The Value of Usage-Based Insurance beyond Better Targeting: Better Driving

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Abstract

Usage-Based Insurance (UBI) is a recent auto insurance innovation that enables insurance companies to collect individual consumer's driving data and provide individually targeted price discounts based on each consumer's driving behaviour. In this paper, using detailed information on insurance premium, retention rates of customers and individual driving behaviour for the UBI adopters, we examine and estimate the effect of the UBI policy on changing the customers' driving behaviour, which is a potential source of profit improvement for the insurance company beyond better selection among customers and higher retention rates. The key results of our analysis are as follow: First, after controlling for age and gender, we find considerable variation in individual level UBI scores, thus providing evidence that UBI can help the company better estimate a driver's risk and price accordingly. Second, among the company's customers, adopters of UBI have higher retention rates than non-adopters; moreover, among UBI customers, safer drivers have higher retention rates. Third, very importantly, our results show that after UBI adoption, the drivers improve their driving behaviour, resulting in lower risk of an accident, providing a meaningful benefit for both the driver and the insurance company. We find that not all components of the UBI measure appear to change over time. In particular, we find that customers decrease their daily average hard brake frequency by an average of 21% after using UBI for six months, but we cannot find any significant effects on the mileage driven by customers after UBI adoption. We also find heterogeneous effects across different demographic groups. For example, younger drivers are more likely to adopt UBI and they also improve their UBI scores faster than older drivers after the UBI adoption. We also find that economic incentives lead to higher adoption rates of UBI and greater improvements in driving behaviour. Our results suggest that UBI is not only beneficial to the insurance company, but also to consumers who become better drivers.

Key words: Usage Based Insurance, Economic Incentives, Feedback and Information, Driving Behaviour

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1. Introduction

Companies across a broad spectrum of industries are increasingly using new technologies to increase their business productivity. In the highly competitive auto insurance industry, which we study here, insurers are attempting to find ways to more precisely predict risks, sharpen pricing strategies, and provide better value to their policyholders. Usage-based insurance (UBI) is becoming a popular alternative to traditional automotive insurance. UBI is a recent innovation that more closely aligns individual's own driving behaviours with premium rates for auto insurance. Mileage and driving behaviours are tracked using odometer readings or in-vehicle telecommunication devices (telematics) that are usually self-installed into a special vehicle port or already integrated in original equipment installed by car manufactures. The basic idea of telematics auto insurance is that a driver's behaviour is monitored directly while the person drives. These telematics devices measure a number of elements of interest to underwriters: miles driven, time of day, where the vehicle is driven (GPS), rapid acceleration, hard braking, and hard cornering. The telematics device is typically self-installed by the driver and then continuously monitored by the auto insurer. After a period of time, 6 months in our empirical setting, the device is removed and returned to the firm. The insurance company then assesses the data and charges insurance premiums accordingly. Unlike traditional insurance models, which try to identify safe and unsafe drivers based on their driving history, age, gender, and even marriage status, UBI uses actual driving data to determine an appropriate premium for each client. In other words, usage-based insurance is about measuring time, distance, driving behaviour and driving location to determine who should pay less for their automotive insurance.

UBI can offer many potential benefits for insurers, consumers and society as a whole. Insurers benefit by being able to differentiate their product offerings, enhance pricing, lower claim costs, enhance brand awareness and create new revenue streams. For consumers, telematics-based UBI offers certain advantages over traditional insurance, including the ability to control premium and receive ancillary benefits based on their own behaviour. Society as a whole accrues benefits from improved road safety, less road congestion and lower emissions resulting from drivers' focus on vehicle-usage and driving performance.

Despite all the potential benefits of UBI that we mentioned for customers and insurers above, there is little knowledge about whether this strategy will improve the insurance companies' profits. The potential sources of profit improvement from the UBI can be divided into three categories: (1) better selection (along with the ability to price discriminate) among customers, (2) higher retention rates, and (3) improvements in customers' driving behaviour, that is, customers who receive UBI feedback may become better drivers. As improved driving performance has not been previously studied with an extensive, individual level database, we focus on the last source of profit improvement by exploring customers' driving performance after their UBI adoption.

1.1. Literature Review

To our knowledge, our study is the first empirical study on how usage-based insurance affects drivers' driving behaviour. Our paper is related to three streams of research including studies on (1) usage-based pricing in the service industry, (2) the effect of feedback on consumer behaviour, and (3) economic incentives and behaviour change.

Usage-Based Pricing. UBI is one type of Usage-based pricing (UBP) system that sets prices based on consumer's usage of a product. Most of the papers on UBP are in the telecommunication and software subscription industries. For example, Nevo et al. (2016) study the demand for residential broadband facing a usage-based, three-part tariff pricing scheme and find that consumers respond dynamically to the price and usage-block levels. Bauer and Wildman (2012) summarize the substantial research literature on differential pricing in broadband networks based on usage and service quality (e.g., speed and capacity) and suggest that there are potential efficiency benefits of differential pricing for both consumers and sellers. One of the key mechanisms through which positive welfare effects are realized is the design of lower-priced plans for users who otherwise might not buy the service, while users who have a more intensive demand for broadband are able to take advantage of quantity discounts and contract for more advanced services. UBP also has flexibility advantages for users whose data service needs vary over time. Altmann and Karyen (2001) empirically compare flat-rate and usage-based plans to charge for internet services and find that UBP plans have advantages for both users and providers as compared to flat rate plans. Bala and Carr (2010) develop a theoretical model to study both fixed and usage-based pricing schemes in a competitive setting where the firm incurs a transaction cost of monitoring usage when it implements usage-based pricing. They show that offering different pricing schemes helps to differentiate the firms and relax price competition, particularly at higher monitoring costs, even when competing firms offer the same service quality. However, the low usage customers acquired by offering usage-based pricing are unable to compensate for the monitoring costs incurred. This implies that managers should be cautious about implementing usage-based pricing.

Our research on UBI relates more particularly to Pay-as-you-drive (PAYD) auto insurance in which the premium depends upon the miles drive. The major distinctions between UBI and PAYD are: first, the premium for PAYD only depends on a driver's mileage driven, but for UBI, a driver's premium also depends on how she drives; second, unlike PAYD, on which a driver's mileage only affects her current period's premium, the UBI affects both the current and future insurance discount. Lindberg, et al. (2011) and Arvidsson, (2010) argue that usage-based premiums foster self-selection amongst motorists, which positively affects an insurer's risk portfolio by attracting low-risk customers. They show theoretically that once offered, usage-based policies are assumed to cause three distinct effects on the insurer's risk portfolio: good risks enter the insurance pool of

the company, bad risks transform into good risks (without describing the mechanism by which this might happen), and bad risks leave the company's insurance pool. The research on PAYD by Edlin (2003) and Parry (2005) finds that drivers reduce their mileage in order to lower the insurance premium. Specifically, in their empirical setting, they expect motorist's annual mileage to decline by about 10% after switching to per-mile insurance plans. Our results do not find a similar drop in mileage, as for UBI several factors other than mileage can also change the premium costs. In our context, we directly examine how customers change the quality (e.g., fewer hard brakes) of their driving beyond reducing the vehicle usage under UBI policy. Our work is related to an early correlation study by Fincham, et al. (1995) who examine the impact of telematics technology on accident rates apart from mileage-based premium schemes. They find that the mere presence of event-data-recorders, which record vehicle acceleration data in accident situations, correlates to reduced accident frequency. Our paper, by contrast, measures driving behaviour more generally, and uses statistical controls to better understand the underlying process. In our paper, we also examine an additional issue–drivers with a limited driving record may receive a relatively higher premium rate than more experienced drivers, and so opt for UBI to get a more accurate reading of their true driving behaviour.

In summary, UBP appears to have three primary benefits as compared to uniform pricing: (1) consumers can choose the consumption level that best suits their needs, both for low usage and high usage customers, thus allowing for preference based segmentation, (2) as a result, there is the potential for enhancing welfare for consumers as well, and (3) firms can enjoy a competitive advantage by adopting UBI. That is, firms that offer UBI can acquire customers from firms that do not.

Information and Feedback. Our paper is also related to behavioural and psychological literature on the effect of information and feedback on behaviour change. For example, Taniguchi, et al. (2003), in a study of pro-social behaviour, show how getting feedback can modify travel behaviour based on the hypothesis that automobile-use reduction or pro-environmental behaviour is influenced by moral obligation, and moral obligation is in turn influenced by awareness of the negative environmental consequences of automobile use. The study's psychological and behavioural data confirm the set of hypotheses and also that the travel feedback program had a significant positive effect on pro-environmental behaviour even one year after participation in this program. Fujji, et al. (2005) also shows the effectiveness of a travel feedback program aimed at reducing family car-use.

A number of studies examine the effect of information warning a consumer that she is about to incur a (higher) fee for a service. Jiang (2012) shows how "bill shock" regulation, alerting consumers when they are about to use up the monthly allowance of calls or data, in the mobile phone industry

can affect the consumers' usage and welfare. She shows that providing this information can increase the consumer surplus, primarily for heavy users. In another paper related to providing feedback and additional information for consumers, Liu, et al. (2014) study how sending dynamic alerts can help consumers to better track their banking activities and change their behaviour in a way to avoid overdraft fees in financial activities. Gopalakrishnan, et al. (2014) study the consumer learning in cellphone usage under multipart tariff plans and find that consumers can learn to use their cellphones more efficiently when they receive information and feedback. Grubb (2014) obtains similar results.

Economic Incentives. Beyond information and feedback, other authors examine the effect of economic incentives for behaviour changes. This is particularly important, as authors such as Lowenstein[1] have argued for the limited impact on behaviour change of just providing information. Stern (1999), for example, in a study of pro-environmental behaviour, concludes that incentives and information have different functions, so that efforts focused on only one may be misplaced; however, properly deployed, they can have synergistic effects on behaviour. Stern (1999) demonstrates the presence of an interactive effect of information and incentives beyond the independent importance of incentives. Heberlein and Baumgartner (1985) reports similar results in that the type of information provided influences the extent to which people respond to incentives to switch their household electric usage from peak to off-peak periods. On the other hand, Holt and Laury (2002) show that in the presence of higher economic incentives, consumers become sharply more risk averse, which may lead to changes in their behaviour and decisions. While we cannot directly test for risk aversion, we employ a quasi-experimental design to examine whether there is a greater change in drivers' behaviour when UBI programs have higher economic benefits.

Little work has been done on the differential effects of incentives across demographic factors (other than income). We study here whether the results of participating in the UBI program vary by such demographic factors as age and gender. In a study to examine the effects of incentives on educational attainment, Croson and Gneezy (2009) find that the provision of incentives led to a substantial increase in school completion rates and college attendance for girls, but had no effect for boys. These findings, although in a very different context, seem to be consistent with our results showing that females improve their driving performance more than males enrolled in the UBI program.

An important component of the UBI program studied here is that the driving behaviour is monitored for a maximum of 26 weeks, but the discount earned is a permanent one. This suggests that

[1] According to George Loewenstein, an economist at Carnegie Mellon University, "There are very few cases where social scientists have documented that giving people information has changed their behaviour very much. Changing prices and changing convenience have a big impact. Providing information doesn't" (Tavernise, 2014).

insurers expect the behaviour to continue. This is consistent with Becker and Murphy's (1988) economic model of habit formation, which defines habitual behaviour as displaying a positive relation between past and current consumption. For example, if exercising can become a habitual behaviour, then providing incentives to go to the gym for a while may increase future likelihood of exercising even after removing incentives. Gneezy et al. (2011) provide some examples and experiments, which support this argument that the incentives can also improve the long run behaviour of customers after removing the incentives that first motivated the behaviour. In this paper, we examine the weekly driving behaviour of UBI participants and find that most improvements in safer driving behaviour occur early in the program and remain consistent, once achieved.

1.2. Research Summary

In this paper, we use a unique database from a major US insurance company to examine the impact of participation in UBI on driving behaviour. We observe information from more than 100,000 new customers who submitted a quote request to purchase an insurance policy from March, 2012 to November, 2014. For all customers who adopted the UBI policy, we have daily information of their driving behaviour and by using these data we can understand how the drivers in this program change their driving behaviour while being monitored by telematics device.

By estimating fixed effect models for panel data of UBI customers' driving behaviour, we find that these customers generally improve their driving behaviour by increasing (improving) their UBI driving score and reducing the number of daily hard brakes during UBI usage. However there is no evidence to show that the drivers in the UBI program significantly change their daily mileage driven. The degree of change is heterogeneous across our sample. For example, we find that UBI is relatively more appealing to younger customers, who typically are charged the highest rates and consequently have a higher incentive to earn a UBI discount than older, more experienced drivers, ceteris paribus. Importantly, we find that the youngest group of UBI customers are more likely to change and improve their daily UBI score and reduce the number of hard brakes by receiving driving feedback during monitoring device usage. Comparing male to female customers, we find that females tend to improve their driving performance more than males.

We also investigate the effect of economic incentives on improving the driving behaviour of customers. We divide states into those, which offer no-Fault vs. traditional insurance, a policy decision that is exogenous to our research question. No-Fault states typically have higher average premiums than traditional states [2]. We show that UBI drivers improve their driving behaviour more in the higher premium, no-Fault states. This suggests that the change in driving behaviour

[2] See Rand study (2012)

cannot just be because of receiving driving feedback in the UBI policy and there may also be economic incentives that encourage customers to be safer driver.

The rest of this paper is organized as follows. We first discuss the industry background on UBI policy in auto insurance industry and then the data used in our analysis and some key patterns in the data. We then present the empirical models to estimate the changes in driving behaviour of different group of customers and the empirical results for our models. Next, we discuss the role of economic incentives and propose an approach to identify the effect of economic incentives on driving behaviour improvement. Finally we provide some concluding comments.

2. Industry Background

2.1. History of UBI and Current Market Share

Usage-based pricing is a popular pricing scheme among service industries especially in mobile and residential broadband industries, however UBI is a recent auto insurance innovation that is expected to play a prominent, future role in this industry.

The auto insurance market is the largest insurance market segment in the US, and it is fiercely competitive, as insurers strive to attract the more profitable low-risk drivers. Hundreds of auto insurance writers are essentially competing for the same premium base, whose dollar value is not growing in the US. As vehicles and roads are becoming safer, premium are falling. In such an environment, the opportunity for growth appears to be limited. Total premium in the private passenger auto insurance market (liability and physical damage) have only grown from $158 billion to $175 billion in the last 10 years in the US, less than the rate of inflation. For some large insurers showing strong growth, most of the growth is primarily a result of increasing their market share. The stagnant growth in a competitive market makes the attraction, retention and accurate rating of policyholders all the more important, and any tools that can help achieve these goals are immensely valuable. UBI insurance policies based on telematics devices are believed to provide one way to achieve these goals.

Although it is difficult to have an accurate estimate of the overall size of the UBI market, according to Towers Watson survey in July 2014, 8.5 percent of consumers had a UBI policy in force, up from 4.5 percent in February 2013[3]. According to SMA[4] Research, approximately 36 percent of all auto insurance carriers are expected to use telematics UBI by 2020. Based on the CIPR survey of state insurance departments, in all but two states (California and New Mexico)insurers currently offer telematics UBI policies. In 23 states, there are more than five insurance companies active in the telematics UBI market[5].

[3] http://www.insurancejournal.com/news/national/2014/09/05/339731.htm

[4] Strategy Meets Action

[5] http://www.insurancejournal.com/magazines/features/2013/10/21/308181.htm

2.2. Insurer Benefits

UBI's focus on tying driver behaviour to pricing also allows insurers to better monitor and control their risk exposure, potentially raising their risk tolerances and allowing them to reach new customer bases. The ability for insurers to charge drivers less for safer driving habits provides a powerful incentive to consumers to improve their driving behaviours in order to lower their premium. This affords insurers using these programs to gain several competitive advantages. First, insurers can identify their lowest-risk drivers, raising retention levels for preferred risks. Secondly, they are also likely to gain new customers by offering all drivers the opportunity to pay less for their car insurance. This could particularly help reach younger drivers who are generally riskier but possibly more amenable to modifying their behaviour in order to earn a discount.

SAS Institute (2014) predicts insurers will receive more than 25 percent of their premium revenue, representing $30 billion, from telematics-based insurance programs by 2020. Early corporate adopters would most likely have a competitive advantage due to the detailed driving behaviour data they have collected for pricing analysis. The proprietary nature of the collected data available to an insurer would make it exceedingly difficult for its competitors who do not have historical driving data to appropriately price their products. Moreover, customers who have already enrolled in one company's monitoring program may be less inclined to switch to another insurer for whom they would again need to be monitored to earn a UBI discount[6].

2.3. Consumer Benefits

Telematics-based UBI programs offer several potential consumer advantages. Consumers benefit most by having the ability to reduce their auto insurance costs. Premium reductions can come from the insurer's participation discounts, improved driving performance or voluntary reductions in mileage driven. Consumers initially receive a discount on their regular premium rates for enrolling in the program and then, after a period of being monitored, are offered a permanent discount rate. Participants in the program never pay a surcharge, so participation is risk-free to consumers.

Consumer surveys indicate premium discounts and the ability to control premium are the primary drivers for consumer adoption of telematics-based UBI programs. According to the 2014 Annual LexisNexis Insurance Telematics study, 78 percent of respondents cited discounts as an incentive to adopt telematics insurance programs. Seventy-four percent cited the ability to control their auto insurance costs as an incentive[7].

This pricing scheme also eliminates the cross-subsidy between higher risk and lower risk drivers, benefiting the majority of consumers. According to a study done by the Brookings Institute, 63.5

[6] https://www.lexisnexis.com/risk/downloads/whitepaper/2014-ubi-research.pdf

[7] https://www.lexisnexis.com/risk/downloads/whitepaper/2014-ubi-research.pdf

percent of households with insured vehicles would save an average of $496 a year (a 28 percent average reduction in premium) under a fully variable mileage-based UBI program. This saving is primarily from eliminating the subsidy for high mileage drivers, who account for the majority of miles driven within each risk class, but pay a disproportionately lower premium. Eliminating this cross subsidy increases affordability for lower-mileage drivers, many of whom are also lower-income drivers. Those who do not initially save still benefit by having the ability to shrink premium by changing their driving habits.

Telematics-based UBI programs also benefit consumers by incentivizing them to increase their safety through better driving habits. Safer drivers become even safer while riskier drivers, whose premium are typically highest, are educated to modify their high risk behaviour. This focus on educating and promoting safety can be particularly appealing to households with young divers. According to the 2014 LexisNexis study, young driver programs were cited as one of the most popular value-added features among consumers, with 56 percent of respondents with children on their policy indicating interest in telematics programs which track and provide feedback on their teens.

3. Data

3.1. Description of the UBI Policy

We study an individual's automobile insurance choices and their driving performance based on data from a major US insurance company that offers the UBI program as an optional policy alongside the traditional car insurance policy. The data cover all new customers that the company added in 15 states in a 32 month time period from March 2012 to November 2014. All new customers receive both a traditional premium quote based on a formula filed with each state's regulators[8] and the offer of a discount if they enrol in the UBI program. Customers are free to leave the UBI program at any time and continue with the firm's traditional insurance even though participation in the UBI program cannot lead to a higher premium. The UBI discount depends upon a score based on a number of factors related to actual driving behaviour. The actual formula is not disclosed, but the firm has provided information on the overall driving behaviour score and two components of the score, daily miles driven and number of hard brakes per day, which are major components of the score. Internal corporate documents show that these variables are highly correlated with the likelihood of an automobile accident[9].

[8] Age, gender, driving history (e.g., previous claim costs), credit history (in some states credit history is not allowed to be included in the calculation), vehicle year, vehicle model, and some other safety factors of a vehicle are important in setting the premium

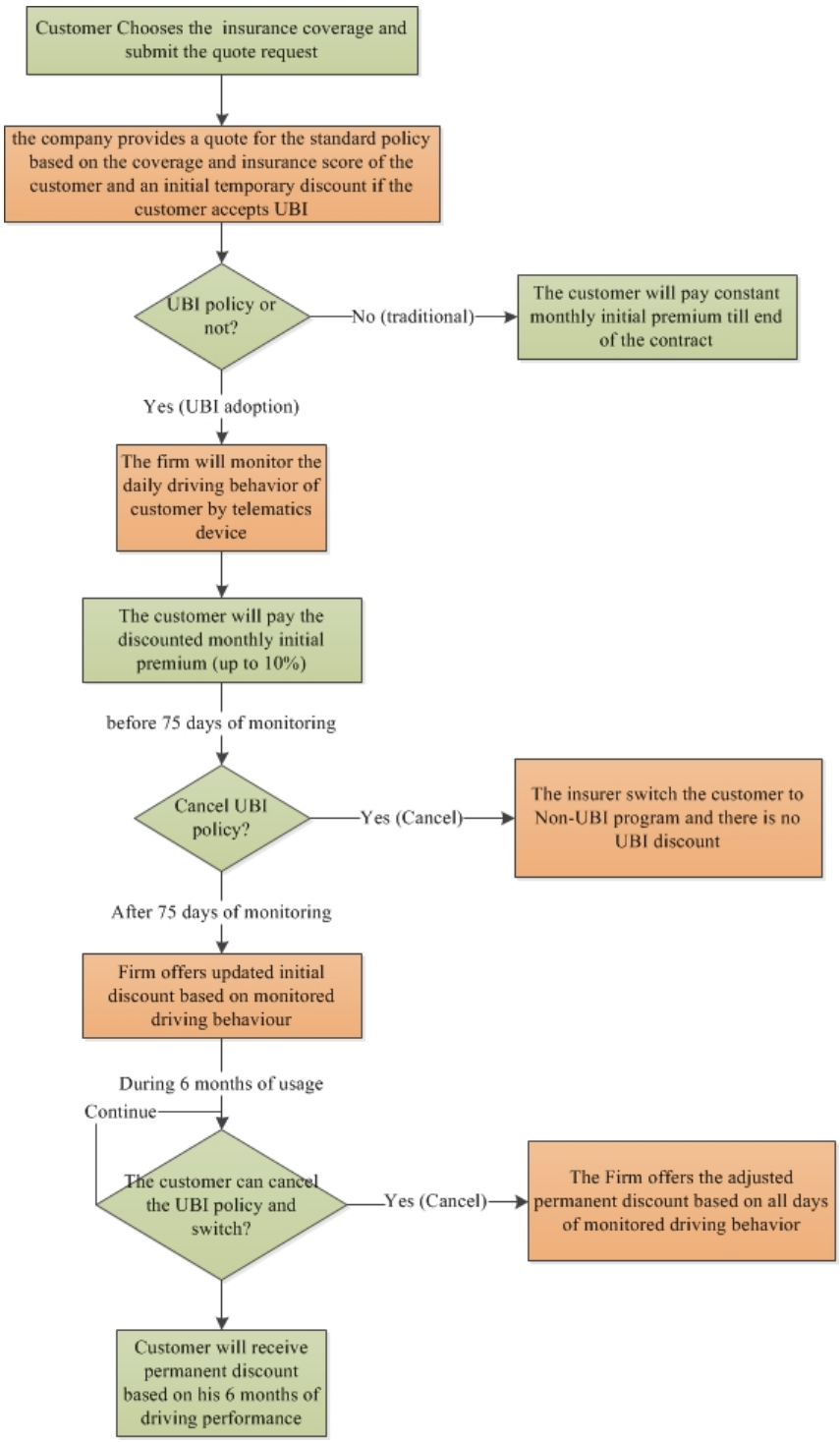
[9] "Comparing Real-World Behaviours of Drivers with High versus Low Rates of Crashes and Near-Crashes", US department of transportation, National highway traffic safety administration, February 2009.

Based on information in corporate annual reports, the insurance company started to offer usage based insurance as a new policy in order to better target safer drivers and thus to increase their profit by attracting and keeping more profitable customers. Like almost all the UBI policies in United States, this firm's UBI policy was introduced as an optional one that allows the customers to receive a personalized premium rate based on their actual driving behaviour. The pricing strategy of the insurance company is to encourage the new customers to sign up for a UBI policy by offering an initial (temporary) discount (up to 10%). The initial discount is given to the customers as soon as they enrol in the UBI program. If the policyholder accepts the UBI policy, she will receive a telematics device that should be plugged into the car. This device enables the insurance company to monitor many aspects of the driving behaviour of the customer. The customer can monitor her performance from real time feedback – whenever the customer "hard brakes," the telematics device beeps to let the driver know or the driver can monitor her performance on a daily basis via an app. After 75 days of using the monitoring device, the customer will receive an updated discount, which is based on the customer's actual driving performance. From 75 days until 26 weeks, the customer can remove the telematics device and ask the company for a permanent UBI discount based on performance to date. The monitoring period lasts for a maximum of 26 weeks, at which time, the telematics device is removed and the customer is offered a permanent UBI discount. The driver will receive up to 25% permanent discount based on her daily driving scores after six months of usage, but as we discuss more fully below, the average discount rate is 12% with a standard deviation of 5%. While some drivers (less than 1% in our sample) may be offered no discount, a surcharge is never imposed. Figure 1 illustrates the sequential process of the insurer and policyholder actions in the UBI program.

Our empirical analysis builds on a number of data sets that contain information about individual drivers' auto insurance choices, their demographic characteristics, and risk scores defined by the insurance company. For the drivers who chose UBI, we observe additional information on their UBI scores and indicators of their driving behaviour, including the number of hard brakes per day and daily driving mileage.

Our first data set contains information on 135,540 customers who submitted a quote request to purchase auto insurance from March 2012 to November 2014. All these customers had the option to choose between a traditional insurance policy and UBI. In this dataset, we observe all the customers' demographic information (including age, gender and the state where the customer lives), the insurance score that the firm assigns to each customer, the insurance coverage and the initial premium the customers would pay under their policies. There is also the UBI acceptance decision for all customers and the initial discount for each UBI customer who adopted this program. Table 1 summarized some summary statistics of the customers in our sample.

Figure 1: Flowchart of customer and firms decisions in UBI policy.



The first column of Table 1 shows a data summary for all customers, while the second and third columns are related to the data summary of non-UBI and UBI customers respectively. The average UBI acceptance rate is about 30%. In addition, the average age of UBI main policyholders (39) is

Table 1: The summary statistics of all customers.

	Total	**Non-UBI**	**UBI**
Number of customers	135540	95013	40527
Average age	45.8	48.7	39.3
Fraction male	0.53	0.53	0.52
Average initial insurance score	52.06	53.31	49.14
Average renewal insurance score		54.8	52.8
Average initial premium	109.1	107.6	112.4
Average renewal premium (discount excluded)		104.12	106.5
UBI acceptance rate	0.3		
Average initial discount			0.05
Average permanent discount			0.12
First year renewal rate	0.8	0.77	0.86

much lower than non-UBI customers (48), suggesting that the UBI program is more attractive for younger drivers. One possible explanation is that the insurance company assigns relatively high risk level to the young drivers due to the lack of sufficient driving history. Hence, this group of customers pay substantially higher initial premium. The UBI program can provide a great opportunity for the young drivers to show their actual driving behaviours and as a result they can receive a discount rate according to their performance. Therefore, the incentive for younger drivers seems to be higher to adopt the UBI program comparing to older, or experienced drives. Table 1 also includes the insurance score, which is a measure of the customer's risk that the insurer considers when setting the premium. The score depends on multiple factors, such as the driver's age, gender, and past claims. Each company files the formula for its insurance score in each state, so that by regulation the insurance score is based on different factors than is the UBI score. We test the relationship between the UBI score and the insurance score and do not find a statistically significant correlation between average UBI score of drivers and their insurance score (See Appendix1). A low (less favourable) insurance score for a driver could occur either because of the high number of accidents and claims or the lack of sufficient driving history. In Table 1, the average insurance score for UBI is lower than for non-UBI customers, which is consistent with our argument that the UBI program is most appealing to younger drivers, who typically have a limited driving history. We also find that although both UBI and non-UBI customers on average improve their insurance score at renewal time, Table 1 shows that the improvement is higher for UBI customers. Given that UBI customers have a younger average age, it is possible that for younger drivers, the insurance score changes more by adding a year of driving history than for older drivers.

The average initial discount for UBI customers in our sample is 5% (sd= 2.4%) to encourage the drivers to enrol in UBI program, and the average permanent discount is about 12% (sd= 5.1%) that the UBI drivers get after monitoring the driving behaviours by telematics device. The UBI

customers' average monthly initial premium is \$112 (before discount), which is higher[10] than that for non-UBI customers (\$107) due to the higher insurance score; however, the premiums for the two groups (UBI discount excluded for UBI customers) are closer at the renewal time. As shown in the Appendix1, the renewal premium is not significantly related ($p > .05$) to participation in the UBI program and the performance of customers in the UBI program. In terms of renewal rate, the renewal rate of UBI customers is 9% higher than for non-UBI customers.

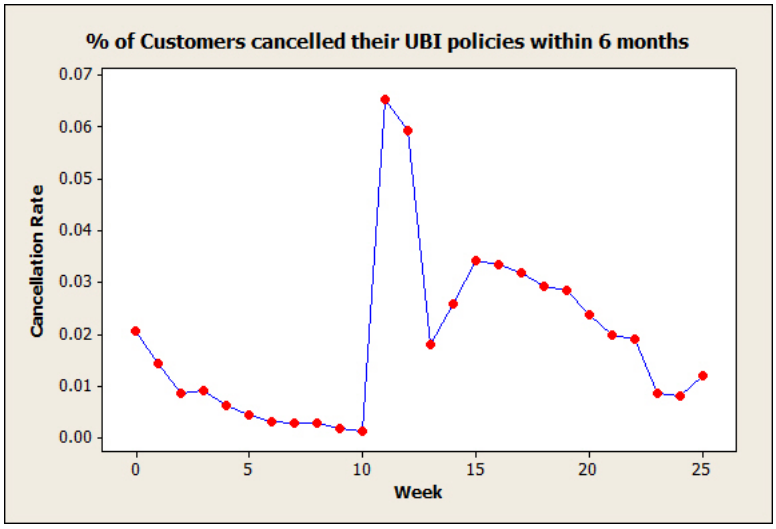
The second dataset contains several measures of the UBI customers' daily driving behaviour. The data are collected by the telematics device for up to 6 months after its installation. We have access to daily mileage driven and number of hard brakes of all UBI customers as long as they are in the UBI program and have plugged the telematics device into their automobile. In addition to mileage and hard brakes, we also observe the daily driving score that all UBI customers receive at the end of each day. In other words, the daily UBI score represents the daily driving performance of a driver by aggregating the measures of all factors that are considered to be important by the insurance company. Although these factors are more than just mileage and number of hard brakes, which we observe in our dataset, we show in table A-3 of appendix1 that daily hard brakes and mileage are two key derivers of the daily UBI score. These two factors explain about 60% of variation in observed daily UBI score of customers. In summary, we have a panel data of UBI customers for up to 180 days (or 26 weeks) for whom we observe three daily measures of the customers' driving behaviour: daily driving score, number of hard brakes, and mileage driven.

It is important to note that we do not observe all UBI customers' driver behaviours for the 26 weeks, since many customers withdraw from the UBI program before 6 months of usage. As shown in Figure 2, about 2% of UBI customers enrolled in this program but never installed the telematics device. We observe some patterns in the cancellation rate of UBI customers. There are two spikes in weeks 11 and 12 during which the insurance company updates the initial discount based on the first 75 days of driving and the UBI customers decide whether they want to continue in this policy. About 12% of UBI customers dropped out of the UBI policy in weeks 11 and 12 combined. As discussed below, the cancelation pattern seems to be related to the revised UBI score and it can potentially lead to selection issue in our latter analysis. By cancellation, we mean that the customer no longer agrees to be monitored and receives the (adjusted) UBI permanent discount at the time the telematics device is removed based on her actual driving performance during monitoring. However, we will show that our main results hold for both all the observations we have and for only those customers who continue in the program and are monitored for the full 26 weeks[11].

[10] P-value = 0.06

[11] 63% of UBI customers remain in this program for the entire 26 weeks. As shown in Appendix A1.3, withdrawing early decreases the level of permanent discount that a customer receives.

Figure 2: The cancellation rate within UBI program.



In next section we look at the weekly changes in our driving performance measures (UBI score, mileage, and hard brakes).

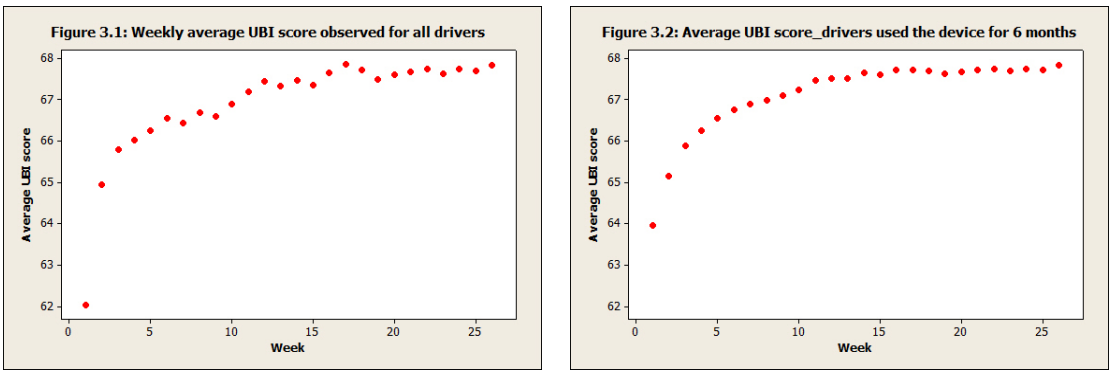
3.2. Descriptive Evidence of Improvement in Driving Behaviour

We start by presenting some basic descriptive evidence about the changes in driving behaviour of UBI customers and the improvement that happens in some measures of driving performance. Our data suggest that the UBI cancellation decision may be correlated with these customers' driving behaviour, so we need more rigorous empirical models to show that the improvement in driving behaviour are robust to these sample selection issues. We also examine the heterogeneity of changes in driving performance across different group of customers.

- **Average changes in UBI driving score**

Figure 3.1 shows the weekly average UBI driving score of all UBI customers observed in our dataset. We observe an increasing (improving) pattern in driving score from 62.05 in week 1 to 67.87 in week 26. As noted above, some customers cancel their UBI policies before 6 months and so that we cannot observe the driving score of these customers for all 26 weeks. For example, the number of UBI customers for whom we observe driving scores for the last week (week 26) is 35 percent lower than first week because of UBI policy cancellation during this time. Figure 3.2 helps us to better understand this issue; the plot shows the weekly average UBI driving score of customers who used the monitoring device for 6 months. The average UBI score in this sample for week 1 was 63.92 and increased to 67.87 in week 26. Although there are some differences in the weekly average values of the UBI score, the overall pattern across the two samples is similar, a finding supported later in the paper when we employ a more fully developed econometric model of driving performance.

Figure 3: The weekly average UBI score.



- **Average changes in number of hard brakes**

The daily number of hard brakes is a direct measure of driving behaviour that we can observe for all UBI customers as long as they are monitored. Previous studies have shown that the drivers who use fewer hard brakes are safer drivers because they did not put themselves in a risky situation in which they needed to brake hard[12]. Figure 4.1 shows the average daily number of hard brakes observed in 26 weeks of UBI usage. We find that the daily number of hard brakes has a notable decreasing pattern during the 26 weeks of our dataset for all UBI customers. For example, in the first week, the UBI customers who were monitored had on average 5.5 hard brakes in a day, while in last week of our dataset, the average number of hard brakes is less than 3, a significant change and improvement in driving behaviour. A steep change happens around week 10 to week 12, which is the time that the insurance company will update the discount rate, but it is also the time when some customers cancelled their UBI policy. Therefore we should be cautious in interpreting this figure, because the UBI cancellation by bad drivers may be the main reason for the changes in number of hard brakes. Figure 4.2 shows the average daily hard brakes just for the customers who used the device for all 26 weeks, i.e., those who did not cancel their UBI policy. Comparing these two graphs shows that while the steep drop in weeks 11 and 12 is most likely due to relatively high hard brake customers opting out of the UBI policy, the overall decline in hard braking holds for the sample of people who are monitored for all 26 weeks.

- **Average changes in daily mileage**

The daily mileage is also tracked by the UBI telematics device. Average daily mileage per week of UBI customers is shown in Figure 5. Interestingly, the weekly mileage driven first increases, although not uniformly, and then appears to be relatively constant (within in $+/-.5$ miles compared to an overall average of 27 miles per day). The general pattern in this plot is different than

[12] "The Lead Foot Report", Progressive Insurance Co. , November 2015

Figure 4: The average daily number of hard brakes.

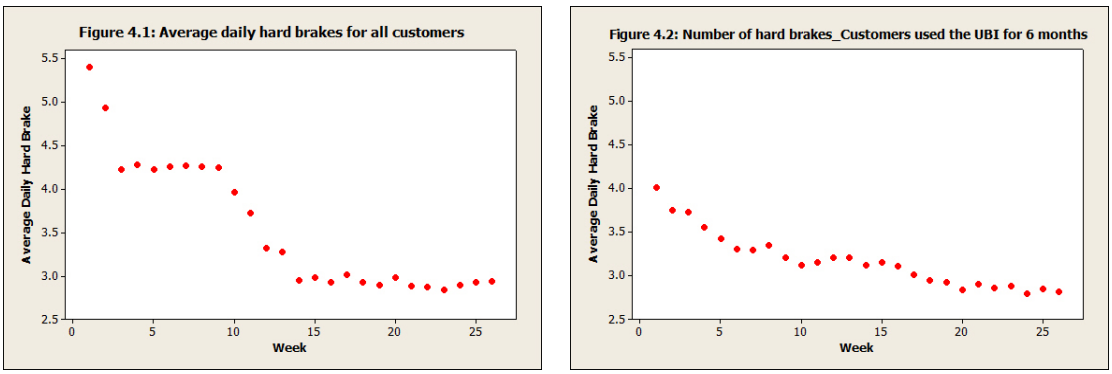
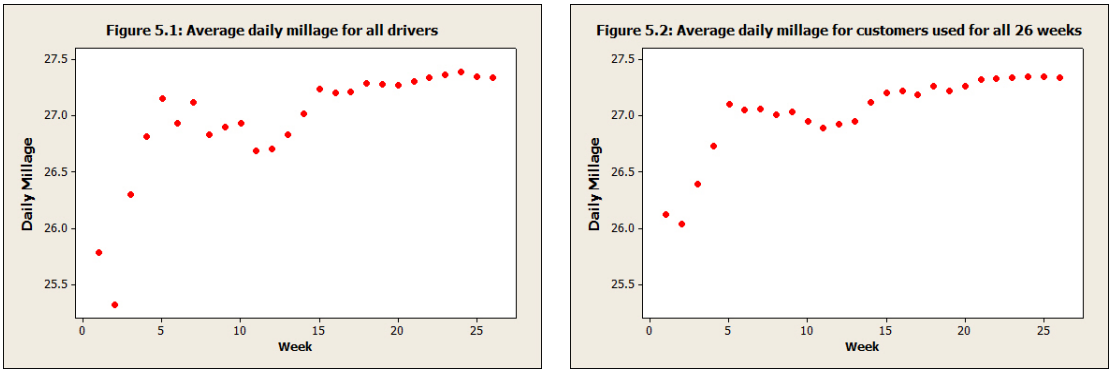


Figure 5: The average daily mileage.



that for the hard brakes and UBI scores shown above. In both Figures 3 and 4 the pattern shows that the drivers may be safer week by week by increasing their average driving score and decreasing the number of hard brakes, however the descriptive plot of mileage does not show such improvement, suggesting that outside factors (such as daily commuting) are the prime determinants of mileage.

The descriptive analysis in this section of the paper provides suggestive evidence of improvement in the driving behaviour of auto insurance customers who adopt the UBI policy, however the cancelation decision of customers, which seems to be related to their driving behaviour suggests that we need a more nuanced analysis. Moreover, there may be other idiosyncratic effects that should be controlled for. Therefore, we need more rigorous empirical methods to conclude that the improvement in driving behaviour of UBI customers is robust to such factors and to test for the existence of heterogeneity across different group of customers. In next section of this paper, we propose a fixed effect model our panel data to address these issues.

4. Empirical Analysis and Results

In this section, we analyze how the customers have changed their driving behaviour during their UBI adoption period. We first describe our empirical approach and the construction of our key explanatory variables. Our baseline specifications are regressions of observed UBI scores and indicators of driver behaviours on the time period from when they enrolled in the UBI program and control variables. We consider both age and gender of each customer as control variables in the regression and estimate the weekly changes in driving behaviour of UBI customers by cross sectional regression analysis. As we explained in the data section, for UBI customers we have their driving behaviour measures (UBI scores, daily number of hard brakes, and daily mileage) for up to 6 months of monitoring by a telematics device. We first demonstrate the overall effects of the UBI adoption, and then explore the heterogeneous effects on different consumer segments.

4.1. Model Specification

We first consider a simple, cross-sectional, regression model,

$$S_{it} = \alpha_0 + \alpha_1 \times Age_i + \alpha_2 \times Gender_i + \beta' \times week_dummies_{it} + \varepsilon_{it}. \tag{1}$$

where,

$$S_{it} : \textit{the UBI score of driver } i \textit{ at week } t.\ t = 1, ..., 26$$

$$Age_i : \textit{the age of driver } i.$$

$$Gender_i = \begin{cases} 1 & \textit{if the driver } i \textit{ is female} \\ 0 & \textit{otherwise} \end{cases}$$

$$dummy_{it} = \begin{cases} 1 & \textit{if the observation is in week } t \textit{ after UBI adoption} \\ 0 & \textit{otherwise} \end{cases}$$

$$\beta = \left[\beta_2,\ ...,\ \beta_{26}\right]'$$

$$week_dummies_{it} = \left[dummy_{i2},\ ...,\ dummy_{i26}\right]'$$

$$\varepsilon_{it} : \textit{identical and independent distributed across time } t \textit{ and individual } i.$$

In this specification the age (at time of enrolment) and gender of driver i are considered to control the changes across these groups of customers. The coefficients of week dummies in this specification capture the UBI score changes compared to the first week average UBI score.

Table 2 shows the estimation results of cross sectional regression analysis. The age variable has a negative correlation with average UBI score, which means that older drivers have a lower UBI score on average. This is an interesting finding that younger customers on average seem to have higher

Table 2: Cross sectional regression analysis results for UBI score.[13]
(***): p-value < 0.05

Cross sectional regression analysis results for UBI score			
	Estimate	Std. Error	Significance (0.05)
(Intercept)	63.47	0.08	***
Age	-0.12	0.01	***
Gender (Female)	3.12	0.03	***
Week_dummy2	3.6	0.1	***
Week_dummy3	3.95	0.1	***
Week_dummy4	4.06	0.1	***
Week_dummy5	4.18	0.1	***
Week_dummy6	4.14	0.1	***
Week_dummy7	4.3	0.1	***
Week_dummy8	4.43	0.1	***
Week_dummy9	4.59	0.1	***
Week_dummy10	4.76	0.1	***
Week_dummy11	5.13	0.11	***
Week_dummy12	5.34	0.11	***
Week_dummy13	5.39	0.11	***
Week_dummy14	5.32	0.11	***
Week_dummy15	5.37	0.11	***
Week_dummy16	5.33	0.11	***
Week_dummy17	5.32	0.12	***
Week_dummy18	5.34	0.12	***
Week_dummy19	5.41	0.12	***
Week_dummy20	5.53	0.12	***
Week_dummy21	5.48	0.13	***
Week_dummy22	5.48	0.13	***
Week_dummy23	5.6	0.13	***
Week_dummy24	5.52	0.13	***
Week_dummy25	5.64	0.13	***
Week_dummy26	5.68	0.14	***
Multiple R-squared: 0.135			Adjusted R-squared: 0.1349

UBI scores, implying that they are safer drivers. Females' UBI scores are 3.12 points higher than males' on average, suggesting that females on average have better driving behaviour than males in the UBI program. As we had previously explained, the week dummies represent the changes in UBI score compared to the first week. Considering all positive and significant coefficients of week dummy variables, the UBI customers achieve higher UBI scores in comparison to the first week during UBI usage, which means that they are becoming safer and better drivers.

To better control for heterogeneity, we now turn to fixed effects models to take advantage of the panel nature of our data. As discussed in the last part of the previous section, the length of time a customer stays in the UBI program may be correlated with behaviour changes. In particular, since a good driver could earn an even higher discount if he retains his UBI telematics monitor for the full 26 weeks, our estimates could be biased due to sample selection issues. To address this

[13] Sample size: 705,752 weekly UBI score observations

challenge, we estimate regression (equation 2) with customer individual fixed effects. The approach identifies β using variation within each individual driver.

$$S_{it} = \alpha_0 + \beta' \times week_dummies_{it} + driver_i + \varepsilon_{it}, \tag{2}$$

where $driver_i$ is the fixed effect parameter of driver.

Table 3 is the estimation result of the fixed effect regression model for UBI score. The fixed effect model controls for the consumer's individual heterogeneity and alleviates the sample selection issue mentioned before. Based on Table 3, all 25 coefficients are significantly positive, implying that customers have better UBI scores on average compared to those from the first week. The last column of this Table 3 indicates whether the weekly changes in UBI score in week t is significant in comparison to previous weeks (week $t-1$). We find that in the first 11 weeks, customers improve their UBI scores significantly (.05 level) every week and after that these changes lessen and drivers have more consistent UBI scores. This suggests that UBI customers learn to drive more safely (higher UBI score) by using monitoring devices in the first three months of usage and their behaviour is relatively consistent afterwards. In addition, by comparing Table 2 and Table 3, we observe the differences that arise when comparing the coefficient estimates of week dummy variables in the fixed effect model with the cross sectional regression analysis. This comparison suggests that the cross sectional regression results are biased due to selection issue.

Furthermore, we also consider the other measures of driving behaviour (number of hard brakes and mileage) as dependent variables in our fixed effect regression (2) to capture the weekly changes in driving behaviour of UBI customers in terms of number of hard brakes and mileage driven.

Table 4 shows the result of fixed effect model estimation for the number of hard brakes. We observe that the number of daily hard brakes decreases significantly when compared to the first week in our fixed effect model. In addition, the last column represents whether the number of hard brakes is significantly at .05 level less than the previous week. We find that during the first 6 weeks, the UBI customers improve their driving performance weekly by reducing the number of hard brakes. Table 4 shows evidence that UBI customers can significantly reduce their daily hard brakes and maintain that reduced rate to be better drivers.

In terms of daily mileage driven by UBI customers, we run a similar fixed effect model to explore any possible changes in the mileage driven per day for up to 6 months. As Table 5 shows, the coefficient estimates for the weekly dummies are not statistically significant, suggesting that the UBI customers don't change the mileage per day after using telematics devices for 26 weeks (except for only one significant mileage increase compared to first week mileage at 0.05 level in week 5)[14].

[14] The limited effect of the UBI policy on daily mileage driven is consistent with that in a number of small-scale studies about rewarding safe-driving, see Elvik (2014).

Table 3: Fixed effect regression analysis results for UBI score.
(***): p-value < 0.05

Fixed effect regression analysis results for UBI score			
	Estimate	Std. Error	Significance weekly improvement (0.05)
Week_dummy2	2.57	0.01	***
Week_dummy3	2.93	0.01	***
Week_dummy4	3.06	0.01	***
Week_dummy5	3.14	0.01	***
Week_dummy6	3.28	0.01	***
Week_dummy7	3.4	0.01	***
Week_dummy8	3.41	0.01	
Week_dummy9	3.49	0.01	***
Week_dummy10	3.77	0.01	***
Week_dummy11	4.34	0.01	***
Week_dummy12	4.42	0.01	
Week_dummy13	4.27	0.01	
Week_dummy14	4.33	0.01	
Week_dummy15	4.29	0.01	
Week_dummy16	4.24	0.02	
Week_dummy17	4.29	0.02	
Week_dummy18	4.37	0.02	***
Week_dummy19	4.36	0.02	
Week_dummy20	4.4	0.02	
Week_dummy21	4.44	0.02	
Week_dummy22	4.47	0.02	
Week_dummy23	4.5	0.02	
Week_dummy24	4.54	0.02	
Week_dummy25	4.57	0.02	
Week_dummy26	4.59	0.02	
Multiple R-squared: 0.419			Adjusted R-squared: 0.396

In conclusion, we run three fixed effect models in this section to capture weekly driving behaviour in terms of UBI score, number of hard brakes, and mileage in UBI program. We find that unlike UBI score and hard brakes, the mileage driven by UBI customers doesn't change significantly during 26 weeks of UBI usage. One possible explanation for the different patterns between hard brakes changes and mileage is related to the effort involved or implicit cost of these changes in driving behaviour for customers. For drivers, it is more convenient and less costly to change the number of hard brakes and learn from the feedbacks in order to improve their driving safety level, than to reduce their automobile usage (mileage). Another interesting point is that after the UBI and hard brakes stabilize at a level at which the scores do not improve weekly (after week 12) or the number of hard brakes does not continue to reduce (week 6), we do not observe any backsliding in which the driving score declines or hard brakes increase. That means that drivers in UBI program sustain for at least 26 weeks the driving behaviour changes they make in first 3 months of UBI usage.

4.2. Heterogeneity across Different Group of Customers

In this section, we investigate possible heterogeneity in driving behaviour changes across different age groups and gender. The cross sectional regression results in the first part of the empirical

Table 4: Fixed effect regression analysis results for number of "Hard Brakes".
(***): p-value < 0.05

Fixed effect regression analysis results for number of Hard Brakes			
	Estimate	Std. Error	Significance weekly improvement (0.05)
Week_dummy2	-0.26	0.02	***
Week_dummy3	-0.28	0.02	
Week_dummy4	-0.41	0.02	***
Week_dummy5	-0.45	0.02	***
Week_dummy6	-0.48	0.02	***
Week_dummy7	-0.47	0.02	
Week_dummy8	-0.43	0.02	
Week_dummy9	-0.48	0.02	
Week_dummy10	-0.51	0.02	
Week_dummy11	-0.48	0.02	
Week_dummy12	-0.48	0.02	
Week_dummy13	-0.47	0.02	
Week_dummy14	-0.49	0.02	
Week_dummy15	-0.48	0.02	
Week_dummy16	-0.5	0.02	
Week_dummy17	-0.51	0.02	
Week_dummy18	-0.53	0.02	
Week_dummy19	-0.57	0.02	
Week_dummy20	-0.61	0.02	
Week_dummy21	-0.59	0.03	
Week_dummy22	-0.59	0.03	
Week_dummy23	-0.6	0.03	
Week_dummy24	-0.62	0.03	
Week_dummy25	-0.6	0.03	
Week_dummy26	-0.61	0.03	
Multiple R-squared: 0.386			Adjusted R-squared: 0.378

analysis shows that the average UBI score is different across age groups and for females versus males, but in this section we consider a model to capture the weekly changes in driving behaviour for different customer groups.

Age groups. In order to estimate the weekly changes in driving behaviour for the different age groups of drivers, we add interaction effect of week dummies and age group indicators to the fixed effect regression model (2). Therefore the fixed effect model to capture heterogeneity across different age groups can be specified as:

$$S_{it} = \alpha_0 + \beta' \times week_dummies_{it} + \gamma_2' \times age_group2_i \times week_dummies_{it} + \gamma_3' \times age_group3_i \times week_dummies_{it} + \gamma_4' \times age_group4_i \times week_dummies_{it} + driver_i + \varepsilon_{it}. \quad (3)$$

Where,

$$age_group1_i = \begin{cases} 1 & age\ of\ driver\ i \leq 35 \\ 0 & else \end{cases}$$

$$age_group2_i = \begin{cases} 1 & 35 < age\ of\ driver\ i \leq 50 \\ 0 & else \end{cases}$$

$$age_group3_i = \begin{cases} 1 & 50 < age\ of\ driver\ i \leq 65 \\ 0 & else \end{cases}$$

Table 5: Fixed effect regression analysis results for daily driven mileage.
(***): p-value < 0.05

Fixed effect regression analysis results for daily Driven mileage			
	Estimate	Std. Error	Significance (0.05)
Week_dummy2	-0.06	0.05	
Week_dummy3	0.13	0.07	
Week_dummy4	0.1	0.09	
Week_dummy5	0.26	0.12	***
Week_dummy6	0.19	0.13	
Week_dummy7	0.16	0.13	
Week_dummy8	0.07	0.14	
Week_dummy9	0.1	0.15	
Week_dummy10	0.06	0.15	
Week_dummy11	0.04	0.2	
Week_dummy12	0.02	0.21	
Week_dummy13	0.15	0.23	
Week_dummy14	0.35	0.24	
Week_dummy15	0.46	0.24	
Week_dummy16	0.45	0.26	
Week_dummy17	0.48	0.26	
Week_dummy18	0.54	0.28	
Week_dummy19	0.53	0.29	
Week_dummy20	0.53	0.3	
Week_dummy21	0.55	0.31	
Week_dummy22	0.57	0.31	
Week_dummy23	0.6	0.32	
Week_dummy24	0.61	0.35	
Week_dummy25	0.6	0.34	
Week_dummy26	0.59	0.36	
Multiple R-squared: 0.296			Adjusted R-squared: 0.285

$$age_group4_i = \begin{cases} 1 & 65 < age\ of\ driver\ i \\ 0 & else \end{cases}$$

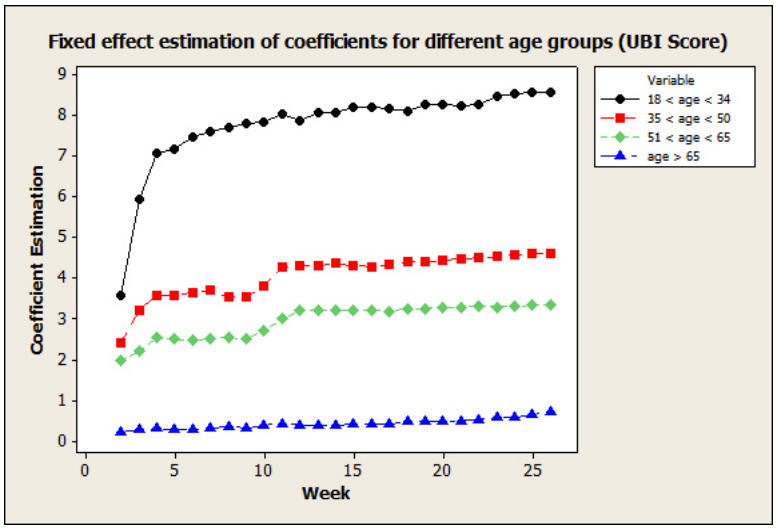
$$\gamma_k = \left[\gamma_{2k},\ ...,\ \gamma_{26k}\right]'\ for\ k = 2, 3, 4.$$

In the above setting, we consider four age groups which are commonly defined in the auto insurance industry[15]. The youngest group consist of all drivers younger than 35 years old (millennials), while the digital natives (35-50), baby boomers (50-65), and seniors (above 65) are the other groups of customers in our setting. The millennial group of customers is considered as baseline in our fixed effect model, therefore the β represents the changes in UBI score for the youngest age group of customers and γ_k represents the difference between the weekly changes in UBI score of the age group k and the youngest group of drivers.

Since there are multiple parameters to estimate in the fixed effect model with interaction effects ($4 \times 25 = 100$ parameters), the results in this section are represented by plots. The full Table of results for all fixed effect models can be found in the Appendix.

[15] http://www.datamentors.com/blog/insurance-generations-marketing-boomers-and-millennials

Figure 6: Weekly changes in UBI score estimation for different age groups.
Note: The average UBI score in first week for each group of drivers: 1- millennia (<35): 61.78, 2- digital natives (35-50): 61.65, 3- baby boomers (50-65): 63.14, and 4- seniors (>65): 65.73

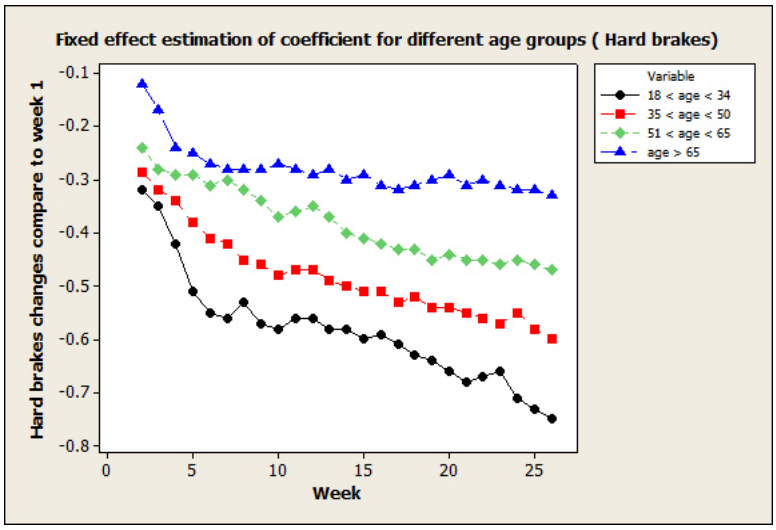


First we discuss the heterogeneity in *changes of UBI score* in 26 weeks among four different age groups. Figure 6 shows the estimate of weekly changes in UBI score for four age groups in the fixed effect regression model by estimating the coefficients of 25 week dummy variables and 75 parameters related to interaction effects. As we can see in this Figure 6, the change patterns in UBI score are different for the four age groups. For example, the senior drivers have more consistent UBI scores than other segments with limited improvements, however the young drivers increase their UBI scores to become better drivers.

Each point in Figure 6 represents the change in UBI score in week t compared to the first week. For instance, the initial point of the black line shows that the average UBI score of the youngest group of drivers in the second week is 3.6 points higher than their UBI scores in the first week, however the other age groups don't have this amount of improvement in weekly UBI scores. Note that figure 6 only shows the estimated weekly changes. If we want to compare the driving behaviour of different age group customers in terms of UBI score we need the estimated average UBI score for the first week. The estimated values for the first week UBI scores shows that the newest, youngest age groups have lower starting UBI scores as compared to the oldest drivers. The senior drivers have the highest starting UBI scores among all age groups, however the much lower weekly UBI score improvement for this group of drivers compared to younger drivers leads to a lower average UBI score after 26 weeks of UBI usage for senior drivers[16]. This result seems to be consistent with negative estimation of age coefficient in the cross sectional regression analysis, which means the

[16] The estimated UBI score after 26 weeks for all age groups: 1- millennia: 70.34, 2- digital natives: 66.27, 3- baby boomers: 66.47, 4- senior: 66.43

Figure 7: Weekly changes in daily hard brakes estimation for different age groups.
Note: The average daily number of hard brakes in first week for each group of drivers: 1- millennia (<35): 4.14, 2- digital natives (35-50): 4.08, 3- baby boomers (50-65): 3.95, and 4- seniors (>65): 3.93



average UBI score of older drivers is lower than for younger ones. It can be interpreted by noting the significantly lower improvement in UBI score of senior drivers compare to younger customers.

The heterogeneity in the changing number of hard brakes across different age groups has similar results. Figure 7 shows the changes in daily number of hard brakes for the four age groups of drivers. Similar to the UBI score results, the daily number of hard brakes reduction (driving behaviour improvement) for youngest drivers is stronger than for senior drivers.

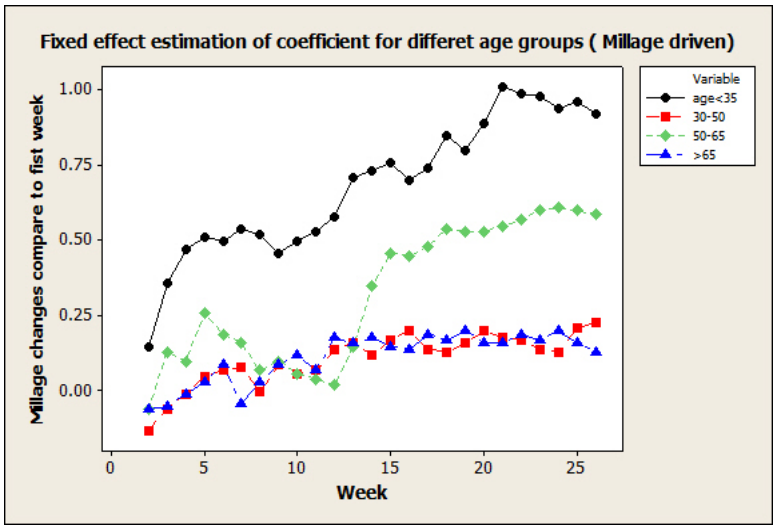
The youngest group has the highest initial number of hard brakes, but this group of drivers significantly reduced their number of hard brakes (about 20% reduction after 26 weeks) and finally became the safest drivers in terms of number of hard brakes.

The changes in mileage driven by different age group customers are explained by the fixed effects model for mileage with the addition of interaction effects of age groups and week dummy variables. Figure 8 shows the estimated changes in driving mileage compared to the first week for different age groups.

Interestingly, the youngest drivers have relatively low average mileage for the first week (25.73) compared to older drivers, but their mileage driven increases more and faster than that for the other groups of customers. Perhaps surprisingly, the mileage driven by young drivers in week 26 is significantly ($p < 0.05$) higher than in the first week, which, if anything, would limit their improvement in UBI score. No other age group exhibits a significant change in mileage.

We find that the UBI customers' driving behaviour changes, in terms of UBI score and number of hard brakes, differ across customer age groups and that the youngest drivers are more responsive

Figure 8: Weekly changes in daily mileage driven estimation for different age groups.
Note: The average daily mileage driven in first week for each group of drivers: 1- millennia (<35): 25.73, 2- digital natives (35-50): 31.45, 3- baby boomers (50-65): 30.54, and 4- seniors (>65): 24.96



than older age groups to UBI usage for changing their driving performance for both UBI score and number of hard brakes.

Gender. In this section, we recast the above analysis to explore whether there is any heterogeneous effect of UBI usage on driving behaviour improvement for females versus males.

We add the interaction effect of gender and week dummies to the fixed effect regression model (2) to capture the heterogeneity across males and females. So we will have:

$$S_{it} = \alpha_0 + \beta' \times week_dummies_{it} + \delta' \times Gender_i \times week_dummies_{it} + driver_i + \varepsilon_{it}. \tag{4}$$

Where,

$$Gender_{it} = \begin{cases} 1 & driver\ i\ is\ female \\ 0 & else. \end{cases}$$

Figure 9 shows the result of the fixed effect model for UBI score when we add the interactions of gender and week variables. We find heterogeneity between males and females but the pattern appears to be more complicated than for age. In the early weeks, the female drivers on average improve their driving behaviour less than the male drivers, however later it seems that female drivers improve their UBI score more than males. We can explain this result through possible different learning patterns for males and females, as introduced by Dweck (1986). According to our results, the male drivers improve their UBI score more quickly than females, but after four months of learning, which leads to higher UBI score, improvements in UBI scores diminish for male drivers while the females are more likely to improve in later weeks. In Appendix 3 we show the week in

Figure 9: Weekly changes in UBI score estimation for different genders.
Average UBI score in first week for each group of drivers: 1- Males: 60.92, 2- Females: 63.34

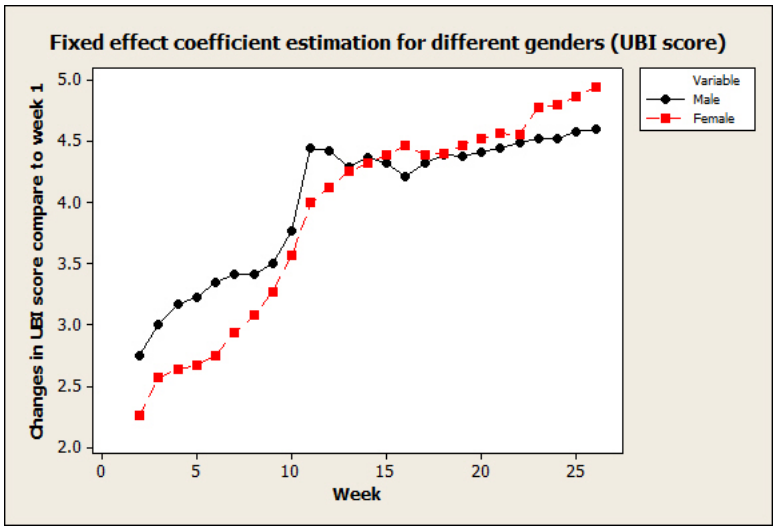
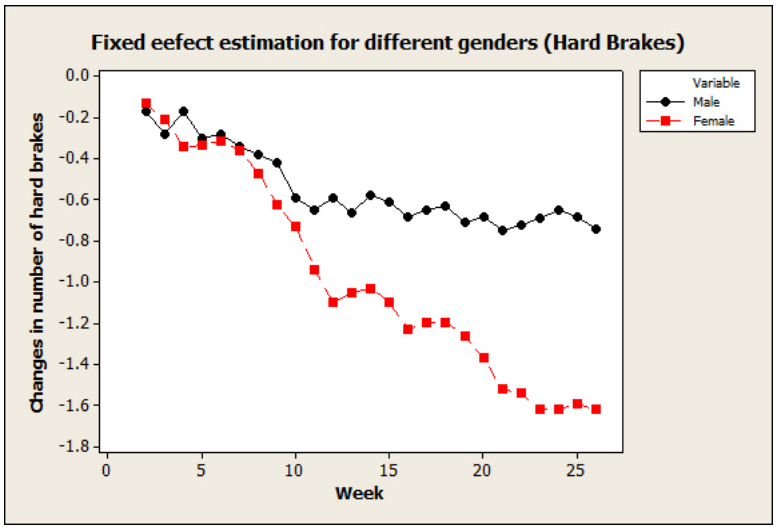


Figure 10: Weekly changes in hard brakes reduction estimation for different genders.
Average daily number of hard brakes in first week for each group of drivers: 1- Males: 3.64, 2- Females: 5.55



which drivers stop improvement in their driving behaviour compared to the last week performance for different groups of drivers. In addition to different patterns for males versus females, we note that females have both a higher UBI score at both the beginning (63.34 vs. 60.92) and end (68.24 vs. 65.31) of the monitoring period than males.

We have done similar analysis for changes in number of hard brakes by gender. Figure 10 shows the results of estimation for both males and females. Each plot point represents the weekly changes in daily number of hard brakes for males and females compared to that in first week.

The average daily number of hard brakes in the first week for females (5.55) is substantially higher than for males (3.64), but females reduce the number of have significantly more than males. Nevertheless, after 26 weeks, females still have a higher number (3.92) of hard brakes than males (3.02).[17]

5. Economic Incentives

In previous section, we found that the customers who adopted the UBI program improved their driving behaviour while being monitored by the telematics device. There are at least two motivations for the improvement in behaviour: first, the improvement that occurs because consumers respond to feedback from telematics device. That is, drivers will learn and improve their driving performance by getting daily feedback on different factors (mileage, number of hard brakes, UBI score, etc.) even without an economic incentive. In this case, the UBI device works very similarly to wearable technology devices (Apple watch, Fitbit, etc.) that measure the number of steps walked, heart rate, and other personal metrics, because from a consumer's perspective, the wearable devices help the users to change their healthy behaviour by just receiving feedback from that device. In addition, a second source for driving behaviour improvement is its economic incentives. In other words, the benefit of discount and net premium reduction from the UBI policy may lead to customers' improvement in driving performance. Both effects are likely present in the empirical results we present above.

In this section, we try to test the economic incentives (lower premium as a result of the UBI discount) effects on improving the UBI drivers' performance. In other words, we want to see how lowering the premium in the UBI policy can encourage the drivers to be safer and better drivers while using the UBI device. In order to identify the effect of economic incentives, we look for some exogenous differences in the premium that UBI customers pay, in order to analyse how the improvement in driving behaviour changes in different base amounts of premiums paid before the UBI discount is applied. It's crucial to find exogenous variations because the difference in the premiums should be independent of a customer's insurance choice and his risk preferences to avoid the selection issues in our identification.

The customers in our dataset are from 15 states in United States, which allows us to explore the regulation differences in auto insurance across states. The regulations in auto insurance market in different states affect the insurance companies' cost and the premium for consumers. Such policy differences are exogenous factors that generate variations in insurance premium among consumers in different geographic markets. We leverage this fact in our further analysis to identify

[17] Neither males nor females change their mileage driven.

Table 6: Data summary for No-Fault states versus Fault insurance states.

	No-Fault	**Fault**
Average monthly premium	130.7	102.1
Average age	46.8	45.3
Fraction male	0.53	0.53
UBI acceptance rate	0.31	0.29

the economic incentives effect on changing the driving behaviour. In below, we introduce the No-Fault insurance system versus Fault (or Tort) auto insurance in different states as they are set in states by regulation.

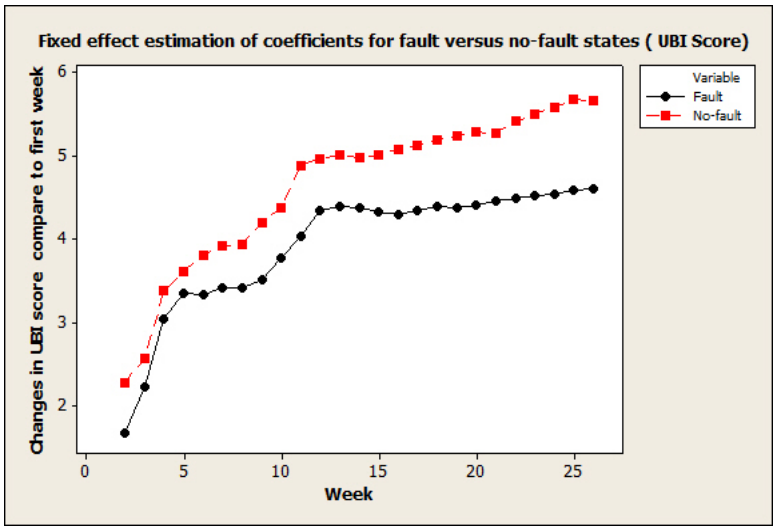
5.1. No-Fault auto insurance

By definition, No-Fault auto insurance system means that each insurance company compensates its own policyholders for the cost of their own personal injuries and property damage, regardless of who was at fault in the accident. (Fault is still assigned for purposes of calculating future premiums.) When first enacted in the 1970s in some states, No-Fault automobile insurance had many advocated. Its central idea was simply that an injured accident victim would simply receive compensation from his or her own insurance company instead of having to show the fault of another driver to recover losses from the other driver's insurance company. Many insurers and consumer groups supported the new concept as a way to mitigate the problems of resolving disputes through the courts, such as high legal costs, long delays, incentives for making dishonest claims, and the unfairness of compensating some victims much more than others. Despite its initial promise, however, the no-Fault approach has had only limited success. Several states have repealed their No-Fault laws and gone back to the traditional fault system. All states that adopted (or dropped) the No-Fault policy did so by 2001, while UBI was first introduced in the US in 2011. Therefore, there is no system change during our sample period.

In 2015, 13 states in the US mandate the use of a No-Fault auto insurance policy. (Some states, but none in our dataset, allow both No-Fault and tort insurance.) A 2012 RAND Corporation study found that costs and premiums are significantly higher in No-Fault than Fault (tort) systems. Following the previous studies, we assume that the No-Fault insurance system in some states induce higher premium which helps us to identify the effect of economic incentives on changing driving behaviours in UBI program.

As we explained in the data section of the paper, the customers in our dataset are from 15 different states and four of these states (Minnesota, Michigan, Pennsylvania, and New Jersey) have the No-Fault insurance system by regulation. Table 6 shows data summary on no-Fault versus Fault (tort) insurance system states in our dataset.

Figure 11: Weekly changes in UBI score estimation for customers in Fault versus No-Fault states. Average UBI score in first week for each group of drivers: 1- Fault: 61.82, 2- No-Fault: 62.51



Although the average monthly premium in No-Fault states is significantly higher than in traditional Fault states[18], the demographic variables age and gender are not significantly different ($p > 0.05$) between the two types of states. Since the premium is higher in No-Fault states, the UBI policy seems to be more attractive in these states and it is reflected in significantly higher UBI acceptance rate ($p - value < 0.05$) in No-Fault states. As the UBI discount is a percentage applied to the total premium, the economic incentives for better driving are higher in No-Fault insurance states because of the greater saving that UBI customers can gain from better performance. Consequently, comparing the changes in driving behaviour of UBI customers in these two types of states after controlling for other factors (age, gender) can help us to detect the economic incentives effect on driving behaviour improvement in the UBI program.

We employ a fixed effect model to test for changes in driving behaviours across two types of states by considering the interaction of state type variable (Fault & No-Fault) and week dummy variables. (See Figure 11). We find that the average UBI score in No-Fault insurance states in the first week is marginally higher ($p - value < 0.07$) than in Fault states. More interestingly, the estimated changes in the weekly UBI score of No-Fault insurance states (mean =5.66) where the premium (and economic incentive) of the UBI policy is significantly higher ($p < 0.05$) than in Fault states (mean = 4.6). We find similar results for the number of hard brakes. (See Appendix.) These results suggest that the greater economic incentives in No-Fault states lead to higher improvement in UBI score and driving performance than in Fault states.

[18] Consistent with Rand study which shows the premium in No-Fault states is higher

6. Discussion

UBI auto insurance was introduced in the US in order to help insurers improve their profits by better targeting their pricing (premiums) to the actual driving behaviour of their customers, to attract customers from other insurers who did not (yet) offer UBI, and to increase customer retention. In this paper, we go beyond those motivations to study whether the monitoring inherent in the UBI system could result in improved driving performance and to examine, in part, the role of economic incentives in achieving any such improvement. To study the effect of the UBI program on changing driving behaviour, we use a unique dataset, which allows us to observe the customers' information of a major US insurance company and track the driving behaviour at the individual level of customers who enrolled in the UBI program for up to 6 months. Our empirical results show that UBI customers improve their driving behaviour by increasing their UBI score by about 9% and reducing by 21% the number of daily hard brakes, which is an important factor affecting the occurrence of accidents. However, drivers do not generally change the daily number of miles driven, another factor related to the likelihood of an accident. In contrast to research on PAYD (Edlin (2003) and Parry (2005)) which finds that drivers reduce their mileage to lower auto insurance premiums, in the UBI program, mileage driven is not the only factor by which the drivers can lower premiums. UBI customers can change such other behaviours as the number of daily hard brakes. Changing such behaviours as the number of hard brakes may be easier for drivers than mileage reduction, which typically involves finding substitute means of transportation or reducing the number of trips made. In-car feedback whenever a hard brake is made may have a particularly strong effect, but the multi-dimensional overall UBI scores improves as well.

Importantly, behaviour changes almost immediately and continues throughout the observation period. For both the overall UBI score and hard brakes, we observe improvement, as compared to the first week, as soon as the second week. After 12 weeks for the UBI score and 8 weeks for the number of hard brakes, the average score reaches its best level and then remains at that level without declining for the rest of the observation period. By definition, we cannot observe behaviour after the removal of the UBI device (at most 26 weeks), but this provides strong evidence that once participants learn to drive more safely, they maintain that performance over an extended period of time. This conclusion is consistent with the firm's practice of setting a permanent discount after 26 weeks of observation.

In addition, we find that these improvements in driving behaviour vary across age groups and by gender. Although the youngest group (those less than 35 years of age, the millennials) of UBI customers have significantly lower initial UBI score than the oldest group of drivers (those over 65), they improve their driving behaviour such that after 6 months of UBI usage, the youngest group has the highest average UBI score among all age groups. Higher economic incentives and

different learning patterns for younger drivers compare to seniors are two key factors that can explain their greater improvement in driving behaviour. In other words, since the initial premium of younger drivers in average is higher than for seniors, younger drivers can save more than older drivers by improving the driving behaviour, possibly leading to a greater effort to improve their driving performance. Younger drivers, particularly those with limited driving experience, may be better able to learn and adjust their driving behaviour by getting feedback. In this paper, we don't identify separately these key factors in deriving the differences in driving behaviour changes across age groups, but leave those issues for future research.

In terms of gender, males have a lower overall initial UBI score, even though they have fewer hard brakes to start with, a specific element in the UBI score. Females improve their driving behaviour on average more than males during 26 weeks of UBI usage, so there is a greater difference between male and female UBI scores at the end of the 26 weeks. This finding suggests that females are more responsive in changing their driving behaviour due to the feedback obtained and the economical incentives to lower the premium by better driving performance. This finding, although in a different context, seems to be consistent with Croson and Gneezy (2009).

In addition to the above results, we show in this paper how different regulations across states in our dataset can allow us to identify the economic incentives effect on changing driving habits of UBI customers. We find that in a states where state regulations mandate No-Fault insurance, premiums are exogenously higher than in the other states. Importantly, we find that customers in higher premium, No-Fault states improve their driving performance significantly more than customers in the other ones. Therefore, we can argue that since the customers who enrol in the UBI policy in No-Fault states (higher premium states) can save more than the other states, these customers try to improve their driving behaviours more in order to get a higher discount rate on their initial premiums.

Managerial implications. As we discussed in the Introduction, a higher retention rate for UBI as compared to non-UBI customers is one potential source of profit improvement. We have shown in this paper that the renewal rate of UBI customers is significantly higher than non-UBI customers. Combining this result with improvement in driving behaviour of drivers in UBI program may make the adoption of a UBI a way to improve profits, even after considering the costs of the program and the discounts provided. In other words, the insurance company not only can benefit from improvement in customers' driving performance, but also they can keep a higher percentage of these safer drivers in the UBI program compare to the non-UBI policies.

The heterogeneous effect of UBI policy on changing driving behaviour across age groups might be another interesting result for an insurance company. Despite the fact that the youngest group of drivers (millennials) have the lowest insurance score, likely because of insufficient driving history,

both (1) the improvement in their driving behaviour (UBI score and number of hard brakes) and also (2) their average UBI score after 6 months of monitoring are higher than for the other age groups. In other words, the youngest group of drivers are an attractive target market for companies offering UBI programs as these younger drivers have highest learning rate among all groups of customers. The under 35 years of age millennial segment is estimated to comprise about 80 million individuals, making this a particularly important target market. In a competitive environment, more innovative insurers can not only attract more younger drivers by offering UBI program, but also this group can be profitable for the insurance company by improving the driving behaviour in the long term.

In addition, analyzing the effect of the economic incentives in UBI policy, beyond getting feedback on improving driving behaviour of customers, might be crucial for insurers to design more efficient and win-win pricing strategies. We have shown that drivers improve their driving behaviour more in the presence of higher economic incentives. Pricing policy for the UBI program needs to consider these effects. Our results can help a firm to set the premium and discount policy in UBI program in a way to both attract drivers and encourage them to drive more safely, which leads to higher profit for the firm.

Limitations and future research. One caveat of our findings is that the behaviour changes we document are based on the six-month driving data collected by the insurance company. An important question is whether the changes are temporary to earn a discount or are permanent even after the telematics device is removed. To answer this question, we need additional behaviour data for the UBI subscribers. However, it is challenging and ethically questionable to collect such information without consent. Perhaps, the increased use of computers, GPS devices, and other in-car electronic devices that consumers authorize may provide information to resolve some of these issues.

There are also several avenues in which the model and empirical analysis can be extended in future research. First, as we mentioned earlier, the customers' decision to adopt the UBI and continue or withdraw from this program can be related to their expectations about and realized driving performance while being monitored by a telematics device. It would be interesting to develop a structural empirical model to understand how the customers decide to participate in the UBI program and continue to do so. Another issue to explore is consumers' concern about privacy and the implicit cost of allowing themselves to be monitored, which makes UBI unattractive for some customers. It's worthwhile for insurance companies to develop and estimate models to extract the privacy cost of different group of customers, which affects the adoption and retention rate of drivers in UBI program in order to set more efficient personalized pricing strategies in UBI. Another issue to explore is the effect of enrolment and performance on the UBI measure on

customer retention. While our data show broadly that UBI customers are more likely to renew than non-UBI customers, more systematic investigation of this issue is worth pursuing. Finally, but more speculative, our findings have implications for helping consumers to engage in safe and healthy behaviours. For examples, Patel et al. (2016) in the health care sector examine how daily information on exercise level combined with financial incentives can increase physical activity among overweight and obese adults. Our findings demonstrate that these issues extend beyond the level of personal health.

Appendix

- **Appendix 1**

In this section, we provide some further analyses that support the validity of our primary analysis and results. Four arguments are tested in this appendix to support our primary results.

A1.1: *Average UBI score of drivers in UBI program does not affect directly the insurance score at renewal time.*

We want to test this argument that the company does not consider the average UBI score of customers to set the insurance score of drivers at renewal time. However, we know that the insurance companies can't use the telematics data to change the insurance score and increase the premium rate. The formula for setting the premium (and insurance score) is predetermined and fixed. We consider the age, gender, initial insurance score and average UBI score of customer i as the covariates in our linear regression and renewal insurance score as dependent variable as below:

$$\textit{renewal score}_i = \beta_0 + \beta_1 \times \textit{Age}_i + \beta_2 \times \textit{Gender}_i + \beta_3 \times \textit{Initial score}_i + \beta_4 \times \textit{UBI score}_i + \varepsilon_i$$

Table A1: Regression analysis results for renewal insurance score.
(***): p-value < 0.05, (**): p-value < 0.1

	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	4.11	0.26	15.338	<2e-16***
Age	-0.06	0.01	-6.12	<2e-6***
Gender(Female)	0.56	0.27	2.074	0.032***
Initial score	0.99	0.002	409.26	<2e-16***
UBI score	0.02	0.019	1.692	0.091**
Multiple R-squared: 0.63			Adjusted R-squared: 0.62	

The above result table supports our assumption. The average UBI score coefficient in the regression is not significantly different from zero in 0.05 level. So, it shows that the UBI score does not derive directly the insurance score at renewal time.

A1.2: *Setting renewal premium doesn't depend on whether the driver used UBI or not.*

As discussed in the paper, we assume that the UBI policy is just an additional discount for drivers and there is no direct effect of drivers' performance on setting their premium. In other words, we assume that the company considers the same formula for both UBI and non-UBI customers to set the premium based on the coverage, insurance score, age, state and etc.

In order to test this assumption we consider the following model:

$$renewal\ premium_i = \beta_0 + \beta_1 \times Age_i + \beta_2 \times Gender_i + \beta_3 \times renewal\ score_i + \beta_4 \times dummy\ UBI_i + \beta_5 \times State\ factor_i + \beta_6 \times coverage_i + \varepsilon_i$$

In this model, we consider a dummy variable to capture the effect of enrolling in UBI program on renewal premium when we control the renewal insurance score and another factors. In other words, the coefficient of *dummy_UBI* variable shows the difference in setting the renewal premium of two groups of customers.

Table A2: Regression analysis results for renewal premium.
(***): p-value < 0.05, (**): p-value < 0.1

	Estimate	Std. Error	Pr(> |t|)
(Intercept)	104.52	0.17	<2e-16***
Age	0.16	0.18	0.07**
Gender(Female)	0.52	0.34	0.12
Comprehensive	4.66	0.08	<2e-16***
Renewal insurance score	-0.81	0.01	<2e-16***
UBI dummy	0.91	0.71	0.12
Arkansas	8.92	0.21	<2e-16***
Connecticut	39	0.16	<2e-16***
Georgia	27.34	0.15	<2e-16***
Maryland	32.39	0.15	<2e-16***
Michigan	90.81	0.14	<2e-16***
Minnesota	8.23	0.18	<2e-16***
New Jersey	32.81	0.15	<2e-16***
Oregon	7.38	0.17	<2e-16***
Pennsylvania	13.41	0.14	<2e-16***
South Carolina	7.1	0.17	<2e-16***
Texas	22.79	0.14	<2e-16***
Virginia	-6.17	0.16	<2e-16***
Washington	0.85	0.15	<2e-7***
Wisconsin	-11.36	0.15	<2e-16***
Deductible (100)	31.85	0.1	<2e-16***
Deductible (200)	20.36	0.09	<2e-16***
Deductible (500)	11.24	0.08	<2e-16***
Deductible (1000)	3.77	0.09	<2e-16***
Multiple R-squared: 0.65		Adjusted R-squared: 0.64	

The results show that enrolling in UBI program does not change significantly the formula that insurance company consider to set the premium based on predefined factors.

A1.3: *Average UBI score and the week in which customers cancel the UBI policy are significant determinants of the permanent discount.*

In third argument, we want to check this assumption that the permanent discount is related to the average UBI score of customers and their decision about continuing the UBI program during 6 months.

$$permanent\ discount_i = \beta_0 + \beta_1 \times UBI\ score_i + \beta_2 \times Age_i + \beta_3 \times Gender_i + \beta_4 Cancelation\ week_i + \varepsilon_i$$

In the above model, we consider the permanent discount that the UBI customers receive after monitoring as the dependent variable and the average UBI score, age, and the week that driver i cancels the UBI policy as covariates. The results are as follow.

Table A3: Regression analysis results for permanent discount.
(***): p-value < 0.05, (**): p-value < 0.1

	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	-1.30e-01	4.65e-04	-280.388	<2e-16***
UBI score	1.98e-03	6.32e-06	320.278	<2e-16***
Age	6.79e-06	2.58e-06	2.634	0.073**
Gender (Female)	3.25e-03	2.61e-03	1.24	0.215
Cancelation Week	6.19e-03	5.31e-05	119.962	<2e-16***
Multiple R-squared: 0.67			Adjusted R-squared: 0.66	

We find that the model can explain about 65% of the variation in the permanent discount observations and average UBI score and cancelation week are two key factors in determining permanent discount as we expected.

A1.4: *Daily hard brakes and mileage are two key drivers of daily UBI score.*

We explained in the data description section of the paper that although there are many elements that the insurance company monitors and assesses the actual driving performance based on them, in our datasets we have 3 measures. The primary measure in our dataset is daily UBI score and also daily number of hard brakes and mileage driven as two factors which show the driving behaviour of UBI customers. We need to test the assumption that both daily hard brakes and mileage have significant effect on UBI score and also these factors can explain high percentage of variation in daily UBI scores.

$$UBI\ score_{it} = \beta_0 + \beta_1 \times mileage_{it} + \beta_2 \times Hard\ brake_{it} + \varepsilon_{it}$$

For each UBI customer, we have daily observations for up to 180 days.

The results show that both mileage driven and hard brakes have significant negative effects on daily UBI score. More importantly, just these two factors can explain about 60% of variation in daily UBI score observations in our dataset which means mileage and number of hard brakes are two key factors to determine the UBI score based on the company's policy.

Table A4: Regression analysis results for daily UBI score.
(***): p-value < 0.05, (**): p-value < 0.1

	Estimate	Std. Error	t value	Pr(> |t|)
(Intercept)	82.113	0.168	815.338	<2e-16***
mileage	-0.18	0.01	-18.01	<2e-16***
Hard brake	-3.796	0.014	-299.26	<2e-16***
Multiple R-squared: 0.58			Adjusted R-squared: 0.57	

- **Appendix 2**

In this part we add all tables of fixed effect regression results for heterogeneity section.

Table A5: Fixed effect regression analysis results for UBI score across age groups.
(***): p-value < 0.05 , (**): p-value < 0.1

	Coefficients estimation			
	age_group 1	age_group2 * week _dummies	age_group3 * week _dummies	age_group4 * week _dummies
Week_dummy2	3.58 (***)	-1.18 (***)	-1.61 (***)	-3.36 (***)
Week_dummy3	5.93 (***)	-2.73 (***)	-3.72 (***)	-5.66 (***)
Week_dummy4	7.07 (***)	-3.48 (***)	-4.53 (***)	-6.76 (***)
Week_dummy5	7.17(***)	-3.6 (***)	-4.67 (***)	-6.9 (***)
Week_dummy6	7.48 (***)	-3.83 (***)	-5 (***)	-7.19 (***)
Week_dummy7	7.6 (***)	-3.88 (***)	-5.09 (***)	-7.29 (***)
Week_dummy8	7.71 (***)	-4.18 (***)	-5.16 (***)	-7.36 (***)
Week_dummy9	7.8 (***)	-4.27 (***)	-5.3 (***)	-7.48 (***)
Week_dummy10	7.84 (***)	-4.04 (***)	-5.12 (***)	-7.45 (***)
Week_dummy11	8.05 (***)	-3.77 (***)	-5.05 (***)	-7.63 (***)
Week_dummy12	7.86 (***)	-3.55 (***)	-4.66 (***)	-7.47 (***)
Week_dummy13	8.07 (***)	-3.77 (***)	-4.87 (***)	-7.67 (***)
Week_dummy14	8.06 (***)	-3.7 (***)	-4.85 (***)	-7.68 (***)
Week_dummy15	8.21 (***)	-3.89 (***)	-5.01 (***)	-7.8 (***)
Week_dummy16	8.2 (***)	-3.93 (***)	-4.98 (***)	-7.79 (***)
Week_dummy17	8.17 (***)	-3.84 (***)	-4.98 (***)	-7.75 (***)
Week_dummy18	8.11 (***)	-3.71 (***)	-4.86 (***)	-7.64 (***)
Week_dummy19	8.28 (***)	-3.88 (***)	-5.02 (***)	-7.8 (***)
Week_dummy20	8.26 (***)	-3.83 (***)	-4.97 (***)	-7.79 (***)
Week_dummy21	8.25 (***)	-3.78 (***)	-4.96 (***)	-7.75 (***)
Week_dummy22	8.27 (***)	-3.77 (***)	-4.96 (***)	-7.75 (***)
Week_dummy23	8.48 (***)	-3.94 (***)	-5.19 (***)	-7.9 (***)
Week_dummy24	8.54 (***)	-3.97 (***)	-5.22 (***)	-7.94 (***)
Week_dummy25	8.58 (***)	-3.97 (***)	-5.25 (***)	-7.94 (***)
Week_dummy26	8.56 (***)	-3.94 (***)	-5.23 (***)	-7.86 (***)
	Multiple R-squared: 0.536		Adjusted R-squared: 0.528	

Table A6: Fixed effect regression analysis results for hard brakes across age groups.
(***): p-value < 0.05, (**): p-value < 0.1

	Coefficients estimation			
	age_group 1	age_group2 * week _dummies	age_group3 * week _dummies	age_group4 * week _dummies
Week_dummy2	-0.32 (***)	0.034 (*)	0.08 (***)	0.2 (***)
Week_dummy3	-0.35 (***)	0.03 (*)	0.07 (***)	0.18 (***)
Week_dummy4	-0.42 (***)	0.08 (***)	0.13 (***)	0.18 (***)
Week_dummy5	-0.51 (***)	0.13 (***)	0.22 (***)	0.26 (***)
Week_dummy6	-0.55 (***)	0.14 (***)	0.24 (***)	0.28 (***)
Week_dummy7	-0.56 (***)	0.14 (***)	0.26 (***)	0.28 (***)
Week_dummy8	-0.53 (***)	0.08 (***)	0.21 (***)	0.25 (***)
Week_dummy9	-0.57 (***)	0.11 (***)	0.23 (***)	0.29 (***)
Week_dummy10	-0.58 (***)	0.1 (***)	0.21 (***)	0.31 (***)
Week_dummy11	-0.56 (***)	0.09 (***)	0.2 (***)	0.28 (***)
Week_dummy12	-0.56 (***)	0.09 (***)	0.21 (***)	0.27 (***)
Week_dummy13	-0.58 (***)	0.09 (***)	0.21 (***)	0.3 (***)
Week_dummy14	-0.58 (***)	0.08 (**)	0.18 (***)	0.28 (***)
Week_dummy15	-0.6 (***)	0.09 (**)	0.19 (***)	0.31 (***)
Week_dummy16	-0.59 (***)	0.08 (**)	0.17 (***)	0.28 (***)
Week_dummy17	-0.61 (***)	0.08 (**)	0.18 (***)	0.29 (***)
Week_dummy18	-0.63 (***)	0.11 (***)	0.2 (***)	0.32 (***)
Week_dummy19	-0.64 (***)	0.1 (**)	0.19 (***)	0.34 (***)
Week_dummy20	-0.66 (***)	0.12 (***)	0.22 (***)	0.37 (***)
Week_dummy21	-0.68 (***)	0.13 (***)	0.23 (***)	0.37 (***)
Week_dummy22	-0.69 (***)	0.13 (***)	0.24 (***)	0.39 (***)
Week_dummy23	-0.61 (***)	0.04 (***)	0.15 (***)	0.3 (***)
Week_dummy24	-0.72 (***)	0.17 (***)	0.27 (***)	0.4 (***)
Week_dummy25	-0.73 (***)	0.15 (***)	0.27 (***)	0.41 (***)
Week_dummy26	-0.75 (***)	0.15 (***)	0.28 (***)	0.42 (***)
	Multiple R-squared: 0.487		Adjusted R-squared: 0.479	

Table A7: Fixed effect regression analysis results for mileage across age groups.
(***): p-value < 0.05, (**): p-value < 0.1

	Coefficients estimation			
	age_group 1	age_group2 * week _dummies	age_group3 * week _dummies	age_group4 * week _dummies
Week_dummy2	0.15	-0.28 (**)	-0.21 (**)	-0.21 (**)
Week_dummy3	0.36 (**)	-0.42 (***)	-0.23 (**)	-0.41 (***)
Week_dummy4	0.47 (**)	-0.48 (***)	-0.37 (***)	-0.48 (***)
Week_dummy5	0.51 (**)	-0.48 (***)	-0.25 (**)	-0.48 (***)
Week_dummy6	0.5 (**)	-0.44 (***)	-0.31 (***)	-0.41 (***)
Week_dummy7	0.54 (**)	-0.46 (***)	-0.38 (***)	-0.58 (***)
Week_dummy8	0.52 (**)	-0.45 (***)	-0.45 (***)	-0.49 (***)
Week_dummy9	0.46 (**)	-0.37 (***)	-0.36 (***)	-0.37 (**)
Week_dummy10	0.5 (**)	-0.44 (***)	-0.44 (***)	-0.38 (***)
Week_dummy11	0.53 (**)	-0.46 (***)	-0.49 (***)	-0.46 (***)
Week_dummy12	0.58 (**)	-0.44 (***)	-0.56 (***)	-0.4 (***)
Week_dummy13	0.71 (***)	-0.55 (***)	-0.56 (***)	-0.55 (***)
Week_dummy14	0.73 (***)	-0.61 (***)	-0.38 (***)	-0.55 (***)
Week_dummy15	0.76 (***)	-0.59 (***)	-0.3 (***)	-0.61 (***)
Week_dummy16	0.7 (***)	-0.5 (***)	-0.25 (**)	-0.56 (***)
Week_dummy17	0.74 (***)	-0.6 (***)	-0.26 (**)	-0.55 (***)
Week_dummy18	0.85 (***)	-0.72 (***)	-0.31 (***)	-0.68 (***)
Week_dummy19	0.8 (***)	-0.64 (***)	-0.27 (**)	-0.6 (***)
Week_dummy20	0.89 (***)	-0.69 (***)	-0.36 (***)	-0.73 (***)
Week_dummy21	1.01 (***)	-0.83 (***)	-0.46 (***)	-0.85 (***)
Week_dummy22	0.99 (***)	-0.82 (***)	-0.42 (***)	-0.8 (***)
Week_dummy23	0.98 (***)	-0.84 (***)	-0.38 (***)	-0.81 (***)
Week_dummy24	0.94 (***)	-0.81 (***)	-0.33 (***)	-0.74 (***)
Week_dummy25	0.96 (***)	-0.79 (***)	-0.36 (***)	-0.8 (***)
Week_dummy26	0.92 (***)	-0.74 (***)	-0.33 (**)	-0.79 (***)
	Multiple R-squared: 0.445		Adjusted R-squared: 0.441	

Table A8: Fixed effect regression analysis results for UBI score across age groups.
(***): p-value < 0.05, (**): p-value < 0.1

	Coefficients estimation	
	Male	Female* week _dummies
Week_dummy2	2.75 (***)	-0.49 (***)
Week_dummy3	3 (***)	-0.43 (***)
Week_dummy4	3.17 (***)	-0.53 (***)
Week_dummy5	3.22 (***)	-0.55 (***)
Week_dummy6	3.34 (***)	-0.59 (***)
Week_dummy7	3.41 (***)	-0.48 (***)
Week_dummy8	3.41 (***)	-0.33 (***)
Week_dummy9	3.51 (***)	-0.24 (***)
Week_dummy10	3.77 (***)	-0.2 (**)
Week_dummy11	4.44 (***)	-0.45 (***)
Week_dummy12	4.43 (***)	-0.3 (***)
Week_dummy13	4.29 (***)	-0.03
Week_dummy14	4.37 (***)	-0.04
Week_dummy15	4.32 (***)	0.07
Week_dummy16	4.22 (***)	0.25 (***)
Week_dummy17	4.32 (***)	0.07
Week_dummy18	4.39 (***)	0.01
Week_dummy19	4.38 (***)	0.09
Week_dummy20	4.41 (***)	0.1
Week_dummy21	4.45 (***)	0.12
Week_dummy22	4.49 (***)	0.07
Week_dummy23	4.52 (***)	0.25 (***)
Week_dummy24	4.53 (***)	0.27 (***)
Week_dummy25	4.58 (***)	0.29 (***)
Week_dummy26	4.6 (***)	0.34 (***)
Multiple R-squared: 0.496		Adjusted R-squared: 0.488

Table A9: Fixed effect regression analysis results for hard brakes across age groups.
(***): p-value < 0.05 , (**): p-value < 0.1

	Coefficients estimation	
	Male	Female* week _dummies
Week_dummy2	-0.17 (**)	0.04
Week_dummy3	-0.28 (***)	0.07
Week_dummy4	-0.17 (**)	-0.17 (**)
Week_dummy5	-0.3 (***)	-0.03
Week_dummy6	-0.28 (***)	-0.03
Week_dummy7	-0.34 (***)	-0.02
Week_dummy8	-0.38 (***)	-0.09 (**)
Week_dummy9	-0.42 (***)	-0.2 (**)
Week_dummy10	-0.59 (***)	-0.14 (**)
Week_dummy11	-0.65 (***)	-0.29 (***)
Week_dummy12	-0.59 (***)	-0.51 (***)
Week_dummy13	-0.66 (***)	-0.39 (***)
Week_dummy14	-0.58 (***)	-0.45 (***)
Week_dummy15	-0.61 (***)	-0.49 (***)
Week_dummy16	-0.68 (***)	-0.55 (***)
Week_dummy17	-0.65 (***)	-0.55 (***)
Week_dummy18	-0.63 (***)	-0.57 (***)
Week_dummy19	-0.71 (***)	-0.55 (***)
Week_dummy20	-0.68 (***)	-0.69 (***)
Week_dummy21	-0.75 (***)	-0.77 (***)
Week_dummy22	-0.72 (***)	-0.82 (***)
Week_dummy23	-0.69 (***)	-0.93 (***)
Week_dummy24	-0.65 (***)	-0.97 (***)
Week_dummy25	-0.68 (***)	-0.91 (***)
Week_dummy26	-0.74 (***)	-0.88 (***)
Multiple R-squared: 0.427		Adjusted R-squared: 0.424

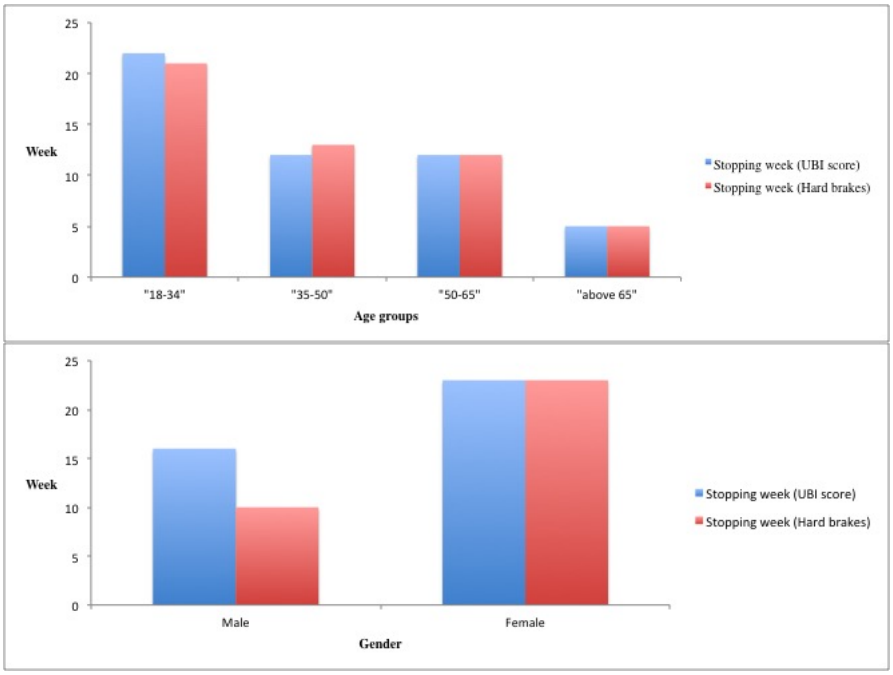
Table A10: Fixed effect regression analysis results for UBI Score across states.
(***): p-value < 0.05, (**): p-value < 0.1

	Coefficients estimation	
	Fault states	No-Fault states* week _dummies
Week_dummy2	1.67 (***)	0.6 (***)
Week_dummy3	2.23 (***)	0.34 (**)
Week_dummy4	3.04 (***)	0.34 (**)
Week_dummy5	3.35 (***)	0.26 (**)
Week_dummy6	3.34 (***)	0.47 (**)
Week_dummy7	3.41 (***)	0.5 (**)
Week_dummy8	3.41 (***)	0.53 (**)
Week_dummy9	3.51 (***)	0.69 (***)
Week_dummy10	3.77 (***)	0.61 (***)
Week_dummy11	4.03 (***)	0.85 (***)
Week_dummy12	4.34 (***)	0.62 (***)
Week_dummy13	4.39 (***)	0.61 (***)
Week_dummy14	4.37 (***)	0.6 (**)
Week_dummy15	4.32 (***)	0.69 (***)
Week_dummy16	4.29 (***)	0.79 (***)
Week_dummy17	4.34 (***)	0.78 (***)
Week_dummy18	4.39 (***)	0.79 (***)
Week_dummy19	4.38 (***)	0.86 (***)
Week_dummy20	4.41 (***)	0.87 (***)
Week_dummy21	4.45 (***)	0.82 (***)
Week_dummy22	4.49 (***)	0.92 (***)
Week_dummy23	4.52 (***)	0.97 (***)
Week_dummy24	4.53 (***)	1.05 (***)
Week_dummy25	4.58 (***)	1.09 (***)
Week_dummy26	4.6 (***)	1.06 (***)
Multiple R-squared: 0.464		Adjusted R-squared: 0.462

- **Appendix 3**

In this appendix we study the time when the UBI customers stop improving their driving behavior compare to their behavior in the last week (week 26). In other words, we compare a consumers driving behavior measurements at each week with the last week to find the stopping time of improvement. In order to do that, we change our fixed effect regression model by considering week 26 as the base week and 25 dummy variables for the weeks 1 to 25. Therefore, the coefficient for each dummy variable shows the difference between the UBI score (Hard brakes) of that specific week and the last week. Figure A1 shows the improvement stopping time (the last week with a significant difference compare to week 26). As can be seen, improvement stops well before week 26 overall for all subgroups, although females have week 23 as their last week of no significant difference between that weeks driving behavior and week 26. In addition, the improvement of the youngest group of drivers last longer than seniors.

Figure A1: The week in which drivers stop improvement across different groups.



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