Sensor Data, Privacy, and Behavioral Tracking: Does Usage-Based Auto Insurance Benefit Drivers?

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Abstract

Usage-Based Insurance (UBI) is a recent auto insurance innovation that enables insurance companies to collect individual-level driving data, provide feedback on driving performance, and offer individually targeted price discounts based on each consumer's driving behavior. In this paper, using detailed information on insurance premiums, retention rates of customers, and individual driving behavior (from sensor data) for the UBI adopters, we examine and estimate the effect of the UBI policy on changing the customers' driving behavior, 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 show that after UBI adoption, motorists improve their driving behavior, resulting in being safer drivers, 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 UBI adoption; and females show more improvement than males. We also find that economic incentives lead to higher adoption rates of UBI and greater improvements in driving behavior. Our results suggest that by sharing private consumer information with the insurance company, UBI is not only beneficial to the company, but also to consumers who become better drivers.

Key words: Usage-Based Insurance, Privacy, Sensor Data, Economic Incentives, Feedback and Information, Driving Behavior

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1. Introduction

Companies across a broad spectrum of industries are increasingly using new technologies based on real-time consumer data to increase their business productivity. For instance, Waze, now owned by Google, used real-time information from its GPS subscribers to build an implicit network of traffic sensors that allowed it to provide driving directions at much less cost compared to the extensive physical network of monitoring devices operated by its competitors. As mobile devices, GPS systems, and sensors proliferate there are more and more opportunities for companies to offer consumers' goods and services at prices tied to their behaviors.

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. As the price of sensors and communications devices continues to fall and by considering the value of sensor-based information, usage-based insurance (UBI) is becoming a popular alternative to traditional automobile insurance. The basic idea of telematics UBI auto insurance is that a motorist's behavior is monitored directly while the person drives. The telematics devices measure some key elements of interest to the underwriters: miles driven, time of the 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, six 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 the 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. Importantly, at least in our study, the insurer never raises the rates for those participating in the UBI programs as compared to those who do not enroll in it. 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 behavior. 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.

On the other hand, there are some challenges and barriers to the growth of UBI policy in the insurance industry. The UBI program uses location-based services (LBS) to measure the different elements of actual driving behavior, thus allowing the firm to monitor behavior that was previously private. Prior to the introduction of LBS, firms were not able to observe consumer actions and personal information at such a detailed level. Such capabilities generate the possibility of an inherent tension between innovations that rely on the use of data and the protection of consumer privacy. From the customer's perspective, although the privacy concern can limit the adoption rate of the UBI policy, we find that it can encourage UBI adopters to improve their driving behavior and get a higher UBI discount[1], possibly compensating for the cost of losing privacy. Despite the potential benefits of UBI for customers and insurers, there is little knowledge about whether this strategy will improve the insurance companies' profits or be beneficial for customers. 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 behavior, 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 this last issue. As we describe more fully below, participants in the UBI program improve their driving performance while enrolled in the UBI program and receive permanent discounts averaging 12% below what they would have been charged if they had not enrolled in the program.

1.1. Literature Review

To our knowledge, our study is the first empirical study analyzing customers' sensor-based data to research how usage-based insurance affects drivers' driving behavior. Our paper is related to four streams of research including studies on (1) usage-based pricing in the service industry, (2) the effect of feedback on consumer behavior, (3) economic incentives and behavior change, and (4) the effect of privacy on innovations and customer responses.

Usage-Based Pricing. UBI is one type of usage-based pricing (UBP) system that sets prices based on consumers' usage of a product. Some papers on UBP studies are in the telecommunication and software subscription industries. For example, Nevo et al. (2016) study the demand for residential broadband under a usage-based, three-part tariff pricing scheme and find that consumers respond dynamically to the price and usage-block levels. 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. The UBP plan allows the internet provider to differentiate between those who want basic bandwidth and high bandwidth services and to charge a premium price for the higher bandwidth service, both to better satisfy consumer needs and improve corporate profits. 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

[1] Rainie et al. (2015) "Privacy and Information Sharing", PewResearchCenter.

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.

Our research on UBI relates more particularly to Pay-as-you-drive (PAYD) auto insurance in which the premium depends upon the miles driven. 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 among 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. Edlin (2003) and Parry (2005) find that PAYD drivers reduce their mileage 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. In our paper, although we cannot observe the mileage driven by customers before UBI adoption, our results do not find any changes in mileage after UBI adoption; however, 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 the 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 behavior more generally, and uses statistical controls to better understand the underlying process. In addition, we demonstrate that beyond the mere presence of the feedback data collected by the telematics, the economic incentives play a role in consumers' behavior changes.

Information and Feedback. One key feature of the UBI program is that the consumers receive timely feedback about their driving behavior. The drivers receive immediate warnings when they, for example, exert a hard brake and also receive weekly emails about their driving performance. Our study is related to behavioral and psychological literature on the effect of information and feedback on behavior change. For example, Taniguchi et al. (2003), in a study of pro-social behavior, show how getting feedback can modify travel behavior. Their key finding is that automobile-use reduction or pro-environmental behavior is influenced by moral obligation, and moral obligation is in turn influenced by awareness of the negative environmental consequences of automobile use. They further find that the travel feedback program had a significant positive effect on pro-environmental behavior even one year after participation in this program. Fujji et al. (2005) also show the effectiveness of a travel feedback program aimed at reducing family car use. Outside the auto industry, other studies examine the effect of information warning a consumer that she is about to incur a (higher) fee for a service. For example, in a 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 behavior 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 behavior changes. This is particularly important, as authors such as Lowenstein[2] have argued for the limited impact on behavior change of only providing information. Stern (1999), for example, in a study of pro-environmental behavior, 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 behavior. More specifically, he demonstrates the presence of an interactive effect of information and incentives beyond the independent importance of incentives. Heberlein and Baumgartner (1985) report 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. While all participants in the UBI program have access to the same UBI feedback information, we employ a quasi-experimental design to examine whether there is a greater change in driver's behavior when UBI programs have higher economic benefits. We also study 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 females, but had no effect for males. 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

[2] 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 behavior very much. Changing prices and changing convenience have a big impact. Providing information doesn't (Tavernise, 2014)".

the UBI program.

Privacy and Innovation. As discussed above, the innovative UBI policy helps the insurance company to set more accurate premiums by observing individual-level sensor-based data. The program also provides information to consumers that may help them to improve their driving. At the same time, the UBI policy may raise privacy issues for consumers who may not want the firm to know where, when, and how they drive or to provide that information to other companies or government agencies. Martin et al. (2017) study how concern about data privacy can affect the customer's attitude to the firm and the firm's performance. Experimental manipulations reveal that mere access by the firm to personal data can inflate feelings of violation and reduce trust.

The potential for a trade-off between innovation and privacy spans many industries. Surveys of individuals repeatedly find that people are concerned about the sharing of their private information—for example, in the health care sector regarding digital medical records (e.g., Westin 2005), in customizing online advertising (e.g., Turow et al. 2009), and in setting insurance premiums (e.g., Rainie and Duggan 2015). Mao and Zhang (2014) more generally study the effect of privacy on location-based services available on mobile phones and find that higher privacy concern is negatively related to customers' adoption of LBS services. In brief, consumers are concerned about the protection of their personal information, and this concern about privacy has a negative effect on adoption of new technologies and their relationship with companies who have access to private information. Goldfarb and Tucker (2013) summarize these concerns and suggest approaches that firms can use to proactively address consumer issues about privacy.

Early work on privacy primarily concentrated on the collection and release of information about well-known individuals. This is because until recently, the cost of obtaining such information per individual was high and thus could not be easily gathered. In this context, legal scholars and public policy officials attempted to identify the most significant substantial harms that arise from sharing private information and particularly from its becoming public (FTC 2010). Austin (2006) and Solovo (2008) classify pubic concerns about privacy into a number of distinct groups, the two most important of which are: (1) Public disclosure of embarrassing private facts about the individual (in short, publication of private facts) and (2) Publicity that places the individual in a false light in the public eye (in short, false light publicity). (See also, Prosser (1960).).

More recently, as Goldfarb and Tucker (2012) discuss, technological innovation has made it very inexpensive, and in some cases, nearly costless, to gather and store previously private information about ordinary individuals. Thus, privacy concerns affect nearly everyone, not just a select few famous figures or public personalities. More specifically, Goldfarb and Tucker (2012) examine the trade-off between the benefits of data-based innovations and the harm caused by the sharing of consumers' private information. Better targeting of products to consumer needs is a clear benefit of these innovations, but companies may use targeted pricing so that the benefits may largely go to the firms. A number of studies have documented the value to companies of detailed, individual-level behavioral data.

In online advertising, by examining past surfing and click behavior, firms can learn about current needs as well as general preferences. Beales (2010) documents that in 2009 the price of behaviorally targeted advertising was 2.68 times the price of untargeted advertising. Lambrecht and Tucker (2011) further show that the performance of behavioral targeting can be improved when combined with clickstream data that help to identify the consumer's degree of product search. In the health care sector, Miller and Tucker (2011) document that the use of patient data by hospitals helps to improve monitoring and the accuracy of patient medical histories. However, none of these studies shows a direct benefit to the individual consumer who (knowingly or unknowingly) shares private behavioral data with the firm. In our study, by contrast, we find direct positive effect on driving performance of the consumers who are willing to share their private information.

1.2. Research Summary

In this paper, we use a unique database from a major US automobile insurance company to examine the impact of participation in UBI on driving behavior. To our knowledge in the marketing and economics literature, this paper is the first study to use sensor-based, individual-level data to examine customer responses to a new pricing strategy like the UBI policy that offers a discount for providing private information to the insurer. 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 on their driving behavior; and by using these data, we can understand how the drivers in this program change their driving behavior while being monitored by a telematics device. By estimating fixed effects models for panel data of UBI customers' driving behavior, we find that these customers generally improve their driving behavior 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. Across demographic groups, we find that younger drivers improve their performance more than older drivers and that females improve more than males. We also investigate the effect of economic incentives by dividing states into those which offer No-Fault vs. traditional insurance[3], a policy decision that is exogenous to our research question. No-Fault states typically have higher average

[3] That is, states using a tort auto insurance system

premiums than traditional states[4]. We show that UBI participants improve their driving behavior more in the higher-premium, No-Fault states. This suggests that the change in driving behavior 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 drivers. More generally, we find that consumers who enroll in the UBI program and allow the automobile insurance company to access their otherwise private driving behavior data become better drivers by the end of the monitoring period and receive discounts (on average of 12%) that apply to all future insurance premiums as long as they remain policy holders with this company. In the case we study here, there is a clear economic benefit to the individual of allowing access to private, sensor data.

The rest of this paper is organized as follows. We first review the industry background, focusing on the UBI policy, and then discuss the sensor data used in our analysis and some key patterns observed in the data. We then present the empirical models to estimate the changes in driving behavior of different groups 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 behavior improvement. Finally, we provide some concluding comments on managerial and public policy issues, including the potential benefits to individuals for making private information available to external organizations, in our case, insurance companies.

2. Industry Background

2.1. History of UBI and Current Market Share

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 attempt to attract the more profitable low-risk drivers to their policies. Hundreds of auto insurance companies are competing in a stable market. Total premiums in the US private passenger auto insurance market (liability and physical damage) have only grown from $158 billion to $175 billion in the decade from 2004 to 2013, below the rate of inflation. The stagnant growth in a competitive market makes the attraction, retention, and accurate rating of policyholders critically important; 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 a Towers Watson survey in July 2014, 8.5% of US consumers had a UBI policy in force, compared to 4.5% in February 2013[5]. According to SMA[6] Research, approximately 36% of

[4] See Anderson et al. (2010)

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

[6] Strategy Meets Action (SMA) is a leading strategic advisory services firm exclusively serving the insurance industry.

all auto insurance carriers are expected to use telematics UBI by 2020. Moreover, SAS Institute (2014) predicts that insurers will receive more than 25% of their premium revenue from telematics-based insurance programs by 2020. In all but two states (California and New Mexico), insurers offer telematics UBI policies. In 23 states, more than five insurance companies are active in the telematics UBI market[7].

2.2. Insurer Benefits

UBI's focus on tying driver behavior to pricing allows insurers to better monitor and control their risk exposure. The ability of insurers to charge drivers less for safer driving habits provides a powerful incentive to consumers to improve their driving behavior. This affords insurers using these programs the opportunity to gain several competitive advantages. First, insurers can identify their lowest-risk drivers, raising retention levels for preferred risks. Second, 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 behavior in order to earn a discount.

Early corporate adopters would most likely have a competitive advantage due to the detailed driving behavior 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, according to the 2014 Annual LexisNexis Insurance Telematics study, 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[8].

2.3. Consumer Benefits and Costs

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. In the UBI programs offered by virtually all companies, 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 that premium discounts and the ability to control premiums are the primary reasons for consumer adoption of telematics-based UBI programs. According to the 2014 LexisNexis study cited above, 78% of respondents cited discounts as an incentive to adopt

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

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

telematics insurance programs. Seventy-four percent cited the ability to control their auto insurance costs as an incentive.

This pricing scheme also limits 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% of households with insured vehicles would save an average of $496 a year (a 28% 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 their premium by changing their driving habits.

Despite these many benefits, a majority of the market is not expected to adopt UBI policies in the near future. For many drivers, the cost savings may not be significant enough to either switch to a new company if their current insurance provider does not offer the UBI program or to make the effort to obtain, install, and maintain the UBI telematics device in their car. Most importantly, as discussed in the literature review section, as is common with other new technologies requiring the sharing of personal information, consumers may not be willing to share their personal information with a company. Our focus in this paper, however, is not on the decision to adopt the UBI, but rather on whether adopters of the UBI policy become better drivers and receive lower premiums.

3. Data

3.1. Description of the UBI Policy

We study an individual's 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[9] and the offer of a discount if they enroll 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 behavior. The actual formula is not disclosed, but the firm has provided information on the overall driving behavior score and two components of the score, daily miles driven and number

[9] 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.

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[10].

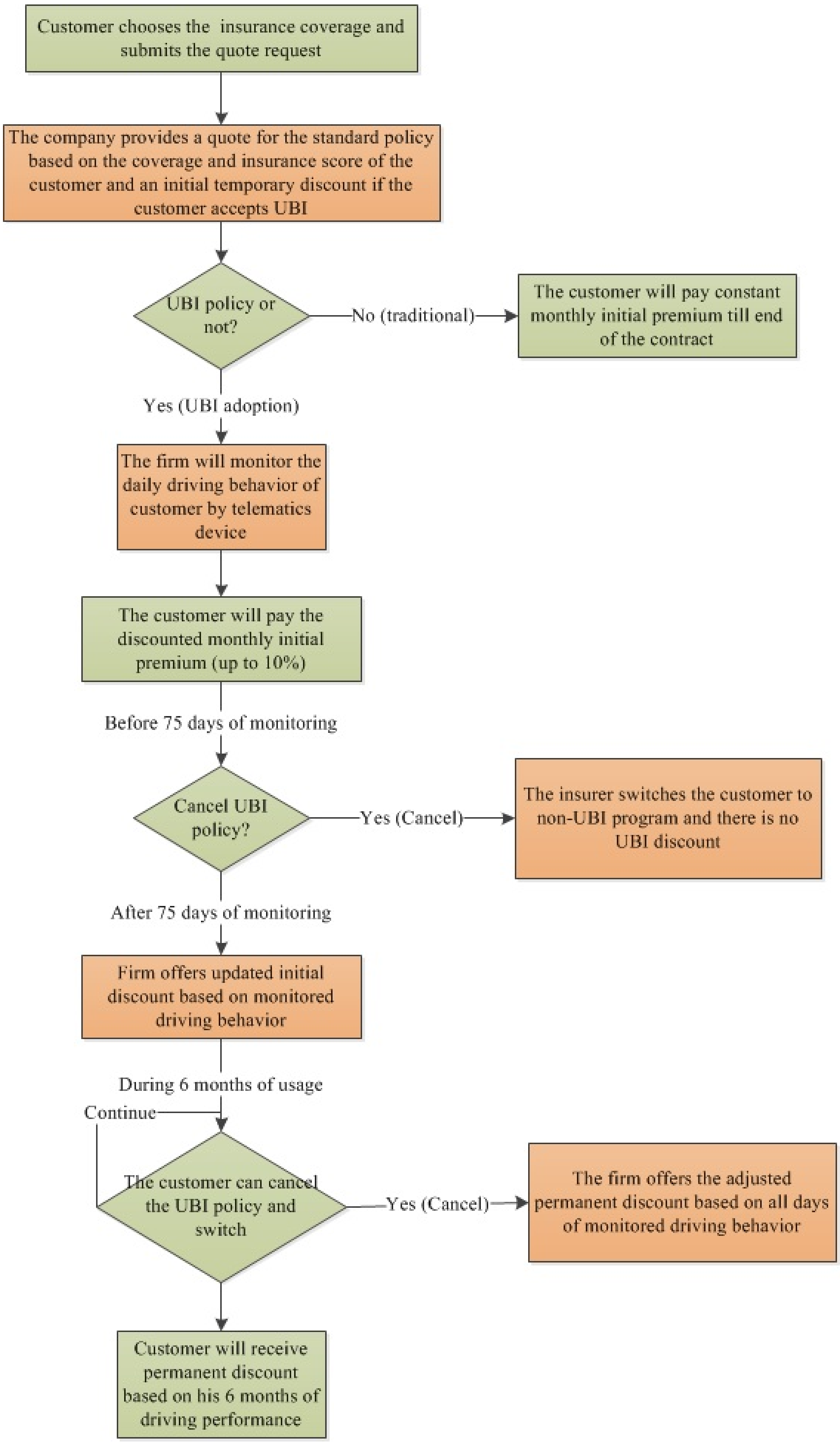
Based on information in corporate annual reports, the insurance company started to offer usage-based insurance as a new policy in order to better target safer drivers and thus to increase their profit by attracting and keeping more profitable customers. Like almost all the UBI policies in United States, 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 behavior. 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 enroll 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 behavior 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 sensor-based information on their UBI scores and indicators of their driving behavior, 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 data set, we observe some of

[10] "Comparing Real-World Behaviors of Drivers with High versus Low Rates of Crashes and Near-Crashes", US Department of Transportation, National Highway Traffic Safety Administration, February 2009, is another source of information on this issue.

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



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

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

decision for all customers and the initial discount for each UBI customer who adopted this program. Table 1 reports some summary statistics of the customers in our sample.

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 the UBI policyholders (39.3) is much lower than for the non-UBI customers (48.7), suggesting that the UBI program is more attractive for younger drivers. One possible explanation is that the insurance company assigns a relatively high-risk level to the young drivers due to the lack of sufficient driving history. Hence, this group pays a substantially higher initial premium. The UBI program can provide a great opportunity for younger drivers to show their actual driving behaviors, 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 drivers. 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 Table A1 of Online Appendix 1). A low (less favorable) 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 more 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= 2.1%) to encourage the drivers to enroll in the UBI program, and the average permanent discount that the UBI drivers get after monitoring the driving behaviors by the telematics device is about 12% (sd= 5.1%).

The UBI customers' average monthly initial premium is \$112 (before discount), which is higher[11] than that for non-UBI customers (\$107) due to the lower insurance score; however, the premiums for the two groups (UBI discount excluded for UBI customers) are closer at the renewal time. As shown in Online Appendix 1 (Table A2), 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.

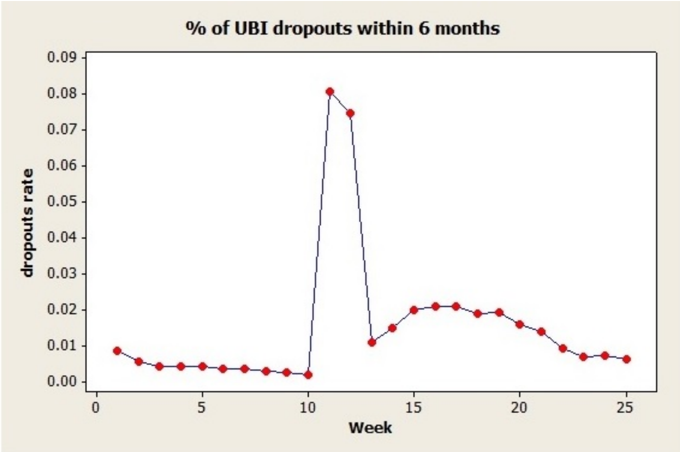
The second dataset contains several sensor-based measures of the UBI customers' daily driving behavior. The data are collected by the telematics device for up to 6 months after its installation. We have access to daily mileage driven and number of hard brakes of all UBI customers as long as they are 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 A4 of Online Appendix 1 that daily hard brakes and mileage are two key drivers of the daily UBI score. These two factors explain about 60 percent of the variation in the observed daily UBI score. In summary, we have a panel data of UBI customers for up to 26 weeks for whom we observe three daily measures of their driving behavior: daily driving score, number of hard brakes, and mileage driven[12].

It is important to note that we do not observe all UBI customers' driving behavior for the 26 weeks, since about 35% of participants withdraw from the UBI program before 6 months of usage. As shown in Figure 2, less than 1% of UBI customers enrolled in this program but never installed the telematics device. We observe some patterns in the dropout 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 15% of UBI customers dropped out of the UBI policy in weeks 11 and 12

[11] P-value = 0.06

[12] To analyze the changes in driving behavior of customers, we use the data from customers who adopted the UBI policy before June 2014 whose entire driving behavior in six months can be observed in our dataset.

Figure 2: The dropout rate within UBI program.



combined. As discussed below, the dropout pattern seems to be related to the revised UBI score and it can potentially lead to a selection issue in our later analysis. By dropping out after receiving the updated discount, we mean that the customer no longer agrees to be monitored and she receives the (adjusted) UBI permanent discount at the time the telematics device is removed based on her actual driving performance during monitoring. However, we find that our main results hold whether or not people drop out after receiving the initial feedback[13].

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

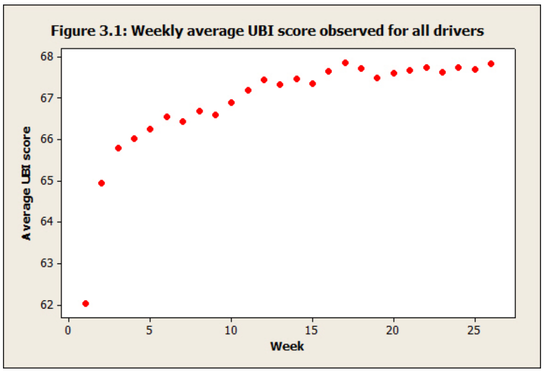
We start by presenting some basic descriptive evidence about the changes in driving behavior of UBI customers and the improvement in some measures of driving performance. Our data suggest that the UBI dropout decision may be correlated with these customers' driving behavior, so we need more rigorous empirical models to show that the improvements in driving behavior are robust to these sample selection issues.

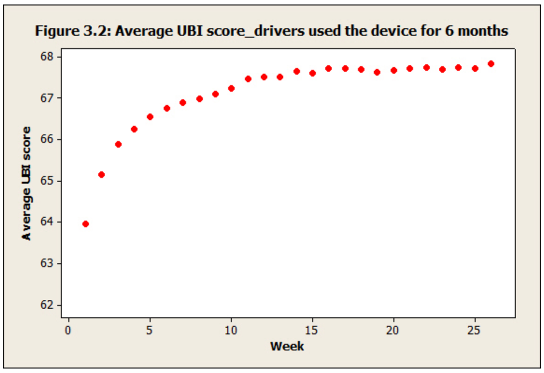
- **The weekly average UBI score.**

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, we cannot observe the driving score of some customers for all 26 weeks because they cancel their UBI policies before 6 months. For example, the number of UBI customers for whom we observe driving scores for the last week (week 26) is about 35 % lower than the first week

[13] 63% of UBI customers remain in this program for the entire 26 weeks. As shown in Online Appendix A1.3, withdrawing early decreases the level of permanent discount that a customer receives, but they still receive a discount on average.

Figure 3: The weekly average UBI score.





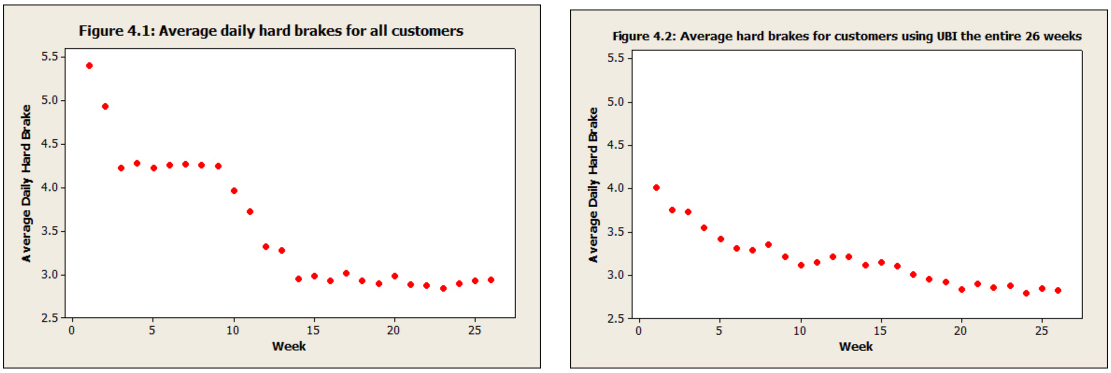
because of UBI policy dropouts during the 26 weeks. Figure 3.2 helps us better understand this issue; the plot shows the weekly average UBI driving score of customers who used the monitoring device for 6 months. The average UBI score in this sample for week 1 was 63.92 and increased to 67.87 in week 26. Although there are some differences in the weekly average values of the UBI score across the two samples, the overall pattern is similar, a finding supported later in the paper when we employ a more fully developed (fixed effects with panel data) econometric model of driving performance.

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

The daily number of hard brakes is a direct measure of driving behavior that we 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 risky situations in which they needed to brake hard[14]. 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 had on average 5.5 hard brakes in a day, while in the last week of our dataset, the average number of hard brakes is less than 3, a significant change and improvement in driving behavior. A steep change happens around week 10 to week 12, which is the time that the insurance company updates 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 a factor 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 may in part be due to relatively high hard-brake customers opting

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

Figure 4: The average daily number of hard brakes.



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**

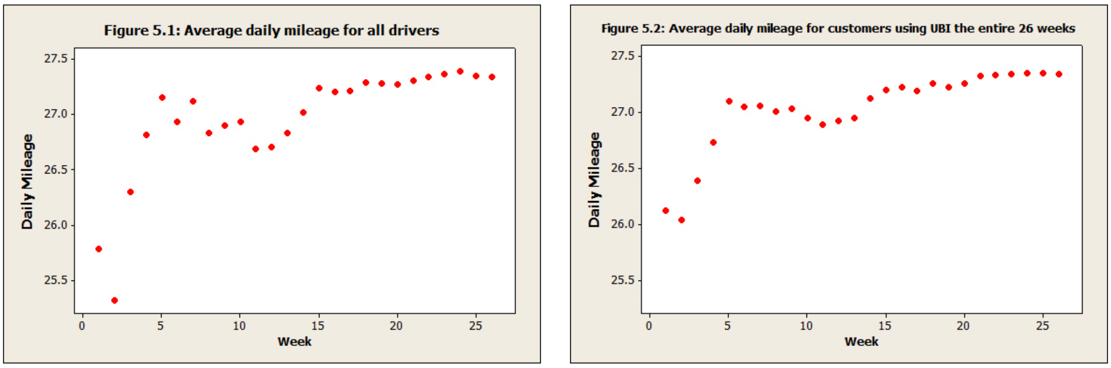
Daily mileage is also tracked by the UBI telematics device. Average daily mileage per week of UBI customers is shown in Figure 5. Interestingly, the weekly mileage driven first increases, although not uniformly, and then appears to be relatively constant (within +/- .5 miles compared to an overall average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

The descriptive analysis in this section provides suggestive evidence of improvement in the driving behavior of auto insurance customers who adopt the UBI policy. However, the dropout decision of customers, which may be related in part to their driving behavior, 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 behavior of UBI customers is robust to such factors and to test for the existence of heterogeneity across different groups of customers. In the next section of this paper, using our panel data we propose a fixed effects model to address these issues.

4. Empirical Analysis and Results

In this section, we analyze how the customers have changed their driving behavior during their UBI adoption period. We first describe our empirical approach and the construction of our key

Figure 5: The average daily mileage.



explanatory variables. Our baseline specifications are regressions of observed UBI scores and indicators of driver behaviors during the time period when they are enrolled in the UBI program and control variables. We consider both age and gender of each customer as control variables in the regression and first estimate the weekly changes in driving behavior of UBI customers by cross-sectional regression analysis. As we explained in the data section, for UBI customers we have their driving behavior measures (UBI scores, daily number of hard brakes, and daily mileage) for up to 6 months of monitoring by a telematics device. We start by examining 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,

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

$$Age_i : the\ age\ of\ driver\ i.$$

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

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

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

$$week\_dummies_{it} = [dummy_{i2},\ ...,\ dummy_{i26}]'$$

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

Table 2: Cross-sectional regression analysis results for UBI score.[15]
(*): p-value < 0.05, (**): p-value < 0.01

Cross sectional regression analysis results for UBI score			
	Estimate	Std. Error	Pr(> $\|t\|$)
(Intercept)	63.47	0.08	**
Age	-0.12	0.01	**
Gender (Female)	3.12	0.03	**
Week_dummy2	3.60	0.10	**
Week_dummy3	3.95	0.10	**
Week_dummy4	4.06	0.10	**
Week_dummy5	4.18	0.10	**
Week_dummy6	4.14	0.10	**
Week_dummy7	4.30	0.10	**
Week_dummy8	4.43	0.10	**
Week_dummy9	4.59	0.10	**
Week_dummy10	4.76	0.10	**
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: 0.134	

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

Table 2 shows the estimation results of the cross-sectional regression analysis. The age variable has a negative relationship with the 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 UBI scores, implying that they are safer drivers. Females' UBI scores are 3.12 points higher than male scores on average, suggesting that females on average have better driving behavior than males in the UBI program. Considering all positive and significant coefficients of week dummy variables, the UBI customers achieve higher UBI scores over the total period of UBI usage in comparison to the first week, 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. This approach allows us to better control for individual variations in

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

driving ability, willingness to remain in the UBI program, and other idiosyncratic factors. Consequently, we estimate a regression model (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-effects parameter of driver.

Table 3 is the estimation result of the fixed effects regression model for UBI score. Based on Table 3, all 25 weekly coefficients are significantly positive, implying that customers have better UBI scores on average compared to those from the first week. The last column of Table 3 indicates whether the weekly change in UBI score in week t is significant in comparison to the previous week (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 and receiving feedback in the first three months of usage, and their behavior 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 effects 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 behavior (number of hard brakes and mileage) as dependent variables in our fixed effects regression (2) to capture the weekly changes in driving behavior of UBI customers in terms of number of hard brakes and mileage driven.

Table 4 shows the result of fixed effects 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 effects 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 over the monitoring period.

In terms of daily mileage driven by UBI customers, we run a similar fixed effects 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).

Table 3: Fixed effects regression analysis results for UBI score.
(*): p-value < 0.05, (**): p-value < 0.01

Fixed effects regression analysis results for UBI score			
	Estimate	Std. Error	Weekly improvement Pr(> $\|t\|$)
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	3.40	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	4.40	0.02	
Week_dummy21	4.44	0.02	
Week_dummy22	4.47	0.02	
Week_dummy23	4.50	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 effects models in this section to capture weekly driving behavior 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.[16] 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 behavior for customers. For drivers, it is more convenient and less costly to change the number of hard brakes and learn from the in-car feedback in order to improve their driving safety level, than to reduce their automobile usage (mileage). Another interesting point is that after the UBI score and hard brakes stabilize at a level at which the scores do not improve weekly (after week 11) 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 the UBI program sustain for at least 26 weeks the driving behavior changes they make in the first 3 months of UBI usage.

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

Table 4: Fixed effects regression analysis results for number of “Hard Brakes”.
(*): p-value < 0.05, (**): p-value < 0.01

Fixed effects regression analysis results for number of Hard Brakes			
	Estimate	Std. Error	Weekly improvement Pr($>\lvert t\rvert$)
$Week\_dummy2$	-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	
$Week\_dummy16$	-0.50	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	
$Week\_dummy23$	-0.60	0.03	
$Week\_dummy24$	-0.62	0.03	
$Week\_dummy25$	-0.60	0.03	
$Week\_dummy26$	-0.61	0.03	
Multiple R-squared: 0.386			Adjusted R-squared: 0.378

4.2. Heterogeneity across Different Groups of Customers

In this section, we investigate possible heterogeneity in driving behavior changes across different age groups, genders, and enrollment status. The cross-sectional regression results show that the average UBI score is different across age groups and for females versus males, so in this section we consider fixed effects models to capture the weekly changes in driving behavior for different customer groups. In addition, we compare the changes in driving behavior of loyal customers who keep the UBI device for six months and UBI dropouts who cancel this policy before six months of usage.

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

$$S_{it} = \alpha_0 + \beta' \times week\_dummies_{it} + \gamma_2' \times age\_group2_i \times week\_dummies_{it} + \gamma_3' \times age\_group3_i \times week\_dummies_{it} + \gamma_4' \times age\_group4_i \times week\_dummies_{it} + driver_i + \varepsilon_{it}. \quad (3)$$

Table 5: Fixed effects regression analysis results for daily driven mileage.
(*): p-value < 0.05, (**): p-value < 0.01

Fixed effects regression analysis results for daily Driven mileage			
	Estimate	Std. Error	$\Pr(>\lvert t\rvert)$
Week_dummy2	-0.06	0.05	
Week_dummy3	0.13	0.07	
Week_dummy4	0.10	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	0.10	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	0.60	0.32	
Week_dummy24	0.61	0.35	
Week_dummy25	0.60	0.34	
Week_dummy26	0.59	0.36	
Multiple R-squared: 0.296			Adjusted R-squared: 0.285

Where,

$$age\_group1_i = \begin{cases} 1 & age\ of\ driver\ i \leq 35 \\ 0 & else \end{cases}$$

$$age\_group2_i = \begin{cases} 1 & 35 < age\ of\ driver\ i \leq 50 \\ 0 & else \end{cases}$$

$$age\_group3_i = \begin{cases} 1 & 50 < age\ of\ driver\ i \leq 65 \\ 0 & else \end{cases}$$

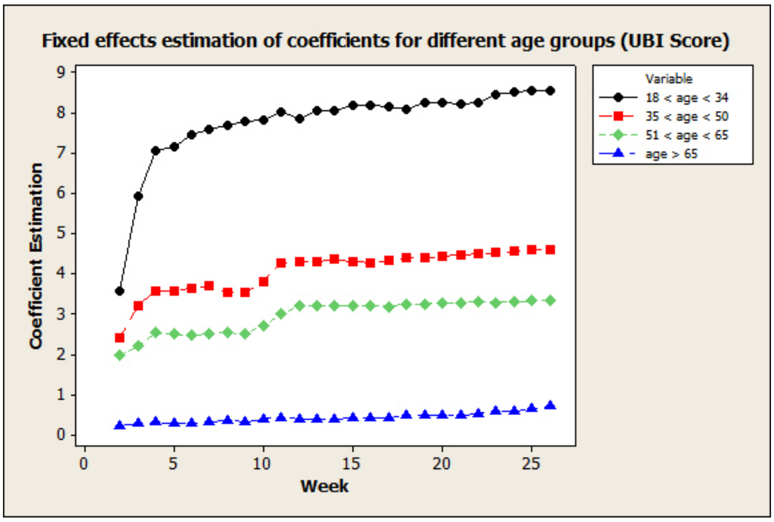
$$age\_group4_i = \begin{cases} 1 & 65 < age\ of\ driver\ i \\ 0 & else \end{cases}$$

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

In the above setting, we consider four age groups, which are commonly employed in the auto insurance industry[17]. The youngest group consists 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 the baseline in our fixed effects model, therefore the β represents the changes in UBI score for the youngest age

[17] 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- millennials (<35): 61.78, 2- digital natives (35-50): 61.65, 3- baby boomers (50-65): 63.14, and 4- seniors (>65): 65.73



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.

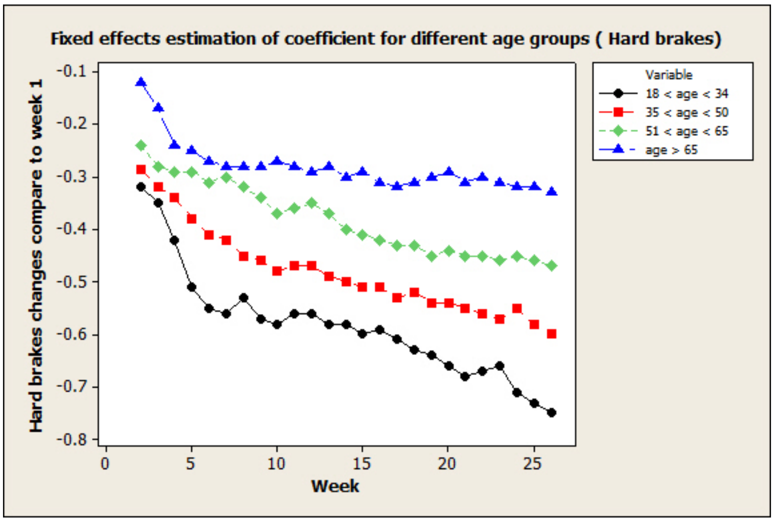
Since there are multiple parameters to estimate in the fixed effects model with interaction effects ($4 \times 25 = 100$ parameters), the results in this section are represented by plots. The full set of results for all fixed effects models can be found in the Online Appendix 2.

Figure 6 shows the estimate of weekly changes in UBI score for four age groups in the fixed effects regression model by estimating the coefficients of 25 week dummy variables and 75 parameters related to interaction effects. As we can see in 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 during their participation in the program.

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 behavior 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 score 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

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- millennials (<35): 4.14, 2- digital natives (35-50): 4.08, 3- baby boomers (50-65): 3.95, and 4- seniors (>65): 3.93



UBI score after 26 weeks of UBI usage for senior drivers[18]. This result seems to be consistent with negative estimation of age coefficient in the cross sectional regression analysis, which means the 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 ones. 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.

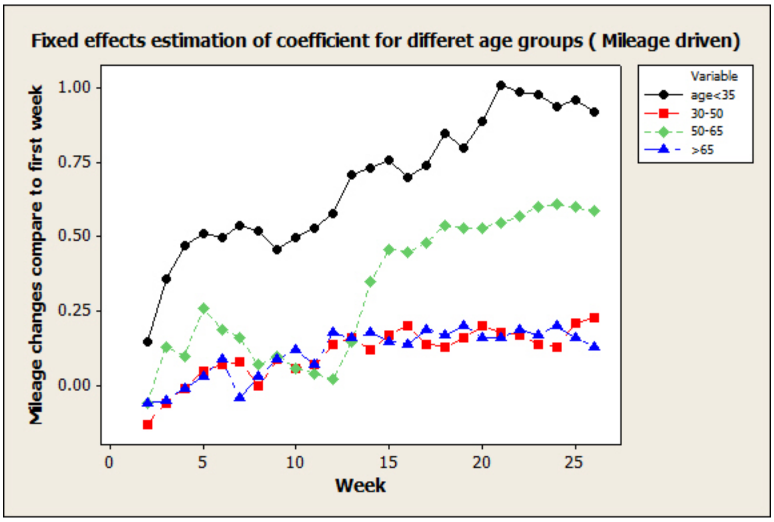
Similar to the UBI score results, the daily number of hard brakes reduction (driving behavior improvement) for the youngest drivers is stronger than for senior drivers. The youngest group has the highest initial number of hard brakes, but this group of drivers significantly reduced their number of hard 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

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

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- millennials (<35): 25.73, 2- digital natives (35-50): 31.45, 3- baby boomers (50-65): 30.54, and 4- seniors (>65): 24.96



is significantly ($p < 0.05$) higher than in the first week[19], which, if anything, would limit their improvement in UBI score. No other age group exhibits a significant change in mileage.

We find that the driving behavior changes of UBI customers, in terms of UBI score and number of hard brakes, differ across customer age groups; and that the youngest drivers are more responsive than older age groups to UBI usage in terms of 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 behavior improvement for females versus males.

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

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

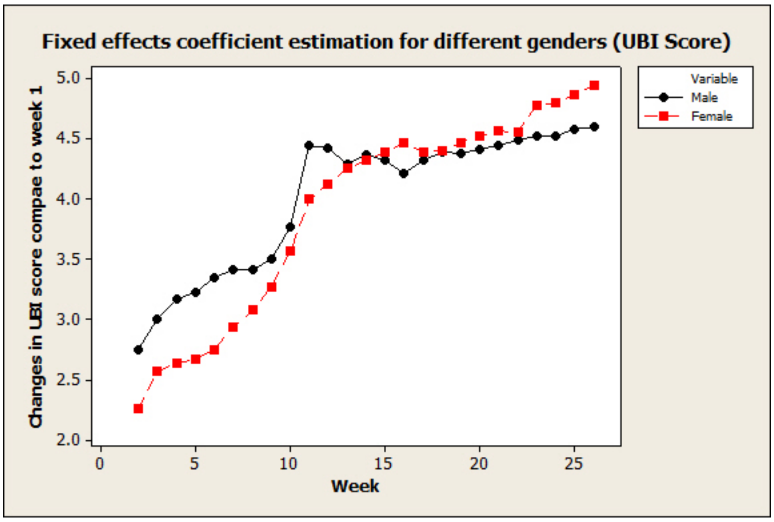
Where,

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

Figure 9 shows the result of the fixed effects 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

[19] The mileage in week 26 is 0.92 miles higher than in the first week.

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



improve their driving behavior less than the male drivers; however, later it appears 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 advancing, which leads to higher UBI score, improvements in UBI scores diminish for male drivers while the females continue to improve in later weeks. In Online Appendix 3 we show the week in which drivers stop improvement in their driving behavior compared to the last-week performance for different groups of drivers and find that improvement ends in week 15 for males and week 23 for females. In addition to different patterns over time for males versus females, we note that females have 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.

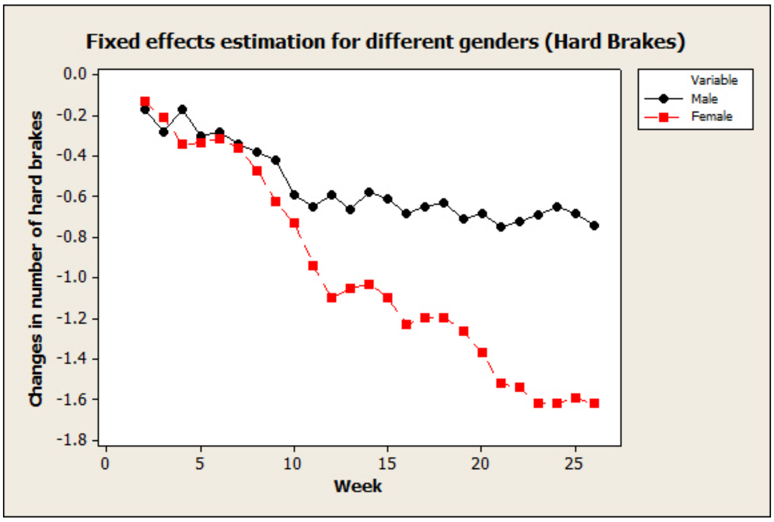
We have done similar analysis for changes in number of hard brakes by gender. Figure 10 shows the results of estimation for both males and females. Each plot point represents the weekly changes in daily number of hard brakes for males and females compared to that in the first week.

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 hard brakes significantly more than males. Nevertheless, after 26 weeks, females still have a higher number (3.92) of hard brakes than males (3.02).[20]

UBI dropouts and loyal customers. In this section, we further examine the differences in driving behaviors of the customers who withdraw from the UBI monitoring program before 6

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

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



months (dropouts) and the UBI customers who continue to use the telematics devices for the full 6 months (loyals), the maximum time for monitoring. As we discussed earlier, the driving behavior of customers, which leads to a UBI discount rate, may affect the customer's decision to keep the UBI policy or withdraw from it. For instance, if a customer has a lower UBI score improvement on average, then he or she may be more likely to terminate the UBI monitoring early. This selection issue may adversely affect our analysis. In this section, we want to focus more directly on dropouts and loyal UBI customers to capture differences in their behavior changes after UBI adoption. To do so, we divide the drivers who enroll in the UBI program into four groups: (1) loyals, who continue in the monitoring program for all 26 weeks, (2) early dropouts, who remove their devices within the first 10 weeks before obtaining an updated UBI discount, (3) informed dropouts, who remove their UBI device in weeks 11 and 12, just after being informed of their updated UBI discount, and (4) late dropouts, who drop out in weeks 13-25. The last two groups, despite dropping out early, receive a (revised) discount that applies to their automobile insurance premiums. It is important to note that for 3 groups of customers (loyal, informed, and late dropouts), their UBI scores at the time when their telematics devices are removed are significantly higher than in the initial week of enrollment. But for early dropouts, there is no significant difference. Table 6 compares the 4 groups on a number of variables of interest.

As can be seen in Table 6, only 4% of UBI adopters remove their device within the first 10 weeks. As a group, they are slightly older than the other groups, have a better insurance score and a lower premium; most importantly, they have a much higher rate of non-renewal. It is unclear why they choose to drop out so early in the program, but perhaps they found the inconvenience of having the device in their car, the immediate feedback on hard brakes, and privacy costs as being too high, even considering that they were giving up a UBI discount. Furthermore, they only include 4% of the UBI enrollees. Therefore we do not investigate their behavior further. On the other hand, in weeks 11 and 12 (just after getting the updated discount), we observe a spike to 15% in dropouts. The weekly dropout rate declines sharply after that, and only 17% of enrollees drop out in the remaining 13 weeks before the end of the monitoring period. Both the informed dropout group and the late dropout group are informed about their updated UBI scores, receive (on average) an upwardly revised discount rate, and have presumably adjusted to the inclusion of a monitoring device in their car. As shown in Table 6, late dropouts are quite similar to loyals in many ways, except that they are less likely to renew with the focal company. By contrast, the informed dropouts seem to be quite different from the loyals, especially with regard to their driving behavior. Figure 11 shows the average UBI score of customers who disconnect their UBI device in week 11 or later. This graph shows that the late dropouts' UBI score does not seem to be significantly different from loyal customers; but informed dropouts, who disconnect in weeks 11 and 12 after receiving their updated discount, differ from loyal customers in a number of important ways. Consequently, we focus on these two groups of customers in our further analysis. Online Appendix 4 provides a comparison of loyal and late dropout customers in terms of their UBI score in the first ten weeks of UBI usage where most of the improvement in driving behavior happens in this period of time.

Table 6: Loyal and dropouts.

	Loyal	Early dropouts (<week11)	Informed dropouts(11&12)	Late dropouts (>week12)
Number of Customers	18067	1159	4222	4876
Age	38.43	42.54	41.17	39.15
Fraction Male	0.51	0.52	0.53	0.51
Average Initial Discount	0.05	0.05	0.05	0.05
Insurance Score	49.19	51.43	50.37	49.43
Initial Premium	114.83	109.86	111.03	113.04
Updated Initial Discount	0.091	0	0.074	0.081
First Renewal Rate	0.9	0.44	0.73	0.77
Fraction of Enrolls	0.638	0.041	0.149	0.172

To model the heterogeneity between the informed dropouts' (weeks 11 and 12) and loyal customers' improvement in UBI score, we estimate a fixed effects model that allows for different behavior changes for loyals and informed dropouts.

$$S_{it} = \alpha_0 + \beta' \times week\_dummies_{it} + \delta' \times Loyal_i \times week\_dummies_{it} + driver_i + \varepsilon_{it}. \tag{5}$$

Where,

$$Loyal_{it} = \begin{cases} 1 & \textit{UBI driver i is loyal} \\ 0 & \textit{driver i cancel the UBI at week 11 or 12 (Informed dropouts)} \end{cases}$$

Figure 11: Average UBI score of dropouts and loyal customers.

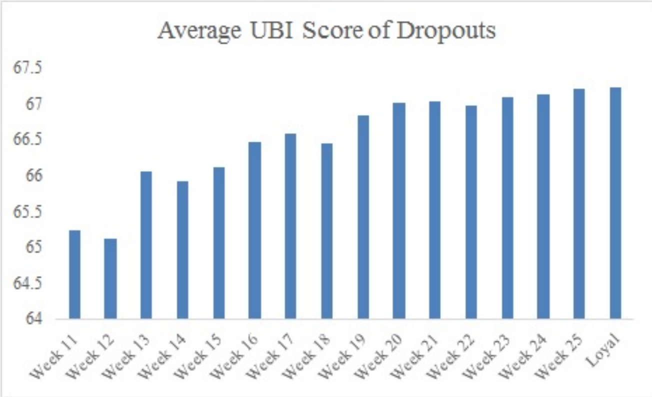


Table 7: Fixed effects regression analysis results for UBI score of informed dropouts and loyal customers.

(*): p-value < 0.05, (**): p-value < 0.01

	Base_Estimation	Loyalty interaction	Loyalty Pr($>\|t\|$)
Week_dummy2	1.23	0.52	**
Week_dummy3	1.72	0.65	**
Week_dummy4	1.90	0.64	**
Week_dummy5	2.29	0.51	**
Week_dummy6	2.66	0.52	**
Week_dummy7	2.89	0.40	*
Week_dummy8	2.93	0.42	*
Week_dummy9	3.08	0.41	*
Week_dummy10	3.14	0.43	*
Multiple R-squared: 0.364		Adjusted R-squared: 0.360	

Table 7 shows the result of the fixed effects model for UBI score when we add the interactions of loyal customers and week variables. The results show that there is improvement in driving behavior of both groups after adopting the UBI policy, but the improvement in driving behavior of loyal customers is significantly higher than that of dropouts in the first 10 weeks of UBI usage.

In summary, we show that informed dropouts, late dropouts, and loyals all improve their driving behavior while being monitored by the UBI telematics device that was installed in their automobiles. However, learning rates vary across groups. The results show that the loyal customers change their driving behaviors more than informed dropouts in the first 10 weeks of UBI usage; that is, the improvement in driving behavior of loyal customers is faster than for informed dropouts. As a result of their faster improvement, customers in the loyal group received a higher average updated UBI discount (9.1%) than informed dropouts (7.4%).

5. Economic Incentives

In the previous section, we found that the customers who adopted the UBI program despite the privacy issues improved their driving behavior while being monitored by the telematics device. There are at least two motivations for the improvement in behavior: first, the improvement that occurs because consumers respond to feedback from the 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 gauge their healthy behavior via receiving feedback from that device. In addition, a second source for driving behavior improvement is its economic incentives. In other words, the benefit of discount and net premium reduction from the UBI policy may lead to customer's improvement in driving performance. Both effects are likely present in the empirical results we report 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 driver performance. In other words, we want to see how the opportunity of lowering the premium in the UBI policy can encourage 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 analyze how the improvement in driving behavior changes in relation to 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 risk preferences to avoid the selection issues in our identification.

The customers in our dataset are from 15 states, which allows us to explore the regulatory differences in auto insurance across states. The regulations in auto insurance markets in different states affect the insurance companies' cost and the premiums for consumers. Such policy differences are exogenous factors that generate variations in insurance premiums among consumers in different states. We leverage this fact in our further analysis to identify the economic incentives effect on changing driving behavior. Next, we introduce the No-Fault insurance system versus Fault (or Tort) auto insurance as they are regulated in different states.

5.1. No-Fault auto insurance

By definition, a 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.)

Table 8: 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

When first enacted in the 1970s in some states, No-Fault automobile insurance had many advocates. Its central idea was simply that an injured accident victim would 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.

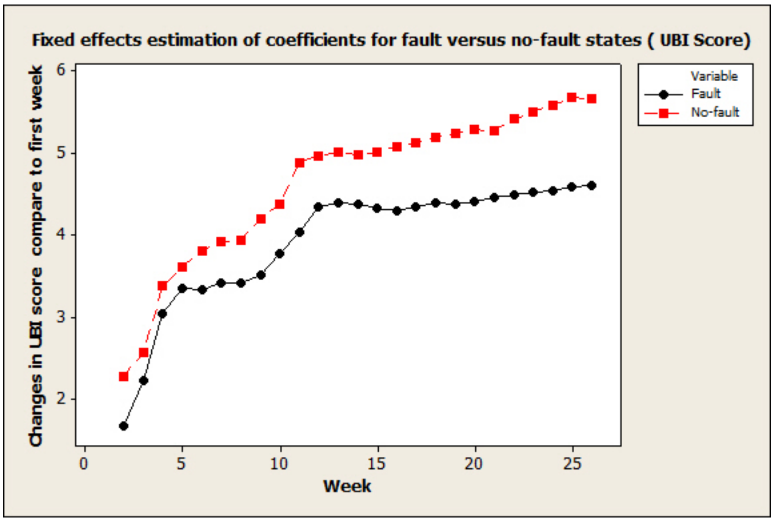
In 2015, 13 states in the US mandate the use of a No-Fault auto insurance policy. (Some states, but none in our dataset, allow both No-Fault and tort insurance.) A 2012 RAND Corporation study found that costs and premiums are significantly higher in No-Fault than Fault (tort) systems. Following the previous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

As 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 8 shows the data summary on No-Fault versus Fault (tort) insurance system states in our dataset.

Although the average monthly premium in No-Fault states is significantly higher than in traditional Fault states[21], the demographic variables of 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 a significantly higher UBI acceptance rate ($p < 0.05$) 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,

[21] This is consistent with the Rand study, which shows that the premium in No-Fault states is higher.

Figure 12: 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



comparing the changes in driving behavior 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 behavior improvement in the UBI program.

We employ a fixed effects model to test for changes in driving behaviors across two types of states by considering the interaction of state type variable (Fault & No-Fault) and week dummy variables (See Figure 12). We find that the average UBI score in No-Fault insurance states in the first week is marginally higher ($p < 0.07$) 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 greater, is significantly higher ($p < 0.05$) than in Fault states ($mean = 4.6$). We find similar results for the number of hard brakes. (See Online Appendix 2.) 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.

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 behavior 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 this innovation and the monitoring inherent in the UBI system could result in improved driving performance despite the privacy issues from the customer's perspective, 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 behavior, we use a unique sensor-based dataset, which allows us to observe the individual-level customer data from a major US insurance company and track the driving behavior of customers who enrolled in the UBI program for up to 6 months. Our empirical results show that UBI customers improve their driving behavior by increasing their UBI scores by 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; 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 other behaviors such as the number of daily hard brakes. Changing such behaviors 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 that signals whenever a hard brake is made may have a particularly strong effect, and the multi-dimensional overall UBI scores improves as well.

Importantly, behavior changes occur immediately after a consumer adopts the UBI program, and continues throughout the observation period. For both the overall UBI score and number of hard brakes, we observe their improvement, as compared to the first week, as soon as the second week. After 11 weeks for the UBI score and 6 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 periods. Due to the limitation of the technology, we cannot observe the drivers' behavior after the removal of the UBI device (at most 26 weeks), but behavior patterns in the 26 weeks provide 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 behavior 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 scores than the oldest group of drivers (those over 65), they improve their driving behavior so much that after 6 months of UBI usage, the youngest group has the highest average UBI scores among all age groups. Higher economic incentives and different learning patterns for younger drivers compared to seniors could be the key factors that can explain their greater improvement in driving behavior. In other words, since the initial premium of younger drivers on average is higher than for seniors, younger drivers can save more than older drivers by improving the driving behavior, possibly leading to greater effort to improve their driving performance. Younger drivers, particularly those with limited driving experience, may learn faster and may adjust their driving behavior more easily after getting feedback. In this paper, we don't separately identify these key factors underlying the differences in driving behavior changes across age groups, but leave those issues for future research.

With regard to gender, females have a higher initial UBI score than males and improve their score more while being monitored, resulting in 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 behavior due to the feedback obtained and the economic 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).

Further, we find that there is heterogeneity in changing the driving behavior of loyal UBI customers who use the UBI device for the entire 6 months and informed dropouts who remove the UBI monitoring device shortly after getting the updated discount, 75 days after the start of UBI usage. Loyal customers tend to have better UBI scores than the informed dropouts. These results can be evidence that the customer's decision to keep or cancel the UBI policy after adoption may be related to their observed driving behavior and the expected discount from the UBI program. For motorists concerned about the privacy of their information, those who drop out after being informed of their 75-day score are limiting the insurance company's monitoring to the minimum possible time needed to earn a permanent discount.

To further understand the potential underlying mechanisms driving the behavior changes, we explore the different regulations across states in our dataset. In states where 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 states. Therefore, we argue that since the customers who enroll in the UBI policy in No-Fault states (higher-premium states) can save more than in the other states, these customers try to improve their driving behaviors more in order to get a higher discount rate on their initial premiums, suggesting that economic incentives are important in the level of driving improvement that occurs.

Privacy issues and consumer benefits. As Goldfarb and Tucker (2013) indicate, new technologies allow companies to monitor a consumer's actual behavior at very low cost. However, people are increasingly concerned about the privacy of their information and may be reluctant to share their information. At times, such as in credit card transactions, individuals have minimal control over how their information is used and stored. In other cases, such as in the installation of the UBI telematics devices studied here, consumers can decide to install the devices or not and to remove them at any point in time.

Importantly, in this study we show that there are direct benefits to the individuals from agreeing to have their behavior directly monitored. We observe two main benefits: (1) driving performance (as measured by the overall UBI score and the number of hard brakes) improves, and (2) participants (who remain in the program for at least 75 days) receive a discount on the auto insurance premium that they would have been charged if they had not been in the UBI program. While our data suggest that the improvement in driving behavior starts early after the monitoring period begins and is maintained throughout the participation period, we cannot directly measure whether the improvement continues over time; by contrast, the discount is permanent for as long as the person remains in the contract with the company. Participants in the UBI program have higher renewal rates than non-participants, suggesting that these benefits are of value to individuals who enrolled in the program.

While we are able to show benefits of the program to the individual, we do not have an accurate reading on the costs. While the costs to the individual go beyond privacy concerns, we note that approximately 70% of the firm's new customers choose not to enroll in the programs and about 15% of enrollees remove the devices after 75 days, the minimum time to receive a permanent discount. As we discuss below, investigating consumers' concerns about privacy is worthwhile.

Managerial implications. While our research raises issues of privacy that the firm must address, it also uncovers some areas that are important for considering the profitability of such a program. From the company's point of view, the higher renewal rate of UBI customers as compared to non-UBI customers is managerially significant, as customer acquisition is typically very costly in any service business. Combining this result with the improvement in driving behavior of drivers in the UBI program may further justify the firm's adoption of UBI as a way to improve profits, even after considering the costs of the program and the discounts provided.

The heterogeneous effect of UBI policy on changing driving behavior across age groups is another interesting managerial result. The youngest group of drivers (millennials) has the lowest insurance score, likely because of insufficient driving history. However, the improvement in their driving behavior (UBI score and number of hard brakes) resulting in their average UBI score after 6 months of monitoring being higher than for the other age groups suggests that the youngest group of drivers comprise an attractive target market for companies offering UBI programs. In a competitive environment, more innovative insurers can not only attract more younger drivers by offering a UBI program, but also this group can be profitable for the insurance company by improving the driving behavior in the long term. If the company can retain these younger drivers over the long term, this would be an important benefit to the company.

On the other hand, the difference between the driving behavior and renewal rates of loyal UBI customers and dropouts may be another important finding for managers. In particular, the company needs to decide when and how often to provide updated discounts, what those discounts (and the initial one) should be, and how long the monitoring period should last. In our paper, we show that about 15% of participants drop out after receiving feedback on driving performance and updated discounts after 75 days. Hence from the firm's perspective, providing driving feedback to the customers and updating the initial discount may affect the customer's decision to keep using the UBI device or to remove it. Our data show that customers who maintain the device for the full 26 weeks are more likely to renew their insurance with the company than those who drop out earlier. These results suggest that the firm should consider alternative feedback and discounting programs, at a minimum to encourage current enrollees to stay for the full 26 weeks. While examining the effects of changes in the initial discount is beyond the scope of the present paper, it would seem likely that changing the initial discount levels would have an impact on the pool of customers who choose to enroll in the UBI program.

Similarly, analyzing the effect of the economic incentives in a UBI policy may help companies improve the efficiency of their pricing strategies. We have shown that drivers improve their driving behavior 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 design the premium and discount policy in a UBI program in a way to both attract drivers and encourage them to drive more safely, which should lead to higher profit for the firm.

Limitations and future research. One caveat of our findings is that the behavior 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 behavioral 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. One interesting aspect of the UBI program is that the terms of the program make it quite explicit that the company will be monitoring individual driving behavior, where possibly many individuals may not realize the monitoring that is taking place due to factory-installed electronic devices or their use of such apps as Waze.

There are also several avenues in which the model and empirical analysis can be extended in future research. First, as we mentioned earlier, the customer's decision to adopt 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 the 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 behaviors. For example, 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 could extend beyond the level of personal health.

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