral hazard effect using a fixed effects approach. This provides the strongest control for unobserved heterogeneity since it compares the same individuals over time.[25] We estimate that receiving company insurance increases the accident rate by twelve percentage points at the individual level. This is a

[23] Recall that in the previous analysis we did not find a significant effect of previous accident occurrence on the probability of an accident.

[24] Following Puhani's approach we check the sign and significance of the treatment effect as the marginal effect on the interaction term (Puhani, 2008).

[25] In the previous specification we controlled for unobserved heterogeneity via first period accidents ($\tau_1 y_{i0}$). In this specification we apply a stricter control for unobserved individual heterogeneity by comparing the same individual pre- and post- change. We cannot estimate ψ_1 when using fixed effects.

very high estimate, taking into account that the average accident rate in the data is 16.3 percent indicating an increase of over 70 percent in the accident rate for those receiving company coverage.

These results can provide an explanation for the distinct change in the moral hazard estimate occurring between specifications (i) and (ii) in Table 3 of the previous specification. In column (i) first period driving behavior is included in the sample and thus, the coefficient on company includes a moral hazard effect (increasing the accident rate), and an unobserved heterogeneity effect (decreasing the accident rate) - resulting in a small and not statistically significant moral hazard estimate. From specification (ii) onwards we only consider the accident rate after the first period of insurance (excluding the initial lower accident rate of those with company coverage) and allowing a distinct estimate of moral hazard.

The moral hazard effect estimated in this subsection is much larger than the effect obtained from the full sample. A possible explanation is that the drivers in this subsample are likely to be new to the company and therefore tend to be younger than the employees already insured at the beginning of the sample period. Since younger drivers have been found to be more prone to accidents it is possible that moral hazard has a larger effect on this group than on the full sample. This may overestimate the moral hazard effect in the population as it has been applied to a specific subset of employees who are assumed to be younger than the average person in the data.

6 Conclusion

For over 50 years economists have been analyzing the existence of moral hazard and the role it plays in human behavior. There is much debate today over whether our basic assumptions on rational decision making hold true in reality. Ultimately when dealing with car accidents and the physical harm connected with risky driving behavior, it is especially important to understand if moral hazard has a significant affect. This paper addresses the question: do changes in financial incentives affect behavior even when physical injury could result?

In order to analyze whether moral hazard exists in car insurance contracts it is essential to control for the confounding effect of adverse selection. In prior research this has been a constant obstacle, since car insurance is selected by the policy owner and thus personal preferences play a direct role in coverage. In Israel, where people are given company insurance regardless of their preferences, it is possible to analyze the direct effect of moral hazard. After controlling for observed and time-invariant unobserved differences between private and company policy holders, I find that employer-paid insurance coverage increases the probability of a car accident by at least 3.6 percentage points. This research adds to the literature on moral hazard, showing that when people are allocated to high coverage insurance they tend to have more accidents. It points to a situation where people take accident costs into consideration when choosing their driving behavior.

The use of company insurance packages is widespread throughout Israel due to their direct inclusion in company leased vehicles. During 2008 there were 2,322,200 active cars in Israel, and 304,100 of these vehicles were registered as company cars. Thus, approximately 13 percent of vehicles in Israel are not privately owned. This percentage increases enormously when considering new cars of which 56 percent of those purchased in 2008 were company cars.[26] The prevalence of company cars in Israel is attributed to the significant tax benefit provided for these cars, and is often used as an additional salary incentive (or fringe benefit) for employees. The analysis in this paper applies directly to these groups who are receiving high insurance coverage at low costs. My findings show that increasing rates of car accidents are an unintended consequence of increasing implementation of this type of salary incentive scheme.

[26] The Economics and Development Division of the Israel Tax Authority (Document 501369 May 19, 2009).

This paper emphasizes the general implications of moral hazard but also holds an important contribution to policy. Car accidents are an issue of concern for countries around the world. Motor vehicle related injuries are the leading cause of death for people aged 1 to 34 in the United States.[27] The estimated cost of these accidents in the US alone amounted to over 230 billion dollars in the year 2000. Israel faces a similar relative cost estimated to be about 2% of GNP. While the largest monetary benefit of company coverage for employees in this dataset was employer coverage of their policy cost (averaging $803), we believe that the smaller differential cost of an accident (ranging between $80 and $400) was the cause of the moral hazard effect. My analysis suggests that both government and car insurance providers can play a significant role in reducing accidents at the relatively low cost of redesigning insurance contracts that will ensure drivers bear sufficient consequences after involvement in an accident.

[27] CDC Centers for Disease Control and Prevention: Motor Vehicle Safety http://www.cdc.gov/Motorvehiclesafety/index.html

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A A Nonlinear Panel Data Model to Estimate the Effect of Moral Hazard on Car Accidents in Israel

In this Appendix we develop the econometric model estimated in Section 5. Let y_{it} be a binary variable taking the value of 1 when person i in period t is involved in an accident, and zero otherwise. Rewrite η in equation (4) as $\eta = \widetilde{v} - \widetilde{\varepsilon}$, where $\widetilde{v} = v + \beta_1 u, \widetilde{\varepsilon} = -\varepsilon$ and let y_{it}^* be a latent variable defined by the same equation (4),

$$y_{it}^* = w_{it}\widetilde{\pi} + \pi_2 y_{it-1} + \pi_3(z_i \times y_{it-1}) + \widetilde{v}_i - \widetilde{\varepsilon}_{it}$$

where $w_{it} = (x_{it}, z_i)$ is the vector of explanatory variables (including car characteristics, personal characteristics, and an indicator z for holding company insurance), y_{it-1} is an indicator for involvement in an accident last period, $\widetilde{v}_i$ are unobserved personal characteristics that do not change over time and $\widetilde{\varepsilon}_{it}$ is a random term uncorrelated with $(w_{it}, y_{it-1}, \widetilde{v}_i)$.

We only observe $y_{it} = I(y_{it}^* > 0)$. The probability of an accident for individual i in period t is therefore $P(y_{it} = 1 | y_{it-1}, w_{it}, \widetilde{v}_i) = F(w_{it}\widetilde{\pi} + \pi_2 y_{it-1} + \pi_3(z_i \times y_{it-1}) + \widetilde{v}_i)$, while,

$$P(y_{it} | y_{it-1}, w_{it}, \widetilde{v}_i) = F(q_{it})^{y_{it}} \left[1 - F(q_{it})\right]^{1-y_{it}}$$

where

$$q_{it} = w_{it}\widetilde{\pi} + \pi_2 y_{it-1} + \pi_3(z_i \times y_{it-1}) + \widetilde{v}_i$$

and F is the cumulative distribution function of $\widetilde{\varepsilon}_{it}$.

The joint distribution function of accident occurrence for person i during the sample period, $y_{i1}, .., y_{iT}$, conditional on observables $w_i = (w_{i1}, \ldots, w_{iT})$, on initial y_{i0} and on the unobserved individual effect $\widetilde{v}_i$ is

$$P(y_{i1}, .., y_{iT} | y_{i0}, w_i, \widetilde{v}_i) = \prod_{t=1}^{T} P(y_{it} | y_{it-1}, \ldots y_{i1}, y_{i0}, w_{it}, \widetilde{v}_i)$$

and assuming that, for any $t = 1, \ldots, T$,

$$P(y_{it}|y_{it-1}, \ldots y_{i1}, y_{i0}, w_{it}, \widetilde{v}_i) = P(y_{it}|y_{it-1}, w_{it}, \widetilde{v}_i)$$

we get

$$P(y_{i1}, .., y_{iT}|y_{i0}, w_i, \widetilde{v}_i) = \prod_{t=1}^{T} F(q_{it})^{y_{it}} \left[1 - F(q_{it})\right]^{1-y_{it}} \tag{6}$$

Equation (6) cannot be used for estimation due to the presence of unobserved personal characteristics contained in $\widetilde{v}_i$. Different methods exist in the literature to cope with this problem. Heckman (1981) suggests using the joint distribution function from all periods (including period 0) conditional on $(w_i, \widetilde{v}_i)$ and then integrating out $\widetilde{v}_i$. This is done by assuming a distribution of y_{i0} conditional on observed variables and the unobserved individual effect $\widetilde{v}_i$, $P(y_{i0}|w_{i0}, \widetilde{v}_i)$, as well as a distribution of $\widetilde{v}_i$ conditional on observables, $h(\widetilde{v}_i|w_i)$. We can then integrate out the individual effect to obtain,

$$\begin{aligned} P(y_{i0}, .., y_{iT}|w_i) &= \int_{\widetilde{v}_i} P(y_{i0}, y_{i1}, .., y_{iT}|w_i, \widetilde{v}_i) h(\widetilde{v}_i|w_i) d\widetilde{v}_i = \\ & \int_{\widetilde{v}_i} P(y_{i1}, .., y_{iT}|y_{i0}, w_i, \widetilde{v}_i) P(y_{i0}|w_{i0}, \widetilde{v}_i) h(\widetilde{v}_i|w_i) d\widetilde{v}_i \end{aligned}$$

and we can build a likelihood function to estimate the parameters $(\widetilde{\pi}, \pi_2, \pi_3)$ based on this joint probability for accidents which is dependent only on observed explanatory variables.

Blundell (1999) and Wooldridge (2002) suggest focusing on the joint distribution of $y_{i1}, .., y_{iT}$ conditional on y_{i0} as well as on $(w_i, \widetilde{v}_i)$. This avoids making any assumptions regarding the distribution of y_{i0}, $P(y_{i0}|w_{i0}, \widetilde{v}_i)$ – the "initial conditions" problem – although it still requires an assumption on the distribution of $\widetilde{v}_i$, $h(\widetilde{v}_i|y_{i0}, w_i)$.[28] This

[28] Akay (2009) analyzes performance of both the Heckman and Wooldridge approach and finds that the Wooldridge and Heckman methods yield similar results in panels with over 5 time periods, while

results in

$$
\begin{aligned}
P(y_{i1},..,y_{iT}|y_{i0},w_i) &= \int_{\widetilde{v}_i} P(y_{i1},..,y_{iT}|y_{i0},w_i,\widetilde{v}_i)h(\widetilde{v}_i|y_{i0},w_i)d\widetilde{v}_i = \\
&\int_{\widetilde{v}_i} \prod_{t=1}^{T} F(q_{it})^{y_{it}} \left[1-F\left(q_{it}\right)\right]^{1-y_{it}} h(\widetilde{v}_i|y_{i0},w_i)d\widetilde{v}_i \qquad (7)
\end{aligned}
$$

Assuming F is standard normal (implying a probit model for y_{it}) and that $\widetilde{v}_i$ follows a normal distribution we use (7) to form a likelihood function. This likelihood function is identical to that corresponding to the likelihood of a standard random effects probit model and the model can therefore be estimated using standard software for random effect models. More precisely, we assume

$$\widetilde{v}_i = \tau_0 + \tau_1 y_{i0} + \overline{x}_i \tau_2 + a_i \qquad (8)$$

where a_i is independent of $(y_{i0}, \overline{x}_i, z_i, \widetilde{\varepsilon}_{it})$ and $a_i \sim N\left(0, \sigma_a^2\right)$.

Note that, given y_{i0} and $\overline{x}_i$, z_i is not a determinant of $\widetilde{v}_i$. This is a crucial identification assumption, because otherwise we would not be able to differentiate between the moral hazard effect of z_i (π_1) and the effect of individual driving tendencies ($\widetilde{v}_i$) on car accidents that can be predicted by allocation to company coverage (z_i). It follows that, conditional on y_{i0}, w_i, $\widetilde{v}_i$ is also normally distributed with mean $\tau_0+\tau_1 y_{i0}+\overline{x}_i\tau_2$ and variance σ_a^2. This method introduces another random variable a_i to the probability of having an accident: $P(y_{it}=1|w_{it}, y_{it-1}, y_{i0}, \overline{x}_i) = G(w_{it}\widetilde{\pi}+\pi_2 y_{it-1}+\pi_3(z_i \times y_{it-1})+\tau_1 y_{i0}+\overline{x}_i\tau_2)$, where G is the cumulative distribution function of $a_i - \widetilde{\varepsilon}_{it}$. We can then rewrite (7) as

$$P(y_{i1},..,y_{iT}|y_{i0},w_i) = \int_{a_i} \left(\prod_{t=1}^{T} G(m_{it})^{y_{it}} \left[1-G\left(m_{it}\right)\right]^{1-y_{it}} \right) \frac{1}{\sigma_a}\phi\left(\frac{a_i}{\sigma_a}\right) da_i \qquad (9)$$

---

the Heckman technique performs better in shorter panels.

$$
\begin{aligned}
G(m_{it}) &= P\left(m_{it} + a_i - \widetilde{\varepsilon}_{it} > 0\right) = \Phi\left(\frac{m_{it}}{\sqrt{\sigma_a^2 + 1}}\right) \\
V(a_i - \widetilde{\varepsilon}_{it}) &= V(a_i) + V(\widetilde{\varepsilon}_{it}) + 2Cov(a_i, \widetilde{\varepsilon}_{it}) = \sigma_a^2 + 1 \\
m_{it} &= \pi_1 z_i + x_{it}\pi_x + \pi_2 y_{it-1} + \pi_3(z_i \times y_{it-1}) + \tau_1 y_{i0} + \overline{x}_i \tau_2
\end{aligned}
$$

which is the likelihood function of a probit model with an expanded set of regressors and random effect $a_i - \widetilde{\varepsilon}_{it}$.

Due to the nonlinearity of the model the coefficient π_1 allows us to only assess the significance of moral hazard via company insurance and the direction of the effect. A positive coefficient on z_i implies a positive effect of company insurance on accidents. The marginal effect of z_i on the probability of an accident is given by

$$
E[P(y_{it} = 1 | x_{it}, z_i = 1, y_{it-1}, y_{i0}, \overline{x}_i)] - E[P(y_{it} = 1 | x_{it}, z_i = 0, y_{it-1}, y_{i0}, \overline{x}_i)]
$$

where,

$$
E\left[P(y_{it} = 1 | x_{it}, z_i, y_{it-1}, y_{i0}, \overline{x})\right] = E\left[\Phi\left(\frac{m_{it}}{\sqrt{\sigma_a^2 + 1}}\right)\right] = \frac{1}{N\left(\sum_{i=1}^{N} T_i\right)} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \Phi\left(\frac{\widehat{m}_{it}}{\sqrt{\widehat{\sigma}_a^2 + 1}}\right)
$$

We estimate this partial effect by

$$
\begin{aligned}
&= \frac{1}{N\left(\sum_{i=1}^{N} T_i\right)} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \Phi\left(\frac{ind_{it} + \widehat{\pi}_1 + \widehat{\pi}_3 y_{it-1}}{\sqrt{\widehat{\sigma}_a^2 + 1}}\right) - \Phi\left(\frac{ind_{it}}{\sqrt{\widehat{\sigma}_a^2 + 1}}\right) \\
ind_{it} &= x_{it}\widehat{\pi}_x + \widehat{\pi}_2 y_{it-1} + \widehat{\tau}_1 y_{i0} + \widehat{\overline{x_i}\tau}_2
\end{aligned}
$$

using the estimated parameters.

B Data

B.1 Variable Definitions

1. *Time Period* in this dataset is defined as a chronological ordering of insurance policies from the point that the client joins the insurance firm. This allows us to utilize all of the available data using panel data techniques while controlling for the years in which the policy was active.

2. *Policy Length* denotes the length of time between the start date and end date of a given policy. Most policies last for about a year, but in cases where the insured switched a car mid-policy or began an insurance policy mid-year the length can be significantly shorter. In order to allow comparison of policies with similar lengths, when a policy length is less than six months and the adjacent policy insures the same car they are combined into one policy (see Data Cleaning).

3. *Client Identifier* is a unique number that classifies the owner of a policy. There exist cases in the raw data where the same client holds policies for different cars that overlap (see Data Cleaning: Dealing with Overlap).

4. *Matriculation Exam Completion* is defined as the percent of 12th graders in the client's city of residence who completed their matriculation exams in the year the current policy ended.

5. *Average Family Income* is defined as average family income in the client's city of residence in 2001 NIS in the year the current policy ended.

6. *Winter* is defined both for accidents and policy coverage as including the months between November and March.

7. *Distance from Work* is defined using a mapping program as the kilometers between the client's city of employment and city where the accident occurred.

8. *Accident Distance* is defined using a mapping program as the kilometers between the client's city of employment and city of residence.

B.2 Data Cleaning

B.2.1 I. Privately Insured

1. 2,223 Observations - Base Data.

2. 1,486 Observations holding full coverage insurance.

3. 1,468 Observations deleting expanded policies.

4. 1,391 Observations combining policies under 6 months.

5. 1,387 Dropping observations that do not have information on city of residence.

6. 1,363 Dropping observations where one car is insured separately from others.

7. 1,245 Including only clients insured for over 1 period.

B.2.2 II. Company Insured

1. 4,590 Observations - Base Data.

2. 4,557 Observations deleting expanded policies.

3. 4,372 Observations combining policies under 6 months.

4. 4,354 Dropping observations that do not have information on city of residence.

5. 4,347 Dropping observations where one car is insured separately from others.

6. 4,232 Including only clients insured for over 1 period.

B.2.3 III. Dealing with Overlap

1. In cases where the overlap is under one year - the end date of the earlier policy is set to one day prior to the start date of the overlapping policy.

2. In cases where the overlap is over one year - we assume multiple drivers are insured under the same client (i.e. he/she can be insuring both his/her car and that of a spouse or child). We therefore create a separate client identifier for the overlap and treat those observations as a separate client.

Table 1: Summary Statistics

		Private Insurance[a]	Company Insurance[a]	Difference[b]
Policy Holder Characteristics:	Male	0.835	0.760	0.075*
		(0.372)	(0.427)	(2.63)
	Years Insured	5.405	6.464	-1.058*
		(2.022)	(1.942)	(-7.81)
	Policy Start Year	2002.2	2001.9	0.218
		(1.642)	(1.613)	(1.95)
	Policy End Year	2006.6	2007.4	-0.840*
		(1.750)	(1.309)	(-8.43)
Policy Holder Residence:	Distance from Workplace (km)	24.37	16.71	7.659*
		(27.91)	(27.54)	(2.56)
	Reside in City of Workplace	0.244	0.270	-0.026
		(0.430)	(0.444)	(-0.86)
	Reside NE of Workplace	0.155	0.0927	0.062*
		(0.362)	(0.290)	(2.88)
	Reside NW of Workplace	0.412	0.434	-0.022
		(0.493)	(0.496)	(-0.65)
	Reside SE of Workplace	0.0790	0.0675	0.011
		(0.270)	(0.251)	(0.65)
	Reside SW of Workplace	0.110	0.135	-0.025
		(0.313)	(0.342)	(-1.09)
	Average Monthly Family Income (NIS) [c]	15735.1	15037.1	698.1*
		(2646.3)	(2644.3)	(3.83)
	Matriculation Exam Completion	62.35	61.11	1.245*
		(6.338)	(6.205)	(2.89)
Car Characteristics:	Engine Size	1600.5	1680.3	-79.81*
		(359.6)	(346.1)	(-7.09)
	Year	1998.4	1998.0	0.402*
		(3.610)	(4.506)	(2.89)
N:	Number of Clients	291	755	
	Number of Policies	1,245	4,232	

[a] Standard deviation in parenthesis.
[b] *t* statistics in parenthesis , * $\rho < 0.05$
[c] The NIS conversion rate during this period varied between 3.38 shekel to the dollar and 4.99 shekel to the dollar. The average exchange rate was $1=4.41 NIS.

Table 2: Collision Summary Statistics

		Private Insurance[a]	Company Insurance[a]	Difference[b]
All Years:	Involved in Collision (0/1)	0.152	0.167	-0.015
		(0.359)	(0.373)	(-1.24)
		[1,245]	[4,232]	
	Collision Damage Estimate (NIS) [c]	9345.9	10168.5	-822.6
		(15424.6)	(10168.5)	(-0.49)
		[101]	[371]	
	Collision Distance from Workplace (km)	24.88	15.84	9.035*
		(30.33)	(28.77)	(3.41)
		[153]	[566]	
	Collision Occurred During Winter	0.386	0.435	-0.049
		(0.488)	(0.496)	(-1.22)
		[189]	[705]	
By Period:	Involved in Collision 1st Period	0.144	0.087	0.057*
		(0.352)	(0.283)	(2.72)
		[291]	[755]	
	Involved in Collision 2nd Period	0.124	0.193	-0.070*
		(0.330)	(0.395)	(-2.67)
		[291]	[755]	
	Involved in Collision 3rd Period	0.160	0.188	-0.028
		(0.367)	(0.391)	(-0.95)
		[219]	[680]	
	Involved in Collision 4th Period	0.158	0.181	-0.023
		(0.365)	(0.385)	(-0.69)
		[165]	[592]	
	Involved in Collision 5th Period	0.144	0.189	-0.045
		(0.353)	(0.392)	(-1.18)
		[125]	[512]	
	Involved in Collision 6th Period	0.223	0.193	0.030
		(0.419)	(0.395)	(0.67)
		[94]	[466]	
	Involved in Collision 7th Period	0.200	0.154	0.046
		(0.404)	(0.361)	(0.88)
		[55]	[423]	
	Involved in Collision 8th Period	0.000	0.122	-0.122
		(0.000)	(0.331)	(-0.82)
		[5]	[49]	

[a] Standard deviation in parenthesis, Number of policies in brackets.
[b] *t* statistics in parenthesis, * $\rho < 0.05$
[c] The NIS conversion rate during this period varied between 3.38 shekel to the dollar and 4.99 shekel to the dollar. The average exchange rate in this period was $1=4.41 NIS.

Table 3: The Effect of Company Provided Car Insurance on Accidents

Variables	(i)	(ii)[a]	(iii)[a]	(iv)[a]	(v)[a]
Company	0.033	0.151**	0.154**	0.152**	0.157**
	(0.062)	(0.071)	(0.071)	(0.072)	(0.072)
Male	0.027	0.020	0.020	0.020	0.018
	(0.060)	(0.066)	(0.067)	(0.067)	(0.067)
High Traffic Density Commute	0.230**	0.271**	0.277**	0.278**	0.276**
	(0.101)	(0.112)	(0.113)	(0.113)	(0.113)
Policy Length	0.093	0.725**	0.717**	0.720**	0.614**
	(0.217)	(0.268)	(0.269)	(0.269)	(0.295)
Total Years Insured	0.049**	0.064**	0.065**	0.065**	0.066***
	(0.016)	(0.020)	(0.020)	(0.020)	(0.020)
Lagged Large Accident[b]			-0.167	-0.258	-0.242
			(0.147)	(0.397)	(0.398)
Company × Lagged Large Accident[b]				0.104	0.098
				(0.423)	(0.424)
Accident 1st Period					0.163*
					(0.092)
Additional Individual Controls[c]	Yes	Yes	Yes	Yes	Yes
Time Averaged Controls[d]	No	No	No	No	Yes
Observations	5477	4431	4431	4431	4431

[a] Does not include first period of insurance.
[b] Lagged large accident=1 if a large accident occurred within the six months preceding the start date of the current policy. An accident is considered large if its reported damage estimate was over $1,034 (the median reported damage estimate in the data).
[c] Additional individual controls: policy year, car year, engine type, commute distance, matriculation completion, average income, and coverage over winter months.
[d] Time averaged controls: mean car year, mean engine type, mean matriculation completion, and mean average income.
* $p < 0.1$
** $p < 0.05$
*** $p < 0.01$

Table 4: Estimated Marginal Effects of Company Provided Car Insurance on Accidents

Variables	Probit Marginal Effects[a]	Linear Random Effects[b]
Company	0.036**	0.034**
	(0.016)	(0.016)
Male	0.004	0.002
	(0.017)	(0.016)
High Traffic Density Commute	0.071**	0.069**
	(0.032)	(0.028)
Policy Length	0.135**	0.127*
	(0.067)	(0.074)
Total Years Insured	0.015***	0.014***
	(0.004)	(0.004)
Lagged Large Accident (LLA)[c]	-0.036	0.021
	(0.030)	(0.034)
Accident 1st Period	0.041*	0.038*
	(0.023)	(0.022)
Additional Individual Controls[d]	Yes	Yes
Time Averaged Controls[e]	Yes	Yes
Observations	4431	4431

[a] See Appendix A for detailed information on the calculation of marginal effects in this nonlinear framework. Standard errors are calculated via the bootstrap method and account for clustering at the individual level (400 replications).

[b] This is the average effect in the dataset. For example the company effect is calculated as $\hat{\pi}_1 + \hat{\pi}_3 \frac{I(LLA=1)}{I(LLA=0)+I(LLA=1)}$.

OLS standard errors account for clustering at the individual level.

[c] Lagged large accident=1 if a large accident occurred within the six months preceding the start date of the current policy. An accident is considered large if its reported damage estimate was over $1,034 (the median reported damage estimate in the data).

[d] Additional individual controls: policy year, car year, engine type, commute distance, matriculation completion, average income, and coverage over winter months.

[e] Time averaged controls: mean car year, mean engine type, mean matriculation completion, and mean average income.

* $p < 0.1$
** $p < 0.05$
*** $p < 0.01$

Table 5: The Effect of Company Provided Car Insurance on Accidents: DID Approach

Variables	(i) Linear Random Effects	(ii) Linear Random Effects	(iii) Probit Marginal Effects[a]	(iv) Linear Fixed Effects
Company×Post	0.129***	0.128**	0.122**	0.120**
	(0.050)	(0.053)	(0.048)	(0.051)
Company	-0.103***	-0.102**	-0.103**	
	(0.043)	(0.045)	(0.048)	
Post	-0.092**	-0.094**	-0.093**	-0.097**
	(0.043)	(0.046)	(0.046)	(0.045)
Male		0.043*	0.043*	
		(0.025)	(0.025)	
High Traffic Density Commute		0.041	0.046	
		(0.040)	(0.043)	
Policy Length		-0.001	-0.004	-0.018
		(0.077)	(0.080)	(0.092)
Total Years Insured		0.004	0.004	
		(0.008)	(0.008)	
Additional Individual Controls[b]	No	Yes	Yes	No
Time Varying Individual Controls[c]	No	Yes	Yes	Yes
Observations	1225	1225	1225	1225

Standard errors account for clustering at the individual level.
[a]Average partial effects calculated using technique in Appendix A with bootstrap standard errors (400 replications).
[b]Additional individual controls: commute distance, mean car year, mean engine type, mean matriculation completion, and mean average income.
[c]Time varying individual controls: policy year, car year, engine type, matriculation completion, average income, and coverage over winter months.

* $p < 0.1$
** $p < 0.05$
*** $p < 0.01$